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Towards an Intelligent Bed Sensor: Non-intrusive Monitoring of Sleep Irregularities with Computer Vision Techniques

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Abstract

This paper proposes a novel approach for monitoring sleep using pressure data. The goal of sleep monitoring is to detect and log events of normal breathing, sleep apnea and body motion. The proposed approach is based on translating the signal data to the image domain by computing a sequence of inter-frame similarity matrices from pressure maps acquired with a mattress of pressure sensors. Periodicity analysis was performed on similarity matrices via a new algorithm based on segmentation of elementary patterns using the watershed transform, followed by aggregation of quasi-rectangular patterns into breathing cycles. Once breathing events are detected, all remaining elementary patterns aligned on the main diagonal are considered as belonging to either apnea or motion events. The discrimination between these two events is based on detecting movement times from a statistical analysis of pressure data. Experimental results confirm the validity of our approach.

1. Introduction

Sleep of poor quality is a very common condition in our modern society. The quality of sleep is directly influenced by sleep disorders such as apnea and restlessness, which cause sleep fragmentation [1].

Monitoring the quality of sleep is typically done in sleep clinics via Polysomnography (PSG). The high cost associated with PSG makes it applicable only for the diagnosis and monitoring of severe sleep disorders. The proposed research addresses the development of a non-intrusive technique for monitoring sleep at home using pressure maps. The pressure maps are acquired continuously during the monitored period of sleep. Breathing, apnea, and motion-induced events are analyzed using the concept of inter-frame similarity matrix introduced by Cutler and Davis [2].

From a theoretical standpoint, a major novelty in the proposed approach consists in the processing of non-visual input data (pressure signals) with computer vision techniques. This is possible because sleep irregularities induce variations in the periodicity of the studied signals. These variations are represented as visual patterns in the inter-frame similarity matrix.

The remainder of this paper is structured as follows. Section 2 discusses related work. Next, the proposed approach is presented, followed by its experimental validation. The last section draws conclusions.

2. Related work

Research in sleep monitoring technology has been largely focused on two main directions, namely on biomedical sensors, and on signal processing techniques for the analysis of data produced by simple inexpensive sensors. This section discusses related work on signal processing techniques, as this is the closest area to the proposed approach.

Watanabe et al [3] measure heartbeat, respiration, snoring and body movement using a pressure sensor placed under the bed mattress; their approach extracts and analyzes vital signals in the frequency domain. Pressure sensors are also used by Zhu et al [4], who perform real-time measurements of the respiration rhythm and pulse rate during sleep using the *a trous* algorithm.

The approach proposed in this paper works with input signals extracted from an inexpensive (under 500 $) full body pressure sensor [5] installed under the bed mattress. The main difference from existing approaches based on periodicity analysis consists in the translation of a signal processing problem in the video analysis domain. Working with image data rather than 1D signal data offers the advantage of processing in parallel all pressure signals from the individual cells of the sensor, therefore exploiting their correlation.

3. Proposed Approach

The data acquisition process is discussed in 3.1.

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Next, the transition from signal data to image data is described in 3.2. This transition generates the interframe similarity matrix which is the primary input for the proposed approach. Section 3.3 describes the segmentation of the interframe similarity matrix into patterns representing breathing, motion, and apnea.

3.1. Data acquisition

The bed sensor that was used in this work consists of 144 optical pressure sensors placed on a regular 3x8 inches grid. Pressure values are digitized and sent to a computer via the data acquisition board that samples each sensor at 5.3 Hz.

The observation at moment k is thus recorded as a 1D array $\overline{X_k} = [x_1, x_2, ..., x_{144}]$ where each x_i represents the value at individual pressure sensor i at time k. The data acquisition set-up is shown in Fig. 1.

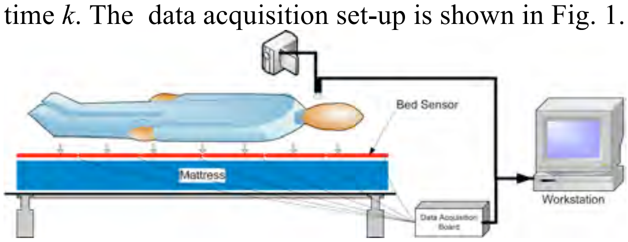

Figure 1. Data acquisition set-up. The video camera was only used for collecting ground truth data.

3.2. Image generation from pressure signals

Pressure signals are integrated into a sequence of pressure maps. Periodic pressure changes induced in the pressure maps by breathing are detectable using the inter-frame similarity matrix [2] (further referenced as as *similarity matrix* in this paper). Given a window of N maps, the similarity matrix is of size N x N; the pixel at (i,j), i=1..N, j=1..N represents the correlation coefficient of the maps at times i and j respectively.

Sleep monitoring requests data acquisition for long continuous time intervals. Therefore, using one similarity matrix for the whole duration of the acquisition process is not computationally feasible. This work implements a sliding version of the similarity matrix. The output is therefore a sequence of similarity matrices computed for a sliding fixed length window. The window size is set to 400 samples, which corresponds to 75 seconds of pressure data sampled at 5.3Hz. At each iteration, the window shifts 50 samples (9.5 seconds) and a new instance of the similarity matrix is calculated. This instance contains 9.5 seconds of new information appended to it, while its oldest 9.5 seconds are shifted out. The window and shift sizes have been set as a trade off between the computational cost and the amount of information contained in each window. The partial overlap enables tracking events across adjacent instances of the similarity matrix.

3.3. Segmentation of the similarity matrix

To detect the patterns associated with breathing, apnea, and body movement, a bottom-up approach is proposed. Elementary patterns aligned to both sides of the main diagonal are detected first. Next, they are aggregated into event-representative patterns.

The detection of the elementary patterns is achieved via the watershed transform. This transform is suitable because every local minimum in the proximity of the main diagonal corresponds to an elementary pattern of interest. A typical result of the watershed segmentation is shown in Fig. 2b.

From the segmented image, only patterns in the immediate proximity of the main diagonal are of interest. Due to the smoothness and the temporal symmetry of the pressure changes induced by breathing, elementary patterns corresponding to breathing are quasi-rectangular. Each complete cycle of breathing contains four rectangular patterns along both sides of the main diagonal of the similarity matrix. The more profound the breathing, the larger is the size of its patterns. Fig. 2 c and d show a similarity matrix containing shallow and profound breathing, as well as the patterns that were extracted along the main diagonal and grouped into breathing cycles.

Breathing events are detected by aggregating along both sides of the main diagonal the elementary patterns with high rectangularity. The rectangularity is measured via the compactness factor, defined as $C = \frac{P^2}{A}$, where P is the perimeter of the elementary pattern and A is its area. All patterns with C less than the compactness factor of a square (C_{square}=16) are aggregated into breathing cycles, which are further grouped into breathing-representative events.

The remaining elementary patterns detected by the watershed transform along the main diagonal that do not satisfy the compactness criterion are considered as belonging to events other than breathing, namely apnea or body movement.

Body movements are characterized by pressure values of large variability and higher amplitude than for apnea and breathing. Jones at al [6] showed that pressure values recorded for body movements fall outside the normal distribution of pressure values.

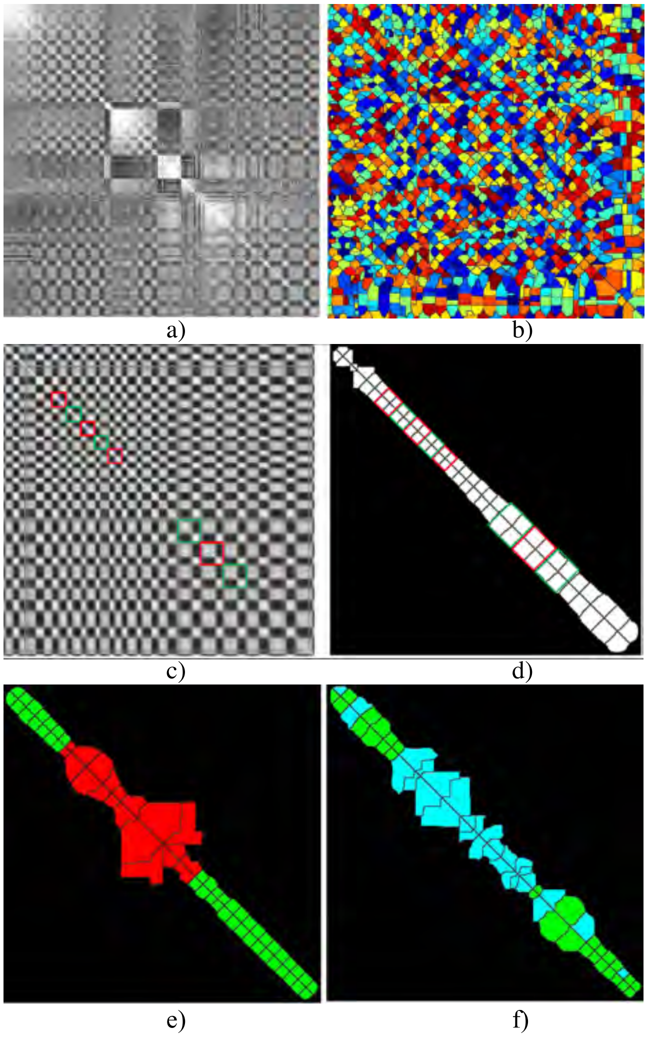

Figure 2. a) similarity matrix; b) result of watershed segmentation; c) rectangular breathing patterns overimposed onto the similarity matrix; d) aggregation of patterns (breathing cycles are in red and green); e) example of breathing (in green), and movement (in red) events; f) example of breathing (in green), and apnea (in blue).

This paper adopts a similar approach to [6] for detecting temporal instances where movement occurs (i.e. *movement times*). Specifically, for a sliding temporal window (the same as for the generation of the sequence of similarity matrices), the distribution of the measured pressure values is described by first and second-order statistics $(\mu_i, \sigma_i)_{i=1..144}$ i=1..144. All time instances k located inside the current sliding window are evaluated as follows:

$$k = \begin{cases} \text{movement time if there exists } l \text{ such that} \\ x_l > \mu_l + 3\sigma_l \text{ OR } x_l < \mu_l - 3\sigma_l \text{ for } l = k, k+1 \\ \\ \text{non-movement} \qquad\qquad \text{otherwise} \end{cases} \quad (3)$$

All detected movement times are marked in the sequence of similarity matrices. Elementary patterns containing pixels located at movement times are considered as belonging to a body movement event. Fig. 2 e shows an example of movement detection.

Since apnea is a temporary stop in breathing, it should be represented by homogeneous rectangular patterns aligned to the main diagonal. However, due to the low signal to noise ratio of the bed sensor, the homogeneity criterion was not accurate enough for detecting apnea. Therefore, apnea events are detected after excluding previously detected body movements and regular breathing events. Fig. 2f shows an example of apnea detection.

The output of the proposed approach for sleep monitoring consists in a sleep log text file, which can be read using standard text viewers. This file logs all events of normal breathing, apnea and movement with their start and end times computed from their corresponding spatial locations in the similarity matrices.

4. Experimental evaluation

The experimental database contains pressure data collected from 10 healthy young adults in two modes, namely scripted and unscripted.

The unscripted mode confirmed the feasibility of monitoring long periods of sleep (1 night) from a computational viewpoint. The total computation time necessary to generate the sleep log for one night was 8 hours and 27 minutes on a 2.4 GHz PC equipped with 2 GB of RAM and using the Matlab environment.

The scripted mode refers to acquisitions where each subject was instructed to breathe normally, simulate apnea, and perform body motions at precise time intervals, according to a predefined scenario. The scenario was designed to contain 50 events of apnea (5 per subject), 30 events of limb movements (3 per subject), and 20 events of posture changes (supine to lateral and back- 2 per subject). Shallow and profound breathing are also present in the scenario. The sequencing and duration of events is predefined. The total acquisition time per subject is 17 minutes and 20 seconds.

The ground truth database consists of video sequences captured at 30 fps showing only the subjects' face. A human operator, who generates an output in the same format as the sleep log, segmented this database into breathing, motion, and apnea events. The performance of the proposed approach is evaluated in terms of precision and recall. Results are shown in Table 1.

Table 1. Precision, recall, and misclassifications for the detection of apnea and movement events

Subject	Resp as Apn	Resp as Mov	Apn Correct	Apn as Resp	Apn as Mov	Mov Correct	Mov as Resp	Mov as Apn	Apn Recall	Apn Precision	Mov Recal	Mov Precision
AM	2	0	3	2	0	2	0	1	**60.00%**	**100.00%**	**100.00%**	**66.67%**
ES	0	0	4	0	1	6	0	0	**100.00%**	**80.00%**	**100.00%**	**100.00%**
FK	0	0	1	0	4	6	0	1	**100.00%**	**20.00%**	**100.00%**	**85.71%**
KJ	0	0	2	2	1	3	0	3	**50.00%**	**66.67%**	**100.00%**	**50.00%**
MD	0	0	1	2	2	2	0	4	**33.33%**	**33.33%**	**100.00%**	**33.33%**
MG	0	0	2	1	2	2	0	4	**66.67%**	**50.00%**	**100.00%**	**33.33%**
NY	0	0	4	0	1	5	0	1	**100.00%**	**80.00%**	**100.00%**	**83.33%**
SM	0	1	3	1	1	1	3	1	**75.00%**	**75.00%**	**25.00%**	**50.00%**
SK	0	0	5	0	0	5	0	0	**100.00%**	**100.00%**	**100.00%**	**100.00%**
VT	1	0	5	0	0	4	0	2	**100.00%**	**100.00%**	**100.00%**	**66.67%**
Total	3	1	30	8	12	36	3	17				
Average									**78.50%**	**70.50%**	**92.50%**	**66.90%**
STD									**25.07%**	**28.24%**	**23.72%**	**25.03%**

Recall and precision vary widely among subjects. This effect is due to the limited number of events per subject; one single apnea event counts 20% per subject. The majority of misclassifications involve apnea and movement. Movement misclassifications as apnea occur mostly for limb movements. Such small amplitude movements are visible as distorted elementary patterns in the similarity matrix. These movements do not alter significantly the statistics of the pressure values, and therefore they are misclassified as apnea.

One major source of error is the low signal to noise ratio for the bed sensor. Moreover, apnea misclassifications as movement occur mostly because of the scripted nature of the event. The study of the ground truth video data has proven that, in preparation for simulating an apnea event, some subjects took a deep inhalation. This sudden change in pressure changed the statistics of the pressure signals and therefore resulted in misclassifying apnea as motion.

Considering the low spatial and temporal resolutions of the bed sensor, as well as its low signal to noise rate, the presented results are considered promising.

5. Conclusions

This paper proposes a novel approach for monitoring sleep; its goal is to detect events of normal breathing, apnea and body motion. The proposed approach translates the signal data into the image domain by processing a sequence of inter-frame similarity matrices from pressure maps acquired with the array of pressure sensors. The main theoretical contribution of this work consists in the successful application of computer vision techniques for processing non-visual data. From a practical standpoint, the proposed system for sleep monitoring offers a cost-efficient, portable, and non-intrusive solution for the home monitoring of the quality of sleep. Future work will focus on improving the signal to noise ratio and the spatiotemporal resolution of the input pressure signals, and on extensive validations performed in a clinical environment on extended periods of sleep.

References

[1] S. Martin, P.Wraith, I. Deary, and N. Douglas, “The effect of non-visible sleep fragmentation on daytime function,” Am. J. Respir. Crit. Care Med., 155(5): 1596-1601, 1997.

[2] R. Cutler and L. Davis, “Robust Real-time periodic motion detection, analysis, and applications,” IEEE Trans. on Patt. Anal. and Machine Intell., 22(8): 781-796, 2000.

[3] K. Watanabe, T. Watanabe, H. Watanabe et al, “Noninvasive measurement of heartbeat, respiration, snoring, and body movements of a subject in bed via a pneumatic method,” IEEE Trans. on Biomed. Engr., 52(12):2100-2107, 2005.

[4] X. Zhu, W. Chen, T. Nemoto et al, “Real-Time monitoring of respiration rhythm and pulse rate during sleep,” IEEE Trans. on Biomed. Engr., 53(12):2553-2563, 2006.

[5] http://www.tactex.com/BEDsensor_Pro, retrieved Jan 10 2010.

[6] M. Jones, R. Goubran, and F. Knoefel, “Identifying movement onset times for a bed-based pressure sensor array,” IEEE Int. Workshop on Med. Measurements and Appl., 111-114, 2006.