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Noise Removal in EMG Signal Using Data Fusion Techniques

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ABSTRACT

One of the main challenges in processing the biomedical signals, such as ECG , EEG and EMG is noise removal as they are easily get affected by various noises arising from different environmental conditions. Filtering out the noise from EMG signal improves the accuracy and performance of signal processing systems. But in practice, it is very complicated to filter out noise from the desired EMG signals to obtain noise corrupted raw signal. This paper proposes a new data fusion techniques to reduce the effect of noise on electromyography signals, that are to be further processed to get the required information. The proposed method results in EMG signal enhancement when a corrupted emg signal with an additive white Gaussian noise is the only available information. The main idea is to utilize the kalman filter to remove the noise and enhance the performance of electromyography signals.
Keywords: EMG, Datafusion, Kalman Filter.

I. INTRODUCTION

The bioelectric potentials related with muscle action constitute the Electromyogram (EMG). These potentials possibly measured at the surface of the body near a muscle of concern or directly from the muscle by penetrating the skin with needle electrodes. while most EMG measurements are estimated to achieve an indication of the amount of action of a given muscle, or group of muscles, rather than that of an individual muscle fiber, the pattern is usually a summing up the individual action potentials from the fibers constituting the muscle or muscles being measured. EMG electrodes lift up potentials from all muscles within the range of the electrodes, and so potentials from nearby large muscles may hold up with attempts to measure the EMG from smaller muscles, although the electrodes are placed directly over the small muscles. The action potential of a given muscle (or nerve fiber) has a predetermined magnitude, apart from the concentration of the stimulus that generates the response. Therefore, in a muscle, the concentration with which the muscle works does not enhances the net height of the action potential pulse but does increase the rate with which each muscle fiber and the number of fibers that are activated at any given time. The magnitude of the calculated EMG waveform is the immediate sum of all the action potentials generated at any given time. These action potentials happen in both positive and negative polarities at a given pair of electrodes, they sometimes add and at times cancel. Hence, the EMG waveform shows very much like a random-noise waveform, with the power of the signal a function of the amount of muscle activity and electrode position. EMG is used as a diagnostics tool for recognizing neuromuscular diseases. several methods have been studied in the past 3 decades to eradicate the noise from the emg signal [3], [5], [6].To eliminate the noise from emg signals, kalman filter is used. The Kalman Filter (KF) is a dominant tool in the analysis of the development of a dynamical model in time. The filter gives with a flexible manner to attain recursive evaluation of the parameters, which are most favorable in the mean square error sense. The properties of KF along with the simplicity of the derived equations make it precious in the investigation of signals.

The summary of the Kalman Filter, its properties and its applications is presented. More particularly, center on the application of Kalman Filter in the Electroencephalogram (EEG) processing, tackling development of Kalman Filter such as the Kalman Smoother (KS) in the time varying autoregressive model. This model can be represented in a state – space form and the employment of KF offers with an evaluation of the AR constraints which can be used for the evaluation of the dynamic signal. The KF is an estimator with attractive properties like optimality in the Minimum Mean Square Error (MMSE). Later than its discovery, this estimator has been used in several fields of engineering. These are as follows: control theory, communication systems, speech processing, biomedical signal processing, etc. The KF is not only an estimator but also a learning method. The observations are helpful to learn the states of the model. The Kalman Filter is also a computational tool and may exist some problems as a result of the finite precision arithmetic of the computers.

The paper is organized as follows: Section II, presents the system model and signal generation. The two fusion techniques are applied to EMG signals in the existence of failures while a comparative performance under simulated noise conditions is given in Section III. Finally, in the results, Performance of these algorithms are discussed.

II. SYSTEM MODEL

The processing scheme of the overall emg signal is seen in the below figure,

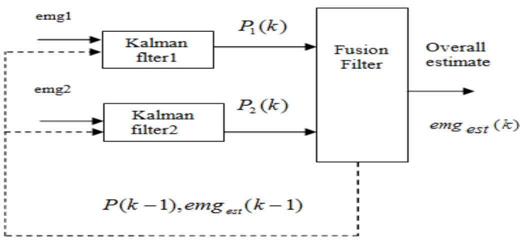
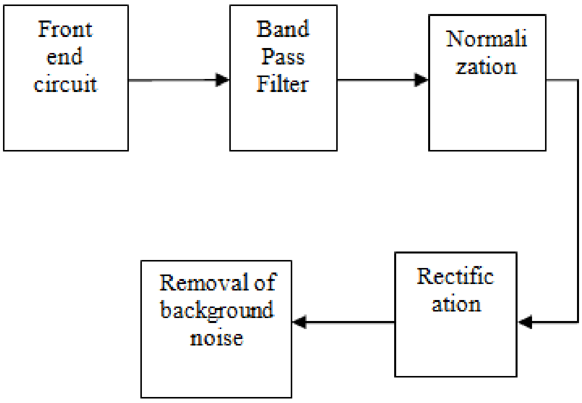


Fig.1. Outline of an overall fusion

In this two Emg signals were taken as the input signal to do the simulation. These two signals are obtained from adjacent muscles by two different electrodes.emg signals from the different electrodes are then fused using the variance weighted average to give the overall estimation of the signal.



Above figure shows the signal generation of Emg. EMG is presented as a time sequence, which must be mapped to a smaller dimension vector by the computation of several features leading to a muscle force estimator and input to the classifier. A wide spectrum of features can be found in the literature, computed either in the time or frequency domain, or both, as can be seen in [13] and the references therein cited. Time domain features are widely used due to computational simplicity and real-time control possibilities. For choosing the most adequate, the statistical set proposed by [8] was evaluated in terms of computational cost and repeatability.

III. METHODOLOGY

There are Two proposed algorithms were used: Variance Weighted Average (VWA) and Kalman Filter (KF). while the EMG signal recorded during voluntary dynamic contractions can be considered as a zero-mean Gaussian process, modulated by muscle activity and corrupted by a Gaussian additive white noise [2], its instantaneous transformation of variance produces an indicator of muscle activity as well as the existence of fault-induced noise. For this basis, the variance was chosen as weighting function. In what follows, $emg_m(k)$ indicates the value of the EMG signal in channel *i* at the time of step *k*. With this value, the recursive computation of the instantaneous temporal mean (average) signal $emg_m(k)(k)$ and the instantaneous variance $\sigma^2_{emg_m}(k)(k)$ was calculated for each sample time,

$$\overline{emg_m}(k) = \overline{emg_m}(k-1) + \frac{1}{k}(\overline{emg_m}(k) - \overline{emg_m}(k-1)) \qquad (1)$$

$$\sigma^2_{emg_m}(k) = \sigma^2_{emg}(k-1) + \frac{1}{k}\left([emg_m(k) - \overline{emg_m(k)}]^2 - \sigma^2_{emg_m}(k)\right) \quad (2)$$

A. Variance Weighted Average

A modified average was used in the first algorithm that is,

$$VWA(k) = w_0(k)emg_1(k) + w_1(k)emg_2(k) \quad (3)$$

where signal weights are represented as $w_0(k)$ and $w_1(k)$ respectively, and represents the normalized coefficients, which are variable with the variance of the signals $\sigma^2_{emg_1}(k)(k)$ and $\sigma^2_{emg\,2}(k)(k)$ in the time step *k*,

$$w_0(k) = \frac{\sigma^2_{emg_1}(k)}{\sigma^2_{emg_1}(k) + \sigma^2_{emg\,2}(k)}, w_1(k) = \frac{\sigma^2_{emg_1}(k)}{\sigma^2_{emg_1}(k) + \sigma^2_{emg\,2}(k)} \quad (4)$$

where co-efficients $w_0(k)$ and $w_1(k)$ satisfy the ewfollowing conditions,

$0= w_0(k)$, $w_1(k) = 1$

$w_0(k) + w_1(k) = 1$

To understand this concept, we give an analytical example, i.e.,

If $\sigma^2_{emg_2}(k) >> \sigma^2_{emg_1}(k)$ then VWA(k) $\cong emg_1$

If $\sigma^2_{emg_2}(k) \approx \sigma^2_{emg_1}(k)$ then VWA(k) $\cong \frac{emg_1 + emg_2}{2}$

A. Kalman filter

The Kalman filter processes data from many electrodes to provide a total state estimation in multi-sensor fusion. The Kalman filter can be used to combine or fuse information from different media or sensors and it is one of the Stochastic estimation tools. The Kalman Filter (KF) produces the overall estimate by reducing the variances [6]. Theoretically, in the system there is no performance loss, it delivers the same results as the centralized kalman filter, but the benefits of the KF are the modular concept that allows to add more sensors to the system, as needed, and an easier parallel implementation [2].

Figure 1 summarizes the concept of a KF, where the local filter outputs converge to the overall fusion filter via the respective variance and the estimated local outputs. In fact, as mentioned above, many local filters can be added as needed, and always the data are fused at the final filter.

As in the previous algorithm, the instantaneous variance is the decision parameter. Therefore, instantaneous mean and variance must be recursively computed with equations (1) and (2), thereafter; these values are inserted in the local filter (6). Finally, the vectors are fused in the overall filter (8), according to the procedure described by Soria et al. [4].

Based on the information available from *emg*1(*k*) and *emg*2(*k*) , each kalman filter produce estimates (*k*) using the standard Kalman Filter equations. The Fusion Filter block fuses these estimates together to form the overall state estimate $emg_{est}(k)$.

$$P_m^{-1}(k) = P_m^{-1}(k-1) + (\sigma_m^2)^{-1} \quad (5)$$

$$emg_{est_m}(k) = P_m(k)\left(P_m^{-1}(k-1)emg_{est_m}(k-1) + (\sigma_m^2)^{-1} emg_m(k)\right) \quad (6$$

$$P^{-1}(k) = P^{-1}(k-1) + \sum_{m=1}^{n} P_m^{-1}(k) - P_m^{-1}(k-1) \quad (7)$$

$$emg_{est}(k) = P(k)(P^{-1}(k-1)emg_{est}(k-1) + \sum_{m=1}^{n} P_i^{-1}(k)emg_{est_m}(k) -$$

$$P_m^{-1}(k-1)emg_{est_m}(K-1)) \quad (8)$$

where *m* represents the local filter, *n* is the number of local filters, P_m stands for the local variance, (*k*) is the filtered (estimated) signal, *P* represents the global variance, and $emg_{est}(k)$ describes the global estimated vector.

IV. RESULTS

To achieve the aim of this paper the simulation is written in matlab. In this paper EMG signal is added with additive white Gaussian noise is chosen for simulation. Two emg signal from same muscle using different is taken for this experiment. Below figures shows that the fusion techniques of kalman filter and variance weighted average produces a more precise estimation of emg signal from the input signal by filtering out additive white Gaussian noise.

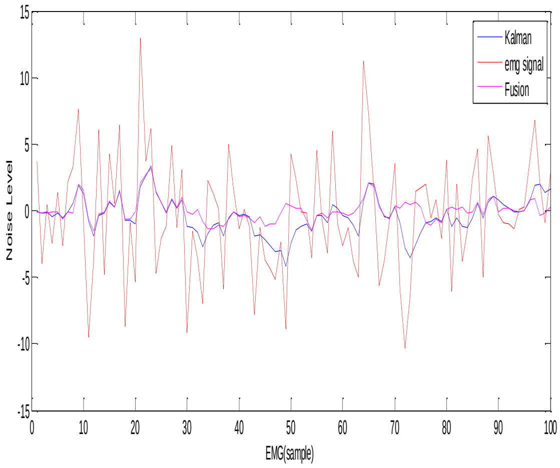


Fig. 3. First emg signal compared against fusion results

From figure (3), the first emg signal is compared with the kalman filter and fusion results, thus reduces the noise level. A graph will be drawn against the emg signal samples and the noise variance.

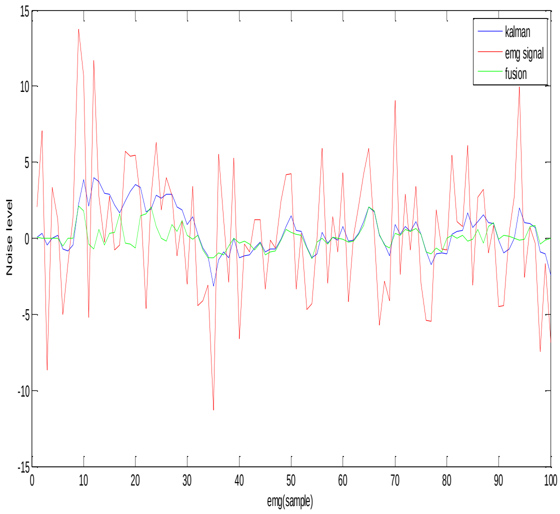


Fig. 4 . second emg signal with kalman filter and fusion.

Fig. 4. shows the second emg signal with the kalman filter and fusion results. Here, we have seen the fine difference between before and after the fusion. Kalman filter along with the variance weighted average method helps to remove the noise from the emg signal.

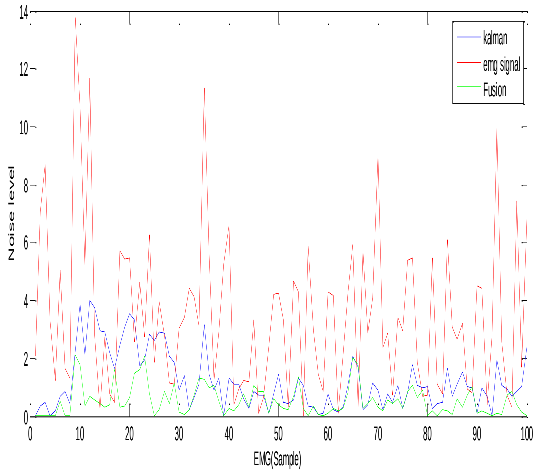


Fig. 5. Noise reduction using fusion at the positive co-Ordinates

From the above figure, it is shown that absolute values of signals have been taken with respect to the positive co-ordinates.

Table 1: Maximum absolute error for fusion algorithms,

When the EMG signals were corrupted by Gaussian white noise.

Noise Level	**White Gaussian Noise**	
	Before Fusion	***After fusion***
0,1	0,972	0,174
0,2	0,710	0,242
0,3	1,094	0,286
0,4	0,693	0,416
0,5	0,692	0,403

When the benefits of each algorithm are investigated, as in any robustness scheme, two aspects must be taken into account: noise sensitivity and computational cost. On one hand, VWA appears as more efficient due to its better sensitivity to noisy signals, but the KF algorithm is suggested in fusion where the signals come from sensors whose nature is different, like electrodes for electromyography, piezoelectric contact for mechanomyography, accelerometers for acceleromyography (AMG), and condenser microphones for phonomyography (PMG). On the other hand, the computational cost for both algorithms is the same, therefore, this is not a decision factor, and the choice would depend on the expected perturbations and the possibility of incorporating new sensors.

V. CONCLUSION

Two data fusion algorithms of EMG signals are proposed in this paper with the aim of improving performance of the emg signal. The main contribution of the work proposed here can be the improvement of emg signal under noisy conditions. The fact that two simple data fusion algorithms based on the variance analysis and without much computational cost were applied to EMG. The two algorithms used established an acceptable performance.

VI. REFERENCES

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