Designing of Algorithmfor Calculation of Signal to Noise Ratio for Paralytic Patients Performing Various Activities

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Abstract: Surface electromyography has been used to disease diagnosis, pathologic analysis and muscular disorder. In this paper, we introduce an MATLAB based algorithmfor processing of sEMG signals of paralytic patients. The signal to Noise ratio has been investigated using Hamming window, Hanning window and Rectangular window. In this paper ten paralytic subjects have contributed by performing different finger movement activities. A comparative analysis of signal to noise ratio for finger movement activities has been calculated using hamming, hanning and rectangular window.

Keywords: *sEMG, Hamming, Hanning, Rectangular,Window, Paralytic, signal to noise ratio.*

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I. INTRODUCTION

Muscle fibers generate electrical current before enhancing the muscle power. Due to exchange of ions across muscle fiber surfaces electrical current generates. The ion exchange is an important step of signaling process for muscle fiber to contract. The electromyogram EMG has been measured by implementing conductive components or electrodes to the skin or invasively within muscle. TheEMG appears to offer a promising alternative for control using muscle contraction. Since it is capable of detecting very small contractions, it may be useful in cases of very severe disability where the individual has very limited muscle contracting abilities. The EMG provides a useful method of supporting interaction by those people who cannot interact using conventional means. Further research should be carried out on this system to assess its performance with paralytic people and its ability to detect muscle contractions in these subjects. Pattern recognition techniques that allow differentiation between different muscle actions should also be investigated in more detail for the EMG, ultimately to provide a means of operating multiple-switch operated systems.

II. SYSTEM MODEL

The loss of the human forearm is a major disability that profoundly limits the everyday capabilities and interactions of individuals with upper-limb amputation. The interaction capability with the real-
world can be restored using myoelectric control, where the electromyogram (EMG) signals generated by the human muscles are used to derive control commands for powered upper-limb prostheses. Typically a pattern recognition framework is utilized to classify the acquired EMG signals into one of a predefined sets of forearm movements. Various feature sets and classification methods have been utilized in the literature demonstrating the feasibility of myoelectric. Given the success of utilizing EMG signals in decoding the intended forearm movements, there have been re- cent attempts to achieve more dexterous individual finger control employed.

Surface EMG signals to identify when a finger is activated and which finger is activated using only two electrodes placed on the forearm. However, many attempts did not consider combined fingers movements. The proposed research involve the idea of EMG based finger control into movements that consisted of flexion and extension of all the fingers individually and of the middle, ring, index and little finger with thumb.

III. EMG SIGNAL ACQUISITION

The EMG may be measured invasively or non-invasively. Clinical electromyography almost always uses invasive needle electrodes as it is concerned with the study of individual muscle fibers [1]. It produces a higher frequency spectrum than surface electromyography and allows localized measurement of muscle fiber activity [2].

For simple detection of muscle contraction, it is usually sufficient to measure the electromyogram non-invasively, using surface electrodes. The standard measurement technique for surface electromyography uses three electrodes. A ground electrode is used to reduce extraneous noise and interference, and is placed on a neutral part of the body such as the bony part of the wrist. The two other electrodes are placed over the muscle. These two electrodes are often termed the pick-up or recording electrode (the negative electrode) and the reference electrode (the positive electrode) [1].

The surface electrodes used are usually silver (Ag) or silver-chloride (Ag- Cl). Saline gel or paste is placed between the electrode and the skin to improve the electrical contact [3]. Over the past 50 years it has been taught that the electrode location should be on the motor point of a muscle, at the innervation zone. According to De Luca [8], this is probably the worst location for detecting an EMG. The motor point is the point where the introduction of electrical currents causes muscle twitches. Electrodes placed at this point tend to have a wider frequency spectrum [2] due to the addition and subtraction of action potentials with minor phase differences. The widely regarded optimum position to place the electrodes over the muscle is now on the belly of the muscle, midway between the motor point and the tendinous insertion, approximately 1cm apart [2].

IV. DATA COLLECTION

Ten subjects, eight male and two female, age between 40 and 65 years were enrolled to carry out the required finger movements. The individuals were all paralytic Sufferers with one side nerve or muscle problems. Subjects were relaxing on bed, with their arm reinforced and glued at one position to avoid the effect of different limb positions on the produced EMG signals [9].

The EMG information was gathered using one EMG programs (Delsys DE 2.x sequence EMG sensors) and prepared by the Bagnoli computer EMG Techniques from Delsys Inc. A 2-slot sticky skin interface was put on each of the sensors to strongly keep the sensors to the skin. A conductive sticky reference electrode has been used on the hand of each patient as shown in fig. 1

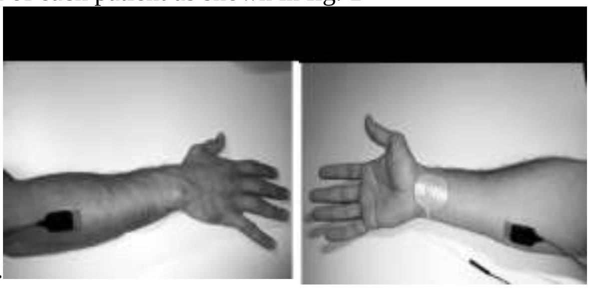


Fig 1 Position of First Electrode Position of Second Electrode

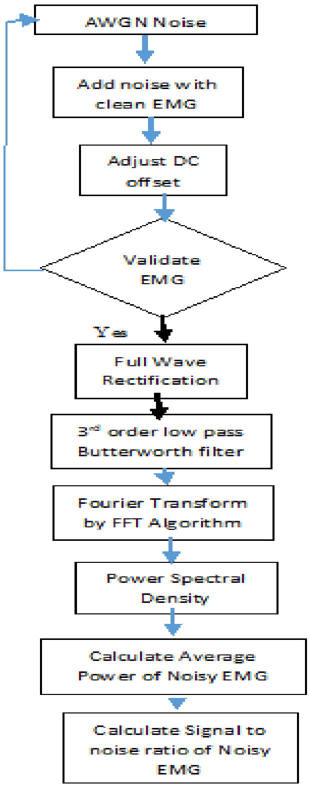
Ten classes of individual and combined fingers movements were implemented including: the flexion of each of the individual fingers, i.e., Thumb (T), Index (I), Middle (M), Ring (R), Little (L) and the pinching of combined Thumb–Index (T–I), Thumb–Middle (T– M), Thumb–Ring (T–R), Thumb–Little (T–L), and hand close (HC) as shown in Fig. 2

Fig. 2 Different Movement Classes

ALGORITHM 1

A. Add additive white Gaussian noise AWGN to clean EMG.
B. Remove DC offset and rectify the signal.
C. Use 3rd order FIR low pass Butterworth filter.
D. Calculate power to apparent power ratio.
E. Apply FFT technique to find the Fourier transform of noisy EMG signal.
F. Calculate average power of noisy Filtered EMG signal.
G. Calculate Signal to noise ratio by mean (noisyEMG.^2)/ mean (noise.^2).

V. FLOW CHART



ALGORITHM 2

A. Apply different windowing methods like hamming window, hanning window and rectangular window on noisy EMG signal for filtering.
B. Calculate Power to Apparent power ratio for hamming, hanning and rectangular window.
C. Apply FFT method for power spectral density of windowing EMG signal.
D. Calculate average power and signal to noise ratio and EMG rejection ratio for windowing EMG signal.
E. Compare the parameters for different windowing EMG signals and find the best suitable window for processing of EMG signal
F. Compare the parameters by specific window for various finger movement activities and find the best possible activity for paralytic patients.

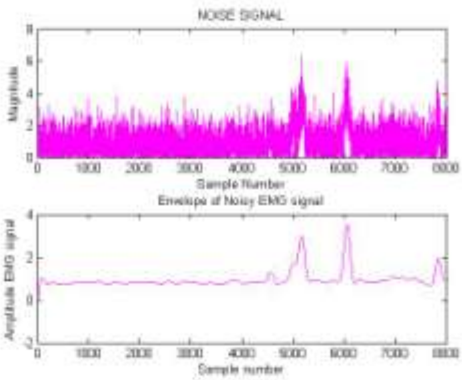


Fig. 3 Noise signal and envelope of noisy EMG signal

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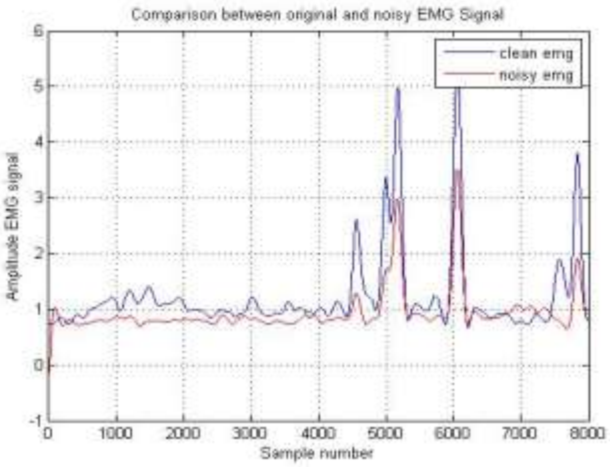


Fig. 4 Original clean EMG and Noisy EMG comparison

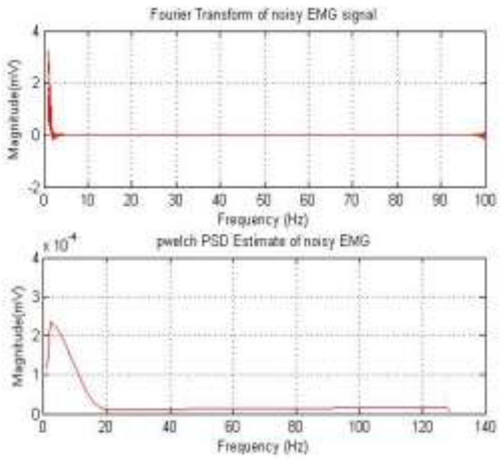


Fig. 5 Fourier Transform and power spectral density

VI. REAL TIME RESULTS

	PERSON 1	PERSON 2	PERSON 3	PERSON 4	PERSON 5	PERSON 6	PERSON 7	PERSON 8	PERSON 9	PERSON 10
SNR HAMMING WINDOW	0.2511	0.2559	0.2566	0.2532	0.2527	0.2514	0.2533	0.2554	0.2557	0.2534
SNR HANNIING WINDOW	0.2366	0.2415	0.2422	0.239	0.2384	0.237	0.2389	0.2411	0.2414	0.2392
SNR RECTANG ULAR WINDOW	0.4946	0.4993	0.5003	0.4961	0.4964	0.4947	0.4952	0.4955	0.4946	0.4936

Table 1 Signal to Noise Ratio for Hamming, Hanning and Rectangular Window during performing hand closed activity

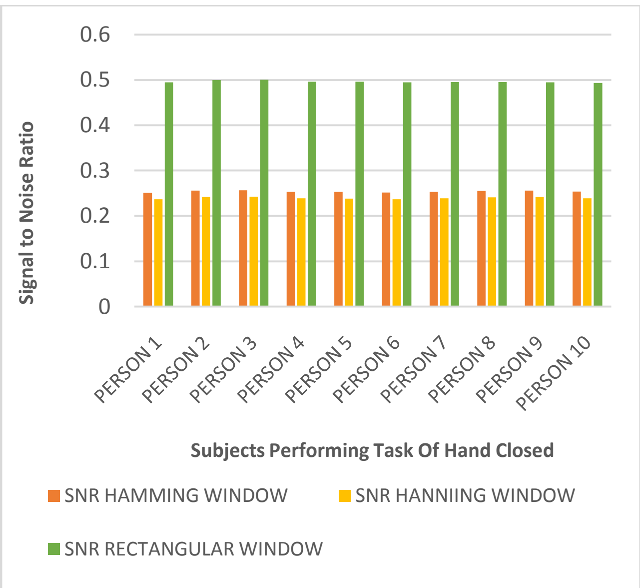


Fig.6 Signal to Noise Ratio comparison for hand closed activity

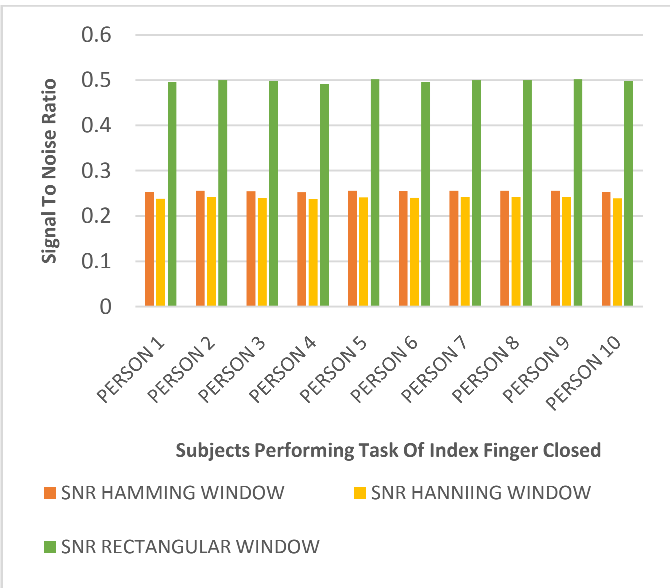


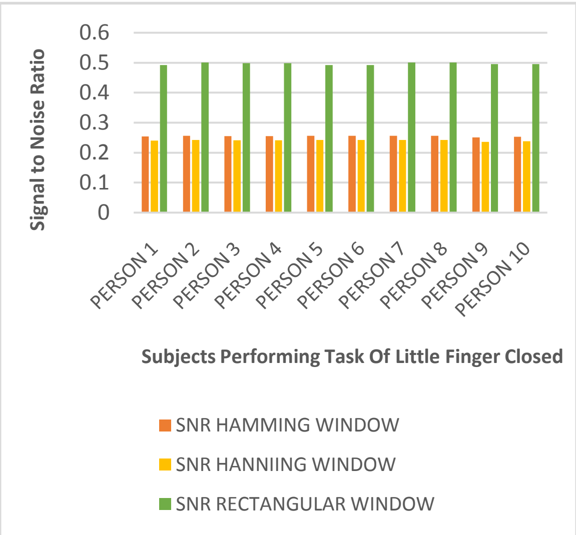
Fig.7 Signalto Noise Ratio comparison for index finger closed activity

	PERSON 1	PERSON 2	PERSON 3	PERSON 4	PERSON 5	PERSON 6	PERSON 7	PERSON 8	PERSON 9	PERSON 10
SNR HAMMING WINDOW	0.2527	0.2559	0.2543	0.252	0.2557	0.2548	0.2559	0.2559	0.256	0.2533
SNR HANNIING WINDOW	0.2384	0.2415	0.2399	0.2378	0.2413	0.2404	0.2415	0.2415	0.2416	0.2389
SNR RECTANGULAR WINDOW	0.4964	0.4993	0.4982	0.4917	0.5015	0.4955	0.4993	0.4993	0.5019	0.4977

Table 2Signal to Noise Ratio for Hamming, Hanning and Rectangular Window during performing Index finger closed activity

	PERSON 1	PERSON 2	PERSON 3	PERSON 4	PERSON 5	PERSON 6	PERSON 7	PERSON 8	PERSON 9	PERSON 10
SNR HAMMING WINDOW	0.254	0.2566	0.2555	0.2555	0.2566	0.2566	0.2566	0.2566	0.2508	0.2527
SNR HANNIING WINDOW	0.2397	0.2422	0.2412	0.2412	0.2426	0.2426	0.2422	0.2422	0.2364	0.2384
SNR RECTANGULAR WINDOW	0.4917	0.5003	0.4983	0.4983	0.4924	0.4924	0.5003	0.5003	0.4949	0.4955

Table 3Signal to Noise Ratio for Hamming, Hanning and Rectangular Window during performing Little finger closed activity



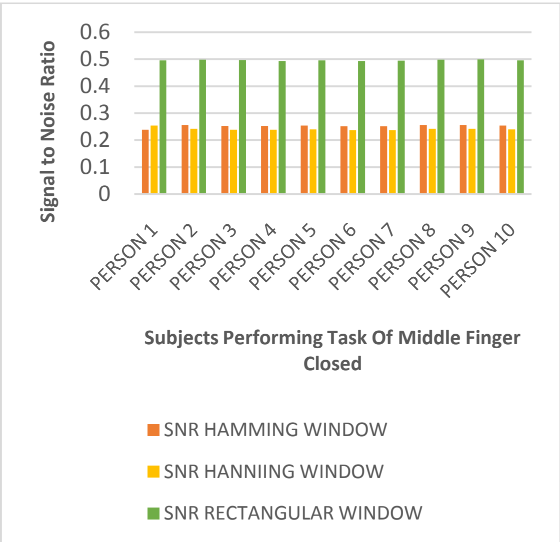


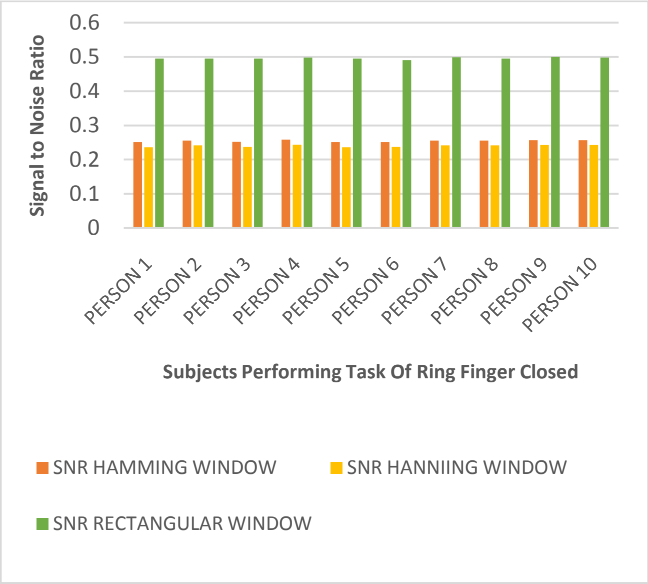
Fig.8 Signal to Noise Ratio comparison for little finger closed activity **Fig.9 Signal to Noise Ratio comparison for middle finger closed activity**

	PERSON 1	PERSON 2	PERSON 3	PERSON 4	PERSON 5	PERSON 6	PERSON 7	PERSON 8	PERSON 9	PERSON 10
SNR HAMMING WINDOW	0.2389	0.2557	0.2527	0.2526	0.2532	0.2518	0.2511	0.2557	0.2559	0.2534
SNR HANNIING WINDOW	0.2533	0.2415	0.2384	0.2383	0.239	0.2375	0.2366	0.2415	0.2415	0.2392
SNR RECTANGULAR WINDOW	0.4952	0.4984	0.4964	0.493	0.4961	0.4937	0.4946	0.4984	0.4993	0.496

Table 4 Signal to Noise Ratio for Hamming, Hanning and Rectangular Window during performing middle finger closed activity

	PERSON 1	PERSON 2	PERSON 3	PERSON 4	PERSON 5	PERSON 6	PERSON 7	PERSON 8	PERSON 9	PERSON 10
SNR HAMMING WINDOW	0.2506	0.2554	0.2514	0.2579	0.2506	0.2512	0.2559	0.2554	0.2566	0.2566
SNR HANNIING WINDOW	0.2362	0.2411	0.237	0.2438	0.2362	0.2369	0.2415	0.2411	0.2422	0.2423
SNR RECTANGULAR WINDOW	0.4954	0.4955	0.4947	0.4976	0.4954	0.4902	0.4993	0.4955	0.5003	0.4983

Table 5 Signal to Noise Ratio for Hamming, Hanning and Rectangular Window during performing ring finger closed activity



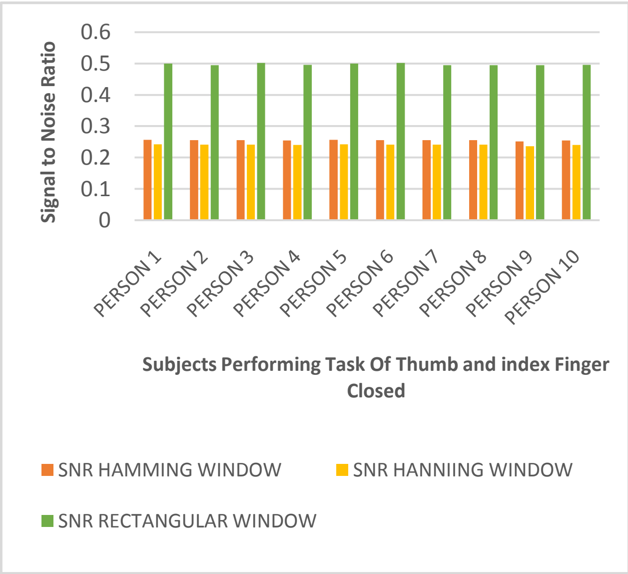


Fig.10 Signal to Noise Ratio comparison for ring finger closed activity **Fig.11 Signal to Noise Ratio comparison for thumb & index finger closed activity**

	PERSON 1	PERSON 2	PERSON 3	PERSON 4	PERSON 5	PERSON 6	PERSON 7	PERSON 8	PERSON 9	PERSON 10
SNR HAMMING WINDOW	0.2565	0.2557	0.2557	0.2545	0.2566	0.256	0.2557	0.2557	0.2511	0.2542
SNR HANNIING WINDOW	0.2422	0.2414	0.2413	0.2402	0.2422	0.2416	0.2414	0.2414	0.2366	0.2398
SNR RECTANGULAR WINDOW	0.5003	0.4946	0.5015	0.4956	0.5003	0.5019	0.4946	0.4946	0.4946	0.4957

Table 6 Signal to Noise Ratio for Hamming, Hanning and Rectangular Window during performing thumb and index finger closed activity

	PERSON 1	PERSON 2	PERSON 3	PERSON 4	PERSON 5	PERSON 6	PERSON 7	PERSON 8	PERSON 9	PERSON 10
SNR HAMMING WINDOW	0.254	0.2534	0.2566	0.2534	0.2557	0.2508	0.2534	0.2508	0.2559	0.2498
SNR HANNIING WINDOW	0.2397	0.2392	0.2426	0.239	0.2415	0.2364	0.2392	0.2364	0.2415	0.2355
SNR RECTANGULAR WINDOW	0.4917	0.4936	0.4924	0.4923	0.4984	0.4949	0.4936	0.4949	0.4993	0.4935

Table 7 Signal to Noise Ratio for Hamming, Hanning and Rectangular Window during performing thumb and little finger closed activity

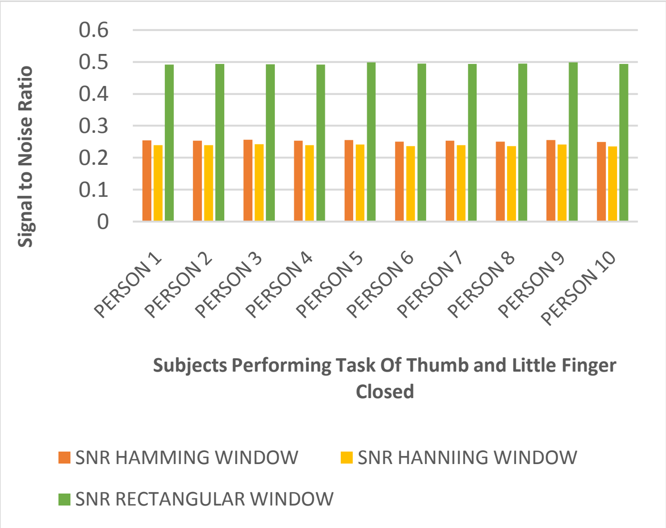


Fig.12 Signal to Noise Ratio comparison for thumb and little finger closed activity

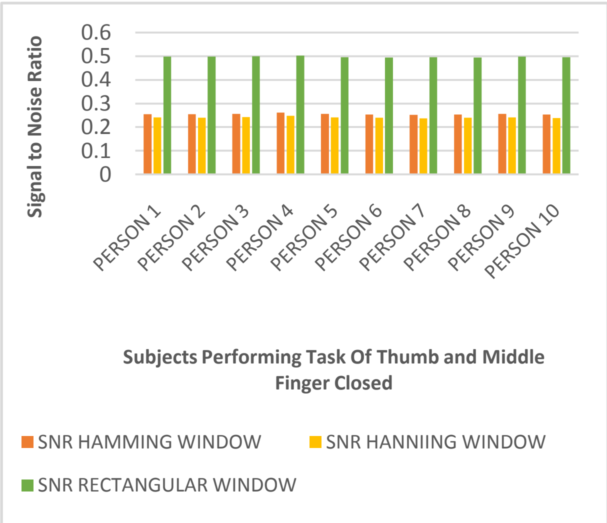


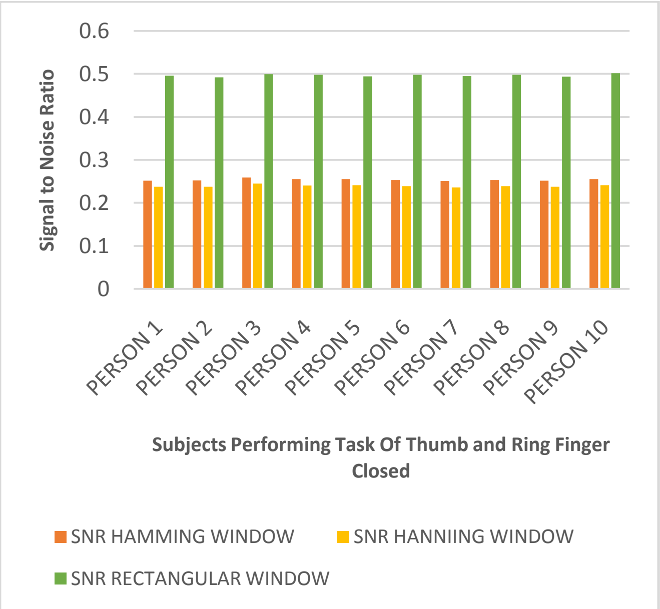
Fig.13 Signal to Noise Ratio comparison for thumb & middle finger closed activity

	PERSON 1	PERSON 2	PERSON 3	PERSON 4	PERSON 5	PERSON 6	PERSON 7	PERSON 8	PERSON 9	PERSON 10
SNR HAMMING WINDOW	0.255	0.2543	0.2565	0.2615	0.2554	0.2538	0.2521	0.2538	0.2555	0.2532
SNR HANNIING WINDOW	0.2406	0.2399	0.2422	0.2472	0.2411	0.2397	0.2376	0.2397	0.2412	0.239
SNR RECTANGULAR WINDOW	0.4986	0.4982	0.5003	0.5031	0.4955	0.4943	0.4963	0.4943	0.4983	0.4961

Table 8 Signal to Noise Ratio for Hamming, Hanning and Rectangular Window during performing thumb and middle finger closed activity

	PERSON 1	PERSON 2	PERSON 3	PERSON 4	PERSON 5	PERSON 6	PERSON 7	PERSON 8	PERSON 9	PERSON 10
SNR HAMMING WINDOW	0.2516	0.252	0.2589	0.2551	0.2557	0.2533	0.2506	0.2533	0.2518	0.2557
SNR HANNIING WINDOW	0.2372	0.2378	0.2446	0.2407	0.2414	0.2389	0.2362	0.2389	0.2375	0.2413
SNR RECTANGULAR WINDOW	0.4956	0.4917	0.4998	0.4977	0.4946	0.4977	0.4954	0.4977	0.4937	0.5015

Table 9 Signal to Noise Ratio for Hamming, Hanning and Rectangular Window during performing thumb and ring finger closed activity



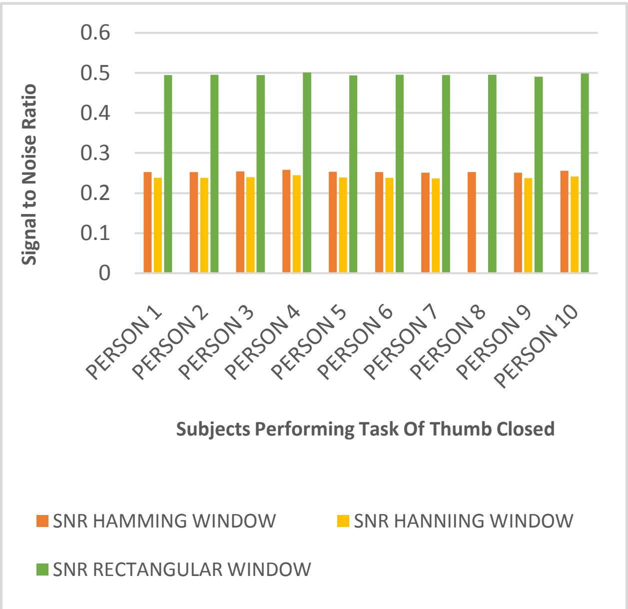


Fig.14 Signal to Noise Ratio comparison for thumb and ring finger closed activity Fig.15 Signal to Noise Ratio comparison for thumb closed activity

	PERSON 1	PERSON 2	PERSON 3	PERSON 4	PERSON 5	PERSON 6	PERSON 7	PERSON 8	PERSON 9	PERSON 10
SNR HAMMING WINDOW	0.2526	0.2523	0.2542	0.2584	0.2534	0.2527	0.2511	0.2527	0.2512	0.2555
SNR HANNIING WINDOW	0.2383	0.2379	0.2399	0.2441	0.2392	0.2384	0.2366	0.2387	0.2369	0.2412
SNR RECTANG ULAR WINDOW	0.4946	0.4956	0.4949	0.5012	0.4936	0.4955	0.4946	0.4955	0.4902	0.4983

Table 10 Signal to Noise Ratio for Hamming, Hanning and Rectangular Window during performing thumb closed activity

VII. ANALYSIS

The signal to noise ratio for three windowing methods has been considered in this paper. It is observed that rectangular window have highest signal to noise ratio with respect to hamming and hanning window. Hamming window have larger SNR than hanning window. Rectangular window have 50% more SNR than hamming and hanning window. Hamming window have 8% more SNR than hanning window.

We observe, from the comparison of simulated result & real time results, that the proposed observations are nearly identical & efficient. The proposed digital processing Technique can be extensively used in bio-medical engineering field. This can also be used in précised equipment manufacturing for low signal analysis.

VIII. FUTURE SCOPE

Digital signal processing is a rapid growing field; the most of work in signal processing is being digitized for the accessibility and the reliability of digital signal processing. It is good era to work in this field for the research scholars. The key factor in digital signal processing is the filter designing to meet the requirements in various applications.

IX. CONCLUSION

The proposed method is highly effective in analyzing the EMG signals. It is easy to use & apply in real time processing of any random signal obtained from the bio-medical sensors. In this paper, we developed an algorithm on MATLAB for calculating signal to noise ratiousing Hamming, Hanning and Rectangular window for various activities performed by paralysis patients. From our result studies, we observe that the proposed method is highly effective & efficient.

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