Transparent authentication: Utilising heart rate for user authentication

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Transparent Authentication: Utilising Heart Rate for User Authentication

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***Abstract*—There has been exponential growth in the use of wearable technologies in the last decade with smart watches having a large share of the market. Smart watches were primarily used for health and fitness purposes but recent years have seen a rise in their deployment in other areas. Recent smart watches are fitted with sensors with enhanced functionality and capabilities. For example, some function as standalone device with the ability to create activity logs and transmit data to a secondary device. The capability has contributed to their increased usage in recent years with researchers focusing on their potential. This paper explores the ability to extract physiological data from smart watch technology to achieve user authentication. The approach is suitable not only because of the capacity for data capture but also easy connectivity with other devices – principally the Smartphone. For the purpose of this study, heart rate data is captured and extracted from 30 subjects continually over an hour. While security is the ultimate goal, usability should also be key consideration. Most bioelectrical signals like heart rate are non-stationary time-dependent signals therefore Discrete Wavelet Transform (DWT) is employed. DWT decomposes the bioelectrical signal into *n* level sub-bands of detail coefficients and approximation coefficients. Biorthogonal Wavelet (bior 4.4) is applied to extract features from the four levels of detail coefficents. Ten statistical features are extracted from each level of the coffecient sub-band. Classification of each sub-band levels are done using a Feedforward neural Network (FF-NN). The 1st, 2nd, 3rd and 4th levels had an Equal Error Rate (EER) of 17.20%, 18.17%, 20.93% and 21.83% respectively. To improve the EER, fusion of the four level sub-band is applied at the feature level. The proposed fusion showed an improved result over the initial result with an EER of 11.25%. As a one-off authentication decision, an 11% EER is not ideal, its use on a continuous basis makes this more than feasible in practice.**

***Keywords—User Authentication, Bioelectrical Signals, Discrete Wavelet Transform, Smart Watch, Smart Phone*.**

I. Introduction

Authentication is the process of accurately authorizing a person to access secured information but it comes with some inconvenience on the part of the subject because the subject will need to provide the correct credentials to access the information [1-4]. Transparent authentication has been proposed as a possible improvement over these inconveniences by applying biometric modalities in a non-intrusive manner (i.e. the user does not explicitly provide the sample, rather the sample is captured during a user's normal device interactions) [5-8]. These emerging biometric modalities include gait, body odour, ear resonance, lip print and bioelectrical signals [9-12]. The use of emerging biometric modalities is on the increase because of their advantages with respect to reliability, usability and accuracy in a transparent capture mode [13]. Recent research on emerging biometrics applying bioelectrical signals have focussed more on the use of Electrocardiogram (ECG), Electroencephalogram (EEG), Electromyogram (EMG), Mechanomyogram (MMG) and Electrooculography (EOG) with more emphases on EEG and ECG as shown in the work of Faust [14], Mporas [15], Borghini [16], Thomas [17], Suja Priyadharsini [18], Sabow [19], Miramontes [20] and Ito [21].

The direct involvement of a subject in the authentication process brings about usability issues at the point of entry. As stated earlier, in as much as security is the major concern in designing an authentication system, usability still plays an important role in the use of the of the system [3, 4, 22] but it comes with its own issues too [6]. The level of trade-off between security and usability plays a role in the choice of authentication system, a factor worth considering [4, 23, 24]. It is also expected that the security mechanism of a computing device should be robust and adapt to different environment [25]. The application of bioelectrical signals extracted via a smart watch for user authentication should improve usability as well as convenience due to the non-intrusive nature of the technique [26, 27]. In this paper, the authentication system builds the subject's profile by extracting the heart rate through a smart watch. Two experiments were conducted; the first experiment determined the persistency of the signal pattern of the heart rate while the second experiment determined the viability of using the signal to authenticate a subject.

II. BACKGROUND

Much of the previous research has used bioelectrical signals obtained from ECG's where the signals were extracted from the heart beat using specialized devices that were often intrusive in nature. Table 1 presents a summary of the studies on ECG bioelectrical signals, their methods for feature extraction, classification and results.

Table 1. Study showing the use of Electrocardiogram (ECG) for authentication (MF: Morphological Features; LDA: Linear Discriminant Analysis; QDM: Quartile Discriminant Measurement; QRS :QRS Detection; MD; Mahalanobis Distance; PCA :Principal Component Analysis; KNN; Knearest Neighbor; LDA; Linear Discriminant Analysis; WT: Wavelet Transform; CC; Correlation Coefficient; ICA: Independent Component Analysis; SVM: Support Vector Machine ; LZ: Lempel-Zil; RBF: Radian Basis Function)

Author	**Feature Extractor**	**Classification**	**No of Subj.**	**Length**	**Success rate**
[28]	MF	LDA	29	2 mins.	97 & 98%
[29]	MF	QDM			100%
[30]	QRS	MD	10	30 sec.	
[31]	QRS MF & PCA	KNN and LDA	20		94.47% & 97.8%
[32]	MF	MD	16	2 min.	100%
[33]	WT	CC	50	32-51 ms	89% - 95%,
[34]	QRS	CC	10		99%
[35]	ICA And WT	SVM	47	20 mins.	98.11 -99.33%
[36]	MF	LZ	19	10 mins.	100%
[37]	WT	RBF	16		91%
[38]	QRS	SVM			99.52%

Isreal [28] used the fiducial points from 29 subjects as the feature for authentication. The fiducial collection point includes the neck and the chest. The neck achieved a result of 82% while chest achieved 79%. [29] investigated the possibility of using the normalized time-domain features of Electrocardiogram (ECG) for improving of identification. The ECG signal is measured and extracted between the right and left arm using a Biopack MP-150. The first was to measure the ECG during rest and the second measurement was when the individual is active. The recording is done in 30 seconds on 10 male subjects in two sequences. The reading at a normal heart rate using ECG at a slow rate is 60 ~ 80 and 120 ~ 140 at a fast rate. For Feature Extraction and Classification, after analyzing the sampled data sequence of the ECG beat by beat, the characteristic points of its waveform of P-wave, QRS complex and T-wave are computed as the features for classification of the subjects.

Morphological Features, QRS Detection and Wavelet Transform are among the most used feature extraction methods listed in Table 1. Each of the methods has advantages and disadvantages depending on the type of signal and condition of the features were extracted. The morphological features method is suitable for ECG feature extraction and is suitable for heart rate because this rate varies from one heartbeat to the next [39]. This can show variable fiducial points for feature extraction which will affect the morphological features. QRS Detection has the advantage of efficient extraction of beat-tobeat intervals (RR) from long electrocardiogram (ECG) recordings, it is also suitable for real-time analysis of large datasets but has a disadvantage with regards to its of implementation in software as it is difficult to operate it in real time [40]. Wavelet Transform is chosen for the feature extraction because it has a varying window size, being broad at low frequencies and narrow at high frequencies. It is better suited for analysis of sudden, transient signal changes [41] and irregular data patterns, that is, impulses existing at different time instances [42]. From the works discussed earlier, it shows that the most used classification method is Neural Network and SVM. The two methods have thier own advantage depending on the type of bioelectrical signal. Research suggest that neural networks can perform better in nonlinear statistical modeling and is an alternative to logical regression [43] while SVM performs better classification on emotional features which is prevalent in EEG signals [44].

III. EXPERIMENTAL METHODOLOGY

A. Data Collection and Experimental Design

Most of the data samples from the previous experiments are control samples [28, 30, 34]. While this is ideal some experimental studies, a typically highly controlled lab environment fails to understand the variance that would be exhibited from a real-life data capture. This study investigates several areas, the viability of the underlying technology to measure the signals successfully, a small-scale study to investigate the nature of the signal given a variety of tasks (e.g. walking, sitting) and also to determine the feasibility of the approach using real-life activity data. This led to the development of three experiments:

1. A technology evaluation of smart watches
2. An activity based experiment to examine the variability in the underlying signal
3. A real-life data capture to determine the feasibility of the approach.

The technology evaluation used three smartwatches Mio Fuse, Fitbit, Microsoft Band. A chest-band Polar H7 heart rate monitor was used as a reference signal against which the smartwatches were compared. To appraise the accuracy of the signals extracted from the watches, the extracted heart rate signal from a subject wearing all the smart watches and the chest band were capture and analyzed. The signal extracted was compared again the chest band which is more accurate around the chest compared with other parts of the body [40]. An android smart phone with a third party application was installed on the phone to enable it to store the heart rate signals. The extraction from the smartwatch to the phone was via a Bluetooth connection. Taking usability into consideration, the mobile application and the smartwatch communicates without the intervention of the subject when extracting the bioelectrical signal. The application starts as the phone comes on and establishes a connection with the watch. The heart rate is extracted in beat per minute at a rate of 8 samples per second.

To study the variation of signals from one subject to another using the Microsoft band, the heart rate signal was extracted from five subjects. A predefined task was given to the five subjects to be repeated three times. These tasks included a combination of both low and high speed of walking, climbing up and down stairs, standing and sitting. The time between the three tasks ranged from a day to two days between tasks.

In the real-life data capture experiment, the aim was to develop a unique identifier for each of the 30 subjects by extracting features from the heart rate. The subjects were recorded for one hour without a predefined task to make it as natural as possible. As expected in a real life scenario, the possibility of environmental interference like noise (i.e. wireless and other Bluetooth connection) is expected. The data collected through the Microsoft band faced a number of issues including:

- Disconnection: The Microsoft band sometimes loses connection with the phone but with the application setting, it can re-establish connection without the intervention of the subject. To make up for this, the data collection time frame is increased makes room for any disconnection gap. The disconnection duration is indicated with a '*Null*' which is deleted in processing the data.

- Heart rate acquisition: the heart rate sensor takes some time to start recording the heart rate. At this stage the heart rate output remains constant and it is indicated as "*Acquiring*" until the band is locked to the app. The same remedy for the disconnection is applied to this too.

- Sampling Rate: the sampling can be set at 16 Hz, 32Hz and 64Hz. Due to android issues, the sampling rate setting can return to the default rate at the start of each extraction, it can be monitored to make sure the sampling rate is right at the beginning of each extraction. To solve this, after extraction all signals are down-sampled to 8 samples per second.

B. Feature extraction

The feature extraction algorithm converts bioelectrical signal information into sets of feature vectors. The feature extraction method should be good enough and should meet some properties like repeatability, distinctiveness, quantity, accuracy, and efficiency [45]. However, the extraction technique will need to be carefully considered taking note of the nonstationary nature of bioelectrical signals. There are different types of techniques as earlier discussed which include Wavelet Transform [46,47,48], Independent Component Analysis [49], Morphological Features [31] , Discrete Cosine Transform [50]. After investigating the properties of the heart rate signals, the Wavelet feature extraction technique is adopted using discreet wavelet transforms.

The use of discreet wavelet transforms is becoming popular in the measurement and analysis of time-frequency nonstationary signals and the spectral component variation [51,52]. It is widely used in feature extraction as in the case of Mallat [51], Subasi [53] and Jahankhani [48]. Wavelet transform is also useful in processing different types of transient signal analysis [54]. It decomposes a signal into a subband of wavelet signals which can be implemented with several wavelet families. The wavelet families include Biorthogonal, Morlet, Symlets, Mexican Hat, Haar, Daubechies, Coiflets, Meyer [55, 56]. Wavelet transform is classified into two types, continuous wavelet and discrete wavelet transform. Existing literature has shown that noise is an issue when processing a signal; this also applies to bioelectrical signals. To achieve an acceptable noise level in a signal, a filter is applied to increase the SNR. As stated earlier, the use of wavelet transform eliminates the direct application of a filter in this work because wavelet transform decomposition is used to implement noise reduction [57, 58]. Discreet wavelet transform decomposition splits the input signal into approximation of coefficients and detail coefficients [59,54]. This depends on the type of wavelet family used as a suitable wavelet can concentrate 90% of the signal energy on the decomposed coefficient [58]. The decomposition enables the signal to be analyzed at the different *n* levels [60]. Each *n* level is further decomposed into a high and low frequency signal component using a filter bank [54, 61].

Ten statistical features are extracted from each level of the sub-band levels are the Variance, Maximum, Amplitude Minimum Amplitude, Maximum Energy, Minimum Energy, Standard deviation, Peak2peak, Root mean square level(RMS), Mean or Median absolute deviation and Peak magnitude to RMS ratio.

C. Classification

To classify the features extracted, a Nueral Network (NN) is used. The classification evaluation metric calculates the Equal Error Rate (EER) using False Acceptance Rate (FAR) and False Rejection Rate (FRR).

- *The Equal Error Rate (EER)* is the point at which the False Acceptance Rate (FAR) and False Rejection Rate (FRR) meets also known as Receiver operating characteristic (ROC)

- *The False Acceptance Rate (FAR)* is the rate at which a subject that is legitimate is falsely refuse access to the system and

- *The False Rejection Rate (FRR)* is the rate at which an impostor is accepted as a legitimate subject.

IV. RESULTS

From Figure 1 it is observed that the Fitbit, Mio Fuse and the Microsoft Band perform consistently with the Polar H7 in sequence as shown in Table 2.

The result from the 30 subjects applying the four sub-band classifications are encouraging as illustrated in Figure 3. The use of a Neural Network (NN) feed forward classifier achieved 17.2% EER at the first level which is the best result and 21.8 % at the fourth level as the worst. Level 1 and 2 sub-bands have a higher score compared to level 3 and 4. This means that level 1 with the lowest score has 82.8% of all subjects accurately

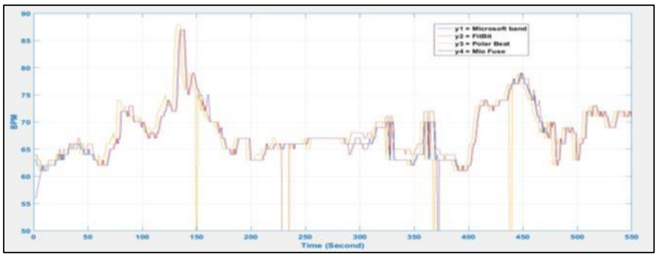

Figure 1. Bioelectrical recording from the Microsoft Band, Fitbit, Polar HR & Mio Fuse

Table 2. Fitbit, Mio Fuse and Microsoft Band sensor comparison

Sensors	**Microsoft Band**	**Mio Fuse**	**Fitbit**	**Polar H7monitor**
Heart Rate	X	X	X	X
Accelerometer	X	-	X	-
Pedometer	X	X	-	-
Walking Speed	X	-	X	-
Calories	X	X	-	-
Distance	X	X	X	-
Gyroscope	X	-	-	-
Magnetometer	X	-	-	-
Altimeter	-	-	X	-
Ambient Light	X	-	-	-
Thermometer	X	-	-	-
Ultraviolet	X	-	-	-
Light Sensor	X	-	-	-
Galvanometer	X	-	-	-
Microphone	X	-	X	-

The result of the variability of subjects as illustrated in Figure 2 shows that the five subjects have different signals amplitude that are not close and subjects can be differentiated and shows a potential to use this approach for authentication. There are changes depending on the activity carried out by the subjects. This shows that different activities affect the heart rate pattern therefore there is a need to categories the activities into high and low activities for effectivity analyzing the bioelectrical signals that will be extracted from the subjects.

identified. The continuous reduction as the level increases does not mean that all subjects performed badly at the individual rate.

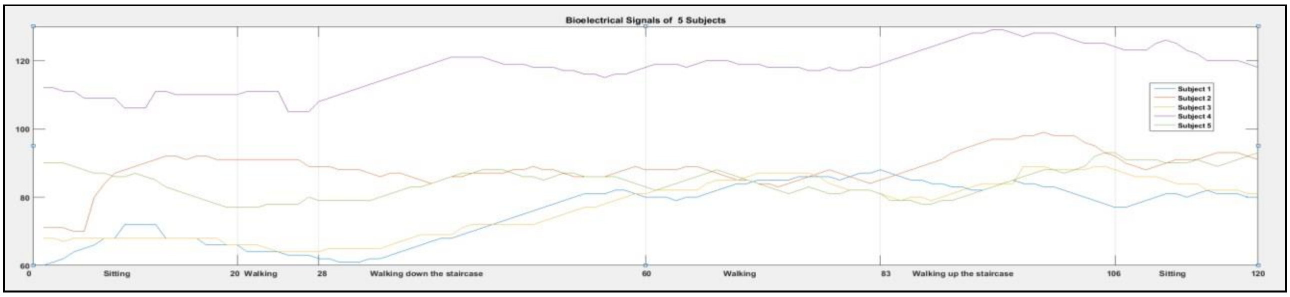

Figure 2. Bioelectrical signal of 5 subjects showing the pattern variance among the subject

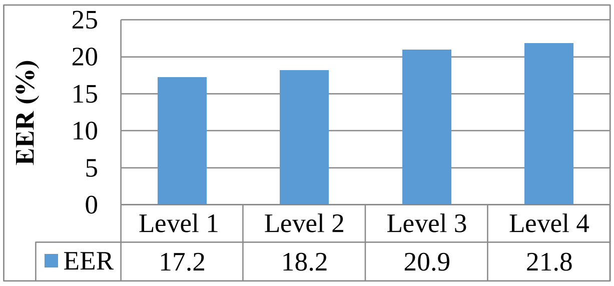

Figure 3. The EER sub-band classifications of subjects from level 1 to 4.

From Figure 4 the EER of individual results across the four levels of sub-band shows that individual's performance varies depending on the levels therefore fusion of the feature is undertaken to improve the result. The fusion is done after extracting the feature at various levels. The features are first normalized at each level before the fusion is done. The result at the fusion level has shown an improved EER of 11.25%.

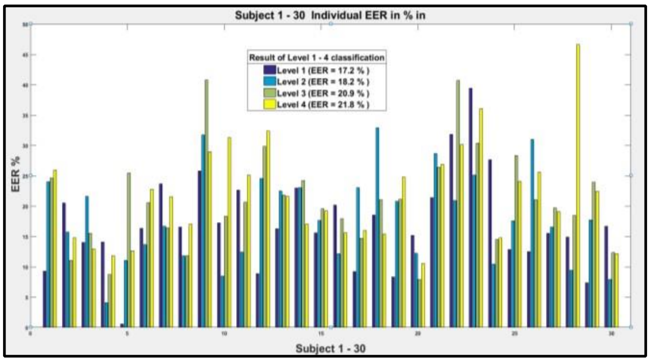

Figure 4. Showing result of individually performance

V. Discussion

A close look at the Table 3 shows the performance between subjects at the different levels of the sub-band. The best individual performance at the first level is subject 5 with an EER of 0.6%, best at the second level is subject 4 with EER of 4.1%. Subject 20 has the best performance at the third and fourth levels with EER's of 7.9% and 10.6% respectively. This mean performance cuts across difference sub-band levels.

It will be ideal to achieve a system performance of EER below 10% for the system which some subjects achieved. The performance of individual subjects achieving below the EER of 10 % cut across all levels. In level one, subject 1 (9.3%), 5 (0.6%), 12 (8.9%), 17 (9.2%), 19 (8.3%) and 29 (7.4%) achieved less than 10%. Level two results below 10% are recorded for subject 4 (4.1%), 10 (8.5%), 28 (9.4%) and 30 (7.9%). Level three shows subject 4 scoring 8.8% and 10 scoring 7.9% and level four has none though subject 20 achieved 10.6% which is closest to the expected mark.

Table 3. Results of EER of Subjects at different levels of the sub-band

Subject's EER result at different levels (%)									
ID	Level				ID	Level			
	1	2	3	4		1	2	3	4
1	9.3	24.0	24.6	25.9	**16**	20.1	12.1	17.9	15.6
2	20.5	15.7	11.0	14.8	**17**	9.2	23.0	14.7	16.0
3	14.0	21.6	15.5	12.9	**18**	18.6	32.9	21.0	15.4
4	14.1	4.1	8.8	11.8	**19**	8.3	20.8	21.1	24.8
5	0.6	11.0	25.4	12.6	**20**	15.2	12.2	7.9	10.6
6	16.3	13.7	20.6	22.8	**21**	21.4	28.7	26.4	26.9
7	23.7	16.7	16.4	21.5	**22**	31.8	20.9	40.7	30.1
8	16.6	11.8	11.8	17.0	**23**	39.4	25.1	30.3	36.1
9	25.8	31.7	40.8	29.0	**24**	27.7	10.4	14.5	14.8
10	17.2	8.5	18.3	31.2	**25**	12.8	17.6	28.3	24.1
11	22.6	12.4	20.6	25.1	**26**	12.5	31.0	21.0	25.6
12	8.9	24.6	29.9	32.3	**27**	15.5	16.6	19.7	19.1
13	16.3	22.5	21.8	21.6	**28**	14.9	9.4	18.5	46.6
14	23.0	23.0	24.2	17.0	**29**	7.4	17.7	23.9	22.4
15	15.6	17.7	19.6	19.2	**30**	16.7	7.9	12.3	12.1

The use of multiple instance of a biometric can add value to the result but it can also have implications depending on the dataset [62]. Fusion of biometric is done at different levels, the feature extraction level, match score level; and the decision level. The fusion of all level sub-bands is done at the feature level and the results showed an improved EER of 11.25%. This is an improvement of 5.95% which mean 88.75% of all subjects were accurately identified as shown in Figure 5.

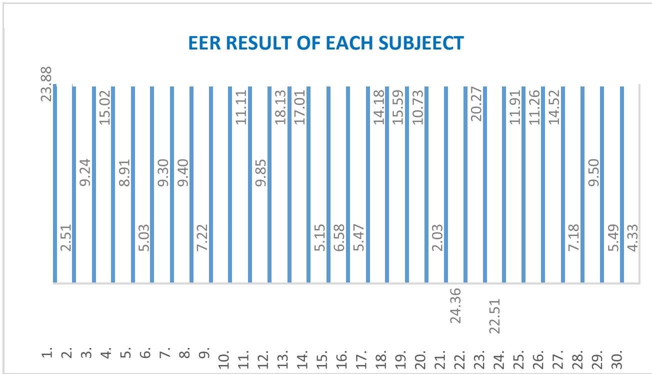

Figure 5. Showing classification result of all 4 levels individually

The experiment showed different subjects performed differently depending on the sub-band levels and the sub-band fusion classifications. Some subjects performed well on both while others on only one of the classification. It is expected that with the fusion of the sub-band, there should be improvement across all subjects but that is not the case. From the result of the sub-band fusion, it shows more subjects perform better while some unexpectedly did not improve in performance. This is seen in subject 3's performance, there is little change in the sub-band fusion classification where they scored 15.02% which is almost the same on the 3 level subband results at 15.50%. It has a better result at level 4 scoring 12.9% compared to the sub-band fusion with 15.02%. The same is for subject 10 with the best result on level 1 at 8.5% compared to the sub-band fusion at 11.11%. Other subjects scoring the best result at level 1 of the sub-band level include subject 12 scoring 8.90% compared to sub-band fusion scoring 18.13%, subject 13 at 16.3% (sub-band fusion 17.1%), subject 17 at 9.2% (sub-band fusion 14.18%), subject 19 at 8.3% (subband fusion 10.73%), subject 21 at 21.4% (sub-band fusion 24.36%) and subject 26 at 12.5% (sub-band fusion 14.52 %). The best results at the sub-band level 2 include subject 24 at 10.4% and subject 28 at 9.4% compared to the scoring at the sub-band fusion at 11.91% and 9.5% respectively. At Level 4, only subject 18 recorded their best performances at 15.4% compare to sub-band fusion at 15.59%. In term of individual performance, the fusion of all levels has shown to be effective in discrimination of subjects. 60% of individual results improved with the fusion introduced. While 40% of the subjects scored a better EER at the sub-band level. The best for each of them showed that subject 4 scored 8.8%, 12 (8.9%), 17 (9.2%), 19 (8.3%) at the 1st level, 2nd level have subject 10 scoring 8.5%, 28 (9.4%). These subjects individually performed below the expected 10% of EER. This brings to a total of subjects scoring below 10% of EER across the sub-band and the fusion classification to about 66%.

VI. CONCLUSION

Over 66% of individuals achieved an EER below 10% across the fusion of sub-bands; the performance is promising noting that the overall EER performance of the fusion was 11.25%. The use of one bioelectrical signal is a limitation to the fact that it is affected by aging, emotional factors [63]. Therefore, the use of multi-instance, multi-modal or multibioelectrical signals is expected to enhance the performance and overcome these limitations. The use of the Microsoft band will be beneficial in this regard because as stated earlier, the sensors in the Microsoft band 2 can extract other bioelectrical signals like skin temperature, Galvanize Skin Response (GSR), Heart Rate Variability (HRV) and gyroscope and accelerometer for orientation. With these available signals on the Microsoft band, the system can be improved upon by applying multi-bioelectrical signals for Transparent User Authentication.

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