

A Feasibility Study on the Automatic Detection of Atrial Fibrillation using an Unobtrusive Bed-Mounted Sensor

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Abstract

We present a feasibility study on the automatic detection of atrial fibrillation (AF) from a cardiac vibration signal (ballistocardiogram). Signals were recorded by means of an electromechanical foil attached to a bed's mattress. A clinical study with 10 AF patients was conducted to assess whether ballistocardiograms (BCG) provide sufficient information to automatically distinguish atrial fibrillations from normal sinus rhythms. For this purpose, the BCGs were split into 30 s long epochs which were manually labelled as AF or sinus rhythm. Using features extracted from an auto-regressive time-frequency representation of the BCG, a support vector machine classifier was trained to detect AF epochs. The classifier was evaluated on a set of 245 epochs by means of leave-one-out cross-validation. Our results (sensitivity: 96.2 % / specificity: 91.9 %) suggest that it is indeed feasible to use bed-mounted BCG sensors to screen for atrial fibrillations.

1. Introduction

Atrial fibrillation (AF) is one of the most common cardiac arrhythmias. The prevalence of AF is about 1 % in the general population with an emphasis on the elderly [1]. AF can persist clinically asymptomatic and is liable for increasing the rate of death, hospitalization, stroke and other thromboembolic events as well as causing severe heart failure and left ventricular dysfunction. Knowing that 70 % of the patients affected by AF are at least 65 years old [1] and considering the risk of silent and undetected AF, there is a need for screening this population.

In recent years, the bed has emerged as a promising place for long-term monitoring of cardiopulmonary activity at home. Furthermore, instrumented beds could be applied in the general wards of hospitals to increase the safety of the patients and improve patient outcome.

One promising approach for unobtrusively measuring cardiopulmonary activity is the integration of highly sen-

sitive mechanical sensors into the bed-frame or mattress which record the vibrations of the body caused by the mechanical activity of the heart. Techniques measuring cardiac-related vibrations of the body are known under a variety of terms such as ballistocardiography [2], seismocardiography [3], apexcardiography [4], mechanocardiography [5], as well as kinetocardiography [6]. New sensor modalities and applications have blurred the lines between the original definitions of these terms. Since we feel that ballistocardiography (BCG) is the most widely used term in recent literature, we will continue to use it to describe our method which records any and all movements of the cardiovascular system as they affect the thorax and can be registered by a mattress-mounted sensor along its vertical axis.

Modern BCG systems have been integrated into objects of daily life, such as beds [7,8] or chairs [9]. These systems share the common advantage that they are unobtrusive and that they do not require direct skin contact, such as, for example, a conventional ECG. Hence, they are very well suited for long-term monitoring. It is important to distinguish this application, where only the BCG signal is available, from the BCG's other major use, where an ECG is recorded simultaneously and, for example, hemodynamic parameters are derived from the combination of both signals [10].

This work focuses on the automatic detection of cardiac arrhythmias using a single BCG sensor. For this purpose, we obtained BCG recordings of 10 patients with atrial fibrillation (AF). Time-domain and time-frequency-domain features were used to train a support vector machine (SVM) classifier to detect AF episodes in the BCG.

2. Methods

2.1. BCG acquisition

The BCG data in this study were acquired using a single electromechanical-film (EMFi) sensor (Emfit Ltd,

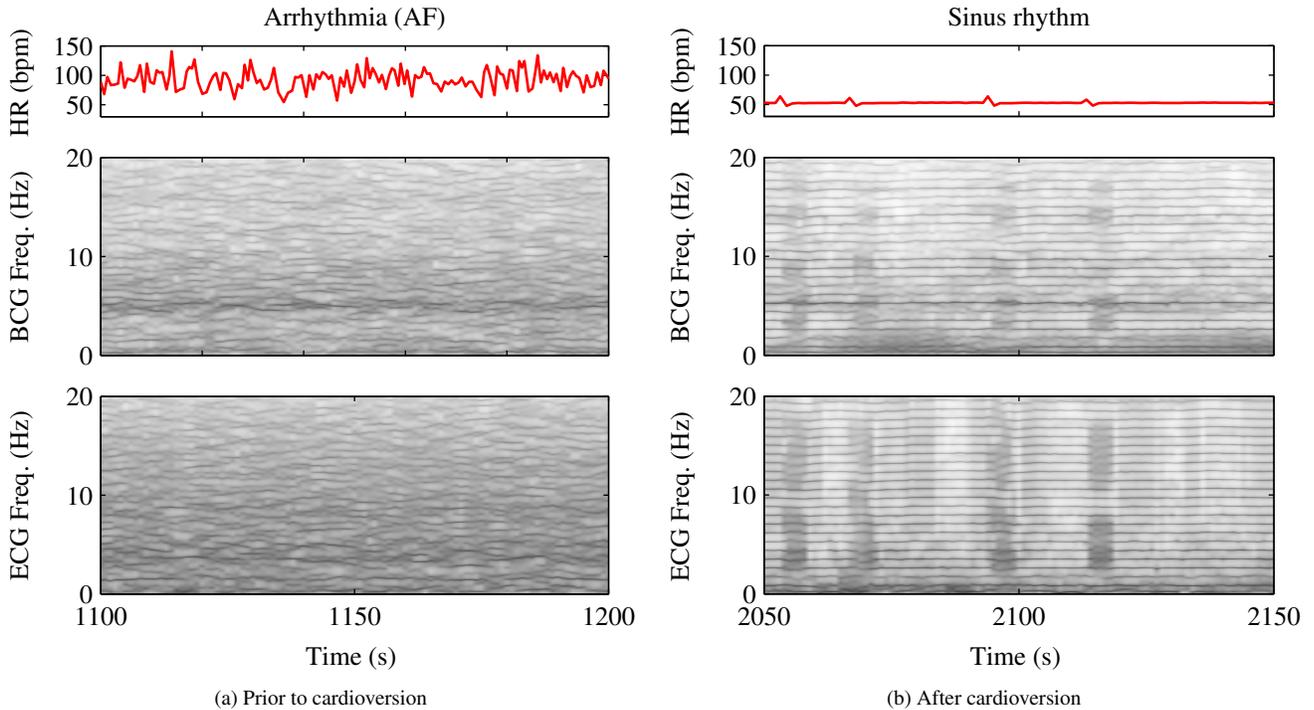


Figure 1: Time-frequency analysis of the BCG and the reference ECG of a patient before and after the cardioversion is performed. (From top to bottom: 1. beat-to-beat heart rates computed from the reference ECG, 2. spectrogram of the BCG signal, and 3. spectrogram of the reference ECG signal.)

Vaajakoski, Finland; dimensions: 30 cm \times 60 cm, thickness $<$ 1 mm). Mechanical deformation of the electromechanical film generates a signal which is proportional to the dynamic force acting along the thickness direction of the sensor. The resulting signal was digitized with 12 bits at 128 Hz. The EMFi foil is mounted on the underside of a thin foam overlay which is then placed on top of the mattress of a regular bed. The sensor was positioned where the subjects' thoraxes will usually lie. Using this system, cardiac vibrations of the person lying in bed can be recorded.

2.2. Measurement scenario

The following study was performed at the University Hospital in Aachen, Germany. Approval of the study was granted by the ethics board of the University Hospital Aachen (ref. number: EK075/10, date: 05.05.2010). A total of 10 patients (1 female, 9 male, age: 63.1 ± 18.0 years, BMI: $28.9 \pm 4.8 \frac{\text{kg}}{\text{m}^2}$) who were visiting the hospital to undergo ambulatory treatment for atrial fibrillation gave their informed written consent. To return the patients' heart rhythm to a regular sinus rhythm, a routine procedure called synchronized electrical cardioversion was performed on each patient. During this procedure, an electri-

cal current is administered to the heart.

The subjects were placed in a hospital bed instrumented with an EMFi foil sensor as described above for the entire duration of their treatment. As reference, a 3-lead ECG was recorded with a sampling rate of 500 Hz. BCG and ECG data was continuously acquired before, during, and after the procedure.

The study scenario was chosen because it allows the same patient to be recorded while exhibiting the pathology (i.e. atrial fibrillations) as well as when the patient's heart has returned to a normal sinus rhythm.

2.3. Time-frequency analysis

Biosignals, such as the ECG or the BCG, are highly non-stationary in nature (especially in the presence of arrhythmias). Deeper insights into these signals' properties can be achieved by analysing their time-frequency distributions.

For this purpose, the BCG signals and the lead II ECG signals recorded during our study were low-pass filtered with a corner-frequency of 20 Hz and then downsampled to 40 Hz. Afterwards, the signals were split into 5 s long epochs with 4 s of overlap, thus resulting in one epoch every second. In the case of sinus rhythms, we assume

Table 1: Features extracted from 30 s long BCG epochs.

	#	Feature description
Time	1	skewness($x[n]$) = $\frac{m_3(x[n])}{m_2(x[n])^{3/2}}$
	2	kurtosis($x[n]$) = $\frac{m_4(x[n])}{m_2(x[n])^2} - 3$
Time-Frequency	3	skewness($\bar{P}[f]$)
	4	kurtosis($\bar{P}[f]$)
	5	skewness($\Delta f_{\text{peak}}[k]$)
	6	kurtosis($\Delta f_{\text{peak}}[k]$)
	7	mean($w_{\text{peak}}[k]$)
	8	$\max_{f_b} \sum_{k=1}^{\lfloor F/f_b \rfloor} \log_{10} \left(\frac{\bar{P}[kf_b]}{\bar{P}[(k+\frac{1}{2})f_b]} \right)$
	9	$\sum_{t=1}^{T-1} \text{kurtosis}(\text{xcorr}(S[f, t], S[f, t + 1]))$

the signals to be quasi-stationary during these epochs. For each epoch, the power spectral density (PSD) was estimated using a parametric auto-regressive (AR) method. We applied Burg’s method [11] and an AR model of order 70. This model order was empirically found to provide a good trade-off between high frequency resolution and spectral over-fitting. Spectrograms were then obtained for each signal from the sets of estimated PSDs.

For illustration, Figure 1 shows spectrograms of one of the patients in our study. When inspecting the spectrograms of the ECG and the BCG, respectively, the change of state induced by the cardioversion is visible in their appearance. While the spectrograms during atrial fibrillation appear smeared, the spectrograms change into a pattern of distinct lines, representing a base frequency and its harmonics, when the subject’s heart returns to a sinus rhythm. The observation that ECG and BCG spectrograms undergo the same qualitative changes leads us to believe that the BCG signal recorded using our unobtrusive, non-contact sensor system does indeed contain similar information as the ECG with respect to the presence of arrhythmias.

2.4. Feature extraction

For the automatic classification, the raw BCG recordings were split into 856 non-overlapping, 30 s long, epochs. Epochs containing motion artefacts were manually labelled and excluded from further analysis. Each of the remaining $N = 245$ epochs was assigned a label $y \in \{\text{AF}, \text{normal}\}$ based on manual analysis of the reference ECG by an expert. In general, the epochs prior to cardioversion were labelled as AF while the epochs after the cardioversion were labelled as normal. The resulting

dataset is unbalanced ($N_{\text{AF}} = 183$, $N_{\text{normal}} = 62$) which was taken into account during training of the classifier.

From each epoch, a set of 2 time-domain and 7 spectrogram features, which are detailed in Table 1, was extracted. The time-domain features are the signal’s skewness and kurtosis which are computed using the k -th sample moments m_k around the mean. The moments of a signal $x[n]$ with the mean \bar{x} and length N are defined as:

$$m_k(x[n]) = \frac{1}{N} \sum_{n=1}^N (x[n] - \bar{x})^k. \quad (1)$$

In the time-frequency-domain, features were chosen with the intention to capture the presence (or absence) of the equidistant spectral lines that were discussed in the previous section. Let $S[f, t]$ denote the spectrogram of the epoch and $\bar{P}[f]$ the mean PSD of the epoch obtained by averaging $S[f, t]$ along the time axis. Furthermore, let $f_{\text{peak}}[k]$ and $w_{\text{peak}}[k]$ denote the peak-to-peak distances of spectral peaks along the frequency axis of $S[f, t]$ as well as their widths at half-maximum-height, respectively.

Features 3–7 compute the skewness and kurtosis or the mean of these functions to, for example, quantify how regular the distances between spectral peaks are. The maximum power ratio between a base frequency f_b (within physiological heart rate limits) with its harmonics and the frequencies which lie exactly halfway between these harmonic frequencies is used as feature 8. The final feature measures the similarity between consecutive frequency slices of the spectrogram by computing the mean kurtosis of the cross-correlation series of these pairs of PSDs.

During cross-validation, each feature is scaled across all training observations to zero mean and a standard deviation of one. Principal component analysis is then applied to reduce the dimensionality of the feature set by removing the dimensions with the lowest variance from the transformed feature matrix. The target dimensionality is automatically found as the minimum number of dimensions (usually 5) necessary to maintain at least 90 % of the overall variance of the training set. The respective test data is scaled and transformed according to the parameters derived from the training data.

2.5. Support vector machines

Support vector machines (SVM) are a supervised statistical learning method [12]. Using a kernel function, the algorithm projects a labelled set of training vectors into a higher dimensional space where a maximum-margin hyperplane is computed that best separates the two classes. The computed hyperplane then serves as the decision surface to classify further test vectors.

For our study, we have chosen to use the common radial basis function kernel. In order to obtain optimal classifica-

Table 2: Classification performance of the SVM classifier using leave-one-out cross-validation.

Accuracy	Error	Sensitivity	Specificity	Kappa ¹
95.1 %	4.9 %	96.2 %	91.9 %	0.87

¹ Cohen’s Kappa

tion results, two parameters of the SVM must be selected: the soft-margin parameter C and the Gaussian kernel parameter γ . Using a logarithmic grid search, we have found a set of suitable parameters for our application. In order to improve classification performance on our unbalanced data set, we used class-wise weight factors for the soft-margin parameter C . This increases the penalty for misclassifying a sample of the “normal” class which is underrepresented in our dataset. Computations were performed using MATLAB and libSVM [13].

3. Results and discussion

The quality of the proposed arrhythmia detector was evaluated by performing leave-one-out cross-validation on the entire dataset of 245 epochs (≈ 2 hours of BCG signal). Table 2 shows the resulting performance measures. The high classification performance suggests that an automatic detection of arrhythmia epochs based solely on a single mechanical vibration signal is indeed possible.

However, further studies are needed to obtain larger and more balanced datasets. The observed difference between sensitivity and specificity, for instance, is likely an artefact of our unbalanced dataset which favoured AF epochs. Furthermore, datasets containing other types of arrhythmias are necessary to analyse how these affect the BCG signal.

4. Conclusion

We presented a feasibility study on using a bed-based sensor system to unobtrusively monitor the person lying in bed for cardiac arrhythmias. Using time-frequency analysis, we could show that the proposed BCG system does indeed exhibit similar time-frequency characteristics compared to a reference ECG. Based on these findings we derived time-frequency features which were used to train a SVM classifier for the automatic detection of AF episodes in the BCG signal. This classifier achieved a sensitivity and specificity of 96.2 % and 91.9 %, respectively, thus showing the feasibility of automatic arrhythmia detection from BCG signals.

Finally, our goal is to develop an automatic heart rhythm diagnosis tool for in- and outpatient situations. Hence, in future studies, other arrhythmias and heart rhythms, espe-

cially ventricular arrhythmias such as ventricular premature beats, should be analysed.

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