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HOW SIGNIFICANT IS THE INDIVIDUAL DIFFERENCES IN FINGER BASED GESTURES ON SMARTPHONES' TOUCH-SCREEN FOR USER IDENTIFICATION?

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ABSTRACT

This paper analyses the variations in the identification power among set of four features, namely Signature Precision (SP), Finger Pressure (FP), Movement Time (MT), and Speed that were extracted from finger gesture of touch-screens. The differences across users were studied using the above features individually and combined for the purpose of user identification based on the Euclidean distance and the k-nearest neighbour classifier. The paper investigates the performance variations across users using a dataset of 50 users, and concludes that the discrimination power of different feature is heavily user dependant i.e. while some features achieve 100% identification accuracy for some users, they perform poorly for others. On small smartphone 19% and on mini-tablet 42% of the users have unique FP compared to other features. We concluded that FP could be used alone to perfectly identify users for 100% accuracy.

Keywords: *User Identification, Security Of Touchscreen Patterns Based Unlock Systems, Smartphones.*

1. INTRODUCTION

The popularity of smartphones devices make them a frequent storage medium for the users sensitive information such as personal photos, email, credit card numbers, and banking passwords. As smartphone devices are easily lost or stolen, the problem of securing the user access to this data considers one of paramount importance [1]. Unlock screens using text based password, graphical based password, or grid based schemes are most current access systems prompt users to authenticate themselves. This authentication method relies on the password's/username's secrecy. If this secrecy is not breached, the assertion is that these tokens uniquely identify a valid user. The problems of user authentication associated with maintaining password secrecy are well understood. Passwords that consist of common words, or terms associated with a particular user are generally considered weak because of the relative ease with which a malicious users can guess them [2].

The need for strong authentication is influenced by the input methodology of touchscreen devices and the different expectations of user for interaction models [1]. As shown in a study [3] over 3.3 million leaked passwords, number of their list was still "123456". Moreover, the additional cost makes biometric authentication techniques to be still unpopular on mobile devices [1].

The main motivation of finger based gestures on smartphone and tablet for user identification is preventing a malicious users from breaching the unlock screen of smartphone devices. As mentioned early, users prefer using text based password, graphical based password, and grid based schemes because of it is easy to remember. The need to enhance the authentication users on smartphones is required in order to make the illegal user access on smartphones impossible; because of this required we examined finger based features on smartphone and tablet for user identification. Our study relay on the users attributes and behaviours on touchscreen, so breaching unlock screen will not be easy even if the password also was stolen. In our study, the features were analysed individually and combined to increase the accuracy as well as the performance variations across different users was considered in the analysis.

In the results, the paper investigates the performance variations of different features across users using a dataset of 50 users, and concludes that the discrimination power of different feature is heavily user dependant i.e. while some features achieve 100% identification accuracy for some users, they perform poorly for others. On small smartphone 19% and on mini-tablet 42% of the users have unique FP compared to other features. We concluded that FP could be used alone to perfectly identify users for 100% accuracy.

The contributions of this work can be highlighted as follows. First, we use widely available consumer devices in our experiments (e.g. small smartphone, 4 inch, and mini-tablet, 7 inch). Secondly, our experimental procedure was designed differently to previous studies; the required gesture remained displayed on the screen as a guide whilst the participant executes the gesture. Thirdly, the way on how we analysed data is different from previous studies, as Dynamic Time Warping algorithm was used to calculate distances between the optimal path of a gesture and the executed one considering all points along the trajectory of the gesture to produce a signature precision. Fourthly, our study is first study considered the combined features (e.g. FP + MT) in many orders and the individually, which provides new insight to this kind of research. Fifthly, we considered the performance variations across different users that will enhance the authentication accuracy.

The limitation for this study can be highlighted as follows: First, as this kind of researches depends on collecting data from participants; finding a large number of participants considered as a challenge for this research. Secondly, limited numbers of gestures were used to collect data. Thirdly, the representation of users' experience when using smartphones and tablets could be refined.

The rest of this paper is organized as follows. Section 2 discussed the related work on which we prepared our study. Section 3 explained the analysis of our experimental results. The data collection processes are described in Section 4. The experimental results are explained in Section 5. As well as the final conclusions are presented in section 6.

2. RELATED WORK

The need for finger based gestures on smartphones for user identification is increasing day by day because text or graphical based passwords and grid based schemes are easy to recall and stolen from a malicious users. Finger based gestures on smartphones for user identification has greater potential to provide a more dynamic movement for users on screen for using some a specific features (e.g. SP, FP) than other used in text based passwords. Many researchers are working on the concept of user identification using finger based gesture; some of them also introduced new ideas to provide more secure approach related to text or signature passwords. One of the studies that examined finger based gesture for user identification was conducted by [1]. The researchers Tao Feng and Nguyen in [1] use touch data collected from 40 users based on sensor gloves in order to collect information of finger movement for six types of gestures: down to up swipe, up to down swipe, left to right swipe, right to left swipe, zooming, and zoom-out. The two features used in the study are: the length of touch input sequences and the authentication threshold (i.e., number of accepted touch inputs during one sequence). Their results showed that 4.66% a false accept rate and 0.13% a false reject rate.

In early researches, the examining focused on the possibility of applying keystroke dynamics and typing patterns for user identification. Keystrokes were used as samples by intercepting output from a keyboard [1]. But the researchers Mäntyjärvi, et al. in [4] examined identifying people by their gait using accelerometers worn. Also, the researchers in [5] and [6] examined user identification using gait recognition. The researchers Koreman, et al. in [7] proposed a multi-modal biometric for user identification.

Some of the researchers' efforts were put on a graphical authentication approaches that use the doodles for user authentication. The researchers Jermyn, et al. in [8] proposed and evaluated graphical password schemes that exploit features of graphical input displays to achieve better security than text based passwords. Furthermore, doodles method was proposed by [9] rather than signatures. Several methods were investigated to confirm the identity of the doodle; distribution grid, speed, point variance across the distribution grid, and a combination of all the above. The analysis showed that the combined three features of the system yields extremely accurate results. There have been a number of studies on combining multiple biometric inputs to produce user identification results. The researchers Indovina, et al. in [10] examined a biometric integration of fingerprint and face biometrics on a population of 1000 users. The biometric integration can occur on the feature level, or the score level. In feature level integration, all of the initial features are grouped together into a one feature vector. Their work showed that multimodal fingerprint and face biometric systems achieved significant accuracy gains over any biometric alone.

Grid technique based schemes are also examined in the body of the literature which uses recall method. This technique allows a user draws the password on a 2D grid, and then the information of an occupied grid (e.g. coordinates) will be recorded. The user will be authenticated when drawing touches the grid in the same order. In order to enter the password correctly and distinguishable, the drawing must be sufficiently away from the grid lines and intersections [1] and [8].

A signature using a mouse approach for an authentication user was conducted [11]. The advantage of using a mouse to draw a signature is that the signatures are hard to fake. It can therefore be hard to drawn, as not everybody is familiar with using mouse as a writing device [12]. A graphical authentication scheme was also conducted in [13], in that a set of pictures are presented on the interface, where some of these pictures are taken from the user's portfolio, and some pictures are

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selected randomly. During registration, the user should select some number of pictures from a set of random pictures. For successful authentication, the pictures must be correctly selected amongst the distracters by the users.

There were number of studies conducted for user' identification using a stylus device. The researchers Orozco, et al. in [14] examined users' haptic characteristics for 4 users. The results showed that the probability of verification reached up to 78.8% with 25% false acceptance rate. The researchers Alsulaiman, et al. in [15] examined user identification for 16 users based on handwritten signatures and haptic information such as velocity and angular rotation gathered during the creation of the user's handwritten signature and the consistency in the user's behaviour. The users were identified at an average success rate of 81%.

Some the latest studies were conducted for authentication users to unlock interfaces on smartphones using gestures. The researchers Xu, et al. in [16] examined an authentication biometrics for 32 users on slide, pinch, handwriting, and finger based keystroke that involves a series of taps on the soft; on-screen keyboard. A classification algorithm of Support Vector Machine (SVM) was used in the analysis. The researchers considered the data of the position, pressure, and size of a touch, as well as a timestamp in order to calculate the accuracy and error rate as two straightforward metrics. They concluded in their study that touch operation can be a form of good biometrics. And they found that there is still room for the accuracy to reach up to 100%, and it is a promising solution to consider a join of a set of touch operations for making an authentication decision rather than using one at a time. This indicates a need for further research to make touch-based authentication a practical solution. Another study proposed gestures and algorithms (using Support Vector Distribution Estimation (SVDE)) as classifier to model multiple behaviours of a user in performing each gesture. The study used seven types of features: velocity magnitude, device acceleration, stroke time, inter-stroke time, stroke displacement magnitude, stroke displacement direction, and velocity direction. The feature values were extracted based on sub-strokes and strokes for some features. The total data collected is 15009 gesture samples from 50 users. Experimental results showed that their scheme achieves an average equal error rate of 0.5% with 3 gestures using only 25 training samples [17]. In what follows, we will discuss the processes on how the data was analysed considering the algorithms used in this study.

Such of this study will provide the literature with new research conducted based on new features, as well as the individual and features combined that were not used before in previous studies; this is to enhance the accuracy for user identification.

3. USER IDENTIFICATION PROCESSES

Following to the analysis conducted based on Dynamic Time Warping (DTW) in study ([18]: section 6.2), the same users (i.e. 50 users), and feature (i.e. SP, FP, MT, and Speed) were involved in this paper. As each user has six samples of performing eight different gestures on smartphones; where 26 users were involved in small smartphone, and 24 users were involved in mini-tablet.

After extracting data using DTW and ED in the study [18], then we arranged them into two parts: testing dataset and training dataset (Reference). On small smartphone the testing dataset consists of (130) samples, and the training dataset consists of (26) samples. On mini-tablet the testing dataset consists of (120) samples, and the training dataset consists of (24) samples.

Figure 1 below shows set of numbered processes used in user identification study on each smartphone device, as follows: 1. Feature Extraction. After collecting data were entered into set of analysis processes to produce SP using DTW, Speed using ED, MT, and FP. This part one in the Figure 1 was prepared in the study ([18]: Section 6.2). 2. Part two of Figure 1 reviews user identification processes in three subsections. 2.1. Training. One trial of six was used in the training dataset for each user across eight gestures; as each feature has eight different gestures, and this will be 32 if the four features were combined (SP, FP, MT, and Speed) and so on, as shown in Figure 2 that shows feature factor of all trials we collected on smartphones for study's features in the training and testing datasets. The matrix D [8 x N] in the Figure 1 represents training dataset for 1 feature, where 1 feature (8 gestures) and N users. 2.2. Testing. The remaining five trails of six for each user are in the matrix M [8 x Z] and considered to be testing section, where 1 feature (8 gestures) and Z is (number of users * 5 trials of each user). 2.3. User identification. Based on using the ED between the matrices M [8 x Z] and D [8 x N], and KNN used to compare the trail in M [8 x Z] to which exemplar in D [8 x N] is the user belong to. We will discuss the eight gestures that were collected from the 50 users in the next section.

4. DATASET AND EXPERIMENTAL PROTOCOL

Each user repeated eight different gestures six times producing a total of 48 trials per user.

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Therefore, the total number of trials collected from 50 users is 2400, and this number will be 9600 when implemented the combination of four features. The Gesture Applications used in the research were illustrated earlier in Section 4.8 of the study [18].

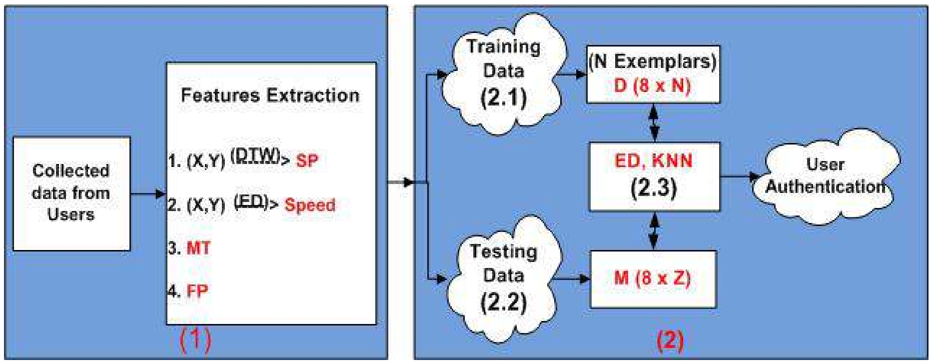

Figure 1. Users identification process.

$$D\,[32 \times N] = \{\underbrace{G1F1, G2F1, \ldots, G8F1}_{\boxed{MT}}, \ldots, \underbrace{G1M4, G2F4, \ldots, G8F4}_{\boxed{FP}}\}$$

Figure 2. Feature factor for all trials (i.e. G: gesture and F: feature).

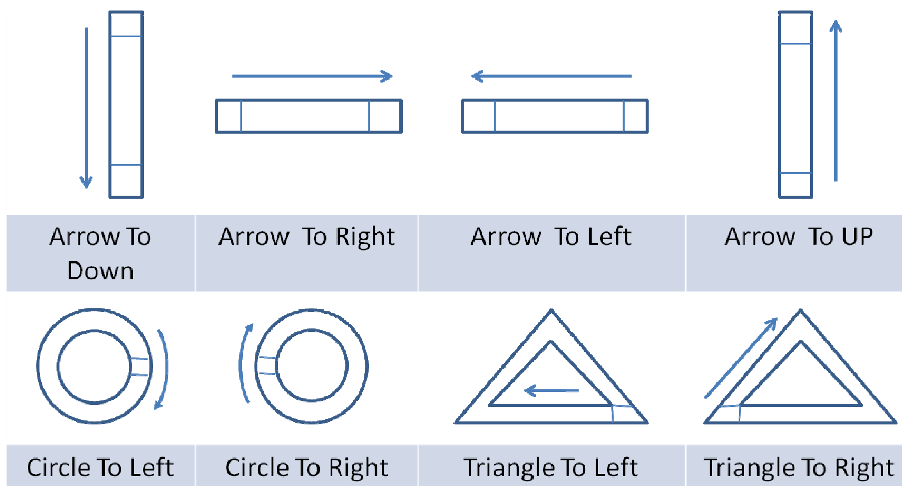

Figure 3. Eight Gesture Applications.

This research includes eight gestures (i.e., circle to right, circle to left, triangle to right, triangle to left, arrow down, arrow left, arrow right, and arrow up) as shown in Figure 3. Each user was asked to trace gestures for each of the two circles and two triangles from the centre of the box (start point) through the middle of the path to the centre of the same box (start and the end points of the triangle and circle are represented by the same box). With regard to the remaining four gestures (i.e., arrow down, arrow left, arrow right, and arrow up), the start and the end points of the gestures were represented by two boxes. In all gestures, an arrow was used as a guide to indicate the direction of the gesture. Following the instruction of [19], the participants were asked to trace the complete gestures as quickly and accurately as possible. In what follows, the results of this study will be discussed considering the user identification accuracy and performance variations across different users.

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5. RESULTS AND DISCUSSIONS

In this study, performance variations across different users, and individual variations of users for each feature were considered, as follows:

5.1 Performance Variations across Different Users

This section aims to provide a brief analysis of the performance of individual and combined features in terms of their discrimination power across different users. In term of analysing the results based on the individual features, Figure 4 shows that on small smartphone 19% and on mini-tablet 42% of the users have unique FP compared to other features. This FP could be used alone to perfectly identify users for 100% accuracy. But the results for SP is the least accuracy, this is because of the minimal samples were used in the training dataset, as this feature depend on how accurately the user can perform the gesture. If partly, the gesture is not performed correctly, the SP will decrease the accuracy.

While in term of combined features, Figure 5 and Figure 6 show that user's discrimination was high for (FP+MT), where the accuracy on small smartphone is 38% and on mini-tablet is 42% of the users have unique FP+MT compared to other combined features that could be used alone to perfectly identify users for 100% accuracy. This indicates that the combined features have high accuracy results compared to the individually features, and this provides evidence that the combination can enhance the accuracy results, this is agree with the study [18] in the field of the combination influence on the accuracy results.

Based on performance variations across different users' results, we concluded that the accuracy could be enhanced if we combine only the features that have high performance discrimination for users to perfectly identify the users for 100% accuracy.

The results of performance variations across different users and individual user performance variations for each feature were not high and they need to be enhanced by conducting more analysis using a percentage of power discrimination of users for the used features (e.g. FP), and increasing the sample size.

To the best of our knowledge we have not came across a study conducted for biometric identification on smartphones using eight different gestures, the way on how we analysed the data using DTW and ED algorithms to calculate the accuracy and speed in order to prepare the features to the user identification processes, as well as the way on how we combined features to enhance the accuracy and the performance variations across different users that were not considered in the previous study.

5.2 Individual User Performance Variations for each Feature

This section aims to provide more details on analysis of the individual variations of users for each feature on both smartphones devices. On small smartphones, the Figures from Figure 7 to Figure 10 show users who have scored almost high accuracy results. The almost high accuracy was for users on FP, where on 100% there was 5 users, and on 80% there was 4 users that total 9 users who almost scored high accuracy compared to other features. While the second total number of users was on MT, where there were 8 users who scored 100% and 80%.

On Speed, there were the total 7 users who scored 100% and 80% ; however the total number of users who scored only 100% accuracy on Speed is greater than on MT. This provides evidence that increasing number of users who almost scored high accuracy (e.g. 80%) may influence largely on user identification accuracy if the combination is implemented, as shown on FP and MT in Figure 5.

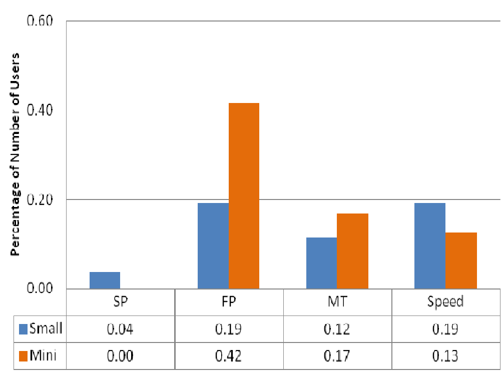

Figure 4. Individually feature influence on users

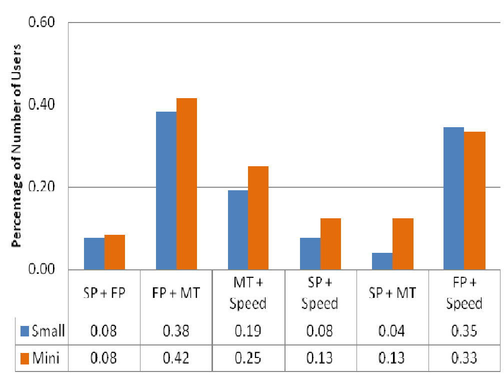

Figure 5. Two features combination influence on users.

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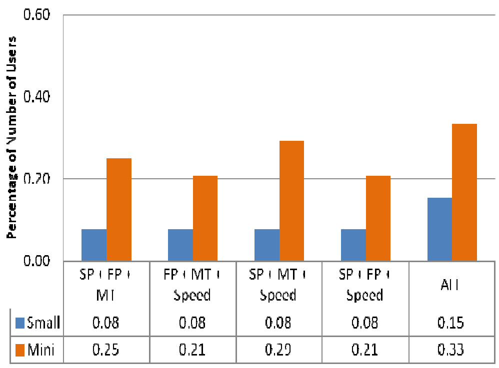

Figure 6. Three features combination and all influence on users

While on mini- tablet, the Figures from Figure 11 to Figure 14 show that the total number of users who scored 100% or almost scored high accuracy (e.g. 80%) for FP, MT, and Speed are greater than the results on small smartphone. But the number of users who scored high accuracy for SP was on small smartphone compared to mini-tablet, this needs more investigation to find out the influence of features on screen sizes for users especially for SP.

The importance of investigating the influence of features on screen sizes for users will provide insight about the influence of feature weight on accuracy when they are implemented.

6. CONCLUSION AND FUTURE WORK

This paper presents methodology for user identification on smartphone and mini-tablet using finger based gestures, which improves user identification. The individually and combined features were considered in this paper to verify the user. After extracting the gestures trails from users, the trials then compared with trusted user values using ED and KNN.

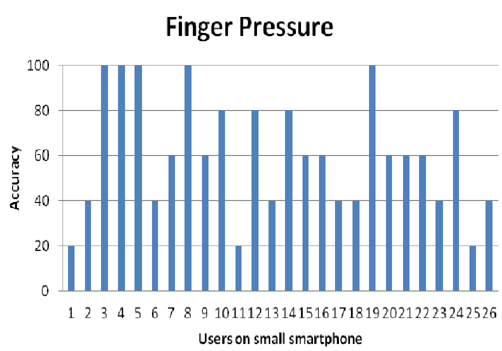

Figure 7. The results of 26 users on small Smartphone for FP

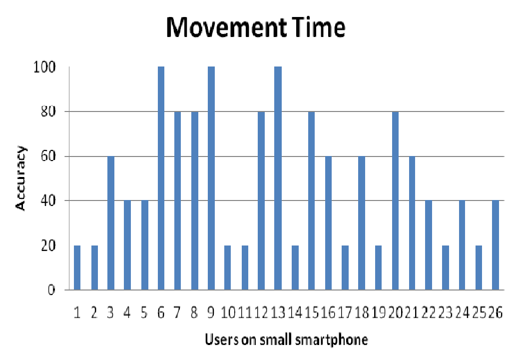

Figure 8. The results of 26 users on small Smartphone for MT.

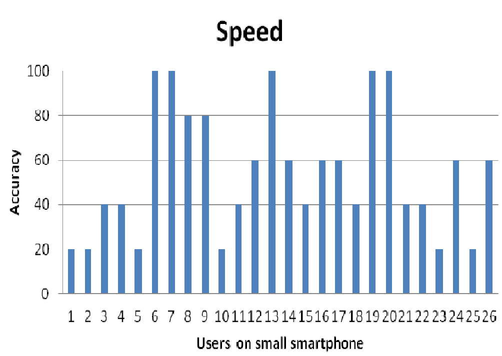

Figure 9. The results of 26 users on small Smartphone for Speed.

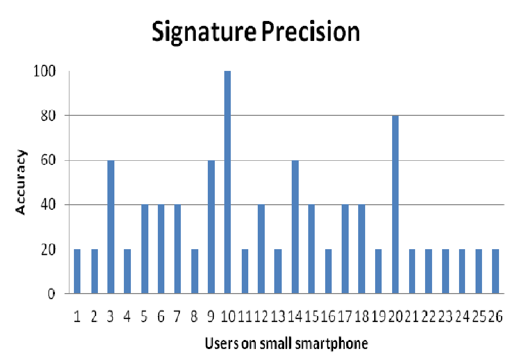

Figure 10. The results of 26 users on small Smartphone for SP.

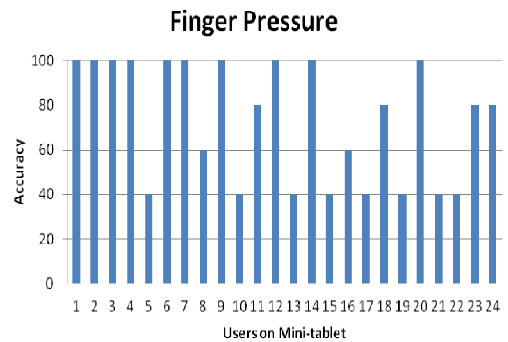

Figure 11. The results of 24 users on mini-tablet for FP.

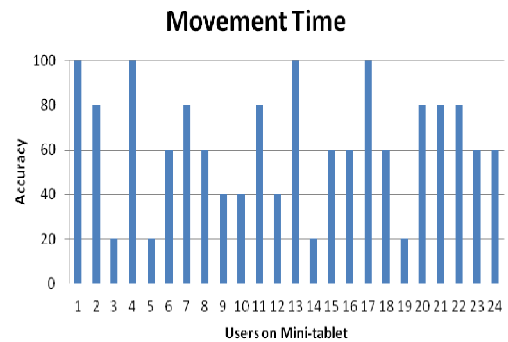

Figure 12. The results of 24 users on mini-tablet for MT.

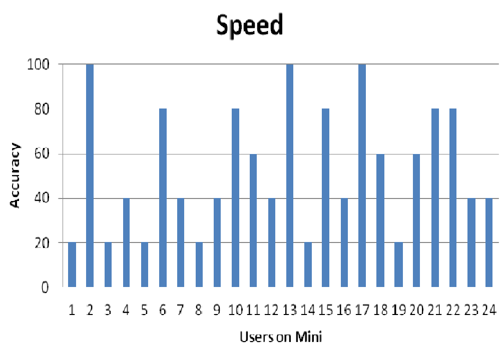

Figure 13. The results of 24 users on mini-tablet for Speed.

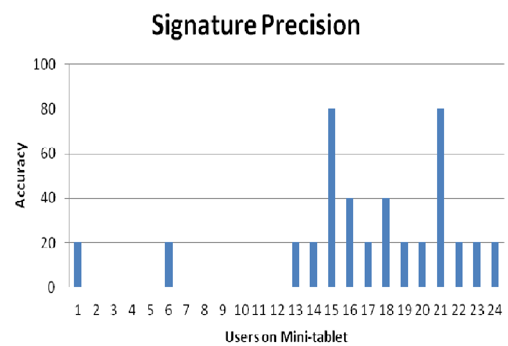

Figure 14. The results of 24 users on mini-tablet for SP.

The results provide evidence that the combined features can enhance the accuracy results. In addition, some of features (e.g. FP) has discrimination power for user compared to other features, which would be used to improve the accuracy if implemented largely or when combined with another feature that has only high accuracy in order to verify the user perfectly. Using minimal number of samples in the training dataset results least SP accuracy.

This research could be implemented largely to unlock screen system used in most smartphones. In addition, the accuracy needs to be enhanced by adding new combination based on the percentage of power discrimination of users for the used features (e.g. FP), as well as increasing the number of participants.

In the future work, we are planning to consider the combined features based on the percentage of power discrimination of users improve the user identification accuracy. Also, we are going to conduct the same study using image processing.

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