Real-time Classification of Finger Movements using Two-channel Surface Electromyography

Khairul Anam$^{1,2}$ and Adel Al-jumaily$^2$

$^1$University of Jember, Jember, Indonesia
$^2$University of Technology, Sydney, Australia
khairol.anam@student.uts.edu.au, adel.al-jumaily@uts.edu.au

Keywords: Surface EMG, Extreme Learning Machine, Finger Movements.

Abstract: The use of a small number of Electromyography (EMG) channels for classifying the finger movement is a challenging task. This paper proposes the recognition system for decoding the individual and combined finger movements using two channels surface EMG. The proposed system utilizes Spectral Regression Discriminant Analysis (SRDA) for dimensionality reduction, Extreme Learning Machine (ELM) for classification and the majority vote for the classification smoothness. The experimental results show that the proposed system was able to classify ten classes of individual and combined finger movements, offline and online with accuracy 97.96% and 97.07% respectively.

1 INTRODUCTION

The electromyography signal has been used widely to control the upper-limb prosthetic robot to recover the quality of life of the amputee. Many attempts have been made to decode the hand movements as the control sources of the hand robot (Oskoei and Huosheng, 2008); (Sang Wook et al., 2011); (Micera et al., 2010). The dexterous control system should involve not only the hand movements but also the finger movements (Tenore et al., 2009); (Khushaba et al., 2012). Some efforts have been done to recognize the finger movements. Tenore et al decoded ten classes of the individual finger movements by using up to 32 sEMG channels with accuracy ~ 90% (Tenore et al., 2009). In addition, Al-Timemy et al (Al-Timemy et al., 2013) classified 15 individual finger movements and achieved 98% accuracy by using 6 sEMG channels.

The use of few numbers of electrodes in a finger recognition system without compromising the decoding accuracy is a challenging task. Tsenov et al used two sEMG channels for 4 class finger movements i.e. the thumb, index, middle finger and hand closure with the best accuracy was nearly 93% in offline classification (Tsenov et al., 2006). Moreover, Khusaba et al classified 10 classes of individual and combined finger movements which consisted of five individual finger movements by using two sEMG channels (Khusaba et al., 2012). This work could achieve 92% and 90% of accuracy for the offline and online classification respectively.

To achieve good classification results, it demands the proper and right decoding methods. Tsenov employed time domain feature extractions and Artificial Neural Networks (ANNs) to process the sEMG signals from two channels (Tsenov et al., 2006). This recognition system gave a good accuracy in offline classification but no evidence in online classification. In addition, this system only decoded for finger movements which were only three individual finger movements and one hand close. More finger movements are needed in real-time application.

The best improvement was proposed in (Khusaba et al., 2012). The sEMG signals from two channels were extracted by using time domain features and reduced by Linear Discriminant Analysis (LDA) and then classified by using Support Vector Machine. The final results were refined by using a Bayesian fusion vote. Ten classes of individuated and combined finger movements were able to recognize with 92% offline classification accuracy and 90% online classification accuracy.

The achievement attained by previous system is good but not good enough for the implementation in real-time application. Many attempts should be made to achieve more accurate system recognition. For that goal, this paper proposes the novel recognition system which uses two sEMG channels.
in recognizing the individual and combined finger movements. A number of features are extracted by using time domain feature extraction and then reduced by using Spectral Regression Discriminant Analysis (SRDA) (Cai et al., 2008). SRDA is an extension of Linear Discriminant Analysis which is fast and able to work on a large dataset.

Extreme Learning Machine (ELM) (Huang et al., 2012) is used for classification. ELM is generalized single-hidden-layer feedforward networks (SLFNs) whose hidden layer does not need to be tuned. It needs fewer optimization constraint, has better generalization functioning and faster learning time than SVM (Huang et al., 2012). This combination, SRDA and ELM along with the majority vote (Chan and Green, 2007), provide a fast and an accurate classification system for individuated and combined finger movements.

2 METHOD

2.1 Experiment Procedures

The data in this work were acquired from six subjects, one female and five males. All subjects were normally limbed with no muscle disorder. To avoid the effect of position movement on EMG signals, subject’s arm was supported and fixed at certain position as described in fig. 2. (Khushaba et al., 2012).

The FlexComp Infiniti™ System from Thought Technology was used to process the signals from two EMG MyoScan™ T9503M Sensors which were put on the subject’s forearm as seen in the figure 1. The acquired EMG signals were amplified to a total gain of 1000 and sampled at 2000 Hz.

The collected EMG signals were processed in the Matlab 2012b installed in the Intel Core i5 3.1 GHz desktop computer with 4 GB RAM running on Windows 7 operating system. The signals were filtered by a band pass filter between 20 and 500 Hz with a notch filter to remove the 50 Hz line interference. Finally, the EMG signals were down sampled to 1000 Hz.

Fig. 2 shows ten classes of the individual and combined finger movements consisting of the flexion of individuated 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 the hand close (HC).

The offline classification was performed based on data from the data acquisition. In this stage, the subjects asked to perform a certain posture of a finger movement for a period 5 s and then take a rest for 5 s. Each movement was repeated six times. Therefore 30 minutes of data are collected for each trials and 180 minutes for all repetitions. The data collected were divided into training data and testing data. Four of six trials were training data and the rest were testing data.

In the online stage, the subject performed similar activities. The difference is the repetition which is only four times instead of six and all are for testing only. Another difference is the recognition system is performed each 100 ms and then the result is displayed on the screen.

2.2 Proposed Method

The proposed recognition system consisted of two stages, an offline and online classification stages. In the offline stage, the EMG signals were acquired by a data acquisition device from 6 subjects. The filtering and windowing was applied to the collected data before being extracted by using a time domain feature set. To reduce the dimension of the features, SRDA was employed. Then, the reduced data were classified using ELM and refined by using the majority vote. The trained ELM which is produced by the offline classification is stored and used in the online classification stage.

In the online stage, the trained ELM is restored and used to classify the sEMG signals which are captured every 100 ms. The acquired signals are extracted by using time domain feature extractions and reduced their dimensionality by using SRDA.
Then, the reduced features are recognized by the trained ELM and the output classification is refined by using majority vote.

2.3 Feature Extraction

The features were extracted from a time domain feature set which consists of Waveform Length (WL), Slope Sign Changes (SSC), Number of Zero Crossings (ZCC), and Sample Skewness (SS). In addition, some parameters from Hjorth Time Domain Parameters (HTD) and Auto Regressive (AR) Model Parameters were included as used in (Khushaba et al., 2012). All features were extracted by using myoelectric toolbox (Chan and Green, 2007) and Biosig toolbox (Schlogl and Brunner, 2008).

The AR model parameters have been proven to be stable and robust to the electrode location shift and the change of signal level (Tkach et al., 2010). Moreover, aforementioned time domain features were windowed by using disjoint window instead of sliding window to keep computational cost low. A 100 ms window and a 100 increments were used to form a system which is suitable for real time application.

2.4 SRDA

SRDA is an improvement of LDA which is better than LDA in the computational aspect and the ability to cope with a large dataset (Cai et al., 2008). Let eigen problem of LDA is

\[ \bar{X}W\bar{X}^T a = \lambda \bar{X} \]

(1)

where \( \bar{X} \) (1 x c) is centered data matrix, \( W \) is eigenvector matrix (m x m), \( \lambda \) = eigenvalue, \( a \) = transformation vector, c = the number of classes, and m = the number of total training data points. Modification of the equation (1) gives:

\[ W\bar{y} = \lambda \bar{y} \]

(2)

where

\[ \bar{X}^T a = \bar{y} \]

(3)

The solution of LDA problem by SRDA is to get \( y \) by solving eq (2) and then use the \( y \) obtained to find \( a \). To solve \( a \), the least square sense could be employed by using:

\[ a = \arg \min_a \sum_{i=1}^{m} \left( \bar{x}_i^T a - \bar{y}_i \right)^2 \]

(4)

Regularize least square problem of SRDA, we get:

\[ a = \arg \min_a \sum_{i=1}^{m} \left( \bar{x}_i^T a - \bar{y}_i \right)^2 + \alpha a^T a \]

(5)

Derivative of equation (5) gives:

\[ \bar{X}\bar{X}^T + \alpha I = \bar{X} \bar{y} \]

(6)

\[ a = \left( \bar{X}\bar{X}^T + \alpha I \right)^{-1} \bar{X} \bar{y} \]

2.5 Extreme Learning Machine

ELM is a learning scheme for single layer feedforward networks (SLFNs). While the network parameters are tuned in classical SLFNs learning algorithms, most of these parameters are analytically determined in ELM. The hidden parameters can be independently determined from the training data, and the output parameters can be determined by pseudo-inverse method using the training data. As a result, the learning of ELM can be carried out extremely fast compared to the other learning algorithms (Huang et al., 2012).

The output function of ELM for generalized SLFNs (for one output node case) is:

\[ f(x) = \sum_{i=1}^{L} \beta_i h_i(x) = \mathbf{h}(x)\mathbf{\beta} \]

(7)

where \( \mathbf{\beta} = [\beta_1, \ldots, \beta_L]^T \) is the vector of the output weight between hidden layer of L nodes and the output node, \( \mathbf{h}(x) = [h_1(x), \ldots, h_L(x)] \) is the output vector of hidden layer.

The objective of ELM is to minimize the error and the norm of weight:

\[ \text{Minimize} : \| \mathbf{H}\mathbf{\beta} - \mathbf{T} \| \text{ and } \| \mathbf{\beta} \| \]

(8)

where \( \mathbf{T} \) is the target. For classification purpose, the output function of ELM in equation (7) could be modified to be:

\[ f(x) = \mathbf{h}(x)\mathbf{\beta} = \mathbf{h}(x)\mathbf{H}^T \left( \frac{1}{C} \mathbf{H}\mathbf{H}^T \right)^{-1} \mathbf{T} \]

(9)

where

\[ \mathbf{H} = \begin{bmatrix} \mathbf{h}(x_1) \\ \vdots \\ \mathbf{h}(x_n) \end{bmatrix} = \begin{bmatrix} h_1(x_1) & \cdots & h_L(x_1) \\ \vdots & \ddots & \vdots \\ h_1(x_n) & \cdots & h_L(x_n) \end{bmatrix} \]

(10)

as well as C is a user-specified parameter and N is the number of the training data. In the equation (10),
h(x) is a feature mapping (hidden layer output vector) which can be:

\[ h(x) = \left[ G(a_1, b_1, x), \ldots, G(a_n, b_n, x) \right] \]  \(11\)

where G is a non-linear piecewise continuous function such as sigmoid, hard limit, Gaussian, and multi quadratic function.

If the feature mapping \( h(x) \) is unknown to the user, a kernel function can be used to represent \( h(x) \). Then, the equation (9) would be:

\[
f(x) = h(x)^\top \left( \frac{1}{C^2} + \Omega_{\text{ELM}} \right)^{-1} T
\]

\[
= \begin{bmatrix}
  K(x, x_1) \\
  \vdots \\
  K(x, x_n)
\end{bmatrix}
\left( \frac{1}{C^2} + \Omega_{\text{ELM}} \right)^{-1} T
\]

where

\[
\Omega_{\text{ELM}} = \Omega_{\text{ELM},ij} = h(x_i)h(x_j) = K(x_i, x_j)
\]

and K is a kernel function such that:

\[
K(u, v) = \exp \left( -\gamma \|u - v\|^2 \right)
\]  \(13\)

2.6 Majority Vote

The majority vote was used to refine the classification results. It utilizes the results from the present state and \( n \) previous states and makes a new classification result based on the class which appears most frequent. This procedure produces the finger movement class that removes specious misclassification. Besides majority vote, the transition states in the classification results are removed too. This method gives the recognition system that works in steady state only regardless the transition state.

3 RESULT AND DISCUSSION

The two experiments have been performed, the offline and online classification. In the offline stage, the possibility of adding new channel which was extracted from summing up of two original channels is verified. Next, the best result of the offline stage was utilized in the online classification stage. In the both offline and online stage, the signals were extracted from six subjects with 100 ms windows length and 100 increment as recommended in (Khushaba et al., 2012). In addition, the Gaussian kernel based ELM is used as the classifier. It has two importance parameters, C and \( \gamma \) as showed in equation 9 and 12. This paper used the optimized ELM presented in the (Anam et al., 2013) with \( \gamma=2^{-5} \) and \( C=2^0 \). The majority vote method with 9 decision voting was employed to refine the classification result.

The first experiment was the offline classification. In this stage, the performance of the classification system using only two original signals (ch1, ch2) was compared to the two signals plus the new additional channel from summing up of the both channels (ch1, ch2, ch1+ch2). From six trials across each subject, four trials were used to train the ELM and the rest were the testing data. The classification result is shown in the table 1.

Table 1: The classification results averaged for six subjects.

<table>
<thead>
<tr>
<th>Subject</th>
<th>Ch1 &amp; Ch2 (%)</th>
<th>Ch1, Ch2, Ch1+Ch2 (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>98.48 ± 2.87</td>
<td>97.10 ± 4.13</td>
</tr>
<tr>
<td>2</td>
<td>100.00 ± 0</td>
<td>100.00 ± 0</td>
</tr>
<tr>
<td>3</td>
<td>94.95 ± 11.38</td>
<td>96.42 ± 8.26</td>
</tr>
<tr>
<td>4</td>
<td>98.61 ± 3.93</td>
<td>98.34 ± 4.02</td>
</tr>
<tr>
<td>5</td>
<td>98.89 ± 2.43</td>
<td>98.89 ± 3.51</td>
</tr>
<tr>
<td>6</td>
<td>93.81 ± 8.39</td>
<td>96.99 ± 5.49</td>
</tr>
<tr>
<td>Average</td>
<td>97.46 ± 2.35</td>
<td>97.96 ± 1.47</td>
</tr>
</tbody>
</table>

Table 1 shows that both configurations achieved good accuracies across six subjects. However, the additional signal of the summation of two channels gave better average accuracy than two channels only even though the difference is not so significant. The significance of the second configuration is depicted in figure 3. Even though both configurations achieve similar accuracy in recognizing the ten finger movements, the standard deviation of second one is better than first one.
The online classification is the second experiments performed. The individual and combined finger movements were recognized in real-time based on the matrix projection of SRDA and the trained ELM kernel from offline stage. In this experiments, the configuration of (ch1, ch2) achieve 93.36% accuracy while the (ch1,ch2, ch1+ch2) configuration attained better accuracy which is 97.07%. The performance of finger recognition is depicted in the figure 4 and the table 2.

Table 2: The confusion matrix of the classification results averaged for SIX subjects.

<table>
<thead>
<tr>
<th>Intended task (%)</th>
<th>T</th>
<th>I</th>
<th>M</th>
<th>R</th>
<th>L</th>
<th>T-I</th>
<th>T-M</th>
<th>T-R</th>
<th>T-L</th>
<th>HC</th>
</tr>
</thead>
<tbody>
<tr>
<td>T</td>
<td>98.7</td>
<td>0.1</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.3</td>
</tr>
<tr>
<td>I</td>
<td>0.0</td>
<td>99.3</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.3</td>
<td>0.0</td>
<td>0.3</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>M</td>
<td>0.0</td>
<td>0.0</td>
<td>98.0</td>
<td>0.2</td>
<td>0.0</td>
<td>0.0</td>
<td>1.3</td>
<td>0.0</td>
<td>0.0</td>
<td>0.5</td>
</tr>
<tr>
<td>R</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>99.9</td>
<td>0.0</td>
<td>0.0</td>
<td>0.1</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>L</td>
<td>1.1</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>97.3</td>
<td>0.6</td>
<td>0.0</td>
<td>0.0</td>
<td>0.1</td>
<td>0.0</td>
</tr>
<tr>
<td>T-I</td>
<td>0.5</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>1.5</td>
<td>95.1</td>
<td>1.0</td>
<td>0.0</td>
<td>1.9</td>
<td>0.0</td>
</tr>
<tr>
<td>T-M</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.9</td>
<td>0.0</td>
<td>0.7</td>
<td>13.9</td>
<td>96.1</td>
<td>0.0</td>
<td>0.1</td>
</tr>
<tr>
<td>T-R</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.3</td>
<td>0.5</td>
<td>99.1</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>T-L</td>
<td>0.0</td>
<td>0.1</td>
<td>0.0</td>
<td>0.0</td>
<td>6.0</td>
<td>0.3</td>
<td>0.7</td>
<td>0.5</td>
<td>92.3</td>
<td>0.0</td>
</tr>
<tr>
<td>HC</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.2</td>
<td>0.0</td>
<td>99.8</td>
<td>0.0</td>
</tr>
</tbody>
</table>

Figure 4 shows that the T-L movement is the most difficult one to recognize. It was misclassified to the L movements as seen in the confusion matrix table 2. It was probably caused by the facts that the T-L was composed of Thumb(T) and Little(L) finger movement therefore there is possibility each movement affects the combined movements.

Besides the classification performance, the processing time of the real-time application has been also tested which the result is presented in table 3. The acquisition, filtering, feature extraction and reduction, ELM and majority vote processing time were record during the experiment. This recognition system took 112.13 ms in average. It is verified that processing time of this system is in between the optimal processing time for real-time myoelectric control, 100-125 ms, as suggested in (Farrell and Weir, 2007).

Table 3: The processing time of the online experiment.

<table>
<thead>
<tr>
<th>Class</th>
<th>Acquiring</th>
<th>Filter</th>
<th>Extraction /reduction</th>
<th>ELM</th>
<th>Vote</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>T</td>
<td>100</td>
<td>3.9</td>
<td>7.6</td>
<td>0.5</td>
<td>0.1</td>
<td>112.1</td>
</tr>
<tr>
<td>I</td>
<td>100</td>
<td>3.5</td>
<td>7.2</td>
<td>0.5</td>
<td>0.1</td>
<td>111.3</td>
</tr>
<tr>
<td>M</td>
<td>100</td>
<td>3.5</td>
<td>7.3</td>
<td>0.5</td>
<td>0.1</td>
<td>111.4</td>
</tr>
<tr>
<td>R</td>
<td>100</td>
<td>3.6</td>
<td>7.4</td>
<td>0.5</td>
<td>0.1</td>
<td>111.6</td>
</tr>
<tr>
<td>L</td>
<td>100</td>
<td>3.7</td>
<td>7.6</td>
<td>0.6</td>
<td>0.1</td>
<td>111.9</td>
</tr>
<tr>
<td>T-I</td>
<td>100</td>
<td>3.5</td>
<td>7.3</td>
<td>0.5</td>
<td>0.1</td>
<td>111.4</td>
</tr>
<tr>
<td>T-M</td>
<td>100</td>
<td>3.6</td>
<td>7.5</td>
<td>0.5</td>
<td>0.1</td>
<td>111.7</td>
</tr>
<tr>
<td>T-R</td>
<td>100</td>
<td>3.6</td>
<td>7.6</td>
<td>0.6</td>
<td>0.1</td>
<td>111.8</td>
</tr>
<tr>
<td>T-L</td>
<td>100</td>
<td>3.5</td>
<td>7.3</td>
<td>0.5</td>
<td>0.1</td>
<td>111.4</td>
</tr>
<tr>
<td>HC</td>
<td>100</td>
<td>3.5</td>
<td>7.3</td>
<td>0.5</td>
<td>0.1</td>
<td>111.4</td>
</tr>
<tr>
<td>Avg</td>
<td>100</td>
<td>3.6</td>
<td>7.4</td>
<td>0.5</td>
<td>0.1</td>
<td>112.1</td>
</tr>
</tbody>
</table>

This promising result could be implemented to the hand exoskeleton to recover the motor function of the patients post stroke. It could move all individual fingers and some combined movements. However, it is aimed for finger extension only. In addition, it would not work properly if the EMG signal of the subject is very weak. Therefore, it could only be applied to the partially paralyzed subject.

Furthermore the proposed system could be implemented to the prosthetic hand device. It is promising because it used few electrodes which enhance the user’s comfort. However, it needs more validation for amputee subjects.

4 CONCLUSIONS

The two channel sEMG signals were used in this paper to recognize the ten individual and combined finger movements. The extracting more feature from summation of the signals from the two channels improves the classification accuracy in both offline and online classification system. By using this combination, the recognition system was able to achieve in average 97.96% in offline and 97.07% in online one. These results show the feasibility of the proposed system in classifying ten different finger movements.

REFERENCES


Anam, K., Khushaba, R. & Al-Jumaily, A. 2013. Two-Channel Surface Electromyography for Individual and


NEUROTECHNIX

2013

Proceedings of the
International Congress on Neurotechnology,
Electronics and Informatics

Vilamoura, Algarve, Portugal

18 - 20 September, 2013

Sponsored by
INSTICC – Institute for Systems and Technologies of Information, Control and Communication

In Cooperation with
Neurotech Network
Nansen Neuroscience Network
APEEGNC – Associação Portuguesa de EEG e Neurofisiologia Clínica
SPN – Sociedade Portuguesa de Neurologia
Enlightenment FP7

In Collaboration with
antibodies-online.com – The Marketplace for Research Antibodies
BRIEF CONTENTS

INVITED SPEAKERS ................................................................. IV
SPECIAL SESSIONS CHAIRS ....................................................... V
ORGANIZING AND STEERING COMMITTEES ............................... VI
PROGRAM COMMITTEE .............................................................. VII
AUXILIARY REVIEWERS ........................................................... IX
SPECIAL SESSIONS PROGRAM COMMITTEE ............................... X
SELECTED PAPERS BOOK .......................................................... X
FOREWORD .......................................................... XI
CONTENTS .......................................................... XIII
INVITED SPEAKERS

Kevin Warwick
University of Reading
U.K.

François Hug
The University of Queensland
Australia

Aldo Faisal
Imperial College London
U.K.

Alexandre Castro-Caldas
Portuguese Catholic University
Portugal
SPECIAL SESSIONS CHAIRS

SPECIAL SESSION ON VIRTUAL AND AUGMENTED REALITY SYSTEMS FOR UPPER LIMBS REHABILITATION
Alessandro de Mauro, Vicomtech-IK4, Spain
Iris Dimbwadyo Terer, National Spinal Cord Injury Hospital - SESCAM, Spain
Gorka Epelde, Vicomtech-IK4, Applications for Independent living Group, Spain

SPECIAL SESSION ON DECODING THE NEURAL DRIVE TO MUSCLE THROUGH THE ANALYSIS OF MOTOR NEURON SPIKE TRAINS
Juan Álvaro Gallego, Spanish National Research Council (CSIC), Spain
Jose Luis Pons, Instituto de Automatica Industrial, Spain

SPECIAL SESSION ON SENSORY FUSION FOR DIAGNOSTICS AND NEUROREHABILITATION
Diego Torricelli, Consejo Superior de Investigaciones Cientificas (CSIC), Spain
Rafael Raya, Spanish National Council for Science Research, Spain

SPECIAL SESSION ON WEARABLE ROBOTICS FOR MOTION ASSISTANCE AND REHABILITATION
Nicola Vitiello, Scuola Superiore Sant’Anna, Italy
Samer Mohammed, Lissi - Université Paris-Est Créteil, France
Juan Moreno, CSIC, Spain

SPECIAL SESSION ON BRAIN-COMPUTER INTERFACES AND BRAIN STIMULATION FOR NEUROREHABILITATION
Martin Bogdan, Universität Leipzig, Germany
Ander Ramos-Murguialday, Eberhard-Karls-University, Germany
Armin Walter, Eberhard-Karls-University Tübingen, Germany
Francisco Perales, Uib, Spain
ORGANIZING AND STEERING COMMITTEES

CONFERENCE CHAIR
Ana Rita Londral, Universidade de Lisboa, Portugal

PROGRAM CO-CHAIRS
Pedro Encarnação, Universidade Católica Portuguesa, Portugal
Jose Luis Pons, Instituto de Automatica Industrial, Spain

PROCEEDINGS PRODUCTION
Marina Carvalho, INSTICC, Portugal
Helder Coelhas, INSTICC, Portugal
Bruno Encarnação, INSTICC, Portugal
Ana Guerreiro, INSTICC, Portugal
Andreia Moita, INSTICC, Portugal
Raquel Pedrosa, INSTICC, Portugal
Vitor Pedrosa, INSTICC, Portugal
Sara Santiago, INSTICC, Portugal
José Varela, INSTICC, Portugal

CD-ROM PRODUCTION
Pedro Varela, INSTICC, Portugal

GRAPHICS PRODUCTION AND WEBDESIGNER
André Lista, INSTICC, Portugal
Mara Silva, INSTICC, Portugal

SECRETARIAT
Cláudia Pinto, INSTICC, Portugal

WEBMASTER
Susana Ribeiro, INSTICC, Portugal
**PROGRAM COMMITTEE**

Amr Abdel-Dayem, Laurentian University, Canada  
Gregor Adriany, University of Minnesota, U.S.A.  
Lyuba Alboul, Sheffield Hallam University, U.K.  
Pedro Almeida, University of Lisbon, Portugal  
Alexandre Andrade, Faculdade de Ciências da Universidade de Lisboa, Portugal  
Helder Araújo, University of Coimbra, Portugal  
Sabri Arik, Istanbul University, Turkey  
Tetsuya Asai, Hokkaido University, Japan  
Jose M. Azorin, Miguel Hernandez University, Spain  
Reneta Barneva, State University of New York, U.S.A.  
Ammar Belatreche, University of Ulster, U.K.  
Alexandre Bernardino, Instituto Superior Técnico, Portugal  
Fernando Brunetti, Consejo Superior de Investigaciones Científicas, Spain  
Barbara Caputo, IDIAP Research Institute, Switzerland  
Xin Chen, Georgia Health Sciences University, U.S.A.  
Albert C. S. Chung, The Hong Kong University of Science and Technology, Hong Kong  
Emmanuel Conchon, University of Toulouse, IRIT/ISIS, France  
Lei Ding, University of Oklahoma, U.S.A.  
Dominique Durand, Case Western Reserve, U.S.A.  
Jimmy T. Eifrd, East Carolina Heart Institute, U.S.A.  
Gary Egan, Monash University, Australia  
Patrícia Figueiredo, Instituto Superior Técnico, Portugal  
Alexander Fingelkurts, BM-Science – Brain & Mind Technologies Research Centre, Finland  
Andrew Fingelkurts, BM-Science - Brain & Mind Technologies Research Centre, Finland  
Anselmo Frizera, UFES, Brazil  
Colin Fyfe, University of the West of Scotland, U.K.  
Vasco Galhardo, Faculdade de Medicina - Universidade do Porto, Portugal  
Petia Georgieva, University of Aveiro, Portugal  
Michele Giugliano, University of Antwerp, Belgium  
Jordi González, Universitat Autònoma de Barcelona - Centre de Visió per Computador, Spain  
Jay Gunkelman, Brain Science International, U.S.A.  
Chung Y. Hsu, China Medical University, Taiwan  
Xavier Intes, Rensselaer Polytechnic Institute, U.S.A.  
Pasi Karjalainen, University of Eastern Finland, Finland  
Jonghwa Kim, University of Augsburg, Germany  
Frank Kirchner, DFKI, Germany  
Andrzej Kloczkowski, Ohio State University, U.S.A.  
Constantine Kotropoulos, Aristotle University of Thessaloniki, Greece  
Ondrej Krejcar, University of Hradec Králové, Czech Republic  
Hongan Liao, The University of Tokyo, Japan  
Diego Liberati, National Research Council, Italy  
Xiao Liu, Brunel University, U.K.  
Christos Loizou, Intercollege, Cyprus  
Ana Rita Londral, Universidade de Lisboa, Portugal  
Nigel Lovell, University of New South Wales, Australia  
Mai S. Mabrouk, Misr University for Science and Technology, Egypt  
Alessandro de Mauro, Vicomtech-IK4, Spain
Program Committee (cont.)

Javier Melenchón, Universitat Oberta de Catalunya, Spain
Paulo Mendes, University of Minho, Portugal
Susana Novais, Carnegie Mellon University, U.S.A.
Calogero Maria Oddo, Scuola Superiore Sant’Anna, Italy
Haluk Ogmen, University of Houston, U.S.A.
Joao Papa, Sao Paulo State University - Unesp, Brazil
Francisco Perales, Uib, Spain
George Perry, University of Texas at San Antonio, U.S.A.
Victor Pikov, Huntington Medical Research Institutes, U.S.A.
Armando J. Pinho, University of Aveiro, Portugal
Susana Pinto, Institute of Molecular Medicine - Faculty of Medicine, University of Lisbon, Portugal
Gabriel Pires, Institute for Systems and Robotics - Coimbra / Polytechnic Institute of Tomar, Portugal
Hemerson Pistori, Dom Bosco Catholic University, Brazil
Mirjana Popovic, University of Belgrade, Serbia
Ales Prochazka, Institute of Chemical Technology, Czech Republic
Rafael Raya, Spanish National Council for Science Research, Spain
Despina Sanoudou, Medical School, University of Athens, Greece
André Saúde, Federal University of Lavras, Brazil
Friedhelm Schwenker, University of Ulm, Germany
Mário Forjaz Secca, CEFITEC, Departamento de Física, FCT/UNL, Portugal
Tapio Seppänen, University of Oulu, Finland
Miguel Tavares da Silva, Instituto Superior Técnico, Portugal
Claudia Sommer, University of Würzburg, Germany
Armando J. Sousa, Faculdade de Engenharia da Universidade do Porto, Portugal
Sundaram Suresh, Nanyang Technological University, Singapore
João Manuel R. S. Tavares, FEUP - Faculdade de Engenharia da Universidade do Porto, Portugal
Marc Tittgemeyer, Max-Planck-Institut für neurologische Forschung, Germany
Diego Torricelli, Consejo Superior de Investigaciones Científicas (CSIC), Spain
Carlos M. Travieso, University of Las Palmas de Gran Canaria, Spain
Nicola Vitiello, Scuola Superiore Sant’Anna, Italy
Zeyun Yu, University of Wisconsin at Milwaukee, U.S.A.
Inga Zerr, University of Göttingen, Germany
Djemel Ziou, Université de Sherbrooke, Canada

Auxiliary Reviewers

Maria Laura Blefari, EPFL, Switzerland
Henrik Jörntell, Lund University, Sweden
Aikaterini Koutsou, CAR-CSIC, Spain
Cristina Santos, University of Minho, Portugal
Shingo Shimoda, RIKEN, Japan

VIII
SPECIAL SESSIONS PROGRAM COMMITTEE

SPECIAL SESSION ON VIRTUAL AND AUGMENTED REALITY SYSTEMS FOR UPPER LIMBS REHABILITATION

Gorka Epelde, Vicomtech-IK4, Applications for Independent living Group, Spain
Nestor Garay-Vitoria, University of the Basque Country/Euskal herriko Unibertsitatea, Spain

Alessandro de Mauro, Vicomtech-IK4, Spain
Iris Dimbwadyo Terrer, National Spinal Cord Injury Hospital - SESCAM, Spain

SPECIAL SESSION ON DECODING THE NEURAL DRIVE TO MUSCLE THROUGH THE ANALYSIS OF MOTOR NEURON SPIKE TRAINS

Jakob Lund Dideriksen, Göttingen University, Germany

Aleš Holobar, University of Maribor, Slovenia

SPECIAL SESSION ON SENSORY FUSION FOR DIAGNOSTICS AND NEUROREHABILITATION

Rafael Raya, Spanish National Council for Science Research, Spain

SPECIAL SESSION ON WEARABLE ROBOTICS FOR MOTION ASSISTANCE AND REHABILITATION

Luka Ambrozic, Faculty of Electrical Engineering, University of Ljubljana, Slovenia
Alícia Casals, Institute for Bioengineering of Catalonia.IBEC and Universitat Politècnica de Catalunya.UPC, Spain
Marco Cempini, The Biorobotics Institute - Scuola Superiore Sant’Anna, Pisa, Italy
Mario Cortese, The Biorobotics Institute - Scuola Superiore Sant’Anna, Pisa, Italy
Simona Crea, The BioRobotics Institute - Scuola Superiore Sant’Anna, Pisa, Italy
Antonio J. del-Ama, National Hospital for Spinal Cord Injury, Spain
Georges Fried, Lissi - UPEC, France
Francesco Giovacchini, The Biorobotics Institute - Scuola Superiore Sant’Anna, Pisa, Italy

Jian Huang, Huazhong University of Science and Technology, China
Ning Jiang, Universitätsmedizin Göttingen Georg-August-Universität, Germany
Kyoungchul Kong, Sogang University, Korea, Republic of
Stefan Lambrecht, CSIC, Spain
Samer Mohammed, Lissi - Université Paris-Est Créteil, France
Luis Montano, Universidad de Zaragoza, Spain
Juan Moreno, CSIC, Spain
Sehoon Oh, Sogang University, Korea, Republic of
Hala Rifai, Lissi - Université Paris-Est Créteil, France
Jan Veneman, Tecnalia, Spain
Nicola Vitiello, Scuola Superiore Sant’Anna, Italy
SPECIAL SESSIONS PROGRAM COMMITTEE

SPECIAL SESSION ON BRAIN-COMPUTER INTERFACES AND BRAIN STIMULATION FOR NEUROREHABILITATION

Martin Bogdan, Universität Leipzig, Germany
Francisco Perales, Uib, Spain

Ander Ramos-Murgualday, Eberhard-Karls-University, Germany
Armin Walter, Eberhard-Karls-University Tübingen, Germany

SELECTED PAPERS BOOK

A number of selected papers presented at NEUROTECHNIX 2013 will be published by Springer-Verlag in Springer Series in Computational Neuroscience. This selection will be done by the Conference Chair and Program Co-chairs, among the papers actually presented at the conference, based on a rigorous review by the NEUROTECHNIX 2013 Program Committee members.
FOREWORD


NEUROTECHNIX 2013 is co-sponsored by INSTICC - Institute for Systems and Technologies of Information, Control and Communication and MedinRes – Medical Information and Research, held in cooperation with Neurotech Network, Nansen Neuroscience Network, Associação Portuguesa de EEG e Neurofisiologia Clínica, Sociedade Portuguesa de Neurologia and Fp7 Project Enlightenment, and held in collaboration with Antibodies Online.

The Congress Technical Program includes oral presentations (full papers, short papers, and posters) organized around several topics such as: Neuromuscular Diseases, Parkinson Disease, Developmental Disorders, Dementia, Epilepsy, Sleep Disorders, Multiple Sclerosis, Neuroinfections, Brain Tumors, Stroke, Traumatic Brain Injuries, Cerebral Palsy, Spinal Cord Injury, Vision and Hearing Disorders. All full papers and short papers were included in the proceedings. The congress includes also several thematic sessions organized by specialized researchers: VirtRehab 2013 - Virtual and Augmented Reality Systems for Upper Limbs Rehabilitation; DeNeuro 2013 - Decoding the Neural Drive to Muscle through the Analysis of Motor Neuron Spike Trains; SensoryFusion 2013 - Sensory Fusion for Diagnostics and Neurorehabilitation; RoboAssist 2013 - Wearable Robotics for Motion Assistance and Rehabilitation; and BrainRehab 2013 - Brain-computer Interfaces and Brain Stimulation for Neurorehabilitation. A major aspect of the program is the inclusion of a set of four plenary keynote lectures given by internationally distinguished researchers, namely: Kevin Warwick (University of Reading, United Kingdom), François Hug (University of Queensland, Australia), Aldo Faisal (Imperial College London, United Kingdom) and Alexandre Castro-Caldas (Catholic University of Portugal, Portugal).

NEUROTECHNIX received submissions from 21 countries, in all continents. To evaluate each submission, a double blind paper review was performed by the Program Committee, whose members are highly qualified researchers in the NEUROTECHNIX topic areas. A post-congress Special Issue of the Springer Series in Computational Neuroscience is planned for publication of extended and revised versions of a restricted number of high quality papers presented during NEUROTECHNIX 2013. All papers presented at this congress will be available at the SciTePress Digital Library.

Congress are also meeting places where collaboration projects can emerge from social contacts amongst the participants. Therefore, in order to promote the development of research and professional networks, the congress includes in its social program a Congress Social Event & Banquet in the evening of September 20.

We would like to express our thanks to all participants. First of all to the authors, whose quality work is the essence of this congress; secondly to all members of the Program Committee and auxiliary reviewers, who helped us with their expertise and valuable time. We
would also like to deeply thank the invited speakers for their excellent contribution in sharing their knowledge and vision. Finally, a word of appreciation for the hard work of the secretariat: organizing a congress of this level is a task that can only be achieved by the collaborative effort of a dedicated and highly capable team.

Ana Rita Londral
Universidade de Lisboa, Portugal

Pedro Encarnação
Universidade Católica Portuguesa, Portugal

Jose Luis Pons
Instituto de Automatica Industrial, Spain
CONTENTS

INVITED SPEAKERS

KEYNOTE SPEAKERS

The Disappearing Human-Machine Divide
Kevin Warwick IS-5

Analysis of Muscle Coordination in Sports - Perspectives from Electromyography and Elastography
François Hug IS-7

Breaking into your Brain with Neurotechnology
Aldo Faisal IS-9

The Working Brain - Windows to the Outside World
Alexandre Castro-Caldas IS-11

PAPERS

FULL PAPERS

Robotic Grasp Initiation by Gaze Independent Brain-controlled Selection of Virtual Reality Objects
Christoph Reichert, Matthias Kennel, Rudolf Kruse, Hans-Jochen Heinze, Ulrich Schmucker, Hermann Hinrichs and Jochem W. Rieger 5

Striving for Better and Earlier Movement Prediction by Postprocessing of Classification Scores
Sirko Straube, Anett Seeland and David Feess 13

A Low Cost Platform based on FES and Muscle Synergies for Postural Control Research and Rehabilitation
D. Galeano, F. Brunetti, D. Torricelli, S. Piazza and J. L. Pons 21

SHORT PAPERS

Proposal of a P300-based BCI Speller using a Predictive Text System
Ricardo Ron Angevin and Leandro da Silva-Sauer 35

Memory and Processing Efficient Formula for Moving Variance Calculation in EEG and EMG Signal Processing
Mario Michael Krell, Marc Tabie, Hendrik Wöhrle and Elsa Andrea Kirchner 41

A Dataflow-based Mobile Brain Reading System on Chip with Supervised Online Calibration - For Usage without Acquisition of Training Data
Hendrik Wöhrle, Johannes Teiwes, Mario Michael Krell, Elsa Andrea Kirchner and Frank Kirchner 46

A Method to Detect Keystrokes using Accelerometry to Quantify Typing Rate and Monitor Neurodegenerative Progression
Ana Londral, Mafalda Câmara, Hugo Gamboa, Mamede de Carvalho, Anabela Pinto and Luís Azevedo 54

Comparison of Neural Networks for Prediction of Sleep Apnea
Yashar Maali and Adel Al-Jumaily 60
SPECIAL SESSION ON VIRTUAL AND AUGMENTED REALITY SYSTEMS FOR UPPER LIMBS REHABILITATION

FULL PAPERS

Virtual Arm Representation and Multimodal Monitoring for the Upper Limb Robot Assisted Teletherapy
Gorka Epelde, Xabier Valencia, Aitor Ardanza, Elsa Fanchon, Alessandro De Mauro, Francisco Molina Rueda, Eduardo Carrasco and Shabs Rajasekharan 69

Clinical, Functional and Kinematic Correlations using the Virtual Reality System Toyra© as Upper Limb Rehabilitation Tool in People with Spinal Cord Injury
Iris Dimbwadyo-Terrer, Fernando Trincado-Alonso, Ana de los Reyes-Guzmán, Alberto Bernal-Sahún, Patricia Lópe-Monteagudo, Begoña Polonio-López and Ángel Gil-Agudo 81

Rehabilitation for Children while Playing with a Robotic Assistant in a Serious Game
L. V. Calderita, P. Bustos, C. Suárez Mejías, B. Ferrer González and A. Bandera 89

SHORT PAPERS

Illusion Approach for Upper Limb Motor Rehabilitation
Yee Mon Aung and Adel Al-Jumaily 99

New Developments in the Gesture Therapy Platform - Past, Present and Future of our Research
Felipe Orihuela-Espina, Paloma Álvarez-Cardenas, Lorena Palafos, Israel Sánchez-Villavicencio, Alberto L. Morán, Jorge Hérnandez-Franco and Luis Enrique Sucar 106

SPECIAL SESSION ON DECODING THE NEURAL DRIVE TO MUSCLE THROUGH THE ANALYSIS OF MOTOR NEURON SPIKE TRAINS

SHORT PAPERS

Multi Channel Surface EMG - Detection and Conditioning
M. Gazzoni and U. Barone 119

On the Impact of Pathological Tremor Intensity on Noninvasive Characterization of Motor Unit Discharge Properties
Petra Povalej Bržan, Vojko Glaser, Simon Zelič, Juan Álvaro Gallego, Juan Pablo Romero Muñoz and Aleš Holobar 126

Motor Unit Properties and Underlying Determinants in Pathological Tremor
J. A. Gallego, J. L. Dideriksen, A. Holobar, J. P. Romero, J. L. Pons, E. Rocon and D. Farina 133

SPECIAL SESSION ON SENSORY FUSION FOR DIAGNOSTICS AND NEUROREHABILITATION

FULL PAPERS

Assessment of Walker-assisted Human Interaction from LRF and Wearable Wireless Inertial Sensors
Maria Martins, Carlos Cifuentes, Arlindo Elias, Valmir Schneider, Anselmo Frizera and Cristina Santos 143

Human-like Sensor Fusion Mechanisms in a Postural Control Robot
Georg Hetitich, Vittorio Lippi and Thomas Mergner 152
Assessment of the Suitability of the Motorized Ankle-Foot Orthosis as a Diagnostic and Rehabilitation Tool for Gait
Guillermo Asín, Filipe A. Barroso, Juan C. Moreno and José L. Pons

Error Augmented Robotic Rehabilitation of the Upper Limb - A Review
Aris C. Alexoulis-Chrysovergis, Andrew Weightman, Emma Hodson-Tole and Frederik J. A. Deconinck

SPECIAL SESSION ON WEARABLE ROBOTICS FOR MOTION ASSISTANCE AND REHABILITATION

FULL PAPERS

A Double-differential Actuation for an Assistive Hip Orthosis - Specificities and Implementation
Jeremy Olivier, Mohamed Bouri and Hannes Bleuler

Feasibility of Hybrid Gait Training with Kinesis Overground Robot for Persons with incomplete Spinal Cord Injury
Antonio J. del-Ama, Ángel Gil-Agudo, José L. Pons and Juan C. Moreno

A Light-weight Exoskeleton for Hip Flexion-extension Assistance
Francesco Giovacchini, Matteo Fantozzi, Mariele Peroni, Matteo Moisè, Marco Cempini, Mario Cortese, Dirk Lefeber, Maria Chiara Carrozza and Nicola Vitiello

Human Motion Assistance using Walking-aid Robot and Wearable Sensors
Jian Huang, Wenxia Xu, Zhen Shu and Samer Mohammed

Human-based Lower Limb Movement Assistance and Rehabilitation through an Actuated Orthosis
Samer Mohammed, Hala Rifaï, Walid Hassani and Yacine Amirat

SHORT PAPERS

Humanoids Meet Rehabilitation - Concept and Potential
Diego Torricelli and Jose L. Pons

Real-time Classification of Finger Movements using Two-channel Surface Electromyography
Khairul Anam and Adel Al-Jumaily

Ankle-Knee Prosthesis with Powered Ankle and Energy Transfer - Development of the CYBERLEGs Alpha-Prototype
Louis Flynn, Joost Geeroms, Rene Jimenez-Fabian, Bram Vanderborght, Nicola Vitiello and Dirk Lefeber

SPECIAL SESSION ON BRAIN-COMPUTER INTERFACES AND BRAIN STIMULATION FOR NEUROREHABILITATION

FULL PAPER

Efficiency of SSVEF Recognition from the Magnetoencephalogram - A Comparison of Spectral Feature Classification and CCA-based Prediction
Christoph Reichert, Matthias Kennel, Rudolf Kruse, Hermann Hinrichs and Jochem W. Rieger
SHORT PAPERS

Dynamics of a Stimulation-evoked ECoG Potential During Stroke Rehabilitation - A Case Study
Armin Walter, Georgios Naros, Martin Spüler, Wolfgang Rosenstiel, Alireza Gharabaghi and
Martin Bogdan

A Serious Game Application using EEG-based Brain Computer Interface
Francisco José Perales and Esperança Amengual

Monitoring Depth of Hypnosis under Propofol General Anaesthesia - Granger Causality and Hidden
Markov Models
Nicoletta Nicolaou and Julius Georgiou

AUTHOR INDEX