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Utilizing Kohonen Maps in Electromyography Recognition System for Upper Limb Prosthetics

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Abstract

This study focuses on evaluating a specific type of artificial neural network known as Kohonen Map (KM) or Self-Organizing Map (SOM), for the characterization of Electromyography datato utilize in upper limb prosthetics. Prosthetic devices aim to assist individuals by restoring some of the functions of a lost limb. Significant research has been dedicated to developing artificial hands that replicate the capabilities of human hands. However, the complexity of the human hand makes it difficult to imitate. Various classifiers have been investigated to enhance the performance of prosthetic hands. In this work, the Kohonen map was utilized on a dataset obtained from a sensor which was built bya local research team called Electronic Prostheses Engineering Team (EPET). This dataset includes 36data sets representing open and closed hand movements from three individuals. Experiments were conducted to classify two hand gesture types open and closed for three individuals, and results displayed as 2D maps indicate that an accuracy exceeding 97% was achievable.

Keywords: upper limp prosthesis, Kohonen map, Self Organizing map.

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استخدام خرائط كوهونين في نظام التعرف على الموجات الكهروعضلية لاستخدمها في الاطراف الصناعية العلوية

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الملخص

تتناول هذه الدراسة تقييم نوع محدد من الشبكات العصبية الاصطناعية المعروف باسم خريطة كوهونين (Kohonen Map) أو الخريطة الذاتية التنظيم (Self-Organizing Map)، من أجل تحليل بيانات الموجات الكهروعضلية لاستخدامها في الأطراف الاصطناعية العلوية. حيث تهدف الأطراف الاصطناعية إلى مساعدة الأفراد من خلال استعادة بعض وظائف الأطراف المفقودة. وقد تم تكريس أبحاث هامة لتطوير أيدٍ اصطناعية تحاكي قدرات الأيدي البشرية. ومع ذلك، فإن تعقيد اليد البشرية يجعل من الصعب تقليدها. تم في دراسات سابقة تطويرتقنيات متنوعة من أنظمة التصنيف للإشارات الكهرو عضليةلتعزيز أداء الأيدي الاصطناعية. في هذا العمل، تم استخدام خريطة كوهونين على بيانات تم الحصول عليها من حساسات تم بناؤها بواسطة فريق بحث محلي يُعرف بفريق هندسة الأطراف الاصطناعية الإلكترونية .(EPET) وتتضمن هذه البيانات 36 مجموعة بيانات تمثل حركات اليد المفتوحة والمغلقة من ثلاثة أفراد. تم إجراء تجارب لتصنيف نوعين من إيماءات اليد (مفتوحة ومغلقة) لثلاثة أفراد، وأظهرت النتائج المعروضة كخرائط ثنائية الأبعاد ممثلة في خريطة كوهنين أن دقة تتجاوز 97% كانت قابلة للتحقيق.

الكلمات المفتاحية: الاطراف الصناعية العلوية، خريطة كوهونين، خريطة التنظيم الذاتي.

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INTRODUCTION

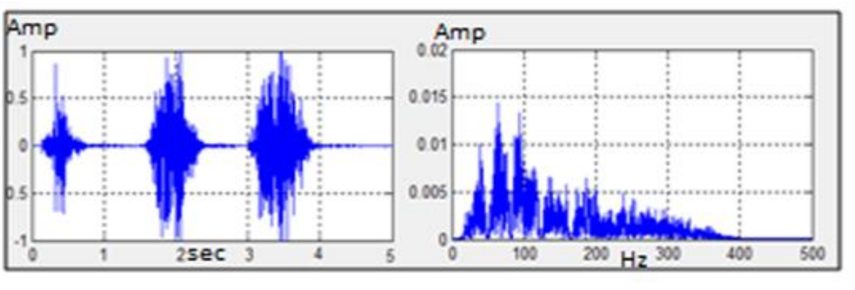
Prostheses are artificial devices designed to replicate the appearance and functionality of a lost limb. They are commonly used following limb loss due to accidents or congenital conditions.

The development of electronic prosthetic technology is crucial, as it significantly aids patients in resuming their daily activities. Additionally, these devices provide essential support, enabling individuals to engage and participate fully in their communities.

Various types of prosthetic hands have been developed, ranging from purely cosmetic models to more advanced options such as Mechanical and Myoelectric hands that offer some degree of functionality. [1]

Recent developments in prosthetic technology have focused on creating artificial hands that can perform multiple actions. Nevertheless, simulating the complexity of the human hand remains a significant challenge. [2] One of the most difficult aspects of recent research in this area is connecting human neural signals to artificial hands and utilizing these signals to control the prosthesis. The electrical characteristics of the human nervous system can help identify various nerve signals, with several bio signals, including electrooculogram (EOG), electroencephalogram (EEG), and electromyogram (EMG), being relevant. [3]

EMG signals can be recorded on the skin's surface using standard electrodes. Figure 1 shows an EMG signal capturing three opening gestures over a duration of 5 seconds, with EMG frequencies typically ranging from 20 to 400 Hz.



A: Time Domain B: Frequency Domain

Figure 1. A,B: An EMG Signal

EMG signals are particularly valuable in prosthetic research because they reflect the electrical activity generated by muscle contractions, making them more acceptable and convenient for amputees since they can be collected using surface sensors.[2]

LITERATURE REVIEW

The control of myoelectric prostheses through EMG pattern recognition systems has been explored extensively in research over the past decade, with some of the earliest efforts dating back to the 1970s. [4] These methods have evolved significantly, resulting in recognition systems with satisfactory performance.

Since the early 1990s. [5] advanced pattern recognition techniques have been employed to classify EMG signals. Various approaches have been proposed, including artificial neural networks [6,7]and Gaussian mixture model classifiers [8]. These methodologies have notably enhanced the accuracy of EMG signal classification and increased the diversity of hand motions that can be recognized.[5]

A virtual myoelectric prosthesis controlled by an EMG pattern recognition system was introduced in one study, designed to simulate the behaviour of real prosthetic devices in a virtual environment.[9] This system aids amputees during training, allowing them to practice without needing to wear the prosthesis continuously. In one research, the EMG signals collected from upper arm muscle groups were modelled using an auto-regressive (AR) model, which served as input for an artificial neural network classifier. The neural network's outputs were then utilized to control the movements of the virtual prosthesis.

The classification of EMG signals showed that the AR coefficients could be effectively segmented into distinct pattern classes by the neural network. Furthermore, the results indicated several advantages of using neural networks over traditional methods, such as Bayesian approaches. However, the computation of AR coefficients can be relatively complex. [9]

Another approach was described in studies [10,11], detailing the systematic development of an active myoelectric transhumeral prosthesis. This prosthesis enables the opening, closing, and rotation of the hand while simultaneously allowing for the flexion and extension of the elbow joint. During the feature extraction stage, the root mean square (RMS) method was utilized, while the Support Vector Machines (SVM) algorithm was employed to classify surface EMG signals obtained from residual humeral muscles to control the movements of the virtual prosthesis. The results indicated an average accuracy of 90.85% for prosthesis control; however, this level of accuracy may not be sufficient for optimal prosthetic operation.

Kohonen Map:

This technique employs unsupervised learning to map points from an input space to an output space while maintaining topological relationships. The input space is typically high-dimensional, whereas the output is usually one or two dimensions. [12]
The key mechanism behind (KM) is the concentration of network activity on the cell or its neighbouring cells that best correspond to the current input.[12] Self-Organizing Maps identify the cell that most closely matches the input and then enhances the response of that cell and its topological neighbours.[13]
Two fundamental effects contribute to the formation of spatially organized maps:

1. The spatial concentration of network activity on the cell (or its neighbourhood) that is most finely tuned to the current input.
2. The further sensitization of the tuning of the best-matching cell and its topological neighbours to that input. [12]

The algorithm for producing Kohonen maps involves Selecting Network Topology by choosing the arrangement of the network nodes, which can be hexagonal, rectangular, or another configuration as shown in Figure 2.

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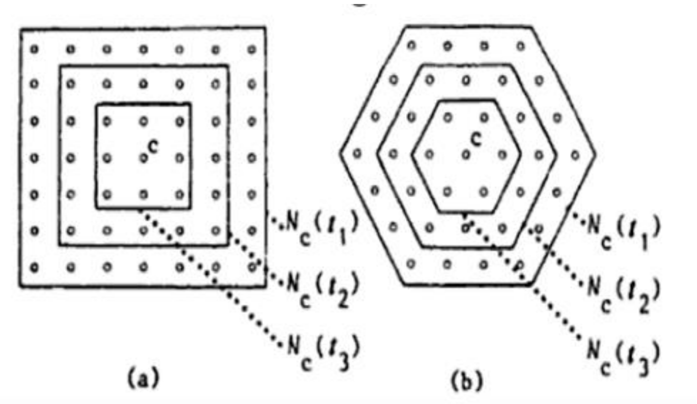

Figure 2. example of topological neighbourhood (t_1<t_2<t_3) [14]

Also Initialize Weights to Small Random Values then identify the best matching node, which is the node whose weight vector is most similar to the input vector. In many applications, this is determined by finding the node with the smallest Euclidean distance from the input vector. Finally, After the best matching unit is found the KH algorithm updates the "winning" node and its topological neighborhood according to equation (1) [13]

$$mi(t+1) = \begin{cases} mi(t) + \propto(t)[x(t) - mi(t)] & if\ \ i \in Nc(t) \\ mi(t) & if\ \ i \notin Nc(t) \end{cases} \quad \ldots\ldots(1)$$

Where:

$mi(t+1)$: *is the new weight*

$mi(t)$ *is the old weight*

$t = 0,1,2,3, \ldots\ldots\ldots\ldots\ldots\ldots\ldots..$ *is an integer representation*

SYSTEM ARCHITECTURE:

The proposed system responsible for building the recognition system involves several key functions including digital filtering using filters like Notch filters and Band Pass filters to eliminate unwanted frequencies and enhance the desired signals. Features havee different dimensionality and types, artificial neural networks capable of learning the hidden representation of an input features vector.[14]

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The root mean square (RMS) envelope values were extracted as the primary feature parameters. The RMS of the signal's envelope calculates the average values, effectively reducing redundant data.[15]

Finally based on the extracted feature, the system classifiers based on Kohonen map will classify the signals into predefined categories or classes.These processes are illustrated in Figure 3.

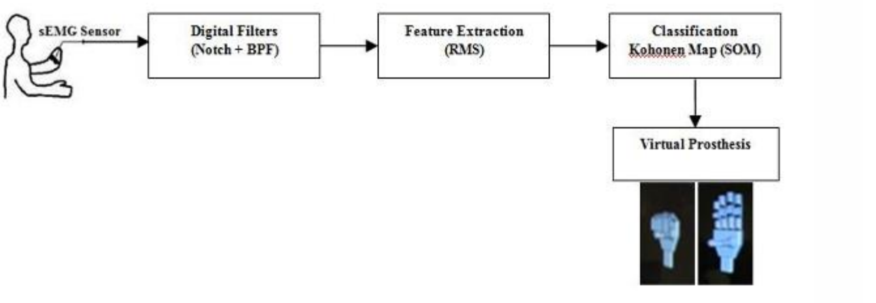

Figure 3. The proposed system architecture.

Collecting Data

The EPET technical support team has designed and built a surface sensor to collect electromyography (EMG) signals from the residual limb muscles. The signals captured by the sensors are treated as sounds signals; the outputs are amplified and then transmitted to a computer via the sound card, where they are saved as MAT files. The proposed system is designed to recognize two specific movements: opening and closing the hand. Data were gathered from one male and two female subjects, each performing thirty-six gestures.

Additionally, active regions of the signal were identified using a blocking technique to exclude time periods where no signal was present.

Experimental Plan and Results

Three experiments were conducted to classify the data as either "open" or "closed." Each experiment involved a different

participant. Since the data collected from the sensor circuit were treated as sound signals, a total of one hundred gestures were recorded from each person; however, thirty-six gestures were deemed sufficient for analysis.
The dataset was divided into two groups: training and testing, with eighteen samples allocated to each group.
The results from the three experiments were evaluated based on the average classification accuracy and the training time for the input set. Each experiment was repeated ten times to assess statistical significance.
Figure 4 illustrates a representative Kohonan map (SOM) used for classifying hand gestures. In this map, the green (light grey) cells indicate regions that represent opening hand data after training, while the blue (dark grey) cells correspond to closing hand data. The boundary conditions for all trained maps are toroidal, meaning the edges wrap around and connect to each other.

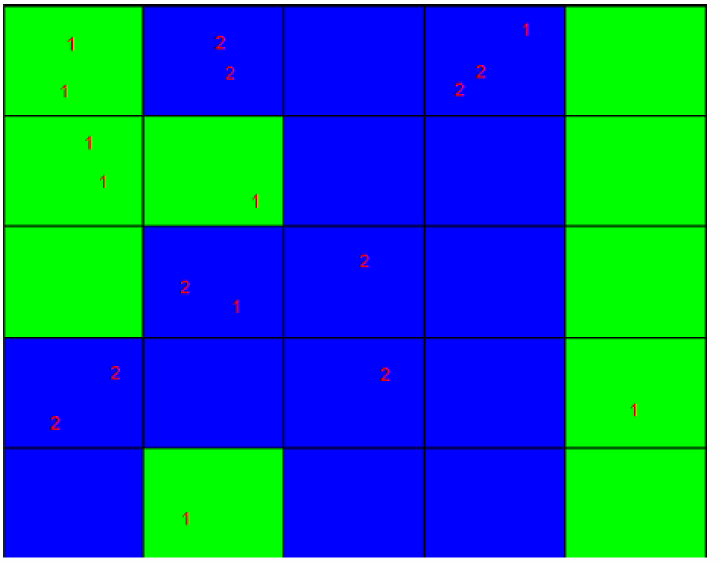

Figure 4. Classifier Kohonen map

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The numbers within the cells denote the locations of the test data on the trained map when presented to the network, where “1” represents opening hand data and “2” represents closing hand data. Ideally, all "1"s should be located in the green (light grey) areas, and all "2"s should be in the blue (dark grey) areas. The results indicate that most test data files were correctly classified on the map. From the ten repeated tests, the average accuracy for classifying hand gestures was approximately 97.22%.

Conclusion

The results from this preliminary study suggest that Kohonan maps or Self-Organizing Maps can effectively classify open and closed hand gestures, demonstrating high performance with an accuracy of 97.26%. Table 1 summarizes these findings. However, it is important to note that the dataset is limited. Future work should aim to encompass a broader range of gestures and datasets, utilizing a high-performance data acquisition circuit and ensuring robust statistical significance.

Table 1: Summary for all experiments

#	Person 1	Person 2	Person 3
Training samples	18	18	18
Training time	< 1 min	< 1 min	<1 min
Average accuracy	97.22%	96.96%	97.62%

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