Proceedings Paper:

Abass, Z, Meng, W orcid.org/0000-0003-0209-8753, Xie, SQ et al. (1 more author) (2019) A robust, practical upper limb electromyography interface using dry 3D printed electrodes. In: 2019 IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM). IEEE/ASME International Conference on Advanced Intelligent Mechatronics, AIM, 08-12 Jul 2019, Hong Kong. IEEE , pp. 453-458. ISBN 9781728124933

https://doi.org/10.1109/AIM.2019.8868500

A Robust, Practical Upper Limb Electromyography Interface Using Dry 3D Printed Electrodes*

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***Abstract* – This study aims to develop a practical, robust and reliable human-machine interface using gesture recognition based on surface electromyography (sEMG) signals from the forearm. This technology is developed to be employed medically in stroke rehabilitation or prosthetic control. So far, studies have been conducted that improved the accuracy of such systems, but little has been done to avoid using wet (gelled) electrodes and hence improve their reliability and robustness for long-term use. Through this study, a comfortable and wearable bio-signal acquisition device is designed and developed that uses dry EMG electrodes. 3D printed electrodes are compared with ready-made dry ones to choose the better option, and an interface is established that allows control of any mechatronic system such as a prosthetic arm.**

***Index Terms*—EMG interface, 3D-printed electrodes, neuromuscular interface, wearable.**

I. Introduction

For a muscle to contract, the brain sends a signal to that specific muscle through motor neurons. The change in electrochemical gradient (polarisation) at the muscle due to that stimulation signal is a change in voltage which can be picked up by electromyography (EMG) [1]. This change is proportional to how many muscles are contracting and by how much each one is.

Sensing EMG signals and analysing them to identify and differentiate between limb gesture has been a field of huge interest to many researchers for the past few decades [2] [3] [4] [5]. This is due to the various engineering and medical applications of systems which allow accurate gesture recognition [6] [7]. According to the World Health Organisation, there are 15 million strokes occurring each year. Around half of survivors are left reliant on others for performing regular tasks, [8], due to muscle weakness or even paralysis. Neuromuscular interface using EMG signals is the light at the end of the tunnel for stroke victims. This interface can be used to control robotic prosthetics for them [9], or exoskeletons for amputees [3] [10], giving these people back the ability to continue with their lives normally.

A series of steps must be taken to successfully interpret EMG signals and translate them into hand/arm gestures. These are, in turn, signal extraction, filtering, feature extraction and classification [11]. Filtering is not essential but, if used correctly, has been proven to improve the signal's feature space [12]. As mentioned in the literature review, there are numerous features one can extract from EMG signals to analyse, just as there are numerous classifiers one can use to categorise the data. Past studies have compared the usefulness of certain features [13] [12], and it has been difficult to conclude that one specific feature is the best to go with. Choosing the features to extract involves a trade-off between classification accuracy and system practicality [14]. The same goes for choosing a classifier to use, but with the trade-off being between the number of gestures wanting to be identified, computation time and the number of input channels [15].

Signal extraction itself should not be overlooked, since choosing the right electrode and using it correctly is paramount to having a reliable neuromuscular interface. Most studies so far have used wet (gelled) adhesive electrodes. These are very conductive, ensure excellent skin contact and are cheap [10]. However, they may be considered impractical since the conductivity drops as the gel dries with time and since they take time to set up [7]. The alternative is to use dry electrodes, which are reusable and need no gel. Although the poor skin contact increases their resistance and may cause signal distortions [16], they are very useful for wearable applications. Compared to gelled ones, they are significantly more comfortable and durable [17].

- This study aims to produce an interface combining certain system criteria which, based on reviewing past literature, have not been combined effectively before. The unique features of this study include: a real-time (online) response, Being dry and wearable; Able to identify five gestures; Being accurate and responsive; Being inexpensive. The rest of the paper is organized as follows: …

II. Related Work

Capturing and analysing EMG signals has been the attention of numerous researchers for over two decades. Some focused on varying the features extracted from signals [1] while others focused on choosing the best classifier [15]. Artificial Intelligence was used by Kale [18] to improve accuracy by creating a neural network. Looney et al. [4] created an elaborate system with robustness in mind – one that used phase synchrony features and produces an interface that does not depend on electrode placement. Furthermore, an elaborate study was done by Tavakoli et al. [19] that utilised a Support Vector Machine to classify 4 gestures using a single

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EMG channel. Their system was extremely responsive and required very short calibration times.

The mentioned studies contribute massively to the field of neuromuscular interface; however, they have all used wet, gelled electrodes. As mentioned before, this kind is not practical for long term use in wearable devices. Li et al. [16] in 2011 started to explore the potential of dry electrodes by comparing their effectiveness to wet (gelled) ones using an LDA classifier with four time-domain features. Although their accuracy comparison was not based on real-time analysis, they found that using dry electrodes reduced the classification accuracy by only 0.3%. This study may be considered the opening doors of employing dry electrodes in prosthetic control. The accuracy recorded, however, is calculated based on processing EMG signals offline (not real-time) after they were recorded and hence are subject to change in online control. Also, no wearable was designed in that study. Tavakoli continued after his aforementioned study and worked on a wearable armband with an addition to the system [17] – a specific gesture which locks/unlocks the system so that gestures are only captured when needed. A support vector machine (SVM) was used as a classifier to identify four gestures through 2 EMG channels. The electrodes used were too bulky however, making up a wearable that is very large and uncomfortable.

Ergeneci et al. [7] successfully came up with an Embedded, Eight Channel, Noise Cancelling, Wireless, Wearable sEMG Data Acquisition System With Adaptive Muscle Contraction Detection. They carefully studied all the systems in the market, found out what each lacked and created one of their own with an impressive signal-to-noise ratio, accuracy and responsiveness. They utilised two embedded digital methods – adaptive contraction detection and online adaptive power line noise (PLN) cancellation. This system only detected muscle contractions though, not hand gestures. Also, 8 EMG channels were used, which can be reduced to reduce the computation time required. A new approach was taken by Wolternik et al. [20]; using 3D printed dry electrodes. Their performance was compared to that of regular gelled electrodes but never used for actual gesture recognition. This study aims to produce an inexpensive system that uses small dry passive electrodes in a comfortable wearable device to control a robotic arm using gestures of the arm or hand. Control will be online and accurate.

III. The Choice of Electrodes

As described above in the literature review, most studies to date have utilised gelled, adhesive electrodes for surface EMG signal capture. This is simply due to their ease-of-use, superior conductivity and cheapness. In deciding between wet and dry electrode usage, a trade-off arises between practicality and signal conductivity. The option to use wet electrodes in this study was dismissed for several reasons, including the fact that they are difficult to remove and that they can cause skin irritation. The main reason, however, was because of them being disposable/single-use.

A further choice had to be made between active and passive dry electrodes. While active ones may contain a useful ultra-low built-in noise amplifier [24], they require a power supply which would complicate the wearable's wiring and reduce its battery life. It was hence decided to go with passive electrodes as they could be conveniently fixed onto the wearable. Useful noise filters such as the aforementioned one could be implemented programmatically.

Being narrowed down to dry and passive ones, the electrode options that were finally considered were:

a) Custom-designed 3D printed electrodes using conductive PLA.
b) Flat, metal electrodes that are ready-made and can fit into standard snap-on electrode cables (Figure 1).

Figure 1 - The snap-on flat electrodes

A. 3D Printing Electrodes

A 3D electrode model was created from scratch on CAD software. Various aspects had to be taken into account when designing, such as how exact the dimensions of the extrusion should be to attach perfectly with the standard snap-on electrode cable shown in Figure 2. Also, according to Ertan et al.'s findings [7], the diameter of the electrode had to be decided on wisely, as being too large would lead to higher crosstalk and signal noise. Since the conductive PLA is not flexible, the electrodes were best to have curved, filleted corners and be as small as possible for maximum user comfort. Holes were also added to the design to allow stitching them onto a fabric wearable.

Figure 2 - The standard electrode cable

Figure 3 shows the final design on SOLIDWORKS, and Figure 4 shows one of the finalised electrodes printed in conductive PLA.

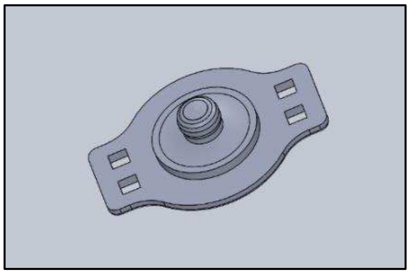

FIGURE 3 - THE 3D ELECTRODE MODEL ON SOLIDWORKS

FIGURE 4 - ONE OF THE FINAL 3D PRINTED ELECTRODES

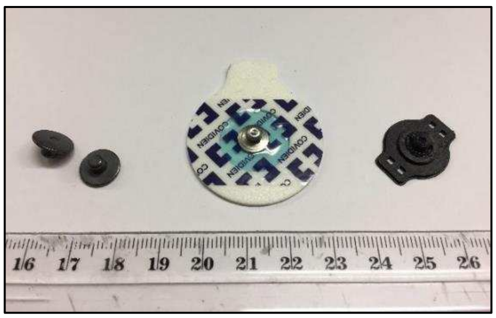

FIGURE 5 - THE TWO DRY ELECTRODES (SNAP-ON AND 3D PRINTED) NEXT TO A STANDARD, GELLED ELECTRODE

Once 3D printed, these electrodes were compared with the simple, snap-on flat ones to decide which would help create a more robust, reliable system. This was done by stitching 2 of the former type to an armband (Figure 6), and 2 of the latter to an identical armband (Figure 7). Each armband was worn in turn by the same person (setup shown in Figure 8) performing the same hand/forearm gestures with each multiple times. It was concluded that they both had very similar conductivities. Since neither types were more informative than the other, the 3D printed ones were chosen to continue with as they are cheaper to produce, much more readily available and easily customisable in terms of size and shape.

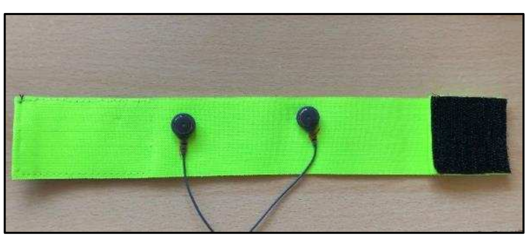

FIGURE 6 - SNAP-ON ELECTRODES SEWED ONTO THE ARMBAND

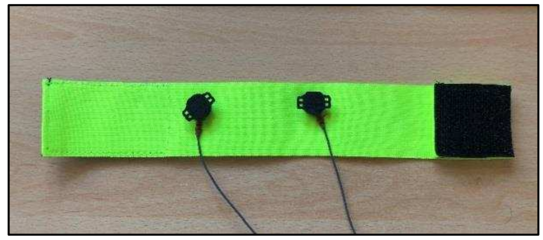

FIGURE 7 - 3D PRINTED ELECTRODES SEWED ONTO AN IDENTICAL ARMBAND

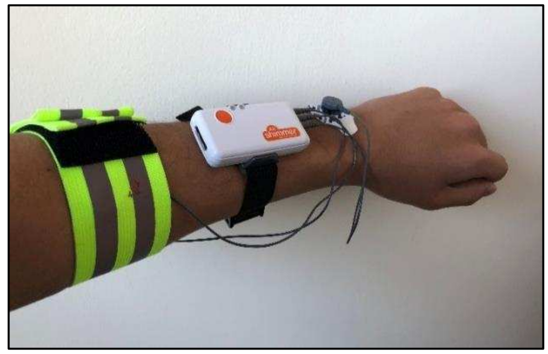

FIGURE 8 - THE SETUP FOR COMPARING THE ELECTRODES

IV. DESIGNING THE WEARABLE USED TO CAPTURE EMG SIGNALS

For a robust, reliable and practical system, the wearable had to be sturdy and long-lasting, while being designed with user comfort in mind. An elastic forearm sleeve was used as the base component of the wearable (Figure 9) to allow for various forearm sizes. Five 3D printed electrodes were sewed onto the sleeve from the inside, with the electrode cables attached to them beforehand, as shown in Figure 10 and 11. The locations of the electrodes were based on the findings of Rubio et al. [1] on the most informative electromyography locations on the forearm. It was necessary to use a sleeve with a thumb opening, as that would prevent it from rotating when being worn a long time and hence keep the electrodes more or less in fixed positions over the forearm. The final setup is shown in Figure 12.

FIGURE 9 - THE SLEEVE TO BE USED AS THE WEARABLE. IT WAS FOLDED AND STITCHED TO MAKE IT TIGHTER ON THE FOREARM AND HENCE ENSURE BETTER ELECTRODE-SKIN CONTACT

FIGURE 10 - THE SLEEVE INSIDE-OUT. THIS SHOWS HOW THE ELECTRODES WERE STICTHED ONTO THE SLEEVE

FIGURE 11 - SHOWING HOW THE ELECTRODE CABLES WERE FORCED THROUGH THE WEARABLE TO ATTACH THEM TO THE SHIMMER SENSOR ON THE OUTSIDE

FIGURE 12 - THE FINAL WEARABLE WORN BY THE TEST SUBJECT

V. FEATURE EXTRACTION AND CLASSIFICATION

A. *Implementing a Wireless Communication Protocol*

This study aims to produce an interface that is robust and practical. One of the ways to achieve the latter aim successfully was to make the wearable device being developed wireless. Hence, a wireless communication protocol had to be established to send the information captured by the electrodes to a computer for saving and signal processing. To do that, a Shimmer Sensor (shown in figure 12 above) is used. The device can be connected to two EMG channels and encloses a Bluetooth module that allows it to pair with a computer and send data in real-time.A MATLAB script was created that creates a connection with an active shimmer, sets it to EMG sensing mode, streams live data from its two EMG channels, and saves this data into a CSV file for offline use. Displaying the live data was necessary to ensure the connection is fine while recording.

B. *Collecting and Processing Test Data*

It was decided that a Support Vector Machine (SVM) would be used as a classifier to recognise five different hand/forearm gestures. The SVM had to be initially trained with sample data for each gesture. This was done by wearing the sleeve after sewing the electrodes onto it, then recording the raw data recorded in a 60-second window. During that time, a pre-defined sequence of the five gestures was performed by the user twice. Initially, all the test data was collected by one test user. Readings were collected from two EMG channels by the Shimmer Sensor and sent wirelessly to a PC over Bluetooth, with the sampling frequency set to 500Hz, producing 30,000 sample readings per channel per recording. The signal was amplified and driven through a low-pass filter to minimise the effect of noise.MATLAB was used to collect the streamed data, save it and then process it afterwards.

1) *Feature Extraction*

Inspired by the simplistic yet effective methodology in the work of Osorio et al. [17], an average function was used to extract the signal features that were fed into the classifier. There were two stages, however, before that occurred. Initially, the software had to be able to recognise weather or not a gesture is being performed at any point in time. This is to prevent signal readings being classified when an arm is simply held still for example. This was done by first looping through every reading of each channel (r_i) and obtaining the difference (d_i) between it and its preceding reading:

$$\mathit{Channel}\ 1: \quad {d_i}^1 = {r_i}^1 - {r_{i-1}}^1 \tag{1}$$
$$\mathit{Channel}\ 2: \quad {d_i}^2 = {r_i}^2 - {r_{i-1}}^2 \tag{2}$$

By observing the plots during data livestreams, it was noticed that there were occasional random occurrences of single readings that are obviously incorrect, causing large misleading peaks/drops in the signal shape. To reduce the effect of these anomalies (regardless of their scale), the average of the previous k differences was obtained to give D_i.

$$\mathit{Channel}\ 1: \quad {D_i}^1 = \textstyle\sum_{i=1}^{k} {d_i}^1 \tag{3}$$
$$\mathit{Channel}\ 2: \quad {D_i}^2 = \textstyle\sum_{i=1}^{k} {d_i}^2 \tag{4}$$

Feature extraction was triggered whenever D_i^1 or D_i^2 cross a pre-set threshold, Th^1 or Th^2 respectively. These thresholds were determined by experimentation. A timeframe had to be defined in which a 'gesture' can be defined. After some trials, this was found best to be 1000ms (i.e. 500 readings at a sampling frequency of 500Hz). Once feature extraction is triggered, the next 500 readings being looped through are saved as a gesture vector.

This resulted in each gesture vector being 500 readings long. To successfully achieve a responsive, reliable interface, the system had to be quick in classifying, and having 500

Manuscript 322 submitted to IEEE/ASME International Conference on Advanced Intelligent Mechatronics. Received March 7, 2019.

features to classify would certainly slow it down. Considering the aim of producing a responsive interface, dimension reduction had to be implemented to reduce the number of features being extracted from 500 and hence speed up the classification process. This was done by averaging every M readings in each gesture vector. This reduced the number of readings (r_i) describing each gesture from 500 to $\frac{500}{M}$. With M set to 25, each gesture was defined by 20 values ($\frac{500}{25}$).

2) Classification

The choice of a Support Vector Machine classifier was based on extensive research on previously used classifiers in various studies. Linear Discriminant Analysis was considered after reviewing studies such as [14] and [16] for its exceptional accuracy, but was dismissed due to its extreme sensitivity to electrode placement [22]. Training a Convolutional Neural Network was also considered due to their excellent feature learning capabilities [22]. However, training one to reach that level of excellence required huge amounts of very specific training data. SVMs were found to be the most optimum for a robust, long-lasting system as they are relatively more resilient to electrode shifting than others. Also, they do not require huge amounts of training data and have very high classification speeds, which help in creating a responsive system.

Since SVM is a binary classifier, a One-Vs-All system was implemented by creating five SVM models – one trained for each gesture wanting to be classified. The training data for the first model for example was simply all of the gestures vectors recorded for the first gesture inputted as group 1 and all other gesture vectors inputted as group 0.

The interface was then tested in real-time using the Shimmer's live data streaming and MATLAB's live data analysis. Whenever a gesture beginning was detected, the software collected the next R readings, performed the feature extraction protocol mentioned above, then fed the features into the five SVM classifiers, classifying the gesture performed as the one corresponding to the only SVM that gave a positive classification. If more than one gave a positive classification (or none), the percentage certainties were compared and that was used to classify.

VI. RESULTS

The five gestures the SVMs were trained for include Pronation, Supination, Wrist Flexion, Wrist Extension, and Fist Clenched. As mentioned, five SVM models were created using 20 features to describe each gesture. These models are shown below.

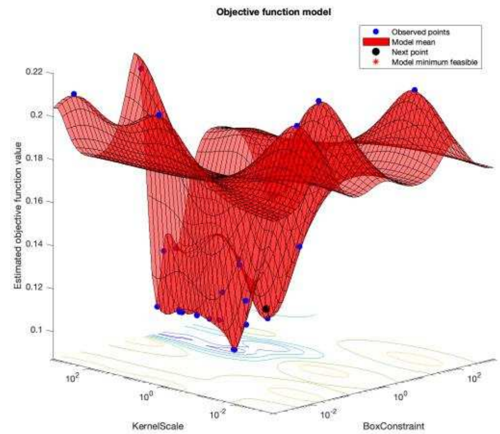

FIGURE 13 - SVM HYPERPLANE FOR GESTURE 1

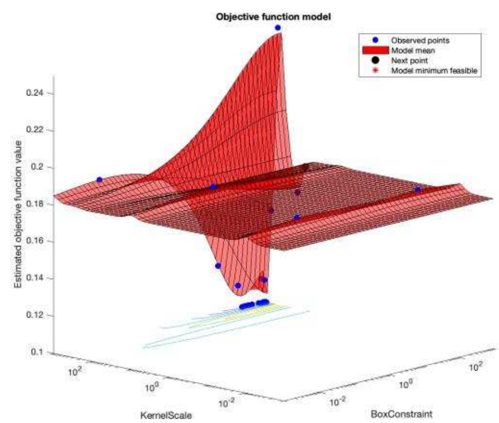

FIGURE 14 - SVM HYPERPLANE FOR GESTURE 2

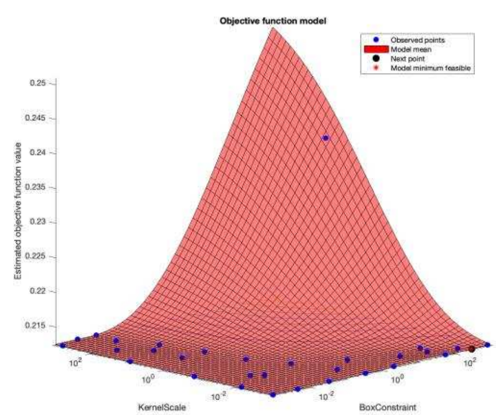

FIGURE 15 - SVM HYPERPLANE FOR GESTURE 3

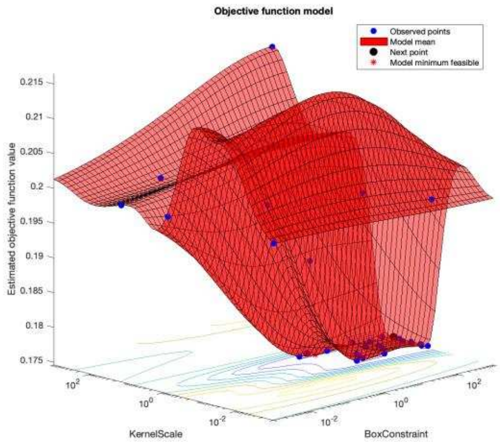

FIGURE 16 - SVM HYPERPLANE FOR GESTURE 4

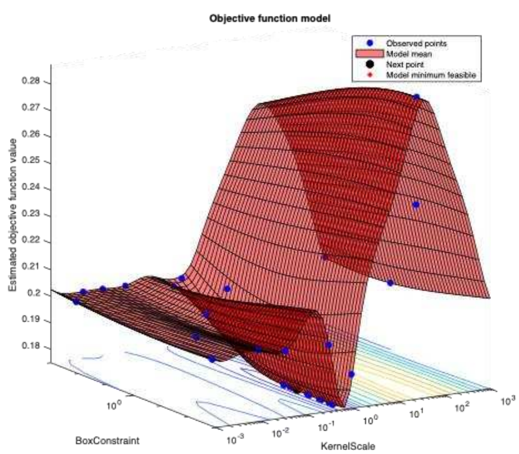

FIGURE 17 - SVM HYPERPLANE FOR GESTURE 5

These images show the hyperplane for each gesture modelled by MATLAB based on training data. The SVM classifies by plotting any new gesture vector inputted onto the model. The side of the hyperplane the plot ends on determines the classification result. These models were used by MATLAB to classify previously unseen gestures in real-time. Since SVM is a binary classifier, five checks have to be done whenever the feature extraction threshold is crossed (One-Vs-All). The accuracy results obtained were as follows:

TABLE 1 - SHOWING CLASSIFICATION ACCURACY OF EACH GESTURE

Feature Number	**Classification Accuracy**
1	85%
2	90%
3	85%
4	75%
5	80%
Average Classification Accuracy	83%

VII. DISCUSSION AND CONCLUSIONS

EMG interface is a pillar in the world of rehabilitation that brings back hope for incapable stroke victims. There has been extensive work in improving upper limb EMG interface systems in the past decade to make them more accurate and able to capture more gestures. Neuromuscular interface systems aimed for stroke patients should be created with the users in mind, and hence considering the practicality and robustness of them is as important as considering their accuracy. This study aimed to demonstrate the feasibility of a robust and practical EMG interface system that is simple yet accurate, and consists of components readily available. The sleeve produced is able to slide onto anyone's forearm and is fully reusable, as opposed to previously developed systems that are either too bulky/uncomfortable or are based on using adhesive, gelled electrodes that are single-use.

Furthermore, this study successfully demonstrated, for the first time, that it is possible to have a functional informative EMG system able to classify five gestures using custom-made 3D-printed electrodes printed in conductive PLA material. Such electrodes are very cheap to produce and the fact that they are modelled on software allows full customisation in terms of shape and size. Both the above points stress on how this study aimed to produce a wearable that is actually usable, not one to be used in a 'perfect world' that is just for experimental purposes. Average readings of recorded data were the features extracted from the filtered EMG data and used to train five SVM classifiers in a One-Vs-All system. Testing the classifier yielded an online classification accuracy of 83% on average.

Taking the findings of this study further is essential. Future work includes attempting to extract different features from the signal, such as Root Mean Square [23] [6] or Wavelet Packet Transform [24] in hopes of them being more informative. Also, the trained SVM being used may be more accurate if more training data was fed into it from more people. Inspired by the work of Benussi et al [17], a lock/unlock gesture can be defined, where gesture recognition is activated only after that specific gesture is performed. The effect of customizing the shape/size of the 3D electrode model on the system's robustness and accuracy can be explored as well.

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