AN UNOBTRUSIVE SYSTEM FOR SLEEP MONITORING BASED ON EMFI SENSOR

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ABSTRACT
Monitoring body movements and vital parameters during sleep provides crucial information regarding the general health of a subject, and can therefore be used to detect trends leading to severe illnesses such as dementia or heart defects. With the development of new sensors and the general improvement in computing power, ballistocardiography has been recently revived and is again seen as a promising technology specifically for heart rate monitoring. In this paper, we present a low-cost, low-complexity, unobtrusive system for assessing the heart rate, the breathing rate, the body movement and the sleep type based on the signal from an EMFI sensor. All algorithms have been implemented on an iMote2 wireless module that sends the estimated values of the aforementioned quantities to a server or a remote computer using the .NET Microframework SDK. We validated our test-bed results by comparing with a more sophisticated and costly system, Embla N7000. The proposed system paves the way for affordable large scale epidemiology studies of health parameters during sleep using unobtrusive sensors.

KEY WORDS
Ballistocardiogram, EMFI Sensor, Sleep Monitoring.

1. Introduction

Monitoring body movements and vital parameters during sleep provides crucial information regarding the general health of a subject, and can therefore be used to identify trends leading to severe illnesses such as dementia or heart defects as well as to detect emergencies. This is increasingly relevant given the demographical, structural, and social trends in most industrialized countries towards an aging population and an increase in single households. The typical modern monitoring systems used in hospital, in particular in sleep laboratories, are extremely costly, obtrusive and complex systems whereas they generate precise and accurate measurements. They include, e.g., an electrocardiogram (ECG), a pulse oximeter, an electroencephalogram (EEG), an electrooculogram (EOG), an electromyogram (EMG), thermistors for oral and nasal air flow and respiratory inductive plethysmographs (RIPs) for abdomen and thorax movements. Those monitoring systems typically require a qualified personal to be operated. The cost and complexity of such systems clearly prevent their adoption in each home.

Ballistocardiography [1] is an old, noninvasive technique utilized to record the movements of the body as a function of the heartbeat due to left ventricular pump activity. The modern ballistocardiography is considered to have begun in 1936 when Isaac Starr introduced a bed ballistocardiogram (BCG) measurement device [2]. The BCG used in [2] consisted of a table suspended from the ceiling on wires and braced to prevent motion in any but the longitudinal direction. A new type of BCG based on a static charged-sensitive bed has been presented in 1981 in [3] which measures the movement in the direction perpendicular to the body main axe.

More recently, a new electret material with a cellular structure called ElectroMechanical Film (EMFi) [4] paved the way for mass production of very cheap ballistocardiogram devices. EMFi sensors are now commercialized by EMFIT [5] and their sensors have successfully been used as BCG in [6]. A recent research [7] has shown that heart beat intervals as measured from BCG signals providing from an array of EMFi sensors BCG signal match R-R intervals in ECG signal.

One of the issues when using EMFI sensors for sleep monitoring which requires estimation of the heart rate but also of the breathing rate as well as other body movements is that the measured signal is a superposition of these quantities. Due to the strong overlapping, sophisticated algorithms are required in order to separate the components of interest.

In this paper, we present a low-cost consumer equipment system for assessing heart rate, breathing rate, body movement and sleep type accurately. The system is based on a single EMFI sensor with a wireless module transmitting the measurements to a remote PC, and requires minimal setup. Among the possible usages of our system, we see a strong interest for monitoring elderly persons living alone and babies.

The rest of this paper is organized as follows. The overall system is described in Section 2. The algorithms for
extraction of the quantities of interest are explained in Section 3 and their implementations are described in Section 4. A comparison of the computed values with those obtained in sleep laboratory is provided in Section 5. A discussion with existing methods is done in Section 6 and we terminate with some conclusions in Section 7.

2. System Description

An overview of the system is displayed in Figure 1.

Our system is built upon an EMFi sensor, the EMFIT L-series pressure mat sensor [5] whose prices range from 30 to 50 euros. The EMFIT pressure mat basically generates a charge proportional to the changes in pressure applied on the mat. The EMFIT L-Serie pressure mat, lying under the mattress, is connected to a charge amplifier. The amplifier circuit is powered with a voltage VCC of 3V and the output value of the amplifier is centered around 1.5V in order to match the input range of the analog-to-digital converter (ADC). The output of the amplifier circuit is connected to an ADC of an imote2 sensor board [8] running .NET microframework [9]. The iMote2 is either running with batteries for around 3 hours or in case of extended testing period it can also be connected to the main power. We scan the digital values as converted by the ADC at a sampling rate of 50 samples/sec as in [7]. A sample of raw values covering 10 seconds obtained at this stage is provided in Figure 2 when a person is lying quietly on the bed, in Figure 3 when person is moving, in Figure 4 when nobody is on the bed. Note that when moving on the mat, the amplifier circuit saturates which explains the lack of fluctuations in Figure 3.

The raw data are then processed as described in Section 3 in order to assess the relevant vital parameters. The estimated values of all the parameters are then transmitted to a remote PC using a network stack based on the 802.15.4 communication protocol [10], characterized by a low transmit power and a maximal transfer rate of 256 kbits/sec which is largely sufficient in our case. We use a service-oriented approach based on the Decentralized Software Service Protocol [11] whereby the client service subscribes to receive notifications whenever the values exposed by the data provider changes.
3. Estimation of the Parameters

The sleep monitoring should first assess whether there is a living person on the bed as well as his/her general body movement level. When the system detects that someone is lying on the bed, the heart and breathing rates are estimated. In addition, we assess sleep level as a measure comparable to the sleep stages [12]. An important objective is to have a system requiring no set up so that the user could install or restart the system without help.

3.1 Presence

In order to detect presence, it suffices to measure the amplitudes of the signal. If nobody is lying on the mat, the signal amplitudes are very small compared to the amplitudes when someone is lying even quietly as it can be seen in Figure 4. The algorithm for detecting the presence simply computes the variance of the signal and comparing it to a threshold $t_{\text{presence}}$. Any value above $t_{\text{presence}}$ indicates that someone is lying on the bed, and conversely, a value below $t_{\text{presence}}$ is associated with the absence of a person on the mattress. The threshold $t_{\text{presence}}$ has been determined manually in this study.

3.2 Body Movement

The body movement computation proceeds similarly to the presence indicator by inspecting the amplitudes of the signal and is computed as the variance of the raw data. In order to normalize the value, we express the body movement level as the computed variance over the whole samples block divided by the maximal variance corresponding to a saturated signal. If the person lying on the bed moves significantly, the amplifier saturates in low and high levels as shown in Figure 3. Those movements can therefore easily be detected given the high value of the body movement index.

3.3 Heart Rate Detection with Automatic Detection of Spurious Values

The signal from the EMFI is a superposition of contributions from multiple sources, including the heart beat but also the breathing and any body movement. In case the person lying on the mattress is quiet, the major contributions are from the breathing and the heart rate as shown on the power spectral densities of the raw data depicted in Figure 5. The major contribution comes from the breathing at 0.23 Hz. The other peaks correspond to the heart rate contribution at 0.88 Hz and its harmonics at $k \times 0.88$ Hz.

Figure 5 Power spectral density of the signal from EMFI sensor over a 10 seconds interval. The major contribution comes from the breathing at 0.21 Hz. The other peaks correspond to the heart rate contribution at 0.88 Hz and its harmonics at $k \times 0.88$ Hz.

The first possible approach would be to identify the heart beats based on a characterized pattern. A typical pattern from a BCG signal has been presented in [2], identifying seven phases, referred as H, I, J, K, L, M, N. However, the pattern highly depends on each individual (body mass, general fitness of the heart,…) as well as his/her breathing phase (typically, the heart beats more strongly during inspiration compared to expiration to take advantage of the oxygen in the lungs).

As described in [7], a more robust approach consists in considering the larger fluctuation around the IJK phase only in the BCG pattern. The method consists in applying a high pass filter on the signal, squaring all the values and then applying a low pass filter to create a pulse. A typical graph of the signal obtained at this stage is displayed in
Figure 6. The heart beats appear more clearly than in the original graph but the peaks have different heights and secondary peaks are also present. In order to avoid some complex peak identification algorithms with empirical thresholds, we perform a Discrete Fourier Transform (DFT) to identify the frequency of the main contribution in the spectrum. We refer this approach as the Pulse-FFT approach. We however observe that this approach leads to a large number of spurious values due to its high sensitivity to body movement and breathing pattern. We also noticed that it often falsely identify the first harmonic as being the heart rate. In order to identify the spurious estimations, we combine the Pulse-FFT method with two alternate methods, the FFT-harmonics and the correlation methods, which are described below. Whenever the measurements provide by all three methods match, the value generated is the mean of all measurements, and when the values differ, we suspect that the signal was not appropriate for a good measurement and we discard the computed value. This original approach of combining the results from these three methods in order to reject the spurious estimates is called the combined method. The idea of the FFT-Harmonics is to take advantage of the harmonics components of the heart rate signal as shown in Figure 5. More precisely, for each frequency \( f \) in the range of interest of the heart rate (0.65 Hz – 2.5 Hz), we sum up the contribution in the power spectrum of the harmonics \( 2f, 3f, 4f \) and \( 5f \). The computed heart rate value is then the frequency whose harmonics provide the largest contribution. If we mistakenly assume that the harmonic \( 2f \) is actually the main one, i.e. \( f \), the other contributions would come from \( 4f, 6f, 8f \) and \( 10f \) which overall would be less important than \( f, 2f, 3f, 4f \) and \( 5f \). The same reasoning holds if we mistakenly assume that main harmonic is \( f/2 \) with other contributions in \( f, 3f/2, 2f \) and \( 5f/2 \).

The second alternate method, called Correlation, relies on the periodic structure of the heart beat contribution in the EMFI signal. To do this, we apply first a pass-band filter with cut-off frequencies of 0.65 Hz and 2.5 Hz in order to remove the breathing contribution and other interference outside the band of interest and then apply an auto-correlation over a 10 seconds signal chunk, with a time shift ranging from 1/2 to 1/0.65 seconds. The computed frequency is then the frequency \( f \) such that the time shift \( 1/f \) corresponds to the largest peak among the auto-correlation values.

### 3.4 Breathing Rate Detection

The breathing rate as such is not a typical value provided by medical equipments which rather provide air flow, oxygen level in the blood and changes in the thorax volume. However, even a rough estimation may give a good hint of the sleep dynamic of the patient. In order to isolate the breathing component, we apply a low pass filter with a cut-off frequency of 0.5 Hz to the raw data. We have opted to identify the breathing component by selecting the strongest component after DFT. This method does not require any threshold.

### 3.5 Sleep Stage Detection

We have considered the relationship between heart rate variation and sleep levels mentioned in [13] to design a simple algorithm which distinguishes between the sleep and non-sleep phases, and the REM and non-REM (NREM) phases within the sleep phases.

The algorithm works as follows. We compute the variance of the heart rates as computed with the combined method over the last 3 min, which matches the period used in [14] for their computation. The variance is related to the activity of the person on the mat so that a larger variance corresponds to a higher activity. Based on this observation, we set two thresholds \( T_{\text{REM}} \) and \( T_{\text{NREM}} \) such that when the variance is lower than \( T_{\text{NREM}} \), a NREM phase is identified, when the value is between \( T_{\text{NREM}} \) and \( T_{\text{REM}} \) a REM phase is detected, and finally, all values above \( T_{\text{REM}} \) are related to non-sleep phases.

The thresholds and \( T_{\text{NREM}} \) have been chosen manually so as to get the best result. \( T_{\text{REM}} \) can be determined empirically by observing the time when the person is sleeping and then fit the parameter accordingly. Determining \( T_{\text{NREM}} \) is more problematic since it involves having a mean to assess the sleep level of the person. The simplest approach would consist in assuming a typical ratio of REM phase over NREM phases and then setting \( T_{\text{NREM}} \) so that the computed ratio matches the expected ratio.

### 4. Implementation

Our algorithms have been implemented in C# on an iMote2 running the .NET Microframework. The .NET Microframework provides an opportunity for fast prototyping (support for threading, for floating point computation, memory management, code can be tested on a PC, …) at the expense of a computational cost since the code is interpreted in the .NET virtual machine.

The algorithms used to detect the different parameters presented in the previous section form the building blocks of our implementation, as shown in Figure 7. The system continuously acquires blocks of 512 discrete values of the input signal at a rate of 50 Hz, the acquisition of each block of samples corresponding therefore \( \approx10 \) seconds.

The sampling frequency and duration have been determined empirically considering the following constrains. First, the sampling frequency must be sufficient to capture the signal components of interest (harmonics of heart rates). For efficiency reason, the DFT should be performed on data arrays whose sizes are a power of 2. Lastly, the computation should not take longer than the acquisition so that the parameters are computed as the samples are collected. The choice of 10 seconds has also proved to be a good value for the heart rate computation using the Pulse-FFT and FFT-
Harmonics. The reason should lay in the fact that the faster heart rate variations [15] are averaged out over 10 seconds.

The presence detection module assess the presence on the mat of a living person. In case of presence, one proceeds further to the heart rate, breathing rate and body movement assessments. The heart rate is evaluated with 3 different methods, the Pulse-FFT, FFT-harmonics and Correlation methods. If all methods provide consistent values, the computed heart rate value is fed to the sleep level detection module.

All filters used in our implementation are Chebyshev filters of order 2 which provide a good balance of high effectiveness, low computational complexity at runtime and easy implementation.

The presence detection and the body movement level computation are variance analysis performed directly on the raw data. Their computational complexity is linear with respect to the number of samples, i.e. 512, and represent only a small fraction of the computation. Pulse-FFT and the FFT-Harmonics methods for computing the heart rate relies on the application of a Chebyshev filter and an DFT, the complexity is therefore in both cases $O(n \log n)$ where $n$ is the number of points in the DFT computation. Our analysis have shown that increasing the number of points in the DFT computation above 512 does not lead to significant precision gain and does not justify the incurred computation penalty. The third method, Correlation, comprises a Chebyshev filter as well as an auto-correlation and its complexity is $O(k * n)$ where $n$ is the number of samples, i.e. 512, and $k$ is the number of time shifts considered. We restrict the shifts in the range between 60/150 and 60/40 seconds, so with a sampling rate of 50 Hz, $k$ is 55.

The total computation time on the iMote2 for processing a block of 512 data is 2.5 seconds, most computation effort being for the heart rate assessment module, where the time is shared equally between the different methods. Since the code is interpreted, we can assume that an implementation on smaller sensor platforms is also possible given the small memory requirement thanks to the linear space complexity and the small data block sizes.

5. Validation

The presence and body movement computation have been evaluated by having different persons successively lying and getting up from the bed, and when lying on the bed, perform different type of movement from no movement to full body movement. Based on those experiments, we have seen that whenever someone is lying on the bed, the presence is correctly detected independently of the morphology of the individuals. On the other hand, the body movement level roughly matches the activity of the person lying on the bed up to a point where the amplifier saturates.

In order to validate the heart rate, the breathing rate and sleep stage computations of our system, we have compared our results with the measurements obtained by a professional system used in a sleep laboratory. One healthy 35 years old man has spent one night in a medical sleep laboratory, and both an Embla N7000 system[16] and our sleep monitoring device recorded the vital parameters during the night. All the data from the Embla system were recorded and stored in an EDF file, and similarly, all the data generated from our sleep monitoring were recorded in a XML file. Then, we compare the result of both systems.

For the reference heart rate, we use R-R periods as computed by the Embla averaged over 10 seconds. First, we compared separately the different methods proposed in the previous section with respect to the reference measurements. The benefit of combining the different individual methods is shown in Table 1. In this table, a value is considered erroneous if it differs by more than 4% relatively to the reference measurement. An estimate is rejected if the variance of the values obtained by the methods used in the computation is larger than 3%. Note that we cannot distinguish true and false negatives with our approach since in the case of value rejection, the
different computation methods provide different results. We therefore group true and false negative as rejected values. Taking a method individually does not allow to reject any value since there is no variance. The correlation method is the most accurate method with 81% of correct values. The table shows that combining the Pulse-FFT with either the Correlation or the FFT-Harmonics is already effective in decreasing the amount of erroneous values and might be preferred for more resource constrained devices. Combining all three methods further improves the filtering of the values, at the cost of increase resource and more values rejected (34%).

Table 1 Repartition of correct values accepted (true positive), erroneous values accepted (false positive) and rejected values (negative) when using the different heart rate computation methods as a percentage of the total number of values computed.

<table>
<thead>
<tr>
<th>Methods</th>
<th>True Positives (%)</th>
<th>False Positive (%)</th>
<th>Rejected values (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pulse-FFT</td>
<td>71.0</td>
<td>29.0</td>
<td>0.0</td>
</tr>
<tr>
<td>FFT-Harmonics</td>
<td>78.9</td>
<td>21.1</td>
<td>0.0</td>
</tr>
<tr>
<td>Correlation</td>
<td>81.6</td>
<td>18.4</td>
<td>0.0</td>
</tr>
<tr>
<td>Combined (Pulse-FFT, FFT-Harmonics)</td>
<td>64.1</td>
<td>4.8</td>
<td>31.1</td>
</tr>
<tr>
<td>Combined (Pulse-FFT, Correlation)</td>
<td>65.7</td>
<td>3.4</td>
<td>31.0</td>
</tr>
<tr>
<td>Combined (Correlation, FFT-Harmonics)</td>
<td>75.2</td>
<td>6.9</td>
<td>17.9</td>
</tr>
<tr>
<td>Combined (all methods)</td>
<td>63.4</td>
<td>2.8</td>
<td>33.8</td>
</tr>
</tbody>
</table>

A direct comparison between the combined method and the reference measurements is displayed in Figure 8. This shows that the remaining erroneous values correspond to the awake phase and are therefore associated with higher movement level. Also, the ECG method detects heart rate increases related to small movements, lasting typically 20 to 30 seconds which are not detected with the combined method.

We conclude that the heart rate computation using the combined method is an accurate average over 10 seconds of the heart rate as measured with R-R intervals from ECG. A limitation of our approach is that we cannot detect rapid heart rate variations since we effectively average the values over 10 seconds. An extension to our method would be to use the computed heart rate value as a first estimation before using another method for detecting individual heart pulse. The latter could use filters with refined cut-off frequencies to isolate the heart rate component of the signal and work on smaller time period.

The validation of the breathing rate is more difficult than for the heart rate because the Embla system does not compute directly the breathing rate but provides only the raw values provided by the RIPs located at the thorax and abdomen. In order to validate our algorithm based on DFT with a low sampling rate, we have applied another simple algorithm on the raw data provided by RIPs in order to extract the breathing rate. The algorithm basically computes each breath period by identifying the maxima.

Figure 8 Heart rate values expressed in bpm from the combined method using the EMFi signal (top) and using the ECG (bottom). The combined method gives accurate measurements but fails to identify small pikes in the heart rate related to small movements.

Figure 9 compares the breathing rates computed with the EMFi sensor (top) and those provided by the maxima algorithm applied to the RIP data from the thorax (bottom). Since there is one measurement for each breathing when using the RIP data as compared to one value every 10 seconds from the EMFi data, there are more points located at the bottom graph. More than 80% of our values are within 20 % of the RIP values. Most significant spurious values occur when the person lying on the bed is awake. In this case, the DFT-based method does not perform well since it requires some regularity in the signal pattern.

Finally, for the sleep levels, the Embla system provides an assessment of the sleep stage using the Rechtschaffen and Kales (R-K) classification [12] based on the EEG, EOG and EMG signals every 30 seconds. Based on those values, we classify each value as an awake, REM or NREM phase. The comparison between those values and the values computed using the variance method explained in the previous section is displayed in Figure 10. The main
discrepancies occur either when the variance method falsely detects an awake phase or conversely, when it fails to detect an awake phase. The variance method is correct for 96% of the measurement when distinguishing the sleep and non-sleep phases, and 85% correct when further distinguishing REM and NREM phases, which is sufficient to detect anomalies or changes in sleeping patterns.

Figure 9 Comparison: Breathing rates (top: our system, below: RIP).

6. Related Work

Although some works have already been done to assess vital data with an EMFi sensor, we are first to demonstrate a system using one single EMFi mat covering a large range of values and kind of vital data. Indeed, the main focus in [6] is to analyze the heart rate signal rather than detect the heart rate. In [6], two EMFi sensors are used and in addition, the method applies to a person sitting and the heart rate range covered does not include values much higher than 60 BPM since they apply a pass-band filter between 0.1 and 1 Hz on the raw signal. Also, their method works best when an additional ECG sensor is providing the reference heart rate. In [7], a grid composed of 160 small EMFi sensors is used to measure the ballistocardiogram interbeat interval (BCG IBI) which is shown to be equivalent to the R-R interval. The method relies on averaging DFT performed on all the 160 channels and it therefore requires higher computational processing power (~160x) to carry the computation than our method.

Breathing is typically assessed by using some combination of respiratory inductive plethysmographs and flowmeters located near the mouth and nose, and oximeters measuring the oxygen saturation of blood. Those sensors can easily detect breathing disorder such as apnea. Compared to this, the information regarding the breathing provided by our system is more limited. This is due to the fact that the signal provided by the EMFi sensor is a combination of all body movements with overlapping frequency ranges.

Sleep stage is currently evaluated by medical specialists using polygraph data such as EEG, EOG, and EMG and are based on the K-R classification. Those methods are clearly obtrusive and require specialists with a high degree of technical expertise to operate the system. Different works have tried to access the sleep stages based on measurements of vital parameters using BCG. For example, Watanabe and Watanabe have shown that an estimate of the sleep stages can be computed from a pneumatic sensor below the mattress [14]. They have created a sleep model and a sleep index based on the power spectrum of the signal. The models used in those methods are elaborated and require extended calibration.

Figure 10 Comparison between the sleep phases using the variance method (top) and the EEG measurement (bottom). There is a good match except that the variance method falsely detects some awake phases.
In contrast, our method is straightforward and does not need any calibration. Finally, the company EMFIT [5] is commercializing its own sleep monitoring solution but we did not find any publication regarding the accuracy and performance of their system.

7. Conclusion

We presented a low-cost, low-complexity, unobtrusive system for assessing heart rate, breathing rate, body movement and sleep type based on the signal from an EMFI sensor placed under the mattress. The main advantages of our system are its unobtrusiveness, its simple setup and its cost whereas the computed values are almost as accurate and detailed as those provided by existing solutions found in medical sleep laboratories. This paves the way to a lot of applications outside of specialized health establishment, such as monitoring elderly persons, sportsmen/women or babies as well as large epidemiological studies regarding sleep over longer periods.

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