Towards a Low-Complex Breathing Monitoring System Based on Acoustic Signals

Pere Martí́ć-Puig, Jordi Solé-Casals, Gerard Masferrer, and Esteve Gallego-Jutglà

Digital Technologies Group, University of Vic,
Sagrada Família 7, 08500 - Vic, Catalonia, Spain
{pere.marti,jordi.sole,gerard.masferrer,
esteve.gallego}@uvic.cat

Abstract. Monitoring the breathing is required in many applications of medical and health fields, but it can be used also in new game applications, for example. In this work, an automatic system for monitoring the breathing is presented. The system uses the acoustic signal recorded by a standard microphone placed in the area of the nostrils. The system is based on a low-complex signal parameterization performed on non-overlapped frames. From this parameterization, a reduced set of real parameters is obtained frame-to-frame. These parameters feed a classifier that performs a classification in three stages: inspiration, transition or retention and expiration providing a fine monitoring of the respiration process. As all of those algorithms are of low complexity and the auxiliary equipment required could only be a standard microphone from a conventional Bluetooth Headset, the system could be able to run in a smartphone device.

Keywords: Breathing monitoring, low-complex system, linear discriminant analysis, smartphone app.

1 Introduction

The breathing is one of the body's few autonomic functions that can be controlled and can affect functioning of the autonomic nervous system [5]. This paper specifically considers the fine real-time breathing monitoring using an acoustic signal recorded by a standard microphone placed in the area of the nostrils. By analyzing this acoustic signal, the breathing is continuously classified in terms of its cycles of inspiration-expiration and an intermediate stage that we call retention. A real-time breathing monitoring system can be used in some biofeedback applications and in this preliminary design it is thought to work in low noise environments.

The human breathing has been deeply studied in the context of respiratory illnesses and has received great attention from the biofeedback framework. Following the biofeedback breathing approach, some relevant works have been done in relation with stress and health [21-23],[25],[26], [30] especially in the area of respiratory illnesses [22], [32]. Respiratory sinus arrhythmia (RSA) is the phenomenon by which respiration modulates the heart rate in normal humans. As a result, the respiration affects the arterial blood pressure and the volume pulse, so, nowadays, an important part of those

T. Drugman and T. Dutoit (Eds.): NOLISP 2013, LNAI 7911, pp. 128–135, 2013.

biofeedback clinical studies relate the breath control with the heart rate coherence [28] and with the idea of developing a non-pharmacological treatment for hypertension. Many clinical studies are being done under this assumption [21], [31], [20], [10], [24].

Another interesting area in which the breathing monitoring can be of interest is the area of emotion detection. As it was early reported in [27], emotions are associated with distinct patterns of cardiorespiratory activity. According to [6][13], fast and deep breathing can indicate excitement such as anger or fear, but sometimes also joy. Rapid shallow breathing can indicate tense anticipation including panic, fear or concentration. Slow and deep breathing indicates a relaxed resting state, while slow and shallow breathing can indicate states of withdrawal, passive like depression or calm happiness. In the literature several non-intrusive methods have been proposed to detect the breathing. Some other classical methods are based on movement, volume and tissue composition detection. Methods included in this category are the transthoratic impedance monitoring, the measurement of chest and/or the abdominal circumference, the electromyography, various motion detectors and the photoplethysmography. A good compilation of these methods can be found in [11]. Recently, in [19], [12], [14] the breathing is detected using far-infrared (FIR) cameras by monitoring the air flow temperature in the nasal hole due of the inspiration and expiration. Those approaches involve some image processing techniques and have to deal with practical questions as head rotation, distance between camera and human and camera angle. Our approach follows the acoustic signal approximation like those appeared in [7], [8], where the respiratory sound is measured using a microphone placed either close to the respiratory airways or over the throat to detect the variation of sound. The acoustic breathing signal have been studied and modelled in different works [16-17], [29], [33].

On the other hand, today the smartphones have become more ubiquitous and provide high computing and connectivity capabilities, incorporating high-resolution touchscreens, portable media players, 3-axis accelerometers, 3-axis gyroscopes, cameras and microphones, among other accessories. So it is reasonable to consider trying advantage of those devices by developing biofeedback apps specifically for them, in order to allow a patient to perform training at home. A potential advantage of using smartphone's apps is the opportunity to collect large amount of data -with user permission if the apps are distributed for free- enabling large scale clinical studies.

Nowadays there are several applications available for Smartphone, mainly for iOS and Android operating systems, which work on different breathing aspects. Most of these apps come from fields like health [2], [5] relaxation [3] or meditation [1] techniques, and have a careful presentation but have a little control on monitoring the quality of the exercise as most of those apps are limited to provide breathing rhythms that should guide the exercise. Our system can overcome these limitations and provide an accurate control on breathing monitoring.

1.1 Acoustic Data Registration

A microphone detects the airflow due to the sound created by turbulence that occurs in the human respiratory system because, even for shallow breathing, turbulence occurs in parts of this system creating a noise which is transferred through tissue to the surface of the skin [15]. Some works have analyzed the acoustic breathing signal from the physical production and some models are proposed [16, 17, 29, 33]. In some of these the same studies the problematic of finding the best place to allocate the microphone is addressed, finding different appropriate locations on the human body where acoustic breathing signals may be detected.

In our case an inexpensive standard microphone from a conventional Bluetooth Headset is placed very close to the nostrils area with the amplifier gain near of its maximum. The signal is sampled at 8000 Hz and it is processed in a personal computer (PC). The recoding environment in which the user performs the breathing exercises is recommended to be noiseless. By means of an envelope detector the cycles of breathing are easy characterized as it is shown in figure 1. In order to detect the envelope, the input signal is digitally rectified and filtered by an infinite impulse response filter of one single pole at z = 0.995 that has been prepared to work frame-to-frame. The breathing signal can be automatically segmented in its three stages using a threshold on the envelope.

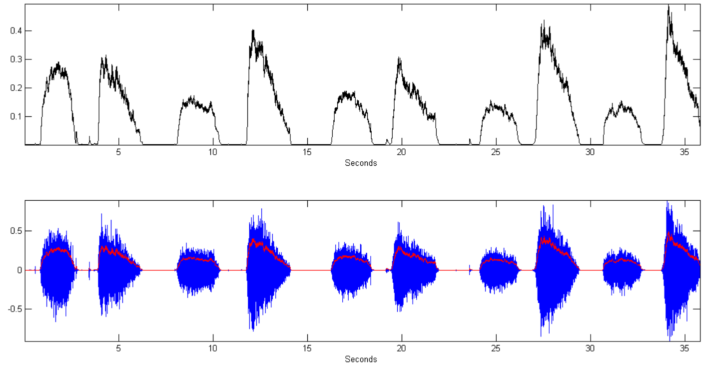

Fig. 1. On the top, 36 seconds of an acoustic breathing signal envelope. On the bottom, the same detected envelope represented together with the breathing signal.

1.2 Low-Complex Parameterization Method

The proposed simple parameterization is as follows: The signal is segmented into non-overlapped frames. The band of interest is divided into a given number of sub-bands and the frame is parameterized with the energy that has in each of this sub-bands. In order to simplify the process, a fast Fourier Transform (FFT) is performed with a square window. Only the moduli of the discrete Fourier coefficients are considered and the values belonging to the same sub-band are added in order to obtain a real parameter per sub-band. It means that if we consider, for example, a band partition in 4 sub-bands then only 4 real parameters are required to parameterize a frame. Those parameters are normalized. The normalization value is a reference value obtained from the highest parameter of a test signal.

To perform the experiments we have selected a group of 5 users and we have recorded their breathing for 5 minutes. In order to verify that the proposed parameterization is suitable for detecting the three stages considered in the respiration process, a manual segmentation is performed considering different frame lengths and different sub-band partitions. Figure 2 shows the process of the manual segmentation and the parameterization process.

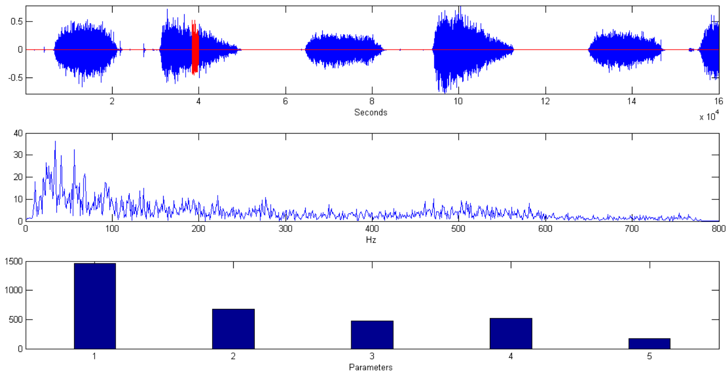

Fig. 2. On the top, a frame of 200 ms is represented (in red) that corresponds to an expiration breathing sound. In the middle, the modulus of the Fast Fourier Transform applied to this frame. On the bottom, the frame parameterization obtained from the integration of all coefficients of each equal-spaced sub-band, considering a five sub-band partition.

2 Experiments

2.1 Classification Techniques

Many possible techniques for data classification are available. Among them, Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA) or Neural Networks (NN) are techniques commonly used for data classification and/or dimensionality reduction [9]. In our experiments we will use LDA due to his properties: the system works by projecting the data onto a lower-dimensional vector space such that the ratio of the between-class distances to the within-class distance is maximized, thus achieving maximum discrimination. The optimal projection (transformation) can be readily computed by applying the eigendecomposition on the scatter matrices. See [9] and [18] for details on the algorithm.

In our experiments we will hence use LDA and a variation of it, called Quadratic discriminant Analysis (QDA). The difference of both systems relies on the assumptions made for the distributions of each class. While for LDA a normal distribution is assumed with a pooled estimate of covariance, in QDA there is no assumption that the covariance of each of the classes is identical, and for each class this covariance matrix is estimated from training data.

2.2 Results and Discussion

In the following experiment we mixed all the users in order to have a more general system, not focussed in one solely user. After applying the pre-processing step explained in Section 2.2, we obtained the total number of frames per class depicted in Table 1, where C0 is inspiration, C1 is expiration and C2 is retention.

Table 1. Number of available frames for each class, for different considered configurations

Length of the frame\ class	**C0**	**C1**	**C2**
50 ms	156	112	132
100 ms	66	56	78
200 ms	33	28	39

For each frame we considered a different number of sub-band partitions (parameters), ranging from 3 to 10. We explored all these 24 configurations (3 different frame lengths x 8 different number of parameters considered) using LDA and QDA.

For the training and validation phases, Leave-One-Out (LOO) cross-validation was used [9] in order to obtain solid results, due to the limited number of examples per class (156 in the best case and 33 in the worst case). With this methodology for a data set with N samples, a single sample is retained as a validation, and all the N-1 samples are used as a training data. Then cross-validation process is repeated N times, using each time a different sample as a validation data. The obtained results once all the samples have been used as a validation data are averaged in order to compute a single measure of classification rate. The advantage of this method is that all observations are used for both training and validation, and each observation is used for validation exactly once. LOO could be computationally expensive because it requires many repetitions of training, but it is successful in dealing with very small data sets as it is our case.

In figure 1 we shown the evolution of the classification rate (in %), obtained with the LOO cross-validation strategy when LDA is used as classification system. We can observe that higher frame length obtains always better performance independently of the number of parameters considered. The best case is a 93% of classification rate, obtained with 4, 8, 9 or 10 sub-bands and frame length of 200 ms. For all the 3 cases, 8 parameters seems to be the best option, as the maximum classification rate is achieved in all configurations (93% for 200 ms frame length, and 90.5% for 100 ms and 50 ms frame length), but also 4 parameters is a good choice for 200 ms frame length.

On the other hand, using QDA results are improved as shown in figure 2. The best frame length is still 200 ms and the number of parameters is again 4 for this case, where the maximum classification rate of 96% is achieved, representing an improvement of 3 points compared to LDA case.

For the other frame lengths results also improve when QDA is used. For 100 ms frame length we achieve 95% of classification rate, with again 4 parameters, representing an improvement of 4.5 points compared to LDA case, while for 50 ms frame length we obtain a maximum of 94.75% of classification rate, for 8 parameters, that represents an improvement of 4.25 points compared to LDA case.

It seems that high frame lengths tend to be more adapted to our parameterisation system, and small number of parameters can be used. This result is interesting in the sense that audio signal will be faster processed if we have an small number of frames and also the classification system will be faster with less number of parameters.

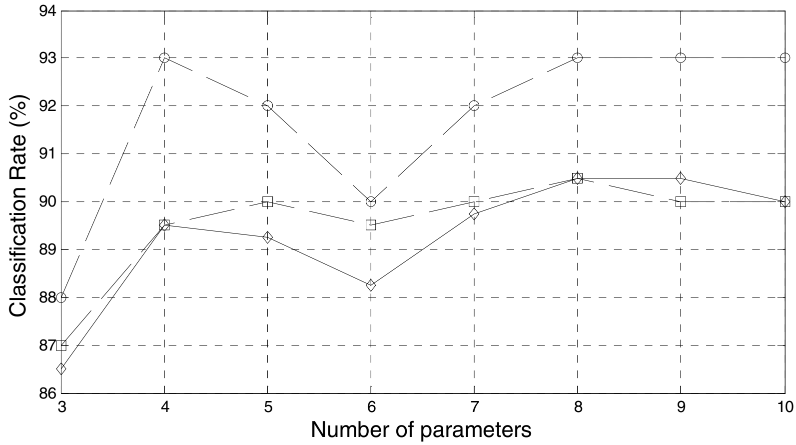

Fig. 3. Classification Rate (%) obtained for LDA, different number of sub-bands considered (different number of parameters for the classification system), from 3 to 10, and different frame lengths (50 ms, diamond marker; 100 ms, square marker; and 200 ms circle marker)

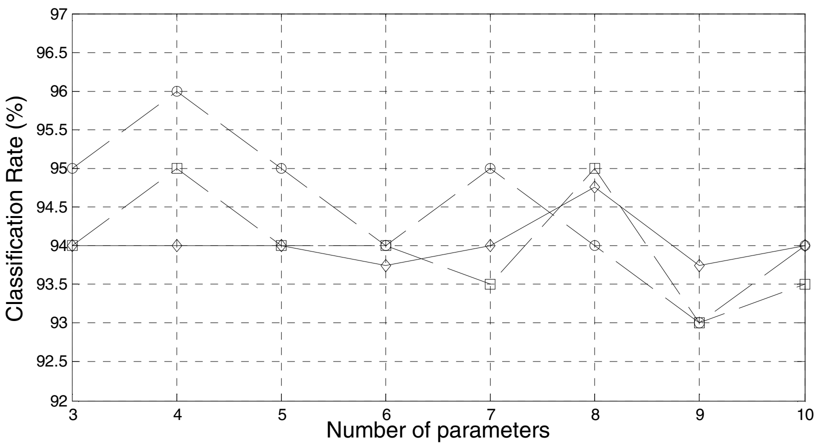

Fig. 4. Classification Rate (%) obtained for QDA, different number of sub-bands considered (different number of parameters for the classification system), from 3 to 10, and different frame lengths (50 ms, diamond marker; 100 ms, square marker; and 200 ms circle marker)

3 Conclusions

In this work, a preliminary study for developing a system for monitoring the breathing is presented. The system is designed in order to use the acoustic signal recorded by a standard microphone placed in the area of the nostrils, and based on a low-complex signal parameterization performed on non-overlapped frames. Parameters are obtained from the moduli of the discrete Fourier Transform coefficients considering a predefined number of sub-bands, so that the values belonging to the same sub-band are added in order to obtain a reduced set of real values frame-to-frame. These parameters feed a very simple classifier based on LDA that performs classification in three stages: inspiration, retention (or transition phase) and expiration.

The best configuration obtained during the experiments is a frame length on 200 ms, 4 sub-bands for characterizing the acoustic signal, and QDA as a classification system. With this configuration, and with a LOO scheme, we obtain a 96 % of classification rate, which is a promising result. This encourages us to explore this way for designing a real system using only a smartphone. Increasing the number of sub-bands does not significantly improve the classification results. All sub-band partitions explored have the same bandwidth however other irregular partitions could be considered. Frame windowing and frame overlapping are not considered because neither significantly improve the classification and only increase the system complexity. More users have to be tested in order to quantify the user dependency and the system robustness.

Acknowledgments. This work has been partially supported by the University of Vic (grant R904) and under a predoctoral grant to Mr. Esteve Gallego-Jutglà ("Amb el suport de l'ajut predoctoral de la Universitat de Vic").

References

1. Pranayama -yoga breathing, https://play.google.com/store/apps/details?id=pranayama.home
2. Breath health tester pro, https://play.google.com/store/apps/details?id=org.app.breath_rate
3. Relax: Stress anxiety relief, https://play.google.com/store/apps/details?id=com.saagara.relax
4. Breathng for life, https://play.google.com/store/apps/details?id=com.soniq.breathingforlife1
5. Badra, L.J., Cooke, W.H., Hoag, J.B., et al.: Respiratory modulation of human autonomic rhythms. American J. of Physiology-Heart and Circulatory Physiology 280(6), H2674–H2688 (2001)
6. Cacioppo, J.T., Berntson, G.G., Larsen, J.T., Poehlmann, K.M., Ito, T.: The psychophysiology of emotion. Handbook of Emotions 2, 173–191 (2000)
7. Corbishley, P., Rodriguez-Villegas, E.: A nanopower bandpass filter for detection of an acoustic signal in a wearable breathing detector. IEEE Transactions on Biomedical Circuits and Systems 1(3), 163–171 (2007)
8. Corbishley, P., Rodríguez-Villegas, E.: Breathing detection: Towards a miniaturized, wearable, battery-operated monitoring system. IEEE Transactions on Biomedical Engineering 55(1), 196–204 (2008)
9. Duda, R.O., Hart, P.E., Stork, D.G.: Pattern classification and scene analysis, 2nd edn. (1995)
10. Ferreira, J.B., Plentz, R.D.M., Stein, C., Casali, K.R., Arena, R., Lago, P.D.: Inspiratory muscle training reduces blood pressure and sympathetic activity in hypertensive patients: A randomized controlled trial. Int. J. Cardiol. (2011)
11. Folke, M., Cernerud, L., Ekström, M., Hök, B.: Critical review of non-invasive respiratory monitoring in medical care. Medical and Biological Engineering and Computing 41(4), 377–383 (2003)

12. Goldman, L.J.: Nasal airflow and thoracoabdominal motion in children using infrared thermographic video processing. Pediatr. Pulmonol. (2012)
13. Haag, A., Goronzy, S., Schaich, P., Williams, J.: Emotion recognition using bio-sensors: First steps towards an automatic system. Affective Dialogue Systems, 36–48 (2004)
14. Hanawa, D., Morimoto, T., Tearda, S., et al.: Nasal cavity detection in facial thermal image for non-contact measurement of breathing, 586–590 (2012)
15. Harper, V.P., Pasterkamp, H., Kiyokawa, H., Wodicka, G.R.: Modeling and measurement of flow effects on tracheal sounds. IEEE Trans. on Biomedical Engineering 50(1), 1–10 (2003)
16. Hossain, I., Moussavi, Z.: Relationship between airflow and normal lung sounds 2, 1120–1122 (2002)
17. Hossain, I., Moussavi, Z.: Respiratory airflow estimation by acoustical means 2, 1476–1477 (2002)
18. Fukunaga, K.: Introduction to statistical pattern recognition. Academic Pr. (1990)
19. Koide, T., Yamakawa, S., Hanawa, D., Oguchi, K.: Breathing detection by far infrared (FIR) imaging in a home health care system, 206 (2009)
20. Linden, W., Moseley, J.: The efficacy of behavioral treatments for hypertension. Appl. Psychophysiol Biofeedback 31(1), 51–63 (2006)
21. McGrady, A.: The effects of biofeedback in diabetes and essential hypertension. Cleve Clin. J. Med. 77(suppl. 3), S68–S71 (2010)
22. Mikosch, P., Hadrawa, T., Laubreiter, K., et al.: Effectiveness of respiratory-sinus-arrhythmia biofeedback on state-anxiety in patients undergoing coronary angiography. J. Adv. Nurs. 66(5), 1101–1110 (2010)
23. Moore, S.: Tools & toys: Calm in your palm. IEEE Spectrum 43(3), 60 (2006)
24. Mourya, M., Mahajan, A.S., Singh, N.P., Jain, A.K.: Effect of slow-and fast-breathing exercises on autonomic functions in patients with essential hypertension. The Journal of Alternative and Complementary Medicine 15(7), 711–717 (2009)
25. Pokrovskii, V.M., Polischuk, L.: On the conscious control of the human heart. Journal of Integrative Neuroscience 11(2), 213–223 (2012)
26. Rafferty, G.F., Gardner, W.: Control of the respiratory cycle in conscious humans. J. Appl. Physiol. 81(4), 1744–1753 (1996)
27. Rainville, P., Bechara, A., Naqvi, N., Damasio, A.: Basic emotions are associated with distinct patterns of cardiorespiratory activity. International Journal of Psychophysiology 61(1), 5–18 (2006)
28. Sharma, M.: RESPeRATE: Nonpharmacological treatment of hypertension. Cardiol. Rev. 19(2), 47–51 (2011)
29. Shykoff, B.E., Ploysongsang, Y., Chang, H.: Airflow and normal lung sounds. American Journal of Respiratory and Critical Care Medicine 137(4), 872–876 (1988)
30. Stock, M., Kontrisova, K., Dieckmann, K., Bogner, J., Poetter, R., Georg, D.: Development and application of a real-time monitoring and feedback system for deep inspiration breath hold based on external marker tracking. Med. Phys. 33(8), 2868–2877 (2006)
31. Tsai, P., Chang, N., Chang, W., Lee, P., Wang, M.: Blood pressure biofeedback exerts intermediate-term effects on blood pressure and pressure reactivity in individuals with mild hypertension: A randomized controlled study. The J. of Alternative and Complementary Medicine 13(5), 547–554 (2007)
32. Van Gestel, A.J.R., Kohler, M., Steier, J., Teschler, S., Russi, E.W., Teschler, H.: The effects of controlled breathing during pulmonary rehabilitation in patients with COPD. Respiration 83(2), 115–124 (2012)
33. Yap, Y.L., Moussavi, Z.: Acoustic airflow estimation from tracheal sound power 2, 1073–1076 (2002)