Fast Analysis for Emergency Critical Warning in Heart Failure Using Impact Integration Component Analysis combination with Electrocardiography Plate Waveform Recognition

Khammapun Khantanapoka

Advance Medical Science and Bio-engineering (AMSB) Research Center
Department of Bio-engineering, Faculty of Medical, Canterbury University, UK.
doramon86@hotmail.com

***Abstract*—In Intensive Care Unit (ICU) Room , there are normally several sensors connected to each patient receiving intensive care and the several processors monitors and analyzes. If the processor discovers an abnormality then alerts the medical technique office. However, the most patients in heart disease concerns in the daily activities such as activity in hard work, exercises , surprise, altercation, battle. Become due to Clinical depression and Erectile Dysfunction (Impotence) which causes of anxiety and fear. They are unknown the limits of your cardiac muscle and vascular resistance. They want warning which is fast and accurate before losing control. We develops signal recognition for algorithm which is very fast and accurate. It helps warning patients to stop risk activity. However, it is able to transfer data of heartbeat pass network system for guidance of doctor. This research proposes: 1) Framework of data operation in fast Electrocardiography analysis. 2) Impact Integration Component Analysis which use for feature extraction and Electrocardiography signal recognition 3) Electrocardiography Plate waveform for identify risk condition 2 layer which are Cardiac Arrhythmia layer and identify layer of symptom. This system support expert system of medical field. Result of the experiment which test signal 100 pattern of Cardiac Arrhythmia. Impact Integration Component Analysis is able to abnormal recognition accuracy than Automata matching 12.65 – 28.11 average percentage and spends time less than other algorithm 20.54 average percentage and be able to warning within duration 15 sec.**

Keywords- Electrocardiography; Cardiac Arrhythmia; waveform.

I. INTRODUCTION

Heart failure, often called congestive heart failure (CHF) or congestive cardiac failure (CCF), occurs when the heart is unable to provide sufficient pump action to distribute blood flow to meet the needs of the body. Heart failure can cause a number of symptoms including shortness of breath, leg swelling, and exercise intolerance. The condition is diagnosed with echocardiography and blood tests.

Biomedical signal come in all shapes and sizes. We study about performance to capture and analyze these signals; the same general processing steps are required for all the signals. The function of a digital filter is the same as its analog counterpart, but its implementation is very different. There are basic techniques used in clinical electrocardiography. The most familiar is the standard clinical electrocardiogram. This is the test done in a physician of office in which 12 different potential differences or ECG leads are recorded from the body surface of a resting patient. Adding we uses an other set of body surface potentials as inputs to a three-dimensional vector model of cardiac excitation. The result produces a graphical view of the excitation of the heart or the vector cardiogram. However, for long-term monitoring in the intensive care unit or on ambulatory patients, ECG leads are monitored or recorded to look for life-threatening disturbances in the rhythm of the heartbeat.

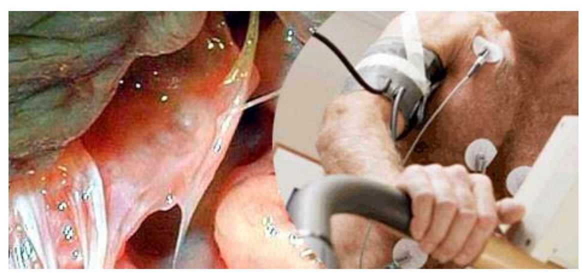

Figure 1.show patients which risk for heart failure in life routine

Electrocardiography (ECG) interpretation techniques ware initially developed and nowadays used on computation with electronic machine. The ECG ware transmitted to the computer from remote hospital sites using a specially designed ECG acquisition cart that could be rolled to the patient's bedside .As technology evolved, microcomputers located within hospital took over the role of the remote large computer .The ECG acquisition cart began to include embedded microprocessor in order to facilitate ECG capture. The interpretation algorithm had increased failure rate if the ECG was noise signal. The microprocessor increased the signal to noise ratio by performing digital signal processing algorithms to remove baseline drift and attenuate liner interference.

II. LITERATURE REVIEW

The clinic medical bandwidth used for recording the standard 12 lead ECG is 0.05-100 Hz. We are estimate intensive care patients and for ambulatory patients. The bandwidth is restricted to 0.5-50 Hz. Most patients' environment and rhythm disturbances are principally of interest rather than subtle morphological changes in the waveforms. Thus the restricted bandwidth attenuates the higher frequency noise caused by muscle contractions and lower frequency noise caused by motion of the electrode. The peak amplitude of an ECG signal is in the range of 1 mV. An ECG amplifier typically has again of about 1,000 in order to bring the peak signal into a range of about 1 V.

Signal processing has contributed significantly to a understand in the ECG and its dynamic properties as expressed by changes in rhythm and beat morphology. For example, techniques have been developed that characterize oscillations related to the cardiovascular system and reflected by subtle variations in heart rate. The detection of low-level, alternating changes in *T* wave amplitude is another example of oscillatory behavior that has been established as an indicator of increased risk for sudden, life-threatening arrhythmias. Neither of these two oscillatory signal properties can be perceived by the naked eye from a standard ECG printout. Common to all types of ECG analysis whether it concerns resting ECG interpretation, stress testing, ambulatory monitoring, or intensive care monitoring is a basic set of algorithms that condition the signal with respect to different types of noise and artifacts, detect heartbeats, and extract basic ECG measurements of wave amplitudes and durations, and compress the data for efficient storage or transmission; the block diagram below presents this set of signal processing algorithms.

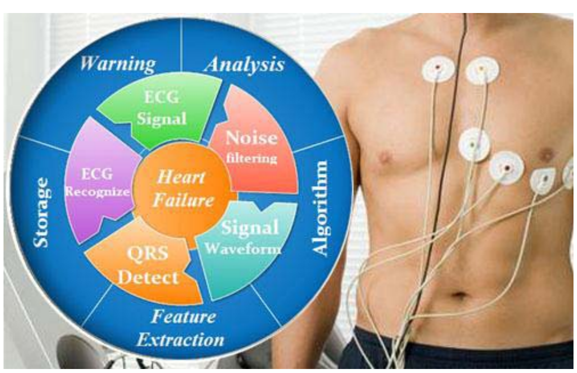

Figure 2. Framework of ECG signal processing

III. EXPERIMENTIAL OF EPL TECHNIQUE

This research propose Electrocardiography Plate Liner Technique which has components as hardware and several algorithms for fast analysis and emergency critical warning in heart failure.

A. Sensor Electronic Kit

We use circuit of ECG kit for input real-time signal. The medical device community recognizes embed technology. However, embedded technology has become increasingly complex making it more challenging for non-technical experts to design full-featured medical device prototypes. Therefore, a new approach to design is needed. Graphical System Design is a revolutionary approach to solving design challenges that blends intuitive, graphical programming and flexible, commercial-off-the-shelf hardware, while still allowing for customization. Graphical System Design bridges the abilities of the embedded design expert with the domain expert, such as a medical device expert, to accelerate innovation. The Electrocardiography (ECG) Reference Design Embedded Starter Kit combines a Texas Instruments ECG module, a National Instruments Single Board RIO, and a application into a working ECG prototype. The prototype can operate as a stand-alone application or as a component within a higher level integrated system, which may include components such as motor control or high speed data acquisition.

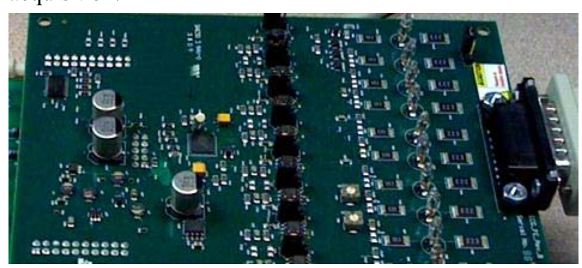

Figure 3. Sensor Electronic Kit

The Texas Instruments TMDXMDKEK1258 (ECG) Analog Front End (AFE) module reads 8 out of 12 ECG leads as analog signals and provides the digital output to the LabVIEW-based, processing subsystem of the FPGA and real-time processor. The front-end board is interfaced with the NI sbRIO board through the custom adapter board connector. The 16 channel analog-to-digital converter (ADC) (ADS1258) is configured for a 500Hz sampling rate per channel and has 24-bit data resolution. The sbRIO controls the ADC with SPI communication and has the ability to do I2C communication to implement lead-off detection.

B. Noise Reduction with Wiener Filter algorithm

Consider a signal *x(m)* observed in a broadband additive noise n(m) and framework as

$$y(m)=x(m)+n(m) \tag{1}$$

Assuming that the signal and the noise are uncorrelated, it follows that the autocorrelation matrix of the noisy signal is the sum of the autocorrelation matrix of the signal *x(m)* and the noise *n(m):*

$$R_{yy} = R_{xx} + R_{nn} \quad \text{or} \quad r_{xy} = r_{xx} \tag{2}$$

Where R_{yy}, R_{xx} and R_{nn} are the autocorrelation matrices of the noisy signal, the noise-free signal and the noise respectively, and r_{xy} is the crosscorrelation vector of the noisy signal and the noise-free signal. Substitution of Equations (1) and (2) in the wiener filter as follow

$$w = R_{yy}^{-1} r_{yx} \tag{3}$$

$$w = (R_{xx} + R_{nn})^{-1} r_{xx} \tag{4}$$

This is the optimal linear filter for the removal of additive noise. In the following, a study of the frequency response of the Wiener filter provides useful insight into the operation of the Wiener filter. In the frequency domain, the noisy signal *Y(f)* is given by

$$Y(f) = X(f) + N(f) \tag{5}$$

where *X(f)* and *N(f)* are the signal and noise spectra. A signal observed in additive random noise, the frequency-domain Wiener filter is obtained as

$$w(f) = \frac{P_{xx}(f)}{P_{xx}(f) + P_{NN}(f)} \tag{6}$$

where $P_{xx}(f)$ and $P_{NN}(f)$ are the signal and noise power spectra. Dividing the numerator and the denominator of equation (6) by the noise power spectra $P_{NN}(f)$ and substituting the variable $SNR(f) = P_{xx}(f) \; / \; P_{NN}(f)$ yields.

$$w(f) = \frac{SNR(f)}{SNR(f) + 1} \tag{7}$$

where *SNR* is a signal-to-noise ratio measure. Note that the variable, *SNR(f)* is expressed in terms of the power-spectral ratio, and not in the more usual terms of log power ratio. Therefore *SNR(f)* =0 corresponds to $-\infty$ *dB*. From equation (7), the following interpretation of the Wiener filter frequency response *w(f)* in terms of the signal-to-noise ratio can be deduced. For additive noise, the Wiener filter frequency response is a real positive number in the range $0 \leq W(f) \leq 1$. Now consider the two limiting cases of (a) a noise-free signal $SNR(f) = \infty$ and (b) an extremely noisy signal *SNR(f)=0*. The filter applies little or no attenuation to the noise-free frequency component. At the other extreme, when *SNR(f)=0, W(f)=0.* Therefore, for additive noise, the wiener filter attenuates each frequency component in proportion to an estimate of the signal to noise ratio. The variation of the wiener filter response *W(f)*, with the signal-to-noise ratio *SNR(f).* An alternative illustration of the variations of the wiener filter frequency response at *SNR(f)* . It illustrates the similarity between the wiener filter frequency response and the signal spectrum for the case of an additive white noise disturbance. Note that at a spectral peak of the signal spectrum, where the *SNR(f)* is relatively high, the Wiener filter frequency response is also high, and the filter applies little attenuation. At a signal trough, the signal-to-noise ratio is low, and so is the Wiener filter response. Hence, for additive white noise, the Wiener filter response broadly follows the signal spectrum.

C. Separability of Signal and Noise

A signal is completely recoverable from noise if the spectra of the signal and the noise do not overlap. An example of a noisy signal with separable signal and noise spectra . In this case, the signal and the noise occupy different parts of the frequency spectrum, and can be separated with a low-pass, or a high-pass, filter. We can represent illustrates a more common example of a signal and noise process with overlapping spectra. For this case, it is not possible to completely separate the signal from the noise. However, the effects of the noise can be reduced by using a Wiener filter that attenuates each noisy signal frequency in proportion to an estimate of a signal-to-noise ratio as described by equation (7).

D. Reduction with signal shot-repeated particularities

The sample correlation corresponds to a value predicted using past samples. It is redundant and removable. We are then left with the uncorrelated part which represents the prediction error or residual signal. The amplitude range of the residual signal is smaller than that of the original signal. It requires less bits for representation. We can further reduce the data by applying Huffman coding to the residual signal. We briefly describe two ECG reduction algorithms that make use of residual differencing as Equation

$$x'(nT) = \sum_{k=1}^{P} a_k x(nT - kT) \tag{8}$$

where $x(nT)$ are the original data. $x'(nT)$ are the predicted samples, P is the number of samples employed in prediction. The parameters a_k are chosen to minimize the expected mean squared error $E[(x - x')^2]$. when $p=1$, we choose $a_1=1$ and we are taking the first difference of the signal. In interpolation, the estimator of the sample value consists of a linear combination of past and future samples. The results for the predictor indicated a second order estimator to be sufficient. The interpolator uses only a past and a future sample

$$x'(n) = ax(nT - T) + bx(nT + T) \tag{9}$$

where the coefficients a and b are determined by minimizing the expected mean squared error. The

\residuals of prediction and interpolation are encoded using a modified Huffman coding scheme, where the frequent set consists of some quantized levels centered about zero.

E. Impact Integration Component Analysis(I^2CA) using Signal Electrocardiography recognition process

We develop this algorithm for fast feature extraction and fast recognition. Normally, Principle Component Analysis (PCA) is mathematical procedure that uses a orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called Impact Integration Component Analysis (I^2CA).It is novelty method in ECG signal which is focus speed in computation. Generally, Impact Integration Component Analysis will consider parallel dimension while feature extraction of signal at the same time. Procedures of traditional algorithm are projecting data vectors to the $(2D)^2$PCA eigen space combination processing the mapped new data with non-Gaussianity ICA which is pattern recognition of high dimension data. non- Gaussianity is performed directly to eigen matrix of feature of signal recognition. The original data is directly projected to the final eigen space. Repeated operations of high dimensional data are avoided and the computation amount is reduced. The combination of two algorithms is high performance method. $(2D)^2$PCA and alternative 2DPCA only works in the row and column direction of pattern respectively. $(2D)^2$PCA learns an optimal matrix X from a set of training pattern reflecting information between rows of pattern, and then projects an m by n dimension A onto X, yielding an m by d matrix $Y=AX$ Similarly, the alternative 2DPCA learns optimal matrix Z reflecting information between columns of dimension, and then projects A onto Z, yielding a q by n matrix $B=Z^TA$. In the following, we will present a way to simultaneously use the projection matrices X and Z Suppose we have obtained the projection matrices X and Z projecting the m by n dimension A onto X and Z simultaneously, yielding a q by d matrix C.

$$C=Z^TAX \tag{10}$$

The *matrix C* is also called the coefficient matrix in data representation, which can be used to reconstruct the original signal A by

$$A=ZCX^T \tag{11}$$

When used for signal recognition, the *matrix C* is also called the feature matrix. After projecting each training data dimension. A_k by $k=1,2,\ldots M$ onto X and Z, we obtain the training feature matrices C_k by $C=1,2,\ldots M$. Given a test signal recognition. Here the distance between C and C_k is defined by

$$d(C,C_k)=\|C-C_k\|=\sqrt{\sum_{i=1}^{q}\sum_{j=1}^{d}(C^{(i,j)}-C_k^{(i,j)})^2} \tag{12}$$

We estimate the independent component is by focusing on non-Gaussianity. Since it is assumed that each underlying source is not normally distributed, one way to extract the components is by forcing each of them to be as far from the normal distribution as possible. Negentropy can be used to estimate non-Gaussianity. In short, negentropy is a measure of distance from normality defined by:

$$N(X)=H(X_{Gaussian})-H(X) \tag{13}$$

where X is a random vector known to be non-Gaussian, $H(X)$ is the entropy

$$H(X)=-\Sigma_X P(x)\log P(x) \tag{14}$$

where $X_{Gaussian}$ is the entropy of a Gaussian random vector whose covariance matrix is equal to that of X. For a given covariance matrix, the distribution that has the highest entropy is the Gaussian distribution. Negentropy is thus a strictly positive measure of non-Gaussianity. However, it is difficult to compute negentropy using equation 13. which is why approximations are used. For example, Hyvärinen & Oja (2000) have proposed the following approximation:

$$N(V)=E(j(V))-E(j(U))^2 \tag{15}$$

where V is a standardized non-Gaussian random variable for zero mean , unit variance, U a standardized Gaussian random variable and $\phi(.)$ a non-quadratic function. After some manipulation to first step, set initialize algorithm for w_i from probability.

$$w_i^+=E(j'(w_i^TX))w_i-E(xj(w_i^TX)) \tag{16}$$

$$w_i=\frac{w_i^+}{\|w_i^+\|}\Big|i^1\neq 1 \tag{17}$$

if $i\neq 1$ then compute in the next step

$$w_i^+=w_i-\sum_{j=1}^{i-1}w_i^Tw_j\Big|i^1\neq 1 \tag{18}$$

If not converged reverse back to equation 16. if consider is else then go back to Initialize w_i from probability again by i = i + 1 until all components are extracted. where w_i is a column-vector of the immixing *matrix W*, w_i is a temporary variable used to calculate w_i. It is the new w_i before normalization, $\phi'(.)$ is the derivative of $\phi(.)$ and $E(.)$ is the expected mean value . Once a given w_i has converged, the next one (w_i+1) must be made orthogonal to it and all those previously extracted with equations 17 and 18 in order for the new component to be different from previous component.

E. Signal Detection&Compare with ECG Plate waveform

We use classification techniques for identifier pattern in ECG signal that are quite related to machine recognition process. We use pattern crosscorrelation in recognize several signal patterns. Signal correlated are the shapes of the waveforms of two signals match one another. The correlation coefficient is a value that determines the degree of feature between the shapes of two signals from ECG plate waveform recognition which used Impact Integration Component Analysis (I^2CA) for pattern recognition.

F. Detection&Compare with Automata-base template Matching

We use set of tokens that would represent a normal ECG. This set of tokens is input to the finite state automaton. The sequence of tokens must be derived from the ECG signal data. This is done by forming a sequence of the difference of the input data. The algorithm can now assign a waveform token to each of the groups formed previously based on the values of the number and the sum in each group of differences. We use ranges of a QRS upward or downward deflection, then a *normup* or *normdown* token is generate for that group of differences. If the number and sum values do not fall in this range, then a *noiseup* or *noisedown* token is generated. A zero token is generated if the sum for group of differences is zero. The algorithm reduces the ECG signal data into a sequence of tokens which can be fed to finite state automata for QRS detection. It is conservative pattern for ECG detection.

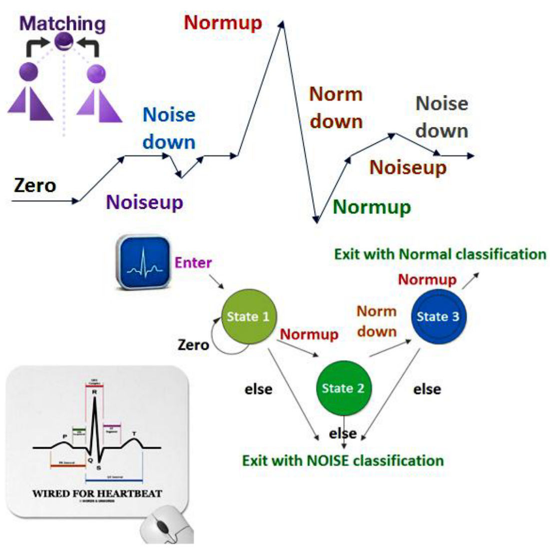

Figure 4. show about Automata-base template matching.

F. ECG Plate waveform and identifier feature heart failure

Figure 5. Signal character of Sinus Rhythm plate waveform

1) Sinus Rhythm plate waveform : Sinus rhythm also as regular sinus rhythm (RSR) or normal sinus rhythm (NSR) is the most common adult rhythm with rate between sixty to one hundreds per minute .The QRS is most often narrow with upright *P* waves in Lead II. It is standard of rhythm of heartbeat which is comparing every time in warning first level.

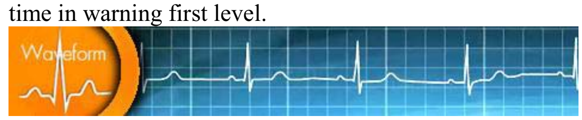

Figure 6. Signal character of Sinus Bradycardia plate waveform

2) Sinus Bradycardia plate waveform with rates greater than fifty per minute may be well tolerated by healthy adults. Athletes may routinely be in Sinus bradycardia due to a optimal cardiac stroke volume that requires less HR to yield acceptable cardiac output. Sinus bradycardia may also be produced with vagal stimulation or due to Sick Sinus Syndrome. Expect a narrow QRS with upright *P* waves in Lead II.

Figure 7. Character of Sinus Tachycardia plate waveform.

3) Sinus Tachycardia most often results from increased sympathetic stimulation such as due to pain fever, increased oxygen demand, and hypovolemia.It usually has a narrow QRS.The rate is often limited to below 150 per minute.

Figure 8. Character of Sinus Arrthythmia plate waveform.

4) Sinus Arrthythmia : Sinus Arrhythmia is most often a benign rhythm,comman children and less common with older adults.The irregular pattern of this rhythm fluctuates with inspiration or HR increases and expiration or HR decreases. A narrow QRS and upright *P* waves in Lead II is expected.

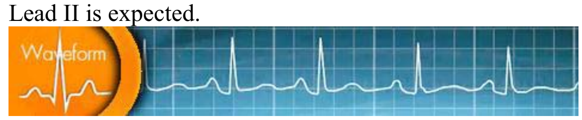

Figure 9. Character of Sinus Exit Block plate waveform.

5) Sinus Exit Block: Sinus exit block or senatorial blocked sinus impulses-impulses not getting though to depolarize the atria. While the sinus is firing on schedule. The tissue around the SA node is not carrying the impulse. The seriousness of this dysrhythmia is related to the frequency and duration of the blocks. Each pause is equal to a multiple of previous *P-P* intervals.

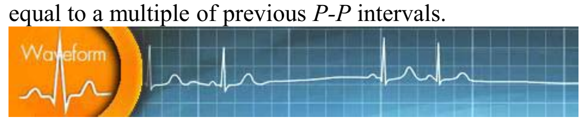

Figure 10. Character of Sinus Arrest plate waveform.

6) Sinus Arrest occurs when the SA node fails to fire. The resulting pause is often not equal to the multiple of *P-P* interval seen in Sinus Exit Block. Instead, often an

escape pacemaker such as the AV junction will assume control of the heart .A gain, like Sinus Exit Block, treatment is related to the frequency and duration of the periods of sinus arrest.

Figure 11. NSR with Premature Atrial plate waveform.

7) Premature Atrial Complexes is result from irritability to the atria resulting in increased automaticity of atria initiate an impulse earlier than expected from the SA node. This is a premature complex. Expect narrow QRS and flattened, notched, peaked or biphasic *P* waves for the PAC.

Figure 12. Supraventricular Tachycardia plate waveform.

8) Supraventricular Tachycardia is an ominous rhythm with rates often between 170-230 per minute. The telltale sign of supraventicular tachycardia is the narrow QRS which defines its supraventricular origin and its regular, rapid pattern. The rhythm is most likely not sinus tachycardia due to its very fast rate. For those who are at rest, narrow QRS tachycardia over 150 per minute is most often supraventricular tachycardia.

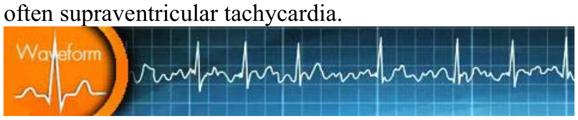

Figure13. Atrial Fibrillation plate waveform.

9) Atrial Fibrillation: Atrial Fibrillation is a chaotic rhythm with recognizable QRS complexes. The Chaotic rhythm pattern and the absence of *P* waves are the hallmarks of this dysrhythmia. The chaotic baseline known as fibrillatory waves. It is quickly seen. It is risk of thrombus formation is particularly significant after 48 hours.

Figure14. Atrial Flutter plate waveform.

10) Atrial Flutter: Atrial Flutter results from the development of reentry circuit within the atria generating a loop that discharges impulses at a flutter rate of 250-350 per minute. Most often the AV junction passes every second or every fourth impulse through to the ventricles.

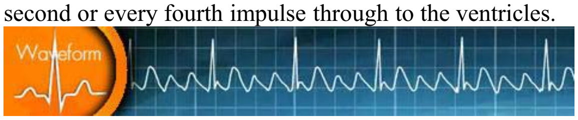

Figure 15. Paced Atrial Atrial plate waveform.

11) Paced Atrial : Paced Atrial rhythm is result from the electronic pacing of an atrium. The vertical spike before the *P* wave. An electronic pacemaker lead repeatedly generates a small but sufficient current to begin depolarization of the atria and the resulting *P* wave.

Figure 16. Wandering Pacemaker plate waveform.

12) Wandering Pacemaker: Wandering Pacemaker rhythm is a supraventricular rhythm with varying locations of impulse formation resulting in three or more difference P waves. With a narrow QRS complex.

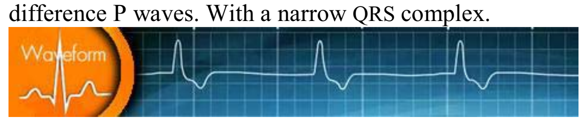

Figure 17. Accellerated Idioventricular plate waveform.

13) Accellerated Idioventricular rhythm is a ventricular rhythm occurring at a rate between 41-100 per minute faster than typical pacemaker rates expected of the ventricles at 20-40 per minute and less than what is considered at a tachycardia more than 100 per minute. It is possibly due to hypoxia or abundant sympathetic stimulation.

Figure 18. Ventricular Fibrillation plate waveform.

14) Ventricular Fibrillation : Ventricular Fibrillation is a chaotic rhythm originating in the ventricles.Resulting in no cardia output. VFib is less than 3 mm in height and signified less electrical energy within the myocardium which less opportunity for a successful defibrillation.

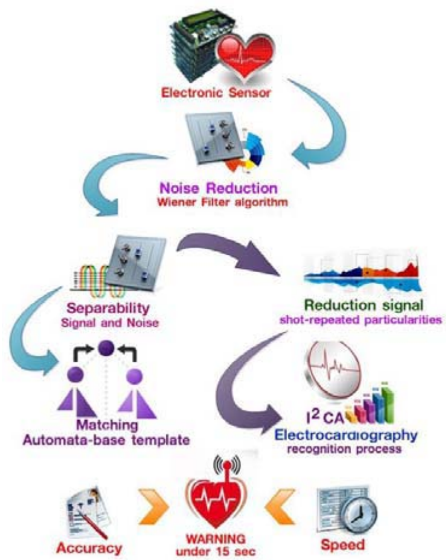

Figure 19. Eexperimental framework compare algorithm between Automata matching with Impact Integration Component Analysis (I^2CA)

IV. RESULT OF EXPERIMENTAL

We test 100 signals which are several pattern of ECG. We develop software with Java language in programming field. Result of the experiment as below table;

TABLE 1. SHOW RESULT OF SIGNAL IDENIFY RECOGNITION

Plate Waveform Warning	I^2CA Average Time (Sec)	Automata Average Time (Sec)	Accuracy Warning Identify
1.Sinus Rhythm	3.750	5.635	True
2.Sinus Bradycardia	5.358	6.821	True
3.Sinus Tachycardia	5.454	6.533	True
4.Sinus Arrthythmia	6.416	8.021	True
5.Sinus Exit Block	3.741	5.137	True
6.Sinus Arrest	4.225	5.952	True
7.Premature Arial	3.813	4.974	True
8.Supraventricular Tachycardia	5.137	5.884	True
9.Atrial Fibrillation	4.110	5.021	True
10.Atrial Flutter	5.494	6.713	True
11.Wandering Pacemaker:	3.127	4.855	True
12.Paced Atrial	5.152	4.970	True
13.Accellerated Idioventricular	3.013	5.135	True
14.Ventricular Fibrillation	2.171	3.366	True

The result is experiment, Impact Integration Component Analysis (I^2CA) algorithm is efficiency and quickness in signal recognition more than Automata matching. Fallow as hypothesis of research. Impact Integration Component Analysis (I^2CA) uses $2D^2$PCA in feature extraction quickly and combination with fast independent component analysis which both decreases noise and recognition from separate processing. These algorithms are fast method and high effect to less time more than Automata matching. It is enough to sent warning signal to device at patient. We use warning two layers. First level, this system will show warning when heartbeat difference from Sinus Rhythm plate waveform which is standard pattern of normal human. Second level, this system will identify unusual signal. However, two levels must spend time less than 15 second. Because, it is period of Emergency Critical for patient which is Heart Failure. The experiment tests signal 100 patterns from several signal of ECG. Impact Integration Component Analysis (I^2CA) is able to abnormal recognition accuracy than Automata matching method 12.65 – 28.11 average percentage and spends time less than other algorithm 20.54 average percentage and be able to warning within duration 15 sec. It cannot detection in some pattern which are difference from without recognize waveform. In experiment uses signal within recognize 14 waveforms.

V. CONCLUSION

The trend of DSP software include the following: Support of a wide variety of signal conversion board, Comprehensive library of signal processing algorithm including FFT, convolution, low/high-pass and band pass filters and novelty platform.

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