Sleep monitoring using body sounds and motion tracking

Christoph Kalkbrenner[1], Philipp Stark[1], Guy Kouemou, Maria-Elena Algorri[1], Rainer Brucher[1]

Abstract— **This paper presents a system for sleep monitoring that can continuously analyze snoring, breathing, sleep phases and the activity of the patient during the night and the beginning of the day. Early results show that the system can be used to detect the occurrence of obstructive sleep apnea syndrome (OSAS). OSAS is traditionally diagnosed using polysomnography, which requires a whole night stay at the sleep laboratory of a hospital, where the patient is attached to multiple electrodes and sensors. Our system detects heartbeats, breathing, snoring, sleeping positions and movements using a special electret microphone and an inertial measurement unit (IMU). The system first analyses the sleep using the acoustic information provided by the electret microphone. From the acoustic information breathing events and heartbeats are identified. The system also analyses the patient's activity and positions from data delivered by the IMU. The information from both sensors is fused to detect sleep events. First experiments show that the system is capable of detecting and interpreting relevant data to improve sleep monitoring.**

I. INTRODUCTION

Two common sleep-related breathing disorders are snoring and obstructive sleep apnea syndrome (OSAS). Snoring is the more common of the two respiratory disorders. During a so-called apnea episode, the breathing amplitude of a patient falls below 20% of the baseline over a period of more than 10 seconds [1]. Normally an initial drop in heart rate and a decrease of O_2 saturation occurs a few seconds afterwards. An alarm signal to the central nervous system, the so-called arousal, terminates the apnea phase. About 2-4% of the adult population suffer from OSAS with clinical symptoms. The consequences of this disease vary from extreme daytime sleepiness to high blood pressure to heart attacks [1]. Usually, the patients are made aware of OSAS as a possible cause of their clinical symptoms only after the appearance of serious complications. At that point, a detailed diagnosis is carried out in a clinical environment such as a sleep laboratory. Such a diagnosis involves a great technical effort since several sensors placed on the patient must remain connected by tubes or cables to the measuring devices. The extensive wiring affects the patients sleep and may, in some cases, falsify the results. An early diagnosis of respiratory disorders and a more comfortable way of sleep monitoring would open up a wide market of applications in the field of homecare.

*This study is part of the the project entitled "SomnoSound" supported by the Arbeitsgemeinschaft industrieller Forschungsvereinigungen AiF (KF2186205AK3)

[1]Faculty of Medical Engineering, Hochschule Ulm, University of Applied Sciences, Prittwitzstrae 10, 89075 Ulm, Germany `kalkbrenner at hs-ulm.de`, `brucher at hs-ulm.de`

II. RELATED WORK

A considerable amount of literature has been published on human body sound monitoring. Studies show that it is possible to differentiate between healthy subjects and patients suffering from OSAS using only body sound [2]. Different techniques are used to record body sound such as attaching a polyvinylidene fluoride (PVDF) film sensor to the bed of the patient [3], inserting a bone-conduction microphone in the ear of the patient [4] or using a simple electret microphone as a stethoscope [5]. Although snoring and/or heart sounds can be recoded using all these techniques, there are some limitations: When using a PVDF film attached to the patients bed or body [6] it is only possible to record an audio signal while the patient does not move because motion induces vibrations which strongly disturb the recorded signal. The bone-conduction technique is restrained to recording breathing and snoring sounds. Because of this, we use an electret microphone to record body sounds that include breathing, snoring and heartbeats. The way in which body sound can be used to classify sleep phases was studied extensively by Kouemou [7]. The authors registered heartbeats and breathing sounds using an electronic stethoscope. They were able to recognize the deep sleep phases and the non-deep sleep phases in healthy subjects and subjects suffering from sleep apnea. With this study, it was demonstrated that snoring and sleep apnea can be detected using only body sound signals. The results suggest that a miniaturized microphone combined with a new approach to record the movements of the patient, could be used for sleep monitoring. We present such a system next.

III. METHOD

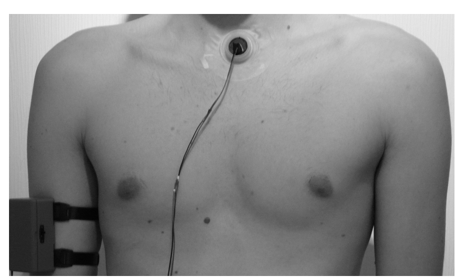

Fig. 1. Sensor attached to volunteers chest. To make the sensor comfortable to wear, the electronics, including the rechargeable battery and the bluetooth gateway are stored inside the case strapped to the right arm of the volunteer.

The sleep monitoring system developed by our research group consists of one electret microphone, an inertial measurement unit (IMU) MPU-6000 (from *InvenSense*), a

978-1-4244-7929-0/14/$26.00 ©2014 IEEE

rechargeable battery and a bluetooth gateway. This system is used to monitor and evaluate the sleep of a patient during the night. The audio data recorded with the electret microphone is sampled at 2.8KHz in 16 bit samples. The IMU delivers position and motion data as three gyroscope values (x, y, z orientation) and three accelerometer values (x, y, z acceleration) sampled at 100 Hz. Each value is coded in 16 bits. An embedded micro-controller carries out the analog-digital conversion and sends the data to the bluetooth module which then transfers the data to a computer where the following processing and analysis steps are executed.

A. Audio Processing

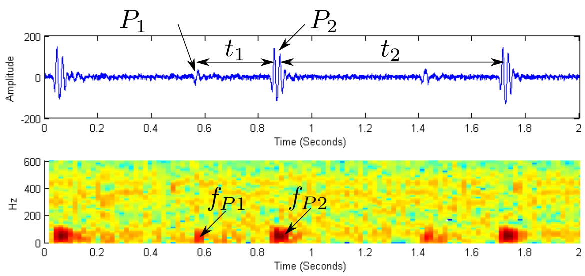

Fig. 2. Detected features of a heartbeat recorded with the proposed system are shown in the time domain and in the frequency domain spectrogram.

The electret microphone is used to record heart and breathing sounds. To amplify the audio signal that reaches the microphone we adapt a cone shaped mechanical piece to the microphone, making it look like a stethoscope (see Figure 1). The microphone is placed at the suprasternal notch attached with a tracheostoma adhesive. This position is chosen because it allows the recording of both breathing sounds (close to the trachea) and heart sounds (which are transfered by the brachiocephalic artery).
To extract the heart beats from the audio signal a simple feature extraction algorithm is developed. The algorithm is executed by the computer in real time. Figure 2 shows a recording of heartbeat sounds. Due to the contraction and relaxation of different parts of the heart during a heartbeat the sound signal has multiple peaks. As can be seen in Figure 2 a heartbeat is characterized in the time domain by two peaks with amplitudes P_1 and P_2. These peaks can also be detected from their frequencies f_{P_1} and f_{P_2} in the frequency domain. We also calculate the time t_1 between P_1 and P_2 and the time t_2 from P_2 of one heart beat to P_2 of the next heart beat. Because the anatomy of each individual patient has a strong influence on the audio signal that is recorded, we estimate the feature parameters during a training phase. During the first minute of the recorded signal we estimate the parameters P_{e1}, P_{e2} $f_{P_{e1}}$, $f_{P_{e2}}$ t_{e1} and t_{e2}. Starting at the second minute of the recorded signal, the algorithm searches into segments of length t_{e2} which get shifted every $t_{e2}/2$ that is, two sequentially analysed segments have an overlap of $t_{e2}/2$. A heartbeat is detected when a segment contains two peaks meeting the following requirements:

$$\text{if for every measured value } x\text{: } P_1, P_2, f_{P_1}, f_{P_2}, t_1$$
$$\text{with estimated parameter } x_e\text{: } P_{e1}, P_{e2}, f_{P_{e1}}, f_{P_{e2}}, t_{e1}$$
$$\text{it applies that: } x_e \cdot (1-\lambda) \leq x \leq x_e \cdot (1+\lambda)$$

a heartbeat is detected. λ sets the tolerance for x based on x_e and is empirically set to 0.1. After detecting a heartbeat t_2 can be determined. t_{e2} gets adapted after every detected heartbeat to adjust the size of the searching window if the heart rate changes.

$$t_{e2(n+1)} = 0.8 \cdot t_{e2(n)} + 0.2 \cdot t_2 \tag{1}$$

Heartbeats per minute can now be calculated by $60s/t_2$.
For the detection of breathing and snoring our algorithm makes an analysis in the frequency domain. In contrast to heartbeats, breathing and snoring events do not produce specific peaks or amplitudes in the time domain. As shown later in the results section, a significant increase of all frequency energies from 10 Hz to 600 Hz occurs during breathing and snoring. In principle, the spectrogram patterns during snoring are very similar to those created by breathing. They simply differ in the frequency amplitudes. It can also be seen that breathing-in produces smaller frequency amplitudes than breathing-out. An average total spectral power A_b of all frequencies from 10 Hz to 600 Hz is calculated for every frequency vector in the spectrogram corresponding to the time periods when breathing or snoring takes place. As is done for heartbeat detection, the time between breathing-in and breathing-out t_{b1} as well as a threshold γ for detecting the spectral power of breathing events are determined during the training phase of the algorithm. After training, the algorithm searches into segments of length $2 \cdot t_{b1}$ which get shifted every t_{b1}. A breathing cycle is detected if a segment contains two events $A_{b1} \geq \gamma$ and $A_{b2} \geq \gamma$ where $A_{b1} < A_{b2}$ has to be met. Like in Eq. (1) t_{b1} gets corrected after every detected breathing cycle. By classifying A_{b1} and A_{b2} depending on their magnitude, we are able to differentiate between calm breathing and heavy breathing or snoring. Single events (not inside a breathing cycle containing 2 events) that meet the requirement $A_b \geq \gamma$ are marked as specific breathing events. These events can represent a snoring event outside the normal breathing cycle, at end of an apnea phase or be noise generated by movement of the patient or the environment.

B. Sleeping position determination

An IMU is a device that measures acceleration, orientation, and gravitational forces, using a combination of

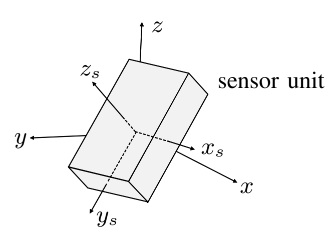

Fig. 3. Global coordinate system and sensor coordinate system [8]

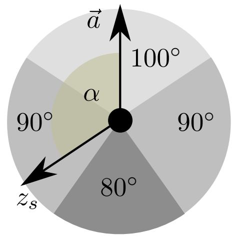

Fig. 4. Defined areas in the transverse plane to determine sleep position; from light to dark grey: supine position, left and right lateral positions and face down position based on the IMU data.

accelerometers and gyroscopes. This information can be used to track the movements and sleeping positions of the monitored patient.Using the acceleration data from an IMU the speed of movement and distance can be determined by integration. A downside is that integration of the IMU data adds drifting to the results. This effect is shown in (2).

$$\int cos(2\pi ft)\,dt = \frac{1}{2\pi f}sin(2\pi ft) \tag{2}$$

As can be seen, the amplification term $(2\pi f)^{-1}$ is inversely proportional to frequency, so high frequencies fall off after integration and low frequencies get amplified. As a result, high frequency noise is filtered and offset is amplified, which causes drift. As presented in our previous work [9], the use of a Madgwick Filter [10] reduces drift issues while tracking orientation to a negligible problem. Using the algorithm presented in [9] we continuously track the orientation of the sensor coordinate system, defined by axes x_s, y_s and z_s. This coordinate system is defined by the rotation of the axes in the global coordinate system x, y, z (see Figure 3).

The IMU sensor is placed on the patient's chest. While the patient is lying on his back a reference vector $\vec{a} = z_s$ is defined (see Figure 4). If the patient turns himself during the night z_s changes. The relative orientation of z_s at any given time falls into one of four areas indicating four different sleeping positions: supine, face down and left and right lateral positions. The relative orientation of z_s is calculated as an angle displacement,

$$\alpha = \sphericalangle(z_s, \vec{a}) \tag{3}$$

with respect to the reference vector $\vec{a}$.

To measure the activity A of the patient during the night we calculate the difference in orientation between the sensor coordinate system and the global coordinate system at time t and at time $t+1$:

$$A = \left| \begin{pmatrix} x_s \\ y_s \\ z_s \end{pmatrix}_t - \begin{pmatrix} x_s \\ y_s \\ z_s \end{pmatrix}_{t+1} \right| \tag{4}$$

The normalized variable A ranges from 0% to 100%. This range is quantized in 10 different levels where the lowest level belonging to $A = 0\%$ thru $A = 10\%$ means no activity, and the hightest level where $A \geq 90\%$ means intense activity. If the activity $A \geq 30\%$ the audio pattern recognition algorithm is switched off because the movements produce audio artifacts. If $A \geq 30\%$ lasts longer than 10 seconds this phase is classified as *disturbed/awaken*. Such a phase may occur if the patient is sleeping very uneasily or is standing up during the night.

IV. RESULTS

The detection algorithm for heartbeats and breathing/snoring was tested on ten healthy volunteers. For each volunteer, data was collected over ten minutes. During the ten minutes each volunteer was breathing normally and was simulating snoring randomly. While the data was being collected, the volunteers were also monitored using an electronic stethoscope. The digital data provided by the stethoscope gave us a reference against which to compare the system results. The first minute of collected data was used for estimating the parameters of the algorithm. The rest of the data was then analyzed by our system and the hearbeats, breathing cycles and snoring events were identified. Validation of the algorithm by comparing the results to the data obtained with the electronic stethoscope showed a detection rate of 74%-92% for all heartbeats, 21%-80% for all breathing cycles and 86%-96% for all forced snoring events. Figure 5 shows short sections of the recorded data of four volunteers. The graph of Subject 1 shows a problem due to very silent breathing. Even though the subject was breathing the whole time, neither the time domain nor the frequency domain detected any breathing. This explains the very low accuracy of 21% for the detected breathing cycles. This same behavior was observed in 2 of the 10 volunteers. The graph of Subject 2 shows the simultaneous presence of breathing (spectrogram) and heart sounds (time domain). The data collected in six out of ten volunteers presented similar patterns and here the algorithm showed the best results. The data from Subject 3 shows snoring instead of breathing. Compared to the data of Subject 2 (normal breathing), Subject 3 showed a higher energy spectrogram. The algorithm showed here the best results in the detection of snoring. Even though Subjects 1, 2 and 4 were breathing normally during data collection, a clear difference in the signal shape and spectral amplitudes is observed. This can be explained by the anatomical differences and a slight variation in the position of the sensor from subject to subject.

Another interesting observation is that the heartbeat sounds of some volunteers were invisible during a short period of breathing-out (Subject 3) or breathing-in (Subject 4). This can be due to a slight lifting of the skin at the suprasternal notch during breathing which reduces body sound transmission to the microphone.

During the test, the volunteers were asked to change their sleeping position multiple times. The determination of the sleeping position had an accuracy of nearly 100%. During the change of sleeping positions the motion was recognized and the associated noise created by the movement was ignored e.g. rejected by the pattern recognition algorithm.To test the *disturbed/awaken* phase three volunteers were lying down for more than an hour. During this time they would randomly stand up, walk around for one minute and lay back down.

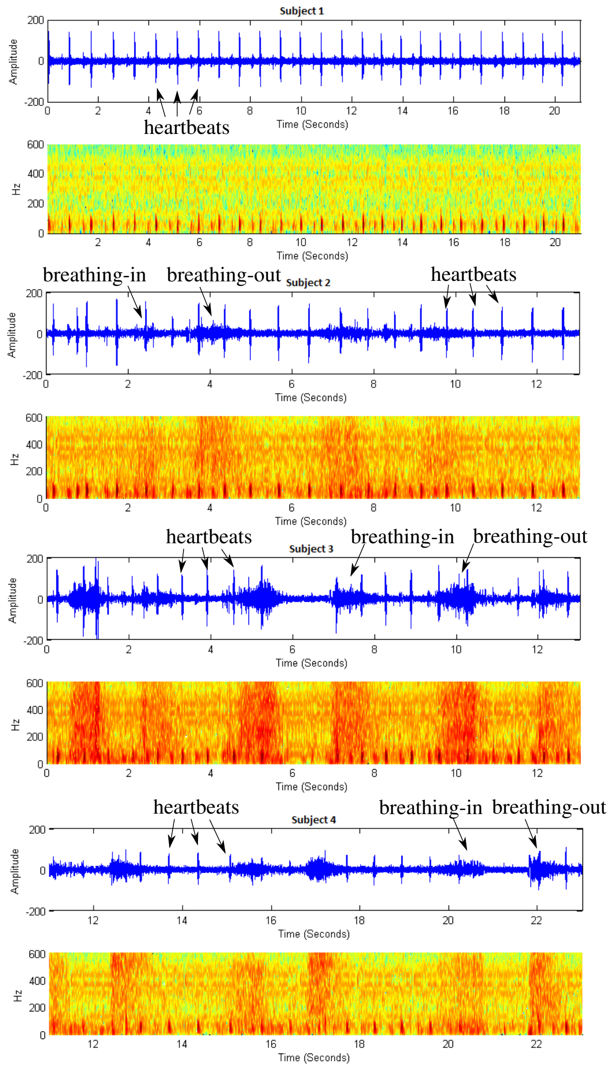

Fig. 5. Body sound signal acquired with the proposed system. The graphs show a segment of the recorded audio data of four volunteers in time and frequency domain. Volunteers were breathing normally except for volunteer 3 who was snoring. The graphs show differences in frequency distribution and spectral amplitudes with respect to heart and breathing sounds.

The algorithm was able to detect all activity events, mark them in the data and deactivate the audio pattern recognition algorithm for the artifact rejection (an example is shown in Figure 6). After the activities the volunteers laid down again and the sound recognition algorithm was reactivated.

V. DISCUSSION AND CONCLUSIONS

The first step in the creation of a reliable system for sleep monitoring is presented in this paper. Our system is capable of detecting heartbeats, breathing, snoring, sleeping positions and movements of the volunteer. However, a future study should examine large, randomly selected samples of volunteers including patients suffering from OSAS. For this purpose, a comparison with standard polysomnography methods inside the sleep laboratory of the University Medical Center Ulm with a large number of patients is planned in the near future. The next step to improve our system and

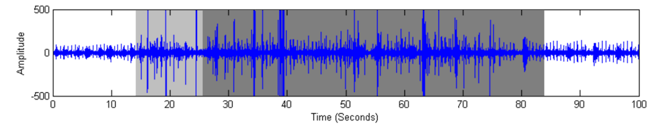

Fig. 6. Body sound signal captured with the proposed system. After 15 seconds the volunteer stood up and walked around for 65 seconds creating lots of noise. The light grey marker indicates the detected movement of the IMU thus deactivating the audio pattern recognition. After 10 seconds of movements the data is marked as a *disturped/awake* event (dark grey). After a few seconds of lying still the event ends and the audio pattern recognition algorithm is reactivated.

the accuracy of the results will be to implement a neural network to substitute our simple feature extraction algorithm. The neural network will work based on audio and position data and will be trained using available monitoring data. This should increase the accuracy of the current results including the detection of apnea intervals. Finally by combining the information about movement (position changes and intense activity) with the information about heartbeat frequency, breathing cycles and snoring, a determination of the different sleep phases and their ocurrence during the night can be produced. This information is a valuable clinical indication about the quality of sleep.

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