A GENETIC ALGORITHM BASED OPTIMIZATION OF EMG SIGNAL PERFORMANCE

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Abstract—
Genetic algorithm (GA) is a method that can be used to discover and manage a population of useful patterns in which this study implements; specifically, in optimization. This algorithm is a powerful tool to find the best solution in problems such as prediction and data fitting due to its ability for fast adaptation in the problem environment. Continuous or discrete parameters can be optimized by GA even without requiring derivative information by simultaneously searching from a wide sampling of the cost surface even if it deals with large number of parameters. The paper makes use of this algorithm to optimize the surface electromyography (SEMG) signal from the skeletal muscle force of a transradial amputee in controlling a surface myoelectric prosthesis. The SEMG signals patterns are acquired from the two devices: the microcontroller unit and the EMG simulator. The signals from these two devices are processed and optimized using GA. The optimized signal is used to test the surface myoelectric prosthesis. In this paper are obtain average error in result and simulation section. Now GA gives a better error reduction as compare to previous optimization approach.

Index Terms—Genetic algorithm, optimization, surface electromyography signal (SEMG), surface myoelectric prosthesis, T-test.
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I. INTRODUCTION

Limb amputation brings emotional and financial crisis along with the physical disability. It causes an inability to support oneself and the family. In India, nearly 1.4 million people are upper limb amputees and around 10,000 added each year [1].

The upper limb loss is mainly due to trauma with upper limb amputations and vascular disease accounted for the vast majority (68.6%) of all trauma-related amputations [2]. Upper limb amputation is mainly divided into four levels: below elbow, above elbow and elbow disarticulation, shoulder and hand/wrist. It is necessary to use an artificial limb for improving the Quality Of Life (QOL) of such people [3].

EMG SIGNAL CATEGORY

The development of interfaces that link the human musculoskeletal system with robotic devices has been a major area of research. Most of the research is focused on restoration of motor and sensory functions to those with degenerative diseases, injury or amputees. The basic goal is to enhance capability for independent living and vocational productivity by restoring the physical functionality through use of prosthesis [4].

II. NATURE OF EMG SIGNAL

The EMG signal, acquired using surface electrodes, measures the potential from some motor units. The magnitude of the MUAPs is directly related to the contraction of the muscles. The biological explanation for the generation of these potentials is called Sodium-Potassium bomb. When the motoneurone stimulates the contraction of the fiber, the membrane of this fiber changes its potential. This stimulus is transmitted across the membrane. The speed of transmission of this stimulus is called conduction speed [5].

The magnitude of the signal acquired using surface electrodes is from 0.1mV to 5 mV peak to peak. The frequency content range varies from 2 Hz to 10 kHz, but the most relevant information concerning the movement is below 500 Hz. However, the range of the magnitude and of the bandwidth of the EMG signal can be changed depending on the physiological, anatomical and biochemical characteristics of the muscle and the electrode configuration and location. An unfiltered and natural signal detecting the superposed MUAPs is known as a raw EMG Signal [6].

A more or less noise-free EMG baseline can be seen while relaxation of muscle. The raw EMG baseline noise depends on many aspects, especially the standard of the EMG amplifier, the atmosphere noise and the standard of the given recognition situation. The average baseline disturbance should not be more than 3mV to 5 mV and 1 mV to 2 mV should be the objective while supposing a state-of-the-art amplifier efficiency and appropriate skin planning. The research of the EMG baseline quality is a very important aspect of every EMG statistics [7].

III. FACTORS AFFECTING THE MEASURED EMG

In measuring an EMG signal there are two factors that affect the measured signal, namely: the recording apparatus used, and the physiological make-up. Physiological factors that are affecting the measured EMG signal are as follows [8]:

Fiber distribution

It is important to consider that the individual fibers are not usually located in close proximity to each other, but are spread throughout in the muscle. Due to different kinds of fibers being distributed throughout the muscles, recording electrodes pick up signals from many different fibers and from different motor units that are firing asynchronously [9].

Fiber diameter

The diameter of a muscle fiber has a direct effect on the conduction velocity of the MUAP (Motor Unit Action Potential). Conduction velocity is directly proportional to the fiber diameter which means larger fibers have a greater conduction velocity, and hence the MUAP travels faster, elongating the signal, increasing the wavelength, or dipole separation of the action potential[10]. The concept of wavelength, and dipole separation is useful when looking at the measurement of EMG using more than one electrode. When a measurement is made of several different muscle fibers all firing together, even if they are part of a single motor unit the variation in fiber diameter can have a marked effect on the signal. Fibre diameter variations in the order of 10 % change the phase relationship of Muscle fiber action potential (MFAP) with each other, subtracting instead of adding, and give the recorded EMG from the motor unit (MU) a poly phase nature [11].

IV. PREPROCESSING OF EMG SIGNALS

Small electrical voltages are produced by muscular tissues prior to the development of muscular power. These voltages are produced by the exchange of ions across muscular fibers membranes, a part of the signaling process for muscular tissues to contract. The signal called the electromyogram (EMG) can be measured by making use of conductive elements or electrodes to the surface of the skin, or invasively within the muscle. EMG signals can be used in various fields that may include clinical diagnosis, managing and controlling motor disability through rehabilitation engineering, biomedical applications, human machine interface systems, and interactive virtual-reality games even in many recreational and exercise equipment. EMG signal can also be used to find the cause of weakness, paralysis or muscle twitching and muscle disorders. Since EMG signals have noisy and sensitive characteristics so it is difficult to analyze and apply the EMG signal on above mentioned fields [12].

V. SIGNAL PROCESSING OF ELECTROMYOGRAPHY DATA

Raw sEMG data has a Gaussian distribution and must be processed to provide information useful for exposure estimation. There are currently no standards for processing electromyography data, and researchers must select processing techniques most relevant to their research aims. In occupational studies, the root-mean-square (RMS) amplitude of the raw sEMG signal is often utilized to compute estimates of muscular exertion intensity. During digital RMS processing of sEMG time series data, windowing parameters are selected and RMS values have been calculated from a specified number of continuous samples (window length), and windows overlap each other by specified number of samples (window overlap) for the entire time series. Therefore, sEMG data that are digitally RMS-processed are effectively down-sampled from the original sampling rate. For example, given raw sEMG data originally sampled at 1000 Hz RMS-processed with a 100 sample window length and a 90 sample window overlap, the processed data will have an effective sampling rate of 100 Hz. Depending on research objectives, alternative signal processing techniques may be employed. Spectral analysis is another technique utilized to summarize raw sEMG data, which examines sEMG in the frequency domain (as opposed to the time domain) [13].

CROSS TALK

The bipolar sEMG is not always a selective representation of the electrical activity of a single muscle directly underlying the recording electrodes. With smaller muscles the electrodes may overlook the electrical activity of one or more neighboring muscles and their signals may crosstalk with the sEMG from the desired muscle. While signal sources close to the electrode will dominate the recorded sEMG signal, more distant sources from other muscles may experience crosstalk. Radius about the electrode where the amplitude of signal contributions is larger than the standard deviation of the signal noise provides the distance for effective electrode measurement. As the distance from the recording electrode increases, the amplitude of the bipolar sEMG signal decays exponentially (Day, 1997). This is due to the fact that muscle fibres, subcutaneous fat and skin are anisotropic and act as a spatial filter with low pass frequency properties, where an increase in the distance between the muscle fibre and electrode increases the filtering effect [14].

VI. PROPOSED METHODOLOGY

In signal processing, a finite impulse response (FIR) filter is a filter whose impulse response (or response to any finite length input) is of finite duration, because it settles to zero in finite time. This is in contrast to infinite impulse response (IIR) filters, which may have internal feedback and may continue to respond indefinitely (usually decaying).[15]

The impulse response (that is, the output in response to a Kronecker delta input) of an Nth-order discrete-time FIR filter lasts exactly N+1 samples (from first nonzero element through last nonzero element) before it then settles to zero.

FIR filters can be discrete-time or continuous-time, and digital or analog [16].

FIR Properties

An FIR filter has a number of useful properties which sometimes make it preferable to an infinite impulse response (IIR) filter. FIR filters:

- Require no feedback. This means that any rounding errors are not compounded by summed iterations. The same relative error occurs in each calculation. This also makes implementation simpler [17].
- Inherent stability. This is due to the fact that, because there is no required feedback, all the poles are located at the origin and thus are located within the unit circle (the required condition for stability in a Z transformed system) [18].
- Phase Issue: can easily be designed to be linear phase by making the coefficient sequence symmetric; linear phase, or phase change proportional to frequency, corresponds to equal delay at all frequencies. This property is sometimes desired for phase-sensitive applications, for example data communications, crossover filters, and mastering.

Implementation issues

A digital IIR filter can generally approximate a desired filter response using less computing power than a FIR filter, however this advantage is more often unneeded given the increasing power of digital processors. The ease of designing and characterizing FIR filters makes them preferable to the filter designer (programmer) when ample computing power is available. Another advantage of FIR filters is that their impulse response can be made symmetric, which implies a response in the frequency domain that has zero phase at all frequencies (not considering a finite delay), which is absolutely impossible with any IIR filter [19].

The finite impulse response digital filter has the characteristics of absolute stability, and it is easy to design directly according to the impulse response technical conditions; it can achieve a symmetrical impulse response while approaching any amplitude characteristic; it can achieve strict linear phase characteristics. Because it has the above advantages, it is widely used in data communication and digital communication systems [20].

SIGNAL Optimization

In a genetic algorithm, a population of candidate solutions (called individuals, creatures, organisms, or phenotypes) to an optimization problem is evolved toward better solutions. Each candidate solution has a set of properties (its chromosomes or genotype) which can be mutated and altered; traditionally, solutions are represented in binary as strings of 0s and 1s, but other encodings are also possible [21].

The evolution usually starts from a population of randomly generated individuals, and is an iterative process, with the population in each iteration called a *generation*. In each generation, the fitness of every individual in the population is evaluated; the fitness is

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usually the value of the objective function in the optimization problem being solved. The more fit individuals are stochastically selected from the current population, and each individual's genome is modified (recombined and possibly randomly mutated) to form a new generation. The new generation of candidate solutions is then used in the next iteration of the algorithm. Commonly, the algorithm terminates when either a maximum number of generations has been produced, or a satisfactory fitness level has been reached for the population [22].

A typical genetic algorithm requires:

1. a genetic representation of the solution domain,
2. a fitness function to evaluate the solution domain.

A standard representation of each candidate solution is as an array of bits (also called *bit set* or *bit string*).[4] Arrays of other types and structures can be used in essentially the same way. The main property that makes these genetic representations convenient is that their parts are easily aligned due to their fixed size, which facilitates simple crossover operations. Variable length representations may also be used, but crossover implementation is more complex in this case. Tree-like representations are explored in genetic programming and graph-form representations are explored in evolutionary programming; a mix of both linear chromosomes and trees is explored in gene expression programming [23-30].

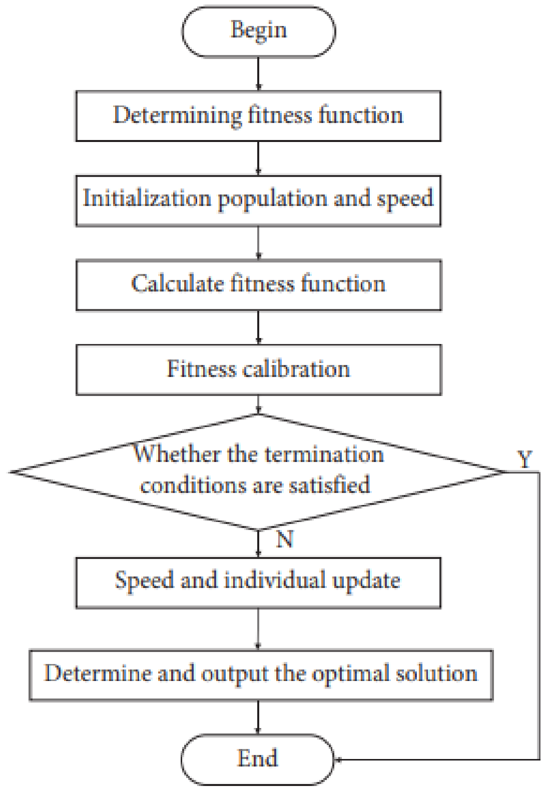

Fig.1 Flowchart.

VII. RESULT AND SIMULATION

The generated signal from the signal processor using MATLAB and the simulated signals using EMG analysis such as the poly or linear GA are plotted using MATLAB toolbox, which are represented by the dashed lines and smooth line respectively, shown in the figures below. This analysis is only filter oriented and analysis is without any data sets (signal is self-Generated in MATLAB coding).

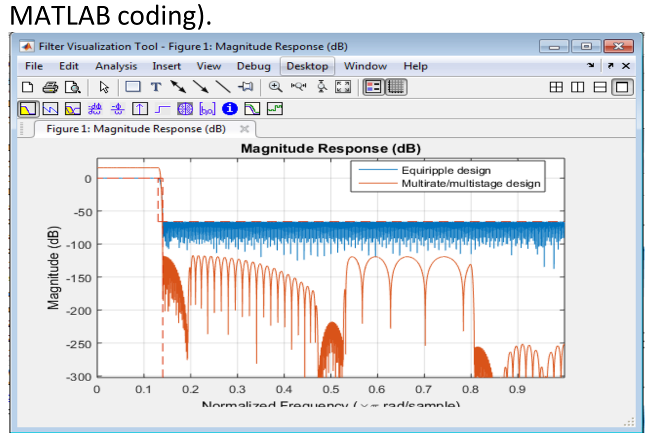

Fig. 2 Filter response.

Table 1.Define parameters.

S.N.	Previous method average Error	proposed method average Error
1.	2.5000e-04 [30]	2.705e-08

Table 2.Comparison between previous and proposed method results-

S.N.	Parameters	Values
1	Passband edge	0.13Hz
2	Stopband edge	0.14 Hz
3	Passband ripple	0.001
4	stopband ripple	0.0005
5	Passband Frequency	0.45 Hz
6	Stopband Frequency	0.55 Hz
7	Passband Attenuation (dB)	1
8	Stopband Attenuation (dB)	60

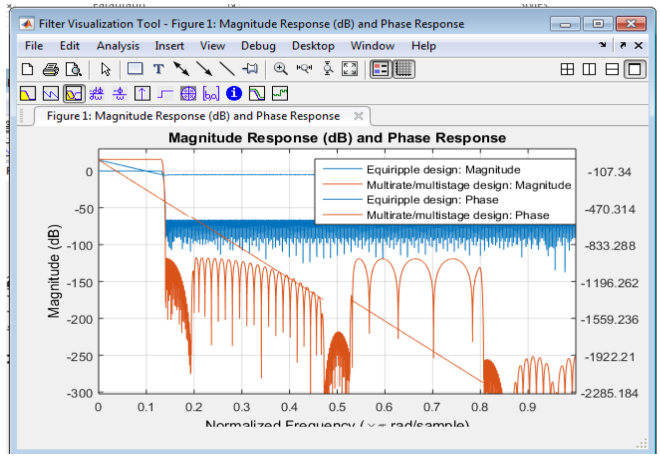

Fig. 3 Filter stability.

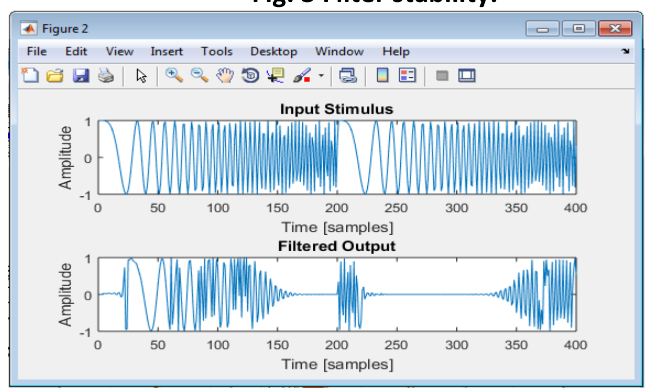

Fig. 4 GA Optimized response.

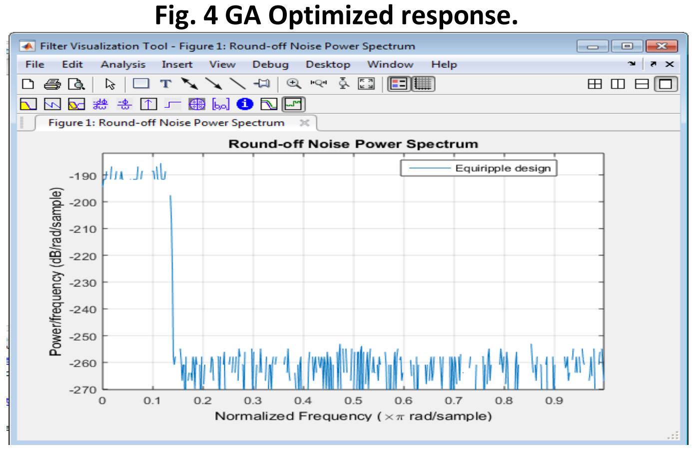

Fig. 5 Power spectrum Density.

VIII. CONCLUSION

In this paper, a new FIR and GA algorithm is proposed and successfully applied to low sampling rate sEMGgesture recognition. In order to improve the adaptability of gesture recognition technique, a new mutation probability calculation method is defined in particle mutation, which can effectively solve the premature problem of GA. In the aspect of feature extraction, five features with a high correlation to muscle contraction have been selected. This combination of calculations is simple and fast and can effectively obtain the sEMG signal information. The genetic algorithm is used to solve the problem of high dimension and redundancy of multichannel sEMG signals, which effectively reduces the complexity of subsequent classification. -e comparisons of results show that the algorithm is capable of recognizing the sEMG signals with sampling rate accurately. It provides an effective method for gesture recognition of low sampling rate sEMG signal.

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