Detection and Classification of P Waves Using Gabor Wavelets

M Michaelis, S Perz, C Black, and G Sommer †

GSF-Medis-Institut, Neuherberg, Germany
† Institut für Informatik, Christian-Albrechts-Universität, Kiel, Germany

Abstract

The wavelet transform of an ECG with a complex Gabor filter can be changed to two representations where the real and imaginary part are combined in a nonlinear way to an energy signal and a phase signal. The energy signal is used to detect and localize P waves, whereas the phase signal is used to classify the P waves as monophasic, M-shaped or biphasic.

1. Introduction

Automatic P wave detection is still a not satisfyingly solved problem in surface ECG analysis. The difficulties in P wave detection are due to the low amplitudes, widely varying shapes, low signal-to-noise ratios, and adjacent QRS complexes or T waves. Mostly, P wave detection is based on local measurements like derivatives, amplitude, or spatial velocity [3, 4, 8]. Even though these quantities allow an efficient measurement of signal activities connected to the presence of P waves, they are likely to fail in the presence of noise or small amplitudes, because they do not take into account the signal energy of the P wave as a whole.

To improve this weakness, we use a wavelet transform of the ECG signal in our approach. Whereas wavelet transforms became a widely used tool for the analysis of nonstationary signals in general during the last years [1], their application to ECG analysis is restricted to a few investigations [6]. The mother wavelet of our transform is a complex Gabor function with considerably fewer oscillations (≈ 1) than those used in most other applications (see Fig.1). This means that at coarse scales, where the size of the wavelet is approximately the size of a P wave, the wavelet transform is rather a template matching for P waves than a local frequency analysis of the signal. At the small scales, it is qualitatively a first (real part) and second (imaginary part) derivative of the signal. These derivatives are used to localize the onset and offset of the P wave. The scales in between offer additional information because they provide the connection from events at small scales to the detected P wave at a coarse scale.

The real and the imaginary part of the transform are combined in a nonlinear way to the two new representations 'energy' and 'phase'. The energy allows the detection of P waves independently of their shape whereas the phase distinguishes between the different shapes.

2. Material

We used twelve lead resting ECGs with a record length of 5 sec. The sampling rate was 250 per sec with a resolution of 12 bit for the range of ± 5mV. From a large data base 50 cases were selected, covering a variety of P wave shapes (monophasic, M-shaped, biphasic, noisy, and low voltage signals) according to different atrial diseases and also different signal conditions. Because of the exploratory character of the studies, beside a weak low pass filtering, no pre- or postprocessing like averaging several beats or using information from parallel leads was made, even though this would improve the performance of the method.

3. Methods

The procedure to detect, localize and classify P waves relies basically on a representation of the ECG signal where three parameters are made explicit: (1) scale by using a wavelettransform, (2) energy, and (3) phase by using a complex (pseudo) quadrature pair of filters as the mother wavelet.

3.1. Quadrature Filters

Quadrature filters are complex filters where the imaginary part is the Hilbert transform [7] of the real part. The Hilbert transform changes the symmetry type of a function from odd to even. The complex response of such a filter to a signal can be changed to an energy and phase representation:

$$\text{energy} = |\text{Re}|^2 + |\text{Im}|^2 \qquad \text{phase} = \arg\left(\frac{\text{Im}}{\text{Re}}\right). \quad (1)$$

The response signal from linear filtering is never an unambiguous measure of signal energy because it always mixes the presence of signal structure (energy)

Int. Congr. Cardiology, London, 1993
531.534
IEEE Comp. Society Press, Los Alamitos, Calif., 93

and the symmetry type of the signal structure which results from the structure shape and the displacement to the filter function (phase).

3.2. Gabor-Wavelets

The detection of patterns in nonstationary signals is closely connected to local frequency analysis. This implies that a filter should have a good localization in the time domain as well as in the frequency domain. Now the uncertainty principle (D. Gabor 1946 [2]) limits this joint localization. If σ_t and σ_ω are the variances of a function in the time and the frequency domain, the joint localization cannot be better than $\sigma_t\sigma_\omega \geq 1/2$. Taking this into account, several methods were developed recently to solve the problem of detection and localization of signal structure [9]. One of these methods is the Gabor wavelet transform, introduced by J. Morlet [5]:

$$g_{\sigma,t_0}(t) = e^{ic\frac{(t-t_0)}{\sigma}} e^{-\frac{1}{2}\frac{(t-t_0)^2}{\sigma^2}} \quad . \qquad (2)$$

Here 'c' is a fixed constant which gives the number of oszillations of (2) (Fig.1). The parameters σ and t_0 indicate the scale and the shift in the time domain of the function g. The projection on such a set of functions with varying σ and t_0 is called a wavelet transform.

4. Detection of P Waves

The choice of the parameter 'c' in (2) is of crucial importance. A larger 'c' leads to more oszillations of the function giving it a better localization in the frequency domain, but, according to the uncertainty principle, at the cost of its localization in the time domain. Figure 1 shows two Gabor functions with $c = 1.9$ and $c = 5.3$ which is used in most other investigations. Figure 2 shows the energy distribution by time and scale for a P wave for these functions.

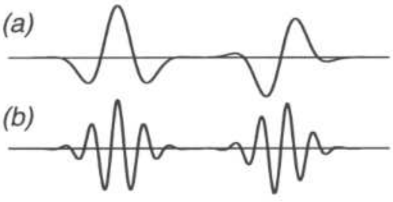

Figure 1: Gabor wavelets (a) $c = 1.9$, (b) $c = 5.3$.

The Gabor function as well as the energy distribution is better localized in the time domain for $c = 1.9$ than for $c = 5.3$. This helps localizing and classifying the P wave, and separating it from the energetically much more prominent QRS complex. Compared to the Gabor function with $c = 5.3$, the one with $c = 1.9$ roughly resembles a P wave or the first and second derivative of a Gaussian. Therefore the interpretation of the wavelet

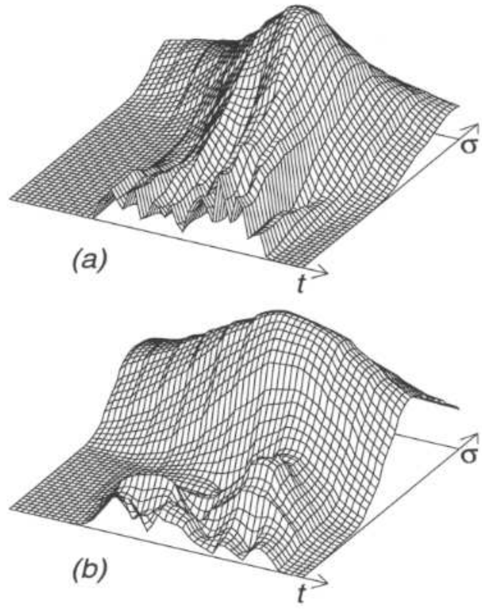

Figure 2: Energy distributions for a P wave for the Gabor wavelets with (a) $c = 1.9$ and (b) $c = 5.3$.

transform in our case is a template matching for the P wave at coarse scales and taking the derivatives of the ECG signal at fine scales. We also examined the wavelet transform with Gaussian derivatives, but we got better results using Gabor functions.

The choice of $c = 1.9$ has two drawbacks. First the real part of (2) has a not negligible DC component that is remedied by the following modification (N is a normalization to $L^1(g) = 1 + i$):

$$g_{\sigma,t_0}(t) = N(e^{ic\frac{(t-t_0)}{\sigma}} - e^{-\frac{1}{2}c^2})e^{-\frac{1}{2}\frac{(t-t_0)^2}{\sigma^2}} \quad . \qquad (3)$$

Second, the real and imaginary part are no longer in quadrature. We accept this drawback, because it is not too severe and, in addition, the exact Hilbert transform of the real part has a very slow decay. Bevor transforming the ECG signal, it is low pass filtered with a Gaussian ($\sigma = 4\ldots8$ms).

Figure 3 shows an energy and phase image obtained with the function (3). The detection of the P wave is done by analysing the energy signal at some favorable scales which were determined empirically. The figures 3e-g show the energy at the scales $\sigma = 4.8, 9.6$, and 22ms. First the absolute maximum on a length of $\pm$400ms, which stems from a QRS complex, is searched at a coarse scale (22ms).

After detecting the QRS complexes, the P waves are found by searching the energy maxima before the Q onset at a scale of $\approx$ 30ms. At this scale, the energy maxima are caused by the P wave as a whole and not just by its steep onset or offset. The details of the P

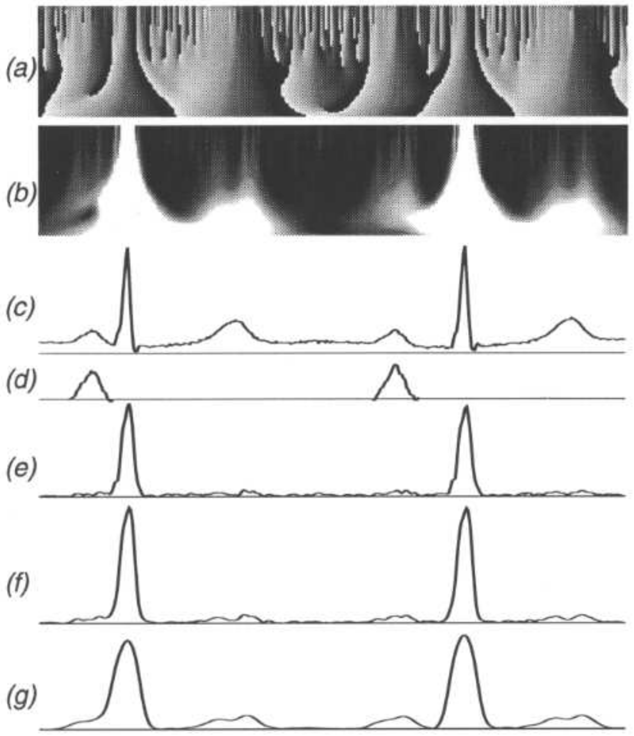

Figure 3: Wavelet analysis of an ECG signal: (a) phase and (b) energy. The scale ranges from $\sigma = 3$ms (top) to $\sigma = 96$ms (bottom). In the energy image the brightness of the P and T waves is raised compared to the QRS complex. (c) ECG signal with short PQ distance in the first beat, (d) detected P waves, (e) - (g) energy to the scales $\sigma = 4.8, 9.6, 22$ms.

wave and the noise are not visible. Now the next finer scales are used successively to narrow down the region of the P wave. The energy signal then divides into several maxima; their connection is given by the coarse scales. The procedure stops when the signal cannot be distinguished from the noise any longer. At the cost of a precise localization, the procedure ensures that the P wave is entirely contained in the detected region.

Figure 4 shows an example of a noisy ECG signal with a low amplitude P wave. Nevertheless the P wave could be correctly detected, the localization, however, is impeded. The energy signal which is used to detect the P wave ($\sigma = 31.2$ms) is not affected by the noise.

5. Classification of P Waves

Morphologically, three different shapes of P waves are distinguished: monophasic, M-shaped, and biphasic. The recognition of these shapes is essential for the diagnosis of several atrial diseases. The information to

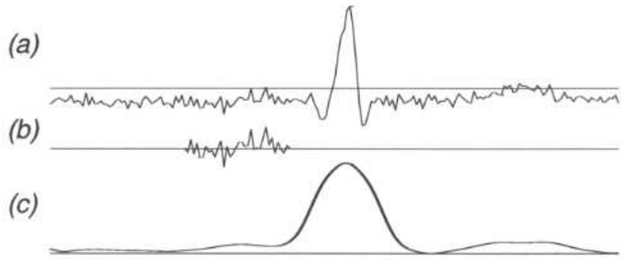

Figure 4: Example of a noisy lead with a low amplitude P wave. (a) signal, (b) detected P wave area, (c) energy to the scale $\sigma = 31.2$ms.

classify a P wave as one of these types is comprised in the phase.

The relative contribution of the even real part and the odd imaginary part of the analysing function (3) to the energy is given by the phase. For an odd signal structure the main contribution to its energy comes from the imaginary part of (3). The phase will be approximately $+\pi/2$ or $-\pi/2$. Accordingly, an even signal structure has a phase of $0, +\pi$ or $-\pi$. To classify the P waves, we investigated two methods:

A: Interpretation of the phase at the absolute energy maximum

The goal of this method is to classify the P waves in a fast and simple way as biphasic or not biphasic. This can be done by taking the phase at the absolute energy maximum of the P wave. To make this maximum as distinct as possible, the choice of $c = 1.9$ in (3) is advantageous (see Fig.2). Figure 5 shows the result from the classification of about 1100 P waves which where automatically detected and extracted from the ECG signal by the method desribed in section 4.

As the result in Fig.5a shows, the biphasic P waves can be classified properly. Taking into account that the majority of all P waves are nonbiphasic with a phase outside the biphasic range, this method can classify about 75% of all P waves as certainly nonbiphasic. The nonbiphasic P waves cannot be properly classified for the following reasons: (1) no proper localization of the P wave, (2) an asymmetric shape of the P wave, (3) no distinct energy maximum.

B: Detection of local extrema

To obtain a robust classification of all three types of P waves, we have to examine the whole phase image. This is illustrated in Fig.6 showing a phase image where all regions with negative phase are rendered dark and those with positive phase bright. Now we are interested in the lines of changing sign of the phase. At these locations in time and scale, the signal locally shows a maximum (phase 0) or minimum (phase π). We are only interested in those regions where the energy is high. At small scales, this is the width of the P wave, at larger scales,

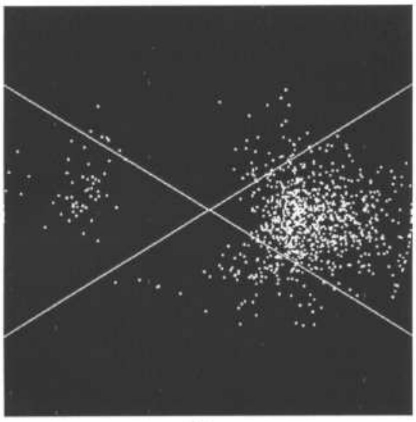

Figure 5: Phase (angle) and energy (distance from centre) of about 1100 P waves, classified by an expert as biphasic (a) or nonbiphasic (b), and analysed with method A. The phase areas of the upper and lower quadrants are assigned to odd structures (biphasic P waves), the left and right quadrants to even structures (nonbiphasic P waves).

it increases with the size of the analysing wavelet.

Biphasic P waves are characterized by having a maximum **and** minimum even at coarse scales. Hence the phase image shows two lines of changing sign running through all scales.

Accordingly, monophasic and M-shaped P waves only have one line of changing sign running through all scales. M-shaped P waves have, in addition, a maximum and a minimum which exists only up to a certain scale. At the small scales, the exact localizations of the maxima and minima can be detected. Their connection to the larger scales distinguishes them from noise artifacts. This is used to determine the distance of the two peaks in a M-shaped P wave.

6. Conclusion

We have presented a method which shows promise for the detection of P waves in the surface ECG. A good

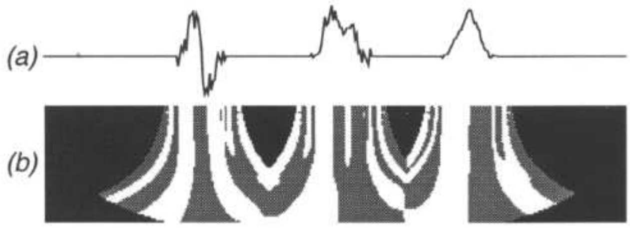

Figure 6: (a) Biphasic, M-shaped, and monophasic P wave. (b) The phase image used in classification method B. Positive phases are represented in bright, negative phases in dark.

performance is achieved by this method, even if no information of parallel leads or several beats of longer recordings is used. The complex wavelet transform, we employed for the detection of the P waves, includes the phase information of the signal which allows the distinction between monophasic, M-shaped, and biphasic P waves.

References

[1] Combes JM, Grossmann A, Tchamitchian P (Eds). *Wavelets: Time-Frequency Methods and Phase Space.* Proc. of the Int. Conf., Marseille 1987, Springer (1989).

[2] Gabor D. *Theory of Communication.* IEE Part III 1946;93:429-57.

[3] Laguna P, Vigo D, Jane R, Caminal P. *Automatic Wave Onset and Offset Determination in ECG Signals: Validation with the CSE Database.* Computers in Cardiology 1992. Los Alamitos: IEEE Computer Society Press, 1992:167-70.

[4] McManus CD. *A Re-Examination of Automatic P-Wave Recognition Methods*, in Wolf HK, Macfarlane PW (Eds.): *Optimization of Computer ECG Processing.* North-Holland, 1980:121-27.

[5] Kronland-Martinet R, Morlet J, Grossmann A. *Analysis of sound patterns through Wavelet Transforms.* Int. Journal of Pattern Recognition and Artificial Intelligence 1987;1:97-126.

[6] Morlet D, Peyrin F, Desseigne P, Touboul P, Rubel P. *Time-Scale Analysis of High-Resolution Signal-Averaged Surface ECG Using Wavelet Transformation.* Computers in Cardiology 1991. Los Alamitos: IEEE Computer Society Press, 1991:393-6.

[7] Oppenheim A, Schafer R. *Digital Signal Processing.* Prentice-Hall International 1975.

[8] Reddy BRS, Elko PE, Christenson DW, Rowlandson GI. *Detection of P Waves in Resting ECG: A Preliminary Study.* Computers in Cardiology 1992. Los Alamitos: IEEE Computer Society Press, 1992:87-90.

[9] Sommer G. *Bivariate Local Signal Representations*, in Klette R, Kropatsch W (Eds.): *Theoretical Foundations of Computer Vision.* Akademie Verlag, Berlin 1992:119-30.

Address for correspondence.

Markus Michaelis. GSF-Medis, Postfach 1129, 85758 Oberschleissheim, Germany, Email: michaeli@gsf.de