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A ROBUST METHOD FOR CLASSIFICATION OF MYOCARDIAL INFARCTION SIGNALS FROM VIDEO IMAGES USING FAST ICA AND ANFIS

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Abstract

This paper presents a simple, low-cost method for measuring multiple physiological parameters using fast ica and an intelligents system to classify myocardial infarction signal using adaptive neuro-fuzzy inference system (ANFIS) model, using a basic webcam. By applying FAST ICA algorithm for independent component analysis on the color channels in video recordings, we extract the blood volume pulse from the facial regions. Heart rate (HR), respiratory rate, and HR variability were subsequently quantified. The developed method classifies cardiac signal as normal or carrying an AtrioVentricular heart Block (AVB).

Keywords*: Aadaptive neuro fuzzy inference system (ANFIS),Blood volume pulse (BVP); FAST independent component analysis (FAST ICA); Heart rate variability (HRV); RR-interval.*

1. Introduction

Heart failure is the most common reason of death. Now a days, but if the medical help is given directly, the patient's life may be saved in many cases. Numerous heart diseases can be detected by means of analyzing cardiac signals. Wireless ECG sensor, local access unit, remote centre server, and remote surveillance terminal[4]. Computer system has a important role in structuring systems. The explosive growth of high performance computing technique in recent years with regards to development of good and accurate model of biological system have contributed significantly to new approaches to fundamental problems of modelling biological system. Computer based analytical tool for in-depth study and classification of data over day long interval can be very useful in diagnostics[12].

The option of monitoring a patient's physiological signals and classifying myocardiac signals via a remote, noncontact means has promise for improving access to and enhancing the delivery of primary health care. Currently, a method has proposed for noncontact measurement of vital signs, such as heart rate (HR) and respiratory rate (RR) and heart rate variability include laser doppler, microwave doppler radar, and thermal imaging. Despite these impressive advancements, a common drawback of the aforementioned proposals is that the systems are expensive and require specialist hardware. A method for automated computation of HR from digital colour video recordings of the human face, quantification of multiple physiological parameters has been developed[1]. But myocardiac signals were not classified.

A new method for the classification of the cardiac rhythms were introduced. Feature extraction using independent component analysis (ica) and power spectrum, together with the RR interval then serve as input feature vector. These features were classified using ANFIS [2],[3].

This paper suggest a method that is simple, non-invasive and low cost to classify myocardiac signals using basic webcam. Blood volume pulse for computation of HR, RR, as well as HRV extracted from video images using FAST ICA and myocardiac signals are classified using ANFIS.

2. Recognition Of Myocardiac Signals

Electrical activity of the heart is the cardiac signal[13] . The first deflection of the cardiac signal is the P wave. Then the QRS complex is greater than the P wave. The QRS complex is as follows. Q: any initial downward deflection followed by an upward deflection. R: any upward deflection. S: any downward deflection preceded by an R wave. The T wave is considerably longer than that of the QRS complex After inscription of the P wave, the signal returns to its baseline. It is the interval between the P wave and the QRS complex. It represents an important index of impulse propagation through the AtrioVentricular (AV) node, AV bundle, and bundle branches. The time needed for the impulse to pass from the atria to the ventricles can be estimated from the *P-R interval*, which extends from the beginning of the P wave to the first deflection of the QRS complex. The S-T Segment following the inscription of the QRS complex II.

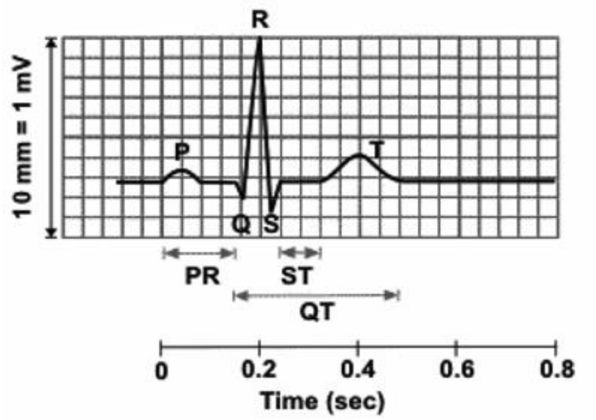

Fig1. Typical cardiac signal

When myocardial blood supply is abruptly reduced or cut off to a region of the heart, a sequence of injurious events occur beginning with subendo cardial or transmural ischemia, followed by necrosis, and eventual fibrosis (scarring) if the blood supply isn't restored in an appropriate period of time.. The cardiac signal changes usually follow a well-known pattern depending on the location and size of the MI. MI's resulting from total coronary occlusion result in more homogeneous tissue damage and are usually reflected by a Q-wave MI pattern on the signal. MI's resulting from subtotal occlusion result in more heterogeneous damage, which may be evidenced by a non Q-wave MI pattern on the ECG. Two-thirds of MI's presenting to emergency rooms evolve to non-Q wave MI's, most having ST segment depression or T wave inversion.

Usual of a Q-wave MI[14],[15]; not all of the following patterns may be seen; the time from onset of MI to the final pattern is quite variable and related to the size of MI, the rapidity of reperfusion (if any), and the location of the MI. A)Normal signal prior to MI B)Hyperacute T wave changes - increased T wave amplitude and width; may also see ST elevation C) Marked ST elevation with hyperacute T wave changes (transmural injury) D) Pathologic Q waves, less ST elevation, terminal T wave inversion (necrosis) (Pathologic Q waves are usually defined as duration $\geq$0.04 s or >25% of R-wave amplitude) E) Pathologic Q waves, T wave inversion (necrosis and fibrosis) F) Pathologic Q waves, upright Twaves(fibrosis)[15]

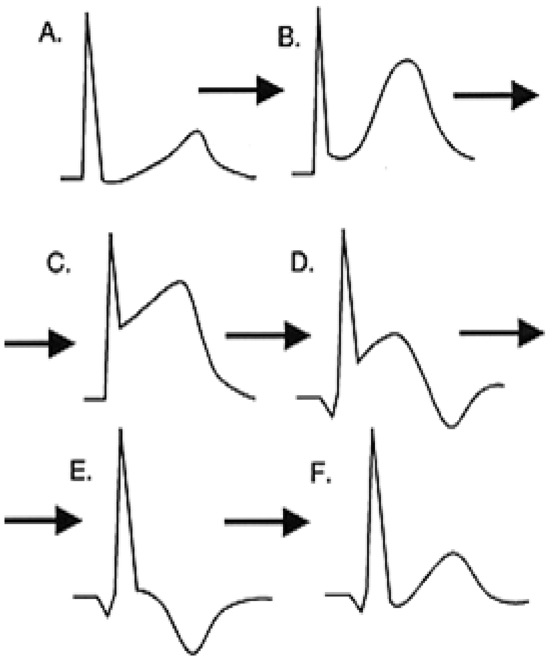

Fig2. Evolution of MI

3. Fast Ica

In a variety of ICA algorithms, Fast ICA algorithm with features of fast convergence speed and good separation effect is widely used in the field of signal processing .This algorithm can estimate statistically independent components which are mixed with unknown factors from the observed signals, for it is based on the fixed point recursive algorithm which is proposed by Hyv¨arinen from Finland University of Helsinki. It’s approved that Fast ICA is applicable to any type of data even can be used to analyze high dimensional data.ICA is usually optimization algorithms. The most basic independent criteria is probability density function, while working at a probability density function is difficult for it is usually unknown and complicated to estimate, it is common to use objective function derivates from probability density as the criterion function . ICA optimizate W based on the criterion function which means that when we get the extreme of W, we also get the recovery signal y as the best estimation of s[5].

In the process of establishing the objective function, two rules are necessary .(1) If the variable is Gauss distribution, the objective function is maximum or minimum.(2) As non-Gauss nature of the variable is increasing strong, the value of the object function Bor absolute value should become greater or smaller stablely, when the objective function reaches extreme, each component is independent with each other.

In practical application negentropy is usually used as a objective function to measure the non-Gauss signal. The larger the random variable entropy is, the greater its uncertainty. If all the random variables have same variance, the entropy of the Gauss random variables is Maximum. Based on this characteristic, the definition of negentropy as a objective function to measure the non Gauss nature of random variables can be get by modifying the definition of entropy

From above, the criterion of Fast ICA algorithm based on the negentropy maximization, is defined as follow

$$J(y) = HG(y) - H(y) \qquad (1)$$

where, y=WT z, W is separation matrix, z is a column vector after whitening the observation column vector. H(y) is the joint differential entropy of random vector y, HG(y) is the differential entropy of Gauss distribution has the same covariance matrix with y. To avoid the complex of direct calculation, the approximation of the negentropy criterion is proposed as

$$J(y) / [E\{G(y)\} - E\{G(v)\}]^2 \qquad (2)$$

where, v is a zero mean, unit variance Gauss variables, G as a nonlinear function, this paper define it as

$$G(y) = 1/a[\lg \cosh(ay)] \qquad (3)$$

where, h is the derivative of H, usually take a=1, let W is orthogonal, the extreme of formula (4) can be got as follow

$$wi+1 = E\{zg(w_i{}^T{}_I z)\} - E\{g(w^T{}_i z)\}w_i$$

$$W = (WW^T)^{-1/2} W \qquad (4)$$

where, W=(w1,w2, ...,wN), g is the derivative of G.ICA theory can be used to separate the observed BVP that are mixed with noise signals The extracting of relative bvp signal by Fast ICA algorithm is shown in Fig1.[5],[7]. The process includes data matrix construction, data whitening processing, independent component extraction, finally the noise and the useful signal separation.

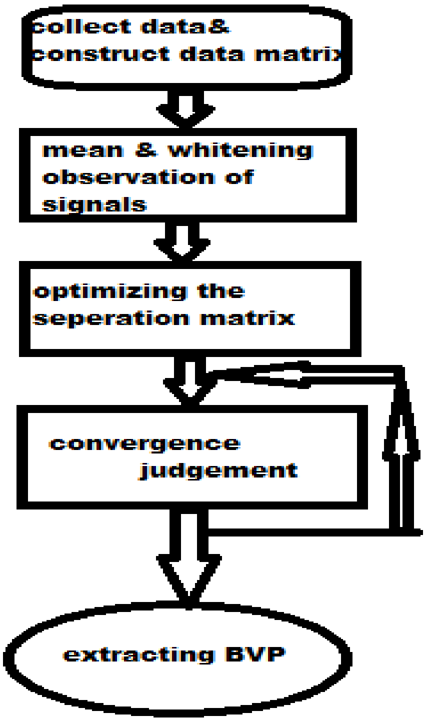

Fig.3. The extracting of relative bvp signal by FastICA algorithm

4. Adaptive Neuro-Fuzzy InferenceSystem

ANFIS is one of hybrid neuro-fuzzy inference expert systems and it works in Takagi-Sugeno-type fuzzy inference system, which was developed by Jang. ANFIS[2],[3] has a similar structure to a multilayer feed forward neural network but the links in an ANFIS only indicate the flow direction of signals between nodes and no weights are associated with the links. ANFIS architecture consists of five layers of nodes. Out of the five layers, the first and the fourth layers consist of adaptive nodes while the second, third and fifth layers consist of fixed nodes. The adaptive nodes are associated with their respective parameters,
get duly updated with each subsequent iterations while the fixed nodes are devoid of any parameters.

Rule 1: If (x is A1) and (y is B1) then (f1 = p1x +q1y + r1)

Rule 2: If (x is A2) and (y is B2) then (f2 = p2x +q2y + r2)

where x and y are the inputs, Ai and Bi are the fuzzy sets, fi are the outputs within the fuzzy region specified by the fuzzy rule, pi, qi and ri are the design parameters that are determined during the training. ANFIS using a strategy of hybrid training algorithm to tune all parameters. It takes a given input/output data set and constructs a fuzzy inference system whose membership function parameters are tuned, or adjusted, using either a back propagation algorithm in combination with a least squares type of method.

5. Proposed Method

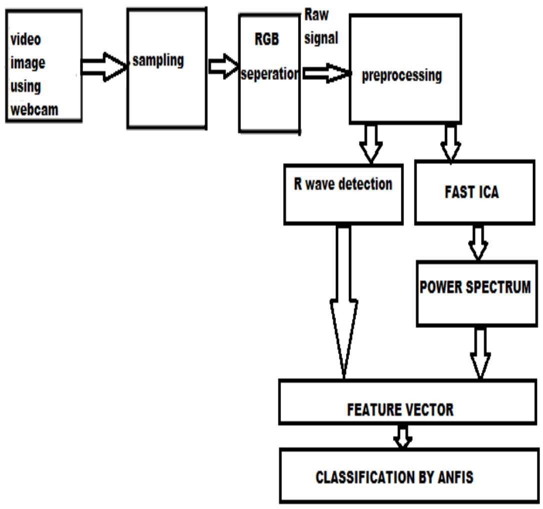

Fig4.proposed method

5.1.Recovery of BVP

All the video and physiological recordings were analyzed offline using custom software written in MATLAB. We utilized the Open Computer Vision library to automatically identify the coordinates of the face location in the first frame of the video recording using a boosted cascade classifier. The algorithm returned the *x* and *y*-coordinates along with the height and width that define a box around the face. Select the center 60% width and full height of the box as the region of interest (ROI) for our calculations. The ROI was then separated into the three RGB channels and spatially averaged over all pixels in the ROI to yield a red, blue, and green measurement point for each frame and form the raw signals. Raw traces are then pre-processed and decomposed into three independent source signals using ICA based on FASTICA algorithm. Pre-processing steps involve centering and whitening[5],[10]. The raw traces were detrended using a procedure based on a smoothness priors approach. Centering the input data X is process by computing the mean of each component of X and subtracting that mean. This has the effect of making each component have zero mean. Whitening the data involves linearly transforming the data so that the new components are uncorrelated and have variance one. The covariance matrix of the whitened data is the identity matrix.

ICA is able to perform motion-artifact removal by separating the fluctuations caused predominantly by the BVP[10],[1] from the observed raw signals. However, the order in which FAST ICA returns the independent components is random. Thus, the component whose power spectrum[11] contained the highest peak was then selected for further analysis.

5.2. Determining of Physiological Parameters and calculation of feature vector

The separated source signal Obtained by applying FAST ICA was smoothed[1] using a five-point moving average filter and bandpass filtered Hamming window. To refine the BVP peak fiducial point, the signal was interpolated with a cubic spline function at a sampling frequency of 256 Hz. We developed a custom algorithm to detect the BVP peaks in the interpolated signal and applied it to obtain the interbeat intervals (IBIs). To avoid inclusion of artifacts, such as ectopic beats or motion, the IBIs were filtered using the non-causal of variable threshold (NC-VT) algorithm. HR was calculated from the mean of the IBI time series. Analysis of HRV was performed by power spectral density (PSD) estimation using the Lomb periodogram. . The term power spectrum means the amount of power per unit (density) of frequency. The RR interval between successive QRS peaks is considered as another important feature for recognizing many ECG arrhythmias. The RR[6] interval (spectral) as a function of the frequency is calculated as the time difference between the R points of the present and previous beat. There are several algorithms to Detect R-wave, we used Pan-Tompkins algorithm. The low frequency (LF) and high frequency (HF) powers were measured. as the area under the PSD curve and quantified in normalized units (n.u.) to minimize the effect on the values of the changes in total power. The LF component is modulated by baroreflex activity and includes both sympathetic and parasympathetic influences. The HF component reflects parasympathetic influence on the heart through efferent vagal activity and is connected to respiratory sinus arrhythmia (RSA), a cardio respiratory phenomenon characterized by IBI fluctuations that are in phase with inhalation and exhalation. We also calculated the LF/HF ratio[1], considered to mirror sympatho/vagal balance or to reflect sympathetic modulations. Since the HF component is connected with breathing, the RR can be estimated from the HRV power spectrum. When the frequency of respiration changes, the center frequency of the HF peak shifts in accordance with RR. Thus, we calculated RR from the center frequency of the HF peak fHFpeak in the HRV PSD derived from the webcam recordings. The different features extracted from PSD together with RR interval serves as input to feature vector. The RR interval is calculated as the time difference between the R points of the present and previous beat. There are several algorithms to Detect R-wave[14], here used Pan-Tompkins algorithm[15].

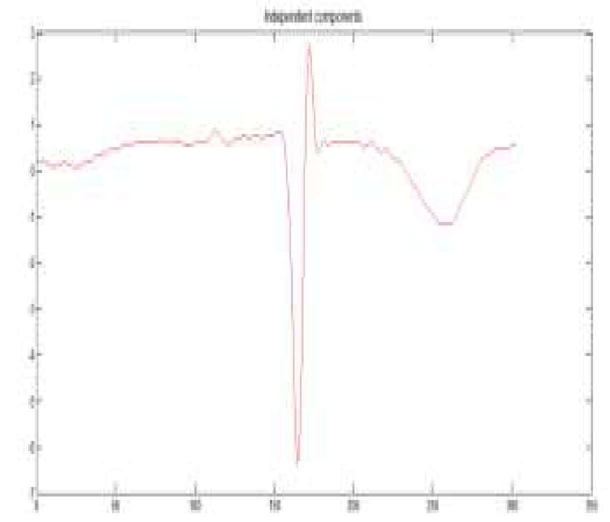

Fig5.Raw signal obtained after applying FAST ICA

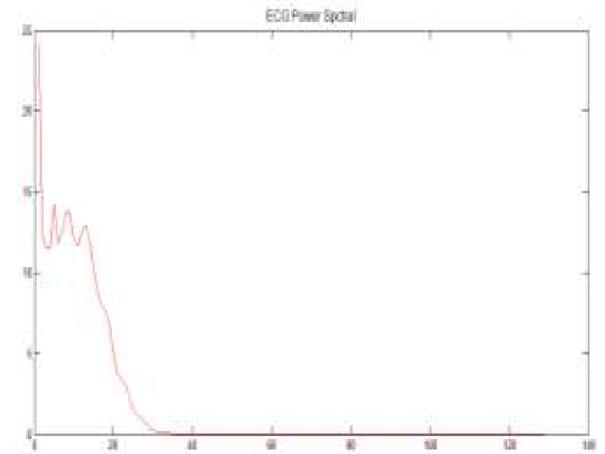

Fig6.power spectral density

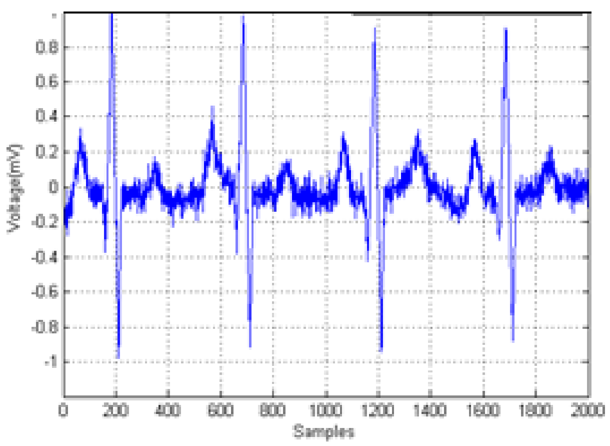

Fig7.R wave detected

5.3. Classification using ANFIS

An ANFIS[2] based classifier is presented as a diagnostic tool to aid physicians in the classification of heart diseases. ANFIS using a strategy of hybrid approach of adaptive neuro-fuzzy inference system, we compose these two intelligent approaches, it will be achieve good reasoning in quality and quantity. In other words we have fuzzy reasoning and network calculation. The objective of classification is to classify the different types of myocardiac signals. The feature vectors were applied as the input to an ANFIS classifier. The ANFIS network has a total of 128 fuzzy rules and one output. The classification by ANFIS should be performed using MATLAB.

7. Conclusion

This paper presented a simple, low-cost method for measuring multiple physiological parameters such as HR,HRV, RR using FAST ICA and a hybrid classifying system using ANFIS model. Thus different types of myocardiac signals will be able to classified. power spectrum[1],[3] and R wave serves as the input to feature vector extraction. System has many advantages including efficiency, accuracy, and simplicity. It can be used for myocardiac infarction detection in clinical practice.

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