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Spirometry Data Analysis and Monitoring in Medical and Physiological Tests

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Abstract

Research on the computational breath analysis constitute important part of current challenges within the medical sciences, artificial intelligence, and biomedical engineering. Despite efforts of scientists and clinicians current results seem be not satisfying. Computational models of breath processes based e.g. on fuzzy logic may constitute another breakthrough in aforementioned area offering completing position to the current state of the art, both in the area of theoretical and experimental computational neuroscience, and clinical applications. Aim of the study was to find out whether is true if our new concept of intelligent breath analysis system can constitute another step toward better analysis and understanding of the aforementioned processes.

Keywords: breath measure; computational breath analysis; breath disorders; computational models; artificial intelligence.

1. Introduction

Spirometry is the most common medical technique that measures volume and/or the flow of inhaled and exhaled air. It is used to monitor patients with asthma, pulmonary and cystic fibrosis, but also to detect symptoms of breathlessness and various respiratory disease, distinguish them from cardiac problems, and in many other applications. Current spirometers require patient cooperation and thus cannot be used with patients in coma or with children below 6 years of age. Moreover, classical spirometry does not measure breathing patterns that carry information about the activity of the central respiratory rhythm pattern generation circuitry of the Pre-Bötzinger Complex. Recording of the breathing patterns, together with EMG signals from lung muscles, may carry important information pertaining to prognosis of the patients in coma. A breathing sensor may also be used to record withholding the breath in anticipation of certain stimuli in psychological experiments. There is a clear need for a new type of breathing sensor that can be used without a mask or without cooperation of the patient [1]. Moreover importance of effective, reliable and accurate predictive tools, and better ways for diseases simulation was recently emphasized by Henry Markram in his challenges for neuroscience [2].

Aim of the study was to find out whether is true if our new concept of intelligent breath analysis system can constitute another step toward better analysis and understanding of the aforementioned processes.

2. Models and methods

Besides the typical spirometric parameters various processing methods are applied to the respiration time series signal. The goal of modeling is finding the dependences of latent parameters like emotion state (or medical diagnose) with parameters of breathing and prediction the state during the time. We propose to consider model that is based on time series of breathing prediction. Then we will use the set of parameters of breathing for clustering of breathing cycles.

2.1. Model of breathing prediction based on time series

The parameter of breathing measure is flow-rate, that is why the input signal for analysis is a velocity of breathing $\dot{V}(t)$. Figure 1 shows the typical record of the input signal.

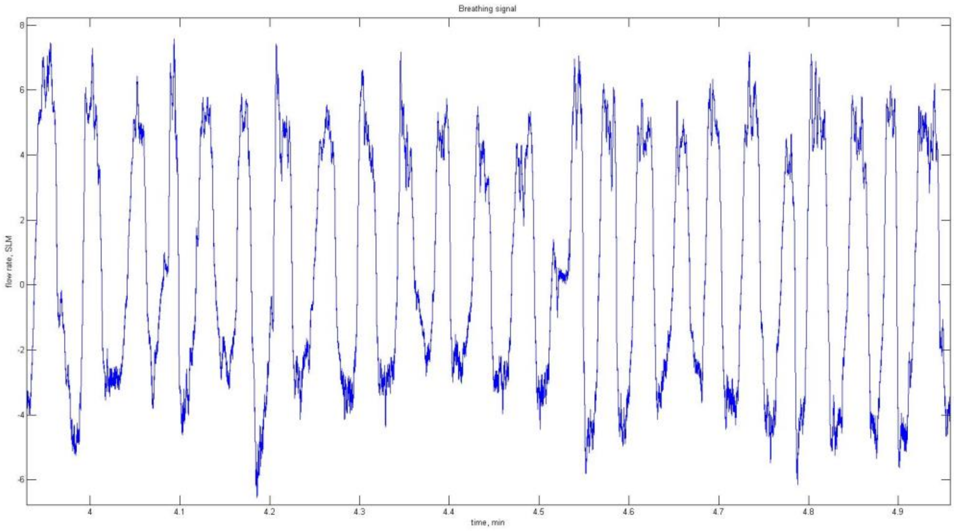

Fig. 1. Signal of breathing

To design model based on prediction of time series we need to reconstruct the attractor of input signal. Based on signal reconstruction methods we construct the breathing model in the state space

$$X(t)=\left(x(t),x(t-\tau),x(t-2\tau),\ldots,x(t-(m-1)\tau)\right) \qquad (1)$$

where $x(t)=\dot{V}(t)$ is input signal and time delay τ and memory index (embedding dimension) m have to be found from the time series signal.

We use the autocorrelation function $\psi(\tau)=\int x(t)x(t-\tau)dt$ of input signal $x(t)$ to find time delay τ, namely the first crossing of this function with x-axes (fig.2) in positive part of x-axes.

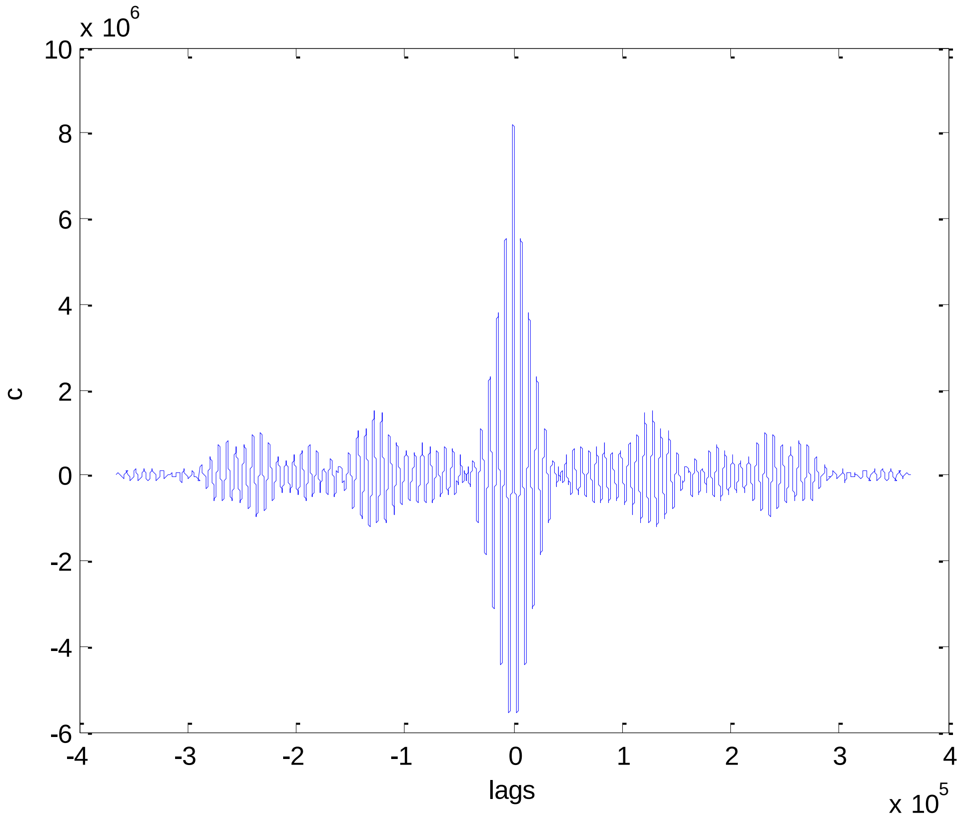

Fig. 2. Autocorrelation function

To find optimal memory index m we calculate the correlation integral and Takens' theorem [3]. Correlation integral shows the mean probability that the states at two different times are close and it is calculated as

$$C(\varepsilon) \approx \frac{1}{N^2} \sum_{i,j=1}^{N} H\left(\varepsilon - \left\| X_i - X_j \right\|\right) \tag{2}$$

where $X_i = \left(x(i), x(i-\tau), x(i-2\tau), \ldots, x(i-(m-1)\tau)\right)$, $H(x)$ is the Heaviside step function. If there is value D that reflects functionality dimension $C(\varepsilon) \propto e^D$, then Takens' theorem can be applied, namely if $D \approx \dfrac{\log C(\varepsilon)}{\log \varepsilon}$ then embedding dimension m can be found in the interval $2D < m \leq 2D + 1$.

Using calculated parameters of time delay and memory index we can build the recurrent model of breathing that can be used for prediction. We propose to use hybrid intelligent system called Takagi-Sugeno fuzzy model of 1t order using ANFIS (the adaptive neuro fuzzy inference system). The set of rules look like following

$$\begin{aligned}
&Rule\ R1: if\ \ x(i)\, is\ A^1{}_1\ and\ \ x(i-\tau)\, is\ A^1{}_2 \ldots\ and\ \ x(i-(m-1)\tau)\, is\ A^1{}_m \\
&then\ \ x(i+m\tau) = a^1{}_1 x(i) + a^1{}_1 x(i-\tau) + \ldots + a^1{}_m x(i-(m-1)\tau) + a^1{}_{m+1}, \\
&Rule\ R2: if\ \ x(i)\, is\ A^2{}_1\ and\ \ x(i-\tau)\, is\ A^2{}_2 \ldots\ and\ \ x(i-(m-1)\tau)\, is\ A^2{}_m \\
&then\ \ x(i-m\tau) = a^2{}_1 x(i) + a^2{}_1 x(i-\tau) + \ldots + a^2{}_m x(i-(m-1)\tau) + a^2{}_{m+1}, \\
&\vdots
\end{aligned} \tag{3}$$

where $A^j{}_i$ are membership functions and a_i^j are real parameters.
The rule base (3) will be used for predict of breathing by current and previous measures of signal $x(t)=\dot{V}(t)$ that allows to estimate the changes of breathing during the psychological test.

2.3. Clustering of breathing cycles

The goal of clustering is finding such samples of breathing cycles that associate with some external events, for instance, emotion changes. So, we have to solve the task of grouping a set of objects in such a way that objects in the same group (called a cluster) are more similar (in some sense or another) to each other than to those in other groups (clusters). To find the changes during breathing under psychological tests we draw our attention on minimal element of breathing time series, namely one cycle of the breathing. These elements will be such samples (or objects) for clustering. Figure 3 shows the parameters of the breathing cycle that are taken for clustering procedure.

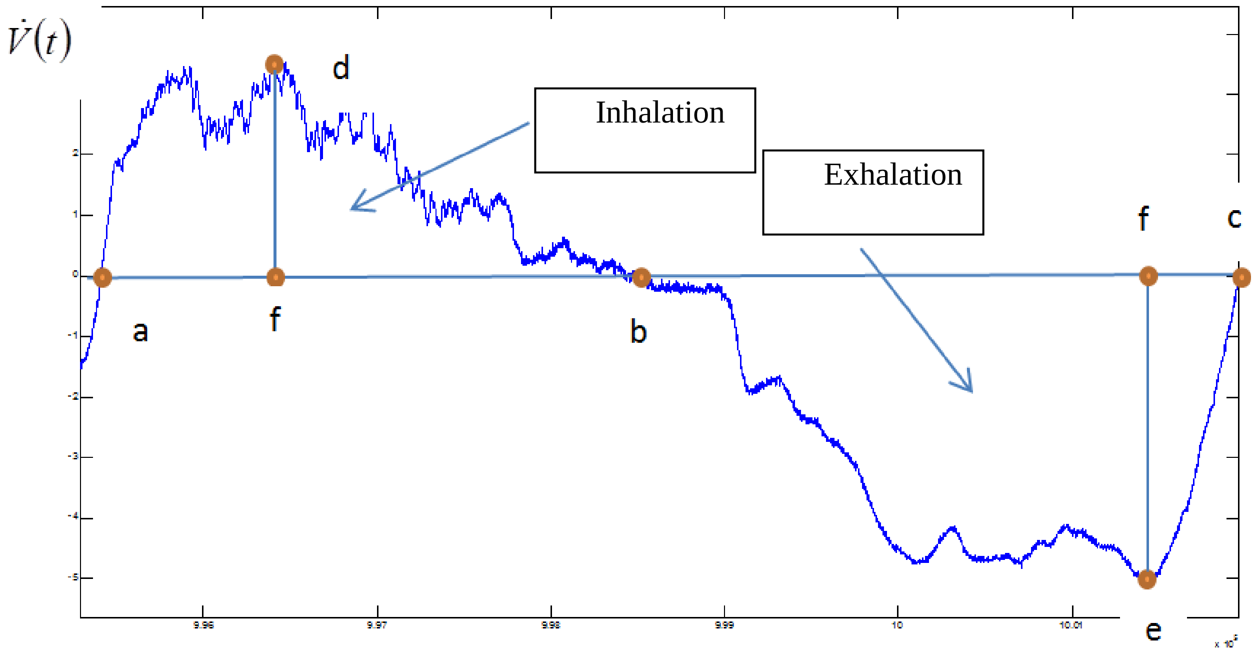

Fig. 3. Breathing cycle

These parameters are in table 1.

Table 1. Parameters of the breathing

Number	Parameter	Name
1	|ac|	Length of cycle
2	|fd|	Maximum of inhalation
3	|af|	Maximum inhalation rise time
4	|fe|	Maximum of exhalation
5	|bf|	Maximum rise time of exhalation
6	|ab|	Length of exhalation
7	S	Integral volume-flow

8	M	Maximum value of the volume
9	Vin	Inhalation volume
10	Vex	Exhalation volume

Here $V = \int_a^c \dot{V}(t)dt$ and $S = \int_a^c \dot{V}dV$, $Vin = \int_a^b \dot{V}(t)dt$ $Vex = \int_b^c \dot{V}(t)dt$.

Hence we consider the matrix of breathing cycles (rows) that are characterized with parameters from table above (columns). The parameters are normalized as a percent of the maximum values (fig.4).

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	1	2	3	4	5	6	7	8	9	10	11	12
1	0.4663	0.3754	0.0651	0.2810	0.4982	0.4713	0.1580	0.3442	0.4030	0.3539	1	
2	0.4590	0.5556	0.1087	0.2628	0.5008	0.4437	0.1795	0.3786	0.4448	0.3397	1	
3	0.5047	0.5075	0.1641	0.2847	0.4268	0.6002	0.1717	0.4738	0.5097	0.2395	1	
4	0.4138	0.3634	0.1468	0.3723	0.3714	0.3880	0.2076	0.3024	0.3422	0.3352	1	
5	0.4497	0.3694	0.0940	0.2883	0.4018	0.4948	0.1117	0.2953	0.3464	0.2186	1	
6	0.4317	0.2823	0.0928	0.2664	0.4012	0.3438	0.1466	0.1889	0.1917	0.3434	1	
7	0.5635	0.4294	0.0771	0.3066	0.5487	0.5559	0.1938	0.3638	0.4183	0.4204	1	
8	0.5307	0.5676	0.0780	0.4434	0.5299	0.5376	0.2673	0.4681	0.5392	0.4404	1	
9	0.5441	0.5345	0.0834	0.3394	0.4391	0.5546	0.2332	0.4546	0.5169	0.4147	1	
10	0.5954	0.3784	0.0573	0.2792	0.4376	0.6129	0.1820	0.4085	0.4371	0.3863	1	
11	0.5713	0.4234	0.1323	0.2847	0.4378	0.6146	0.1725	0.3844	0.4144	0.3487	1	
12	0.5454	0.4505	0.1120	0.2938	0.4286	0.5738	0.1864	0.3889	0.4457	0.3640	1	
13	0.5351	0.4565	0.1128	0.3193	0.4356	0.5621	0.2223	0.4532	0.5021	0.4102	1	
14	0.5532	0.5976	0.0925	0.2938	0.5796	0.5864	0.1975	0.4388	0.4918	0.3263	1	
15	0.4793	0.4024	0.1326	0.3230	0.4389	0.4851	0.1915	0.3575	0.4162	0.3448	1	
16	0.5328	0.3784	0.1651	0.3266	0.5434	0.5253	0.1719	0.3391	0.3973	0.3505	2	
17	0.5028	0.3874	0.2133	0.3139	0.4785	0.4829	0.1857	0.3290	0.3857	0.3994	2	
18	0.5514	0.4715	0.1400	0.3923	0.4740	0.5400	0.2907	0.4465	0.5166	0.5014	2	
19	0.5948	0.4414	0.1563	0.3996	0.4998	0.5653	0.3038	0.4344	0.4969	0.5681	2	
20	0.6100	0.4745	0.1933	0.3723	0.4697	0.6692	0.2701	0.5459	0.5549	0.4176	2	
21	0.5722	0.5075	0.1398	0.3285	0.4716	0.5858	0.2456	0.4486	0.5119	0.4275	2	
22	0.5991	0.4535	0.1398	0.3303	0.6323	0.4894	0.2537	0.3463	0.4057	0.5521	2	
23	0.5931	0.4955	0.2056	0.3047	0.4575	0.6435	0.2160	0.4426	0.4776	0.3554	2	
24	0.5052	0.3694	0.2382	0.3522	0.5849	0.4574	0.2325	0.3266	0.3829	0.4879	2	
25	0.5347	0.5315	0.1773	0.3339	0.4834	0.5753	0.2348	0.5056	0.5774	0.3719	2	
26	0.5354	0.4384	0.0774	0.3741	0.5204	0.4750	0.2373	0.3336	0.3919	0.4554	2	
27	0.5249	0.4955	0.0958	0.3960	0.5068	0.5824	0.2436	0.3879	0.4231	0.3510	2	
28	0.5233	0.4745	0.1471	0.3613	0.5677	0.4405	0.2536	0.3129	0.3677	0.4905	2	

Fig. 4. Coding of breathing cycles

Using correlation analysis of parameters above we could exclude from the list of parameters some of them, namely No 6 and 9 for example in Fig.5.

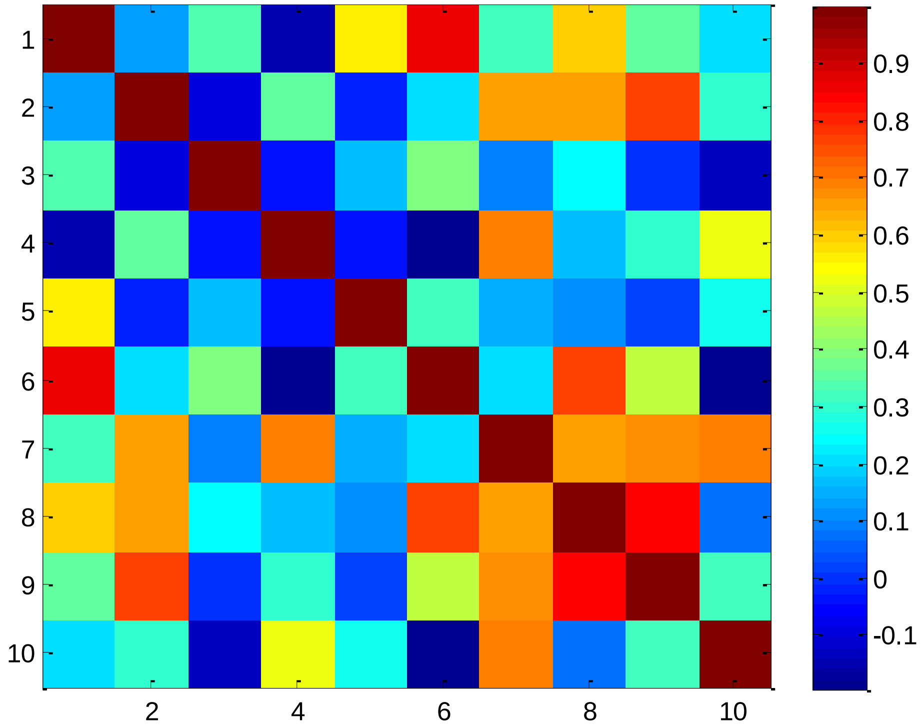

Fig. 5. Correlations matrix

One of effective and most widely used algorithms of clustering under large set of parameters is fuzzy C-mean clustering that we use to find changes between breathing cycles during psychological test. In hard clustering, we should divided the breathing cycles into distinct clusters, where each data element belongs to exactly one cluster. In fuzzy clustering, each object can belong to more than one cluster, and associated with each breathing cycle is a set of membership levels. These indicate the strength of the association between that data element and a particular cluster. In our investigation we perform the two-clusters identification.

Decomposition on two clusters implies that we have to find such difference between breathing cycles that explain the nature of breathing change from one emotion state to another.

We have to partite a set of breathing cycle parameters $B = \{b_1, \ldots, b_N\}$ where N is number of cycles observed during test, into collections of two fuzzy clusters $C = \{c_1, c_2\}$. The partition matrix $W = w_{i,j} \in [0,1], i = 1, \ldots, N, j = 1,2$ shows the degree to which element b_i belongs to cluster c_j. For this purpose it is necessary to minimize an objective function. In our case it looks like

$$J_k(b) = \frac{1}{\left(\frac{d(center_k, b)}{d(center_1, b)}\right)^{\frac{2}{m-1}} + \left(\frac{d(center_k, b)}{d(center_2, b)}\right)^{\frac{2}{m-1}}}, k = 1,2$$

The fuzzifier m determines the level of cluster fuzziness.

Different types of nonlinear dynamical models may be constructed, for example neural networks or recurrent fuzzy models. These models may be used for short-term forecasting of respiration patterns and extraction of new informative parameters from respiratory signals. More sophisticated neural models that can capture real dynamics are based on parametric neural network models, first proposed by Butera et al. [4], have also been developed. Recent studies performed with reference to clinical spirometry data for comatose patients revealed correlations between clinimetric parameters and neuronal dynamics [5]. Visualization techniques applicable to time series, such as the Fuzzy Symbolic Dynamics and Recurrence Plots can also be used to analyze different breathing patterns in respiratory data for different neuronal parameter ranges [6].

Further development of novel computing technologies may increase our understanding of severe changes in breath associated with various states of the human body (from leisure&sport activities to various illnesses or injuries), significantly improve early diagnostics, and provide novel approaches allowing for better therapy [7].

3. Implementation and analysis of psychological test

The relationship between emotional feelings and respiration is surveyed and well known. Researchers use standardized images databases eliciting required emotional states, but these databases need validation using physiological features [8].

The aim of this study was to compare normative ratings of the Nencki Affective Picture System - NAPS [9] standardized images database with the emotional respiratory patterns. To control possible influence some personality traits (anxiety) and mood (symptoms of depression) on affective pictures perception the polish version of the both Spielberger's State-Trait Anxiety Inventory and Beck Depression Inventory-II were implemented. All subjects were naïve with respect to the aim of the study. They all gave written informed consent.

Each subject was presented with 120 images of three categories (pleasant, neutral and unpleasant) selected from the Nencki Affective Pictures Systems [12]. Each category of images was divided into three series. Images were presented for 6 seconds each. After registration of breathing signals and building the table for clustering we used the fuzzy C-means clustering procedure.

The example of clustering result is shown in fig. 6. We are interesting of change of type of breathing during test.

As we can see the breathing character of the person is changed about 5 minute later after starting of the test. Then after next about 5 minute character of breathing returns to first cluster.

Parameters of breathing that are quite different for two clusters are No 2,4,7,8 (table 2).

Table 2. Parameters characteristics for the clusters

Parameter	1 cluster		2 cluster	
	Mean	Std	Mean	Std
1	0.5347	0.0476	0.5875	0.0528
2	0.4568	0.0898	0.6028	0.0860
3	0.1406	0.0784	0.1820	0.0572
4	0.3612	0.1140	0.4162	0.0448
5	0.5000	0.0825	0.4924	0.0744
7	0.2475	0.1244	0.4125	0.0622
8	0.3903	0.0836	0.6049	0.0715

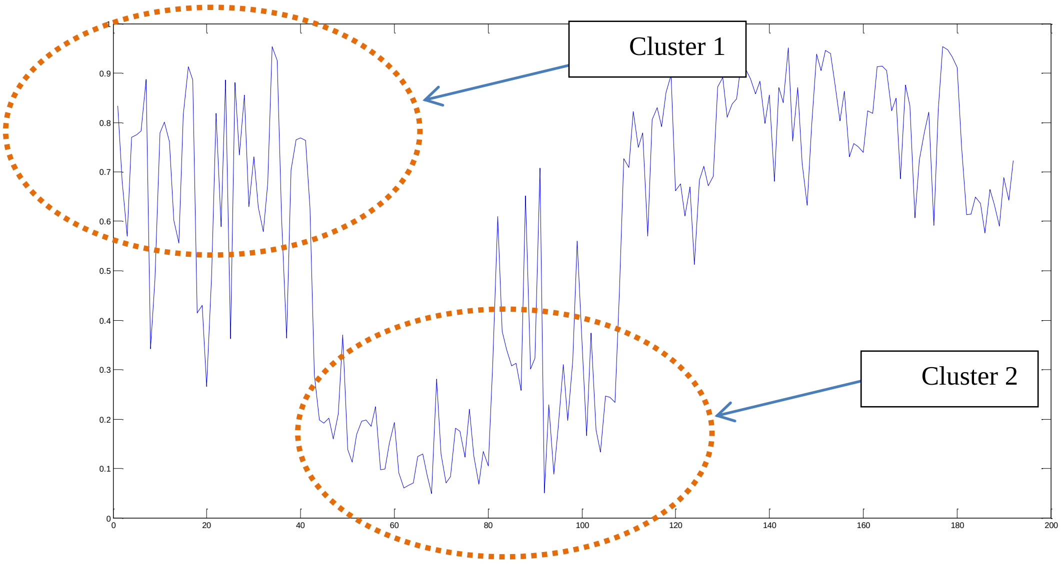

Fig. 6. Clustering of breathing cycles

We could propose hypothesis about results of psychological test in point of view of breathing changing.

1. All subjects were changing the type of breathing (we observe the two different clusters). Details of each clusters may vary
2. Moment of changing the breathing is different for the subjects, that can means different resistance to stimuli.
3. Some people returned to breathing type 1.
4. For the fuzzy classification division it can be add 3 or more clusters but it is hard to interpret them
5. In addition to the above suggested parameters the fractal dimension of each breathing cycle can be used
6. Using model of prediction we can predict permanently possible future changes of breathing, and according to future cycle classification in the sense of emotion states, predict the emotions and control them.

4. Sensors and hardware

Our investigations of breathing are based on the SFM3000 sensor [10], a digital flow meter designed for high-volume applications. It measures the flow rate of air, oxygen and other non-aggressive gases with high accuracy, providing about 2000 points per second with 12-bit resolution, recording data with flow range ±200 SLM (Standard Liters per Minute). It can be attached to a flexible long handle for recording of coma patients or attached like a microphone to the head for local measurements (table 3).

Table 3. SFM3000 technical specification (Sensor Technical Documentation).

Parameter	Value	Remarks
Flow range	200 SLM	Bidirectional
Accuracy	3 % m.v.	
Processing time	0.5 ms	
Other important features	Low pressure drop, full calibration, temperature compensation, digital interface (PC)	

4. Discussion

Proposed computational models of breath may constitute another breakthrough in aforementioned area offering completing position to the current state of the art. Novel, more effective approach can provide better, clear and easy understanding of processes underlying breath processes. Whole family of such models can reflect various sub-levels of breath processes and constitute important contribution to breath mechanisms analysis.

Using a new spirometric hardware and data analysis method, we have presented a reliable and repeatable method of breath collection for analysis of their features. Proposed technique is simple to perform and uses equipment compatible with equipment readily available in the hospital environment, thus making it attractive for use in routine clinical practice. Disruption to a patient's ventilation pattern was minimized as much as possible.

This is the first study to collect and analyse breath features using proposed method. Directions of further research vary from research on breath in healthy people (sportmens, choir singers, etc.) and patients with various conditions, including the most severe neurological cases (e.g. patients with disorders of consciousness). This research allows for classification of breathing patterns according to the characteristics of selected emotions [11]. These results may also be useful in a reverse task, namely using breathing signals to estimate emotional states. Such approach can open novel methods for control of emotions, combining analysis of breathing patterns with appropriate sets of images (e.g. in affective computing applications). Further common effort of medical staff and engineers can provide unified strategy resulting in technical problem solving, improved databases of breath signals in healthy subjects and patients in various pulmonological conditions, and also models of pathogenic mechanism useful in everyday clinical practice. Next generation of such sensors with built-in gas sensors are also our important focus [12-15]. Such built-in emiconductor based gas sensors, including acetone analyzers, can significantly improve continuous diagnostics during therapy and care.

In conclusion, we were able to accurately and reliably measure selected breath features. The new spirometric hardware device together with various data analysis models and neural system models will be used in the Centre for Modern Interdisciplinary Technologies [16] by neurologists for evaluation of prognostic outcomes for patients after stroke, disorders of consciousness in the InteRDoCTor project [27], and in assessing of emotional states and the anticipatory reward attention reactions.

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