Supervised and unsupervised learning in processing myographic patterns

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Abstract. Synaptic connections in neocortex are assumed to be formed by a self-organizing process leading to emergence of the so-called self-organized maps (SOMs). Formation of SOMs is based on the unsupervised Hebbian learning rule, according to which the weight of a synaptic connection depends on the co-activation of pre- and postsynaptic neurons. On the other hand, a variety of human-machine interfaces employ supervised learning based on the correction of synaptic weights in proportion to the network error. But this learning rule has not been verified as biologically relevant. In our work, we study artificial neural networks (ANN) that classify hand gestures through electromyographic recordings (EMG). We use eight-channel electromyographic (EMG) signals acquired by a Thalmic labs Myo device as an input to a multilayer perceptron (MLP) and Kohonen’s SOM. We compare supervised (MLP) and unsupervised (SOM) learning in the task of EMG-classification. The median value of recognition fidelity (F-measure) for SOM-based recognition is F=0.87 and for MLP classification F=0.96. Also we reveal strong correlation between F-measures for classification EMG patterns of 37 subjects by MLP and SOM. For estimation of clustering quality of SOM we introduce two indexes: the intra-cluster index describing the cluster “compactness” and the inter-cluster index measuring the degree of cluster overlapping. There are strong correlations between F-measures for SOM classification and introduced indexes. Differences in the significance level of the correlations suggest that the classification with SOM is more negatively affected by overlapping clusters than their large size.

1. Introduction

Recent years machine learning has become increasingly employed in neurotechnologies, in particular in neurointerfaces, including electroencephalographic (EEG) and electromyographic (EMG) interfaces. In turn, such interfaces developed to control powered prostheses [1, 2] and exoskeletons [3–5]. Despite differences in the implementation, these devices in general exploit quite similar controlling strategies mainly based on pattern classification and regression [1, 6].

Artificial neural networks (ANNs) have been widely used to solve classification problems. In the case of neurointerfaces artificial neurons can be considered as virtual counterparts of real neurons in human nervous system [7]. The idea of expanding the nervous system due to the virtual
neural networks can indeed be implemented if processing of information in living and artificial neural networks will be self-consistent.

Currently, the multi-layered perceptron (MLP) is typically used in neurointerfaces. To adjust the synaptic weights (the force of connections between neurons), the back propagation algorithm is employed [8]. This is supervised learning aimed to minimize the classification error. The accuracy of MLP is rather high in comparison to other approaches [6, 9]. Despite good efficiency (at least in the case of a small number of hidden layers in the network), the back propagation has not been verified as biologically relevant. There is still no evidence that a biological neuron can adjust the strength of its synapse to minimize the overall network error in any task.

At the same time, it was experimentally proved [10] that in living neural networks the Hebbian unsupervised learning works in the sense that the weight of the synapse increases in response to the co-activation of pre- and postsynaptic neurons [11]. Moreover, it was assumed that self-organizing neural maps (SOMs) are formed in neocortex on the basis of the Hebbian plasticity. Such a mapping is inherent in the primary somatosensory cortex (the so-called homunculus of somatosensory cortex) [12], the entorhinal cortex [13], and it is the principle of retinotopy [14] and tonotopy [15].

Kohonen proposed an artificial neural network that implements the SOM on the base of Hebbian learning and neural competition [16]. The main property of SOM is the ability to represent data in an output layer, while preserving the topological features of the original input space. The practical significance of this property implies the possibility of reducing the dimensionality of the input data [17]. In addition, SOM can be used as an intermediate stage in the data classification system [18], [19]. However, at the moment existing neurointerface solutions have not used the SOM to implement the recognition task.

In previous studies we showed that MLP can be used for simultaneous proportional-command control of robotic devices [20]. In some problems, fuzzy classification with overlapping classes can be used [21]. The accuracy of recognition when using MLP and linear discriminate analysis (LDA) is comparable and is mainly limited by the anatomical and physiological characteristics of the subjects [22].

In this work, we compare supervised (MLP) and unsupervised (SOM) learning. We propose novel EMG classification system based on the Kohonen’s SOM and evaluate the recognition fidelity by calculating the F-measure. Besides we estimate the quality of obtained SOMs by applying intra- and inter-cluster indexes. The intra-cluster index describes the cluster “compactness”, whereas the inter-cluster index measures the degree of cluster overlapping. We show that the F-measure of gesture recognition by MLP and SOM is close to each other and correlates with intra- and inter-cluster indexes of SOM.

2. Materials and methods

2.1. Collecting and processing EMG data

For experimental purpose we recruited 37 healthy volunteers of either sex from 21 to 41 years old. The study complied with the Helsinki declaration adopted in June 1964 (Helsinki, Finland) and revised in October 2000 (Edinburgh, Scotland). The Ethics Committee of the Lobachevsky State University of Nizhny Novgorod approved the experimental procedure. All participants gave their written consent.

A MYO Thalmic bracelet is used for collecting of raw EMG data. The bracelet is equipped with eight sensors equally spaced around forearm that simultaneously acquire myographic signals. The signals are sent through a Bluetooth interface to a PC. The collected data were processed off-line.

In the current study we used synthetic tests. The subjects were asked to perform sequentially individual static gestures as basic motor patterns: $G_0$, hand at rest; $G_1$ and $G_2$, wrist flexion and extension; $G_3$ and $G_4$, radial and ulnar deviations. Besides, we included four additional gestures that are combinations of pairs of $G_1$-$G_4$. For example, simultaneous wrist flexion, $G_1$, and radial deviation,
G1. In classification problem solving MLP and SOM (see later) we used basic G0-G4 gestures only, whereas for SOM clustering and SOM quality estimation additional gestures were taken into account.

We divide the sEMG data flow, \( x(t) \), into 100 ms time windows \((x(t) \in \mathbb{R}^8)\). Windowing is performed every 50 ms. At the first step the root mean square (RMS) of the EMG activity over 100 ms time window is evaluated:

\[
V^{(i)}(t) = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} x^{(i)}(t-n)^2,
\]

where \( N \) is the number of samples in time window. The RMS data, as a composite feature of the current hand gesture, are fed into an ANN.

2.2. Classification of EMG-patterns by MLP

For classification of EMG-patterns we use a MLP with one hidden layer containing eight neurons. Each network neuron applies weighted sum over its inputs and uses sigmoidal activation function to generate the output, \( y \):

\[
y = F(\vec{w} \cdot \vec{v}), F(u) = \frac{1}{1+e^{-u}}
\]

where \( \vec{w} \in \mathbb{R}^8 \) is the vector of synaptic weights related to the given neuron and \( \cdot \) stands for inner product. The learning, i.e., adjustment of the neuronal weights \( \{w\} \), is achieved by the standard back-propagation algorithm [8]. The classification was implemented following the "winner takes all" rule, the response of MLP (class of EMG pattern) was defined as:

\[
k = \arg \max_{j \in [1:M]} y_j
\]

where \( y_j \) – the output of neuron in the last MLP layer and \( M \) – number of gestures classes.

For training and testing purposes we use sets containing 40-60 samples corresponding to each class. The classification error is calculated both for the training and for testing sets. It serves as a criterion for stopping the learning procedure as soon as the error starts increasing on test samples. In average the learning process on an MLP requires about 5000 training epochs and takes less than 1 min on a standard Intel Core i5 PC.

2.3. Mapping EMG by SOM with unsupervised learning

The SOM model is a system of two layers (input and output). The input layer is a vector of features for clustering: \( \vec{v} \in \mathbb{R}^8 \). Each neuron of the output layer SOM (from the number of \( N \) neurons) corresponds to a vector of weight coefficients \( \vec{W}^{(i)} \in \mathbb{R}^M, i \in [1,N] \). As a result, the input vector is mapped onto the output layer of the map as one winning neuron with index \( j \) according to the "winner takes all" principle:

\[
j = \arg \min_{i \in [1,N]} \| \vec{W}^{(i)} - \vec{v} \|_2
\]

Learning of ANN is carried out in several stages. We used the following algorithm:

- Initialization of weight vectors \( \vec{W}^{(i)} \) by random vectors
- Random selection the training vector \( \vec{v} \) from the training sample
- Determination a neuron-winner:

\[
k = \arg \min_{i \in [1,N]} \| \vec{W}^{(i)} - \vec{v} \|_2
\]

- Correction all the weight vectors \( \vec{W}^{(i)} \) in some region near the found winner neuron according to the Kohonen rule:

\[
\vec{W}^{(i)}(t) = \vec{W}^{(i)}(t) + \alpha(t) \, H_d(\vec{x}, \vec{v}) \, (\vec{W}^{(i)} - \vec{v}), j \in [1,N],
\]
where $d_{jk}$ – is the distance function between the j-th neuron and the neuron-winner with the index k. 

$\alpha(t)$ – is exponentially decreasing with time function. In the classical case, it is customary to use the following function $H(d_{jk}, t)$:

$$H(d_{jk}, t) = \exp \left( - \frac{d_{jk}^2}{2\sigma(t)} \right).$$  \hspace{1cm} (7)

where $\sigma(t)$ performs the role of an effective radius, within which the adjustment of the weight coefficients of neurons SOM is quite active.

- Repeating all above steps in a new era of learning. $\alpha(t)$ causes the convergence of $\overline{W}^{(j)}$ to the optimal set $\overline{W}_{opt}^{(j)}$ suitable for a qualitative clustering. In our case it was enough to use a little number of epochs (N=100).

As a result of this training, ANN could be used for clustering. The procedure for using SOM as a classifier is described below, in the Results section.

2.4. Calculation of classification accuracy

For calculation of classification accuracy we employed $F$-measure [23], which is based on the precision and recall values obtained from the classification results:

$$P = \frac{TP}{TP+FP}, \quad R = \frac{TP}{TP+FN}.$$  \hspace{1cm} (8)

where $TP$ is the number of true positives, i.e., correctly recognized gestures; $FP$ is the number of false positives, i.e., a classifier recognizes other gesture as its own; and $FN$ is the number of false negatives, i.e., a classifier does not recognize its own gesture. Then the $F$-measure is given by:

$$F = \frac{2PR}{P+R}.$$  \hspace{1cm} (9)

3. Results

3.1. Processing EMG patterns

During performance of various movements, in particular hand gestures, various muscles exert certain effort. This effort depends on the gesture, which leads to a EMG-pattern particular for each gesture. Figure 1 shows an example of two EMG-patterns recorded during wrist flexion and extension. In the case of wrist flexion EMG-signals from flexor muscles (mostly captured by channels 1, 2, 8) are much higher than from extensor muscles (channels 4, 5, 6). For wrist extension we observe an opposite situation. Then classification algorithms with supervised learning (e.g., MLP with the back propagation algorithm) can recognize gestures with some degree of accuracy.

![Figure 1. Examples of EMG-patterns recorded during wrist flexion (left epoch from 2.1 to 5.7 s) and extension (right epoch from 8.8 to 12.4 s): A) Raw signals, B) RMS signals.](image)

In the case of unsupervised learning, in particular SOMs, the neural network learns the differences between the EMG-patterns without class label and can cluster EMG in such a way that certain areas
of network response to certain EMG-patterns. Neurons in close regions respond to similar inputs and form clusters representing EMG-patterns. Figure 2 represents two examples of hitting diagram formed in the network after applying 60 times four main gestures $G_1$-$G_4$ and hand resting $G_0$. Different EMG patterns grouped into five clusters. Note that the "quality" of SOM in these two pictures is different. In the case of "good" SOM (figure 2A) clusters are compact and have clear boundaries. The "bad" SOM (figure 2A) is characterized by overlapping clusters of large sizes.

For quantitative description of SOMs obtained from experiments with subjects we introduce two indexes. The first, intra-cluster index, describes the within cluster properties, i.e., the cluster compactness. The second, inter-cluster index, is determined by the degree of overlapping clusters of different gestures on each other. Both indexes are evaluated from a diagram of hitting of a learned SOM.

![Figure 2](image)

**Figure 2.** Examples of “good” (A) and “bad” (B) hit diagrams of SOMs. Different colors correspond to responses of winner neurons to different EMG-patterns.

### 3.2. SOMs clustering indexes

#### 3.2.1. Intra-cluster index.

The quality of SOM built in an experiment depends on the quality of clustering of different gestures. Then the cluster size, i.e. the degree of scattering of cells activated by a gesture plays an important role. We thus introduce an intra-cluster index as weighted mean of the distances to activated cells from a cluster center. This index describes the cluster “compactness”.

For building a SOM we use a 10x10 network of hexagonal cells. Figure 3 illustrates the diagrams of hits for the gesture $G_2$ (wrist extension, figure 3A) and $G_3$ (radial deviation, figure 3B). The distribution of hits is grouped into a cluster. The size and scattering properties of such a cluster depends on different factors such as the type of gesture, anatomical and physiological properties of subject and the ANN learning process.

Let $x_i \in \mathbb{R}^2, i = 1, 2, ..., N (N = 100$ in our case) be the location of the center of the $i$-th cell in the network. Then

$$d_{ij} = \left\| x_i - x_j \right\|_2$$

is the Euclidian distance between the $i$-th and $j$-th neurons. We denote by $h_{mi}$ the number of activations of the $i$-th neuron by gesture $m$. Then it is convenient to normalize this number by the total number of activations induced by gesture $m$:

$$H_{mi} = \frac{h_{mi}}{\sum_{j=1}^{N} h_{mj}}$$

(11)
Now we can define a 2D vector pointing to the center of gesture $m$ as the weighted sum:

$$
c_m = \sum_{i=1}^{N} H_{mi} x_i
$$

$$
E_m = \sum_{i=1}^{N} ||x_i - c_m||_2 H_{mi}
$$

This index describes the “compactness” of a cluster of neurons responding to a given gesture. In the examples presented in figure 3 in one case ($G_2$, wrist extension, figure 3A) activated neurons are widely scattered over the network and accordingly we get high index $E_2 = 7.96$. In the second case ($G_3$, radial deviation, figure 3B) the cluster is more compact and the error is low, $E_3 = 3.91$. Finally we can get the common intra-cluster index as a simple sum that reflects an average “compactness” of all gestures presented:

$$
E^{(\text{intra})} = \sum_{i=1}^{M} E_m
$$

where $M$ is a gestures quantity. “Good” and “bad” hit diagrams presented on the figure 2 give different inter-cluster indexes $E^{(\text{intra})} = 0.59$ (figure 2A) and $E^{(\text{intra})} = 1.23$ (figure 2B).

### 3.2.2. Inter-cluster index

Besides the intra-cluster compactness the other characteristic of the clustering quality is the degree of cluster overlapping. To introduce this characteristic let us consider two closely related gestures: $G_2$, wrist extension ($m = 2$) and $G_3$, radial deviation ($m = 3$).

The activation sets for a pair of gestures $m$ and $n$ are $\{H_{mi}\}_{i=1}^{N}$ and $\{H_{nj}\}_{j=1}^{N}$.

In this case one may get the vector of intersecting hits with an implementation of the fuzzy conjunction:

$$
H_{2,3,i}^{(\text{inter})} = \min(H_{2,i}, H_{3,i})
$$

An example of applying a fuzzy conjunction to a pair of clusters is shown in figure 3, where the cluster with a large scatter (figure 3A) partially covers the cluster with a smaller scatter (figure 3B) with resulting hit diagram (figure 3C).

**Figure 3.** Principles of a two ways for estimation SOM quality. Big cluster (A) leads to a high intra-cluster index $E=7.3$. Compact cluster (B) causes low intra-cluster index $E=2.9$. Fuzzy conjunction of two hit diagrams is equal to the resulting diagram (C) that is used for the calculation of inter-cluster index.

One may introduce the value $p$ defining the degree of gestures pair intersection as the sum of vector’s $H_{2,3,i}^{(\text{inter})}$ elements:

$$
E_{2,3} = \sum_{i=1}^{N} H_{2,3,i}^{(\text{inter})}
$$

To obtain the final value of the clusters intersection error taking into account the mapping of all gestures, we should to sum the matrix $E^{(\text{inter})}$ elements:

$$
E^{(\text{inter})} = \sum_{i,j=1}^{M} E_{ij}
$$
For example “good” and “bad” hit diagrams presented on the Figure 2 give different inter-cluster indexes \( E^{(\text{inter})} = 0.4 \) (figure 2A) and \( E^{(\text{inter})} = 2.3 \) (figure 2B).

3.3. MLP and SOM classification of EMG patterns

Perceptrons (including MLP) were created to solve the classification problem. In contrast, SOMs as a rule are used for data clustering. We introduce the SOM classification according to the following principle: on the basis of the training samples the activation regions of individual patterns are singled out and labeled. Other SOM neurons that remained inactive in the process of such a procedure formed a region of the zero class (an area not recognized by the ANN as its own gestures). Then, the test dataset was classified by determining the affinity of the activity of the neuron in this or that region of the output SOM layer.

As expected, we obtained higher classification fidelity in the case of MLP. The median value of F-measure for SOM-based recognition is \( F=0.87 \) (\( Q_1=0.81, Q_3=0.89 \)) whereas for MLP classification \( F=0.96 \) (\( Q_1=0.93, Q_3=0.97 \)). We explain this gap by using a universal algorithm for the formation of SOM, which is not optimized for the separation of classes. Obviously fidelity can be increased by eliminating the possibility of generation of negative (FN) responses.

Figure 4A shows the values of F-measure in case of MLP and SOM for 37 subjects and linear regression:

\[
F_{\text{SOM}} = a \times F_{\text{MLP}} + b, \quad a = 0.84 \pm 0.93, \quad b = 0.05 \pm 0.04, \tag{18}
\]

which confirm strong correlation between the selected measures \((p = 0.0001)\). Thus, we can conclude that two approaches (MLP and SOM) provide complementary data and can be used in parallel.

3.4. Relationship between clustering quality and classification fidelity of SOM

The results of the introduced mapping error indexes were compared with the fidelity of EMG patterns classification. According to the obtained data, regression lines were constructed (figure 4B, 4C): and coefficients of cross-correlation for two values were obtained \( c = 0.7 \) (Fig. 4A); \( c =-0.49 \) (figure 4B) and \( c=-0.64 \) (figure 4C).

\[
E^{(\text{intra})} = a \times F_{\text{SOM}} + b, a = -1.88 \pm 0.48, b = 2.65 \pm 0.35 \tag{19}
\]
\[
E^{(\text{inter})} = a \times F_{\text{SOM}} + b, a = -4.31 \pm 0.64, b = 4.66 \pm 0.52 \tag{20}
\]

Correlation is statistically significant: \( p = 0.002 \) in the case of intra-cluster index and \( p = 0.0001 \) for inter-cluster index. A bigger value of \( p \) for the intra-cluster index obviously indicates that the classification with SOM is more negatively affected by overlapping clusters than their large size.

**Figure 4.** Comparison of classification accuracy and clustering quality for 37 subjects. Researched pairs are: SOMs F-measure and MLPs F-measure (A), intra-cluster-index and SOMs F-measure (B), inter-cluster-index and SOMs F-measure (C).
4. Conclusions

In this study we have implemented a SOM-based system that can cluster and classify myographic patterns.

In the classification problem, we have compared the fidelity of recognition by SOM and MLP. The median value of F-measure for SOM-based recognition is F=0.87 whereas for MLP classification F=0.96. We explain this gap by using a universal algorithm for the formation of SOM, which is not optimized for the separation of classes. Obviously fidelity can be increased by eliminating the possibility of generation of negative (FN) responses. Also we have found strong correlation between F-measures for classification by MLP and SOM.

For estimation of clustering quality of SOM we have introduced two indexes: the intra-cluster index describing the cluster “compactness” and the inter-cluster index measuring the degree of cluster overlapping. We have found correlations between F-measures for classification by SOM and introduced indexes. Differences in the significance level of the correlations suggest that the classification with SOM is more negatively affected by overlapping clusters than their large size. Consequently, further efforts to improve the classification fidelity can be aimed at reducing the cluster overlapping.

Another interesting area is the implementation of a SOM-based neuromuscular interface for controlling a robotic device taking into account the nature of EMG patterns. So far we have used separate (synthetic) gestures for SOM learning. In future studies, it is interesting to implement "dynamic" SOMs and use the entire set of movements, including transient gestures as a training set.

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