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Sudden Cardiac Death Risk Estimation Algorithms; A Review

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Abstract: *The Objective of the work is to assess the improving risk stratification of measurements, unadjusted and adjusted for heart rate, of heart rate variability (HRV) and the average amplitude values and average time intervals between different peaks based on 2 to 24-h ambulatory electrocardiographic recordings; and to relate this to the decision to use an Ventricular Fibrillation and cost-effectiveness.*

Background: Risk stratification for high risk or low risk of lethal ventricular arrhythmic events, and hence for a decision about defibrillator implant, most commonly utilizes the left ventricular ejection fraction (LVEF). Electrocardiographic (ECG) approaches include 24-h ambulatory ECG recordings, with counts of ventricular premature contractions (VPCs), measures of heart rate variability (HRV) average amplitude and time average values.

Methods and results: We evaluated the qualifying ambulatory ECG recordings from 20 patients in the active treatment arms of the Cardiac Arrhythmia Suppression Trial (CAST). Beat characteristics, VPC counts, normal-to-normal beat intervals, and time-domain measures of HRV and HRT were calculated. Tachograms were rescaled to a heart rate of 75 and the resulting bnormalized Q measures evaluated as risk predictors for death, compared to unnormalized measures. Measures based on 2-h ECGs were also evaluated as risk predictors.

The most powerful univariate predictor of survival was the normalized turbulence slope. The best multivariate prediction model had six components: history of angina, hypertension, diabetes, and absence of post-myocardial infarction revascularization, the log of LVEF, normalized TS, HR, and an interaction term of HR and normalized TS.

Conclusions: Turbulence slope substantially exceeded other ECG-based measures in improving prediction of subsequent death in models which included LVEF, and other clinical parameters. Use of this model would improve the effectiveness and cost-effectiveness of the ICD.

Keywords: *Cardiac arrhythmias; Electrocardiogram; Data Analysis; Principle Component Analysis.*

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I. INTRODUCTION

The heart is an electrical pump, where the electricity is generated in special pacemaker cells in the upper chamber, or atrium, of the heart. This electrical spark is carried through pathways in the heart so that all the muscle cells contract at once and produce a heartbeat. This pumps blood through the heart valves and into all the organs of the body so that they can do their work.

This mechanism can break down in a variety of ways, but the final pathway in sudden death is the same; the electrical system is irritated and fails to produce electrical activity that causes the heart to beat. The heart muscle can't supply blood to the body, particularly the brain, and the body dies. Ventricular fibrillation (V Fib) is the most common reason for sudden death in patients. Without a coordinated electrical signal, the bottom chambers of the heart (ventricles) stop beating and instead, jiggle. Ventricular Fibrillation is treated with electrical shock, but for it to be effective, the shock usually needs to happen within less than four to six minutes, not only for it to be effective, but also to minimize brain damage from lack of blood and oxygen supply. Automatic external defibrillators (AEDs) are commonly available in public places to allow almost anybody to treat sudden death. Less commonly, the heart can just stop beating. The absence of a heart beat is known as asystole. Cardiac arrhythmias are disturbances in the rhythm of the heart, manifested by irregularity or by abnormally fastrates (tachycardias) or abnormally slow rates (bradycardias). Patients who perceive these abnormalities most frequently observe palpitations, which some describe as the sensation of 'my heart turning over in my chest', or awareness that their hearts are beating rapidly or slowly. Premature beats, which may originate in the atria or the ventricles, are the most common cardiac arrhythmia. They occur in subjects with normal hearts and in patients with heart disease of lesser or greater severity. Palpitations are the principal symptoms produced by premature beats, whatever their origin. The sensation is produced by the early contraction of the ventricles followed, after a pause, by a stronger than normal contraction. Other symptoms include weakness, shortness of breath, light headedness, dizziness, fainting (syncope) and, occasionally, chest pain. The symptoms tend to be more severe when the rate is faster, the ventricular function is worse, or the arrhythmia is associated with abnormalities of autonomic tone. Sudden cardiac death (SCD), generally defined as death within one hour of symptom onset or during sleep in a patient who was previously stable, is a clinical syndrome that is a final common pathway of a number of disease conditions and states. Arrhythmic SCD may be due to ventricular fibrillation (VF)/tachycardia (VT) [SCD-VT/VF] or asystole/pulse less electrical activity (PEA).

Epidemiologic studies suggest that there has been a decline in cardiac arrest due to VT/VF and a concomitant increase in PEA/asystole. the surface electrocardiogram (ECG) and ECG-related assessment techniques are being evaluated to determine if they can be used to identify patients at high risk for Sudden Cardiac Arrest (SCA). The ECG is an especially attractive screening tool because of its low cost and noninvasive application. Various classifier techniques could be implemented on the ECG waveform to interpret and analyze various features for recognizing any kind of abnormalities in the functioning of the heart.

II. LITERATURE REVIEW

Tsu-Wang Shen et al. in [1] have developed a personal cardiac homecare system by sensing Lead-I ECG signals for detecting and predicting SCD events, which also builds in ECG identity verification. A MIT/BIH SCD Holter Database plus our ECG database were investigated.

Fijoy Vadakkumpadan in [2] seeks three-dimensional shape metrics of the left ventricle derived from clinical cardiac magnetic resonance images that can predict SCD risk. The present study is a proof-of-concept, where the author has combined image-processing and computational anatomy techniques to develop a processing pipeline to statistically compare localized left ventricular shape metrics between patient groups.

F Chiarugi et al. in [3] have improved the overall performances of the QRS detector evaluated the results on the 48 records of the MIT-BIH Arrhythmia Database where each ECG record is composed by 2 leads sampled at 360 Hz for a total duration of about 30 minutes. The annotated QRSs are 109494 in total. The results have been very satisfying on all the annotated QRSs and, with the inclusion of an automatic criterion for ventricular flutter detection, sensitivity is 99.76% and a positive predictive value 99.81% have been obtained.

Joyce C. Ho et al. [4] have presented two dynamic cardiac risk estimation models, focusing on different temporal signatures in a patient's risk trajectory. These models can track a patient's risk trajectory in real time.

Komala.k et al. in [5] have focused on the development of an accurate, low cost and user friendly real time ECG acquisition using Virtual Instrumentation to know about general cardiac abnormalities and facilitate the improved medical treatment.

Shiying Dong et al. in [6] have analyzed the performance of four R-wave detection methods that were applied on new born piglet ECG data. These methods are based on: first derivative, wavelet transform, and nonlinear transform.

Indu Saini et al. in [7] have presented an application of K-Nearest Neighbor (KNN) algorithm as a classifier for detection of QRS-complex in ECG. A digital band-pass filter is used to reduce false detection caused by interference present in ECG signal and further gradient of the signal is used as a feature for QRS-detection.

H Atoui et al. in [8] described some of the latest ambient intelligence and pervasive solutions that are being designed and are deployed in the PEM device, and more specifically the BN risk factor stratification module and its integration into the overall Personal ECG Monitor telemedical platform.

Hyejung Kim et al. in [9] have proposed an ECG signal processing method with quad level vector (QLV) for the ECG holter system. The ECG processing consists of the compression flow and the classification flow.

Lina Zhang et al. in [10] have used LabVIEW as the professional development environment of virtual monitoring and control equipment, has good man-machine interface, and easy to setup system and reconstruct system and make custom function.

Arriola Z. Héctor Gerardo et al. in [11] have proposed the application of combined neuronal networks with fuzzy logic systems that allow the quantification and characterization of the HRV, helping the identification of patients with low and high probability (risk) of undergoing a cardiac problem.

Zhou Hai-Ying et al. in [12] have proposed an embedded real-time QRS detection algorithm dedicated to PCC systems. After analyzing author suggested QRS complex under PCC environments, this algorithm establishes the correction mechanism of motion artifacts.

Usman Rashed et al. in [13] have introduced work that has been done to distinguish the Electrocardiogram (ECG) of a normal healthy human from that of a patient who may suffer from Sudden Cardiac Death (SCD), but this condition has not been detected.

N.Santhosha Priya et al. in [14] have proposed a system which integrates two separate modules: SCD detection and SCD prediction. The preprocessing of ECG signals is done using Fast Fourier Transform (FFT) as the first step since the signals are subjected to various artifacts and noise.

Inaki Romanio et al. in [15] have proposed a Ventricular tachyarrhythmia's which is potentially a lethal cardiac pathologies and the commonest cause of sudden cardiac death. Efforts to predict the onset of such events are based on feature extraction from the surface ECG.

Saurabh Pal et al. in [16] have suggested an Empirical Mode Decomposition based QRS complex detection algorithm. Other decomposition techniques use some predetermined basis function for transformation and hence may not be applicable for all kind of signals.

Hans-Petter Halvorsen in [17] has discussed the use of LabVIEW in data acquisition. One of the benefit of LabVIEW over other development environments is the extensive support for accessing instrumentation hardware.

Huikuri et al. in [18] have analyzed the problems of predicting arrhythmic deaths and the advantages and limitations of the various methods and studies.

Constantinos O'Mahony et al. in [19] have validated SCD risk prediction model for patients with Hypertrophic Cardiomyopathy (HCM) and provides accurate individualized estimates for the probability of SCD using readily collected clinical parameters.

Elias Ebrahimzadeh et al. in [20] have compared the classification rates for both separate and combined Nonlinear.The TF features found that the combination of Time-Frequency and Nonlinear features have a better ability to achieve higher accuracy.

Mikhled Alfaouri et al. in [21] have proposed an algorithm based on the threshold value of ECG signal determination using Wavelet Transform coefficients. Different ECG signals are used to verify the proposed method using MATLAB software.

S. Muthukaruppan et al. in [22] have presented Heterogeneous Euclidean Overlap Metric (HEOM) distance function , which uses the overlap method for categorical attributes and a normalized euclidean distance for numeric attributes.

Svante Wold et al. in [23] have described that a PCA model has the same approximation property for a data table of similar objects as does a polynomial for bivariate data in a limited interval.

III. METHODS FOR THE ESTIMATION

The use of classifier systems in medical diagnosis is increasing gradually. There is no doubt that evaluation of data taken from patient and decisions of experts are the most important factors in diagnosis. But, expert systems and different artificial intelligence techniques for classification also help experts in a great deal. PCA technique has been employed in this research to analyze the ECG curve for prediction of SCD. Principal Component Analysis (PCA) is a statistical technique whose purpose is to condense the information of a large set of correlated variables into a few variables ("principal components"), while not throwing overboard the variability present in the data set . The principal components are derived as a linear combination of the variables of the data set, with weights chosen so that the principal components become mutually uncorrelated. Each component contains new information about the data set, and is ordered so that the first few components account for most of the variability. In signal processing applications, PCA is performed on a set of time samples rather than on a data set of variables. When the signal is recurrent in nature, like the ECG signal, the analysis is often based on samples extracted from the same segment location of different periods of the signal. Signal processing is today found in virtually any system for ECG analysis, and has clearly demonstrated its importance for achieving improved diagnosis of a wide variety of cardiac pathologies. Signal processing is employed to deal with diverse issues in ECG analysis such as data compression, beat detection and classification, noise reduction, signal separation, and feature extraction. Principal Component Analysis has become an important tool for successfully addressing many of these issues, and was first considered for the purpose of efficient storage retrieval of ECGs. Over the years, this issue has remained central as a research topic, although the driving force has gradually changed from having been tiny hard disks to become slow transmission links. Noise reduction may be closely related to data compression as reconstruction of the original signal usually involves a set of eigenvectors whose noise level is low, and thus the reconstructed signal becomes low noise. Such reduction is, however, mostly effective for noise with muscular origin. Classification of waveform morphologies in arrhythmia monitoring is another early application of PCA, in which a subset of the principal components serves as features which are used to distinguish between normal sinus beats and abnormal waveforms such as premature ventricular beats. A recent application of PCA in ECG signal processing is robust feature extraction of various waveform properties for the purpose of tracking temporal changes due to myocardial ischemia. Historically, such tracking has been based on local measurements derived from the ST-T segment, however, such measurements are unreliable when the analyzed signal is noisy. With correlation as the fundamental signal processing operation, it has become clear that the use of principal components offer a more robust and global approach to the characterization of the ST-T segment. Signal separation during atrial fibrillation is another recent application of PCA, the specific challenge being to extract the atrial activity so that the characteristics of this common arrhythmia can be studied without interference from ventricular activity. Such separation is based on the fact that the two activities originate from different bioelectrical sources; separation may exploit temporal redundancy among successive heartbeats as well as spatial redundancy when multi lead recordings are analyzed. Step by step design methodology is illustrated below:

- Collect the standard reference ECG signal for analysis of sudden cardiac death from the database of MIT BIH.
- Preprocessing the ECG signal with the help of FFT algorithm to avoid artifacts and noise.
- Simulate of proposed set and run the setup for detection of sudden cardiac arrest.
- Compare the result with pre-collected reference signal for estimation and to predict the sudden cardiac death.

IV. CONCLUSION

In future the system could be further modified by using the algorithms to calculate the amplitude and time average in real time. In the area of biomedical signal processing, it is a challenge to set up a fixed threshold for all individuals. However, when ECG biometric element involved, the complexity of healthcare system may potentially be reduced. In general, the abnormal physiology status means the status in the certain degree of difference to compare with self pervious status or other people statuses at overall point of view. Hence, if a person's normal status is known, then the unhealthy status is much easier to be detected. Hardware may be implemented to in this to check the status of sudden cardiac death risk and alarm may be used to alert the critical situation of the patients.

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