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A Gait Based Approach for Implicit Authentication Using Artificial Neural Networks

Hozaifa H. Daoud hdaoud@azhar.edu.eg	Mohamed M. Ezz ezz.mohamed@gmail.com	Mohamed Z. Abdulmaged azhar@mailer.eun.eg
Systems and Computer Engineering Dep., Faculty of Engineering, Al-Azhar University, Cairo-Egypt		

Abstract
Nowadays in order to enhance smartphone security, behavioral biometrics like gait patterns are widely used in human identity recognition. As each person has a unique way of walking, gait is used for authenticating and identifyingpersons. In this paper we used UCI-HAR dataset. This dataset contains gait patterns for 30 person collected by accelerometer and gyroscope of smartphone.Our proposed model used Siamese network with neural network core to apply one shot learning. The experimental results gained encouraging accuracy of 99.3%.Results assured that our proposed model can be considered robust and secure solution for authentication.
Keywords – Smartphone. Behavioral biometrics. Gait analysis.Implicit Authentication.Neural networks.

Introduction

Smartphones became less expensive and easy to use which made it more prevalent than before. Due to its improved interactive features, sensing capabilities and rapid progress in technology, we consider it the key element of our life. It is not only perform our most important activities, like money transfer, suggest navigation directions using GPS, listen and watch record video streams, keep in touch with family and access to email through the internet but also it has internal storage which enables individuals to store their important and valuable data like messages, photos and call history. Thus the necessity of keeping these personal data safe from unauthorized access is also becoming important. The security of smartphones has many threats, if a thief knows the pin code or the password of the phone, then he can explicitly authenticate and steal sensitive data. PIN-based authentication technique not only open to different types of attacks like shoulder surfing and brute force [1], but also it is time consuming and error-prone. More particularly, physically disabled and elderly users find difficulties by entering pin codes or passwords or might be unable to do explicit authentication.

Implicit authentication does not require memorization or input from the user, because it authenticates the person through his unique biometric characteristics which collected by the smartphone sensors without interference from users. Nowadays most of the smartphones have embedded gyroscope, accelerometer and magnetometer of high quality. Recent improvements in wireless communication technologies allow us to record the time series data from those sensors without any hassle to the user.

Considering that there is a unique way of walking containing user-distinctive patterns for each person, inertial sensors embedded in smartphones can be applied to the problem of gait recognition in security-related applications [2]. Human gait has been extensively acknowledged by researchers as a biometric trait that can be used for authentication purposes via recognizing individuals based on their behavioral or physiological characteristics [3].

The benefits of human gait are that it is implicit, unobtrusive, passively observable, concurrent, and continuous, furthermore, it's easily measured when the user takes his phone around. While walking, the phone will recognize him based on his gait, consequently, he can directly use the phone and its services with none further authentication. Hence, compared to password or PIN-based authentication, it requires no extra effort for the user.

In the background while the user is walking, gait recognition will execute, this means that there will not be any delays.

By using these sensor readings we can implicitly detect the phone owner and increase the security by using a simple technique that will lock the phone if it failed to detect the owner.

Deep learning makes it simple to identify a person from a photo, fingerprint and so on. But here we will authenticate the person using his gait as our main feature. Each person has his own gait, yes it might be repeated and intersections might occur but with the choice of a good model that can detect even the small tiny differences between persons gaits , we can assure even with a tiny error that identifies the right person. Many classifiers have been tested but our main purpose was to show that our model architecture is the best classifier that can be used in this case.

There is a class of neural network architectures that contains two or more identical subnetworks called Siamese neural network. Hence, identical means they have the same parameters, configuration and weights. Parameter updating is mirrored across both sub-networks.Siamese NNs are commonly used among tasks that involve finding relationship or a similarity between two comparable things. For instance, signature verification, which figure out whether two signatures are for the same person, or scoring, where the inputs are two sentences and the output is a score of how similar they are. Generally, two identical sub-networks are used to process the two inputsin such tasks, and another module will take their outputs and produce the final output. We have used Siamese network as our proposed architecture for the authentication task. The main contributions of this study are demonstrated as follows:

• To the best of the author's knowledge, this is one of the biggest datasets for smartphone gait authentication, which contains gait data of 30 users.

- Identifying the optimal classifier to be used in such case.
- Highlighting the impact the architecture and layer selection in the core of the Siamese network on the performance.

The remainder of the paper is organized as follows: Section 2 reviews the state of the art in transparent and continuous authentication that specifically uses the accelerometer and/or gyroscope sensors. Dataset, feature extraction, the experimental procedure, and results are outlined in Sections 3, 4 and 5. Conclusions and future work are presents in section 6.

Related work

Recently, a number of researchers using smartphone-based accelerometers and gyroscope have rapidly increased to characterize human movement patterns. Therefore, it integrated into some of mobile applications, and open the door for some new application areas such as authentication of smartphone users [4].

The gait recognition in the wild using smartphones was proposed by Qin Zou et al. in [5]. In their research paper, the authors combine the DCNN and DRNN and generate a hybrid deep learning method to represent the inertial gait feature in a robust way. Also, a fully convolutional neural network, and a hierarchical convolutional features are combined together, the former one is proposed to partition the inertial data, and the latest to semantically segment the people walking. The results show that the proposed techniques was very effective when deployed to identify and authenticate the people.

In [6], a novel context-based authentication system for implicit and continuous authentication was proposed. Their research paper, differentiate the legitimate smartphone owner versus other users based on behavioral characteristics by leveraging the sensors already ubiquitously built into smartphones. The obtained result show that using such method is very convenient because it achieves excellent authentication performance and less battery consumption.

In [7], Jang et al. propose a new method for human's gait recognition features using an enhanced backpropagation neural network algorithm. The human body was extracted from the gait sequences by determining the body points to extract their gait motion and to calculate the trajectory-based kinematic features. The results achieve a higher gait recognition performance.

Muhammad Muaaz and Ren´e Mayrhofer [8] extended their research paper and made many significant improvements. The cross pocket gait authentication method using mobile phone based accelerometer sensor was used. In their research, the approach achieved False Match Rate = 0.0862 and False Non Match Rate = 0.4697) under same session cross pocket scenario at a global threshold, therefore, it is necessary to combine both left and right side templates.

Nigar et al. in [9], design and implement a semi-automated gait features classification system using joint angle and time-distance data. In their research, the gait data are classified into two categories; healthy and patient with knee osteoarthritis using Multilayer Perceptron classifiers. Also, two popular approaches of combining neural

networks are tested and the results are compared with respect to various outputs of combining rules.
In [10], a novel authentication framework was proposed. It is based on physical activity recognition for recognizing the behavioral traits using the embedded sensors. Its contribution is a platform to achieve multi-class smart user authentication, which provides different levels of access to extended smartphone users. The results of the proposed framework showed the effectiveness of it.
Han and Fenggang [11], addressed a new method for human model-free gait recognition using principal curves analysis and neural networks. The results demonstrate that the proposed method has an effective performance for the gait recognition problem.
In [12], a user authentication technique for gesture recognition and a tri-axis accelerometer was presented. The method has the potential to enable personalized services on resource constrained smartphones.
In [13], a novel gait authentication mechanism by mining sensor resources on smartphone was used. Also, an effective segmentation algorithm is used to segment signal into separate gait cycles with perfect accuracy. The results show the effectiveness of the proposed method which can be used to support current smartphone authentications.
Robertas et al. [14], presented a technique for gait-based user identification when utilizing some embedded smartphone sensors data such as gyroscope and accelerometer. A selected statistical and heuristic gait features which is based on the application of the Random Projections method for reduction of feature dimensionality is utilized. The results are acceptable and improve the performance and usability of their system.
A comprehensive survey based on smartphone authentication focusing on seven types of behavioral biometrics is discussed in [15], with number of existing solutions from different aspects. Also; some of the promising approach that is utilized to measure user behavior in terms of application that can be used for various purposes are tackled.

Gait Data

The input samples have been taken from a group of 30 volunteers and their ages range from 19 to 48 years. Each person wore wearing the smartphone on the waist and performed the six activities (WALKING, WALKING_UPSTAIRS, WALKING_DOWNSTAIRS, SITTING, STANDING, LAYING). In order to facilitate data labeling, the experiments have been video-recorded. The obtained database has been randomly partitioned into two sets, where 70% of the patterns have been used for training purposes and 30% as test data: the training set is then used to train a neural network classifier which is described in the following section. As Samsung Galaxy S2 smartphone contains an accelerometer and a gyroscope, it was used for measuring 3-axial linear acceleration and angular velocity respectively at a constant rate of 50Hz for the experiments. Rate of 50Hz chosen as it sufficient for capturing human body motion.
Butterworth low-pass filter applied on the sensor acceleration signal which has gravitational and body motion components to separate it into body acceleration and gravity. The gravitational force is assumed to have only low frequency components;

therefore a filter with 0.3 Hz cutoff frequency was used. From each window, a features vector obtained by calculating variables from the frequency and time domain.
For each record it is provided:-

- Triaxial acceleration from the accelerometer (total acceleration) and the estimated body acceleration.
- Triaxial Angular velocity from the gyroscope.
- Its activity label.
- An identifier of the subject who carried out the experiment.

In this paper, we focused only on walking activity.

Experimental procedure

Siamese Network (sometimes called twin neural network) is a man-made neural network that uses the identical weights while working in tandem on two different input vectors to compute comparable output vectors. Often one amongst the output vectors is precomputed, thus forming a baseline against which the opposite vector is compared.

The core of the Siamese network is usually built on CNN but it's changed during this model to be a basic neural network.

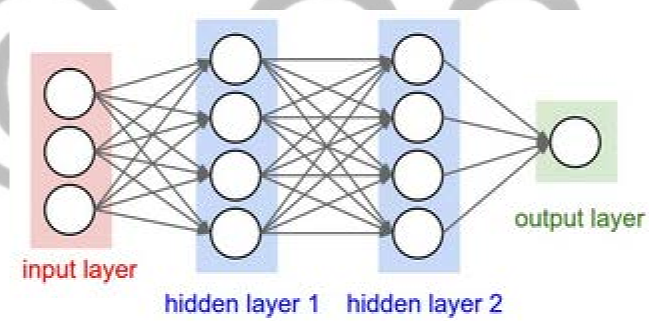

Figure 1: An example of the standard neural network

Neural networks are the techniques of machine learning. They're a touch just like the neural networks in biology. There are many neurons and much of connections between neurons. Figure 1 is an example of the purposed neural network. The white circles represent neurons and also the arrows represent the connections between neurons. Note that we use the arrow to represent the direction of the connection. During this section, we'll introduce what the neural network is.
First, we would like to understand what the neuron is. Neurons have inputs, thresholds, and output. If the input voltage is larger than threshold, the neuron is activated and a sign is transmitted to the output. Note that there's just one output regardless of the number of inputs that fed to the neuron. The operation model of the neuron in machine learning is extremely just like the one in biology. They even have inputs and outputs. Despite the neuron's output is connected to many neurons in Figure 1, the worth of the outputs identical. Of course, there are differences. instead of the edge, the "neuron" in machine

learning uses a function to transfer the inputs to the output. There are many activation functions. We regularly choose it because of the sigmoid functionσ(x).

$$\sigma(x) = \frac{1}{1+e^{-x}} \quad (1)$$

The sigmoid function is extremely just like the step function, which acts like thresholding. When x may be a large positive number, the output of the sigmoid function is regarding 1. When x is way smaller than 0, the output is regarding 0. We will notice these facts in Figure 2. Another good property is that the sigmoid function is continuousand differentiable. So we are ready to apply some mathematics thereon.

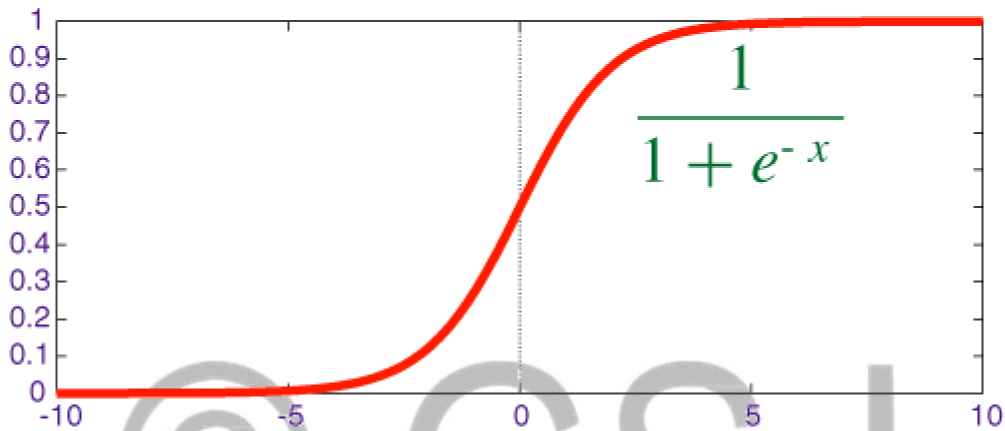

Figure 2: The sigmoid function

Weight is another difference. The weights describe that what quantity each input affects the neuron. That is, we'll not just put every inputs into the activation function. the worth of activation function's input is that the linear combination of the inputs. The mathematical representation is as follows:

$$\sigma(w_1x_1 + w_2x_2 + \cdots + w_Nx_N) \quad (2)$$

Where N is the amount of the inputs, w_i are weights of x_i, and σ( ) is the activation function. However, there's a controversy of it! We reduce the number of inputs to 1 and alter the weight to see how weights influence on the output. The result shown in Figure 3(a). One can see that 0 is viewed because the threshold to see whether the output is near to 0 nor near to 1. However, how will we modify the model if we wish to change the edge to worth 0? During this case, we add a bias θ to achieve that so that we can shift the sigmoid function. Figure 3(b) shows the result of the sigmoid function with bias. So the new relation is:

$$\sigma(\theta + w_1x_1 + w_2x_2 + \cdots + w_Nx_N) \quad (3)$$

The parameter θ is the bias and other notations are identical as above. And $\theta, w_1, \ldots, w_n$ are parameters that are needed to be learned. That is how neuron works.

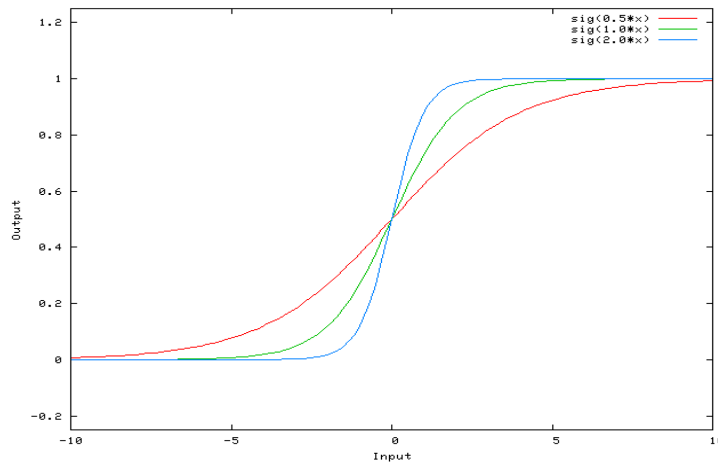

Figure 3: (a) The result sigmoid function with different weights and no bias.

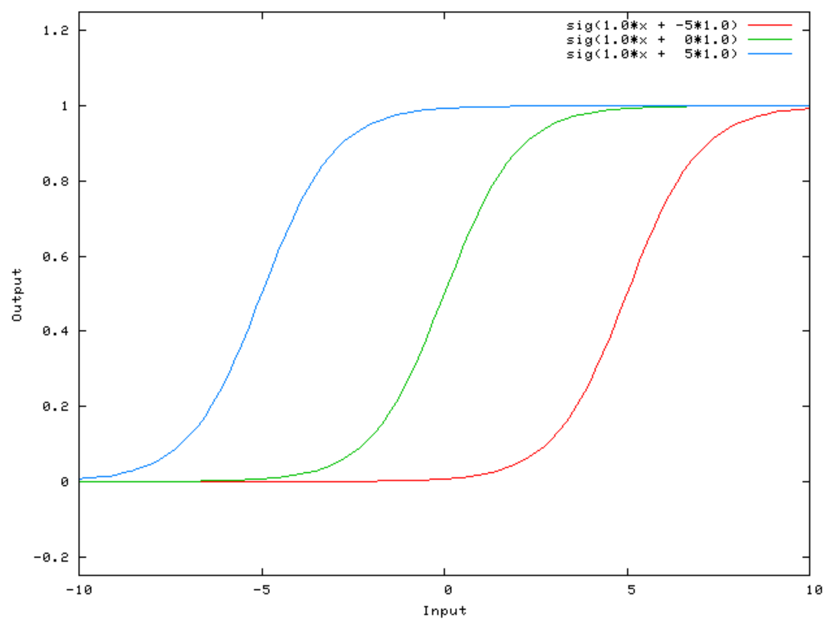

Figure 4: (b) The result of the sigmoid function with different weights of bias.

When many neurons connect, the neural networks appear. Let's return back to work 1. The colored rectangles are consisted of the many neurons and that we call these rectangle layers. The layer contains one or many neurons and these neurons won't attach with each other. We regularly call the primary layer the input layer and therefore the last layer the output layer. Hidden layers are the layers between the input layer and output layer. We frequently connect every neuron in previous layer to every neurons within the next layer. We call it full-connected. Figure 1 may be an exemplar to point out that.
So our model is standard Siamese network with hidden layers fully connected each with N units, where $h_{1,\ell}$ is the hidden vector in layer $\ell$for the first twin, same for $h_{2,\ell}$ for the second twinWe use exclusively rectified linear (ReLU) units[16].

$$h_{1,m} = \max(0, W^{T}_{l-1,l}\, h_{1,(l-1)} + b_l) \qquad (4)$$

$$h_{2,m} = \max(0, W^{T}_{l-1,l}\, h_{2,(l-1)} + b_l) \qquad (5)$$

We have used the concept of 1 shot learning in training as in Figure 4, it's alittle bit different than standard classification, just in case of standard classification, the input is fed into a series of layers, and eventually we generate a probability distribution over all the classes at the output (typically employing a Softmax). For illustration, if we are trying to classify a picture as cat or dog or horse or elephant, then for every input image, we generate 4 probabilities, indicating the probability of the image be a member of every of the 4 classes.

Two critical points must be noticed here. First, during the training process, we'd like a massive number of sample images for every class (cats, dogs, horses and elephants).

Second, if the network is trained only on the mentioned 4 classes of images, then we cannot expect to check it on the other class, example "zebra". If we wish our model to classify the pictures of zebra additionally, then we'd like to first get many zebra images, then we must re-train the model again.

There are applications wherein we neither have enough data for every class and also the entire number classes is large also as dynamically changing. Thus, data collection and periodical re-training cost is extravagant

Contrarily, in a one shot classification, we require just one training example for every class

The one-shot learning problem are often directly addressed by developing domain-specific features or inference procedures which possess highly discriminative properties for the target task. As a result, systems which incorporate these methods tend to shine at similar instances but fail to supply robust solutions which will be generally applied to other sorts of problems[17].

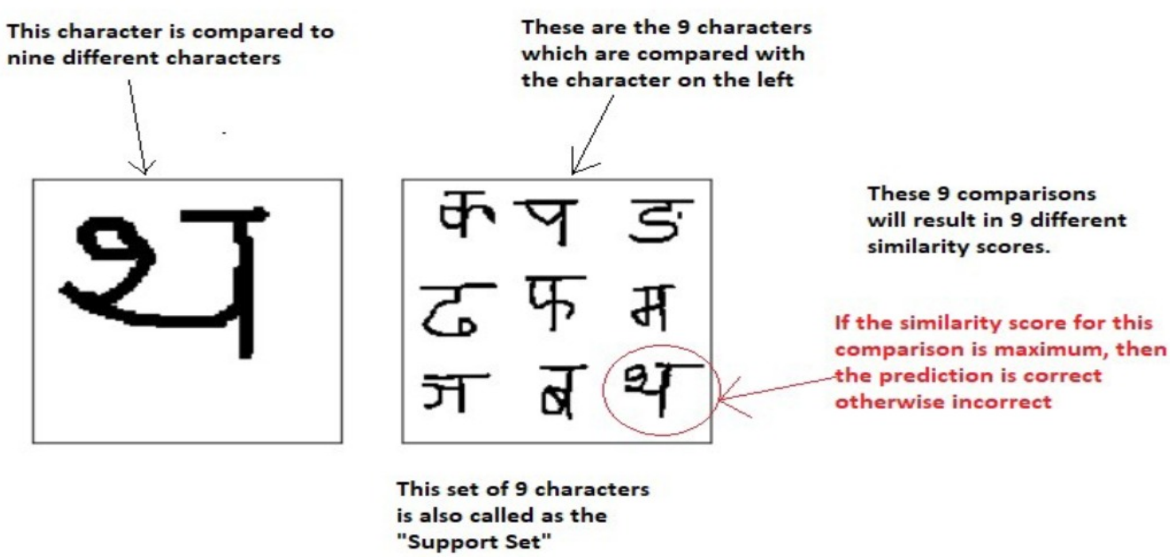

Figure 5 One Shot Learning

Results:

As we see in Figure 5, Siamese network has managed to be the best of our selected models and this table illustrates all of our effort:

POE	Siamese (Core NN)	Siamese (Core CNN)	SVM
Training & testing time	60 & 1	840 & 60	120 & 3
Accuracy	99.3%	82%	89%

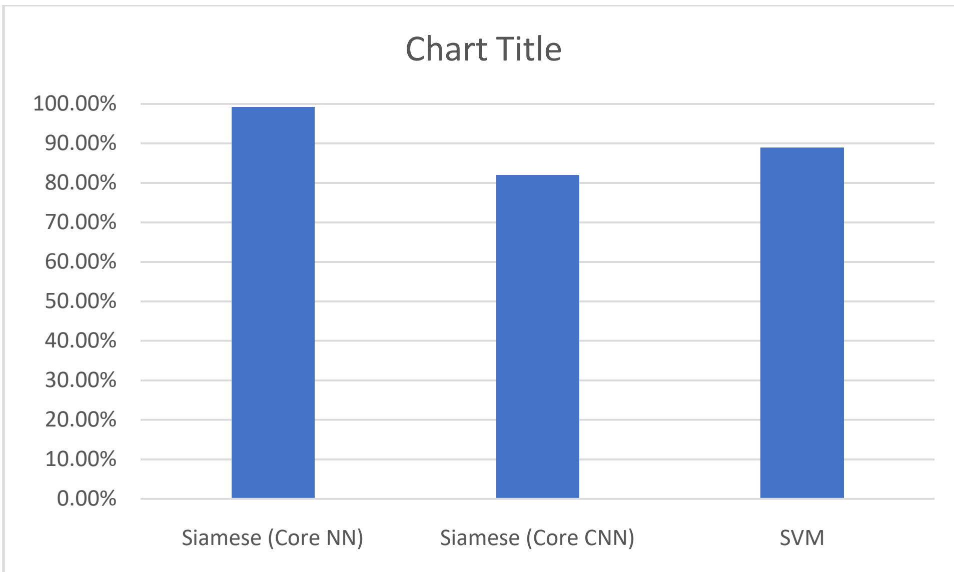

Figure 6 Results

Conclusion:

In this paper, gait recognition using smartphone sensors was studied. A deep learning method was purposed using Siamese neural network. In gait data collection, the OCR dataset was used which is collected using the Accelerometer and Gyroscope to get the Activity of moving of the person for specific time in a condition of unconstrained, and information of when, where, and how the user walks was totally unknown. A fully neural network was presented to partition the inertial data into the walking session and label them, where hierarchical features are fused together for accurate semantic segmentation. Then, a NN with 2 hidden layers was used to apply the Siamese concept and get the similarities between the input and the data, also one shot learning technique was used to train our model. In the experiments we found that the performance on accelerometer data is generally better than that on gyroscope data, and the accelerometer data and gyroscope data can be complementary to further improve the performance. We also found that, Siamese with NN core is so much better than CNN core and SVM for this use case.

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