Biosignal Based Human-Machine Interface for Robotic Arm

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Abstract

Human-robot interaction poses great challenges to disabled people who must be able to control the robot via a limited physical ability. A novel semi-autonomous human-robot system where the robot requires only the commands from the human to perform its tasks as proposed. In this system a relatively more flexible and robust communication technique generates commands from Electromyogram (EMG) signals. Such an autonomous mobile humanoid robot will be able to assist in a workshop environment and interact with a human. Three aspects to reach this target are considered. First, how the brain (embedded system technologies) of the exoskeleton robot is constructed to be able to manipulate objects like humans do. Second, exploration of appropriate biosignals that can be used as an actuating quantity to move the Robotic Arm; and finally how programming of manipulation tasks are realized.

1. Introduction

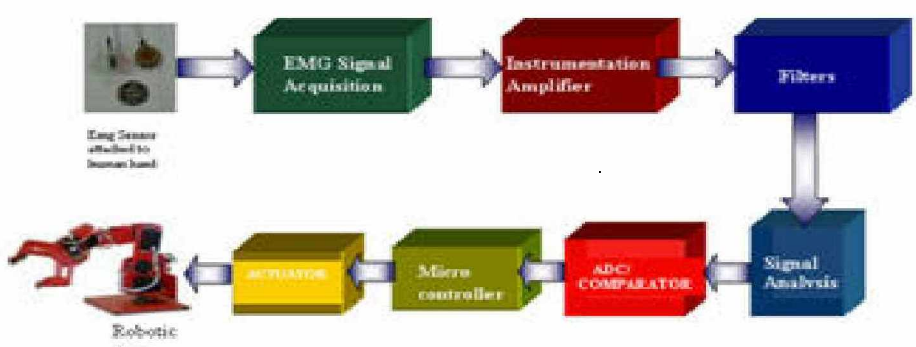
This project describes a human-machine interface using Electromyogram (EMG) signal to artificially control the limb movement usually called Functional Electrical Stimulation and rehabilitation. Each muscle fiber has a potential and Motor Unit Action Potential generated by contraction of muscle is studied and corresponding actuation is provided to robotic arm. Examples of such applications are in air flight control and various rehabilitation aids.

Human hand is attached with EMG sensor and the raw EMG signal is acquired. Since the amplitude of EMG signal is very small, we amplify it using a Instrumentation Amplifier and remove the noise using Twin-T Notch and Band Pass filters. After obtaining the signal, signal analysis is done through pattern classification algorithm such as Discrete Wavelet Transform. Analog signals are converted to digital form using ADC/Comparator which is then fed to a microcontroller which actuates the six servo motors of a robotic arm.

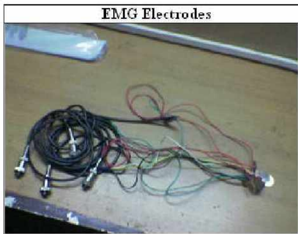
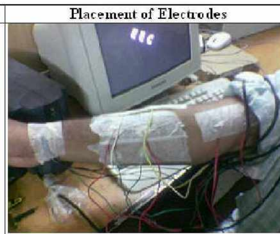
Various works regarding electromyography involves various Human-Machine interaction in which blinking of eye could be used as an input for a mouse cursor and also includes studies of various hand gestures.

2.Placement of EMG Electrodes

EMG Surface Electrodes are used in bipolar configuration where two electrodes with a small distance between each other are placed in the muscle to pick up the local signs with in the muscle of interest.A differential amplifier am[plifies the signals picked up from the two electrodes with respect to the signal picked up by a reference electrode.Because the interference signals from a distant source are essentially equal in magnitude and phase as detected by the two electrodes,the common mode rejection capability of the differential amplifier eliminates the unwanted signals

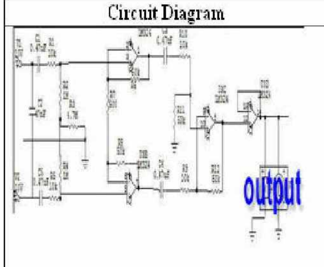
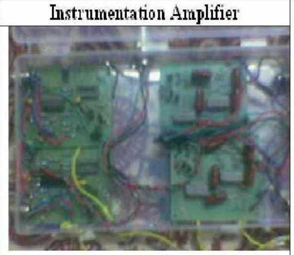


Block diagram representing Human-Machine Interface For Robotic Arm

EMG Electrodes	Placement of Electrodes
	

3.INSTRUMENTATION AMPLIFIER

Instrumentation Amplifier used for this project is LM324.The Instrumentation Amplifier consists of three identical operational amplifiers. The first two amplifiers are working in the non-inverting mode but their inverting terminals are not grounded. The feedback loops are connected with the inverting terminals. The third operational amplifier will act as a Differential Amplifier. The Instrumentation Amplifier is designed to have high input impedance. All the resistors are Metal Film military grade resistors with the tolerance level of 0.1%.All the capacitors are Tantalum capacitors with the tolerance of 1%.The values of resistors and capacitors are exactly identical to ensure high CMRR.The values of R,C are chosen such that the time period T=2 seconds. The high input impedance of 10 Mega-Ohm is provided by resistors R2,R3 and R4.The capacitors C1,C2,C3 are provided to any DC offset.

Circuit Diagram	Instrumentation Amplifier
	

For this project we have fixed value of R_6=500Ω & $R_7=R_8$=50K, $R_{11}=R_{12}$=50K and $R_9=R_{10}$=10K.

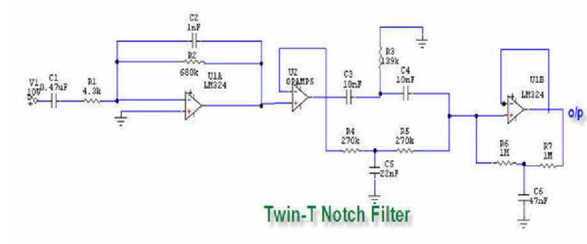
Therefore, a=100 and b=5

Gain= (1+2a) b= (1+200)5

=1005

4.FILTERS

The inherent noise of the electrical mains (i.e.) the 50 Hz signal is first filtered out using a Notch Filter. After the 50 Hz signal is attenuated, the signal is then passed through a band pass filter and the prominent frequencies between 10 Hz and 5 KHz is filtered out.



Wide Band Pass Filter

The wide band pass filter is a Butterworth filter. It contains a high pass filter followed by a low pass filter. The design of low pass filter is as follows:

F_{high}=2KHz

$$= \frac{1}{2*pi*r1*c1}$$

C_1=0.1μfarads

$$2KHz= \frac{1}{2*pi*0.1*10**-6*R1}$$

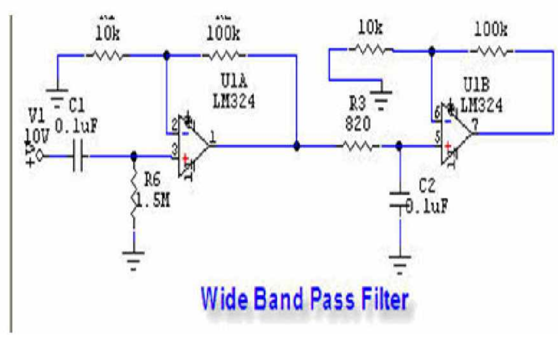
R1=796Ω(820Ω)

The design of High Pass Filter is as follows.First, let us assume the value of C_2=0.1μf .f_1=1Hz for the high pass filter.

$$F_1= \frac{1}{2*pi*r2*c2}$$

$$1Hz= \frac{1}{2*pi*r2*0.1*10^{\wedge}-6}$$

We get R_2=1.59MΩ



5.SIGNAL ANALYSIS

After obtaining the signal,signal analysis is done through Labview 7.1 using a Pattern Classification algorithm such as Discrete Wavelet Transform.

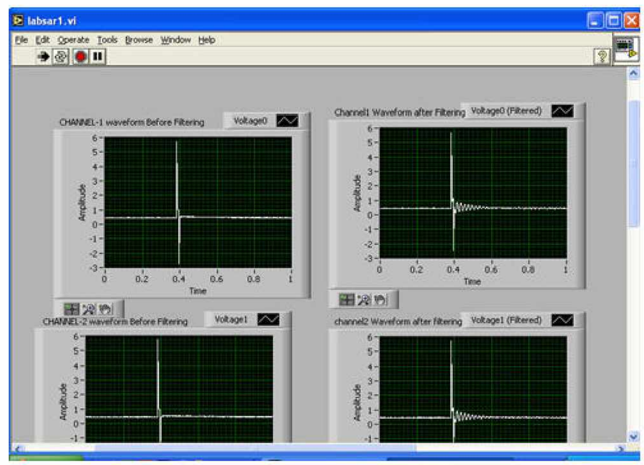
Figure 6: Study of Hand Gestures

6.Experiments

We conducted experiments with the developed manipulator system on eight subjects. Subjects A-D were fully functional, from 21- to 31-year-old men and E-H were four men whose forearms were amputated in their early ages. Rehabilitation training is beneficial before manipulation when the amputee's muscle force declines with long lapses of time after amputation. For this purpose, Subject E was trained using an EMG-based training system for prosthetic control. This system seeks to enhance three kinds of muscle abilities: cooperation among several muscles, timing of EMG generation, and muscular contraction. I first performed control experiments on the hand and wrist part, and examined the effect of online learning while the subject controlled this part for a couple of hours. We then performed experiments on manipulator control using the EMG signals. Finally, to improve the feeling of control in the hand and wrist part, we tried to control the joint angles based on the joint impedance model of the human forearm.

In the experiments, we used six electrodes (: ch. 1 Flexor Carpi Radialis; ch. 2 Flexor Carpi Ulnaris; ch. 3 Pronator Teres; ch. 4 Supinator; ch. 5 Biceps Brachii; ch. 6 Brachialis). If the subject was an amputee, we placed four electrodes (ch.1–4) on the muscles near the amputated part, and two electrodes on the upper arm muscles (ch. 5 Biceps Brachii, ch.6 Triceps Brachii). The sampling frequency for controlling the arm part and hand and wrist part were 60 and 100 Hz, respectively.

The discrimination suspension and the online learning thresholds were determined by trial and error, considering the results of our research. The LLGMN structure was determined based on the number of electrodes, the Gaussian components, and the desired motions. Gaussian components were used to approximate the pdf of the sample data. The numbers of components and learning samples were specified as one and 20 for each motion, which were adequate for achieving high-discrimination performance

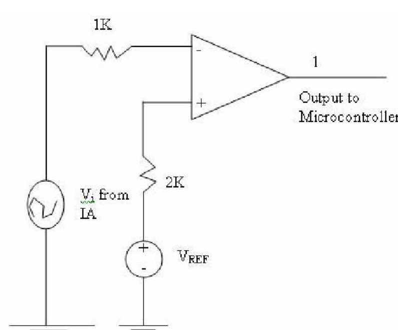


A Discrimination Ability of the Hand and Wrist Motions

First, we examined the EMG pattern discrimination ability. In the experiments, we used the discrimination suspension rule and the online learning method, and determined the thresholds as E4=0.55 and E2=2.0.There were N=160(eight motions, 20 for each motion) learning data inputs. The subject performed eight motions(K=8;(E) extension, (F) flexion, (UF) ulnar flexion, (RF) radial flexion, (S) supination,(P) pronation, (HO) hand open, and (HG) hand grasp) for about 30 s. The figure shows the motion photos and EMG signals.

7 COMPARATOR

The emg signals obtained are converted to digital form using Comparator. Here we make use of LM329.



Comparator

Degree of freedom of motion	4	
Length	from J_1 to J_2	300[mm]
	from J_2 to J_3	250[mm]
	from J_3 to J_4	160[mm]
Motion range	J_1	-150° to +150°
	J_2	-10° to +120°
	J_3	0° to +110°
	J_4	-90° to +90°
Maximum speed	J_1	120° /[sec]
	J_2	72° /[sec]
	J_3	109° /[sec]
	J_4	100° /[sec]
Load capacity	1.2[kgf]	
Drive system	DC servo motor (J1 axis brake attached)	
Position sensing method	Absolute encoder	
Weight	Approx. 19[kgf]	

(a) Robot arm

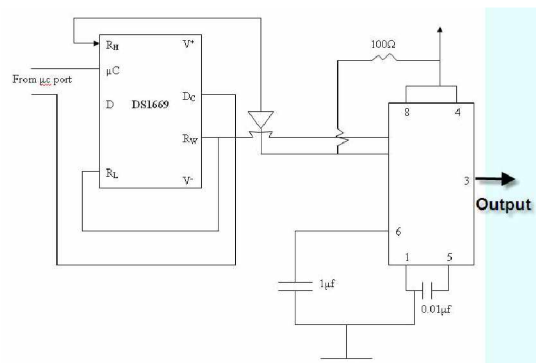
Degree of freedom of motion	3	
Length	from J_4 to J_5	72[mm]
	from J_5 to J_6	135[mm]
	from J_6 to J_7	85[mm]
	hand	58[mm]
Motion range	J_5	-180° to +180°
	J_6	-30° to +30°
	J_7	0° to +120°
Maximum speed	J_5	135° /[sec]
	J_6	104° /[sec]
	J_7	46° /[sec]
Holding force	J_5	6.9[kg/cm]
	J_6	9.0[kg/cm]
	J_7	9.0[kg/cm]
Drive system	Ultrasonic motor	
Weight	Approx. 1.0[kgf]	

(b) Prosthetic hand

Table-I Specifications (a) Robotic Arm (b)Prosthetic Hand

8.MICROCONTROLLER

Here we make use of 89c51 microcontroller. The output of microcontroller is fed to a driver circuit made of DS 1669



9.ROBOTIC ARM

The specifications and sketch of the robotic arm is as depicted in Table –I and figure 7 respectively.

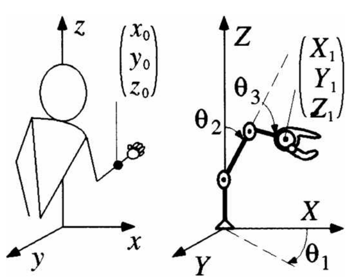


Figure 8: Link model of a manipulator

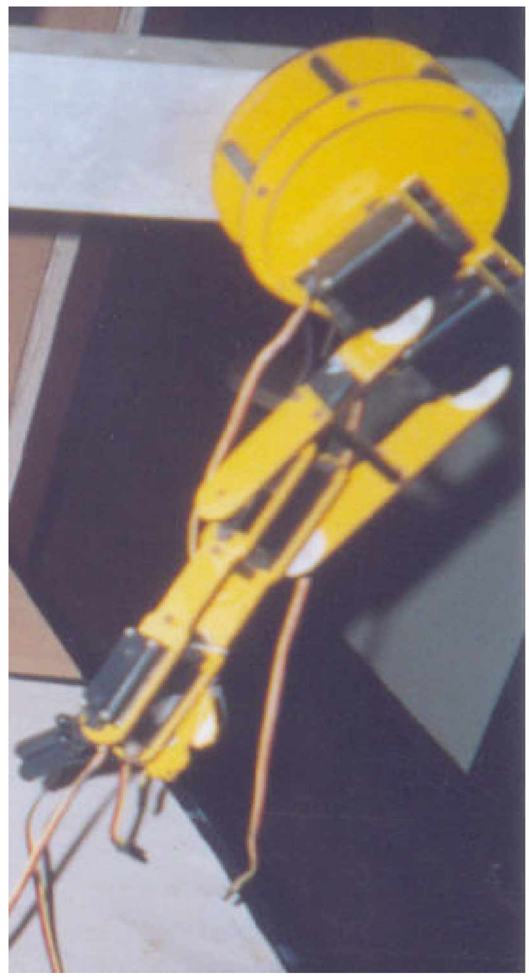


Figure 7: Sketch of the Robotic Arm

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