EVALUATION OF NOVEL ALGORITHM FOR SEARCH OF SIGNAL COMPLEXES TO DESCRIBE COMPLEX FRACTIONATED ATRIAL ELECTROGRAM

V. Kremen and L. Lhotska
Gerstner Laboratory, Department of Cybernetics, Czech Technical University in Prague, Technicka 2,Prague 6, CZ-166 27

Keywords: Wavelet transform, atrial fibrillation, atrial electrogram, signal complexes.

Abstract: Complex fractionated atrial electrograms (CFAEs) represent the electrophysiologic substrate for atrial fibrillation (AF). Progress in signal processing algorithms to identify CFAEs sites is crucial for the development of AF ablation strategies. Individual signal complexes in CFAEs reflect electrical activity of electrophysiologic substrate at given time. We developed and tested a novel algorithm based on wavelet transform. This algorithm enables to find individual signal complexes in CFAEs automatically and based on that the CFAEs complexity can be described in a novel way. The method was tested using a representative set of 1.5s A-EGMs (n = 113) ranked by an expert into 4 categories: 1 - organized atrial activity; 2 - mild; 3 - intermediate; 4 - high degree of fractionation. Individual signal complexes were marked by an expert in every A-EGM in the dataset. This ranking was used as gold standard for comparison with the novel automatic search method. Achieved results indicate that use of appropriate level of wavelet signal decomposition could carry high level of predictive information about the state of electrophysiologic substrate for AF and is efficient to help to describe the level of complexity of CFAEs in a novel way.

1 INTRODUCTION

Atrial fibrillation (AF) is a cardiac arrhythmia characterized by very rapid and uncoordinated atrial activation with a completely irregular ventricular response (Fuster et. al., 2006). Radiofrequency ablation of atrial areas that triggers or sustains AF is a nonfarmacological treatment available recently (Calkins and Brugada, 2007).

During AF, multiple wavefronts propagate continuously through the right and left atria, separated by anatomical and functional barriers (Houben and Allessie, 2006). This can be electrophysiologically manifested as hierarchical distribution of dominant frequency (Sanders and Berenfeld, 2005) or complex fractionated electrograms (CFAEs) (Nademanee and McKenzie, 2004) during endocardial mapping. Local dominant frequency analysis of AF is burdened by many methodological problems of spectral analysis (Kadish and Goldberger, 2006). Therefore the software support for electroanatomical mapping system is focused on objective description and space representation of CFAEs distribution most recently.

Algorithms for automatic classification (pattern recognition) are generally based on classification techniques or description of signal, using features extracted from recorded and preprocessed signals. Such algorithms, if they are implemented, could also suggest level of complexity or degree of fractionation of particular AEGM signals recorded during AF.

Till now there is only a single known approach. However it is not published in full scope, but only in company brochure (user manual) (Ensite NavX^{TM}, 2006). This algorithm assesses level of fractionation of AEGM signal using calculation and signal processing in time domain and describes signal by only one feature which relates to degree of fractionation of the signal.

We aim to describe AEGM signal in a new universal way, which helps us to extract features of the signal and to classify its complexity. There are signal complexes (figure 2) in every AEGM signal, which are related to electrical activation of electrophysiologic substrate during AF. These signal complexes (SCs) can be found automatically and then used for several features extraction (degrees of freedom of the signal), which could be used for

Kremen V. and Lhotska L. (2008).
EVALUATION OF NOVEL ALGORITHM FOR SEARCH OF SIGNAL COMPLEXES TO DESCRIBE COMPLEX FRACTIONATED ATRIAL ELECTROGRAM.
In *Proceedings of the First International Conference on Bio-inspired Systems and Signal Processing*, pages 416-419
DOI: 10.5220/0001069404160419

automatic evaluation of electrogram complexity (or level of fractionation) in next stages.

Therefore in this paper we want to introduce a new method of AEGM signal processing which enables to localize above mentioned SCs automatically with adequate efficacy. We describe a novel method for AEGM processing (searching of SCs), based on the wavelet transform signal analysis, which is a well known technique in the signal processing domain. We also introduce the design of a wavelet filter of AEGM signal which is used before search of SCs itself.

2 METHODOLOGY

We used a representative dataset (n = 113) of atrial electrograms (A-EGMs), which were pre-selected by an expert from a large database of A-EGMs. This database was recorded during AF mapping procedures. Signals were sampled by frequency 977 Hz during AF procedure and resampled to 1 kHz after that. Each pre-selected A-EGM signal in this dataset is 1500 ms long. The expert signal selection was driven by the intention to get a good quality signals with respect to low noise and high information value of signal for later evaluation of degree of A-EGMs fractionation by an expert. Although the degree of fractionation is supposed to be naturally continuous we decided to make a four degree set of classes (Figure 1.).

Three experts used these four categories for ranking (1 – organized atrial activity, n = 24; 2 – mild, n = 40; 3 – intermediate, n = 36; 4 - high degree of fractionation, n = 13.). Individual SCs (points of interest) were found manually by an expert in every A-EGM in dataset (Figure 2). The beginning and the end of every SC was marked by an expert for all found SCs thru the whole dataset of used CFAEs. This expert ranking of the beginnings and the ends of SCs was used as gold standard for comparison with outputs of the newly introduced automatic search method (ASM) and evaluation of ASM effectiveness.

In many applications the Continuous Wavelet Transform (CWT) is used to decompose a signal into wavelets, small oscillations that are highly localized in time. Whereas the Fourier transform decomposes a signal into infinite length sines and cosines, effectively losing all time-localization information, the CWT's basis functions are scaled and shifted versions of the time-localized mother wavelet. The CWT is used to construct a time-frequency representation of a signal that offers very good time and frequency localization. The CWT is an excellent tool for mapping the changing properties of non-stationary signals. When a signal is regarded non-stationary, the CWT can be used to identify stationary sections of the data stream.

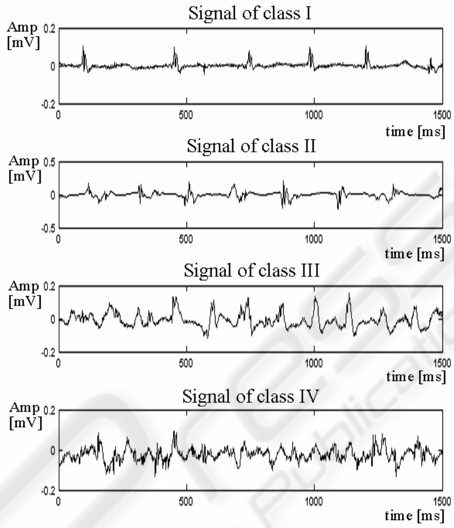

Figure 1: Four complex fractionated electrograms are shown. These are representatives of each ranking class of degree of fractionation ranked by an expert. From the top to bottom: 1 – organized atrial activity; 2 – mild, 3 – intermediate; 4 - high degree of fractionation.

The discrete wavelet transform (DWT) is an implementation of the wavelet transform using a discrete set of the wavelet scales and translations obeying some defined rules. In other words, this transform decomposes the signal into mutually orthogonal set of wavelets, which is the main difference from the CWT. The wavelet packet method is a generalization of wavelet decomposition that offers a richer range of possibilities for signal analysis.

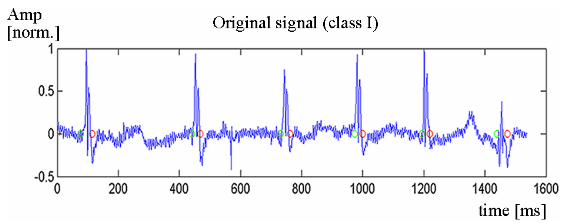

Figure 2: Original CFAE signal recorded during AF mapping procedure. Expert ranking of the signal is into class I. Depicted amplitude is normalized with respect to maximal absolute value of this particular CFAE signal. Green circles denote the beginnings of SCs and red circles the ends of SCs found automatically by ASM with optimized parameters.

We used such multilevel decomposition of CFAE signal for preprocessing (denoising) of the signal and for automatic detection of points of interests (SCs) in the signal. Simple and efficient algorithms exist for both wavelet packet decomposition and optimal decomposition selection. We chose the algorithm implemented and described in Matlab (function „wavedec", „waveden") (Matlab Wavelet Toolbox 3.0, 2006). As a mother wavelet we chose a Coiflet wavelet of order four. The selection of mother wavelet was driven by outcomes of optimization experiments performed using a Particle Swarm Optimalization algorithm (Lhotska and Macas, 2007) where this type of wavelet showed the best results for our purposes of signal preprocessing (filtering) and searching of SCs.

Filtering (de-noising) of CFAEs signals was performed using wavelet transform filter based on multilevel signal decomposition and thresholding of detailed coefficients (Mallat, 1999). The mentioned mother wavelet was used to decompose signal into 5 levels (Daubechies, 1992). Detail coefficients were thresholded by soft-thresholding (Donoho, 1995) with these settings of thresholds (level 1 to level 5): 0.02, 0.04, 0.008, 0.008 and 0.008. Reconstruction of the signal was computed by wavelet reconstruction based on the original approximation coefficients and the modified detail coefficients of levels from 1 to 5. Additional step of CFAEs signals preprocessing was done by thresholding of the signal with value of threshold 0.003 mV. Sample of CFAE signal ranked by an expert into class I, where described preprocessing technique was performed, is shown in Figure 4.

ASM itself was the next step. It was based again on wavelet multilevel decomposition of filtered signal. The signal was decomposed again into 5 levels using Coiflet wavelet of order four. The level 3 of detailed coefficients showed the best transform to find proper SCs (Figure 3). Therefore the reconstruction of the detailed coefficients of a signal (L3) of given wavelet decomposition structure was performed at level 3 (L3). Figure 3 shows the difference between L3 before and after signal preprocessing. Normalization of L3 was performed with respect to maximal absolute value of given L3 values to obtain uniform signals across the dataset for next stages of SCs detection. Thresholding of normalized L3 signal values was performed with value of threshold 0.014. Then all parts of the signal, where absolute value of amplitude was higher than 0, were marked as peaks with amplitude 1. These peaks were related to time localization of electrical activity of AF substrate in individual CFAE signals.

The last step of the algorithm consists in joining all peaks that lie very close to each other into one SC. Therefore all peaks whose inter-distance was closer than threshold 5 ms were joined together and they were marked as one individual SC (Figure 2 and 3).

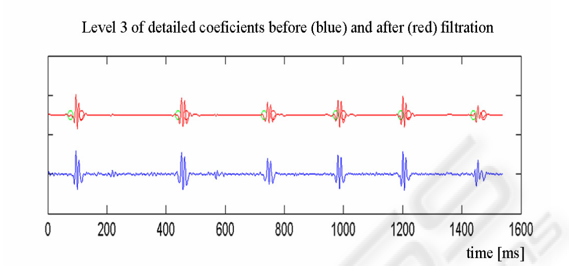

Figure 3: Reconstruction of the detailed coefficients of a signal from figure 1 of given wavelet decomposition structure performed at level 3 (L3). Blue signal shows L3 before wavelet filtering. Red signal is L3 reconstruction after filtering. Green circles denote the beginnings of SCs and red circles the ends of SCs found automatically by ASM with optimized parameters.

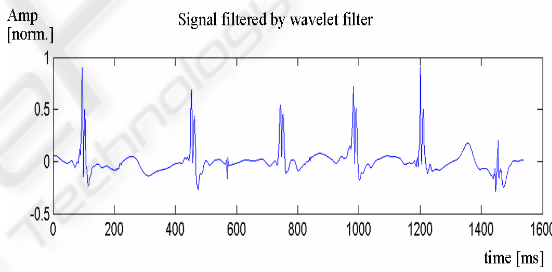

Figure 4: CFAE signal from figure 1 filtered by above mentioned wavelet filter. Depicted amplitude is normalized with respect to maximal absolute value of this particular CFAE signal.

All mentioned optional parameters of CFAE signal preprocessing algorithm and ASM itself (level used for searching of SCs and filtering, thresholds, and inter-segment distance threshold) were optimized by Particle Swarm Optimization algorithm (PSO), to get optimal parameters settings with respect to hit rate of ASM in comparison to expert marking of SC. The details and utilization of PSO is out of scope of this paper.

3 RESULTS

We evaluated the presented algorithm by calculating its hit rate, which was defined by using standard criteria of specificity. The overall results of ASM sensitivity through all classes of CFAEs are shown in Table 1.

The best results were achieved in class I and II, where the signification of SCs can be performed very precisely by an expert. There is low sensitivity of ASM to approach the signals of class IV to find and confirm the SCs signified by an expert.

4 CONCLUSIONS

The newly introduced ASM is able to find SCs with high sensitivity in class I and II and is worse to approach the expert SC classification in classes III and IV in the used dataset. The expert can hardly see and relate the electropathologic AF substrate activation in signal of classes III and IV to individual SCs and he/she can hardly properly mark corresponding beginnings and ends of the SCs. That means there could be incorrective error of classifying SCs in the used gold standard. It could be pandering that ASM could disclose hidden characteristics of the CFAE signal related to electropathologic AF substrate. These could be hardly seen in time domain only, especially at signals of class III and IV.

We could therefore use the features extracted from found SCs for CFAE signal description and evaluation of CFAE signal complexity. Therefore it might be suitable to use description of CFAE signal based on such time domain characteristics. Good descriptor for separation of classes of CFAE signals could be an intersegment distance of SCs or SCs fractionation itself.

Table 1: Hit rate of ASM with optimal parameters setting for each class of AEGM signals separately. SCs of given dataset, marked by an expert were used as gold standard.

	Sensitivity
Class I	100%
Class II	98.2%
Class III	92.6%
Class IV	63.89%

But as the results suggest we could use also CFAEs signals descriptors based on characteristics of mentioned wavelet level decomposition. The decomposition can serve to find more hidden features of CFAE signals, which could help us to distinguish between CFAE classes. Especially class III and IV could be difficult to distinguish with features extracted in time domain only. Future work will show if this new approach of automatic description of level of complexity of CFAE signal will have good results comparable to expert ranking.

ACKNOWLEDGEMENTS

This work has been supported by the MEYS of the Czech Republic (under project No. MSM 6840770012 "Transdisciplinary Biomedical Engineering Research II").

REFERENCES

Fuster V, Ryden LE, Cannom DS, et al. ACC/AHA/ESC 2006. Guidelines for the management of patients with atrial fibrillation. Circulation 2006; 114:257-354.

Calkins H, Brugada J, Packer DL, et al. HRS/EHRA/ECAS expert consensus statement on catheter and surgical ablation of atrial fibrillation: recommendations for personnel, policy, procedures and follow-up. Heart Rhythm 2007;4:816-61.

Houben RPM, Allessie MA. Processing of intracardiac electrograms in atrial fibrillation. Diagnosis of electropathological substrate of AF. IEEE Eng Med Biol Mag 2006; 25: 40-51.

Sanders P, Berenfeld O, Hocini M, et al. Spectral analysis identifies sites of high-frequency activity maintaining atrial fibrillation in humans. Circulation 2005; 112:789-97.

Nademanee K, McKenzie J, Kosar E, et al. A new approach for catheter ablation of atrial fibrillation: mapping of the electrophysiologic substrate. J Am Coll Cardiol 2004; 43:2044-53.

Ng J, Kadish AH, Goldberger JJ. Effect of electrogram characteristics on the relationship of dominant frequency to atrial activation rate in atrial fibrillation. Heart Rhythm 2006; 3:1295-305.

Ensite NavX^{TM} Navigation and Visualisation Technology (Fractionation Mapping Tool Procedure Guide, Ensite 6), pp. 2-8, St. Jude Medical, 2006.

Matlab Wavelet Toolbox 3.0 reference manual. The MathWorks, Inc. 2006.

Lhotská, L. - Macaš, M.: Particle Swarm Optimization for Processing and Analysis of Biological Signals. In Proceedings of Workshop 2007. Prague: CTU, 2007.

Mallat, S. A Wavelet tour of Signal Processing**.** 2. edition. ISBN/ISSN:0-12-466606-X. Academic Press. 1999.

Daubechies I.: Ten lectures on Wavelts, CBMS-NSF, SIAM, 61, Philadelphia, Pennsylvania, USA, 1992.

Donoho, D.L. (1995), "De-noising by soft-thresholding," IEEE Trans. on Inf. Theory, 41, 3, pp. 613-62