Developing Time-Frequency Features For Prediction of the Recurrence of Atrial Fibrillation After Electrical Cardioversion Therapy

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Abstract— **External electrical cardioversion has been used as a therapeutic option to terminate atrial fibrillation (AF) and restore sinus rhythm (SR). However, identifying patients who would benefit from this therapy is still an active area of research. In this study, we develop new time-frequency features to characterize the atrial activity (AA) and to predict the success of electrical cardioversion therapy by identifying the AF patients who will maintain SR in the long term. New features are extracted from the surface AA using a matching pursuit (MP) decomposition with various combinations of wavelet families. The performance of the features is validated using a dataset of AF patients who underwent electrical cardioversion therapy. Results indicate that the developed features are significantly (*p*-value $<$ 0.05) correlated with SR maintenance which suggests that the MP decomposition captures detailed morphological information of AA that may potentially be used to guide the therapy of AF patients.**

I. Introduction

Atrial fibrillation (AF) is one of the most common causes of hospitalization and affects approximately 2.2 million people in the United States. During AF, the atria activate rapidly and irregularly and on the surface electrocardiogram (ECG), consistent P-waves are replaced by a series of low-amplitude oscillations called fibrillatory waves (i.e., F-waves). AF is known to be a progressive arrhythmia. It will worsen with time and become increasingly difficult to treat. Paroxysmal AF is defined by self-terminating AF episodes that last no longer than seven days. Persistent AF is defined by AF which lasts longer than seven days and typically requires medical intervention to be terminated. Lastly, if AF is sustained for over a year and all attempts to eliminate AF fail, the AF is defined as Permanent. Given the progressive nature of AF and potential risks of different AF therapies, it is critical to identify if a given therapy is effective. This could provide invaluable information for effective management of AF.

External electrical cardioversion is a popular treatment to restore rhythm in AF patients [1]. However, a reliable technique for predicting the patients who will benefit from this therapy using the surface ECG has not yet been determined. The most common ECG features proposed in the literature are based on time or frequency domain analysis techniques. For example, AF rate (AFR) which is the inverse cycle length of the AA signal has been shown to be correlated to the success of cardioversion [2]. Other important features include the sample entropy and the Harmonic Decay [3] . The Harmonic Decay is a spectral based method which depends on the relative amplitudes of the fundamental and harmonic frequencies in the AA signal. Holmqvist et al. [3] show that a faster decay of the harmonics is an indicator of AF recurrence after electrical cardioversion.

In the present study, we develop new time-frequency (TF) features from the AA signal to predict AF recurrence after successful electrical cardioversion. First, a pre-processing technique is applied to extract the AA from the ECG and the AA signal is then divided into segments equal to the average heart rate (HR). Each individual AA segment is decomposed using the matching pursuit (MP) algorithm which expresses the AA as a linear combination of wavelet atoms with various wavelet types and scales. A TF feature is defined by the presence of a given wavelet atom type and scale in the AA signal. We validate the developed features on a database containing ECG from persistent AF patients who underwent electrical cardioversion. Details of the feature extraction algorithm are outlined in Section II and a validation of the features against clinical data is provided in Section III.

II. Materials and Methods

A. Database

The ECG data [4] was obtained from 73 persistent AF patients who had a successful external electrical cardioversion therapy. Prior to cardioversion, a 10-minute 12-lead ECG (f_s = 1 kHz) was recorded for each patient. There was a follow-up at 4 weeks and it was found that out of 73 patients, 32 had maintained SR while 41 had a relapse of AF. Throughout this paper, we call the successful SR maintenance and AF recurrence patients as AF-Free and AF-Relapse, respectively.

B. Pre-processing

The proposed analysis is based on a single lead. Hence, we selected Lead V1, which has been shown to provide the best atrial signal [4]. The pre-processing stage is performed in three steps as follows:

Noise and baseline wander removal: A bandpass filter with a passband of 0.01 Hz to 50 Hz was used to remove the noise and baseline fluctuations in the ECG [5].

Atrial activity (AA) extraction: Several techniques have been used to cancel the QRST complexes and obtain the AA from the ECG [6], [7]. In this study, we employ the average beat subtraction method [8] which has been widely used in the literature. First, R-wave fiducial markers are placed at points of maximum absolute derivative on the QRST complexes. We then construct a QRST template by averaging all of the QRST complexes in the entire 10 min ECG. At each fiducial marker, we fit the QRST template to the ECG

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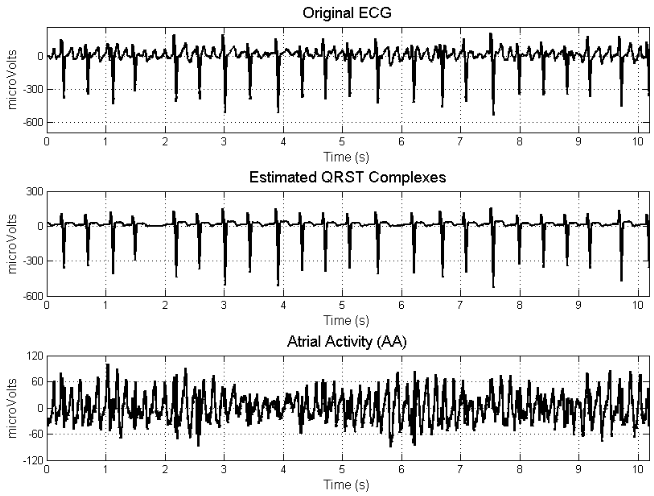

Fig. 1. Illustrative example of an original ECG waveform and the estimated AA using the average beat subtraction method.

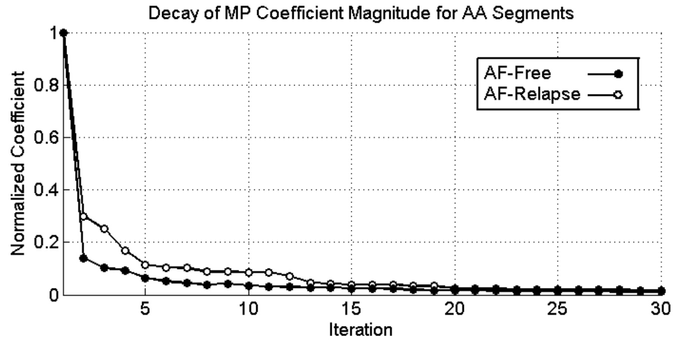

Fig. 2. This plot shows the behavior of the MP expansion coefficients as a function of iteration number. This representation was used to determine the number of iterations in our MP analysis. M, the iteration number in Eqn. 1, was set equal to the average number of iterations required for the expansion coefficients to reach less than 5% of their initial value.

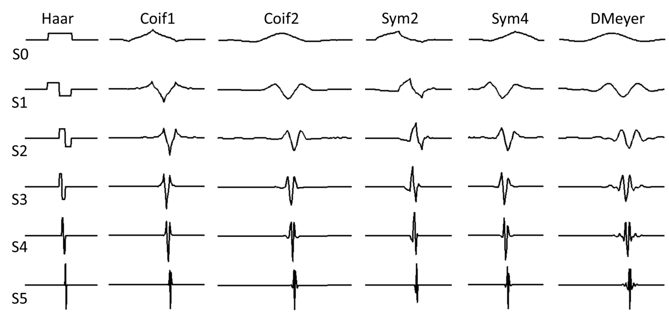

Fig. 3. Complete range of atoms used to construct dictionaries in our study. The dictionaries consisted of all combinations of 2 of these atom types illustrated at every scale shown.

and obtain the estimated QRST signal in the original ECG signal. Finally, we subtract the estimated QRST signal from the ECG to obtain the estimated AA signal. Fig. 1 displays an example where the QRST signal is removed from the original ECG and the atrial activity is successfully obtained.

AA segmentation: The average HR is calculated from the R-wave fiducial markers on the ECG and the extracted AA is divided into multiple segments with duration equal to the average HR.

C. TF Feature Extraction

MP decomposition is applied to the extracted AA signal and the TF features are extracted from the MP expansion coefficients.

Matching pursuit decomposition: MP is an iterative signal decomposition technique that expresses a signal $x(t)$ as a linear combination of functions $A_{(W_m,S_m,T_M)}(t)$ selected from an overcomplete dictionary of TF basis functions [9]. The algorithm has been successful in creating high-resolution TF representations of biomedical and environmental signals [10]. In this study, we apply the MP algorithm to the AA segments obtained from the pre-processing step as follows:

$$x(t) = \sum_{m=1}^{M} b_m A_{(W_m,S_m,T_M)}(t) + R_x^M \tag{1}$$

where $x(t)$ is a signal that represents a single AA segment, and $A_{(W_m,S_m,T_M)}(t)$ is a wavelet with type, scale and temporal location defined by W_m, S_m and T_m, respectively, b_m is the expansion coefficient for $A_{(W_m,S_m,T_M)}(t)$, M is the number of iterations that are performed, and R_x^M is the residue of $x(t)$ after M iterations. In Eqn. 1, the AA signal $x(t)$ is projected onto an overcomplete dictionary of TF functions with a combination of different wavelet types and scales. At each iteration, the best correlated TF function is selected from the overcomplete dictionary by finding the maximum inner product $\left|\langle R_x^M, A_{(W_m,S_m,T_M)}\rangle\right|$ of the current residue with all of the atoms in the dictionary. In the next iteration, the residue is decomposed according to the same rules. After M iterations, the AA signal $x(t)$ is expressed in the form of Eqn. 1 where the first term on the right-hand side represents the decomposition of the original signal by the selected TF functions, and the second term is the residue at iteration M. For M large enough, it can be observed that the residue in Eqn. 1 becomes negligibly small.

There are three ways of stopping the iterative process of MP. The iterations may proceed until the energy of the residue is less than a threshold, the value of the most recent expansion coefficient is less than a threshold, or the number of iterations reaches a pre-assigned maximum. In this study, we used a combination of the last two stopping methods and determined a fixed iteration number based on the average number of iterations required for the expansion coefficients to reach less than 5% of their initial value. Based on this analysis, we found that after $M = 20$ iterations, there is a negligible change in the expansion coefficients. Hence, we used $M = 20$ as the fixed stopping criterion. A plot of the expansion coefficients for an AF-Free and AF-Relapse example is shown in Fig. 2.

MP Dictionary: We use six different wavelet types in this study: Haar, Coiflet1 (Coif1), Coif2, Symlet2 (Sym2), Sym4, and discrete Meyer. Fig. 3 shows these wavelets at six different scales (S_0 to S_5). We build 15 different dictionaries by pairing two types of wavelets (i.e., $W1$ and $W2$). Larger dictionaries with more than two wavelet types can also be constructed; however, we did not find any improvements in the results when we combined three or more different wavelet types.

Feature Extraction: We performed MP on each individual segment of AA and obtained the decomposed wavelets and scales in each segment: A_{W_m,S_m,T_M}, $m = 1, ..., M$. Based on the decomposition, we build two matrices for each wavelet type ($W1$ and $W2$) in a given dictionary: O_{T1} and O_{T2}, respectively. These matrices, which are called the *Occupancy* matrices, are constructed as follows:

$$\begin{aligned} O_{W1}(S_m, T_m) &= \begin{cases} 1 & \text{if} \quad W_m = W1 \\ 0 & o.w. \end{cases} \\ O_{W2}(S_m, T_m) &= \begin{cases} 1 & \text{if} \quad W_m = W2 \\ 0 & o.w. \end{cases} \end{aligned} \tag{2}$$

where m, the iteration, changes from 1 to M. A graphical representation of this process is shown in Fig. 4A and 4B where two *Occupancy* matrices, O_{W1} and O_{W2} are plotted on top of one another for an example of AF-Relapse (Fig. 4A) and an example of AF-Free (Fig. 4B). This example uses a dictionary with Sym2 and Coif1 wavelets (i.e., $W1 =$ Sym2 and $W2 =$ Coif1) for the MP decomposition, where the first six rows show the occupancy for Sym2 wavelets for scales S_0 to S_5, and the next six rows show this information for the Coif1 wavelets. In this plot, each black circle implies the presence of a wavelet at the given time and scale.

Twelve TF features are extracted from each dictionary as follows:

$$F_{W1,S} = \sum_t O_{W1}(S, t) \tag{3}$$

$$F_{W2,S} = \sum_t O_{W2}(S, t) \tag{4}$$

where $S = S_0, \ldots, S_5$. In Eqns. 3 and 4, we obtain the TF features as the total presence of a given wavelet type and scale in the AA signal. There are 15 different dictionaries in this study and 12 TF features are extracted for each dictionary. Hence, a total of 180 (i.e., 15x12) TF features are extracted for each AA segment. In the next section, we select the TF features that show a statistically significant correlation with the long-term success of electrical cardioversion.

The statistical significance is determined for each TF feature using the Mann-Whitney U test, which is a non-parametric method for cases where the probability distribution of the data is not normal. This test is used in this study, because the TF features do not exhibit a Gaussian probability distribution.

D. Atrial Fibrillatory Rate and Harmonic Decay

In addition to the TF features, Atrial Fibrillatory Rate (AFR) and Harmonic Decay features are calculated for the purpose of comparison. These signal features have been previously shown to be associated with electrical cardioversion outcomes in studies similar to the present one [2], [3]. The AFR is defined to be the dominant frequency component of the AA signal. The harmonic decay measures the rate at which the magnitudes of the harmonics of the dominant frequency change as the order of the harmonic increases. In our study, the AFR and Harmonic Decay were determined from a spectral estimate obtained from the short-time Fourier transform (STFT) of the AA. The AA was estimated using the methods described in Section II. The STFT was calculated using 4 s triangular windows with an overlap of 2 s and the AFR was calculated as the frequency at the maximum value of the magnitude spectrum between 2 and 10 Hz. To measure an estimate of the Harmonic Decay we computed the ratio of the magnitude of the spectrum at 2 $\times$ AFR to the magnitude of the spectrum at AFR. This ratio characterizes the relative amplitudes of the first harmonic to the dominant frequency. It is worth mentioning hat the Harmonic Decay described in [3] uses a slightly different method than what we did in this paper. The authors in [3] fit an exponential curve to the magnitudes of all of the harmonics; however, our data did not exhibit significant harmonic components beyond the first one. Hence, we had to use the relative amplitudes of the first harmonic to the dominant frequency as an estimate of the Harmonic Decay.

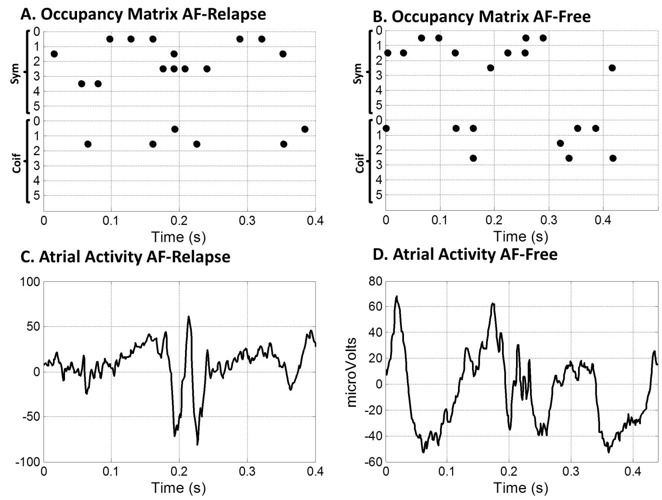

Fig. 4. Occupancy matrices for AF-Relapse and AF-Free Cases (A. and B., respectively) and corresponding AA waveforms (C. and D.). A black dot in the occupancy matrix indicates an active wavelet at the corresponding time, wavelet type, and scale.

III. Results and Discussion

The proposed TF features were extracted for the dataset described in Section II and the Mann-Whitney U test was applied to evaluate the significance of each TF feature. The results did not show any statistical significance for any of the wavelet scales except for scale 3 (S_3). The data presented in Table I lists the statistical significance results of the TF features at S_3. There are 15 possible dictionaries so 30 TF features (Eqns. 3 and 4) are shown in this table. As can be seen in Table I, there are thirteen significant (p-value < 0.05) TF features. We note that the Coif1 features are significant

TABLE I
p-VALUE OF TF FEATURES AND CARDIOVERSION OUTCOMES

Dictionary	Feature 1	p-value	Feature 2	p-value
Coif1, Coif2	$F_{\text{Coif1,S3}}$	n.s.	$F_{\text{Coif2,S3}}$	n.s.
Coif1, Sym2	$F_{\text{Coif1,S3}}$	0.024	$F_{\text{Sym2,S3}}$	0.042
Coif1, Sym4	$F_{\text{Coif1,S3}}$	0.042	$F_{\text{Sym4,S3}}$	n.s.
Coif1, DMeyer	$F_{\text{Coif1,S3}}$	0.057	$F_{\text{DMeyer,S3}}$	n.s.
Coif1, Haar	$F_{\text{Coif1,S3}}$	0.027	$F_{\text{Haar,S3}}$	0.05
Coif2, Sym2	$F_{\text{Coif2,S3}}$	n.s.	$F_{\text{Sym2,S3}}$	0.038
Coif2, Sym4	$F_{\text{Coif2,S3}}$	n.s.	$F_{\text{Sym4,S3}}$	0.01
Coif2, DMeyer	$F_{\text{Coif2,S3}}$	0.047	$F_{\text{DMeyer,S3}}$	0.04
Coif2, Haar	$F_{\text{Coif2,S3}}$	n.s.	$F_{\text{Haar,S3}}$	n.s.
Sym2, Sym4	$F_{\text{Sym2,S3}}$	n.s.	$F_{\text{Sym4,S3}}$	n.s.
Sym2, DMeyer	$F_{\text{Sym2,S3}}$	n.s.	$F_{\text{DMeyer,S3}}$	n.s.
Sym2, Haar	$F_{\text{Sym2,S3}}$	n.s.	$F_{\text{Haar,S3}}$	0.05
Sym4, DMeyer	$F_{\text{Sym4,S3}}$	n.s.	$F_{\text{DMeyer,S3}}$	n.s.
Sym4, Haar	$F_{\text{Sym4,S3}}$	0.01	$F_{\text{Haar,S3}}$	n.s.
DMeyer, Haar	$F_{\text{DMeyer,S3}}$	n.s.	$F_{\text{Haar,S3}}$	0.033

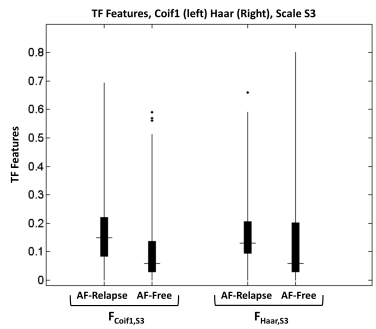

Fig. 5. Plot showing the distribution of $F_{\text{Coif1,S3}}$ and $F_{\text{Haar,S3}}$ obtained for the (Coif1, Haar) dictionary. The features represent a significant discrimination (p-value < 0.05) for th AF-Relapse vs. AF-Free group with an increased activity in the AF-Relapse group.

in 4 cases. Likewise, Coif2, Sym2, Sym4, DMeyer, and Haar are significant in 1, 2, 2, 1, and 3 of the cases, respectively.

Fig. 5 shows a plot of the TF-features grouped by the final study outcome (i.e. AF-Free or AF-Relapse) for the case of a (Coif1,Haar) dictionary. The presence of Coif1 and Haar TF features is elevated in the AF-Relapse cases compared to the AF-Free cases. Using receiver operating characteristic analysis, the best observed sensitivity and specificity achieved was for the (Coif1, Haar) dictionary with values equal to 73% and 66%, respectively. Since the TF features at scale 3 are associated with higher frequency activations and also since Coif1 and Haar wavelets exhibit highly discontinuous behavior, we may hypothesize that the increased activation of these atoms in the recurrence cases is an indicator of worsening of AF such that the electrical cardioversion is not able to terminate AF in the long term. Moreover, the proposed TF approach provides insights into the temporal and frequency content of atrial activations that would be lost in a traditional linear spectral analysis.

Comparison with AFR and Harmonic Decay: We extracted the AFR and Harmonic Decay features in our dataset and applied the Mann-Whitney U test to evaluate the significance of each feature with respect to the long-term success of the electrical cardioversion. We did not find any statistical significance in the Harmonic Decay features (p-value $>$ 0.05). AFR was found to be significantly correlated (p-value $<$ 0.05) with the study outcomes.

IV. CONCLUSION

In this study, we extracted thirteen new TF features that can be used to predict the success of SR maintenance following external electrical cardioversion in AF patients. MP decompositions with different wavelet types and scales were applied to the surface AA and the TF features were extracted based on the presence of each given wavelet and scale in the AA signal. We employed six different wavelet types along with 6 different scales, which provided 180 TF features in total. We found that only thirteen of these features were statistically significant (p-value $<$ 0.05) and the best sensitivity and specificity was achieved for $F_{\text{Coif1,S3}}$ from the (Coif1, Haar) dictionary with 73% and 66% values, respectively. Application of the AFR and Harmonic Decay features in our dataset showed that only the AFR is significantly correlated (p-value $<$ 0.05) with the study outcomes. The novel contribution of this work is that it defines a wide class of new TF features that encapsulate detailed structural information in AF as related to electrical cardioversion. Our future plan is to combine all of the extracted TF features in a single classifier, thereby, develop a technique that can reliably predict the long-term success of electrical cardioversion for AF patients. Such a technique would provide invaluable information to physicians seeking to manage AF and help to properly weigh the risks against potential benefit of SR restoration.

REFERENCES

[1] V. Fuster *et al.*, “2011 ACCF/AHA/HRS focused updates incorporated into the ACC/AHA/ESC 2006 guidelines for the management of patients with atrial fibrillation,” *J. Am. Coll. Cardiol.*, vol. 57, no. 11, pp. e101–e198, Mar. 2011.

[2] F. Holmqvist, “Atrial fibrillatory rate and sinus rhythm maintenance in patients undergoing cardioversion of persistent atrial fibrillation,” *Eur. Heart J.*, vol. 27, no. 18, pp. 2201–2207, Sep. 2006.

[3] ——, “Atrial fibrillation signal organization predicts sinus rhythm maintenance in patients undergoing cardioversion of atrial fibrillation,” *Europace*, vol. 8, no. 8, pp. 559–565, Jun. 2006.

[4] J. Couderc, “The telemetric and holter ECG warehouse initiative (THEW): a data repository for the design, implementation and validation of ECG-related technologies,” in *Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE*, 2010, pp. 6252–6255.

[5] A. Bollmann *et al.*, “Frequency measures obtained from the surface electrocardiogram in atrial fibrillation research and clinical decision-making,” *J. Cardiovasc. Electrophysiol.*, vol. 14, no. s10, pp. S154–S161, Oct. 2003.

[6] J. Rieta *et al.*, “Atrial activity extraction for atrial fibrillation analysis using blind source separation,” *IEEE Trans. Biomed. Eng.*, vol. 51, no. 7, pp. 1176–1186, Jul. 2004.

[7] M. Stridh and L. Sommo, “Spatiotemporal QRST cancellation techniques for analysis of atrial fibrillation,” *IEEE Trans. Biomed. Eng.*, vol. 48, no. 1, pp. 105–111, Jan. 2001.

[8] J. Slocum *et al.*, “Computer detection of atrioventricular dissociation from surface electrocardiograms during wide qrs complex tachycardias.” *Circulation*, vol. 72, no. 5, pp. 1028–1036, 1985.

[9] S. G. Mallat and Z. Zhang, “Matching pursuits with time-frequency dictionaries,” *IEEE Trans. Signal Process.*, vol. 41, no. 12, pp. 3397–3415, 1993.

[10] B. Ghoraani and S. Krishnan, “Time–frequency matrix feature extraction and classification of environmental audio signals,” *IEEE Trans. Audio, Speech, Lang. Process.*, vol. 19, no. 7, pp. 2197–2209, 2011.