Myoelectric control of artificial limb inspired by quantum information processing

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Abstract
Precise and elegant coordination of a prosthesis across many degrees of freedom represents a significant challenge in efficient rehabilitation of people with limb deficiency. Processing the electrical neural signals collected from the surface of the remnant muscles of the stump is a common way to initiate and control the different movements available to the artificial limb. Based on the assumption that there are distinguishable and repeatable signal patterns among different types of muscular activation, the problem of prosthesis control reduces to one of pattern recognition. Widely accepted classical methods for pattern recognition, however, cannot provide simultaneous and proportional control of the artificial limb. Here we show that, in principle, quantum information processing of the neural signals allows us to overcome the above-mentioned difficulties, suggesting a very simple scheme for myoelectric control of artificial limb with advanced functionalities.

Keywords: myoelectric control, artificial limb, pattern recognition, quantum information

(Some figures may appear in colour only in the online journal)

1. Introduction

Information embedded within the electrical neural pulses controlling muscle contractions in our body can be extracted from surface or intramuscular myoelectric signals, which are typically summarized into the so-called electromyogram (EMG). As the acquisition of intramuscular signals might cause ethical concerns, may not be appreciated by the patient and can lead to infection due to the accompanying invasive procedure, for the last forty years, surface EMG signals have offered the primary means of controlling prostheses [1]. Currently, commercial prostheses utilize simple processing of the surface electromyogram, and can provide very limited functionalities [2]. To improve the functionality of myoelectrically controlled prostheses, pattern classification algorithms for surface EMG have been extensively investigated in the academic community [3]. It has been shown, for instance, that with properly selected features and classifiers, one can achieve very high classification accuracy (more than 10 classes of movements with less than 5% classification error) [4].

The academic success of myoelectric control based on pattern classification has not translated into significant commercial and clinical impact as one would have expected. So far, none of the commercial prostheses uses a pattern classification based controller [3]. One of the main problems with the pattern classification for myoelectric control is that it leads to a very unnatural (for the user) control scheme. While natural movements are continuous and require activations of several degrees of freedom (DOF) simultaneously and proportionally, classical schemes for pattern recognition allow activation of only one class that corresponds to a particular action in one decision, i.e. sequential control. Moreover, all these classes as well as their superpositions must be previously learned. Simultaneous activation of two DOFs is thus recognized as a new class of action, but not as a combination of known actions. This means higher complexity of the classifier and consequently less robustness. In addition, this also implies that the user must spend more time in training and learning, resulting in higher rehabilitation cost and more frustration.
Recently, the issue of simultaneous and proportional control of a prosthesis has been addressed. Instead of taking the classical pattern recognition approach, for example, multilayer perceptron neural network was used to estimate joint force [5] and joint angles [6] of the actions from surface EMG. One of the main limitations of this multilayer perceptron approach is that it still requires the data from combined activation of multiple DOFs in the training set. Alternatively, non-negative matrix factorization has been used to estimate the joint force [5] and the joint angles [7, 8]. This approach only requires data from single DOF activations for the controller calibration, but has inferior performance in comparison to the multilayer perceptron network approach. It is worth noting that both mentioned control schemes require solving optimization problems during the training stage, which in turn demands significant computational power for multiple DOFs. The training, moreover, needs to be performed on large data sets with typical size of $10^3 - 10^5$ samples, which need to be acquired during time-consuming sessions. Taking into account that the classical control schemes, such as multilayer perceptron, linear perceptron, linear discriminant analysis, Gaussian mixture model and hidden Markov model, do not show significant difference in classification power [9], in this paper we aim to develop a radically different approach to the problem of myoelectric control based on quantum information processing.

During the last two decades, information encoding into the states of quantum systems and its processing according to the laws of quantum mechanics have demonstrated impressive advantages over classical information processing [10, 11]. Typically these advantages are discussed in the context of computational complexity [12] and communication security [13]. Recently we have shown that quantum information processing can dramatically increase the capabilities of the simplest learning machine introducing a model of quantum perceptron [14]. As its classical counterpart, there are two operational stages for the quantum perceptron: supervised learning and new data classification. During the learning stage all the data are formally represented through quantum states of physical systems. The subject of the learning is a set of positive operator valued measurements (POVM) [10]. The set is constructed by making superpositions of the training data in a way that each operator is designed to detect states from one class. This procedure is linear and does not require solving equations or optimizing parameters. When the learning is over, new data is encoded into the states of the quantum systems and processed with the POVM. Based on the results of the processing, the required classification is achieved. Further details about the quantum perceptron can be found in [14]. It is important to stress that, in this work, we apply only the mathematical formalism of quantum information processing to the problem of myoelectric control: no actual physical systems nor advanced quantum information processing devises, such as quantum computers [10] and quantum simulators [11], are involved.

The quantum perceptron beats its classical counterpart in learning capabilities [14]. In particular, it is able to perform the classification on previously unseen classes and recognize the superpositions of learned classes. Utilizing these properties of the quantum perceptron, in this paper we present a novel simple scheme for simultaneous and proportional myoelectric control of the artificial limb. We also report the first simulation study of the surface EMG signal classification within the presented scheme.

2. Methods

Let us focus on a particular case of limb deficiency—trans-radial amputation, or amputation at the forearm. Our choice is mainly based on two factors. First of all, this type of limb deficiency represents a large portion of the upper-limb amputations [15]. Second, wrist movements are complex and require activation of multiple DOFs. We consider a wrist prosthesis with three DOFs, namely flexion-extension (f-e), pronation-supination (p-s) and radial-ulnar flexion (r-u), as illustrated in figure 1.

Let us suppose that $n$ electrodes are placed on the surface of the deficient limb. The particular choice of the location of the electrodes strongly depends on the particular amputation and remnant musculature; therefore, it is discussed elsewhere. There are four classical features that can be extracted from the raw signals of each electrode channel: mean absolute value (an estimate of the mean absolute value of the signal), zero crossing (the number of times the waveform crosses zero), slope sign change (the number of times the slope of the waveform changes sign) and wave length (the cumulative length of the waveform over the time segment) [16]. Thus, for each of the four features the feature space is of dimension $n$. Let one of these features, mean absolute value for example, be encoded into the states of a (discrete) $n$-dimensional quantum system, so that the component $a_i |i\rangle$ of the state $|\psi\rangle = \sum_{i=1}^{n} a_i |i\rangle$ represents the feature extracted from the $i$th electrode. Here, the amplitude of the signal $a_i$ is normalized over amplitudes from all the channels by factor $\sqrt{\sum |a_i|^2}$ to fulfill the normalization condition $\sum |a_i|^2 = 1$. This condition leads to balanced processing of the feature vectors, i.e. proportional control of the prosthesis.

Let the quantum state $|\psi\rangle$ be the input of a single-layer network of quantum perceptrons. In the most simple architecture that we are going to consider here, the number of the perceptrons in the network is equal to the number of DOFs to be controlled, so that each quantum perceptron governs just one specific DOF. Without loss of generality, let us suppose that the perceptron $D_1$ controls flexion-extension, $D_2$ controls radial-ulnar deviation, while $D_3$ controls pronation-supination. The control scheme is represented schematically in figure 2.

Prior to the use of the prosthesis, the subject with the limb deficiency is instructed to focus on performing particular actions to learn how to control the prosthesis. Technically, the aim of the learning stage is to deduce the association between the EMG features and the joint kinematic. For example, given a corresponding command, the subject is trying to perform


flexion (f) activating D1 DOF. EMG features extracted from received myoelectric signals are encoded into the quantum state $|f_{\mu \alpha}\rangle = \sum_{i=1}^{n} a_{i \alpha} |i\rangle$, where $a$ is the angle of flexion and $a_{i \alpha}$ is the normalized signal from the $i$th electrode that correspond to this angle. Since efficient control of artificial limb demands prediction of a degree of chosen action (angle or force), the learning must be repeated for different angles of flexion. The quantum states, constructed from EMG features corresponding to different angles $\theta_j$ are combined into POVM operator $P^{D1} = \sum |\alpha_j f_i\rangle \langle \alpha_j f_i|$, where $\alpha_j = \theta_j / \sum \theta_j$ and index $j$ runs over all possible angles.

In general, if we are given just two feature vectors $|a\rangle = \sum_{i=1}^{n} a_i |i\rangle$ and $|b\rangle = \sum_{i=1}^{n} b_i |i\rangle$ represented through quantum states of a $n$-dimensional quantum system, and we know that the vectors belong to one class, we can define an operator $P = \frac{1}{\text{Tr}(a \mp b)(a \pm b)} |a \pm b\rangle \langle a \pm b|$. This operator ensures a nonzero probability of the outcome for any given linear combination of vectors $a |a\rangle + \beta |b\rangle$, where $|a|^2 + |\beta|^2 = 1$. Taking into account that statistics of future inputs cannot be deduced, it is reasonable to accept that all superpositions of the vectors $|a\rangle$ and $|b\rangle$ can be observed with equal probability, i.e. the operator $P$ is symmetric with regard to vector permutations. This consideration generalizes straightforwardly to the case of an arbitrary number of feature vectors.

If two feature vectors $|a\rangle = \sum_{i=1}^{n} a_i |i\rangle$ and $|b\rangle = \sum_{i=1}^{n} b_i |i\rangle$ represent activation of the same action but correspond to different angles of the activation $\theta_a$ and $\theta_b$ respectively, the operator $P = |a \alpha \alpha \beta \rangle \langle a \alpha \alpha \beta|$, where $a_{\alpha} = \theta_{\alpha} / (\theta_a + \theta_b)$ and $a_{\beta} = \theta_{\beta} / (\theta_a + \theta_b)$, takes into account contribution of the feature vectors to the activation of the DOF. The construction of the operator $P$ is not unique. It leads, in particular, to the normalization of the all action angles to the maximal angle observed in the training data.

Following the above procedure, the learning of extension leads to the construction of operator $P^{D1}$. The operators $P_f^{D1}$ and $P_e^{D1}$ summarize all training data that activate the D1. However, these operators do not necessarily form a legitimate POVM. The fundamental property of POVM operators is that they form a complete set; therefore, we need to define the third operator $P_0^{D1} = I - P_f^{D1} - P_e^{D1}$ to fulfill this condition. Here $I$ is the identity operator. Operator $P_0^{D1}$ thus collects all features that correspond to EMG activities, which do not lead to activation of the D1 DOF.

In general, operators $P_f^{D1}$, $P_e^{D1}$, and $P_0^{D1}$ are not orthogonal, therefore it could happen that the operator $P_0^{D1}$ is negative (i.e. unphysical). Although in our simulations $P_0^{D1}$ was always positive, the negative value of this operator does not imply that further metamathematical simulations are impossible. As we noted in the introduction, we do not suggest using real physical systems, but applying mathematical formalism of quantum information processing. It is also important to note that the triple structure of the POVM set is the key feature of the quantum perceptron that allows detecting superpositions of different classes [14], i.e. the achievement of simultaneous control.

Similarly to the D1 DOF, the learning procedure is to be repeated for the other two DOFs: D2 and D3. As the result of the learning stage we have deduced nine operators that govern the three DOFs according to the classification of the selected feature (mean absolute value in our case). The learning may be repeated for the other features the same way as discussed above.

Let us now see how the trained network of quantum perceptrons responds to the EMG during the subject’s autonomous control of the artificial limb. Desiring to perform an action, the subject generates neural signals, which are acquired from the limb surface, expressed in EMG and encoded into a quantum state $|\psi\rangle$. Each quantum perceptron computes the expectation values $\langle \psi | P_f^{D1} | \psi \rangle$ for the nine operators. The expectation values are interpreted as the strength of corresponding activation. For D1, for example, the three expectation values are computed as $f = \langle \psi | P_f^{D1} | \psi \rangle$, $e = \langle \psi | P_e^{D1} | \psi \rangle$ and $0_{D1} = \langle \psi | P_0^{D1} | \psi \rangle$. The expectation values $f$ and $e$ contain information of how likely the given EMG correspond to flexion or extension. The expectation value $0_{D1}$ gives the probability that the flexion-extension DOF is inactive. If $f > e$, then the prostheses makes flexion on the degree $\theta_f = \frac{(f - e) \theta_{D1}}{1 - \text{Tr}(P_f^{D1} P_0^{D1})}$, where $\theta_f$ is the maximal flexion observed in the training data and $\text{Tr}(\cdots)$ stands for trace operation and gives the overlap between the operators $P_f^{D1}$ and $P_e^{D1}$. If, in contrast, $e > f$, the prostheses performs extension on $\frac{(e - f) \theta_{D1}}{1 - \text{Tr}(P_f^{D1} P_0^{D1})}$, where $\theta_e$ is the maximal observed

\begin{figure}[h]
\centering
\includegraphics[width=0.5\textwidth]{figure1.png}
\caption{The three DOFs of the wrist to be emulated by the prosthesis.}
\end{figure}
extension. Here, we assumed that a linear combination of DOFs corresponds to a linear combination of corresponding features. This assumption is valid for mean absolute value, although it may not be true for an arbitrary chosen feature [5].

As the result of the analysis of the given state $|\psi\rangle$, which encodes mean absolute value feature, the network of three quantum perceptrons returns three angles to the mechanical system of the prosthesis. These angles define the simultaneous and proportional action completely.

3. Results

We have tested the proposed control scheme on a set of EMG acquired from an able-bodied subject who performed wrist contractions. The data acquisition procedure as well as the experimental setup have been previously reported [3], thus they are not discussed here. During the experiments eight electrodes were placed around the circumference of the forearm with equal inter-electrode distance. The number of electrodes limits the number of input feature vectors to eight. It is also important to note that even for a single DOF there are two types of movements: direct action from the rest position and return action to the rest position. EMG for these actions may differ significantly, although they formally correspond to the same spatial angles. In our analysis we always use direct actions both for the training and recognition of new patterns.

Our training data set collects only those movements of the subject that activate one of the three DOFs. The test data set contains complex movements without any restrictions. The raw EMG that correspond to all these movements were recorded with 1024 Hz sampling rate. The mean absolute value feature was extracted from the EMG averaging the signals over 100 ms window. In our analysis we focused on just two DOFs, $D_1$ and $D_3$, as they are the most desired functions that do not yet have commercial availability for trans-radial amputees. The purpose is to test whether our control scheme can recognize the combinations of these movements, being trained on just single DOF activations, i.e. whether the system can extrapolate automatically from single DOF data to their arbitrary combinations.

To test the control scheme, we initially used small sets for training consisting of just 500 data strings for each action, i.e. flexion, extension, pronation and supination. Each data string consists of the mean absolute values acquired from the eight channels and the respective joint angles of the DOF activation. The testing data contains 8216 data strings divided on 55 blocks; each block encodes a multiple DOF activation in a certain angle range. In 15 of the 55 blocks, the classification error appeared: 5 mistakes in flexion-extension, 9 in pronation-supination and once both DOFs were misclassified.

To analyze the accuracy of classification in cases when it was successful, we used the so-called performance index, which is...
widely used as a global indicator of quality of the estimation [6]. The performance index for an $k$th DOF is given by

$$R^2_k = 1 - \frac{\sum (\alpha_i - \bar{a}_i)^2}{\sum (a_i - \bar{a}_i)^2},$$

where $a_i$ is the actual joint angle of the $k$th DOF, $\bar{a}_i$ is the corresponding estimate of the actual angle by the suggested control scheme, $\bar{a}_i$ is the temporal average (i.e. the mean value) of $a_i$ and the summation is to be done over all data samples. Similarly, the global performance of the estimator is defined through the sum over all $K$ DOFs as

$$R^2 = 1 - \frac{\sum_{k=1}^{K} \sum (\alpha_i - \bar{a}_i)^2}{\sum_{k=1}^{K} \sum (a_i - \bar{a}_i)^2}.$$  

The performance of flexion-extension recognition is found to be 0.834, while the performance of pronation-supination classification is 0.224. It is not surprising that the performance for $D3$ is much lower than for $D1$. Previous studies also reported lower performance on $D3$ than $D1$ [5, 6]. This is mainly due to the fact that muscle responsible for $D3$ are deep muscles. As a result, their EMG are easily masked by the EMG of superficial muscles, such as flexor muscles and extensor muscles. This masking effect is particularly pronounced during combined activations of $D1$ and $D3$. Nevertheless, the global performance of the two degrees of freedom recognition 0.715 is comparable to the performance of classical schemes [5, 6]. In [6], for example, the global performance of the estimator based on the multi-layer perceptron artificial neural network was shown to be in the range from 0.413 and up to 0.906 for simultaneous activation of two degrees of freedom. This study, however, was performed for different groups of subjects with actual amputations.

4. Discussion

In this paper we showed that quantum information processing can be used to realize simultaneous and proportional prosthetic control over multiple DOFs, with only training on individual DOF data.

We suggested the simplest control scheme for the wrist prosthesis, which is free of any optimization during the learning stage and does not demand large training data sets (size of which is proportional to the time spent by a subject in a lab and by implication his/her frustration with the procedure). We also reported the first simulation of EMG data classification using the suggested scheme.

Although our simulation showed promising results, the scheme for myoelectric control by quantum information processing must be further developed before practical utilization. Below, we consider several ways to improve the performance of the suggested scheme.

Using more data for the training is a standard way to improve performance of the model. We checked how the efficiency of the angle estimation changes with the growth of the training set size. We subsequently used large data sets for the training: 2000 samples for each action. For testing we used the same 55 blocks of unseen data. In the results, in 10 blocks errors were detected: 3 for $D1$ and 7 for $D3$. Moreover, the global performance increased to 0.736. Thus, the efficiency of the classification increased with the size of the training set.

It is important to stress the role of the overlap between operators $P^{D1}_f$ and $P^{D1}_s$ and between operators $P^{D3}_p$ and $P^{D3}_s$ in estimation of the activation strength of the respective DOFs. Indeed, these operators by their construction differ specifically in those components that are crucial for activation of the corresponding actions. It has been observed that the overlaps vary in certain range with the growth of training data approaching (on the large scale) some optimal value. The closer the overlap to the optimal values the higher the performance of estimation. In practice, closeness of the overlaps to their optimal values would indicate that further learning is not necessary. Finding the optimal overlap having a small training data set is an important open problem.

Also, there is additional control information encoded into the three expectation values $0_{D1}, 0_{D2}$ and $0_{D3}$. As we have noted before, the expectation value $0_{D1}$ tells us the probability that the state $|\psi\rangle$ represents neither flexion nor extension. This may be interpreted as the given signal activates the other two DOFs, i.e. $0_{D1} = D2 + D3$. Such interpretation gives us three additional equations with three unknowns. Resolving this system of linear algebra equations, we can deduce additional proportionality between the activation of the three DOFs.

Finally, we would like to admit that there are many other nontrivial ways to further improve our control scheme. For example, it may be beneficial to include more quantum perceptrons in the network, so that several perceptrons control one DOF (direct and return actions, for example). It is also possible to construct a database of POVM operators out of the training data, so that one set of operators controls movements in a particular angle interval. A particular set of operators can be called from the database depending on overall intensity of the EMG. Also, different features may be encoded and analyzed simultaneously due to the fact that quantum amplitudes are complex numbers in general. Finally, our control scheme can be combined with classical control schemes, since its implementation does not demand any optimization. It is certain that further research is required to reveal the full power of quantum information processing in the myoelectric control of an artificial limb.

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References

[1] Oskoei M A and Hu H 2007 Biomed. Signal Process. Control 2 275
[2] Parker P, Englehart K and Hugdins B 2004 Control of Upper Limb Prosthesis (New York: Wiley-IEEE Press)
[3] Jiang N, Dosen S, Müller K-R and Farina D 2012 IEEE Signal Process. Mag. 29 152
[4] Scheme E and Englehart K 2011 J. Rehabil. Res. Deve. 48 643
[5] Jiang N, Englehart K B and Parker P A 2009 IEEE Trans. Biomed. Eng. 56 1070
[6] Jiang N, Vest-Nielsen J L G, Muceli S and Farina D 2012 J. Neuroeng. Rehabil. 9 42
[7] Rehbaum H, Jiang N, Paredes C, Liliana P, Amsüss S, Graimann B and Farina D 2012 Real time simultaneous and proportional control of multiple degrees of freedom from surface EMG: preliminary results on subjects with limb deficiency Proc. of the IEEE Ann. Conf. on Engineering in Medicine and Biology Society (EMBC) pp 1346
[8] Jiang N, Rehbaum H, Vujaklija I, Graimann B and Farina D 2013 IEEE Trans. Neural Syst. Rehabil. Eng. 22 501
[9] Hargrove L J, Englehart K and Hudgins B 2007 IEEE Trans. Biomed. Eng. 54 847
[10] Nielsen M A and Chuang I L 2000 Quantum Computation and Quantum Information (Cambridge: Cambridge University Press)
[11] Georgescu I M, Ashhab S and Nori F 2014 Rev. Mod. Phys. 86 153
[12] Galindo A and Martin-Delgado M A 2002 Rev. Mod. Phys. 74 347
[13] Gisin N, Ribordy G, Tittel W and Zbinden H 2002 Rev. Mod. Phys. 74 145
[14] Siomau M 2014 Quantum Inf. Process. 13 1211
[15] Ziegler-Graham K, MacKenzie E J, Ephraim P L, Travison T G and Brookmeyer R 2008 Arch. Phys. Med. Rehabil. 89 422
[16] Hudgins B, Parker P and Scott R N 1993 IEEE Trans. Biomed. Eng. 40 82