INTERNATIONAL JOURNAL OF RESEARCH
In Advanced Engineering Technologies

Volume 5, Issue 2 FEB 2016

DESIGN AND IMPLEMENTATION OF A WIRELESS MYOELECTRIC CONTROLLED ROBOTIC ARM

P. RAMAKRISHNA [1,] G.SAI THIRUMAL [2]

[1] pramakrishna418@gmail.com [2]saithirumal472@gmail.com

[1] PG Scholar, Dept Of ECE Aurobindo institute of engineering and technology, sheriguda (v), Ibrahimpatanam Mandal, Rangareddy Dist, Telangana, India.

[2] Guide M.Tech, Associate professor, Dept Of ECE Aurobindo institute of engineering and technology, sheriguda (v) ,Ibrahimpatanam Mandal, Rangareddy Dist, Telangana, India.

Abstract:

In today's world, in almost all sectors, most of the work is done by robots or robotic arm having different number of degree of freedoms (DOF's) as per the requirement. The paper describes a robustness of Myoelectric based Gesture Controlled Robot is a kind of robot that can be by our hand gestures rather than an ordinary old switches or keypad. In Future there is a chance of making robots that can interact with humans in a natural manner. Hence our target interest is with hand motion based gesture interfaces. An innovative Formula for gesture recognition is developed for identifying the distinct action signs made through hand movement. A MEMS Sensor was used to carry out this and also an Ultrasonic sensor for convinced operation. In order to full-fill our requirement a program has been written and executed using a microcontroller system. Upon noticing the results of experimentation proves that our gesture formula is very competent and it's also enhance the natural way of intelligence and also assembled in a simple hardware circuit

Key words: *Mems, Zigbee, Rfid, Motors, Wi -Fi,*

Introduction

Myoelectric controlled interfaces have become a major research area in recent years due to their applications in advanced prostheses, exoskeletons, and robot tele operation. Advances in electro encephalographic (EEG) and electro myographic (EMG) signal detection and processing have given researchers reliable and noninvasive access to brain and muscle activity, which has shifted research in prosthetics, exoskeletons, and tele operation towards establishing a connection between electromechanical systems and humans . This technology offers promise to help amputees regain independence , humans to perform tasks beyond their found at the junior or senior level in Electrical Engineering (EE) physical capabilities, and robotic devices and machines to be teleoperated with precision.The main challenge in myoelectric controlled interfaces lies in decoding neural signals to commands capable of operating the desired application. Many decoding algorithms have been developed using machine learning techniques, but these currently suffer from subject speci ficity and require intense training phases before any real-time application is feasible. A few other approaches have implemented simple decoders meant to be intuitive for users to control simple commands, but these intuitive mappings suffer from task specificity and assume that intuitive commands translate to maximal performance for a given task . In both cases,the decoders are designed to maximize the initial performance of the user, which does not take advantage of a human's natural ability to form inverse models of space, optimize control strategies and learn new muscle synergies while completing precise physical tasks. Thus, these approaches do not necessarily provide a foundation for maximal performance over time. Before presenting the novelty of the proposed technique, it is useful to give the definitions of two concepts that will be frequently used in the paper.

1) Control task: task to be executed by the subject using the myoelectric interface, implying both the *device* to be controlled (e.g., a robot hand) as well as its possible *functions* (e.g., open/close fingers etc.);
2) Mapping function: mathematical function that maps myoelectric activity to control actions for the task, e.g., a function that will translate myoelectric signals to opening the fingers of a robot hand.

This paper proposes a paradigm shift on myoelectric control interfaces that extends beyond using trainable decoders, by suggesting arbitrary mapping functions between the neural activity and the control actions. More specifically, this paper investigates user performance with myoelectric interfaces and arbitrary mapping functions which were neither designed for the subject nor the task. By expanding on recent conclusions that online closed loop feedback control is advantageous and effective for learning decoders in myoelectric interfaces, the contribution of this paper is two fold.

1) We demonstrate that a user-speci fic decoder is not required for myoelectric interfaces, as arbitrary mapping unctions can be learned without need for intuitive mappings.

2) Evidence is provided that prior learning and muscle synergies developed from a specific mapping function are retained and can transfer to new tasks. While Pistohl *et al.* have recently evaluated performance of proportional control of multi-fingered prostheses with respect to simple 2-D cursor controls [28], to the best of the authors' knowledge, no other study has evaluated the transfer of learning for multiple control tasks nor the performance of mapping functions with regard to myoelectric control. Four distinct mapping functions are used to control a set of two distinct tasks, using EMG signals as commands. EMG signals are collected from two biomechanically independent pairs of antagonistic muscles to encourage flexible control of the task space and avoid low-level habitual synergies that have been shown to hinder user control of the task space. Evaluating user control for a given trial consisting of a single task, using a speci fic mapping function, provides information about learning and inferred muscle synergy development. Chronological evaluation of all trials then provides information about the in fluence of previous trials on performance and reveals a transfer of learning signi ficantly dependent on the previous use of a given mapping function. There stof the paper is organized as follows: Section II explores related works involving decoders

INTERNATIONAL JOURNAL OF RESEARCH
In Advanced Engineering Technologies

Volume 5, Issue 2 FEB 2016

for myoelectric controlled interfaces. Section III details the method used for this experiment.SectionIVpresentstheresultsoftheexperimentsandsupportsthe major findings. Finally, Section V concludes the paper with a brief discussion and summary of the contribution.

I. The Hardware System

Micro controller: This section forms the control unit of the whole project. This section basically consists of a Microcontroller with its associated circuitry like Crystal with capacitors, Reset circuitry, Pull up resistors (if needed) and so on. The Microcontroller forms the heart of the project because it controls the devices being interfaced and communicates with the devices according to the program being written.

ARM7TDMI: ARM is the abbreviation of Advanced RISC Machines, it is the name of a class of processors, and is the name of a kind technology too. The RISC instruction set, and related decode mechanism are much simpler than those of Complex Instruction Set Computer (CISC) designs.

Liquid-crystal display (**LCD**) is a flat panel display, electronic visual display that uses the light modulation properties of liquid crystals. Liquid crystals do not emit light directly. LCDs are available to display arbitrary images or fixed images which can be displayed or hidden, such as preset words, digits, and 7-segment displays as in a digital clock.

II. Design of Proposed Hardware System

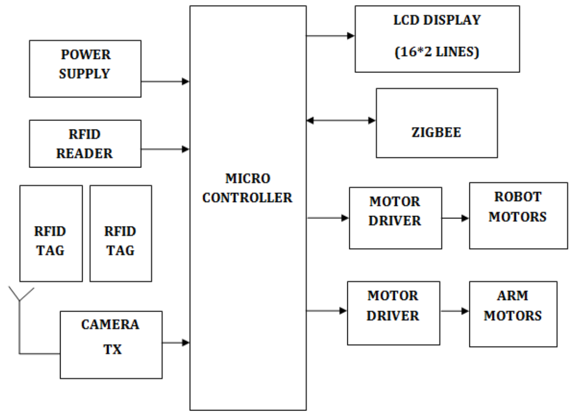

Fig.1.Robotic Section Block diagram

With the advancement of technology, we can overcome above drawbacks we are going this proposed method. In this method we are going to maintain a library using my controller based system. Here in this system we will be using touch panel to operate my robot section like move front, back, left, right and placing wireless camera on the robot section. It will capture the images of books in shelf and send data to receiver section. Then we can monitor the captured images using software and we will be using here MEMS technology to pick and place the objects like books and we are maintain the information in memory. They maintain records for giving books and taking books from the users. This leads time consuming, wastage paper books and also maintaining of more workers that means cost is increased. These are the drawbacks of above system.

INTERNATIONAL JOURNAL OF RESEARCH
In Advanced Engineering Technologies
Volume 5, Issue 2 FEB 2016

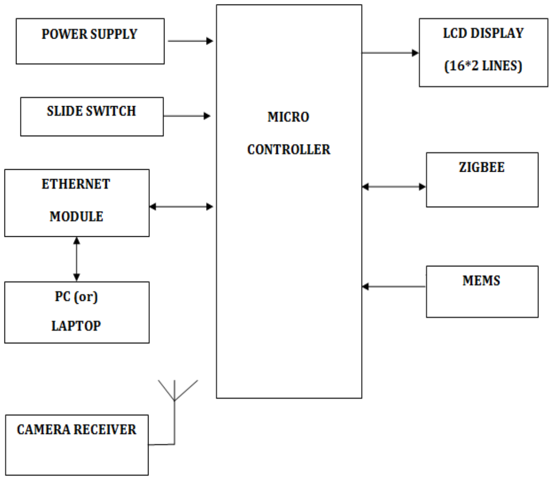

Fig.2. Monitoring Section Block Diagram

III. Board Hardware Resources Features

ETHERNET:

Networking is playing vital role in current IT era where data distribution and access is critically important. As the use of communication between two or more entities increases the networking technologies need to be improved and refurbished over time. Similarly the transmission media, the heart of a network, has been changed with the time improving on the previous one. If you know a little bit about networking you surely have heard the term Ethernet which is currently the dominant network technology. Wide spread of the Ethernet technology made most of the offices, universities and buildings use the technology for establishment of local area networks (LANs).

To understand what actually Ethernet is, we need to know about IEEE first which is a short of Institute of Electrical and Electronics Engineers. IEEE is a part of International Organization for Standardization (ISO) whose standard IEEE 802.3 is defined for Local Area Network. The standard 802.3 commonly known as ETHERNT defines the communication standards for how data is transferred from one network device to another in a local area network. Since the limit for Ethernet cable is few hundred meters Ethernet is commonly deployed for networks lying in a single building to connect devices with close proximity. The same standard for Ethernet enables manufactures from around the earth to manufacture Ethernet products in accordance with the ISO standards that are feasible for all computing devices worldwide.

ZIGBEE:

Zigbee modules feature a UART interface, which allows any microcontroller or microprocessor to immediately use the services of the Zigbee protocol. All a Zigbee hardware designer has to do in this ase

is ensure that the host's serial port logic levels are compatible with the XBee's 2.8- to 3.4-V logic levels. The logic level conversion can be performed using either a standard RS-232 IC or logic level translators such as the 74LVTH125 when the host is directly connected to the XBee UART. The below table gives the pin description of transceiver. The X-Bee RF Modules interface to a host device through a logic-level asynchronous Serial port. Through its serial port, the module can communicate with any logic and voltage Compatible UART; or through a level translator to any serial device.

Data is presented to the X-Bee module through its DIN pin, and it must be in the asynchronous serial format, which consists of a start bit, 8 data bits, and a stop bit. Because the input data goes directly into the input of a UART within the X-Bee module, no bit inversions are necessary within the asynchronous serial data stream. All of the required timing and parity checking is automatically taken care of by the X-Bee's UART.

Features:

- Internal Sourcing of almost all of main Parts

Almost all components - frame, key switches and membrane sheet - other than connecters and cord are manufactured in-house, giving Minebea an un-matched advantage in terms of quality, supply capabilities, cost-competitiveness and speed of delivery.Especially, these products capitalize on Minebea's ultra-precision machining technology of components.

- Efficient Production System

Plant in China which supplys the global market employs the Minebea's vertically integrated manufacturing system, whereby all process, from machining components to final assembly are conducted in-house.

RFID:

Many types of RFID exist, but at the highest level, we can divide RFID devices into two classes:active and passive.

Active Tag Passive Tag

Active tags require a power source i.e., they are either connected to a powered infrastructure or use energy stored in an integrated battery. In the latter case, a tag's lifetime is limited by the stored energy, balanced against the number of read operations the device must undergo. However, batteries make the cost, size, and lifetime of active tags impractical for the retail trade.

Passive RFID is of interest because the tags don't require batteries or maintenance. The tags also have an indefinite operational life and are small enough to fit into a practical adhesive label. A passive tag consists of three parts: an antenna, a semiconductor chip attached to the antenna and some form of encapsulation. The tag reader is responsible for powering and communicating with a tag. The tag antenna captures energy and transfers the tag's ID (the tag's chip coordinates this process). The encapsulation maintains the tag's integrity and protects the antenna and chip from environmental conditions or reagents.

MEMS:

Micro electro mechanical systems (MEMS) are small integrated devices or systems that combine electrical and mechanical components. Their size range from the sub micrometer (or sub micron) level to the millimeter level and there can be any number, from a few to millions, in a particular system. MEMS extend the fabrication techniques developed for the integrated circuit industry to add mechanical elements such as beams, gears, diaphragms, and springs to devices. Examples of MEMS device applications include inkjet-printer cartridges, accelerometers, miniature robots, microengines, locks, inertial sensors, micro transmissions, micromirrors, micro actuators, optical scanners, fluid pumps, transducers and chemical, pressure and flow sensors. Many new applications are emerging as the existing technology is applied to the miniaturization and integration of conventional devices.

These systems can sense, control and activate mechanical processes on the micro scale and function individually or in arrays to generate effects on the macro scale. The micro fabrication technology enables fabrication of large arrays of devices, which individually perform simple tasks, but in combination can accomplish complicated functions. MEMS are not about any one application or device, or they are not defined by a single fabrication process or limited to a few materials. They are a fabrication approach that conveys the advantages of miniaturization, multiple components and microelectronics to the design and construction of integrated electromechanical systems. MEMS are not only about miniaturization of mechanical systems but they are also a new pattern for designing mechanical devices and systems.

RESULT

The proposed system “Myoelectric Interfaces Based Assistive Robot for Human Collaborative Work” prototype existence is as shown below

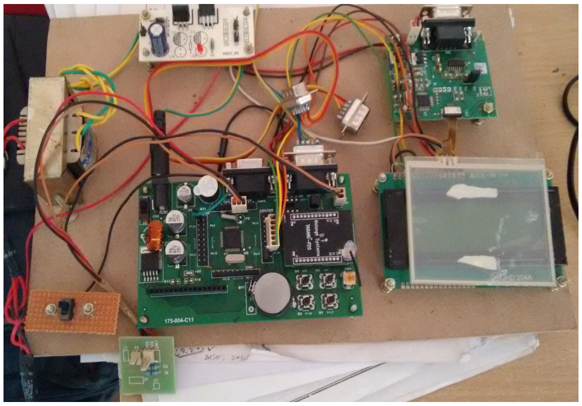

Fig: Prototype of Monitoring Section

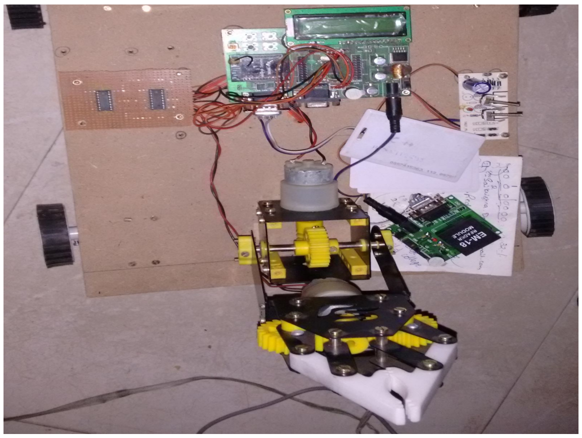

Fig: Prototype of Robot Section

CONCLUSION

This paper investigates the role of mapping functions in myoelectric controlled interfaces. It is shown that subjects are not only able to learn the inverse model of arbitrary mapping functions, but more importantly are capable of generalizing this model to enhance performance on new control tasks containing similar mapping functions. Performance is determined to be more dependent on familiarity with a given mapping function than familiarity with a given control task, indicating that subjects can learn new control tasks so long as they know how to explore the task space.This control is robust to variability caused by small changes in sensor placement that occurred while performing the experiment over multiple days. These findings imply that subjects are able to develop and re fine muscle synergies for a given mapping function which enables them to explore the task space more efficiently. As mentioned in , the synergy development is enhanced by the choice of two pairs of antagonistic muscles, with each pair biomechanically independent. Including biomechanically dependent muscles, such as in, would likely hinder a subject's ability to learn these synergies due to low level mechanical restraints. The study also reveals that the specific choice of mapping function may not be as relevant as previously emphasized in the literature. Even though mapping appears to be the most intuitive for a majority of the subjects, the best overall performance occurs using the randomly generated mapping, and end performance for all mapping functions is more similar than the large discrepancies in initial performance. This is consistent with previous findings using closed loop feedback to learn inverse models of mapping functions, and another indicator of muscle synergy development to allow more efficient performance. Thus, we have proposed a myoelectric controlled interface which is not subject-specific and we also show that learning of a mapping for a particular task can still be transferred to new tasks.

REFERENCES

[1] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller,and T. M. Vaughan, "Brain-computer interfaces for communication and control," *C l i n . N e u ro p h y s i o l .*, vol. 113, no. 6, pp. 767–791, Jun. 2002.

[2] O. Fukuda, T. Tsuji, M. Kaneko, and A. Otsuka, "A human-assisting manipulator teleoperated by EMG signals and arm motions,"*I E E E Tr a ns . R ob o t . A u t o m a t .*, vol. 19, no. 2, pp. 210–222,Apr. 2003.

[3] S. Bitzer and P. van der Smagt, "Learning EMG control of a robotic hand: Towards active prostheses," in *Proc. IEEE Int. Conf. Robot. and Automat. ICRA*, May 2006, pp. 2819–2823.

[4] C. Castellini, A. E. Fiorilla, and G. Sandini, "Multi-subject/daily-life activity EMG-based control of mechanical hands," *J. Neuroeng.Rehab.*, vol. 6, no. 41, 2009.

[5] L. Lucas, M. DiCicco, and Y. Matsuoka, "An EMG-controlled hand exoskeleton for natural pinching," *J. Robot. Mechatron.*, vol. 16, no. 5, Oct. 2004.

[6] P. Artemiadis and K. J. Kyriakopoulos, "EMG-based position and force estimates in coupled human-robot systems: Towards EMG controlled exoskeletons," in *Experimental Robotics*, O. Khatib, V. Kumar, and G.J. Pappas, Eds. Berlin, Germany: Springer, 2009, vol. 54, Springer Tracts in Advanced Robotics, pp. 241–250.

[7] C. Zhu, S. Shimazu, M. Yoshioka, and T. Nishikawa, "Power assistance for human elbow motion support using minimal EMG signals with admittance control," in *Proc. Int. Conf. Mechatron. Automat. (ICMA)*,Aug. 2011, pp. 276–281.

[8] T. S. Saponas, D. S. Tan, D. Morris, and R. Balakrishnan,"Demonstrating the feasibility of using forearm electromyography for musclecomputer interfaces," in *Proc. SIGCHI Conf. Human Factors in Comput. Syst.*, New York, NY, USA, 2008, CHI '08, pp. 515–524.

[9] J. Vogel, C. Castellini, and P. van der Smagt, "EMG-based teleoperation and manipulation with the DLR LWR-III," in *Proc.IEEE/RSJ Int. Conf. Intelligent Robots and Syst. (IROS)*, Sep.2011, pp. 672–678.

[10] P. K. Artemiadis and K. J. Kyriakopoulos, "A switching regime model for the EMG-based control of a robot arm," *IEEE Trans. Syst. Man,Cybern., Part B: Cybern.*, vol. 41, no. 1, pp. 53–63, Feb. 2011.

[11] P. K. Artemiadis and K. J. Kyriakopoulos, "EMG-based teleoperation of a robot arm in planar catching movements using ARMAX model and trajectory monitoring techniques," in *Proc. IEEE Int. Conf. Robotics Automat.*, 2006, pp. 3244–3249.

[12] M. S. Erkilinc and F. Sahin, "Camera control with EMG signals using principal component analysis and support vector machines," in *Proc.*

IEEE Int. Syst. Conf. (SysCon), Apr. 2011, pp. 417–421.

[13] P. K. Artemiadis and K. J. Kyriakopoulos, "Teleoperation of a robot manipulator using EMG signals and a position tracker," in *Proc. IEEE/RSJ Int. Conf. Intelligent Robots Syst.*, Aug. 2005, pp. 1003–1008.

[14] U. Sahin and F. Sahin, "Pattern recognition with surface EMG signal based wavelet transformation," in *Proc. IEEE Syst., Man, Cybern.Conf. (SMC)*, pp. 295–300.

[15] G. Naik, D. Kumar, and Jayadeva, "Twin SVM for gesture classi fication using the surface electromyogram," *IEEE Trans. Inform. Technol. Biomedicine*, vol. 14, no. 2, pp. 301–308, Mar. 2010.

[16] P. K. Artemiadis, P. T. Katsiaris, and K. J. Kyriakopoulos, "A biomimetic approach to inverse kinematics for a redundant robot arm," *Autonomous Robots*, vol. 29, no. 3-4, pp. 293–308, Nov. 2010.

[17] F. Orabona, C. Castellini, B. Caputo, A. Fiorilla, and G. Sandini,"Model adaptation with least-squares SVM for adaptive hand prosthetics," in *Proc. IEEE Int. Conf. Robot. Automat.*, May 2009, pp.2897–2903.

[18] C. Cipriani, F. Zaccone, S. Micera, and M. Carrozza, "On the shared control of an EMG-controlled prosthetic hand: Analysis of user-prosthesis interaction," *IEEE Trans. Robot.*, vol. 24, no. 1, pp. 170–184,Feb. 2008.

[19] P. Nilas, P. Rani, and N. Sarkar, "An innovative high-level humanrobot interaction for disabled persons," in *Proc. IEEE Int. Conf. Robot.Automat. ICRA '04*, Apr.-May 1, 2004, vol. 3, pp. 2309–2314.

[20] F. A. Mussa-Ivaldi, M. Casadio, Z. C. Danziger, K. M. Mosier, and R. A. Scheidt, "Sensory motor remapping of space in human-machine interfaces," *Progr. Brain Res.*, vol. 191, p. 45, 2011.

[21] K. M. Mosier, R. A. Scheidt, S. Acosta, and F. A. Mussa-Ivaldi,"Remapping hand movements in a novel geometrical environment,"*J. Neurophysiol.*, vol. 94, no. 6, pp. 4362–4372, Dec. 2005.

[22] J. P. Cunningham, P. Nuyujukian, V. Gilja, C. A. Chestek, S. I. Ryu,and K. V. Shenoy, "A closed-loop human simulator for investigating the role of feedback control in brain-machine interfaces," *J. Neurophysiol.*, vol. 105, no. 4, pp. 1932–1949, Apr. 2011.

[23] D. M. Taylor, S. I. H. Tillery, and A. B. Schwartz, "Direct cortical control of 3D neuroprosthetic devices," *Science*, vol. 296, pp. 1829–1832,2002.

[24] K. Nazarpour, A. Barnard, and A. Jackson, "Flexible cortical control of task-speci fic muscle synergies," *J. Neurosci.*, vol. 32, no. 36, pp. 12 349–12 360, Sep. 2012.

[25] S. P. Kim, J. D. Simeral, L. R. Hochberg, J. P. Donoghue, and M. J.Black, "Neural control of computer cursor velocity by decoding motor cortical spiking activity in humans with tetraplegia," *J. Neural*, vol. 5,p. 22, 2008.

[26] S. M. Chase, A. B. Schwartz, and R. E. Kass, "Bias, optimal linear estimation, and the differences between open-loop simulation and closed-loop performance of spiking-based brain-computer interface algorithms," *Neural Networks*, vol. 22, no. 9, pp. 1203–1213, Nov.2009.

[27] S. M. Radhakrishnan, S. N. Baker, and A. Jackson, "Learning a novel myoelectric-controlled interface task," *J. Neurophysiol.*, vol. 1, p. 47, 2008.

[28] T. Pistohl, C. Cipriani, A. Jackson, and K. Nazarpour, "Abstract and proportional myoelectric control for multi- fingered hand prostheses,"*Anna. Biomed. Eng.*, vol. 41, no. 12, pp. 2687–2698, Dec. 2013.

[29] A. de Rugy, G. E. Loeb, and T. J. Carroll, "Muscle coordination is habitual rather than optimal," *J. Neurosci.*, vol. 32, no. 21, pp. 7384–7391,May 2012.

[30] D. Graupe and K. W. Cline, "Functional separation of EMG signals via ARMA identi fication methods for prosthesis control purposes," *IEEE Trans. Syst., Man Cybern.* , vol. SMC-5, no. 2, pp. 252–259, Mar. 1975.

[31] D. Nishikawa, W. Yu, H. Yokoi, and Y. Kakazu, "EMG prosthetic hand controller using real-time learning method," in *Proc. IEEE Int. Conf. Syst., Man, Cybern.*, 1999, vol. 1, pp. 153–158.

[32] M. V. Liarokapis, P. K. Artemiadis, P. T. Katsiaris, K. J. Kyriakopoulos, and E. S. Manolakos, "Learning human reach-to-grasp strategies: Towards EMG-based control of robotic arm-hand systems," in *Proc. IEEE Int. Conf. Robot. Automat. (ICRA)*, May 2012, pp.2287–2292.

[33] P. K. Artemiadis and K. J. Kyriakopoulos, "An EMG-based robot control scheme robust to time-varying EMG signal features," *IEEE Trans. Inform. Technol. Biomedicine*, vol. 14, no. 3, pp. 582–588, May 2010.

[34] A. B. Ajiboye and R. F. Weir,"Muscle synergies as a predictive framework for the EMG patterns of new hand postures," *J. Neural Eng.*, vol.6, no. 3, p. 036004, Jun. 2009.

[35] F. E. Zajac, "Muscle and tendon: Properties, models, scaling, and application to biomechanics and motor control," *Stanford Univ.*, vol. 17,p. 52, 1989.