EmgAuth: Unlocking Smartphones With EMG Signals

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Abstract—Screen lock is a critical security feature for smartphones to prevent unauthorized access. Although various screen unlocking technologies, including fingerprint and facial recognition, have been widely adopted, they still have some limitations. For example, fingerprints can be stolen by special material stickers and facial recognition systems can be cheated by 3D-printed head models. In this paper, we propose EmgAuth, a novel electromyography (EMG)-based smartphone unlocking system based on the Siamese network. EmgAuth enables users to unlock their smartphones by leveraging the EMG data of the smartphone users collected from Myo armbands. When training the Siamese network, we design a special data augmentation technique to make the system resilient to the rotation of the armband, which makes EmgAuth free of calibration. We conduct extensive experiments including 80 participants and the evaluation results verify that EmgAuth can effectively authenticate users with an average true acceptance rate of 91.81% while keeping the average false acceptance rate of 7.43%. In addition, we also demonstrate that EmgAuth can work well for smartphones with different screen sizes and for different scenarios when users are placing smartphones at different locations and with different orientations. EmgAuth shows great promise to serve as a good supplement for existing screen unlocking systems to improve the safety of smartphones.

Index Terms—Electromyography, authentication, Siamese network, unlocking, smartphone

1 INTRODUCTION

The safety of smartphones is very critical as devices store lots of individual private data, from emails to e-wallet payment details. Fortunately, screen lock helps us protect personal information from being accessed by others. A research shows that American people check their phones 96 times a day [1], which means that the smartphone is unlocked every ten minutes. However, it is not convenient to directly enter password when facing such a high frequency of use. Researchers began to develop more effective technologies to unlock smartphones. In particular, biometric-based technologies, including fingerprint, facial recognition, and iris [2], have gradually replaced the traditional password-based methods [3] in recent years, providing better convenience for users. Fingerprint and facial recognition are widely used in smartphones unlocking, however, certain security risks still exist. For example, fingerprints can be easily obtained with packing tapes. Facial recognition can also be deceived, and studies have shown that 3D printed head models plus taped glasses can easily fool Apple’s Face ID authentication system [4].

Different from the above-mentioned biometric features, EMG signals, collected by placing electrodes on the skin to detect the electrical activity of muscles, show unique features for individuals and therefore has great potential for smartphone authentication [5]. In particular, we observe that when different people pick up their smartphones, the speed, wrist movement, fingers movement and the positions they grab smartphones are generally different from each other. In contrast, for a certain person, the movement when picking up a smartphone is generally consistent, which can be attributed to the memory of one’s muscles accumulated over a long period of time. Compared with fingerprint and face-based authorisation methods, EMG-based methods are safer, because EMG signals are dynamic and therefore harder to be obtained by others.

Based on these observations and analyses, we propose smartphone unlocking utilizing EMG signals. The uniqueness of the EMG signals and the consistency of motion movements are crucial for EMG-based authentication. Although there are some existing works that utilize EMG signals to unlock smartphones [6], [7], they require users to make a series of pre-defined gestures. In addition, the systems to collect EMG signals, such as the Myo armbands, need to be placed in the same position on the arm for both training and testing stages. These constraints limit the applicability of the EMG-based unlocking system as well as other EMG-based applications [8], [9].
In this paper, we propose EmgAuth, a new EMG-based smartphone unlocking system based on the Siamese network. EmgAuth utilizes data collected from the Myo armband and allows users to unlock their smartphones when picking up and watching their smartphones without making any pre-defined gestures. A convolutional Siamese network is proposed to extract EMG features and achieve few shot learning. More importantly, when training the Siamese network, we design a special data augmentation technique to make the system resilient to the rotation of the armband. These two improvements significantly enhance the usability of the unlocking system. We implement EmgAuth on Android smartphones and recruit 80 participants to collect training and testing data for EmgAuth. EmgAuth will be an easy-to-use authentication method with great potential to unlock different personal devices, when the EMG sensor will be generally integrated into personal wearable devices, such as smartwatches, in the near future.

We conduct a series of experiments to choose the proper parameters of EmgAuth, including the hyperparameters of the Siamese network and the threshold of the classifier. The results of cross validation demonstrate that EmgAuth can achieve good authentication accuracy in a real-time manner. It can authenticate users with an average true acceptance rate of 91.81% while keeping an average false acceptance rate of 7.43%, and the overall accuracy reaches 92.06%. Experiments show that EmgAuth is rotation-independent. We also discuss some influencing factors in real-world scenarios to verify the feasibility of EmgAuth, such as the non-sitting scenario, the impact of smartphone shape, the performance for left-handed users, etc. In addition, the authentication latency of EmgAuth that runs on an Android smartphone is about 0.16 s, which fulfills the requirement of real-time unlocking.

This paper is an extended version of [10] with a more detailed literature study, an upgraded Android-implemented prototype system, a bigger dataset and a deeper analysis to investigate the effect of rotation-independency and non-sitting scenarios. The contributions of this paper are summarized as follows:

- EmgAuth, a system that unlocks smartphones by natural motions based on EMG signals and Siamese network. This is one of the first research efforts that combines EMG signals with deep learning to unlock smartphones.
- A novel method based on the structure of Myo armband to make EmgAuth resilient to armband rotation. With this method, users do not need to calibrate or remember the position of their armbands.
- Extensive experiments to verify the feasibility and reliability in different conditions.

The remainder of this paper is organized as follows. In Section 2, we discuss related work about common biometric authentication methods, EMG-based applications, and the Siamese network. Section 3 details our EmgAuth system architecture and each module. We then describe our dataset and provide the experimental results of our system in Section 4. In Section 5, we discuss some influencing factors in real-world scenarios. In Section 6, we discuss the advantages of EmgAuth with some practical issues and highlight our contributions. Finally, we conclude the paper with discussing limitations and future research directions in Section 7.

2 RELATED WORK

In this section, we discuss existing literature studies that relate to our work, including biometric authentication, EMG-based applications, and the Siamese network.

2.1 Biometric Authentication

Biometric authentication is widely used in daily life applications, such as transactions and user device login. Among various authentication methods, fingerprints are one of the most widely-used technologies. Anil Jain et al. [11] first described the design and implementation of an online fingerprint authentication system. An alignment-based elastic matching algorithm is developed to find the correspondences between minutiae in the input image and the stored template. Facial recognition is another popular technology for identity authentication. Sun et al. [12] combined deep learning techniques with face identification. They used deep convolutional neural networks to learn features to reduce intra-personal variations while enlarging inter-personal differences and the accuracy can achieve a value of 99.15%. Besides, iris and voice are also used in mobile device authentication [13], [14].

In addition to physiological characteristics related methods, behavioral characteristics also attract attention from researchers. Keystroke dynamics is used as a kind of biometrics for authentication [15]. Monrose et al. [16] innovatively proposed a new authentication method based on analyzing habitual rhythm patterns when users type. They present data extraction methods, as well as classification strategies to achieve user authentication and the accuracy can reach 92.14%. Conti et al. [17] used the movement that users perform when answering a phone call to achieve authentication. Specifically, they collected the signal from both accelerometer and orientation sensors when users doing the answer phone call movement, then leveraged dynamic time warping distance and dynamic time warping similarity to measure the similarity to enable authentication. Electrocardiographic (ECG), the signals of the electrical activity of the heart, can also be used for authentication. Arteaga et al. [18] first used ECG biometric signals to achieve authentication on mobile devices and the algorithm has 1.41% false acceptance rate and 81.82% true acceptance rate. Gait, hand-waving, signature and even the interaction with touchscreens are also used to enable authentication [19], [20], [21], [22].

2.2 EMG-Based Applications

EMG records the movement of muscles. Based on the simple fact that whenever a muscle contracts, a burst of electric activity is generated which propagates through adjacent tissue and bone which can then be recorded from neighboring skin areas. Therefore, EMG signals are widely used in medicine [23], control [24], human-computer interaction [25] and games [26]. Kiguchi et al. [27] used EMG signals to control an upper-limb power-assist exoskeleton robot, which is easy simple, human-like and adaptable to any user. EMG-based hand gesture identification can help develop a better human-computer interaction interface. In [28], Ahsan...
described the process of detecting different hand gestures using an artificial neural network (ANN). They used a series of statistical methods to extract features and then fed these feature vectors to ANN to obtain a classification result. EMG signals are also combined with other sensors to achieve accurate control. Yoo et al. [29] proposed an input device for a virtual reality game, which is based on EMG and accelerometers. The results show the device can offer good experiences for players.

In addition, Myo armbands are one of the most popular devices for EMG-related research because of the portability and efficient data transmission mechanism. Becker et al. [30] used the Myo armband to classify figures used for touching and estimate the touch force, which gives a new way to interact with digital devices. [31] leveraged Myo armband to achieve real-time hand gesture recognition with machine learning. [32] estimated the usage of EMG data collected by Myo armband as the features to classify sign language. Some research utilize EMG in authentication. Shin et al. [33] proposed an authentication algorithm using the EMG signal. However, they simply achieved authentication by classifying different people, e.g., collecting data from five persons and training a neural network for classification, each person is a class. Apparently, this method cannot be utilized in practice as we cannot train a model with millions of classes. [34] utilized EMG data for personal authentication and achieved hand motion recognition at the same time. However, similar to [33], they mapped the subjects to classes, changing the authentication problem to a classification problem, which is hard to use when there are lots of users. Yamaba et al. [35] collected EMG data by performing a list of hand gestures to serve as the password. They utilized dynamic time warping and support vector machines (SVM) to identify different gestures. However, this work just gave some examples to show that the EMG signal is different among different people, without describing the dataset and overall system performance, which is less convincing. In [36], the authors studied a personal recognition method based on EMG signal collected by Myo armband. They proposed two ways to achieve identification. One was Discrete Wavelet Transform with ExtraTreesClassifier and the other was Continuous Wavelet Transform with Convolutional Neural Network (CNN). They treated each subject as a class and changed it to a classification problem, which is not suitable when the number of users is huge. The model has to be retrained every time when there is a new user, despite they utilized transfer learning to mitigate this problem, a big amount of data is needed to train it.

Comparing with the above work, EmgAuth does not need extra training datasets and is resilient to the positions of EMG sensors, and does not need users to conduct specific actions. Moreover, this is the first EMG-based system for smartphone unlocking with both hardware and software.

2.3 The Siamese Network

Deep neural networks have excellent performance in the fields of image classification, speech recognition, and natural language processing. They can automatically extract features from large-scale data rather than conducting feature engineering manually. Many network structures are proposed to deal with different kinds of tasks [37], [38], [39]. In general deep learning methods, each category must have a very large amount of data to train a good model, which is not suitable for small datasets. Siamese network was first introduced by Bromley et al. [40] to solve the problem of signature verification. They designed two identical sub-networks to extract features and combine them with a layer that computes the distance between the two outputs. Thus, it does not need a large dataset to learn, but just learns the difference between a pair. Inspired by them, many researchers leverage the Siamese network structure in various kinds of fields. Bertinetto et al. [41] designed a novel fully-convolutional Siamese network trained end-to-end on the ILSVRC15 dataset for object detection in video. In [42], the authors trained a Siamese network to enable human identification based on gait recognition. Siamese network is also the main technique in one-shot learning, Koch et al. [43] used a Siamese neural network for one-shot image recognition, which does not need a very large dataset. Jianbo et al. [44] leveraged convolutional Siamese neural network for fine-grained relation extraction, the result shows that this network can effectively extract features with limited samples.

3 SYSTEM DESIGN AND COMPONENTS

This section introduces the hardware and architecture of our EmgAuth system and the three main components, including data segmentation, the Siamese network, and the unlocking simulation system. We also detail the novel method to make EmgAuth resilient to the rotation of the Myo armband.

3.1 System Architecture

EmgAuth consists of components deployed on a Myo armband and an Android smartphone. Myo armband is a device collecting EMG signals. It has eight channels, corresponding to eight sensors in different positions. Each channel has a sample rate of 200 Hz and the data can be transferred over Bluetooth. Users’ EMG signals can be easily retrieved by wearing the device on their arms. We design two Android applications. The first one is for collecting and labelling data, and the second is an unlocking simulation application. The deep learning model trained on a GPU server is then deployed to an Android smartphone and runs using TensorFlow Mobile.

Fig. 1 presents the architecture of the system. The left side presents the offline model training. The data is collected by a Myo armband and transferred to the smartphone by Bluetooth in real-time. After we get the data, we conduct data segmentation to extract the valid EMG signals and make pairs to prepare training data. Data augmentation is also conducted to expand the dataset, and for achieving rotation-independence. Next, during the model training step, all pairs are fed into the neural network to train a convolutional Siamese neural network.

The right side of Fig. 1 describes the process of online authentication. We transplant the trained Siamese neural network to an Android smartphone so we can evaluate the performance in real scenarios. Similar to most authentication systems, the first step that the user needs to do is enrollment. The enrollment phase requires four sets of motions with the user only needing to execute each motion once. The system
stores the EMG signals of these motions on the database and names them by the user’s name and corresponding executed motion as identifiers. Next, when the user picks up the smartphone, the new EMG signal produced from the process will be compared with the previously stored signal and put into the model that we train in the offline phase. The Siamese neural network computes the distance of the input EMG pairs. If the output is less than the pre-defined threshold, the user will be successfully authorized and the smartphone unlocks, otherwise the user will be rejected.

### 3.2 Data Segmentation

In most cases, data collected by sensors should be denoised. Various filters are applied to make the signals smoother and more stable [45]. In the popular EMG-based applications, such as gesture recognition, the signals should be roughly the same when different people do the same action [46]. While in the area of user authentication, the tiny differences are crucial. Here, we keep the raw signals without any filtering to maintain the uniqueness and use the convolutional neural network to extract features. EMG is the external quantified expression of the bioelectrical signals, which represents the structure of muscles and the amount of muscle contraction. Fig. 2 presents the raw EMG signals from Myo, showing five similar partial waves which present five times of picking up and putting down the smartphone. The parts contained in the five red dotted line squares are valid data and we need to extract them as the EMG matrices which will be described later.

We observe that the time from picking up the smartphone to watching the screen is generally no longer than two seconds. Hence, we set the valid action time to two seconds. Thus, when we wear it, which is inconvenient. To address this challenge, we propose a novel method based on the structure of Myo armband to make it rotation-independent. The Myo armband consists of eight rectangular sensors and they have unified sizes. Due to the fixed relative positions among these sensors, i.e., if the first sensor rotates to the position of the second, all the rest seven sensors will move in order and the last sensor will replace the position of the first sensor, we leverage the data augmentation technique from image classification tasks to expand our dataset. In our dataset, the eight channels correspond to eight sensors and they have unified sizes. Due to the fixed relative positions among these eight sensors, i.e., if the first sensor rotates to the position of the second, all the rest seven sensors will move in order and the last sensor will replace the position of the first sensor, we leverage the data augmentation technique from image classification tasks to expand our dataset. In our dataset, the eight channels correspond to eight sensors. Every time we wear it, which is inconvenient. To address this challenge, we propose a novel method based on the structure of Myo armband to make it rotation-independent. The Myo armband consists of eight rectangular sensors and they have unified sizes. Due to the fixed relative positions among these eight sensors, i.e., if the first sensor rotates to the position of the second, all the rest seven sensors will move in order and the last sensor will replace the position of the first sensor, we leverage the data augmentation technique from image classification tasks to expand our dataset. In our dataset, the eight channels correspond to eight sensors. Every time we roll the channels, a new dataset is created. Fig. 3a shows the result of rolling one channel. We get an eight times dataset until we roll a complete circle.

From the Fig. 3b, we can see there is a gap between two sensors. When the user wears the armband, we cannot guarantee the position is just one of the eight positions that we expanded and the sensor may cover the gap area when the rotation is

### 3.3 Armband Rotation-Independence Method

One significant challenge that we need to address is the rotation problem of Myo armbands. There are eight EMG sensors in the armband and each sensor corresponds to a specific skin area. We can not rotate the armband freely because the EMG signal is unique among different skin areas. However, fixing the position means we have to mark the position or calibrate every time we wear it, which is inconvenient. To address this challenge, we propose a novel method based on the structure of Myo armband to make it rotation-independent. The Myo armband consists of eight rectangular sensors and they have unified sizes. Due to the fixed relative positions among these eight sensors, i.e., if the first sensor rotates to the position of the second, all the rest seven sensors will move in order and the last sensor will replace the position of the first sensor, we leverage the data augmentation technique from image classification tasks to expand our dataset. In our dataset, the eight channels correspond to eight sensors. Every time we roll the channels, a new dataset is created. Fig. 3a shows the result of rolling one channel. We get an eight times dataset until we roll a complete circle.

From the Fig. 3b, we can see there is a gap between two sensors. When the user wears the armband, we cannot guarantee the position is just one of the eight positions that we expanded and the sensor may cover the gap area when the rotation is
less than one channel. However, the distance of this gap is much less than the width of a sensor, the impact of the gap on EmgAuth is in turn limited. Rotation leads to many possibilities but we can only choose some representative positions to train the model. There is a trade-off between the accuracy and the computation complexity. Moreover, the probability that the sensor exactly falls on the gap is very small, and the system accuracy will increase as the area touched by the gap decreases.

In the task of image classification, flipping, cropping and scaling are the common data augmentation techniques [47]. After these operations, the label of an image does not change. In our labeling process, after channel exchange, the expanded dataset still belongs to the same person. In this way, the deep neural network can learn enough features and make reliable decisions, no matter how the user wears the Myo armband and whether the user rotates it or not.

### 3.4 Siamese Network

A standard CNN typically requires a large amount of data to train a robust model. While we use our own dataset, the amount is limited and each class has only 70 pieces of data, which are far less than the empirical amount of data for CNN training. Besides, the users of an authentication system are highly dynamic, as there are always new users to join and register. CNN needs to get enough amount of data from new users to train a new model. However, retraining the model when user group changing introduces very high costs for data collection and periodical re-training. Considering these requirements, we select the Siamese network as our deep learning model.

Siamese networks do not require too many instances of a class and only a few are enough to build a satisfactory model. Instead of calculating many probabilities and directly classifying an input data to one of the classes, the Siamese network takes an extra data of the person as input and will produce a similarity score denoting the chances that the inputs belong to the same person. To be more specific, it has two inputs and one output whose value corresponds to the similarity between the two inputs. This network consists of two identical sub-networks with the same layers and weights. In addition, we add a layer to calculate the distance of the outputs of these two sub-networks, which will be used to compare with the threshold to decide the authentication result.

For the type of sub-networks, we choose CNN as it can achieve extraordinary performance in local feature extraction. In our application, EMG signals are collected by eight sensors and we need to obtain the features of a single one and the combination. Therefore, we design a convolutional Siamese network and the architecture is shown in Fig. 4. Our network architecture consists of three convolutional layers with different numbers of filters and one fully connected layer with 128 units.

Considering the Myo armband returns eight channels’ signals at the same time, we need to combine the data of these. Convolution operations can achieve this by sliding the convolution kernel. In the first convolutional layer, we set the kernel size to $8 \times 1$ to learn features among eight channels. We set the stride to one so that the first convolutional layer can focus on finding features among different channels. Since our input is an $8 \times 400$ matrix, the output size of the first layer is $1 \times 400$, which achieves the combination of eight channels. Next, we set the kernel size to $1 \times 3$ to

![Fig. 3. Myo rotation sketch map.](image)

![Fig. 4. Structure of our convolutional Siamese network.](image)
extract features during the process of picking up a smartphone and we get a size of $1 \times 398$ in this layer. To reduce the number of feature maps, we add a convolutional layer with $1 \times 1$ filters. These take all features from the previous layers into the next fully-connected layer. Besides, we add dropout layers after each convolutional layer to prevent overfitting. The dropout rate is increasing with the depth of the network from 0.1 to 0.2. As for activation, we use Rectified Linear Unit (Relu) for nonlinear transformation. Relu can reduce the likelihood of vanishing gradient, which results in faster learning.

In the last two layers of the network, we use a flatten layer and a fully-connected layer. The flatten layer is used to flatten the output of previous convolutional layers so the features can be fed into a fully-connected layer. The fully connected layer takes every combination of features from the outputs of previous layers into account. Here, we do not have a softmax layer as usual since we prefer a vector that represents the original EMG input rather than a classification possibility. We define the number of units to 128, so we could get a 128-length vector as the map of the input EMG signals.

After defining the sub-network of our Siamese network, we need an extra layer to combine the outputs of them. In this layer, we use the euclidean distance to measure the differences between two output vectors from the last two fully connected layers. Loss function is used in supervised machine learning to minimize the differences between the predicted output of the model and the ground truth labels. In our task, we use the contrastive loss to train our model. This loss function encourages the neural network to learn an embedding to place samples with the same labels close to each other, while distancing the samples with different labels in the embedding space.

We train the network to make the distances of data from different participants be as far as possible, while from the same participant be as close as possible. In the long run, the network will learn to extract meaningful features and has the ability to distinguish different people. The input shape is $(8, 400, 1)$, where 8 means the data has eight different channels, 400 is the valid signal length, and 1 means each cell of the signal matrix has only one value.

### 3.5 Unlock Prototype System

To prepare the training data and make EmgAuth easy to use, we have developed a prototype system on Android, which can perform data collection and unlocking simulation.

#### 3.5.1 Data Collection Interface

The data collection interface is shown in Fig. 5. There are four action buttons in the upper left corner, which are “FORWARD,” “LEFT,” “RIGHT” and “LEG,” respectively. “LEFT,” “RIGHT,” and “FORWARD” refer to the different positions on the table. “LEG” refers to a position that the hand is initially placed on the leg and the smartphone is placed nearby on the table. These four positions will be described in detail in Section 4.1.

The two input text fields in the right are used to input the participant’s name and the corresponding sampling time. The sampling time is the time from pressing the corresponding action button to the end of the action. During this time, the system will tag the EMG signal with the corresponding action label. We use a flag bit appended in each piece of data to mark if it is valid data. Specifically, tagging action label means 1) marking the data within the sampling time as the valid data; and 2) labeling the data from different phone positions. For the first meaning, when the button is clicked, the flag bits of the data received within the sample time will be set to 1, showing that this is the valid data, corresponding to the picking up smartphone action. When the sampling time ends, the flag bit of new data will be set to 0. In this way, we can extract valid data from the raw EMG data during the data collection process. For the second meaning, it labels which action the data corresponds to, so that we can analyze the authentication performance of EmgAuth for different phone positions. The middle text field shows the real-time EMG signals in numeric form and the lower area presents the real-time signal graph. The collected data will be saved in the format of a CSV file to facilitate data preparation for model training. In the process of data collection, due to the possibility of some fluctuations in the sampling capacity of the equipment, the application can fix the length of the data to 400 automatically, adding 0 to the length is less than 400, and randomly deleting data, i.e., when over 400.

#### 3.5.2 Unlocking Simulation Interface

Considering that smartphones have two primary states before it is used, i.e., horizontal placement (for sitting) and vertical placement (for standing and walking), the system should automatically select the model according to the state of the smartphones. This can be achieved by using the built-in accelerometer. The accelerometer has three axes, namely, the $x$, $y$, and $z$-axis. When a smartphone is horizontal, the absolute value of $z$-axis is the largest; when the phone is vertical, $z$-axis has the minimum value. Therefore, the system can easily choose the proper model to load based on this rule.
We transfer the fine-tuned models to the smartphones. Fig. 6 presents the user interface of the unlocking simulation application. As the first step, the user needs to input his or her name as the index of later EMG signals. In the second step, the user performs different actions to save their unique EMG signals in the database. We name these two steps as the enrollment stage. In the authentication stage, users open the simulation interface and take their smartphones as normal. The application saves the EMG signals from the Myo armband in real-time and implements segmentation in the time window of two seconds, so the processed signals can be fed into our model. The signals after segmentation are then paired with the previously stored different types of EMG matrices, respectively. These pairs are fed into the model, if one of the output is less than the threshold, the system considers the authentication successful; otherwise, the newcomer user is rejected.

4 EXPERIMENT AND EVALUATION

This section presents the experiments and implementation details of the EmgAuth system. We collect data and use this dataset to train a neural network. We then present the training process and show the influence of related parameters. The performance of EmgAuth is tested in several experiments as well as the impact of different factors. We also verify the rotation-independence feature through additional experiments.

4.1 Dataset

We invite 80 participants to help us build three kinds of EMG signal datasets: sitting dataset, non-sitting dataset and rotation-independence verification dataset. Participants include 47 males and 33 females, with a mean age of 24.2 and a range from 18 to 47, which is considered to be typical for user groups of smartphones.

They are required to wear the Myo armband on the forearm. The position of Myo armband is shown in Fig. 7. The process is conducted in an academic environment and all participants are free from being disturbed. An Android smartphone runs our data collection application and the EMG signals are recorded into CSV files. There is an assistant to help us operate the application during the data collection phase. To investigate where people are used to placing their smartphones, we design a questionnaire to record smartphone positions when people are studying or working. 40 respondents are asked to choose one from the four representative positions, which are left (P1), nearby (P2), right (P3) and forward (P4), as we can observe in Fig. 8, where the numbers refer to the count result, these places are popular places for placing smartphones when people are sitting. This survey contributes to a better design of the data collect motions.

For the sitting scenario, we require the participants to sit in front of a desk and place their smartphones on the desk. As shown in Fig. 9, the motion they need to do is just picking up their smartphones and watching the screens as usual. Here, we design four scenes and the only difference among them is the location of the smartphone and hand. There are two initial positions for hand, representing two most common hand positions when sitting at a desk, which are shown in Figs. 9a and 9b. One is putting hand on the leg and another one is putting hand on the table. For the phone positions, there is just one smartphone position (P2) corresponding to the former initial hand position while the rest three positions corresponding to the latter hand position. The four smartphone positions are shown in Fig. 8. When the assistant says “start” every time, the participant clicks the corresponding button to start appending labels for the data. Meanwhile, the participant picks up the smartphone and watches the screen. The data label process will
automatically stop when the sampling time ends. The above mentioned process is a valid data collection cycle.

In position P1, P2, and P3, participants are required to repeat the cycle twenty times while for position P4, ten times. As a result of our survey, we decrease the number of times for the last scene because most people do not place their smartphones in such a position. The valid time starts from the user beginning to move his or her hand to look at the screen and this time is normally less than two seconds, we therefore set the valid time to two seconds. Considering the sample rate is 200 Hz and the Myo armband has eight channels, so one piece of valid data is an $8 \times 400$ matrix. With 40 participants, we collect a dataset with 2,800 pieces of valid data.

We invite 13 participants to help us build the dataset for rotation-independence verification. To collect data for this experiment, participants are required to do the following steps. First, they wear the Myo armband on the right arm, record the wearing position at this time, and perform the pick-up action ten times. Second, they rotate the armband clockwise by one sensor position, then do the same action ten times. Third, they rotate four sensor positions clockwise, do the same action ten times. Finally, they rotate the position to the gap, and record the wearing position at the same time, and perform the pick-up action ten times. According to the previous data processing method, we collect a small verification dataset of 520 pieces of data.

Except for the sitting scenario, we also invite 40 new participants to help us build two datasets for the non-sitting scenarios, i.e., standing and walking. For the first scenario, participants wear the Myo armband on the right arms, hold the smartphone in their right hands, naturally raise their hands to look at the phone and then place it down. This action is required to be repeated ten times. Similarly, for the walking scenario, participants are required to walk around while doing the same action with the standing one. In this way, two validation sets with 800 valid pieces of data can be collected and used to train a tiny Siamese network to test the non-sitting scenario.

We implement our model using Keras, a Python-based deep learning platform. We train our model on a server machine equipped with an NVIDIA Tesla V100 GPU, 128 GB memory, and an Intel Xeon E5 2560 processor. We use an Adam optimizer with a learning rate of 0.002 and a batch size of 32. For loss function, we choose contrastive loss rather than cross entropy loss. Contrastive loss runs over pairs of samples. During training, an EMG signal matrix pair is fed into the model with their ground truth relationship $Y$. If the two matrices are similar, $Y$ equals 0; otherwise, $Y$ equals 1. The loss function is defined as (1), where $d$ is the euclidean distance between the two EMG feature vectors. The margin term is used to keep the loss within a valid range. For example, if two EMG signal matrices in a pair are dissimilar, then their distance should be at least the value of margin, otherwise the loss will be 0.

\[
\text{Loss} = (1 - Y) d^2 + Y \max(0, \text{margin} - d)^2.
\] (1)

We evaluate the performance of EmgAuth using metrics that are commonly used in evaluating authentication systems. These metrics include accuracy, true acceptance rate (TAR), false acceptance rate (FAR) and false rejection rate (FRR). Equal error rate (EER) is also leveraged to find an appropriate classification threshold. With an increased threshold, FAR drops while FRR increases. EER is the point that FAR equals with FRR. We decide to choose the threshold corresponding to the EER. The reason is twofold. First, EmgAuth aims to improve security and convenience, leveraging EMG signal to achieve authentication just by detecting the process of picking up the phone. Although reducing FAR and increasing FRR may increase the security of the system, it will affect the efficiency of unlocking. We want the smartphone to be unlocked as soon as the user picks up it, rather than repeating it multiple times. Second, EMG signal enables high safety, because everyone’s muscle structure is unique. Considering that, we will mainly focus on improving efficiency and convenience. Therefore, choosing the threshold at EER, which FAR is equal to FRR, is our best option. We plot the Detection Error Trade-off (DET) curve and the result is presented in Fig. 10. The corresponding threshold of this EER point is 0.55, so we use it as the final threshold of our system.

We then study the effect of the different hyperparameters on the system performance, including the number of CNN layers, filter shape, learning rate, dropout rate, batch size,
and the number of epochs. Table 1 shows the initial hyperparameters used in the evaluation section. We use the hold-out validation to check the performance and the ratio of train set and test set is 4:1. Also, we use accuracy as the only metrics of this evaluation.

4.2.1 Effect of the Number of CNN Layers

Fig. 11a presents the effect of changing the number of layers. The system reaches the highest accuracy when the number of layers is 3. We find as the number of layers increases, the accuracy drops, which is because the EMG signals are not as complex as the images. With too many layers, this may lead to overfitting and only two layers are not sufficient to learn enough features. Three layers are therefore the best choice for our task.

4.2.2 Effect of Different Filter Shapes

Fig. 11b shows the effect of the number of convolution filters in each layer. A suitable number of convolution kernels can fully extract the features of the signals. We try five different number of filter combinations because there are three convolutional layers. The A, B, C, D and E lettering corresponds to [16,16,16], [16,32,32], [16,32,64], [32,32,32] and [32,32,64], respectively. Combination B performs best, so we choose [16,32,32] as the filter number in the three convolutional layers.

4.2.3 Effect of Different Learning Rates

The learning rate is a hyperparameter that controls how much to change the model in response to the estimated error each time the model weights are updated. Too big or too small learning rates can both have negative effects on the learning result, for example, resulting in the model to not converge or train too slowly. Therefore, we use a series of values to choose the best hyperparameter. Fig. 11c shows that 0.002 is the most appropriate learning rate.

4.2.4 Effect of Different Dropout Rates

Dropout is the simplest way to prevent a neural network from overfitting. Considering that each convolutional layer has a dropout layer, we try different dropout rate combinations and name them as in Fig. 11b. Here, the A, B, C, D, and E correspond to [0.1,0.1,0.1], [0.1,0.2,0.2], [0.1,0.2,0.3], [0.2,0.2,0.2] and [0.2,0.2,0.3]. Fig. 11d shows that the dropout rate combination [0.1,0.2,0.2] is the most desirable.

4.2.5 Effect of Different Batch Sizes

Fig. 11e shows how the batch size affects our system. The batch size is a hyperparameter that defines the number of samples to work through before updating the internal model parameters. Considering that the size of our dataset is not very large, a big batch size is not a good choice. From the figure, we see that the accuracy reaches the highest when the batch size is 32.

4.2.6 Effect of the Number of Epochs

Fig. 11f presents the effect of training epochs. The number of epochs is the number of complete passes through the

| TABLE 1 | Training Hyperparameters of the Model |
|----------|--------------------------------------|
| **Parameter** | **Range** | **Initial Value** |
| Number of CNN layers | 2 - 6 | 2 |
| Filter number | 16 - 64 | 16 |
| Dropout rate | 0.1 - 0.3 | 0.1 |
| Batch size | 16 - 256 | 16 |
| Number of epochs | 10 - 50 | 10 |
| Learning rate | 0.001 - 0.005 | 0.001 |

Fig. 11. Effect of different hyperparameters on authentication accuracy.
training dataset. If the number of epochs is too high, the model is easily overfitted as we have a small dataset. From the experiment, the model has the best accuracy when we set the number of epochs to 20.

4.2.7 Effect of Different Distance Functions

As mentioned above, we add a distance layer to combine the outputs of two identical sub-networks for measuring the similarity of them. Here, we evaluate three different functions including Manhattan distance \[48\], euclidean distance, and Cosine distance \[49\] to find the best option. To take a closer look at the system performance under different distance functions, we leverage the Receiver Operating Characteristic (ROC) curve in the study. ROC curve is an effective method to graphically reflect and compare the performance of different classifiers. Each point on an ROC curve corresponds to a certain detection threshold. Fig. 12 presents the ROC curves of different distance functions, the Area Under the ROC Curve (AUC) of euclidean distance is the biggest while Cosine distance performs worst. The AUC of Manhattan distance is between the other two distance functions. Therefore, we use euclidean distance to measure the similarity of two feature vectors of the EMG signals.

After these experiments, we list the best hyperparameters in Table 2. We use our fine-tuned network to evaluate the performance of the EmgAuth system. We divide our dataset into five subsets, which means each has 8 participants’ EMG signals. These five subsets are marked as A, B, C, D, and E. Cross-validation is applied to handle the problem of insufficient data. We set the ratio of the training set and validation set to 4:1, as we can train the model for five times. The results of 5-fold cross-validation are listed in Table 3. From the table, the average accuracy reaches 92.06% and the other three metrics are 91.81%, 7.43%, and 8.29%, respectively.

Except for the third group, the accuracies of the other four groups are more than 90%. In the third group, the accuracy is only 87.50%, severely lowering the average performance. The other three metrics are also not very good. We investigate the reasons behind it from the corresponding data. We find the EMG signal waves are different sometimes even when they belong to the same motion of one person. Two reasons may lead to this situation. First, the user may not perform the action in the sampling time, therefore time drifting will lead to incorrect labeling, which misleads our system. Second, during the data collection step, some participants perform the movements unnaturally, which may produce unqualified data and affect the performance of our system. These reasons also lead to the fluctuations of these metrics in the results of cross validation.

4.3 Rotation-Independence Verification

We conduct several experiments to verify the rotation-independence of EmgAuth. The data structure we use in this section is shown in Fig. 13. In the high level part, the number of rows represents the number of people (13 in our dataset), and the number of columns represents the four wearing positions collected by each person. The middle level part shows each item in the high level has ten pieces of data and the low level part describes the shape of the data which is \(8 \times 400\). The number 8 and 400 are the same meaning with the previous introduction. Therefore, we treat the \(8 \times 400\) matrix as a valid data and there are in total, 280 pieces of data to verify the rotation-independence feature of EmgAuth.

For the same user, we use the original data to compare with the rotated data with to verify the effectiveness of EmgAuth, when authenticating the same user, in other words, testing the TAR. Specifically, for the same user, we pair the EMG data of one position with the other three positions. In this way, we can obtain 420 pairs of EMG signals. Then we input them into the fine-tuned Siamese network and compare the output with the threshold, which is 0.5. If the output value is less than 0.5, the authentication is considered as successful.
For different users, we use the original data of one user to compare the rotated data of other users to verify whether EmgAuth can correctly identify after rotation, in other words, testing the FAR. Specifically, we pair the EMG data of one position from one user with the four positions from other users, the rest operation is the same with the above. For the result, if the output is bigger the 0.5, we can say the rotation does not mislead EmgAuth to recognize different users as the same one.

Fig. 14 presents the results of TAR and FAR when the Myo armband rotates at different angles. x1 means the armband rotates one sensor position and x4 means the armband rotates four sensor position. Gap means the armband rotates to a gap position. We can see that TAR is the highest when the armband rotates one sensor position, which is about 0.95. When the rotation angle is 180 degrees, the TAR drops a little to 0.925. EmgAuth performs worst when the armband rotates to a gap position, the corresponding TAR is just 0.88.

The reason is that when we apply data augmentation, the expanded data are all in integer multiples of the sensor position and the gap position is not counted. However, the width of gap is much less than sensor’s, leading to an acceptable result. Unlike TAR, FAR shows the reverse trend. It reaches the lowest when the position is in the gap. The reason is similar with the above analysis, the model does not see the EMG data in the gap during the training process, which naturally believes two unknown EMG signals are from different users.

5 Influencing Factors in Real Scenarios

The reliability of EmgAuth under various working conditions is critical for real-world deployment. In this section, we discuss the scenarios that EmgAuth might encounter in practice, including non-sitting scenarios, different enrollment actions, left-handed suitability. We also investigate the impact of smartphone type and the unlocking speed.

5.1 Performance in Non-Sitting Scenarios

In addition to sitting scenario, we additionally verify EmgAuth with two common non-sitting scenarios, i.e., standing and walking, and experimental results show good performance of EmgAuth. To prove EmgAuth works in both scenarios, we use the 800 valid pieces of data from 40 participants, which were previously mentioned in the Section 4.1, to train a tiny Siamese network. We choose 30 people for the training set and the other 10 people for testing and leverage cross-validation to repeat this experiment four times. Considering that the action time of non-sitting is less than the sitting scenario, we adjust the sampling time and change the data shape from (8, 400, 1) to (8, 240, 1), the other hyperparameters remain. Fig. 15 presents the experimental results. The system performance of the walking scenario is slightly better than the standing scenario, because walking introduces more muscle movements, such as swing arms while walking, which include more personal features in the EMG signal. The average accuracy rates in standing and walking scenarios reach 92.1% and 93.1%, respectively.

5.2 Impact of Different Smartphone Positions

As mentioned before, there are in total four different smartphone positions that we use during the data collection phase. However, in the real scenario, the position of the smartphone is random. In this section, we would like to investigate whether EmgAuth can handle other positions besides the above four locations. We invite five participants to do this experiment. First, they are allowed to place their smartphones as they want (except the above four positions) and we record the positions of them. Then they take the enrollment step to store their EMG signals. The results of the authentication are shown in Fig. 16. The green markers are the positions that EmgAuth authenticates correctly while the red markers are the positions that our system detects by mistake. There is just one position that EmgAuth fails and the accuracy reaches 93.33%. From Fig. 16, we find the failed position is in the left of users, where leads to unnatural movements for users when taking their phones using...
the right hands. We believe it is the reason that EmgAuth fails the authentication. From this experiment, we can conclude that our deep learning model learns the features well and has an excellent possibility for generalization. We also find that no matter where the smartphone is placed, the finger-level movements are similar when the user grabs his or her smartphone and it is the main reason why the system has good capacity to be generalized.

5.3 Impact of Smartphone Size and Weight
To investigate the influence of different types of smartphones, we invite four participants with four different smartphones. We design five sets of trials and every trial corresponds to a specific smartphone. In each trial, the four participants are asked to use the same smartphone to do the enrollment step and authentication step. Then in the next experiment, they change to another smartphone at the same time. We do not set attackers in this experiment so TAR is the only metric to measure the performance. The brands and parameters are listed in Table 4, as well as the experiment result. For the results of TAR, the overall performance is good except for Huawei Honor 10. The TAR of Honor is just 80% while the others are all more than 90%. The reason is that the size of Honor 10 is much bigger than the other three smartphones. A participant who gets used to the standard size of a certain smartphone will find it hard to adopt a bigger size one within a short time, which leads to the varying motions in the trials. In addition, we do not find the weight of the smartphone to be an influencing factor of EmgAuth. Therefore, we conclude that EmgAuth is device-independent.

5.4 Performance on Left Hand
In real life, there are left-handed people as well as those who are right-handed, and this section is to evaluate whether EmgAuth can accommodate with this scenario. We invite two left-handed people to help us perform this experiment. The data collection process is identical with the right hand scenario except for the wearing position. They are required to do the enrollment first and repeat an action five times during the authentication phase. From the experiment, our system fails just once among the ten times, achieving the accuracy of 90%. Therefore, we can say that EmgAuth is also suitable for left-handed people.

5.5 Unlocking Speed
In this section, we test the speed of EmgAuth on both the server and the Android smartphone. The whole unlocking process includes four steps: 1) loading stored EMG metrics, 2) data segmentation, 3) making pairs, and 4) model calculation. Among the above four steps, loading data consumes the most amount of time because it is an I/O operation. Therefore, we load the EMG matrices in memory after a user finishes the enrollment phase to accelerate the process. Then we test the time both on the server and a Xiaomi 8 smartphone. Specifically, we add two system time functions, one is placed before the data input function and the other one is placed after the model output function. By calculating their difference, we can get the time required for the authentication. When the process runs on a server machine, the authentication time is about 0.048 s. Due to the limited computing resource of the smartphone, the authentication time of the simulation application running on a Xiaomi 8 smartphone is about 0.16 s, which fulfills the requirement of real-time unlocking.

6 Discussion
In this work, we use EMG signals to enable smartphone unlocking without any additional actions, which is a promising supplement to the existing unlocking (or authentication) methods. Unlike other static biometric features, EMG signals are dynamic and changes with body movement, but follows a specific pattern for the same person due to unique and individual muscle structure. Therefore, it naturally enables authentication methods which are hard to acquire without the owner noticing, thus reduces the risk of privacy leakage. Unlike other research that involves the Myo armband, we are inspired by image augmentation in the field of computer vision and propose EMG signal-based augmentation to free calibration. In other words, people can wear the armband freely rather than fixing to a set position.

We notice that not every time users pick up their smartphones to use them, sometimes they just want to put them in their pockets or change their device’s positions. In these scenarios, they do not expect their smartphones to be unlocked. On the one hand, the unlocked phone in the pocket may make a call by mistake. On the other hand, if a user moves the phone on the table and leaves it without locking it again, it may lead to privacy leakage. We perform preliminary experimentation for this situation and find that EmgAuth does not trigger unlocking when the user does the above two motions. The reason is that, when we train the Siamese network, the data we labeled starts from picking up the smartphone but is stopped at the point the user is looking at it. In other words, the authentication process is completed by looking at phone, not putting it into the pocket or moving it from one place to another place. If EmgAuth receives wrong EMG signal sequences, the built-in Siamese network will find it and output a big value that is much bigger than the threshold, so the smartphone will not be unlocked by mistake. In addition, in our experiments, we do not find gender ratio is an influential factor. Everyone, regardless of gender, has a unique muscle structure, which allows EmgAuth to divide them through the Siamese network.

EmgAuth allows users to directly use their smartphone devices instead of entering passcodes or waiting for other recognition systems, such as fingerprint or facial recognition systems to finish authenticating, and EmgAuth will not be affected if a user is wearing gloves or masks, which could be used in more environments, especially during Covid-19-like pandemics.

EmgAuth has to rely on the Myo armband to obtain EMG signals, which is troublesome for real daily life use.
People would not like to wear additional devices just to make their smartphones safer. However, we aim to propose a prototype system to verify the feasibility of using EMG signals to unlock smartphones without calibration and pre-designed actions. We believe this paper could give other researchers ideas to explore more biometric signals that can be used for authentication, combining with the powerful feature extraction ability of deep learning to achieve more innovative applications.

7 Conclusion

We present EmgAuth, an EMG-based smartphone unlocking system, which leverages EMG signals and a Siamese network to unlock smartphones. In particular, when training the Siamese network, we design a special data augmentation technique to make the system resilient to the rotation of the armband, which lets the system be free of calibration. We conduct experiments with 80 participants for collecting datasets and design a convolutional Siamese network for analysing the EMG signals. Our system can authenticate users effectively with an average TAR of 91.81% while keeping an average FAR of 7.43%. Extensive experiments are conducted to test the rotation-independence feature and the performance in the non-sitting scenario, demonstrate the usability of EmgAuth for smartphones with different sizes and at different locations, as well as users with different postures.

Although the experimental results are promising, the limitation of EmgAuth also exists. First, it is not convenient to wear an armband for unlocking a smartphone. Second, our system may not work well in the humid environment as the EMG signal becomes unstable if the skin surface is wet. In the future, we will evaluate the performance of EmgAuth in a long-term stability study. In particular, we will design a smaller EMG sensor to make the system easier to use and discover more application scenarios.

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**FAN ET AL.: EMGAUTH: UNLOCKING SMARTPHONES WITH EMG SIGNALS**