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Reduction Noise of ECG Signal Using Extended Kalman Filter

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***Abstract*-The Electrocardiogram (ECG) signal is one of the recognizing approaches to discover heart disease. One of the major difficulties in biomedical data processing like electrocardiography is the separation of the original signal from noises affected by body movement and respiration, electromagnetic field, power line and high frequency interference. Various methods of digital filters are exploited to delete signal parts from unnecessary frequency ranges. It is hard to use filters with constant coefficients to reduction random noises, as human behavior is not accurate known depending on the time. Adaptive filter method is needed to overcome this difficulty. In this paper the Extended Kalman Filter is applied and proposed for ECG signal modeling and noise reduction, the results of simulations in Maltab are presented. The results show that the EKF output is capable to track the original ECG signal form even in the noisiest period of the ECG signal.**

Keyword-ECG signal, Extended Kalman Filter, Denosing, noise reduction, ECG simulator.

I. INTRODUCTION

The electrocardiogram demonstrated the electrical activity in the heart, when an ECG is recorded, it may be contaminated with various kinds of noise. Hence, extraction of pure cardiological indices from noisy measurements has been one of the important concerns of biomedical signal processing and needs reliable techniques to maintain the diagnostic information of the recorded signal [1], [2].

On the other hand, ECG simulator is to generate the typical ECG waveforms of different leads and many arrhythmias possible.

The simulator has many benefits in the simulation of ECG waveforms. The important is saving of time and removing the difficulty of taking real ECG signals with invasive and noninvasive methods. The ECG simulator enables us to analyze and study normal and abnormal ECG waveforms without actually using the ECG machine.

A typical electrocardiographic lead is shown in Fig.1, where the shows significant and features of the waveform are the P, Q, R, S, and T waves, the duration of P,Q,R,S and T wave, and time intervals such as the P-R, S-T, and Q-T intervals. The Important features of this type simulator are: we can set any value of heart beat even intervals between peaks, amplitude. It can be simulate the fibrillation and noise due to electrodes and device. Heart pulse of ECG specific can be show in separate graph. About the simplicity and flexibility of this model it is believed that it can be easily adapted to a broad class of normal and abnormal ECG signals. This model may be further used in dynamic adaptive filters, such as the Kalman filter, for ECG filtering applications. In this paper, the *Extended Kalman Filter* (EKF) has been applied to noisy ECG data. The results represent that the offered method can totally track the ECG signal even in the period with a high level of noise, where the observed ECG signal is lost.

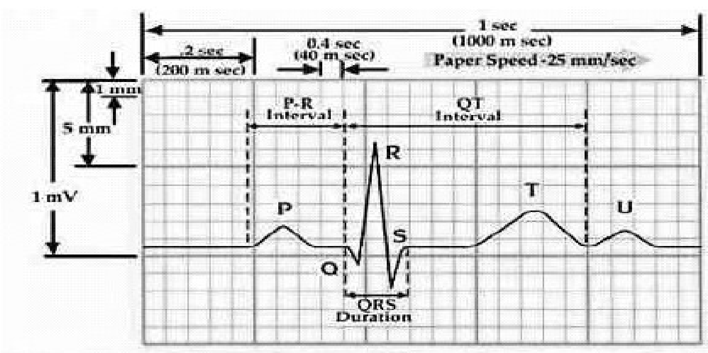

Fig.1 Typical ECG signal

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II. THEORY

A. *Extended Kalman filter review*

The *Extended Kalman Filter (EKF)* is a nonlinear extension of conventional Kalman Filter that has been specifically developed for systems having nonlinear dynamic models [3]. For a discrete nonlinear system with the state vector $\underline{x}_k$ and observation vector $\underline{y}_k$, the dynamic model may be formulated as follows:

$$\begin{cases} \underline{x}_{k+1} = f(\underline{x}_k, \underline{w}_k, k) \\ \underline{y}_k = g(\underline{x}_k, \underline{v}_k, k), \end{cases} \quad (1)$$

Where $\underline{w}_k$ and $\underline{v}_k$ are the process and measurement noises respectively with covariance matrices $Q_k=E\{\underline{w}_k\underline{w}_k^T\}$ and $R_k=E\{\underline{v}_k\underline{v}_k^T\}$.

The initial state estimate of the state $\underline{x}_0$ is defined as

$$\overline{\underline{x}}_0 = E\{\underline{x}_0\} \text{ with } P_0 = E\{(\underline{x}_0 - \overline{\underline{x}}_0)(\underline{x}_0 - \overline{\underline{x}}_0)^T\}.$$

In order to use a Kalman Filter formalism for this system, it is necessary to derive a linear approximation of (1) near a desired reference point (x_k, w_k, v_k) This

$$\begin{cases} \underline{x}_{k+1} \approx f(\hat{\underline{x}}_k, \hat{\underline{w}}_k, k) + A_k(\underline{x}_k - \hat{\underline{x}}_k) + F_k(\underline{w}_k - \hat{\underline{w}}_k) \\ \underline{y}_k \approx g(\hat{\underline{x}}_k, \hat{\underline{v}}_k, k) + C_k(\underline{x}_k - \hat{\underline{x}}_k) + G_k(\underline{v}_k - \hat{\underline{v}}_k) \end{cases} \quad (2)$$

Approximation will lead to the following linear estimate: Where

$$A_k = \left.\frac{\partial f(\underline{x}, \hat{\underline{w}}_k, k)}{\partial \underline{x}}\right|_{\underline{x}=\hat{\underline{x}}_k} \qquad F_k = \left.\frac{\partial f(\hat{\underline{x}}_k, \underline{w}, k)}{\partial \underline{w}}\right|_{\underline{w}=\hat{\underline{w}}_k}$$
$$C_k = \left.\frac{\partial g(\underline{x}, \hat{\underline{v}}_k, k)}{\partial \underline{x}}\right|_{\underline{x}=\hat{\underline{x}}_k} \qquad G_k = \left.\frac{\partial g(\hat{\underline{x}}_k, \underline{v}, k)}{\partial \underline{v}}\right|_{\underline{v}=\hat{\underline{v}}_k} \quad (3)$$

In order to implement the EKF, the time propagation is done using the original nonlinear equation, while the Kalman filter gain and the covariance matrix are calculated from the linearized equations. Further issues concerning the implementation of the EKF may be followed in [3], [4].

B. Synthetic ECG Generator

From Fourier series any periodic functions which satisfy dirichlet's condition can be expressed as a series of scaled magnitudes of sin and cos terms of frequencies which occur as a multiple of fundamental frequency.

$$f(x) = (a_o/2) + \sum_{n=1}^{\infty} a_n \cos(n\pi x / l) + \sum_{n=1}^{\infty} b_n \sin(n\pi x / l),$$

$$a_o = (1/l) \int_T f(x)\, dx \qquad , T = 2l \qquad (4)$$

$$a_n = (1/l) \int_T f(x) \cos(n\pi x / l)\, dx \qquad , n = 1,2,3\ldots. \qquad (5)$$

$$b_n = (1/l) \int_T f(x) \sin(n\pi x / l)\, dx \qquad , n = 1,2,3\ldots. \qquad (6)$$

ECG signal is periodic with fundamental frequency determined by the heartbeat. It also satisfies the dirichlet's conditions: single valued and finite in the given interval, absolutely integrable, finite number of maxima and minima between finite intervals, it has finite number of discontinuities, hence Fourier series can be used for representing ECG signal.

According the figure1, it shows that a single period of an ECG signal is a combination of triangular and sinusoidal waveforms. Each main specification of ECG signal can be represented by shifted and scaled versions one of these waveforms for examples: QRS, Q and S waves of ECG signal can be represented by triangular waveforms as shown in fig.3 and P, T and U waves can be represented by sinusoidal waveforms in fig.4 respectively.

Once it generates each of these waves, it can be added to finally get the ECG signal.

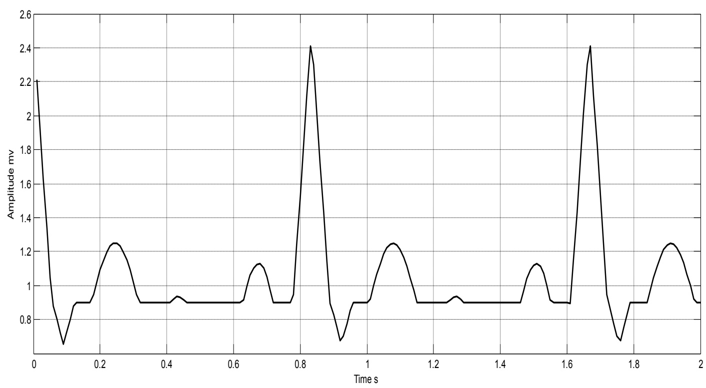

Fig 2.Synthics of ECG

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III. METHOD

A. Construction of the EKF Model

The relation across the states and measurements of the proposed EKF appertain on the place of the electrodes and the source of the measurement noise. For example bioelectrical artifacts, motion artifacts, environmental noises or such as the Electrogastrogram (EGG), the Electromyogram (EMG) or may be assumed as the measurement noises. While the measurement noise can usually take a nonlinear form and complex, the outcome of this paper are relying on a simple random noise. So describing the state vector $\underline{X}_k=[x_k\ y_k\ z_k]^T$, the observation may be depend to the state vector as follows:

$$s_k = [0 \quad 0 \quad 1]\underline{X}_k + v_k \quad (7)$$

With $R_k=E\{v_k v_k^T\}$. Note that in the case of a single channel observation R_k is a scalar value rather than a matrix. In the base of appraisal theory, the variance of the observation noise in (7) someway represents the degree of dependability of a single observation. In other hand, when a rather accurate measurement of the states of a system is credible the value of R_k is low, and the Kalman filter gain is adjust such as to rely on that particular measurement. While for the period that there are no measurements available or the measurements are too noisy, the value of R_k is high and the Kalman filter endeavor to follow its underlying dynamics rather than relying on the observations. This intuition about the observation noise will be further referred to in the following section.

B. ECG Model design

The simulated ECG signal prepares a quantitative analogy amongst the techniques. The simulate signal for a single beat is shown in fig.2.To generation QRS- waveform we use from Fourier series equation (4) and show in fig.3:

$$f(x) = (-bax/l) + a \qquad 0 < x < (1/b)$$
$$= (bax/l) + a \qquad (-1/b) < x < 0$$

$$a_o = (1/1)\int_T f(x)\,dx$$
$$= (a/b) * (2 - b)$$

$$a_n = (1/1)\int_T f(x)\cos(n\pi x / l)\,dx$$
$$= (2ba / (n^2\pi^2)) * (1 - \cos(n\pi/b))$$

$$b_n = (1/1)\int_T f(x)\sin(n\pi x / l)\,dx$$
$$= 0 \text{ (because the waveform is a even function)}$$

$$f(x) = (a_o/2) + \sum_{n=1}^{\infty} a_n \cos(n\pi x / l)$$

And also we can generate P-wave from Fourier series equation (4) and show in fig.4:

$$f(x) = \cos((\pi bx)/(2l)) \qquad (-l/b) < x < (l/b)$$

$$a_o = (1/1)\int_T \cos((\pi bx)/(2l))\,dx$$
$$= (a/(2b))(2-b)$$

$$a_n = (1/1)\int_T \cos((\pi bx)/(2l))\cos(n\pi x / l)\,dx$$
$$= (((2ba)/(i^2\pi^2))(1-\cos((n\pi)/b)))\cos((n\pi x)/l)$$

$$b_n = (1/1)\int_T \cos((\pi bx)/(2l))\sin(n\pi x / l)\,dx$$
$$= 0 \text{ (because the waveform is a even function)}$$

$$f(x) = (a_o/2) + \sum_{n=1}^{\infty} a_n \cos(n\pi x / l)$$

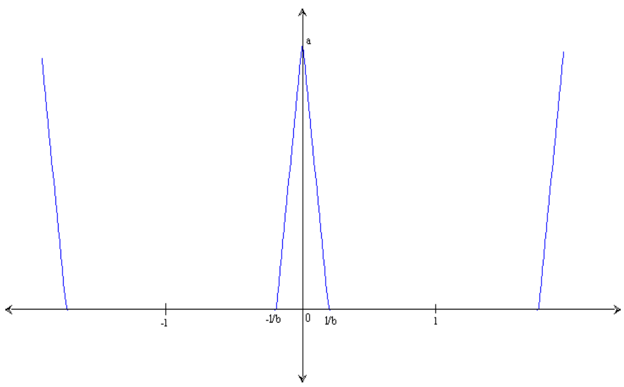

Fig.3 Generating QRS waveform

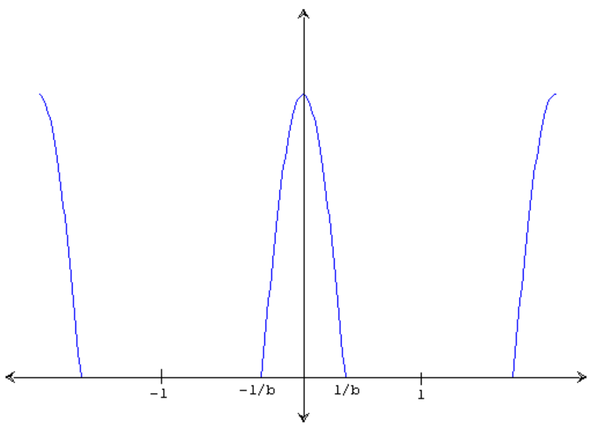

Fig.4 Generation of P-wave

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IV. RESULT

The proposed EKF model was finally implemented in Maltab®. The noisy ECG signal consisted of a random noise. Fig.5 and fig.6 shows the typical results noisy ECG signal and denoising ECG signal with Extend Kalman Filter. It can be seen that the method successfully modeled the ECG signal and removed noise. In fig.7 we show the corresponding errors, where we note declare that the error after denoising is smaller than error before denoising, which corroborate the performance of EKF in synthetic ECG denoising.

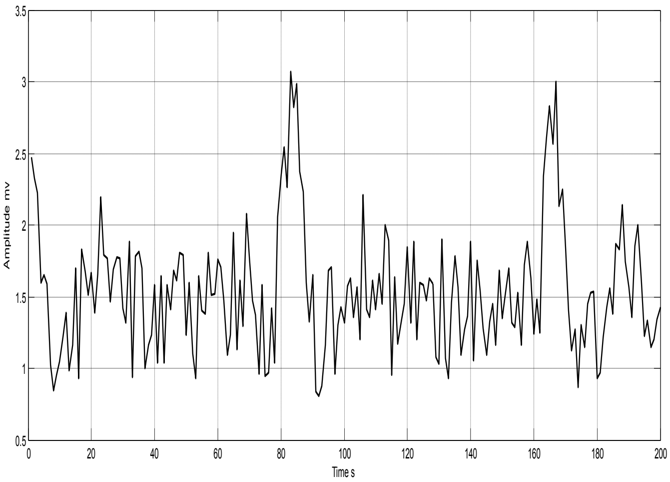

Fig.5 Noisy ECG Signal

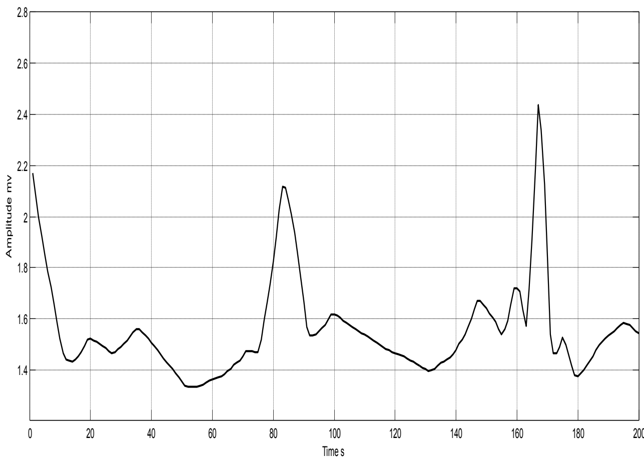

Fig.6 Denoising ECG Signal

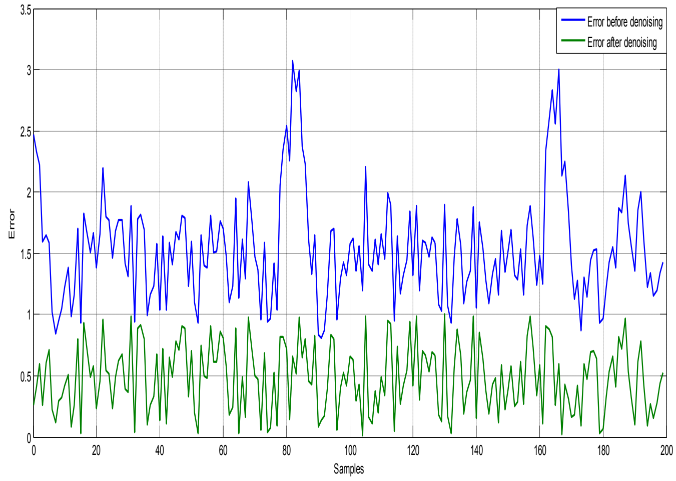

Fig.7 Comparison Error before and after denoising

V. CONCLUSION

In this paper, a simulated ECG signal with noise is introduced by using Extended Kalman Filter .As shown in Fig.8 the proposed method contain a good efficiency. Noisy data was simulated by adding random noise data, and result of Error before and after denoising in Fig.7.Extended Kalman Filter is a robust model for ECG denoising, hence the proposed method possesses high efficiency even in noisy data. As can be seen from Fig.8, the proposed method propositions a better efficiency with noisy data in comparison to existing methods.

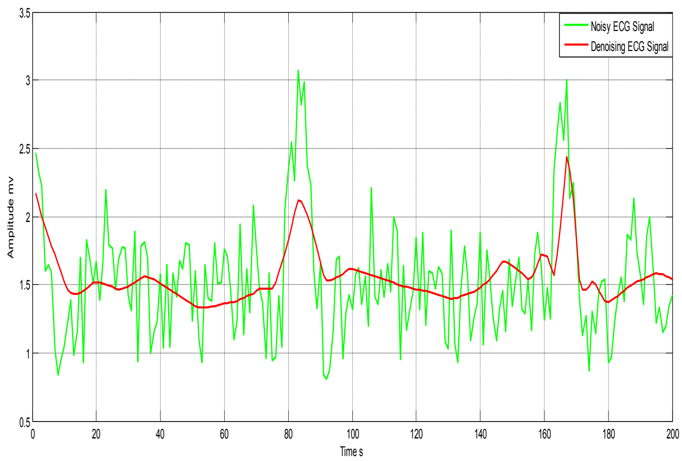

Fig.8 Comparison noisy and denoising ECG signal using EKF

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REFERENCE

[1] R.M.Rangayyan, Biomedical Signal Analysis: A Case-Study Approach, New York, NY: Wiley, 2002.

[2] W.J Tompkins, Biomedical Digital Signal Processing: C Language Examples and *Laboratory Experiments for the IBM PC,* Englewood Cliffs, NJ: Prentice Hall PTR, 1993.

[3] Kay SM. Fundamentals of Statistical Signal Processing: Estimation Theory. Prentice Hall PTR: 1993.

[4] Grewal MS, Andrews AP. Kalman Filtering: Theory and Practies Using Matlab®, 2nd ed.John Wiley &Sons Inc: 2001.

[5] Ouali, M.A. ; Chafaa, K. ; Ghanai, M. ; Lorente, L.M. ; Rojas, D.B. "Denoising ECG signal using Extended Kalman Filter" . Conference on Computer Applications Technology (ICCAT), 2013 International. Publication Year: 2013 , Page(s): 1 – 6.

[6] R Sameni, MB Shamsollahi, C Jutten, M Babaie-Zadeh, "Filtering Noisy ECG Signals Using the Extended Kalman Filter Based on a Modified Dynamic ECG Model" Computers in Cardiology, Publication Year: 2005 , Page(s): 1017 - 1020 .

[7] Omid Sayadi, Reza Sameni, Mohammad B. Shamsollahi," ECG Denoising Using Parameters of ECG Dynamical Model as the states of an Extended Kalman Filter"Engineering in Medicine and Biology Society. Publication Year: 2007 , Page(s): 2548 – 2551.

[8] Omid Sayadi,Mohammad Bagher Shamsollahi,"ECG Denoising and Compression Using a Modified Extended Kalman Filter Structure".IEEE Transaction on Biomedical Engineering,VOL.55.NO.9.Septemeber 2008.

[9] Morteza Eahi Naraghi, Ali Almasi, Mohmmad Bagher Shamsollahi "Human Identification Using ECG Feature Extracted from Innovation of Extended Kalman Filter" Biomedical Engineering and Informatics (BMEI), Conference on 2012 5th International , Publication Year: 2012 , Page(s): 545 – 549.

[10] Nagendra Sen , Chinmay Chandrakar," Development of a Novel ECG signal Denoising System Using Extended Kalman Filter "International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering.vol.3, Issue 2, February 2014.

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