

# An HMM-based Behavior Modeling Approach for Continuous Mobile Authentication\*

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## ABSTRACT

This paper studies continuous authentication for touch interface based mobile devices. A Hidden Markov Model (HMM) based behavioral template training approach is presented, which does not require training data from other subjects other than the owner of the mobile. The stroke patterns of a user are modeled using a continuous left-right HMM. The approach models the horizontal and vertical scrolling patterns of a user since these are the basic and mostly used interactions on a mobile device. The effectiveness of the proposed method is evaluated through extensive experiments using the Touchalytics database which comprises of touch data over time. The results show that the performance of the proposed approach is better than the state-of-the-art method.

## Keywords

Touch pattern, Continuous authentication, Hidden Markov Model, Behavioral biometric, Security

## 1. INTRODUCTION

Existing technology typically requires users to authenticate themselves based on passwords, which have been shown to be vulnerable to various attacks, including password guessing and eavesdropping ([13, 6]).

Multiple methods were proposed to replace text passwords with graphical passwords [8, 7, 1, 25, 3, 9]. With the growing popularity of touch interface based mobile devices, the touch-surface has become the dominant human-computer interface. This has led to the need for authentication techniques better suited to a touch interface, such as [18, 23]. Research by Sae-Bae et. al [17, 19] showed that users can be uniquely identified from their multi-touch gestures on multi-touch devices with high-probability. However, just like text passwords, graphical and gesture password alternatives authenticate users only at the time of login and they do not address unauthorized access by an attacker after the user initially logged on into the device.

In this context, continuous authentication or active authentication [22, 2, 15] mechanisms have emerged as a very promising approach to alleviate the security problems that

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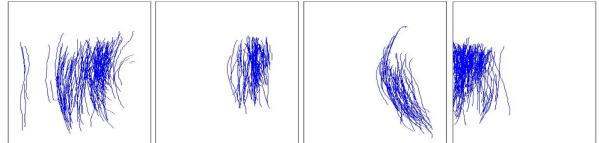


Figure 1: Spatio-temporal touch patterns of four users

stem from poor authentication technology. Here, instead of authenticating a user at the time of login, the system continuously monitors aspects of the user behavior biometrics in order to maintain authentication after login. Some earlier work on behavior biometrics based continuous authentication include keystroke dynamics [5, 20], speaking pattern [26] and device use patterns [12, 14].

Based on touch behavior biometrics, a continuous authentication method has been developed by Frank et. al. [11] (Touchalytics). They observed that during a stroke on the touch screen of the mobile device, the spatio-temporal pattern (as shown in Figure 1) of fingers along with the area of touch and pressure is quite distinctive for every person. They reported high performance when using multiple movements to authenticate the users. Based on this observation various systems have been developed, like, SenGuard [21], FAST [10], and SilentSense [4]. Most of them used other modalities along with touch behavior biometrics, like, motion, voice, location history, walking pattern, to increase accuracy.

However, the classifiers (k-Nearest Neighbor, Support Vector Machine) employed by the above mentioned approaches including [11] require training data from both the owner as well as other users for training. Since obtaining training data from other users is not feasible, an authentication method that does not need data from other users during training is desirable.

This paper presents an HMM based algorithm for continuous authentication on touch devices which serves this purpose. This research is built on the premise that to implement continuous authentication in a feasible way, a method which offers the possibility of being trained with only users data and can be updated with new data over a period of time is needed. HMM can be trained and updated with time, and is also relatively simple and feasible to use, which makes it a good choice for continuous authentication.

The key contributions of this paper are twofold. First, an

HMM based behavior model from the owner's touch information is developed. Second, an in-depth analysis of the proposed method is carried out in different usage scenarios.

The proposed HMM system is tested and compared to the performance of the Touchanalytics system [11]. The rest of the paper is organized as follows. Section 2 presents the proposed approach in detail. In Section 3 the extensive experimental results are discussed and finally Section 4 concludes the paper.

## 2. PROPOSED APPROACH

The proposed framework works in two steps: training and authentication. During training, a behavior model is created based on the horizontal or vertical touch behavior (pressure, area, duration and position) of a user using HMM. At the time of authentication, the test observations are compared with the stored behavior model to establish the identity of the user.

As mentioned in Section 1, HMM is considered for modeling the stroke patterns of a subject since it is able to capture the local dynamic characteristics of a stroke as well as its shape and length. The touch pattern of a subject is modeled by a double stochastic process, characterized by a given number of states each of which is modeled by a mixture of Gaussians. The left-right topology is chosen with no state skip allowed since it can efficiently describe continuous processes. HMM allows modeling of temporal variations, where the duration of the state is variable. The states then capture the transitive properties of the consecutive coordinates of the stroke. Thus, the state transition matrix represents the dynamic properties of the strokes. The state sequence that maximizes the probability of observing the training strokes becomes the corresponding model of a subject.

### 2.1 Training HMM

After normalizing the data set, it is used for training the HMMs and finding the optimum parameters. As a first step, the state transition matrix is initialized and the prior probability matrix by random variables without making any assumptions on the touch patterns. Then, training of HMM is done from the initial set of strokes of a subject. The optimum number of states and mixtures of an HMM depend on the complexity and average length of strokes in the training sequences and their inter-variations. To provide sufficient evidence to every Gaussian of every state in the training stage, the number of mixtures times the number of states should be much smaller than the length of the strokes. The Baum-Welch algorithm [16] has been employed for estimating the HMM parameters for each subject. Five-fold cross validation principle is used to estimate the optimal number of states and the associated HMM parameters. Since the parameters yielding the highest likelihood on the validation set has been chosen, the model conveniently characterizes the distinct stroke patterns for each subject while avoids over-fitting.

### 2.2 Authentication using HMM

Once the behavioral models for all subject classes have been learned through HMMs, authentication of the subjects can be performed by computing the log-likelihood of the input strokes using the Viterbi algorithm [16]. Since the length of the stroke influences the log-likelihood (the log-likelihood de-

creases exponentially with the increase of the stroke length), the latter is normalized by the stroke length.

However, since the normalized log-likelihood is length-invariant, two strokes, one being a part of the other, may produce similar normalized log-likelihood despite being of different lengths. So, an additional measure named as *stroke kinematics* is introduced. It represents the percentage of time spent in each state. Since states represent segments of atomic motions between points of change in motion pattern, the stroke kinematics captures the detail dynamic properties of the strokes. The same Viterbi algorithm [16] is used to compute the most likely path. Then, if there are  $N$  states in the claimed identity's HMM, stroke kinematics is computed as an  $N$ -component vector where the  $i^{th}$  component represents the fraction of time spent in the  $i^{th}$  state. Next, the similarity scores derived from the normalized log-likelihood value and the stroke kinematics for authentication are described.

#### 2.2.1 Similarity Score Computation

**Likelihood Score:** The likelihood distance  $D_l$  between the normalized log-likelihood of the test stroke  $L_t$  and the average log-likelihood  $L_a$  of the training database is calculated as:  $D_l = L_a - L_t$ . Then the Likelihood score  $S_l$  is computed as follows:  $S_l = \exp^{\frac{-D_l}{P}}$ , where  $P$  is the number of touch features.

**Kinematic Score:** The stroke kinematics  $SK_i$  for each of the training strokes  $i$  are computed beforehand. Then, for a test stroke, the Euclidean distance  $D_e^i$  between its stroke kinematics ( $SK_t$ ) and all the stroke kinematics of the training database ( $D_e^i = \|SK_i - SK_t\| \forall i$ ) is calculated. Next, the average of

these distances ( $\mathbb{D}$ ) is computed as:  $\mathbb{D} = \frac{1}{M} \sum_{i=1}^M D_e^i$ , where  $M$  is the size of the training data set. This average distance  $\mathbb{D}$  is then used to compute the Kinematic Score  $S_k$  by an exponential function:  $S_k = \exp^{\frac{-\mathbb{D}}{Q \cdot N}}$ . The normalization factor  $Q$  in the denominator corresponds to the number of Gaussian mixtures and  $N$  is the number of components of the stroke kinematics.

After getting the two similarity measures ( $S_l$  and  $S_k$ ) of a test stroke, these two scores are combined by taking simple arithmetic mean. The combined similarity score ( $S_c$ ) is used for final authentication.

#### 2.2.2 Multiple Strokes Fusion

Since authentication using single stroke is highly volatile, to increase the robustness of the authentication method, multiple consecutive strokes are used for the final decision. The average of all the combined similarity scores  $S_c$ , obtained from a sequence of strokes, is employed for this purpose.

## 3. EXPERIMENTAL RESULTS AND DISCUSSION

The authentication system is evaluated through calculation of *False Acceptance Rate (FAR)* and *False Rejection Rate (FRR)*. Since these two error rates are inversely related (lower FAR increases the system security while lower FRR increases its usability) *Equal Error Rate (EER)* is also measured, where FAR is equal to the FRR value.

### 3.1 Data Set Description

In absence of any other public touch databases, the data

Table 1: Median EER rates - the newly proposed HMM-based approach reaches low EER levels for all scenarios

No. of Strokes	Equal Error Rate EER (%)					
	Horizontal HMM			Scrolling HMM		
	Short-term	Inter-session	Long-term	Short-term	Inter-session	Long-term
1	5.35	7.42	9.91	5.63	8.17	8.51
11	0.43	1.88	1.75	0.31	1.53	2.80

set of Frank et al. [11] was chosen for its varied test scenarios and realistic nature. Scrolling and horizontal stroke data sets were collected from 41 subjects using four Android phones with similar specification. More details about the data set can be found in [11]. Based on this data, experiments were designed to analyze three different application scenarios with increasing problem difficulty, namely, short-term, inter-session and long-term authentication. The same experimental setup was followed to compare this approach with [11]. The experimental results of the proposed approach in each of the three situations are described in the following subsections.

### 3.2 Short-term or Intra-session Authentication

Short-term authentication is carried out to check whether the authorized user is actually using the phone after successful login. Therefore, authentication is done during the same session of interaction. The training data set was created by randomly drawing data from all available sessions of the two days and the remaining data were used for testing.

**EER Performance:** Since training and testing is done in the same session, authentication in this case is less challenging. For single stroke, the median EER is found to be 5.35% for horizontal stroke HMM and 5.63% for scrolling stroke HMM.

When computing the performance for 11 strokes (similar to [11]), the EER of the proposed method decreases to 0.43% and 0.31% for horizontal and scrolling HMMs

respectively (see Table 1).

**FAR and FRR Performance:** Application where security is not so much of importance (like

games), low FRR is desired.

When the HMM system FRR is zero, the median FAR is 6.78% using one stroke for scrolling HMM and 7.13% for horizontal HMM. After observing 11 strokes, the FAR is reduced to 0.17% and 0.54% for scrolling and horizontal HMMs, respectively.

This shows that the proposed method is highly secure even when FRR is zero, i.e. most usable.

For application where high security is required (like banking), FRR performance of the HMM algorithm is evaluated keeping zero FAR. For one stroke, the median FRR was found to be 19.19% for horizontal HMM and 18.28% for scrolling HMM. The FRR becomes 0.97% after observing 11 strokes for horizontal HMM and 1.65% for scrolling HMM. The results indicate that in highest security situation (FAR = 0), the usability of the proposed method is quite high (<2% FRR).

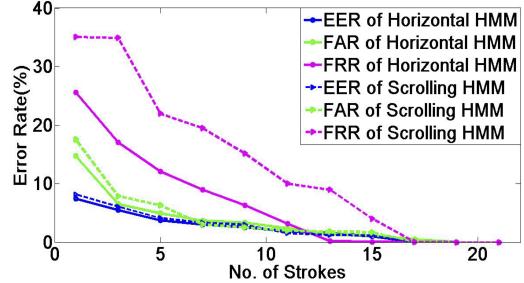


Figure 2: Error rate variation as a function of the number of strokes during inter-session authentication

Since training and testing is done in the same session, the short term test case is more of a ‘proof of concept’ and less challenging. If the attacker gets hold of the device just after successful login, the short-term behavior model will be built from the data of the attacker (since there are no data of the user in the current session and the short-term model does not consider owner’s data from previous sessions). Thus, the attacker will be recognized as the legal one for all further interactions in that session. Therefore, the short-term classifier does not depict realistic situation. The inter-session and long-term or inter-week sessions represent more feasible scenarios since the owner’s data from previous sessions are considered during authentication.

### 3.3 Inter-session Authentication

In inter-session authentication, the user is authenticated across multiple sessions with a brief time gap. Continuous authentication in such scenario would enable the user to use the phone seamlessly without unlocking each time after short burst of activity.

In this case, there was a time gap (of 10-12 minutes) between the initial training session and the following two testing sessions.

**EER Performance:** The EER performance variation with the number of strokes is shown in blue lines in Figure 2. Using single stroke, the median EER is 8.17% for scrolling HMMs.

(see Table 1).

The median EER is 1.88% for horizontal and 1.53% for scrolling HMM. The EER becomes zero after 17 horizontal or scrolling strokes.

**FAR and FRR Performance:** The FAR performance of the proposed approach is shown in green lines Figure 2 while FRR is zero. For 11 strokes, FAR is 1.83% for scrolling HMM and 2.33% for horizontal HMM. Similarly, keeping FAR value zero, the variation of FRR with respect to stroke number is plotted in magenta lines in Figure 2. After 11 strokes, FRR is found to be 10.00% for scrolling HMM and 3.20% for horizontal HMM.

### 3.4 Long-term Authentication

Here the training set comprises of the data collected during multiple sessions of the first day. Then, testing is done using the data captured a week later. Thus, long-term authentication tries to evaluate the classifier when the time gap

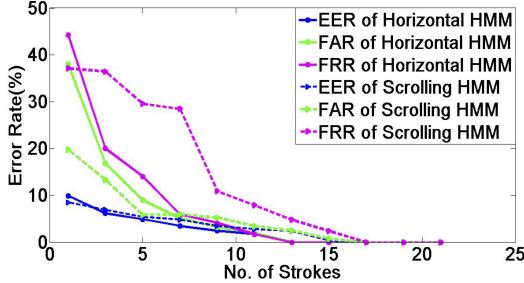


Figure 3: Error rate variation as a function of the number of strokes during long-term authentication

Table 2: Comparative results of the proposed approach against the Touchanalytic approach using 11 strokes

	Touchalytics [11]		HMM-based Approach	
	Worst EER(%)	Median EER(%)	Worst EER(%)	Median EER(%)
Short-term	12	~0%	5	~0%
Inter-session	28	2-3%	12	<2%
Long-term	38	<4%	28	<3%

between the training and testing is quite high. Due to this time gap, authentication in this case is the most challenging one.

**EER Performance:** The EER performance variation with the number of strokes is shown in blue lines in Figure 3. For single stroke, the median EER is found to be 9.91% for horizontal HMM and 8.51% for scrolling HMM. Using 11 strokes, EER decreases to 1.75% for horizontal HMM and 2.8% for the scrolling HMM.

**FAR and FRR Performance:** The green lines of Figure 3 plot the FAR performance of the proposed approach, while FRR is zero. For 11 strokes, FAR is found to be 3.39% for scrolling HMM and 1.96% for horizontal HMM. The FRR variation with stroke number is plotted in magenta lines in Figure 3, while FAR is zero. For 11 strokes, FRR is 7.9% for scrolling HMM and 1.69% for horizontal HMM.

### 3.5 Performance Comparison

The results of the HMM algorithm are compared to the Touchanalytic algorithm in all three scenarios, i.e., short-term, inter-session and long-term, in Table 2. The HMM algorithm performs better in all the test scenarios than [11]. A special case is the long-term situation, which is the most challenging one due to one week time gap between training and testing. Since there are only 14 users' data for this study, the HMM algorithm used all of them without classifying any as outliers. Due to the small data set size, using all 14 users' data is expected to provide more accurate results and therefore these results are more indicative of the expected performance. This is in contrast to the Touchanalytic, which classified the worst 3-5 results as outliers and did not use them for computing the overall median EER. Therefore, the results cannot be compared directly (the Touchanalytic authentication achieves less than 4% for the long-term using only the best 9-11 users).

In addition, since the proposed HMM based approach trains

the model based on only the owner's data, it basically acts as one class classifier to detect whether the current user is legitimate or not. On the contrary, all the state-of-the-art approaches including [11] employ binary classifiers that are expected to give good results due to use of training data from the owner as well as other users [4].

Better performance of the proposed approach indicates inherent strength of the HMM based behavior model.

## 4. CONCLUSIONS

This work introduces a new touch behavior modeling approach using HMM. Since HMM allows automatic continuous training and data updating, it offers significant advantage for continuous authentication. This work is the first one that uses HMM for continuous authentication based on mobile-phone user input.

The authentication method is based only on the stroke patterns recorded from the owner's touch interactions on his mobile device. Extensive evaluation of the proposed approach on the

Touchanalytic database has been carried out.

The results of the HMM algorithm were compared to the Touchanalytic algorithm and found to be superior, without using any training data from other users. The benefits of using only the device owner's data are twofold. First, in case of personal devices, data from other users may not be available. Thus, training the classifier with other users' data is not possible. Second, authentication results with only owner's data reflect the real-life situation in a better way.

This work also looks at the security and the usability of the proposed approach (i.e., in cases where security is critical and FAR=0, or when high usability is needed and FRR=0). The results show that the approach has the potential to be used for user authentication in continuous and implicit manner. Future work involves more extensive evaluation of the approach with a newly generated data set featuring other types of touch patterns and sensory information.

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