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Research Article

Comparison of gesture classification methods with contact and non-contact sensors for human-computer interaction

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ABSTRACT

Classification of signals that are received from the human body and control systems is one of the most important subjects of the machine learning application. In this study, classification algorithms were used to classify electromyography and depth sensor data. First, electromyography and joint angle data were obtained from software developed in Python environment. Five different types of movements have been identified for classification and thousand different samples have been collected as training for each of these movements. Support Vector Machine, Random Forest, and K-Nearest Neighbour algorithms were used for classification. To measure success algorithms, results have been compared for achieving criteria. The results show which of three different algorithms was the most successful on two different sensors. While Random Forest provides the best results for non-contact sensor, K- Nearest Neighbour produces the best results for contact sensors. This paper evaluated the classification success of two different sensors. The results will be utilized in online classification to control a graphical user interface.

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INTRODUCTION

There is a growing body of literature that recognizes the importance of sensing technologies for human-computer interaction (HCI) [1]. Low-cost and compact sensing has become more advanced and accessible in the last decade [2], largely due to improvements in digital computing. Such technologies have numerous applications such as rehabilitation and human-computer interaction [3,4]. Thus, accurately sensing the movements of the hand for the development of HCI system is crucial with its complex movements [1].

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Gesture control is one of the most exciting evolutions of human-computer interaction and has been replacing traditional methods such as fiber-optic-, image processing, or accelerometer-based techniques. The process of quantifying muscle activation by measuring the electrical activity of the muscle is referred to as electromyography (EMG). EMG data technology is a prime example of this type of gesture control technology and is based on processing EMG signals from different muscles. Instead of using camera data directly, it estimates muscle activity and the corresponding motion of the user and can detect changes down to each finger. When tracking the position of the arm and hand, it can detect subtle movements and rotations in all directions according to the position of the hand and the gesture of the arm. A leading example of this kind of device is the Myo Armband produced by Thalmic Labs Inc., Kitchener, Canada, which is one of several new companies working on gesture control using EMG sensors. As shown in Fig. 1 the device has an expandable design to fit forearm circumferences between 190 mm and 340 mm, with 10 mm thickness.

Another prime example of gesture control is the depth-sensing technology. The release of depth cameras has revolutionized non-contact motion capture by providing software development kits and pre-calibrated out of the box hardware, which has vastly reduced the associated hardware and software costs [5]. Kinect, PrimeSense, and DepthSense are some examples of these kinds of sensors. One of the low-cost and small footprint sensor is called Leap Motion which is currently developing advanced motion-sensing technology for HCI. It is aimed at precise short-range hand recognition as shown in Fig. 2.

Sueaseenak et al. classified the EMG signals in their study and examined the virtual prosthetic arm with 12 degrees of freedom [6]. The authors first filtered the signals obtained with the two surface electrodes using the Independent Component Analysis (ICA) method. Then, they classified twelve different movements from filtered signals and observed that the ICA method improved the classification success. Zhang et al. has developed a virtual dice game that captures humanoid movements with EMG sensors and a 3D accelerometer [7]. The authors received 10 training sessions for 18 different movements. They classified this data using the Hidden Markov Model (HMM) method and processed it in real-time and found the classification success at 91.7%. Simone et al. performed a motion estimation of EMG signals in their study [8]. The authors detected seven different motions from four users. The SVM algorithm was implemented for motion detection with 90% real-time classification success. Rezwanul et al. estimated motion with EMG signals [9]. The motion was classified via an Artificial Neural Network (ANN) algorithm called the Back Propagation (BP) with 88.4% classification success. Lucas et al. classified the EMG signals [10]. First, the Discrete Wavelet Transform (DWT) algorithm was used for feature extraction. Then, the SVM algorithm was performed for classification. Without using the DWT algorithm, they found a false classification ratio of 4.7 ± 3.7% and a DWT algorithm and a false classification ratio of 11.1 ± 10.0%. Ahmet et al. also classified the EMG signals from surface electrodes via the SVM algorithm [11]. The authors increased the classification success rate from 96% to 98% using the 10-fold cross-validation method. Ercan et al. classified EMG signals using a decision tree algorithm [12]. First, received signals were filtered via the Multiscale Principal Component Analysis (MSPCA) method. Then, the feature was extracted using the DWT algorithm and classified the person as an Amyotrophic Lateral Sclerosis (ALS) patient or normal person through a Random Forest (RF) decision tree algorithm. The classification success rate was 96.67% with the MSPCA algorithm and 73.33% with the MSPCA algorithm. Hassan et al. controlled the 5 degrees of freedom Aideepen ROT3 robot arm using the MYO armband. First, they extracted features from the EMG signals they received from 6 people with the MYO armband. Later, they were classified with 3 different classification algorithms and compared their success performance [13]. Feng et al. tried on the surgical operation using the leap motion device and the Kinect device, and then the success of the devices was compared. As a result of the study, they determined that the leap motion device takes less processing time and works more precisely [14]. Arshad et al. controlled robot arm with a MYO armband. First, they cleared the noises from the signals they received from 10 different people. Later, they classified 4 different movements with the KNN classification algorithm and controlled the robot arm [15].

The system developed in this paper utilizes depth sensor and EMG sensors to classify five different movements

Figure 1. Myo Arm Band.

simultaneously. EMG and joint angle signals are classified via machine learning algorithms developed in Python environment. 1000 samples were collected from both sensors for 5 different movements and the offline classification was performed in the Python environment. SVM, RF, and KNN algorithms were selected for the classification process. The most successful algorithm, which is the result of offline classification, was used as an online algorithm to control a graphical user interface. The results from the paper are expected to lead better human-computer interface for rehabilitation engineering. The system components are described in the next section. Following this, Section 3 details the methodology for classification. Section 4 contains experimental evaluation results, with both EMG and depth sensors. Section 5 provides discussion and further suggestions. Section 6 details conclusion and future works.

SYSTEM OVERVIEW

The system comprises two different sensors. Leap Motion is employed to acquire hand and wrist joint data. Myo Armband is employed to collect EMG data from the forearm muscle. A custom made Python application comprises Myo Armband (Myo Armband SDK) and Leap Motion (Leap Motion SDK) middle-wares, which in turn collects data from Myo Armband and Leap Motion via a Client/Server (Transmission Control Protocol/Internet Protocol (TCP/IP)) connection with its associated middle-wares.

Figure 2. Myo Arm Band.

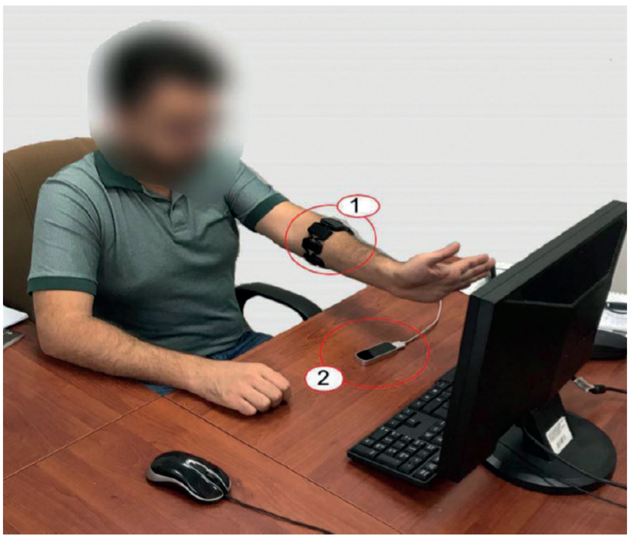

Figure 3. System Overview 1) Myo Arm Band, 2) Leap Motion Controller.

EMG AND MOTION TRACKING

Leap Motion (120 Hz) captures joint center locations x_i, y_i, z_i for the fingers, i = 1… 10 m, p, and f similarly denote the metacarpophalangeal (MCP) joints, proximal interphalangeal (PIP) joints, and fingertips respectively. The dot product is used to calculate the associated joint angle variables. See details in [16].

Myo Armband collects EMG signals (200 Hz) from forearm muscles. It embeds 8 EMG sensors and inertial measurement units. The collected data is transferred via Bluetooth low energy (BLE) protocol.

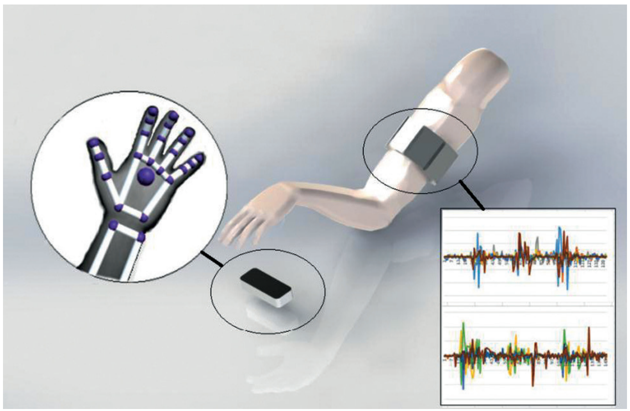

Figure 4. Myo Arm Band and Leap Motion Data.

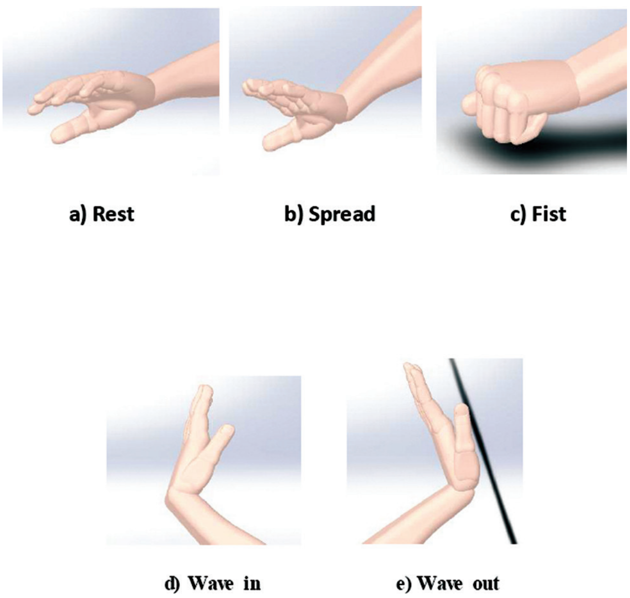

Figure 5. Classified Hand Movements.

EXPERIMENTAL PROTOCOL

5 participants (three male and two female) aged between 25 and 31 (M = 28.2) were recruited. All participants complied with the study inclusion criteria and there was no withdrawal. All participants were right-handed and EMG signals were collected on the left arm. Figure 3 shows a system overview.

To evaluate the success of each machine learning method with two different sensors, five movements were defined as illustrated in Fig. 5. During the process of data collection, the participant's elbow was supported. Defined movements comprising of rest, open-hand, fist, wave in, and wave out movements are shown in Figs. 5a to 5e respectively. Fig. 4 shows hand position and EMG data collected simultaneously by Leap Motion and Myo Armband. Collected data is then classified by machine learning algorithms to compare which success of algorithms with different sensors.

METHODOLOGY

SUPPORT VECTOR CLASSIFICATION

Support Vector Machine is a machine learning algorithm developed by Vapnik et al. [17]. The SVM is one of the most effective and simplest classification methods. It is possible to distinguish these data groups by drawing a boundary in a level for classifying data using the SVM. The SVM's goal is to predict the best case of a hyperplane function to be classified. Support vectors are produced with the nearest data from the hyperplane. This algorithm can obtain multiple levels when classifying data. The algorithm aims to maximize the distance between class and object when unknown data is encountered. The hyperplanes are represented by Eq. (1) and the classification level is shown in Eq. (2).

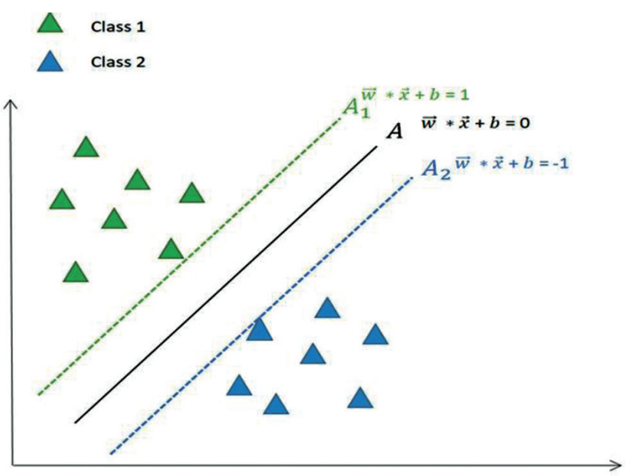

Figure 6. Linearly Classified Data Set.

$$\vec{w} * \vec{x}_i + b = \mp 1 \quad (1)$$

$$f(x) = sign((w * x_i) + b) \quad (2)$$

For the most suitable separation plane, the values of w and b must be found. Using Eq. (1), the distance between the hyperplanes could be calculated as $2 / ||w||$ as shown in Fig. 6. For optimum hyperbola, this distance must be maximal. If the training data can be completely separated by the linear separator, Eq (3) can be fitted with the appropriate hyperplane. Eq. (3)

$$\min \frac{1}{2} \|w\|^2 \, y_i(\vec{w} * \vec{x}_i + b \geq 1) \quad (3)$$

where w, b and x are weight vector, bias and data respectively

RANDOM FOREST CLASSIFICATION

The Random Forest algorithm is a classification algorithm created by combining multiple decision trees [18]. In random forest classification, the data set is divided into nodes until a single data class is available. Two criteria can be used to determine which data goes into which branch. These criteria are the regression criterion and the Gini index as given in Eqs. (4) and (5).

$$Regression = \sum_{left} (y_i - y_l)^2 + (y_i - y_r)^2 \quad (4)$$

$$Gini = N_l \sum_{k=1}^{K} p_{kl}(1 - p_{kl}) + N_r \sum_{k=1}^{K} p_{kr}(1 - p_{kr}) \quad (5)$$

The values y_l and y_r in Equation 4 represent the average of the data in the right and left nodes. The values N_l and N_r in Eqs (5) represent the numbers of the elements in the right and left nodes, respectively. The values p_{kl} and p_{kr} given in the equation shows the ratio of the classes on the right and the left side. The structure of the random forest classification is shown in Fig 7.

K – NEAREST NEIGHBOUR CLASSIFICATION

K-Nearest Neighbor (KNN) is one of the commonly used classification algorithms. Due to its simple structure, it is successfully utilized in many classification problems. No training data is required in this method. In the KNN algorithm, the classification operation is performed based on a selected number of K (K needs to be defined).

The nearest K samples are selected for the data classification to be tested. In this case, the class that belongs to the latest sample belongs to the class that contains the most data. Different classification methods can be used to select distance between samples. The most commonly used method for determining distance is the Euclidean Equation. For example, if the selected K parameter is 5, the class identification method is shown in Fig 8

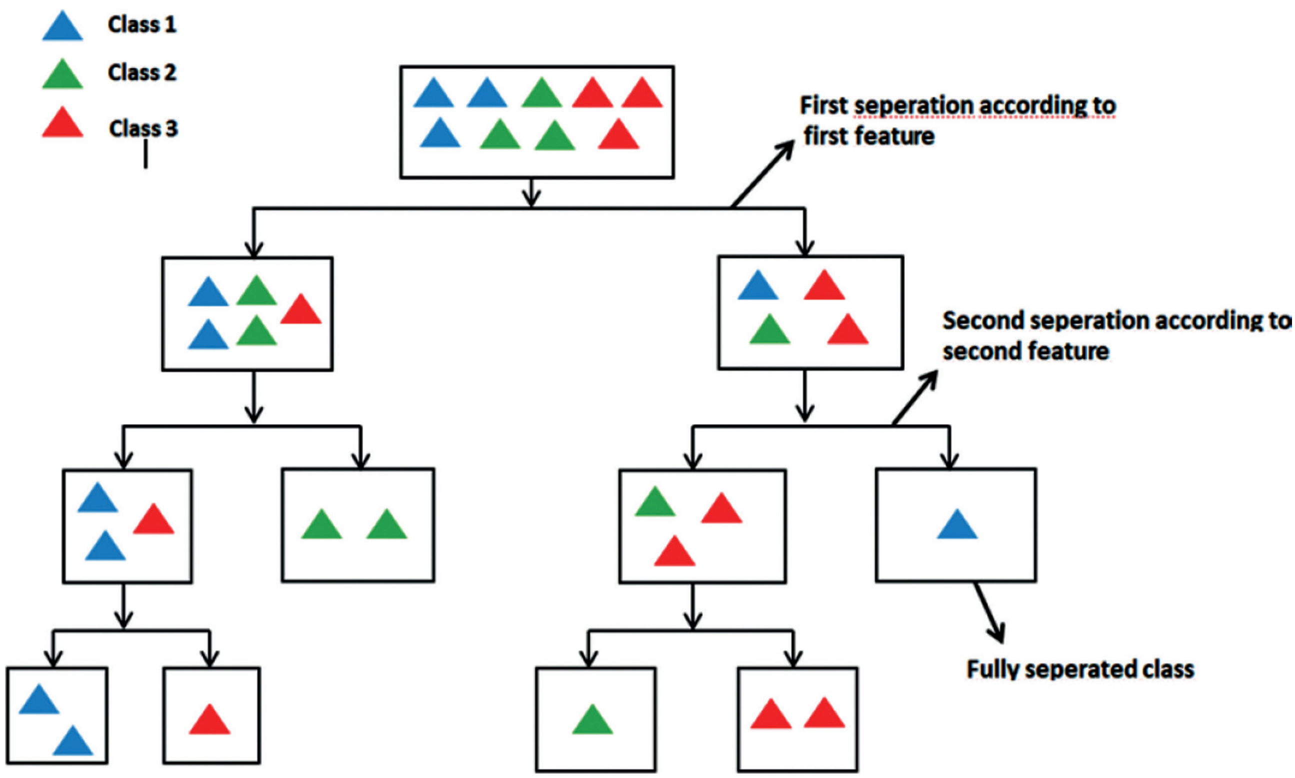

Figure 7. Random Forest Tree Structure.

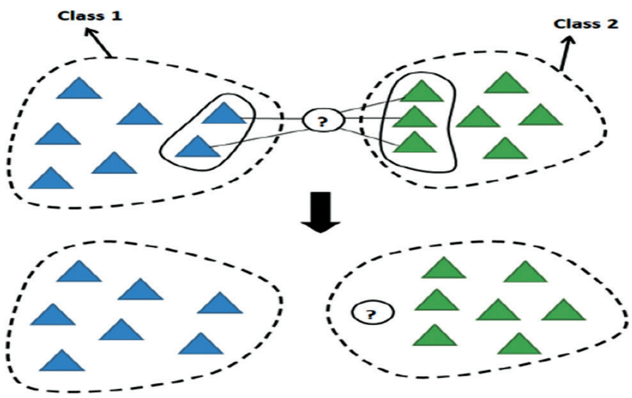

Figure 8. KNN Classification Algorithm.

Algortihm : Pseudo Code Of Classification Hand Gesture via Myo Arm Band and Leap Motion

1: START

2: Data Collection

3: Separation of data into training and testing.

4: Entering machine learning parameters

5: Classification of hand gestures

6: Confusion Matrix and Results

7:END

Figure 9. Classification Algorithm.

EXPERIMENTAL SETUP

Myo armband (Thalmic Labs) and Leap-Motion sensors were used in the study. EMG signals from the muscles are retrieved via Myo armband and Joint angle signals are collected via Leap Motion in real-time. In the study, the gestures were predicted. For this study, initially 1000 samples from 5 different movements were received to create data set in the Python environment. The data set was then employed to train algorithms. Then, when the trained algorithms are given unknown data, a prediction is made to determine which of the 5 different motions is being made. In the training phase, it was determined which algorithm was more successful in offline mode. The algorithm is shown in Figure 9

RESULTS AND DISCUSSION

Following University of Sakarya Ethical approval (71522473/050.01.04/94), five participants were recruited. The Leap-Motion and Myo Armband data were used for 5 movements from participants. These data were used for the testing, while 800 samples were used for the test set and the remaining 200 samples were used for the training set. K-fold cross-validation method were utilized to define test and training samples. The classification was performed using the SVM, KNN, and RF algorithms. The results of this classification were then compared. The performance of the classifiers was evaluated based on the success rate in Equation 6. The results of the classifications are shown in Table 1 and Table 4.

$$Success\ Rate = \frac{Correctly\ Classified\ Data}{All\ Data} \quad (6)$$

As can be seen from the table above, the K-Nearest Neighbour Algorithm reported significantly more classification success than other algorithms with 94.3% for the Myo Armband.

The best and the worst subject's confusion matrices for the chosen classification method of the Myo armband are shown in Table 2 and Table 3 respectively.

Table 4 shows, the best results for classification success are achieved with Random Forest Algorithm for Leap Motion. It has 95.3% classification success.

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The best and the worst subjects' confusion matrices for the chosen classification method of Leap Motion are shown in Tables 5 and 6 respectively.

Results confirm that both contact and non-contact sensors provide data with classification success above 94% with KNN and RF respectively. A limitation of this study is that Leap-Motion has limited range. However, the sensor will be replaced with a wide-range depth sensor as shown in [19].

CONCLUSION

The main aims of the study were to investigate the feasibility of motion estimation via machine learning algorithms for EMG and joint angles signals. When the classification success was evaluated, the best classification algorithms were determined to be KNN for EMG data and RF for joint angle data. While motion estimation is required, care should be taken to ensure that motion signals are not close to each other.

An important finding from this study is that in this sample of users, it is difficult to don and doff the EMG system, while non-contact sensors have a limited range. Indeed, there are differences between systems such as usability, data type, and processing. Both provide human-computer interfaces with more than 94% classification success.

In conclusion, this is the first time comparing depth cameras and EMG sensors for different classification methods.

Table 1 . Myo Armband Classification Success Rate

Classifiers	Subject 1	Subject 2	Subject 3	Subject 4	Subject 5	Mean
SVM	89.6	84	93.5	98	88.4	90.7
KNN	97.6	87.4	96	98.2	92.2	94.3
RF	97	80.2	93.4	95.8	93	92.2

Table 2. Myo Armband Best Subject

	Rest	Fist	Spread	Wave-in	Wave-out
Rest	200	0	0	0	0
Fist	0	196	0	0	4
Spread	0	0	196	0	4
Wave-in	0	0	10	190	0
Wave-out	0	0	0	0	200

Table 3. Myo Armband Worst Subject

	Rest	Fist	Spread	Wave-in	Wave-out
Rest	196	0	0	4	0
Fist	6	22	76	60	36
Spread	0	0	194	6	0
Wave-in	0	0	2	198	0
Wave-out	0	62	0	0	138

Table 4. Leap Motion Classification Success Rate

Classifiers	Subject 1	Subject 2	Subject 3	Subject 4	Subject 5	Mean
SVM	96.8	87.7	89.9	90.7	97	92.4
KNN	93	92.7	88.4	95.6	94.2	92.8
RF	92.3	92.4	93.7	100	98.2	95.3

Table 5. Leap Motion Best Subject

	Rest	Fist	Spread	Wave-in	Wave-out
Rest	200	0	0	0	0
Fist	0	200	0	0	0
Spread	0	0	200	0	0
Wave-in	0	0	0	200	0
Wave-out	0	0	0	0	200

Table 6. Leap Motion Worst Subject

	Rest	Fist	Spread	Wave-in	Wave-out
Rest	200	0	0	0	0
Fist	1	175	0	24	0
Spread	7	0	193	0	0
Wave-in	0	0	0	200	0
Wave-out	0	0	61	30	109

These positive results indicate that the application of sensing technology with respect to human-computer interface is promising. In the future, they are planned to be utilized for online classification and aimed to control the various systems with the obtained movements. This includes:

1. Implementing results in human-robot interaction such as robots in dangerous environments,
2. Embedding the low-cost sensors into home-based rehabilitation systems to precise control user interface [20].

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AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

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