33rd Annual International Conference of the IEEE EMBS
Boston, Massachusetts USA, August 30 - September 3, 2011

Predicting Refibrillation from Pre-shock Waveforms in Optimizing Cardiac Resuscitation

E. Afatmirni[1], K. Nanthakumar[2], S. Masse[2], K. Nair[2], T. Farid[2], S. Krishnan[1], P. Dorian[3], K. Umapathy[1],
Ryerson University[1], Toronto General Hospital[2], and St. Michael's Hospital[3], Toronto

***Abstract*— Ventricular fibrillation (VF) is a lethal cardiac arrhythmia that if untreated within minutes of its occurrence will lead to sudden cardiac death. Defibrillation using electric shocks is the only choice of treatment to restore the heart to normal rhythm especially in out-of-the-hospital VF incidents. Refibrillation (i.e., recurrence of VF) is a common and significant problem in cardiac resuscitation as it negatively impacts the survival rates. In such refibrillation cases administration of anti-arrhythmic drugs could improve the shock outcomes or prevent refibrillation. In cases of prolonged VF, cardio pulmonary resuscitation (CPR) prior to the shocks have been shown to improve the survival rates. The proposed work using wavelet analysis of the pre-shock VF electrograms attempts to predict the shock outcomes as successful, refibrillation, and unsuccessful categories. This feedback in real-time would be of immense assistance to the Emergency Medical Services (EMS) personnel in choosing the right combination of therapies (i.e., shock, CPR, pharmacology interventions) in improving the shock outcomes. Using a real-word database of 34 pre-shock VF electrograms obtained from Toronto area EMS personnel, the proposed method achieved classification accuracies of 76.5% and 75% for a two level binary classification of the three groups.**

***Index Terms*— Refibrillation, Ventricular Fibrillation, Wavelet Analysis, Feature Extraction, Pattern Classification.**

I. INTRODUCTION

About 350,000 sudden cardiac deaths are reported every year in NA [1], most of which are VF related. Defibrillation using electric shocks is the only choice of treatment especially for out-of-the hospital VF incidents in restoring the heart to normal rhythm. During the process of resuscitation it would be of immense help if the EMS personnel could have a real-time feedback on the electrical state of the heart so that they could choose the right combination of therapies before applying the shock. While there exist many works (including our previous work [2], [3]) that have analyzed the pre-shock waveforms and predicted the outcome of shock to be successful or unsuccessful, little to no work has been done in predicting refibrillation after a shock in human VF data. In cases of refibrillation, anti-arrhythmic drugs prior to subsequent shocks could improve the survival rates [4], [5]. Hence predicting the state of refibrillation from the pre-shock VF electrogram analysis is of critical importance that would enable the EMS personnel to choose the pharmacological option before applying subsequent shocks which could convert these usually unsuccessful shocks to successful outcomes.

Thanks to NSERC(K. Umapathy) and [CIHR, HSFC-CPR federation fund grant](K. Nanthakumar) for funding this project.

Over the years many techniques have been proposed in predicting shock outcomes using pre-shock electrogram analysis. Some of the well known features include median or centroid frequency (CF), amplitude spectral area (AMSA), scaling exponent (SCE), and wavelet-based entropy [3]. Our previous work introduced a wavelet-based scale distribution width feature that performed comparatively better in classifying the shock outcomes as successful and unsuccessful categories [2], [3]. Wavelet analysis is better suited for VF electrograms due to the non-stationary characteristics of VF and the flexibility they provide in extracting morphologically distinct features. Wavelet analysis is also computationally less expensive and can be realized in hardware to provide near real-time feedback. In the proposed work we extend our previous work in predicting the state of refibrillation in addition to successful and unsuccessful outcomes by analyzing the pre-shock electrograms using wavelet analysis. Fig. 1 shows the block diagram of the proposed work. The paper is organized as follows: Section II provides details on the database, Section III presents the methodology, Results and discussions are presented in Section IV, and Conclusions are provided in Section V.

II. DATABASE

The human VF database was extracted from the defibrillator recordings collected during out-of-the-hospital cardiac arrests by Toronto, Canada area EMS agencies personnel, recorded using Zoll Inc. (Model AED Pro) external defibrillators. Fourteen successful cases (criteria: after shock, normal sinus rhythm at least for 60s), seven refibrillation cases (criteria: after shock, less than 10 normal sinus beats followed by VF), and thirteen unsuccessful cases (criteria: after shock, continues to be in the state of VF) were used in this study. All of the 34 pre-shock VF electrograms were pre-processed to remove low and high frequency artifact using a bandpass filter (2 to 10 Hz). In choosing the pre-shock segments care was exercised that the data was not corrupted by the CPR artifact. The length of the pre-shock waveforms were restricted to a maximum of 10s backwards from the start of the shock or the duration that was not corrupted by the CPR artifact. Sample cases of successful, refibrillation, and unsuccessful cases are presented in Figs. 2 - 4.

978-1-4244-4122-8/11/$26.00 ©2011 IEEE

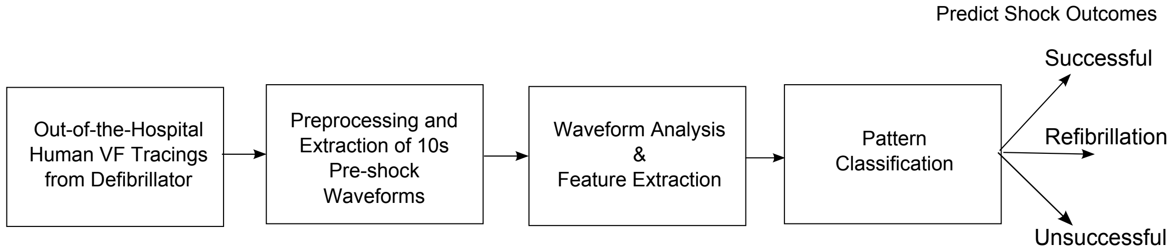

Fig. 1. Block diagram outlining the study

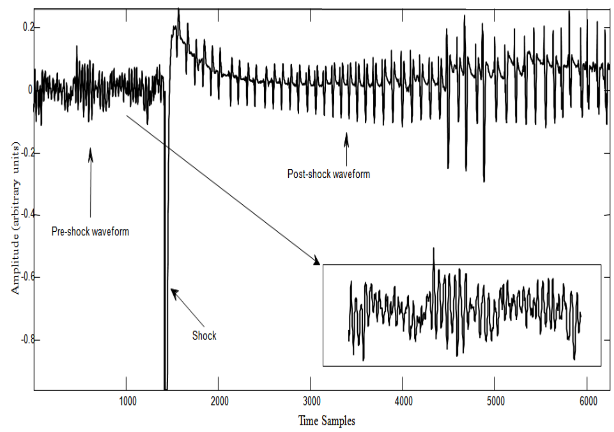

Fig. 2. A sample successful case showing the pre-shock, shock, and the post-shock portions of the electrogram. The zoomed pre-shock waveform in the inset not to scale.

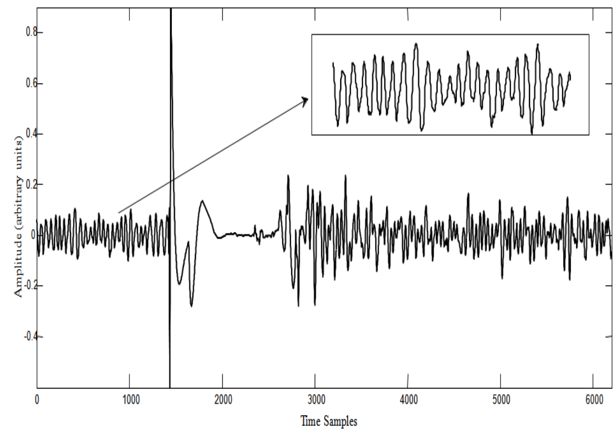

Fig. 4. A sample unsuccessful case showing the pre-shock, shock, and the post-shock portions of the electrogram. The zoomed pre-shock waveform in the inset not to scale.

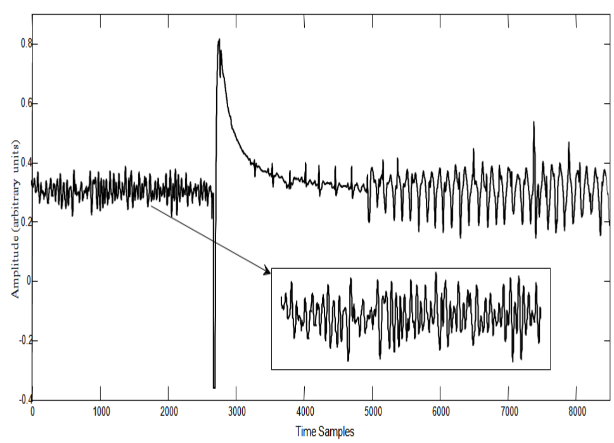

Fig. 3. A sample refibrillation case showing the pre-shock, shock, and the post-shock portions of the electrogram. The zoomed pre-shock waveform in the inset not to scale.

III. Methodology

A. Wavelet Analysis

The proposed wavelet features are based on the continuous wavelet transform (CWT). In CWT a signal $x(t)$ is modeled using all possible translated and dilated version of a mother wavelet $\psi_{a,b}$ where a and b are the dilational (or scale) and translational parameters. It is given by

$$T_x(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\, \psi^* \left(\frac{t-b}{a}\right) dt \qquad (1)$$

and the energy captured by a scale is given by

$$E(a) = \frac{1}{C_g} \int_{-\infty}^{\infty} |T_x(a,b)|^2 db \qquad (2)$$

where C_g is the admissibility constant.

The signal $x(t)$ in our case will be the pre-shock portion of the VF waveform and the wavelet that was found to be suitable for the analysis is Gaussian wavelet of order 6. Prior to decomposing the VF waveforms the signals were filtered as stated earlier and the filtered VF waveforms were then segmented into 3s (i.e. 750 samples at 250 Hz sampling) segments to mimic a real-time acquisition with a buffer of 3s data. The 3s window was then sequentially slided with a 90% overlap for each translation of the window and the data was decomposed using a range of wavelet scales.

B. Scale Distribution Width and Center Scales

Scale Distribution Width (SDW) is the width of the normalized distribution of the energy captured by the scales measured around the dominant scale at half the height of the distribution [2]. The amount of energy captured by each of the scales $E(a)$ depends on the signal characteristics and thus the normalized energy distribution of the scales is representative of the signal content. The width of the distribution indirectly provides us a measure of signal composition, for example the degree of multi or mono component nature of the signal. Due to the inverse relation between scale and frequency, SDW can be seen as a function of frequency and bandwidth of a signal. SDW is computed for each 3s segment of data to mimic a real time acquisition and processing. The segments were slided with a 90% over lap covering the entire lenght of the pre-shock waveforms.

Center Scales (CS) are the dominant scales extracted from the normalized distribution of the energy captured by the scales. Here dominant means the scale with the highest energy [$\max(E(a))$]. CS provides an indirect measure of dominant frequency and in combination with SDW, provides an index on the rate and morphological changes occurring during VF. Similar to SDW, CS was computed for every 3s sliding segments with 90% over lap. Both SDW and CS were extracted for all the 34 pre-shock waveforms and the median value over all the sliding segments was extracted as a representative feature for each of the 34 cases. So in total we extracted a feature matrix of size 34 X 2 for the 3 categories.

C. Pattern Classification

We used a linear discriminant analysis (LDA) based classifier [6] to evaluate the discriminating capacity of the proposed features. Since the database size is small we employed leave-one-out method (LOOM) for cross validation. In LOOM, from a database of N samples, N-1 samples are used for training and the left out 1 sample is used for testing. This is repeated by leaving out each of the sample and training the classifier with the rest of the samples and evaluating the classification accuracy with the left out sample. After all the iterations, the average classification accuracy is computed over all the iterations as the final classification accuracy.

IV. Results and Discussions

SDW and CS were extracted for all the 34 cases as explained in the previous section. Figs. 5 and 6 show the box plots of SDW and CS respectively for the 3 categories. The rectangular boxes show the 25th and 75th percentile of the data and the horizontal line inside the boxes show the median values of the feature distribution. A direct 3 group classification (i.e. successful, refibrillation, and unsuccessful) did not yield good results as could be seen from the overlaps between the refibrillation with the other groups in the box plots. However, analyzing Fig. 5, we could observe that SDW demonstrates a better separation between the successful and unsuccessful cases and interestingly that most of the refibrillation cases are overlapping with the successful cases. This could be inferred as that refibrillation can be seen as a subclass of successful category for the SDW feature. On the other hand, from Fig. 6, although CS demonstrates separation between the successful and unsuccessful groups, unlike SDW there is an over lap between the groups. However, the distance between the median of successful and the refibrillation cases is comparable to SDW. Since the direct 3 group classification did not yield good results but there seem to be an imaginary boundary between successful and refibrillation (i.e., medians of refibrillation fall towards the 75th percentile of the successful category box), it motivates us to perform a 2 level binary classification. The proposed scheme of binary classification is shown in Fig. 7. By combining the refibrillation cases with the successful cases, we obtain a two class problem with "successful and refibrillation" in one class and the "unsuccessful cases" in the other. For this level 1, 2 class classification the SDW is expected to perform better due to the fact the there is larger separation between the combined successful and refibrillation cases with unsuccessful cases in comparison with CS. For the second level classification (i.e. between correctly classified successful and refibrillation cases from level 1) we expect SDW and CS to have comparable performance.

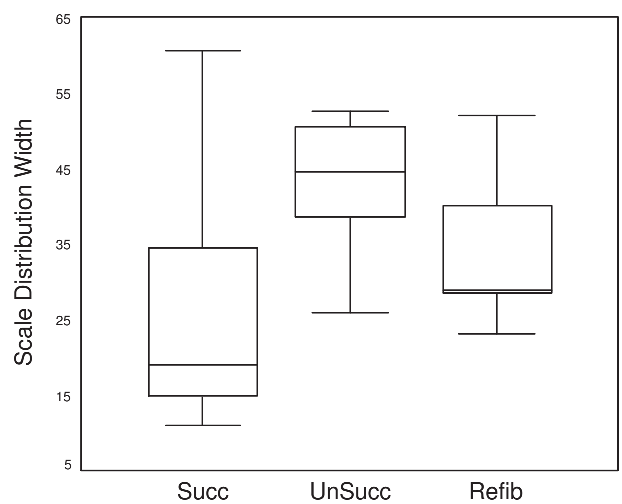

Fig. 5. Boxplot of the SDW feature distribution for the 3 categories.

Method	Groups	Succ+Refib	Unsucc	Total
CV	Succ+Refib	**16**	5	21
	Unsucc	3	**10**	13
%	Succ+Refib	**76.2**	23.8	100
	Unsucc	23.1	**76.9**	100

TABLE I

CV: Cross-validated: Linear discriminant analysis with LOOM method, % - Percentage of classification.

Table 1 shows the results obtained for the level 1 classification using the LOOM method. From the table we could observe as expected SDW performs better in classifying the successful and unsuccessful cases with a

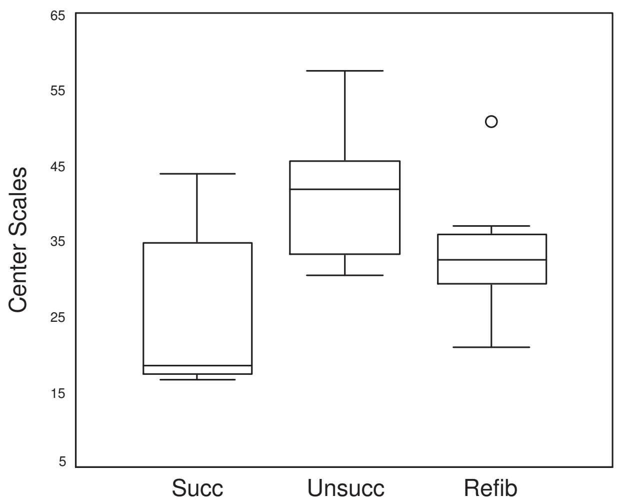

Fig. 6. Boxplot of the CS feature distribution for the 3 categories.

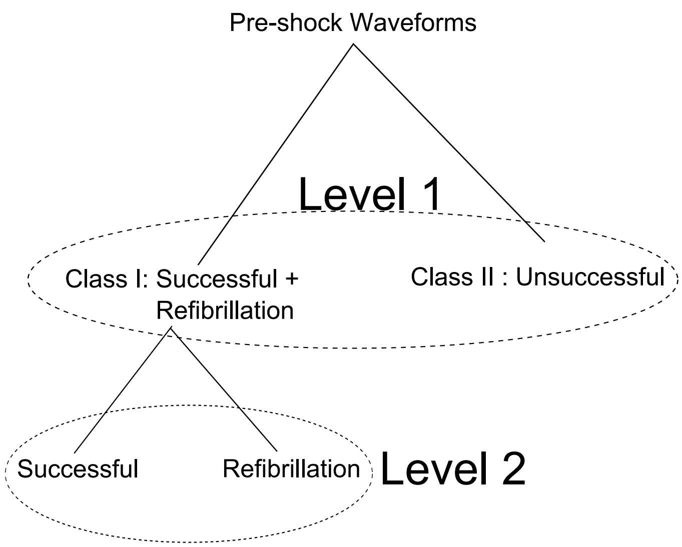

Fig. 7. Proposed 2 level binary classification scheme

classification accuracies of 76.5 % (with a p value of 0.0028). Out of the 21 (14 successful + 7 refibrillation cases), 16 of them were correctly classified. We analyzed the misclassified signals and found out of the 14 successful cases, 3 were misclassifed and out of the 7 refibrillation cases 2 were, misclassified. For the second level classification we discarded these misclassified signals to form a new database with 11 (i.e., 14 - 3) successful cases and 5 (i.e., 7 - 2) refibrillation cases. We tested both CS and SDW in classifying this new database into successful and refibrillation.

Table 2 shows the results obtained for this level 2 classification using LOOM method. An overall classification of accuracy of 75% (with a p value of 0.26) is achieved. However focussing only on the refibrillation prediction, although the level 2 classification shows a 80% accuracy for detecting refibrillation cases, considering it is a 2 level classification effectively it is only 80% (level 2) of 76% (level 1) which is around 61%. For CS and SDW we obtained the same results. The significance of the statistical analysis in this study is limited due to the small database size especially for level 2 classification with only 5 refibrillation cases.

Method	Groups	Succ	Refib	Total
CV	Succ	**8**	3	11
	Refib	1	**4**	5
%	Succ	**72.7**	27.3	100
	Refib	20	**80**	100

TABLE II
CV: Cross-validated: Linear discriminant analysis with LOOM method, % - Percentage of classification.

V. Conclusions

Predicting refibrillation using pre-shock waveforms has immense benefits in assisting EMS personnel to choose the right therapy in optimizing the resuscitation outcomes. Using a real-world human VF database we have presented a classification approach for a 3 group classification including refibrillation. The proposed features that were introduced in our previous work did demonstrate discrimination between the 3 categories however with only a moderate effective detection accuracy for refibrillation. Considering that every opportunity to improve the shock outcomes is valuable the proposed classification scheme has yielded positive results and is one of the initial works on predicting refibrillation in human VF. Future work involves in increasing the refibrillation database and verifying the robustness of the features.

VI. Acknowledgment

The authors would like to thank Dr. Farbod H Foomany for his software contribution to this work.

References

[1] H. Huikuri, A. Castellanos, and R. Myerburg, "Sudden death due to cardiac arrhythmias," *New England Journal of Medicine*, vol. 345, no. 20, p. 1473, 2001.

[2] K. Umapathy, S. Krishnan, S. Masse, X. Hu, P. Dorian, and K. Nanthakumar, "Optimizing cardiac resuscitation outcomes using wavelet analysis." in *Conference proceedings: IEEE Engineering in Medicine and Biology Society*, vol. 1, 2009, p. 6761.

[3] F. H. Foomany, K. Umapathy, S. Krishnan, S. Masse, T. Farid, K. Nair, P. Dorian, and K. Nanthakumar, "Wavelet-based Markers of Ventricular Fibrillation in Optimizing Human Cardiac Resuscitation," in *Conference proceedings:IEEE Engineering in Medicine and Biology Society*, 2010, pp. 2001–2004.

[4] R. KOSTER, "Refibrillation during out-of-hospital arrest: A frequent event with clinical consequences," *SIGNA VITAE*, vol. 5, no. 1, pp. 66–68, 2010.

[5] P. Dorian, D. Cass, B. Schwartz, R. Cooper, R. Gelaznikas, and A. Barr, "Amiodarone as compared with lidocaine for shock-resistant ventricular fibrillation," *New England Journal of Medicine*, vol. 346, no. 12, p. 884, 2002.

[6] SPSS Inc., "SPSS advanced statistics user's guide," in *User manual, SPSS Inc., Chicago, IL*, 1990.