Statistical Approaches for Personal Feature Extraction from Pressure Array Sensors

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***Abstract*—We propose two statistical probability approaches to extract personal feature from the user's grip force data. One approach is based on grip force changes predicted by the Kalman filter, the other is based on distributions of grip force changes by Jensen-Shannon(JS) divergence. Personal feature is the customary behavior that repeatedly appears without the user being aware of it. The personal feature is used for not only user-authentication, but also user-special commands. We mount pressure array sensors on a mobile phone and show that our proposals can extract personal feature from the user's grip force data with $10[\%]$ error in FAR-FRR by the Kalman filter approach and the accuracy of $100[\%]$ by the JS divergence approach.**

I. Introduction

As mobile phones are always interacting with their users, they know a lot about the user's customs. Owing to the emergence of smart phones, mobile phones are becoming more sophisticated with a variety of sensors that can easily capture information specific to not only the immediate environment but also the user. In order to realize more sophisticated mobile services, we have already researched the ”Personal Context Extractor (PerContEx)” which extracts personal feature in the form of ”personal habits” from a variety of data such as sensor data logs. (We have shown ”gait analyzer with a mobile phone”[1] as an application based on PerContEx.) In this paper, we target the extraction of personal feature created while the user holds and uses his/her mobile phone. This makes user-authentication as well as indirect command input possible. Of particular importance, this concept can prevent illegal use and increases the range of commands available to the user without demanding that the user learns more complicated operations or key-chords.[2] The user's grip force consists of time-series data that exhibits, in regular use, a repeatable pattern. If a sufficiently unique personal feature can be detected while key-operations are in progress, we can realize ”soft authentication”. Soft authentication is different from hard authentication in terms of the use case requirements. Hard authentication requires that the user does some special action for authentication such as putting his/her finger on a sensor or directly facing a camera. In contrast, soft authentication does not need any special action because user authentication is performed in the background. Moreover, the personal feature can be also applied to implement user-specific command actions if the temporal-spatial patterns in the user's key-operations can be recognized as ”his/her habits”. Most conventional methods[3], [4], [5] create a command interface from the two-dimensional static grip patterns identified from changes in grip positions and finger-touches. Since the variation in grip positions and finger-touches is quite limited, the resulting command interface is not so useful and the mobile phone is insecure since it can be operated by a person other than the owner. If user-specific commands based on his/her habits can be defined, it is possible to reduce the risk of the device being operated by a person other than the owner. Some user-authentication schemes utilize the temporal-spatial patterns in the user's actions such as key-typing for computers[6] and gait[7] for mobile phones. The former cannot be applied to smart phones because they do not have keyboards. The latter can be used when the device is carried, but it is difficult to apply when the user is accessing a mobile service. In order to realize soft authentication without requiring specific actions, we must identify which actions of the user are natural when using a mobile phone. Therefore, we extract personal feature from grip patterns. Examples of mobile services based on personal feature use the user's log data such as service-recommend and auto-complete of character input, and user's bodily characteristics and behavior data such as biometrics. In the case of service-recommend and auto-completion, personal feature is extracted from symbolic data not signal data, so statistical approaches such as Bayesian are used most often. To achieve high accuracy, however, a lot of data is required. In the case of biometrics, signal processing approaches are used, but the user must perform unnatural actions. This paper targets the extraction of personal feature during natural interactions between the user and the phone because doing so can realize not only user-authentication but also user-special commands.

II. Preparation For Experiments

A. Experimental Conditions

1) Pressure sensors: We assume four pressure sensor (PPS, Inc.) arrays are mounted on the mobile phone, each with 226 cells (see Fig. 1). The pressure sensors are capacitance sensors. Their sensibilities have a sensible range from 0 to $100[kPa]$ and are linear to grip forces with less than $2[\%]$ hysteresis error. As they are less than $1[mm]$ thick, they can be mounted within the body of conventional mobile phones. The pressure data are saved in the phone's memory. When the user holds the phone with pressure sensors, we can extract pressure data $\{f_{ij}(t)\}$ where (i, j) represents a position of the array sensor. We denote all pressure data $\mathbf{f}_t = (f_{11}(t), \cdots, f_{N_x N_y}(t))^T$ extracted by N_x and N_y which represent pressure sensor cell number along x and y-axis, respectively. In the evaluation

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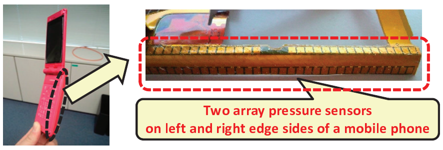


Fig. 1: A Mobile Phone with Pressure Sensors

experiments, all processing is done on a personal computer.

2) Our subjects: Our subjects were eight men and two women with ages ranging from 20 to 40; all had better than average skill in mobile phone operation. The assumption is that subjects who are well experienced in mobile phone operation would exhibit quite clear personal habits as user behaviors that repeatedly appear without the user being aware of them. To emphasize their habitual actions, we set them the task of "random browsing mails received on the mobile phone" by using key-strokes for $60[sec]$. We obtained their data for the same task for about one month.

3) Sensory data: Pressure data was captured every $100[msec]$ when the subject was browsing the mail on the mobile phone. Each set of pressure data has $600[frames]$. Only the $500[frames]$ yielded by cutting the head and tail frames were analyzed (this yields more stable data). The 10 subjects generated from 3 to 11 sets of pressure data each. (Three sets are used for user discrimination and the 11 sets used for repeatable and minimal data volume to realize identification.)

B. Preprocessing sensory data

In the experiments, the sensors mounted on the phone consist of arrays of small tile sensors. They offer high resolution in terms of spatial pressure distribution. Since the sensor arrays are very flexible, the alignment of the sensor arrays can become deformed if the user holds the mobile phone strongly. This is characteristic of the hysteresis effect and the raw sensor data is not always accurate. Indeed, we recognized this in our preliminary experiments. Therefore, we performed some preprocessing operations such as noise reduction by wavelet transform and removal of DC component.

III. Our Proposed Algorithm

In our experiments, as subjects browsed their mails freely as normal, the sensor data captured could contain some kinds of fluctuations. Generally, it is difficult to extract features reliably from this type of sensor data by using conventional signal processing techniques such as FFT and High-order Local Auto Correlation(HLAC). Indeed, in our preliminary experiments, we already confirmed that FFT and HLAC approaches could not reliably extract personal feature. Therefore, we adopted two statistical probability approaches: the Kalman Filter method and the Jensen-Shannon(JS) divergence[8] method. The former is used in the estimation of flexible objects such as object tracking[9]. The latter is used to handle the dissimilarity between probability distributions such as topic models. In order to evaluate these methods, we set the following criteria for personal feature extraction as follows; 1) Feature offers user discrimination. 2) They are repeatable. 3) Minimal data volume to realize identification. Under these criteria, we evaluate our two methods for personal feature extraction.

A. Probability Statistics approach 1: Kalman filter

1) Feature Extraction by Kalman filter: The approach tries to model grip force changes mathematically. We deal with similarities of personal features by comparing the grip force changes observed and those estimated by this method. Because state estimation by a Kalman filter offers robustness with respect to data fluctuations by use of a time-series filter, it can estimate temporal-spatial data from the last set of sequential data. The sensory data noise is similar to a Gaussian distribution and grip force changes can be assumed to be a central force like spring motion. Therefore, this means that the Kalman filter assumptions are satisfied. We use a Kalman filter to predict changes in pressure data. It has a two step learning process: prediction step and update step. In the prediction step, based on the state at the last time, the state at the present time is predicted. In the update step, based on the error between the state predicted at the former step and the state observed, the predicted state is updated. In the experiments, we denote the observation state $\mathbf{y}_t$ as changes $\{y_{ij}^{(u_{ID})}(t)\}$ of user u_{ID}'s grip force $\{f_{ij}^{(u_{ID})}(t)\}$. At time t, system state (change in grip force) is represented by $\mathbf{x}_t$. Assuming that state transition matrix $\mathbf{F}_t$ and observation matrix $\mathbf{H}_t$ are linear models and system noise and observation noise have Gaussian distributions, we obtain the following formulas. In this approach, we try to model grip force changes mathematically.

$$\mathbf{x}_{t+1} = \mathbf{F}_t\mathbf{x}_t + \mathbf{G}_t\mathbf{w}_t \tag{1}$$

$$\mathbf{y}_t = \mathbf{H}_t\mathbf{x}_t + \mathbf{v}_t \tag{2}$$

where $\mathbf{w}_t \sim N(\mathbf{0}, \mathbf{R}_t)$ and $\mathbf{v}_t \sim N(\mathbf{0}, \mathbf{Q}_t)$, $N(\mathbf{0}, \mathbf{R}_t)$ and $N(\mathbf{0}, \mathbf{Q}_t)$ represent a normal distribution with mean of 0, covariance $\mathbf{R}_t$ and $\mathbf{Q}_t$, respectively. Then, $\mathbf{G}_t$ represents the state noise matrix. In the prediction stage, system $\hat{x}_t$ state is calculated as follows;

$$\hat{\mathbf{x}}_t = \hat{\mathbf{x}}_{t/t-1} + \mathbf{K}_t(\mathbf{y}_t - \mathbf{H}_t\hat{\mathbf{x}}_{t/t-1}) \tag{3}$$

where $\hat{\mathbf{x}}_{t/t-1}$ represents the system state $\hat{x}$ predicted at time t by using $\hat{x}$ at time $t-1$. Then, we can obtain the prediction of observed system $\hat{\mathbf{y}}_t$. $\mathbf{K}_t$ is called "Kalman gain", and is adjusted based on the errors of observations and predictions identified in the learning stage.

$$\mathbf{K}_t = \hat{\mathbf{P}}_{t/t-1}\mathbf{H}_t^T(\mathbf{H}_t\hat{\mathbf{P}}_{t/t-1}\mathbf{H}_t^T + \mathbf{R}_t)^{-1} \tag{4}$$

where $\hat{\mathbf{P}}_{t/t-1}$ represents the covariance of errors in updated system status. Based on the above equations, we can obtain the likelihood distribution $LH_{\mathbf{y}^{(u_{ID})}}$ as the reliability of grip force changes in $\mathbf{y}^{(u_{ID})}$. Then, we define the likelihood distribution as feature vector as follows;

$$\mathbf{V}_{KF}^{(u_{ID})} = LH_{\mathbf{y}^{(u_{ID})}} \tag{5}$$

2) Validation of personal feature: In order to verify that the above feature vector is valid for personal feature, we calculate the probabilities $LH_{\mathbf{y}^{(u_{ID})}}(\mathbf{y}^{(u'_{ID})})$ of verification data $\mathbf{y}^{(u'_{ID})}$ with the likelihood distribution $LH_{\mathbf{y}^{(u_{ID})}}$. Indeed, we count the number of grip force changes whose prediction reliability values are larger than threshold value Th_{Pr}. We define criteria $Cr_{KF}(u_{ID}, u'_{ID})$ to evaluate similarity between learning data and verification data as follows;

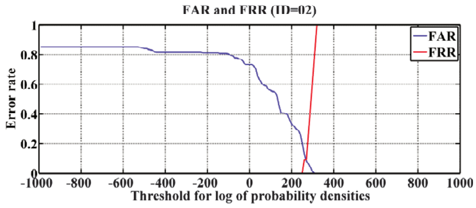


Fig. 2: Accuracy of user-authentication by FAR-FRR curve

$$Cr_{KF}(u_{ID}, u'_{ID}) = \sum_{observation\ time} \delta\ (LH_{\mathbf{y}^{(u_{ID})}}(\mathbf{y}^{(u'_{ID})}), Th_{Pr}) \tag{6}$$

$$\delta\ (LH_{\mathbf{y}^{(u_{ID})}}(\mathbf{y}^{(u'_{ID})}), Th_{Pr}) = \begin{cases} 1 & (LH_{\mathbf{y}^{(u_{ID})}}(\mathbf{y}^{(u'_{ID})}) > Th_{Pr}) \\ 0 & otherwise \end{cases} \tag{7}$$

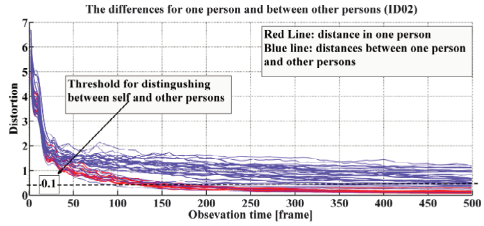
If $Cr_{KF}(u_{ID}, u'_{ID}) > Th_{Cnt}$ is satisfied, we judge that u'_{ID} is similar to u_{ID}. (Th_{Cnt} is a threshold of ratio of satisfied data points in verification data.)

To evaluate stability when learning for generalization, we use the Jack-knife method; one set of pressure data is used as verification data and the remaining sets of pressure data are used as learning data. We calculate the average accuracy in user-authentication for all combinations of learning and verification data sets obtained according to the Jack-knife method. Then, we calculate the averages of the errors yielded by the recognition of the different data sets as criteria.

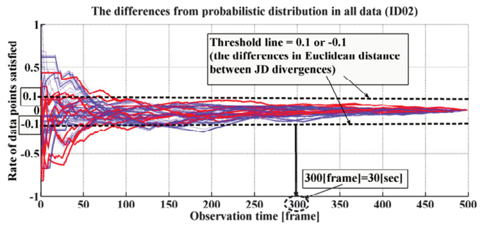
Moreover, for the repeatability of personal feature extraction, we evaluate what amount of data would be needed to ensure the repeatability of personal feature extraction; we compare the distributions based on all data and different amounts of data. In order to evaluate the degree of stable convergence, we use the square Euclidean distance between JS divergence[10] vectors among one subject u_{ID} and the other subjects u'_{ID} as the criterion. JS divergence $JSD(p \parallel q)$ basically represents the dissimilarity of probabilistic distributions $p(x)$ and $q(x)$ where $r(x) = (p(x) + q(x))/2$.

$$JSD(p \parallel q) = \frac{1}{2}(\sum_x q(x) \log \frac{q(x)}{r(x)} + \sum_x q(x) \log \frac{q(x)}{r(x)}) \tag{8}$$

3) Results: We evaluated the accuracy of user-authentication by FAR-FRR curves. Fig. 2 plots FAR-FRR curves for each sensory data format for user-authentication based on grip force. We found that this method could hold the FAR-FRR error rate to 10[%]. The results show that dealing with the sensor cells as patterns allows the realization of user-authentication. We also evaluated what amount of data would be needed to ensure the repeatability of personal feature extraction; Fig. 3 shows the amount of verification data needed for stable convergence. Fig. 3 (a) shows the ratio of the data that are assured of exceeding the probability threshold. Fig. 3 (b) shows the differences in Euclidean distance between JS divergence distribution at the verification time and that at the time of convergence. We have two findings as follows; First, the differences in Euclidean distance for one person and between people lie in the range of 0.1 to 1.3 and about 0.1 at convergence, respectively. In other words, 0.1 can be taken as the threshold for distinguishing between people. Second, the corresponding amount of verification data needed



(a)



(b)

Fig. 3: Amount of Verification Data Necessary for the Kalman filter approach

would take about $30[sec]$ to acquire since the method needs to confirm the ratio of data that can be assured of exceeding the threshold.

B. Probability Statistics approach 2: JS divergence

1) Feature Extraction by JS divergence: While the above approach used the reliability of predicted grip force changes in an observation period, the next approach uses distributions of grip force changes in an observation period. Our pressure sensors are so sensitive that it is difficult to remove some noise components such as hysteresis and fluctuation. To suppress the effects of these noises, we calculate the differences between the distributions of grip force changes in an observation period and a static condition by using JS divergence. Because the distributions express the likelihood of the appearance of grip force changes in an observation period, JS divergence can also represent the difference between two probabilistic distributions. As the user's grip positions are not always same, the user's holding patterns contain some untouched areas in pressure sensor array. In these conditions, Kullback-Leibler(KL) divergence can not always be applied since some signal components are missing. Accordingly, we use JS divergence, which is defined as the mean of KL divergence. We set the histogram of grip force changes in static situation as a standard distribution. Then, we use differences in the histograms of grip force changes in key-operation as the personal feature. We generate histograms of the temporal differences of grip forces as follows;

$$hist_{ij}^{(u_{ID})}(k) = \sum_t \delta(y_{ij}^{(u_{ID})}(t), r(k)) \tag{9}$$

where $r(k)$ represents the kth bin in the histogram.

JS divergence $D_{ij}^{(u_{ID})}$ is represented as follows;(see eq.(8))

$$D_{ij}^{(u_{ID})} = JSD(hist_{ij}^{(u_{ID})}(k) \parallel hist_{ij}^{(static)}(k)) \tag{10}$$

We define feature vector $\mathbf{V}_{JS}^{(u_{ID})}$ as follows;

$$\mathbf{V}_{JS}^{(u_{ID})} = \{D_{ij}^{(u_{ID})}\} \qquad (1 \le i \le N_i, 1 \le j \le N_j) \tag{11}$$

2) Validation for personal feature: Using the Jack-knife method, we verify that the above feature distances between each user's feature vectors. In order to evaluate the degree of stable convergence, we use the square Euclidean distance between Jensen-Shannon divergence vectors among one subject u_{ID} and the other subjects u'_{ID} as the criterion.

$$Cr_{JS}(u_{ID}, u'_{ID}) = \|\mathbf{V}_{JS}^{(u_{ID})} - \mathbf{V}_{JS}^{(u'_{ID})}\|^2 \tag{12}$$

If $Cr_{JS}(u_{ID}, u'_{ID}) > Th_{JS}$ is satisfied, we judge that u'_{ID} is similar to u_{ID}. (Th_{JS} is a threshold of JS divergence.)

Moreover, to evaluate the repeatability of personal feature extraction, under the assumption that the changes in grip force present in all data sets of a user contain personal features such as "user's habits", that is to say, the distribution based on all data is assumed to be the target distribution that contains personal features, we evaluate what amount of data would be needed to ensure the repeatability of personal feature extraction. We compare the distributions based on all data and different amounts of data. The amount of data represents the minimum time needed to accumulate verification data. In order to evaluate the amount of verification data needed for stable convergence, we calculate the ratio of data that exceeded the discrimination threshold.

3) Results: The 3D bar graph in Fig. 4 shows the differences between individuals in terms of JS divergence in case of using all datasets. JS divergences were calculated from the difference distributions of grip force changes in user's key-operations from distribution based on fluctuations of sensor data in static situation. x-axis, y-axis and z-axis represent user ID in learning data, user ID in verification data and differences in Euclidean distance, respectively. The figure indicates that the differences of Euclidean distance in individuals had values of around 0.2, whereas differences of Euclidean distance between individuals had values of more than 0.5. This means that the JS divergences approach can yield the accuracy of $100[\%]$ if the threshold of the Euclidean distances is set to the value which is between 0.2 and 0.5. Therefore, this approach has the potential to yield effective personal features.

We also evaluated what amount of data would be needed to ensure the repeatability of personal feature extraction; we compared the distributions based on all data and different amounts of data. The amount of data represents the minimum time needed to accumulate verification data. (one data set is equal to 60 seconds.) In order to evaluate the amount of verification data needed for stable convergence, we calculated the ratio of data that exceeded the discrimination threshold. Also, in order to evaluate the degree of stable convergence, we used the square Euclidean distance between JS divergence vectors among one subject and the other subjects as the criterion. Fig. 5 plots the sum of deviation in JS divergence versus the number of datasets. We can see that at least two data sets(120 seconds) are needed to extract personal feature because the differences of Euclidean distance in individuals had values of around 0.2.

IV. Conclusion

We evaluated the extraction of personal features from user's grip force in key-operation of a mobile phone; we examined two probability-based approaches for data processing. Only these probability approaches could adequately extract

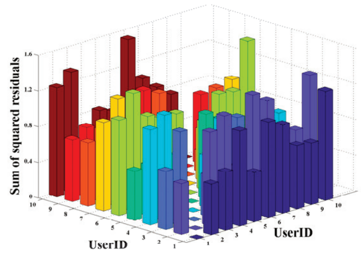


Fig. 4: Accuracy of user-authentication by Distortion between JS divergences

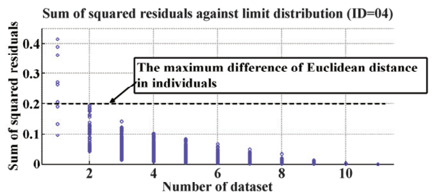


Fig. 5: Amount of Verification Data Necessary for the JS divergence approach

the personal habits containing personal feature so as to allow people to discriminated. The Kalman filter approach yielded the accuracy of $10[\%]$ error in FAR-FRR according to the Jack-knife method; $30[sec]$ of verification data is needed. The JS divergence approach was shown to need at least $120[sec]$ of learning data in order to extract personal feature with the accuracy of $100[\%]$. To create a more useful interface for mobile phones, we will try to evaluate personal feature discriminators based on machine learning such as Bayesian and kernel methods.

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