Journal of Theoretical and Applied Computer Science
ISSN 2299-2634 (printed), 2300-5653 (online)
Vol. 7, No. 3, 2013, pp. 51-60
http://www.jtacs.org

Signal processing approach for breath prediction pattern recognition

Michał Twardochleb, Tomasz Król

Faculty of Computer Science and Information Technology, West Pomeranian University of Technology, Szczecin, Poland

mtwardochleb@wi.zut.edu.pl

Abstract: *In this paper, a new approach of signal processing for breath prediction pattern recognition is proposed and further analyses are presented. In order to extract key values from raw data, a shift from time domain to phase space has been utilized. It helped to achieve clearer peak-to-peak measurements which are crucial for breath prediction pattern recognition. Based on a special software tool for breath prediction pattern recognition several different algorithms have been compared. As a result, a reduction in error rate can be achieved when applying a new signal processing approach in comparison to the previous designs.*

Keywords: *pattern recognition, signal processing, neural network*

1. Introduction

Breath is a part of human activity. Simultaneously with movement, skin tension, eye reaction, heartbeat, blood pleasure and other parameters describing our bodies' state, we breathe. Breath can describe our feelings, happiness, fear, anxiousness or relax. Thus, being able to predict breath pattern equals to being able to predict our near-future behavior according to current state and changes in error rate of breath prediction [4][5]. On the other hand it's possible to track changes in our current state according to past behavior. For example, when we are calm and suddenly something disturbs us, the error rate between predicting signal and current state rises. Moreover, when a person listens to music, this kind of tracking changes, in his breath pattern, can be useful to alter main pitch in order to make him feel relaxed. Several similar researches have been conducted to predict cardiovascular symptoms [1]. As stated in [2][3] breath can be tracked and measured by respiratory motion and local regressions method. However, these analyses are done completely in time domain, taking into consideration only raw data without any further transformations.

The most important features of our breath are peak-to-peak distances which show the length of a breath in time [6][10]. Thus, transformation of a respiration signal into a phase space highlights this feature, diminishing other properties. Generally it is really hard to predict accurately future breath pattern having only past data. There are two major reasons. First of them is irregularity of breath pattern caused by random reasons e.g. movement of a person or external stimulus. The second reason is an influence of other human organs e.g. heart beat rate [2][7]. It has been investigated that there is a correlation between breath pattern and heart beat rate [1]. Thus, without knowing that parameter and heart beat rate we have to treat it as a noise that increases prediction error.

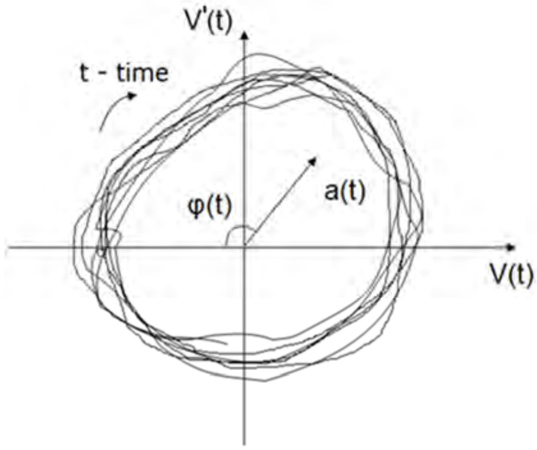

Figure 1. Signal *V*(*t*) in a phase space *V'*(*t*), where $\phi(t)$ is an angle in *t*-moment

2. Methodology

The respiration signals V(t) were collected during research and represented as a movement of chest position in time. First of all, by applying a phase space to a respiration signal a part of useless data can be reduced and also noises. However, peak-to-peak distances are preserved and underlined. It's clear when a full breath takes place and a signal in a phase space moves from 360 degrees to 0. A schema of this process is presented in Fig. 1, where a signal V(t) is transformed into phase space V'(t).

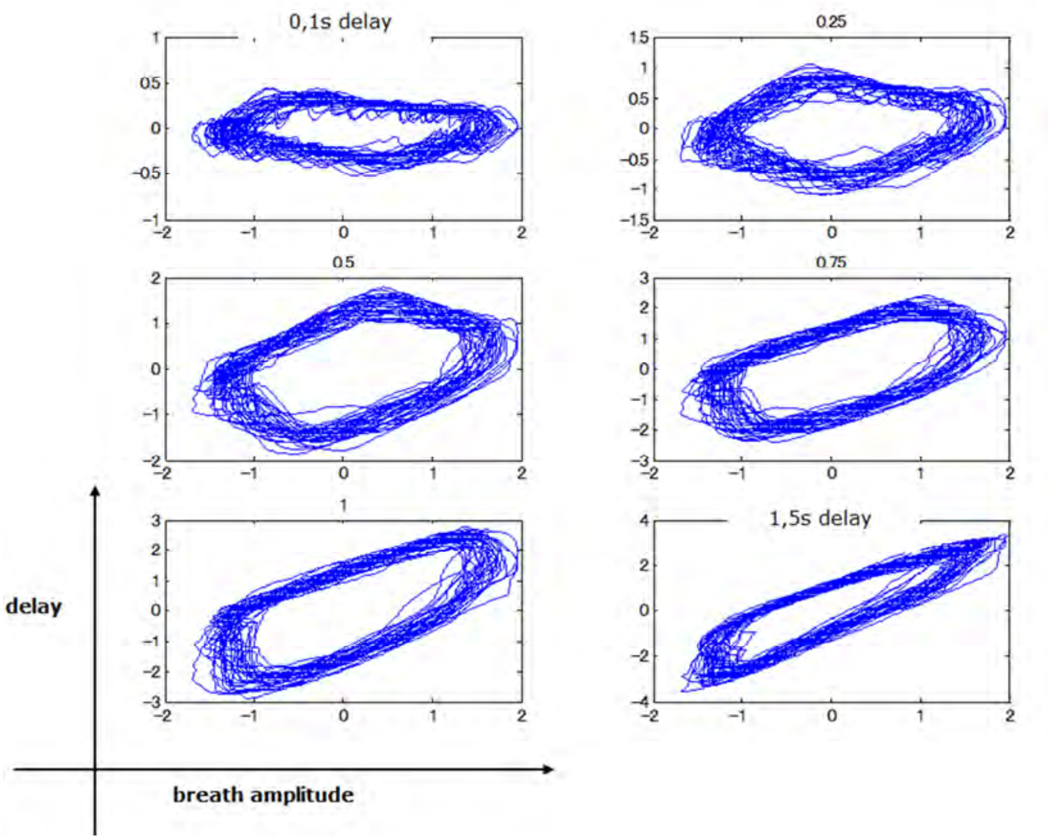

Figure 2. Signal in a phase space according to different time delays

Moving into phase space can be done, for instance, by Hilbert transform of V(t):

$$H(V)(t) = -\frac{1}{\pi}\lim_{\varepsilon\to 0}\int_{\varepsilon}^{\infty}\frac{V(t+\tau)-V(t-\tau)}{\tau}d\tau \tag{1}$$

or by time delay and further calculations of an angle between two delayed points. Both of these methods generate initial delay to a processed signal. The delay equals usually from 0,2 – 0,5 second. Differences in phase space between different time delays can be observed in Fig. 2.

Whole signal after moving into a phase space is presented as a set of clearly insulated cycles (Fig. 3). Each period is separated by changing value from -2∏ to 2∏. Each such a transition means that a full breath is done.

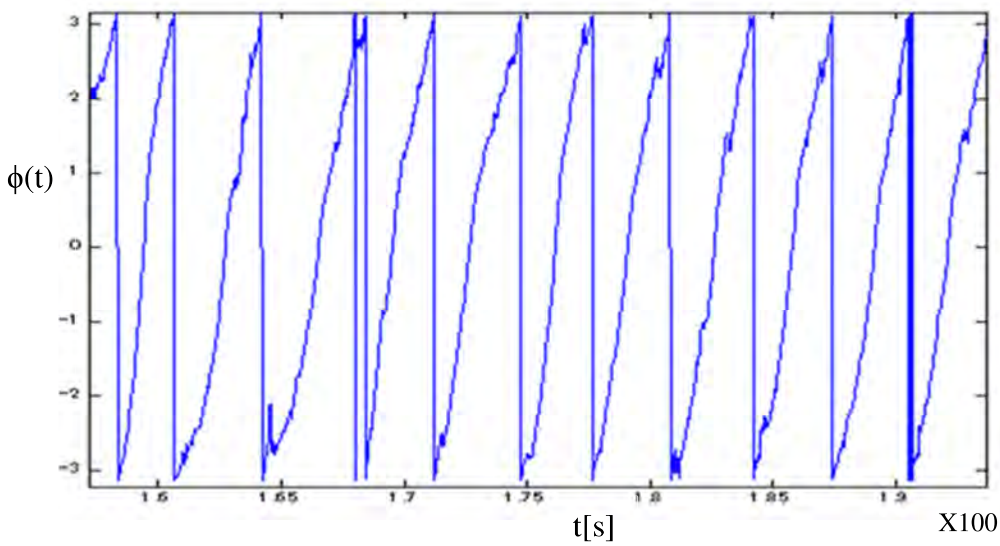

Figure 3. Sample breath pattern in a phase space $\phi(t)$ with 0,3s time delay transformation

3. Simulations

In order to run numerous simulations, a special tool has been designed in Matlab environment (Fig. 4). It allows a user to model breath pattern prediction according to many parameters. The most important are prediction algorithm, number of samples in an applied breath pattern data, low pass filter to reduce noise, spectrogram of an input wave. Low pass filter (LPF) was implemented here as a finite impulse response filter created by a simple moving average:

$$LPF_t = \frac{x_t + x_{t-1} + x_{t-2} + x_{t-3} + x_{t-4}}{5} \tag{2}$$

where *x* means a signal value in *t* moment.

Moreover, we can set constraints which describe a threshold after which all predicted points are reduced to a maximal/minimal value according to training data. Middle table contains neural network input points. Finally an average error for different algorithms can be observed.

In order to compare a new approach, three algorithms (including the new one) have been programmed and tested against predicting breath patterns. Two of them based on the phase space, whereas third on a raw data.

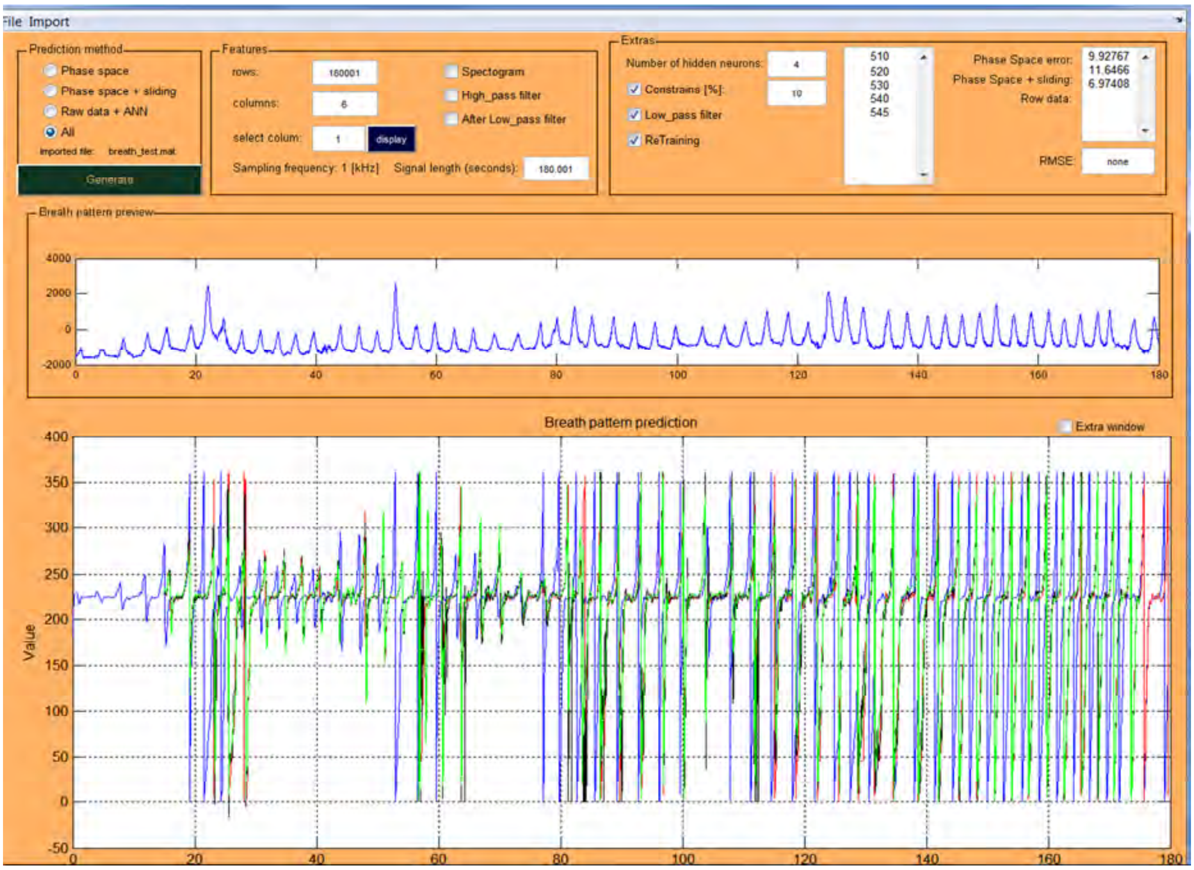

Figure 4. Breath prediction simulator

Phase space: In this approach raw data is transformed into phase space (φ). It is accomplished by applying time delay method between set of points x,y:

$$\varphi = atan2(y, x), \tag{3}$$

$$x = r\cos\varphi, \tag{4}$$

$$y = r\ \sin\varphi, \tag{5}$$

$$r = \sqrt{x^2 + y^2}, \tag{6}$$

where delay between x,y equals to 300 ms. Next, having phase space data, neural network is trained with 20 sec of a transformed breath pattern with fixed set of points. The points are taken from “the past” signal according to different patterns, which are described later. There are several input points and one output point. It is possible to retrain neural network every 5 sec with new data. Neural Network input points [8][9][11] as well as predicted point can be adjusted manually according to desired prediction length.

Phase space with sliding: This method is similar to phase space prediction. However, additional feature is applied. In order to avoid discontinuity in the phase space data, the following period of breath pattern is predicted, as it would be higher than possible values (Fig. 5.). For instance, when the input points are relatively close to next period and the predicted point should be predicted in the next period, the predicted point of breath is moved 2∏ up (in neural network training phase). Thus, it creates one line with former breath period. This change is hold on only during crossing the discontinuity by input and output points of neural network. Moreover, during this state, every predicted data that has a value higher than possible (max 2∏) is subtracted by this value. Next, all data is returned to its original values and prediction proceeds according to normal phase space prediction. In case of long input e.g. 10 seconds more than 2 consecutive breath periods are necessary to be combined together.

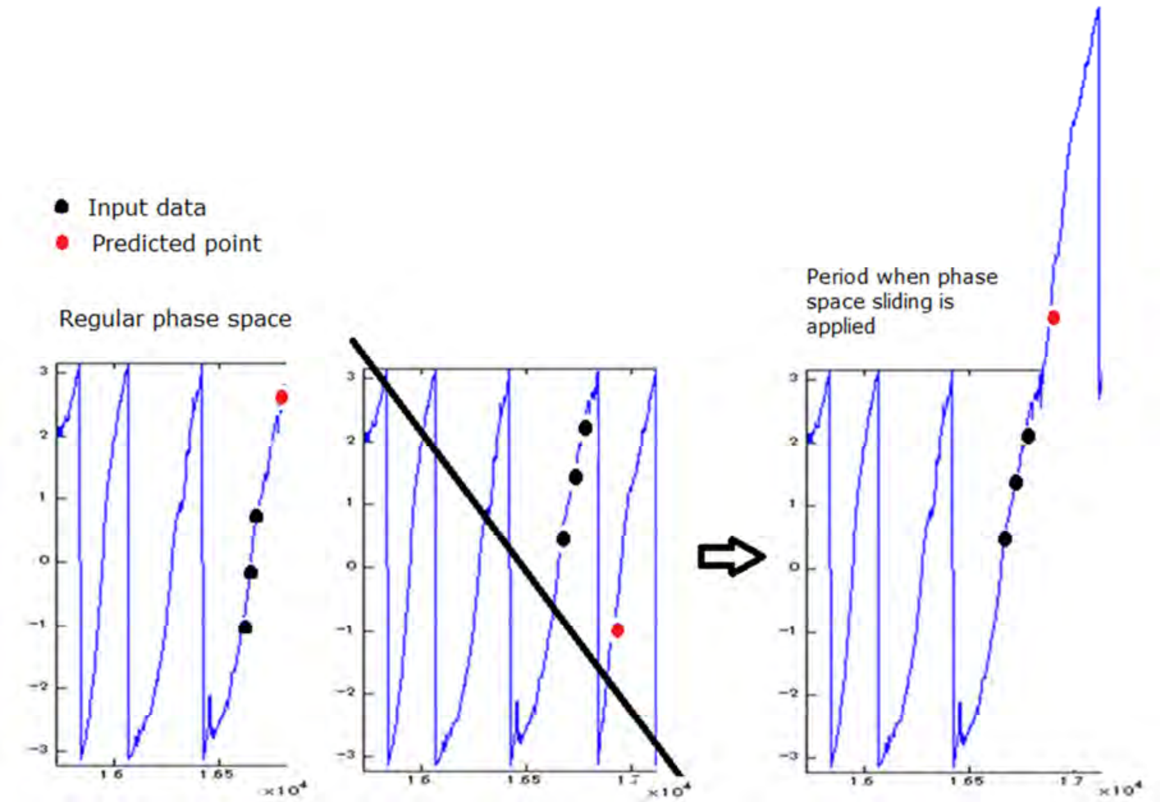

Figure 5. Phase space with sliding – two "combined" periods in order to avoid discontinuity

Raw data: This method consists in predicting raw data. Input points are taken directly from signal. However, to be able to perform comparison between this method and phase space algorithms further transformation to phase space is required.

4. Results

Primary investigations were conducted on a sample breath wave of a 27 year old male to establish the best number of neurons in hidden layer of Neural Network (Fig. 6). Settings of simulations were as following. Input points: 500 ms, 600 ms, 800 ms, 900 ms, 1000 ms, 1200 ms, 1600 ms, 2000 ms, 2400, 2600 ms before predicted point. Moreover, a low pass filter (Eq. 2.) has been applied and retraining of neural network was set to every 5 s. The average error is defined as an average distance between predicted and real values – mean absolute error (MAE). The structure of neural network that has been utilized is presented in Fig. 7. Sigmoid neurons in a hidden layer are defined as:

$$S(t) = \frac{1}{1 + e^{-t}} \tag{7}$$

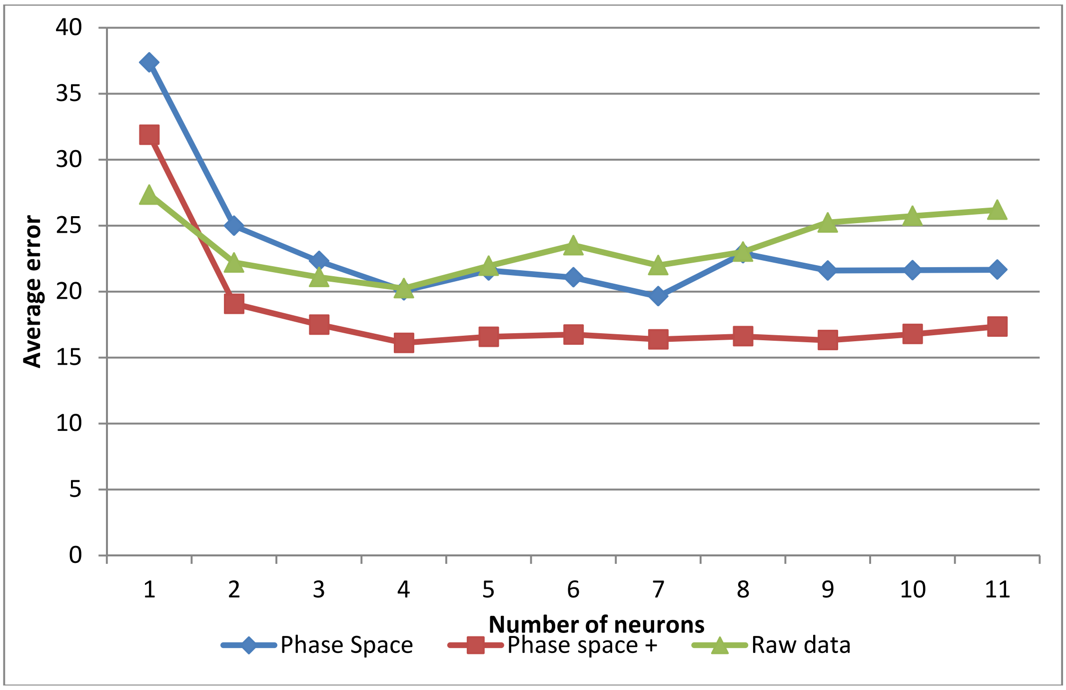

Figure 6. Quality of prediction according to number of neurons in hidden layer of Neural Network with retraining

We can notice in Fig. 8. that the best quality of prediction and performance is achievable with 4 neurons in a hidden layer. Further increase of number of neurons results in longer calculations without any significant improvement. It is clear that the best error rate in this case has phase space method with sliding. However, this matter will be later analyzed.

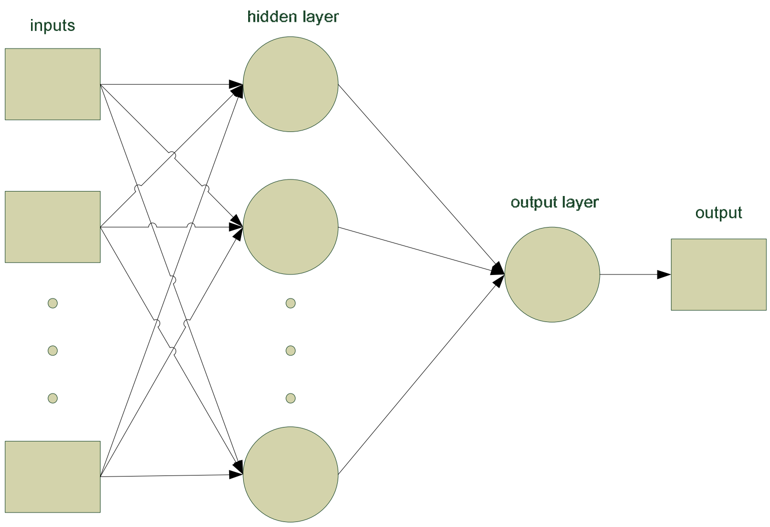

Figure 7. A two-layer feedforward network with sigmoid hidden neurons and linear output neuron

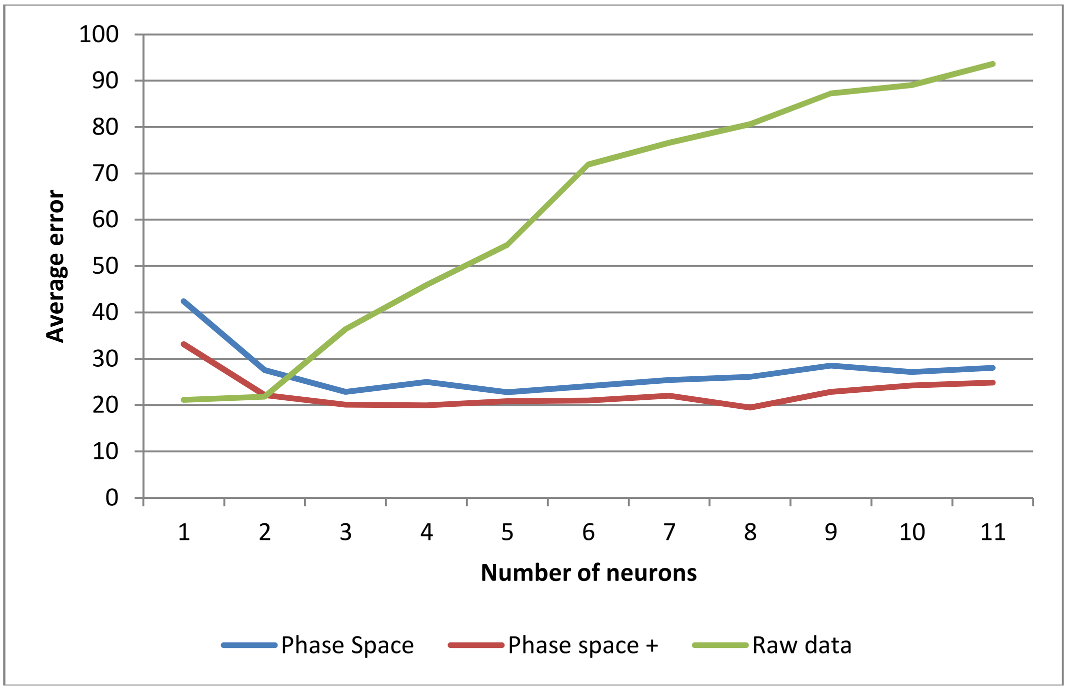

Figure 8. Quality of prediction according to number of neurons in hidden layer of Neural Network without retraining

In Fig. 8. results of simulations without retraining are presented. We can observe that all results are at least 5 points worse than for the method with retraining. It is worth to notice that the raw data prediction becomes really unstable when the number of neurons is increased in that case. It means that neural network is significantly over trained when too many neurons are applied.

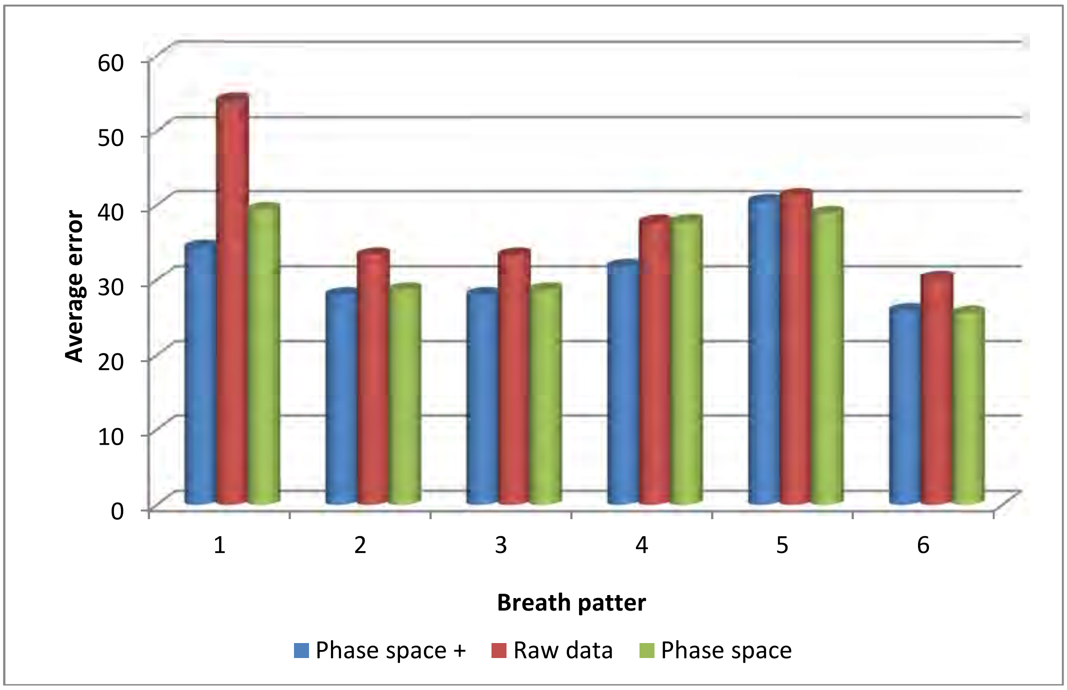

Figure 9. Comparison of prediction quality with 6 different input signals

Next, several simulations were run to check how the algorithms are stable against various types of input respiration signals. For that reason, 6 patterns derived from 6 different people were investigated (Fig. 9.). Settings of simulations were following: input points: 1000 ms, 1100 ms, 1300 ms, 1400 ms, 1500 ms before predicted point. 4 neurons are set in a hidden layer. Applied low pass filter (Eq. 2) and retraining of neural network every 5 s.

We can notice that in all cases the best is "phase space +" approach. Moreover, results can vary up to 15 points when comparing different breath patterns. It is caused generally by irregularities in breath pattern of various people.

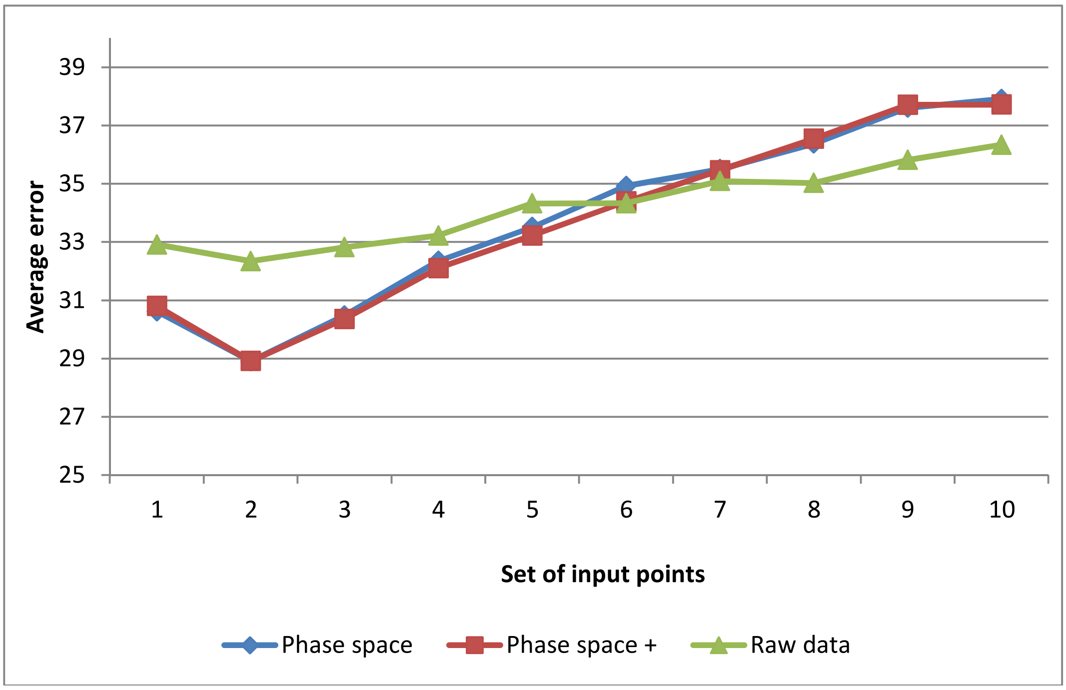

Figure 10. Influence of input data length on error rate

Table 1. Time stamps' sets used for checking influence of input length on error rate

Set	1	2	3	4	5	6	7	8	9	10
Time stamps [ms] before predicted point	1200	1400	1800	2200	2600	3000	3400	3800	4200	4600
	1000	1200	1600	2000	2400	2800	3200	3600	4000	4400
		1000	1400	1800	2200	2600	3000	3400	3800	4200
			1200	1600	2000	2400	2800	3200	3600	4000
			1000	1400	1800	2200	2600	3000	3400	3800
				1200	1600	2000	2400	2800	3200	3600
				1000	1400	1800	2200	2600	3000	3400
					1200	1600	2000	2400	2800	3200
					1000	1400	1800	2200	2600	3000
						1200	1600	2000	2400	2800
						1000	1400	1800	2200	2600
							1200	1600	2000	2400
							1000	1400	1800	2200
								1200	1600	2000
								1000	1400	1800
									1200	1600
									1000	1400
										1200
										1000

Fig. 10 presents how the input data length influences the average error rate. Sets of input points are presented in Tab. 1. The described values represent time-stamps before predicted point and are considered as input points for the neural network. According to the chart (Fig.10.), the minimum is at around 2-3 points. It means that the best results for all approaches are achieved when only 2 or 3 points are taken before predicted one. Moreover, such a number of input points reduces calculations when only few inputs are delivered to neural network.

5. Conclusions

Although prediction of breath pattern, based only on a passed data, is not a trivial task, it has been presented that a satisfactory solution is achievable. Numerous simulations proved that the most flexible is phase space approach proposed in this paper. However, when the input respiration signal is too short to extract all necessary data, better results can be achieved with "Phase space with sliding" algorithm. Furthermore, the best number of neurons in hidden layer of neural network is 4. Decreasing or increasing that value can cause worse performance rate, longer calculations or both of them. Thus, 4 neurons are recommended for all the approaches. Additionally, in all cases retraining of neural network is necessary to reduce error rate. Because breath pattern is changeable in a time, the most recent samples are required to retrain neural network in order to keep it state up to date. It is most visible with raw data example in Fig. 6 and 8 . Moreover, only few last points before predicted point are useful. The higher number of input points, the worse the performance. It was tested if increasing the number of neurons with extended input can reduce error. However, results were negative.

Presented above approaches will be further analyzed in a real-time tool. Minor changes might be applied to Matlab model and real time algorithms. It is caused by different programming environment and timing constraints.

References

[1] Chen, Z., Brown, E. N., Barbieri, R.: Assessment of Autonomic Control and Respiratory Sinus Arrhythmia Using Point Process Models of Human Heart Beat Dynamics. IEEE Transactions on Electromagnetic Compatibility, 56(7), July 2009.

[2] Ruan, D., Fessler, J. A., Balter, J. M.: Real-time prediction of respiratory motion based on local regression methods. Phys. Med. Biol. 52(23), pp. 7137–7152, 2007.

[3] Sharp, G. C., Jiang, S. B., Shimizu, S., Shirato, H.: Prediction of respiratory tumor motion for real-time image-guided radiotherapy. Phys. Med. Biol. 49, 2004, pp. 425–440.

[4] Batzel, J. J., Novak, V., Kappel, F., Olufsen, M. S., Tran, H. T.: Introduction to the special issues: Short-term cardiovascular-respiratory control mechanisms. Cardiovasc. Eng., 8(1), pp. 1–4, 2008.

[5] Hirsch, J. A., Bishop, B.: Respiratory sinus arrhythmia in humans: How breathing pattern modulates heart rate. Amer. J. Physiol., 241(4), pp. H620–H629, 1981.

[6] Saul, J. P., Berger, R. D., Chen, M. H., Cohen, R. J.: Transfer function analysis of autonomic regulation. II. Respiratory sinus arrhythmia. Amer. J. Physiol. Heart Cicr. Physiol., 256(25), pp. 153–161, 1989.

[7] Pinna, G. D., Maestri, R., La Rovere, M. T., Gobbi, E., Fanfulla, F.: Effect of paced breathing on ventilatory and cardiovascular variability parameters during short-term investigations of autonomic function. Amer. J. Physiol. Heart Cicr. Physiol., 290(1), pp. 424–433, 2006.

[8] Lippmann, R. P.: An introduction to computing with neural nets. IEEE Acoustical Speech and Signal Processing Magazine, 3(4), pp. 4–22, 1987.

[9] Murphy, M. J., Dieterich, S.: Comparative performance of linear and nonlinear neural networks to predict irregular breathing. Phys. Med. Biol. 51, pp. 5903–5914, 2006.
[10] Ruan, D., Fessler, J. A., Balter, J. M., Sonke, J.-J.: Exploring breathing pattern irregularity with projection-based method. Med. Phys. 33(7), pp. 2491–2499, 2006.
[11] Bishop, C.: Neural Networks for Pattern Recognition. Oxford University Press, 1995.