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Planning and development of a bio-feedback music advisory system for training activities

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Abstract

Physical and mental wellness represents one of the most pursued and desired aims nowadays. Health, in its most general sense, is of a major concern in the present world scenario.

Many people usually perform running activities to keep the body fit and healthy; within this context, the heart rate results in a vital measure of a person's health and it can be used to monitor the body's present condition and provide ways to improve it.

The heart rate, in particular, is a revealing indicator for the training intensity and stabilizing it can help the user increase the efficiency and guarantee the safety of exercise. According to the desired intensity training level, certain limits for the heart rate can be determined using the maximum heart rate.

The objective of this thesis is to demonstrate the feasibility of a support system able to rely on music application to enhance trainers' performances while performing a running activity. A motivational support is then provided to the final user to generate a positive perception of the physical effort. Thus, some advanced solutions can be adopted to achieve satisfactory results when deploying music-based support systems.

This project aims at providing a fully operative service to users interested in reaching desired training performance with the help of properly selected music tracks. The novelty of the proposed solution consists in an adaptation of individual physiologic characteristics to provide an always updated and fully personalized experience that continuously keeps track of cardiac responses to external audio stimulus.

After a preliminary evaluation of results achieved by administrating different audio tracks to a trainers' sample, an improved solution based on artificial intelligence and regression analysis was developed for adapting the support service with individuals' performance and cardiac responses.

Contents

Chapter 1

Introduction

It is widely known that physical exercise is fundamental for body and mind wellness. It keeps the body young, delaying ageing of muscles, articulations and organic structures. In the last decades, sedentary lifestyle is largely grown, thanks to the "modern wellness" that induces less physical exercise. Human body is not suited for inactivity, which causes very frequent diseases like diabetes, cardiovascular illnesses and even tumors.

Physical activity, conducted with moderation and regularity, since the very early ages, allows the human body to be efficient and healthy for a longer period, preventing muscle and articulation failures. Sport, moreover, is associated with a reduction in blood pressure, cholesterol and diabetes. Then, it is straightforward to notice how physical activity is fundamental for reducing heart related diseases. For these reasons, physical exercise is extremely important both for healthy individuals and cardiopathic patients, which also need a non-pharmacologic aid for the cardiac illness treatment.

The relationship between exercise and heart health is so deep that many innovative solutions have been devised and developed to help the trainer in maintaining an healthy lifestyle. Many devices, such as modern workout equipment and jogging accessories are provided with built-in receivers that continuously collect heart rate information coming from wearable monitoring devices placed on different parts of the human body.

The effects that exercise produces on people's health are strictly dependant on the specific physical activity, in particular its intensity and duration. From this perspective, an intelligent workout session could be guided by heart rate parameter that drives the trainer to achieve his/her training goals. The individual, then, can be at a different heart rate training zone, whose definition depends on the percentage of his/her maximum heart rate. Many formulas are already available to evaluate this threshold parameter.

For instance, a relatively low heart rate value allows to burn fat or pace for a longer workout, whereas a higher heart rate value may improve effort resistance. Maintaining a stable heart rate can help the user increase the efficiency and guarantee the safety of exercise.

Table 1 shows 5 heart rate zones, the intensity ranges and their corresponding effects.

Intensity range	Zone Effect
50%-60%	Reduces fat, cholesterol, and blood pressure. Temperate. Basic endurance.
60%-70%	Fat burning. Aerobic. Strengthen cardiovascular system.
70%-80%	Step up lung capacity. Anaerobic. Getting faster.
80%-90%	Getting fitter. Red Line. Working out here hurts.
90%-100%	Increased potential for injury.

Table 1. Heart rate training zones.

Nowadays, MP3 players and heart-rate monitors are becoming increasingly pervasive when exercising, especially when walking, running or jogging outdoors. This habit usually leads trainers to maintain a stable heart rate while performing such activities. Starting from this last observation, this thesis project aims at integrating the concepts of adaptive systems, user music preference, and methods of using the music to adjust the user's heart rate into a linear biofeedback control system.

The purpose of the presented work is to devise a solution for Android systems able to provide a smart support for users interested in performing physical activity, mostly characterized by a cyclical nature (walking, running, biking). The designed system represents a biofeedback-based and automated music recommendation tool that uses the sensed data and runner's contextual information to provide dynamic music suggestions. The final aim is to help the user achieve a target heart rate.

Users willing to achieve specific fitness performances can tune the application to set arbitrary physiological constraints related to individual heart rate values. In other words, the system is tailored on user's context, that is, the user sets his/her personal goal (in terms of desired heart rate), and the device recommends and plays appropriate music. The choice depends on the current heart rate, target heart rate, past responses to music and activity level.

The playback of proper music tracks, categorized and selected by the application itself, represents the driver with which the system acts on user's behaviour during his/her training session. Decision-make component of the system is constantly fed with data coming from a wireless device (smartwatch, thoracic band...), worn by the individual to detect real-time heart rate values during the activity progress.

The contents within this thesis are organized and presented following a specific logical process. Starting from a general overview of the main available solutions and results about the proposed use context, the focus is then shifted towards the analysis, design and implementation of the system aimed at supporting physical activity by means of proper music playback.

In *Chapter* 2, useful literature material about the topic of interest is analyzed. In particular, a quick description of some relevant IEEE papers is presented and main achievements reported on them are discussed and commented. This chapter, moreover, contains other references retrieved from PubMed academic portal about medicine and health. Starting from these conclusions and results, the purpose is to extend these concepts and achievements to a wider range of activities, from swimming to biking, walking, gym workout, etc. . . .

Chapter 3 focuses its attention on the definition and description of the designed architecture aimed at providing the support service to the final users. A deep description of each component features and objectives allows to have a clear idea about the decisional rules for adapting the general idea to the more concrete use case.

An empirical study in *Chapter* 4 shows the effect of music on heart rate through a customized ad-hoc training experiment which involves a sample of 15 individuals that perform running activity. The aim of this analysis is to understand how music, in particular its tempo, expressed as BPM (beats per minute), is related to human body frequencies, in terms of heart beat, and what is the response of particular music inputs observed on people's activity. The achieved conclusions are then exploited to design the characteristics of the final support system.

Eventually, *Chapter* 5 presents the adopted solution based on artificial intelligence and machine learning to recommend appropriate music to the user. Also, the core decision algorithm, based on previous analysis outcomes, that selects the "best" music track to play is deeply described.

A conclusive section of this thesis summarizes the main achievements, limitations and concrete application of the implemented solution. Moreover, some hints for future developments and enhancements are mentioned as well.

Chapter 2

State-of-the-art

2.1 Introduction

This chapter aims at describing the main contributions that music brings to the physiological cardiac functionalities of a generic individual. In particular, the effects that the application of sound stimuli, with its own specific physic properties, produces on the human vital parameters, and how they can be properly exploited to improve user training experience, are the core topic of this chapter.

Moreover, since the proposed thesis study deeply relies on the evaluation of results about music application in training contexts, a special interest is addressed to the field of workout and well-being. From this perspective, a clear and meaningful observation about music components that mainly affects human body during a training session is hereby mentioned.

In the next subsections of this chapter, the most relevant results and achievements related to the proposed scenario are gathered and presented: they derive from recent studies about medical response of heart activity in the face of a specific audio stimulus and a motor action. In fact, starting from a more general view of the effects that music produces on the human heart functions, the attention is then moved towards the specific training use case and the already existing system solutions. The most evident and concrete implications that an automated system based on sound reproduction may induce on a person that desires to train under some arbitrary constraints are finally highlighted.

Summarizing, the following chapter is structured to clearly separate the underlying experimental evidences about the project basics with respect to the music applications on different scopes. In particular, the sections of the chapter are:

- **Music effects on cardiac activity**, which explains, through documented experiments, when and how music affects the human physiology and which effects it produces on vital functions and mood of the individuals.
- **Music and training**, that describes the results of music application during training session and how the motor system is influenced by audio stimuli presence.
- **Implemented solutions**, which describes and lists the most advanced solutions in the training contexts that help trainers during the workout by means of music reproduction. In particular, a comparison between the proposed system and other advanced projects is provided, to promote the novelty of this project and justify the need of deploying a similar solution with slight but important differences.

Furthermore, an extra section (**Heart rate monitor technologies**) is devoted to describe general aspects of the available technologies and hardware implementations for measuring heart rate, listing the pros and cons of each typology. Even though the choice of a specific hardware device was made based on specific requirements, the entire system is still compatible with any sensor device that satisfy a small set of hardware and software constraints.

2.2 Music effects on cardiac activity

Music represents one of the most relevant element of the entire study. From a mere physical point of view, it is an art form composed of sounds, whose representative elements include pitch, rhythm, sonic qualities of timbre and texture. Music can be interpreted as a powerful stimulus that may evoke and modulate emotions and moods [1][2], and it influences brain structures that modulate heart activities [3][4][5].

In fact, some studies state that when listening to music, song, or speech, the auditory cortex, the somatosensory and motor systems are activated. Activation of these systems may reflect an association between music and dancing, rhythmic tapping, clapping and similar musical associated activities [6].

Moreover, musical beat perception is strictly related to perceiving a periodic pulse in a complex sound sequence and it can be expressed by head movement, tapping with feet or fingers, and so on [7].

According to the Action Simulation for Auditory Prediction Hypothesis (ASAP) [8], humans move rhythmically to music because motor planning system in the brain tries to predict the timing of beats, turning moving to a music-beat into a predictive action, instead of a reactive one.

Other researches reveal the ability of the heart to beat rhythmically without any form of nerve stimulation. The heartbeat is especially affected by the autonomic nervous system [9].

Instead, only few studies have been accomplished to evaluate the effects of the acoustic characteristics of music (tempo, harmonic structure, rhythm or sound pressure level) on the cardiac activity. Among the mentioned sound features, **tempo** plays a critical role for determining whether the effect of listening to music is exciting or relaxing [10]. In musical terminology, tempo is the speed or pace of a given piece and it is typically measured in beats per minute (bpm or BPM).

Earlier studies reported that listening to music with a fast tempo caused an increase in the heart rate (HR) and the respiratory rate [10] [11].

Furthermore, listening to music with a slow or meditative tempo has a relaxing effect on people, slowing breathing and the heart rate. Listening to faster music with a more upbeat tempo, instead, has an opposite effect (speeding up respiration and the heart rate) [10]. Same results have been confirmed by other successive studies on this topic [12].

Also, it has been found that people prefer music with the tempo ranging from 70 to 100 per minute which is similar to that of adults' heart rate in normal daily situations [13].

Music is also considered a very effective tool to attenuate blood pressure and heart rate after a stressful task, as well as to reduce the level of stress. Tempo of the sound is the key to achieve these objectives [14].

Based on the tempo of a song, the response on the human body "machine" is quite different: music items with tempos of 60 to 80 BPM reduce the stress and induce relaxation, while music items with tempos between 100 and 120 BPM stimulate the sympathetic nervous system [15]. Then, other studies confirm that tempos (40 to 60 BPM) slower than the average human's heart rate induce suspense, while tempos of 60 BPM are the most soothing [16].

To conclude, individual music preference has an important role in generating a sense of relaxation in people. User preference, familiarity or past experiences with the music have an effect on positive behavior change [17].

2.3 Music and training

After knowing the effects that music produces for the human being, it is useful to understand which kind of applications are more suitable and adapt to maximize the benefits of sound stimuli. In particular, music, human body physiology and training exercise can be mixed to establish a synergy that may improve the quality and the experience of an individual that aims at doing workout in a pleasant, yet effective, way.

During a training session, tracking heart rate evolution can be seen as a useful way to determine and monitor the training intensity. Establishing some constraints on the values that this cardiac parameter can assume allows to control the effort and improve the global performance: for this reason, studies and proposed systems related to heart monitoring usually refer to the maximum heart rate value. Cardiac rhythm is also important to ensure the individual to train in a safe manner.

The heart rate, which is closely related to breaths and strides, varies throughout the run depending on factors such as the duration and intensity of the exercise, and training and fitness level of the runner [18]. Though, it happens that, for experienced runners, heart rate is maintained stable with an external auditory stimulus such as a proper music [19][20]. Among the several benefits that music introduce in vital activities (sleep quality [21], brain activity [22] and motor coordination [23]), it is important to mention its presence in the exercise routine of many people from every age [24]. In particular, music players (MP3, smartphones, ...) and heart-rate monitors are becoming increasingly pervasive when exercising, especially when walking, running or jogging outdoors. In fact, it is common to detect a strong tendency in the running community to prepare a "running music playlist" that leads runners to maintain a stable heart rate during exercise.

As previously said, music has three important features including tempo, pitch, and energy, which have correlations with changes in heart rate [25]. However, due to different individuals and different activity levels, the effects vary significantly. Generally, tempo is more effective in raising the heart rate when a person is running in rhythm with the music. On the other hand, pitch and energy have greater effect than tempo during the low activity level.

2.4 Implemented solutions

The following subsection describes the most influential and advanced solutions that have been designed to help people achieve their prefixed training objectives with the support of the music. Then, the main novelties and improvements this thesis desires to import in the current literature are described and motivated.

After an intense scouting and analysis of the systems that offer a similar service to the presented one, only a few can provide a convenient and unobtrusive way of maintaining a stable heart rate continuously and exploit the effects of music on physiology and physical activity in an adaptive and real-time manner.

Hereby, the most relevant solutions are listed, with their main characteristics, pros and cons. Starting from this initial comparison, the implemented solution tries to overcome the main issues each system presents and provide a new technological realization that may result in a interesting trade-off between ease of usage, implementation effort and quality of the offered service.

The discovery of analogous systems to the presented project was performed by considering, one at a time, the most advanced hardware and software devices able to monitor and collect body data (e.g. heart rate, blood pressure, strides and breaths frequency, ...) and music-based solutions that support trainers' activity.

Among all the sensory data collection devices discovered in the scientific literature, Cardiopulmonary Exercise Testing (CPET) is a widely adopted clinical tool to evaluate exercise capacity. It provides an analysis of respiratory gas exchange and cardiac function during exercise. However, due to high cost (about $20,000/unit) and complicated procedure, CPET is not suitable for daily exercise. Recently, several wireless CPET products have been developed. For example, Oxycon Mobile[1] integrates various lightweight sensors into a vest, which is worn by the subject during the exercise. However, designed for short-term evaluation of professional training, such devices are too bulky to wear for everyday use. Moreover, it is too expensive for ordinary runners.

Several smartphone applications that can detect heart rate without extra devices are already available on the app market. Code4food[2] developed Heart Rate Monitor which can measure the pulse by placing a finger on the camera lens. Azumio's Cardio Buddy[3] estimates heart rates from the facial expressions captured by cameras, in which the system proposed in [26] also adopts this method to detect heart rate. Sumida et al., [27] leverages machine learning techniques to predict heart rate variation from the acceleration and speed during walking. In [28], the authors present a smartphone-based system to estimate caloric expenditure of bicyclists. They improve the accuracy by considering multiple inputs such as GPS signals and map information. It is not convenient for runners to know the real-time heart-rate values during running due to the large size and modest weight of smartphones. Moreover, they require to capture images of fingers or faces precisely, thus it is difficult to be used while running.

Existing approaches for automatic music recommendation are: using one or more seed songs [29][30], retrieving similar music by matching the tempo [31], and learning the habit (e.g., music genre, preferences, or time of day) of the user [32][33]. None of these approaches considers any physiological effects of music on the user. Physiological information, such as gait and heart rate, have been considered in [24][34][35]. But the downside of these approaches are, first, the user has to use a separate device (e.g., ECG or pulse oximeter) which is an inconvenience; second, the music recommendation

[1] Oxycon mobile, http://www. carefusion.com/

[2] Code4food, "Heart rate monitor", https://www.quixey.com/app/2207732023/heart-rate-monitor

[3] A. Inc, "Cardio buddy-touchless camera heart rate monitor", https://itunes.apple.com/us/app/cardiobuddy-touchless-camera

is based on an overly simplistic and general rule of thumbs, i.e., to suggest music with a matching tempo, which is not personalized. Although a music recommendation system - MusicalHeart - is proposed in [18], it has some shortcomings. First, MusicalHeart needs a customized hardware (earphones and a baseboard), which is not convenient for ordinary person to implement the system. Second, due to the limitation of the smartphone's computing ability, MusicalHeart can hardly response to the change of the heart rate in real time. Third, MusicalHeart did not consider the breaths and strides, which are also important for the runners. At the same time, the system can not give real-time suggestions to help them to improve their breaths and strides. Lastly, MusicalHeart uses a Proportional Integral Controller (PI-Controller) to recommend music to the user based on past history of responses to different music, which can not satisfy the requirements that the system can help the runner to forecast the next song that the user wants to listen to according to his/her habits during running.

Finally, RunnerPal [36] is a very recent project that acts as runner monitoring and advisory system, which tries to harmonize the rhythms of breathing, heart beating and striding based on smart devices. This infrastructure reflects very well the same characteristics and features that the implemented system wants to realize, therefore, a deeper description of this tool is provided.

RunnerPal is a convenient, biofeedback-based, automated music recommendation system, which utilizes Bluetooth headset, Apple Watch and smartphone to obtain body sensed data. RunnerPal uses the sensed data and runner's contextual information to provide dynamic music suggestions to help the user achieve a target heart rate. RunnerPal has been validated by extensive experiments, and experimental results demonstrate that it can help runners achieve a target heart rate and maintain a stable running rhythm for indoor/outdoor running 91.6 percent of the time. In addition, RunnerPal can provide some advice to improve exercise effectiveness for runners.

Compared with existing exercise monitoring systems, RunnerPal distinguishes itself as it is the first Apple Watch-based mobile system that senses runners' heart rates, breathing and striding frequencies, and then advises runners to maintain a stable heart rate by recommending proper music to them.

RunnerPal represents a very complete and advanced solution that may be adopted to satisfy the same requirements of this thesis project; nevertheless, its realization might result in a quite complicate combination of several components that may interfere among each other. Moreover, it is built over the assumption of owning an Apple Watch device that measures the heart beat during the session. It is very expensive and not compatible with the majority of Android smartphones on the market, thus, a huge portion of population that desires to train is then excluded from using this particular solution.

For this reason, this thesis project extends the range of compliant heart rate monitors that can be used to measure the heart rate values. It allows then to ensure connectivity with every heart beat detector that use the same standard communication protocol: this feature permits the application to be inter-operable with a wider range of monitoring devices already available in the market.

Another difference between the two systems is that RunnerPal considers a very specific type of training (running) while designing the system, instead the proposed system aims at working for a larger variety of training (swimming, biking, walking, kayaking ...).

In order to choose the proper music during the training session, RunnerPal implements a PID (Proportional-Integral-Derivator) controller that traces the current training session to decide which song to play. The presented designed system, instead, uses linear regression techniques that are suitable for adapting the behavior of the application with the history of each trainer. This characteristic reveals the adaptive trait of the system to follow the physiological evolution of the individual under some generic kind of exercise.

Finally, information about heart rate response to a specific music stimulus is saved in remote storage servers (anonymously), to allow further analysis and improvements to enhance the users' experience.

2.4.1 Heart rate monitor technologies

Choosing a proper device to collect physiological characteristics, such as heart rate and movement behavior, is another aspect that has to be properly taken into account. A devoted part of the study is focused on analyzing and comparing some high-tech devices, even mass-market ones, among wristbands and thoracic bands, that exploit different technologies in determining the heart beat. Trade-off has to be considered to evaluate which device (technology and physical support) is best suited to satisfy all the requirements, both in energetic and in application concerns.

In this discussion, only monitors able to detect just heart rate value are subject to analysis, since the current version of the project only requires to work with this physiological parameter. In future enhancements, though, a more adaptive solution to individual's behaviour may be realized considering more complex devices that collect also movements, pulse, breaths rythm, ...

A first study focuses on the comparison between two main categories of devices that allow to detect heart rate. In fact, wristbands and chest strap monitoring bands represent the most advanced and valuable categories of device that fulfill this task. Even if they pursue the same objective, their technological mechanisms to evaluate this parameter are very different.

A chest strap heart rate monitor typically measures your pulse via electrical signals and sends the data to a connected device (e.g. a smartphone), while wrist-based monitors detect the blood pulsing through your veins with the help of its optical heart rate sensors.

From an operational point of view, chest straps read the small electrical signal the body creates to make the heart constrict. The transmitter is typically the only part of the chest strap that is detachable. Inside is a microprocessor that records and analyzes heart rate from those electrical signals, as well as a battery and the chips needed for Bluetooth connectivity. Using Bluetooth and a connected smartphone, the transmitter can consistently send heart-rate data to your mobile device, which acts as the receiver.

Optical technology, instead, sends light into the skin and reads the light coming back: most of optical heart-rate monitors glean heart-rate data through "photoplethysmography" (PPG), or the process of using light to measure blood flow. Wearables with optical heart-rate monitors have small LEDs on their undersides that shine green light onto the skin on your wrist. The different wavelengths of light from these optical emitters interact differently with the blood flowing through the wrist. When that light refracts (or reflects) off the flowing blood, another sensor in the wearable captures that information.

That data can then be processed, along with motion information detected by the device's accelerometer, with algorithms to produce understandable pulse readings.

Thus, the concept behind the two typologies is the same, but the difference is that the fitness wristbands are measuring the downstream flow of blood, rather than measuring the beats of the heart right at the source. Optical heart rate tracking is an excellent option for continuous heart rate tracking.

Taking a measurement from the arm or wrist is more difficult because it's a part of the body that can swing rapidly during activity, creating more data noise that must be accounted for when computing the final reading. Electrical technology, though, tends to be more accurate: the sensor is placed closer to the heart than a wristband is, allowing it to capture a stronger heart-beat signal.

Another reason why chest straps tend to be more accurate than wristbands is that there's less room for user error. As long as you purchase the right sized strap, it's very difficult to wear a chest strap too loosely. Also, the electrodes are typically fixed on the strap, so you can only fiddle with the placement so much.

In case of wrist bands usage, movement can disrupt the accuracy on an optical heart-rate monitor, mostly because the fast-paced movements can push the monitor around on the wrist. Unlike a chest strap, wristbands are much easier to adjust for comfort and fit. While that makes wristbands easier to wear, they can also be moved out of place more easily.

For heart-rate zone training, the chest heart rate monitor represents the best option: this device typology is more reliable and consistent in reading the heart rate accurately. People like triathletes, marathon runners, athletes training to compete in a specific sport, and the like should invest in a chest strap because most of them offer flexibility on top of consistent accuracy. Comfort is however a sensible drawback when wearing it. One of the biggest benefits of optical heart rate tracking is ease of use.

The key point here is that the sensor should be touching your skin and it shouldn't be moving about much. Besides this very human source of error there are some technical limitations that are being solved as the technology advances, such as skin temperature affecting readings in the cold or at the beginning of a training session.

Chapter 3

Architecture

3.1 Introduction

This chapter converges its focus on the main components that build the proposed architecture. The several "actors" that synergistically communicate to provide a fully functional service to the end user are mentioned and described in detail, depicting requirements, tasks, feasibility limits and considerations about compatibility and their interoperability. A specific section is then devoted to describe software techniques that are aimed at improving the user experience and deploying tailored services on system requirements and design choices.

A first look at the proposed infrastructure of the system is provided, highlighting communication links and network topology. This general visualization aims at clarifying where each system element is placed within the overall architecture and how it is interconnected to the other entities to provide its functionalities.

Then, the several sections that are presented in this chapter refer to the main elements of the system infrastructure.

3.2 System architecture

A general view of the designed infrastructure represents a visual support to understand how architecture elements interact to provide the final user with the training service.

Figure 1 shows the designed topology and the "actors" that synergistically cope within the developed system:

- **Front end**, which generically refers to any smartphone that runs a dedicated application that allows to access the system and exploit the whole set of functionalities. *Section* 3.3 describes the implementation of the Android application designed to give the user the chance to concretely experience the services and verify the results in a fully personalized way.

- **Heart rate monitor device**, a compliant hardware device able to measure body data, e.g. the heart rate of an individual, and communicate it to the personal device owned by the trainer (smartphone). *Section* 3.4 describes the main aspects behind the adopted hardware solution, along with its characteristics and benefits in accomplishing the targeted task.

- **Back end**, which refers to the core intelligence of the system, that handles user's history, training data storage and music selection during training sessions. This element main purpose is to run the music advisory system algorithm that selects the most suitable song for the user to reach his/her training target. The description of the mentioned algorithm is provided in *Chapter* 5 of this thesis. In *Section* 3.5, the design choices that drove the creation of this architectural element are deeply explained.

- **Google services**, that allow multi-user utilization of the system, authentication for customized experience and backup of personal user data. *Section* 3.6 is aimed at providing general information about Google services used to deploy system services and provide a better support of the overall infrastructure.

Even though next sections are aimed at depicting, in details, the characteristics and features of the system elements, a brief description about the main tasks of each block is hereby given.

A first distinction about local and remote components can be done:

- Through a dedicate Bluetooth wireless connection, the front end application (an Android app) directly communicates with the heart rate monitoring device attached to trainer's body. The latter component detects and transmits heart rate values to the front end application, in order to tailor the training session to the real-time heart feedback. This first communication represents the locally-based communication that happens during any training session.
- During a training session, the user application periodically asks a web service (the back end) for the proper music track to achieve its prefixed target based on the heart rate value. Through an Internet connection with an ad-hoc server, the remote routine evaluates the "best" music track that lets the user achieve its goal.
- Furthermore, a specific routine within the front end application allows to store and fetch user related data about saved training and heart rate evolution throughout the past exercise sessions. In particular, this procedure relies on Google's Firebase service, that represents a well supported and fully functional solution to store and retrieve on-demand data for future analysis and visualization.

Last two points describe the remote connection part of the whole system, which require an active Internet connection that ensures a consistent service provision to the user.

3.3 Front end - Android application

The front end component is responsible of allowing the user of the system to access the offered functionalities and perform a supported training with the help of a smart assistant. It is represented as a generic smartphone, which is a quite convenient solution since it is nowadays available for anyone, and whose required characteristics are not prohibitive.

In this thesis project, front end element consists of a software that has been deployed with the purpose of providing the user with a tool to enjoy the system. Through this application, installed in a smartphone, the user is able to intervene on many aspects of the service itself: in fact, the experience of the service is not static but customizable and adaptable to the user's needs and his/her specific physiologic response to training efforts.

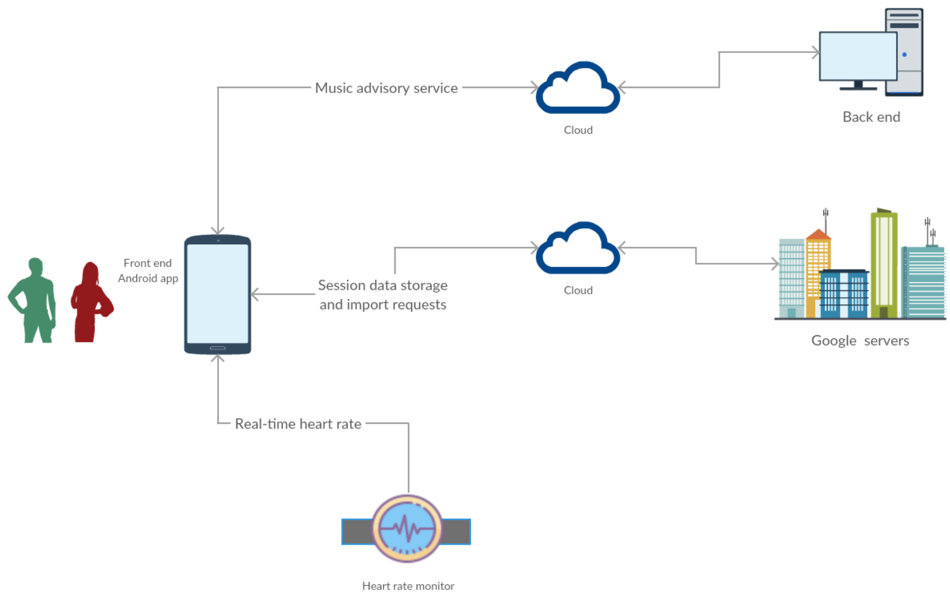


Figure 1. General overview of the infrastructure.

3.3.1 Objective

The front-end user application is an Android software which provides a smart support to users willing to train and perform predominantly cyclical activities, such as running, walking and cycling. The offered service is constrained by the physiological conditions about personal heart rate evolution.

The reproduction of proper music tracks, categorized and selected by the application itself, represents the driver with which the system acts on the trend of the user during its training session. The decision component of the software is continuously fed with data coming from a wireless device, wore by the individual with the purpose of detecting real-time heart rate value throughout the advancement of the guided service.

The front end allows to select the music playlist over which the remote decision algorithm runs to choose the proper song, based on user's personal characteristics and desired target. In the current phases of the system development, music is assumed to be stored locally in the smartphone. Further improvements may consist in retrieving audio tracks also from cloud services, which may lead to a more practical and convenient usage of the system.

A visual output of the real-time performance, expressed in terms of current heart rate value (BPM), is showed to the trainer during the activity, so as to individuate his/her heart status with respect to the target value.

Finally, since the system uses personal information to provide the best song that leads the heart rate to the desired target, the application allow to visualize and modify user's data related to physical characteristics and fitness routine.

3.3.2 Requirements

Hardware and software requirements

The implemented system relies on the usage of smartphones which run the Android operative system. This specific design choice aims at ensuring the usability of the system for a huge portion of the population that owns an Android smartphone: the high popularity and full "open" support of this kind of systems makes these devices very suited to such application. Moreover, there are no constraints on battery consumption and network/location services usage, in contrast to what happens for Apple devices; nevertheless, a future improvement of this system may include also the Apple market.

Finally, the operative system firmware version must be, at least, 4.4 (KitKat), since underlying software stack must support Bluetooth Low Energy (BLE) standard protocol to communicate with heart rate monitoring devices. At this moment, lower versions are not supported. It is necessary that the device supports Bluetooth and Bluetooth Low Energy (BLE) connectivity, both software and hardware side. The app is able to communicate with heart rate monitor devices that implement the standards defined by Bluetooth protocol about services and characteristics definitions (GATT specifications).

User's permissions

The application, in order to provide services and functionalities to the final user, requires the explicit consent to access data related to:

- User location, to ensure Bluetooth Low Energy connectivity to the heart rate monitor device. The Android framework requires permissions about location data to discovery BLE devices and establish a connection with them;

- Access storage data, to get information about music tracks stored in the internal and external smartphone drives.

3.3.3 Functionalities

Access to the system

Since the system operation tracks and hardly relies on user's behaviour and characteristics, the software application permits to authenticate and register accounts uniquely associated with any individual that wants to train. Each registered person is individuated by an identification string that point to sensible information about training sessions, heart rate evolution and personal credentials. The usage of such identification methodology allows a safe and privatized usage of the system, since no sensitive information about users' characteristics are remotely stored.

When the application starts, the user has the chance to select the method to access the system. In particular, it is possible to log in by means of email and password, telephone number (with international prefixes) or through a Google account previously configured on the smartphone. For new users, it is also possible to register an email to create a new account. Access methods mentioned so far use services and libraries offered by Firebase platform of Google and described in section 3.6 of this chapter.

At the beginning, the system automatically checks the presence of an already active session, avoiding the user to perform a new log in procedure and letting him/her access to the personal area.

Once authentication phase through Firebase is done, an additional check verifies the presence of user's data in the device, by comparing the identification code of the user: if there is a match between Firebase ID and the identifier in the local database, the user is immediately redirected to the personal area, in which previously saved data and stored music are shown, otherwise an initial tutorial phase allows him/her to select music tracks and maximum heart rate value.

Registration to the system

In case the user never used the application, or he/she is trying to access the system with an existing account with a new device for the first time, he/she is driven throughout an initial configuration procedure of the app. During this phase, the application asks the user to:

- Provide information about weight, height, gender and activity frequency. This data is required for customization of the music advisory system that tunes its choices for the specific user's characteristics;
- Select a subset of music tracks from the list of available music stored in the phone. This selection is used during the training session and it represents the pool in which the core algorithm selects the proper song to reproduce;
- Insert the age, thanks to which the maximum heart rate values is calculated by applying Tanaka's formula:

  $$\mathrm{HR}_{\mathrm{max}} = 208 - (0.7 \times \mathrm{age}) \tag{1}$$

  Moreover, the user is provided with the possibility to manually modify the calculated value in case in which he/she has more specific personal information related to health conditions.

Eventually, the user is redirected to his/her personal area, from which he/she can start exploiting functionalities offered by the system.

Music Beat Detection algorithm

One of the core procedures of the whole system is represented by the **Beats Per Minute** (BPM) detection of the songs chosen by the user. In particular, when the user imports audio tracks from the personal local library into the application, a devoted service is run to evaluate the value of BPM: this parameter is then used to individuate the most suitable song for letting user's heart rate to reach the prefixed cardiac target.

It is important to specify that BPM unit of measurement is used for indicating both heart rate and music speed: although quite confusing, they refer to two different physical quantities, so the actual meaning of the measurements is always clearly expressed.

This phase is extremely delicate, since it is susceptible to sound noises and audio characteristics of the music. A wrong miss-classification of the songs leads to inconsistent results and a song decision which is not compliant nor reasonable with respect to the achievement of the prefixed target. Thus, the core music advisory algorithm may suggest a song during the training which not only doesn't respect the desired goal, but may be harmful for the system that registers the evolution of the heart rate and invalidates the whole analysis.

A verification mechanism of information about songs stored in the local database allows to speed up the whole detection process, so far as a specific track has been already analyzed and information about its audio characteristics are already available.

Many studies have tried to determine this value in a very accurate way, however this operation tends to be quite harsh to accomplish. After a deep scouting of the existent solutions that perform music BPM detection procedure, resulting considerations are:

1. The majority of current solutions are web-based, without giving the chance to perform audio BPM recognition in offline mode. They rely on databases with already mapped information about the most popular songs with their related speed. This results in a network resource demanding procedure that involves many requests to determine the BPM of each users' song. Another issue consists in the fact that local songs may be renamed with names that do not correspond with the actual song title, so a web-based approach doesn't allow to perform this analysis. For this reason, a local solution is required.

2. Many local libraries that perform this operation are not for free. Some others, instead, allow for a free detection, but require for the subscription of a contract that may be restrictive in case of commercialization of the software.

Nevertheless, a suitable alternative that fulfills the requirements is represented by a free Java library, called **TarsosDSP**, which locally performs audio signal analysis to detect the speed and other useful characteristics of the input signal [37].

TarsosDSP is an Open Source Java library for real time audio processing without external dependencies. It allows real-time pitch and onset extraction, a unique feature in the Java ecosystem. It also contains algorithms for time stretching, pitch shifting, filtering, re-sampling, effects, and synthesis. TarsosDSP serves an educational goal, therefore algorithms are implemented as simple and self-contained as possible using a straightforward pipeline. The library can be used on the Android platform, as a back-end for Java applications or stand alone.

Data storage and consultation

The proposed system uses two different strategies to memorize and consult user data related to saved training, statistics and music tracks. In detail, a local relational database MySQL keeps track of details about registered users, music playlists and association between users and selected songs.

Moreover, the Firebase platform offered by Google is used to save and consult registered users' data, saved training profiles and performed training sessions. The technique to link the two databases is to associate the generated Firebase ID to the user entry in the local database. Furthermore, this mechanism guarantees the access to the system in a multi-device contexts, that is, in the case in which a user desires to use the app with different devices: he/she is able to access his/her own data from different access points (saved training sessions and personal information).

The front-end application relies on API (Application User Interface) provided by Firebase framework to access user's data stored in the remote Google servers. The information in the remote database so as to split different scopes of the overall training service. In particular, there are 3 different branches that store information about:

- User related data (name, surname, address, username and password)
- Stored training specifics (duration and intensity)

- History of past training sessions (hear rate evolution and played song list)

Moreover, the local database installed on the smartphone aims at collecting data related to user's physical characteristics inserted during registration phase and song library preprocessed by the application itself. A reference between each registered user and his/her personal playlist is maintained in the database as well.

In this relational database, data is structured in the following tables:

- *User*, with individual information about gender, height, weight, age and activity frequency;
- *Song*, with BPM value from the beat detection algorithm;
- *UserSong*, which stores correspondence between users and their selected music playlist;
- *RegressionElement*, which contains users' personal information about his/her physiology, and values of initial heart rate, final heart rate and value of music speed that led the user towards the modification of the heart rate value during a user-defined period. The content of this table is used when the application has learnt much information about how a specific user reacts to different music tracks application and must decide the next tracks. This argument is object of discussion in *Chapter 5*.

Training creation

Front end gives the chance to the user to decide how to "build" the training to perform (the target to achieve), specifying the intensity and the duration of the session. In fact, a training is seen as the composition of one or more blocks, each one defined by an intensity and duration values, and the user can save the workout profile to repeat the same training in a later time. Intensity is defined as percentage of the maximum heart rate value that the person can reach, and it is evaluated through Tanaka's formula.

The training profiles are stored in Firebase remote database and can be imported for consulting or modification.

Connection to the heart monitor

An ad-hoc service handles the connection between the smartphone and the heart rate monitor: it allows to activate the Bluetooth service of the smartphone, start compatibility device discovery in the area and establish a wireless connection with the selected device. When a training session ends, or when the user decides to stop the current training, the service performs the disconnection from the monitor.

Proper checks allows the system to guarantee a persistent connection: if the training session is active and communication between the two devices is involuntarily interrupted, the service allows to scan and reconnect automatically to the same device.

Through a timer mechanism, the system reacts to possible delays in connection between two devices by interrupting the scan in progress, to ensure a better stability and resilience, as well as a energy saving plus for the smartphone battery.

Among the services offered by the Bluetooth device, the smartphone scans for the heart rate and battery ones.

Training service

This service represents the smart component of the front-end application, since it deals with the selection of the most suitable songs during the training based on proper verification on measured heart rate value. The routine receives, as input, the selected training, the list of music tracks selected by the user and the maximum heart rate value calculated during the app configuration phase (it is calculated thanks the Tanaka's formula but it is possible to modify it manually).

The algorithm handles in parallel the timers that track the progress of the session, so as to recalculate the new parameters for music selection when a new "block" has to start.

During an active session, the energetic level of the Bluetooth monitor is detected to alert the user when its charge level is low.

The values of heart rate at the beginning and at the end of each training block are stored in the remote Firebase database, along with the list of played song during the training.

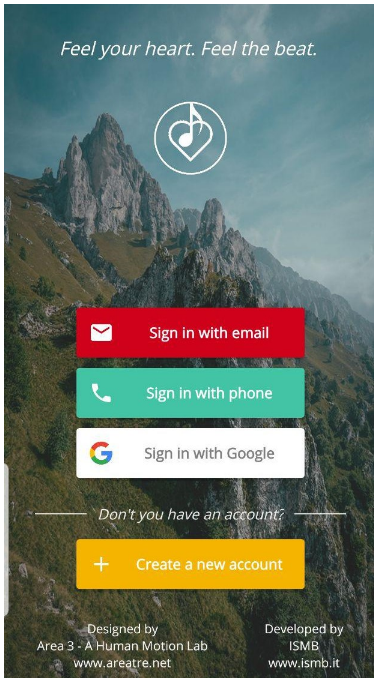


Figure 2. Initial page of the Android application for log in and sign up procedures.

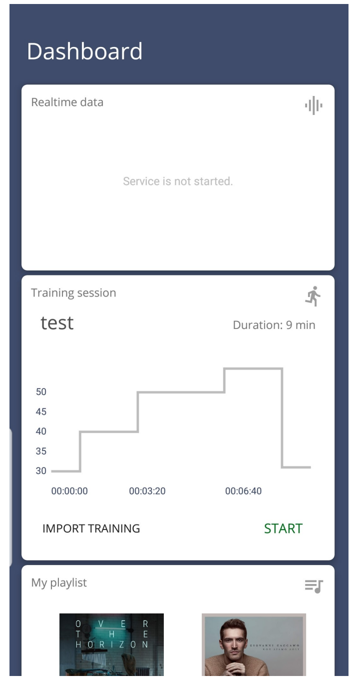


Figure 3. Main dashboard of the Android application related to individual users' context.

Finally, this service allows to handle incoming calls during the training: the music is paused until the end of the call, while the service continues with all the timers.

Chapter 5 is aimed at describing in detail the algorithm and communication between actors that constitute the core procedure behind music advisory support tool.

Figure 2, 3, 4 and 5 show some screenshots of the final Android app, related to each provided functionality.

3.4 Heart rate monitor device

One of the main features and novelties that this thesis project brings refers to the capability of tailoring the training experience based on real-time human sensory data. In fact, decision of the proper song that allows to achieve the user's objective (in terms of heart rate target) is hardly dependent on sensed data coming from a devoted "monitor" attached to user's body.

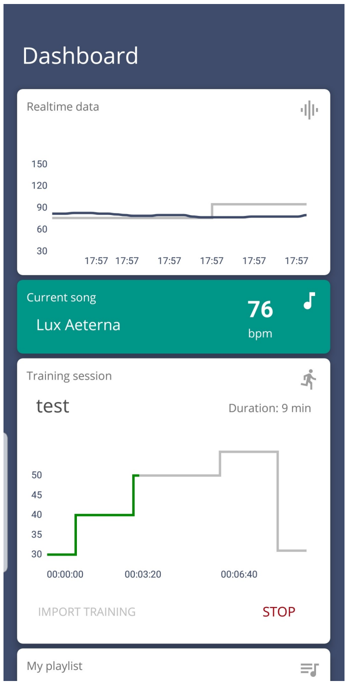


Figure 4. Example of active training session with users' real time heart rate, current music playback and workout progress.

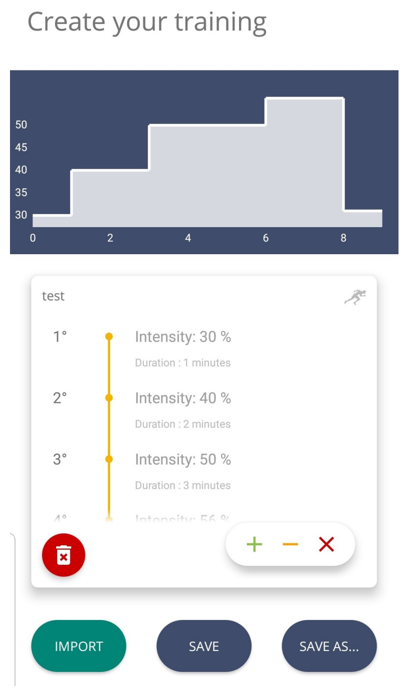


Figure 5. Creation page of the training profile specifying duration and intensity for each activity block.

3.4.1 Adopted solution

A special deepening is addressed to the adopted monitor device for training heart rate recording, which falls in the chest-based monitors category.

Polar H10 is an upgrade of Polar's most accurate chest strap heart rate monitor (Polar H7): with enhanced battery life (about 400 hours) and improved strap design that prevents slipping and improves comfort while running, it represents a very suited solution to achieve the pursued objectives. It also possible to use this device for underwater heart rate monitoring, allowing the usage of the application for swimming purposes as well.

The H10 chest strap is one of the best on the market for accurate heart rate readings. Its relative economic price (less than $100) makes this device one of the most popular thoracic heart rate monitor available on the market. The strap provides improved electrodes, and it has silicone dots that reduce unwanted movements. More importantly, it supports BLE connectivity with external devices to send collected data for further analysis and to deploy heart rate based solutions.

The lightweight clip-on transmitter for the Polar H10 also weighs less than the H7 (21 g vs. 25.3 g). This is powered by a CR2025 coin battery, which is easily replaceable.

One of the main strengths of this project consists in the capability of the designed system to work with a wide set of heart rate monitors that are well supported and already available on the market. In fact, the front end application, thanks to its standardized implementation, allows to establish a Bluetooth communication with every monitoring sensor that uses Bluetooth Low Energy standard protocol.

Bluetooth Low Energy is a wireless personal area network communication technology which has been deployed and supported by Bluetooth Special Interest Group (Bluetooth SIG). Its adoption is quite extended, and it covers many application fields, such as health assistance, beacons communications, security, home entertainment, fitness, home and transport automation. This relative new technology, with respect to the classic Bluetooth, is characterized a very limited energy consumption and low costs, while keeping a satisfying communication range among involved devices. Knowing the format in which body sensory data is represented when transmitted through this communication technology makes the system fully compliant with both chest-based and wrist-based heart rate monitors.

The specific pieces of information the training service needs to operate and provide the service to the final user are related to the real-time heart rate value and the battery level of the slave device (the generic monitor device).

Polar H10, which is the device selected for prototyping and testing the whole system, implements the Bluetooth standard GATT profile in which the Heart Rate service and Heart Rate measurement characteristic are present. A specific method call within the Android app allows to enable/disable the heart rate characteristic notification, so as the application is advertised when a new heart rate measurement is detected.

When the user application establishes the connection with the monitor device, a request for enabling the exchange of this parameter is sent. After this initialization phase, the smartphone and the band are connected and can start a master/slave communication.

3.5 Back end

The back end element represents the core component of the whole infrastructure which is in charge of defining decision policies and implementing proper techniques that support trainers' activity with a music help.

Besides functionalities that are clearly visible to the user, such as music track selection, it locally deploys methods that are aimed at improving experience quality and offering many services that enhance system performance.

In this section, the following aspects are treated, so as to provide the reader with a full knowledge of the "smart" element of the system:

- An explanation of the main reasons that led to the design of a remote service that handles music training support. Principally, project requirements that are necessary to deploy a system with certain characteristics are the basis over which the back end acquires its usefulness.

- Concrete fulfillment of the requirements though software implementation is described, along with frameworks and tools used to realize such system.

- Exposed services towards the user application, in order to be visible to external world and interact with clients demanding for the music requirements for the training.

- Internal routines and algorithms that handle many underlying aspects of the system, such as cookie management, user information update and analysis of the training data.

The central algorithm that provides the indications about the best track to play during users' training is object of discussion of *Chapter 5*.

3.5.1 System requirements and back-end characteristics

The reasons for which the back-end is a necessary component of the overall system refer to the need, in terms of computational capacity, of having a powerful and fast elaboration terminal that performs resource demanding operations.

Moreover, a common hub that acquires information of all the users of the platform is necessary to guarantee a private and customizable service for each individual. A devoted procedure, in fact, is aimed at handling user's data within a constricted and personal context, in which each trainer can store, access and exploit only his/her data.

Another aspect that led to the insertion of this specific block in this project is about the collection of data related to heart rate evolution during a training of any user, which allows to improve overall performance of the system when it has to decide the most suited song to reach a target. Through this mechanism, every user that performs a supported training with this system contributes in making the entire intelligence aware of the body response of a wider portion of population. These data are then used to feed a proper algorithm which well train itself to adapt heterogeneous population physiology. Summarizing, the entire system is not statically suited, but instead keeps learning from incoming data collected during exercise sessions.

For analysis purposes, the back end implements some local functions that can be performed to inspect data characteristics, trends, or just to measure training performance parameters, useful for trainers to check their fitness goals.

The back-end communicates with the front-end apps by means an Internet connection and ad-hoc web-based services.

3.5.2 Implementation design

The back-end system was developed by means of Python language, a high-level general-purpose programming language that can be applied to many different classes of problems. The language comes with a large standard library that covers areas such as string processing (regular expressions, Unicode, calculating differences between files), Internet protocols (HTTP, FTP, SMTP, XML-RPC, POP, IMAP, CGI programming), software engineering (unit testing, logging, profiling, parsing Python code), and operating system interfaces (system calls, file systems, TCP/IP sockets). A wide variety of third-party extensions are also available[4].

Thanks to highly performing libraries offered by Python community, it was possible to deploy a system able to process data and perform data analysis in a simplified, yet efficient way. Data parsing, web service deployment, data visualization and analysis are some of the features the system implements thanks to powerful software routines.

To be reachable from the outer world, it is necessary that the designed back-end application is run on a host machine whose network-layer IP address is public and active.

3.5.3 Exposed services

Among the several services this software implements, a RESTful web based server[5] is maintained to provide the user with an access point to obtain the desired functionalities.

In particular, two main exposed functions allow the user to communicate with the system in order to:

- Receive the value of BPM that best suites the needs of the specific user during a training. In fact, by sending personal data related to body characteristics and current values of heart rate and target, the remote algorithm computes the outcome through a linear regression technique and then sends it back to the front-end application. This argument is object of deep discussion in *Chapter 4*.
- Update the system database about body response due to the application of a given audio stimulus (i.e. the song that is played during the workout). This information is really fundamental since it allows the system to learn and have a better knowledge of the evolution of the heart rate in the population when a music track, with its related speed, is administered to the trainer.

3.5.4 Additional functionalities

Internally, the back-end application executes some routines that improve the quality of the provided service and handle several aspects related to user identification in the system

[4]Python Software Foundation, https://docs.python.org
[5]What Are RESTful Web Services?, https://docs.oracle.com/javaee/6/tutorial/doc/gijqy.html

and data analysis.

More in depth, the Python application deals with the following tasks:

- **User identification** through cookie mechanism: the application locally stores a file in which associates the identification code of the users generated during registration procedure (Firebase ID) with a local identifier which is used to tailor the given training service with the past history of the same user. The input user identifier is sent through a web request from the front-end application whenever it requires the evaluation of the proper music that has to be selected. Moreover, it represents a piece of information required to store and update user-related data into the local input file about the heart rate evolution history. Learning much information about user's history is really useful to maximize the benefits brought by the music to a specific individual: the reason is clearly explained with the learning process and described in *Chapter 4*.

- **Data analysis** related to users' heart rate values and other individual characteristics. A deep study of the cardiac response in the face of a music input stimuli may provide a clear indicator of both the performance of the service in the evaluation of the required parameters and the similarities and correlation among the features registered by the users. This additional feature, which may be not of interest for final user of the infrastructure, can be of use for analysts and designers that could have the need of trace users' tendency in absorbing music effects during training and understanding which trainers' elements may take a huge meaning in applications similar to the proposed one.

3.6 Google services

A special section is devoted at describing the main Google services that were employed to add further functionalities to the system. Their introduction helps facilitate and improve the development of extremely important features such as user authentication and remote database.

Firebase is a very powerful online service built on Google infrastructure that allows to save and synchronize data elaborated by web and mobile applications. It is used to build solutions in a fast way, without managing infrastructure, and gives functionalities like analytic, database, messaging and crash reporting. Automatic scalability is one of the main advantages the network designers experience and exploit when they need to deal with large apps.

3.6.1 Authentication

Firebase authentication service allows user to perform secure and easy access to the infrastructure. The proposed application needs to know the identity of a user to allow it to securely save user data in the cloud and provide the same personalized experience across all of the user's devices.

Firebase Authentication provides back-end services, easy-to-use SDKs (Software Defined Kits), and ready-made UI (User Interface) libraries to authenticate users to the app. It supports authentication using passwords, phone numbers, popular federated identity providers like Google, Facebook and Twitter, and more[6].

The authentication methods available in the current version of the front-end application are:

- **Email and password based authentication**. Authenticate users with their email addresses and passwords. The Firebase Authentication SDK provides methods to create and manage users that use their email addresses and passwords to sign in. Firebase Authentication also handles sending password reset emails.

- **Phone number authentication**. Authenticate users by sending SMS messages to their phones.

- **Federated identity provider integration**. Authenticate users by integrating with federated identity providers. The Firebase Authentication SDK provides methods that allow users to sign in with their Google, Facebook, Twitter, and GitHub ac-

[6] Firebase Authentication, https://firebase.google.com/docs/auth

counts. Only Google authentication, though, is implemented in the deployed Android app.

To sign a user into the app, authentication credentials are collected from the user. Then, Firebase Authentication SDK uses these credentials to make Firebase back-end services verify them and return a response to the client.

After a successful sign in, it is possible to access the user's basic profile information, and control the user's access to data stored in other Firebase products. Finally, the authentication token can be used to verify the identity of users in the deployed back-end services. The generated identifier is used to create a linkage between information locally stored in the smartphone (accessed via the Android app) and values in the remote Firebase database.

Firebase authentication procedure is integrated in the Android app and the user can interact with this service when he/she has to decide whether to log in with an existent account or register a new account based on email and password.

3.6.2 Firebase database

The Firebase Realtime Database[7] is a cloud-hosted database, in which data is stored as JSON (NoSQL database) and synchronized in real-time to every connected client.

The main features of the Realtime Database service are:

- **Realtime**. Instead of typical HTTP requests, the Firebase Realtime Database uses data synchronization: every time data changes, any connected device receives that update within milliseconds.

- **Offline**. Firebase apps remain responsive even when offline because the Firebase Realtime Database SDK persists user data to disk. Once connectivity is reestablished, the client device receives any changes it missed, synchronizing it with the current server state.

[7] Firebase Realtime Database, https://firebase.google.com/docs/database

- **Accessible from client devices**. The Firebase Realtime Database can be accessed directly from a mobile device or web browser; there's no need for an application server. Security and data validation are available through the Firebase Realtime Database Security Rules, expression-based rules that are executed when data is read or written.

The Firebase Realtime Database allows to build reliable and functional applications by allowing secure access to the database directly from client-side code. Data is persisted locally, and even while offline, real-time events continue to fire, giving the end user a responsive experience. When the device regains connection, the Realtime Database synchronizes the local data changes with the remote updates that occurred while the client was offline, merging any conflicts automatically.

Moreover, the Realtime Database provides a flexible, expression-based rules language, called Firebase Realtime Database Security Rules, to define how stored data should be structured and when data can be read from or written to. When integrated with Firebase Authentication, developers can define who has access to what data, and how they can access it. This ensure a better security and personalized access to sensitive users' information.

Firebase Realtime Database service is invoked when the user demands the saving of a newly created training profile or it asks to retrieve information about previously generated training profiles. It is also used to store heart rate evolution during the exercise activity, along with the music playlist chosen throughout the session by the music support algorithm. Thanks to this data, it is possible to track the correspondence of the music progress with the cardiac response, for further analysis on music effects on human body. Eventually, this service is used to store user's data when the account creation procedure is accomplished.

Chapter 4

Data collection and analysis

4.1 Introduction

Cardiac signal, in particular, represents the most valuable contribution for designing the system and enhancing its performance. The music support service offered to trainers requires a constant feeding source, that is, the heart rate value coming from the monitoring device attached to user's body. Decisions about proper music tracks to reproduce are always made by considering the heart rate characteristic detected during the session; nevertheless, this information acquires a more important meaning since it influences future exercise activities in a very pervasive way.

This last aspect also reveals one the most significant features the system owns: learning trends and responses from the population and then adapt the service to the specific user. Anyone experiencing the training service significantly contributes to the boost of the system.

The core intelligence, then, is not a static and insensitive element that is invariably tuned during design phase, but keeps improving itself to provide a better service to the users of the system. Data is a fundamental component of the system, thanks to which it was possible to evaluate first conclusion of the effectiveness of music during training sessions, and then to develop a smart tool able to transfer these benefits to users' training activities.

While *Chapter 3* describes the hardware technology used to collect this kind of information and software requirements to access this data from a devoted monitoring device, this chapter instead analyzes raw collected data as it is.

An accurate attention is then devoted to users' data, which represents the base over which the whole system is built on. Privacy concerns are also mentioned, along with techniques and software design choices aimed at granting user's data security.

This chapter aims at highlighting the several aspects behind data collection and analysis, showing both acquisition methods and further processing procedures that were performed to extract the information content and define tasks and system requirements.

The following arguments are discussed to emphasize the role and the ways of usage of this information:

- **Data in system prototyping**. It describes the main purposes for which this information is gathered. A clear discussion about the application of knowledge extracted from user's cardiac activity is provided.
- **Acquisition methodology and data storage**. This section describes the methodology used to collect user's data during an initial training phase of the system. Moreover, storage procedures of acquired data are mentioned, along with the adopted solution to grant user's data privacy.
- **Results and comments**. In the final section, analysis results and related observations are provided to give a better understanding of how the music influences heart signal and formulate first conclusions about potentialities and limitations of the system. Moreover, a useful comparison among results achieved through many measurement aims at tracing a first "common" behavior of the heart response when a specific song is administered to different trainers during the session. Finally, some suggestions and food for thought are offered in order to improve the analysis and the acquisition of useful data.

4.2 Data in system prototyping

As said in the introduction section of this chapter, data represents the fundamental element that allows to design, develop and test the entire system. It is essential to create a highly performing solution that takes into account the variability and complexity introduced by human interaction with the system.

Two principal objectives in system design pipeline lead to different ways to collect and treat users' data. Based on this distinction, the entire design of the proposed system can be split in two different consequent phases:

1. An initial evaluation analysis, in which heart rate responses from trainers that listen to a fixed set of songs during a running activity were retrieved;

2. Starting from previously achieved results, the design of the final application that allows a generic final user of the system to define heart rate targets and use his/her personal music to achieve the prefixed goal.

4.2.1 Initial training process

With reference to point 1, a secondary support system trained with a sample of the population was deployed, in order to provide the newly created architecture with a very generic "common" ground over which the final prototype could operate.

The specific choice to build a base layer above which the proposed system is structured and provides the final user with the desired service is determined by the following reasons:

- Obtaining a composed view of the effects (both positive and negative) the music induces on people's cardiac activity. Considerations on gathered results are meaningful for evaluating whether such approach could result in a useful method for justifying music assistance during training.

- Improving system performance in the initial phase of the application utilization by the final users. When a new individual experiences the service for the first time, the implemented algorithm manages to select the proper music to reproduce according to the decision rules already established during this initial phase. By doing so, the decisions about the strategies to accomplish for the specific user are not random, instead they are made in reference of the similarities of the targeted user with people belonging to the initial training sample. Thus, the system always ensures the playback of the song as accurately as possible during the workout.

- Collecting further parameters about a set of people with different characteristics and habits to determine, in future developments of the system, more efficient ways to enhance performances. A recording of a wider set of features related to users' conditions may lead to the creation of different solutions aimed at providing the same support service.
- Gathering feedback about the utility of the system, as well as advice from people with different level of training, which can contribute with their experiences and knowledge to the development of the project. Their support could represent a tangible help when designing secondary components of the system (e.g. user experience); furthermore, personal preferences about music and fitness habits is a crucial aspect when tuning the "best" music asset during training.

During the initial phase of the project development it was necessary to collect enough information from an heterogeneous sample of the population about the cardiac response to an audio input stimulus during a workout. In particular, a fixed set of songs, chosen so as to cover the majority of available music tracks in terms of speed (BPM), was given to trainer that contributed to instruct the system in its primordial stages.

This knowledge was hardly required to provide the system with an initial background of the heart rate evolution experienced by a consistent group of trainers performing a training activity while listening to music.

This database is then enriched with useful information in the moment in which a generic individual uses the application and sends its own data to the back-end of the system.

Thanks to this initial procedure, it was possible to understand the trend, similarities and differences of the cardiac activities of the several trainers involved in the experimentation. They represent a valid starting point thanks to which requirements definitions and problem resolution methodologies were analyzed and implemented.

4.2.2 Learning process

While the first phase concerns the training of the system and performed only at the beginning of the designing step, the second important aspect refers to the continuous learning of the intelligent machine thanks to data streams coming from the real users of the platform. This information is used to guarantee a proper and reliable service to the trainers, with updated music decision-making strategies.

Data is then used as learning flow to feed devoted machine learning algorithm implemented in the back-end element. After a suitable number of training exercises, it is then possible to evaluate the real benefits that the music provides to users' training sessions. Moreover, analyzing results of a music supported training allows to verify whether a given individual is actually influenced by outer stimulus while training, or he/she doesn't perceive a concrete advantage from such system. It can be reasonably expected that music perception and reaction are very personal conditions that influence each individual in very different manners. Further considerations about this aspect are object of discussion in *Section* 4.4.

By collecting trainers' heart rate values, it is possible to define training-associated parameters related to the adherence of the cardiac activity to the objective heart rate target. These evidences allow to improve user awareness about his/her physical achievements, design new strategies to enhance system performance and provide new functionalities.

4.3 Acquisition methodology and data storage

This section precisely describes the methodology through which training data was collected to start prototyping the primordial system. The newly created architecture represents the starting point on which the user can start experiencing the service and improve the offered functionalities with his/her active contribution.

More in depth, a description of the population sample involved in the training phase is presented, specifying general characteristics related to physiology and training attitude. Moreover, the criterion used to select a proper music list to play during the training is provided as well. Then, a devoted subsection aims at explaining the procedure with which examined individuals performed the object activity, highlighting practical recommendations and training protocol to follow. Finally, the adopted solution for storing collected data and granting, at the same time, privacy guarantees is mentioned.

4.3.1 Training sample

In order to proceed with initial training of the system and analysis of music application results on training sessions, a group of 15 volunteering healthy people, with heterogeneous physiologic characteristics, was selected to perform a data collection procedure.

Each individual, during the test, was asked to provide information about age, weight, height, gender and activity frequency. *Table 2* shows the list of features inserted by each individual before starting the training session.

From a first analysis of the trainers' characteristics, the majority of involved people is male, while only two women are present in the group. This condition translates in the fact that the system is initially more prone to follow and predict heart rate evolution for male population using the system. Age, instead, ranges between 24 and 37 years: this element tells that a huge portion of younger and older population is excluded from the analysis, so it is not represented by the chosen people sample. Height values cover a really variegate range of people while weight only represents individuals lighter than 80 kilograms, which is quite restrictive for the whole population.

Surely, a larger number of involved people in the data acquisition phase would significantly improve the overall service and give more meaningful information about music effects on trainers' activity. Nevertheless, for this thesis purposes, a smaller set composed of only 15 people is considered sufficient to express useful considerations about the solution effectiveness and deploy a smart system able to exploit the effects the music induces on the cardiac activity.

User ID	Firebase UID	Age [years]	Weight [kg]	Height [cm]	Gender	Activity freq.
1	0XIRMbA2JWM5IZDdiQtnlviEHrc2	28	74	169	Male	Regular
2	Ewb3D64VeMOS2MDO7aBUwaBJIYd2	26	70	180	Male	Occasional
3	HlC62QYvywPjvDh3Ra5NUuwVjRv2	24	66	162	Female	Not runner
4	J51xyo1ShWMxAMi4LyKpxqvNis42	37	49	168	Female	Regular
5	K0FNAsmuXqcOGuN7kvukdF9zWij1	25	80	180	Male	Regular
6	LN66KcjRCRg7Fa643SgT4rf8a4n1	24	70	190	Male	Regular
7	MUvvToLA13PaBFhgQ6x19HSithU2	33	77	191	Male	Regular
8	NvTnrPFXgKQvvR7iLwsgLxEjmtx2	28	62	176	Male	Occasional
9	h0mda76APSeuEHeP6kQuAg1Hu8L2	26	68	175	Male	Not runner
10	hkbtFCCBiFS0GQkXpiJE4pjLYkM2	28	79	174	Male	Occasional
11	jYIxLLitP5UFgFoLGoIornuXX7O2	26	77	180	Male	Occasional
12	o2uZc7tpVXXTCuRZdJg11fU5mMf1	26	70	181	Male	Occasional
13	qHZ8ObdEa1RYBpKfCoE00xb6xml2	26	69	176	Male	Occasional
14	thrnbPB5rGRE0JMLOycBGcGjDTs2	25	72	180	Male	Occasional
15	zDcJ8PJjogS8r75upB4mo62cW922	24	59	170	Male	Not runner

Table 2. Training data features of volunteering trainers.

Furthermore, *Table 2* shows other two attributes: the Subject Firebase ID and the Activity frequency. While the former is generated by Firebase remote servers when the training session is started and identifies the user within the system, the latter is specified by the user and can assume three possible values:

- Regular, if the user runs at least twice per week;
- Occasional, if the user runs less than twice per week but more than once per week;
- Not runner, if the user runs less than one time per week.

4.3.2 Music selection

Music playlist was chosen so as to simulate, in the most likely way, the general use of the final application: in fact, 17 predefined audio tracks, with different tempo characteristics, spacing from calmer songs to more rhythmic ones, were selected and administered to the trainers. Each individual was guided through the activity session by means of the same songs set, following with the same order.

Table 3 shows the list of the selected songs that were provided for the training phase, with related tempo values (expressed in BPM) and duration of the audio track. In order to provide the correct BPM value of each song, different web services[8][9][10] were queried and the most reasonable tempo choice was considered (the one that reflects natural beating of the song just by listening to it).

Song ID	Tempo [BPM]	Duration [m:s]
1	94	04:20
2	90	03:31
3	180	04:20
4	156	03:43
5	125	04:26
6	180	04:08
7	135	03:08
8	140	03:50
9	82	03:26
10	180	01:04
11	103	04:14
12	100	04:10
13	112	03:12
14	128	03:20
15	72	04:33
16	150	04:01
17	145	03:42

[8] SongBPM, https://songbpm.com/
[9] GetSongBPM, https://getsongbpm.com/
[10] Tunebat, https://tunebat.com/

Song ID	Tempo [BPM]	Duration [m:s]

Table 3. List of training song features.

4.3.3 Running test

The initial training of the system was accomplished by performing a uniform protocol composed of a set of steps to follow.

Each trainer was equipped with a heart rate monitoring device (the Polar H10 thoracic band mentioned in *Chapter 3*) and a smartphone with an already installed Android app. This application lets the user access the list of available playlist and select, one by one, each song when he/she is ready to play a new track. Furthermore, an initial in-app setup phase allows the individual to insert his/her own personal information (described in *Training sample* section). More importantly, it collects heart rate values throughout the training session, so as to track the cardiac evolution of the trainer while running and listening to a specific song.

The common protocol that was given to each trainer is the following:

1. The user has to start the training in **rest conditions**, that is, he/she has to stabilize the heart rate value (monitored from the app itself) for 2 minutes, without performing any activity. The provided concept of "rest conditions" is not accurately scientific and doesn't coincide with the resting heart rate physical parameter: this last value, in fact, is very subjective and depends on many different physical aspects and it has to be measured in the morning after waking up. For practicality matters, we assume that heart rate value after 2 minutes without performing activities may be a good approximation of the real resting heart rate value.

2. The user is subject to an initial recording of the heart rate values in absence of audio input stimulus. This phase lasts 4 minutes, during which the cardiac activity is recorded. This information is useful to check the influence of music application during a training session, with subjective and indistinguishable effects on the heart rate evolution. At the end of this "mute" warming-up, the user is advertised with

an acoustic notification in his/her headphones: he/she has to stop and rest for 3 minutes.

3. The user starts playing a new song in the playlist and begins to run. The major recommendations to follow during the training path are:

    - Avoiding steep slopes (both ascending and descending);
    - Avoiding stopping during a song playback;
    - Avoiding sudden bursts during the running.

    These three occurrence could insert biasing elements within the measurements, since heart activity can be subject to relevant changes due to discontinuous motor actions.

4. When a song ends, the individual has to stop and rest for 3 minutes without performing any activity. The heart rate should return to almost rest conditions in this time laps. When the timer of 3 minutes elapses, an acoustic sound notices the trainer that he/she can select the following song in the list and repeat the same procedure described in point 3.

5. Points 3 and 4 are iteratively repeated until the user has listened to all available songs in the playlist. When he/she finishes the training session, a specific command in the Android app allows to transfer the collected data to the Firebase server that links initial physiological information with the heart rate evolution tracked during the service.

4.3.4 Data storage solution

In order to store data and retrieve it for further analysis, Google's Firebase Realtime Database service was used. Thanks to its straightforward implementation in Android environments, it allows to save both users' personal data and heart rate evolution in the remote servers.

More precisely, when each trainer finished the session, a storage request was sent to Firebase servers, containing information about his/her personal data inserted during the app configuration phase, and the heart rate values. They were collected along with timestamps in which heart rate monitor sent them to the smartphone, to allow a time representation of the evolution of the cardiac signal throughout the activity. In fact, *Results and comments* section of this chapter aims at showing the plots referred to individuals' cardiac signal trends, measured during the running with a specific soundtrack.

It is important to highlight that the application doesn't require the insertion of details such as name, surname or other sensitive credentials from the individual.

4.4 Results and comments

The final discussion about data collection phase is devoted to present a clear and pictorial view of the achieved results coming from the training procedure previously described. Starting from a visual observation of the measured signals in time, some useful conclusions about the approach methodology, as well as design hints in building a music support system, can be expressed.

This analysis allows to determine, if possible, any kind of relationship between individuals' cardiac activity and audio stimuli applied during a running session. Nevertheless, during a training activity, many factors may influence the overall outcome, in terms of both physical meaning and the reliability of the measurement.

Before showing and discussing obtained results, some useful a-priori reflections have to be made. They derive from first reasoning about the applied methodology and the background idea over which the analysis was accomplished. Furthermore, by interviewing volunteering trainers after the exercise activity, they told important "technical" aspects about their experience and, as a consequence, deriving effects were present in the collected data.

Since training sample was composed of a few number of individuals (only 15 people), resulting considerations may be not reflecting and representing a general trend of the whole population; however, they represent a starting point for designing and tuning the implemented objective music advisory system.

Moreover, some collections revealed discontinuities in heart rate values (a short collapse of the cardiac signal) and after a quick survey with the interested individuals, they revealed that, due to an excessive physic effort, the training was temporarily paused. In other occasions, instead, due to obstacles, the running had to be slowed down, or even interrupted sometimes. These occurrences determined the posterior cleaning of the collected data, in which strongly biased signals were discarded, since anomalous values could have affected the "good" measurements.

Furthermore, a deep discussion with involved runners revealed that many of them, especially those that regularly perform physical exercise, experienced a strange behavior when they listened to slower songs: since tempo was quite slow, they couldn't follow the rhythm the music suggested, so they didn't pay attention to the music while running. Some others, instead, noticed that music characteristics, such as texture, pitch and intensity, led them to a "confusion" state, in which no specific nor constant pace could be followed.

The artistic nature of the music makes it a very personal and subjective stimulus for any individual: it means that people react to the same soundtrack in different ways. Preferences about genres, textures and even memories associated to a specific event, determine a different effect on anyone's response. Even though songs may share the same tempo, and other physical characteristics, many other factors related to human physiology and psychology influence the human body reaction to music. For this reason, a fixed selection of music tracks represents a sub-optimal solution, since it doesn't respect user preferences in the same way for every runner; nevertheless, for technical practicality matters and the specific interests in relationship between cardiac response and music speed, it was preferable to provide all the volunteers with the same song set to ensure an equally tempo selected tracks.

Next subsections are aimed at showing results obtained during the training phase. They are organized such as to emphasize the cardiac activity during the exercise without music, then the attention is focused on results achieved with soundtracks playback.

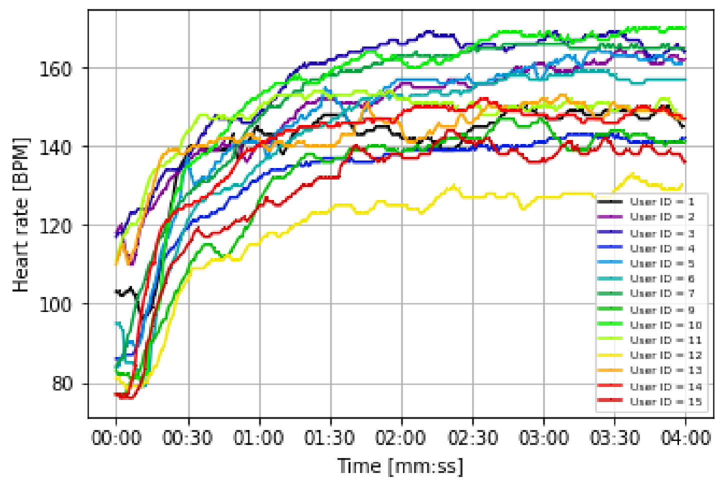


Figure 6. Heart rate evolution of training sample individuals without music playback.

4.4.1 Training without music

A first important study refers to the observation of heart rate values when no audio input was provided to the runners.

Figure 6 shows the trend of each individual throughout the training session: in general, no uniform behavior can be appreciated by analyzing this scenario. Three main considerations can be expressed:

1. Each person, without any external stimulus, runs with his/her own pace; moreover, they all have different health conditions which determine diverse heart rate responses. It is not surprising that heart rate signals, especially, at the end of the session, assume very far values.

2. Initial heart rate value is not an indicator, by itself, of the future evolution of the cardiac activity. In fact, it is possible to notice profiles starting with relatively high heart rate values and doesn't have a high increment during the session; instead, some other profiles that start the activity with lower values, eventually reach very high heart rate values.

3. A similarity among all the several trends can be noticed. For each signal, two different "parts" are present: in the initial part (about the first 60 seconds) there is a steep ascending slope which refers to the adaptation of the heart to the incoming train-

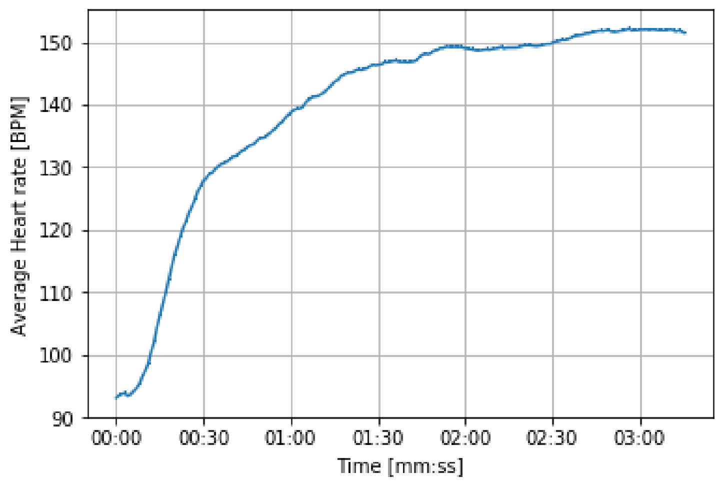


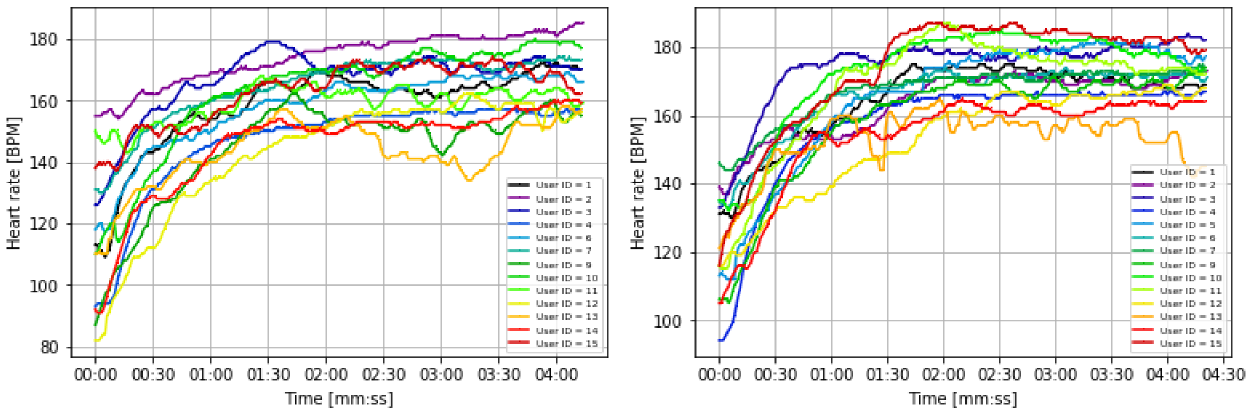
Figure 7. Average heart rate evolution of training sample individuals without music playback.

ing effort. In this first period, heart rate values normally increases rapidly. Then heart rate values tend to stabilize into an almost steady state, which is more or less followed during the remaining part of the training. This common trend is also noticeable in *Figure 7*, in which an average visualization of the cardiac signals collected from each individual of the training set is presented.

4.4.2 Training with music

Analogous observations about cardiac response to input stimuli application are mentioned as well, to clearly individuate the effects of the music playback during individuals' training. In particular, the purpose of this analysis is to detect, when present, the modality and the entity of effects the tempo of a song, expressed in BPM, affect the heart rate value during a running activity.

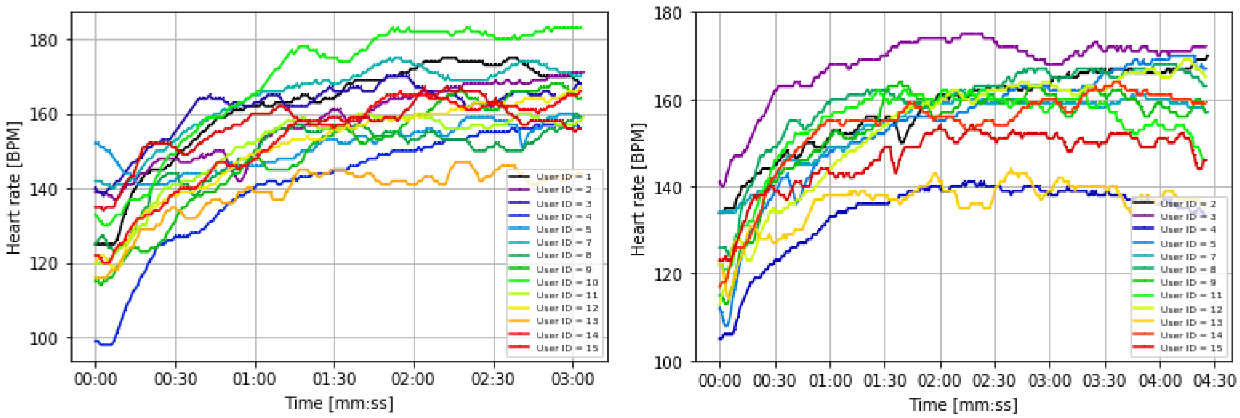
By considering the playback of just one music track at a time (*Figure 8* shows plots related to a subset of selected tracks with representative BPM values), it is possible to visualize how the several individuals of the training sample react to the same input music. In this chaotic representation of signals, it is still evident how each trainer is physiologically different with respect to the other sample components. Although the procedural methodology taught to the trainers for the initial acquisition phase provides that a rest of 2 minutes between two consequent songs is required to lower the heart rate value (in



(a) (b)

order to start a new run with almost resting conditions), this amount of time was not enough. As all subplots of *Figure 8* show, some individuals did not reach the aimed initial resting conditions, starting a new exercise with very high heart rate values. Nevertheless, it is evident that heart rate in the second part of the exercise (after the first minute) does not exceed an upper threshold: the final trend of each signal is still contained within a range that cannot exceed, for obvious reasons, an upper limit (the maximum heart rate value depends on the specific individual characteristics). Moreover, the heart rate variability is quite subjective, in the sense that any user maintains the same value of heart rate with different levels of regularity: for some trainers, in fact, it is possible to notice a quite inconstant cardiac signal. This fact is not clearly detectable from a mere visual inspection of the collected signals and with the proposed acquisition methodology; in fact, the heart rate variability aspect depends on a very huge set of externalities and physiological conditions. Thus, no further analysis, nor design choices, are related to this aspect, whose appearance may be caused by different methodological behaviours adopted by each single individual while running.

Figure 9 shows different behaviours of cardiac activity when the users are requested to listen to a specific song while running: the average evolution of the heart rate parameter reveals some important aspects related to the way the speed of a track influences the heart of the sample components. An averaged analysis is performed to understand and detect a more general behaviour of the representative portion of the population, so as to mitigate very specific and personal alterations (e.g. due to physiological or music preference



(c) (d)

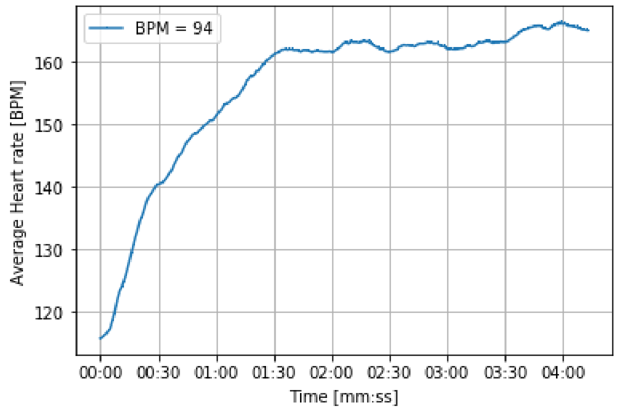
Figure 8. Heart rate evolution of each individual of the training set with the playback of track with: (a) Song ID 1 (BPM = 94); (b) Song ID 3 (BPM = 180); (c) Song ID 7 (BPM = 135); (d) Song ID 15 (BPM = 72).

differences) recorded in the cardiac signal during the workout.

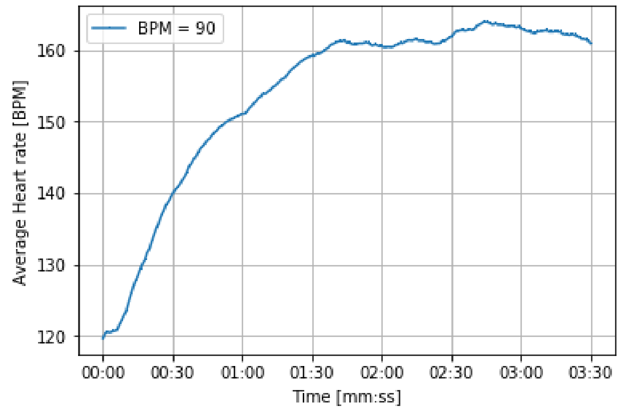
Also in case in which music was administered for users' training, the cardiac response spanned two main different stages: in the former, a steep increment in heart rate values was perceived, whereas, in the latter, a more constant evolution was present.

Another interesting conclusion derives from the observation of *Figure 9 (j)*, in which a very short music track, whose duration is about 1 minute, was played during the training: it shows that heart rate response is not immediate when listening to any song and a higher amount of time is needed so as to lead the cardiac rythm to the desired target value. The curve in question, in fact, does not reach a stabilization phase, instead it keeps increasing in an indeterminate way: for this reason, the information related to this music track were excluded from following analysis in order not to interfere with signals showing a full evolution of the heart rate.

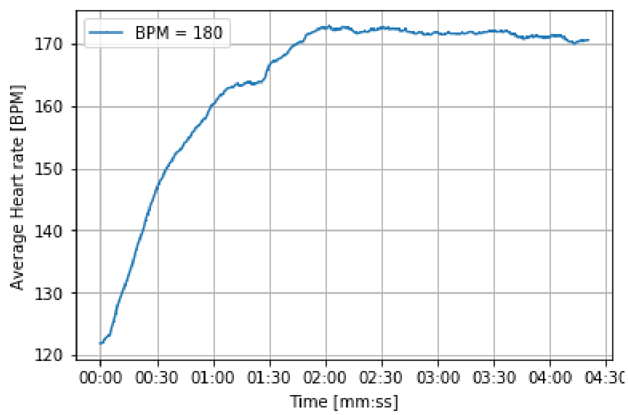
All cardiac signals shown in *Figure 9* reveal that each music track induced a different heart rate, in average, of the individuals. The second half of each subplot (almost after time 02:00) tends to stabilize around a range of heart rate values which might depend on several factors, such as tempo, music preference, fitness level and level of tiredness. Since this study focuses only on the tempo of the song and its relationship with heart rate values, a simplified analysis is hereby provided to check whether a possible link between the two aspects is present.



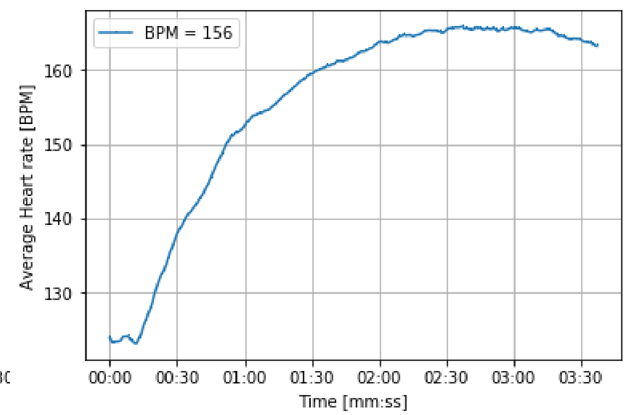
(a) Song ID 1



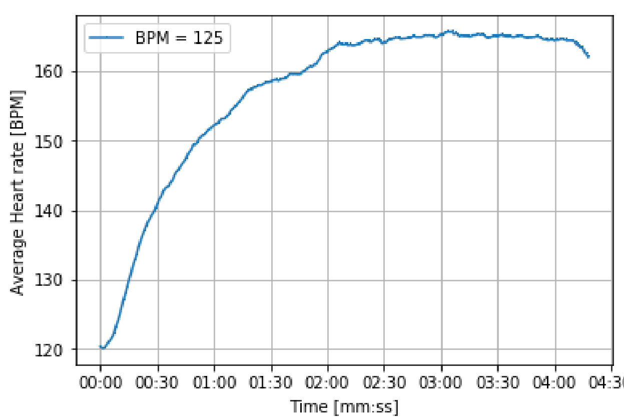
(b) Song ID 2



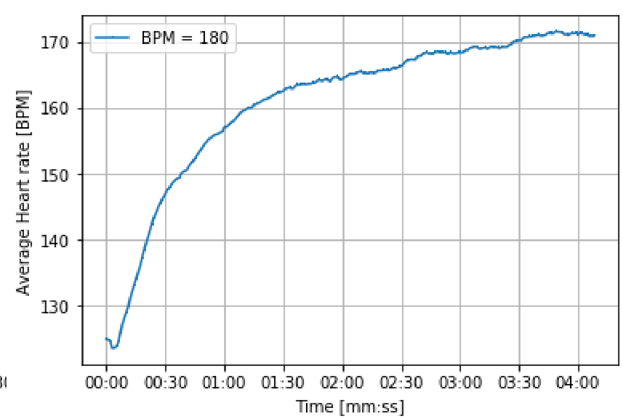
(c) Song ID 3



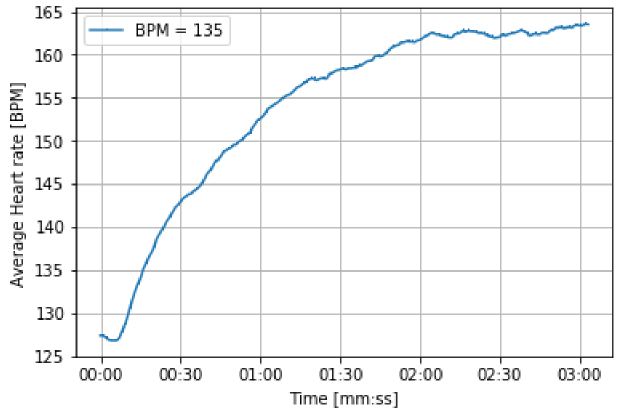
(d) Song ID 4



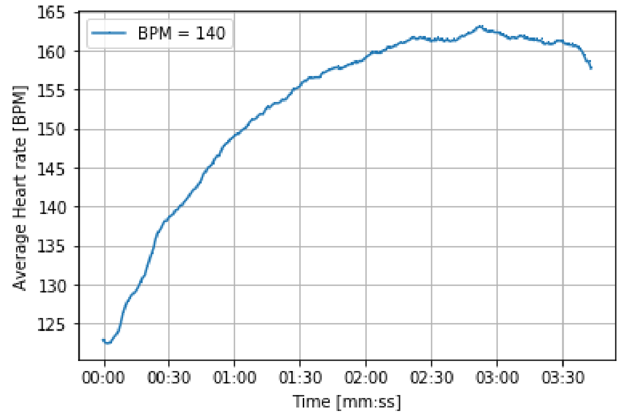
(e) Song ID 5



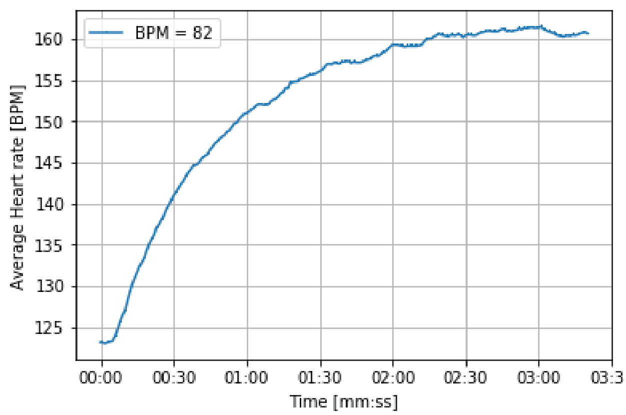
(f) Song ID 6



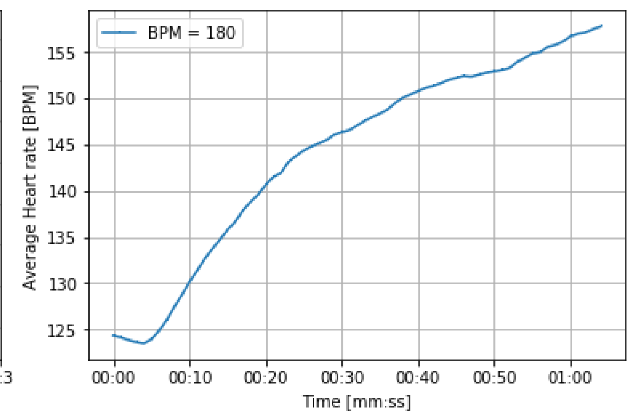
(g) Song ID 7



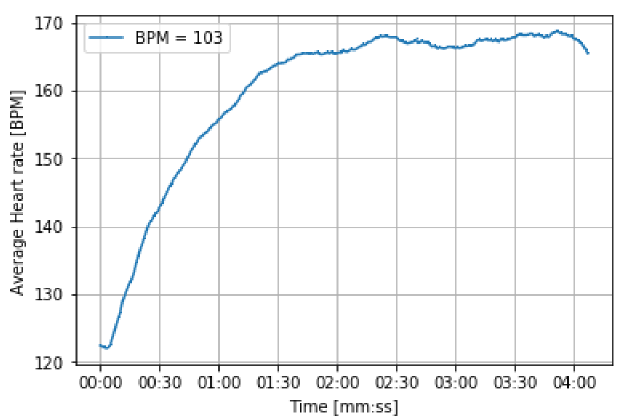
(h) Song ID 8



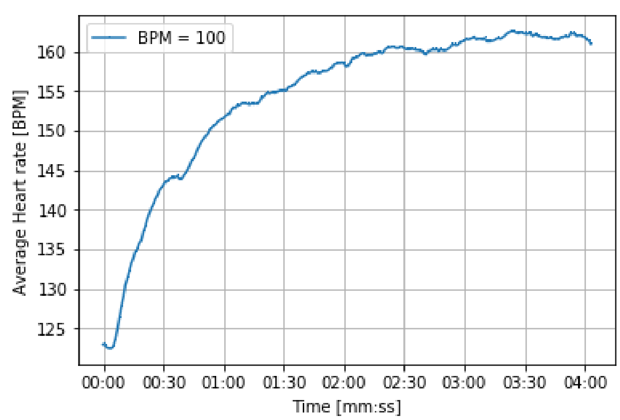
(i) Song ID 9



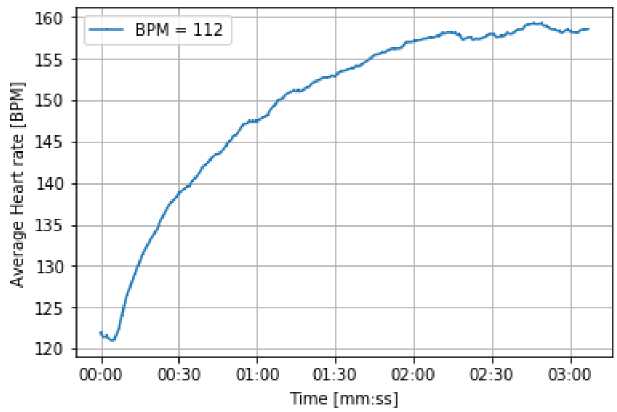
(j) Song ID 10



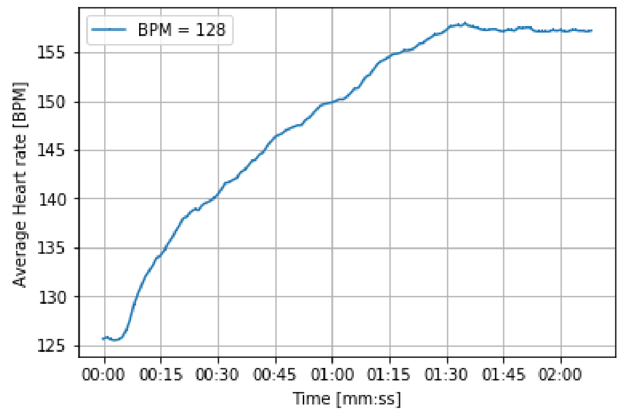
(k) Song ID 11



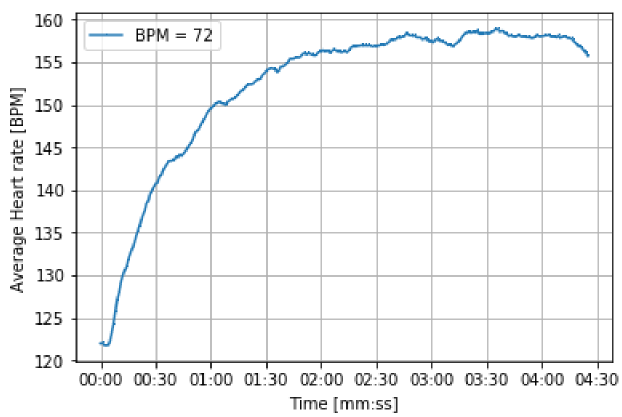
(l) Song ID 12



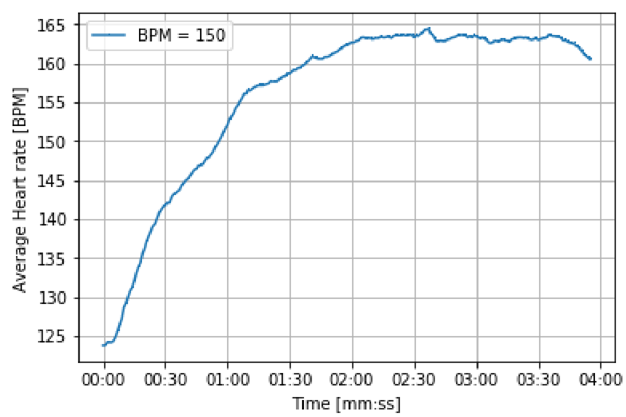
(m) Song ID 13



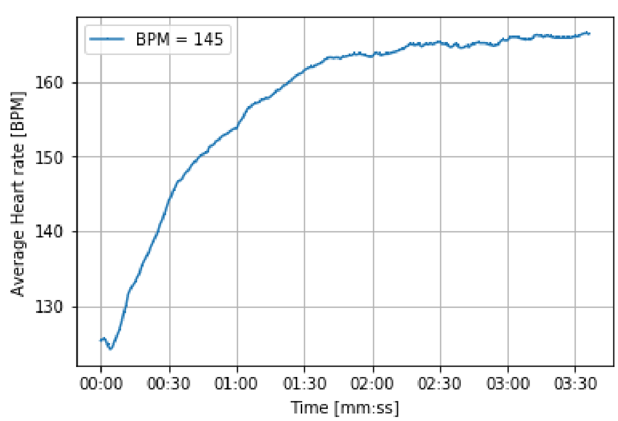
(n) Song ID 14



(o) Song ID 15



(p) Song ID 16



(q) Song ID 17

Figure 9. Average behaviour of cardiac response to different audio stimulus application.

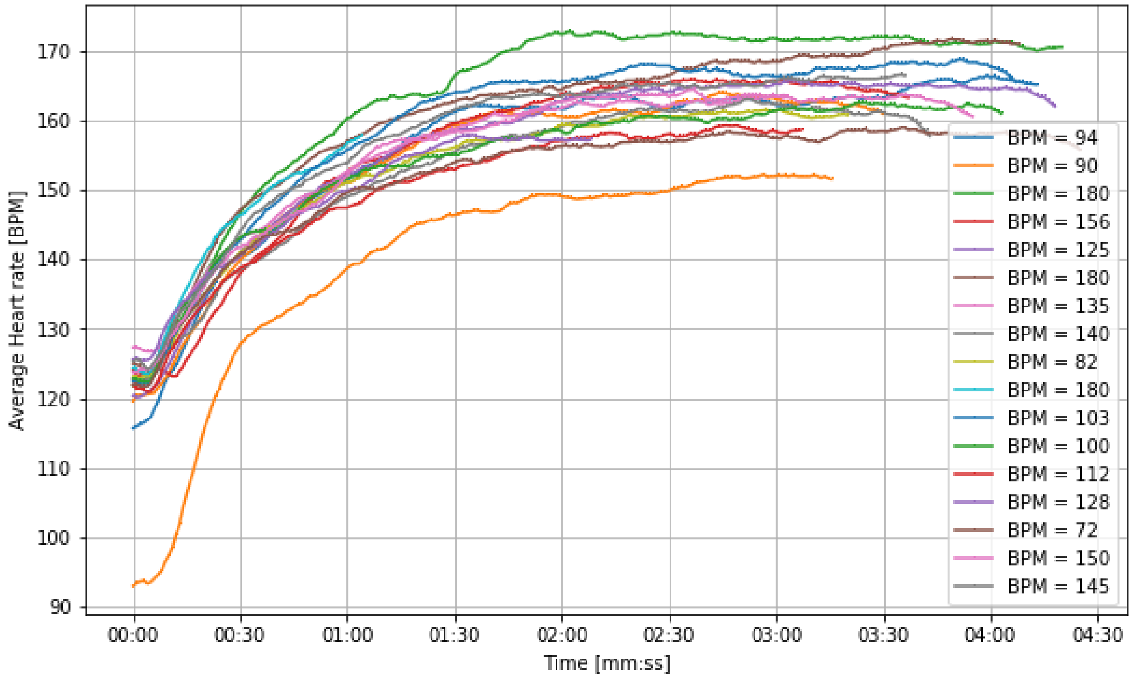


Figure 10. Means of the heart rate values for each music track.

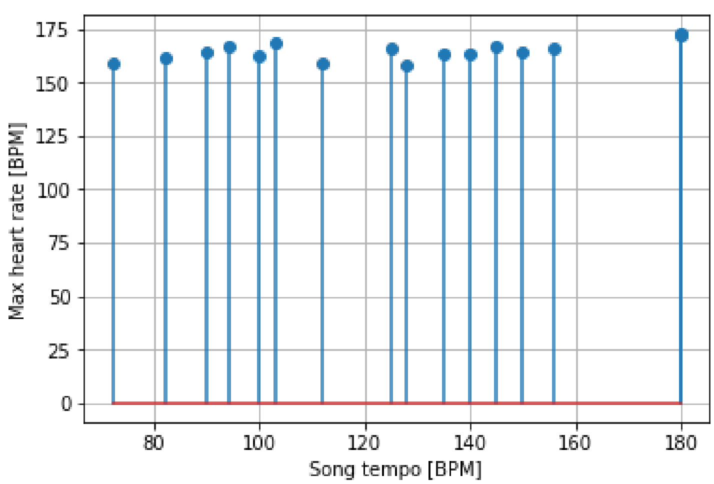


Figure 11. Distribution of maximum heart rate values of the averaged cardiac responses of the training sample with respect to music tempo.

Figure 10 shows a quite discouraging scenario in which signals interlace, becoming almost indistinguishable: except from signals referred to music with BPM equal to 94 and 180 (the upper green curve) that are almost separable from the rest, the other averages show a very similar behaviour that leads to a very difficult interpretation of the results. A further confirmation of this conclusion is evidenced by looking at *Figure 11* that shows only the distribution of the maximum values for the averaged heart rate signals. From this picture, it is very clear how heart rate is not subject, at least in a direct way, to music tempo: for instance, heart rate values do not always follow the increment of the music tempo, while instead they have a quite oscillating behaviour. Possibly, only a subset of tempo ranges affects the cardiac response of an individual: from what raises by looking at *Figure 11*, the first four BPM values (music tempo from 72 to 94 BPM), plus the final entry (music tempo at 180 BPM), follow the increment of the heart rate values. The central BPM section, instead, seems quite insensitive to different music tempo application, showing different levels of heart rate adaptation. If this assumption were true, a deeper study could be devoted at investigating which music tempo intervals are more influential in causing a variation in individuals' cardiac signal.

In conclusion, music tempo does not represent a sufficiently valid knowledge, on its own, to understand and predict the future evolution of the heart rate of an individual performing physical exercise. The high complexity of the human body and mind, along with personal sensitivity to music, makes the creation of such system, based only on music speed, a really challenging task. Thus, it is not reasonable to develop a system which simply assigns a tempo value to a target heart rate as decisional rule when it has to select the proper song to play.

A smarter solution is then proposed and described in the *Chapter 5*, which considers a more advanced model that takes other elements into account to try following the heart rate evolution and predicting its future behaviour in a more accurate way.

Chapter 5

Music advisory system

5.1 Introduction

The core decision process that drives the activity of the individuals during their training is hardly influenced by numerous factors related to human physiological aspects as well as cardiac response to sound stimuli application. While the user is performing any kind of physical exercise guided by the support service, the system provides a continuous and unobtrusive assistance to suggest the most suited settings to reach the targeted objectives. An underlying distributed algorithm exploits a set of signals collected from the individuals to regulate users' behaviour according to his/her needs and desires.

The main aspects about the implemented routine of the support service are described in this chapter, emphasizing the design rules adopted to determine an automated way to suggest the best music track for the training experience.

The sections that compose the following chapter are:

- **Model definition and input data**. The model that was defined to describe the relationship between the heart rate and other reasoned parameters is highlighted in this section. A clear description of the elements taken into account for representing the cardiac evolution is provided as well. Finally, a detailed view of the characteristics of feeding data aims at providing a better understanding of the decisional choices made to build the core system. This last analysis is supported by several visualizations of data distribution and comments about similarities and possible relationships among the features.

- **Learning technique and performance evaluation**. This section aims at giving useful hints about the used machine learning algorithm for treating and processing collected data. This phase is extremely important since it represents the actual operation that the core intelligence performs when it has to decide the proper song to reproduce. Moreover, application of the proposed technique to the given use case is described, emphasizing the main components that play a crucial role in predicting the objective variables. In conclusion, a discussion about obtained results performance reveals clarifying aspects about the adopted model and the chosen regression solution.

- **Decision algorithm**. The main operative procedure that the system performs to provide the final user with the desired service is deeply focused in this section. The steps that define the interaction between the components of the architecture are subject to a fully detailed analysis.

5.2 Model definition and input data

Due to unsatisfactory results about determining the contributions of music tempo in altering the heart rate, the choice of selecting the proper music during the training was demanded to a learning machine algorithm which was properly tuned and fed with many input features.

The emphasis was then addressed to the estimation of the heart rate value in a future time instant by knowing a previous heart rate value, along with a set of parameters directly linked to the individual that used the services. In particular, the objective of the analysis method refers to the prediction of the value of heart rate after 60 seconds a song was played, exploiting the knowledge of the measured starting point (the initial heart rate) and physiological parameters inserted by the user in the final front end system.

5.2.1 Data set structure

The procedural steps accomplished to create a data set with which a machine based on artificial intelligence could be deployed are the following:

- The training user was asked to insert information about gender, height, weight, age and fitness level at the beginning of their training experience. Since the proposed algorithm works with numerical data, some features were then mapped as follows:
  - **Gender**. "Male" was represented as 1; "Female" was represented as 2.
  - **Activity Frequency**. "Regular" was represented as 1; "Occasional" was represented with 2; "Not runner" was represented as 3.
  - **Age**, **Height** and **Weight**. These features were numerical, so no mapping procedure was required.

  Furthermore, in order to include the possibility for the users to specify their training activity (not necessarily running) in future versions of the system, another "hidden" parameter was introduced in the general model: it refers to **Activity type**, whose constant value was set to 1 and refers to running activity.

- After collecting cardiac signals throughout the diverse phases of the training session, a sampling procedure of the heart rate evolution was accomplished. In fact, by selecting a sampling period of 60 seconds, a set of points (denoted as **HR_target**) was retrieved and linked with related initial heart rate value (denoted as **HR_init**). The cardiac signal was split in equal intervals of duration equal to 60 seconds, in which the first heart rate measurement was set as initial heart rate, while the last one was set as target heart rate. *Figure 12* shows an example of the sampling procedure applied to a generic cardiac signal. Each couple of points determines the initial and final heart rate values for each interval and are the representative entries that are considered in the final model; for each interval, the ending point represents the initial point of the subsequent interval.

- Finally, a file containing the observations used as training set for the learning machine model was created. *Table 5* shows an example of generated data set. All the

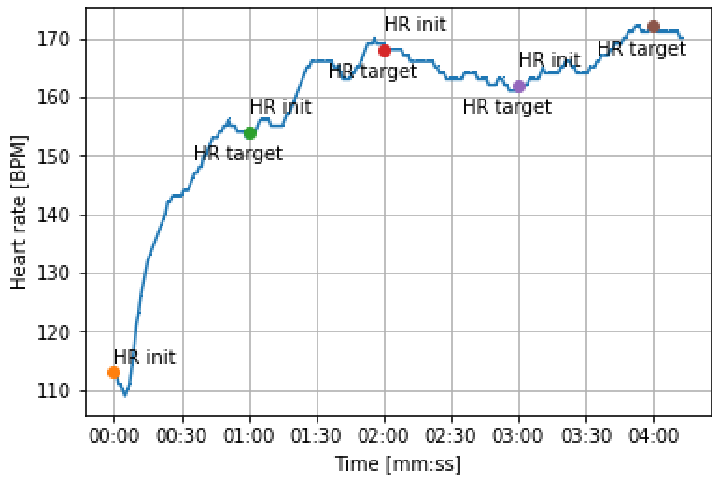


Figure 12. Sampled points of a cardiac signal.

entries are related to the same subject (*Subject ID = 1*): the first two entries refer to a music track application with BPM equal to 90, which contributed in determining a variation of heart rate from 162 BPM to 167 BPM, then another variation from 167 BPM to 172 BPM. The last entry, instead, refers to another track with tempo equal to 180 BPM which caused a variation in heart rate from 139 BPM to 154 BPM. The final data set contains entry with the described structure, listing information about each sampled data: for each sampling, a new entry is generated.

Subject#	Age	Weight	Height	Gender	ActivityFreq	ActivityType	BPM_song	HR_init	HR_target
1	26	70	180	1	2	1	90	162	167
1	26	70	180	1	2	1	90	167	172
1	26	70	180	1	2	1	180	139	154

Table 5. Example of data set.

This input data set was generated by sampling signals collected during the training phase of the system and serves as feeder of the implemented system decisional algorithm. It is stored in the back end component of the architecture, whose content is retrieved whenever a trainer demands the service to provide the most suited song to play during the activity. It is continuously updated when a new running session starts: when the user uses the application on his/her personal device, the collection of useful information about heart rate allows to create new entries that are added in the current input data file. With this method, a more consistent and generalized input set is originated, and following users may perceive a more performing experience.

User profiling

In order to improve users' experience of the system, the way in which measurements of heart rate signals are treated was enhanced and adapted to the real use cases of the service.

When the sampling procedure has generated enough measurements of the cardiac signal, a different implementation of the decision rule in selecting the proper audio track replaces the usual communication with the remote music selection algorithm. Instead, a local routine running on the smartphone allows to fetch the best music track by querying the internal relational database. In fact, a temporized process allows to store data about heart rate values both remotely and locally. Thanks to the latter procedure, the user owns in its smartphone a complete record file containing measurements about its personal experience and heart response. A chronology of past heart rate evolution, along with music selected by the system, is continuously maintained and updated.

This approach aims at providing a more personalized service to the final user by favoring the personal heart rate responses to a given input stimulus when the system has collected a sufficient number of measurements. The driving reasoning is that a too wide and general input data set stored in the unique remote point about all the users of the system may result in a weaker and less performing solution when many diverse users share their own specific cardiac events.

The design choice to store a local copy of personal measurements arises from the fact that a more customized solution may provide a better service in terms of adherence and coherence between the targets and the actual heart rate values. In this way, people with different physiological conditions, levels of fitness and personal characteristics generate measurements useful for the general system that do not influence very specific knowledge about other trainers.

Obviously, a proper value for the number of observations above which the local procedure has to start is fundamental: it is necessary to understand when the system has gathered a reasonable amount of information to efficiently describe the heart rate evolution when the user is listening to a song.

5.2.2 Designed model

A more formal definition of the implemented model that describes the evolution of the future heart rate is the following:

$$\begin{aligned} HR_{target} = & w_0 * HR_{init} + w_1 * \text{Age} + w_2 * \text{Weight} + w_3 * \text{Height} + \\ & w_4 * \text{Gender} + w_5 * \text{Subject\#} + w_6 * \text{ActivityFreq} + \\ & w_7 * \text{BPMsong} \end{aligned} \tag{1}$$

where each feature is a specific "characteristic" retrieved by the user and whose meaning is mentioned in the previous subsection.

Equation 1 describes a linear relationship between the future value for the heart rate (*HR_target*) and all the parameters previously defined. This assumption may be quite inconsistent and simplistic to reproduce the evolution of the target variable, but it is still a quite easy and clear representation to which it is possible to apply well-known resolution techniques to find valid coefficients w_i with $i = 0, 1, .., 7$. In particular, a linear regression approach was applied to create a machine based on artificial intelligence able to estimate future values of the cardiac signals: this knowledge was then exploited to drive the selection of proper music tracks based on cardiac training targets.

By considering the input data set, the variable *HR_target* was chosen as regressand feature, while the remaining ones were selected as regressors (independent variables) to predict the evolution of the future heart rate.

A devoted section of this chapter clearly explains how regressed information is used by an internal routine of the back-end component to decide which song to suggest to the final user.

5.2.3 Measurements analysis

Before proceeding with explaining the operation of the decision-make algorithm, a quick and useful analysis of the measurements stored in the input data set is provided.

Boxplots are a measure of how well distributed the data in a data set is. It divides the data set into three quartiles: this graph represents the minimum, maximum, median, first quartile and third quartile in the data set. It is also useful in comparing the distribution of data across data sets by drawing boxplots for each of them. *Figure 13* shows boxplots related to each feature belonging to the data set. Thanks to this representation, it is possible to visualize the range of values each variable assumes, along with the presence of outliers in each feature column.

Figure 14, instead, shows a correlation plot between features of the data set. This useful data representation allows to visually detect any possible relationship between two variables at a time (e.g. to establish whether two variables are related one to each other through some particular function). In the main diagonal of this matrix, an histogram representing the distribution of the elements of each variable is visible.

By looking at *Figure 14*, an almost linear relationship between final and initial heart rate is present, while for the remaining feature no clear relationship is present. Thus, using the heart rate value at the initial time instant (the first value of each sampling interval) in estimating the final heart rate value (the last value of each sampling interval) may result in a quite performing implementation choice.

Figure 15 highlights these two features and, in addition, the *BPM_song* feature is added to the plot. For this last variable, a random and not deterministic behavior is present with respect the other two cardiac feature.

5.3 Learning technique and performance evaluation

A quick overview about the regression technique, used to create an intelligent machine able to predict future values of heart rate feature, allows both to have a clearer idea of the underlying algorithm operation and to raise possible suggestions to improve the pro-

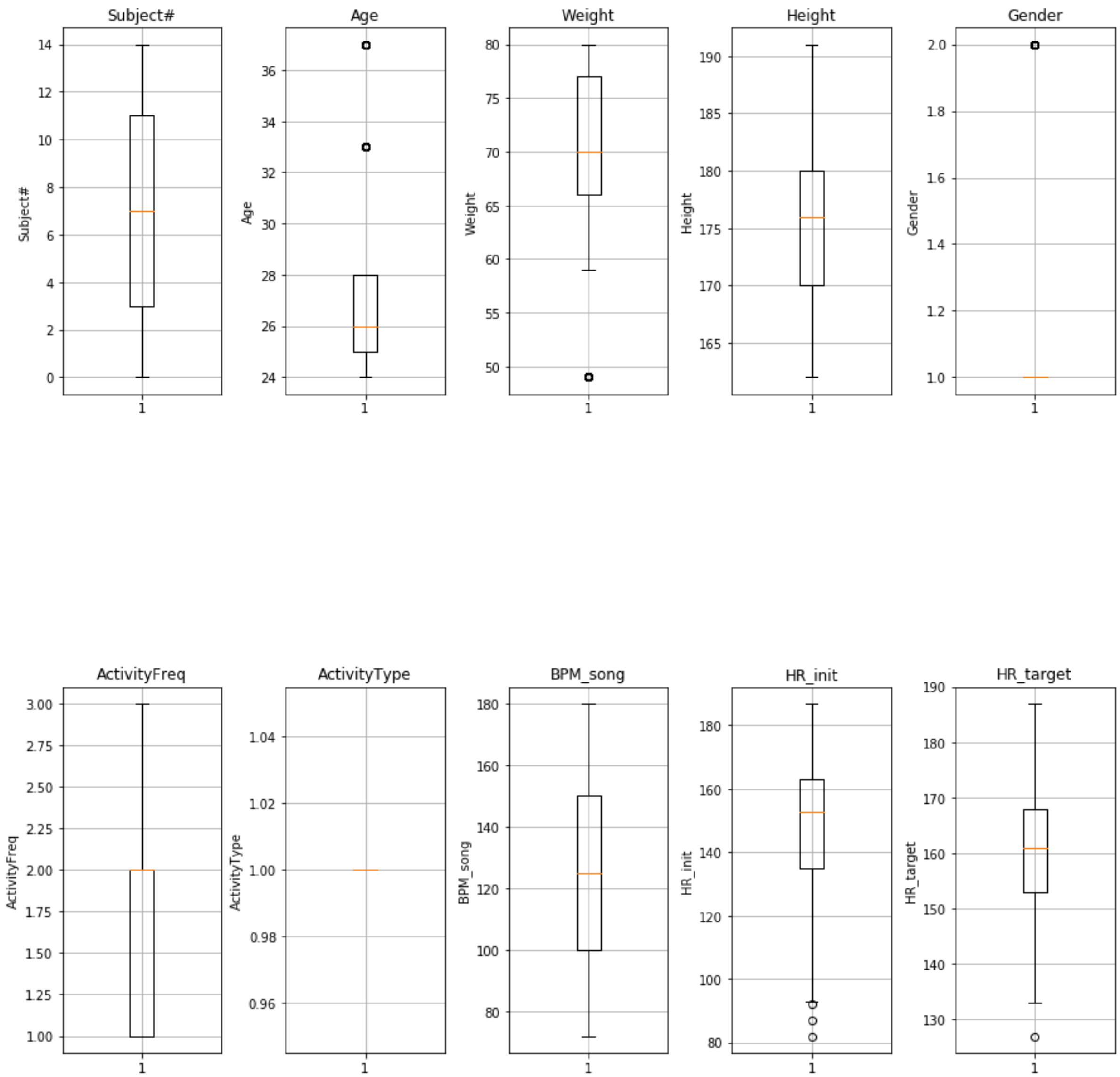


Figure 13. Box plot representation of measurement features distribution.

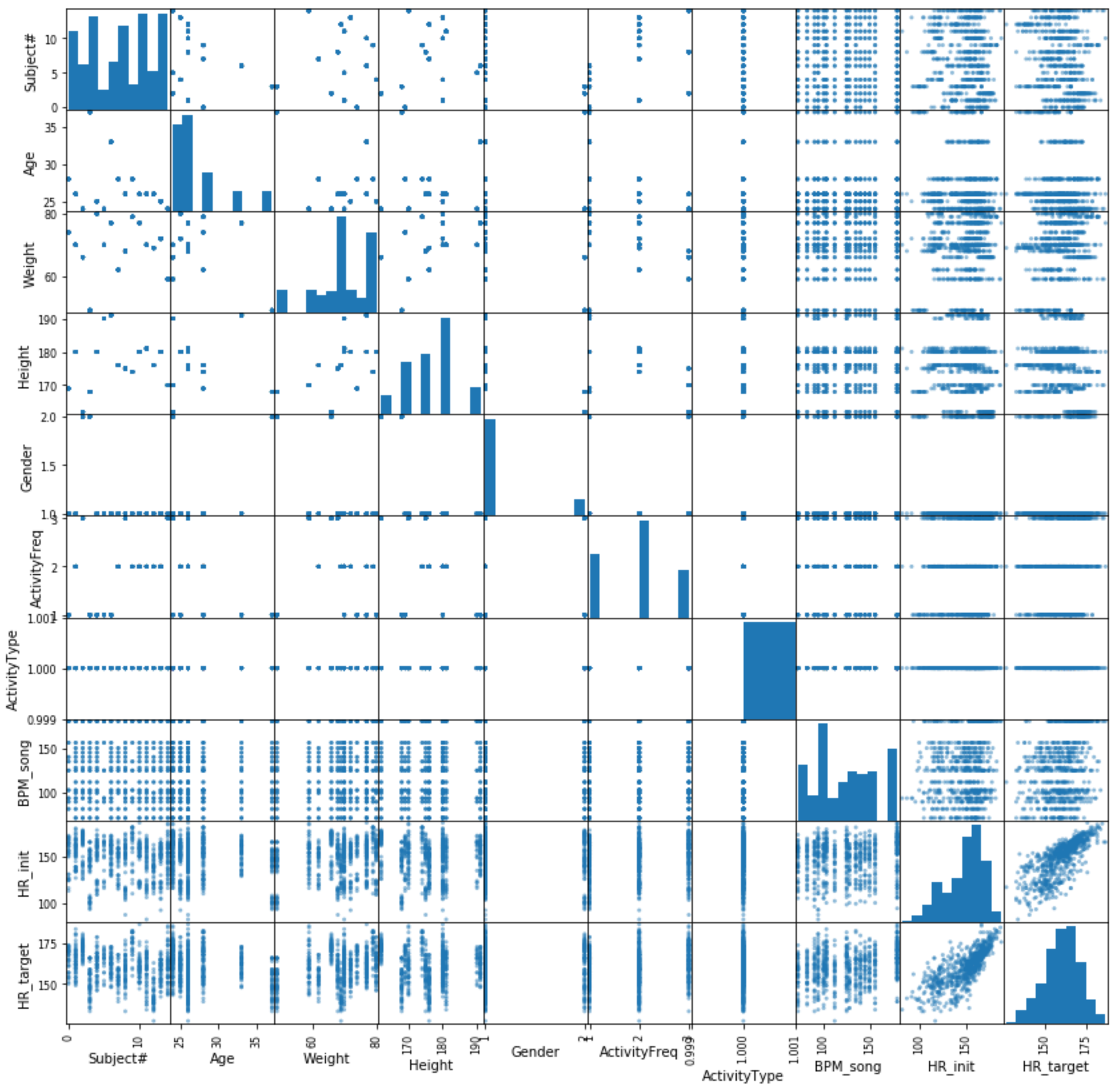


Figure 14. General view of the relationship between couples of features through scatter matrix representation (matrix of scatter plots).

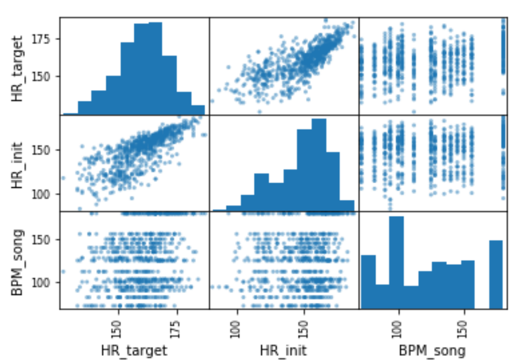


Figure 15. Inspection of the relationship between the two cardiac signals plus the song BPM value.

posed solution.

In order to select the best algorithm, among all the available alternatives that may be suitable for linear models, an initial evaluation phase was accomplished. The purpose of this preliminary study consisted in determining the performance, in terms of RMSE (Root Mean Squared Error), of each analyzed algorithm in efficiently predicting the heart rate values in future time instants, based on input data collected during the initial training step. Then, the solution that provided the best results (the lowest value for RMSE) was chosen as linear machine learning algorithm to be applied to the specific use case.

The Root Mean Squared Error is a frequently used measure of the differences between values (sample or population values) predicted by a model or an estimator and the observed values. The RMSE serves to aggregate the magnitudes of the errors in predictions for various times into a single index, which represents a measure of accuracy, to compare forecasting errors of different models for a particular data set.

In this study context, the algorithm under analysis were:

- Minimum Mean Square Error (MSE) algorithm;
- Steepest Descent algorithm;
- Ridge Regression algorithm;
- Principal Component Regression (PCR) algorithm.

To compare performance of each technique taken into account, the following set of tuning parameters was chosen:

- Minimum Mean Squared Error (MSE) does not require the specification of parameters to operate;
- Steepest Descent method was run with a threshold value equal to 10^{-3} which establishes the stopping condition for the iterative algorithm termination;
- Ridge Regression algorithm was run 1000 times, in which, at each iteration, a different value for the penalty factor was set. In particular, the values taken by this penalty variable were multiples of 1 (from 1 to 1000,with incremental step equal to 1). A trial and error experiment determined the performance of the algorithm for each studied penalty factor and, eventually, the best result determined the final as-

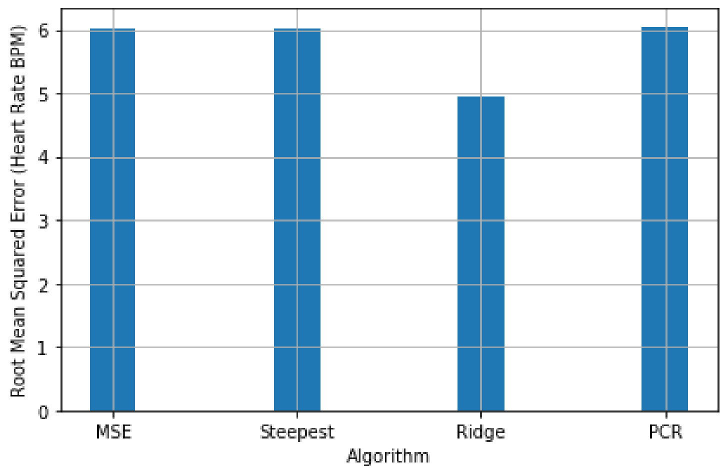


Figure 16. Comparison of different linear regression algorithms with respect to produced Root Mean Squared Error

set of the regression machine. Only results obtained with the best tuning are shown in comparison plots;

- Principal Component Regression (PCR) was tuned with a retain factor equal to 0.9, which consists in the fraction of the total variance of the model features. It determines the number of features in the new system that are considered to perform the regression. Only 3 features were retained after performing this regression technique.

After applying each regression algorithm to the same data set, using the model described by (1), results were gathered and they are clearly visible in *Figure 16*. The regressed variable is the heart rate value at a time $t_1 = t_0 + 60$ (*HR_target*), while the regressors have been already defined in the previous sections. In order to instruct the machine, a training set composed of the first 550 measurements was created, while the remaining observations (163) composed the test set (total data set size equal to 713 entries). The RMSE performance metric refers to the residuals related to testing set, so prediction of values that were not used to train the system.

Figure 16 describes a scenario in which every analyzed algorithm produces similar performances in prediction. In fact, by looking at the height of each plotted bar, the deviation between estimated and observed values for heart rate in a future time instant is pretty similar in all cases ($\pm 5/6$ BPM). *Table 4* quantitatively lists entities of this index for each proposed algorithm.

Algorithm	Root Mean Squared Error (BPM)
Minimum Mean Squared Error	**6.022031945608527**
Steepest Descent	**6.022026635466598**
Ridge Regression	**4.939081522617546**
Principal Component Regression	**6.045481625252948**

Table 4. List of RMSE values for each analyzed algorithm.

Even though results listed in *Table 4* are not very distant among each other, and quality of the methods hardly depends on many factors, such as model definition, input data characteristics and regression technique tendency in face problems like overfitting, the final choice was to select the one that provided the lowest RMSE metric.

Figure 17. Relationship between *HR_target* observed values (X-axis) and regressed values (Y-axis) (Ridge Regression algorithm with penalty factor equal to 151 applied to training set).

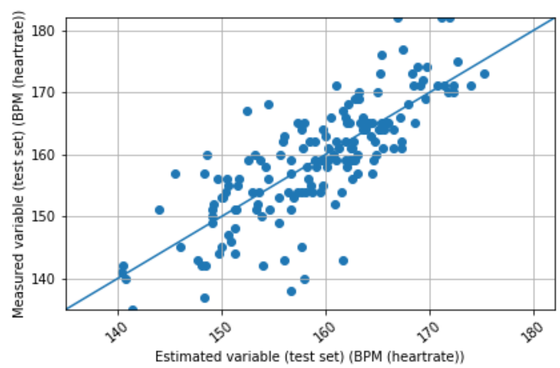


Figure 18. Relationship between *HR_target* observed values (X-axis) and regressed values (Y-axis) (Ridge Regression algorithm with penalty factor equal to 151 applied to test set).

For this specific use case, the Ridge Regression technique was applied to find the correct coefficients $w_0, w_1, ...w_7$ described in (1) that permit to estimate the target variable, since it shows the best performance in estimating the regressand variable. The best penalty factor value found by the "trial and error" experiment was 151. *Figure 17, 18, 19, 20, 21, 22 and 23* show visual outcome generated by the application of Ridge Regression algorithm for this use case problem.

Figure 17 and *Figure 18* show the relationship between the regressed (X-axis) and observed (Y-axis) values of target heart rate (the regressand feature): in the former plot, the prediction applied to the training set is shown, whereas the latter shows results of

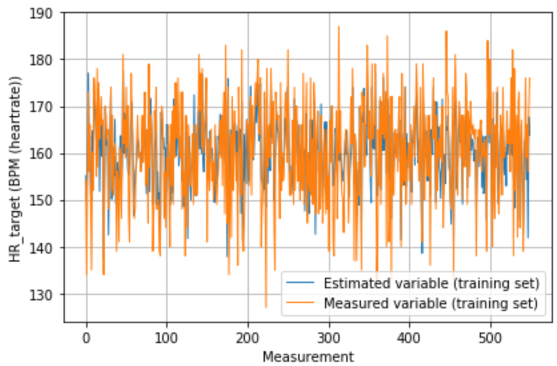


Figure 19. Comparison between observed and regressed *HR_target)* values for each measurement (Ridge Regression algorithm with penalty factor equal to 151 applied to training set).

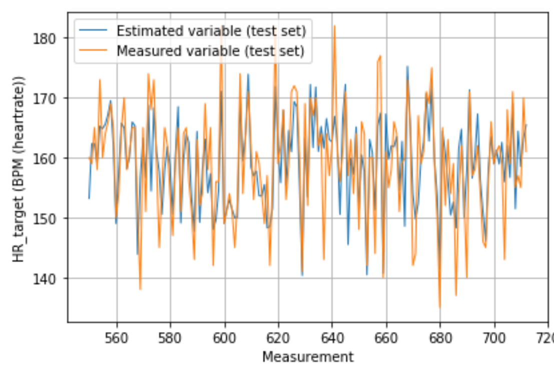


Figure 20. Comparison between observed and regressed *HR_target)* values for each measurement (Ridge Regression algorithm with penalty factor equal to 151 applied to test set).

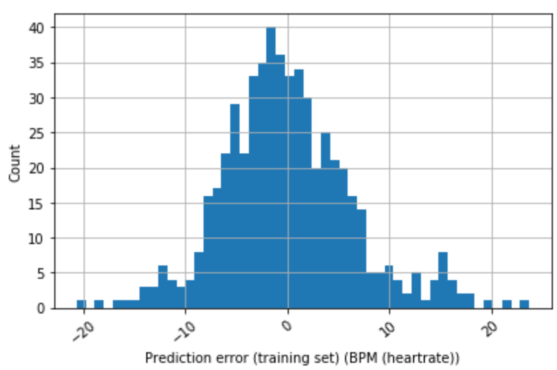


Figure 21. Prediction error distribution for *HR_target* (Ridge Regression algorithm with penalty factor equal to 151 applied to training set).

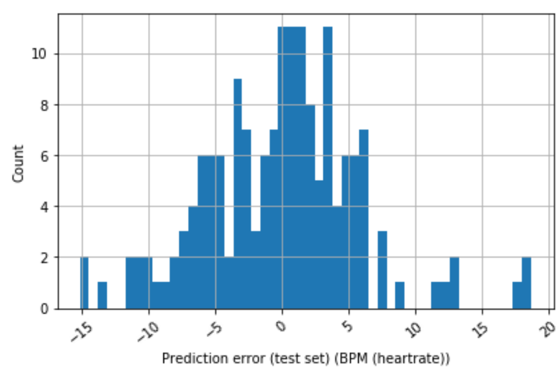


Figure 22. Prediction error distribution for *HR_target* (Ridge Regression algorithm with penalty factor equal to 151 applied to test set).

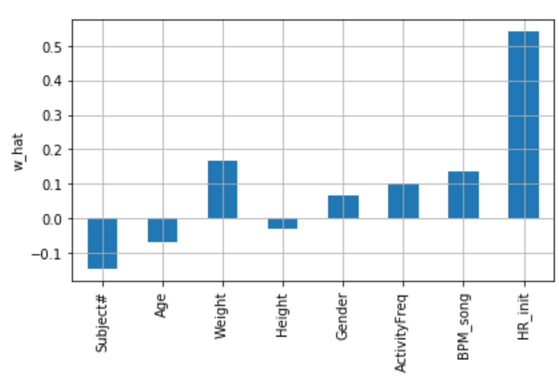


Figure 23. Regression vector $\hat{w}$ for *HR_target* (Ridge Regression algorithm with penalty factor equal to 151).

the same procedure applied to the test set. In both plots, a straight trend line individuates the best line in the bi-dimensional space in which the best scenario appears: when points are close to the straight line, the estimation procedure has correctly predicted the value of a specific target variable (the estimation tends to coincide with the observation). In both plots, eventually, it is possible to notice that predicted points tend to follow the observations in a quite satisfying way.

Figure 19 and *Figure 20*, instead, provide a general view of overall performance of the regression analysis: for each entry available in the input data set, the achieved prediction results are compared with observed values.

Figure 21 and *Figure 22* allow to understand the entity and distribution of prediction errors thanks to an histogram representation. As expected, a more irregular distribution, with larger prediction error magnitudes, is present in the case in which linear regression is applied to the test set (*Figure 22*); instead, when testing system performance with training set (*Figure 21*), error distribution is more regular (almost Gaussian distribution) and constrained (close tails of the "bell").

Eventually, *Figure 23* gives a useful and clear indication about the contribution of each regressor in predicting the response variable. It is possible to notice that the initial heart rate value plays a crucial role in the regression analysis, while other factors, such as age and height, does not represent a very contributing support for describing the evolution of the target variable.

Summarizing, the adopted approach based on the linear model and Ridge Regression algorithm can be deemed as quite satisfying, considering the limitations of a simplistic representation of the cardiac signal evolution. Still, the system outcome cannot be considered fully performing, since many target heart rate observations are far from the predicted values. A finer results granularity can be obtained by feeding the system with more observation points that can properly generalize the complicate variability of the population; furthermore, more complex regression models and regression techniques can be explored to observe and compare the difference of results goodness and estimates reliability. For this thesis project, a simpler yet effective solution described in this section represents a valid solution thanks to which the music service algorithm can be implemented.

5.4 Decision algorithm

The following discussion highlights the main procedure the system performs to provide the final user with a training service with the support of a proper music track. The synergistic communication among the several component of the architecture allows to provide a fully performing machine that guides the trainer throughout his/her physical activity.

The tailoring of the communication flow was accomplished referring to the specifications and guidelines that the final system had to respect. While features and tasks of each component are logically defined and circumscribed, the implementation methods, communication technologies and further software design choices may be tuned according to specific needs and requirements. For this reason, the following discussion aims at describing the interaction among the actors of the infrastructure in a pure functional perspective.

5.4.1 Initial setup of the system

When a trainer desires to start a new training session, a few parameters have to be set in order to let the system understand the goal of the activity and music availability.

From the user point of view, it is necessary to specify the training profile (created and saved by means of a devoted section of the user's application) and the playlist of song already imported and elaborated by a tempo detector service. The user, during the setup phase of the app, is required to insert his/her personal data required by the remote backend to make music decisions. Moreover, the trainer can modify an adherence threshold that defines a region, around the target heart rate, within which a measured heart rate value is considered valid with respect to the objective heart rate value. This information is required to decide whether changing song is necessary to influence cardiac activity.

After defining the desired objectives and playlist to use during training, the connection with the heart rate monitoring device is established and the service can start. Collected real-time heart rate values are sent to user's application with a transmission rate that depends on the Bluetooth stack protocol (in this experiment, Polar chest monitor sends values about every second); then, they are properly managed by the local routine that handles the forwarding to the remote server.

From the back-end perspective, instead, the measurements file described in this chapter is the only initial requirement to make to system fully operative. As already said, it contains data acquired during a training phase with trainers' cardiac information, along with their physiologic characteristics. However, this file is continuously updated to provide a better service to the infrastructure users.

5.4.2 Core training support process

A sequence of steps aims at describing the functions and roles of each system component when a support for trainers has to be provided:

1. The local service on users' smartphone initialize two different timers that regulate the main functions of the front-end component:
   (a) A timer individuates the several blocks that compose the training profile. By setting the timer to the duration of the next training block (the first block when the service starts), the service always knows the target heart rate value the user wants to achieve. This information is used to evaluate the proper song to play and it is handled by a specific in-app routine.
   (b) Another timer checks current heart rate value with the desired target value every minute. If the condition is respected, that is the current heart rate is between an acceptability range around the target value, then the algorithm keeps the current song playing, otherwise a request for a new song is performed. This timer is also needed to perform saving of the current state in both the local database and remote measurements file. This last procedure allows to update the input file for linear regression performed by the back-end so as to provide a more powerful and customized experience for any user of the system.

   Referring to the case in which the current heart rate does not respect the given constraints, a new procedure is run to decide how to select the new song to play. Moreover, this function is repeated every time the training block changes (the first timer elapses) and when a current song ends.

If local database does not have enough information about the specific user (established through a static algorithm variable), then the remote server is asked to select the next song:

(a) A new song request is forwarded to the back-end: it contains information about user's characteristics, current and target heart rate values, list of song tempos (BPM) he/she added in the playlist and individual system identification code (Firebase UID). Adding user profile pointers to each request allows to maintain a continuous and linked track of same users' experience, so as to favour individual physical responses in the proper tempo selection process.

(b) The remote server response contains the best BPM value for the proper song selection. A devoted routine randomly selects a new song from the playlist whose tempo is within a range (± 10 BPM) of the retrieved tempo and that was not the last played. This choice aims at avoiding repetitiveness in selecting the music tracks from the playlist, adding some randomness in songs retrieval.

In case in which a local-based song selection is performed (the front-end component has acquired much data from users' training activities), the following steps are performed:

(a) The local database is queried to verify whether, among all the records about relationship between song tempo and heart rate evolution, there is at least one whose final heart rate value is far from the current target value at most of ± 10 BPM. If the local database query produces a void result list, then the remote server is asked to select a new song to play (as described in the previous paragraph).

(b) The song BPM values related to the entries that respect this condition are then returned to the decision service, which randomly selects one of the closest songs with similar tempo.

2. The remote back-end component performs two main actions, that is, it listens for

incoming requests for new song detection, and updates measurement file that is used to enhance the model performance for proper tracks selection. In particular, the decision-make routine works as follows:

(a) When a new request arrives, sent parameters are fetched from the request: they are immediately stored in the measurements file.

(b) The regression algorithm is run to update the coefficient values needed to estimate the final heart rate value.

(c) For each tempo value among all the available song BPM values sent by users' application, the regression coefficients are applied to the independent variables (the set of parameters) to detect which input asset produces the closest final heart rate value to the current target.

(d) Eventually, the selected value is sent back to the front-end application that selects a suitable song to play.

During the training advancement, support variables trace the behavior of the current heart rate values with respect to the fixed target: by counting the amount of time the measured heart rate is above, below or within the target range, some performance metrics can be evaluated to provide the final user with a quantitative index about his/her training progress. A possible metric useful for understanding the success of the training service consists in an adherence value, evaluated as the ratio between the amount of time in which the heart rate was maintained in the valid range by the total duration of the training session. Many other parameters, however, can be properly defined and evaluated to give a clearer and fully detailed profile about users' performances during the running activity.

Chapter 6

Conclusion

The objective of this thesis was to demonstrate the feasibility of a support system able to rely on music application to enhance trainers' performances while performing a running activity. As said in the literature review of this document, music influences human physiology in many different ways, from both mental and physical points of view. It is then reasonable to engineer a system that emphasize music effects to adapt to a specific use case and drive the interested users to reach their fixed targets in an effective and pleasant way.

From a deep analysis activity of scientific literature and technological scouting, the following elements raised:

- Many studies about psycho-physical music influence in sportive activity scopes, but a few of them treat the application of sounds in enhancing training performance;
- Usually, a customization of administered music is not provided;
- Also technologies deployed in this context are numerous, but in many cases there is no reasoned linkage between music and training exercise.

The proposed system tries to solve these gaps, using music as an instrument to increase performance, through the chance to adapt it to training objectives, caring also about the safety aspect. A motivational support is then provided to the final user to generate a positive perception of the physical effort. Thus, some advanced solutions can be adopted to achieve satisfactory results when deploying music-based support systems.

This project aims at providing a fully operative service to users interested in reaching desired training performances with the help of properly selected music tracks. The novelty of the proposed solution consists in an adaption of individual physiologic characteristics to provide an always updated and fully personalized experience that continuously keeps track of cardiac responses to external audio stimulus.

After a preliminary evaluation of results achieved by administrating different audio tracks to a trainers' sample, an improved solution based on artificial intelligence and regression analysis was developed for adapting the support service with individuals' performance and cardiac responses. This approach provided nearly acceptable outcomes that could justify, only for a first prototypical stage, the choice of a linear model and regressors subset to describe and predict the future heart rate evolution in future time instants. Anyway, a deeper study, involving a large set of people, about the effectiveness of the developed system is strongly suggested. Many other aspects, such as quickness in reaching the final target, need to be assessed and properly managed.

As a general observation about the achieved results, due to the experimental nature of this project and its implementation, the proposed solution and methodology may be not suited to fulfill the fixed objective with a satisfying reliability. A wider analysis, which includes several resolution alternatives (bio-feedback controllers, non-linear machine learning models, more complex system architecture ...), is then needed to find the option that best fits with the faced problem typology.

A first version of the implemented software has been released in the Google Play Store, under the name of **Music Training System**, in order to analyze the impact of such system within the interested users' context. This Android application is available for a free download by any interested user that desires to try the training support system. Particular attention was devoted to verify the compatibility of the heart rate monitors with the provided Android application, to estimate a future release plan and compatibility concerns for interfacing the system towards a more generic and wider set of use case scenarios.

Given the interest aroused among a wide trainer audience, and a quite satisfactory number of downloads of the first version of the application, the final designed system will be subject to a packaging process aimed at building a deliverable solution for a wider set of interested people. By applying a release pipeline in the design of the application, a prototypical version of the analyzed and implemented system will be created and then released on the Google Play Store. The main purposes of the released app will be:

- Collecting feedback from final users that experience the service and may provide useful information about possible improvements of the visual appearance of the application and replies about their training performance results;

- Validating outcomes deriving from the data analysis on the basis of the core decision process. The analysis on collected results may provide valid hints in order to proceed with confirming the used approach, or to lead towards new possible alternatives;

- Increasing the number of training data, which represent the major driver in enhancing learning techniques performance in predicting future heart beat values and properly describing the relationship between the cardiac signal and specific songs application;

- Understanding the benefits and utilization ways of the application to improve skills and physical performance of athletes and sport teams: a future development of Music Training System could be devoted at enlarging the field of interest towards competitors and professional contexts.

Referring to the last aspect, a real test process will be performed with Dinamo Sassari basketball team, whose player will be asked to use Music Training System to evaluate performance boosts while playing training sessions. The field tests of the application with a highly performing team, as well as innovative solution promoting, will help the spread of the system and future improvements of the support service.

Finally, many possible design choices and alternative technological solutions could be adopted in future so as to enhance the support tool performance in leading the heart rate towards the desired target values. For instance, many systems on the market already propose complex solutions that include movement analysis, breath and strides detection, to build a complicate model that tries to merge those factors that can be observed during a training exercise.

Another possible use case in which the devised system could be really useful refers to the extension of such system for ill people suffering from heart diseases or presenting some particular characteristics related to their cardiac activity (bradycardia or tachycardia). Understanding how a session suited for healthy people can be applied, with proper adjustments, for ill people, could represent a very interesting application for safely providing a service which tries to optimize performance while respecting physiological limitations.

A deeper analysis of the above mentioned solutions and related outcomes can result in the starting point for making Music Training System a complete and fully functional service that exploits a rich synergy among all the components involved in the trainers' physical activities.

Bibliography

[1] T. Baumgartner et al. "The emotional power of music: how music enhances the feeling of affective pictures." In: *Brain Res* 1075 (2006), pp. 151–164.

[2] T. Baumgartner, M. Esslen, and L. Jancke. "From emotion perception to emotion experience: Emotions evoked by pictures and classical music." In: *Int J Psychophysiol* 60 (2006), pp. 34–43.

[3] S. Koelsch. "Brain correlates of music-evoked emotions." In: *Nat Rev Neurosci* 15 (2014), pp. 170–180.

[4] S. Koelsch and S. Skouras. "Functional centrality of amygdala, striatum and hypothalamus in a 'small-world' network underlying joy: an fMRI study with music." In: *Hum Brain Mapp* 35 (2014), pp. 3485–3498.

[5] J.A. Armour and J.L. Ardell. "Basic and Clinical Neurocardiology." In: *USA: Oxford University Press* (2004).

[6] N.L. Wallin et al. "The origins of music." In: *Cambridge, Mass.: MIT Press. Press* (2000).

[7] A.D. Patel et al. "Experimental evidence for synchronization to a musical beat in a nonhuman animal." In: *Current Biology* 19(10) (2009), pp. 827–830. DOI: 10.1016/j.cub.2009.03.038.

[8] A.D. Patel and J.R. Iversen. "The evolutionary neuroscience of musical beat perception: the Action Simulation for Auditory Prediction (ASAP) hypothesis." In: *Front Syst Neurosci* 8(57) (2014). DOI: doi:10.3389/fnsys.2014.00057.

[9] Bjålie et al. “Menneskekroppen Fysiologi og anatomi (2 ed.)” In: *Oslo: Universitetsforlaget AS.* (1999). DOI: doi:10.3389/fnsys.2014.00057.

[10] L. Bernardi, C. Porta, and P. Sleight. “Cardiovascular, cerebrovascular, and respiratory changes induced by different types of music in musicians and non-musicians: the importance of silence.” In: *Heart* 92 (2006), pp. 445–452.

[11] P. Gomez and B. Danuser. “Relationships between musical structure and psychophysiological measures of emotion.” In: *Emotion* 7 (2007), pp. 377–387.

[12] M. Atluri. “Does Music Affect Blood Pressure and Heart Rate?” In: *California State science fair* J1103 (2008).

[13] M. Iwanaga. “Relationship between heart rate and preference for tempo of music.” In: *Perceptual and motor skills* 81(2) (1995), pp. 435–440.

[14] W. Knight and N. Rickard. “Relaxing music prevents stress-induced increases in subjective anxiety, systolic blood pressure, and heart rate in healthy males and females.” In: *Journal of Music Therapy* 38(4) (2001), pp. 254–272.

[15] V. Steelman. “Relaxing to the beat: music therapy in perioperative nursing.” In: *Today’s OR nurse* 13(7) (1991), p. 18.

[16] J. White and C. Shaw. “Music therapy: a means of reducing anxiety in the myocardial infarction patient.” In: *Wisconsin medical journal* 90(7) (1991), pp. 434–437.

[17] V. Stratton and A. Zalanowski. “The relationship between music, degree of liking, and self-reported relaxation.” In: *Journal of Music Therapy* 21(4) (1984), pp. 184–192.

[18] S. Nirjon and al. “MusicalHeart: A hearty way of listening to music.” In: *Proc. 10th ACM Conf.Embedded Netw. Sensor Syst.* (2012), pp. 43–56.

[19] C.P. Hoffmann, G. Torregrosa, and B.G. Bardy. “Sound stabilizes locomotor-respiratory coupling and reduces energy cost.” In: *PloS One* 7.9 (2012).

[20] W.J. McDermott, R.E. van Emmerik, and J. Hamill. “Running training and adaptive strategies of locomotor-respiratory coordination.” In: *Eur. J. Appl. Physiology* 89.5 (2003), pp. 435–444.

[21] L. Harmat, J. Takacs, and R. R. Bodizs. "Music improves sleep quality in students." In: *J. Adv. Nursing* 62.3 (2008), pp. 327–335.

[22] N. N. Jausovec, K. Jausovec, and I. Gerlic. "The influence of Mozart's music on brain activity in the process of learning." In: *Clinical Neurophysiology* 117.12 (2006), pp. 2703–2714.

[23] G. Bernatzky et al. "Stimulating music increases motor coordination in patients afflicted with Morbus Parkinson." In: *Neuroscience Lett.* 361.1 (2004), pp. 4–8.

[24] N. Oliver and F. Flores-Mangas. "MPTrain: A mobile, music and physiology-based personal trainer." In: *Proc. 8th Conf. Human- Comput. Interaction Mobile Devices Services* (2006), pp. 21–28.

[25] J. Escher and D. Evequoz. "Music and heart rate variability. Study of the effect of music on heart rate variability in healthy adolescents." In: *Praxis* 88.21 (1999), pp. 951–952.

[26] L. Zhang, F. Liu, and J. Tang. "Real-time system for driver fatigue detection by RGB-D camera." In: *ACM Trans. Intell. Syst. Technol.* 6.2 (2015).

[27] M. Sumida, T. Mizumoto, and K. Yasumoto. "Estimating heart rate variation during walking with smartphone." In: *Proc. ACM Int. Joint Conf. Pervasive Ubiquitous Comput.* (2013), pp. 245–254.

[28] A. Zhan et al. "Accurate caloric expenditure of bicyclists using cellphones." In: *Proc. 10th ACM Conf. Embedded Netw. Sensor Syst.* (2012), pp. 71–84.

[29] J. C. Platt et al. "Learning a Gaussian process prior for automatically generating music playlists." In: *Proc. 14th Int. Conf. Neural Inf. Process. Syst. Natural Synthetic* (2001), pp. 1425–1432.

[30] A. Flexer et al. "Playlist generation using start and end songs." In: *Proc. Int. Symp. Music Inf. Retrieval* (2008), pp. 173–178.

[31] X. Zhu et al. "An integrated music recommendation system." In: *IEEE Trans. Consum. Electron.* 52.3 (2006), pp. 917–925.

[32] J. Sang, T. Mei, and C. Xu. “Activity sensor: Check-in usage mining for local recommendation.” In: *ACM Trans. Intell. Syst. Technol.* 6.3 (2015).

[33] N. H. Liu, S. J. Hsieh, and C. F. Tsai. “An intelligent music playlist generator based on the time parameter with artificial neural networks.” In: *Expert Syst. Appl.* 37.4 (2010), pp. 2815–2825.

[34] N. Oliver and L. Kreger-Stickles. “PAPA: Physiology and purpose- aware automatic playlist generation.” In: *Proc. 7th Int. Conf. Music Inf.* (2006), pp. 250–253.

[35] R. De Oliveira and N. Oliver. “TripleBeat: Enhancing exercise performance with persuasion.” In: *Proc. 10th Int. Conf. Human Comput. Interaction Mobile Devices Services* (2008), pp. 255–264.

[36] F. Gu et al. “RunnerPal: A Runner Monitoring and Advisory System Based on Smart Devices.” In: *IEEE Transactions on services computing* 11.2 (2018), pp. 262–276.

[37] J. Six, O. Cornelis, and M. Leman. “TarsosDSP, a Real-Time Audio Processing Framework in Java.” In: *AES 53RD International Conference* (2014).