Scientific Journal Impact Factor (SJIF) : 1.711
International Journal of Modern Trends in Engineering and Research
ISSN (ONLINE) : 2349 - 9745
ISSN (PRINT) : 2393 - 8161

Combination of ECG Features with Artificial Neural Networks for the Detection of Ventricular Fibrillation

Karthika V S
M.Tech, Electronics & Communication Engineering, Mohandas College of Engineering & Technology
Anad, Nedumangad

Abstract—Early detection of cardiac pathologies is crucial for the success of the defibrillation therapy. A wide variety of detection algorithms have been proposed based on temporal, spectral or complexity parameters extracted from the ECG. However, these algorithms are mostly constructed by considering each parameter individually. This study presents a novel life-threatening cardiac pathology detection algorithm that combines ECG parameters to a single feature vector and classifies using machine learning techniques. A total of 16 ECG parameters were computed accounting for morphological, spectral, complexity features and statistical measures of the ECG signal. A wavelet based feature extraction for statistical parameters was proposed to analyze, how they affect the detection performance. The proposed methodology was evaluated in the scenario, VF versus non-VF rhythms using the information contained in the medical imaging technology database. The combination of ECG parameters using statistical learning algorithms may improve the detection efficiency of life-threatening cardiac pathologies.
Keywords-Feature extraction, Ventricular fibrillation(VF) detection, Wavelet, Neural Networks.

I. INTRODUCTION

Sudden cardiac arrest (SCA) is a major health problem that accounts approximately for six millions deaths in Europe and in the United States[1;6]. SCA is a sudden, abrupt loss of heart function, most often caused by a rapid ventricular tachycardia (VT) that quickly degenerates into ventricular fibrillation (VF). Prompt detection of VT and VF episodes is crucial to deliver an electric shock therapy and in this way increase the probability of survival from a SCA incident. This has impelled the development of automated external defibril-lators that analyze the surface electrocardiogram (ECG) signal deliver and electric shock if either rapid VT or VF is detected. However, though extensively tested and studied during the last decades both by the industry and by the scientific community, reliable detection of life-threatening arrhythmias remains an open problem.

A wide variety of detection algorithms have been devel-oped based on morphological[2;7;13], spectral[15] or complexity parameters[11;13] extracted from the ECG signal.For each detector, different separation scenarios have been considered, such as VF versus nonVF rhythms, VF plus VT versus non

Volume 02, Issue 06, [June – 2015] ISSN (Online):2349–9745; ISSN (Print):2393-8161

VTVF, or VF versus VT, making it difficult to assess the real performance of the proposed algorithms. When compared in a standardized way, their real performance is reduced from the values presented in the original investigations. The combi-nation of ECG parameters using machine learning techniques such as an artificial neural network has been suggested as a useful approach to improve the detection efficiency.

The present study aims to build a high-performance life threatening cardiac pathology detector by combining ECG parameters in which spectral parameters are extracted through wavelet transform and using ANN learning algorithms.In this context, the objective is twofold: to assess the performance of the proposed ANN detection algorithm over previously defined methods by carrying out a comparative analysis on the out of sample test data. The second aim was to examine the discriminatory properties of each ECG parameter individually and how, in combination, these affect the learning process.The proposed methodology was evaluated in the scenario, VF versus non-VF rhythms using the information contained in the medical imaging technology database.

The preliminary version of this paper appeared in show-ing the usefulness of SVM classification methodology for the detection of life-threatening arrhythmias. Here present a much-extended version of this study that includes: 1) ECG feature extraction with wavelet transform 2) comparative analysis with previously defined detectors on the out of sample test set.

II. METHODOLOGIES

A. Feature Extraction

This section illustrates the process of building the input space data to feed the ANN classifier from the ECG raw data signals.

1) ECG data collection: Here the complete ECG sig-nal recording files from the MITDB[10] is used, which are available at the physioNet repository. The MITDB contains 48 Holter recording files of slightly over 30-min length, two channels per file, sampled at 360 Hz. The MITDB includes 15 rhythm labels differentiating between VT, ventricular fluter (VFL), normal sinus rhythm (NSR), among other rhythms.

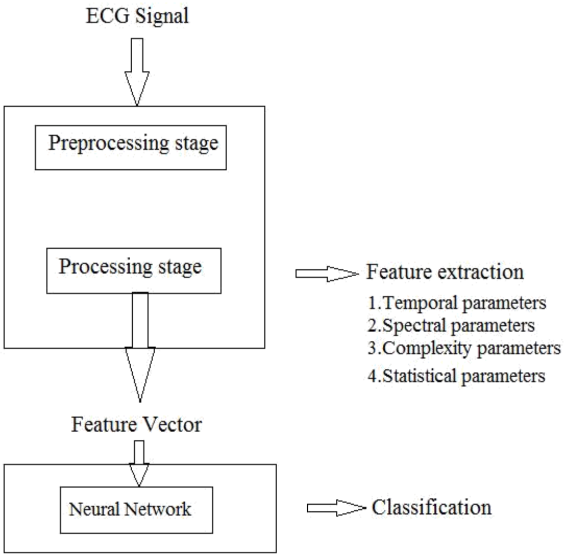

Fig. 1. Block diagram of proposed method

2) Preprocessing: All ECG signals were preprocessed using the filtering process[13],which works in four successive steps: 1) mean subtraction; 2) five-order moving average filter-ing; 3) high-pass filtering with fc = 1 Hz (drift suppression); and 4) low-pass Butterworth filtering with fc = 30 Hz. Then, noise, asystole, and low-quality (artifacts) episode segments were removed according to the corresponding annotation la-bels. Finally, only the first channel of the MITDB , VFDB has been considered, to avoid redundancy of samples during the learning process.

3) ECG parameters: Each preprocessed ECG signal is divided in non overlapping 8s segments. This window length has demonstrated to give the best performance in a number of investigated detection algorithms. For each Le = 8s segment, a set of 12 previously defined parameters were computed. These can be broadly classified in three major categories,

1.Temporal/Morphological Parameters: are defined in the time domain.

a)Threshold Crossing Interval(TCI)[36]: The threshold crossing intervals algorithm (TCI) operates in the time domain. Decisions are based on the number and position of signal crossings through a certain threshold.

A binary signal is generated from the preprocessed ECG data according to the position of the signal above or below a given threshold. The threshold value is set to 20% of the maximum value within each one-second segment S and recalculated every second. Subsequent data analysis takes place over successive one-second stages. The ECG signal may cross the detection threshold one or more times, and the number of pulses is counted. For each stage, the threshold crossing interval TCI is the average interval between threshold crossings and is calculated as follows,

Volume 02, Issue 06, [June – 2015] ISSN (Online):2349–9745; ISSN (Print):2393-8161

$$TCI = \frac{1000}{(N-1) + \frac{t_2}{t_1+t_2} + \frac{t_3}{t_3+t_4}} \qquad (1)$$

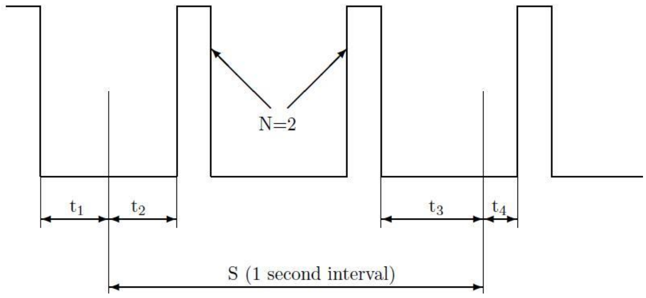

Fig. 2. Binary signal with 2 pulses in threshold crossing intervals algorithm

Here, N is the number of pulses in S. t1 is the time interval from the beginning of S back to the falling edge of the preceding pulse.t2 is the time interval from the beginning of S to the start of the next pulse.t3 is the interval between the end of the last pulse and the end of S and t4 is the time from the end of S to the start of the next pulse.

If TCI >= TCI_0 = 400ms, SR is diagnosed. Otherwise sequential hypothesis testing is used to separate ventricular tachycardia (VT) from VF.As stated above, the original algo-rithm works with single one-second time segments. To achieve this the algorithm picks a 3-second episode. The first second and the third second are used to determine t1 and t4. The 2nd second yields the value for TCI. When picking an 8-second episode we can hence evaluate 6 consecutive TCI values. Final SR decision is taken if diagnosed in four or more segments otherwise the signal is classified as VF.

b)Threshold Crossing Sample Count(TCSC)[7]: TCSC refers to the number of samples that cross a given threshold V_0 within a 3-s ECG interval. On a Le duration episode, TCSC is evaluated by averaging Le 2 consecutive TCSC values.

c)Standard exponential (STE)[13]: The standard expo-nential (STE) algorithm counts the number of crossing points of the ECG signal with an exponential curve decreasing on both sides. The decision for the defibrillation is made by counting the number of crossings. This simple algorithm is probably well-known, but did not find any description of it in the literature.

The ECG signal is investigated in the time domain. The absolute maximum value of the investigated sequence of the signal is searched. An exponential function is put through this point.This function is decreasing in both directions. The number of intersections n of this curve with the ECG signal is counted and a number N is calculated by,

$$N = \frac{n}{T} \qquad (2)$$

where T is the time length of the investigated signal part. If $N > N_0 = 250$ crossings per minute (cpm), the ECG-signal is classified as VF. If$N < N_1 = 180$cpm, SR is identified. Otherwise the signal is classified as VT.A shock is recommended only if $N > N_0$.

d) Modified exponential (MEA)[13]: A modified version of STE, called MEA lifts the decreasing exponential curve at the crossing points onto the following relative maximum. This modification gives rise to better detection results.

This algorithm works in the time domain. First, the first relative maximum value of the investigated sequence of the signal is searched and an exponential like function $E_{n;1}(t)$ is put through this point.

The difference to STE is, that here the function does not have the above representation over the whole investigated signal part, but only in the region from the first relative maximum to the first intersection with the ECG signal. Then, the function $E_{n;j}(t)$ coincides with the ECG signal until it reaches a new relative maximum. In some way one can say that the function MEA(t) is ”lifted” here from a lower value to a peak. From that peak on it has again the above representation with M being the value of the next relative maximum. This is done until the curve reaches the end of the investigated ECG sequence.

e) Mean absolute value (MAV)[9]: The MAV of 2-s ECG segments. On a Le duration episode, MAV is obtained by averaging Le 1 consecutive 2 s values.

2.Spectral parameters: are calculated in the frequency domain.

a) VF filter (VFleak): The VF filter algorithm (VF) applies a narrow band elimination filter in the region of the mean frequency of the considered ECG signal.

After preprocessing, a narrow band-stop filter is applied to the signal, with central frequency being equivalent to the mean signal frequency f_m. Its calculated output is the VF filter leakage. The VF signal is considered to be approximately of sinusoidal waveform. The number N of data points in an average half period N.

b) Spectral algorithm (M and A2 parameters)[15]: The spectral algorithm (SPEC) works in the frequency domain and analyses the energy content in different frequency bands by means of Fourier analysis. The ECG of most normal heart rhythms is a broadband signal with major harmonics up to about 25 Hz. During VF, the ECG becomes concentrated in a band of frequencies between 3 and 10 Hz.

After preprocessing, each data segment is multiplied by a Hamming window and then the ECG signal is transformed into the frequency domain by fast Fourier transform (FFT). The amplitude is approximated in by the sum of the absolute value of the real and imaginary parts of the complex coefficients.

Volume 02, Issue 06, [June – 2015] ISSN (Online):2349–9745; ISSN (Print):2393-8161

Let be the frequency of the component with the largest amplitude (called the peak frequency) in the range 0.5-9 Hz. Then amplitudes whose value is less than 5% of the amplitude of are set to zero. Four spectrum parameters are calculated, the normalized first spectral moment M,
J_{max} being the index of the highest investigated frequency, and A1, A2, A3. Here w_j denotes the j^{th} frequency in the FFT between 0 Hz and the minimum of (20 , 100 Hz) and a_j is the corresponding amplitude. A1 is the sum of amplitudes between 0.5 Hz and /2, divided by the sum of amplitudes between 0.5 Hz and the minimum of (20 , 100 Hz). A2 is the sum of amplitudes between 0.7 and 1.4 divided by the sum of amplitudes between 0.5 Hz and the minimum of (20 , 100 Hz). A3 is the sum of amplitudes in 0.6 Hz bands around the second to eighth harmonics (2 8), divided by the sum of amplitudes in the range of 0.5 Hz to the minimum of (20 , 100 Hz).

c) Median frequency (FM): FM is the central frequency of the spectral mass contained in the power spectrum of the considered ECG signal segment. This parameter was defined to estimate the duration of the cardiac arrest, and therefore it has not been usually use for detection purposes. However, since it provides information about the duration of the VF episode, included it here to analyze its discriminatory properties.

3.Complexity parameters: provide with different measures of the complexity of the ECG signal.

a)Phase space reconstruction (PSR)[12]: The phase space reconstruction (PSR) is based on a method which is used to reconstruct the so-called phase space. It analyzes signals in order to identify a dynamic law or random behavior. The signal x(t) is plotted in a diagram in the following way: on the x-axis plot x(t), on the y-axis x(t +), being a proper time constant. Such a plot is called a two dimensional phase space diagram.

Here observe that a typical VF signal produces a curve in the diagram, that fills the area in an irregular way. The curve is almost uniformly distributed over the entire diagram. However, for a normal sinus rhythm (SR) the curve in the phase space diagram shows a regular structure, only small parts of the area are filled, and the curve is concentrated to a restricted region of the plot. In the special case of a periodic signal for example, where is a multiple of the period all points lie on a line of 45 degrees.

Based on phase space plots (x(t); x(t +)) differentiate SR from VF,determine the area of the plot filled by the curve. To achieve this, produce a 40× 40 grid and count the boxes visited by the ECG signal. The 40× 40grid stretches from the minimum to the maximum of the investigated raw ECG signal. Then calculate a measure d defined by,

$$d = \frac{\text{Number of visiteboxes}}{\text{number of all boxes}} \qquad (3)$$

Volume 02, Issue 06, [June – 2015] **ISSN (Online):2349–9745; ISSN (Print):2393-8161**

If d is higher than a certain threshold d_0, classify the corresponding ECG episode as VF,choose = 0.5s and for the threshold d_0 =0.15 The number of boxes is 1600. in the

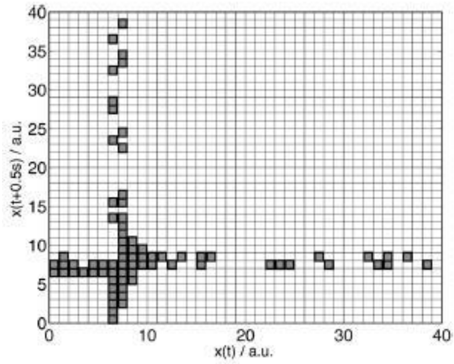

Fig. 3. Data points of SR episodes in the ECG signal, visited boxes visualized in a phase space diagram, $d = {}_{1600}{}^{74} = 0:05$

phase space plot, only consider the positions of the discrete ECG data points to calculate the measure d and do not connect the data points by straight lines or any other curves, which would indicate the underlying dynamics. The reason is, that connected data in the phase space plot do not improve the quality of the algorithm, but rather decrease it.

b)Hilbert transform (HILB)[11]: This algorithm (HILB) is based on a method which is used in analyzing nonlinear signals. From a real signal x(t) a complex valued signal z(t) is obtained by z(t) = x(t) + ix_H (t),x_H (t) being the Hilbert transform of x(t). Then z(t) = r(t)exp(i'(t)). Usually the Hilbert transform is used to compute this phase '(t).

Hence a two dimensional phase-space plot is generated in the following way:

On the x-axis we plot the ECG signal x(t) and on the y-axis we plot the Hilbert transform x_H (t) of the ECG signal x(t). Due to the properties of convolution, the Fourier transform x_H (ώ) of x_H (t) is the product of the Fourier transforms of x(t) .This means that the Hilbert transform can be realized by an ideal filter whose amplitude response is unity and phase response is a constant $_2$ lag at all frequencies > 0.

c)Sample entropy (SpEn)[11]: Sample entropy is a measure of the rate of information production, which was proposed by Richman and Moorman. Sample entropy is precisely the negative natural logarithm of the conditional probability that two sequences similar for m points remain similar at the next point, where self-matches are not included in calculating the probability. A lower value of sample entropy indicates more self-similarity in the time series. Sample entropy is a modified approximate entropy. Compared with approximate entropy, sample entropy has two major advantages.

Firstly, sample entropy eliminates self-matches, which is more simple than approximate entropy, requiring approximately one-half as much time to calculate.

Secondly, sample entropy is largely independent of record length and displays relative consistency under circumstances where approximate entropy does not. That is, if a time series has a higher sample entropy value than the other one, with another value of m and threshold distance r ,it also has a higher value.

4.Statistical parameters

Wavelet transform enables a signal to be decomposed into signal coefficients derived from the filter bank. There are two types of coefficients coming out from the filter bank, the approximation coefficient and the detailed coefficients. These coefficients provide appear to be a very useful tool as features for classification of ECG signal. Signals are decomposed using the Discrete Wavelet Transform (DWT) into time-frequency representations. The major advantage of the DWT is its great time and frequency localization ability, which enables it to reveal the local characteristics of the input signal.

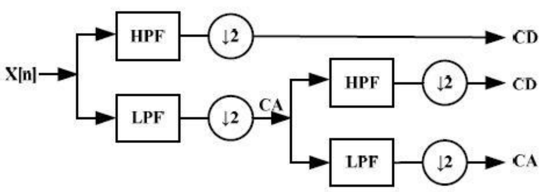

Fig. 4. Wavelet decomposition process

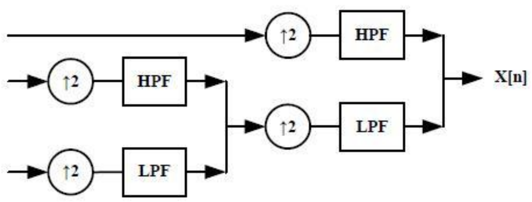

Fig. 5. Wavelet reconstruction process

There are no specific rules to determine which mother wavelet is the most suitable for particular cases but it is appropriate to do some performance test on different mother wavelet for selection of best mother wavelet to be used in a particular case.Few different studies used different mother wavelet for decomposition depending on the features and the cardiac beats set used because different methods for feature selection with different cardiac beats set produce a different set of results. In order to determine which mother wavelet to use, analysis results of the different mother wavelet is obtained and the one with the best results will be chosen.

In this study Daubechies wavelet(db4) is used as mother wavelet for statistical parameter extraction.

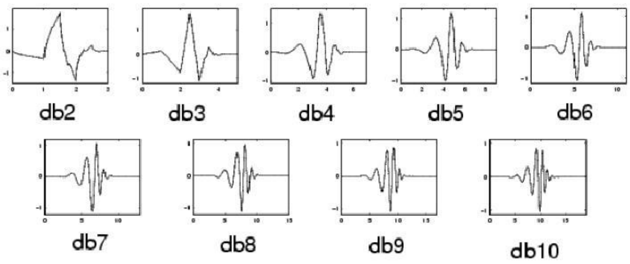

Fig. 6. Nine members of the Daubechies family

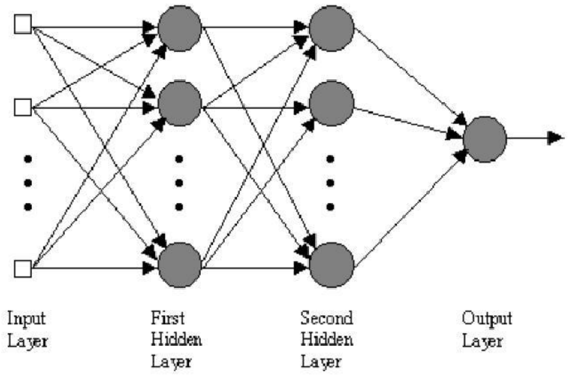

Fig. 7. MLP architecture with two hidden layers

Statistical measure of the ECG signals used in this study are the kurtosis, skewness, mean and standard deviation of the approximation coefficients and all the subband detail coeffi-cients obtained from the decomposed ECG signal. Kurtosis measures the degree of outlier prone to the distribution of a sample data is while, skewness measures the asymmetry of the data around the sample. Mean is the average value of the data points of the sample and standard deviation measures of how much each data point varies to each other in a sample. Among these measured values, only few of them show obvious discriminative characteristic between different classes of heartbeat. Classification performance of each one of the statistical properties needs to be tested and observed. After computing all the aforementioned parameters, labels were assigned to each 8-s segments.

The combination of the above mentioned ECG parameters using statistical learning algorithms may improves the detection efficiency of life-threatening cardiac pathologies. Hence next these extracted feature are given to a machine learning technique such as an Artificial neural network classifier(ANN) for proper classification and hence detection of cardiac disorders.

B. ANN Classifiers

Machine Learning is considered as a subfield of Artificial Intelligence and it is concerned with the development of techniques and methods which enable the computer to learn. In simple terms development of algorithms which enable the machine to learn and perform tasks and activities. Machine learning overlaps with statistics in many ways. Over the period of time many techniques and methodologies were developed for machine learning tasks.

The Artificial Neural Networks (ANN) are the tools, which can be used to model human cognition or neural biology using mathematical operations. An ANN is a processing element. It has has certain performance characteristics in common with biological neural networks. A neural network is characterized by 1) its pattern of connections between the neurons (called its architecture), 2) its algorithm of determining the weights on the connections (called its training, or learning algorithm), and 3) its activation function. The Multi Layer Perceptron (MLP) is the most common neural network. This type of Artificial neural

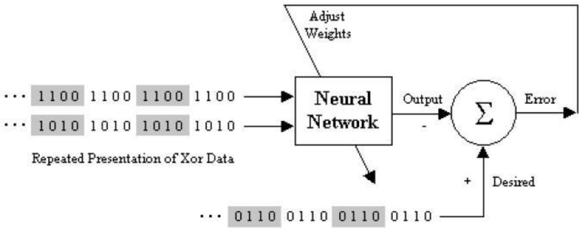

Fig. 8. Neural network learning algorithm

network is known as a supervised network because it requires a desired output in order to learn. The purpose of the MLP is to develop a model that correctly maps the input data to the output using historical data so that the model can then be used to produce the output result when the desired output is unknown.

In the first step, the MLP is used to learn the behavior of the input data using back-propagation algorithm. This step is called the training phase. In the second step, the trained MLP is used to test using unknown input data. The back-propagation algorithm compares the result that is obtained in this step with the result that was expected. This kind of classification is called supervised classification. The MLP computes the error signal using the obtained output and desired output. The computed signal error is then fed back to the neural network and used to adjust the weights such that with each iteration the error decreases and the neural model gets closer and closer to produce the desired output.

There are different training algorithms, while it is very difficult to know which training algorithm is the fastest for a given problem. In order to determine the fastest training al-gorithm, many parameters should be considered. For instance, the complexity of the problem, the number of data points in the training set, the number of weights, and biases in the network and the error goal should be evaluated

III. RESULTS

A. Individual parameter performance

The performances of the detection parameters were as-sessed in terms of evaluating the sensitivity (SE), i.e, the pro-

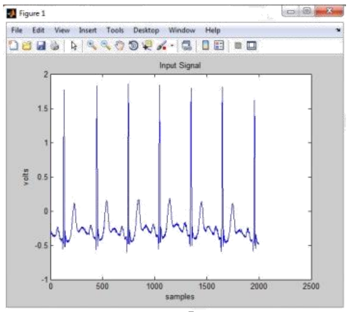

Fig. 9. A single ECG sign

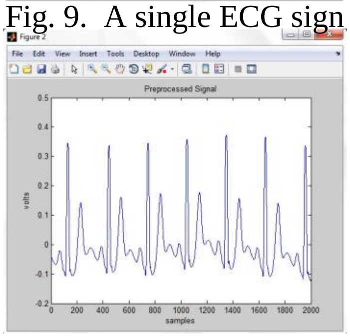

Fig. 10. Preprocessed ECG signal

portion of correctly detected VF/Shockable observations, and the specificity (SP), i.e., the proportion of correctly identified nonFV/nonShockable samples. SE and SP are calculated as

$$SE = \frac{TP}{TP + FN} \quad (4)$$

$$SP = \frac{TN}{TN + FP} \quad (5)$$

where where TP represents the number of true-positive de-cisions, FN the number of false-negative decisions, TN the number of true negative decisions, and FP the number of false-positive decisions.Hence obtained the sensitivity of 97.22% and specificity of 99.9%.

B. ANN Performance

In order to test the performance of the trained MLP ANN was assessed in terms of the accuracy(A) calculated over the

Volume 02, Issue 06, [June – 2015] ISSN (Online):2349–9745; ISSN (Print):2393-8161

```
Threshold crossing sample count (TCSC):5
Threshold crossing interval (TCI): 1298.7329ms
Standard exponential (STE):1.5
Mean absolute value (MAV): 0.069098
Modified exponential (MEA): 0.75
Spectral analysis M: 2.5074
Spectral analysis A2: 0.35118
Median frequency (FM): 30Hz
VF Filter: 0.7209
Sample entropy (SpEn):0.085505
Phase space reconstruction (PSR):0.26063
Hilbert transform (HILB):0.28313
```

Fig. 11. ECG Parameters of a single signal from the database

```
Mean: 0.00044106
standard deviation: 0.0076088
Skewness: -0.26606
Kurtosis: 5.0873
```

Fig. 12. Statistical ECG Parameters of a single signal

Fig. 13. Message box shows a NVF signal

test set as,

$$A = \frac{N_c}{N_t} 100 \qquad (6)$$

Where A is the Accuracy, Nc is the number of correctly classified patterns, and Nt represents the total number of patterns. In the VF rhythms scenarios, the ANN classifier outperformed individual detectors in all analyzed metrics and obtained the accuracy of 98.8%.

C. Detection of VF & nonVF(NVF)

When an unknown input ECG signal is given to the system which analyze features and after the classification process obtained a message box which effectively shows the signal is either VF or NVF.

IV. DISCUSSION & CONCLUSIONS

In this study, a novel detection algorithm that combines ECG parameters with ANN to identify VF arrhythmia has been presented. Together with this algorithm, Statistical features of ECG signal were extracted using a wavelet transform technique to analyze more relevant features for classification purpose. The detection performance of the developed method-ology is remarkable, and it significantly outperforms previous proposed detection algorithms.

In this study used the complete records of the MITDB. No preselection of episodes was made. In the preprocessing task, noise, and asystole segments were removed from the classification procedure, as done in other studies. For this purpose used the information contained in the annotation files. Nevertheless, usual signal processing algorithms could be applied instead. Noise can be detected by examining the slew rate of the ECG

Fig. 14. Message box shows a VF signal

signal while asystole intervals can be identified by amplitude and signal power analysis.

ECG parameters have been computed to characterize VF/shockable rhythms. These include widely analyzed param-eters, such us TCI, CM, PSR, HILB, STE, A2, M, and VFLeak and relatively recent proposals, namely TCSC, SpEn, MEA, MAV, FM and statistical parameters(for detection purposes). The overall detection performances, when considering each parameter individually, are in agreement with previous studies to improve the detection efficiency.

In this study, it has been shown that the use of ANN algorithms combining ECG features significantly improves the efficiency for the detection of life-threatening ventricular fib-rillation. ANN classifiers have been extensively used with the ECG signal in the context of wave delineation, beat detection, general arrhythmia discrimination, and in other application, such as heart rate variability or detection of ischemia[8]. However, the proposed utilization of ANN algorithms to detect VF/shockable episodes using a number of well-known ECG features has not been widely explored.

Combining the information from a number of features to perform a given learning tasks requires FS methods to analyze the relevance of those features, in order to eliminate unnecessary or redundant information, and this way to construct a robust and well-performed machine learning algorithm. The individual discriminative power of a variable is not sufficient to build a robust detector.

In conclusion, the present study has shown that the use of ANN learning algorithms can improve the efficiency for the detection of life-threatening cardiac pathologies. In this scenario, feature extraction techniques might help to better understand the data and to provide valuable insights to build highly accurate detection algorithms. Also, in the case of ANN classifiers using unbalanced datasets, which constitute the standard case in life-threatening cardiac pathology detection problems.

V. ACKNOWLEDGMENT

I would also like to extend my whole hearted gratitude to the HOD of the Electronics and Communication Department and PG Co-ordinator . who was always ready to help me with ideas and suggestions for rectifying the mistakes that crept up from time to time during the completion of this venture. I also extend my whole hearted gratitude to my guide who was always ready to help me with

Volume 02, Issue 06, [June – 2015] ISSN (Online):2349–9745; ISSN (Print):2393-8161

ideas and helped me a lot in rectifying the mistakes. I would also like to thank my friends and last but not the least the staff of ECE department for their whole hearted support and encourgement.

REFERENCES

[1] Felipe Alonso-Atienza,Eduardo Morgado, Lorena Fernandez-Martinez, Arcadi Garcia-Alberola, and Jose Luis Rojo-Alvarez, ”Detection of Life-Threatening Arrhythmias Using Feature Selection and Support Vector Machines,” IEEE Trans.Biomed. Eng., vol. 61 PP, no.3, Mar.2014.
[2] M. Harris, ”A shocking truth” IEEE Spectr., vol. 49, no. 3, pp. 30-58, Mar. 2012.
[3] F. Alonso-Atienza, J. L. Rojo-Alvarez, A. Rosado-Mun, J. J. Vinagre, and A. Garcia-Alberola, G. Camps-Valls, ”Feature selection using sup-port vector machines and bootstrap methods for ventricular fibrillation detection,” Expert Syst. Appl., vol. 39, no. 2, pp. 1956-1967, 2012.
[4] F. Alonso-Atienza, E. Morgado, L. Fernandez-Martinez, A. Garcia-Alberola, and J. Rojo-Alvarez, ” Combination of ECG parameters with support vector machines for the detection of life-threatening arrhythmias,” in Proc. Comput. Cardiol., pp. 385-388,2012.
[5] U. Irusta, J. Ruiz, E. Aramendi, S. R. de Gauna, U. Ayala, and E. Alonso, ”A high-temporal resolution algorithm to discriminate shockable from nonshockable rhythms in adults and children,”Resuscitation, vol. 83, no. 9, pp. 1090-1097, 2012.
[6] Y. Li, J. Bisera, M.Weil, and W. Tang, ”An algorithm used for ventric-ular fibrillation detection without interrupting chest compression,” IEEE Trans.Biomed. Eng., vol. 59, no. 1, pp. 78-86, Jan. 2012.
[7] M. Arafat, A. Chowdhury, and M. Hasan, ”A simple time domain algo-rithm for the detection of ventricular fibrillation in electrocardiogram,” Signal, Image Video Process., vol. 5, pp. 1-10, 2011.
[8] J. L. Rojo Alvarez, G.Camps Valls, and A.J.Caamano Fernandez, J.F.Guerrero Martinez, ”A review of kernel methods in ECG signal clas-sification, in ECG Signal Processing”, ”Classification and Interpretation: A Comprehensive Framework of Computational Intelligence” A.Gacek and W.Pedrycz,Eds. Berlin, Germany:Springer-Verlag, 2011.
[9] E. Anas, S. Lee, and M. Hasan, ”Sequential algorithm for life threatening cardiac pathologies detection based on mean signal strength and emd functions,” BioMed. Eng. OnLine, vol. 9, no. 1, 2010.
[10] G. Moody and R. Mark, ”The impact of the MIT-BIH Arrhythmia Database,” IEEE Eng. Med. Biol.Mag., vol. 20, no. 3, pp. 45-50, May/Jun. 2001.
[11] H. Li,W. Han, C. Hu, and M.-H. Meng, ”Detecting ventricular fibrillation by fast algorithm of dynamic sample entropy,” in Proc. IEEE Int. Conf. Robot. Biomimet.,pp. 1105-1110,Dec.2009.
[12] A. Amann, R. Tratnig, and K. Unterkoer, ”Detecting ventricular fibril-lation by time-delay methods,” IEEE Trans. Biomed. Eng., vol. 54, no. 1, pp. 174-177, 2007.
[13] A. Amann, R. Tratnig, and K. Unterkoer, ”A new ventricular fibrilla-tion detection algorithm for automated external defibrillators,” in Proc. Comput. Cardiol., pp.559-562, Sep.2005.
[14] N. V. Thakor, Y. S. Zhu, and K. Y. Pan, ”Ventricular tachycardia and fibrillation detection by a sequential hypothesis testing algorithm,” IEEE Trans. Biomed. Eng., vol. 37, no. 9, pp. 837-43, Sep. 1990.
[15] S. Barro, R. Ruiz, D. Cabello, and J. Mira, ”Algorithmic sequential decision making in the frequency domain for life threatening ventricular arrhythmias and aimitative artifacts: A diagnostic system,” J. Biomed. Eng., vol. 11, no. 4, pp. 320-328, Jul. 1989.

