ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 10, October 2015

Atrial Electrical Action Finding by Using ECG Lead Signals

B.Madhan Mohan[1], Dr.G. Umamaheswara Reddy[2]

M.Tech [Communication Systems], Dept. of ECE, Sri Venkateswara University College of Engineering, Tirupati, India[1]

Associate Professor, Dept. of ECE, Sri Venkateswara University College of Engineering, Tirupati, India[2]

ABSTRACT: ECG analysis is used to find cardiac arrhythmia analysis. This ECG signal can be acquired by using led methodology in common we use 12 lead ECG for acquiring ECG signal. This 12 lead ECG will describe 3 directional blood flow within heart. Atrial electrical action (AEA) waves play important role in diagnosis of arrhythmias. When ECG signal is acquired in noisy conditions (due to external radiations) AEA waves cannot be accurately extracted because AEA waves are hidden in other waves. To extract AEA waves precisely for further arrhythmia diagnosis we use SUMER method based on band pass filtering and threshold based segmentation and synthetic extraction based on minimum MSE value. These methods will work efficiently for different arrhythmia cases we can prove that our method will yield better results compared to state-of-art criteria like PCA based AEA extraction method using sensitivity and positive predicted values as metrics.

KEYWORDS: Atrial electrical action (AEA) detection, cardiac arrhythmia, electrocardiogram, linear combiner.

I. INTRODUCTION

Diesis of heart is expressed as cardiac arrhythmia showing irregular [1] activity of electrical action which leads to malfunctioning of mechanical activity of heart. Arrhythmia [2] symptoms, implications leads to dizziness[3], syncope and stroke rarely to death[4]. For successful diagnosis arrhythmia type doctor should clearly verify 12-lead ECG [5]. AEA waves depict key features for diagnosis as they are having relationships to QRS complexes. The type arrhythmia [6] is decided by finding ratio between AEA wave numbers to QRS complexes. Detecting AEA waves is a difficult task in some arrhythmias where AEA waves are mixed [7] in other ECG components. this may lead to improper diagnosis of arrhythmias. The important for making appropriate diagnosis of arrhythmia detection of AEA is crucial.

Due to some issues related to QRS complexes, Ventricular Tachycardia (VT) and Super Ventricular Tachycardia (SVT) [8], Detection of AEA has inability in many cases like arrhythmia confirmative diagnosis. There is significant insufficiency in AEA detection is observed over past decades. The adaptive filtering method using impulse train the coincides with QRS complexes in order reduce them and T waves from ECG signals [9] .

The system using low pass [11] separation AEA waves are found using derivative zero crossing in particular sorting windows related to QRS complex. it shows good results in pathologies and sinus rhythm. a recent method using T wave filtration and wavelet [14] is performed but this method has validations in QRS complexes. For the detection AEA waves in artial fibrillation various algorithms were used .The important used method was QRST cancellation. The other approach is blind source separation where AEA and Ventricular electrical activity are taken as two different sources mixed to compose ECG signals.

In this paper we proposed a classical method that follows ICA and PCA [17] methods assumptions that atrial action is retrieved from linear ECG leads, that alleviates limitations of correlation between AEA and ventricular action. The proposed method is a semi automatic with two variations in both of them first we refer to the ECG signals as mixed of two elements named as ventricular and atrial and try to exploit mathematical methods for separation of the

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 10, October 2015

two elements, followed by finding the AEA waves in perfect time locations, the sensitivity and positive predicted[6] values of ECG signals are calculated and significant improvement is observed for different ECG signals.

II. PROPOSED METHOD

Various ECG signals were taken from deciding objective of AEA distinguishing proof in atrial fibrillation. By and large used procedure is the spatiotemporal QRST [13] fixing. Another fundamental procedure is outwardly weakened source division, in which the AEA and the ventricular electrical activity are considered as two various sources that were straightly mixed to make the ECG signal.

The allotment of the sources is supervised using principal portion examination (PCA) [17] or self-ruling fragment examination these routines rely on upon the uncorrelated additionally, self-sufficiency of the AEA and the ventricular development. Here, we propose a system that relies on upon the same assumption as in the ICA and PCA methods that the atrial activity can be imitated from an immediate blend of 12-lead ECG signs, however does not oblige any further limitations as for the relationship or dependence between the AEA and ventricular activity. Likewise, likeness with a different number of arrhythmias is proficient, including covered AEA-waves cases.

The introductory stage in the proposed count (SUMER) [11] is physically stamping of no under one P wave in the ECG signal. The researcher partitions the sign into AA segments (P-waves) and NAA (non-AA) parcels Rather than manual stamping of the P wave, there is an option of finding the P waves hence using SUMER with unsupervised gathering, this decision is under investigation and is out of the degree of this paper. Without further ado we're looking for 12 weight coefficients, one weight coefficient for each ECG lead signal.

The straight mix using these weights should convey a yield signal with complemented we are in AA.. The figuring subtracts the mean of every part. In case, If we have one AA part and two NAA Fragment the count subtracts the mean from the 12 signs in the AA section and from the 24 banners in the NAA pieces. Next, the computation picks 12 coefficients subjectively (initial qualities). In no time the estimation figures the cost limit which is the imperativeness extent between the stamped likewise, the non-stamped parts in the yield the imperativeness extent between the stamped likewise, the non-stamped parts in the yield sources. The marked segment is between the two vertical lines

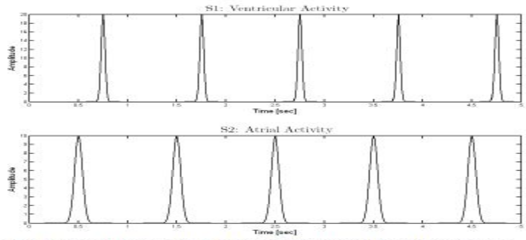

Fig 1. Simulated ventricular and atrial activity source signals

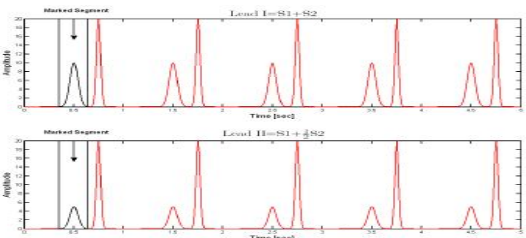

Fig 2: The leads are linear combinations of the

Now, we mark one segment in the ECG leads. The marked segment contains one P-wave; we are looking for a linear combination of the two leads that will produce the highest ratio between the marked segment's energy and the non-marked segment's energy. Since it can't reduce the other P-waves' amplitude without reducing the marked P-wave's amplitude, the energy ratio will get its maximum when the QRS [13] complexes will reduce to zero but the amplitude

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 10, October 2015

of the P-waves doesn't have an influence on the energy ratio. The desired signal can be obtained by a linear combination of the two leads with the coefficients[9]. The obtained signal contains the atrial activity source signal only.

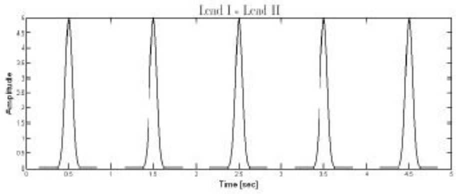

Fig 3: Linear combination of the leads produces the atrial activity source signal.

SEPARATION USING MAXIMUM ENERGY RATIO (SUMER):

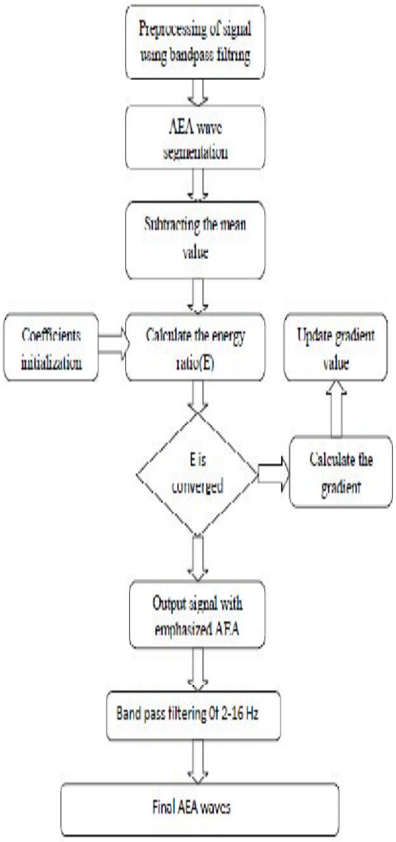

Fig4: Block diagram of sumer technique

In this approach, the ECG signal is initially divided into two parts a manually delineated segment (by a physician expert cardiac electro physiologist) that contains a single AEA-wave, and the under lineated surrounding segments are shown in figure1. The main concept is forcing the linear combination of ECG signals to converge to a signal that has the maximum ratio between the energy in the marked segment and the energy in the non marked segments; this resulting signal is expected to have amplified AEA-waves and reduced QRS[13] and T waves.

The flow chart of the SUMER as shown in figure4

(1) Manually segmenting one AEA-wave, which is in effect equivalent to dividing the signals to a marked segment and residual unmarked segments.

(2) Subtracting the mean of each segment.

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 10, October 2015

(3) Creating a cost function of the energy ratio between the marked segment and the residual signal segments with initial random weight coefficients for the linear combination.

AEA Detection Using Synthetic AEA Signal

In this variation, we alter the classic linear combiner, which is a known method for removal of noise and artefacts[11], blinks and eye movements (EOG) artefacts cancellation from EEG recordings and ECG artefacts removal from EEG. Adaptations and variations of this technique are widely used for many purposes, such as detecting ventricular late potentials in ECG [14] and estimating event-related smooth sensory evoked potential signals. The main concept of the classic linear combiner for the noise removal task is subtracting an appropriate linear combination of reference signals from the observed signal, in order to remove the noise.

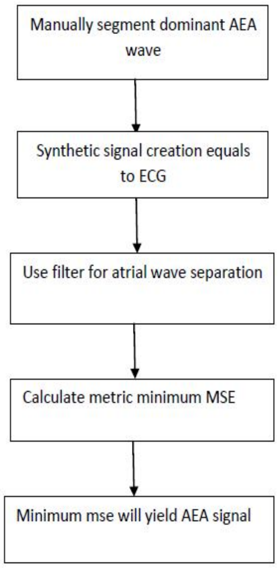

Fig5: flow chart for synthetic AEA technique

One of the late strategies presents division of AA from VA utilizing the ICA [17] system. The ICA strategy depends on the presumption that the AA can be built by a straight blend of the 12 ECG leads. This proposed strategy, called partition utilizing most extreme vitality proportion (SUMER), depends on the same supposition however takes an alternate methodology. Utilizing from the earlier data, the doctor/client marks no less than one P wave portion, and at that point the calculation constrains the straight blend of the 12 prompts unite to the sign that has the greatest proportion between the vitality in the checked fragments and the vitality in the non-checked segments. The outcome is a sign with underscored P waves and diminished QRS [13] and T waves.

The focal points and burdens over the ICA system are examined later. For test setup signals from the GE Cardio lab IT which produces standard 12 lead ECG were taken. Obtrusive estimations from the high right chamber (HRA) which help the specialist to distinguish AA and imprint it (for the to begin with venture of the calculation), and for execution assessment of the calculation, 5 sinus rhythms, 3 AV hub re-passage tachycardia (AVNRT) signals, an AV re-section tachycardia (AVRT) signal, 2 atrial ripple and 2 atrial fibrillation signals. The atrial fibrillation signs are from the St Petersburg INCART 12-lead Arrhythmia Database. In the pre-processing phase, the ECG signs were separated utilizing a band-go with band between 0.5-60 Hz. Disposal of the 50Hz force supply commotion had been done by the Cardio lab machine itself utilizing score channel. All the calculations were computed by using MATLAB 14 version.

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 10, October 2015

III. RESULTS

Matlab tool is developed for effective detection and classification of arrhythmia using ECG signals. Totally 19 ECG samples are tested, table (1) shows results of our proposed method for some ECG samples. Algorithm works fine for noise contaminated signals also. We consider the entire duration ECG recordings since the proposed method does not require any learning phase. ECG samples taken from physio net bank databases, some are from MIT-BIH and some from Creighton University arrhythmia databases. It contains 48 half-hour of two channel ECG recordings sampled at 360 Hz with 11-bit resolution over a 10 mV range.

In the MIT-BIH arrhythmia database, ECG records 104, 105, 108, 200, 203, 210, and 228 contain high-grade noise and artifact. Records 108, 111, 112, 116, 201, 203, 205, 208, 210, 217, 219, 222, and 228 include severe baseline drifts and abrupt changes. Records 201, 202, 203, 219 and 222 exhibit various irregular rhythmic patterns. Records 201, 219 and 232 include long pauses up to 6 s in duration. Records 108 and 222 contain tall sharp P waves. Record 113 has tall sharp T waves. For these ECG recordings, the number of false positive detections is more in all the algorithms. Records 200, 203 and 233 contain multiform ventricular arrhythmia, negative QRS polarity and sudden changes in QRS morphology. Record 208 has wider premature ventricular contractions (PVCs). Record 223 exhibits sudden changes in QRS amplitudes Records 116 and 208 contain smaller QRS complexes than the others. Cu01, cu03 signals are from Creighton University arrhythmia databases.

The sensitivity and positive predicted values are calculated for proposed and PCA method significant improvement is observed and tabulated in Table I

Table I Accuracy Analysis for AEA wave Detection

Test database														
Method			*SUMER*						*Synthetic AEA*					
Threshold Type			Fixed		Adapted				Fixed		Adapted			
Rhythm case	No of patients	No of waves	Se(%)	p	Se(%)	P	Se(%)	P	Se(%)	P	Se(%)	P	Se(%)	P
Sinus rhythm	9	1,142	98.82	47.05	98.21	62.33	97.76	72.11	98.777	54.35	98.48	73.51	98.18	83.79
Artial Tachysardia	10	2,356	82.49	83.57	87.26	78.75	87.26	78.75	90.34	97.81	94.12	96.95	93.98	96.94
AVRT	10	1,476	88.3	87.3	92.07	82.2	92.01	82.2	92.07	82.2	95.35	97.55	97.83	93.69
AVNRT	3	210	89.86	75.32	92.18	67	92.18	67.43	96.43	96.47	97.69	93.26	97.69	93.63
PVC	6	936	84.98	72.03	91.18	80.05	72.08	81.38	86.61	77.56	90.52	83.86	73.73	87.23
Pac	4	341	95.19	46.84	94.2	42.54	91.07	75	97.62	50.37	97.62	44.62	93.33	82.01
Total	42	6,461	88.59	81.97	88.13	81.97	81.76	83.96	92.09	90.41	92.21	86.44	94.99	94.32

.

IV.CONCLUSIONS

ECG signal analysis is used to diagnosis and detects arrhythmias in human. AEA waves play a vital role in detection of arrhythmias [7]. When ECG signal is acquired in noisy conditions (due to external radiations) AEA waves cannot be accurately extracted (because AEA waves are hidden in other waves) [4].To extract AEA waves precisely for further arrhythmia diagnosis we use SUMER method based on band pass filtering and threshold based segmentation and synthetic extraction based on minimum MSE value. This method may serve as a non-invasive tool for physicians to detect AEA, as a crucial step toward arrhythmia [16] diagnosis. It may facilitate patient diagnosis and treatment at

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 10, October 2015

earlier stages, thereby greatly diminishing the risk of future major health implications. This relatively fast and uncomplicated technology may be applied in medical centres diagnostic ECG instruments.

REFERENCES

[1] Wattigney WA, Mensah GA. Croft JB.. Increased atrial fibrillation mortality: United States, 1980-1998. Am J Epidemiol 2002; 155: 819–826.
[2] Oral H. Atrial fibrillation: mechanisms, features, and management," In: D.P. Zipes and J. Jalife, editors. Cardiac Electrophysiology, from cell to bedside. 5th ed. Philadelphia, Saunders Elsevier; 2009. p. 577.
[3] Atienza F, Almendral J, Jalife J, Zlochiver S, Ploutz-Snyder R, Torrecilla EG, Arenal A, Kalifa J, Fernandez-Aviles F, Berenfeld O. Real-time dominant frequency mapping andablation of dominant frequency sites in atrial fibrillation with left-to-right frequency gradients predicts long-term maintenance of sinus rhythm. Heart Rhythm 2009; 6:. 33- 40.
[4] Lim KT, Knecht S, Wright M, Haissaguerre M. Atrial substrate ablation in atrial fibrillation. In: D.P. Zipes and J. Jalife, editors. Cardiac Electrophysiology, from cell to bedside. 5th ed. Philadelphia, Saunders Elsevier; 2009. p. 1059.
[5] Mandapati R, Skanes A, Chen J, Berenfeld O, Jalife J. Stable microreentrant sources as a mechanism of atrial fibrillation in the isolated sheep heart. Circulation 2000;.101: 194-199.
[6] Tanaka K, Zlochiver S, Vikstrom KL, Yamazaki M, Moreno J, Klos M, Zaitsev AV, Vaidyanathan R, Auerbach DS, Landas S, Guiraudon G, Jalife J, Berenfeld O, Kalifa J.
Spatial distribution of fibrosis governs fibrillation wave dynamics in the posterior left atrium during heart failure. Circ Res 2007; 101: 839-847.
[7] Sachse FB, Moreno AP, Seemann G, Abildskov JA. A model of electrical conduction in cardiac tissue including fibroblasts. Ann Biomed Eng 2009;37: 874-89.
[8] Courtemanche M. Ramirez RJ, Nattel S. Ionic mechanisms underlying human atrial action potential properties: insights from a mathematical model. Am J Physiol 1998;275: H301-
21.
[9] Kneller J, Zou R, Vigmond EJ, Wang Z, Leon LJ, Nattel S. Cholinergic atrial fibrillation in a computer model of a twodimensional sheet of canine atrial cells with realistic ionic properties. Circ Res 2002;. 90: E73-87.
[10] MacCannell KA, Bazzazi H, Chilton L, Shibukawa Y,. Clark RB, Giles WR. Mathematical model of electrotonic interactions between ventricular myocytes and fibroblasts. Biophys J 2007;92:4121–4132
[11] Goldman MJ (1986): *Principles of Clinical Electrocardiography*, 12th ed., 460 pp. Lange Medical Publications, Los Altos, Cal. Macfarlane PW, Lawrie TDV (eds.) (1989): *Comprehensive Electrocardiology: Theory and Practice in Health and Disease*, 1st ed., Vols. 1, 2, and 3, 1785 pp. Pergamon Press, New York.
[12] F. Portet, "Pwave detectorwith PP rhythm tracking: Evaluation in different arrhythmia contexts," *Physiol. Meas.*, vol. 29, no. 1, pp. 141–155, Jan. 2008.
[13] C. Lin, C. Mailhes, and J.-Y. Tourneret, "P and T-wave delineation in ECG signals using a Bayesian approach and a partially collapsed Gibbs sampler," *IEEE Trans. Biomed. Eng.*, vol. 57, no. 12, pp. 2840–2849, Dec. 2010.
[14] D. Goldwasser, A. Bay´es de Luna, G. Serra, R. Elos´ua, E. Rodriguez, J. M. Guerra, C. Alonso, and X. V. Prat, "A new method of filtering T waves to detect hidden P waves in ECG signals," *Europace*, vol. 13, no. 7, pp. 1028–1033, Jun. 2011.
[15] M. Stridh and L. S¨ornmo, "Spatiotemporal QRST cancellation for analysis of atrial fibrillation," *IEEE Trans. Biomed. Eng.*, vol. 48, no. 1, pp. 105– 111, Jan. 2001.
[16] D. Rainde, P. Langley, A. Murray, A. Dunuwille, and J. P. Bourke, "Surface atrial frequency analysis in patients with atrial fibrillation: a tool for evaluating the effects of intervention," *J. Cardiovasc. Electrophysiol.*, vol. 15, no. 9, pp. 1021–1026, Sep. 2004.
[17] J. J. Rieta, F. Castells,C. Sanchez,V. Zarzoso, and J.Millet, "Atrial activityextraction for atrial fibrillation analysis using blind sourceseparation," *IEEE Trans. Biomed. Eng.*, vol. 51, no. 7, pp. 1176–1186, Jul. 2004.

BIOGRAPHY

B.Madhan Mohan(1) completed his B.Tech in Electronics and Communication Engineering at Vemu Institute of Technology (VEMU), JNTU-A, Chittoor, INDIA in 2012. He is pursuing his M.Tech Degree with specialization of Communication Systems (CS) at Sri Venkateswara University College of Engineering (SVUCE), S.V.University, Tirupati, INDIA. His areas of interest include Antennas, RF and Microwave components.

Dr. G. Umamaheswara Reddy(2) received B.Tech degree in Electronics and Communication Engineering and M.Tech degree in Instrumentation & Control Systems and obtained Ph.D. from Sri Venkateswara University, Tirupati in 1992, 1995, and 2013 respectively. He is a member in ISTE, IE, and BMSI. Currently, he is working as Associate Professor in the Department of Electronics and Communication Engineering, Sri Venkateswara University, Tirupati, Andhra Pradesh, India.