Towards an EMG-Controlled Prosthetic Hand Using a 3-D Electromagnetic Positioning System

Yu Su, Mark H. Fisher, Andrzej Wolczowski, G. Duncan Bell, David J. Burn, and Robert X. Gao, Senior Member, IEEE

Abstract—This paper proposes a novel method of using electromyographic (EMG) potentials generated by the forearm muscles during hand and finger movements to control an artificial prosthetic hand worn by an amputee. Surface EMG sensors were used to record a sequence of forearm EMG potential signals via a PC sound card and a novel 3-D electromagnetic positioning system together with a data-glove mounted with 11 miniature electromagnetic sensors used to acquire corresponding human hand pose in real time. The synchronized measurements of hand posture and associated EMG signals stored as prototypes embody a numerical expression of the current hand shape in the form of a series of data frames, each comprising a set of postures and associated EMG data. This allows a computer generated graphical 3-D model, combined with synthesized EMG signals, to be used to evaluate the approach. This graphical user interface could also enable handicapped users to practice controlling a robotic prosthetic hand using EMG signals derived from their forearm muscles. We believe this task might be made easier using a dictionary of stored task-specific prototype data frames acquired from able-bodied users. By comparing the resulting EMG data frames with stored prototypes, the most likely data frame sequence can be identified and used to control a robotic hand so that it carries out the user’s desire. We explore the feasibility of this approach by applying frequency analysis on the signal derived from a multichannel EMG measurement device and identify pattern recognition techniques in the time and frequency domains to determine plausible hand shapes. This approach offers several advantages over existing methods. First, it simplifies the classification procedure, saving computational time and the requirement for the optimization process, and second, it increases the number of recognizable hand shapes, which in turn improves the dexterity of the prosthetic hand and the quality of life for amputees. The database of EMG prototypes could be employed to optimize the accuracy of the system within a machine learning paradigm. By making a range of EMG prototype databases available, prosthetic hand users could train themselves to use their prosthesis using the visual reference afforded by the virtual hand model to provide feedback.

Index Terms—Electroencephalographic (EEG), electromagnetic sensor, electromyographic (EMG), 3-D electromagnetic positioning system.

I. INTRODUCTION

This paper considers the possibility of using forearm muscle potentials to infer corresponding hand shape. A novel method using a database of stored prototype 3-D posture and EMG data frames is used, together with EMG data captured from an amputee’s forearm muscles, to infer corresponding hand shapes and finally, to control a prosthetic hand in real time. Preliminary results of simultaneous measurement and recording of human hand motion and EMG signals acquired from the forearm muscle are presented, and an algorithm is developed for hand shape identification.

An EMG signal is an electric potential generated by muscle contraction; it may be measured on the skin surface or by embedding sensors into deeper layers of the muscle. Medical reference suggests that different compartments of the forearm muscle relate to hand and finger movement, and EMG signals can still be measured from the forearm muscle even after the hand is amputated. Therefore, theoretically, it is possible to use the EMG signal to control hand and finger movements. Fig. 1 shows the cross section of the radial, median, and ulnar nerves and their branches traversing the forearm muscle compartments; the courses of these nerves as they traverse the compartments relay instructions from the brain and enable the muscle to carry out contractions [1].

II. PROPOSED APPROACH

A. Posture Acquisition System

The 3-D positioning system shown in Fig. 2 exploits the electrototive force (EMF) induced in an inductive sensor, as determined by electromagnetic theory (Fig. 3) [2], [3]. The 11 miniature electromagnetic sensors are mounted on a glove and used to capture the anatomical position of the hand and each finger in real time as shown in Fig. 4 [4]. Three generator assemblies, each comprising three coils wound on a square former, being sequentially excited at 10 kHz, produce sequential magnetic fields forming a reference plane (Fig. 5). When placed in the magnetic field, each sensor measures the field component along its axis (Fig. 6) as an electrical potential, \( V_c \).

The induced voltage signal level is a function of both sensor position, \( x, y, \) and \( z \), and its orientation expressed as the Euler angles, \( \theta \) and \( \phi \), referenced to an origin, the source of magnetic field, of which the position is represented as \( X_{Gi}, Y_{Gi}, \) and \( Z_{Gi} \), is set to 0. This function is described in (1), where \( V_{Si} \) represents...
the induced voltage, and $k_G$, $k_S$ are two constant coefficients. Further details can be found in [2].

$$V_{Si} = \frac{k_G k_S}{L_0^2} \left[ 3z \sin \theta \left( (x - X_{Gi}) \cos \phi + (y - Y_{Gi}) \sin \phi \right) + \cos \phi \left( 2z^2 - (y - Y_{Gi})^2 - (x - X_{Gi})^2 \right) \right]$$  \hspace{1cm} (1)

In the present system, the generators are switched sequentially and the EMF induced in the sensor is measured using a...
matched filter tuned to the generator frequency of 10 kHz. The use of an alternating magnetic field allows the signal-to-noise ratio (SNR) of the system to be improved. The current system provides 16 sensor readings at a maximum rate of 10 frames per second; however, an improved version is currently under development with an estimated data capture rate of 50 frames per second [18]. Experiments confirm that the system can achieve high accuracy and precision [4].

B. Graphical Interface

In order to generate visual feedback of the hand movement, a graphical hand model has been produced to visualize the hand. The data glove captures 11 anatomically strategic points on the hand in real time, and this data is then used to drive the graphical hand model. Fig. 7 shows a series of virtual hand shapes generated by real-time hand posture data [4]. As each sensor works independently and measures the absolute position and orientation of the fingers and palm, the system is a very useful method of calibrating the forearm muscle potentials measured due to hand movements.

C. EMG Signal Measurement Device

Many excellent EMG measurement devices are commercially available at present, but suffer disadvantages due to an insufficient numbers of channels, inadequate signal conditioning, and inconvenient connectivity [5], [6]. A customized double-channel EMG measurement device with appropriate signal conditioning has been used to measure the differentiated EMG signal. An example of the signal conditioning can be seen in Figs. 8 and 9. Here, a PC sound card has been used as an analog-to-digital converter (ADC).

Further improvements needed for a working prototype include more data channels, micro-controller logic, improved ADC, and robust connectivity (e.g., via a Serial/USB interface).

A C++ program has been developed to simultaneously record posture data from a subject’s hand motion and EMG signals from their forearm muscle (Figs. 10 and 12) in the following format. First, positional \((x, y, z)\) and orientation \((\theta, \pi)\) parameters are consecutively recorded from 11 electromagnetic sensors followed by 256 (or 512) EMG samples in a time frame 0.032 s (0.064 s) from the moment when hand posture recording has finished. These two different sets of data are saved in the form of one prototype record in text format for use in later data analysis.

III. DATA ANALYSIS

Pattern recognition is needed to compare current EMG candidate signals with the prototype EMG data records and thus infer a numerical representation of the current hand shape. A pattern recognition approach allows the most likely EMG pattern to be identified and the corresponding hand shape to be predicted. This may subsequently be used for future bio-prosthesis control. This process is illustrated in Figs. 10 and 11. In this scheme, only EMG data is involved in the pattern recognition process. This simplifies the classification procedure, saving computational time, thereby reducing the need for optimization and increasing the number of recognizable hand shapes.

Fig. 12 shows the system used in EMG data collection with the 3-D positioning system, data glove and the 2-channel EMG measurement system on a subject’s forearm.

Three-dimensional hand posture may be inferred from EMG data analysis in either the time or frequency domain. Processing in the time domain is considered for EMG devices employing 5–6 channels (Fig. 13) and frequency domain techniques are proposed for those using 1–2 channels (Fig. 16).

A. Raw Data Pattern Analysis in the Time Domain—EMG Sensor Layout 1

A 5–6 channel EMG measurement device is currently under consideration, the sensors are to be arranged into an array on a sensing sleeve around the forearm muscle (Fig. 13). The advantages of this arrangement are the position the sensor is less critical; a richer set of hand posture can be captured and fewer anatomical details are needed. Disadvantages are that as there are more sensors, each needing signal conditioning, the sampling rate may be lower. The processing is carried out in the time domain for this “sensing sleeve” arrangement, and the similarity of two sets of EMG data, expressed as Frame A and Frame B (Fig. 14) are analysed, with Frame A representing a data frame acquired at real-time and Frame B representing the corresponding frame in the sample dataset. It seems logical to assume that this sensor layout may be more suitable for an EMG-controlled prosthesis hand, in which the biological status is not quite stable given the constant hand movements but sensor locations are relatively easier to be defined.

EMG sensor outputs may be compared in the time domain using the root mean square deviation (RMSD) [7] over two or
Fig. 7. Graphical hand model.

Fig. 8. EMG signal.

Fig. 9. EMG signal after conditioning.
For example, between two data frames in comparison (Frame A and Frame B)

\[
\text{RMSD} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (E_{Ai} - E_{Bi})^2}
\]  

(2)

where \( E \) represents EMG sensor readings, \( i \) represents the number of current sensors, and \( N \) is the total number of sensors.

Comparing the similarity among multiple frames is used in classifying hand shapes, for multiple frames, each frame will be compared over the “averaged” mean frame, the RMSD will be summed up and the average will be used as the similarity coefficient

\[
\text{RMSD} = \frac{1}{M} \left\{ \frac{1}{N} \sum_{k=1}^{M} \sum_{i=1}^{N} (E_{ki} - \bar{E}_i)^2 \right\}
\]  

(3)

where \( E \) represents EMG sensor readings, \( i \) represents the number of current sensors, \( k \) is the number of current frames, \( N \) is the total number of sensors, \( M \) is the number of frames participating in the similarity measurement, and \( \bar{E}_i \) is the mean EMG reading of sensor number \( i \) obtained by averaging over \( M \) frames, expressed as

\[
\bar{E}_i = \frac{1}{M} \sum_{j=1}^{M} E_{ji}
\]  

(4)

However, particular caution needs to be taken in the EMG pattern analysis, firstly, to normalize the frames by subtracting the offset, which is the least value in the frame, and secondly, to choose those frames in which all the prototype points have the same sign margin compared with those in the reference frame, as expressed in Fig. 15(b). All the prototype points, dots on the dashed line, are above those on the solid line; this will ensure that the cross sign margin distribution displayed in Fig. 15(c), which may have the same or an even better similarity coefficient based on the RMSD calculation, is filtered out. Thus, calibration ensures that measurements are only a function of the shape of EMG distribution to be compared [Fig. 15(a), (b)] and not artefacts of the measurement system and/or the physical structure of the muscle. These steps improve the recognition accuracy.
B. Spectrum Pattern Analysis in the Frequency Domain—EMG Sensor Layout 2

EMG sensors are located at strategic anatomical positions on the forearm muscles responsible for generating hand movement (Fig. 16). The advantages of this arrangement are that a higher sampling rate is possible as fewer sensors are involved. The disadvantages are that the system is more anatomically sensitive and there is a possibility that some anatomical information may be missing.

A set of 512 signal samples of each EMG sensor is captured together with 3-D hand posture data. The fast Fourier transform (FFT) is applied on the two sets of EMG recording to obtain spectral information from each sensor corresponding to each hand shape, then each spectrum is divided into a fixed number of frequency bands and the components in each band are summed and averaged. These spectral features are used by the structure similarity analysis protocol as prototype points. Fig. 17(a)–(c) shows the three consecutive steps of spectrum pattern analysis for layout 2. To achieve an efficient real-time implementation, a filter-bank approach for extracting spectral features could be employed.

Layout 2 requires periodic EMG data sampling for frequency analysis. As the EMG data set is used to infer a single hand shape, reliable data can only be obtained when the biological status is relatively stable. Therefore, layout 2 may be less suitable for an EMG-controlled prosthetic hand, in which biological status exhibits some instability due to the constant hand movements.

IV. RESULTS

Preliminary data has been recorded with the above-mentioned system assembly. A data record for each frame includes
the positional and orientation data of 11 electromagnetic sensors followed by 512 EMG data samples from each channel. A graphical user interface (GUI) for the system incorporating a virtual hand model, simultaneous raw EMG measurement recorded from the PC sound card, and frequency analysis (Fig. 18) has also been developed.

V. DISCUSSION

Other researchers using pattern classifiers for prosthetic hand control do not directly measure hand shape, and therefore have access to a much sparser set of training examples. Nevertheless, they have reported some success using multichannel EMG data [8], [9]. Other research has been reported using multichannel electroencephalographic (EEG, brain wave) measurement [10], [11]. All the methods may be categorized as single-sensing model-based approaches. The novelty in the approach introduced here lies in employing a multisensing strategy combining EMG signals and positional information to capture an accurate, real-time, hand model. Thus, our approach does not suffer the limitations of existing systems and can, in theory, infer a wider range of hand shapes, using a simpler classifier design.

There is, of course, uncertainty in this approach. For example, no amputee has been involved so far, and based on the researcher’s personal experience, it is difficult to control the forearm muscle without the coordinating feedback provided by the hand and fingers. Further research will have to address these issues [12]–[14].

Mostly, we believe the multisensing algorithm is very promising. In a worst case scenario, if the EMG control of the prosthetic hand does not prove to be feasible, a similar algorithm may be used to combine the 3-D positioning system with EEG measurements. We believe the disadvantages of this approach will be due to difficulties in classification, and therefore, research in the near future will focus on the “3-D posture + EMG” approach introduced in this paper.

The multisensing system may potentially be adopted for a wide range of applications. For example, the 3-D positioning system has already proved successful in teleoperation research [15] and could be improved using prototype records together with EMG signals to more accurately control a robot arm. The system may also be used to help other amputees, e.g., requiring leg prosthesis. Such work may also benefit from the multisensing approach we have described.

VI. FUTURE WORK

Further research in the near future will focus on the development of the EMG signal pattern recognition program. Both “Amplitude + RMSD” and “FFT + RMSD” methods will be explored and compared in terms of synchronization, repertoire of hand shapes, recognition accuracy, and computational complexity.

The use of an “Amplitude + RMSD” approach would inevitably require the development of a multichannel (5–6) EMG measurement device with reasonable signal conditioning and a convenient interface. Therefore, the extension of the EMG measurement system will be crucial. The introduction of wireless embedded EMG sensors is also being considered as an additional enhancement. A series of experiments to measure finger and hand motions simultaneously with the EMG signal arising from the muscle activity with or without amputee subjects will also be a high priority.

A database and machine learning implementation [16] would also be necessary to define similarity thresholds and optimize the prototype records. For training purposes, the prototype
record and the graphical engine may also be made available online to help the prosthetic hand user. Ideally, the online function will be bilateral in the sense that the user’s EMG data can be collected while they are using the system and used to interactively refine the prototype file.

Initially, the system will have to be used in the real-time control of a robotic hand. However, it is hoped that the multisensing system introduced in this paper may be used in the future for prosthetic hand control [17].

VII. CONCLUSION

This paper shows how a novel data-glove can be used to monitor and capture the exact motions of the human hand while simultaneously recording forearm muscle stimulus with EMG sensors located at strategic anatomical positions. The equipment and software necessary to capture and record the EMG signals (2 channels) and the complete 3-D hand postures in a text file have been tested.

We propose to use pattern recognition to map the forearm muscle stimulus to the hand shape. This mapping will then be used to drive a prosthetic hand. A preliminary study using pattern recognition on both raw EMG data and EMG spectrum has been carried out. Further work is needed to improve this system.

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REFERENCES


Yu Su received the B.Sc. degree from Beijing University of Aeronautics and Astronautics, Beijing, China, in 1991 and qualified from the University of Newcastle upon Tyne, Newcastle, U.K., in 2004 after a few years working for the Ministry of Aeronautics of China and Siemens Ltd., Beijing. Her Ph.D. work, carried out at the Newcastle upon Tyne School of Electrical, Electronic and Computer Engineering, was in the 3-D electromagnetic positioning, tele-robots, and quantitative diagnostic of Parkinson’s Disease.

She is a Senior Research Associate with the School of Computing Science, University of East Anglia, Norwich, U.K. She is a member of British Machine Vision Association and the European Society of Biomechanics. She is currently working on the European Frame 6 MAESTRO project in the area of computer-controlled radiotherapy. Her research interests include medical signal analysis and applications such as EMG-controlled prosthetic hand, computer-controlled radiotherapy and medical imaging. She has published several papers in these areas.

Mark H. Fisher received the B.Sc. degree in electrical and electronic engineering from Aston University, Birmingham, U.K., and the M.Sc. degree in microprocessor engineering and digital electronics, and the Ph.D. degree from the Department of Computation, Institute of Science and Technology, University of Manchester, Manchester, U.K.

He is currently a Lecturer with the School of Computing Sciences, University of East Anglia, Norwich, U.K. His research interests are in medical applications of signal and image processing and pattern recognition.

Andrzej Wolczowski received the M.S. degree in automatics and Ph.D. degree in computer engineering from the Wroclaw University of Technology, Wroclaw, Poland, in 1974 and 1980, respectively.

He is an Assistant Professor with the Institute of Computer Engineering, Control and Robotics at the Wroclaw University of Technology. He is the author of the robot Ulysses—the first mobile robot constructed in Poland. His main research interests are in the fields of mobile robot navigation, sensor-based decision control, and medical robotics. Currently, he is working on a project of applying the EMG signals for dexterous hand prosthetic control.
G. Duncan Bell received the M.D. degree from Bartholomew’s Hospital Medical School, London, U.K., in 1968. He received the MRCP (U.K.) in 1970 and then went into gastroenterology/general medicine. While working at the Royal Postgraduate Medical School, London, he received the M.Sc. degree in biochemistry as well as the M.D. degree by thesis. He was a Senior Lecture of therapeutics at Nottingham University Medical School, Nottingham, U.K., from 1976 to 1983. He then spent 14 years as a busy NHS Consultant at the Ipswich Hospital, Suffolk, U.K., during which time he forged close research links with British Telecom’s Unit in Martlesham, U.K. He spend five years as a Consultant Gastroenterologist/Visiting Professor in the Medical Sciences Faculty, Sunderland University, Sunderland, U.K., during which time he forged close research ties with Dr. Charles Allen’s research team at the University of East Anglia’s School of Computing Sciences, Norwich. His research interests are wide, and he has authored over 100 original papers.

David J. Burn is Consultant Neurologist and Reader in Movement Disorder Neurology at the Regional Neurosciences Centre, Newcastle upon Tyne, and University of Newcastle upon Tyne. He qualified from Oxford University and Newcastle upon Tyne Medical School in 1985. His M.D., carried out at the MRC Cyclotron Unit, Hammersmith Hospital, was in the functional imaging of parkinsonism. He runs Movement Disorders clinics in Newcastle upon Tyne. He represents the Royal College of Physicians on the NICE National Guidelines writing group for Parkinson’s disease and is a member of the Movement Disorder Society Task Force for Parkinson’s Disease with Dementia. He is a member of the Medical Advisory panels for the Parkinson’s Disease Society, PSP (Europe) Association and National Tremor Foundation and is on the Editorial Board for the Journal of Neurology, Neurosurgery and Psychiatry and Advances in Clinical Neuroscience and Rehabilitation. Clinical research interests include nonmotor complications of Parkinson’s disease, particularly dementia, depression, and falls, and also progressive supranuclear palsy. He has published more than 95 articles on movement disorders.

Robert X. Gao (M’91–SM’00) received the B.S. degree from the (former) Central Academy of Arts and Design, Beijing, China, in 1982, and the M.S. and Ph.D. degrees from the Technical University Berlin (TU Berlin), Germany, in 1991 and 1985, respectively. He is a Professor at the Department of Mechanical and Industrial Engineering, University of Massachusetts, Amherst, where he conducts research and teaching in the areas of physics-based sensing, self-diagnostic and energy-efficient sensors and sensor networks, mechatronic systems design, medical instrumentation, and signal processing for machine health monitoring, diagnosis, and prognosis. Dr. Gao was a recipient of the 1996 National Science Foundation CAREER Award, the 1999 University of Massachusetts Outstanding Junior Engineering Faculty Award, and the faculty advisor and co-recipient of the inaugural Best Student Paper Award from the SPIE’s 1997 International Symposium on Smart Structures and Materials. He guest-edited a Special Section on Built-In-Test for the IEEE TRANSACTIONS ON INSTRUMENTATION AND MEASUREMENT in 2005 and a Special Section on Sensors for the Journal of Dynamic Systems, Measurement, and Control, published by the American Society of Mechanical Engineers, in 2004. He is currently an Associate Editor of the IEEE TRANSACTIONS ON INSTRUMENTATION AND MEASUREMENT, an Associate Editor of the ASME Journal of Dynamic Systems, Measurement, and Control, and a member of the editorial board of the International Journal of Manuacturing Research. He also serves as a co-chair of the Technical Committee on Built-in-Test and Self-Test of the IEEE Instrumentation and Measurement Society.