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Automated Macro-Texture Characterization of Road Surfaces Using Photogrammetric 3D Models



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TABLE OF CONTENTS

INTRODUCTION.....	
1 State of the Art and Theoretical Foundations.....	1
1.1 Road Pavement Texture: Hierarchy of Irregularities and Influence on Skid Resistance .	3
1.1.1 Correlation between Texture and Skid Resistance: Surveying Methodology	6
1.2 Descriptive Parameters of Macro-Texture: MTD (Mean Texture Depth) and MPD (Mean Profile Depth)	10
1.2.1 Mean Texture Depth (MTD) and the Volumetric Method.....	10
1.2.2 Mean Profile Depth (MPD) and Digital Analysis	11
1.2.3 Correlation between the parameters: the Estimated Texture Depth	12
1.2.4 Research Approach.....	13
1.3 Non-Destructive Survey Techniques: Digital Photogrammetry and Structured Lights .	14
1.3.1 The Digital Photogrammetry	14
1.3.2 The Structured Light Method: Principles and Operational Challenges	17
2 Experimental Setup and Data Acquisition Instrumentation	19
2.1 Structured Light Scanning: Mantis Vision F6-SR.....	23
2.2 Smartphone Optical Sensor: iPhone 15 Plus	25
2.3 Study Materials: Granite Slab and Bituminous Mixture Specimen	28
2.3.1 Reference Surface: Granite Slab	28
2.3.2 Real-World Sample: Bituminous Mixture Specimen	29
2.4 Software Ecosystem	30
2.4.1 Agisoft Metashape Professional	30
2.4.2 CloudCompare	32
2.4.3 QGIS.....	33
2.4.4 RealityScan as a Low-Cost Photogrammetric Processing Tool	34
3 Phase I: Data Acquisition Protocol.....	36
3.1 Photogrammetric Survey Planning	36
3.2 Marker Positioning Strategy	39
3.3 Survey Execution: Photographic Series Acquisition via iPhone 15 Plus and Reference Scanning with Mantis Vision F6-SR	42
3.3.1 Structured Light Scanning and Preliminary Procedure.....	43
3.3.2 Smartphone Photogrammetric Acquisition and Execution of the Sand Patch Test.	44
3.4 Post-Test State Sampling: Survey Procedure of the Surface After Sand Spreading for Subsequent Differential Analysis	45
4 Phase II: Digital Processing and 3D Reconstruction	49
4.1 Structure from Motion (SfM) Workflow: Image Alignment and Dense Point Cloud Generation	49

4.2	Scaling and Georeferencing: Utilizing Metashape Pro for Metric Constraints via Graduated Markers	53
4.3	Optimization and Registration: Application of the ICP Algorithm in CloudCompare for Alignment Between Different Surface States	56
4.4	Generation of Raster Products: Creation of High-Resolution Digital Elevation Models and Orthomosaics	60
4.5	Comparative Analysis of Reconstruction Engines: Preliminary Assessment of RealityScan Against Agisoft Metashape.....	63
5	Phase III: 3D Model Analysis and AI-Assisted Algorithm Development.....	67
5.1	Evolution of the Differential Method: From QGIS-Based Processing to Volumetric Calculation in CloudCompare	67
5.1.1	Limitations of the Differential Method: Operational Criticalities and the Need for a “Sand-Free” Approach”.....	69
5.2	From Point Cloud to Numerical Matrix: Transition to Python-Based Automation.....	71
5.3	Development of the Python Algorithm for the “Sand-Free” Approach.....	73
5.3.1	Definition of the Calculation Domain and Boundary Constraints	74
5.3.2	Implementation of the Moving Mask and Extraction of Relative Maxima: Calculation Algorithm and Sand Layer Simulation	77
5.3.3	Operational Architecture of the Application, Control Panel, and Computational Efficiency	82
5.4	Development of the Python Algorithm for MPD Extraction.....	83
5.4.1	Transcoding of the Technical Standard	84
5.4.2	AI-Assisted Code Adaptation and Implementations	86
5.4.3	Architecture of the Configuration Panel and Guided Execution.....	88
5.5	Summary of Automated Extraction of Macro-Textural Parameters.....	89
6	Experimental Analysis and Discussion of Results	91
6.1	Performance Comparison: Actual Sand Volume, Digital Estimation, and Algorithm-Based Estimation for MTD Calculation.....	91
6.1.1	Analysis of the Bituminous Mixture Specimen.....	91
6.1.2	Analysis of the Granite Slabs and the Limitations of Commercial Software.....	97
6.2	Accuracy and Sensitivity of the MPD Algorithm: Method Response to Different Surface Conditions and Survey Densities.....	102
6.2.1	Rationalization of Step Size for Profilometric Analysis	102
6.2.2	Spatial Sensitivity Analysis: Statistical Stability Under Sampling Strides	103
6.2.3	Comparative assessment: Consistency Between Standardized ETD and Custom MTD.....	109
6.3	Workflow Efficiency Assessment: Balancing Metric Accuracy and Software Costs... ..	112
6.3.1	Comparative Analysis of Commercial Software and Traditional GIS	112
6.3.2	Overcoming Programming Barriers and the Potential Role of AI-Assisted Development	113

Conclusions and Future Perspectives	115
References	119

INTRODUCTION

The management and maintenance of road infrastructures represent, within the contemporary engineering landscape, one of the most complex challenges in terms of public safety and resource optimization. In this context, the surface characteristics of the road pavement play a decisive role in defining the tire-road interaction, directly influencing critical parameters such as skid resistance, rainwater drainage, and, consequently, vehicle braking distances. Among these characteristics, macro-texture stands out as a key parameter to ensure safety in wet conditions, contributing to the prevention of aquaplaning phenomena and guaranteeing the rubber hysteresis necessary for the development of frictional forces.

Historically, the evaluation of macro-texture has been entrusted to direct and manual methodologies, among which the so-called *Sand Patch Method* stands out, by international standards EN ISO 13036-1 [1]. Despite its proven theoretical reliability, this approach currently presents evident operational limitations: the discrete nature of the survey, the high dependence on the operator's skill, prolonged execution times, and the need to interrupt traffic flow make the test inflexible and difficult to integrate into modern infrastructure digitalization processes. Furthermore, the impossibility of storing three-dimensional geometric data of the analysed surface precludes the creation of a accessible historical record and the possibility of performing subsequent analysis without new on-site inspections.

The present thesis is situated within this technological path, proposing a digital and systematic alternative to traditional methods. The primary objective of the research is the development and preliminary assessment of a workflow based on close-range photogrammetry, aimed at creating a digital library of road texture. The innovation lies in the effort to democratize technical surveying: the selection of a latest-generation smartphone, specifically an iPhone 15 Plus, represents a precise strategy to investigate whether smartphone photogrammetry can provide comparable texture indicators under controlled laboratory conditions, when supported by a rigorous methodological control.

The technical suitability of the optical sensor used was preliminarily assessed through the determination of the GSD (*Ground Sample Distance*) value, a fundamental parameter to ensure that the spatial resolution of the acquired images was consistent with the millimetric dimensions of the macro-texture to be investigated.

Once the suitability of the instrument was preliminarily assessed, the experimentation followed an iterative path aimed at testing the performance of the digital method.

In a first phase, the research addressed the so-called “boundary case” through the analysis of a granite slab. The choice of a stone material characterized by extremely reduced roughness and an almost smooth texture allowed for testing the sensitivity of the reconstruction and point cloud alignment algorithms (via *ICP algorithms*) under critical conditions. Once the system's response on surfaces with texture parameters lower than typical road ones was evaluated, the experimentation was transferred to a bituminous mixture specimen, representative of actual operating conditions, where the digital accuracy was compared with the reference data obtained in the laboratory through the sand patch test.

The innovative contribution of this work lies in the development of a custom Python script designed to automate and support traditional road texture analysis. Specifically, the algorithm for calculating the Mean Texture Depth (*MTD*) was developed as a custom routine with the support of AI-assisted coding tools. By extracting an altimetric elevation matrix from a dense three-dimensional point cloud, this code digitally simulates the volumetric filling of surface voids through local maxima interpolation and the generation of a “virtual covering”, thereby reducing the need for the physical requirement for the *sand patch test*. In contrast, the phase dedicated to the Mean Profile Depth (*MPD*) evaluation adapts an existing reference implementation [2] developed by the VTI in compliance with the “ISO 13473-1:2019(E) - Corrected version 2021-06” standard. This reference algorithm was transcribed into the Python environment, incorporating custom implementations and optimizations to deliver a fully automated, unified computational routine.

In summary, the proposed approach aims not only to speed up the survey, but to contribute to the digitalization of road monitoring. The transformation of a physical survey into a digital representation of the pavement allows for granular and dynamic data management. The results obtained demonstrate how the integration between digital photogrammetry and numerical analysis can provide results comparable to laboratory ones under the tested conditions, paving the way for future developments in the field of integrated mobile applications, potentially capable of returning macro-texture-related parameters directly on site. The thesis is structured through an initial analysis of the state of the art and current regulations, continues with the detailed description of the experimental protocols adopted on the different samples, and concludes with the presentation of the results obtained through the developed algorithm, discussing their accuracy and potential large-scale applications.

1 State of the Art and Theoretical Foundations

This chapter aims to outline the theoretical and regulatory framework necessary for understanding road pavement texture, analysing the physical phenomena that govern the interaction between the tire and the road surface. The characterization of road roughness does not represent a mere geometric surveying exercise, but rather the foundation for evaluating safety, ride comfort, and infrastructure durability. Surface roughness constitutes one of the pivotal elements to ensure adequate road safety, directly affecting the friction capacity between the vehicle and the pavement.

This interaction is expressed through two fundamental mechanisms:

- **Adhesion**, linked to the molecular bonds established at the microtextured level;
- **Hysteresis**, namely the energy dissipation due to the deformation of the tire rubber induced by the asperities of the macro-texture.

In wet conditions, the latter assumes a “lifesaving” role, as an adequate road texture acts as an instantaneous drainage system, allowing the expulsion of water from the contact patch and preventing the phenomenon of aquaplaning, thereby maintaining the effectiveness of braking systems and the directionality of the vehicle. The systematic importance of these parameters is confirmed by international research, as highlighted in various articles [3-4-5-7], which emphasize how the correct evaluation of macro-texture is essential for maintenance planning and for monitoring safety levels across national road networks. The road pavement must simultaneously fulfil two main functions, the first is structural in nature, aimed at distributing vertical loads toward the pavement bases, the subgrade, and the second is functional in nature, related to the quality of contact with the vehicle. It is precisely on this latter aspect that the attention of modern road engineering is focused, as surface texture is primarily responsible for the development of sliding friction forces, which are essential for guaranteeing skid resistance under all weather conditions. Throughout the discussion in the following chapter, the different levels of irregularity that compose a bituminous mixture surface will be examined, distinguishing among micro, macro, and mega-texture based on their wavelengths and the effects produced.

Subsequently, the analysis will focus on the volumetric and profile parameters most widely used in professional practice for estimating this roughness value, such as the Mean Texture Depth (*MTD*) and the Mean Profile Depth (*MPD*), thus providing the basis for a comparison between the traditional sand patch method and new digital technologies. Finally, a state of the art on non-destructive surveying techniques will be presented, positioning digital photogrammetry as the methodological and technological core of the entire thesis. It is important to emphasize that, at present, the use of this technique for characterizing macro-texture is not yet included in a specific and structured regulatory framework. However, the originality of the research lies precisely in the ability to adapt and apply the potential of digital photogrammetry in compliance with current standards, proposing a protocol that, while being technologically advanced, remains consistent with the metrics and reliability requirements demanded by technical regulations. This approach stems from a careful review of scientific literature and a critical analysis of various past research experiences, from which inspiration was drawn to define the operational parameters without, however, limiting itself to a sterile replication of already codified methodologies. In particular, the research builds upon previous studies [4] which demonstrated the effectiveness of 3D texture surveying using common photographic equipment and volumetric algorithms for calculating digital MTD, despite encountering limitations related to the use of specific software that is no longer available today or difficult to integrate into modern workflows. Similarly, the work engages with recent developments in the three-dimensional reconstruction of macro-texture [5-7], which, although introducing advanced depth estimation techniques, often rely on laser equipment for validation or on iterative processes that limit their operational flexibility. The objective of this thesis lies precisely in enhancing these methodologies, as the aim was to transfer technologies often relegated to ultra-specialized research fields toward a dimension of greater accessibility and practical usability. By demonstrating how the use of instrumentation defined as consumer-grade, such as a latest-generation smartphone, and the development of one or more dedicated Python scripts can bridge the gap between academic theory and management needs, the ambition of this work is to make macro-texture measurement a rapid, cost-effective, and scientifically rigorous process, within reach of the sector technician.

1.1 Road Pavement Texture: Hierarchy of Irregularities and Influence on Skid Resistance

The surface of a road pavement cannot be considered as a perfect geometric plane, as it is characterised by deviations relative to an ideal surface, which constitute the so-called texture. According to the international classification established by PIARC (World Road Association) and adopted by the EN ISO 13473-1 [6] standard, these irregularities are catalogued on the basis of their wavelength (λ) and their vertical amplitude (A).

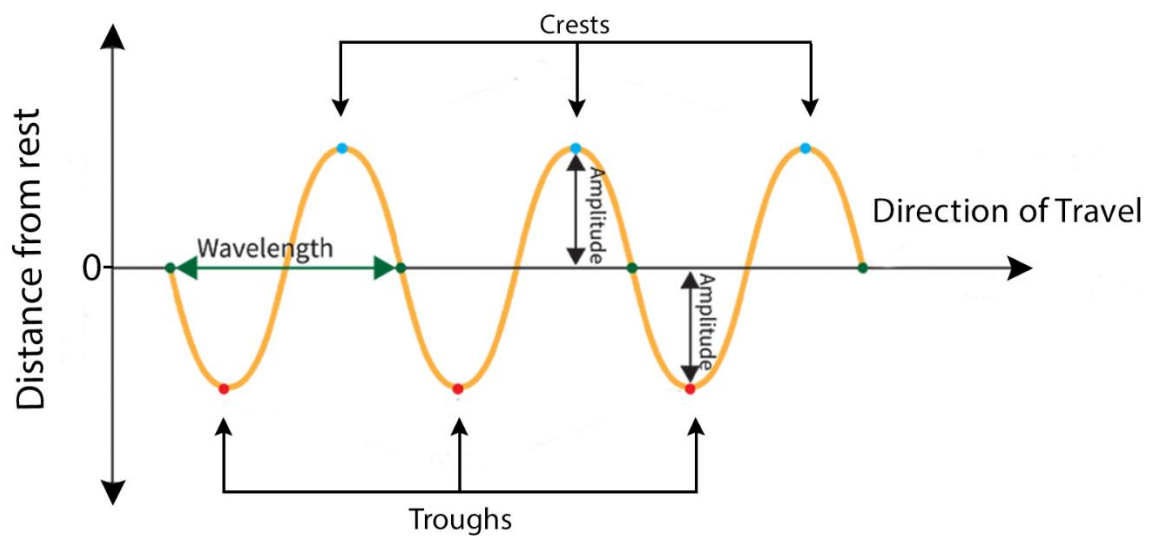


Figure 1.1: Schematic representation of texture geometric parameters, wavelength and amplitude.

This distinction is not purely taxonomic but reflects the specific influence that each scale of irregularity exerts on the interaction between the vehicle and the infrastructure.

Four main categories, described in detail in reference book [8], are distinguished:

1. Micro-texture ($\lambda < 0.5$ mm):

It is determined by the surface roughness of the individual stone aggregates that compose the conglomerate. Although not visible to the naked eye, it is fundamental for skid resistance under dry pavement conditions and at low speeds, as it governs the mechanism of molecular adhesion between the tyre rubber and the aggregate material. As highlighted in the literature, its magnitude depends strictly on the petrographic nature of the aggregate and its resistance to polishing under the action of traffic.

2. Macro-texture ($0.5 < \lambda < 50 \text{ mm}$):

It represents the geometric configuration formed by the arrangement of aggregates and intergranular voids. It plays a decisive role in safety under wet conditions. An adequate macro-texture indeed allows for the rapid removal of water present at the interface, acting as a network of drainage channels that prevents the formation of the continuous fluid film responsible for aquaplaning. From a mechanical point of view, it generates the phenomenon of hysteresis, i.e. the energy dissipation deriving from the cyclic deformation of the tyre which copies the road asperities. The accurate reconstruction of this scale is the main objective of modern computer vision techniques applied to pavements.

3. Mega-texture ($50 \text{ mm} < \lambda < 500 \text{ mm}$):

This scale of irregularity is often linked to laying defects, construction joints or localised distresses such as potholes or cracking. Although it does not directly affect thermodynamic adhesion, mega-texture has a negative impact on vibrational comfort and contributes to the increase in rolling noise. Studies conducted on national road networks indicate mega-texture as a critical parameter for the identification of road sections that require urgent repair interventions.

4. Irregularity or Roughness ($\lambda > 0.5 \text{ m}$):

It comprises long-range undulations that affect the dynamics of the vehicle, determining the ride quality, operating costs and suspension wear.

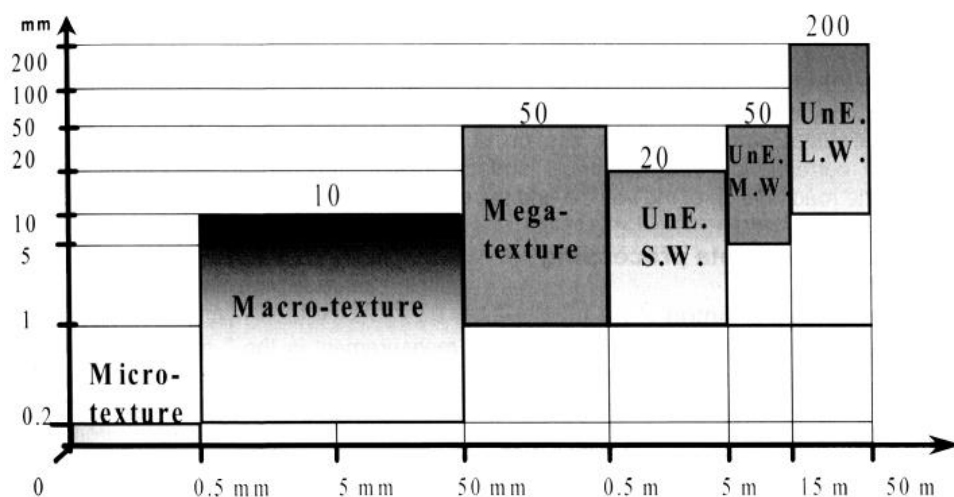


Figure 1.2: Classification of surface irregularities as a function of wavelength and amplitude (according to PIARC standards) [8].

It can be observed in the figure just presented, from left to right, in order of magnitude, micro-texture, macro-texture and mega-texture, short, medium and long-wave irregularities.

This classification also occurs as a function of spatial frequency.

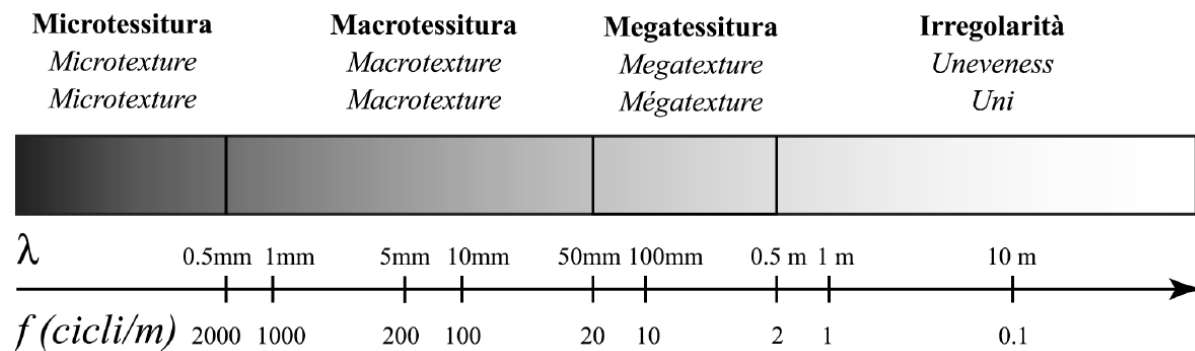


Figure 1.3: Texture classes as a function of wavelength and spatial frequency [8].

1.1.1 Correlation between Texture and Skid Resistance: Surveying Methodology

The adhesion between tyre and road is expressed quantitatively by the coefficient of friction (μ). The capacity of a pavement to guarantee sufficient friction is strictly linked to the synergistic combination of micro and macro-texture.

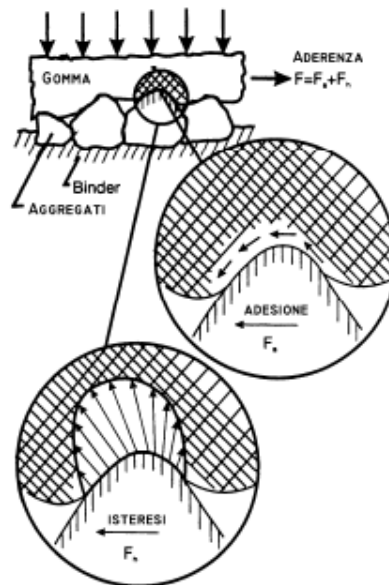


Figure 1.4: Mechanisms of Sliding Friction Generation: The Contributions of Adhesion and Hysteresis [8].

Skid resistance surveying methods are subdivided into two macro-categories [8]:

1. Surveying methods in the absence of traffic

These methods usually require the closure of traffic of the affected lane, as they involve the use of manual or stationary instruments.

- **Sand Patch Test:**

Traditional method standardised by EN ISO 13036-1 [1]. It presents limitations of subjectivity that prompt the transition towards digital techniques [4].

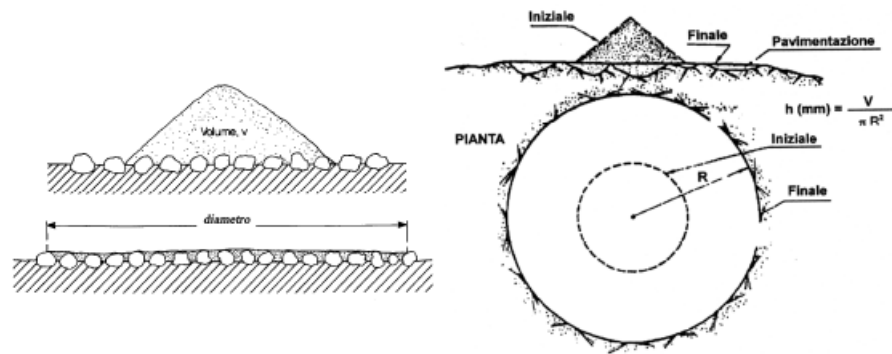


Figure 1.5: Measurement of macro-texture with sand patch test [8].

- **British Pendulum Test/Dynamic Friction Test:**

The operation of both pieces of equipment is based on the measurement of skid resistance determined by the loss of energy caused by the frictional dissipation generated by a rubber element of standardised hardness that is made to slide under pure sliding conditions above the pavement.

In the case of the Dynamic Friction Tester, it requires closure to traffic for road tests. The possibility of determining skid resistance follows the same principle as the British Pendulum Test, in this case, the equipment is equipped with three rubber elements of standardised hardness, arranged with a central angle of 120° on the perimeter of the rotating disc, on each of which a vertical load equal to 11.8 N acts. Furthermore, it is equipped with a device capable of delivering a constant water flow rate equal to 3.6 l/min.

The values obtained can be processed as a function of the sliding speed in order to obtain representative quantities in terms of the International Friction Index (*IFI*) moreover, those obtained on the basis of speed are well correlated with the values obtained with the British Pendulum Test.

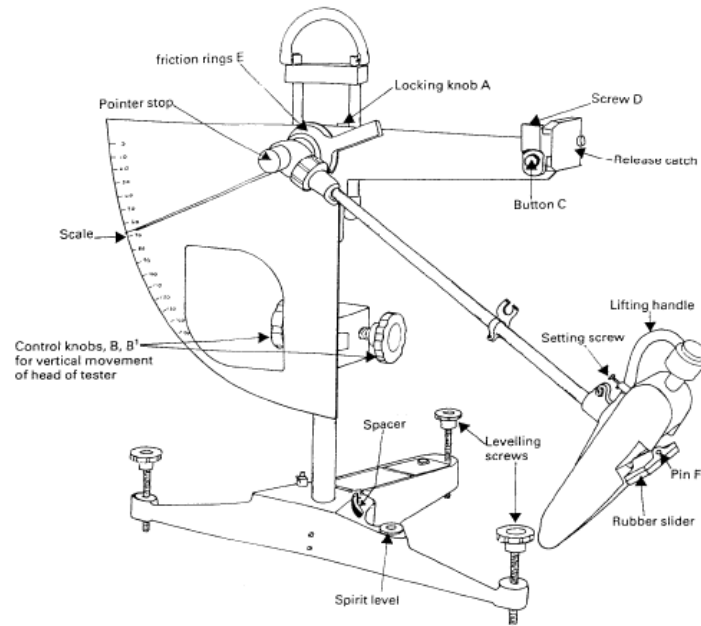


Figure 1.6: Operating diagram of British Pendulum Test [8].

2. Surveying methods in the presence of traffic

They are based on the use of equipped vehicles capable of measuring skid resistance at operating speeds (usually between 40 and 80 km/h), allowing the mapping of extensive road sections without interfering with the traffic flow.

- **Braking or slanted wheel system (e.g. SCRIM, Griptester):**

In this category, we can find both braking wheel instruments, which use towing trailers with locked wheels and a slip percentage equal to 100%. In this way, the characteristics of a road vehicle without an ABS device, engaged in an emergency braking situation, are reproduced. The skid resistance measurement will be associated with a sliding speed, S , equal to the forward speed of the trailer used for the survey. The parameter that translates the skid resistance measurement is represented by the numerical factor called Skid Number (SN), defined as the percentage ratio between the tractive force T , necessary to balance the adhesion F_a at the tyre-pavement interface during translation at a pre-set constant speed V , and the vertical load P acting on the trailer. The test is carried out at a speed of 65 km/h, being able to reach speed intervals up to 100 km/h. Standard tyres are used, regarding their geometry in particular, a smooth tread is used, capable of making the tyre more sensitive to the macro-texture of the road pavement, or a more patterned one with longitudinal grooves. The instrument offers the possibility of delivering a water film during measurements and, if equipped with the appropriate

system, of also performing continuous measurements regarding the Skid Number. It is evident, therefore, how the instrument can be used on straight sections for measuring skid resistance, whilst among the various disadvantages, the impossibility of performing measurements on curves, in roundabouts, and at T-junctions is highlighted. Another type is characterised by towed wheels free to rotate in their own plane, featuring a pre-set slip angle θ formed between the direction of travel and the plane of rotation. In this case, the skid resistance measurement is expressed through the ratio between the tangential adhesion force F_a , transverse to the plane of rotation, and the vertical load P acting on the wheel perpendicularly to the surface of the road pavement. The equipment used for this procedure is named SCRIM (*Sideway-force Coefficient Routine Investigation Machine*) and is widely used in Europe. The skid resistance measurement determined by this instrument is translated in terms of the Coefficient of Transverse Adhesion (*CAT*).

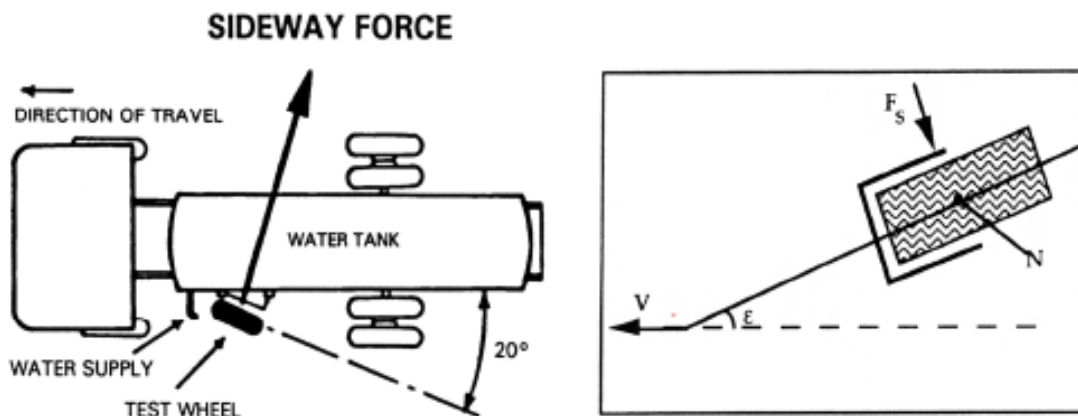


Figure 1.7: Operating diagram of SCRIM [8].

- **High-speed laser system:**

Used for the measurement of macro-texture in motion, from which the Mean Profile Depth (*MPD*) value is derived. Although very precise, these systems present high management costs and a technological complexity that limits their widespread use compared to solutions based on common optical sensors.

Overall skid resistance is therefore the result of a dynamic equilibrium in which macro-texture acts as a “precondition” for the activation of micro-texture. If the macro-texture is not capable of draining the water and allowing physical contact between the tyre and the

aggregate, the micro-texture cannot exert any adhesion force. For this reason, the accurate determination of parameters such as MTD assumes a fundamental value for road managers, allowing them to monitor friction capacity and to plan predictive maintenance interventions aimed at user safety.

1.2 Descriptive Parameters of Macro-Texture: MTD (Mean Texture Depth) and MPD (Mean Profile Depth)

The quantification of road macro-texture occurs mainly through two indicators standardised at an international level, which differ in their methodological approach: the Mean Texture Depth (*MTD*) and the Mean Profile Depth (*MPD*). As far as the first indicator is concerned, it derives from a volumetric approach of a statistical nature, while as far as the second is concerned, it is based on the geometric analysis of linear profiles, typically acquired with laser profilometers or digital reconstruction techniques.

1.2.1 Mean Texture Depth (MTD) and the Volumetric Method

The MTD parameter represents the mean depth of surface asymmetries calculated over a well-defined area. Traditionally, this value is determined through the sand patch test, regulated by the EN ISO 13036-1 standard [1]. The test consists in distributing a known volume, V , of standardised granular material, usually glass microbeads or calibrated silica sand are used, on the road surface, spreading this material in a circular shape, through the use of a metallic disc, until filling the voids of the macro-texture and creating a plane, mostly smooth and in the absence of asperities.

The indicator is calculated by means of the *Equation 1.1*:

$$MTD = \frac{4V}{\pi D^2} \quad (1.1)$$

Where D represents the diameter of the circular patch obtained. Despite its simplicity in being executed, the MTD value provides a global and volumetric indication of the storage capacity of the pavement.

However, as highlighted in the study [4], the main limitation of this measurement lies in its manual nature and in the difficulty of obtaining a continuous mapping of the road, which is why research is orienting itself towards the determination of a digital parameter of the mean depth of surface asperities, extracted from high-resolution three-dimensional models.

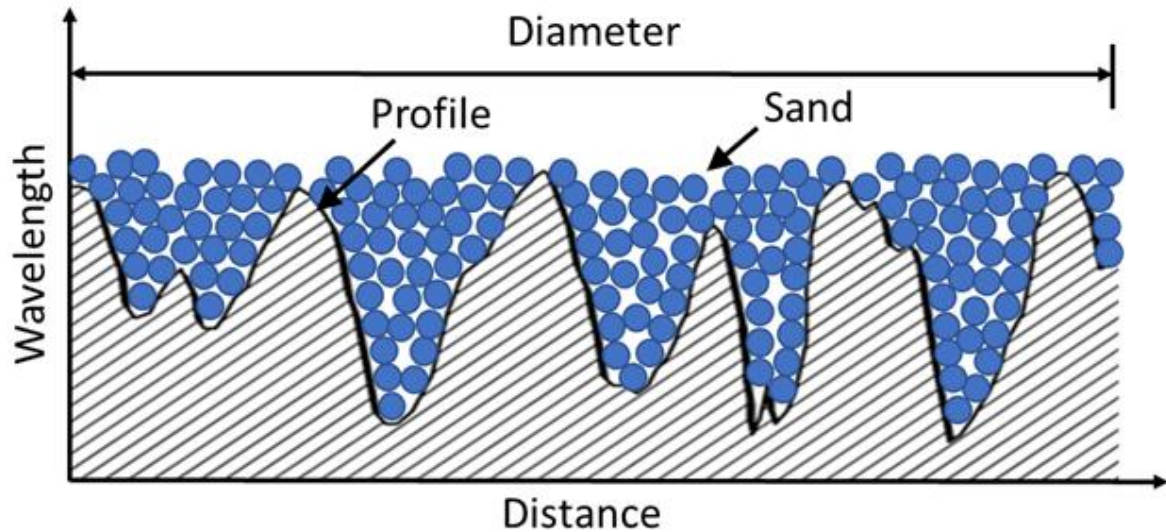


Figure 1.8: Geometric representation of the MTD parameter understood as the volume of voids filled per unit area.

1.2.2 Mean Profile Depth (MPD) and Digital Analysis

Unlike the MTD parameter, the MPD parameter is a two-dimensional indicator derived from the analysis of a profile of a defined length, usually 100 mm, in accordance with the EN ISO 13473-1 standard [6].

The calculation involves the division of the profile segment into two halves of 50 mm each, for each half the maximum height peak is identified, and the final value of the mean profile depth is given by the arithmetic mean of these two peaks, referenced to the mean level of the profile itself.

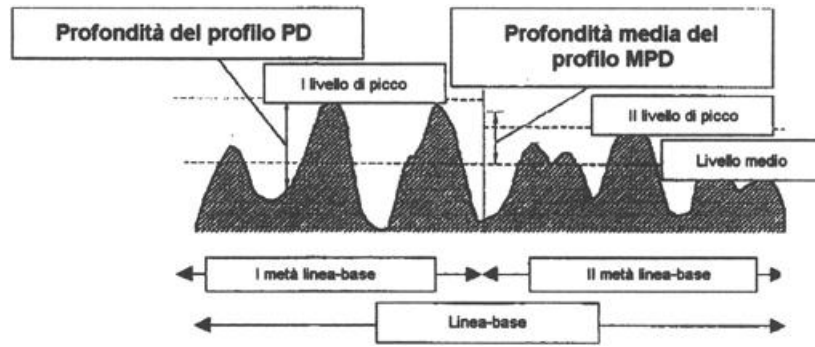


Figure 1.9: Calculation procedure of the MPD on a 100 mm profile according to the EN ISO 13473-1 standard [8].

This parameter is particularly relevant for high-performance surveys executed with laser profilometers, as it allows obtaining real-time data at operating speeds. However, as observed in different studies [5-7], it is highlighted that the accuracy of the MPD value drastically depends on the survey resolution and on the system's ability to correctly read the narrowest valleys between aggregates, a challenge that digital photogrammetry aims to solve through a point density superior to that of common single-line lasers.

1.2.3 Correlation between the parameters: the Estimated Texture Depth

Although MTD and MPD describe similar phenomena, they are not numerically identical due to their different geometric nature: volumetric in the case of the first mentioned parameter, and linear in the case of the second.

To overcome this discrepancy and allow data interoperability, the national EN ISO 13473-1 standard [6] introduces the concept of Estimated Texture Depth (*ETD*). The *ETD* is an estimation parameter that allows transforming the Mean Profile Depth value (*MPD*) into a value equivalent to the Mean Texture Depth (*MTD*), thereby making surveys executed with laser profilometers or digital techniques comparable with historical data deriving from the sand patch method.

The standardized transformation relationship is expressed by means of the *Equation 1.2*.

$$ETD = 1.1 \cdot MPD \quad (1.2)$$

The adoption of this parameter is crucial in Pavement Management Systems (*PMS*) where it is necessary to maintain analytical continuity between different survey campaigns. Studies conducted on different types of bituminous mixtures in Estonia [3] confirm that the correlation between profile and volumetric parameters, mediated by the ETD, presents extremely high coefficients of determination, $R^2 > 0.9$, validating the reliability of this conversion for management and safety purposes.

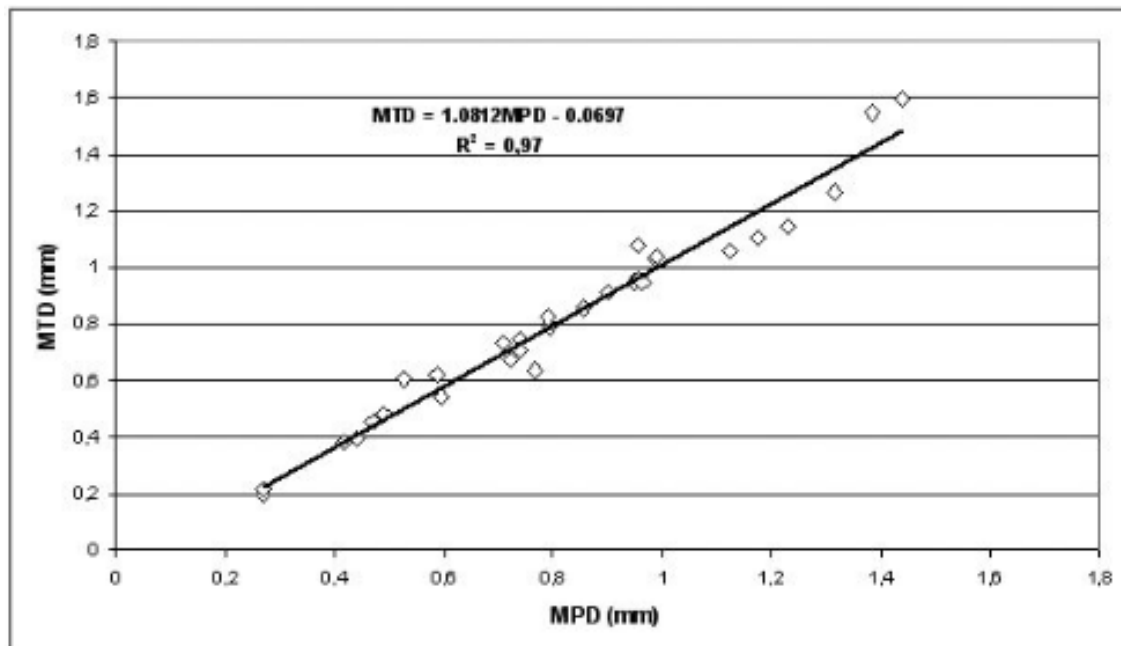


Figure 1.10: Experimental correlation between MPD and MTD and representation of the regression line for the calculation of the ETD [3].

1.2.4 Research Approach

The methodological innovation proposed in this work fits precisely within this context of correlation. While traditional techniques extract the MPD to then estimate the ETD directly, the protocol based on digital photogrammetry developed here aims at an estimating the volume of voids from a three-dimensional surface model. Through the generation of a dense point cloud, the Python script is not limited to sampling linear profiles, but numerically approximates the behaviour of the granular material of the *Sand Patch Test*. This allows the determination of a “digital MTD” value representing a volumetric measurement derived from the three-dimensional model, which can be directly compared with the in-situ test.

This approach offers an alternative solution that combines the volumetric nature of the traditional measurement with the efficiency of modern computer vision techniques.

1.3 Non-Destructive Survey Techniques: Digital Photogrammetry and Structured Lights

The evolution of road diagnostics has accelerated significantly thanks to the development of non-destructive testing (*NDT*) techniques, which allow the acquisition of high-resolution geometric and morphological data without interfering with the physical integrity of the pavement.

In the specific context of macro-texture analysis, the scientific community's focus has shifted from manual and contact-based methods toward methods integrating optical systems, categorized into active and passive systems. These systems are capable of generating digital replicas of the road surface in the form of point clouds and polygonal meshes, potentially achieving sub-millimetre resolution under controlled conditions. The two main technologies used for the various analyses conducted during this research are digital photogrammetry and structured light scanning.

1.3.1 The Digital Photogrammetry

Modern digital photogrammetry is not limited to the simple overlapping of shots, but is founded on a complex algorithmic principle, called Structure from Motion (*SfM*). Unlike traditional stereoscopic photogrammetry, which requires a priori knowledge of the position of the cameras and of the ground control points, the *SfM* approach is capable of simultaneously resolving the geometry of the scene, the so-called structure, and the movement parameters of the camera, the motion, through an iterative process of analysis of the image data.

The algorithm is generally structured into four fundamental computational phases:

1. Feature Detection

The software analyses each image in search of points of interest, key points, which are invariant to changes in scale, rotation, and illumination.

Advanced mathematical descriptors, such as *SIFT* or *SURF*, are used to identify asperities, edges, or chromatic variations on the individual stone aggregates.

2. Matching Points

The identified points are compared among the different frames of the sequence. Through the calculation of epipolar geometry, the algorithm establishes which points belong to the same physical element seen from different angles.

3. Triangulation and Sparse Reconstruction

Utilizing the homologous points found, the software estimates the relative position of the cameras and calculates the three-dimensional coordinates of the points in space, generating an initial cloud that takes the name of “sparse point cloud”.

4. Bundle Adjustment

This is the most critical phase of the process, in which the multiple projection error is minimized. The algorithm iteratively refines the three-dimensional positions of the points and the internal and external parameters of the cameras to ensure that the projection of the reconstructed points perfectly coincides with the corresponding pixels in the original images.

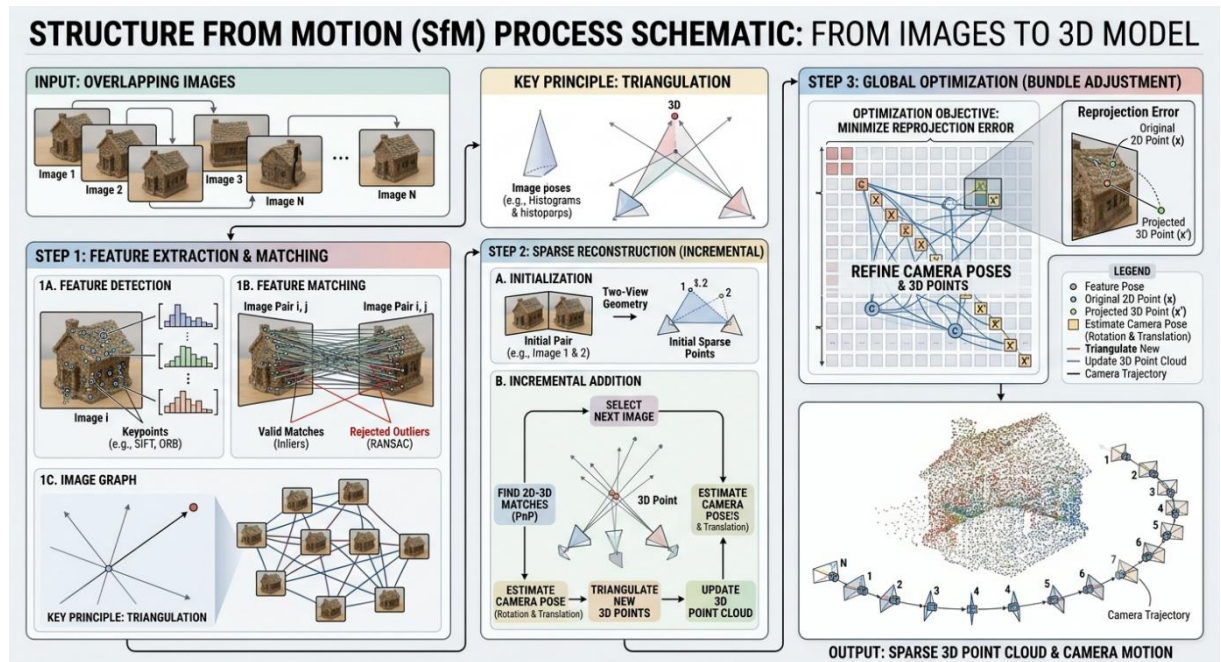


Figure 1.11: Computational Workflow of the algorithm Structure from Motion (SfM) for three-dimensional reconstruction.

Once the sparse cloud is obtained, Multi-View Stereo (MVS) algorithms are applied to densify the cloud, moving from a few thousand to millions of points.

From this dataset, it is possible to generate digital elevation models, termed *DEM*, or more specifically digital surface models, known as *DSM*. In road engineering, the *DEM* is not merely a visual representation, but a mathematical dataset formed by a matrix of rows and columns, in which each pixel of the planimetric projection is associated with an elevation value relative to a reference plane. The generation of a high-resolution *DEM* allows for the analysis of the texture at every single point, enabling the extraction of altimetric profiles along any direction and, above all, the volumetric calculation of intergranular voids.

As highlighted in different studies [4-5], the availability of a digital elevation model transforms the road survey from a punctual and extemporaneous measurement to a continuous and reproducible spatial analysis.

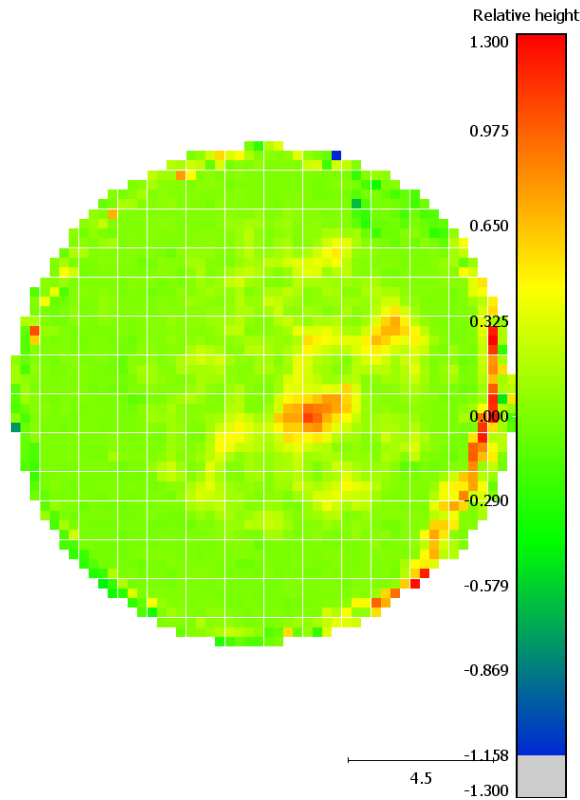


Figure 1.12: Digital Elevation Model (DEM) of the macro-texture obtained through dense photogrammetry.

To ensure that the elevation model is suitable for the scientific estimation of the macro-texture, it is imperative to define the Ground Sample Distance (*GSD*). This parameter represents the physical distance on the road surface corresponding to the distance between

the centres of two adjacent pixels in the digital image. In practical terms, it represents the size of the “pixel on the ground”. The relevance of the *GSD* is absolute, as it determines the physical limit of the spatial resolution of the survey. If the macro-texture presents millimetric-scale asperities, a centimetric *GSD* would be completely inadequate, as it would act as a low-pass filter, “smoothing” the valleys and peaks and leading to an underestimation of the *MTD* and *MPD* parameters. The determination of the *GSD* is a function of the focal length of the lens, the acquisition distance, represented by the camera height, and the physical size of the pixels on the sensor. In the present research, the optimization of the *GSD* was established as a primary constraint to ensure that the equipment used, an iPhone 15 Plus, could capture the finest details of the texture, thereby guaranteeing the metric validity of the “Digital *MTD*”.

1.3.2 The Structured Light Method: Principles and Operational Challenges

In contrast to photogrammetry, which is a passive technique, structured light scanning is an active method that involves projecting a calibrated light pattern, typically consisting of a grid of blue or white light lines, directly onto the pavement surface. As the light strikes the object, the grid deforms in response to the surface asperities. The scanner's camera captures these deformations, which are subsequently processed by the software to accurately reconstruct the surfaces in a digital three-dimensional format. Despite its high precision, this technology poses specific technical challenges related to the inherent nature of bituminous materials:

- **Absorption and Reflection:**

The bituminous mixture specimen tends to absorb light or generate specular reflections, which interfere with the accurate detection of the projected grid pattern.

- **Recessed Geometries:**

If the projected light fails to reach the bottom of the intergranular voids, such as deep cavities, the scanner is unable to sample that specific section. Although Artificial Intelligence-based software solutions exist that attempt to reconstruct these occluded details, the reliability of such reconstructions for calculating precision parameters, such as the Mean Texture Depth (*MTD*), remains a subject of academic debate.

- **Environmental Interference:**

Sensitivity to direct sunlight renders the in-situ operation of these scanners highly complex without heavy shielding, thereby limiting their portability compared to photogrammetry.

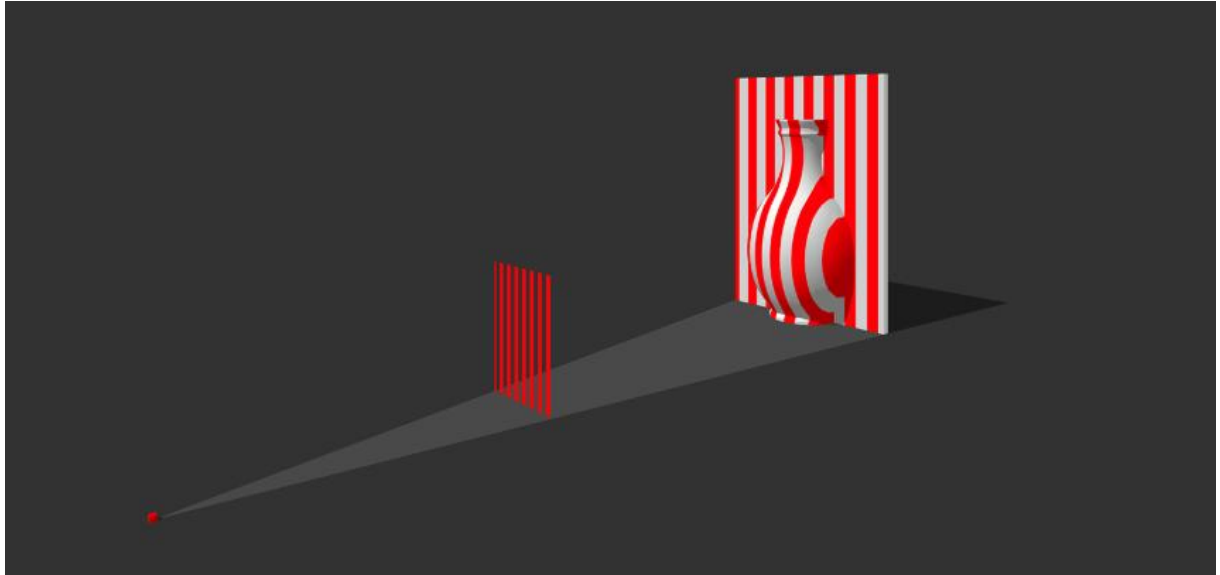


Figure 1.13: Operating principle of structured light scanning on irregular surfaces [9].

The comparison between these technologies highlights that, while structured light offers a superior nominal resolution in controlled environments, digital photogrammetry represents the most suitable solution for the efficient and widespread management of infrastructure. The integration of *SfM* algorithms and the rigorous control of the *GSD* make it possible to overcome the limitations of expensive professional systems, rendering pavement monitoring a scalable and scientifically rigorous process.

2 Experimental Setup and Data Acquisition Instrumentation

This chapter aims to comprehensively outline the experimental architecture and the metrological configuration adopted for conducting the research. The core focus of this work lies in the advanced and non-destructive characterization of road pavement macro-texture, aimed at the quantitative extraction of the two primary standardized geometric indicators: the Mean Texture Depth, traditionally linked to direct volumetric methods, and the Mean Profile Depth, based on the two-dimensional analysis of height profiles. The scientific challenge addressed herein lies in determining these parameters using high-resolution digital photogrammetry, leveraging consumer-grade optical sensors as a flexible, cost-effective, and high information density alternative to traditional methodologies or professional structured light instrumentation. To provide a clear and systematic overview of the entire research framework, the experimental activity has been structured according to a sequential logical operational workflow, divided into macro-phases that will be analytically examined in the subsequent chapters:

- **Phase I - Data Acquisition Protocol:**

This phase encompasses both field and laboratory activities, focusing on the rigorous definition of image acquisition geometries, the stability of illumination conditions, and marker-based metric referencing strategies. It establishes the operational boundary between the investigation of the control surface, namely the granite slab, and the actual bituminous mixture specimen, evaluated both prior to and following the application of the sand.

- **Phase II - Digital Processing and 3D Reconstruction:**

This constitutes the computational phase in which the image datasets are processed using Structure from Motion (*SfM*) algorithms for the generation of dense point clouds, Digital Elevation Models (*DEMs*), and Orthomosaics. This block analyses the geometric optimization achieved through Iterative Closest Point (*ICP*) registration and validates the effectiveness of free digital reconstruction engines, RealityScan, in comparison to commercial software as Agisoft Metashape Professional.

- **Phase III - 3D Model Analysis and AI-Assisted Algorithm Development:**

This phase represents the innovative and heuristic core of the thesis. Initially, a differential approach is tested within a GIS environment, utilizing numerical subtraction between the pre and post-test DEMs to compute the sand volume. Furthermore, this workflow is replicated within CloudCompare software by leveraging a dedicated tool capable of calculating volume relative to a reference element. Subsequently, to overcome the intrinsic limitations of this volumetric method and eliminate the dependency on physical filling materials, the development of a custom Python algorithm is presented. This code, based on the interpolation of local maxima and geometric down sampling, is capable of generating a reference surface directly from the three-dimensional model matrix, thereby automating the extraction of the MTD parameter through an entirely “*Sand-Free*” approach. Finally, building upon a reference implementation [2], which originally utilized a MATLAB script to derive the MPD parameter, the framework was successfully ported to Python. Following specific adjustments and structural adaptations that will be detailed subsequently, and strictly preserving the authors underlying operational logic, this integrated tool successfully extracts the MPD parameter as well.

Regarding the design of the experimental setup, it was driven by the necessity to perform a rigorous comparison between highly specialized acquisition systems and consumer-grade devices, aiming to investigate the accuracy limits and scalability potential of modern optical sensors. This approach is not limited to the mere collection of morphological data but aims to establish a repeatable protocol that can serve as a foundation for developing macro-texture monitoring systems that are more agile and cost-effective than current standards. The entire experimental workflow is structured around three fundamental pillars, which will be further elaborated in the following paragraphs.

- 1. The hardware infrastructure:**

It comprises a professional-grade structured light scanning system, utilized as an independent reference measurement system, enabling the assessment of the model's fidelity in terms of scale and accuracy, and a latest-generation mobile device employed as the primary photogrammetric sensor.

The latter is initially evaluated to verify the compatibility of its photographic characteristics with the overall system workflow, starting with the assessment of the integrated optical sensor's Ground Sampling Distance (*GSD*) parameter.

2. The selection of materials:

It encompasses both a reference surface with high dimensional stability, a granite slab and an actual pavement sample, specifically a bituminous mixture specimen, both of which are necessary to test the algorithm across scenarios of varying optical and geometric complexity.

3. The software pipeline:

An integrated ecosystem of tools for computer vision, geospatial analysis, and algorithmic automation, aimed at transitioning from a dense point cloud to quantifiable performance indicators, namely *MTD* and *MPD*.

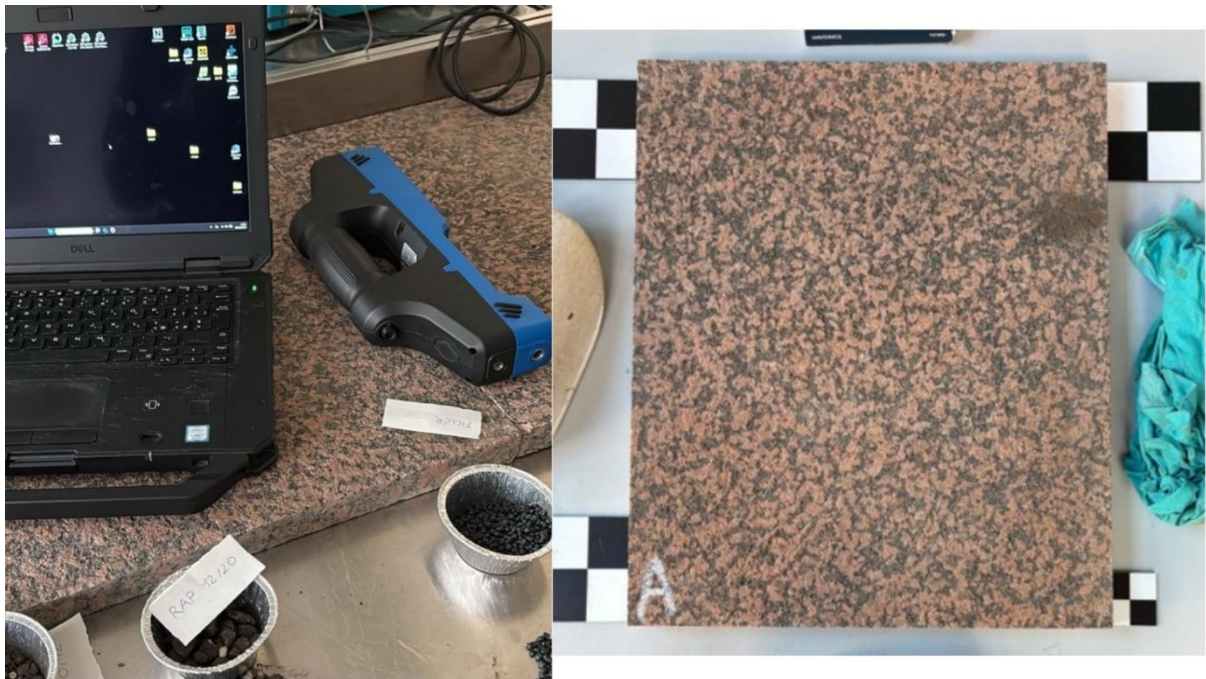


Figure 2.1: Instrumental configuration for the Mantis Vision F6-SR on the granite slab.

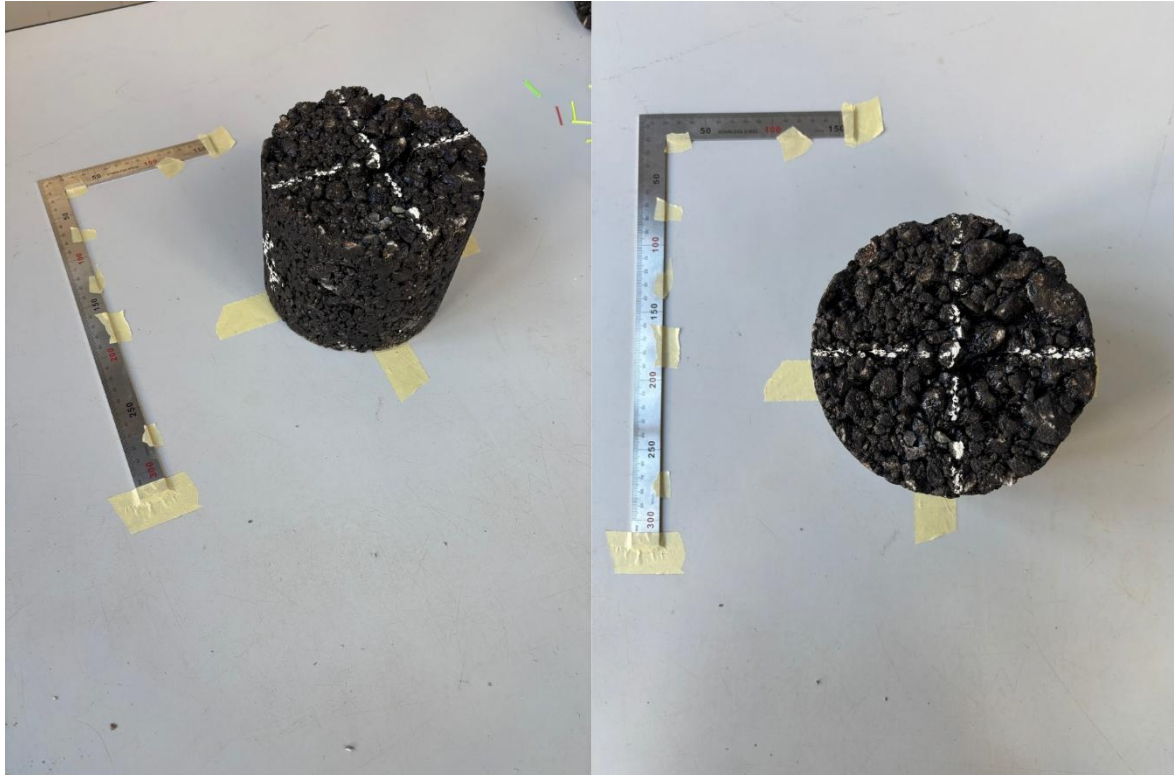


Figure 2.2: Instrumental configuration for the iPhone 15 Plus on the bituminous mixture specimen.

The accuracy of the final data is a function not only of sensor quality but of the entire procedural workflow, which demands constant metric calibration and rigorous control over the acquired parameters. Indeed, in the two images presented above, it can be observed that while the first configuration utilized four markers positioned at the extremities of the granite slab, the second setup transitioned to the use of a steel template featuring millimetric precision. In both instances, these elements constitute GCPs (*Ground Control Points*), points that are strictly and exclusively required in photogrammetry to properly scale the model, thereby ensuring it accurately reflects its real-world dimensions.

In the subsequent paragraphs, it will be detailed how the Mantis Vision F6-SR scanner was deployed as a further verification tool and why it was ultimately decided to rely solely on photogrammetry as the acquisition method.

2.1 Structured Light Scanning: Mantis Vision F6-SR

The acquisition of a reference dataset within this experimental study was entrusted to the Mantis Vision F6 professional 3D scanner, specifically the Short Range (SR) version. This instrument represents an advanced solution among portable, short-range survey systems, being specifically optimized for scanning within an extremely precise operational range between 22 cm and 78 cm. The Mantis Vision F6-SR operates according to the principle of *Structured Light Scanning*, an active technique that, as discussed in the previous chapter, can provide high metric reliability under suitable operating conditions. The technological core of the instrument lies in the projection of a series of coded light patterns onto the pavement surface. Two integrated cameras instantaneously capture the deformations undergone by these patterns due to the pavement morphology; these deformations are then processed by a highly innovative proprietary algorithm capable of calculating the spatial coordinates (X, Y, Z) of every single point on the surface with millimetric-level accuracy. One of the potential advantages of this acquisition tool, compared to passive photogrammetric techniques, is its operational stability under any lighting conditions. While photogrammetry can suffer in the presence of harsh shadows or grazing light, the Mantis Vision F6-SR can provide consistent and repeatable results. Furthermore, the scanner's capability to provide real-time feedback through its dedicated software (ECHO) allows the operator to monitor the acquisition quality during the survey itself, reducing the risk of shadow zones or data gaps in the point cloud. The deployment of the instrument follows a simple yet rigorous workflow. Upon startup, the system interfaces with the ECHO software, which informs the operator of the optimal moment to begin data collection. Within this research, the two primary operational modes offered by the software regarding the acquisition type were explored, and the optimal choice was evaluated to obtain reliable data for the subsequent comparison.

The two modes are the following:

1. Assisted Mode

In this scenario, the software actively guides the operator by identifying *in real time* insufficiently sampled surface areas, should any region be inadequately or improperly scanned, the system requires the operator to re-scan the gaps to ensure complete coverage and a uniform density of the point cloud.

2. Free Mode

The operator autonomously manages the movement of the scanner, relying on visual assessment to evaluate the completeness of the survey displayed on the monitor.

Between these two modes, it was decided to initially utilize the *Assisted Mode* to achieve the maximum possible precision, supplemented by several scans performed in *Free Mode*, which were subsequently merged into a single survey. This procedure aimed to increase the accuracy regarding the texture reconstruction of the examined element. Although the Mantis Vision F6-SR is a system that does not require physical targets for frame alignment, thanks to the geometric recognition algorithms with which the instrument is equipped, four millimetric markers were positioned externally to the granite slab in this study. This choice was dictated by the need for reliable metric references and control points for the subsequent scaling phase and comparison with the models generated via photogrammetry. Upon completing the acquisition, the post-processing phase takes place within the ECHO software environment, following a procedural workflow aimed at maximizing the signal-to-noise ratio:

- **High Quality Registration:**

This represents the first fundamental step, in which the individual acquired frames are registered and aligned with maximum precision. During this phase, it was crucial to enable the texture utilization option, which allows the algorithm to leverage chromatic features in addition to geometric information to refine the alignment of the datasets.

- **Denoising:**

After registration, the noise removal process is executed. The ECHO software performs an automated cleaning operation, eliminating isolated points or spurious signals generated by anomalous reflections. It is important to emphasize that, despite its effectiveness, automated denoising does not eliminate all impurities, therefore, a further manual refinement step was necessary to obtain a point cloud that was as clean as possible.

At the conclusion of this process, the system offers the flexibility to generate a polygonal mesh directly within ECHO or as preferred in this study for methodological purposes, to export the raw point cloud and proceed with advanced analyses within the CloudCompare environment.

This step ensures the preservation of the native data integrity, which is essential for the precise calculation of the MTD and MPD parameters that will be discussed in subsequent chapters.

A methodological aspect of fundamental importance concerns the scope of application of the structured light scanner within this experimental research. It should be specified that the deployment of the Mantis Vision F6-SR was restricted exclusively to the preliminary investigation phase conducted on the granite slab, with the objective of assessing the sensor's performance within a controlled reference context. However, during the initial surveying activities, technical challenges emerged that influenced the remainder of the research in a different direction.

Firstly, the analysis of the extracted data revealed the generation of a point cloud characterized by a sub-optimal density for the ultra-detailed volumetric calculation purposes required by the macro-texture of the bituminous mixture specimen, furthermore, the spatial resolution of the data, albeit accurate, was not sufficiently dense to compete with the potential offered by high-resolution digital photogrammetry.

Secondly, the decision to discontinue the use of the professional scanner for the subsequent phases was made to maintain consistency with the core philosophy of the entire thesis project. Indeed, one of the pivotal objectives of the research is to eliminate the requirement for specialized, expensive, and scarce instrumentation, which cannot be defined as consumer-grade, in favour of a democratization of road surveying. The integration of a highly sophisticated device inaccessible to the average user contrasted with the intention to assess a methodology based on mass-market technology. For these reasons, once the investigation on the granite reference surface was concluded, the experimental activity proceeded exclusively via the photogrammetric method, focusing attention on the optimization of optical sensors integrated into smartphones.

2.2 Smartphone Optical Sensor: iPhone 15 Plus

The technological core of the photogrammetric survey methodology proposed in this study lies in the utilization of a latest-generation smartphone, an iPhone 15 Plus. The selection of this device is not arbitrary but rather responds to the need to validate a consumer-grade acquisition system capable of offering metrological performance comparable to professional equipment, while simultaneously ensuring superior portability and accessibility.

To determine the suitability of the photographic sensor for macro-texture characterization, it is indispensable to introduce and analyse the Ground Sample Distance (*GSD*) parameter. The *GSD* defines the physical dimension that a single pixel within the image represents on the actual surface of the scanned object. In photogrammetry, this value is the primary indicator of the level of detail the sensor is capable of capturing, as a lower *GSD* value indicates that each pixel represents a smaller surface area, translating into a higher spatial resolution and, consequently, a three dimensional reconstruction that is more faithful to the micro-asperities of the road pavement.

The analytical determination of the *GSD* is performed through *Equation 2.1*.

$$GSD = \frac{D \cdot d}{f} \quad (2.1)$$

Where:

- **D** represents the *height/distance* of the camera relative to the surface to be surveyed;
- **d** is the size of the individual pixel on the sensor, known as the *pixel pitch*;
- **f** identifies the *focal length* of the lens utilized.

Within this research, the primary objective is to determine the MTD and MPD values with an extremely high degree of accuracy. Given that the digitally obtained results must be validated through comparison with the benchmarks derived from the preliminary laboratory testing, a target precision on the order of a hundredth of a millimetre was established. This requirement dictates that the *GSD* value be minimized to ensure that each capture gathers the maximum possible detail, preventing the valleys between the aggregates from being “averaged out” or ignored during the point cloud generation.

Based on the technical specifications [10] provided by the manufacturer the parameters necessary for calculating the theoretical resolution of the iPhone 15 Plus were obtained:

- **Optical Sensor:** 48 MP Quad-Pixel system with a physical sensor size of 1/1.3”.
- **Pixel Size (d):** Calculated by dividing the physical width of the sensor by the horizontal resolution, it is equal to 0.0012 mm, taking pixel binning into account.
- **Focal Length (f):** Based on the technical specifications of the rear camera module, this value stands at 52 mm.

Based on these constant parameters, it was possible to estimate the trend of the GSD as a function of the shooting distance.

Furthermore, it should be noted that the values obtained (*Table 2.1*) are applicable assuming that the camera sensor is positioned parallel to the examined object, when the sensor is tilted relative to the surface, and therefore in any non-orthogonal capture, non-perpendicular projection causes distortions, elongation, or compression of the cell representing the individual GSD.

Table 2.1: GSD values as a function of shooting distance for the iPhone 15 Plus.

D [mm]	d [mm]	f [mm]	GSD [mm]
50	0.0012	52	0.00115385
100	0.0012	52	0.00230769
150	0.0012	52	0.00346154
200	0.0012	52	0.00461538
250	0.0012	52	0.00576923
300	0.0012	52	0.00692308

Data analysis highlights how, to comfortably fall within the required tolerance of one-hundredth of a millimetre, it is possible to operate at an acquisition distance of approximately 30 cm, which guarantees a GSD of about 0.007 mm.

This configuration offers an optimal balance between the precision of the captured detail and the width of the field of view, allowing for the collection of sufficient data for a dense and accurate reconstruction of the surface macro-roughness. The analysis of the obtained GSD values confirms that the technical characteristics of the iPhone 15 Plus, despite being a consumer-grade device, are fully compatible with the required metrological demands. The importance of this compatibility emerges clearly when considering the morphological variability of road pavements, depending on the particle size distribution curve of the bituminous mixture, such as the differences between porous asphalt or a dense wearing course, MTD values can vary significantly, generally falling within a range between 0.5 mm and 2.5 mm. The calculated GSD value, which is on the order of thousandths of a millimetre (approximately 0.007 mm at the 30 cm operating distance), is some orders of magnitude

smaller than the dimensions of the asperities and intergranular voids that define the macro-texture. This means that the smartphone sensor is capable of sampling every individual aggregate and valley with an extremely high number of pixels, ensuring a geometric reconstruction that does not suffer from aliasing or data flattening. In conclusion, the high spatial resolution guaranteed by the device makes it possible to cover the entire range of MTD bands expected across different types of bituminous mixtures. The system's capacity to digitally penetrate the texture voids, regardless of whether the particle size distribution curve is open or closed, ensures that the photogrammetric investigations can proceed without technical issues, providing scientifically robust data that is perfectly comparable to that obtainable with far more expensive professional instrumentation.

2.3 Study Materials: Granite Slab and Bituminous Mixture Specimen

The experimental phase of the research was designed to test the effectiveness of the reconstruction on surfaces characterized by varying morphological complexities and dimensional properties. The selection of materials addressed a twofold requirement, initially establishing a surveying protocol on a stable and controlled surface and subsequently validating it on an actual road pavement specimen. Furthermore, utilizing a material with such low roughness and an almost entirely smooth surface allowed for experimentation on an extreme case, where a remarkably *low MTD value* is recorded compared to those typically observed on standard road pavements.

2.3.1 Reference Surface: Granite Slab

The first element analysed is a granite slab, utilized as a control surface for system calibration and for the initial comparison between the structured light scanner and photogrammetry. Granite was selected for its high dimensional stability, a surface that appears nearly smooth to the naked eye, and a surface texture that exhibits uniformly distributed micro-roughness. From a photogrammetric perspective, the granite slab offers optimal natural chromatic contrast, facilitating feature matching algorithms in identifying homologous points.

For the orientation and metric scaling of the model, as seen in the photographic documentation, two different types of markers were employed to investigate the sensitivity of the survey relative to target precision. The first type consists of “home-made” markers, produced by printing four coloured targets onto cardstock.

The second type consists of professional millimetric markers. This choice was dictated by the need to visualize the precision discrepancy between the two systems, as the millimetric markers guarantee superior accuracy and a much more rigorous definition of the coordinate centres compared to the craft-printed supports.

In addition to the nature of the targets, their spatial positioning strategy was also diversified: the *home-made* markers were placed directly on top of the surface under investigation, whereas the *millimetric* markers were positioned at the four external vertices, resting on the same supporting plane as the granite slab. This configuration made it possible to evaluate how the distribution of control points and their metric quality influence the stability of the digital model. Thanks to its natural chromatic contrast, the granite slab facilitated feature matching algorithms in identifying homologous points, making the difference in precision between the two marker sets even more apparent during the point cloud processing phase. This phase was fundamental for determining the MTD value in a context where the uncertainty associated with the complex geometry of the asphalt is minimized.

2.3.2 Real-World Sample: Bituminous Mixture Specimen

The transition to the analysis of the real-world case followed a comprehensive process of methodological refinement. As will be illustrated in detail through the various iterations described throughout this study, the investigation phase on the granite slab served as a fundamental technological proving ground. It should be noted at the outset that while the granite surface exhibited a Mean Texture Depth incomparable to values found in realistic road contexts, this substrate was nevertheless utilized to test the extreme sensitivity limits of the sensors and to evaluate the boundaries of the surveying technology in terms of spatial resolution.

The deployment of a bituminous mixture specimen represents the core of the experimental validation, as it constitutes the actual surface of interest for pavement engineering. This sample introduces significant challenges for the selected surveying system, namely digital photogrammetry, since the presence of sharp-edged stone aggregates and deep intergranular voids generates shadowed areas that can remain occluded if not properly illuminated or captured from multiple angles. Consequently, this requires meticulous planning of both the shooting sequence and the lighting conditions.

Furthermore, bitumen is a highly dark surface, meaning it tends to absorb a substantial portion of the ambient light, thereby complicating the capture of crisp details within

shadowed zones. In some instances, the presence of highly reflective facets can cause lighting anomalies, introducing noise into the point cloud and this necessitates additional filtering and cleaning operations on the cloud before any subsequent analytical steps can proceed.

Much like the granite slab, the specimen underwent a dual investigation: a digital survey aimed at volumetric computation and the traditional sand patch test. The comparison between the volume of sand physically distributed and the volume estimated via point cloud processing serves as the primary validation benchmark for the entire workflow. To enhance metric precision on this complex surface, an evolved experimental setup was implemented involving the use of a millimetric template. This allowed the digital model to be spatially constrained with greater accuracy than with separate markers, establishing a robust, dedicated local reference system.

2.4 Software Ecosystem

The process of transforming iconographic data into three-dimensional metric information and, subsequently, into performance parameters, specifically MTD and MPD, required the integration of a heterogeneous software ecosystem. Each application was selected to perform distinct tasks within a processing pipeline that was not strictly linear but rather evolved through several experimental iterations. The software tools employed are analysed below, outlining their primary functionalities and the decisive role they played in each phase of the research.

2.4.1 Agisoft Metashape Professional

The fundamental pillar of the photogrammetric reconstruction is represented by *Agisoft Metashape Professional*. This processing software is based on Structure-from-Motion (*SfM*) technology, which enables the generation of high-resolution three-dimensional models from digital images. Within this study, the deployment of the Professional version proved indispensable, as it overcomes the functional limitations inherent to the Standard version.

The requirement for the “Pro” version was primarily dictated by its advanced management of markers and Ground Control Points (*GCPs*). This functionality enabled the manual or automated identification of the millimetric targets positioned on the specimens, an operation fundamental to the metric scaling of the model.

Without this step, the three-dimensional model would lack an absolute metric reference, rendering any reliable volumetric or linear calculation impossible.

The workflow implemented within Metashape followed the standard phases of digital photogrammetry:

1. Image Alignment

The phase in which, following the import of the images into the software, the spatial positions of the cameras are calculated, and a sparse/raw point cloud is generated.

2. Dense Point Cloud Generation

In this stage, the spatial resolution of the model is substantially increased using a *dense matching algorithm*.

This achieves a point cloud that is as dense as possible, providing an optimal description of the analysed surface.

3. Digital Elevation Model (DEM) Production

This step involves transforming the point cloud into a continuous raster surface, where each pixel represents the height relative to a reference datum.

Typically, the horizontal XY plane is utilized as the reference base, as all required altimetric elevations are mapped along the vertical Z-axis.

4. Orthograph Generation

The final phase, in which an orthogonal projection of the images onto the reconstructed geometry is performed to obtain a high-resolution, planimetric view of the element under analysis.

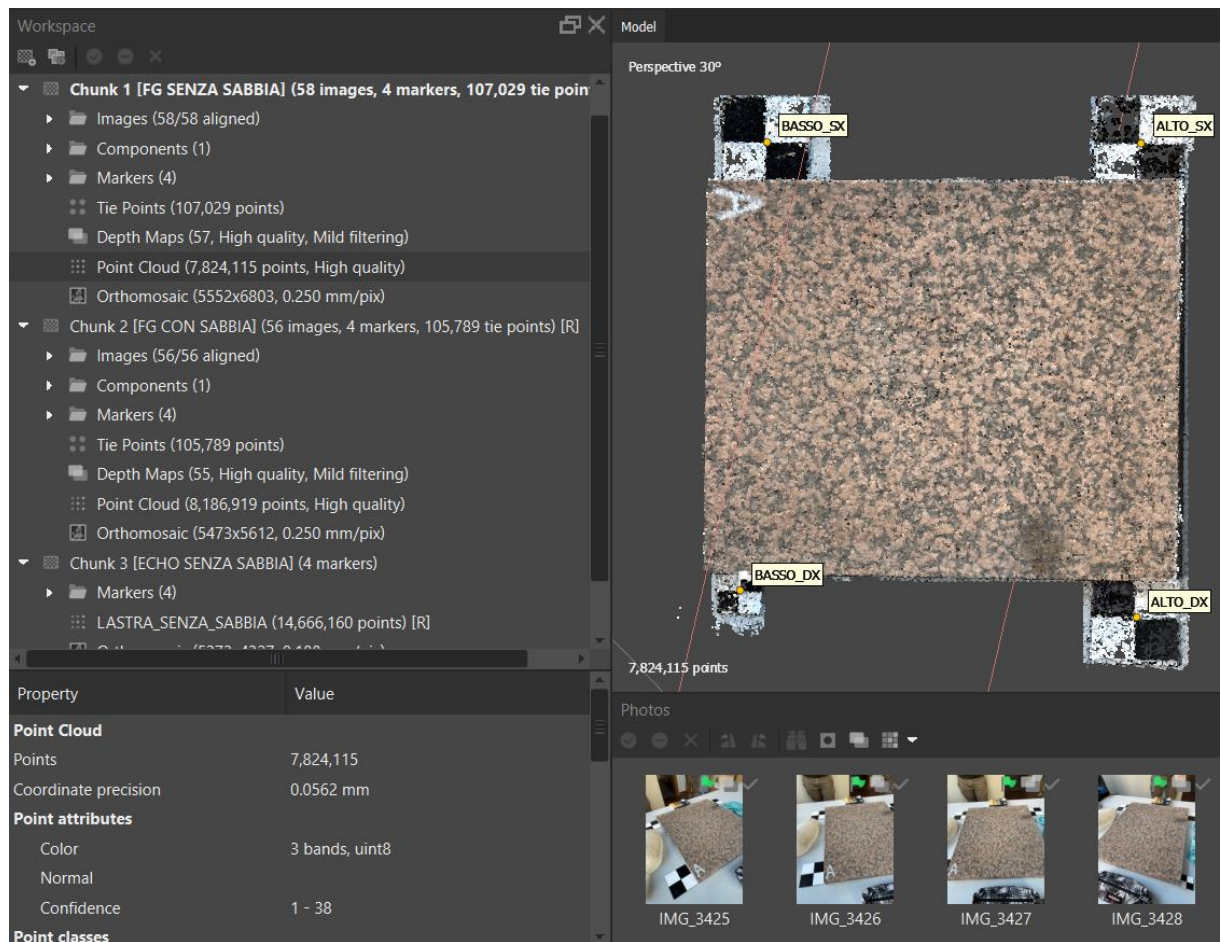


Figure 2.3: Agisoft Metashape Professional interface, granite slab case.

2.4.2 CloudCompare

The deployment of CloudCompare, an open-source software specializing in the processing of three-dimensional point clouds, proved crucial throughout the various iterations of this study, evolving in tandem with the escalating complexity of the problem. While the DEMs produced by Metashape software initially appeared sufficient, the requirement to perform comparative analyses necessitated more advanced geometric manipulation tools.

The role of CloudCompare became central during the first processing phase, when the research focused on the feasibility of calculating the sand volume by difference. The underlying concept initially involved comparing two distinct states of the exact same surface: the bare state, prior to conducting the sand patch test, and the state with the distributed sand, following the execution of the test. To enable this comparison, both point clouds had to be perfectly co-registered within a single, unified coordinate system.

For this purpose, the Iterative Closest Point (*ICP*) algorithm was implemented. Through successive iterations of rigid body transformations (*rotation and translation*), CloudCompare facilitated a millimetric alignment of the surface zones unaffected by the sand. This rigorous registration guaranteed that any calculated spatial deviation was exclusively attributable to the physical presence of the filling material rather than to positioning errors or scaling misalignments between the digital models.

2.4.3 QGIS

For the geospatial analysis and differential computation phase, QGIS an industry-leading, open-source Geographic Information System (*GIS*) software was introduced. Once the DEMs were exported from Metashape or CloudCompare, QGIS was utilized to process these surfaces as numerical data matrices.

The primary tool employed was the “*Raster Calculator*”, however, prior to executing this analysis, it was necessary to generate masks to isolate the specific area covered by the sand from the rest of the model. Subsequently, through extraction workflows, localized DEMs restricted entirely to the region of interest were obtained. Using the Raster Calculator, algebraic operations were then performed between the corresponding pixels of the two digital models, thereby executing the mathematical operation outlined in *Equation 2.2*.

$$\text{Raster Calculation} = DEM_{postTest} - DEM_{preTest} \quad (2.2)$$

The differences between the elevations of individual pixels generated a new layer, also in raster format, designated as the deviation map. The volumetric summation of this layer, computed by multiplying the elevation difference by the surface area of an individual pixel, yielded the estimated digital sand volume.

The parameters subsequently extracted from this layer via the “*Raster pixels to points*” tool were exported into an Excel file format to enable comprehensive analysis, filtering, and, where necessary, targeted investigation into the presence of noise manifest as outliers. Consequently, QGIS enabled the transformation of raw visual data into a rigorous quantitative dataset, while also streamlining the isolation and filtering of potential outliers or background noise.

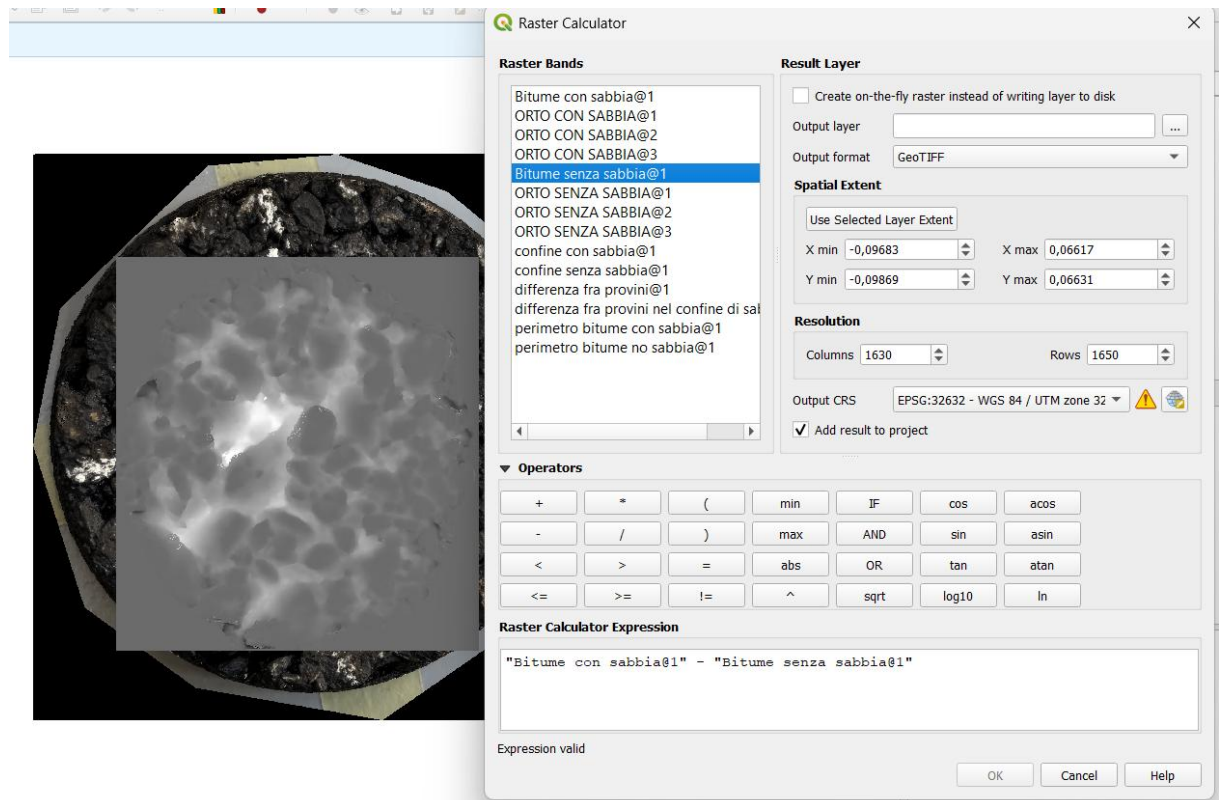


Figure 2.4: DEM subtraction within the QGIS environment, bituminous mixture specimen case.

2.4.4 RealityScan as a Low-Cost Photogrammetric Processing Tool

In the final phase of the research, the software RealityScan, developed by Epic Games, was introduced. The integration of this application aligns with a specific methodological objective: to make the processing workflow more accessible and reduce software-related costs.

Since Agisoft Metashape Professional entails significant licensing costs, the deployment of RealityScan allowed for the evaluation of a pipeline with reduced economic barriers.

This software was incorporated into the methodology exclusively during the processing phase of the bituminous mixture specimen. Its performance was assessed through a rigorous comparative analysis, wherein the identical set of photographic acquisitions was processed within both the Metashape and RealityScan environments.

The results demonstrated highly comparable point cloud density and geometric consistency, suggesting that RealityScan's cloud-based technology may be suitable for pavement

engineering applications. Indeed, the reconstruction of the macro-texture of the specimen under analysis appeared comparable to the geometry generated by Metashape.

However, a notable limitation emerged regarding user experience, the software is less intuitive and demands greater operational proficiency, particularly when defining the bounding volume of interest and managing data upload connections. Nonetheless, its integration into the software ecosystem represents a useful step toward a “*Sand-Free*” and low-cost workflow, executable with freely available software solutions.

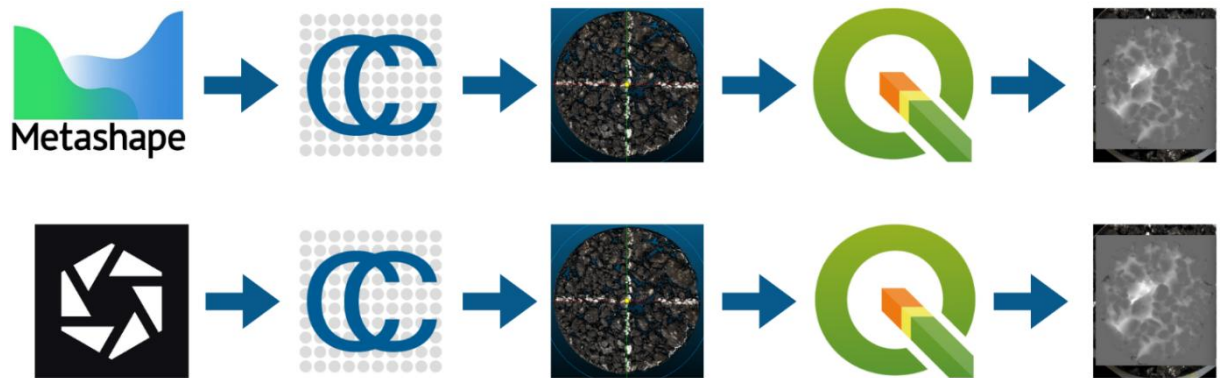


Figure 2.5: Representation of the two software ecosystems utilized, achieving the same result.

3 Phase I: Data Acquisition Protocol

The *initial operational block* of the research comprises *Phase I*, which is entirely dedicated to defining and executing sampling protocols and raw data collection.

Within this stage, the primary objective was to structure an iconographic acquisition methodology capable of guaranteeing maximum geometric fidelity and a subsequent accurate three-dimensional reconstruction, thereby minimizing distortions and data gaps. The geometric, environmental, and operational criteria that guided the photogrammetric survey are analysed below.

3.1 Photogrammetric Survey Planning

Photogrammetric survey planning represents the initial and most critical step of the entire research process, as the metric quality of the three-dimensional models and subsequent volumetric outputs is directly dependent on the spatial configuration and optical properties of the acquired images. To optimize this process and maximize the performance of Structure from Motion (*SfM*) algorithms, a rigid shooting protocol was codified and systematically applied to both the granite control surface and the bituminous mixture specimen.

To guarantee total stereoscopic coverage and prevent shadows, which are particularly critical for the bituminous mixture specimen due to its solid black coloration and deeply interconnected intergranular voids, a mixed image-capture strategy was selected.

The photogrammetric survey phase was consequently structured around three convergent configurations:

1. Convergent Orbital Capture:

A circular orbit was executed around the object under analysis, capturing consecutive images at regular intervals. Throughout this rotation, the tilt angle of the smartphone was kept constant, ensuring that the entire perimeter and the upper surface of the specimen were consistently contained within the primary frame.

2. Peripheral and Grazing-Angle Imagery:

Images were captured with the optical axis parallel to the supporting plane or at a steep grazing angle to precisely record the perimeter profile and thickness of the geometric structure. This approach ensured the comprehensive capture of the three-dimensional morphology of the specimen edges.

3. Nadir (Top-Down) Shots and Macro Details:

The dataset was completed by a series of orthogonal top-down (*nadir*) photographs, which were essential for the accurate projection of the Digital Elevation Model (*DEM*). These were supplemented by targeted close-up imagery, effectively detailed optical zooms on specific surface zones, with the objective of locally increasing the density of homologous points (*tie points*) within the areas of greatest roughness.

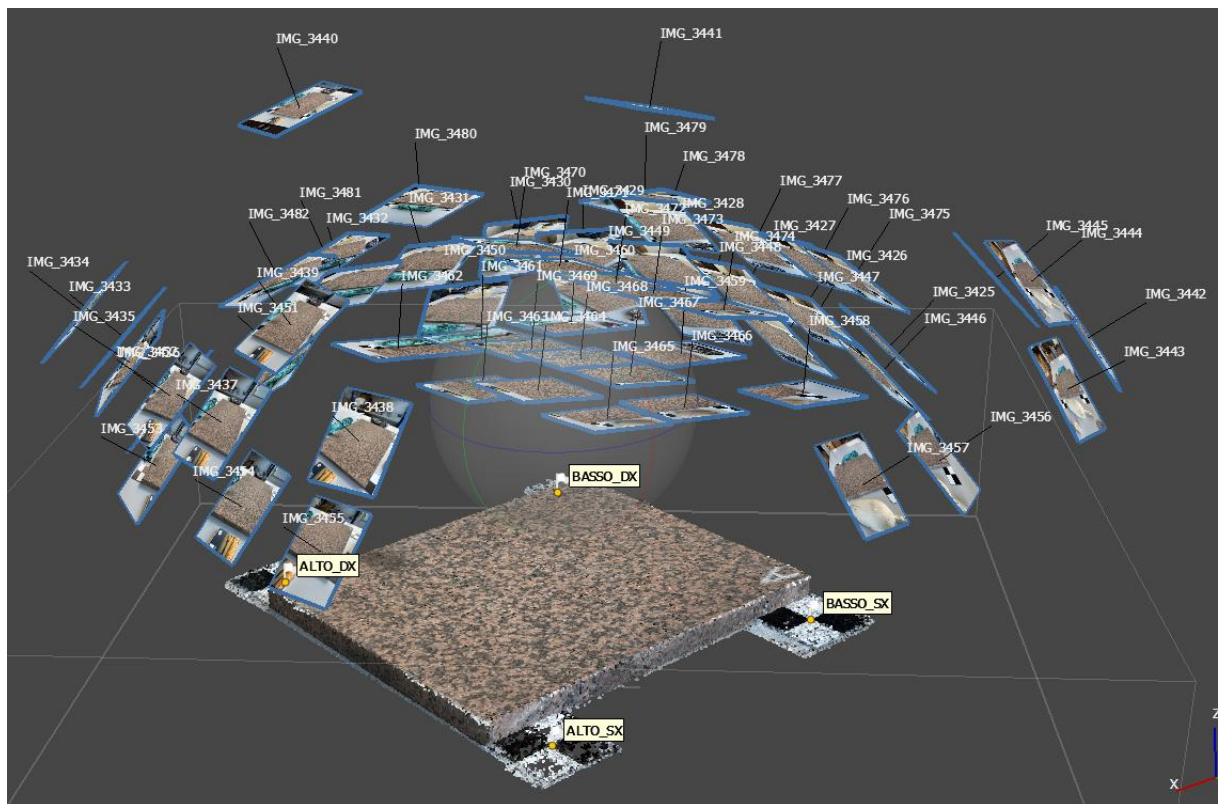


Figure 3.1: Visualization of the photogrammetric acquisition protocol within the Agisoft Metashape environment.

The success of the photogrammetric alignment relies heavily on the software's ability to identify common points of interest, or *key points*, across adjacent frames.

Throughout this experimentation, the overlap degree was maintained at highly conservative levels. By following the orbital and linear trajectories around the object, the operator advanced in small, restricted incremental steps between consecutive shots. This tightly controlled advancement guaranteed longitudinal and transverse overlaps estimated to be well above the standard 70-80% threshold, thereby minimizing the risk of misalignment or feature-matching failures.

The final datasets generated across the various test sessions exhibit strong numerical consistency, stabilizing within an optimal range of 50 to 60 photographs per specimen. This dataset size represents an ideal compromise between the necessity of high-density surface sampling ensuring that millimetres and sub-millimetres features are captured and the requirement to avoid overloading the computational architecture during post-processing.

The survey was conducted entirely within a laboratory environment, leveraging the ambient diffuse artificial lighting of the room. Illumination management required a critical precaution as the absolute exclusion of the smartphone's integrated flash. Utilizing a point-source flash fixed to the camera would have introduced unnatural dynamic shadows, creating frame-to-frame variations and anomalous specular reflections on the surfaces of the two specimens under analysis, which would ultimately mislead the feature-matching algorithms. By operating solely under the laboratory's ambient light, the radiometric homogeneity of the frames was preserved.

Finally, concerning the kinematics of the iPhone 15 Plus sensor, both operating distance and focus constraints were carefully managed. Although the device utilizes an autofocus system whose core internal parameters cannot be deeply customized, every shot was pre-monitored on screen. The camera focus was continuously forced onto the plane of the specimen to ensure maximum sharpness along the boundaries of the aggregates.

In strict alignment with the theoretical Ground Sample Distance (*GSD*) calculations discussed in the preceding chapter, the physical shooting distance between the lens and the target was maintained, as closely as possible through manual control, at a constant height of approximately 30 cm. As analytically demonstrated in *Table 2.1*, this specific distance guarantees a ground resolution of approximately 0.007 mm/pixel. This resolution is more than sufficient to map micro-texture and macro-texture irregularities with centesimal precision, providing the necessary accuracy for calculating the Mean Texture Depth (*MTD*).

3.2 Marker Positioning Strategy

Within the framework of digital photogrammetry operating under the principles of Structure from Motion (*SfM*), three-dimensional models generated solely from iconographic data initially lack an absolute metric scale and a defined spatial orientation. Indeed, the processing software reconstructs the geometry within an arbitrary coordinate system. It is therefore indispensable to introduce geometric elements with known coordinates or distances, referred to as control points or markers, into the field of view to metrically constrain the model and convert pixels into real-world units of measurement. Within the present research, the referencing strategy was not immediate, rather, it underwent a significant methodological evolution driven by the analysis of the critical issues that emerged during the first iterations, as well as the differing morphological properties of the investigated specimens.

The first phase of the experimentation, conducted on the granite control surface, involved the use of a “home-made” referencing system. This initial setup consisted of four two-dimensional geometric targets, characterized by a classic high-contrast yellow and black pattern, printed on standard paper and applied directly onto the surface of the slab. Prior to image capture, the distance between the centres of the respective markers was measured manually using a precision metal ruler. The objective of this configuration was to evaluate the efficacy of a completely artisanal, zero-cost approach. However, the processing phase within the Agisoft Metashape Professional environment revealed severe operational limitations. A lack of structural rigidity was observed in the home-made markers, which exhibited minor surface deflections and warping, alongside software collimation uncertainty resulting from the domestic printing process, which failed to guarantee perfectly sharp pattern edges. Consequently, the software's recognition algorithms encountered significant uncertainty when identifying the geometric centre of the target, thereby introducing a systematic error into the coordinate definitions. Due to these inaccuracies, which would have compromised the centesimal-millimetre accuracy required for macro-texture calculations, the initial point cloud generated from this dataset was entirely discarded.

To overcome the anomalies of the first iteration, and in conjunction with the introduction of the Mantis Vision F6-SR structured light scanner, a radical change in strategy was implemented. The paper markers were replaced with professional, dimensionally stable millimetre targets.

The spatial arrangement logic was also modified, the new markers were no longer applied on top of the slab but were instead positioned at its four outer corners, rigidly anchored to the surface of the workbench supporting the experimental setup. The response of the photogrammetric reconstruction engine was significantly superior, the high contrast and structural stability of the supports eliminated software uncertainty during the point collimation phase carried out within the Metashape environment. This allowed for highly precise scaling of the point cloud based on known distances and established the foundation for the implementation of a rigid *Cartesian reference frame*, designating one marker as the origin and the others ones to define the directions of the spatial axes, the analytical details of which will be thoroughly explored in the subsequent chapter.



Figure 3.2: Configuration of rigid professional markers positioned on the outer vertices for metric alignment optimization.

The transition from the analysis of the granite slab to the real-world case of the bituminous mixture specimen introduced an additional challenge. The surface of the bituminous specimen, inherently highly irregular, porous, and coated with a dark bitumen film, rendered the stable and planar application of adhesive or paper markers technically impossible. Such markers would have ultimately altered the morphology of the macro-texture itself or detached during handling, particularly during the transitional phases preceding and following the *Sand Patch Test*.

To mitigate this issue and achieve a streamlined workflow applicable within real operational contexts, an innovative referencing strategy was devised based on the introduction of a portable, millimetre-scaled template. The instrument selected to fulfil this function is a carpenter's L-square made of high-strength steel, featuring a millimetre scale engraved onto its metallic surface. This template features a long side of 300 mm and a short side of 150 mm.

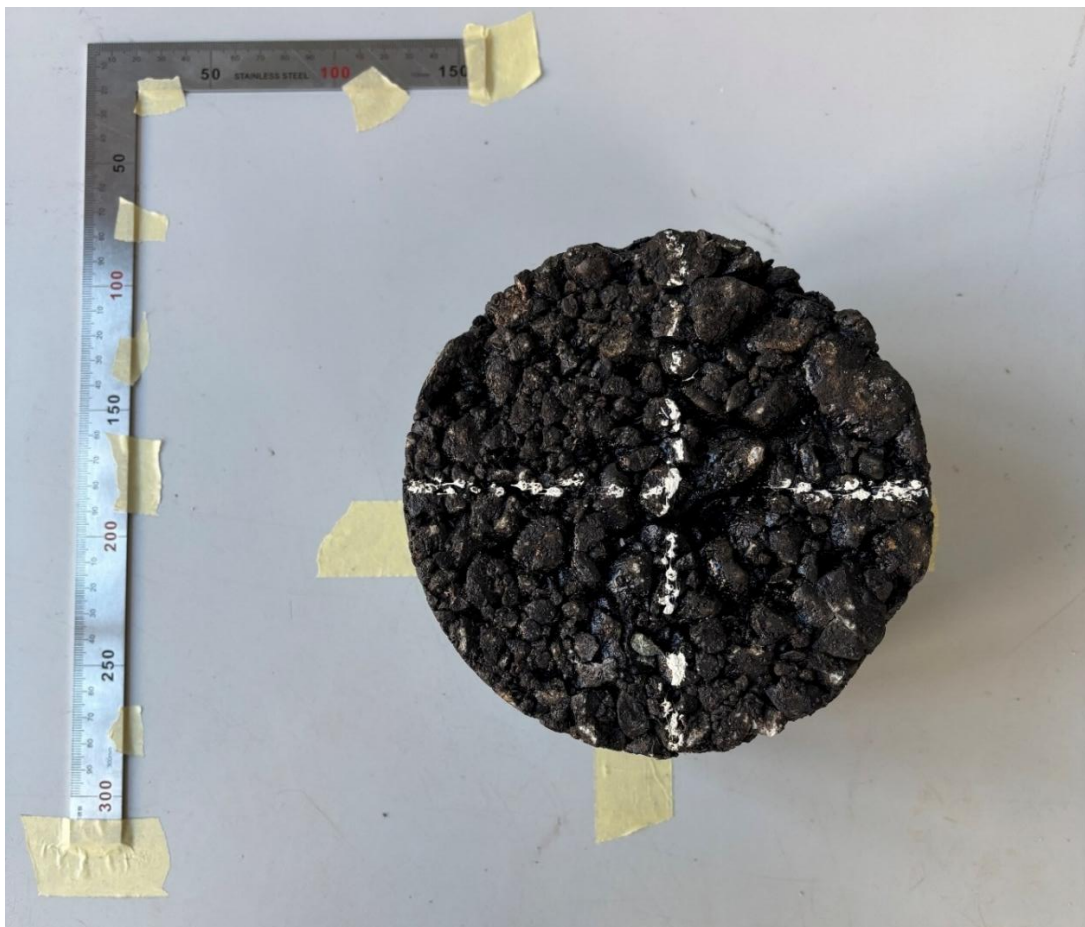


Figure 3.3: Utilization of an L-shaped graduated square as a portable and non-invasive reference system for the asphalt concrete specimen.

The L-shaped template was simply positioned on the supporting surface to frame the bituminous mixture specimen under investigation. This approach offered multiple metrological and operational advantages. First, it guaranteed independence from the surface of the examined specimen, as it was not necessary to glue or fix any element onto the sample or the supporting workbench, thereby preserving the material integrity and ensuring total accessibility to the intergranular voids for the subsequent sand filling. Second, the rigid reference system is completely reproducible, given that the dimensional stability of the steel ensured the absence of geometric deformations between the image-capture sessions. Furthermore, the native engraved millimetre scale was utilized directly within Metashape as a continuous sequence of control points at known distances, enabling an extremely robust millimetre scaling of the three-dimensional model. Finally, the carpenter's L-square perfectly meets the requirements of a low-cost and readily available tool, transforming the setup into a portable system ideal for rapid pavement surveys without the necessity of specialized topographic targets.

3.3 Survey Execution: Photographic Series Acquisition via iPhone 15 Plus and Reference Scanning with Mantis Vision F6-SR

Once the geometric protocols were codified and the metric referencing systems defined, the operational phase of executing the surveys within the laboratory was initiated.

This phase involved a distinct sampling strategy depending on the investigated material:

- The **granite slab** was subjected to a dual, comparative investigation, carried out using both the Mantis Vision F6-SR structured light scanner and the optical sensor of the iPhone 15 Plus. This approach aimed to establish a direct metrological comparison between professional and consumer-grade technologies.
- The **bituminous mixture specimen**, due to the intrinsic complexity of its texture and to validate the financial independence of the proposed workflow, was analysed exclusively through smartphone-based photogrammetric acquisition.

In order to guarantee the perfect comparability of the data and the absence of exogenous error variables, the entire experimental sequence on the granite slab followed a rigorous chronological timeline, maintaining the object and the professional markers in a state of absolute immobility and spatial invariance on the workbench throughout all the sub-phases described below.

3.3.1 Structured Light Scanning and Preliminary Procedure

The survey campaign on the granite slab commenced with the utilization of the Mantis Vision F6-SR structured light scanner. Operating within the working range of the instrument, which spans from 22 cm to 78 cm, the operator maneuvered the scanner over the slab guided by the real-time visual feedback displayed on the screen of the associated computer. In order to maximize the point cloud density and capture the microroughness of the granite, operations were conducted at the minimum distance allowed by the instrument, approaching the lower limit of 22 cm without falling below it to prevent any interruption in the cloud registration.

For the acquisition of the surface geometry, both operational modes offered by the native ECHO software were tested and executed:

1. The **Assisted Mode** was employed during the *first phase* of the survey by virtue of its high metrological rigor.

The software analyses the quality of the reconstruction in real time and, if it detects informational gaps or areas of low point density, automatically halts the progress of the scan, requiring the operator to pass back over the portion of the surface that was not correctly digitized. This enabled the acquisition of an initial dataset entirely free of geometric voids.

2. The **Free Mode** was subsequently utilized to conduct several *freehand scans*.

This approach, relying entirely upon the visual feedback and experience of the operator, significantly accelerated the acquisition process, thereby providing a benchmark to identify the optimal configuration during the post-processing phase.

Regarding temporal efficiency, the kinematics of the Mantis Vision F6-SR proved to be physically slower and more laborious compared to the rapid capture of a photographic sequence.

However, the utilization of structured light introduces a significant “efficiency paradox”, despite a slower field acquisition, the instrument delivers the point cloud almost instantaneously upon completion of the scan. Conversely, smartphone photogrammetry, although immediate during the image-capture phase, requires significant computational processing time to complete the alignment and dense matching stages. Once the scanning was concluded, primary processing was performed within the ECHO software environment.

As an initial step, a High-Quality Registration was executed, enabling the chromatic texture projection algorithm. Subsequently, the integrated automatic denoising tool was applied to achieve a preliminary reduction in background noise. Since this native filter is incapable of eradicating all surface geometric anomalies, it was decided not to generate the Digital Elevation Model directly within the ECHO environment, but rather to export the semi-processed point cloud to undergo fine cleaning and advanced noise filtering within the CloudCompare environment.

3.3.2 Smartphone Photogrammetric Acquisition and Execution of the Sand Patch Test

Immediately following the conclusion of the pre-test structured light scan, and without altering the position of the granite slab in the slightest, the photogrammetric protocol was executed using the iPhone 15 Plus, collecting the first dataset of 50-60 frames corresponding to the clean surface state. Upon completion of this initial macro-session (comprising the pre-test Mantis scan and iPhone image capture), the traditional Sand Patch Test was performed directly in the laboratory. The spreading of the standardized sand enabled the determination of the empirical and standardized value of the Mean Texture Depth (*MTD*). Subsequently, the surfaces of both the granite slab and the bituminous mixture specimen were subjected once again to the same survey workflow to record the post-test state.

For the *granite slab*, the chronological sequence was replicated so as first, the scan with the Mantis Vision F6-SR, managed using the same distance criteria and assisted mode, followed by the second set of photographic captures with the iPhone 15 Plus to conclude the workflow.

Regarding the *bituminous mixture specimen*, acquisition followed the same chronological alternation (pre and post-sand spreading) but focused exclusively on the smartphone photographic datasets integrated with the geometric presence of the carpenter's L-shaped metal template, thereby consolidating the shooting and detailed zoom procedures already extensively tested on the control surface.

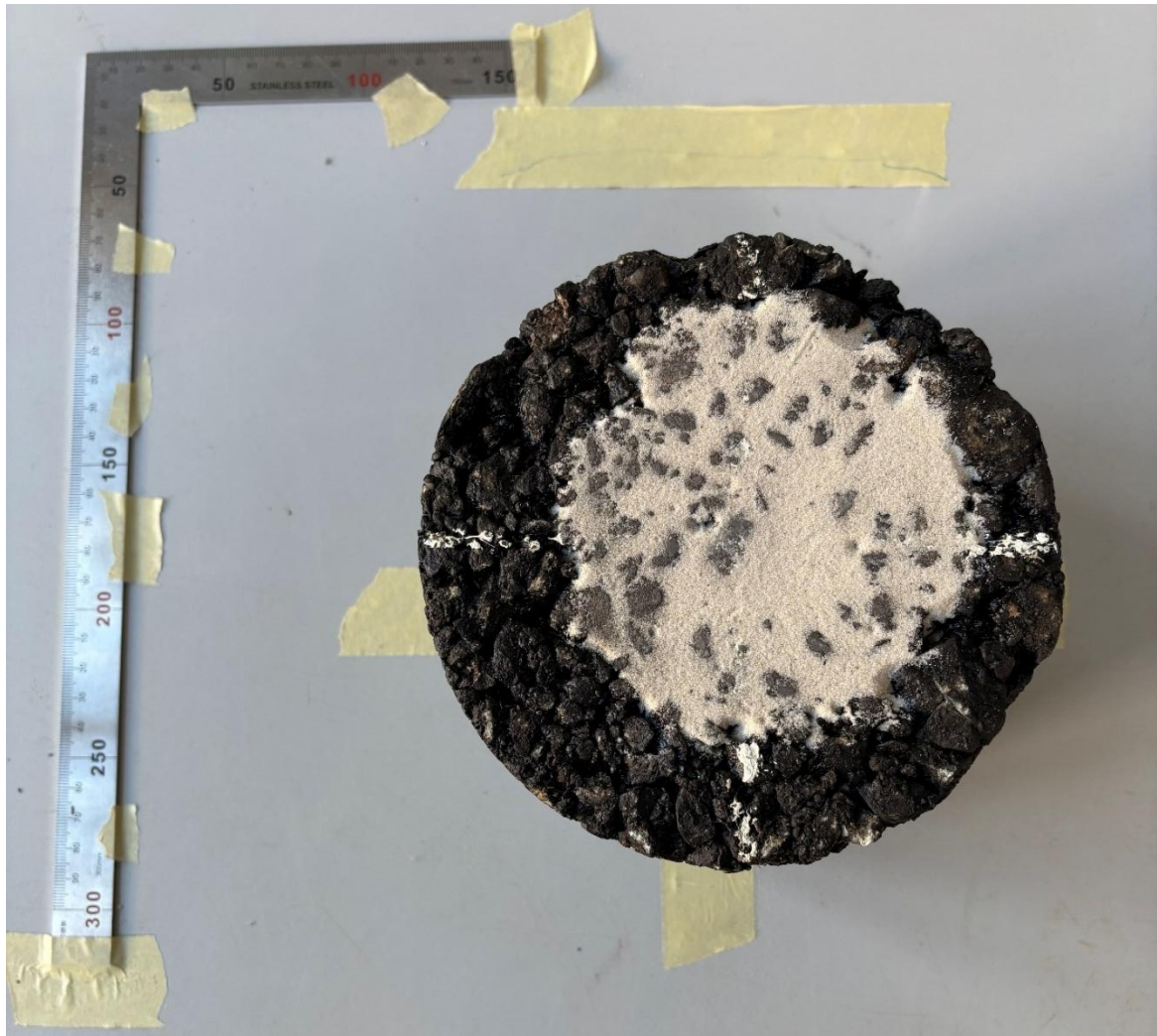


Figure 3.4: Post-test bituminous mixture surface configuration ready for the second digitization session.

The outcome of this phase resulted in the acquisition of consistent raw datasets, comprising structured light points clouds and photographic series, ready for input into the second phase dedicated to digital processing and three-dimensional reconstruction.

3.4 Post-Test State Sampling: Survey Procedure of the Surface After Sand Spreading for Subsequent Differential Analysis

The digital characterization of the post-test state namely, the surface upon which the spreading, compaction, and levelling of the standardized sand were performed, introduced elements of geometric and radiometric variability compared to the original surface.

This survey sub-phase was fundamental for gathering the three-dimensional datasets that, when compared with the pre-test state, enabled the calculation of the residual volume via differential analysis. The introduction of a loose and chromatically distinct material such as sand required a careful evaluation of the response of both optical and structured light sensors, as well as the adoption of rigorous mechanical precautions within the laboratory.

From a photogrammetric point of view, the presence of sand significantly modified the radiometric scenario of the survey. The employed sand, characterized by a very light, white-and-greyish coloration, generated a sharp chromatic contrast relative to the background surfaces, represented by the black bitumen of the specimen or the dark veins of the granite slab. Theoretically, strong localized contrasts and the reflective nature of the quartz grains can mislead photographic sensors, inducing local overexposure phenomena, white clipping, or altering the identification of homologous points due to specular reflections. However, the adoption of diffuse artificial laboratory lighting and the deactivation of the flash, as described in *Section 3.1*, mitigated this risk. In practice, the *Structure from Motion* processing pipeline encountered no anomalies or computational failures, the intrinsic granular texture of the levelled sand offered a high number of stable, artificial key points. Consequently, the point cloud was generated smoothly by the photogrammetry software without geometric discontinuities, faithfully mapping the altimetric profile of the sand patch.

One of the primary critical limitations of structured light projection systems lies in the management of highly rough, non-homogeneous, or geometrically complex surfaces, which can cause scattering of the projected pattern or the onset of high-frequency digital noise. In the case of the granite slab in the post-test state, the interaction between the F6-SR and the sand was positively influenced by the execution quality of the traditional test. Since the sand was carefully levelled by the operator until it skirted the outcropping surface crests, the resulting macroscopic geometry appeared free of discontinuities or abrupt slopes. This relative planarity allowed the structured light grid to reflect uniformly toward the scanner cameras. The raw point cloud delivered by the ECHO software proved clean and free of geometric anomalies or significant background noise, confirming the suitability of the instrument even on artificial filler materials.

A fundamental requirement for the subsequent geospatial analysis phase within the GIS environment, which is comprehensively addressed in *Chapter 4*, lies in the perfect preservation of the zone external to the test area.

To compute the sand volume via numerical subtraction between two Digital Elevation Models (*DEMs*), it is geometrically necessary for the areas not covered by sand to be perfectly matching and unaltered between the two layers. Consequently, during the post-test acquisition, the survey was not restricted solely to the sand patch, rather the photographic sampling and scanning were extended to the entire perimeter area of the specimen, which was free of sand, and to the surrounding markers. This strategy enabled the recording of the transition zone, namely the boundary perimeter where the sand thickness terminates and the underlying material resurfaces. The geometric stability of this external zone established the foundation for applying fine co-registration algorithms and for the subsequent creation, within the QGIS environment, of a specific masking layer designed to restrict the area of interest of the *Raster Calculator* exclusively to the pixels affected by the presence of sand.

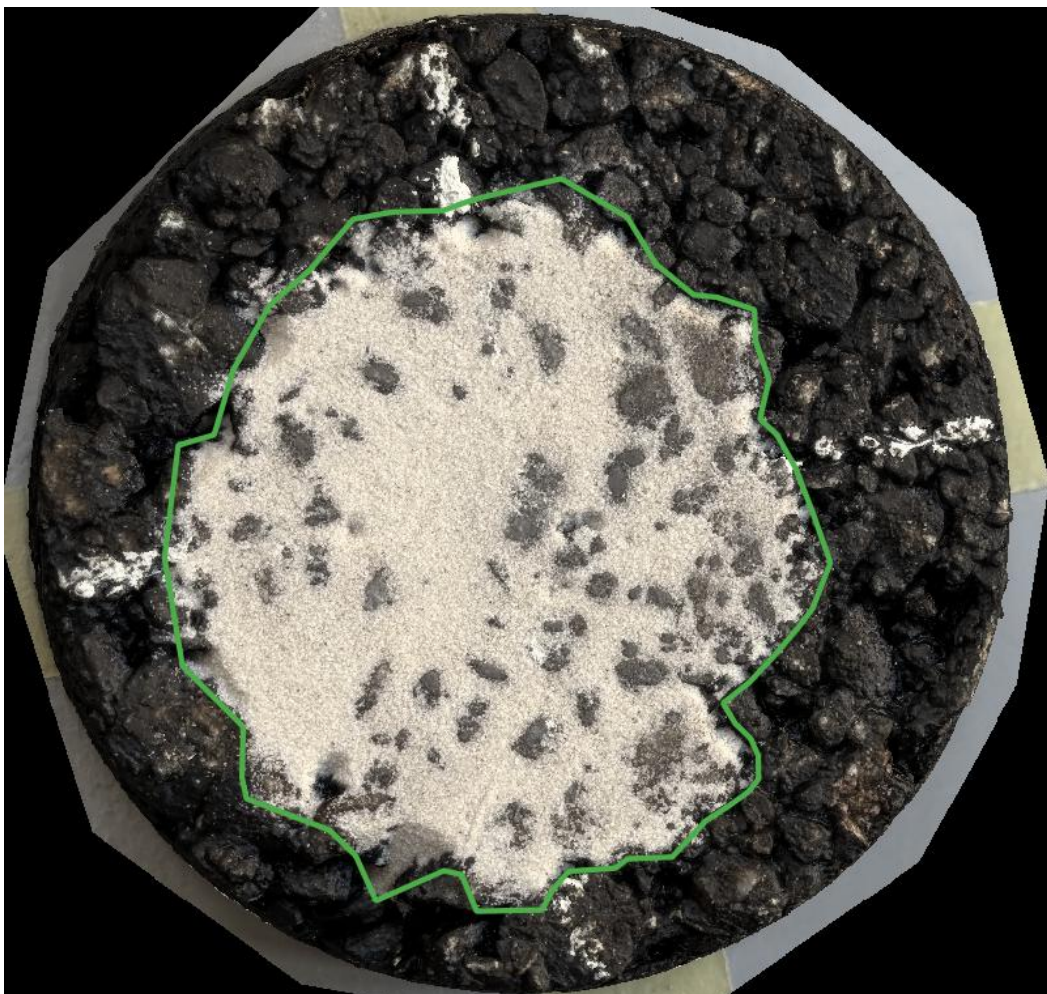


Figure 3.5: Detail of the transition zone between the standardized sand and the bare specimen surface.

Due to its calibrated particle size distribution and complete lack of cohesion, standardized sand represents an extremely volatile and unstable physical system. Any exogenous mechanical stress, such as vibrations of the supporting surface, accidental micro-impacts against the workbench, or sudden air currents could have caused the structural failure of the levelled sand layer, triggering secondary compaction phenomena or particle displacement. Even a millimetre-scale alteration in the sand configuration would have compromised the validity of the volumetric calculation, introducing discrepancies between the ground truth measured in the laboratory and the digital model.

To mitigate such systematic errors, the entire laboratory phase was managed under strict mechanical stability protocols. Throughout all photographic capture sessions with the iPhone and scanning sessions with the Mantis Vision F6-SR, the operator exercised the utmost care to avoid any impact or contact with the supporting workbench. The latter remained isolated from external vibration sources for the entire duration of the experimentation, thereby ensuring perfect spatial invariance and the morphological stability of the post-test dataset.

4 Phase II: Digital Processing and 3D Reconstruction

The *second operational block* of the research focuses on the computational phase, within which the two-dimensional iconographic datasets acquired during the laboratory session are converted into high-density three-dimensional geometric models. The core of this transition is represented by the application of close-range digital photogrammetry algorithms.

The processing workflow for model reconstruction is analysed in detail below.

4.1 Structure from Motion (SfM) Workflow: Image Alignment and Dense Point Cloud Generation

The geometric reconstruction of both the granite slab and the bituminous mixture specimen was entirely executed using Agisoft Metashape Professional software. The program implements Structure from Motion (*SfM*) algorithms to simultaneously estimate the interior and exterior orientations of the photographic captures, followed by dense matching algorithms for the generation of the dense point cloud. In order to standardize the process, minimize operational downtime, and ensure the perfect reproducibility of the workflow, the individual computation phases were not executed manually in a discrete manner, but were instead aggregated and initiated via the “*Batch Process*” feature. This architecture enabled the concatenation of image alignment, dense Point Cloud generation, Digital Elevation Model (*DEMs*) and Orthomosaic production into a single processing queue.

The first procedural step involved the alignment of the frames (via “*Align Photos*” tool). For this operation, the maximum accuracy level, designated as *Ultra High*, was selected. This setting forces the software to process the images at their original native resolution without any subsampling or down sampling, thereby preserving the geometric integrity of each individual pixel from the iPhone 15 Plus sensor.

Regarding the numerical constraints for point extraction, it was decided to maintain the standard default parameters of the software:

- The **Key Point Limit**, set on 40.000 points, defines the maximum number of feature points extracted by the software from each individual photograph during the preliminary texture analysis phase.
- The **Tie Point Limit**, set on 4.000 points, indicates the maximum number of homologous tie points that are effectively matched and validated between adjacent frames to estimate the relative positions of the cameras.

Maintaining the default parameters, in conjunction with the *Ultra High* accuracy setting, achieved a 100% alignment success rate for the frames across both datasets (the granite slab and the bituminous mixture specimen), without any exclusions or failures in camera orientation. Unlike standard workflows, where the sparse cloud is manually cleaned using geometric filtering tools, such as “*Gradual Selection*” based on reprojection error or reconstruction uncertainty, this experimentation adopted an analytical and iterative control approach. The metrological quality of the sparse cloud was directly monitored through the exportation of the technical report natively generated within the Metashape environment. If the global accuracy parameters or residual pixel errors exceeded the predefined centesimal tolerances, the entire process was halted and reprocessed.

During these iterative phases, the optimization and correction of geometric drifts were not reliant on the arbitrary deletion of tie points, but rather on a more rigid and detailed definition of local scaling and georeferencing. This was achieved by refining the placement of digital targets on the centres of the control points, the so-called markers, described in the subsequent section, thereby forcing the camera optimization algorithm to recalibrate the internal sensor parameters based on extremely strict real-world metric distances.

The geometric core of the reconstruction, upon which the accuracy of the macro-texture calculation depends, is the generation of the dense point cloud. In this case as well, within the procedural pipeline, the quality level was set to *Ultra High*. This setting calculates depth maps to maximize the number of final points, albeit at the expense of a higher computational burden. Critical attention was dedicated to selecting the *Depth Filtering* algorithm, for which the *Moderate* mode was chosen. Within the Metashape options, an *Aggressive* filtering mode tends to drastically eliminate points considered as outliers or noise, causing an undesirable geometric smoothing effect on the surfaces.

In the field of road pavement engineering, aggressive filtering would have artificially flattened the microroughness of the granite and, above all, the intergranular voids of the bituminous mixture specimen, irreversibly distorting the final MTD and MPD values. The *Moderate mode* represented the perfect metrological compromise, allowing for the elimination of macroscopic background noise while preserving intact the actual roughness, the sharp peaks of the aggregates, and the true depth of the recesses within the examined material.

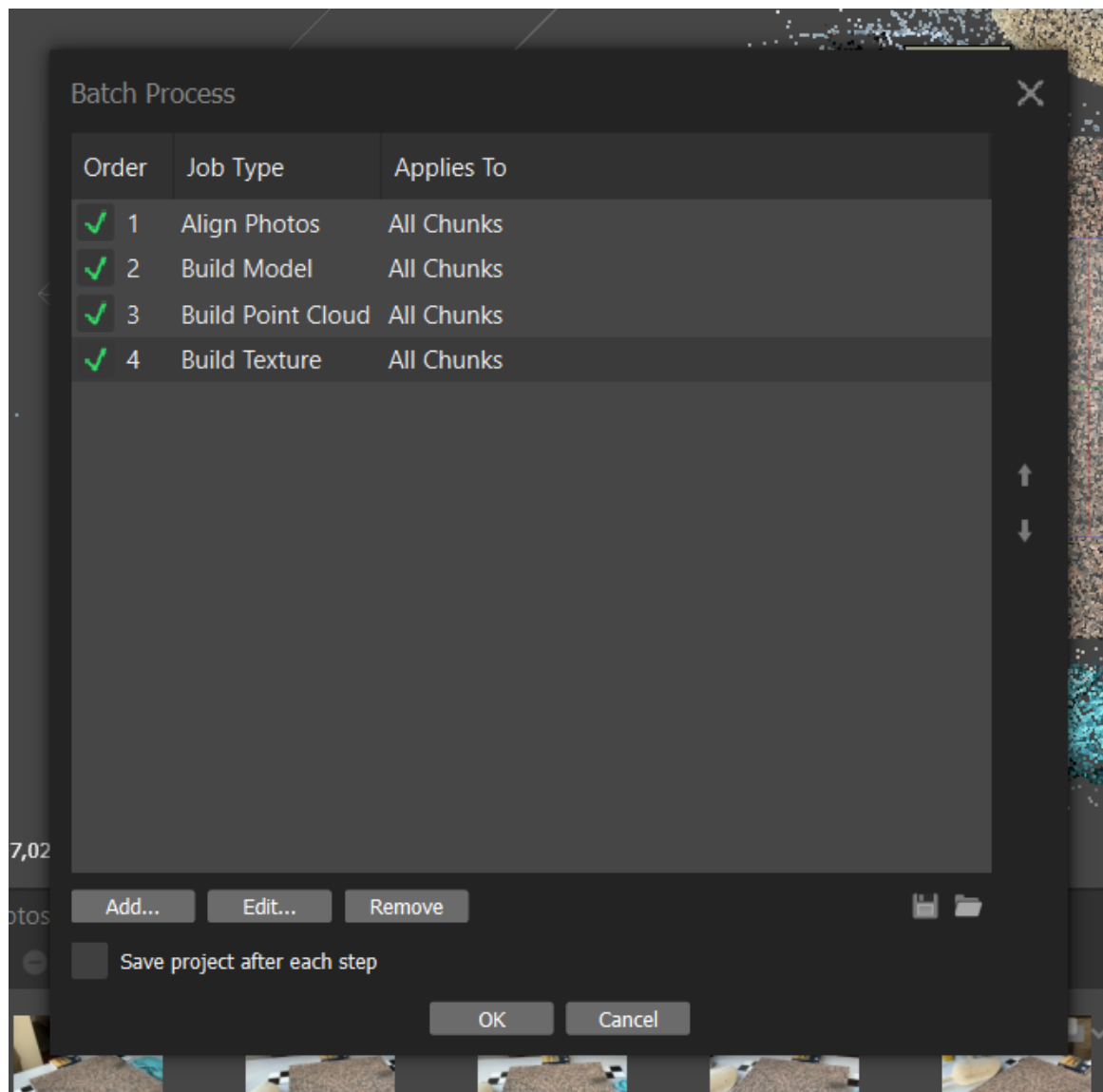


Figure 4.1: Automated processing pipeline configuration using the Batch Process feature in Agisoft Metashape Professional.

Although the alignment achieved a 100% success rate in both laboratory sessions, the intrinsic response of the dense matching algorithms significantly highlighted morphological differences closely related to the nature of the materials, as described below:

- **Granite Slab:**

The reference surface, characterized by a planar geometry and a homogeneous light distribution, was flawlessly reconstructed. The three-dimensional model was continuous, compact, and entirely free of holes or geometric gaps.

- **Bituminous Mixture Specimen:**

Despite the application of maximum processing parameters, the complex architecture of the specimen, characterized by a deep central depression and a dense alternation of voids and protruding aggregates, generated local phenomena of optical occlusion and shadowing. Consequently, the algorithm failed to fully reconstruct the geometric portion at the bottom of the main depression, leaving some gaps in the dense point cloud.

To overcome this intrinsic limitation and avoid affecting the subsequent volumetric calculation, it became necessary to devise a filling strategy for these voids. Specifically, two different geometric compensation methodologies were chosen: the application of spatial interpolation algorithms directly during the DEM export phase from Metashape, and the implementation of the Kriging geostatistical method within CloudCompare software, where their specific application details will be analysed in the dedicated sections.

The adoption of ultra-massive settings entailed a significant workload on the computer hardware resources. The average time required to complete the entire process, including alignment, maximum resolution dense cloud generation, DEM extraction and Orthomosaic texturing settled within a range of 45 to 60 minutes per single dataset. This datum highlights how, compared to an extremely rapid field acquisition phase, approximately 2-3 minutes for taking photos with the iPhone 15 Plus, the photogrammetric workflow shifts most of the temporal burden to the office processing phase. This factor must be duly considered when evaluating the overall efficiency of the method in relation to the timeliness of the data provided by the structured light scanner.

4.2 Scaling and Georeferencing: Utilizing Metashape Pro for Metric Constraints via Graduated Markers

The conversion of the three-dimensional model from an arbitrary, dimensionless numerical space lacking orientation to a real, absolute metric system constitutes the fundamental prerequisite for any engineering-grade quantitative and qualitative analysis. Within this research, this step was performed by leveraging the most advanced features of the “*Reference*” panel in Agisoft Metashape Professional. The objective was twofold, as first to associate a real metric scale with millimetre-level precision to the point clouds, and secondly to rigidly rotate the model in space in order to define an optimal geometric reference plane for the subsequent extraction of Digital Elevation Models.

To avoid the uncertainties of automatic shape recognition algorithms, which are often subject to false positives in the presence of complex or shadowing surfaces, such as the bituminous mixture specimen, an entirely manual approach was chosen for the target identification phase, the so-called “*flags*”. Each control point was individually identified and collimated by the operator on every photograph of the dataset in which it was visible, thereby optimizing the geometric stability of the constraint.

The strategy employed two distinct approaches based on the adopted experimental setup and material:

1. Granite Slab Case:

Manual collimation targeted the geometric centres of the four high-dimensional-stability professional markers positioned on the outer vertices of the laboratory table.

2. Bituminous Mixture Case:

The integration of the L-shaped metal jig required identifying rigid geometric control points directly on the metric scale engraved on the steel. Four discrete points were isolated corresponding to the outer ends of specific graduation marks:

- On the **long side of the L-square**, which has a total length of 300 mm, the outer extremities corresponding to the 100 mm and 300 mm marks were taken as a reference control points;
- On the **short side of the L-square**, with a total length of 150 mm, the outer extremities belonging to the 50 mm and 150 mm marks were selected as reference control points.

Once the manual placement of flags across the entire image dataset was complete, we moved on to setting up the metric structure of the model within the “*Reference*” panel. To bypass unnecessary global coordinates in a lab environment, we implemented a local, relative *Cartesian coordinate system* instead. The spatial coordinates (X, Y, Z) of the points were entered manually following a clear geometric logic: a single marker was chosen as the absolute origin of the system, with coordinates set to (0, 0, 0), while the other points were assigned known coordinates calculated from the actual distances measured beforehand on the slab or read directly off the L-shaped metal template.

Since both the professional markers and the steel square rested on the exact same levelled surface of the lab workbench holding the samples, all control points were given a Z elevation value exactly equal to zero. This setup gave us a huge metrological advantage during georeferencing, forcing the software to align the marker plane perfectly with its own XY equatorial plane.

As a result, the Z-axis of the digital model ended up completely orthogonal to the surface of the slab or specimen. This perfect orthogonality was essential for the subsequent Digital Elevation Models (DEMs) export phase, eliminating any risk of tilted or distorted digital models that would have compromised the differential volumetric calculations.

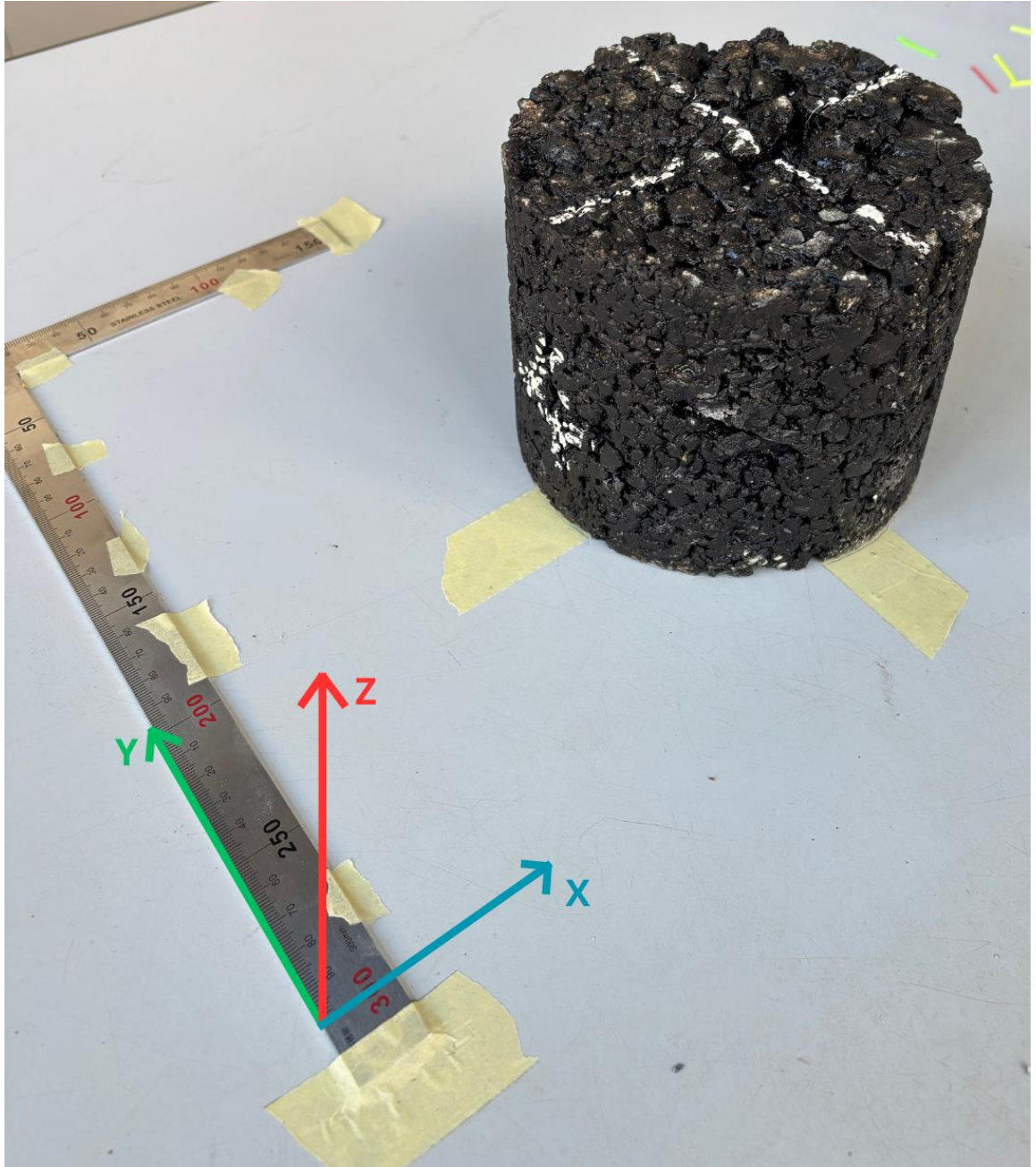


Figure 4.2: Scheme of the local Cartesian reference system established on the L-shaped jig to ensure Z-axis orthogonality relative to the support plane.

Entering these rigid metric constraints allowed us to activate an iterative quality control and residual error reduction routine, executed through the “*Optimize Camera Alignment*” tool. This algorithm recalculates the exterior orientation parameters as well as the intrinsic lens distortion coefficients of the iPhone 15 Plus, both radial and tangential distortion, minimizing the deviation between the theoretical positions of the markers and their actual positions derived from the photograph’s acquisitions.

The workflow was structured according to an iterative logical cycle:

1. Verification of Alignment Residuals:

Upon completion of the initial alignment, the root-mean-square error (*RMSE*), expressed in millimetres, was analysed for each marker.

2. Micrometric Adjustment:

If the software indicated an elevated or unacceptable error on a specific target, the individual images characterized by a high residual were inspected, and the relative control point (represented by the “*flag*”) was precisely adjusted to correct any visual collimation imperfections.

3. Calibration Optimization:

The camera optimization tool was executed to update the matrix of the internal sensor parameters.

This optimization process was repeated until the residual error vectors stabilized at values well within the tolerances required for the research. Thanks to this rigorous calibration, the final metric error on the control points was reduced to the order of hundredths of a millimetre, achieving accuracy values of approximately 0.05 mm. This level of precision ensured the perfect dimensional stability of the three-dimensional model, making it metrologically suitable for the millimetric characterization of road macro-texture.

4.3 Optimization and Registration: Application of the ICP Algorithm in CloudCompare for Alignment Between Different Surface States

The accurate quantification of macro-texture via differential analysis relies on the ability to compare the topography of the same specimen at two distinct points in time: the clean state and the state filled with silica sand. Although the initial alignment in Agisoft Metashape Professional was configured by sharing the same control points between both processing workflows, transitioning to the open-source software environment CloudCompare was essential to perform a fine, mathematically optimized co-registration.

This phase aims to eliminate residual micro deviations between the geometries, ensuring that the only detectable volumetric variation is exclusively attributable to the presence of the sand.

Although the pre and post-test point clouds already appeared largely coincident to the naked eye due to the preliminary workflow executed in the *SfM* software, a manual rough-alignment phase was performed to eliminate any computational ambiguity. Within CloudCompare, the “*Align*” tool was activated, which requires the operator to select a series of easily identifiable homologous points on both models:

- For the **granite slab** the centres of the four rigid professional markers anchored to the workbench were selected.
- For the **bituminous mixture** specimen: the outer extremities of the millimetric graduations engraved on the L-shaped metal template, corresponding to the 100 mm and 300 mm marks on the long side, and the 50 mm and 150 mm marks on the short side were chosen as geometric control points.

This procedure enabled the computation of an initial approximate roto translation matrix, bringing the two datasets closer in virtual space and establishing ideal conditions for the application of the subsequent fine convergence algorithms. The primary metrological challenge in applying the Iterative Closest Point (*ICP*) algorithm lies in the fact that it operates by iteratively minimizing the root-mean-square distance between points belonging to two overlapping clouds, if they represent the exact same object.

In this case, the post-test state introduces a significant local morphological variation determined by the volume of sand, which is absent in the pre-test state. If the *ICP algorithm* had been applied to the entire model, it would have attempted to force a match even in the central zone, thereby distorting the global alignment and artificially flattening the volume of the sand cone. To prevent this systematic error, a rigorous masking and geometric isolation procedure was devised, divided into the following phases:

1. Definition of the Reference Cloud:

The pre-test point cloud was selected as the fixed reference entity, as it was structurally intact and free from geomorphological noise. The post-test cloud point was designated as the moving entity to be aligned with this reference framework.

2. Centre-Periphery Segmentation:

Using the “*Segment*” tool in CloudCompare, the central region affected by the presence of sand was temporarily clipped and isolated from both pre-test and post-test point clouds.

3. Application of ICP to the Outer Perimeter Frame:

The *ICP algorithm* was executed exclusively on the remaining outer perimeter sections. Because these areas remained completely static and unchanged during the laboratory sessions, the algorithm could compute a highly accurate convergence based solely on true geometric invariances.

4. Transfer of the Transformation Matrix:

Upon completion of the computation, the 4x4 roto translation matrix generated by the *ICP algorithm* for the outer frame was copied and applied to the previously isolated central portion containing the sand.

5. Reconstitution of the Integrated Model:

Finally, the central and perimeter components were merged back together using the “*Merge*” tool.

Through this approach, the central after-test cloud underwent the exact same spatial transformation as its outer frame, ensuring perfect alignment with the before-test model without altering or distorting the sand geometry during the computation.

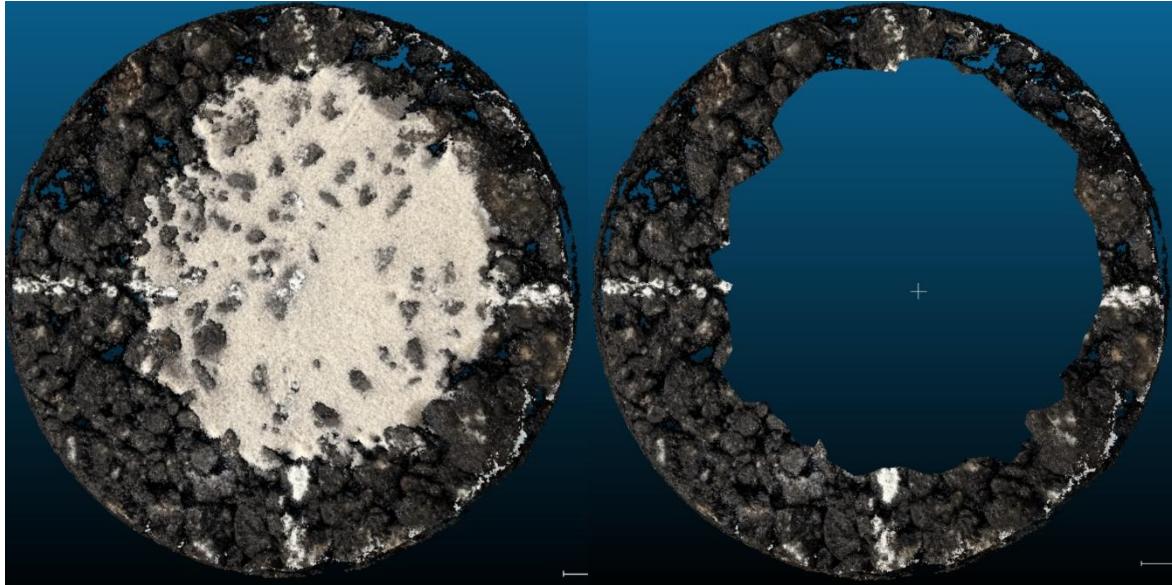


Figure 4.3: CloudCompare segmentation workflow of the sand-affected area for ICP algorithm application strictly on the external perimeter frame.

The execution of the *ICP algorithm* was guided by the configuration of precise computational constraints to maximize metric rigidity:

- **Scale Invariance (Adjust Scale option disabled):**

The option for automatic scale estimation was strictly kept deselected. The model underwent exclusively a rigid roto translation in space, eliminating the risk of dimensional micro-distortions or anisotropic scaling that would alter the actual physical dimensions of the specimens.

- **Overlap and Sampling Estimation:**

The theoretical overlap value between the static portions was set close to 100%, while the percentage of points used for the calculation was managed through the automatic saturation of the sampling resources.

- **Hardware Optimization:**

The computation was parallelized by setting the “*Max thread*” count to 14/16 threads, fully exploiting the multi-core architecture of the computer's CPU to manage the high point density without performance issues.

Once the process was complete, the quality of the fine co-registration was validated by analysing the final Root Mean Square Error (*RMSE*) value returned by the CloudCompare report. The final recorded metric error stood at *one millimetre* for the granite slab and *half a millimetre* for the bituminous mixture specimen. These residual values, calculated over the entire extent of the external control surfaces, demonstrate the extreme structural consistency of the two multi-temporal models.

This sub-millimetric accuracy ensures that the pre and post-test clouds are perfectly overlapped and geometrically crossed, establishing optimal mathematical conditions for the subsequent extraction of differential Digital Elevation Models (*DEMs*) and the isolation of the net sand volume.

4.4 Generation of Raster Products: Creation of High-Resolution Digital Elevation Models and Orthomosaics

The generation of high-resolution raster products represents the link between the three-dimensional point cloud and the subsequent geospatial quantification of the sand volume. Although the initial plan was to exclusively use Agisoft Metashape Professional for the entire computational pipeline but the metrological requirement for a fine, constrained co-registration via the *ICP algorithm* (analysed in *Section 4.3*) necessitated a restructuring of the final workflow. Metashape was therefore utilized as the photogrammetric processing engine solely up to the extraction of the dense point clouds. Once exported, before aligned and millimetric registered within CloudCompare, these clouds underwent the final rasterization process directly in the latter software environment, ensuring the perfect spatial consistency of the reference elevation models and orthomosaics.

A primary objective of the experimentation was to evaluate the influence of raster spatial resolution on the accuracy of the macro-texture volumetric calculation. To achieve this, the rasterization process in CloudCompare was not executed using a single arbitrary value, but was instead structured according to a multi-scale analytical approach:

- **0.5 mm:**
Standard resolution suitable for a macroscopic characterization and a low computable burden.
- **0.2 mm:**
Intermediate resolution for capturing transitional details.

- **0.1 mm:**
High resolution, suitable for identifying the surface micro-roughness of the exposed aggregates.
- **0.05 mm:**
Maximum, sub-millimetric resolution, configured to test the physical limits of the iPhone 15 Plus sensor and evaluate the information saturation of the model relative to the accuracy of the volumetric calculation.

This approach enabled the generation of a comparative matrix of digital models for each specimen, laying the fundamentals for the numerical sensitivity analysis that will be discussed in the subsequent chapter.

During the generation of the Digital Elevation Models (*DEMs*) using the *Rasterize tool* in CloudCompare, a critical issue arose related to the intrinsic characteristics of the bituminous mixture specimen. As highlighted in *Section 4.1*, the complex pavement morphology, characterized by deep voids and cast shadows, resulted in point cloud gaps at the bottom of the main depressions.

Initially, the use of standard linear interpolation functions provided by the software was tested to fill these gaps. However, the application of classical interpolation exhibited significant mathematical limitations, yielding a raster matrix affected by numerical anomalies and an excessive number of void cells (*pixels with a value of zero*). This phenomenon would have introduced a severe systematic error into the differential sand volume calculation.

To overcome this problem, the Kriging interpolation option integrated within CloudCompare was implemented.

Kriging is an advanced *geostatistical interpolation method* that does not rely on a simple linear transition between known points, instead it analyses the overall spatial correlation of the surface using a semi-variogram to estimate the values of the missing pixels.

The application of Kriging successfully reconstructed the geometric continuity at the bottom of the asphalt specimen's depressions in a smooth and mathematically rigorous manner, eliminating null pixels while preserving the actual profile of the road pavement.

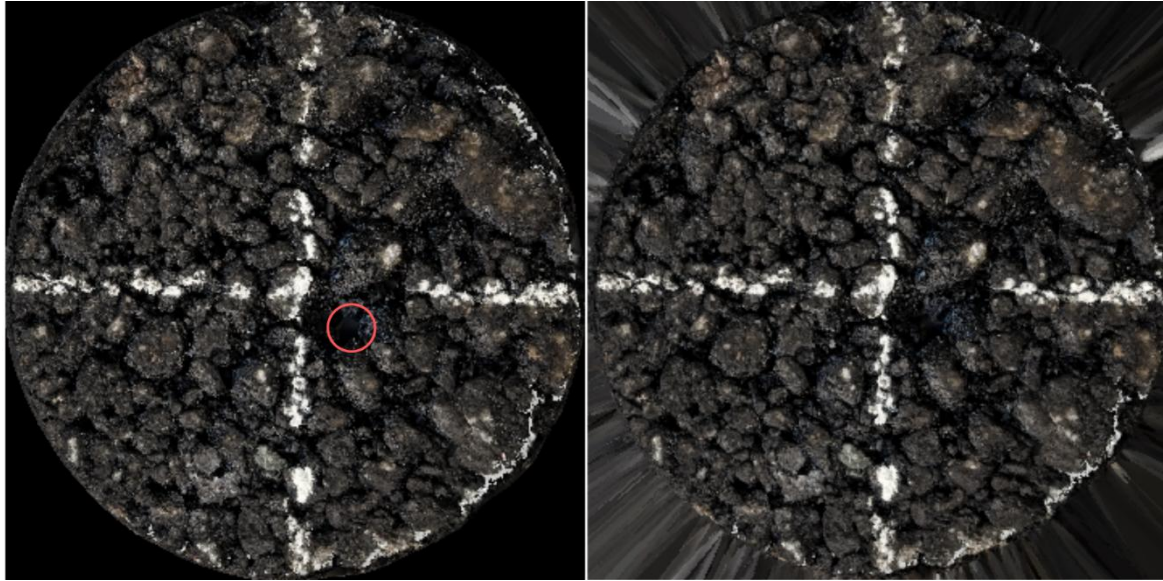


Figure 4.4: Comparison between linear interpolation rasterization (left) and geostatistical optimization via Kriging algorithm (right).

In parallel with the generation of the DEMs, high-resolution orthomosaics were produced. Although during an initial exploratory phase within Agisoft Metashape Professional the orthomosaic was generated primarily as a visual reference to support the operator, the final procedural workflow delegated the production of the orthomosaic to the CloudCompare environment as well.

The *RGB* radiometric channels of the original images were projected directly onto the geometric grid defined by the DEM step size. Consequently, a perfectly corresponding orthomosaic was produced for each of the four tested step sizes, ranging from 0.5 mm down to 0.05 mm.

This rigorous bidirectional geometric correspondence, whereby elevation pixels and colour pixels are spatially identical, proved to be of fundamental importance for visually validating the exact boundaries of the sand across successive overlays.

The final raster products were exported by strictly applying the *Local Coordinate System* defined in *Section 4.2* using the template and markers. This constraint ensured that the raster for the pre-test and post-test states were perfectly matchable on a pixel-for-pixel basis, eliminating any spatial misalignment errors. The export of these data was executed in two distinct formats, structured according to the requirements of the subsequent analysis phases addressed within this research work.

1. GeoTIFF format (.tif):

The DEMs and orthomosaics were saved as georeferenced raster files in the local system to be imported into the QGIS software.

Within this environment, analysed in *Chapter 5*, the (.tif) files were subjected to raster algebra for a rapid volumetric calculation via direct pixel subtraction.

2. ASCII Grid format (.txt):

To fulfil the digitization and automation objectives of the procedure, the same DEMs were exported as numerical matrices structured in *ASCII text* format.

This format explicitly defines elevation values within a readable and manipulable text grid, serving as the essential input for the custom Python algorithms developed to automate the entire volumetric calculation and the determination of MTD and MPD parameters without the need for a traditional GIS interface.

4.5 Comparative Analysis of Reconstruction Engines: Preliminary Assessment of RealityScan Against Agisoft Metashape

At the conclusion of the three-dimensional modelling phase, it was deemed appropriate to include a significant methodological note aimed at testing the potential of modern photogrammetric technologies oriented toward process automation. Alongside the classic and rigorous approach provided by a professional desktop suite such as Agisoft Metashape Professional, the current market offers solutions based on automated algorithms and simplified interfaces, defined as “*User-Free*” due to the total absence of complex technical parameters required from the operator.

To validate the reliability of these tools within an engineering and road pavement context, the same photographic dataset was processed using the desktop version of RealityScan, developed by Capturing Reality and Epic Games. The final model was subjected to a strict geometric compliance assessment to determine whether an automated application could represent a reliable alternative for rapid on-site screening.

The operational architecture of RealityScan differs significantly from that of Metashape due to an approach focused on maximum computational simplification. The alignment of the frames proved highly analogous to the process executed in Metashape, the desktop interface

allowed the operator to manually place control points on individual photographs to guide the relative camera orientation and optimize the spatial coherence of the block.

However, the subsequent processing phase excluded any human intervention in the selection of algorithmic parameters. The processing engine automatically performed feature extraction, camera alignment and dense point cloud generation without requiring the configuration of depth filters, quantitative limits on key points or differentiated accuracy levels delivering the final output in a direct and standardized manner.

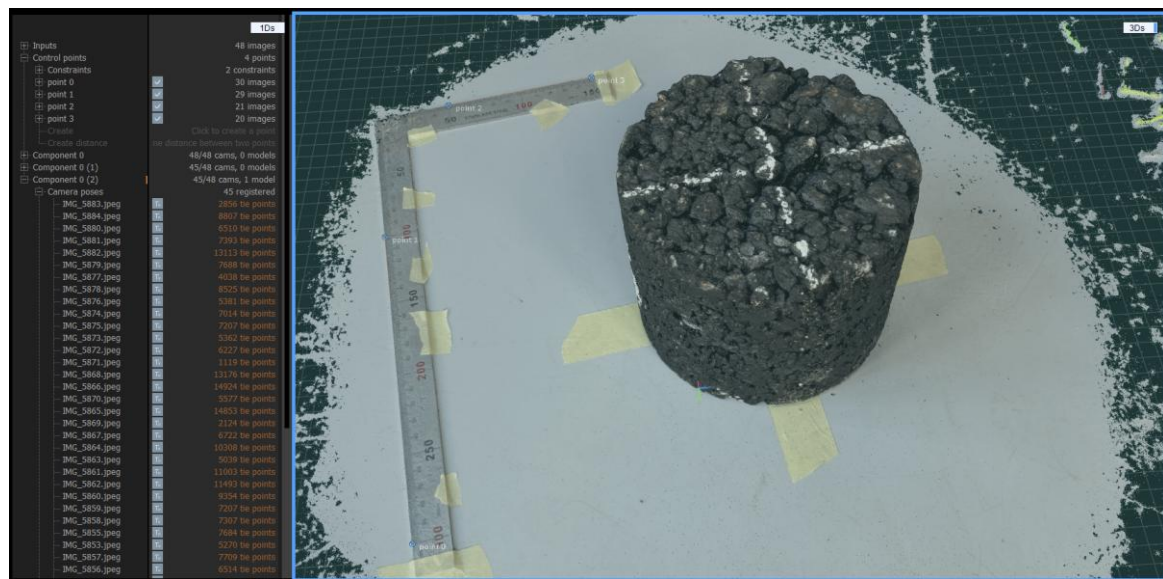


Figure 4.5: Desktop interface for dataset management and automated computation in RealityScan.

One of the primary functional differences observed between the two software applications lies in the management of georeferencing. Within RealityScan, it was possible to successfully complete the direct metric scaling of the model, the software allows the operator to select pairs of control points and define the known real-world distance between them, an operation performed by entering the geometric dimensions of the professional markers and the L-shaped jig.

However, unlike Agisoft Metashape Professional, RealityScan does not provide the option to establish a constrained local reference system through the manual assignment of discrete Cartesian coordinates (X, Y, Z) to individual points.

Consequently, the final scaled model lacked the ideal orientation required for DEM export specifically, with the Z-axis perfectly orthogonal to the plane of the bituminous mixture specimen.

To overcome this limitation and ensure an unbiased geometric comparison, the dense point cloud was exported in LAS (.las) format and imported into CloudCompare. In this environment, the same local roto translation matrix computed for the Metashape models was applied to the RealityScan point clouds, forcing the orthogonality of the Z-axis relative to the laboratory workbench and ensuring perfect procedural symmetry prior to the direct comparison.

The mathematical quantification of the discrepancies between the professional reconstruction engine (Metashape) and the automated one (RealityScan) was performed using the Cloud-to-Cloud Distance (C2C) tool in CloudCompare. This algorithm computes the *Euclidean distance* between the points of the compared cloud and the nearest points of the reference dataset, which in this case is the point cloud generated within the Metashape environment.

The analytical test was conducted separately for both surface configurations:

- **Analysis of the Pre-Test Models:**

The comparison between the two dense point clouds of the clean surface demonstrated a perfect geometric match. The software returned a mean distance of 0.019 mm and a standard deviation of 0.016 mm.

- **Analysis of the Post-Test Models:**

The same outstanding numerical result was observed when analysing the models that included the volume of silica sand, confirming a mean distance of 0.011 mm and a standard deviation of 0.008 mm.

The results show minimal divergence between the two photogrammetric engines. Within the software's computational tolerances and following the application of the same metric constraints, the point clouds are nearly mathematically identical in their spatial distribution, validating the intrinsic accuracy of RealityScan's automated algorithms compared to those meticulously parameterized locally in Metashape.

Although RealityScan proved to be as metrologically valid as the reference desktop suite, the comparative analysis revealed substantial differences in terms of operational workflow and usability:

- **Limitations of RealityScan:**

The primary drawback lies in its desktop graphical user interface, which can occasionally feel clunky, less fluid, and less intuitive than that of Agisoft Metashape, which proves highly user-friendly and clean even for a neophyte operator.

Furthermore, its free-to-use nature prevents the operator from exporting detailed technical camera calibration reports, thereby reducing scientific transparency regarding pixel error residuals.

- **Strengths of Agisoft Metashape:**

The Metashape desktop suite remains the irreplaceable primary choice for research purposes, thanks to the ability to meticulously control every single alignment parameter, export comprehensive technical reports, and natively define complete *Cartesian coordinate systems*.

In conclusion, RealityScan's “*User-Free*” approach showed promising results within the experimental conditions considered in this study. After appropriate scaling and post-processing in CloudCompare, the resulting models were highly comparable with those generated using Agisoft Metashape. Nevertheless, the results should be interpreted as a preliminary assessment rather than as a full validation. The lack of native Cartesian georeferencing tools and detailed processing reports remains a limitation. Therefore, RealityScan may represent a useful supplementary tool for rapid and low-cost photogrammetric processing, provided that the operator has adequate experience with photogrammetry and point-cloud management.

5 Phase III: 3D Model Analysis and AI-Assisted Algorithm Development

5.1 Evolution of the Differential Method: From QGIS-Based Processing to Volumetric Calculation in CloudCompare

The initial quantification of the volume of silica sand deposited on the granite slab and on the bituminous mixture specimen was structured following a principle of differential geometric analysis. Prior to running the algorithm, the two sets of dense point clouds generated by Agisoft Metashape were imported into CloudCompare for a fine co-registration phase. Although the datasets were already partially oriented via physical markers, the Iterative Closest Point (*ICP*) algorithm was applied using the “*Finely Register Already*” tool to maximize spatial congruence, configuring a theoretical overlap of 99%.

To prevent the volumetric presence of the sand from introducing errors into the alignment algorithm, the central region of the cone was temporarily segmented and removed prior to the *ICP* computation and subsequently merged back into the global dataset upon completion of the process. This operation allowed for the quantification of the maximum residual distance between the two clouds in both sets, attributed to photogrammetric background noise and micro-tilts, resulting in a value of approximately 1 mm for the granite slab and 0.5 mm for the bituminous mixture specimen.

Starting from these optimized point clouds, *work began with the cloud dataset dedicated to the granite slab*. Consequently, two different Digital Elevation Models were generated by setting distinct grid steps (“*step size*”) equal to 0.25 mm and 0.5 mm, in order to evaluate the sensitivity of the geospatial calculation with respect to the resolution of the raster matrix. The differential analysis was initially structured through a coupled pipeline within the QGIS and Excel environments, organized into the following phases:

- **Polygonal Masking and Raster Algebra:**

Within QGIS, to optimize the computational load and exclude peripheral noise, a polygonal shapefile was created to accurately crop only the circular area occupied by the sand cone. Using the *Raster Calculator tool*, a pixel-by-pixel algebraic subtraction was performed between the pre-test DEM and the post-test DEM.

Thanks to the precision of the upstream *ICP alignment*, the operation showed no spatial shifts or geometric distortion along the clipping boundaries.

- **Numerical Extraction and Excel Data Processing:**

The difference raster obtained in this manner was converted into a discrete point matrix using the “*Raster to Point*” function and exported in XLSX format for statistical analysis in Excel.

Each cell of the matrix numerically expressed the elevation difference (Δz value) associated with the corresponding pixel.

Direct analysis of the raw matrix in Excel, however, revealed significant numerical anomalies, particularly a conspicuous presence of null values equal to zero and prominent outliers characterized by positive and negative elevation deviations exceeding 1 cm.

These were clearly incompatible with the actual geometry of the test and were induced by photogrammetric noise, shadows, and light refractions in the laboratory.

To isolate the actual geometric data from the noise, a statistical filter was developed based on the physical evidence of the test. Knowing that the experimental value of the Mean Texture Depth, derived from the sand patch test carried out on the granite was equal to 0.252 mm, and integrating this data with the maximum registration error obtained from the application of the *ICP algorithm* (previously quantified as 1 mm), an overall theoretical domain of 1.3 mm was defined.

In order to avoid introducing a systematic error into the numerical integration, the interval was symmetrically distributed to include negative residuals, defining a rigorous filtering range equal to:

$$[-0.00065 \text{ m}; +0.00065 \text{ mm}] \leftrightarrow [-0.65 \text{ mm}; +0.65 \text{ mm}]$$

All values outside this domain were categorized as *outliers* and eliminated.

The final volume of the sand was then calculated by summing the residual elevation differences and multiplying the total by the known area of the individual sampling cell or pixel, *Equation 5.1*.

$$V = \sum_{i=1}^n (\Delta z_i \cdot A_{\text{individual sampling pixel}}) \quad (5.1)$$

The mathematical validity of this specific filtering operation was confirmed by executing the same routine on both generated DEMs (with grid steps of 0.25 mm and 0.5 mm). Despite the cell areas being completely different, the two integrated volumes yielded convergent results that were perfectly consistent with the volume of sand empirically measured in the laboratory.

Despite the consistency of these results, the *QGIS-Excel pipeline* proved to be excessively laborious and hindered by numerous file import, formatting, and export steps, which pose a risk of introducing metadata corruption or spatial misalignment within the native reference systems.

To optimize this intermediate validation step, it was decided to bypass the GIS suite by introducing the utilization of the specific “*Compute 2.5D Volume*” tool integrated directly within CloudCompare. This workflow proved to be significantly more streamlined and rapid: by selecting the two dense point clouds, assigning the pre-test state as the reference entity and the post-test state as the entity for volumetric evaluation, setting the projection direction along the geometric Z-axis and defining the grid step, the software executes the net volumetric calculation, evaluating both added and removed volumes by operating directly within its own three-dimensional geometric engine.

The elimination of intermediate conversion steps successfully minimized processing times, confirming the effectiveness of point cloud processing software for rapid volumetric verifications.

5.1.1 Limitations of the Differential Method: Operational Criticalities and the Need for a “Sand-Free” Approach”

Despite the metrological robustness demonstrated by CloudCompare's 2.5D tool and the precision of the statistical filtering applied to the extracted matrices, the classical differential method suffers from intrinsic operational limitations that drastically reduce its applicability in real-world engineering contexts.

The main critical issues that emerged during the experimental phase can be summarized in the following points:

- **Need for Manual Perimeter Segmentation:**

Differential volumetric calculation is not intrinsically selective.

To isolate the volume and prevent surface micro-variations of the laboratory workbench, the template, or the outer edges of the specimen from corrupting the numerical

integration, the operator is forced to manually perform a highly precise polygonal cropping of the dataset for each individual test. This workflow eliminates any possibility of mass automation of the process.

- **The Operational Paradox of In-Situ Inspection:**

From a strictly road engineering perspective, the most severe limitation lies in the necessity of having two distinct temporal scans: pre and post *Sand Patch Test*.

In a real-world monitoring scenario of in-service road pavements, it is technically impossible to possess a high-resolution digital twin of the clean road surface, captured for the exact same spatial area prior to deterioration or before conducting the test.

- **Methodological Redundancy:**

If, to calculate macro-texture indices, the on-site operator was forced to physically spread the silica sand, perform the test, scan the surface, and carry out a digital subtraction relative to a previous scan, the adoption of photogrammetric technology would be entirely redundant and inefficient. At that point, it would be far more economical and immediate to measure the diameter of the sand circle directly in the field according to traditional standards.

The differential analysis phase described in *Section 5.1* must therefore not be understood as the ultimate technological goal of the research, but rather as an indispensable metrological validation step. It allowed for the scientific demonstration that the quality of the photogrammetric reconstruction derived from the iPhone 15 Plus sensor possesses the sub-millimetre resolution necessary to accurately describe the volumes of a fine granular filling. Having demonstrated the sensor's ability to “see” and quantify these surface micro-geometries, the necessity for a methodological paradigm shift became clear, moving beyond the logic of comparing two states toward a “*Sand-Free*” approach.

The objective of the research shifted to the design of an intelligent algorithm capable of mathematically simulating the spreading of the material starting from a single clean point cloud of an element exhibiting its own roughness, such as a road pavement, and without the physical aid of sand to extract the Mean Texture Depth (*MTD*) road index in a fully automated manner.

5.2 From Point Cloud to Numerical Matrix: Transition to Python-Based Automation

Overcoming the operational constraints and the manual filtering steps required by the differential method led to the transition from the static *GIS/CloudCompare-based processing* to a Python-based workflow. The aim was to reduce repetitive manual operations, improve reproducibility, and enable the direct processing of DEM matrices for macro-texture analysis. The development of the Python scripts was supported by AI-assisted coding tools. In this process, the author defined the engineering framework of the problem, including the physical assumptions, geometric boundary conditions, input data structure, and target metrological parameters. Generative AI was used as a programming aid, supporting code organization, the selection of suitable scientific libraries such as NumPy, Pandas, and SciPy, debugging, and computational optimization. The resulting implementation was then checked and iteratively refined to ensure consistency with the intended calculation logic and with the requirements of the macro-texture analysis.

The starting point of the software architecture lies in structuring a pure, flexible numerical input, free from the metadata overhead typical of commercial raster formats. Leveraging the previously optimized dense point cloud, the rasterization tool integrated within CloudCompare was employed. Instead of exporting a georeferenced image file (*GeoTIFF*), the software was configured to generate a tabulated numerical matrix in ASCII (*.txt*) format.

The extraction process was standardized using the following grid parameters:

- **Active layer:** *Cell height values*, to isolate exclusively the vertical geometric information.
- **Projection direction:** Orthogonal *Z-axis*.
- **Cell parameter/Cell Height:** Set to *Maximum*, to capture the apical geometric peaks of the outcropping aggregates, which is fundamental for the subsequent simulation of the sand layer.

To ensure the statistical robustness of the method and evaluate its sensitivity to variations in spatial resolution, the matrices were exported adopting a multi-scale approach across four different resolutions through the rasterization procedure: 0.5 mm, 0.2 mm, 0.1 mm, and 0.05 mm.

This experimental plan was systematically applied to both the granite slab and the bituminous mixture specimen, generating a highly information-dense database.

Once uploaded into the Python environment, the raw matrix undergoes a pre-processing stage aimed at standardizing the data and preparing the spatial domain for the macro-texture calculation algorithms.

The loading and initial preparation pipeline of the matrix data is structured into the following logical-mathematical phases:

```
# --- DATA LOADING AND MATRIX PREPARATION (Preprocessing) ---

# Reading the tabulated DEM file in discrete spatial coordinates.

df = pd.read_csv(file_path, sep=r'\s+', header=None, decimal='.',
engine='python')

# Conversion of data from meters to millimeters (* 1000) to standardize
the physical unit of measurement.

z = df.values * 1000

# Absolute height normalization: the deepest point (global minimum) is set
to Z = 0 to eliminate scanning offsets and operate solely on relative
texture thicknesses.

z = z - np.nanmin(z)

# Extraction of matrix dimensions (rows and columns)

rows, cols = z.shape

# Generation of spatial coordinate matrices XX and YY (Meshgrid) based on
the actual step (res)

xx, yy = np.meshgrid(np.arange(cols) * res, np.arange(rows) * res)

# Conversion of the metric window (mm) into the corresponding computational
radius expressed in pixels

window_px = int(finestra / res)
```

The logic of the code described above mathematically maps the three-dimensional cloud within a two-dimensional data structure, where the row and column indices of the array uniquely identify the discrete planimetric coordinates of the space mirrored in the “xx” and “yy” matrices via the “*np.meshgrid*” function, while the floating-point numerical value stored in each individual cell expresses the relative elevation Z .

The initial conversion into millimetres and the absolute geometric normalization operation which translates the entire matrix by positioning the deepest point, the global minimum, at an elevation of $Z = 0$ through the subtraction of “*np.nanmin(z)*” represent crucial steps from an engineering perspective. Indeed, this process neutralizes any macroscopic offset or tilt resulting from the positioning of the smartphone during the photogrammetric acquisitions, allowing subsequent algorithms to operate exclusively on the relative thicknesses and the actual morphological asperities of the element texture. Finally, the parameterization of the real resolution (“*res*”) and the calculation window allow the software to dynamically scale its operating radius expressed in pixels (“*window_px*”), rendering the entire software architecture flexible and ready to accommodate the subsequent computation modules for the automated extraction of the Mean Texture Depth (*MTD*) parameter.

5.3 Development of the Python Algorithm for the “Sand-Free” Approach

The innovative core of this research lies in the development of a customized software architecture within a Python environment, aimed at estimating the mean height of the macro-texture using an entirely sand-free approach. The primary objective of the algorithm is the total elimination of the need to perform the *Sand Patch Test*, which is replaced by a high-fidelity three-dimensional numerical simulation capable of operating on a single photogrammetric survey of the road pavement.

To ensure maximum operational flexibility and impart universality to the method, the code was engineered as a single, unified algorithm featuring a dual geometric calculation logic. Rather than employing separate scripts, the workflow adapts dynamically based on the user's input. The distinction between the two operational modes implemented in this research arises from the fundamental need to choose whether to investigate a specific diameter starting directly from the geometric centre of the original matrix, or to analyse a square domain. This flexibility allows for an in-depth multi-scale analysis to observe how the macro-texture parameters fluctuate and respond according to the geometry and size of the investigated window.

1. Circular Operational Mode:

When a nominal investigation diameter is specified, the algorithm replicates the kinematics of the traditional *Sand Patch Test* (EN ISO 13036-1 Standard [1]) by generating a *radial Boolean mask* that expands from the geometric centre of the Digital Elevation Model. The ability to progressively adjust this diameter makes it possible to observe how the MTD parameter changes across different circular windows. Furthermore, this mode is independent of the initial boundaries of the point cloud, as the radial mask is applied directly to the rasterized matrix regardless of its original shape.

2. Square Operational Mode:

When a side length is defined, the algorithm bounds the numerical integration of the volumetric settlement to a designated square domain within the filtered matrix. This configuration allows for the analysis of a regular quadrangular area, providing the option to observe how the texture values vary when modifying the side dimensions. It also removes the strict necessity of pre-cropping the original point cloud to the exact target dimensions before loading it into the algorithm, as the square bounding box is applied directly to the matrix.

Both operational modes rely on a rigorous discretization of the spatial domain. Through the scientific computing libraries “*NumPy*” and “*Pandas*”, the microscopic topography of the material under examination is mapped onto a regular grid of nodes, in which the horizontal micro-morphological variations are governed by the actual resolution step (“*res*”) and the relative elevations are normalized by setting the absolute minimum to zero ($Z=0$), thereby neutralizing any potential macroscopic geometric offset.

5.3.1 Definition of the Calculation Domain and Boundary Constraints

One of the primary computational challenges in discrete surface modelling lies in managing the outer edges of the matrix, which represent what is physically the perimeter.

Along these peripheral margins, the photogrammetric reconstruction can be systematically affected by significant geometric noise resulting from so-called *edge effects*.

This “*edge noise*” is induced by abrupt changes in geometric slope, specifically the sharp drop between the upper face of the specimen under investigation and the laboratory

workbench which generate shadows, visual occlusions, and instabilities within the Structure from Motion (*SfM*) algorithms. If a *moving maximum filter* were applied directly to the raw matrix, the presence of spurious pixels or sudden drops in elevation at the boundaries would cause a mathematical collapse of the virtual sand layer. Consequently, the simulated sand would tend to slide laterally out of the calculation domain, completely distorting the internal volumetric integration.

Under the guidance of the AI, acting as a co-pilot in code development, this issue was resolved by introducing fixed lateral confinement *boundary conditions*. This approach enabled the creation of a perimeter envelope to define a priori the boundaries of the analysed element. The mathematical logic of the code isolates the outer perimeter profile of the matrix and applies a dedicated sub-function named “*calcola_inviluppo_bordo*”.

Crucially, this boundary envelope is always dynamically adjusted to correspond strictly to the specific investigated diameter or side length, rather than defaulting to the nominal dimensions of the element. For instance, if a specimen possesses a nominal diameter of 150 but the analysis is restricted to a smaller target diameter of 140, the perimeter envelope is applied directly at the 140 boundaries. Without this refinement, evaluating any window smaller than the nominal size would cause the peripheral envelope to align with the larger outer boundary, leading to an overestimation of local maxima along the edges. This would consequently distort, either by overestimating or underestimating, the true local maxima relative to the actual perimeter of the investigated domain

```
def calcola_inviluppo_bordo(profilo_z, step_px):
    n = len(profilo_z)
    nodi_indici = list(range(0, n, step_px))
    ...
    # ROBUST IMPLEMENTATION: The 100th percentile (maximum) is utilized.
    # This segment handles geometric peaks on the DEM perimeter.
    val = np.percentile(sotto_profilo, 100)
    nodi_valori.append(val)
    # Linear interpolation between identified points to reconstruct a
    continuous confinement profile
    return np.interp(np.arange(n), nodi_indici, nodi_valori)
```

The actual boundary profile is subdivided into discrete segments with a width equal to a fixed perimeter window set to 10 mm to ensure a detailed analysis for defining local maxima along the perimeter under investigation, which is fully converted into the corresponding computational radius in pixels. For each sub-profile, the algorithm extracts the maximum apical height via the 100th percentile and, through a continuous linear interpolation (“*np.interp*”), constructs a geometric confinement wall passing exclusively through the stable, physical peaks of the perimeter.

This approach offers a dual engineering advantage: on one hand, it mathematically prevents the virtual escape of the filling volume along the sides of the matrix, because if one wishes to investigate a diameter larger than the three-dimensionally reconstructed one using the circular operational mode, the system recognizes this geometric inconsistency and terminates beforehand. On the other hand, it makes the upstream process extremely robust and rapid, as there is no need to worry about including peripheral areas outside the analysis element that are irrelevant to the study. Consequently, the operator does not need to perform precise, millimetric polygonal cropping or flawless geometric masking during the export phases from CloudCompare, since the algorithm is autonomously capable of neutralizing peripheral geometric artifacts by erecting a stable closing envelope.

Furthermore, a graphical visualization of the perimeter envelope has been integrated into the overall visual report provided by the developed algorithm, allowing for an immediate verification of the geometric consistency of the perimeter in its entirety.

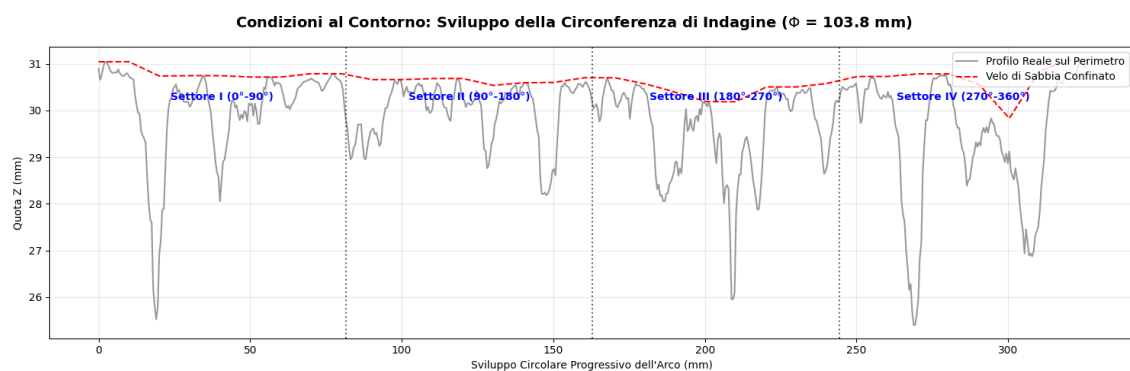


Figure 5.1: Visual Report regarding the implementation of boundary conditions for what concern the perimeter envelope.

5.3.2 Implementation of the Moving Mask and Extraction of Relative Maxima: Calculation Algorithm and Sand Layer Simulation

Once the boundary conditions are established, the code executes the actual physical simulation of the textural filling.

This process is structured into three sequential mathematical phases that combine mathematical morphology tools and signal processing filters:

1. The Moving Maximum Filter (Morphological Dilation):

The spreading of sand using the levelling straightedge prescribed by the EN ISO 13036-1 standard [1] is modelled mathematically by applying a three-dimensional “*maximum filter*” operating with a nearest edge extension mode.

The moving mask has a square geometry, and its physical size represents a critical variable of the analysis. The criterion for selecting the size of the moving mask is based on the scale ratio between the geometry of the tool and the maximum aggregate size of the analysed material.

To ensure that the algorithm correctly simulates the kinematic floating of the sand on the surface peaks without penetrating the voids, since sand itself is a rigid solid and not a fluid, the investigation window must be set to a value equal to approximately 3 to 4 times the maximum diameter belong to the investigated material. This selection criterion will be extensively discussed within *Chapter 6*, where the results of the developed algorithm will be comprehensively analysed.

Moving pixel by pixel across the entire matrix, the mask identifies the relative maximum altimetric peak within its range of action. From a geometric standpoint, this filter performs a “dilation” of the surface, ideally connecting the apical crests of the outcropping aggregates and generating an initial rigid reference surface.

The choice of the mask size governs the distance between the support points of the layer, windows that are too wide tend to overestimate the height of the layer by ignoring micro-undulations, whereas windows that are too narrow cause the sand to artificially sink into the macro-cavities, resulting in an unrealistic representation of the spread sand.

2. Gaussian Smoothing of Granular Settlement:

The theoretical surface derived from the maximum filter describes a perfectly taut layer stretched between the peaks, a behaviour that is physically impossible for a real granular material. Indeed, calibrated silica sand possesses its own average nominal grain size of

approximately 0.20 mm. Sand grains cannot penetrate crevices or micro-fissures narrower than their own diameter and, concurrently, undergo a phenomenon of settling and partial kinetic sliding during manual spreading. To translate this rheological property into mathematical language, the algorithm introduces a “*Gaussian smoothing filter*”.

The computational standard deviation σ is dynamically calibrated by normalizing the physical size of the sand grain against the spatial resolution of the dataset, as mathematically described in *Equation 5. 2*.

$$\sigma = \frac{\emptyset_{\text{grain of sand}}}{\text{res}} = \frac{0.20 \text{ mm}}{\text{res}} \quad (5.2)$$

The *Gaussian smoothing* smooths out the mathematical cusps of the maximum filter, numerically modelling the actual parabolic arrangement and settling of the sand grains within the aggregate interstices.

3. Physical Constraint of Body Non-Interpenetration:

Due to the smoothing effect of the *Gaussian filter*, the surface of the virtual sand layer could locally fall below the geometric profile of the object under examination at the sharpest peaks. To rectify this systematic error, an absolute conditional geometric constraint is applied using the “*np.maximum(sabbia, z) function*”.

This instruction dictates that, within each individual pixel, the elevation of the sand layer must be greater than or at most equal to the elevation of the aggregate skeleton.

From an engineering standpoint, this constraint establishes the fundamental physical principle of the non-interpenetration of solid bodies, meaning that the sand rests on the stone and cannot occupy the volumetric space already occupied by the aggregate.

Once the geometric model of the final sand layer is defined, the filling thickness is calculated through direct subtraction.

$$\Delta z_{i,j} = Z_{\text{sand}} - Z_{\text{real}} \quad (5.3)$$

In the algorithm, the Euclidean distance matrix is then activated, calculated as shown in *Equation 5.4*, from the geometric centre of the specimen (x_c, y_c):

$$d_{i,j} = \sqrt{(x_{i,j} - x_c)^2 + (y_{i,j} - y_c)^2} \leq R_{test} \quad (5.4)$$

In *Equation 5.4*, the parameter R_{test} represents the geometric radius of the nominal investigation area expressed in millimetres, obtained by halving the specimen diameter value entered during the software configuration phase in the dedicated panel.

The introduction of the boundary condition $d_{i,j} \leq R_{test}$ serves a crucial function in resolving the geometric conflict intrinsic to the digitization of the specimen. Digital Elevation Models (DEMs) extracted via photogrammetry and exported from CloudCompare are strictly structured as square or rectangular pixel grids, bituminous mixture specimens compacted in the laboratory exhibit a cylindrical geometry with a circular cross-section.

Indeed, if the algorithm integrated the void volume over the entire extension of the input matrix, spurious pixels located in the four outer corners of the specimen would also be counted, including areas where the elevation Z drops sharply, intercepting the edge of the specimen or the flat surface of the workbench. By imposing the conditional check based on R_{test} , the script generates an active Boolean mask that topologically maps the domain, as each pixel with discrete coordinates (x,y) receives the “*True*” attribute if its Euclidean distance from the centroid is less than or equal to the specimen radius, being otherwise categorized as “*False*” and excluded from any computation.

This circular mask kinematically circumscribes only the active surface, mathematically simulating the perfectly circular patch produced by the sand spreading in the laboratory and isolating the volumetric calculation from any geometric artifacts. The active area is isolated by imposing the condition $d_{i,j} \leq R_{test}$.

The Sand-Free MTD parameter is finally extracted by calculating the discrete integral average of the void thickness included exclusively within the active circular mask,

Equation 5.5.

$$MTD = \frac{1}{N} \sum_{(i,j) \in \text{moving mask}} (Z_{sand,i,j} - Z_{real,i,j}) \quad (5.5)$$

Where N represents the total number of pixels within the test selected domain.

Concurrently, the “*np.isclose*” function identifies the actual contact points where the sand thickness drops to zero, thereby identifying the physical support peaks of the aggregates with a fixed tolerance equal to twice the set resolution (“*res*”) value, and returning the actual contact area expressed in mm^2 .

The entire workflow described does not merely extract a pure numerical value, it generates a set of advanced graphical reports strictly expressed in millimetres, which are crucial for the visual validation of the performed estimation.

- **Diametral Cross-Section:**

It isolates the equatorial row of the element, which intercepts the maximum chord of the circle. It displays the jagged black profile of the asphalt concrete specimen or granite slab, the orange line representing the sand layer, and a chromatic fill that highlights the filling volume. The second panel performs a morphological zoom by adopting a continuous stepped structure, this scientific visualization avoids oblique graphic interpolations, showing the actual, discrete nature of the DEM pixels and highlighting the precise solid-virtual support points with red markers.

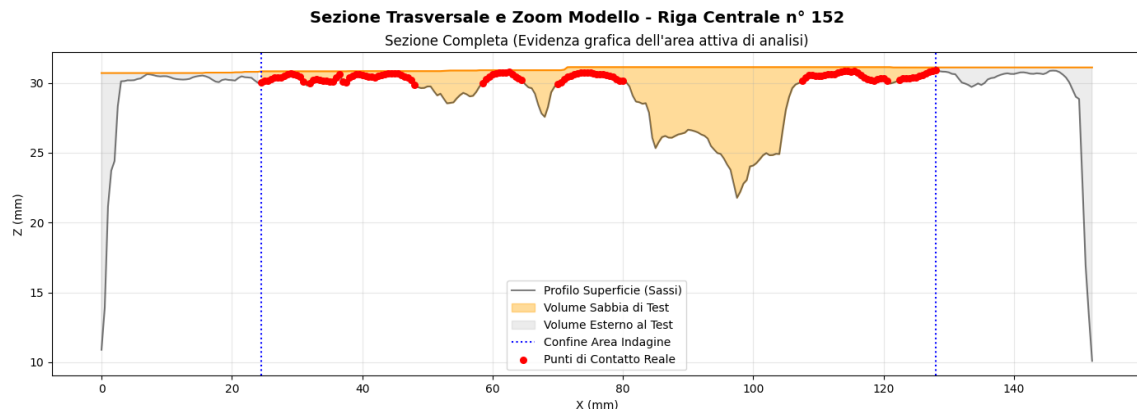


Figure 5.2: Diametral cross-section and stepped morphological detail, with identification of the actual contact points.

- **Perimeter Envelope Representation:**

Thanks to the boundary conditions established upstream in the code, where the algorithm recognizes the perimeter of the input element via the matrix derived from the digital elevation model and, by extracting the local maximum values using an

investigation window fixed at 10 mm, creates the perimeter envelope from which the moving mask analysis subsequently begins.

This envelope is graphically reported (*Figure 5.1*) *a posteriori* alongside the results.

- **Local Three-Dimensional Reconstructed Representation:**

This feature isolates a portion of the investigated zone to generate a detailed three-dimensional surface reconstruction. Rather than extruding individual pixels as discrete, solid volumetric prisms, the algorithm renders a continuous 3D model of the pavement texture. The underlying aggregate skeleton is depicted in dark grey, while the behaviour of the simulated sand is overlaid as a semi-transparent golden veil, visually representing the progressive filling of the macro-interstitial voids. This graphical output provides an immediate and intuitive verification of the Python algorithm's capacity to accurately map and penetrate the surface morphology of the pavement.

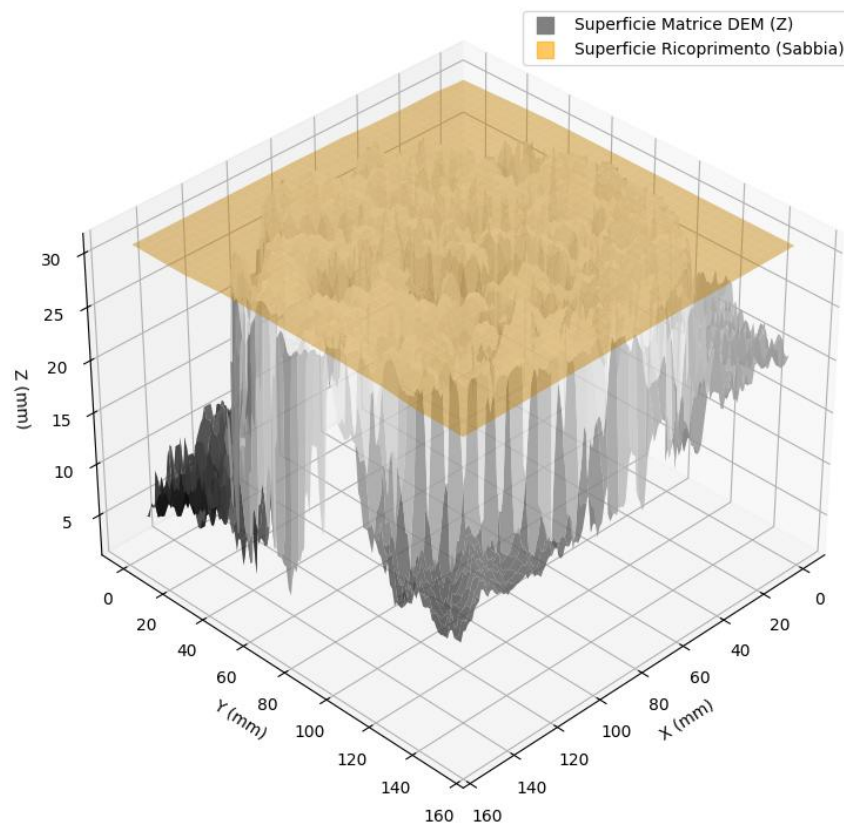


Figure 5.3: Local three-dimensional reconstructed representation for the geometric visualization of granular packing.

5.3.3 Operational Architecture of the Application, Control Panel, and Computational Efficiency

As a culmination of the code development, the script was engineered according to modern programming paradigms, ensuring a clear logical decoupling between the mathematical calculation engine, the analytical filtering and volumetric integration functions, and the operational entry point dedicated to the end user. Under the guidance of artificial intelligence, this architecture had materialized in the final lines of the code through the implementation of the native “`if __name__ == '__main__':`” construct, which acts as a true guided *Control and Execution Panel*.

Thanks to this structural setup, the laboratory operator or pavement designer does not need to interface with the syntactic complexities or the internal programming routines of the script. The entire interaction with the algorithm takes place exclusively by modifying an isolated block of just a few configuration lines, within which the geometric and physical variables of the problem are explicitly declared, such as:

- `FILE_PATH:`
String containing the path, absolute or relative, of the text file (.txt) representing the structured DEM matrix.
- `RASTER_RESOLUTION:`
The actual spatial pitch of the grid in millimetres per pixel, a fundamental parameter to bind the abstract matrix to the real metric dimensions of the specimen.
- `MAXIMUM_LENGTH:`
Physical dimension expressed in millimetres of the square moving mask, which governs the extent of the virtual rigid plate for intercepting local maxima.
- `LAB_TEST_DIAMETER:`
The nominal extent of the circular confinement mask, or the square one, mirroring the physical diameter of the specimen or the theoretical footprint of the sand cone.
- `SAND_PATCH_VALUE:`
If the algorithm is used as a method of comparison or verification against the traditional method, the experimental MTD value empirically obtained in the laboratory is entered here, allowing the algorithm to instantaneously calculate the numerical deviation and validate the accuracy of the model.

The practical execution of the code takes place directly within the PyCharm Integrated Development Environment (*IDE*), a choice that guarantees operational stability, rigorous control over scientific libraries, and an immediate visualization of the three output graphical reports.

From the standpoint of computational efficiency, calculation times vary depending on the density of the points belonging to the Digital Elevation Model under examination, as the resolution increases and, the overall number of rows and columns in the matrix, the computational load grows proportionally. However, thanks to the mathematical optimization guaranteed by the “*NumPy*” and “*SciPy*” libraries, which operate in precompiled *C code* beneath the Python interface by exploiting matrix vectorization, the complete processing never exceeds the threshold from 60 to 90 seconds.

In just over a minute, the algorithm is capable of processing and filtering millions of topographic points, establishing boundary constraints, simulating the granular spreading of the sand, and performing the three-dimensional volume integration, returning both the numerical output and the two and three-dimensional visual reports.

Compared to the traditional physical test, which requires significant execution time, material handling, and meticulous cleaning of the specimens, and is inherently subject to systematic error by the operator performing the test, the developed digital approach stands out as a cutting-edge investigation methodology characterized by extremely high speed, repeatability, and a completely non-destructive nature.

5.4 Development of the Python Algorithm for MPD Extraction

The linear two-dimensional characterization of road pavement surface macro-texture finds its international reference standard in EN ISO 13473-1 [6]. While the sand patch flooding height analyses the overall macro textural volume trapped by a surface, the Mean Profile Depth value examines the geometric morphology of high-resolution discretized linear profiles.

To automate this analysis and eliminate the operator-induced error component inherent in traditional methodologies, a software framework was developed in a Python environment during this research phase, structured for processing three-dimensional digital models of both cylindrical laboratory specimens and flat elements, such as the granite slab.

5.4.1 Transcoding of the Technical Standard

To guarantee the perfect mathematical and metrological compliance of the algorithm with the international requirements of the EN ISO 13473-1:2019 standard [6] (including the 2021 corrected version), the code development originated from the transcoding and adaptation of the original reference standard script written in MATLAB within the study [2] on behalf of VTI (Swedish National Road and Transport Research Institute).

This technical documentation represents the international benchmark for the validation of software dedicated to calculating texture indices. The core function of the calculation engine, named “*mean_profile_depth*”, converts the matrix-based logical-mathematical routines of MATLAB into the high-performance Python language through the extensive use of the “*NumPy*” and “*SciPy*” scientific libraries.

The rigorous transcoding of the standard is divided into five sequential computational phases:

1. Management of Missing Data and Dropouts (*NaN*)

The digital models, deriving from photogrammetric processes or laser scans, can present informational gaps, expressed as Not a Number (*NaN*) values.

The algorithm performs an integrity check, so if the invalid samples exceed 50% of the profile length, the profile is rejected as statistically unsuitable. Otherwise, a hybrid geometric reconstruction is performed based on the “*scipy.interpolate.interpld*” function, through which internal profile gaps are filled via linear interpolation, while voids on the outer boundaries are handled by “*nearest neighbour*” extrapolation, preventing dangerous fictitious alterations of the elevation at the margins of the baseline.

2. Detection and Elimination of Spikes (Instrumental Noise)

According to EN ISO 13473-1 specifications [6], a point is classified as a spike if the absolute change in elevation relative to the immediately preceding point exceeds a threshold linked to the spatial resolution, quantified as three times the sampling interval. To bypass the limitations of unidirectional scanning, which might suffer from transient sensor effects or morphological asymmetries, a dual bidirectional check has been implemented with a forward analysis from left to right and a backward analysis performed by mirroring the profile via “*np.flip*”.

The indices identified as anomalies are converted into *NaN values* and subsequently reconstructed using nearest-neighbour interpolation.

3. Subdivision into Standard 100 mm Segments

The standard mandates that the calculation of the profile depth must strictly take place on geometric samples of a fixed length equal to 100 mm.

The algorithm converts this metric dimension into the corresponding number of discrete pixels as a function of the actual raster resolution (“*sample_per_segment = (100/DX)*”).

The profile is truncated to eliminate excess terminal pixels and reshaped through a resizing operation into a two-dimensional matrix “*TX_MAT*”, where each row represents an independent 100 mm segment.

4. Slope Suppression

The application of this phase is of fundamental importance for measurements located in the laboratory, where the specimen or granite slab might exhibit a microscopic geometric tilt induced by the resting plane.

The code implements a linear regression based on the ordinary least squares method. For each row of the matrix, the profile is centred with respect to its mean elevation and mapped onto a symmetrical spatial axis, ranging from -50 mm to +50 mm.

The slope inclination β , and the intercept α are analytically calculated, the equation of the identified trend line is finally mathematically subtracted from each individual point, resetting the slope and rendering the profile orthogonal to the reference axis.

5. Mathematical Determination of the MSD and Global MPD

The 100 mm long segment is divided exactly into two sub-segments of 50 mm each, designated as sub-segment A and sub-segment B.

The algorithm identifies the maximum peak elevation in the first half, PSA_{max} , and the maximum peak in the second half, PSB_{max} .

Finally, the arithmetic mean elevation of the entire filtered segment, called PS_{mean} , is calculated.

In perfect analogy with the international formula of the standard, the Mean Segment Depth of that single profile is extracted, *Equation 5.6*.

$$MSD = \frac{PSA_{max} + PSB_{max}}{2} - PS_{mean} \quad (5.6)$$

The final global Mean Profile Depth parameter is derived by calculating the arithmetic mean of the MSD values obtained from all valid scanned profiles.

Finally, the algorithm implements the empirical conversion relationship established by the standard to estimate, from the two-dimensional linear data, the three-dimensional volumetric equivalent of Mean Texture Depth represented by the Estimated Texture Depth, *Equation 5.7*.

$$ETD = 1.1 \cdot MPD \quad (5.7)$$

5.4.2 AI-Assisted Code Adaptation and Implementations

The transposition of the EN ISO 13473-1 standard [6] from a single one-dimensional linear profile to the massive processing of two-dimensional Digital Elevation Models (*DEMs*) has raised non-trivial geometric and computational challenges. Indeed, the mathematical formulation proposed by the Swedish VTI study was originally developed to process individual profiles, in our case, working with laboratory specimens, this reasoning had to be extended without compromising metrological rigor, thereby requiring an intensive phase of AI-assisted code co-design and optimization.

This cooperation made it possible to overcome the intrinsic limitations of the specimen geometries and to implement advanced custom functionalities, differentiating the script into two specific variants, one for circular specimens and one for rectangular or square slabs.

Initially, the embryonic approach assumed that linear profiles would be extracted by simply scanning the DEM matrix along its standard orthogonal rows and columns.

However, due to the small size of the laboratory DEM compared to an actual road section, the AI highlighted a severe methodological vulnerability in this strategy, a purely Cartesian scan would have penalized the peripheral portions of the circular specimen and included chordal profiles that were too short, undermining the statistical significance of the global MPD. Under the guidance of the AI, the architecture was radically modified by introducing a multidirectional radial scanning strategy. Leveraging the rotate function from the “*scipy.ndimage*” library, the code applies an iterative geometric rotation to the DEM matrix, from 0° to 180° with discrete increments of 10°. At each rotation, the algorithm extracts a dense band of profiles, equal to plus or minus 10 rows, corresponding to the central diameter where the specimen offers its maximum useful length, i.e., 100 mm.

This custom implementation enables the mapping of the entire circumference of the bituminous mixture specimen through 360°, accumulating hundreds of perfectly centred and uniformly distributed 100 mm profiles, thereby ensuring a statistical stability that would otherwise be unattainable. A side effect of rotating and cropping the profiles arises when the scanning line intersects the empty background of the matrix, that is the geometric space outside the perimeter of the specimen, digitized in the raster with zero or negative elevations.

If included, these discontinuity points would have introduced false macroscopic steps, drastically altering the least-squares calculation during the slope suppression step and injecting destructive artificial peaks into the MSD calculation.

To resolve this issue, the AI guided the integration of a conditional geometric safety filter:

```
if np.any(profile <= 0.1): continue
```

This instruction instantaneously intercepts the presence of even a single pixel with an elevation less than or equal to 0.1 mm, interpreting it as an exit from the body of the specimen under examination. Incomplete profiles or those tangent to the outer edge are thus automatically discarded before reaching the calculation engine, safeguarding the algorithm against any boundary errors. To extend the application to square or rectangular surfaces, such as granite slabs or portions of actual road pavement surveyed in situ, the AI supported the removal of the rotation routines, which are superfluous in non-circularly confined contexts, in favour of a combined orthogonal grid scan.

By modifying a few lines of code to preserve geometric symmetry, the script extracts a central band of profiles in both the horizontal and vertical directions. This implementation renders the workflow flexible and scalable, allowing the algorithm to operate seamlessly both in a controlled laboratory environment and on actual road pavements in service. A further engineering optimization concerned the introduction of the dynamic parameters “*row_step*” and “*column_step*”, whose represent the sampling steps. The AI suggested not hard coding the scanning density but rather making it parametric.

By setting values greater than one, the user can instruct the software to perform skips in the sampling, such as analysing every second row or every third column. This feature was not conceived as a simple expedient to reduce the computational load, but rather as a tool for

sensitivity analysis. By modifying these intervals, it was possible to analytically study how the down sampling of the profiles influences the final accuracy of the Mean Profile Depth and Estimated Texture Depth parameters, the multiple comparative scenarios of which will be the subject of discussion in *Chapter 6*.

5.4.3 Architecture of the Configuration Panel and Guided Execution

In perfect analogy with what was developed for the MTD algorithm, the codes dedicated to the MPD also integrate a guided configuration area in their final lines, protected by the construct “*if __name__ == '__main__':*”.

The operator's interaction with the PyCharm environment is entirely mediated by this panel, thereby eliminating the risk of inadvertent corruption of the underlying mathematical functions. Upon startup, the program proceeds with loading the text matrix via the high-performance “*np.loadtxt*” function, a try-except exception handling block intercepts any file path errors, providing immediate on-screen feedback.

The core of the panel is represented by the metrological options dictionary, within which the user declares the *operational parameters*:

- PROFILE_DX:
The actual scanning pitch in millimetres, configured during the raster export phase in CloudCompare.
- SPOT_MEASUREMENT:
Boolean flag specified with a “*True/False*” option to enable or disable slope suppression.
- CALCULATE_ETD:
Boolean flag to control the automatic calculation of the equivalent volumetric index.

At the end of processing, the interface returns a formatted printout on the screen summarizing the scanning metadata, such as the selection step and the number of profiles actually validated, along with the relative final numerical results, namely the mean row MPD, the column MPD, the global MPD of the element under examination, and the estimated ETD parameter.

5.5 Summary of Automated Extraction of Macro-Textural Parameters

With the development and validation of the two custom algorithms in a Python environment, the definition of the digital workflow for surface macro-texture characterization is concluded.

The methodological approach implemented in this thesis did not seek a simple digital replication of laboratory tests, but rather structured two distinct and complementary computational pathways capable of extracting both volumetric and linear indices starting from the same Digital Elevation Model.

While the dedicated Mean Texture Depth algorithm operates on a three-dimensional and areal logic, simulating the flooding by a volume of sand confined within a geometric moving mask, the transcoded Mean Profile Depth algorithm and the resulting Estimated Texture Depth works according to a two-dimensional and linear philosophy, sampling and eliminating slope trends across a massive series of discrete profiles through 360° or an orthogonal grid, in compliance with international EN ISO 13473-1 standards [6].

To offer a clear synoptic overview of the developed software architecture before proceeding to the discussion of the experimental results, *Table 5.1*, presented on the following page, summarizes the metrological specifications, input data, and calculation logics governing the two Python applications.

Table 5.1: Synoptic Overview of the developed software architecture.

Metrological Characteristic	MTD Algorithm (Sand-Free Virtual)	MPD/ETD Algorithm (Transcoded ISO)
Analysis Dimensions	Three-Dimensional (Volumetric/Areal)	Two-Dimensional (Linear/Profilometric)
Standard/Reference	EN ISO 13036-1 [1]	EN ISO 13473-1[6] Benchmark VTI
Calculation Domain	Local DEM Matrix (entire useful volume)	Linear Profiles extracted from a 100 mm baseline
Scanning Strategy	Circular or Square Mask	360° Radial or Orthogonal Grid
Data Cleaning Filters	Outlier filter based on ICP (Within CloudCompare environment)	Hybrid NaN removal and bidirectional Spike check
Geometric Correction	Subtraction of the lower reference plane	Slope Suppression (Ordinary Least Square)
Mathematical Operation	Volume integration of individual pixels	Mean of maximum peaks over 50 mm segments
Main Output	Numerical MTD, Percentage deviation and 3D Report	Global MPD, Estimated ETD and Standard Deviation

The development of the two Python scripts allowed the computational workflow to be organized into two complementary modules, one dedicated to the areal/volumetric estimation of MTD and the other to the profile-based extraction of MPD and ETD. Although based on different calculation logics, both scripts were designed with a similar user-oriented structure, in which the operator only needs to define the main input parameters before running the analysis. This approach reduces the number of manual processing steps, improves repeatability, and limits operator-dependent variability. The numerical outputs and graphical reports generated by the scripts provide the basis for the experimental analysis presented in the following chapter, where they are compared with traditional laboratory measurements and with the results obtained through GIS-based and point-cloud-based processing.

6 Experimental Analysis and Discussion of Results

6.1 Performance Comparison: Actual Sand Volume, Digital Estimation, and Algorithm-Based Estimation for MTD Calculation

The metrological validation of the developed digital workflow requires a rigorous comparison between traditional empirical laboratory measurements and the numerical estimates obtained via the various computational approaches.

The primary objective of this analysis lies in evaluating the accuracy and sensitivity of the algorithms with respect to the raster discretization step size and the surface morphology of the investigated material. The reference parameters are represented by the results of the *Sand Patch Test*, in accordance with the EN ISO 13036-1 standard [1], physically performed on the two specimens under examination:

- **Granite Slab:**

A surface featuring an extremely reduced, nearly smooth macro-texture, tested using a physical sand volume $V_{sand} = 9820 \text{ mm}^3$, with an average diameter of the circle formed by the spread of sand $D_{AVG} = 222.5 \text{ mm}$, from which a Mean Texture Depth (MTD) parameter equal to $MTD = 0.25 \text{ mm}$ is derived.

- **Bituminous Mixture Specimen:**

A surface featuring an open and discontinuous texture, tested using a physical sand volume $V_{sand} = 19312,78 \text{ mm}^3$, with an average diameter of the circle formed by the spread of sand $D_{AVG} = 103.75 \text{ mm}$, from which a Mean Texture Depth (MTD) parameter equal to $MTD = 2,28 \text{ mm}$ is derived.

6.1.1 Analysis of the Bituminous Mixture Specimen

From a geometric perspective, the bituminous mixture specimen represents a complex computational domain due to its high roughness and the presence of pronounced alternations between aggregate peaks and intergranular voids. The analysis of the volumetric data extracted from CloudCompare, using the Calculate 2.5D Volume tool, demonstrates excellent computational stability, with values fluctuating between 18968 mm^3

and 19185 mm³. The percentage error relative to the laboratory data remains consistently below 2%.

This behaviour highlights how the tool, which is based on the elevation differences between the reference point cloud and the flooded cloud, is highly effective in capturing the overall macro textural volume on rough surfaces, benefiting from the statistical compensation of local errors over macro-areas. As observed in *Table 6.1*, the optimal step size to apply in order to obtain a digital result closest to the physical one is 0.5. The primary reason for this lies in the fact that utilizing a larger, relatively coarse step size mitigates the noise-induced errors arising from the overall analysis performed within CloudCompare.

Table 6.1: Comparison of volumetric calculation results.

Step Size [mm]	Laboratory Sand Value [mm ³]	Digital Sand Volume [mm ³]	Deviation from the laboratory value [mm ³]
0.5	19312.78	19185.38	-127.40
0.2	19312.78	19027.36	-285.42
0.1	19312.78	18968.35	-344.43
0.05	19312.78	19005.43	-307.35

Regarding the analysis using the algorithm for determining the MTD parameter, several investigations were carried out, as the presence of potential undesirable boundary effects was taken into consideration. Consequently, the investigations were conducted directly within the Python environment, leveraging the integrated options features within the developed code. This allowed for the seamless execution of both the circular operational mode and the square operational mode directly on the rasterized matrix of the bituminous mixture specimen, eliminating the need for prior manual cropping or external geometry geometric preprocessing.

It is also worth clarifying the choice to utilize, in an initial investigation phase, a moving mask size equal to $L = 50 \text{ mm}$. As described in *Section 5.3.2*, the selection criterion depends on the maximum aggregate size (D_{max}) belonging to the specimen under examination. Consequently, since L must be equal to 3 or 4 times the D_{max} value, and assuming it to be approximately 16 mm, the use of a 50 mm moving mask fully satisfies this selection

criterion. Examining the responses of the Python algorithm (*Table 6.2*), a phenomenon of significant engineering interest emerges regarding step size sensitivity.

Beginning with the circular operational mode, the analysis focused on a diameter calibrated to the exact diameter obtained in the laboratory after spreading the sand, namely $\varnothing = 103.75$ mm.

At a rasterization step size of 0.05 mm, the algorithm provided the closest agreement with the laboratory measurement, yielding a digital MTD value of 2.09 mm, compared with the experimental value of 2.28 mm. The corresponding difference is 0.19 mm, equal to approximately 8.3% of the laboratory value. This result indicates a promising preliminary agreement, although the deviation cannot be considered negligible. For coarser sampling steps, such as 0.5 mm and 0.2 mm, the algorithm tends to underestimate the MTD value. This behaviour may be attributed to the lower spatial resolution of the DEM, which operates as a spatial low-pass filter, clipping the microscopic peaks of the aggregates within the bituminous mixture specimen and artificially levelling the upper envelope, affecting the reconstruction of the virtual filling surface.

Furthermore, the parameters relative to the investigation diameter of $\varnothing = 150$ mm, equal to the nominal diameter of the specimen, are also reported. In this case, the estimated MTD values are higher than those calculated over the laboratory sand-patch diameter ($\varnothing = 103.75$ mm). This difference suggests that the additional portions of the specimen included in the $\varnothing = 150$ mm analysis are characterized by a different surface morphology, with a greater contribution of local depressions. This highlights the sensitivity of the proposed method to the selected analysis domain and confirms the importance of defining the calculation area consistently when comparing digital and laboratory measurements.

Table 6.2: Comparison between laboratory MTD and algorithm-derived MTD (L=50 mm)

Step Size [mm]	MTD Python (Investigation of Ø=103.75mm) [mm]	MTD Python (Investigation of Ø=150mm) [mm]	Deviation from the laboratory value [mm]
0.5	1.77	2.01	-0.51/-0.27
0.2	1.93	2.17	-0.35/-0.11
0.1	2.00	2.37	-0.28/0.09
0.05	2.09	2.55	-0.19/0.27

Furthermore, an investigation was also conducted using a reduced mask size that does not satisfy the proposed selection criterion. This was intended to assess the influence of the mask-size criterion on the results obtained (*Table 6.3*) when using a 10 mm mask size. Analysing both the diameter corresponding to the sand spread in the laboratory and the specimen nominal diameter in its entirety results in an underestimation of the MTD parameter. This behaviour can be attributed to the fact that a mask size significantly smaller than 3–4 times the maximum aggregate size is not able to properly represent the upper envelope on which the virtual sand layer should rest. Consequently, the simulated filling surface tends to follow local depressions too closely, leading to a lower estimated void volume.

Table 6.3: Comparison between laboratory MTD and algorithm-derived MTD (L=10 mm)

Step Size [mm]	MTD Python (Investigation of Ø=103.75mm) [mm]	MTD Python (Investigation of Ø=150mm) [mm]	Deviation from the laboratory value [mm]
0.5	1.47	1.64	-0.81/-0.64
0.2	1.63	1.86	-0.65/-0.42
0.1	1.70	2.03	-0.58/-0.25
0.05	1.77	2.24	-0.51/-0.05

Furthermore, an analysis with such a small mask would adversely affect the calculation of the local maxima upon which the virtual sand layer rests. This implies that although local peaks are still identified, they fail to represent the true structural maxima of the surface.

As evidence of this, the visual reports implemented within the algorithm enable a cross-sectional view (*Figure 6.1*), which clearly illustrates how an underestimation of the sand volume occurs in the presence of a major depression, a phenomenon that would never occur in actual physical testing.

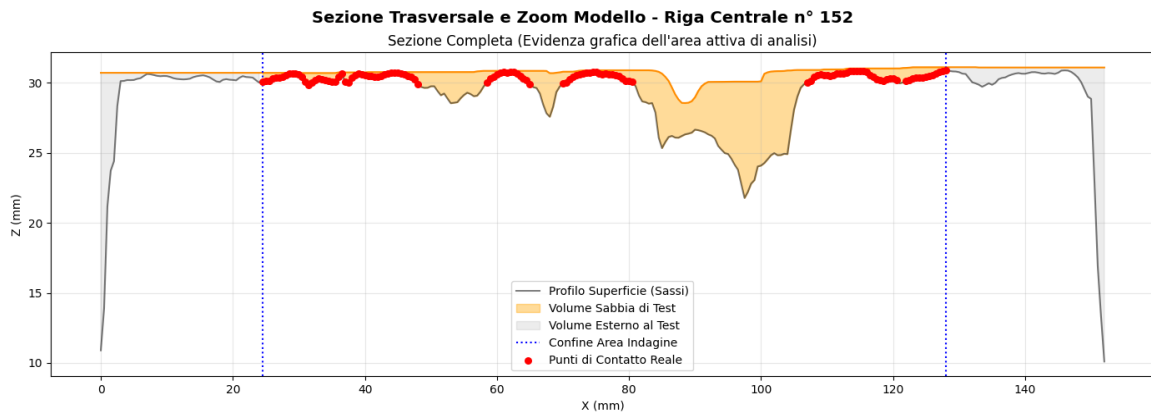


Figure 6.1: Cross sectional view for an investigation occurs with $L = 10$.

At this point, it was decided to use the square operational mode, transitioning from a circular investigation to a square one, in order to observe how boundary effects would be mitigated.

The domain was thus altered for a circular domain investigation of a 150 mm diameter and 103.75 diameter to one with square domain investigations with dimensions, first of 150×150 mm and then with domain of 103.75×103.75 . The same investigation described above was repeated for this different operational mode, thereby observing how the MTD parameter varied in this case as a function of the step size selected during the rasterization phase. By using the square operational mode, the sand patch result inscribed in the square investigation area, ensuring that it was not truncated but rather increased slightly due to this geometric configuration. The results (*Table 6.4* and *Table 6.5*) demonstrate that, in this case as well, varying the mask size, which constitutes non-compliance with the selection criterion, leads to an underestimation of the MTD parameter.

Table 6.4: Comparison between laboratory MTD and algorithm-derived MTD (L=50 mm)

Step Size [mm]	MTD Python (103.75 x 103.75) [mm]	MTD Python (150 x 150) [mm]	Deviation from the laboratory value [mm]
0.5	1.70	4.98	-0.59/2.70
0.2	1.85	5.60	-0.43/3.32
0.1	1.91	5.99	-0.37/3.71
0.05	2.01	6.14	-0.27/3.86

Table 6.5: Comparison between laboratory MTD and algorithm-derived MTD (L=10 mm)

Step Size [mm]	MTD Python (103.75 x 103.75) [mm]	MTD Python (150 x 150) [mm]	Deviation from the laboratory value [mm]
0.5	1.40	2.91	-0.88/0.63
0.2	1.56	3.45	-0.72/1.18
0.1	1.64	3.80	-0.64/1.52
0.05	1.71	3.99	-0.57/1.71

Regarding the step size, for this preliminary investigation on the bituminous mixture specimen, the most favourable value is 0.05 mm, for what concern the investigation via circular operational model, *Table 6.2*. This result is further discussed in Section 6.2.3, where the outputs of the MTD algorithm are compared with those obtained from the MPD algorithm and the corresponding Estimated Texture Depth parameter.

At the conclusion of this investigation on the bituminous mixture specimen, it can be observed that the circular operational mode provide more consistent results for this analysis. In contrast, the square operational mode exhibits convergence only when evaluating a square domain with a side length equal to the diameter of the spread sand patch. Specifically, a clear convergence between the diametrical and square investigations is achieved when utilizing an analysis value of 103. Conversely, when the analysis is extended to the full nominal specimen size, the agreement between the circular and square domains is no longer maintained.

This behaviour suggests that the calculation domain has a significant influence on the estimated MTD value, especially when the analysed surface is not morphologically homogeneous. Since the traditional Sand Patch Test produces an approximately circular spreading area, the circular operational mode is considered more appropriate for comparison with the laboratory measurement. Therefore, for the evaluation of the bituminous mixture specimen, the following discussion focuses primarily on the results obtained using the circular operational mode.

6.1.2 Analysis of the Granite Slabs and the Limitations of Commercial Software

The granite slab represents the most critical case study for algorithm verification due to the minute macro-texture values involved. In this scenario, the data processing performed using commercial software, namely QGIS and CloudCompare, revealed severe operational limitations, which are outlined in *Table 6.6*.

Table 6.6: Comparison of volumetric calculation results.

Laboratory Sand Value [mm ³]	Digital Sand Volume (QGIS Evaluation) [mm ³]	Step Size [mm]	Digital Sand Volume (CC Evaluation) [mm ³]
9820	9259.59	0.5	17984.34
9820	9259.59	0.2	18072.38
9820	9259.59	0.1	18083.66
9820	9259.59	0.05	18088.91

The application of the Raster Calculator within the QGIS environment, constrained to a strictly calibrated inspection interval between $[-0.65 \text{ mm}; 0.65 \text{ mm}]$, yielded exceptionally accurate results. The calculated digital volume is 9259.59 mm^3 , corresponding to an MTD of 0.24 mm . The deviation from the laboratory-derived value is only 0.01 mm , demonstrating that for smooth surfaces, strict fixed-threshold filtering successfully excludes geometric macro-oscillations unrelated to the test. Conversely, CloudCompare's *Calculate*

2.5D Volume tool suffered a massive computational failure, returning volumes ranging between 17948 mm³ and 18088 mm³, nearly double the physical sand volume.

This massive systematic error has a clear engineering explanation, the ICP algorithm in CloudCompare, used to register the pre-test and post-test point clouds, is inevitably affected by microscopic alignment tolerances and instrumental scanning noise. On a rough surface like bituminous mixture specimen, a microscopic residual distance between the planes is mathematically negligible, conversely, on the nearly smooth granite surface, this millimetric residual distance acts as a constant systematic offset error.

When the CloudCompare volumetric calculation tool executes the computation over the entire extent of the slab, it sums this fictitious thickness across millions of pixels, generating a macroscopic and unacceptable overestimation of the volume.

Furthermore, the same investigation conducted for the bituminous mixture specimen was replicated for the granite slab, via square calculation mode and circular calculation mode.

It should be noted that to reduce the computational load, which would have otherwise resulted in loading extremely large matrices, the granite slab was not investigated in its full dimensions of 540 × 450 mm.

Instead, it was cropped to the vicinity of the area affected by the sand patch during the laboratory test, resulting in a square with dimensions of 223 × 223 mm.

In this investigation phase as well, an analysis of the results and their discrepancies was performed, initially considering the entire data, deriving from the square operational mode, and subsequently examining specific well-defined diameters, derived from the circular operational mode with a diameter value equal to the one obtained in the laboratory after the spreading of the sand on the granite slab.

Finally, unlike the bituminous mixture specimen, the granite slab was subjected to additional data cleaning via the application of the SOR (*Statistical Outlier Removal*) filter directly within CloudCompare. This decision was prompted by the presence of several spurious points that exhibited elevation differences relative to neighbouring points on the order of centimetres with respect to the reference plane. Consequently, the application of this cleaning filter made it possible to obtain a more homogeneous point cloud with fewer outliers that could adversely affect the calculation of the Mean Texture Depth parameter. Following the application of the cleaning filter, the point cloud was rasterized to obtain its matrix form, adopting the same sampling step size used for the bituminous mixture

specimen. Once the matrix outputs to be used within the custom algorithms were obtained, an initial investigation through the square operational mode was conducted utilizing three distinct moving mask sizes.

The selected sizes remained $L = 50$ mm and $L = 10$ mm, although they do not satisfy the standard selection criterion. This criterion conventionally depends on the maximum aggregate size D_{max} , whereas a granite slab is not composed of particulate aggregates but is instead an intrusive igneous rock. Consequently, the results regarding the application of these two mask sizes (*Table 6.7* and *Table 6.8*) yield an MTD parameters that are not entirely consistent with the baseline value obtained during the laboratory test.

Table 6.7: Comparison between laboratory MTD and algorithm-derived MTD (L=50 mm)

Step Size [mm]	MTD Python (223 x 223) [mm]	Deviation from the laboratory value [mm]
0.5	0.67	0.42
0.2	0.72	0.47
0.1	0.73	0.48
0.05	0.74	0.49

Table 6.8: Comparison between laboratory MTD and algorithm-derived MTD (L=10 mm)

Step Size [mm]	MTD Python (223 x 223) [mm]	Deviation from the laboratory value [mm]
0.5	0.35	0.09
0.2	0.40	0.14
0.1	0.41	0.16
0.05	0.42	0.17

As third moving mask size, a value consistent with the selection criterion was selected, based on specific underlying assumptions.

First, it must be considered that the granite slab lacks particulate aggregates, being a monolithic specimen characterized by a homogeneous crystalline micro-texture.

Therefore, a maximum grain size D_{max} of approximately 1 to 2 mm can be assumed, consequently a mask size of $L = 4$ mm represents the most coherent and appropriate choice. This choice yields highly satisfactory results (*Table 6.9*), as the MTD value computed by the algorithm converges closely toward the laboratory-derived value, providing further evidence of the validity of the selection criterion.

Table 6.9: Comparison between laboratory MTD and algorithm-derived MTD (L=4 mm)

Step Size [mm]	MTD Python (223 x 223) [mm]	Deviation from the laboratory value [mm]
0.5	0.21	-0.04
0.2	0.26	0.00
0.1	0.27	0.02
0.05	0.28	0.03

At this point, a supplementary investigation can be conducted to further validate the obtained results. Rather than performing the analysis on a square region, using the circular operational mode the investigations go through a diameter value. This approach enables the analysis of an area corresponding exactly to the region covered by the sand during the laboratory test, mirroring the methodology applied to the bituminous mixture specimen.

Using the same mask sizes (50 mm, 10 mm and 4 mm), the investigation was strictly confined to a circular area with a diameter of 223 mm, which corresponds exactly to the diameter of the sand patch measured in the laboratory. The results obtained from this investigation, particularly those concerning the 4 mm mask size (*Table 6.12*), confirm that reducing the mask to such a small dimension is fully justified.

Table 6.10: Square Cloud Point with Diametral Investigation (L=50 mm)

Step Size [mm]	MTD Python ($\varnothing=223$) [mm]	Deviation from the laboratory value [mm]
0.5	0.69	0.43
0.2	0.73	0.48
0.1	0.75	0.50
0.05	0.75	0.50

Table 6.11: Square Cloud Point with Diametral Investigation (L=10 mm)

Step Size [mm]	MTD Python ($\varnothing=223$) [mm]	Deviation from the laboratory value [mm]
0.5	0.35	0.10
0.2	0.40	0.15
0.1	0.41	0.16
0.05	0.42	0.17

Table 6.12: Square Cloud Point with Diametral Investigation (L=4 mm)

Step Size [mm]	MTD Python ($\varnothing=223$) [mm]	Deviation from the laboratory value [mm]
0.5	0.21	-0.04
0.2	0.26	0.01
0.1	0.27	0.02
0.05	0.28	0.03

In this case, identifying 0.05 mm as the optimal rasterization step size is slightly more complex, given that all analysed configurations exhibit minimal deviations, in fact, the 0.2 mm step size yields a deviation of 0.1. Nonetheless, a step size of 0.05 mm is still selected as the optimal value, despite its higher deviation.

This choice is thoroughly justified by the results presented in the subsequent sections regarding the algorithm dedicated to the Mean Profile Depth parameter, which demonstrate that the 0.05 mm step size is the most appropriate to ensure rigorous cross-validation between the two algorithms.

In conclusion, regarding the results reported for the algorithm dedicated to the calculation of the Mean Texture Depth (*MTD*) parameter, it can be observed that in the case of the granite slab investigation, convergence is also successfully validated between both testing methods, namely the circular operational mode and the square operational mode.

The primary justification provided for this semi-convergence, which remains exclusive to the granite slab, is attributed to the fact that the slab exhibits an extremely repetitive surface pattern and a characteristically low *MTD* value. Such a low parameter is inherently difficult to capture accurately without relying on the specific methodological assumptions detailed within this section.

Nevertheless, this structural uniformity benefits the analysis, as both the circular and square operational configurations yield nearly identical results.

6.2 Accuracy and Sensitivity of the MPD Algorithm: Method Response to Different Surface Conditions and Survey Densities

The characterization of road surface macro-texture requires a comprehensive sensitivity analysis aimed at verifying the stability and resilience of the algorithms under varying material morphologies and spatial resolutions of the digital model.

While the previous section highlighted the three-dimensional volumetric response, this section provides an in-depth analysis of the behaviour of the linear two-dimensional (*2D*) algorithm dedicated to computing the Mean Profile Depth (*MPD*) and the resulting Estimated Texture Depth (*ETD*).

6.2.1 Rationalization of Step Size for Profilometric Analysis

As demonstrated in the results reported below, all four step sizes were utilized to perform a comprehensive metrological and cross-validation analysis. However, it is essential to establish that for the algorithm dedicated to *MPD* computation, a highly refined step size is inherently recommended.

This choice effectively satisfies several critical technical and operational requirements:

1. Compliance with EN ISO 13473-1 Requirements:

The international standard [6] for MPD computation imposes strict constraints on the spatial resolution of road profilometers, prescribing a longitudinal sampling interval not exceeding 1 mm and recommending significantly more refined resolutions to faithfully capture asperity waveforms. A highly defined step size guarantees full compliance with the standard, positioning the sampling frequency well below spatial aliasing limits.

2. Local Nature of the Code:

The MPD algorithm operates by dividing each individual 100 mm linear profile into two 50 mm sub-segments, identifying the absolute maximum peak elevation within each sub-interval. When a coarser step sampling size is utilized, such as 0.5 mm or 0.2 mm, the sparse discretization inevitably smooths out the sharp crests of individual mineral aggregates in the bituminous mixture specimen or the micro-undulations of the granite surface.

Consequently, a step size ranging between 0.1 mm and 0.05 mm is established as the recommended parameter during the dedicated point cloud rasterization phase.

This requirement stems from the fact that failing to capture the true elevation of the maximum peak due to sparse sampling introduces a systematic underestimation error in the MPD calculation. High point density is therefore a fundamental prerequisite to ensure the accuracy and robustness of the peak-based linear algorithm.

6.2.2 Spatial Sensitivity Analysis: Statistical Stability Under Sampling Strides

To evaluate the stability of the data obtained via the Python algorithm, a dedicated function was implemented to analyse how the results vary when considering the full grid (all rows and columns) versus when a sampling stride, or skip, is applied to the rows or columns.

Following the established processing pipeline, the analysis began with the bituminous mixture specimen, evaluating first the entire surface and subsequently the square matrix shape.

Analysis of the matrix representation corresponding to the intact bituminous mixture sample reveals that introducing row and column sampling gaps induces varying behaviours

contingent upon the chosen step size. For step sizes of $s = 0.5$ mm and $s = 0.2$ mm, the sampling gaps destabilize the MPD parameter and, consequently, the ETD estimation. In contrast, utilizing finer sampling steps, such as $s = 0.1$ mm or $s = 0.05$ mm, ensures the stability of the output parameter. Notably, even under a gap configuration of 100 rows by 100 columns, the parameter exhibits minimal deviation from the reference value derived from the original, fully sampled matrix.

Furthermore, it is worth highlighting that when using a step size of $s = 0.05$ mm, a marginal difference of only 0.02 mm exists between the analysis of the complete matrix and that of the matrix processed in blocks of 100 rows and 100 columns.

Table 6.13: Sensitivity analysis of the MPD/ETD algorithm for the bituminous mixture specimen ($s=0.5$ mm)

Rows Step	Column Step	MPD [mm]	ETD [mm]
1	1	1.87	2.06
5	5	1.92	2.11
10	10	1.98	2.17
50	50	2.12	2.33
100	100	2.12	2.33

Table 6.14: Sensitivity analysis of the MPD/ETD algorithm for the bituminous mixture specimen ($s=0.2$ mm)

Rows Step	Column Step	MPD [mm]	ETD [mm]
1	1	2.00	2.19
5	5	2.01	2.21
10	10	2.03	2.23
50	50	2.10	2.31
100	100	2.10	2.31

Table 6.15: Sensitivity analysis of the MPD/ETD algorithm for the bituminous mixture specimen (s=0.1 mm)

Rows Step	Column Step	MPD [mm]	ETD [mm]
1	1	2.04	2.24
5	5	2.05	2.25
10	10	2.05	2.25
50	50	2.08	2.29
100	100	2.08	2.29

Table 6.16: Sensitivity analysis of the MPD/ETD algorithm for the bituminous mixture specimen (s=0.05 mm)

Rows Step	Column Step	MPD [mm]	ETD [mm]
1	1	2.06	2.27
5	5	2.07	2.28
10	10	2.07	2.28
50	50	2.09	2.29
100	100	2.09	2.29

Subsequently, the same analysis was performed on the matrix products derived from the bituminous mixture specimen cropped into a square geometry (103.75×103.75 mm).

In this case, the stability observed during the full-matrix analysis is not maintained. On the contrary, significant instability becomes evident when employing larger sampling intervals, such as 50 or 100 rows and columns. which tend to underestimate the parameter under evaluation.

Table 6.17: Sensitivity analysis of the MPD/ETD algorithm for the square bituminous mixture specimen (s=0.5 mm)

Rows Step	Column Step	MPD [mm]	ETD [mm]
1	1	1.93	2.12
5	5	1.94	2.13
10	10	1.89	2.08
50	50	1.27	1.40
100	100	1.14	1.25

Table 6.18: Sensitivity analysis of the MPD/ETD algorithm for the square bituminous mixture specimen (s=0.2 mm)

Rows Step	Column Step	MPD [mm]	ETD [mm]
1	1	2.19	2.41
5	5	2.16	2.37
10	10	2.12	2.33
50	50	1.58	1.73
100	100	1.64	1.80

Table 6.19: Sensitivity analysis of the MPD/ETD algorithm for the square bituminous mixture specimen (s=0.1 mm)

Rows Step	Column Step	MPD [mm]	ETD [mm]
1	1	1.95	2.15
5	5	1.91	2.10
10	10	1.87	2.06
50	50	1.57	1.72
100	100	1.55	1.70

Table 6.20: Sensitivity analysis of the MPD/ETD algorithm for the square bituminous mixture specimen ($s=0.05\text{mm}$)

Rows Step	Column Step	MPD [mm]	ETD [mm]
1	1	1.74	1.91
5	5	1.73	1.90
10	10	1.70	1.87
50	50	1.58	1.74
100	100	1.56	1.71

Subsequent analysis of the granite slab revealed a level of stability consistent with that observed in the full-scale evaluation of the bituminous mixture specimen, demonstrating that the phenomenon is identically replicated.

Table 6.21: Sensitivity analysis of the MPD/ETD algorithm for the granite slab ($s=0.5\text{ mm}$)

Rows Step	Column Step	MPD [mm]	ETD [mm]
1	1	0.37	0.41
5	5	0.37	0.41
10	10	0.36	0.40
50	50	0.34	0.38
100	100	0.39	0.43

Table 6.22: Sensitivity analysis of the MPD/ETD algorithm for the granite slab ($s=0.2\text{ mm}$)

Rows Step	Column Step	MPD [mm]	ETD [mm]
1	1	0.39	0.43
5	5	0.39	0.42
10	10	0.38	0.42
50	50	0.35	0.39
100	100	0.37	0.41

Table 6.23: Sensitivity analysis of the MPD/ETD algorithm for the granite slab (s=0.1 mm)

Rows Step	Column Step	MPD [mm]	ETD [mm]
1	1	0.38	0.42
5	5	0.38	0.42
10	10	0.37	0.41
50	50	0.33	0.37
100	100	0.31	0.34

Table 6.24: Sensitivity analysis of the MPD/ETD algorithm for the granite slab (s=0.05 mm)

Rows Step	Column Step	MPD [mm]	ETD [mm]
1	1	0.40	0.44
5	5	0.40	0.44
10	10	0.39	0.43
50	50	0.33	0.37
100	100	0.33	0.37

In conclusion, the investigation conducted on the granite slab showed a similar trend to the one carried out on the bituminous mixture specimen. The comparative analysis suggests a good statistical stability of the software outputs under the tested conditions.

For the entire sample of bituminous mixture specimen under analysis, transitioning from a full-resolution dense grid to a highly down sampled configuration, such as analysing only one-hundredth of the data rows and columns, produced only a small variation in the final results. In particular, the percentage difference between the ETD value derived from the full-matrix analysis and that obtained from the partially sampled matrix was approximately 0.88%. A similar behaviour was observed for the granite slab, where the ETD remains close to 0.40 mm in all sampling configurations. However, it must be noted that the output in this scenario is not consistent with the laboratory-derived parameter. The calculated ETD values are approximately double the baseline value, even respect the MTD value obtained utilizing the dedicated algorithm with a moving mask length of $L = 4$ mm.

This behaviour suggests that, due to the high initial density of the 0.05 mm regarding the DEM, the population of extracted profiles is so massive and statistically redundant that the introduction of wide sampling strides does not alter the probability distribution of the macro-texture peaks. From a practical application standpoint, this algorithmic resilience represents a major asset because it allows operators to implement sparse sampling intervals on exceptionally large raster files, such as kilometres of road pavement surveyed via mobile profilometers.

Consequently, computational processing times and RAM allocation are drastically reduced without compromising the reliability of the calculated MPD/ETD values.

6.2.3 Comparative assessment: Consistency Between Standardized ETD and Custom MTD

One relevant aspect of the experimental framework of this thesis lies in the numerical agreement observed when comparing the results of the two algorithms: one dedicated to the computation of the Mean Texture Depth (*MTD*), developed with AI assistance, and the other transcribed based on the reference study conducted by the Swedish National Road and Transport Research Institute [2].

This agreement is meaningful regarding the investigations performed on the bituminous mixture specimen. Indeed, the results obtained from the algorithm based on EN ISO 13473-1 [6], which yields both the Mean Profile Depth (*MPD*) and its equivalent Estimated Texture Depth (*ETD*), show reasonable agreement with the Mean Texture Depth (*MTD*) parameters computed by the independently developed algorithm.

Conversely, the same convergence cannot be claimed for the granite slab, although it yields reasonable agreement in terms of Mean Texture Depth (*MTD*) parameter, a similar agreement is not observed for the Mean Profile Depth (*MPD*) and Estimated Texture Depth (*ETD*) parameters.

The primary reason for this lack of convergence on the granite slab stems from the operational flexibility of the models, the custom MTD algorithm offers greater control, allowing the user to calibrate the moving mask size, provided the selection criterion is respected, whereas the standardized MPD/ETD algorithm lacks this structural flexibility. Consequently, analysing a surface as smooth and characterized by such low macro-texture as the granite slab exposes limitations when applying the standardized profile method to very smooth non-road surfaces.

Based on these premises and in view of the obtained results, a preliminary consistency check can only be discussed for the bituminous mixture specimen. The granite slab does not represent an actual pavement surface but rather serves as a boundary case, valuable for the comparative analysis and assessment of the operational limits of the instrumentation deployed across the various research phases. As established at the conclusion of *Section 6.1.2*, the most suitable rasterization sampling step size within this dataset was determined to be $s = 0.05$ mm therefore, to ensure a consistent comparison, only the data corresponding to this specific resolution were considered.

Furthermore, based on this selected step size, the MTD parameters for the diameter-based investigations, specifically using a diameter of $\varnothing = 103.75$ mm for the bituminous mixture specimen and $\varnothing = 223$ mm for the granite slab, are reported to ensure improved consistency with the laboratory test setup.

These values are compared directly against the corresponding ETD values derived from the MPD-based algorithm (*Table 6.25*).

Table 6.25: Comparison between output of different algorithms

Investigated Specimen	ETD INDEX (Standard VTI/ISO) [mm]	MTD INDEX (Custom Python-AI) [mm]	Laboratory Value [mm]
Bituminous Mixture Specimen [Circular Op. Mode]	2.27	2.09	2.28
Bituminous Mixture Specimen [Rectangular Op. Mode]	1.91	2.01	2.28
Granite Slab	0.44	0.28	0.25

To fully appreciate the significance of this result, it is necessary to recall the distinct origins of the two software codes:

- The *MPD/ETD algorithm* was developed by translating a standardized calculation framework into the Python environment. This architecture is derived directly from the international standard EN ISO 13473-1 [6] and the established benchmark provided by the MATLAB code from the Swedish National Road and Transport Research Institute (VTI) [2]. It represents, for all intents and purposes, a calculation routine based on a standardized method.
- The *MTD algorithm* features an entirely custom architecture, developed with artificial intelligence assistance. It is engineered to virtually simulate the three-dimensional physical behaviour of the *Sand Patch Test* under the specific boundary conditions dictated by the Digital Elevation Model (DEM).

The data indicate that, for the bituminous mixture specimen, the Estimated Texture Depth (ETD) evaluated through the MPD-based code stands at 2.27 mm.

This value is very close to the actual *Sand Patch Test* result equal to 2.28 mm, while the custom MTD-based algorithm at the selected step size of 0.05 mm records a Mean Texture Depth (MTD) value equal to 2.09 mm, when the circular operational model is used.

The numerical discrepancy between the two indices may be related to the empirical translation constant established in international literature to compensate for the inherently two-dimensional nature of the MPD as well as to the different calculation domains and assumptions of the two methods.

This convergence breaks down in the case of the investigation conducted on the granite slab. Here, the ETD algorithm yields a parameter nearly double the value recorded in the laboratory, suggesting a limitation of the proposed methodology when applied to very smooth surfaces characterized by extremely low macro-texture. In such cases, reconstruction noise and the profile-based nature of the MPD/ETD calculation may significantly affect the final estimate. Nonetheless, this test was useful for identifying the operational limits.

The agreement observed for the bituminous mixture specimen is relevant because the two indices were obtained through different calculation approaches. The MPD/ETD routine is based on a standardized profile analysis, whereas the custom MTD algorithm estimates texture depth through a volumetric simulation of the sand patch test. The comparable results suggest that, under the tested conditions, the proposed MTD algorithm provides a reasonable representation of the macro-texture of the bituminous specimen.

This outcome demonstrates that the implemented geometric concepts, such as the application of the moving mask, the 360° radial sampling, and the implementation of conditional edge-effect filters, did not appear to introduce major numerical artifacts under the tested conditions. Instead, they provided a reasonable numerical representation of the macro-texture filling process.

6.3 Workflow Efficiency Assessment: Balancing Metric Accuracy and Software Costs

The overall assessment of an engineering methodology requires a careful evaluation of the overall workflow efficiency, defined as the balance among the metric accuracy of the results, computational processing times, software licensing costs, and operational complexity for the end user.

The digital ecosystem developed in this study, based on custom scripts within an open-source Python environment, was compared against procedures executed via commercial proprietary software and traditional GIS platforms. This comparison highlights aspects of significant practical relevance for road infrastructure management and maintenance authorities.

6.3.1 Comparative Analysis of Commercial Software and Traditional GIS

Attempts to extract macro-texture parameters through the exclusive use of point cloud management software or traditional commercial GIS packages revealed a trade-off between accuracy and automation, highlighting relevant operational limitations:

1. Limitations of CloudCompare (*Compute 2.5D Volume*):

Although it is a widely adopted, open-source software for three-dimensional geometric analysis, its integrated volumetric calculation algorithm exhibited a marked limitation when applied to ultra-fine texture surfaces, such as the granite slab, overestimating the actual sand volume by nearly 100%.

This error likely influenced by instrumental noise and microscopic alignment offsets from the ICP (*Iterative Closest Point*) registration procedure, suggests that caution is required when using this tool for very smooth surfaces.

Furthermore, the user interface demands a repetitive sequence of manual steps for each individual sample, limiting any capacity for batch or automated processing.

2. Limitations of QGIS (*Raster Calculator*):

The GIS environment proved mathematically accurate for the volumetric calculation of the granite slab, but only after rigorous, ad hoc manual filtering of the elevation thresholds performed by the operator.

This approach presents two major issues for large-scale applications, it requires an expert user highly skilled in geospatial analysis, and it is geometrically rigid, as it does not automatically adapt to complex analysis domains, such as the circular moving masks required for cylindrical laboratory specimens.

6.3.2 Overcoming Programming Barriers and the Potential Role of AI-Assisted Development

Within this framework, the developed custom Python scripts represent a suitable solution for reducing several limitations of the previously analysed commercial platforms. From a strictly economic perspective, the entire workflow is built upon largely open-source or freely available tools, specifically Python integrated within the PyCharm IDE and supported by specialized scientific libraries. This approach reduces the licensing fees typically associated with proprietary metrological software.

However, the most methodologically innovative aspect of this work lies in the support provided by AI-assisted coding during software development, evaluated in relation to the operator's learning curve. From the perspective of traditional software engineering, developing an automated computational application is typically considered more accessible to specialized programmers. Conversely, the approach implemented in this research demonstrates how, even for an operator with novice-level programming skills in the Python environment, it was possible to achieve the objective within a reasonable development time and with iterative verification.

This milestone was achieved through an AI-assisted development process. Overcoming the syntax barriers of the Python language was not accomplished via passive or generic code generation, but rather through an iterative engineering dialogue.

The key driver behind the workflow's success lies in the AI's capacity to operate as a support tool for translating domain-specific requirements, paying meticulous attention to the highly detailed and stringent technical specifications provided by the user.

The development process was structured around the following interactive pillars:

- **Systematic translation of physical constraints into computational logic:**

The operator rigorously defined the physical boundary conditions of the problem, after which the AI supported the translation of these specific instructions, translating them into the mathematical architecture of the moving mask and the conditional edge-effect filters for the MTD algorithm.

- **Meticulousness in normative transcoding:**

In the case of the standardized Mean Profile Depth (*MPD*) code, attention to algorithmic detail supported the conversion of the logical-mathematical framework from the EN ISO 13473-1 international standard [6] and the MATLAB benchmark provided by the VTI [2].

This aimed to preserve the integrity of both the *NaN* removal filters and the slope suppression (*detrending*) procedures without introducing software artifacts.

The outcome is a flexible prototype metrological application. With limited interaction with the underlying code, the user only needs to import the Digital Elevation Model (*DEM*) matrix into the configuration panel and execute the script. Within a computational execution time of less than 90 seconds, the software autonomously performs data cleaning, applies the necessary filters, and formats the final outputs.

Consequently, this study suggests that AI-assisted coding can reduce the barriers to entry for advanced programming have definitively collapsed. The modern civil engineer may not always require a background as a computer scientist to develop high-precision custom tools. Instead, the ability to steer artificial intelligence through rigorous, informed, and technical prompting enables the seamless transformation of theoretical concepts and normative formulas into working software prototypes, with limited software costs for public administrations and road network managers.

Conclusions and Future Perspectives

The research work carried out in this thesis addressed its primary objective: the digitization, standardization, and automation of road pavement surface macro-texture estimation processes.

Although historically considered a reference method, the traditional *Sand Patch Test* (standardized by EN ISO 13036-1 [1]) suffers from inherent operational limitations. These include a high dependence on the operator's skill, the consumable nature of the testing material, as the standardized sand is scattered and cannot be recovered, and the geometric rigidity of a purely punctual, non-replicable measurement.

The methodology developed in this study addresses this paradigm through the synergistic integration of close-range digital photogrammetry, geospatial analysis, and custom Python programming. The implemented computational architecture demonstrates that a dense point cloud can be successfully converted into a Digital Elevation Model (*DEM*) matrix, onto which two distinct processing engines can be applied:

1. A custom, *AI-assisted three-dimensional (3D) algorithm* designed for the virtual simulation of intergranular void filling.

This engine approximates the physical behaviour of sand as it occurs during the traditional *Sand Patch Test* to subsequently estimate the Mean Texture Depth (*MTD*), leveraging the geometric principle of a moving mask capable of dynamically adapting to the actual boundary conditions of the specimen.

2. A linear, *two-dimensional (2D) profilometric algorithm* dedicated to computing the Mean Profile Depth (*MPD*) and the resulting Estimated Texture Depth (*ETD*).

This code is based on the EN ISO 13473-1 international standard [6] and implemented according to the algorithmic logic of the benchmark MATLAB code provided by the Swedish National Road and Transport Research Institute (*VTI*) [2].

The experimental phase, conducted in parallel on an open-textured specimen and a nearly smooth surface, provided a preliminary consistency assessment of the method. The good numerical agreement between the standard-compliant ETD and the MTD calculated by the custom algorithm, exclusively observed during the investigation of the bituminous mixture

specimen, provided encouraging evidence of the scripts' accuracy under the tested conditions.

Featuring significantly reduced processing times and the reduction of licensing fees owing to an open-source and freely available framework, the tool indicated that digital automation could approach laboratory precision while improving statistical robustness, replicability, and metrological stability.

While the metrological efficacy and automation of the Python calculation code have been preliminary demonstrated, an analysis of the overall workflow highlights what currently represents the final major hurdle to achieving total in-situ portability.

Currently, the process still suffers from software fragmentation during the upstream phases, specifically regarding the photographic acquisition of the target pavement section. This stage requires transferring the data to a desktop computer for image alignment and extraction of Digital Elevation Models (*DEMs*) matrix using external photogrammetry software, such as Agisoft Metashape Professional or RealityScan. This reliance on high-performance hardware and external applications restricts the immediacy of on-site surveys.

Therefore, the natural engineering evolution of this method lies in the development of a single, native software application for mobile devices, such as smartphones and tablets. The lightweight computational footprint of the developed Python scripts suggests potential portability into modern mobile operating systems via dedicated cross-compilation libraries.

The architecture of this mobile application could be structured to internally manage three fundamental operational phases:

1. Smart Shooting Guide:

By leveraging the smartphone's inertial sensors, namely the gyroscope and accelerometer, alongside augmented reality (*AR*), the application could visually guide the operator in the field during image capture.

The app could provide a real-time graphical on-screen overlay to support adherence to geometric overlap parameters, optimal focal length, and controlled orientation of the optical axis relative to the pavement surface, thereby reducing parallax errors.

2. In-App 3D Alignment and Reconstruction:

Utilizing modern on-board mobile GPUs paired with optimized photogrammetry algorithms specialized in feature detection identifying pixels characterized by abrupt brightness gradients, or alternatively supported by lightweight cloud-computing

services, the application could execute image alignment and point cloud generation directly on the device.

This would reduce the dependency on third-party commercial software suites.

3. Immediate DEM Matrix Extraction and Metrological Calculation:

Upon completion of the three-dimensional reconstruction, the application could automatically extract the Digital Elevation Model (*DEM*) matrix file.

This matrix could then be used as an input into the native Mean Texture Depth (*MTD*) and Mean Profile Depth (*MPD*) calculation engines embedded directly within the software architecture of the app itself.

In this manner, the field operator can simply frame the target pavement surface, capture the guided image sequence, and obtain near-real-time digital MTD, MPD, and ETD values directly on the smartphone screen while on-site. This approach could transform a standard mobile device into a portable, autonomous surface-texture assessment tool.

Reducing the computational barriers to entry and centralizing the workflow within a mobile ecosystem could open multiple promising application scenarios in road infrastructure management. The capacity to perform rapid, non-destructive and repeatable surveys could allow the methodology to scale from a single laboratory specimen to an entire regional or national network, laying the groundwork for a transition toward predictive road maintenance strategies.

The *primary future developments* are outlined below:

- **Integration into Pavement Management Systems (PMS):**

The georeferenced texture data extracted via the mobile application could directly populate the databases of pavement management systems run by managing authorities, such as ANAS, highway concessionaires, and municipal administrations.

This could support continuous mapping of potential skid resistance and wearing course degradation.

- **Predictive Modelling of Surface Degradation:**

The historical archiving of replicable digital surveys along the same road section could enable the development of machine learning algorithms capable of predicting the macro-texture aging curve as a function of heavy traffic and weathering agents.

Instead of intervening reactively once the pavement already exhibits initial signs of distress or a critical loss of skid resistance, which consequently increases accident rates,

managing authorities can plan rehabilitation interventions, such as surface treatments, more effectively.

This would contribute to maximizing the infrastructure's service life while reducing social and economic costs.

- **Crowdsourcing and Smart Cities:**

The portability of the code onto off-the-shelf devices opens the possibility of deploying smartphones or dedicated optical micro-sensors aboard public service vehicles, such as local transit buses or waste collection trucks.

The systematic and automated scanning of the pavement during daily routes could allow for real-time monitoring of the city's infrastructure “*health status*”, flagging anomalies and localized texture degradation before hazardous road safety situations arise.

In conclusion, the convergence between road civil engineering and the new frontiers of assisted programming has demonstrated that technological innovation can support the gradual replacement or integration of legacy empirical practices.

The tool developed in this thesis does not merely represent an isolated numerical milestone rather, it may contribute toward a more efficient, secure, cost-effective, and sustainable road management model.

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