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CARDIAC ADVANCED ARRYTHMIA PREDICTION SYSTEMS- CAAPS

Cardiology

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ABSTRACT

There is a constant search for novel methods of classification and predicting cardiac rhythm disorders or arrhythmias. We prefer to classify them as wide complex tachyarrhythmia's or ventricular arrhythmias inclusive of malignant ventricular arrhythmias which with hemodynamic compromise is usually life threatening. Long term and fatality predictions warranting AICD implantation are already available. We have a novel method and robust algorithm with preprocessing and optimal feature selection from ECG signal analysis for such rhythm disorders. Variability of ECG recording makes predictability analysis challenging especially when execution time is of prime importance in tackling resuscitative attempts for MVA. Noisy data needs filtering and preprocessing for effective analysis. Portable devices need more of this filtering prior to data input. Deterministic probabilistic finite state automata (DPFA) which generates a probability strings from the broad morphologic patterns of an ECG can generate a classifier data for the algorithm without preprocessing for atrial high rate episodes (AHRE). DPFA can be effectively used for atrial tachyarrhythmias for predictive analysis. The method we suggest is use of optimal classifier set for prediction of malignant ventricular arrhythmias and use of DFPA for atrial arrhythmias. Here traditional practices of heart rate variability based support vector machine (SVM), discrete wavelet transform (DWT), principal component analysis (PCA), deep neural network (DNN), convoutional neural network (CNN) or CNN with long term memory (LSTM) can be outperformed.

AICD - automatic implantable cardiac defibrillator, MVA - Malignant Ventricular Arrhythmias, VT - ventricular tachycardia, VF - ventricular fibrillation,DFPA deterministic probabilistic finite state automata, SVM -Support Vector Machine, DWT discrete wavelet transform, PCA principal component analysis, DNN deep neural network, CNN convoutional neural network, Convoutional LSTM Long short term memory,RNN recurrent neural network

KEYWORDS

INTRODUCTION

Prediction of cardiac arrhythmias requires signal filtering and preprocessing analyzing fiducial points for optimal feature selection in time and frequency domains and then classifying the features extracted by training of classifiers via ML algorithms. Automatic detection of types of arrhythmia or cardiac conditions encompasses several basic steps, including pre-processing/segmentation, feature extraction, followed by a classifier. Literature is flooded with extraction techniques [1-5].Deep learning methods that do not require specific signal preprocessing methods traditionally calls for larger training datasets. The last few years have seen emergence of recurrent neural network (RNN) and LSTM as learning algorithm of choice [6, 7]. DPFA has lesser expressive power than PFA due the fact that deterministic assignment of transitions to alphabet for a given state. But here the estimate of parameter values is easier and this performs better when running the algorithm in real time for atrial high rate episodes [8]. This already finds applications in biomedical research such as protein structural analysis, language processing and sequence analysis [8, 9].

Arrhythmia prediction has 2 major components. Detection and classification and the more challenging arena of prediction before the event actually occur. This enables the patient to seek medical attention or the clinical to successfully intervene. Prediction is the greatest research challenge [10].

Patients with MVA have risk of sudden death. Algorithms have to have ideal prediction intervention for supportive intervention to be effective. To state in a different way execution times need to be short. Ideal to have an optimal feature set enabled to a decision tree classifier to it to be effective. For a quick execution time the criteria to be tackled include optimal feature selection and timed phased evaluation of predictive algorithm is needed [11, 12].

Methodology for Ventricular Arrhythmias

ECG data needs preprocessing by filtering and fiducial point evaluation. By filtering the raw data is transformed into a noiseless comprehensive format. Redundant information is deleted by this method. Q wave onset (Q on), R wave peak, Off point of S wave (Soff) were the fiducial points selected. This is done using MATLAB Pan Tompkins algorithm [11].Bandpass filter and derivative filters were retained. Single data base evaluation was done by our research team with optimization of data to 35 minute recordings which maximizes the detection rate. 1 min partition segments are created. Initial normal sinus rhythm is needed for inclusion and atrial arrhythmias, conduction blocks and sustained arrhythmias in the first 1 minute should be excluded when only prediction is being attempted. Malignant ventricular arrhythmias were defined as those lasting more than 30 seconds. Single data base evaluations with uniform sampling and sampling frequency of 250 Hz gives best predictive power. Point with zero slopes before R peak is the onset point and after the S wave is the offset point can be detected by window search. Once fiducial points are identified feature extraction can be done mathematical ECG morphology, which is fast and accurate or can be done using support vector machine or neural network which is more costly. Peak, onset and offset points are used in mathematical ECG morphology technique. The trade off is between speed and accuracy. 12 features can be identified [14, 15]. Five amongst these are related to time domain

peaks and remaining seven are derived from the mean and standard deviations of intervals and amplitude of QRS points. These are summarized in Table 1.Predictor of Importance a built in function of MATLAB can be used for optimal feature selection because it considers both interactions and correlations and makes estimates by mean square error method splitting every feature by the sum of branch nodes. For smaller data sets and 10 fold cross validation with a random number generation of 1-5 is done for reliability of results. This is especially so when it is a time series data with no overlap. All folds expect the last is used for training and the last goes for testing or evaluation. Here the out data shows both testing and training. The OUT data shows less bias imbalance against a larger variance in the IN method. Decision tree should be used as a classifier because of its fastest worst-case time complexity provides more time for resuscitation and rescue. Lesser cross validation should be used here owing to lesser data sets available for classification. Sensitivity and specificity of the algorithm has to higher with a shorter execution time to be effective. Sensitivity of over 95% and specificity of over 90% can be obtained.

For atrial fast rhythms classifier sets can be generated by DPFA. From the training data sets the algorithm can extract pre arrhythmia windows which are symbolized into probabilistic strings and fed into the generation module. DPFA construction requires first building a frequency prefix tree and then performing state merging within this.Convolutional neural network can be used for type of atrial arrhythmia detection.AUC of over 0.95 can be achieved by these methods Algorithm performance is strongly affected by the number and relevance of the input features.

CONCLUSION

Machine learning (ML) approaches for arrhythmia detection fall into two main categories based on feature extraction strategies. The first group uses features extraction followed by ML algorithms. These require dimensionality reduction. The optimal 8 feature set as described above can be used for prediction for malignant ventricular arrhythmias or wide complex tachycardia. The second group uses raw ECG data as input without feature extraction. Here data can be directly processed by algorithms. This setting would be ideal for atrial high rate rhythm abnormalities.ML algorithms like neural networks, including their basic and advanced versions, use the raw data for model training and detection of arrhythmia types. But here requirements include larger data sets and higher computational cost.

Table 1.

Feature Selection :12

Domain R-peaks	Q-R-S points
1. mRR	1.sdQRSd
2. mean of heart rate (mHR)	2.mQamp
3. standard deviation of normal-to-normal RR intervals (SDNN)	3.sdQamp
4. root mean square of the successive differences (RMSSD)	4.mRamp
5. mean of QRS duration (mQRSd.	5.sdRamp
	6.mSamp
	7.sdSamp

12 point feature selection. Five features were time-domain R-peaks - mRR, mean of heart rate (mHR), standard deviation of normal-to-normal RR intervals (SDNN), root mean square of the successive differences (RMSSD), and mean of QRS duration (mQRSd). Seven features derived from the mean and standard deviations of intervals and amplitude of Q-R-S points- the standard deviation of QRS duration (sdQRSd), mean and standard deviation for the amplitude of Q (mQamp and sdQamp), R (mRamp and sdRamp), and S Points (mSamp and sdSamp).

REFERENCES

1. Mei Z., Gu X., Chen H., Chen W.Automatic atrial fibrillation detection based on heart rate variability and spectral features IEEE Access, 6 (2018), pp. 53566-53575
2. Jiang X., Zhang L., Zhao Q., Albayrak S.ECG arrhythmias recognition system based on independent component analysis feature extraction TENCON 2006. 2006 IEEE Region 10 Conference, IEEE (2006), pp. 1-4
3. Martis R.J., Acharya U.R., Mandana K., Ray A.K., Chakraborty C Application of principal component analysis to ECG signals for automated diagnosis of cardiac health Expert Syst. ppl., 39 (14) (2012), pp. 11792-11800
4. Ashtiyani M., Lavasani S.N., Alvar A.A., Deevband M. Heart rate variability classification using support vector machine and genetic algorithm J. Biomed. Phys. Eng., 8 (4) (2018), p. 423
5. Kiranyaz S., Ince T., Gabbouj M. Real-time patient-specific ECG classification by 1-D convolutional neural networks IEEE Trans. Biomed. Eng., 63 (3) (2016), pp. 664-675
6. Rajpurkar P., Hannun A.Y., Haghpanahi M., Bourn C., Ng A.Y.Cardiologist-level arrhythmia detection with convolutional neural networks(2017)
7. Acharya U.R., Oh S.L., Hagiwara Y., Tan J.H., Adam M., Gertych A., San Tan R.A deep convolutional neural network model to classify heartbeats Comput. Biol. Med., 89 (2017), pp. 389-396
8. Dorohonceanu B., Nevill-Manning C.G. Accelerating protein classification using suffix trees ISMB, Vol. 2000 (2000), pp. 128-133
9. Oğul H., Mumcuoğlu E.Ü. SVM-based detection of distant protein structural relationships using pair wise probabilistic suffix trees Comput. Biol. Chem., 30 (4) (2006), pp. 292-299
10. Rizwan A., Zoha A., Mabrouk I., Sabbour H., AlSumaiti A., Alomaniy A., Imran M., Abbasi Q.A review on the state of the art in atrial fibrillation detection enabled by machine learning IEEE Rev. Biomed. Eng. (2020)
11. Wollmann CG, Gradaus R, Böcker D, Fetsch T, Hintringer F, Hoh G, et al. Variations of heart rate variability parameters prior to the onset of ventricular tachyarrhythmia and sinus tachycardia in ICD patients. Results from the heart rate variability analysis with automated ICDs (HAWAI) registry. Physiological measurement. 2015; 36(5):1047–61. Pmid: 25903155
12. Bayasi N, Tekeste T, Saleh H, Mohammad B, Khandoker A, Ismail M. Low-Power ECG-Based Processor for Predicting Ventricular Arrhythmia. IEEE Transactions on Very Large Scale Integration (VLSI) Systems. 2016;24(5):1962–1974
13. Sedghamiz H. Matlab Implementation of Pan Tompkins ECG QRS detector; 2014. Available from: https://www.researchgate.net/ publication/ 3136 73153_ Matlab_ Implementation_of_Pan_Tompkins_ECG_QRS_detector
14. Mandala S, Tham CD. ECG Parameters for Malignant Ventricular Arrhythmias: A Comprehensive Review. Journal of Medical and Biological Engineering. 017;37(4): 441–453. Pmid: 28867990
15.. Rizal A, Lestari P, Mandala S, Satrijo B, Widito S. Neural Network based—Arrhythmia Monitoring Device: A Pivotal Clinical Trial. International Journal of Innovative Technology and Exploring Engineering. 2020; 9(3S):346–349.