Politecnico di Torino

1859

Master Thesis Presentation

- Yang Haifeng
- Localization and identification of people in closed spaces with low-power and low-cost environmental and wearable sensors

Introduction

- Identify the person in a closed room by testing vital signs.
  - ✓ Weak chest motion
  - ✓ Motion artifacts & ambient IR noise
  - ✓ Low SNR & embedded processing limits
- Goal: Design a low-cost, TOF-based RR monitoring system.

Objectives

- Build hardware with STM32 + VL53L7CX.
- Apply Pearson correlation & trend cancellation for noise reduction.
- Implement AR-model PSD for frequency estimation.
- Compare AR vs FFT performance.

Background & Literature Review

- Key algorithms: Least Squares, Kalman Filter, PCA, Adaptive Filter.
- Kalman Filter: efficient for dynamic tracking but excessive for respiratory rate.
- PCA: useful for noise reduction.
- AR model: high frequency resolution with short data.

State of the Art Comparison

Sensor Comparison:

- TOF (IR): precise, privacy-safe but sensitive to IR noise.
- mmWave Radar: long range, high cost.
- Ultrasonic: cheap, low precision.
- TOF selected for compactness and low power consumption.

Innovative Gap

- Combine TOF sensing + AR parametric spectral modeling.
- Frequency resolution: $\Delta f \propto 1 / (p \times SNR)$.
- Analytical and efficient for embedded devices.

Methodology – System Setup

- Hardware: STM32 + VL53L7CX (8×8, 15 fps).
- Software: Python & Numpy for data acquisition and processing.
- Calibration: offset, crosstalk, SPAD normalization.
- Pipeline:

➢ Spatial Denoise (Pearson)

➢ Trend Cancellation (Least Squares)

➢ AR-based PSD

➢ SNR Evaluation

Key Algorithms

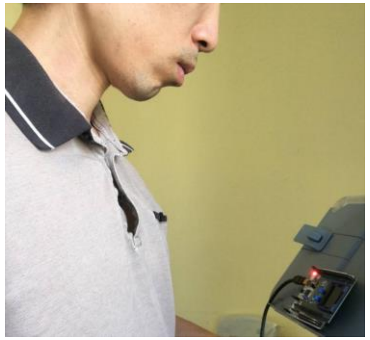
- Pearson Correlation ($\rho > 0.7$) selects reliable pixels.
  Linear fitting removes low-frequency trend.
- AR model PSD:
  $P(f) = \sigma^2 / |1 - \Sigma\ \varphi_k\ e\text{^}(-j2\pi fk)|^2$
- Burg method for stable AR coefficient estimation.

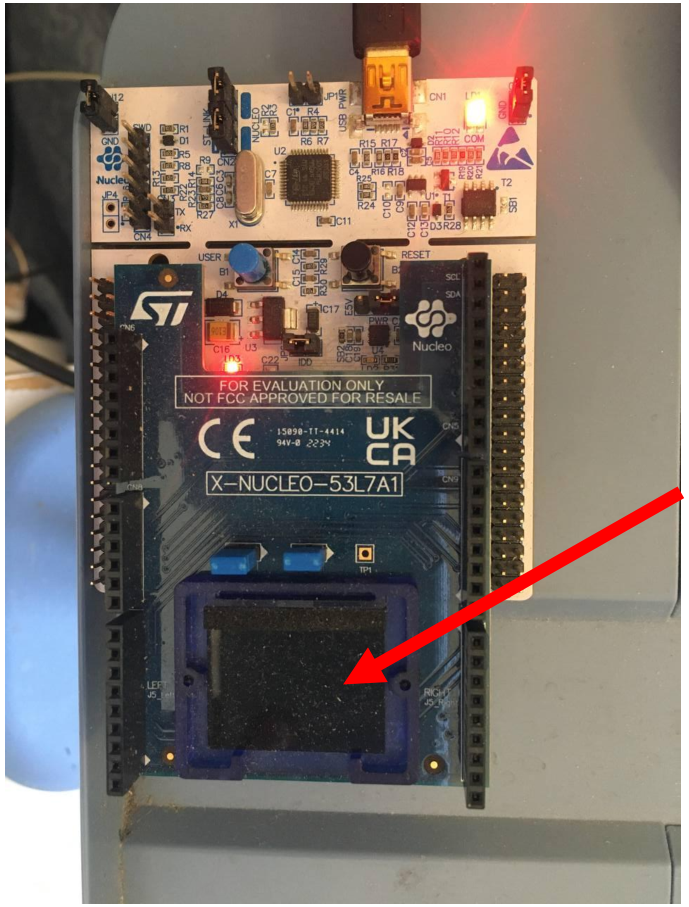
Experimental Results

- 15 FPS, ~12 breathing cycles recorded.
- Compared AR vs FFT at 20 cm, 25 cm.

Results:

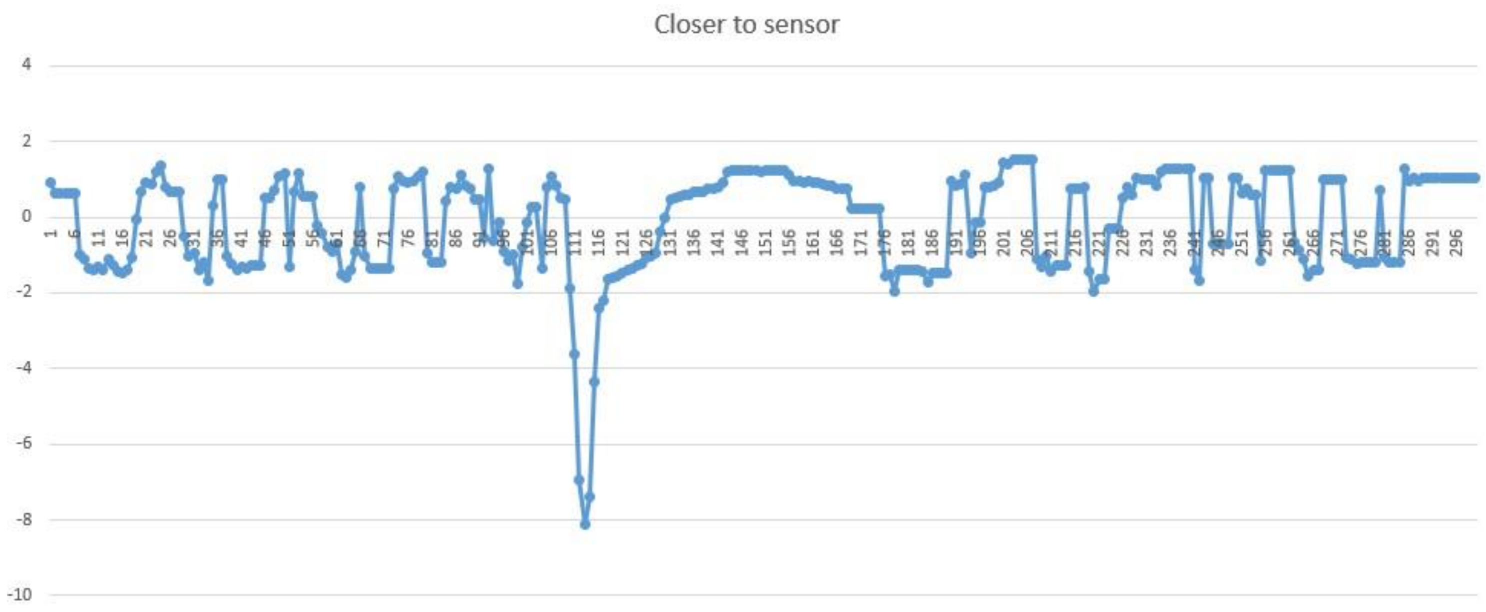
- AR → higher frequency resolution.
- FFT → broader peaks, poor distinction (15 vs 20 BPM).
- AR(32) outperforms AR(20).





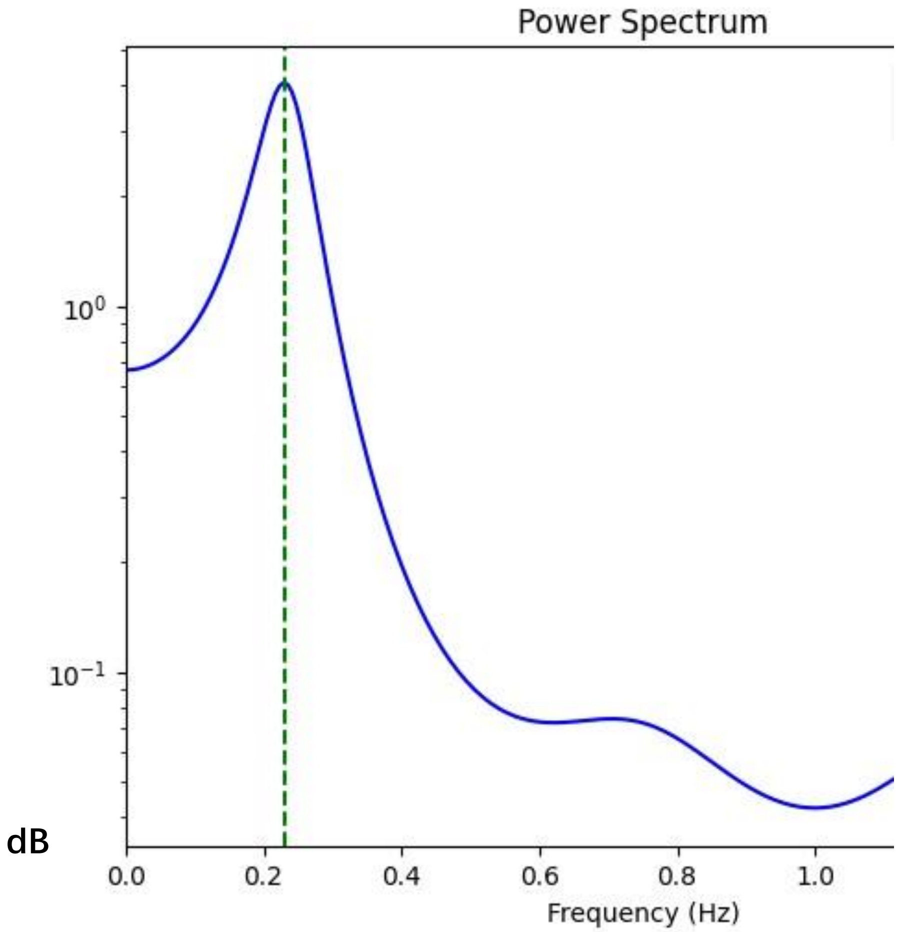
optical filter

Spatial detrend

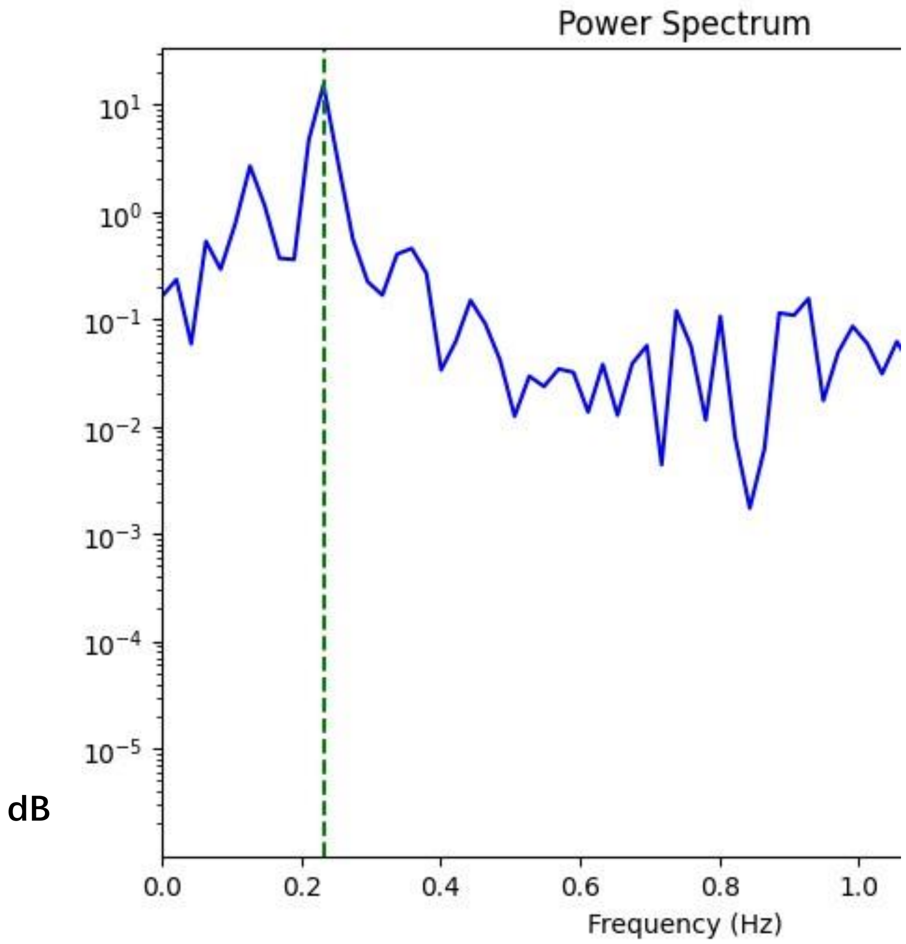


- breathing itself or the body leaning towards the sensor.
- testing whether the zero point is absent or present after one period of time.
- sample points 116 to 186, the system cannot tell the true breathing rate.
- after point 186, a new zero point is detected, and the system can detect the normal breath again.

Time series analysis



PSD of AR method



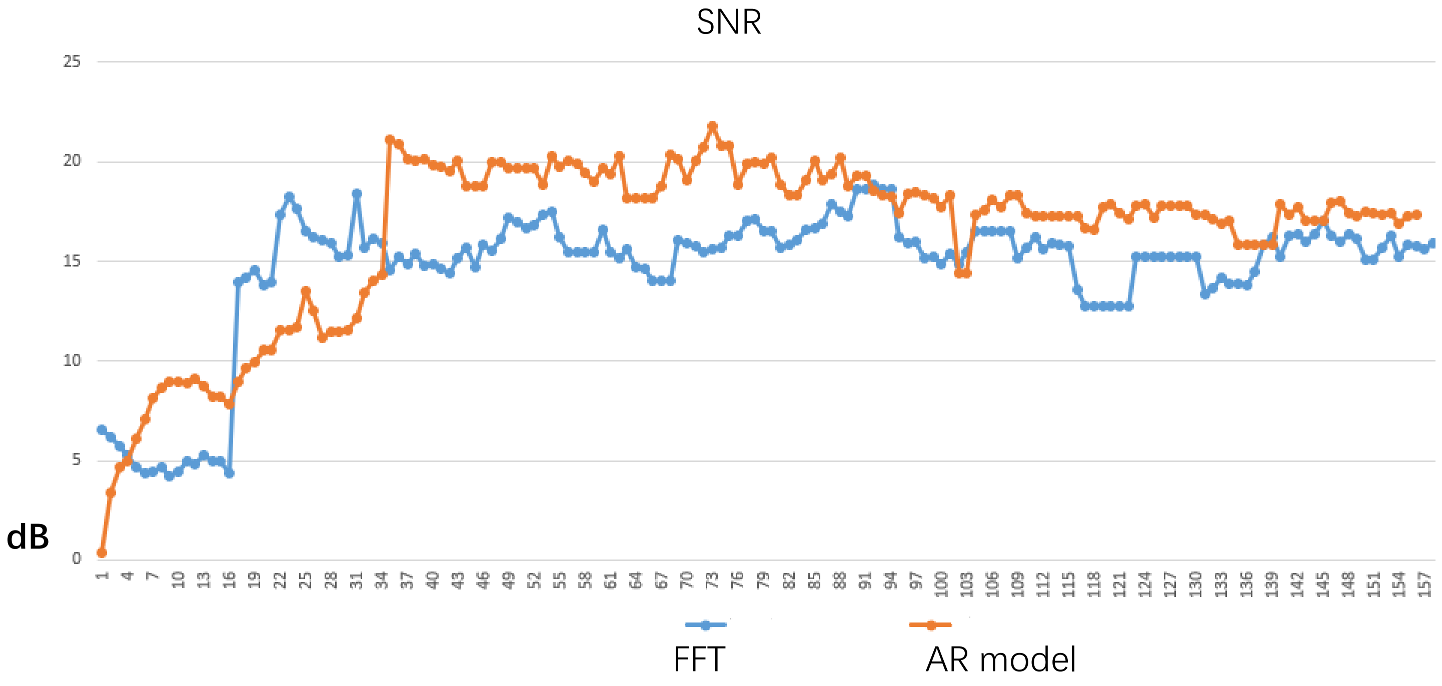
PSD of FFT method

- The AR model PSD has no sidelobes and is smooth
- The FFT method with side lobes and the power density is obviously fluctuating

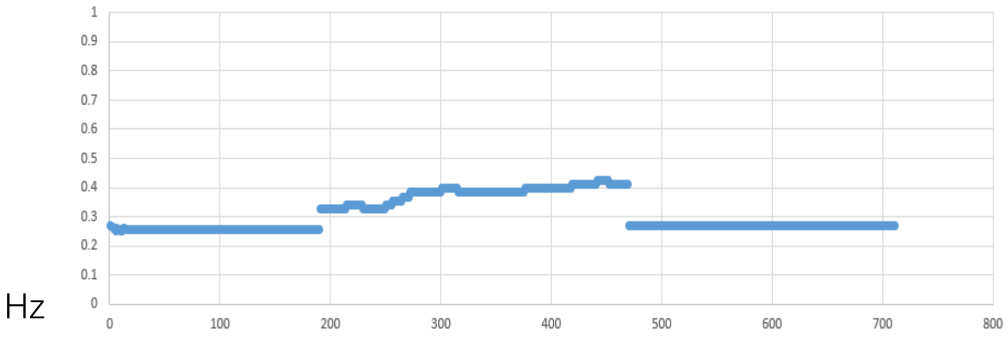
$$\mathrm{SNR_{dB}} = 10\log_{10}\left(\frac{P_s}{P_n}\right)$$

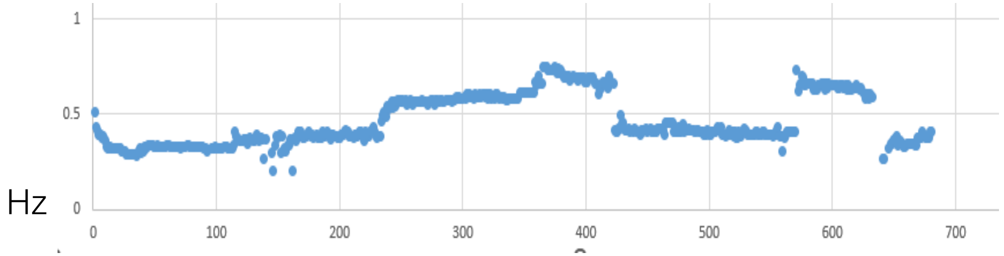
$$P_s = \int_{f_0-\frac{B}{2}}^{f_0+\frac{B}{2}} S(f)df$$

B is the signal bandwidth (here I use 0.2 Hz)



- In the beginning, the AR model's SNR is lower than the FFT’s.
- The AR model requires certain samples to initialize.
- However, after that, the SNR curve of the AR model surpasses the FFT, and almost always remains in a high position at a single point.





The respiration frequency oscillated from 0.2 Hz to 0.8 Hz, and the AR model frequency resolution is higher than the model of the FFT output.

- AR model
  - Parametric spectrum density analysis has the advantage of high-resolution frequency compared to the FFT method.
  - $$P(f) = \frac{\sigma^2}{\left|1 - \sum_{k=1}^{p} \phi_k e^{-j2\pi f k}\right|^2}$$
  - Burg method
- ESPRIT(Estimation of signal parameters via rotational invariance technique)
  - Obtaining the eigen data of an autocorrelation matrix, then finding the principal frequency in the spectrum [1, 2].
  - Subspace-based methods for estimating frequency.
  - The number of signal sources also needs to be indicated.
  - Does not provide pseudo-spectrum.

[1] J. G. Proakis and D. G. Manolakis, Digital Signal Processing: Principles,Algorithms, and Applications, 3rd ed. Upper Saddle River, NJ: Prentice Hall,1996.
[2] T. Katayama, Subspace Methods for System Identification, ser.Communications and Control Engineering. Springer-Verlag London,2005.

Detail for the AR model

Assume time series data $X_1, X_2, ..., X_T$. First compute the mean:

$$\overline{X} = \frac{1}{T}\sum_{t=1}^{T} X_t$$

Estimate the σ^2 of white noise w_t: AR(p) defined as:

$$X_t = w_t + \phi_1 X_{t-1} + \cdots + \phi_p X_{t-p}$$

w_t is white noise, mean 0, square deviation is σ^2.
through autocovariance:

$$k_x(0) = \sigma^2 + \phi_1 k_x(1) + \cdots + \phi_p k_x(p)$$

Such that:

$$\sigma^2 = k_x(0) - \sum_{i=1}^{p} \phi_i k_x(i)$$

Where $k_x(h)$ is lag h autocovariant deviation(i.e, $k_x(h) = \text{Cov}(X_t, X_{t+h})$. In the signal analysis domain, the covariance is noted as k.

Detail for the AR model

Estimate the parameter ϕs [1]

Compute the expectation of X_{t-1} and X_t:

$$E[X_{t-1}X_t] = E[x_{t-1}(w_t + \phi_1 X_{t-1} + ... + \phi_p X_{t-p})]$$

Yule-Walker equation:

$$\begin{aligned}
k_x(1) &= \phi_1 k_x(0) + \phi_2 k_x(1) + \cdots + \phi_p k_x(p-1) \\
k_x(2) &= \phi_1 k_x(1) + \phi_2 k_x(0) + \cdots + \phi_p k_x(p-2) \\
&\vdots \\
k_x(p) &= \phi_1 k_x(p-1) + \phi_2 k_x(p-2) + \cdots + \phi_p k_x(0)
\end{aligned}$$

In matrix form

$$\mathbf{K} = \mathbf{\Gamma}\boldsymbol{\phi}$$

Where: $\mathbf{K} = \begin{pmatrix} k_x(1) \\ k_x(2) \\ \vdots \\ k_x(p) \end{pmatrix}$ auto covariant, vector $\boldsymbol{\phi} = \begin{pmatrix} \phi_1 \\ \phi_2 \\ \vdots \\ \phi_p \end{pmatrix}$ parameters to to estimate.

$\mathbf{\Gamma} = \begin{pmatrix} k_x(0) & k_x(1) & \cdots & k_x(p-1) \\ k_x(1) & k_x(0) & \cdots & k_x(p-2) \\ \vdots & \vdots & \ddots & \vdots \\ k_x(p-1) & k_x(p-2) & \cdots & k_x(0) \end{pmatrix}$ is Toeplitz matrix.

Linear algebra solution:

$$\hat{\boldsymbol{\phi}} = \hat{\mathbf{\Gamma}}^{-1}\hat{\mathbf{K}}$$

Plug in the parameter to the following equation to obtain the PSD:

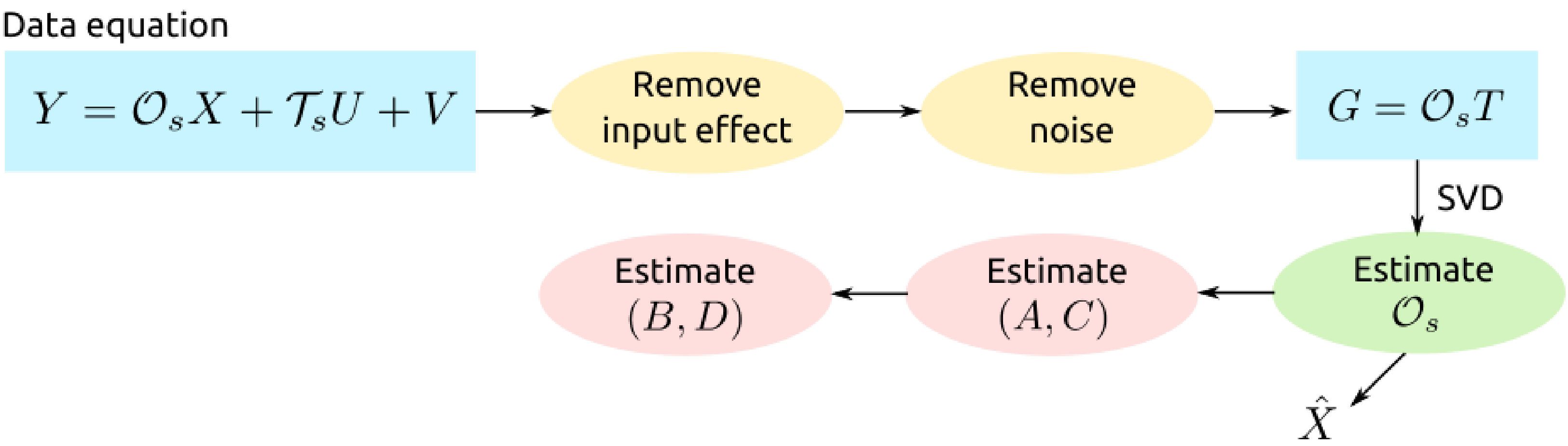
$$P(f) = \frac{\sigma^2}{|1 - \sum_{k=1}^{p} \phi_k e^{-j2\pi fk}|^2}$$

[1]
S. V. Vaseghi, Advanced Digital Signal Processing and Noise Reduction,2nd ed. Chichester, UK: John Wiley & Sons, 2000. Chapter 9
J. G. Proakis and D. G. Manolakis, Digital Signal Processing: Principles,Algorithms, and Applications, 3rd ed. Upper Saddle River, NJ: Prentice Hall,1996. (chapter 11 page 856-857,Chapter 12)

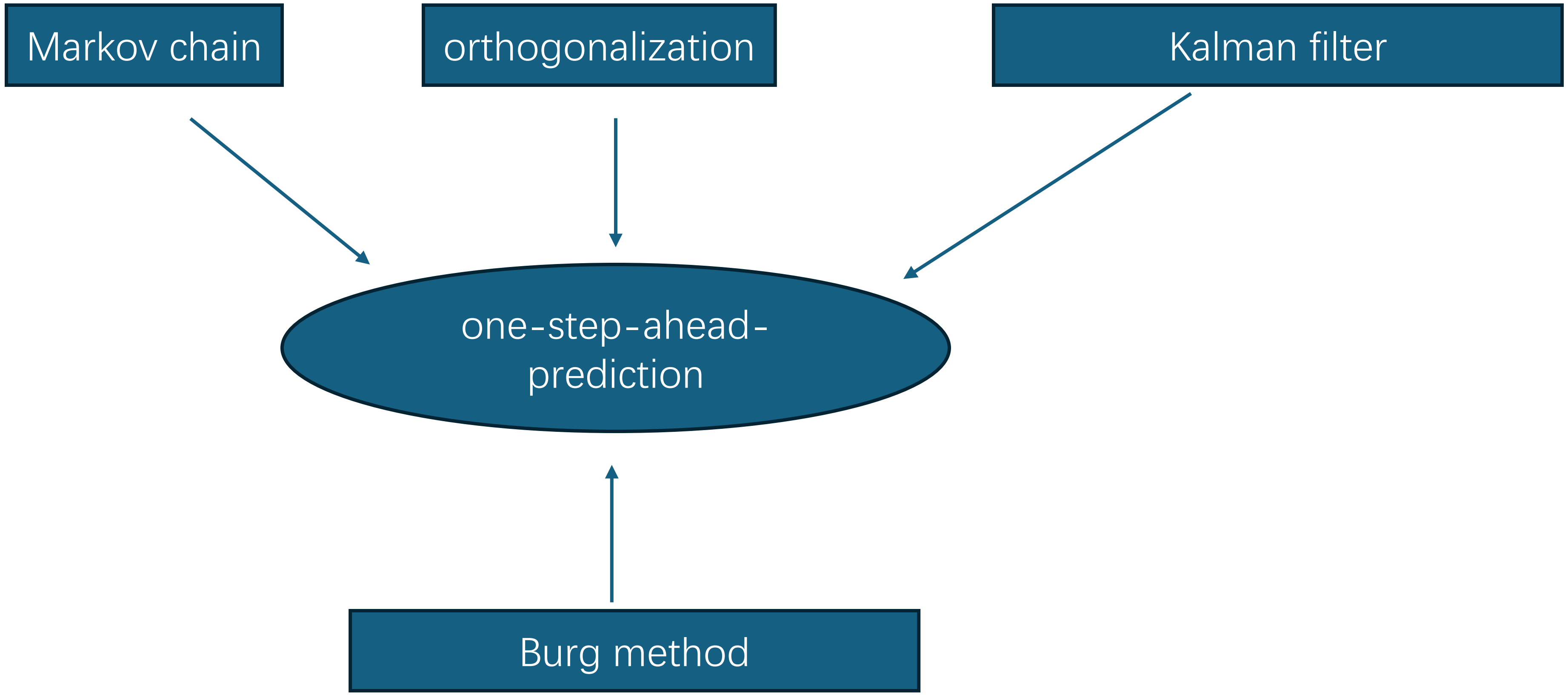
State Space Systems

$$x(t+1) = Ax(t) + Bu(t) + w(t)$$
$$y(t) = Cx(t) + Du(t) + v(t)$$

u(t) is sensor noise
v(t) is process noise



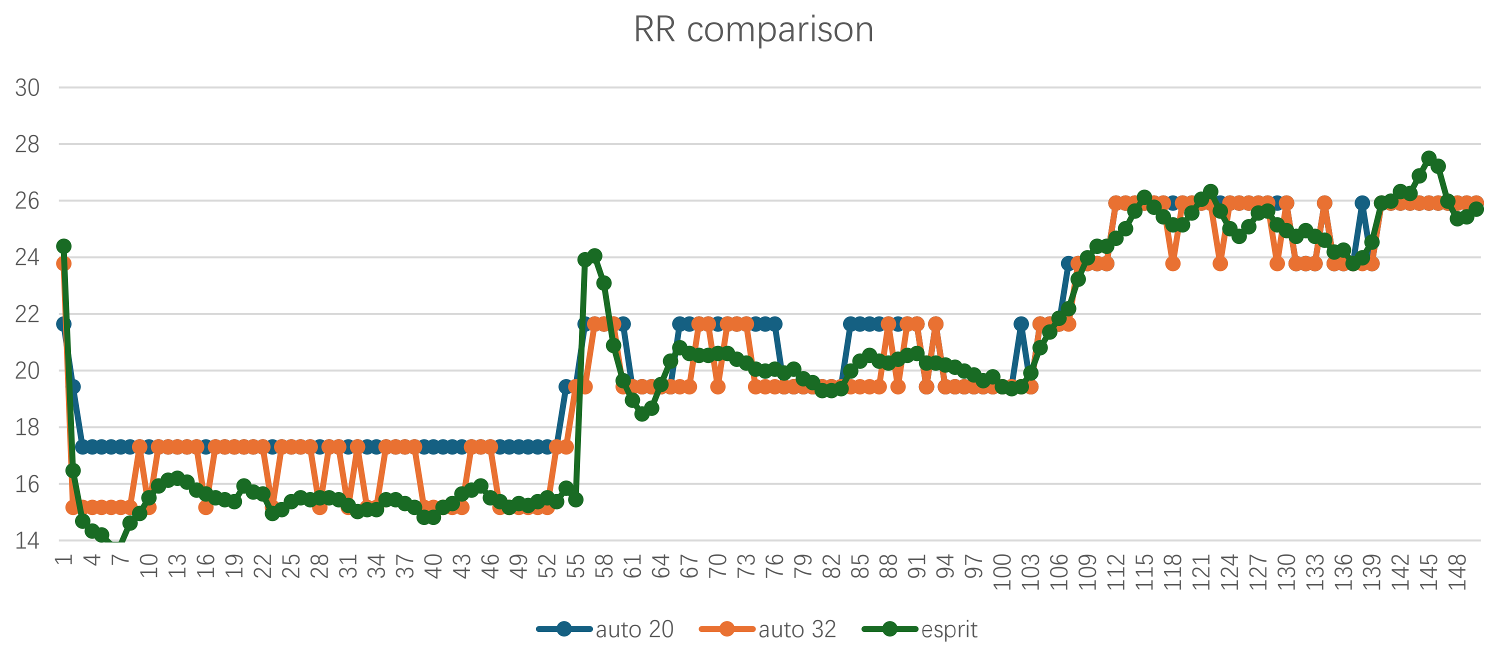
Prof. Jitkomut Songsiri(System identification) Department of Electrical Engineering, Chula Engineering, Thailand. https://www.youtube.com/watch?v=pqqI_ntPP0o


Markov chain
orthogonalization
Kalman filter
one-step-ahead-prediction
Burg method

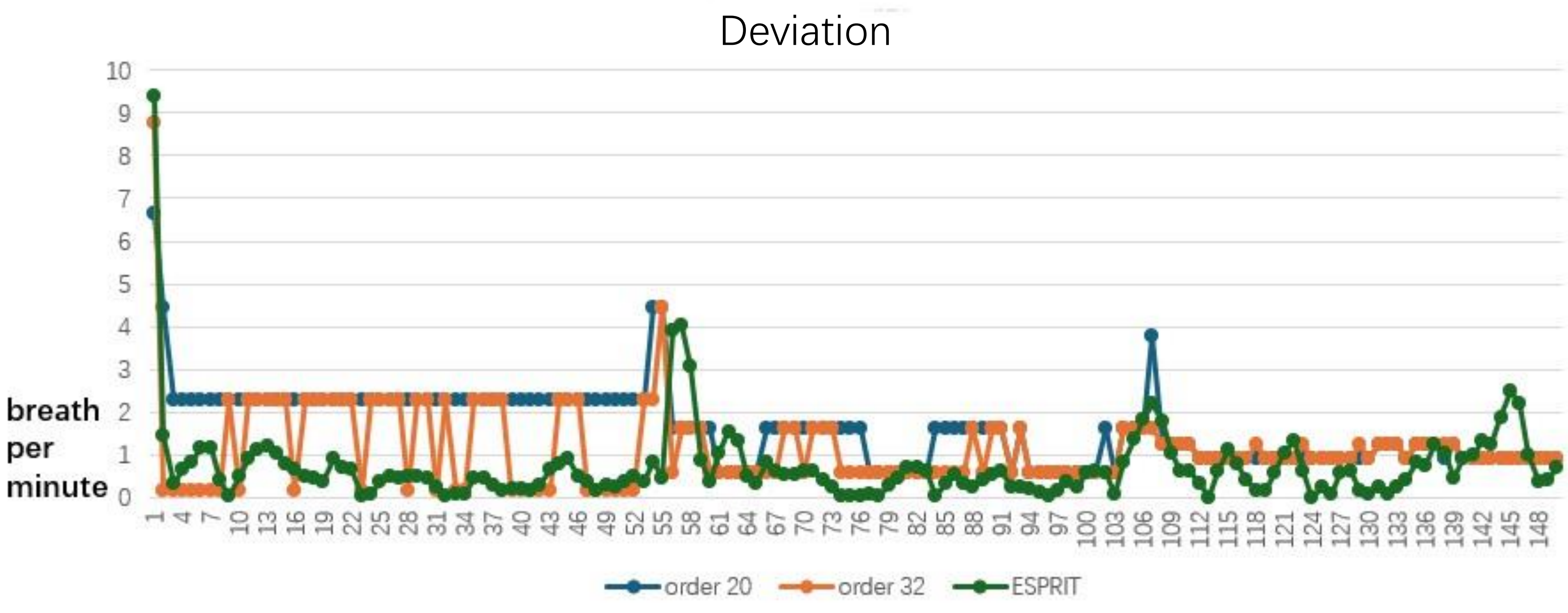
Metronome method

```
phase 1: 15 BPM
0s    < Inhale
0s  > Exhale
4s    < Inhale
4s  > Exhale
8s    < Inhale
8s  > Exhale
```

- Estimate the deviation of the respiratory rate provided by the measurement system.
- Examines our design, which we chose a metronome method.
- Variants from 15 BMP, 20 BMP, 25 BMP.
- Synchronization pace is given via terminal printing for indication of inhalation and exhalation.
- Each phase of RR endures for 2 minutes.

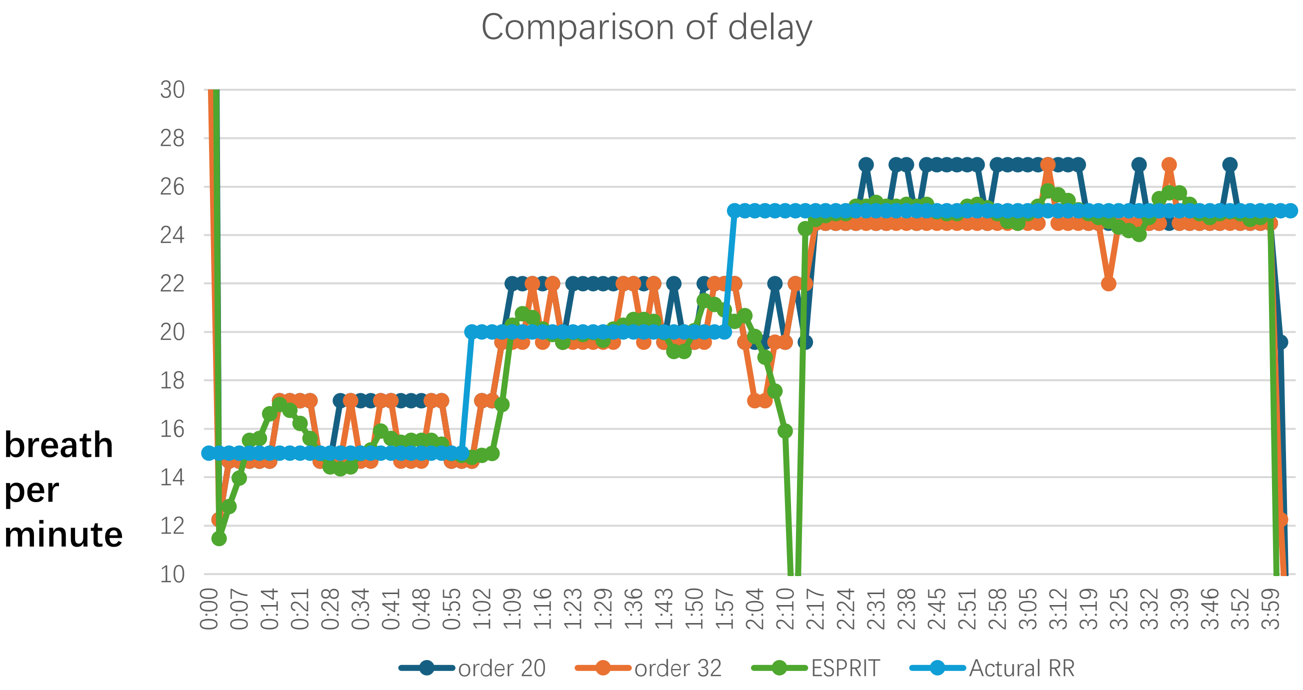


- Setting the sensor in front of the chest wall at a distance of 17cm.



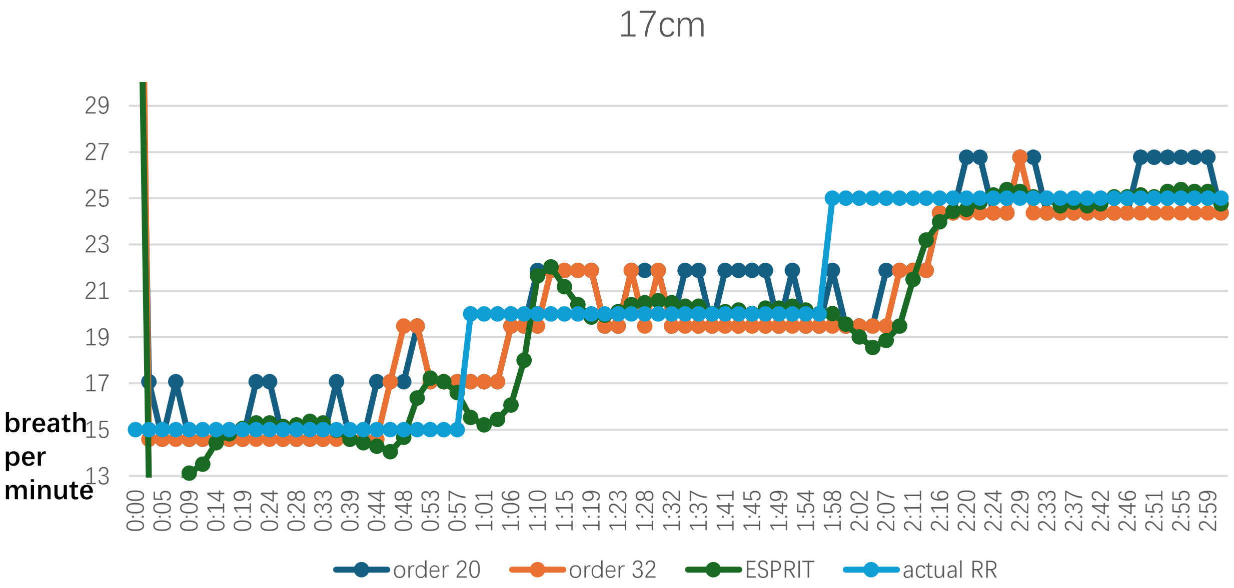
	Order 20	Order 32	ESPRIT
deviation	1.62107	1.14588	0.704715

- The ESPRIT method has the fewest deviation, up to 0.7 BMP.
- The Burg method with 20 order errors is 1.6 BMP, while 32 orders is 1.1 BMP.



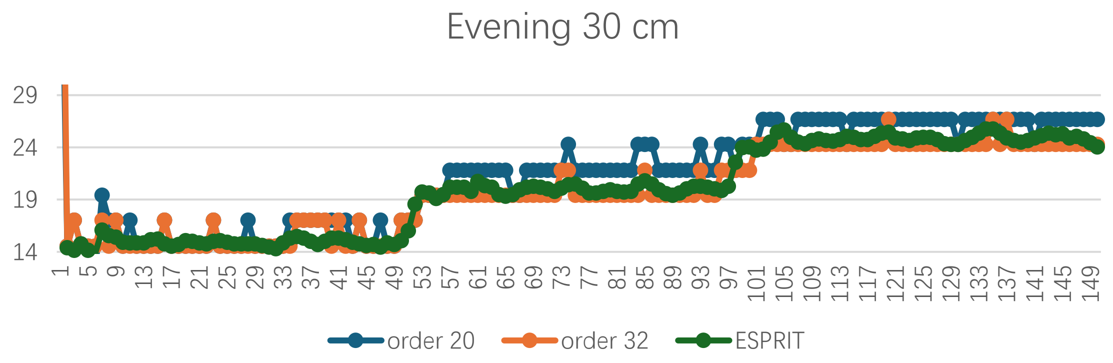
Model	order 20	order 32	ESPRIT
15 bmp	5 s	5 s	7 s
20 bmp	9 s	6 s	9 s
25 bmp	18 s	18 s	16 s
Absolute error	2.5 bmp	1.6 bmp	2.1 bmp

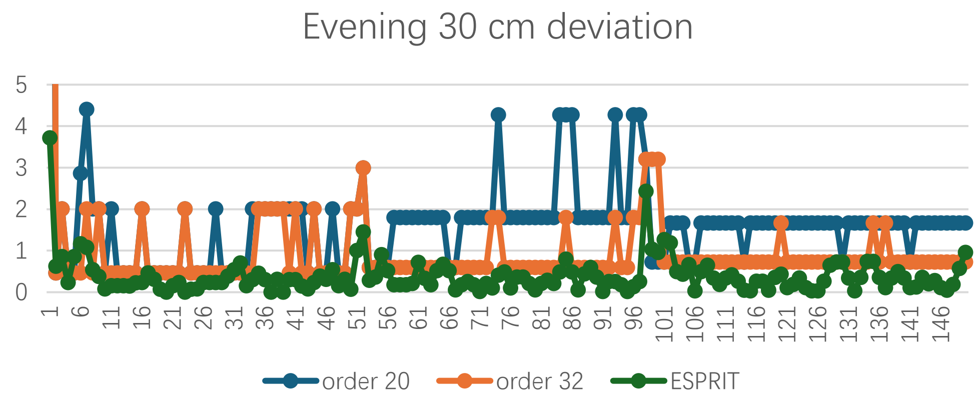
- Record the timestamp and the switching point.
- The average distance is 31cm, and each phase endured for 60 seconds.



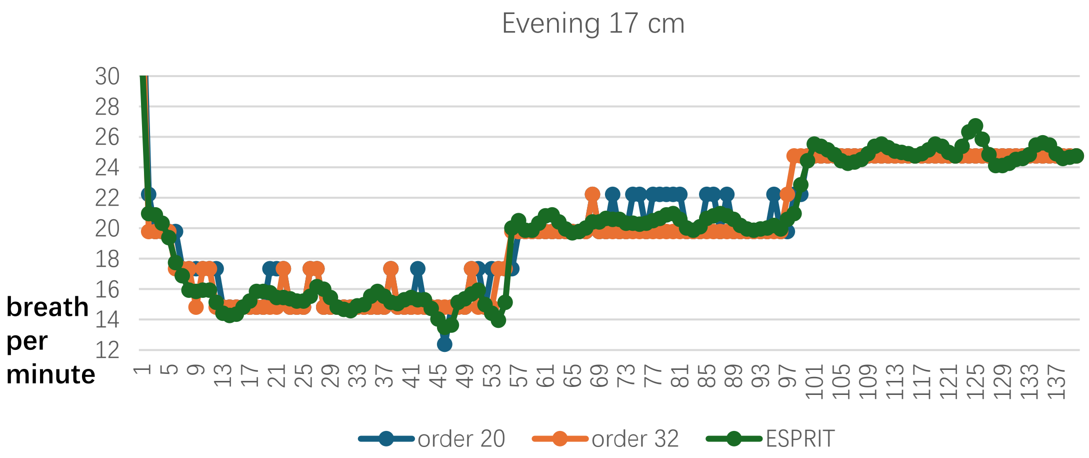
	20th order	32th order	ESPRIT
Absolute error(bmp)	2.013015	1.824439	1.633171

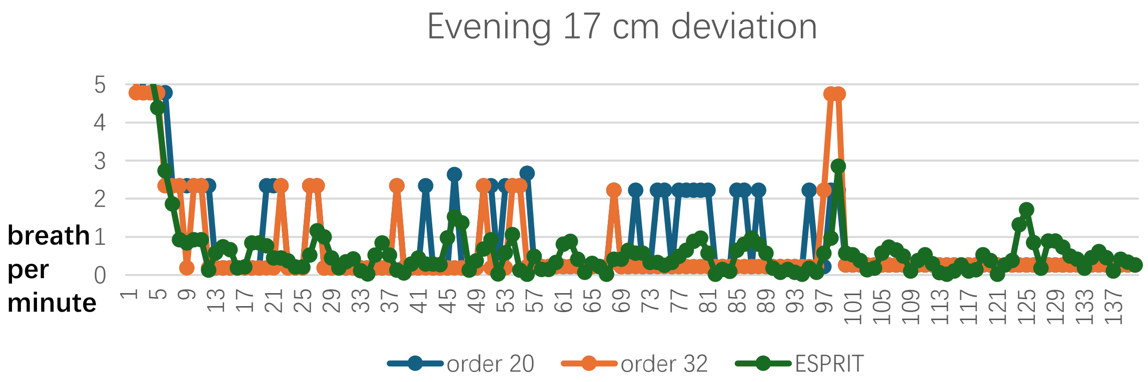
Test in the evening

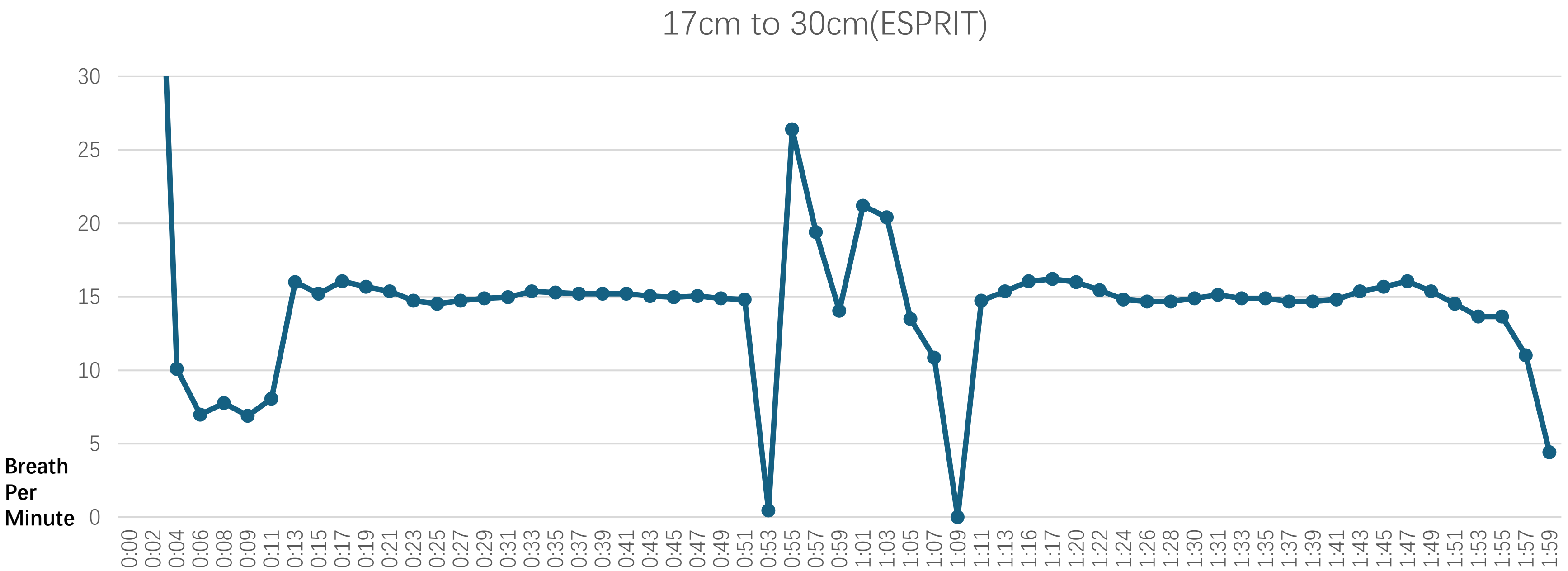




	order 20	order 32	ESPRIT
deviation(BPM)	1.84	1.24	0.39

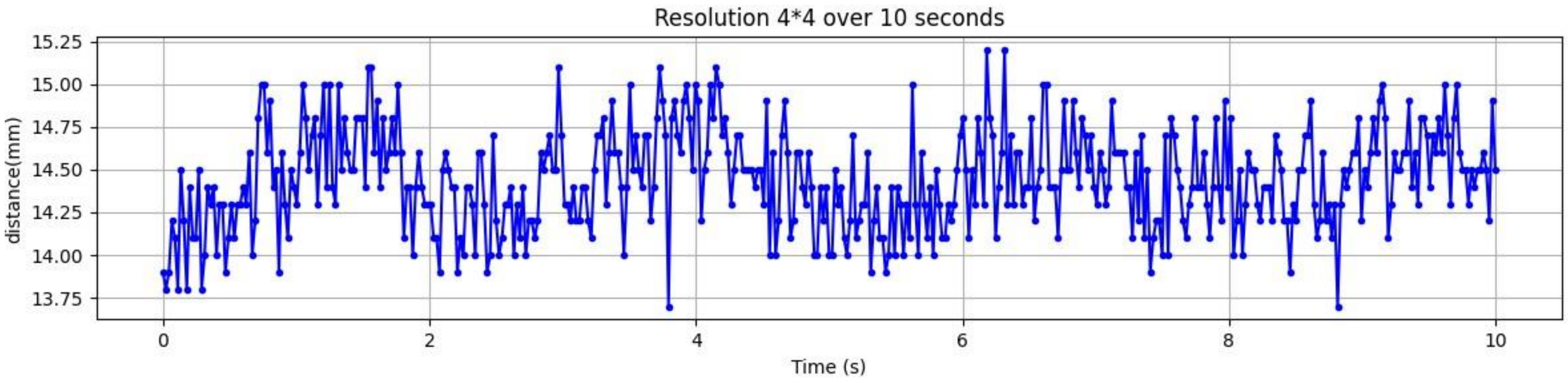

Evening 17 cm
breath per minute
order 20
order 32
ESPRIT

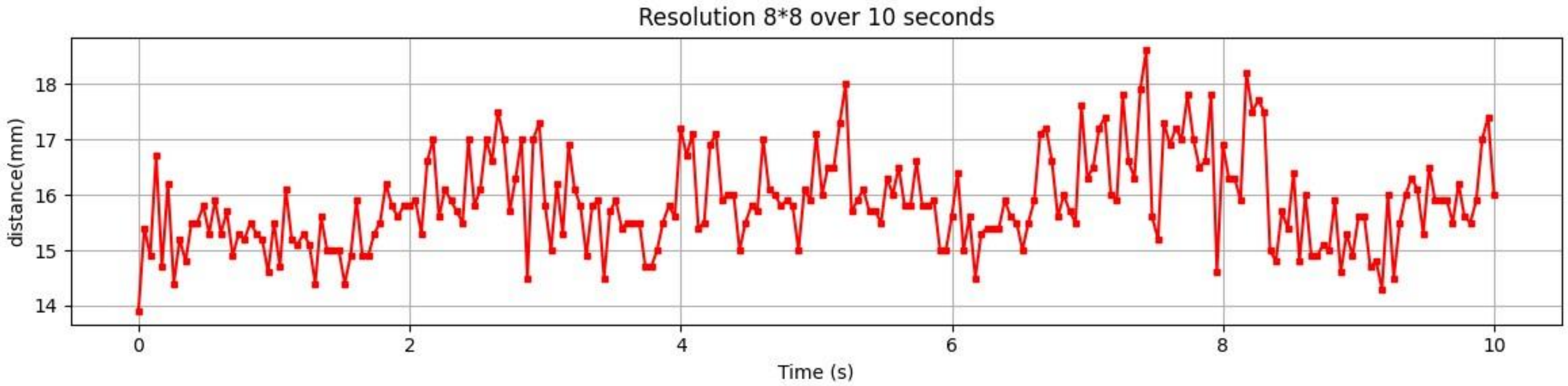

Evening 17 cm deviation
breath per minute
order 20
order 32
ESPRIT

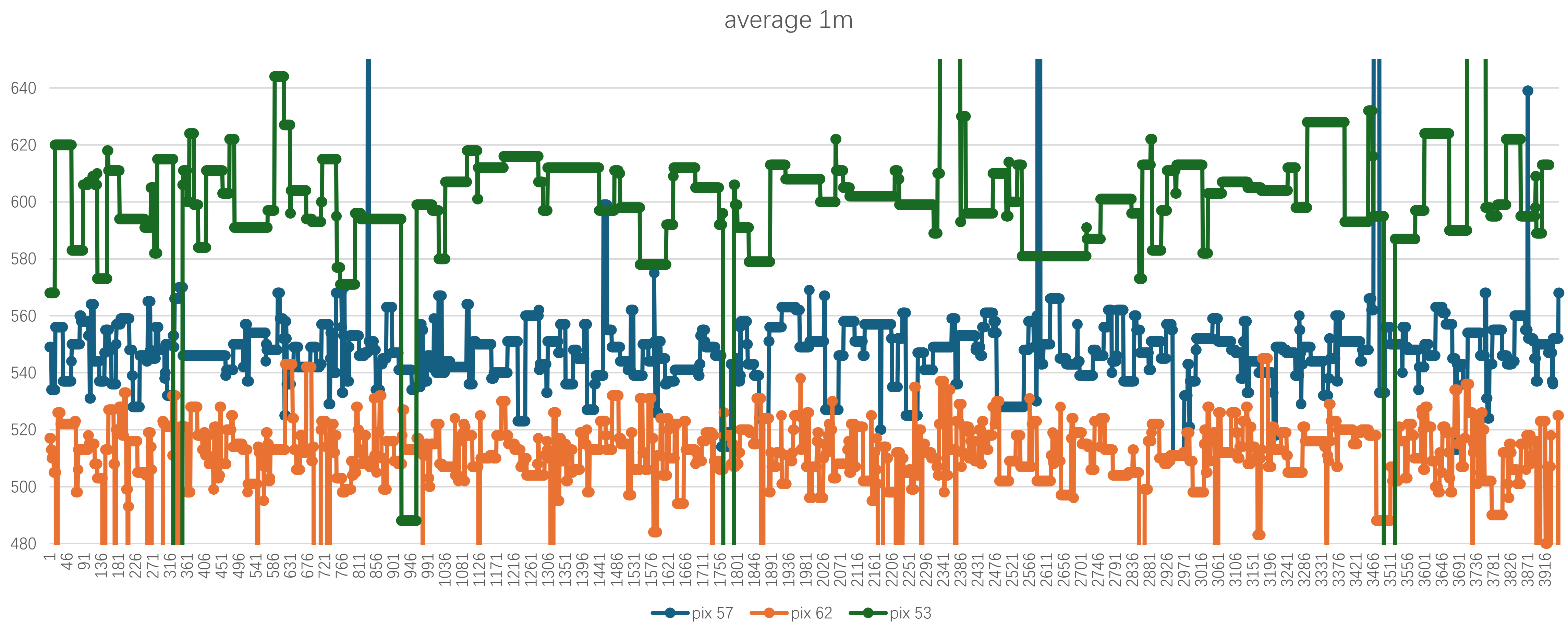


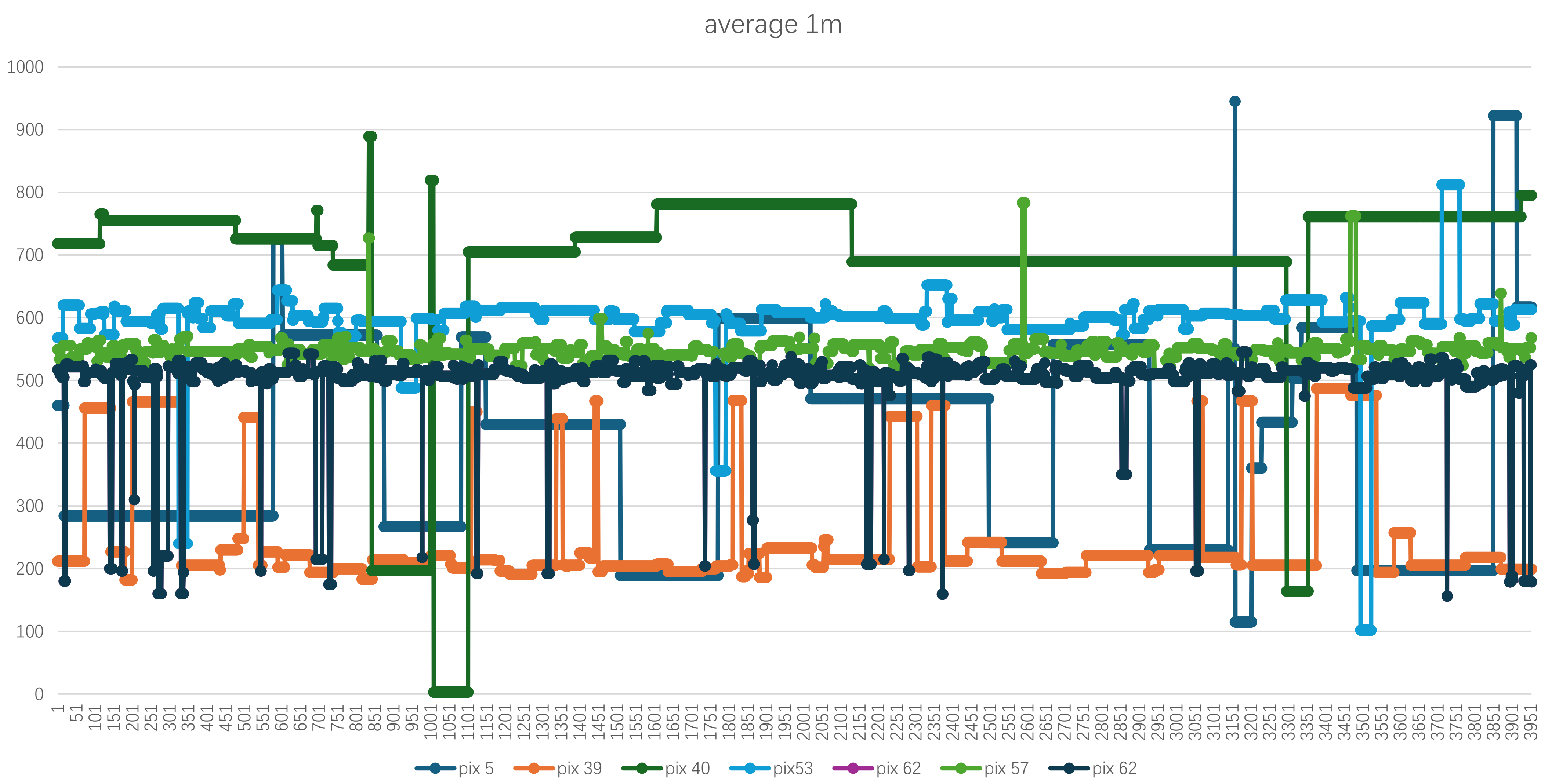
17cm to 30cm(ESPRIT)
Breath Per Minute
30
25
20
15
10
5
0
0:00 0:02 0:04 0:06 0:08 0:09 0:11 0:13 0:15 0:17 0:19 0:21 0:23 0:25 0:27 0:29 0:31 0:33 0:35 0:37 0:39 0:41 0:43 0:45 0:47 0:49 0:51 0:53 0:55 0:57 0:59 1:01 1:03 1:05 1:07 1:09 1:11 1:13 1:16 1:17 1:20 1:22 1:24 1:26 1:28 1:30 1:31 1:33 1:35 1:37 1:39 1:41 1:43 1:45 1:47 1:49 1:51 1:53 1:55 1:57 1:59

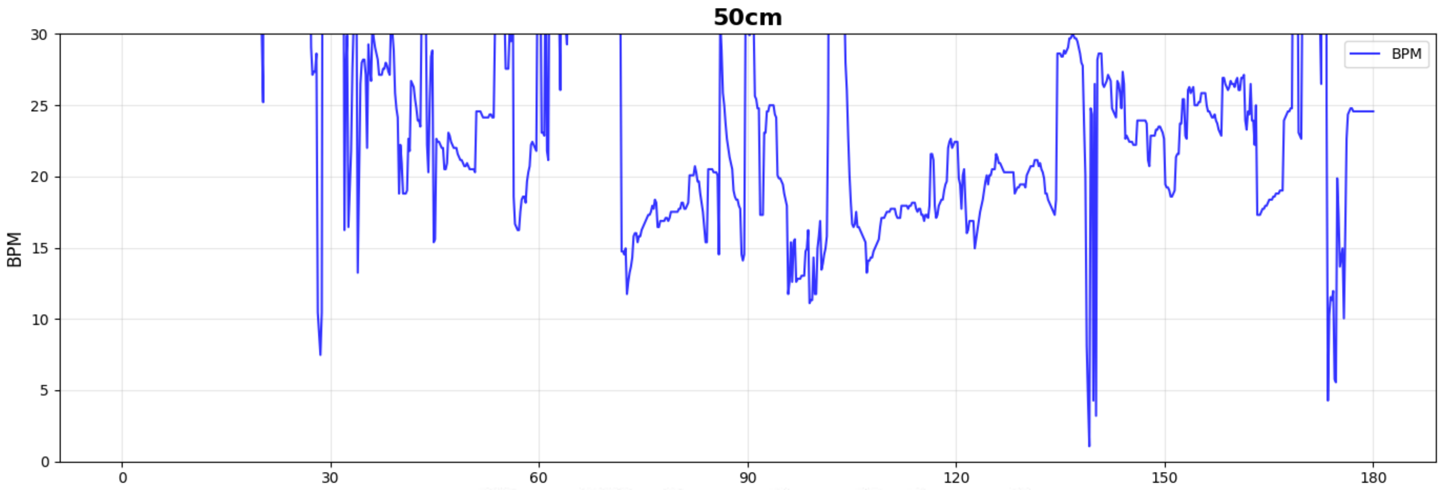
Resolution of 4x4 setting



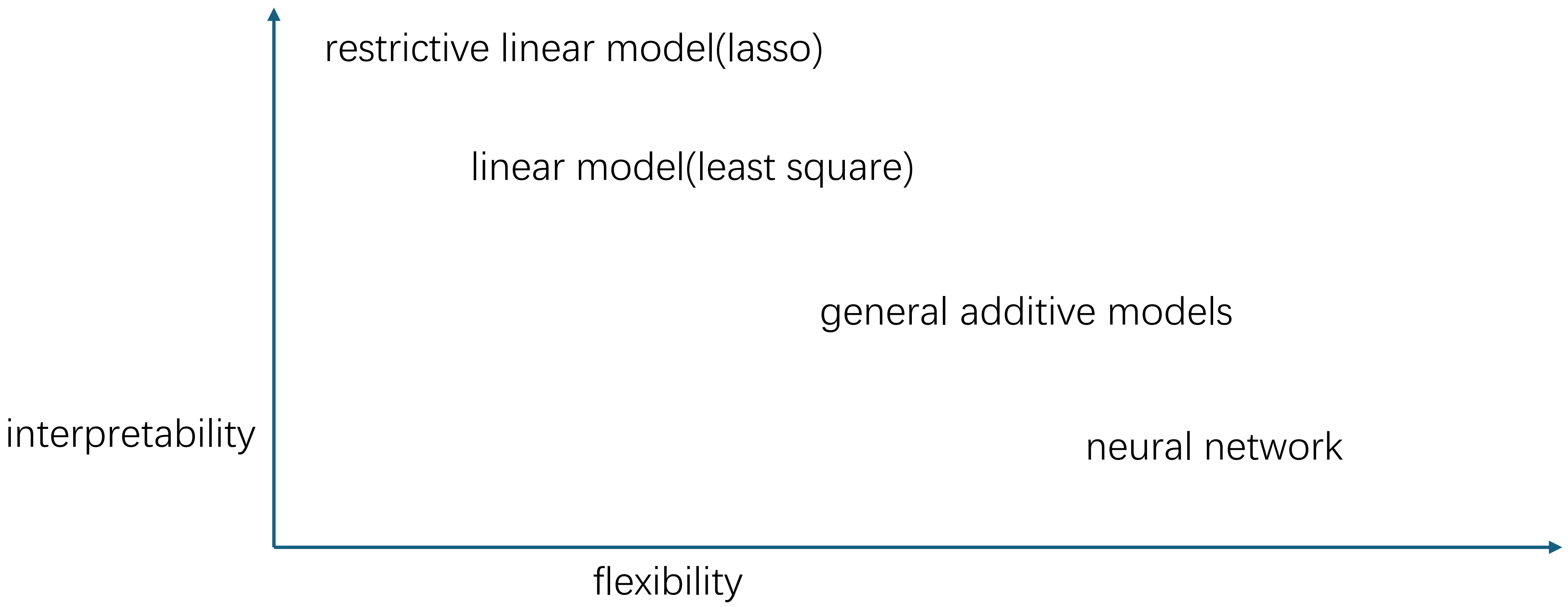


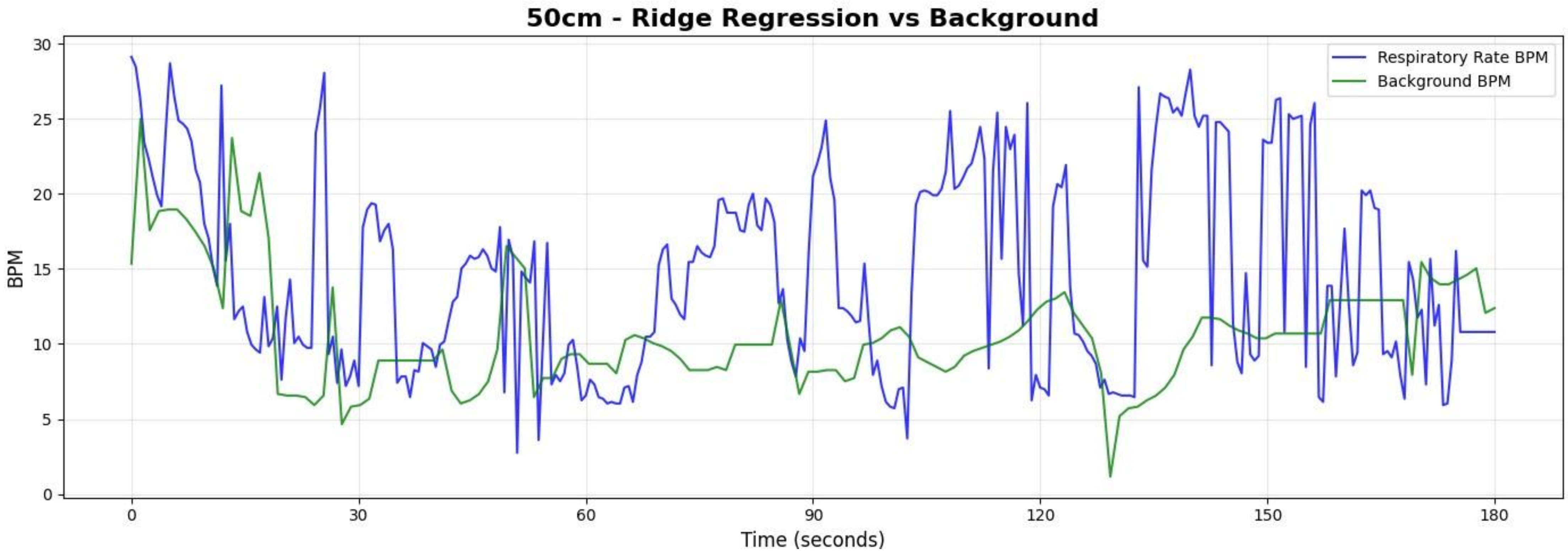

average 1m
640
620
600
580
560
540
520
500
480
1 46 91 136 181 226 271 316 361 406 451 496 541 586 631 676 721 766 811 856 901 946 991 1036 1081 1126 1171 1216 1261 1306 1351 1396 1441 1486 1531 1576 1621 1666 1711 1756 1801 1846 1891 1936 1981 2026 2071 2116 2161 2206 2251 2296 2341 2386 2431 2476 2521 2566 2611 2656 2701 2746 2791 2836 2881 2926 2971 3016 3061 3106 3151 3196 3241 3286 3331 3376 3421 3466 3511 3556 3601 3646 3691 3736 3781 3826 3871 3916
pix 57
pix 62
pix 53


average 1m
1000
900
800
700
600
500
400
300
200
100
0
1 51 101 151 201 251 301 351 401 451 501 551 601 651 701 751 801 851 901 951 1001 1051 1101 1151 1201 1251 1301 1351 1401 1451 1501 1551 1601 1651 1701 1751 1801 1851 1901 1951 2001 2051 2101 2151 2201 2251 2301 2351 2401 2451 2501 2551 2601 2651 2701 2751 2801 2851 2901 2951 3001 3051 3101 3151 3201 3251 3301 3351 3401 3451 3501 3551 3601 3651 3701 3751 3801 3851 3901 3951
pix 5
pix 39
pix 40
pix53
pix 62
pix 57
pix 62

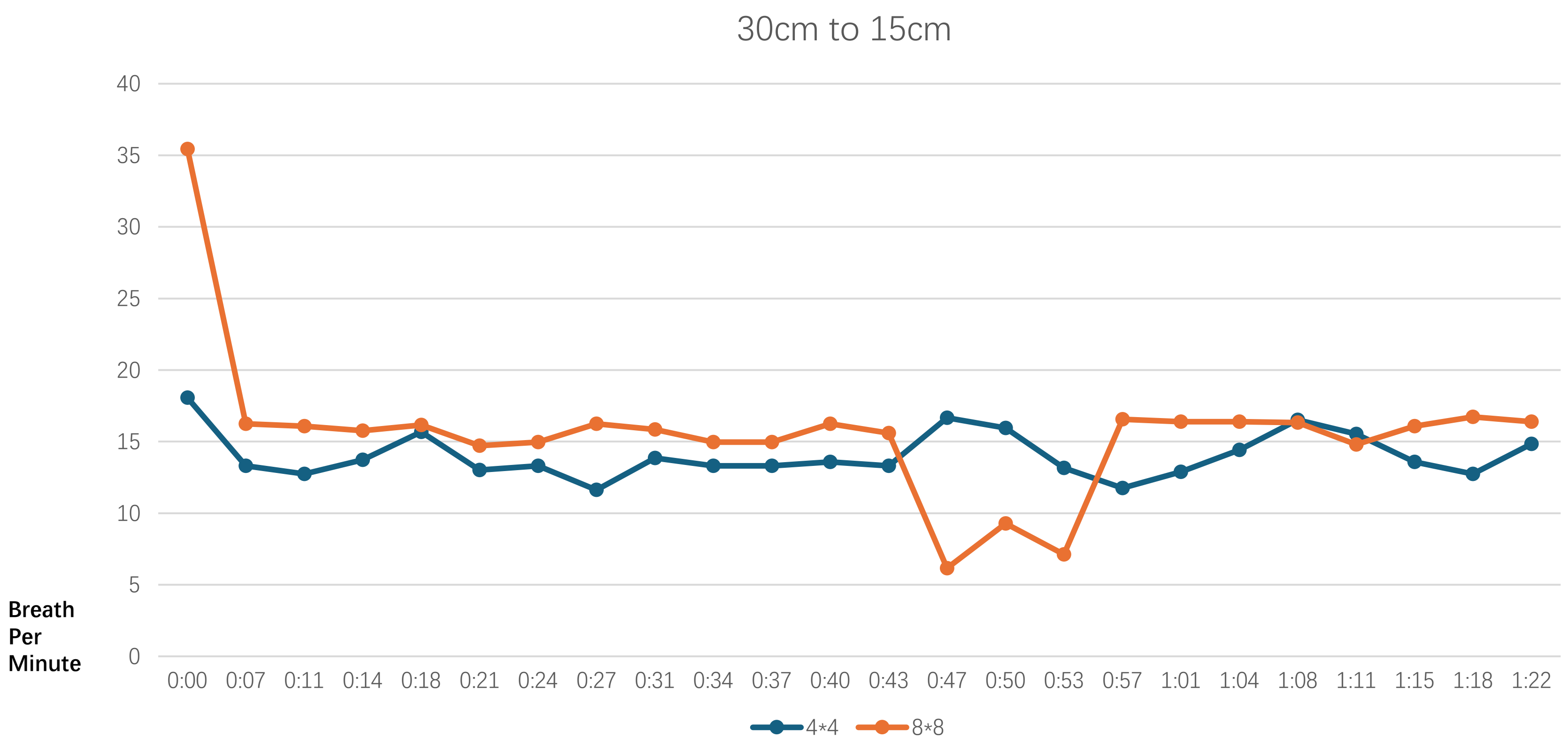


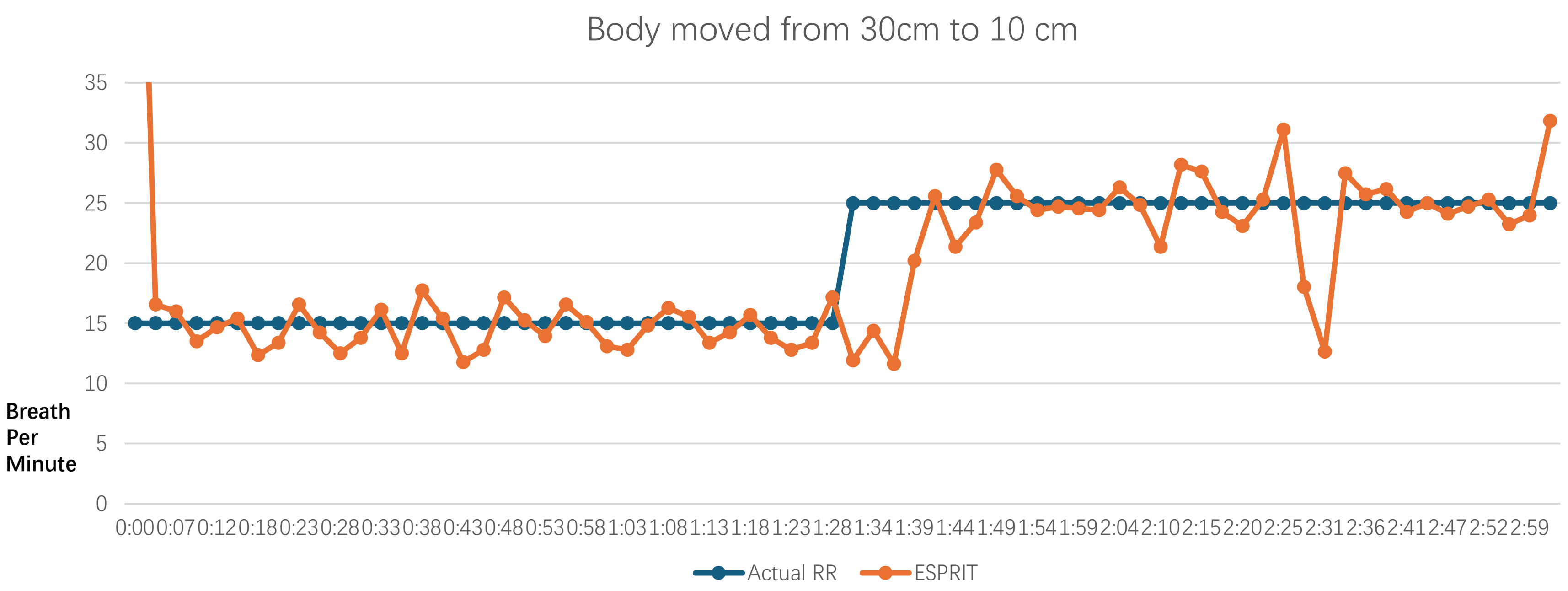
- Statistical analysis of Parameter
- Ridge regression is performed on the statistical analysis of the parameter.
- The Ridge regression is a further estimation based on parameters using the Bayesian model
- The parameters are what the model uses to describe the raw data.


restrictive linear model(lasso)
linear model(least square)
general additive models
neural network
interpretability
flexibility

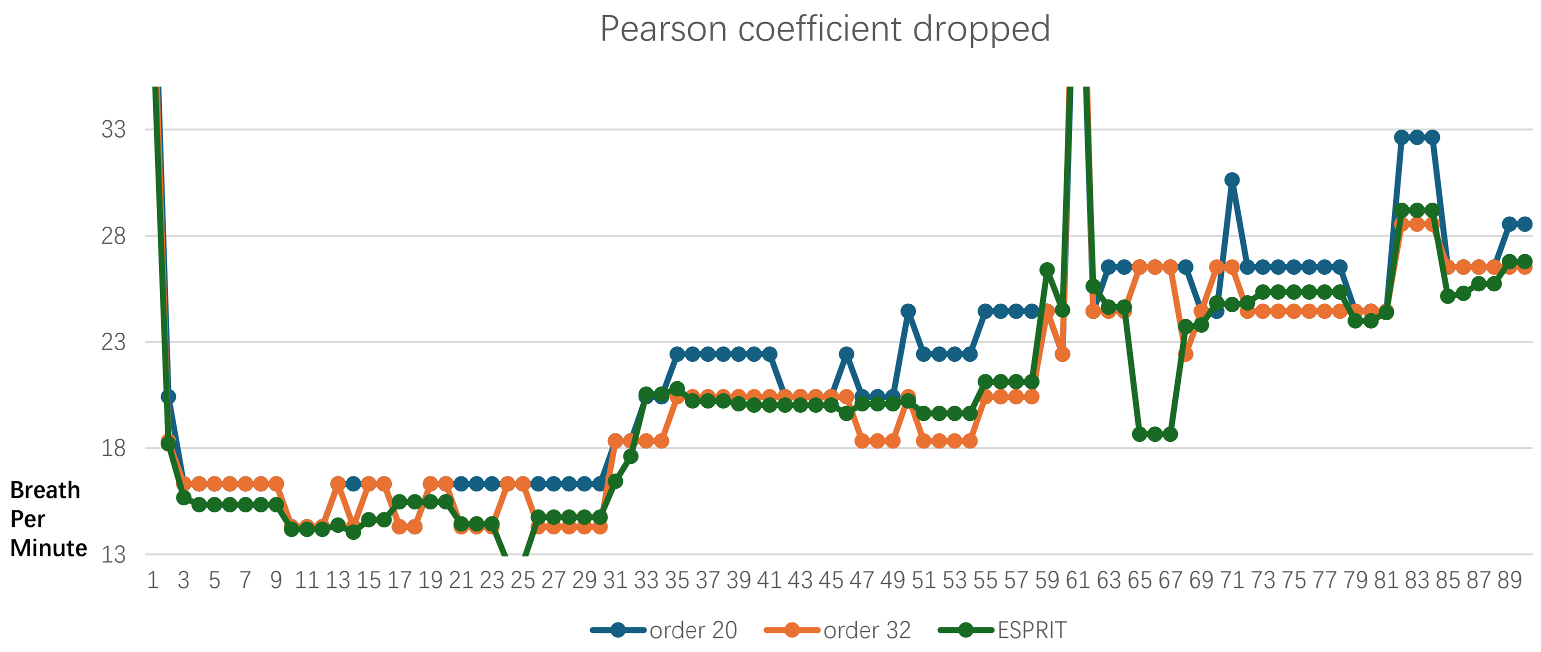


50cm - Ridge Regression vs Background
Respiratory Rate BPM
Background BPM
BPM
Time (seconds)
0
5
10
15
20
25
30
0
30
60
90
120
150
180

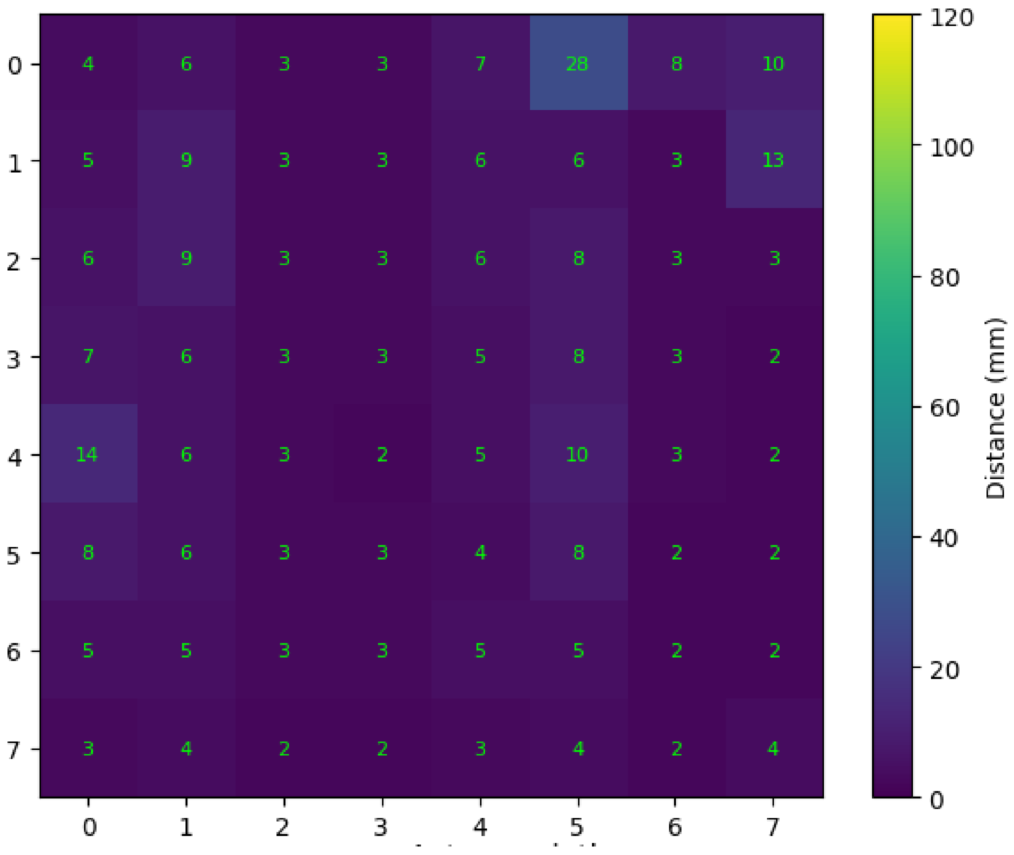

30cm to 15cm
Breath
Per
Minute
0
5
10
15
20
25
30
35
40
0:00
0:07
0:11
0:14
0:18
0:21
0:24
0:27
0:31
0:34
0:37
0:40
0:43
0:47
0:50
0:53
0:57
1:01
1:04
1:08
1:11
1:15
1:18
1:22
4*4
8*8



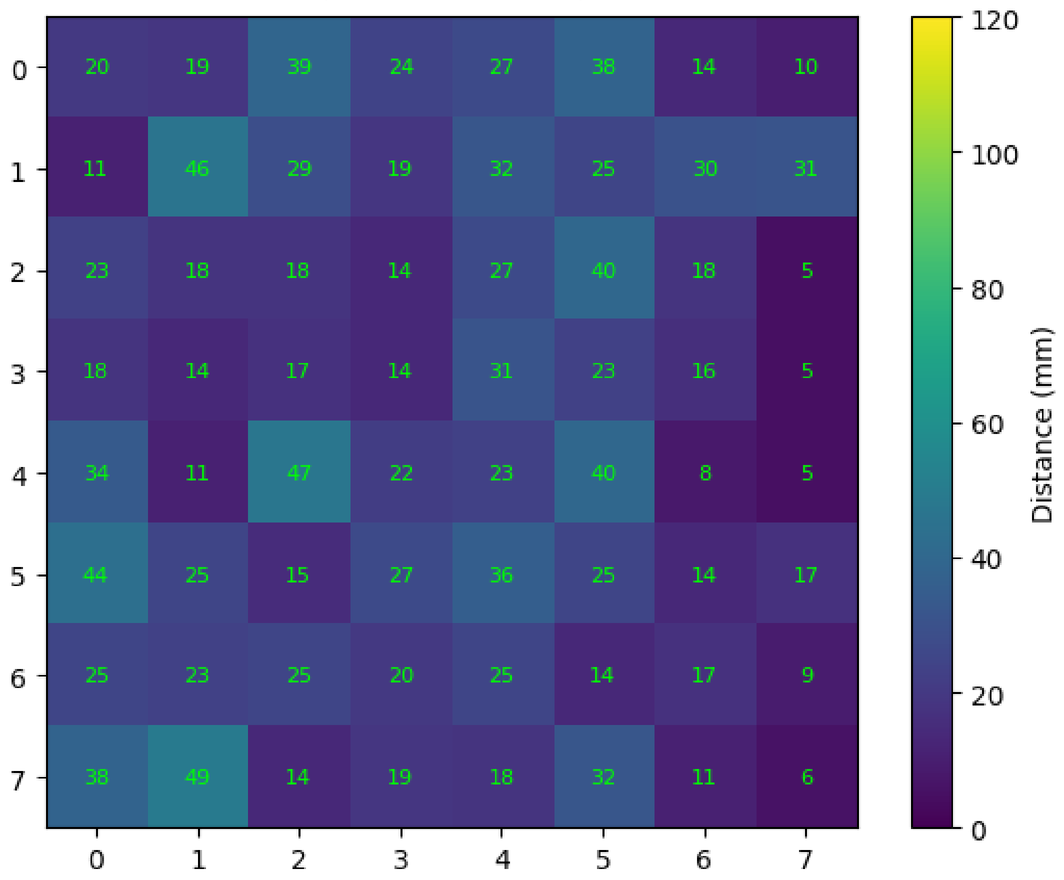
- We set the resolution to 4x4.
- We moved from 30cm to 15cm during both of these phases.
- In contrast, the phase 25BMP experienced a 7BMP drop at 2:31.
- This abnormal time interval, lasting 10 seconds, occurred during the 25BMP phase when the body moved.



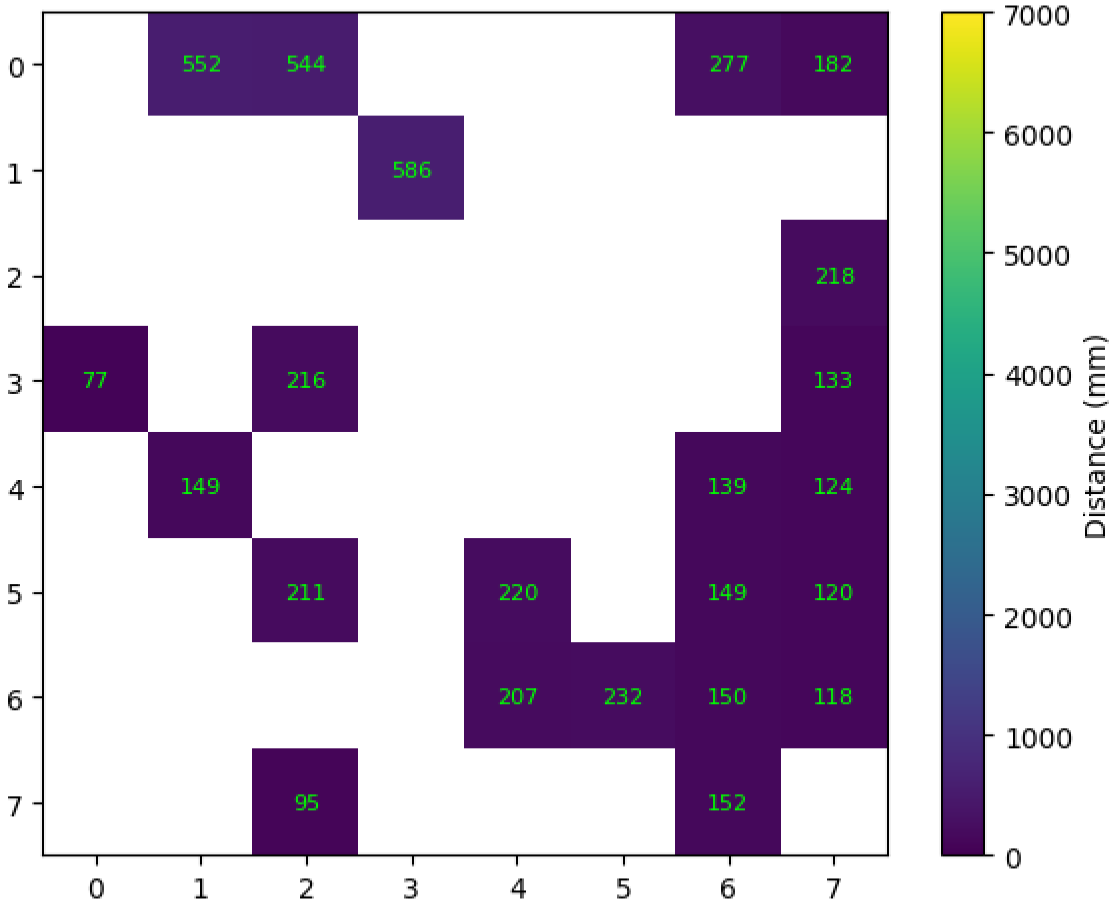
we drop pixels with low time-series coefficients. Dropping those pixels with low Pearson coefficients leads to a smooth curve in the estimation of RR. However, the error becomes large when the RR changes over time, as the Figure \ref{pearsonDropped} shows.



The average distance is 20cm, we obtained a standard deviation



The average distance is 1m, we obtained a standard deviation



setting the threshold of the deviation to 15mm, and the averagedistance is 70cm, we obtained the distance heatmap.

	0	1	2	3	4	5	6	7
0	548.00000	552.00000	565.00000	555.00000	517.00000	486.00000	114.00000	205.00000
1	597.00000	615.00000	127.00000	131.00000	126.00000	122.00000	132.00000	139.00000
2	130.00000	659.00000	138.00000	132.00000	134.00000	130.00000	133.00000	118.00000
3	113.00000	122.00000	138.00000	140.00000	134.00000	123.00000	151.00000	125.00000
4	110.00000	115.00000	122.00000	119.00000	122.00000	146.00000	162.00000	124.00000
5	112.00000	115.00000	124.00000	151.00000	167.00000	179.00000	170.00000	132.00000
6	566.00000	121.00000	577.00000	178.00000	138.00000	185.00000	160.00000	116.00000
7	493.00000	140.00000	516.00000	515.00000	513.00000	172.00000	147.00000	117.00000

- Calculate the averagedistance, then based on the average distance, split the area of noise and signal.
- The blue area represents the signal, and the red area represents thenoise.

alternative:

- standard deviation
- single photon intensity
- valid bit