DESIGN AND IMPLEMENTATION OF ECG BASED CARDIAC RHYTHM ANALYSIS FOR DETECTION OF VENTRICULAR ARRHYTHMIA

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ABSTRACT

This work is a comprehensive technical description of ECG based five class resuscitation rhythm classifiers. It thoroughly describes features derived from the wavelet analysis of the ECG, and combines them with classical shock advice algorithmic features. Currently, cardiac rhythm classification for retrospective review of revival episodes relies on a cumbersome, time-consuming, and error-prone manual annotation process. Resuscitation datasets frequently contain hundreds of cases and several hundred hours of recordings, making manual annotation inefficient and time-consuming .Generally it is possible to classify resuscitation cardiac rhythms automatically, but the accuracy for the organized rhythms (PEA and PR) is low .here we are planning to implement the accurate detection of ventricular arrhythmia through DEAP (Publicly Available Extracted ECG dataset)Input ECG test sets are processed through MATLAB tool. The binary converted into is further given to FPGA architecture. In the proposed system Nested Classifiers is being designed which can classify by comparing the disease threshold and provides accurate detection of Ventricular arrhythmia presence.

Keyword: - *Nested Classifiers, Resuscitation rhythm classification, ventricular arrhythmia, etc*

1. INTRODUCTION

The cardiac arrest victims describes regenerating actions .they are ventilations ,chest compression and electrical shocks also act as key elements in the treatment of cardiac treatment.The remedial action taken for a cardiac rhythm may also convert in to very dangerous VF due to fibrillation shock. The main aim of rhythm classification is to evaluate the treatment and to improve its quality. Currently cardiac rhythm classification relies on cumbersome ,time consuming ,error prone manual annotation process . Revival dataset usually contains several hundred hours for recording and thus results the manual annotation inefficient and consumes more time .This treatment of cardiac arrest or Rhythm classification is done only using ECG. The external defibrillators also record signals like Transthoracic Impedance(TTI) ,chest compression depth and the capnogram which gives the additional information about the ventilations during cardio pulmonary action.Thus these signals are available in only some external defibrillators and even if it is available, they are not recorded with the sufficient amplitude and also it is not done within the time resolution .

During regenerating cardiac rythms from classified in 5 categories . Among five categories VF and VT are more dangerous Ventricular Arrhythmia which can be treated only through electrical defibirillation shock . During Pulseless Electrical Activity (PEA), the Cardiac action only organizes electrical activity and not it does not organize any Myocardial Muscle Activity and no Palpable Pulse. And PR Rhythms is monitored from Cardiac arrest patient which recovers spontaneous circulation. Shock Advice Algorithms splits the rhythm classification in two categories such as shockable (VF,VT) and non-shockable(PR,PEA,AS). The Cardiac Rhythm classification done with ECG is particularly challenging. The ECG classifies the rhythm with different class . Hence it also has many Borderlines in which ECG Rhythms will be more similar.

2 ECG DATASET

ECG data were extracted from 298 cases of out-of-hospital cardiac arrest (OHCA). The original study was conducted by Wik et al. to measure the quality of CPR in three European locations: Akershus (Norway),Stockholm(Sweden),and London (UK), between March 2002 and September 2004. Modified defibrillators based on the Heart start 4000 (Philips Medical Systems, Andover, MA, USA) were placed in six ambulances in each location. Data from each resuscitation case were collected in data cards. The raw data consisted of the ECG, TTI, compression depth related acceleration, and pad pressure signals, all sampled at 500 Hz (fs = 500) with 16 bit resolution. The ECG had a resolution of 1.031 µV per least significant bit. All recordings were originally annotated by expert reviewers into the five resuscitation rhythm categories [8]. AS was defined as peak-to-peak amplitude below 100µV, and/or rates under 12bpm. Rhythms with supraventricular activity (QRS complexes) and rates above 12bpm were labeled as either PR or PEA. Pulse annotations (PR) were based on clinical annotations of return of spontaneous circulation (ROSC) made in patient charts during CPR, and on the observation of fluctuations in the TTI signal aligned with QRS complexes. Irregular ventricular rhythms were annotated as VF (coarse VF was defined for peak-to-peak amplitudes above 200µV). Fast and regular ventricular rhythms without pulse, and rates above 120bpm were annotated as VT. For this study, segments from the original OHCA episodes were automatically extracted using the manually annotatedor immediately rhythm labels and information about the time intervals of defibrillation and chest compression sequences. The following criteria were used: 3-second duration, a single rhythm type, and no chest compression artifacts. These criteria were established to mimic segment durations used in shock advice algorithms [9], and to secure a unique rhythm label on an artifact-free segment, as recommended by the American Heart Association (AHA) for shock advice algorithms [2]. Rhythm analysis during chest compressions is currently unreliable even for shock advice algorithms [2], and is therefore outside the scope of this work. All segments were reviewed and audited to be compliant with the rhythm definitions ,and to the AHA recommendations. Two biomedical engineers, experienced in resuscitation data processing, and not involved in the development of the classification algorithms, double blindedly reviewed the segments. Segments with severe noise, ongoing chest compressions, incorrect rhythm annotations (transitional rhythms), or low ECG signal quality were either relabeled, removed, or reextracted. The final annotated dataset of segments consisted of 388 AS (n = 217 patients), 366 PEA (n = 200), 264 PR (n = 111), 377 VF (n = 157), and 236 VT (n = 32).

3. MATLAB DESIGN ENVIRONMENT

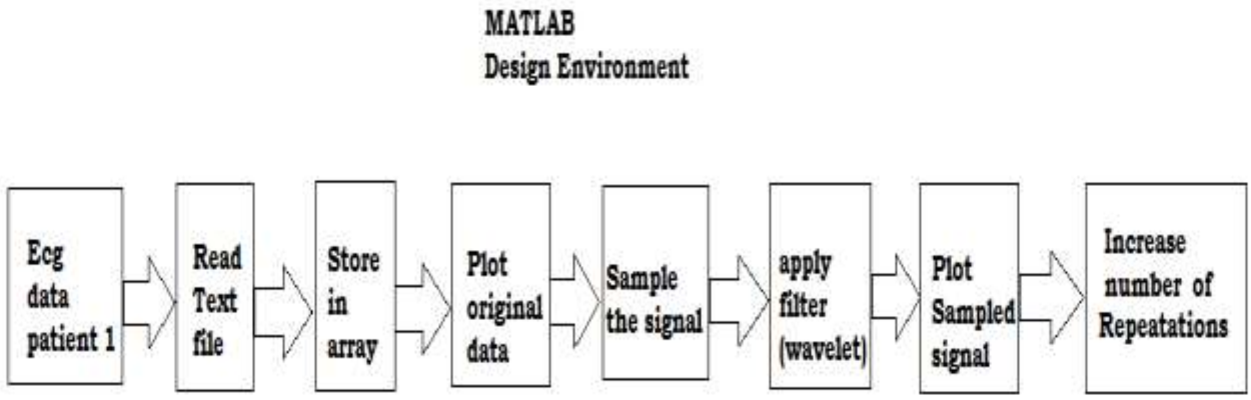

Fig.1 Block diagram of MATLABDesign

The ECG data been kept in text format and that is read by the Text File. The Text file is been stored in an array**.** An array is a systematic arrangement of similar objects, usually in rows and columns. By obtaining the ECG Data patient value plot the original data. The given patients data signal is sampled.Apply filter and plot the sampled signal.

4. VLSI DESIGN ENVIRONMENT

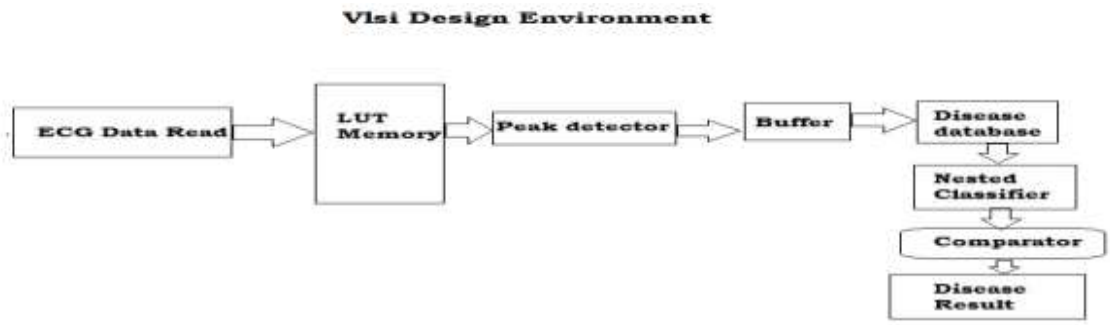

Fig.2 Block diagram of VLSI Design

The Resultant values obtained in the graph is fetched in to the VLSI DESIGN and the data is been Read at ECG Data Read. The Resultant is given to the LUT MEMORY. Lookup table is an array that replaces runtime computation with a simpler array indexing operation. The savings in terms of processing time can be significant, since retrieving a value from memory is often faster than undergoing an "expensive " computation or input/output operation.[1] The tables may be precalculated and stored in static program storage, calculated (or "pre- fetched") as part of a program's initialization phase (memoization), or even stored in hardware in application-specific platforms. Lookup tables are also used extensively to validate input values by matching against a list of valid (or invalid) items in an array and, in some programming languages, may include pointer functions (or offsets to labels) to process the matching input. FPGAs also make extensive use of reconfigurable, hardware-implemented, lookup tables to provide programmable hardware functionality. The output from the LUT MEMORY is given to the Peak Detector. A detector whose output voltage approximates the true peak value of an applied signal; the detector tracks the signal in its sample mode and preserves the highest input signal in its hold mode. The detected Peak value is stored in the Buffer The Buffer is a unity gain amplifier packaged in an integrated circuit. Its function is to provide sufficient drive capability to pass signals or data bits along to a succeeding stage. Voltage buffers increase available current for low impedance inputs while retaining the voltage level. The Disease Database contains the corresponding values of particular Diseases.The Diseases Database is a free website that provides information about the relationships between medical conditions, symptoms, and medications. The database is run by Medical Object Oriented Software Enterprises Ltd, a company based in London. The stated aim is education, background reading and general interest with an intended audience physicians, other clinical healthcare workers and students of these professions.

5 . ALGORITHM NESTED CLASSIFIER

The Algorithm used in the project is NESTED CLASSIFIER.The nested sampling algorithm is a computational approach to the problem of comparing models in Bayesian statistics, developed in 2004 by physicist John Skilling. Bayes' theorem[1] can be applied to a pair of competing models and for data , one of which may be true (though which one is unknown) but which both cannot be true simultaneously. In statistics, the use of Bayes factors is a Bayesian alternative to classical hypothesis testing.

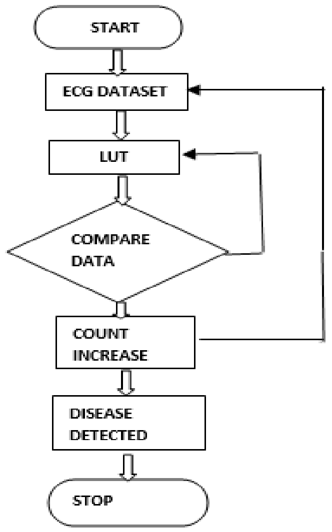

Fig.3 flow diagram

Bayesian model comparison is a method of model selection based on Bayes factors. The models under consideration are statistical models.[3] The aim of the Bayes factor is to quantify the support for a model over another, regardless of whether these models are correct. The Bayes factor is a ratio of the likelihood probability of two competing hypotheses, usually a null and an alternative.The posterior probability is a likelihood, and represents the probability that some data are produced under the assumption of this model, M; evaluating it correctly is the key to Bayesian model comparison. Using the Bayesian Formula.

$$P(M1|D)=\frac{P(D|M1)P(M1)}{P(D)}$$

$$=\frac{P(D|M1)P(M1)}{P(D|M1)P(M1)+P(D|M2)P(M2)}$$

$$=\frac{1}{1+\frac{P(D|M2)P(M2)}{P(D|M1)P(M1)}}$$

Here is a simple version of the nested sampling algorithm, followed by a description of how it computes the marginal probability density

$$Z=P(D|M)$$

Where,

M is M1 or M2.

Thus the value is determined from the Nesting Algorithm. The obtained value and the patient's data value is been compared using the comparator. Comparators, as their name suggests, compare several inputs of internal or external information.

6 RESULT & DISCUSSION

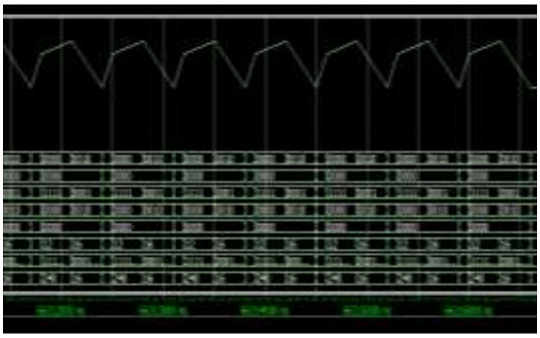

FIG.4 ECG waveform of the VA patient

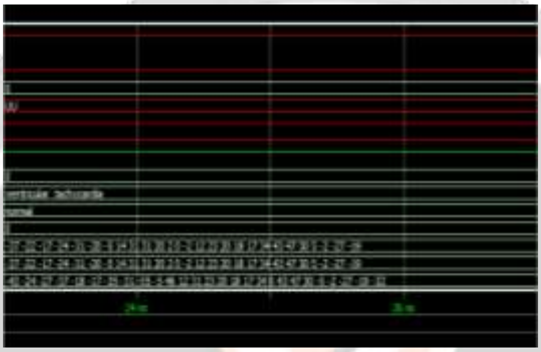

FIG.5 Detection of ventricular tachycardia

Disease ventricular arrthymia of the patient is detected using the algorithm.

7 . CONCLUSION

This paper describes the detection of ventricular arrhythmia using ECG dataset which is extracted from the DEAP(publicly available extracted ecg dataset).It is done using the nested classifier which compares the disease threshold and provides the detection of ventricular arrhythmia presence .Further work is needed for calculating the most accurate detection of Ventricular Arrhythmia.

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