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Review Article

Acquisition of EMG signals to recognize multiple Hand Gestures for Prosthesis Robotic Hand-A Review

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Abstract

Robotic prosthesis hand amputees are highly benefited, which would allow the various hand gestures based on wrist and fingers movements. In the field of Biomedical signal processing, development of an advanced human–machine interface has been an interesting research topic in the field of rehabilitation, in which electromyography (EMG) signals, have a vital role to play. EMG signal is an electrical activity of Muscles and usually represented as a function of time, defined in terms of amplitude, frequency and phase. EMG signal based reliable and efficient hand gesture recognition can help to develop good human computer interface which in turn will increase the quality of life of the disabled or aged people. Acquisition and analysis of EMG signals concerns with the detection, processing, feature extraction, classification and application for control human-assisting Robots or prosthetic applications. This paper reviews recent research and development of hand prosthetic for multiple hand gestures based on wrist-hand mobility subsequent from the EMG signals. To identify the effectiveness of hand prosthesis, forearm muscles are being considered for better exploitation of EMG signals and classification of movements is done by Wavelet transform followed by efficient time-frequency featuring in Artificial Neural Networks (ANN).

Keywords: *Artificial Neural Networks, Classification, EMG signal, Feature extraction, Wavelet transform.*

1. Introduction

The structure of hand prosthetics usually operates in discrepancy of active and passive hand prostheses. Active hand prosthesis is a hand prosthesis which can be freely actuated to some degree by the patient. Moreover, the ideal active hand prosthesis is highly dexterous and easily controlled by the operator. Gestures can originate from any bodily motion or state but commonly originate from the face or hand. The hand gestures are captured through EMG signals by sensors which actually a measure musculature activities. The most difficult part for developing the prosthesis is to control and recognise different patterns from EMG signals. This is because of large variations in EMG signals having different signatures depending on age, muscles activity, motor unit paths, skin-fat layer, and gesture style. Compared to other biomedical signals, EMG signal contains complicated types of noise that are caused by inherent equipment and environment noise, electromagnetic radiation, motion artefacts, and the interaction of different tissues . Sometimes it is difficult to extract useful features from the residual muscles of an amputee or disabled. This difficulty becomes more critical when it is resolving a multiclass classifying problem.

EMG signal is obtained by measuring the electrical activity of the muscles produced during muscle contraction, which is controlled by the nervous system. Muscles consist of muscle fibers, which are activated by motoneurons. Thus, impulses from the spinal cord arrive to the motoneuron which triggers a group of several muscle fibers, called the motor unit. For producing a hand movement, each muscle fiber enclosing the muscle contracts, which then carries the contraction to the whole muscle and achieves the desired action. In most of the cases, even for a fine hand movement, several muscles are simultaneously involved to accomplish that movement action (Claudio Castellini *et al*, 2009). An electrical response of a motor unit is the motor unit action potential (MUAP) which then initiates a train of MUAP form an EMG signal (M.B. Reaz and M.S. Hussain *et al*, 2006). There are several classes of MUAP in an EMG signal, and the necessity is to classify the EMG signal using the hypothesis that the same MUAPs are summed up when the same movement is done, so the EMGs of similar movements should show similarities which can be exploited to build a classifier for multiple hand movements (B. Crawford, K. Miller and R. Rao *et al*, 2005).

Surface electrodes are considered for acquiring EMG signals for prosthesis applications as the signals detected by needle electrodes are more difficult to understand than signals obtained by surface electrodes (J. Perry and C. Schmidt Easterday *et al*, 1981). The surface electrodes are large in size, so the area covered is large and corresponds to the activities of several tens of motor units. Since

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muscles are deep beneath the skin surface, so the power spectrum of EMG is limited to 500Hz. Thus, the electrodes can be positioned on the lower forearm muscles which are responsible for hand movements. For acquiring and discriminate vital movements, namely opening and closing hand, hand pitch up or down, move the thumb in abduction or adduction for prosthesis hand assessment. Thus, the resulting prosthesis can give the user a more natural grasping movement, also allowed to move the wrist. Furthermore, the enhancement for prosthesis field can be carried out for different gripping movements and also to discriminate more natural movements for wrist-hand mobility.

Limited papers presenting results in the classification of EMG signals for different hand movements are available. Some have applied fuzzy rules to analyse EMG signal, others developed neural networks. The review originates the method from Hudgins and co-workers (B. Hudgins and P. Parker *et al*, 1993) who obtained a classifier able to recognize four class labels with a performance about 90%. In addition to their work, the position of electrodes and the kind of data classification can be modified. For classification of the acquired signals the techniques of wavelet and autocorrelation to extract relevant features are able to characterize the signal for classification. A neural classifier in cascade with wavelet analysis can be used for better results in feature classification.

2. Prosthetic Field

The hand prostheses are classified as active and passive hand prostheses. Active hand prosthesis can freely actuated the hand movements to some degree with ease in accessible operation as controlled by the operator (Claudio Castellini and Patrick van der Smagt *et al*, 2009). Operation wise, active hand prosthesis can be classified as:

- Prostheses moved by the patient
- Prostheses with external source of energy, either myo-electric command or electronic command.

The active prostheses use electrical motors power driven by batteries. The regulation of an actuated prosthesis is usually based on EMG, which is the electric activity of activated muscles, measured from surface electrodes. The best known commercially available active hand prostheses are Otto Bock’s Myo hand, Otto Bock’s Sensor Hand and Touch Bionics’s i-Limb. The Myo hand is a simple three fingered hand which is feasible for particular angular movement of opening and closing. The Sensor Hand is a classical one which is proportionally controlled by one or two electromyography electrodes; the i-Limb has five independently moving fingers plus a passively opposable thumb. Nevertheless, one can see a definite move forward as far as the mechatronics is concerned, a drive which mainly comes from confined electronic and humanoid robotic.

While sending commands to the prosthesis, two types of interfaces between the patient and the prosthesis are being observed: invasive and non-invasive. The former gather control signals directly from the user’s nervous system, either via brain implants or surgical use of electrodes. On the other hand, non-invasive interfaces are easier to handle and maintain, but require a much better signal conditioning, since they usually work with surface signals and observation tracking. In the context of non-invasive interfaces for controlling mechanical hands, a concrete possibility arises from forearm surface EMG signals. Surface EMG is therefore, in principle, a cheap and easy way of detecting what the patient wants the prosthesis to do (Claudio Castellini and Patrick van der Smagt *et al*, 2009). Using the EMG for driving control, active hand prosthesis requires adaptively, accuracy and speed: each patient must be able to control the prosthesis accurately in real time.

Thus, it is required to improve the automatic activity of the prostheses, and to make the movement more natural. Ideally, the system should be able to reproduce the natural regulation exerted on the limb by the nervous system. This is still problematic, since the myoelectric signal cannot be used to send a feedback to the muscle that generated it. Without a feedback from muscles, the only feedback can be generated from vision, and so the resulting system is different from the natural one, as illustrated in Fig. 1. Thus a new solutions to give a feedback can be devised (Giuseppina Ginia and Matteo Arvettia *et al*, 2012), for instance physical inducements which can inform the user about the activity going on; however no valid solutions have been provided so far.

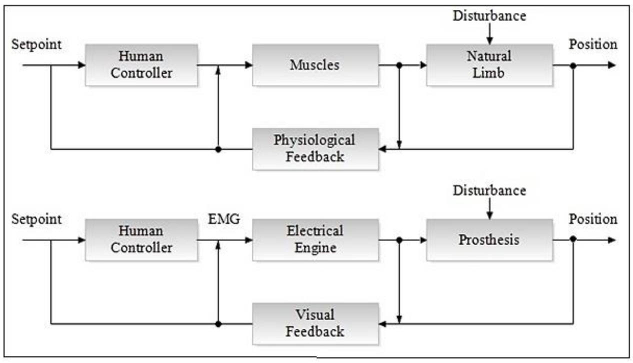

Fig.1 Comparison of Regulation of Natural Limb (upper) and EMG prosthesis (Lower)

3. Acquisition of EMG signals

3.1 Muscles acting on Hand Prosthesis

For signal acquisition and defining scheme there is a need to understand which muscles are relevant and how they are connected to the movements. There are many muscles in the forearm devoted to move the wrist and the hand; we enlist some important muscles and related movements in Table.1 (Henry Gray *et al*, 1918).

The electrical signals are estimated from the front and back side of the lower forearm muscles as indicated in Fig. 2, while the reference electrode is applied on the other limb as per the Right Leg Drive (RLD) conditioning. In case of wrist-hand mobility merely all the muscles are somehow involved in the operation of movement. So mainly operated muscles as given in Table.1 and are globally considered; the signal obtained thus contains different patterns for the different movements, and our goal is to characterize those patterns for different movements.

Table 1 The Forearm Muscles and its related movement used to move the hand.

Muscle	Movement	Action
Abductor pollicis longus	Abduction	Abduction of the thumb and of the wrist
Extensor digitorum communis	Extension	Extension of fingers and wrist
Extensor pollicis brevis	Extension	Extension of thumb and wrist abduction
Extensor pollicis longus	Extension	Extension of thumb and wrist abduction
Extensor indicis	Extension	Extension of thumb and abduction of index
Extensor digiti quinti	Extension	Extension of the little finger

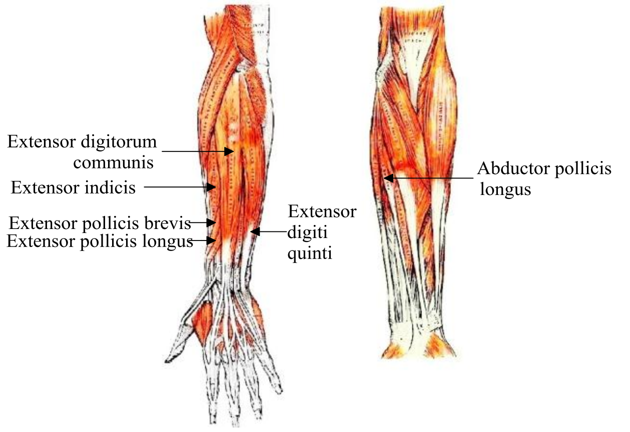

Fig.2 Classification of different forearm muscles

3.2 Kinds of Movement for Prosthesis

Since the hand has too many degrees of freedom (20 only for the fingers) and it is impossible to replicate all of them in a simple way, thus only considering the movements which allows the patient to manipulate objects in a sufficient way. The movements available in commercial prosthesis are only two, namely opening and closing the hand.

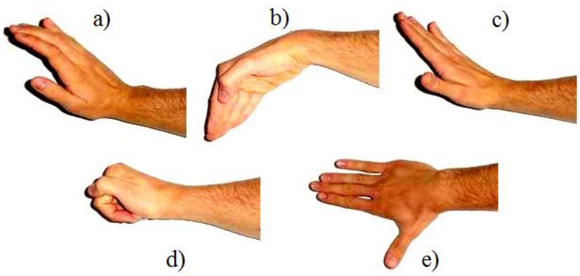

Fig.3 Active hand movement's discriminate: a) wrist extension b) wrist flexion c) hand opened d) hand closed e) thumb abduction

Some more movements like Abduction of the thumb or extension or flexion of the wrist can be considered in prosthesis field. Since the muscles that move the thumb are very deep, we can only consider thumb extension and leave the control of thumb flexion to an empirical supervisor. Some active hand movement's discrimination is illustrated in Fig. 3.

3.2 Electrodes and Signal Acquisition

EMG signals are the appearance of impulses which are initially generated in the central nervous system and then travel to their final destination, where they produce the desired action. The potential differences generated in muscles due to these impulses not only generate muscular contraction, but also propagate to the surrounding tissues, which make it possible to measure them by applying specially designed electrodes. There are two main kinds of electrodes that might be used for measuring EMG signals: surface and inserted electrodes. Inserted electrodes are very thin wires or needles that are inserted inside muscles and, due to their proximity to the signal origin, allow acquiring precise and high quality signals. The problems about them are many; they could be painful, are not removable without surgery, and there are no records about their time duration (J.C.K. Lai, M.P. Schoen *et al*, 2007). Due to this factors surface electrodes are mostly preferred. The utilized electrodes are made of metal and covered with a thin coat of silver chloride (AgCl). A conductive solution is also used to enhance the conductivity between skin and electrode which reduces the noise and improves the results.

The acquired EMG signal contain different patterns for the different movements, the main objective is to characterize those patterns (H. Dickhaus and H. Heinrich *et al*, 1996). The acquired signal contains noise and an offset signal; furthermore not all the sequences are observed properly as the electrode is in practice a low pass filter and distorts some spectral components of the signal. The cut frequency of 5mm diameter electrode is about 360Hz and for a 20mm diameter is about 100Hz. Equation 1 (P.L. Bartlett *et al*, 1997) shows a simple model of the detected EMG signal:

$$x(n) = \sum_{r=0}^{N-1} h(r)e(n-r) + w(n) \tag{1}$$

Where, $x(n)$, Modelled EMG signal; $e(n)$, point processed representing the firing impulses; $h(r)$, represents the MUAP; $w(n)$, zero mean addictive white Gaussian noise and N is the number of motor unit firings.

4. Processing of EMG signals

The different module that develops the acquiesced EMG signals is Preamplifier; Band pass filter; Amplifier and Analog to digital conversion (Ali Salman and Javaid Iqbal *et al*, 2012) as shown in Fig. 4. In presence of muscular activity, the EMG signal is picked up by the electrodes located on the forearm. This signal is amplified by the "Preamplifier" to achieve adequate voltage levels to prevent electrical interferences. Then there is a "Band pass filter" stage, to obtain a signal into the frequency range of interest and to eliminate most of the noise that affects the myoelectric signal. The third stage, the "Amplifier", raises the voltage levels up to the TTL standard, an indispensable requirement for processing data in a computer. The last phase is the “Analogue-to-digital conversion” of the signal that is then transmitted to the computer for signal processing.

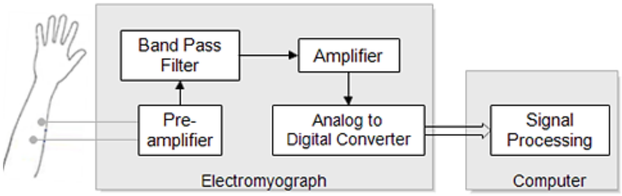

Fig.4 EMG signal development modules (Ali Salman and Javaid Iqbal *et al*, 2012)

The electrical perturbation interfacing in the EMG signal is the main issue for Noise occurrence. Also while using the surface electrodes, still noise factors are encountered in the acquired EMG signal due to their weak potency and several noise factors which affect them are,

- Inherent noise of the electronic components in the instrument itself. This noise has frequency components from 0 to several 1000 Hz. This noise cannot be eliminated; it can only be reduced by using high quality electronic and construction techniques.
- Ambient noise: We are constantly exposed to electro-magnetic radiations. The dominant concern for ambient noise arises from the radiation from power sources (50 or 60 Hz), whose magnitude may be even 5 orders greater than the EMG signal.
- Motion artefacts: There are two main sources of motion artefacts, one from the interface between the detection surface of the electrode and the skin, the other from movement of the wire connecting the electrode to the amplifier. The electrical signals of both noise sources have most of their energy in the frequency range from 0 to 20 Hz (M.B.I Reaz and M.S. Hussain *et al*, 2006).

Practically most important noise is caused by electrical power sources. To prevent these proper shielded wires should be connected to electrodes which then drive to the amplifier. The shield of each of the leads is connected to the circuit and through it to the reference; in this way, perturbations find a fixed potential shield that avoids them to affect the myoelectric signal in the centre of the leads.

5. Classification of EMG Signals

5.1 Basic Design and Constrains

The classifier must be able to provide the class label in a time compatible with a natural controlled loop. According to an empirical analysis, the maximum delay, tolerable by the user, between the commanded movement generated by the signal and the instant when the prosthesis starts moving is about 300ms; since the signal acquisition can require 200ms (fixed by hardware constraints), the classifier should operate in the maximum time of 100ms to output the desired movement (Giuseppina Ginia and Matteo Arvettia *et al*, 2012). The controller uses a pattern recognition approach, as illustrated in Fig. 5 which can acquire and classify data from different electrodes channels. The architecture for the classifier is generally based on artificial neural network (NN); specifically fully connected multilayer network. Thus the processing time from a trained NN is very low, but the time to extract the features from the unknown signal should be compatible with the 100ms time window, that is the above defined maximum time available to remain inside the window of 300ms. For this reason a set of statistical parameters that are easy and fast to compute, and should have separately listed the parameters that require more computing time.

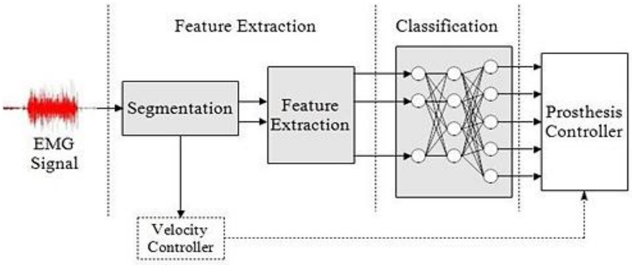

Fig.5 Pattern recognition open loop controller for feature extraction and classification

5.1 Feature Extraction

After the development of the EMG signal the next step is to extract the originated feature from the EMG signal. According to (M.B.I Reaz and M.S. Hussain *et al*, 2006) the time sequence can be characterized with some parameters; the following statistical features can be extracted:

1. Mean Absolute Value (MAV) is the average rectified value and can be calculated using the moving average of full-wave rectified EMG. Since it represents the simple way to detect muscle contraction levels, it becomes a popular feature for myoelectric controlled applications. It is defined as,

$$\overline{X_\iota} = \frac{1}{N}\sum_{n=1}^{N}|x_n| \tag{2}$$

The average of i-segment made of n samples. This parameter can be used by the controller to set the velocity of movement of the prosthesis which will be linearly correlated to MAV.

2. Difference between the MAV of two samples,

$$\Delta\overline{X_\iota} = \overline{X_{\iota+1}} - \overline{X_\iota} \tag{3}$$

3. Variance of EMG (VAR) estimates the EMG signals feature. Generally, the variance is the mean value of the square of the deviation of that variable which is close to zero. Variance of EMG can be calculated by,

$$VAR = \frac{1}{N-1}\sum_{n=1}^{N} {x_n}^2 \tag{4}$$

4. Zero count, i.e. number of times the signal passes through zero. To cut the noise we use a threshold of 0.01V, corresponding to a noise of 4 μV amplified 5000 times. The counter of zero passing is

incremented if the sign of X_n is different from the sign of X_{n+1} and

$$|x_n - x_{n+1}| \geq 0.01V \quad (5)$$

Sign changing; given 3 consecutive samples we increment a counter if,

$$x_n > x_{n-1} \text{ and } x_n > x_{n+1} \text{ and } |x_n - x_{n+1}| \geq 0.01V \quad (6)$$

or

$$x_n < x_{n-1} \text{ and } x_n < x_{n+1} \text{ and } |x_n - x_{n-1}| \geq 0.01V \quad (7)$$

5. Standard Deviation (SD) is used to find the threshold level of muscle contraction activity and can be given as,

$$SD = \sqrt{\frac{1}{N-1}\sum_{n=1}^{N}(x_n - \bar{x})^2} \quad (8)$$

Where, $\bar{x}$ is the mean value of the EMG signal.

6. Waveform Length (WL) is the cumulative length of the waveform over the time segment which is related to the waveform amplitude, frequency and time. It is given by,

$$WL = \sum_{n=1}^{N-1}|x_{n+1} - x_n| \quad (9)$$

7. Slope Sign change (SSC): This feature provides an approximate estimation of frequency information of EMG signal. The number of changes between positive and negative slope among three consecutive segments are performed with the threshold function for avoiding the interference in EMG signal and is calculation as,

$$SSC = \sum_{n=1}^{N-1}\{f[(x_n - x_{n-1}) \times (x_n - x_{n+1})]\} \quad (10)$$

$$f(x) = \begin{cases} 1, & if\ x \geq threshold \\ 0, & otherwise \end{cases} \quad (11)$$

8. Wavelet Transform, Wavelets are one of the important mathematical transformations to extract information from signals. The Wavelet Transform results in signal representation in the time frequency space, i.e., it is possible to know when a certain phenomenon occurs with a specific frequency. Wavelet is a series decomposition of the signal in a set of functions $\psi(t)$, that are different both in the scale factor (s) and in the time shift (σ).

$$Wf(s,\sigma) = \int_{-\infty}^{+\infty} f(t)\frac{1}{\sqrt{2}}\psi\left(\frac{t-\sigma}{s}\right)dt \quad (12)$$

Since directly using s and σ as features in the classifier does not improve the performance, thus can be enhanced by solution proposed in (H.H. Szu and B. Telfer *et al*, 1992). The Neural Network is train with one hidden layer, that takes as input the time t and gives back the signal $s(t)$. After training, the scale and shifts values (s and σ) associated with the maximum weights of the net are used as additional features for the movement's classifier.

5.3 Classifier

A classifier should be devised as a Multi-layered Neural Network, whose inputs are features extracted, and whose output is the class label. The statistical features of the signal should be computed on two consecutive segments of the registered EMG signal; wavelets features have been computed on doubled time sequence segment of the signal, obtaining a total of 12 input features. Since a network with one hidden layer is a universal approximate can be used as a basic architecture. To estimate the number of neurons, the hidden layer can be used as a trial procedure since; there are no general rules to compute it (A.B. Ajiboye and R.F. Weir *et al*, 2005).

The ANN used for classification is a back-propagation (BP) type network which is dynamic and powerful. Its state changes continuously until it reaches to the final equilibrium point which is achieved by successful training. BP is created by generalizing the Widrow-Hoff learning rule to multiple-layer network and nonlinear differentiable transfer function. The learning rule for the propagation of neural network defines how the weights between the layers will change. Here, the input vectors and corresponding target vectors are used to train the neural network until it can approximate a function, associate input vectors with specific output vectors or classify input vectors in an appropriate way based on certain criteria. The respective ANN consists of 3-layers: input layer, tan-sigmoid hidden layer and linear output layer (Md. Rezwanul Ahsan and Md. Ibn Ibrahimy *et al*, 2011). Each layer except input layer has a weight matrix W, a bias vector b and an output vector a. The weight matrices connected to inputs called input weights (IW) and weight matrices coming from hidden layer outputs called layer weights (LW). Additionally, superscripts are used to denote the source (second index) and the destination (first index) for the various weights and other elements of the network.

The feed-forward BP network architecture has shown in Fig.6 with seven neurons in input layer, 10 tan-sigmoid neurons in hidden layer and four linear neurons in output layer. Since there is no specific way to find out the number

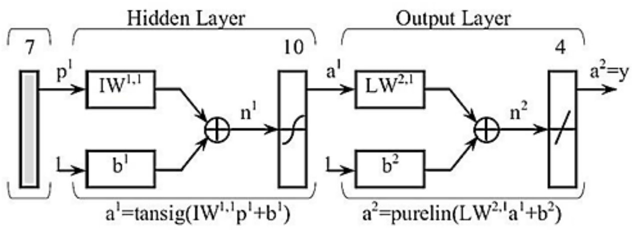

Fig.6 Architecture of Artificial Neural Networks

of hidden neurons, so it has been determined from best classification result by selecting different numbers of neurons. The predefined features were extracted for four types of hand movements from different EMG signals. 204 sets of input vectors and target vectors fed to the network for training purpose. The input feature vectors are normalized for the efficient training of neural network.

Conclusions

EMG signal is obtained via the differentiation of individual action potentials generated by irregular discharges of active motor units in muscle fibers. It contains rich information that can make myoelectric control a pioneer solution for prosthesis application and human-assisting robots. The level of activity of muscles in contraction is the most important factor to be recognized in EMG classification. Therefore, applying wavelet transform to EMG signal will extract the feature for prosthesis; also to estimate the variance, MAV and length of signal results in significant performance.

The accomplishments reviewed in this paper, have led to the modified strategies for the improvement of EMG signal acquisition and classification with wavelet transformation followed by Artificial Neural Network. Since hand motions originates from the concurrent activation of several small and large forearm muscles. Thus, collecting data from different locality on the skin surface involves more muscles in classification and improves the number of functions that a system can manipulate. It also improves accuracy, by providing more discriminative patterns for input signals for each motion. Therefore, for developing the simplex system for EMG signal acquisition minimum numbers of forearm muscles are consider for development of system. Thus, taking this need in consideration the relevant work has been proposed by (Giuseppina Ginia and Matteo Arvettia *et al*, 2012) by using just two electrodes to acquire the EMG signals from forearm with effective feature extraction and classification system.

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