CASA: A Framework for Context-Aware Scalable Authentication

ABSTRACT

We introduce context-aware scalable authentication (CASA) as a way of balancing security and usability for authentication. Our core idea is to combine a number of passive factors for authentication (e.g., a user's current location) with appropriate active factors. In this paper, we provide a probabilistic framework for dynamically selecting an active authentication scheme that satisfies a security requirement given passive factors about a user. We also present the results of two user studies evaluating the feasibility and users' receptiveness of our concept. Our results suggest that location data has good potential as a passive factor, and that users can reduce up to 68% of the number of user authentication when using the user authentication system designed with CASA compared to a authentication that requires a fixed active authentication consistently. Furthermore, more than half of the participants who tested our prototype preferred to use our user authentication system on their phones.

Author Keywords

User Authentication, Context-Aware, Mobile

ACM Classification Keywords

H5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.

General Terms

Human Factor, Security

INTRODUCTION

Reliable authentication is an essential requirement for secure systems. Today, passwords are the most common form of authentication. However, passwords are also a major source of security vulnerabilities, as they are often easy to guess, re-used, often forgotten, often shared with others, and are susceptible to social engineering attacks [5,6,16,22,23,25]. We argue that the commoditization of sensor technologies coupled with advances in modeling people and places offers us unique new opportunities for simplifying and strengthening authentication. This insight is the basis for what we call *context-aware scalable authentication*, or CASA.

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CASA embodies two core ideas. First, these cheap digital sensors combined with models of people and places can offer us *passive and robust multi-factor authentication*. By passive authentication, we mean using background sensing and modeling to help verify or infer an individual's identity (such as location data, Wi-Fi MAC address, IP address, nearby devices detected, number of times having logged in at this place), as opposed to active authentication techniques that require explicit interaction from the end-user (such as passwords and fingerprint biometrics). While behavioral biometric authentication also combines multiple features in authenticating users, these features tend to be constrained to a specific domain (e.g., key typing patterns) [29]. CASA differentiates itself by considering a wide array of features extending across multiple domains. Second, this passive multi-factor authentication can be used to *modulate the level of active authentication needed* based on the situation at hand. For example, with CASA, we want authentication to be quick and easy for situations perceived as low-risk (such as being located at work or home), and tough and reliable for high-risk situations (such as being located in an unfamiliar place). We believe that this approach can improve usability while still maintaining a reasonable level of security in the common case, while also improving security in unusual and risky cases.

In this paper, we take a step towards this vision of CASA, focusing primarily on assessing the feasibility and usability of our ideas. This paper is comprised of three parts. The first part introduces our CASA framework, a probabilistic model for combining passive and active factors to authenticate users. The framework allows us to select active authentication schemes to satisfy particular security requirements based on a set of passive factors.

The second part presents a feasibility analysis of using location data as a passive factor. More specifically, we capture where people use their smartphones and how often they use their smartphones in those places, and use this to estimate of the usability impact of modulating the active authentication factor in different places. We obtained location traces from 36 participants for 7 to 140 days (median of 26.5 days). Based on this data, we found that phones were used 60% of the time at the top two locations

where participants spent their time (presumably home and work). This finding suggests that location data is promising as a passive factor. Furthermore, assuming that these two familiar locations have reasonably good physical security, we can bias authentication more towards usability in these locations with minimal impact on security.

The third part of our paper presents the results of a field study. We built a prototype that uses either weak or strong active authentication based on a person's current location. We had 32 participants test our prototype on their phones for one week. Participants rated our authentication system as easy to use and as secure as a system that consistently requires strong active authentication. They also reported that they would prefer to use our authentication system if it was available on their phones. Furthermore, our results demonstrated that our prototype reduced the authentication time up by 68% compared to a fixed authentication system.

RELATED WORK

Existing user authentication systems primarily depend on three types of mechanisms: *what you know*, *what you have* and *what you are*. Passwords are the most commonly used authentication system based on *what you know*. Password authentication has advantages in its simplicity and convenience [23]. However, many studies have found that passwords still put too much burden on users, resulting in users adopting insecure practices such as choosing weak passwords or reusing passwords [5, 25]. Our work in this paper does not seek to replace passwords, but rather complement it by taking into account passive factors and using those to modulate the level of authentication needed. More specifically, in our second analysis, we look at two cases: (a) no authentication when at home or work, and a PIN when at other places, and (b) a PIN when at home or work, and a password when at other places. We used these combinations as one instance of fast versus reliable authentication. Looking at other appropriate combinations is an area of future work for us.

There are other authentication systems based on *what you have,* including eToken USB devices [1], RSA securID [2], and Google's two-step verification [3]. Our work in this paper involves the user carrying a smartphone, but using the smartphone to gather data rather than being used as a token. We envision in the long-term that the act of having one's smartphone nearby could be used as a passive factor, acting as a sort of token (though not in the traditional sense).

Finally, there are authentication systems leveraging *what you are*, or biometrics. There are a wide range of biometric techniques that have been commercialized, including fingerprint scanners, eye recognition, voice recognition, face recognition, and so on. These kinds of biometrics tend to focus on *physical characteristics* of individuals. Researchers have also investigated a number of novel biometric techniques, including for example walking gait [28], keyboard typing pattern [29], what applications and features on a mobile phone are being used [27], blinking pattern, and writing style. These kinds of biometrics tend to focus on *behaviors* of individuals.

Our work differs from traditional work on biometrics in two ways. First, we seek to use commodity devices as well as sensors that already exist on many computers today. In particular, in this paper, we examine the potential for using location a possible factor for authentication. Second, we seek to understand how to use these passive factors as a continuous and passive form of authentication, as well as how to use this information to influence the level of active authentication needed, as the situation warrants.

Modulating the Level of Authentication

It is worth noting that some online services already modulate the level of authentication based on the situation. For example, many bank web sites ask extra questions when logging in from a previously unseen network IP address. Facebook asks additional questions when using an unusual IP address, using a process called social authentication [4]. Users are asked to correctly identify several of their friends before being allowed to login, based on pictures that those friends have uploaded.

The main difference with our work on CASA is to vastly expand the number of factors used when adjusting the level of authentication needed. Our work will also focus on authenticating primarily with a device rather than an online service, as there are serious privacy issues with having behavioral data being stored on multiple online services. We do believe that, in the long-term, CASA can be used in conjunction with hardware support to simplify authentication with remote online services. However, this is currently out of scope of the current paper.

Authentication Systems Leveraging Context

There have been several past systems using some form of contextual information to authenticate users. For example, proximity (often in the form of some kind of wearable device) has been used to authenticate users [8, 11] and pairing [18]. Hulsebosch et al. proposed context-aware access control architecture where users anonymously access services solely based contextual information [24]. Seifert et al. proposed TreasurePhones that protected information on mobile phones based on a user's location as detected by near field communication technology [33].

The closest work to ours is the implicit authentication work by Jakobsson et al. [27]. Their core idea is to see whether user behavior patterns can be used to authenticate users. They considered two behavioral features from the mobile device: time lapse since the user last checked email and GPS location. The two feature scores are combined through a weighted linear function to calculate an overall "authentication score", which is then compared with a pre-defined threshold to authenticate the user.

We have similar goals, in terms of simplifying and strengthening authentication using sensor-based approaches. However, our work differs from these past

works in several ways. First, we seek ways of combining passive and active authentication in appropriate ways, rather than replacing active authentication. Second, we offer a generalizable framework for combining multiple pieces of context (passive factors, in our terminology). Finally, we offer more empirical data as to the potential of using location data as a passive factor.

Human Mobility Analysis

There has also been prior work examining people's mobility patterns, showing that there are many predictable patterns. For example, past work by Gonzalez et al. [21] analyzed mobile phone cell tower data of 100,000 people over six months (based on call log and SMS log data). They found that people's trajectories had a great deal of temporal and spatial regularity, with people spending a great deal of time in just a few highly frequented locations. Other past work has used GPS data to analyze and find patterns. For example, Amini et al. [7] examined two different mobility data sets based on GPS locations (as opposed to cell tower locations). The larger data set had location data for twenty participants and had 460000 locations. Their analysis showed that a five-mile radius around a person's top two significant places (most likely home and work) could account for over 86% of a person's mobility patterns. Krumm et al. [17,20] found predictable patterns in where people drive, showing that a person's historical data was highly effective in predicting where a person would go (using a 1km square grid). Follow-up work found that after one month, over half of a person's trips were repeat visits to a place they had driven to before. Buthpitiya et al. reported that using n-gram model, they could do anomaly detection in users' mobility patterns [30]. Finally, Hayashi et al. [22] present the results of a diary study investigating where people login to desktop and laptop computers. They found that 84.3% of logins were done at home (59.2%) and work (25.1%).

Combined, this past work suggests that location data may be quite promising in two ways. First, strong, predictable patterns in one's mobility patterns would make location data very useful as a passive factor for authentication. Second, if people often use their smartphones and other devices in just a few places, then modulating the level of authentication needed for those places could improve usability. Furthermore, if these few places have reasonably good physical security (such as a home or a closed office space), then this improvement in usability could come without a significant cost to security.

However, currently, there is little empirical data on where and how often people actually use their smartphones. The above past work only suggests that location may be useful, but has weaknesses in terms of the data used (e.g. call log and SMS log data), looking at regions around home and work rather than specific locations, or the method (looking at logins on PCs and laptops only). This paper contributes to this body of knowledge by providing analyses of where people actually use their smartphones, using GPS and Wi-Fi data for fine-grained information with ground truth.

CONTEXT-AWARE SCALABLE AUTHENTICATION

In this section, we introduce a probabilistic framework for context-aware scalable authentication (CASA). One core aspect of CASA is to combine multiple factors to authenticate a user using a naïve Bayes classifier. This framework can also be used to calculate a "risk assessment" value to determine the appropriate level of active authentication required given other factors.

Most existing user authentication schemes can be considered binary classifiers, classifying a person as a legitimate user ($\hat{u} = 1$) or not ($\hat{u} = -1$). We can also model these schemes probabilistically as shown in Eq. (1) where $\hat{u}$ denotes the prediction (i.e., the result of the user authentication), $P(u = 1|s)$ denotes the probability the requester is the legitimate given the observation s, $P(u = -1|s)$ denotes the probability the person is not the legitimate user given the observation s, and α denotes a how conservative the user authentication is. The α parameter can be set based on one's comfort level with expected costs of false accepts and false rejects.

$$\hat{u} = \begin{cases} 1, & \alpha P(u = 1|s) > P(u = -1|s) \\ -1, & \alpha P(u = 1|s) \leq P(u = -1|s) \end{cases} \quad (1)$$

For instance, for PIN-based authentication, if the system observes that a requester enters the correct PIN, the probability that the requester is legitimate is much higher than the probability he is not. Thus, the system predicts $\hat{u} = 1$ and authenticates the user. Conversely, the system predicts the opposite if the requester enters a wrong PIN.

Many current authentication schemes focus on a single factor that has large differences between the probability distributions of $P(u = -1|s)$ and $P(u = 1|s)$ across the range of values of s. In contrast, CASA combines multiple factors that may or may not have as pronounced of a difference between the probability distributions of $P(u = -1|s)$ and $P(u = 1|s)$, but taken together offer strong advantage over a single factor approach. We define a factor as any data that provides information about a user's identity. Example factors include a user's location; voice obtained through a microphone; time since last login; and the observation that the user enters a correct (or incorrect) PIN; and other biometric information.

In Eq. (2), we show the underlying probabilistic model of multi-factor authenticators such as CASA. Again, u denotes whether (u=1) or not (u=-1) a user is legitimate, and s_i denotes the observation value for the i-th factor.

$$\hat{u} = \begin{cases} 1, & \alpha P(u = 1|s_1, \dots, s_n) > P(u = -1|s_1, \dots, s_n) \\ -1, & \alpha P(u = 1|s_1, \dots, s_n) \leq P(u = -1|s_1, \dots, s_n) \end{cases} \quad (2)$$

We can reformulate Eq. (2) into Eq. (3) using the sign function, which extracts the sign (positive or negative) of a real number.

$$\hat{u} = \text{sign}\left(\log\frac{\alpha P(u=1|s_1,\dots,s_n)}{P(u=-1|s_1,\dots,s_n)}\right) \quad (3)$$

Using Bayes' theorem, $P(u|s_1, s_2, \dots, s_n)$ can be simplified into Eq. (4). Then, by assuming conditional independence between each identifier, Eq. (4) can be written as Eq. (5), where $P(u)$ denotes a prior probability of how likely a person is a legitimate user (or not) in general. $P(u)$ will be canceled in the following reformulations.

$$P(u|s_1, s_2, \dots, s_n) = \frac{P(s_1, s_2, \dots, s_n|u)P(u)}{P(s_1, s_2, \dots, s_n)} \quad (4)$$

$$= \frac{\prod_{i=1}^{n} P(s_i|u)\,P(u)}{P(s_1, s_2, \dots, s_n)} \quad (5)$$

Finally, by substituting $P(u|s_1, s_2, \dots, s_n)$ in Eq. (3) with Eq. (5), we obtain a naïve Bayes classifier (Eq. (6)). Intuitively, the parameter in the sign function increases with the probability that a requester is legitimate and vice versa.

$$\hat{u} = \text{sign}\left[\log\left(\alpha\frac{P(u=1)}{P(u=-1)}\right) + \sum_{i=1}^{n}\log\frac{P(s_i|u=1)}{P(s_i|u=-1)}\right] \quad (6)$$

Note that because each factor might not be conditionally independent, Eq (6) may have approximation errors compared to Eq. (3). However, in Eq. (6), we can discuss each factor independently by estimating $P(s_i|u=1)/P(s_i|u=-1)$. Further, in practice, we believe the approximation errors will be limited because we can choose largely independent factors (e.g. voice and PIN). Thus, we believe that the benefit of the independence assumption outweighs its drawbacks.

One straightforward way of using this model is to compare two sets of security factors. As described above, the term in the sign function denotes the likelihood that the requester is legitimate. For instance, if a system uses a four-digit-PIN as the only factor, $P(\text{Correct PIN}|u=1) = 1$ and $P(\text{Correct PIN}|u=0) = 3/10000$, assuming that a legitimate user does not forget her PIN and that a non-legitimate user randomly guesses the PIN (three attempts).

Consequently, to create a multi-factor authentication system that is as at least as secure as a four-digit-PIN, we should pick a set of factors that satisfy Eq. (7). Note that the first term in the sign function is cancelled.

$$\sum_{i=1}^{n}\log\frac{P(s_i|u=1)}{P(s_i|u=-1)} \geq \log\frac{1}{0.0003} \quad (7)$$

Selecting an Active Factor Given Passive Factors

Another application of our model is to select an active factor that provides enough evidence to authenticate a user, given a set of passive factors. As exemplified in Eq. (7), we can compare the strength of the evidence using the terms in the sign function in Eq. (6), which are shown in Eq. (8).

$$\log\left(\alpha\frac{P(u=1)}{P(u=-1)}\right) + \sum_{i=1}^{n}\log\frac{P(s_i|u=1)}{P(s_i|u=-1)} \quad (8)$$

More specifically, let's assume we want to choose an active identifier *S* that provides as much evidence when a user is at a café as compared to the situation where the user typed her correct PIN at her home. Assuming that location is the only passive factor, the condition that S should satisfy can be written as Eq. (9). The first term in Eq. (8) is canceled. $P_{s,1}(1)$ denotes the probability that the active factor *S* indicates that a person is the legitimate user when a person is actually a legitimate user. $P_{s,\text{-}1}(1)$ denotes the same when a person is not the legitimate user. $P_{L,1}(l)$ (or $P_{L,\text{-}1}(l)$) denotes the probability the person is at the location *l* when she is the legitimate user (or not). *H* and *C* denote *home* and *café* respectively.

$$\log\frac{P_{S,1}(1)}{P_{S,-1}(1)} + \log\frac{P_{L,1}(C)}{P_{L,-1}(C)} \geq \log\frac{P_{PIN,1}(1)}{P_{PIN,-1}(1)} + \log\frac{P_{L,1}(H)}{P_{L,-1}(H)} \quad (9)$$

Eq. (9) can be rewritten as Eq. (10), which quantifies the security criteria that an active factor *S* should satisfy to meet the security of the legitimate user typing her PIN at home, given that the active factor *S* authenticate the person at café.

$$\log\frac{P_{S,1}(1)}{P_{S,-1}(1)} \geq \log\frac{P_{PIN,1}(1)}{P_{PIN,-1}(1)} + \log\frac{P_{L,1}(H)}{P_{L,-1}(H)} - \log\frac{P_{L,1}(C)}{P_{L,-1}(C)}$$

$$= \log\frac{P_{PIN,1}(1)}{P_{PIN,-1}(1)}\frac{P_{L,1}(H)}{P_{L,1}(C)}\frac{P_{L,-1}(C)}{P_{L,-1}(H)} \quad (10)$$

A legitimate user is more likely to be at her home than to be at café. Thus, $P_{L,1}(H)/P_{L,1}(C) > 1$. In contrast, someone else is much more likely to be at the café than to be at the user's home, i.e., $P_{L,-1}(C)/P_{L,-1}(H) \gg 1$.

Therefore, Eq. (10) indicates that the active factor should be stronger than the PIN. Furthermore, Eq. (10) offers a quantitative guideline for the strength of the active identifier *S* could be given the user's location. Our model can also include other passive factors, such as sensor data, time since last login, or number of times logged in at given places. We describe another example of selecting active factor in the user study #2.

USER STUDIES

CASA offers us a model for combining a variety of factors for user authentication. For our next step, we wanted to investigate how useful and feasible this framework might be in practice. To have strong reliability in the results , we opted to start from a relatively simple set of active and passive factors rather than combining many factors at once.

In our first study, we investigated the potential of using location as a passive factor. Past work suggests that location could be potentially useful as a passive factor because people spent most of their time in a few locations [7,21,22]. However, there is little empirical data on how frequently people used their smart phones at these locations. We collected this information to estimate usefulness of location information for CASA.

In our second study, we wanted to understand how well our ideas might work in practice, as well as solicit feedback

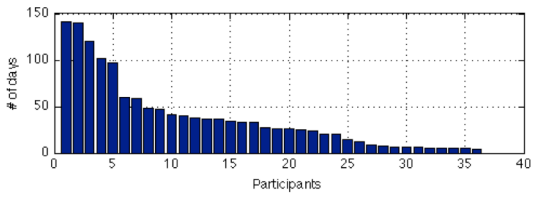


Figure 1. The distribution of the location data collection period. Each bar denotes a participant. The y-axis denotes the length of the period in days. 36 participants had data for seven days or more with the median of 26.5 days.

from participants. We conducted a one-week field study with 32 participants, having them try out our prototype that modulates active factors based on their location.

USER STUDY #1: MOBILITY PATTERN ANALYSIS

We recruited multiple Android phone users through Craigslist and e-mails. Participants were asked to install our logging app from the Android Market. Participants were enrolled in a raffle for $50 Amazon gift cards as compensation. Over five months, we collected data from 128 participants. In this analysis, we focused on 36 participants with at least seven days of logs.

Data Collection Method

Our app sampled location information every three minutes regardless of whether participants were interacting with their phones. Location information was obtained through standard Android APIs using Wi-Fi and cell tower information. The standard API also provided expected error for each location estimate. We discarded location data when the expected errors were greater than 200 meters. As such, our location estimations were accurate to within 50 to 200 meters. Our app also logged the smartphone's running processes every 30 seconds when the smartphone was *not* in sleep mode. The timestamps of these logs let us infer when participants used their phones.

Ratios of Time Spent and Logins at Different Locations

We analyzed location traces from 36 participants. The data collection periods varied from seven days to 140 days. The median length of the data collection was 26.5 days. Figure 1 shows the distribution of the data collection period.

Identifying Frequented Locations

We divided the latitude and longitude space into discrete 0.002 × 0.002 latitude/longitude grids (each cell wsa approximately 200 × 200 meters in/near North America) as previously done in [13]. The particular choice of discretization was based on practical considerations balancing the accuracy of Android's positioning system with granularity of the analysis.

Identifying Phone Activation

To track phone use, the system ran a low level thread that logged active processes every 30 seconds. When the phone was in sleep mode, the thread was automatically paused and no log entries were made. Thus, by examining the timestamps of log entries, the phone state could be determined. Theoretically, intervals between log entries that exceed 30 seconds signified a phone activation event after being in sleep mode once. This detection approach has advantages in sustained deployment study because of its relatively high temporal accuracy, low demand on phone processor, and minimal impact on battery life.

Place	Time		Activations	
	Mean [%]	SD [%]	Mean [%]	SD [%]
1 (Home)	38.9	20.2	31.9	15.6
2 (Workplace)	18.7	12.6	28.9	18.1
3	9.9	8.4	18.5	13.7
4	5.5	4.8	10.8	8.5
5	4.3	4.7	5.2	4.7
Other place	22.6	13.1	4.5	4.6

Table 2. The distribution of the time spent and the phone activation events at the places where participants spent most of their time. Place 1 to 5 denote the places where participants spent most time (1) to fifth most time (5). The top two places where participants spent the most time accounted for 60.8% of the total phone activation events.

However, initial trials of this log analysis identified two common sources of error. The first issue was the low priority of the logging thread leading to fluctuations in the sequentially logged times - variations typically in the region of 5 seconds. To deal with this, we considered valid differences between log time stamps to be in the range 30-35 seconds. The second issue was phone activations caused by push notifications (e.g. email arrival). We observed short phone activations during typical sleeping times (e.g. 4am-5am), in which it seemed unlikely that users engaged with their phones. We adopted a conservative approach to mitigate false positives relating to this issue. Essentially, phone activation events were counted only when there were two successive log timestamps after observing at least a 35 seconds gap. This filtered out short phone activations due to push notifications because the phone went back to the sleep mode quickly after the automatic activations. A consequence of these manipulations was that a certain proportion of valid user activations (e.g. very brief glances and interactions) of the phone would not be counted. However, despite this cost, we believe that these manipulations ensured the validity of the study by counting only real user activations of their phones.

Results of User Study 1

We identified 55840 phone activation events in our dataset. Participants activated their phones 27.4 times a day on average (SD=19.7). Figure 2 shows the distribution of the mean numbers of the events per day for each participant.

Table 2 shows the distribution of time spent and logins at the places where the participants spent most of their time. We first calculated each participant's top five places based on the amount of time spent using location data alone (see the two columns under label "Time"). Then, for each participant, we calculated the number of phone activations at each of these places using location data and process data (see the two columns under label "Activations").

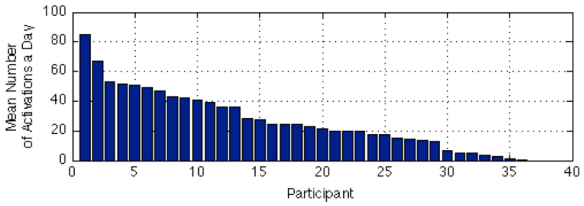


Figure 2. The distribution of the mean number of the smart phone activation events per day, sorted based on the number of activations. The participants activated their phone 27.4 times a day on average (SD=19.7).

The results indicated that people spent 57.8% of their time at two locations, presumably home and work. Before conducting this study, it was unclear to us how often people would use their smartphones at home and work, since these would be places where people would most likely have easy access to other devices with network connectivity and larger displays (e.g., desktop and/or laptop computers) at these locations. Nevertheless, our results showed that these top two places accounted for 60.8% of phone activation events on average (SD=14.5%).

In summary, this result provides supporting evidence that people exhibit strong patterns in where they use their smartphones, suggesting that location could be a very useful passive factor. This result also indicates that we can positively impact both usability and security if we adjust the active factor based on location data coupled with a very trivial user model (home and work). As mentioned previously, this analysis assumes reasonably good physical security at home and work.

USER STUDY #2: FIELD DEPLOYMENT OF CASA

The results of the first user study indicated that location is a promising passive factor. In this field study, we deployed a prototype that dynamically selected active factors based on participants' location (i.e., whether they are at home, work, or some other places) to investigate users' reactions to CASA. Another purpose of this study was to investigate how much effort our participants could reduce in user authentication when using our prototype, using authentication logs collected by our prototype.

Participants

We recruited 32 participants using our university's participant recruitment website. Their age ranged from 18 to 40 years old with a mean age of 24 years. Our participants consisted of 26 students, 5 full-employed and 1 non-employed. Twenty-three out of 32 participants were living with others in their homes. We compensated participants $40 for their participation in the study.

Participants were assigned to one of two conditions based on whether they used any security lock on their phones prior to this study. Participants *not* using a security lock (e.g., PIN, Draw-A-Secret or password) were assigned to the *none-PIN* condition. Those already using a security lock were assigned to the *PIN-password* condition. In essence, participants used the same authentication they already used at home and work, and had stronger active authentication at other places.

Procedure

In the first session, we installed our prototype (see below) on participants' Android phones. We asked participants in the none-PIN condition to choose a PIN. For participants in the PIN-password condition, we asked them to choose a password in addition to a PIN. We asked participants to choose a password at least eight-characters long. We did not set any other restrictions on their PINs and passwords.

During the study period, when the participants turned on their phone displays, the prototype selected an active factor based on the participant's location (home, work, and other) and condition (the none-PIN or PIN-password condition) (see Figure 3 and Table 3). After participants authenticated, the prototype asked the participants to answer two questions asking if they were at home, work, or other, and asking them how safe it would be to leave their smartphone at their current location (see Figure 3 (c)).

After one week, we had a second session where we asked participants to complete a post-survey, and conducted a follow up interview that lasted about 15 minutes.

Prototype with Active Factor Selection

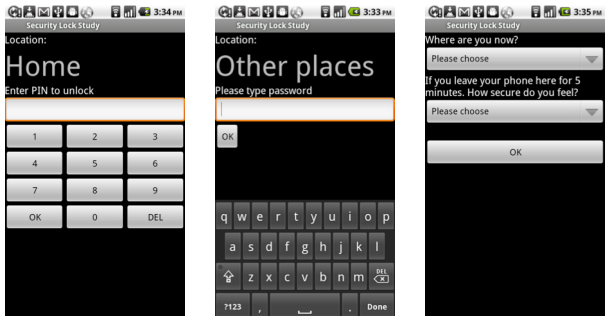
Our prototype used location as a passive factor and selected an active factor from three options: no active factor, a PIN and a password. First, we describe how we can utilize the CASA in selecting active factors using the PIN-password condition as an example. In the PIN-password condition, we selected active factors to provide the same evidence as typing a PIN at workplace.

Because location is the only passive factor in our prototype, Eq. (6) can be simplified to Eq. (11) and (12). These equations denote the conditions that active factors should satisfy to provide no less evidence than being at home (Eq. (11)) or at other places (Eq. (12)), where W, H and O denotes *workplace*, *home* and *other* places respectively, and $f(l_1, l_2)$ and $g(S)$ is defined as shown in Eq. (13). Intuitively, $\log\big(f(l_1, l_2)\big)$ means the likelihood that a person is a legitimate user when she is at l_2 compared to when she is at l_1. If it is less likely, $\log\big(f(l_1, l_2)\big)$ becomes positive. Then, the evidence provided by the active factor (the term on the left side) should be greater than that of PIN. If it is more likely, $\log\big(f(l_1, l_2)\big)$ becomes negative. Then, the active factor could be weaker than PIN. As $\left|\log\big(f(l_1, l_2)\big)\right|$ increases, the user's location information provides stronger evidence towards authentication. $g(S)$ means how strongly an active factor S indicates users' identities.

$$\log g(S) \geq \log g(PIN) + \log(f(W, H)) \qquad (11)$$

$$\log g(S) \geq \log g(PIN) + \log(f(W, O)) \qquad (12)$$

$$f(l_1, l_2) = \frac{P_{L,1}(l_1)}{P_{L,1}(l_2)} \frac{P_{L,-1}(l_2)}{P_{L,-1}(l_1)}, g(S) = \frac{P_{S,1}(1)}{P_{S,-1}(1)} \qquad (13)$$



(a) PIN **(b) Password** **(c) Questionnaire**

Figure 3. Prototype screenshot. Based on users' locations and experimental condition (see Table 3), the prototype either skips authentication, (a) requests PIN, or (b) requests password. After authentication, the prototype showed a questionnaire. When the prototype did not request an active factor, it showed questionnaire directly.

Condition	Home	Workplace	Other places
None-PIN	None	None	PIN
PIN-Password	PIN	PIN	Password

Table 3. Active factors required at different locations. The prototype required the same active factors as participants were using at their homes and workplaces while required stronger active factors at other places.

We estimated $g(S)$ based on the entropy of four-digits PINs (~9 bits) and passwords (~18 bits) [9]. Assuming that the authentication system allows three trials and that a legitimate user always type a PIN and a password correctly, then we have $P_{PIN,1}(1)=1$, $P_{PIN,-1}(1)=3/2^9$, $P_{Pwd,1}(1)=1$, $P_{Pwd,-1}(1)=3/2^{18}$ and $P_{None,1}(1) = P_{None,-1}(1) = 1$. Thus, $g(PIN) = 2^9/3$, $g(Pwd) = 2^{18}/3$ and $g(None) = 1$.

To calculate $\log(f(W,H))$ and $\log(f(W,O))$ accurately, we need further empirical data collection. However, because our primary purpose in this study was to investigate participants' responses to our concept rather than applying CASA precisely, we approximated these values. We approximate the values in a way that $|\log(f(l_1,l_2))|$ becomes smaller to avoid overestimating the strength of the evidence provided by location information. We discuss the data collection issue more in the discussion section.

For $P_{L,1}(H)$ and $P_{L,1}(W)$, we used 0.389 and 0.187 that were obtained in the first study (Table 2). For $P_{L,1}(O)$, we used 0.099 to be conservative. Additionally, we assumed that $P_{L,-1}(l)$ was proportional to the number of people who can physically come into the location. Because we do not have empirical data about $P_{L,-1}(l)$, we make assumptions after showing how it affects the active factor selection.

In Figure 4, the diagonal plots show how the right sides of the Eq. (11) and (12) change along with $P_{L,-1}(l_2)/ P_{L,-1}(l_1)$. The horizontal lines show $\log g(S)$ for each factor. Thus, satisfying Eq. (11) is equivalent to the condition that the lower diagonal plot is below one of the horizontal lines at given $P_{L,-1}(l_2)/ P_{L,-1}(l_1)$. We assume that the number of people who can access *home* is less than that of *workplace*

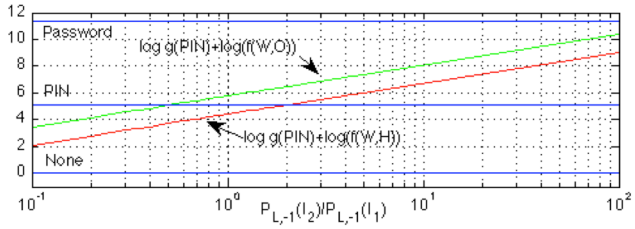


Figure 4. The diagonal plots show how the right sides of the Eq. (12) and (13) change along with $P_{L,-1}(l_2)/ P_{L,-1}(l_1)$. The horizontal lines denote log $g(S)$.

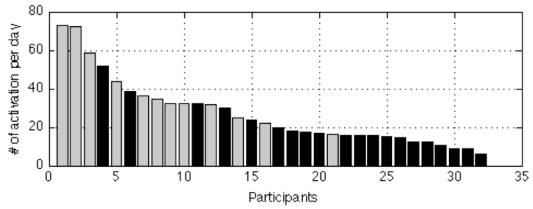


Figure 5. The number of phone activations per day. Gray and black bars denote participants in the PIN-password condition and none-PIN condition respectively.

and more than 1/10 of that of workplace. The lower diagonal plot in the segment $P_{L,-1}(l_2)/ P_{L,-1}(l_1)$ =[0.1, 1] is between the horizontal lines representing *PIN* and *None* under this assumption. Therefore, we select PIN as an active factor that satisfies Eq. (11). Similarly, we assume that the number of people who can access *other places* is more than that of *workplace* and less than 100 times of that of workplace, the upper diagonal plot in the segment $P_{L,-1}(l_2)/ P_{L,-1}(l_1)$ = [1, 100] is between the horizontal lines representing *Password* and *PIN*. Therefore, we select passwords as an active factor that satisfies Eq. (12).

We made two assumptions above; however, we believe that these assumptions are safe to make considering the ranges. Additionally, our choice of active factors (Table 3) made active authentication more secure than what our participants used prior to the study. Our prototype required the same active factors as what they used prior to this study at their homes and work, and required more secure active factors at other places. Thus, we made the authentication more secure than what our participants used prior to our study.

Location Classification

Our prototype estimated the phones' locations using the network positioning system provided by Android OS. This location estimate often took more than a few seconds. However, our prototype needed the location information for user authentication, which should be processed right after users turned on the display. Thus, we pre-fetched the location information every 150 seconds. We chose the sampling frequency to balance freshness of location information with battery life. It is possible to further optimize the frequency, for instance by checking the accelerometer for motion. However, in this prototype, we chose a simple configuration to make our analysis simpler. The positioning system returns latitude, longitude, and estimated error using Wi-Fi and cell tower information.

When the error was greater than 200 meters, our prototype discarded the location as unreliable information.

When the participants turned on their display, our prototype took the latest location information and then classified the location as home, workplace, or other. The classification was done using 5-nearest neighbors within a 100 meter radius. The prototype trained the 5-nearest neighbors using ground truth provided by each participant in the questionnaires.

Questionnaires

After the user authentication, the prototype displayed a questionnaire. The first question asked them to choose their current locations from three options: home, workplace and other places. The responses were used as ground truth to train the location classifier. We did not use the answer to the second question in our analysis.

RESULTS

Location Classification

In the study, our prototype asked for the ground truth of locations after each authentication and trained the 5-nearest neighbor classifier using all the ground truth data collected up to the classification. The classification accuracy was 92%. Most of the misclassifications happened when the participants transitioned from one location to another. Because location information was sampled every 150 seconds, the delay could have caused the misclassification. We could improve the accuracy, for instance, by making the sampling rate higher when users move near the boundaries of known locations.

User Authentication

Our participants activated their phones a median of 20.7 times a day. We used median since some participants activated their phones a lot more or less than others. Figure 5 shows the distribution phone activations per day. The gray bars represent participants in the PIN-password condition, black bars the none-PIN condition. The participants in the PIN-password and the none-PIN condition activated their phone median of 33.6 times and 15.8 times a day respectively. The difference between the two distributions was statistically significant ($p<0.05$ in χ^2 test). This result might be because those who use their phones more frequently are more likely to configure security locks on their phone because they are more likely to have sensitive data on their phone.

Participants in the PIN-password condition activated their phones 55% of the time at home or work, and none-PIN participants 68% of the time (see Table 4). Table 5 shows the authentication time and schemes in each location for each group. Table 4 and 5 show that for participants in the none-PIN condition, 32% of phone activations required authentication (PIN), and 68% of phone activations did not (at home or work). Similarly, for participants in the PIN-password condition, 45% of phone activations required the stronger authentication (password), and 55% used the equivalent to what participants were already using (PIN at home or work).

Participants' Receptiveness

In the post-survey, we asked participants to answer questions about their perceptions of our prototype using a 5-point Likert scale (with higher scores being more positive). Participants in both conditions were very receptive to our prototype. In the followings, the number in the parentheses stands for the median of their ratings.

The participants in the none-PIN condition reported that the concept of not requiring a PIN at home and work while requiring a PIN at other places was useful (4) and very easy to understand (5). They also reported that they felt our prototype was secure (4) compared to not having any security lock on their phone. They also somewhat agreed (3.5) to the statement that they would use our prototype if it was available on their phones. One of the participants commented, "I don't normally use a security lock, but I would be much more inclined to use one if it didn't require constant unlocking."

Similarly, participants in the PIN-password condition reported that the concept of requiring a PIN at home or work while requiring a password was neither useful nor useless (3) and easy to understand (4). They also reported that they felt the prototype was more secure (4), as easy to use as requiring a PIN at all the places. They reported they were neutral to using our prototype if it was available on their phones. In the PIN-password condition, our prototype required a PIN at homes and work while requiring passwords at other places. The configuration might have made participants less positive about our prototype. A participant said, "Typing passwords to check text was annoying. I don't think I will use it."

We further asked about the configuration where our prototype did not require PINs at homes or work while it required a PIN at other place (i.e., the same configuration as one used in the none-PIN condition). The participants reported that the configuration would be easy to use (4) and as secure as a requiring a PIN at all places (3), and they agreed (4) that they would use the system if it were available on their phones. One participant said, "I like the system. It's a great pain to type pin at home, because the nature of the phone, it goes to sleep quickly, then I have to

Condition	Home	Workplace	Other places
None-PIN	10.4	1.9	5.7
PIN-password	13.4	4.3	14.1

Table 4. The median number of the phone activations per day at each location. Both the security lock group and the no security lock group activated phones more than 50% of time at homes or workplaces.

Condition	Home	Workplace	Other places
None-PIN	0 (None)	0 (None)	6.5 (PIN)
PIN-password	5.9 (PIN)	6.0 (PIN)	11.2 (Pwd)

Table 5. The authentication time [sec] and authentication schemes (in parentheses)

type pin again, which is super annoying."

As these results indicate, participants were receptive to our prototype. Although the participants in the PIN-password condition were neutral to use our prototype with the PIN-password configuration, our participants rated the none-PIN configuration as easier to use than the security lock that they used prior to our study, and more or equally secure to the security lock. Furthermore, more than half of the participants preferred to use our prototype on their phones.

LIMITATIONS

In this paper, we investigated the feasibility of a user authentication system that changes active factors based on users' locations. However, our work has several limitations. For example, for each factor, CASA needs estimates of $P(s|u=-1)$, the probability that a person trying to be authenticated is not legitimate. As exemplified in study #2, there are cases where rough estimates are sufficient. For some passive factors, such as behavioral biometrics, it is easy to estimate. However, the estimation could be challenging for other passive factors.

In the evaluations of CASA, we used only one passive factor, i.e., location. Furthermore, location is rather static and transparent to participants compared to other possible passive factors, such as sensor data. We also assume in our work that location is difficult to spoof, which may not always be the case. All of these issues could affect participants' perceptions of CASA.

Our participants rated our authentication system as being as secure as using PIN at all places. However, since users are not always good at evaluating security, it is necessary to conduct a more formal security evaluation. Furthermore, over half of our participants were university students, potentially biasing our results.

DISCUSSION AND FUTURE WORK

In designing our prototype, we approximated the number of people who could physically access certain locations. We believe that our approximation was reasonable for a proof of concept, though more accurate estimates are always better. One possible solution is to aggregate mobility traces from a large number of users. However, in practice, it would be difficult to collect this kind of data. Another approach is to ask users to estimate how many people can access a certain location when they log into their phones at a new location. Such a design might burden users, but users would only have to do it once per location, and could skip it if they do not think they will visit the location frequently enough.

One line of future work is to evaluate other passive factors and user models. Prior work has investigated the security of some passive factors, such as behavioral biometrics. However, the security of other passive factors is not clear, especially when malicious attackers try to impersonate legitimate users. Furthermore, in this paper, we used a very simple model (one passive factor modeling home, work, other). This model had the benefit of being simple to implement and simple to understand. It is clearly possible to build more sophisticated models, combining more passive factors and incorporating more information about the user (e.g. last login time, number of times logged in at a given location). However, this approach raises new questions about how well users can understand what the system is doing, and could lead to frustration if it is hard to predict.

Lastly, we believe it is worth investigating different combinations of active factors as well as new "good enough" forms of active authentication. For example, most active authentication schemes today are designed for high accuracy in differentiating between legitimate and illegitimate users. By leveraging multiple passive factors, it is possible to relax this constraint, requiring only "good enough" accuracy.

CONCLUSION

In this paper, we introduced Context-Aware Scalable Authentication (CASA), which envisions combining multiple passive and active factors to authenticate users. We also proposed a quantitative way of choosing active factors to provide desirable security given passive factors while also improving usability in the common cases..

We also demonstrated the feasibility of selecting an active factor based on passive factors through two user studies. In the first user study, we collected location traces from 36 participants for a range of seven to 140 days. We observed that the participants logged into their phone 60% of the time at their homes or workplace. This data indicated that there was substantial potential to improve both the usability and the security of a user authentication by choosing more secure active factors at other places, and more usable active factors at homes or work, considering that being at home or work had strong indication about users' identities.

In the second study, we developed a user authentication system that changes active authentication schemes (no authentication, PIN, and password) based on users' locations. Through a field study where 32 participants tested our system on their Android phones for one week. We observed that our prototype improved 32% of the user authentication at less frequently visited places without affecting usability of 68% of the user authentication at home or workplaces in the none-PIN condition. Similarly, in the PIN-password condition, our prototype improved 45% of the user authentication at less frequently visited places without affecting usability of 55% of the user authentication at home or workplaces. Furthermore, participants reported that our system was as secure as authentication systems that used only stronger active authentication, and also rated our system as more usable. Additionally, a majority of participants agreed that they preferred our system as a user authentication system if it was available.

Although there is ample opportunity for further investigation, we believe that this paper proposed a novel

authentication framework and demonstrated the feasibility and the effectiveness of the framework. We hope this stimulates future researches towards our vision of developing user authentication systems that require minimum but sufficient active factors and instigates a new research direction in usable authentication field.

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