31st Annual International Conference of the IEEE EMBS
Minneapolis, Minnesota, USA, September 2-6, 2009

Performance Evaluation of a Tri-axial Accelerometry-based Respiration Monitoring for Ambient Assisted Living

Anmin Jin, IEEE Student Member, Bin Yin, Geert Morren, Haris Duric*, Ronald M. Aarts, IEEE Fellow

Abstract—**Ambient Assisted Living (AAL) technology is often proposed as a way to tackle the increasing cost of healthcare caused by population aging. However, the sensing technology for continuous respiratory monitoring at home is lacking. Known approaches of respiratory monitoring are based on measuring either respiratory effect, e.g. tracheal sound recording by a bio-acoustic sensor, or respiratory effort, e.g. abdomen movement measurement by a tri-axial accelerometer. This paper proposes a home respiration monitoring system using a tri-axial accelerometer. Three different methods to extract a single respiratory signal from the tri-axial data are proposed and analyzed. The performance of the methods is evaluated for various possible respiration conditions, defined by the sensor orientation and respiration-induced abdomen movement. The method based on Principal Component Analysis (PCA) performs better than selecting the best axis. The analytical approach called Full Angle shows worse results than the best axis when the gravity vector is close to one of the sensor's axes (<15 degrees). Hybrid-PCA, which is a combination of both methods, performs comparable to PCA. The system is evaluated using simulated data from the most common postures, such as lying and sitting, as well as real data collected from five subjects. The results show that the system can successfully reconstruct the respiration-induced movement, which is necessary to determine the respiratory rate accurately.**

I. INTRODUCTION

THE respiration is one of the most important vital signs. However, sensing technology for automated respiration monitoring is still lacking for ambient assisted living. Respiration monitoring is mostly based on two different principles: the measurement of respiratory effort (e.g. thoracic impedance pneumography, accelerometers, photoplethysmography [1]-[4]) and respiratory effect (e.g. sound recording, temperature sensing, carbon dioxide sensing [5]-[7]). Some sensors have already been used to monitor respiration in other applications. In intensive care units (ICU), thoracic impedance pneumography is considered the "gold standard" for respiration monitoring, whereas in sleep studies, inductive plethysmography, often referred to as respiration band, is commonly used [8].

A tri-axial accelerometer is a device that measures the acceleration in three orthogonal directions (sensing axes). An accelerometer can be used to sense vibrations, e.g. the vibration of a machine [9], orientation, e.g. in human activities monitoring [10] and the inertia, e.g. used in a video game controller [11].

In this paper a tri-axial accelerometer for respiratory monitoring is proposed because it is a promising approach to achieve comfortable, low cost, continuous and ambulatory monitoring. The tri-axial accelerometer is used as an inclinometer to reflect the abdomen or chest movement caused by respiration based on the fact that the magnitude of the inertial acceleration is relatively small compared to the change of gravitational components [12]. Several researchers have adopted this sensing technique in respiratory monitoring [13],[14]. However, this technique requires reliable signal processing methods to enable continuous monitoring under different conditions and postures.

This paper proposes a posture-independent tri-axial accelerometer-based respiration monitoring system and evaluates its performance using both simulated and real subject data.

II. SENSOR PLACEMENT

Since the tri-axial accelerometer is used as an inclinometer, the accelerometer should be placed on the area where the sensor orientation changes during the respiratory movement. The most important muscle involved in respiration is the diaphragm, the dome-shaped skeletal muscle that forms the floor of the thoracic cavity [15]. Therefore, the accelerometer is placed roughly at the position of the diaphragm muscle below the xiphoid process (at the lower end of the sternum).

III. SIGNAL PROCESSING DIAGRAM

A signal processing module extracts the respiratory rate from the measured acceleration data. The block diagram of the signal processing part is presented in Fig.1.

The raw signal is first collected by the data acquisition module and fed into the pre-processing block. Preprocessing includes signal conditioning, segmentation and band-pass filtering. Artifacts, such as speech, motion and eating, are detected and removed by pattern classification methods after preprocessing. An essential step before respiratory rate extraction is axes fusion, which aims at reconstructing the

Manuscript received April 23, 2009.

Anmin Jin is with the Department of Electrical Engineering, Eindhoven University of Technology, The Netherlands.

Bin Yin, Geert Morren and Haris Duric are with Philips Research Europe.

Ronald M. Aarts, is with Philips Research Europe, Eindhoven, The Netherlands and the Department of Electrical Engineering, Eindhoven University of Technology, Eindhoven, The Netherlands.

* Corresponding author at: Biomedical Sensor Systems, Philips Research, High Tech Campus 34, Room 1.037, 5656AE Eindhoven, The Netherlands. (phone: +31 40 274 7623; e-mail: haris.duric@philips.com)

original respiration-induced movement signal from the tri-axial signals, given a posture and sensor orientation. In the final step, the respiratory rate is simply calculated by either peak detection in time-domain or taking the fundamental frequency of the reconstructed signal in frequency domain when the reconstructed signal is artifacts free. The focus of this paper is mainly on investigation of the possible axes fusion methods.

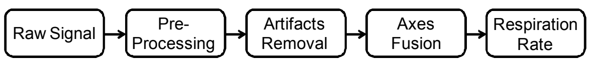

Fig.1. Diagram of the signal processing module.

IV. Model and Methods

Due to the nature of the accelerometer signal, the respiratory signal quality depends not only on respiratory effort but also on body posture and the sensor orientation. It is thus necessary to introduce the mathematical model which shows how the respiration-induced movement projects on the three sensor axes.

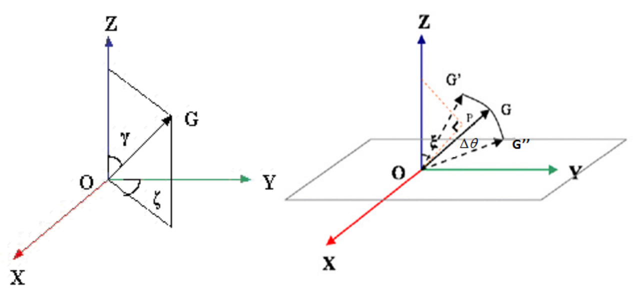

Fig.2. Orientation of the gravity at its nominal position and its moving plane defined in the sensor coordinates.

In the sensor coordinates system, the respiration-induced movement can be represented as the gravity vector G moving around a nominal position in a plane with the maximum angle span $\Delta\theta$ on either side of the nominal position. The resulting projection of the movement onto three axes is determined by the orientation of the sensor coordinates system and the orientation of the moving plane defined by OG'G'' in Fig.2. These two orientations are defined by three variables: γ, the angle between the nominal position of G and z axis; ζ, the angle between the y axis and the projection of G onto x-y plane; ξ, the angle between z axis and its projection in the moving plane. The geometric model in Fig.2 with these four parameters describes how the respiration-induced movement projects on the measured tri-axial signals.

The axes fusion block reconstructs the respiration-induced movement based on measured tri-axial signals, as illustrated in Fig.3. Three methods are investigated for this block:

1. Analytical Approach (referred to as Full Angle)
2. Principal Component Analysis (PCA)
3. Hybrid PCA, the combination of methods 1 and 2.

Full Angle is an analytical approach explicitly making use of sensor orientation information to reconstruct the breathing movement signal based on the model in Fig.2. Full Angle consists of two steps. First, the projection of respiration-induced movement is maximized in each two-dimensional subspace using the DC component and the magnitude of the signal on each axis. In the second step, the respiration-induced movement is reconstructed by calculating vector magnitude of the maximized projection in each two-dimensional subspace.

Axes fusion can be also considered as a dimension reduction problem. PCA is a common method used in dimension reduction. It mathematically rotates the sensor coordinate system to such an orientation that one axis accounts for the largest variance (power) in the data.

Hybrid PCA combines both methods by replacing the second step of Full Angle by PCA.

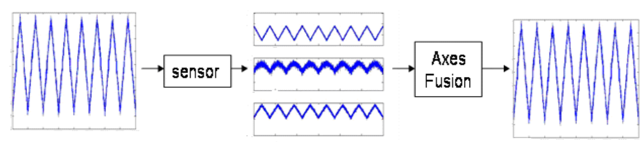

Fig.3. The simulated respiratory effort information (left figure), its projection onto the three axes of the accelerometer (mid figure), and reconstructed respiratory effort information by axes fusion (right figure).

V. Performance Evaluation

A. Overall Evaluation with Simulated Data

By varying the four parameters of the model in Fig.2, it is possible to generate a set of simulated signals that covers all possible conditions. For the accelerometer used in our system, the noise level is close to -30 dB within the relevant frequency band up to 3 Hz on each axis with respect to the gravity. In the simulation, noise of the same level is added on each axis. The performance is measured by the relative Signal-to-Noise Ratio (rSNR) of the data defined after axes fusion with respect to the data of the axis with highest SNR. Equation 1 gives the definition of the SNR and relative SNR,

$$SNR_{AxesFusion} = 10 \cdot \log \frac{Power_{signal}}{Power_{noise}} \qquad (1)$$
$$rSNR = SNR_{AxesFusion} - SNR_{BestAxis}$$

where $Power_{signal}$ is defined as the square of the peak height on the breathing rate in the frequency spectrum and $Power_{noise}$ is defined as the square of the average noise floor.

Three methods for axes fusion are evaluated using the same measure. In Fig.4, the simulation results show that PCA and Hybrid PCA always perform better than selecting the best axis. The best rSNR for both PCA methods can be as high as 5 dB (Fig.4). The overall performances of the two methods are comparable. Full Angle mostly performs better than selecting the best axis with rSNR gain close to 5dB, except when the nominal orientation of the gravity is close to one axis (<15°), as shown in the top plot of Fig.4. The reason for this is that, if the gravity is close to one of the three axes, the breathing information is weak on that axis, which has thus lower SNR. In this case, the Full Angle method can increase the noise level due to the non-linear calculation of the vector magnitude in the second step of Full Angle. On the contrary, PCA employs linear calculation, which avoids increasing noise. However, PCA implicitly assumes that the DC component of the signal on each axis resembles the sensor orientation, which is not accurate especially when the angle span $\Delta\theta$ becomes large. Since Full Angle explicitly calculates sensor orientation, the idea of Hybrid PCA is to combine the advantages of both.

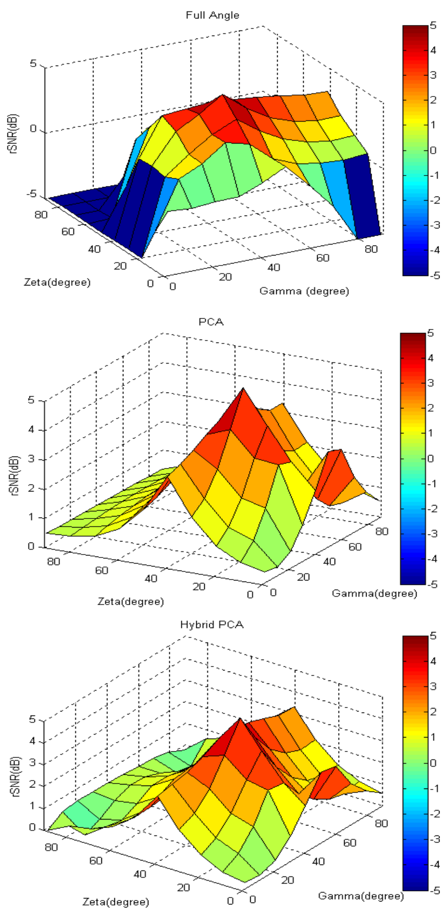

Fig.4. The simulation result of Full Angle, PCA and Hybrid PCA approach with $\Delta\theta$ = 1.8 degrees.

B. Performance Evaluation with Practical Conditions

Assuming an initial mounting position of the sensor and given no relative movement of the sensor with respect to the body, there is a limited range of values for a combination of four angles, as defined before, which occur in real life. In order to evaluate the performance of the system in practical conditions, seven common postures that a subject may assume are selected (Table 1). The parameters are empirically determined. The noise level is set to -30 dB.

Based on the model in Fig.2, it is possible to generate the simulated signals with the parameters given in Table 1. Fig.5 shows the simulated signal of three axes under seven postures that are plotted consecutively. These simulated raw signals are fed into the axes fusion block and the output is evaluated by calculating the relative SNR for each method.

TABLE I
PARAMETERS FOR SEVEN COMMON POSTURES

Postures	$\Delta\theta$	γ	ζ	ξ
1.Standing	3°	86°	5°	5°
2.Sitting	3°	77°	5°	5°
3.Lean45° Back	3°	47°	5°	5°
4.Lean30° Left	2.5°	86°	35°	35°
5.L45B & L30L	2.5°	57°	35°	35°
6.Lying Supine	3°	5°	5°	4°
7.Lying Aside	0.5°	86°	70°	80°

L45B&L30L = lean 45 degrees back & lean 30 degrees to left

It can be seen in Fig.6 that Hybrid PCA and PCA perform better than selecting the best axis at all seven postures. Full Angle mostly performs comparable to or worse than selecting the best axis for most postures, especially for sitting and standing. This is because the orientation of the gravity vector in the sensor coordinates is close to one axis for these postures. The performance is thus affected by this noisy axis.

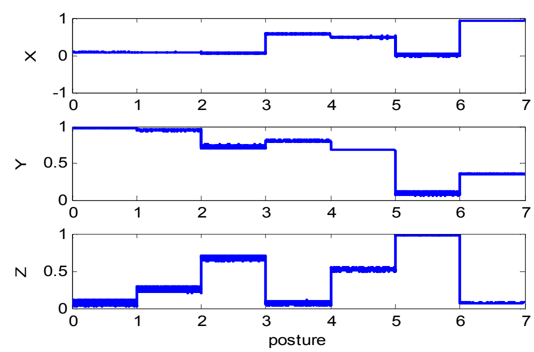

Fig.5. The simulated signals of seven postures, which are represented as seven segments in the plot.

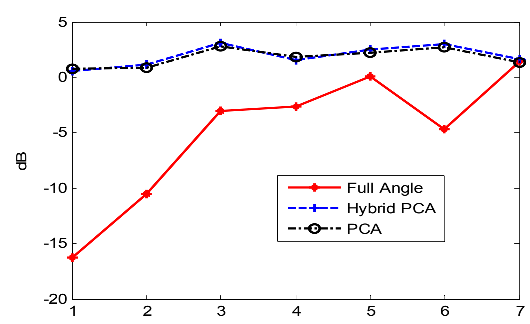

Fig.6. Performance of the system with different signal processing approaches with simulated signal.

C. Evaluation with Real Subject Data

In order to test the system performance in real environment, human testing is arranged to collect the data. Five subjects participated in the test continuously for one hour per person. The accelerometer is connected to a data-acquisition module. The sampling frequency is 10 Hz. The measurement range is ±2g. The data is processed offline using MATLAB® (The Mathworks Inc., MA, US).

In this study, the data segments that do not contain the artifacts were manually selected from this five-hour data. Three approaches are all tested with these segments of data. The test shows that the system is able to recover the respiratory effort information when subjects are in different postures and the sensor is mounted in different orientations. Fig.7 shows an example of raw signals and reconstructed movement using the three methods.

rSNR is calculated in order to compare the performance. The results are in good agreement with those from simulated data. As an example, Fig.8 shows the performance evaluation of a five minute segment of data. Performance of Hybrid PCA is comparable with that of PCA and Full Angle performs worse.

Moreover, Hybrid PCA aims to combine the advantages of PCA and Full Angle. In theory, the larger $\Delta\theta$ becomes the higher the gain Hybrid PCA has over PCA. However, real respiratory data shows that amplitude of $\Delta\theta$ in most cases is less than 3º. Hence, the gain over PCA for this application is limited.

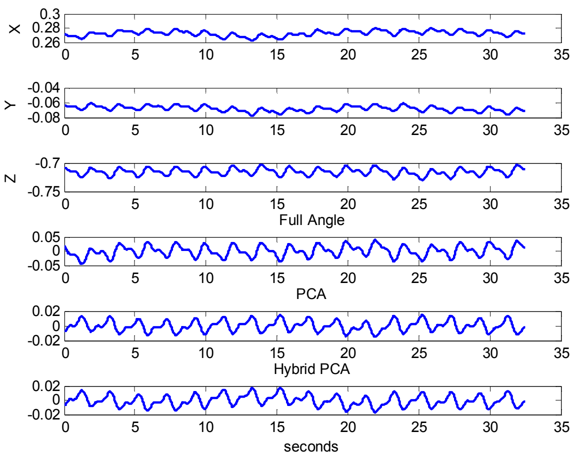

Fig.7. System evaluation with real data; the first three waveforms are raw accelerometer signals of three axes. The bottom three waveforms are the output of the axes fusion block using three different methods.

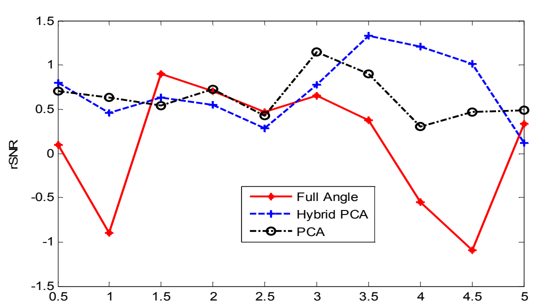

Fig.8. Performance of the system in real data testing with one segment of patient data. Horizontal axis is the time index; each index unit represents a one minute segment. Vertical axis gives the corresponding relative SNR.

VI. Conclusion

A well-placed tri-axial accelerometer can be used to monitor respiratory effort for ambient assisted living. Three different approaches (Full Angle, PCA and Hybrid PCA) are evaluated with both simulated signals and real subject data. Both PCA-related methods perform better than selecting the best axis, independent of postures and sensor mounting orientation. However, Full Angle performs worse than selecting the best axis in the case when the nominal orientation of the gravity is close to one axis.

References

[1] K.P.Cohen, W.M.Ladd, D.M.Beams, W.S.Sheers, R.G.Radwin, W.J.Tompkins, J.G.Webster, "Comparison of Impedance and Inductance Ventilation Sensors on Adults during Breathing, Motion, and Simulated Airway Obstruction," *IEEE Trans. Biomed. Eng.*, vol. 44, no. 7, pp. 555-566, Jul. 1997.

[2] L.Nilsson, A.Johansson, S.Kalman, "Monitoring of respiratory rate in postoperative care using a new photoplethysmographic technique," *J. Clin. Monit. Comput.,* vol. 16, no. 4, pp. 309-315, May 2000.

[3] T.Reinvuo, M.Hannula, H.Sorvoja, E.Alasaarela and R.Myllyla, "Measurement of Respiratory Rate with High-Resolution Accelerometer and EMFit Pressure Sensor," in *IEEE Sensors Appl. Symposium,* Feb. 2006, pp. 192-195.

[4] V.P.Seppa, J.Vaisanen, P.Kauppinen, J.Malmivuo and J.Hyttinen, "Measuring Respirational Parameters with a wearable bioimpedance device," *IFMBE Proc. 13th Int. Conf. Elec. Bioimp. and 8th Conf. Elec. Imped. Tomogr.,* vol. 17, pp. 663-666, 2007.

[5] V.P.Harper, H.Pasterkamp, H.Kiyokawa, G.R.Wodicka, "Modeling and Measurement of Flow Effects on Tracheal Sound," *IEEE Trans. Biomed. Eng.,* vol. 50, no. 1, pp. 1-10, Jan. 2003.

[6] M.Folke, F.Granstedt, B.Hok, H.Scheer, "Comparative Provocation Test of Respiratory Monitoring Methods," *J. Clin. Monit.,* vol. 17, no. 2, pp. 97-103, Feb. 2002.

[7] D.Dodds, J.Purdy, D.Moulton, "The PEP Transducer: A New Way of Measuring Respiratory Rate in the Non-intubated Patient," *J. Accid. Emerg. Med.,* vol. 16, no. 1, pp. 26-28, Jan. 1999.

[8] J.C.T.Khoo, I.T.H.Brown, Y.P.Lim, "Wireless On-Body-Network Breathing Rate and Depth Measurement during Activity," in *30th IEEE EMBS Annual Int. Conf.,* August 20-24, 2008, pp. 1283-1287.

[9] T.W.S.Chow, H.Z.Tan, "HOS-Based Nonparametric and Parametric Methodologies for Machine Fault Detection," *IEEE Trans. Industrial Electronics,* vol. 47, no. 5, pp. 1051-1059, Oct. 2000.

[10] H.J.Luinge, P.H.Veltink, "Inclination Measurement of Human Movement Using a 3-D Accelerometer with Autocalibration," *IEEE Trans. Neural Systems and Rehabil. Eng.,* vol. 12, no. 1, pp. 112-121, Mar. 2004.

[11] T.Schou, H.J.Gardner, "A Wii Remote, A Game Engine, Five Sensor Bars and A Virtual Reality Theatre," *Proc. 19th Australasian conf. Computer-Human Interaction: Entertaining User Interfaces*, pp. 231-234, 2007.

[12] B.Kemp, A.J.M.W.Janssen, and B.van der Kamp, "Body Position Can Be Monitored in 3D Using Miniature Accelerometers and Earth-Magnetic Field Sensors," *Electroencephalog. Clin. Neurophysio. Electromyog. Motor Control,* vol. 109, no. 6, pp. 484-488, Dec. 1998.

[13] M.Guler, S.Ertugrul, "Measuring and Transmitting Vital Body Signs Using MEMS Sensors," in *1st Annual RFID Eurasia,* Sep. 2007, pp. 1-4.

[14] P.D.Hung, S.Bonnet, R.Guillemaud, E.Castelli, P.T.N.Yen, "Estimation of Respiratory Waveform Using An Accelerometer," in *5th IEEE Int. Symp. on Biomed. Imaging: From Nano to Macro,* May 2008, pp. 1493-1496.

[15] G.J.Tortora, B.Derrickson, *Principles of Anatomy and Physiology,* 11th., John Wiley & Sons, Inc., 2000, p. 864.