

Adaptive Laguerre Filters for Elimination of Power Line Noise from EMG Signals: Fixed and Fuzzy Step Size Approaches

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ABSTRACT:

Biomedical signals are always corrupted with different noises and interferences. Power Line Interference (PLI) is one of the most important interferences, which decreases the quality of the biomedical signals significantly. In this paper, a novel algorithm, based on adaptive IIR Laguerre filters has been proposed to eliminate the Power Line Interference (PLI) and its harmonics from Electromyography (EMG) signals. The proposed algorithm has used an internal mathematically constructed reference noise for the adaptive Laguerre filter, thus it is independent of the power line information to eliminate the noise. The Least Mean Square (LMS) algorithm with fuzzy step size has been used to optimize the filter weights which highly increase the filter performance. This proposed filter has consumed fewer computational load than adaptive FIR filters, and also it has shown better stability than IIR filters. Our practical experiments showed that our Laguerre structures could eliminate the PLI from EMG signals successfully and increased the SNR up to 12db that was more efficient than other adaptive algorithms.

KEYWORDS: Adaptive Laguerre Filters, EMG Noise Cancellation, Fuzzy Step Size.

1. INTRODUCTION

Power Line Interference (PLI) is an important unwanted factor that corrupts biomedical signals such as Electromyography (EMG) signals. The EMG signal is generated by the electrical activity within the muscle that passes through muscle fibers under contraction [1]. The signal sources are thus located at the depolarized zones of the muscle fibers [2].

The study of EMG signals is difficult because the signal to noise ratio of these signals is low, and the EMG signals are very low amplitude. On the other hand, since human body acts like an antenna, the EMG signals are corrupted by electromagnetic power line interference from environment [3, 4] and also this PLI is in the same frequency range of important EMG components.

Hence, the elimination of PLI from EMG signals in low SNRs is not only important, but also is a challenging task that many research have been focused on this problem [5]. The studies in this field may be categorized generally into non-adaptive and adaptive methods [6]. Adaptive techniques are preferred because the power line noise changes over the time, and

adaptive filters can perform satisfactorily in an environment where complete knowledge of the relevant signal characteristics is not available [7].

Different adaptive approaches have been proposed in the literature to attenuate this noise, such as: adaptive FIR notch filter [8], adaptive IIR notch filter [9], adaptive notch filter using Fourier transform [10], etc. Although these methods can attenuate the noise successfully, they have some problems such as high computational load, inadequate convergence rate and instability. In addition, some of the algorithms require a reference signal from power line noise.

In this paper, an adaptive IIR Laguerre filter is proposed to eliminate the PLI from EMG signal. This notch filter can decrease the numbers of mathematical operations and is suitable for practical implementations. Furthermore, the characteristics of Laguerre filter make it more stable than other IIR filters. In this work, the reference signal (i.e. 50/60 Hz PLI signal) for adaptive structure is not required. The reference noise and its harmonics are constructed mathematically and applied to adaptive structure. This decreases the complexity of hardware and eliminates the need to supplementary

electrodes that collect the noise reference. Moreover, a fuzzy system is used to choose the best step size of the adaptive algorithm to improve the filter performance.

The rest of this paper is organized as follows. First, the basic structure of Laguerre filter is described. Then, the theory of the application of adaptive Laguerre filter with fixed and fuzzy step size in noise elimination is explained. Next, our simulations and practical experiments in different scenarios are illustrated. Finally, conclusion will summarize the main results of the paper.

2. LAGUERRE FILTERS

2.1. Basic Laguerre Filter

Laguerre filter is a generalization of transversal filter and it has infinite impulse response. By choosing the proper position of the pole of the Laguerre filter, the approximation of systems with long impulse response can be achieved with a much smaller number of parameters than a transversal filter [11]. The basic Laguerre filter is shown in Fig.1. The Laguerre filter can be obtained from transversal filter by applying a single pole low-pass filter, $L_0(z)$, to the input signal and by replacing each delay of transversal filter by a first order all-pass filter, $L(z)$. The pole of all-pass filters are the same as the pole of low-pass filter. Therefore, the transfer functions of the low-pass filter, $L_0(z)$ and all-pass filters, $L(z)$, are given by:

$$L_0(z) = \frac{\sqrt{1-a^2}}{1-az^{-1}} \quad (1)$$

$$L(z) = \frac{z^{-1}-a}{1-az^{-1}}, |a| < 1 \quad (2)$$

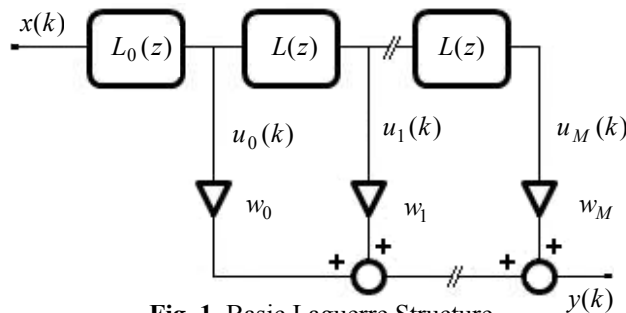


Fig. 1. Basic Laguerre Structure

where a is a real number that determines the position of the pole in Laguerre filter and its modulus should be smaller than one. The output of the Laguerre filter, $y(k)$ is a weighted linear combination of the outputs of the low-pass and all-pass filters represented by

$$y(k) = \sum_{m=0}^M w_m u_m(k) \quad (3)$$

where $\{u_m(k)\}_{m=0}^M$ and $\{w_m\}_{m=0}^M$ are the outputs of filters and their corresponding weight, respectively.

The transfer function of K cascaded section of Laguerre filter in Z space is given by [12]:

$$L_K(z, a) = \sqrt{1-a^2} \frac{(z^{-1}-a)^K}{(1-az^{-1})^{K+1}}, K=0,1,2,\dots \quad (4)$$

It can be shown, this Laguerre sequences form a complete ortho-normal set of Hilbert space. Each sequence of this set has rational Z-transform and it makes Laguerre filter very suitable for practical implementations. Laguerre filters are a kind of IIR filter with satisfactory stability behavior. This filter decreases the number of parameters for approximating systems with long impulse response.

2.2. Adaptive Laguerre Filter

The position of the pole or the weights of the Laguerre filter can be adaptively adjusted in many applications where complete knowledge of environment is not available. There are some methods to iteratively adapt the position of the pole in the literature [13]. However in this paper, the position of the pole was estimated empirically; also, the weights of the Laguerre filter are adaptively changed to track the dynamical behavior of the noise in the environment. A block diagram of adaptive Laguerre filter is shown in Fig. 2. The output of Laguerre filter, $y(k)$ is subtracted from desired signal, $d(k)$, and the error signal, $e(k)$, is formed. As shown in Fig.2 the error signal is used to adapt the weights.

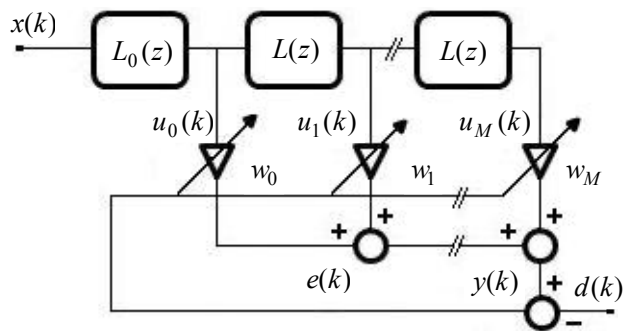


Fig. 2. Adaption of Laguerre Weights

The LMS algorithm is widely used for adapting the transversal structure weights. This algorithm is given by:

$$W(k+1) = W(k) + \mu U(k) e(k) \quad (5)$$

where μ is step size, $U(k)$ is the input vector and $e(k)$ is the error signal obtained from subtracting filter

output, $y(k)$, of desired signal, $d(k)$. The value of step size μ is very important to achieve good convergence rate and low steady state error. In this work we add an efficient fuzzy system to adjust this critical parameter.

3. PLI CANCELLATION OF EMG SIGNALS USING ADAPTIVE LAGUERRE FILTER

3.1. System Description

In this work the reference noise of PLI is not available; hence we construct it mathematically. Each section of Laguerre filter changes the phase of this constructed reference signal. Accordingly, an estimate of the PLI signal can be computed as the weighted linear combination of the outputs of the filters in the structure of the Laguerre filter. With proper adjusting of the positions of the pole and zero and using an adaptive algorithm, the optimum weights of the Laguerre filter are obtained. Consequently, the minimum error is achieved and noise is successfully removed.

The block diagram of proposed algorithm is shown in Fig.3. Here, $z(k)$ is the combination of the EMG signal and 50Hz PLI and its four harmonics (e.g. 100Hz, 200Hz, 300Hz, 400 Hz). The reference noise is constructed mathematically by:

$$\hat{PLI}_{ref} = \cos(2\pi 50t) + \cos(2\pi 100t) + \cos(2\pi 200t) + \cos(2\pi 300t) + \cos(2\pi 400t) \quad (6)$$

And is used as the reference input for adaptive Laguerre structure. This constructed reference noise must have correlation with the real power line interference. In eq.(6) $t = \frac{1}{F_s}$, where F_s is the sampling

frequency. As shown in Fig.3 this reference signal is processed by adaptive Laguerre filter and the output, y , which is similar to real PLI, is obtained. This output is subtracted from noisy EMG signal, Z , to achieve error signal (cleaned EMG signal). LMS algorithm uses this error signal to adapt Laguerre weights for best cancelling of non stationary PLI.

To guarantee the stability of LMS algorithm the step size, should satisfy the following constraint:

$$0 < \mu < \frac{2}{\lambda_{\max}} \quad (7)$$

where λ_{\max} is the maximum eigenvalue of the Laguerre sections outputs covariance matrix. Although by choosing the μ in this interval the LMS algorithm is guaranteed to be stable, many important factors in the algorithm such as convergence rate and steady state error is affected by μ ; that is, large μ causes fast convergence of algorithm and high steady state error while small μ causes the slow convergence and small

steady state error. Therefore, choosing the optimal step size in each time plays a crucial role in the overall performance of the algorithm.

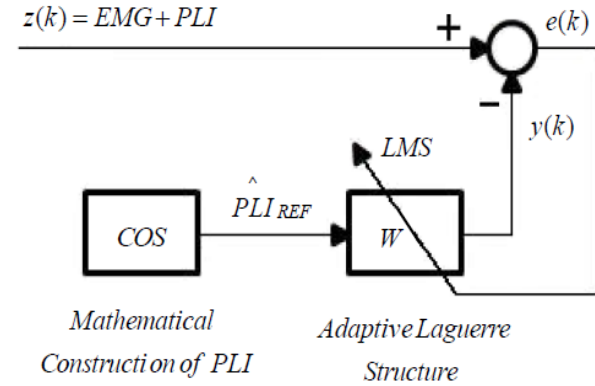


Fig. 3. PLI Elimination of EMG Signal Using Adaptive Laguerre Filter

3.2. Determination of Laguerre Pole Position

A Laguerre filter with a complex pole for its sections is called Kautz filter. In the first approach of this work we consider different complex poles for Laguerre filter sections which are placed between basic noise frequency and its harmonics 75,150,250,350 Hz empirically. If we consider the complex pole $p = a + bi$, then the transfer function of each all-pass filter is:

$$H(z) = \frac{z^{-1} - p^*}{1 - pz^{-1}} \frac{z^{-1} - p}{1 - p^*z^{-1}} \quad (8)$$

Which can be represented by an equivalent second order transfer function :

$$H(z) = \frac{z^{-2} - 2az^{-1} + a^2 + b^2}{(a^2 + b^2)z^{-2} - 2az^{-1} + 1} \quad (9)$$

The coefficients a and b must be chosen properly to place filter poles in desired frequencies. Following equations are used to obtain a and b :

$$\theta = \frac{2\pi f}{f_s} \quad (10)$$

$$a = \text{real}(R e^{i\theta}) \quad (11)$$

$$b = \text{imag}(R e^{i\theta}) \quad (12)$$

Which f is desired frequency, f_s is sampling frequency, and R and θ are modulus and phase of filter complex pole respectively.

3.3. Computational Complexity

The difference equations related to low-pass and all-pass filters in Eq.(1) and Eq.(2) are given by:

$$v_0(n) = a v_0(n-1) + \sqrt{1-a^2} x(n) \quad (13)$$

$$u_0(n) = a u_0(n-1) + x(n-1) - a x(n) \quad (14)$$

It can be seen that the number of real addition and real multiplications for each filter in Laguerre structure is 1 and 2, respectively. In first section of our work each of all-pass sections is constructed by cascading two first order transfer function; therefore, each filter needs 4 multiplication and 4 additions.

The number of multiplications needed for the linear combination the outputs of a low-pass and all-pass filters depends on the number of Laguerre layers. Hence, if a complex Laguerre filter has l all-pass sections, then the number of required additions and multiplications is:

$$\text{Number of multiplications} = l + 4l + 4 = 5l + 4 \quad (15)$$

$$\text{Number of additions} = l + 4l + 4 = 5l + 4 \quad (16)$$

For an adaptive FIR filter, the number of weights of the filter should satisfy the equation $N > f_s / f_{PLI}$, to eliminate the noise properly, where f_s is sampling frequency and f_{PLI} is the basic frequency of the noise [3]. In many applications, the sampling frequency of EMG signal should be high enough for analyzing the electrical activity of muscle properly. Often, f_{PLI} is low (50/60 Hz), and the FIR filter needs the number of signal samples that contains a period of basic frequency of PLI. For an FIR filter with l weights, the number of required multiplications and additions are l and $l-1$ respectively. IIR structure of Laguerre filter makes the filter length independent of a complete period of basic frequency of PLI. This means that Laguerre filter consumes less computational load than FIR filters.

Therefore, the number of required mathematical operations in our proposed method is significantly less than FIR filters and this makes our method suitable for practical implementations.

3.4. Fuzzy System for Choosing the Step Size

In the second approach of this study, a fuzzy system is used to continuously adjust the step size of the LMS algorithm during the adaption process to increase the performance of algorithm. Fig. 4 shows the block diagram of this system.

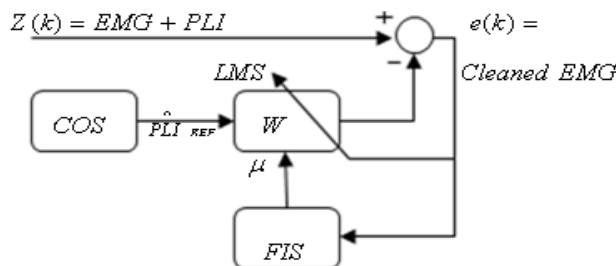


Fig. 4. The Proposed Algorithm Based on Laguerre Filter and Fuzzy Step Size for Cancelling the PLI

The proposed fuzzy system with one input and one output, uses $e(k)-e(k-1)$ as the input to compute the step size μ . This fuzzy system is a Mamdani-type fuzzy system which has easy to compute formulation and can be implemented easily. The basic materials for designing a Fuzzy Inference System (FIS) have been discussed in [14].

The proposed fuzzy system uses triangular membership functions for its input and output fuzzy sets, which are chosen empirically as follows:

Input Membership Functions:

$$mf1: [-5 -5 -3]; \quad mf2: [-3 -2 -1]; \quad mf3: [-1 -0.5 -0.04];$$

$$mf4: [-0.07 0 0.07]; \quad mf5: [0.04 0.5 1]; \quad mf6: [1 2 3];$$

$$mf7: [3 5 5]$$

Output Membership Functions:

$$mf1: [5e-6 5e-6 3e-5]; \quad mf2: [1e-5 5e-5 9e-5];$$

$$mf3: [8e-5 1e-4 2e-4]; \quad mf4: [1e-4 5e-4 5e-4]$$

The rules of the fuzzy system determine the appropriate output membership function based on which input membership function is fired by the input of fuzzy system. Table 1 present the rules of fuzzy system which determines the corresponding input and output membership functions in IF-THEN clauses for fuzzy inference engine.

Table 1. Specifying the Rules of Fuzzy System

Input MF	1	2	3	4	5	6	7
Output MF	1	2	3	4	3	2	1

4. EXPERIMENTS AND RESULTS

4.1. Experiments Setup

In this paper, an adaptive Laguerre filter with fixed step size and an adaptive Laguerre filter with fuzzy step size are used for cancelling power line interference and its harmonic from EMG signal. The EMG signals used in this research were gathered at Isfahan biomedical research center. These signals were obtained from biceps muscle of upper arm using surface electrodes and the sampling frequency is 10000Hz. The Signals are processed to obtain clean EMG signals and then simulated power line noise is added to them in different powers. Signal to noise ratio of cleaned EMG signals can be calculated by:

$$SNR = 10 \log \frac{\sum_{n=0}^N X^2(n)}{\sum_{n=0}^N (X(n) - X_f(n))^2} \quad (17)$$

Which $X(n)$ is the original clean EMG signal and $X_f(n)$ is the filtered EMG signal with added noise. The positions of the Laguerre poles are important in the performance of the filter and it can be chosen

empirically to achieve the best results. We selected different complex and real positions for the poles of low-pass and all-pass filters in Laguerre structure, empirically, because this approach resulted in a better performance than choosing one pole for all Laguerre sections.

A study of using Laguerre filter with different complex poles in PLI elimination has been proposed in [15].

4.2. Evaluation of Laguerre Filter with Fixed Step Size in PLI Elimination

In this experiment, we use an adaptive Laguerre filter with 10 all-pass sections to eliminate the PLI of EMG signal. The step size μ which is used for optimizing the Laguerre weights is chosen to be $6e-5$ empirically. The complex poles of the all-pass filters of the Laguerre filter are placed at frequencies 75,150,250,350 Hz. Also, the pole of the low-pass filter is placed on real axis with modulus 0.5.

The simulated power line noise is added to EMG signal to obtain the noisy EMG. The SNR of noisy EMG is -1 db. Fig.5 and Fig.6 show the noisy signal and the cleaned signal (i.e. the output of the system), respectively.

As it can be observed, the proposed structure can successfully eliminate the PLI noise. The signal to noise ratio of the cleaned EMG is increased to 10.9dB.

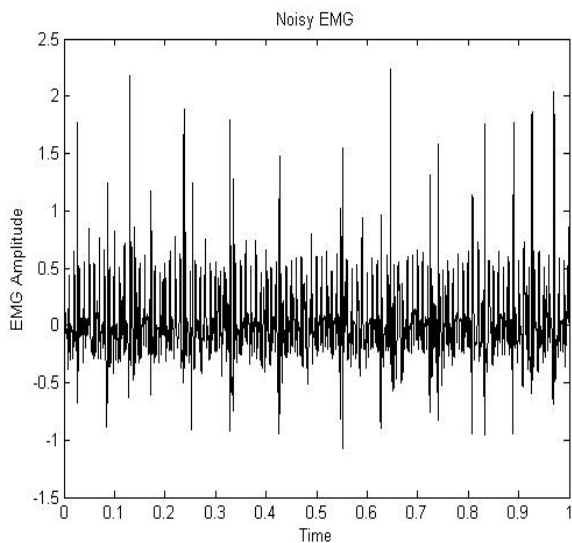


Fig. 5. Noisy EMG Signal

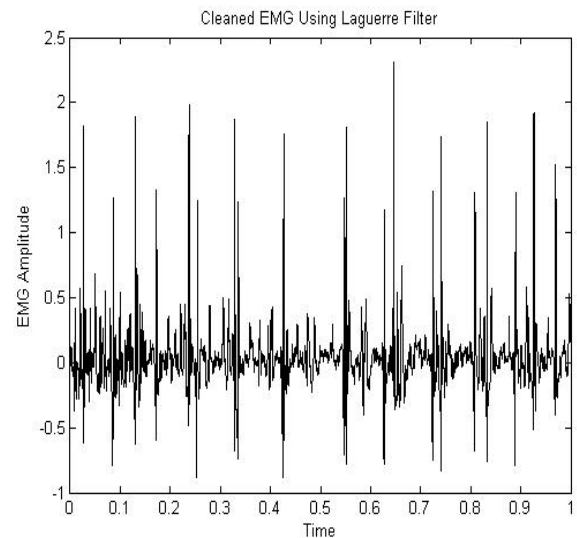


Fig. 6. Cleaned EMG Signal Using Laguerre Filter

4.3. Comparison of Laguerre and FIR Filters

To compare the efficiency of the proposed algorithm, we applied our proposed filter and an adaptive FIR notch filter to noisy EMG in different noise powers. This adaptive FIR notch filter has 45 weights which are combined with reference PLI samples. The LMS algorithm is used to optimize the FIR weights and the step size is chosen to be $1e-4$ empirically. The result is shown in Fig.7.

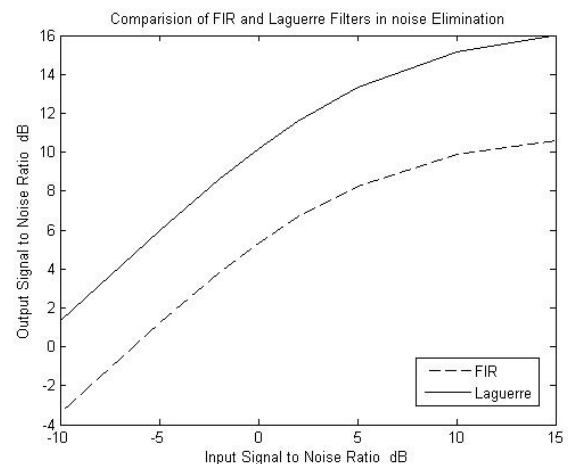


Fig. 7. Output SNR vs Input SNR for FIR and Laguerre Filters

Fig.7 shows the SNR improvement in both filters. It is clear that, the proposed Laguerre algorithm can attenuate noise power successfully, even in very low input SNRs.

This figure also shows that the SNR which is obtained by Laguerre algorithm is higher than that which is obtained by FIR filter. This means our proposed structure is more efficient in the elimination

of noise.

4.4. Comparison of Laguerre Filter with Fuzzy Step Size and Laguerre Filter with Fixed Step Size

In this experiment PLI was added to EMG signal in different powers and then they applied to two filters: 1) a simple Laguerre filter with fixed step size and 2) a Laguerre filter with fuzzy step size. Real positions are considered for the poles in both filters and the step size for the simple Laguerre filter is chosen to be $1.2e-4$. This value is chosen empirically for the step size because it leads to the best performance of filter with fixed step size.

The poles of both adaptive Laguerre filters were placed on real axis with modulus 0.5 for low-pass section and for all-pass sections the poles are chosen in positions: 0.2, 0.3, 0.5, 0.7 on real axis empirically.

Fig. 8 shows the SNRs of cleaned EMG signal versus different SNRs of Input Noisy EMG signal. It is clear that the proposed Laguerre filter with fuzzy step size is more efficient than the simple Laguerre filter with fixed step size.

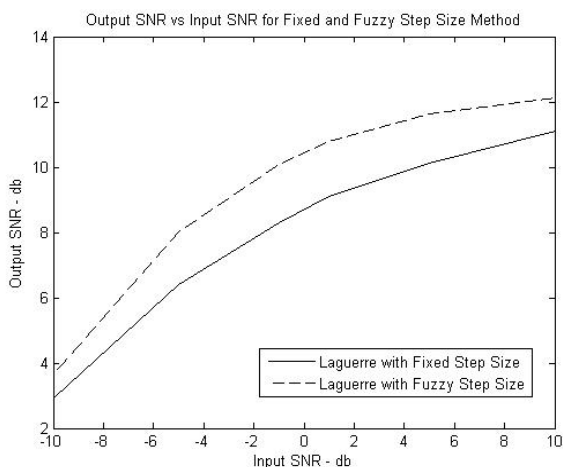


Fig. 10. Comparison of Laguerre Filter with Fixed and Fuzzy Step Size

4.5. Effect of Laguerre Filter Length on Its Performance

The effect of the length of the Laguerre filter in noise elimination process is investigated, here. For this purpose, a noisy EMG signal was applied to our Laguerre structure with different lengths. The SNR of input noisy EMG is chosen to be -1db. In this experiment the pole of all sections of the Laguerre filter is chosen to be the real number 0.5. Fig. 9 shows the result.

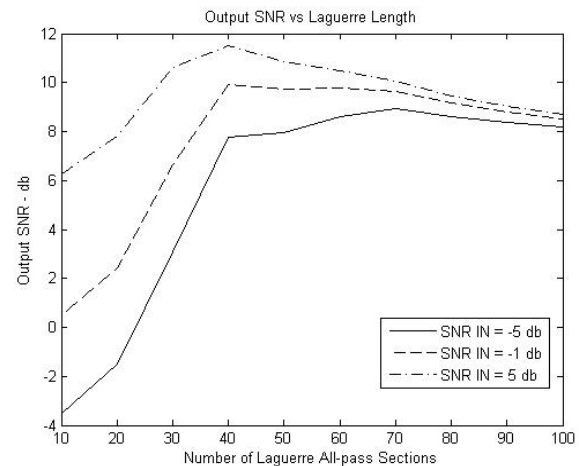


Fig. 9. Effect of Length of Proposed Laguerre Filter on Its Performance

It can be observed that the best performance is obtained in length 40.

During this test we realized that the optimum length of the filter depends on the SNR of the input signal. For example when the SNR of the input EMG is high (for example 10 db) the length which results the best performance is 30.

5. CONCLUSION

One of the principle problems in recording EMG signals is power line interference. Adaptive cancellation of this noise without changing the spectrum of EMG signals is a challenging problem. In this paper an adaptive Laguerre filter was proposed to eliminate the PLI noise from EMG signals. Comparing with IIR filters, the stability of the Laguerre filter is guaranteed; also, it is less complex than other FIR filters. Rational transfer function of Laguerre filter makes it suitable for practical implementations. In this paper we proposed an efficient Laguerre filter that can eliminate power line interference of EMG signals, successfully. This filter can increase SNR of EMG signal significantly without using any information about the power line interference. Moreover, Using a fuzzy strategy to change the step size dynamically made the system more efficient. We showed that the proposed structure can improve the SNR up to 10dB which is significantly more than adaptive FIR filters.

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