Classifying Electrocardiogram Peaks Using New Wavelet Domain Features

E Vansteenkiste[1], R Houben[2], A Pizurica[1], W Philips[1]

[1]Ghent University, Ghent, Belgium
[2]Medtronic Research, Maastricht, The Netherlands

Abstract

We study distinctive properties of normal and malfunction electrocardiogram (ECG) peaks in the wavelet domain and based on this study we propose novel classification features for ECG signals. We analyze different combinations of the proposed wavelet domain and time domain features using multidimensional clustering and dimensionality reduction techniques. The results indicate encouraging accuracy rates.

1. Introduction

Atrial fibrillation (AF) has been found independently associated with significant morbidity and mortality in large population based studies. The Framingham study showed that atrial fibrillation (AF) is associated with a 1.5-1.9 fold increased risk of mortality. It is likely that this mortality increase is multi-factorial in origin and is related to stroke, worsening of heart failure and drug toxicity. Observations suggest that atrial fibrillation may facilitate the induction and perpetuation of life-threatening ventricular tachyarrhythmias.

Detection of unique heart rythm patterns before the onset may enable pacing maneuvers that potentially prevent the onset of tachycardia. This approach requires reliable detection and identification of (supra)ventricular premature beats during normal sinus rhythm and atrial fibrillation. Automatic classification of cardiac beats has been previously reported by several investigators. Most methods rely on specific parameters extracted from the ECG followed by a classifier based on either heuristic reasoning, statistical modeling of the parameters or neural networks.

In this study we propose distinctive properties of normal and malfunction ECG peaks in the wavelet domain and a novel classification framework for ECG signal features. The ECG classification features are calculated from wavelet coefficients and from their propagation across the resolution scales.

We adopt a heartbeat categorization recommended by the Association for the Advancement of Medical Instrumentation (AAMI):

- V - abnormal ventricular beat
- S - abnormal atrial beat
- N - normal beat

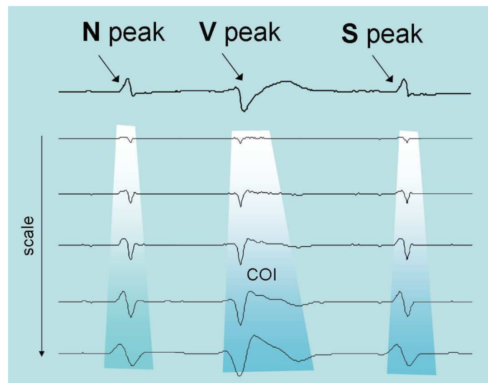

Figure 1. A part of an ECG signal and the wavelet coefficients at 5 consecutive dyadic scales.

The V beats usually have a clearly different shape from the normal ones, which is not true (or much less true) for S beats, see Fig. 1. The S beats are usually best detected based on heartbeat intervals.

The paper is organized as follows: we first analyze different wavelet features in combination with a dimensionality reduction. Next, we introduce a novel feature that captures some specific morphological differences between the ECG peaks in the wavelet domain. Subesequently, we show the clustering results in the analyzed feature spaces and the classification results for the best performing feature set. Finally, we present our conclusions and discussion.

2. Feature extraction

In this study we used a large annotated data set of ECG peaks coming from fifteen Holter Tape recods containing over 360 hours of ECG signals from patients of different age, sex and cardiac symptoms. Medical experts in the field performed the annotation manually. Out of this data set we made a database for our analysis with more than 1,400,000 N-type peaks; more than 37,000 S-type peaks and over 16,000 V-type peaks. The further analysis assumes there is no baseline drift in the signals. In practice, we estimate the baseline drift by applying a median filter to the input and subtracting this drift estimate from the input. We use a non-decimated wavelet transform with the quadratic spline wavelet [2]. This wavelet is often used in biomedical signal processing because it is short, smooth and symmetrical. The resulting wavelet decomposition of an ECG signal with three characteristic peaks is also illustrated in Fig. 1.

A reasonable choice of wavelet features for ECG peaks is extracting certain attributes (like modulus maxima or coefficient energies) within the cone of influence [2] at different scales. The cone of influence (COI) defines a set of wavelet coefficients at each scale that are affected by the same input discontinuity. In our case this translates to the set of wavelet coefficients affected by a given ECG peak. Let $w_{j,m}$ denote the wavelet coefficient at resolution scale j and position m. Further on, let $C(j,l)$ denote the cone of influence at the scale j corresponding to the input discontinuity at position l (in our case this means ECG peak centered at position l). One possibility we investigate is a multi-dimensional feature vector containing the maximum absolute value of the wavelet coefficients at different scales within the COI of the peak. We call this feature the Modulus Maxima feature and define it over J resolution scales as $\mathbf{F}^{MM} = [F^{MM}_{1,l}, F^{MM}_{2,l}, \ldots, F^{MM}_{J,l}]$ with

$$F^{MM}_{j,l} = \max_m w_(j,m) : m \in C(j,l). \tag{1}$$

A related choice is constructing a feature vector of wavelet transform energy within the COI at different scales, this we call the Energy Feature FE and define it for J scales as $\mathbf{F}^{E} = [F^{E}_{1,l}, F^{E}_{2,l}, \ldots, F^{E}_{J,l}]$ with

$$F^{E}_{j,l} = \sum_{m \in C(j,l)} w^2_{j,m}. \tag{2}$$

In practice we can choose five to six scales and possibly reduce the dimension of the feature vector (e.g., to 3, for a nice cluster visualization) by using dimensionality reduction techniques such as Principal Component Analysis (PCA). In a later section we show that PCA applied neither to modulus maxima features alone nor to energy features alone provides a satisfactory cluster separation.

In the rest of this paper, our main idea is to extract relatively simple features that capture distinctive properties of ECG peaks in the wavelet domain. We return to Fig. 1. V-type peaks compared to N-type and S-type peaks show different morphology of the wavelet response and also different rate of increase of the wavelet response across the scales. We will express each of these properties with simple numbers.

2.1. Average coin ratio

The evolution of the wavelet response across the scales is directly related to the local regularity (Lipschitz exponents [3]) in the underlying ECG peak. Some of us have earlier proposed an efficient estimation of the local Lipshitz exponent through the so-called Average Cone Ratio (ACR). Here we define a related ACR-based feature for ECG peaks as follows:

$$F^{ACR}_l = \log_2\left(\frac{1}{J-1} \sum_{j=1}^{J} \frac{I_{j+1,l}}{I_{j,l}}\right) \tag{3}$$

with

$$I_{j,l} = \sum_{m \in C(j,l)} \|w_{j,m}\|. \tag{4}$$

Smooth signal transitions result in positive ACR values, which is the case for all types of ECG peaks, even if they are affected by noise. The robustness of this feature to noise has been proved in terms of image denoising. This property of ACR turns out to be very useful for ECG signal analysis, because the feature can be safely extracted even from noisy ECGs hence without the need for a preprocessing. For V-type peaks the amplitude of the wavelet responses increases across the scales much faster than for the other two types of peaks, and this is clearly reflected in the corresponding ACR values, see again Fig. 1.

2.2. Wavelet alternating sign feature

By analyzing the wavelet transform of ECG peaks, we notice one interesting property clearly visible. The wavelet response for quadratic spline wavelet shows two distinctive lobes starting from a given resolution scale on. For N and S-type peaks a positive lobe is followed by a negative one, while the opposite is true for V-type peaks. In Fig. 1, this is visible already from the 3rd scale (but the scale where the effect becomes prominent depends on the input signal; resolution). If we integrate this response with the sign of the first lobe reversed, we will get a negative number for N and S peaks, and a positive number for V type peaks. In practical calculations, we will replace this integration by a finite sum. Hence, we define the Wavelet Sign Alternating Feature (WASF) as

$$F^{WSAF}_l = \sum_{Z1(l)}^{Z2(l)} w_{j,m} - \sum_{Z2(l)}^{Z3(l)} w_{j,m} \tag{5}$$

where $Z1(l)$, $Z2(l)$ and $Z3(l)$ denote the first, second and third zero-crossing of the ECG peak centered at position l.

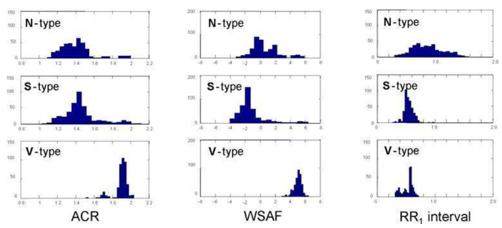

Figure 2. Experimental distribution of ACR, WSAF and RR1 for the three different types of peaks

An experimental evaluation of this feature on an annotated set of peaks is shown in Fig. 2. A clear separation of V-type peaks is evident, but also a clear difference in the behavior of N and S-type peaks, due to subtle differences in their morphology.

2.3. Heartbeat interval feature

Next to features that are related to heartbeat morphology, like the previously defined ones, a good ECG classification system should make use of differences in heartbeat intervals between the normal and malfunction heartbeats. A commonly used feature is the time interval between the R-peaks in the QRS complex of the current and the previous peak, also called ”time to previous peak” or RR1 interval. The S-type and V-type beats are ”premature” beats and hence characterized by a smaller heartbeat interval than most of the normal peaks. Sometimes for normal peaks, this interval is also shorter so there is an overlap in the empirical distributions in Fig. 2.

Anyway, a much clearer difference can be made this way between the S and N type peaks, while this feature has much less potential when it comes to separating V and S type peaks. This behavior is complementary with respect to that of ACR and WSAF features, which encourages examining their combination.

3. Results

The best performing feature set, obtained after Singular Value Decomposition (SVD) and polynomian fitting (see Fig. 3), in our study was a combination of one temporal (RR1) feature and two wavelet domain features: Average Cone Ratio (ACR), which quantifies the evolution of the coefficients across the scales, and a novel feature that we call Wavelet Sign Alternation Feature (WSAF). A very encouraging classification accuracy (93.5%) was established on a large annotated data set of Medtronic using a piece-wise multi-linear Bayesian classifier on these three features.

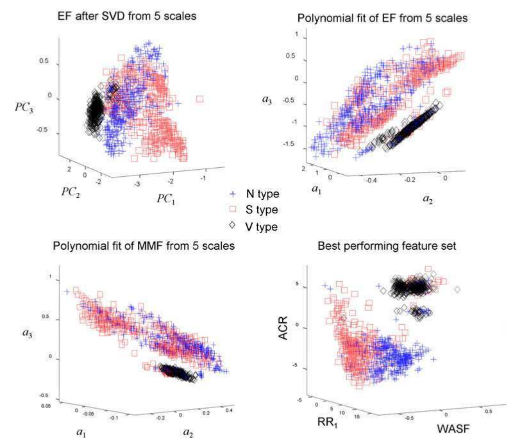

Figure 3. Clustering examples

4. Discussion and conclusions

In this study we proposed distinctive properties of normal and malfunction ECG peaks in the wavelet domain and a novel classification framework for ECG signal features. The ECG classification features are calculated from wavelet coefficients and from their propagation across the resolution scales. We analyzed a number of different wavelet features including amplitudes and energies of the waveletcoefficients within the cone of influence at multiple resolution scales combined with principal component analysis.

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Reliable detection and discrimination of ventricular and supraventricular extrasystoles, as presented here, may also be a valuable asset in detection of the onset of atrial fibrillation. An increased incidence of supraventricular extrasystoles may be an indicator for the onset of AF. Also, after termination of AF, atrial ectopic activity may lead to (early) recurrences of AF.

References

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Address for correspondence:

Ewout Vansteenkiste
Sint-Pietersnieuwstraat 41, 9000 Ghent, Belgium
ervsteen@telin.ugent.be