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Evaluating Different Combinations of Feature Selection Algorithms and Cost Functions Applied to iPCA Tuning in Myoelectric Control Systems*

Guillermo A. Camacho Muñoz[1], Carlos H. Llanos[2],
Pedro de A. Berger[3], Cristiano Jacques Miosso[4], and Adson Ferreira da Rocha[4]

***Abstract*— A myoelectric control system extracts information from electromyographic (EMG) signals and uses it to control different types of prostheses, so that people who suffered traumatisms, paralysis or amputations can use them to execute common movements. Recent research shows that the addition of a tuning stage, using the individual component analysis (iPCA), results in improved classification performance. We propose and evaluate a set of novel configurations for the iPCA tuning, based on a biologically inspired optimization procedure, the artificial bee colony algorithm. This procedure is implemented and tested using two different cost functions, the traditional classification error and the proposed correlation factor, which involves lower computational effort. We compare the tuned system's performance, in terms of correct classifications, to that of a system tuned using two standard algorithms, the sequential forward selection and the sequential floating forward selection. The statistical analyses of the results don't find a significant difference among the classification performances associated with the search algorithms ($p < 0.01$). On the other hand, they establish a significant difference among the classification performances related to the cost functions ($p < 0.02$).**

I. INTRODUCTION

The human hand is a very complex system, with a large number of degrees of freedom, sensors embedded in its structure, actuators and tendons, and a complex hierarchical control [1]. Its loss causes severe physical restrictions and psychological problems [2]. A current technological aid in response to upper limb amputation and deficiency is the myoelectric hand prosthesis. This device increases the range of motion and improves overall function of the upper limb in people with hand amputation.

Myoelectric hand prostheses are governed by a myoelectric control system, whose main task is to classify electromiographic patterns into movement classes. The control strategy widely uses the pattern-recognition approach. In this case the conventional architecture is composed of three stages: (a) feature extraction, (b) dimensionality reduction and (c) classification. In this context, the classification error is the most widely used performance indicator.

The conventional myoelectric control architecture has reached different classification errors, depending on the number of classes and other factors. For instance, in [3] an error of 7.4% is reported in a problem with 7 movement classes and 8 electromyography (EMG) signals channels. Recently, a new strategy has been proposed in which the temporal-spatial information, contained within muscle crosstalk, may implicitly add class discriminatory information to the classification problem [4]. This proposal has been investigated by Hargrove [5] observing a significative reduction in the classification error. In a problem with 7 movement classes and 6 EMG channels the system yielded a classification error of 1.9%.

The proposal in [5] mixes 3 components: (a) a high crosstalk level EMG acquisition system, (b) an iPCA (*individual PCA*) transformation stage and (c) the conventional myoelectric control system. The main disadvantage of the iPCA projection is the dimensionality increment of the electromyographic patterns, in which the pattern dimension is incremented by a factor corresponding to the control system's number of classes.

To deal with the dimensionality problem it is possible to execute a reduced iPCA transformation that generates just the most discriminative dimensions instead of the complete set. This solution is used in [5] and requires an optimization process, which is conducted during a configuration stage, before the classification tasks.

The results in [5] were computed with a combination of the sequential forward selection (SFS) algorithm and the classification error cost function. Despite important reported advantages, there are also some disadvantages. The SFS algorithm presents the *nesting effect*, i.e., once a channel has been selected there is no possibility of discarding it [6]. Also, the SFS algorithm does not use random components [7]; note that this type of components can help finding different solutions and hence potentially lead to better ones [8] in problems with more than one local optimum. Furthermore, the use of the classification error as the cost function requires a supervised procedure, in which the classes associated to each pattern are known, and is computationally expensive, due to the need for evaluating the classifier's output at each iteration.

Therefore, it is important to investigate iPCA tuning alternatives taking into account that: (a) the sequential floating forward selection (SFFS) algorithm treats the nesting effect problem, conserving the most of the advantages of the SFS algorithm [7]; (b) the *bio-inspired* algorithms include random

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[1]G. A. Camacho is with the Mechanical Engineering Department, University of Brasília, Brasília, DF, Brazil (e-mail: gacamacho@unb.br).

[2]C. H. Llanos is with the Mechanical Engineering Department, University of Brasília, Brasília, DF, Brazil (e-mail: hllanos@unb.br).

[3]P. A. Berger is with the Computer Science Department, University of Brasília, Brasília, DF, Brazil (e-mail: berger@cic.unb.br).

[4]C. J. Miosso and Adson F. da Rocha are with the University of Brasilia at Gama - FGA/UnB; (e-mails: miosso@ieee.org and adson@unb.br).

components in their search strategies, allowing the optimization problems to be effectively tackled [9], [10]; and (c) the discriminative information of the EMG input patterns is inversely proportional to the redundancy level of the input signals; therefore, it is possible to use a *correlation factor* as a cost function in the optimization problem. Some properties of this selection are the following: (*i*) not supervised cost function, and (*ii*) relatively low computational complexity.

This paper analyzes the effects of two cost functions and different search algorithms on myoelectric control systems with iPCA tuning. The study is motivated by the fact that we didn't find in the literature studies on the effects of the mentioned disadvantages over the myoelectric control system. Our work focuses on the classification performance, considering two types of cost functions (supervised and non-supervised) and a bio-inspired search algorithm, compared to two sequential algorithms. Specifically, the cost functions considered here are the classification error and the correlation factor. The tested search algorithms are the SFS, the SFFS and the artificial bee colony (ABC), for a total of six treatment alternatives.

II. BACKGROUND

A. Principal Components Analysis

PCA is an orthogonal linear transformation used to transform a set of observations of possibly correlated variables into a set of values of uncorrelated variables, called as principal components. Given M observations of an N dimensional random vector z, the PCA transformation is performed by firstly subtracting the mean of the vector from z [5], $x = z - E\{z\}$, computing the $N \times N$ covariance matrix $C_x = E\{xx^T\}$ and then applying $s = Wx$, where s is the vector of principal component and W is the matrix in which each column is an eigenvector of C_x. Usually the M observations would typically be samples taken from any one of C possible classes. This is termed universal PCA (uPCA) or global PCA [11]. This property, of ignoring class information, permits for arguing that PCA is suboptimal for classification purposes [12].

A recent variation, called individual PCA (iPCA) [12], [11], groups the M observations by their class membership. Separate projection matrices $W_1, ..., W_C$ with size $N \times N$ are found for each class (see Fig. 1). This set of matrices can be interpreted as a unique $CN \times N$ size transformation matrix W_{iPCA} formed by rows concatenation of the separate projection matrices. The iPCA method effectively "tunes" the data prior to classification and has been shown to improve classification accuracies for some pattern recognition problems [13]. Its main drawback is the linear increment of the dimensionality of the patterns with the number of classes C. To overcome this problem, a reduced iPCA transformation matrix W_R is defined in [5]. This solution uses a transformation matrix with the best N_1 bases of the W_{iPCA} matrix ($N_1 < CN$).

B. Channel Optimization

The optimization task of finding a subset of N_1 elements from a given set of CN channels can be interpreted as a discrete optimization problem (integer elements from the selected subset). The optimization scheme in Fig. 1 is used to execute this task. In this scheme a validation data set x_v is projected with the W_{iPCA} matrix. The projected pattern s is a $CN \times M$ size vector. The vector O' is a subset of the CN dimensions in s and its components change at each iteration, following a specific strategy defined by the *search algorithm*. The *cost function* evaluates the quality of an EMG pattern with regard to the discriminative information. The evaluated patterns by the cost function are conformed by the rows of s which form the O' vector. When the stop conditions are reached, the scheme provides as output the selected channel subset O.

C. Search Algorithms

Sequential Forward Selection (SFS): this is one of the first developed search methods in the literature related to feature selection. The search procedure consists of the following steps: (a) compute the cost function for each of the CN channels and then select the channel with the best value, (b) form all possible two dimensional vectors that contain the winner from the previous step and compute the fitness for each of them, (c) select the vector with the best value, (d) continue the process until the N_1 vector length has been founded. The main drawback of this algorithm is the nesting effect: once a channel has been selected, it will never be discarded [7].

Sequential floating forward selection (SFFS): this is a suboptimal search algorithm proposed by Pudil et. al in 1994 [6] for eliminating the nesting effects of the SFS algorithm. This algorithm begins the search with an initial subset of 2 channels. For each subsequent iteration 2 processes are solved: (a) search the candidate channel which minimizes the cost function and add it to the selected subset O', (b) verify if the cost function can be optimized replacing a channel from the selected subset O'. Consequently, the SFFS search is executed dynamically, incrementing and decrementing the selected channels in the subset O' until reach the target length N_1. An efficient way to implement this algorithm is presented in [14], [6].

Artificial Bee Colony (ABC): this is an optimization technique proposed in 2005 by Karaboga [15]. In ABC each solution to the optimization problem is called *food source* and is represented by a N_1-dimensional vector. The colony of artificial bees contains three groups of bees: employed bees, onlookers and scouts. The first half of the colony consists of employed artificial bees and the second half are the onlookers. For each food source there is only one employed bee. Therefore, the number of employed bees equals the number of food sources. An employed bee whose food source has been exhausted becomes a scout. The ABC algorithm can be executed in two steps [10]:

- Initialization step: the algorithm generates a random initial solution set of length S. Each solution $x_i (i = 1, 2..., S)$ is a N_1-dimensional vector. The employed bees measures the nectar amount of each solution, return to the hive and share the nectar information with the onlooker bees.
- Iterative step: the solution set is submitted to repetitive search cycles. During these cycles the bees change their memory contents, searching the source foods with the best fitness. Each bee is able to remember just one source food location x_i. Each cycle is executed in three phases: (a) *employed phase* – at this phase each employed look for a new food source v_i around its

current position x_i using

$$v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj}), \tag{1}$$

where $k \in (1, 2, ...S)$ and $j \in (1, 2, ...N_1)$ are randomly chosen indexes, with $k \neq i$ and ϕ_{ij} is a random number in the range $[-1, 1]$ that controls the production of food source positions around x_i.

Following, if the nectar quantity of this new position improves the previous one then the bee position is updated. Once each employed bee has finished this phase, a probability factor p_i is computed using

$$p_i = \frac{f(x_i)}{\sum_{n=1}^{S} f(x_n)}, \tag{2}$$

where $f(.)$ is the fitness value function and S is the number of food sources.

(b) *Onlooker phase* – at this phase the onlooker bees uses the probability factor p_i of each employed bee and select a source food x_i. Afterwards, a new source food v_i around the selected neighborhood location is computed using (1); finally, if the fitness value of this new position improves the previous one then the bee position is updated.

(c) *Scout phase* – at each time in which the exploration of a source food x_i does not finish with a solution improvement, a counter increments the number of trials of that food source. If the value in this counter is greater than a threshold C_{lim}, this source x_i is abandoned and a new food source is randomly selected by a scout bee.

D. Cost Functions

Classification error: this is the same factor used to measures the performance on the myoelectric control system; hence, it is the ideal function to compare the discriminant information of the EMG patterns. This factor is computed as the relation between the number of incorrect decisions and the total number of decisions. To compute this relation is necessary to know the predicted class vector $\hat{y}$, therefore, the classification scheme composed of the block diagrams inside the dotted line in Fig. 2 (i.e. the conventional myoelectric system) must be used; consequently, the computational complexity is significant.

Correlation Factor. Several factors have been proposed to quantify the amount of common signal presented between two dimensions of a signal, the most common being the cross correlation factor [16]. We then considered the $N \times N$ correlation coefficient matrix R_x. This matrix is symmetric and has ones in its main diagonal; therefore, to quantify the correlation level it is enough to consider the lower or upper diagonal elements. An alternative considering the lower elements is

$$f_c = sum(\texttt{tril}(|R_x|)), \tag{3}$$

where `tril(.)` is a function that returns the lower triangular elements of the matrix without the main diagonal ones. To restrict the correlation factor to $[0, 100]$, we have defined

$$F_c = 100 \times \frac{2f_c}{N^2 - N}, \tag{4}$$

which has been used for computing the correlation factor between dimensions of the EMG signal.

E. Myoelectric Control Systems with iPCA tuning

Fig. 2 depicts the myoelectric control scheme with iPCA tuning [5], which uses an iPCA transformation for tuning input patterns. This transformation is a variation of the PCA which was initially used for improving the classification performance in recognition face problems [11]. The purpose of the iPCA transformation is to generate a new signal space where the discriminative information related to the movement class is amplified, while other types of information are attenuated. However, there is a drawback: the patterns' dimensions increase by a factor of C. Considering an input pattern corresponding to N EMG channels and a classification system with C classes, the use of a transformation matrix W_{iPCA} with size $CN \times N$ is necessary. Therefore, the projection of the input signal results in a new pattern of dimension CN (see Fig. 1) [5].

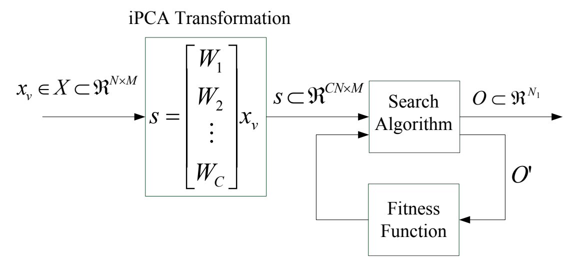

Fig. 1. Optimization scheme used in the parameter configuration stage. W_i is a PCA matrix transformation of size $N \times N$ for $i = 1, ..., C$.

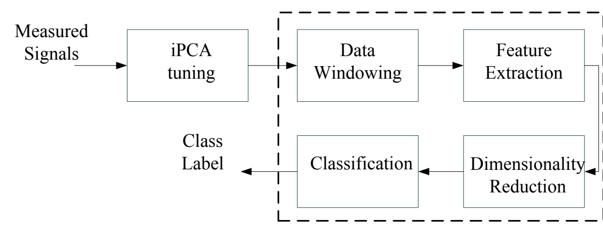

Fig. 2. Steps of the pattern recognition based myoelectric control system with iPCA tuning [5]

A reduced iPCA transformation can be defined for reducing the effects of dimension pattern increments. In this solution, it is necessary to compute a reduced iPCA transformation matrix W_R. This matrix projects the input patterns and generates just the N_1 most discriminative dimensions at the output (with $N_1 < CN$). To compute W_R it is necessary to solve the block diagram in Fig. 1. The output of this scheme is the vector O, which contains N_1 channels selected from the CN set. Using this vector, the relation between the iPCA transformation matrix and the reduced iPCA transformation matrix is defined as $W_R = W_{iPCA}(O, :)$, where the MatLab notation for submatrices is used.

III. METHODS

In order to evaluate the classification performance, for each cost-function/search-algorithm combination, a methodology based in three steps has been applied: (a) EMG signal acquisition, (b) computing the reduced iPCA matrix and (c) system evaluation.

A. EMG signal acquisition

An EMG database has been used in order to perform the experiments. The data are the same used in [5], which were collected from ten healthy subjects performing eleven motion classes. EMG signals were collected from ten sites on the forearm using adhesive duotrodes manufactured by 3M. These signals were amplified to guarantee potentials in range $[+5, -5]V$ and a bandwidth of $1Hz$ to $500Hz$. Afterward, signals were sampled at $1Khz$ and quantized with a 16-bit resolution.

Experimental data were collected during eight trials. Each trial consists of two repetitions of the following eleven motions classes performed in sequential order, namely: wrist pronation/supination, wrist flexion/extension, hand open, key grip, chuck grip, power grip, fine pinch grip, tool grip, and a rest class. The intensity of the contraction was determined by the subject, but they were encourage to contract to a level that they comfortable repeating for the duration of the experiment. During all trials, subjects elicited the contraction from the rest position, held the contraction for 4 s and then returned to the rest position for a predefined intermotion class delay period. Trials 1, 2, 3 and 4 used intermotion class delay periods of 3, 2, 1 and 0 s respectively. Trials 5-8 used intermotion class delay periods of 2 s. In our work, the EMG data recorded from trials 1, 3 were used as a training data set. EMG data recorded from trials 2, 4 were used as a test data set. And finally, EMG data recorded from trials 5 and 6 were used as a validation set to resolve the optimization problem defined in section II.B. Otherwise, for all these sets the intermotion class delays were excluded such as reported in [5].

B. Computing the reduced iPCA matrix

This step has been executed in two sequential tasks: (a) search of the reduced dimension vector O, and (b) building of the reduced iPCA transformation matrix W_R.

The first task began with the computing of the iPCA transformation matrices, using the training data. Afterward, the validation data were projected with iPCA transformation matrices and the transformed patterns were used to execute the optimal subset channel search. The result of this search is the vector O composed by the N_1 channels with most discriminative information. This search was executed with the six possible combinations of cost-function/search-algorithm. Therefore, at the end of this task the subsets O_{ij} were obtained, where the sub-indexes i, j indicate the cost function and search algorithm, respectively, where $i = 1$ and $i = 2$ represent, respectively, the classification error and the correlation factor, and where $j = 1$, $j = 2$ and $j = 3$ represent, respectively, the SFS, the SFFS and the ABC.

For all search algorithms the N_1 parameter was set to 30, such as recommended in [5]. In our case, the SFS algorithm was configured with just one stop criterion, namely: length of the selected subset equal to N_1. The SFFS algorithm used two stop criteria: (a) the same defined in SFS, (b) the maximum number of iterations ($C_{max} = 120$). The ABC algorithm used other kind of parameters, as summed up in Table I.

TABLE I

ABC ALGORITHM PARAMETERS

Symbol	Parameter	Value
ϵ	Minimum value of cost function	0
S	Number of food sources	10
$[v_{min}, v_{max}]$	Limit values	[1, 110]
C_{max}	Number of maximum cycles	120
C_{lim}	Limit of cycles to improve a solution	6

To compute the classification error cost function the processing scheme formed by the blocks inside the dotted line in Fig 2, (i.e. the conventional myoelectric control system) was used. The configuration was the following: overriding windowing feature extraction [17] with lengths of 150ms and sliding windows of 25 ms, features conformed by the first 6 autoregressive coefficients (AR6) [18], dimensionality reduction method based on uncorrelated LDA (ULDA) [3] and LDA (*Linear Discriminant Analysis*) classifier [19]. At this stage, each channel was used independently, to train and subsequently test the control system, like presented in [5].

At the second task we computed the reduced iPCA transformation matrix corresponding to each pair cost function/search algorithm.

C. System evaluation

The last step was the evaluation of the classification system. This was executed in two phases: (a) the test data classification, and (b) the classification error computing. The first phase was achieved with the process architecture depicted in Fig 2, using the same configuration described for the classification error cost function computing (see section III.B). This process was executed for each of the reduced iPCA transformation matrices W_R^{ij}. As the output we obtained the predicted class vector $\hat{y}_{ij}$. The second phase uses the vector $\hat{y}_{ij}$ to compute the classification error as defined in section II.D. The classification error is individually evaluated for each user of the system.

IV. RESULTS

All the simulations have been executed on the MATLAB platform implementing some modifications and adding some new functionalities to the myoelectric control toolbox presented in [3]. The modifications were necessary to interpret the EMG data base that had a different structure than the used in [3]. The added functionalities were done for configuring and executing all the iPCA related functions, namely: optimal search, transformation matrices computing and projections.

The results can be divided in two groups: (a) results registered during reduced iPCA transformation matrix computing and (b) results registered during EMG pattern classification.

TABLE II

COMPARISON OF MEAN-NUMBER-OF-ITERATIONS/MEAN-ITERATION-EXECUTION-TIME FOR THE SIX TREATMENT ALTERNATIVES DURING OPTIMIZATION

Cost Function	SFS	SFFS	ABC
Class. error	30/1282s	64.9/1705s	120/475s
Corr. factor	30/5.62s	78.3/7.61s	120/1.12s

The results on the first group are shown in Fig. 3 and Fig. 4. Fig. 3 displays the mean search time, i.e. the time necessary

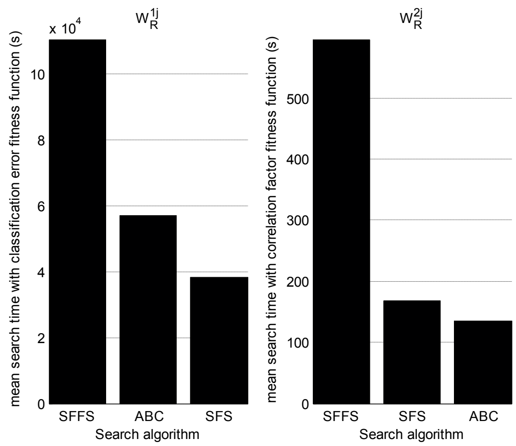

Fig. 3. Comparison of search time used for each of the six treatment alternatives executed during optimization.

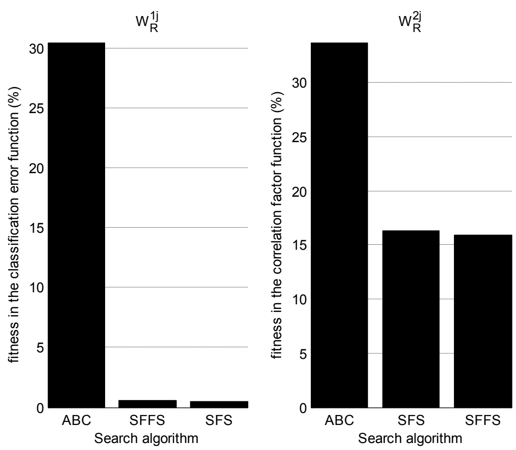

Fig. 4. Comparison of the fitness value reached with each of the six treatment alternatives during the optimization search.

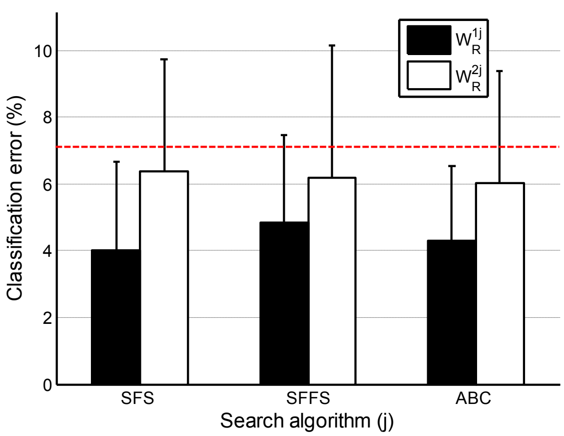

Fig. 5. Comparison of the classification error reached with each of the six treatment alternatives. The error bar represents one standard deviation of intersubject variability.

to compute the optimal vector O. The left figure displays the search time for classification error cost function and the right figure for correlation factor cost function. Complementary information on this subject is presented in Table II. This table reviews the mean values of the number of iterations and the iteration execution time for each cost-function/search-algorithm combination. These times were computed on a PC with 2.8GHz processor, 8Gb RAM memory and 4 cores. Fig. 4 depicts the mean fitness value reached during the optimal search. This value is presented for the six evaluated combinations of search algorithm and the cost function.

The results registered during EMG pattern classification are shown in Fig. 5. This figure displays the mean classification errors generated when each of the six reduced matrices W_R^{ij} were used in the myoelectric control system. The black bars indicate the classification errors obtained with the transformation matrix W_R^{1j} (i.e. the transformation matrices computed with the classification error cost function) and white bars indicate the classification errors obtained with the transformation matrix W_R^{2j} (i.e. transformation matrices computed with the correlation factor cost function). The vertical line on the bars represents one standard deviation of inter-subject error variability. The red line indicates the mean classification error obtained when the EMG patterns were classified without the iPCA transformation. A two way analysis of variances (ANOVA) was performed over the error classification results, which has determined the following behaviors: (a) it was not found sufficient statistical evidence, showing the dependence between the search algorithm and the classification error ($p < 0.01$), (b) it was found statistical evidence indicating the dependence between the cost function and the classification error ($p < 0.02$), and (c) it was not found statistical evidence, indicating the dependence between the interaction of both search algorithm and cost function and the classification error ($p < 0.01$).

V. DISCUSSION

The results obtained during the reduced iPCA matrix computation have been useful to analyze two system characteristics: (a) the execution time of the search process, and (b) the solution fitness. Two metrics have been used to analyzes this execution time (indicating a performance characteristic): number of iterations and the execution time of each iteration (see Table II). The product of these two metrics defines the search time (i.e. the time necessary to find an optimal solution).

The search time in Fig. 3 shows that: (a) search time is not trivial because reaches magnitudes of hours when using the classification error cost function. (b) solutions founded with classification error cost function are more susceptible to long search times. The data have showed a relation of 250:1 between the search time of the classification error cost function and the search time of the correlation factor cost function. This was expected due to the complexity associated with the supervised and non-supervised cost functions (see section II.D); (c) the higher search time, regardless the cost function, is for the SFFS algorithm, while the lower time is for the SFS algorithm, in the case of the classification error function, and the ABC algorithm, in the case of the correlation factor. The difference between the algorithms is significant.

The fitness values showed in Fig 4 indicate the following behaviors: (a) the fitness computed on the classification error cost function were lower than those computed on correlation factor cost function; (b) the optimal solutions computed with sequential algorithms were near to the global minimum than the ones computed with the bio-inspired algorithm. These results suggest a superiority of the solutions computed with sequential algorithms. In order to generalize that behavior, it is necessary to test the bio-inspired algorithm using other configuration parameters; (c) the fitness reached with the sequential algorithms SFS and SFFS are similar, then, we can suggest that the nesting effect associated with the SFS algorithm is not significant in the considered cost functions.

Fig. 5 shows the comparison of the performance reached when the patterns were tuned with the different transformation matrices W_R^{ij} ($i = 1, 2$; $j = 1, ..., 4$). The results indicate the following aspects: (a) the classification rates are similar to the previous ones published in [5] and the classification error of the conventional myoelectric control architecture is superior than the classification error of the myoelectric control architecture with iPCA tuning, (b) there are similar levels on classification error when transformation matrices $W_R^{i\bullet}$ were used (i.e. transformation matrices computed with the i cost function and each of the search algorithms), (c) there are differences between classification errors when transformation matrix $W_R^{\bullet j}$ were used (i.e. transformation matrices computed with the j search algorithm and each of the cost functions).

The (a) behavior validates the superiority of the iPCA tuned architecture over the conventional myoelectric control architecture. Otherwise, the (b) behavior was not expected. Due to the superiority of fitness that were computed with sequential algorithms (see Fig. 4), greater differences between the classification errors were expected. For instance, that classification errors associated to transformation matrices computed with sequential algorithms (W_R^{ij} with $j = 1, 2$) were less than classification errors associated to transformation matrices computed with the bio-inspired algorithm (W_R^{ij} with $j = 3$). This suggests that finding of the minimal value for the cost function is not sufficient condition to guarantee minimal classification errors during the evaluation of the myoelectric control system.

Finally, the (c) behavior was expected, basically by two reasons: (*i*) the superiority of classification error over correlation factor in determining the discriminant information in the selected subsets. (*ii*) The higher fitness of computed solutions by systems with classification error cost function (see Fig. 4).

VI. CONCLUSIONS

The effects of cost function and searching algorithms on myoelectric control systems with iPCA tuning were investigated in terms of execution time, solution fitness and classification performance. The alternatives considered for cost functions were the following: classification error, correlation factor, and search algorithms (SFS, SFFS and ABC). The results showed a significant superiority on classification performance when reduced iPCA matrices computed with classification error cost function were used. The results also showed the independence of classification performance with regard to the search algorithm. Future works will investigate other configuration parameters in the ABC algorithm as well as the effects of the selected subset length on the classification performance.

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REFERENCES

[1] I. Kapandji and L. Honore, *The Physiology of the Joints: The upper limb*, ser. The Physiology of the Joints. Churchill Livingstone, 2007.

[2] S. Micera, J. Carpaneto, and S. Raspopovic, "Control of hand prostheses using peripheral information," *Biomedical Engineering, IEEE Reviews in*, vol. 3, pp. 48 –68, 2010.

[3] A. D. C. Chan and G. C. Green, "Myoelectric control development toolbox," in *30th Conference of the Canadian Medical & Biological Engineering Society, Toronto, Canada*, vol. Paper M0100, 2007.

[4] Y. Huang, K. Englehart, B. Hudgins, and A. Chan, "A gaussian mixture model based classification scheme for myoelectric control of powered upper limb prostheses," *Biomedical Engineering, IEEE Transactions on*, vol. 52, no. 11, pp. 1801 –1811, nov. 2005.

[5] L. Hargrove, G. Li, K. Englehart, and B. Hudgins, "Principal components analysis preprocessing for improved classification accuracies in pattern-recognition-based myoelectric control," *Biomedical Engineering, IEEE Transactions on*, vol. 56, no. 5, pp. 1407 –1414, may 2009.

[6] P. Pudil, J. Novovicov, and J. Kittler, "Floating search methods in feature selection," *Pattern Recognition Letters*, vol. 15, no. 11, pp. 1119 – 1125, 1994.

[7] S. Theodoridis and K. Koutroumbas, *Pattern Recognition (Third Edition)*, third edition ed., Elsevier, Ed. San Diego: Academic Press, 2006.

[8] D. Karaboga and B. Akay, "A survey: algorithms simulating bee swarm intelligence," *Artificial Intelligence Review*, vol. 31, no. 1, pp. 61–85, Jun. 2009.

[9] R. Eberhart and J. Kennedy, "A new optimizer using particle swarm theory," in *Micro Machine and Human Science, 1995. MHS '95., Proceedings of the Sixth International Symposium on*, oct 1995, pp. 39 –43.

[10] D. Karaboga and B. Basturk, "A powerful and efficient algorithm for numerical function optimization: artificial bee colony (abc) algorithm," *J. of Global Optimization*, vol. 39, pp. 459–471, November 2007.

[11] X. Liu, T. Chen, and B. Kumar, "Face authentication for multiple subjects using eigenflow," *Pattern Recognition*, vol. 36, no. 2, pp. 313 – 328, 2003.

[12] K. Das, S. Osechinskiy, and Z. Nenadic, "A classwise pca-based recognition of neural data for brain-computer interfaces," pp. 6519 –6522, aug. 2007.

[13] K. Das and Z. Nenadic, "An efficient discriminant-based solution for small sample size problem," *Pattern Recognition*, vol. 42, no. 5, pp. 857 – 866, 2009.

[14] S. Karlsson, J. Yu, and M. Akay, "Time-frequency analysis of myoelectric signals during dynamic contractions: a comparative study," *Biomedical Engineering, IEEE Transactions on*, vol. 47, no. 2, pp. 228 –238, feb. 2000.

[15] D. Karaboga, "An idea based on honey bee swarm for numerical optimization," Erciyes University, Tech. Rep. TR06, Oct. 2005.

[16] J. P. Mogk and P. J. Keir, "Crosstalk in surface electromyography of the proximal forearm during gripping tasks," *Journal of Electromyography and Kinesiology*, vol. 13, no. 1, pp. 63 – 71, 2003.

[17] K. Englehart and B. Hudgins, "A robust, real-time control scheme for multifunction myoelectric control," *Biomedical Engineering, IEEE Transactions on*, vol. 50, no. 7, pp. 848 –854, july 2003.

[18] A. Chan and K. Englehart, "Continuous myoelectric control for powered prostheses using hidden markov models," *Biomedical Engineering, IEEE Transactions on*, vol. 52, no. 1, pp. 121 –124, jan. 2005.

[19] L. Hargrove, K. Englehart, and B. Hudgins, "A comparison of surface and intramuscular myoelectric signal classification," *Biomedical Engineering, IEEE Transactions on*, vol. 54, no. 5, pp. 847 –853, may 2007.