An SEMG Based Human Robot Interface for Robotic Hands Using Machine Learning

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Abstract: Robotics has huge demand among the technologies existing today. Human Robot Interface is a major method used nowadays. This helps to control the robotic devices by humans. The robotic grasping devices have been widely used in industrial, rescue, and aerospace applications. Electromyography is a medical term which is used to diagonalize the electrical activities of the muscles. The muscles are controlled by nerve cells. The electrical signals transmitted by nerve cells are used by the muscles. In this paper electromyography has been used for human robot interface for robotic hands using machine learning. The detected signals by sensor will be given as input to the machine learning algorithms. Then the processed data will be given to the robotic hand. The robotic hand has to grasp the gesture showed by the human hand. Thus, the factors like work load, human safety, boredom of works are reduced by the implementation and working of robotic hand.

Keywords: Robotics, Electromyography, Machine learning, Grasp device

I. Introduction

Robotics is facing a lot of challenges nowadays. Because interaction and coopera-tion between human and robots have a lot of influence in today's technologies. Robotics deal with designing, manufacturing, and usage of robots along with the computer systems that are used to control those robots. The development of robots has made human work-load much easier. The places were human has to work can be replaced by robots which will do the work more efficiently and accurately. Thus the time can also be saved. The type of robots that just can encounter most often are area unit robots that do dangerous, boring, and time consuming works in a better way. Most of the robots can be used in ma-chine, medical, manufacturing and space industries [5]. In fact, there are over 1,000,000 of those style of robots operating for North American country nowadays. Some robots like the Mars Rover occupier and also the forthcoming Mars Exploration Rover, or the underwater robot Greenland caribou are very popular robots. Popular toys such as Tec-kno, Polly or AIBO ERS-220 appear to hit the shop shelves each year around Christmas time.

A study of artificial intelligence means student's area unit actively engaged with all of those disciplines in a very deeply problem-posing problem-solving environment. Intelligent robot needs some kind of smart actions. This is where programming enters the pictures. A programmer is the person who gives the robot the ability to perform smartly. The robot receive the program so it is aware of what it is to try and do.

HUMAN IN THE LOOP INTEGRATION

Human in the loop is a key element associated with the term Human-Robot Inter-face. Human in the loop includes the integration of data in different sources. The simple definition of HITL describes the process when the machine or computer system is unable to offer an answer to a problem, needing human intervention.

HUMAN ROBOT INTERACTION

Human-robot interaction (HRI) is that the knowledge base study of interaction dynamics between humans and robots. Researchers and practitioners specializing in HRI come from a variety of fields, including engineering (electrical, mechanical, in-dustrial, and design), computer science (human-computer interaction, artificial intelli-gence, robotics, natural language understanding, and computer vision), social sciences (psychology, cognitive science, communications,anthropology, and human factors), and humanities (ethics and philosophy). Robots are pushed in to fill a growing number of roles in today's society, from factory automation to service applications to medical care and entertainment.

Fig1. Example of HRI Testbed

EMG

Electromyography (EMG) is an Associate in Nursing experimental technique in-volved with the event, recording, and analysis of myoelectric signals. Myoelectric signals are shaped by physiological variations within the state of muscle cell membranes.

Unlike the classical neurologic EMG, wherever a man-made muscle respond because of external electrical stimulation is analyzed in static conditions, the main target of Kine-siological EMG is often delineate as the study of the neuromuscular activation of muscles within postural tasks, functional movements, work conditions and treatment, and training regimes.

There are two kinds of EMG: surface EMG and intramuscular EMG. Surface EMG assessesmuscle function by recording muscle activity from the surface above the muscle on the skin. Surface electrodes are able to provide only a limited assessment of the muscle activity. Surface electrodes are able to provide only a limited assessment of the muscle activity. Surface EMG can be recorded by a pair of electrodes or by a more complex array of multiple electrodes. More than one electrode is needed because EMG recordings display the potential difference (voltage difference) between two sepa-rate electrodes. Limitations of this approach are the fact that surface electrode recordings are restricted to superficial muscles, are influenced by the depth of the subcutaneous tis-sue at the site of the recording which can be highly variable depending of the weight of a patient, and cannot reliably discriminate between the discharges of adjacent muscles.

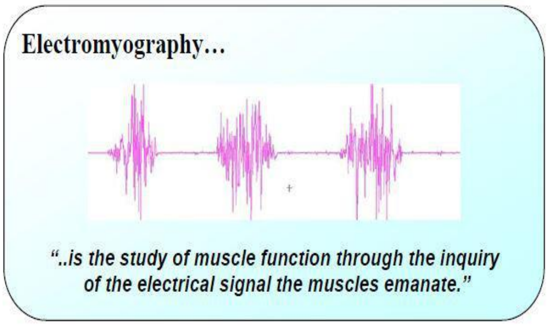


Fig2. EMG

MACHINE LEARNING

Machine learning may be a technique of knowledge analysis that automates analytical model building. It is a branch of AI-supported systems that will learn from information, determine patterns and build selections with stripped-down human intervention. Because of new computing technologies, machine learning today is not like machine learning of the past. It was born from pattern recognition and therefore the theory that computers will learn while not being programmed to perform specific tasks. Researchers are fascinated by AI to visualize if computers could learn from data. The repetitious facet of machine learning is vital as a result of as models square measure exposed to new in-formation, they are able to independently adapt. They learn from previous computations to provide reliable, repeatable decisions and results. It is a science that not new but one that has gained fresh momentum.

II. LITERATURE REVIEW

R. Meattini , S. Benatti, U. Scarcia, D. De Gregorio, L. Benini, and C. Melchiorri proposed a paper. Developing natural control strategies represents an an intriguing challenge within the style of the human-robot interface (HRI) systems. The teleoperation of robotic grasping devices, especially in industrial, rescue, and aerospace applications is mostly based on nonintuitive approaches, such as remote controllers. On the other hands, recent analysis efforts target solutions that mimic the human ability to manage multi-finger grasps and finely modulate grasp impedance. Since electromyography (EMG) contains information regarding human motion management, it is possible to leverage such neuromuscular knowledge to teleoperate robotic hands for grasping tasks. In this paper, an HRI system based on eight totally differential electromyogram sensors con-nected to a wearable sensor node for acquisition and processing are presented.

Christopher Assad has proposed a system of Biosleeve. This paper presents the BioSleeve, a new gesture-based human interface for natural robot control. The detailed activity of the user hand and arm is acquired via surface electromyography sensors and an inertial measurement unit that is embedded in a forearm sleeve. The BioSleeve accompanying software decodes the device signals, classifies gesture type, and maps the result to output commands to associate degree external mechanism. The current BioSleeve system can reliably decode as many as sixteen discrete hand gestures and estimate the continual orientation of the forearm. The gestures are used in several modes: for supervisory point to goal commands, virtual joystick for teleoperation, and high degree of freedom (DOF) mimicked manipulation. The reported results are from three control applications: a manipulation mechanism, a little ground vehicle, and a 5 DOF hand.

This paper presents a new wearable interface, called the BioSleeve, and demonstrates methods for classifying hand and arm gestures using this device.

This paper is proposed by Adam Reust. A prosthetic hand can be designed to repli-cate the normal function of the human hand by obtaining muscle signals associated with finger movements. EMG electrodes were placed on the flexor carpi radialis, palmaris longus, flexor carpi ulnaris, flexor digitorum superficialis, and flexor policus longus to acquire signals during finger movement. Analog integrated circuits were designed to amplify, filter, and rectify the muscle signals with 4550 gain, 20-500 Hz cutoff frequencies from a second-order Butterworth bandpass filter, and a full wave rectifier circuit using LM324 operational amplifiers. A printable circuit board was design using Cadence OrCAD and PCBMaker software. LPKF ProtoMat S103 plotter was used for edge and cutting the PCB. An Arduino Micro ATmega32U4 8 bit microcontroller board was used to convert analog EMG signals to digital. Digital pulse-width modulation (PWM) signals were wont to management servo motors of a 3D written hand epitome [4]. A model prosthesis was made using Siemens NX 10.0 software and printed. The robotic hand was designed to be anatomically almost like the conventional hand exploitation anthropometrical knowledge.

Noman Naseer, Department of Mechatronics, Air University Islamabad, had devel-oped a paper. This paper attempts to provide an enhanced management of individual fingers of robotic hand victimization electromyography (EMG). Eight-channel surface EMG is to acquire signals from the widest part of the forearm of 10 subjects. These sig-nals are corresponding to the movement of five individual fingers, which are the thumb, index finger, middle finger, ring finger, and little finger. Features are extracted from these signals and Deep Neural Network is applied as a classifier to distinguish between the five signals with an average accuracy of around 95 percent In this paper, a novel way of controlling individual finger motion of a robotic hand using EMG is presented. The individual finger motions are recognized with an accuracy of 95 percentage. Although, the proposed objective of mimicking an individual finger is achieved, however, this robotic hand can be introduced with many other and great features such as using a wireless module for wireless communication between the sensor and the controller.

III. METHODOLOGY

Block diagram of proposed model

The transmitter section consists of an EMG sensor, a microcontroller and a bluetooth module. The sensor will detect the electrical activities of the muscles. Then the sensor output will be given to a microcontroller for converting the electrical impulse into digital form. The corresponding microcontroller output will be given to the bluetooth module. The bluetooth module will transmit the appropriate data to the processing section.

The data processing section consists of a system and two bluetooth modules. The con-troller output will be given to the receiving bluetooth module of processing section. The output of receiving bluetooth module will be given to the system. The input data received by system will be given to the machine learning algorithms. The processed output data will be given to transmitting bluetooth module of processing section. Machine Learning is an important part in data processing section. The datasets are collected in the form of EMG values corresponding to each gesture. The dataset is created for each gesture with many EMG values. Then these values are given to machine learning algorithms. The processed output data will be used to train the robotic hand. Thus each gestures showed by human hand will be imitated by robotic hand.

The receiver section consists of a microcontroller, a bluetooth module and a robotic hand. The processed data will be transmitted by transmitting bluetooth module and re-ceived by receiving bluetooth module in receiving section. The received data will be given to the controller. The contoller output will be finally given to the robotic hand. Arduino Nano is used as microcontroller. In Arduino a simple function like pin-Mode() and digitalwrite() can be used to control other operations. There should be a synchronization between transmitter and receiver section. If the exact gestures are re-ceived by the robotic hand, then the receiver section is working efficiently.

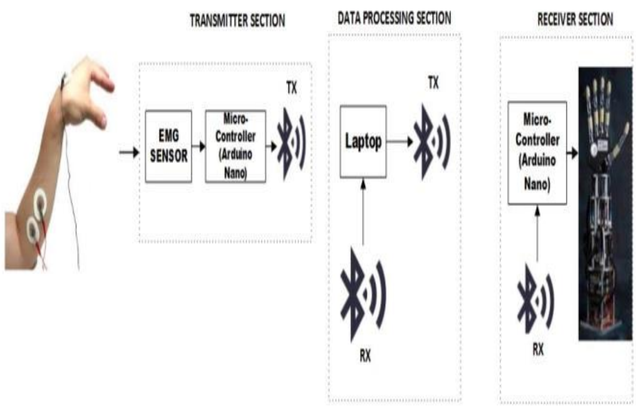


Figure4: Block diagram of proposed system

IV. FINDINGS AND RESULTS

EMG Input Stage

An EMG sensor was purchased and data transmission section was done using the sensor. The sensor was connected to the human hand. The ouput of the sensor was connected to the microcontroller. The bluetooth module was also connected to the microcontroller. Then that bluetooth module was connected to the smart phone. The sensed EMG values were displayed on the phone.

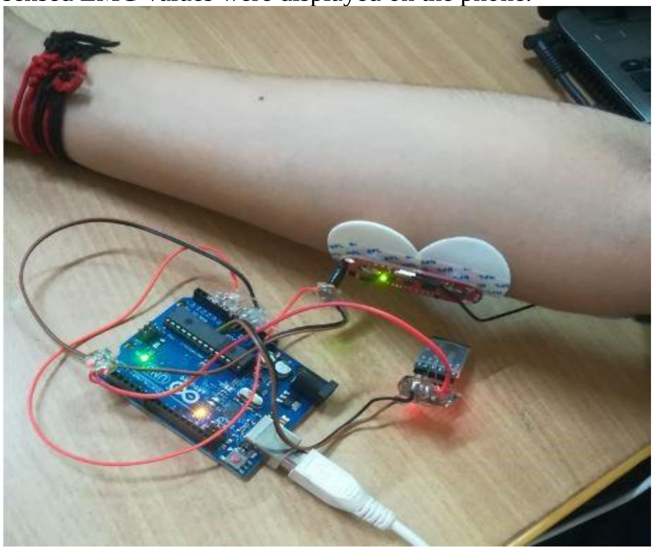
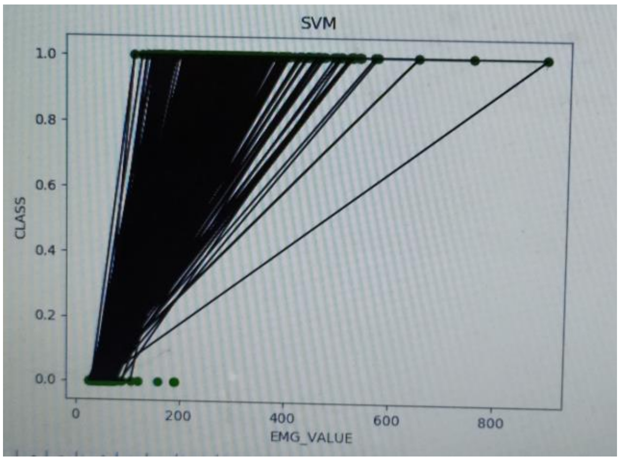


Fig.5 EMG Sensor Connected to the Hand

Sensor output when hand muscle is released

The sensor is connected to the human hand. The sensor is also connected to the microcontroller. The microcontroller coding is done in Arduino. The output of the sensor when the hand is released is tested. When the hand is in release state, the EMG value is recorded as two digit value. The values vary as the muscles release or contract. The dataset is created by observing the values collected when the muscles are released. These values are used to train the robotic hand to show the appropriate gesture when the hand muscles are released. riate gesture when the hand muscles are released.



Sensor output when hand muscle is contracted

The sensor is connected to both human hand and microcontroller. The microcontroller coding is done in Arduino. When the human hand is contracted, the sensor output is checked. At that time the EMG value is recorded as three digit value. When the hand is in contract state, the EMG value is recorded as three digit value. The values vary as the muscles release or contract. The dataset is created by observing the values collected when the muscles are contracted. These values are used to train the robotic hand to show the appropriate gesture when the hand muscles are contracted.

V. RESULT AND DISCUSSION

The improvement of flexibility and functionality of robotic grasping systems emulating human capabilities is a fundamental aspect for the widespread acceptance of HRIs. To improve the integration between subject and robot, we have designed an embedded wearable interface based on a control system that exploits neuromuscular information to allow the user regulating in a natural fashion the behavior of an artificial hand during grasping tasks. Leveraging the combination of ML-based pattern recognition and proportional control of the grasp closure and stiffness, the motor control of the human hand has been emulated since the muscular activation patterns are related with the intended movements, while the antagonist dynamics is responsible of the regulation of the grasp impedance. The human like degrees of control provided to the user of the HRI system combined with the possibility of selecting the grasp shape have been tested through several grasping experiments on a dexterous anthropomorphic robotic hand and on an industrial gripper mounted on a manipulator.

VII. REFERENCE

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