**Smartphone Authentication using Soft Biometrics**

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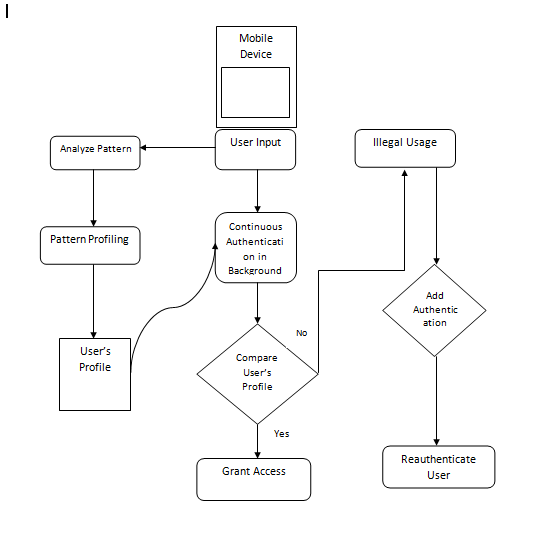
COMPARATIVE ANALYSIS

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| --- | --- | --- | --- | --- | --- |
| Sr No | Year | Method | No of Participants | Performance | Features |
| 1 | 2013 | SVM(kernel fn = Gaussian Radial Basid Function) | 75 CSE grad students in Arizona State University | FAR,FRR,ROC(for block size of ns = 14, ns = 20)  Sliding up = 95% | Potrait Mode(8)  Landscape Mode(8) |
| 2 | 2012 | Euclidean, Manhattan, Mahalanobis, R Part, SVM, Random Forest | 32 participants were asked to draw 3 patterns 50 times | ERR = 10.37%  FAR = 85.32% - 86.35%  FRR = 13% - 14%  ROC :  y = 0.05(0.051 +- 0.002) | 3 Different Lock Patterns(Finger-in-dot time, Finger-in-between-dot time) |
| 3 | 2011 | Gaussian Mixture Model(GMM) | 50 users over the span of 2 weeks | X, Y  Median, 75, 90,95 percentile | GPhone, GBrowser, GSMS, BPhone, BBrowser, BSMS and GPS Location |
| 4 | 2014 | SVM(Radial Basis Function kernel) | 32 users | Distinctiveness, Permanence, Avg ERR = lower than 10% | KeyStroke, Slide, Handwriting and Pinch |
| 5 | 2013 | kNN, SVM(Radial Basis Function kernel) | 41 participants | ERR = 0% – 4%  SVM achieves a lower error rate than kNN | Stroke(30):  Mid stroke area covered, mid stroke pressure, dir of end to end line, avg dir, avg vel,length of trajectory,mean resultant length, phone orientation |
| 6 | 2015 | Bayes Net, kNN, Random Forest | 40 subjects(Hungarian 58-question Eysenck Personality Questionnaire) | ERR,DET curves  ERR(RF) = 0.004 ± 0.001  ERR(knnd) = 0.024±0.020  ERR(parzendd) = 0.023±0.019 | Swipe(11):  Duration, length of trajectory, avg vel, mid stroke press, acceleration start, mean press, |
| 7 | 2019 | kNN, RF,GB,Linear SVM | 14 participants | AUC for GB = 0.97 with SD = 0.0002 | User Gestures are distributed in classes(texting, feed,browser, other,system,launcher,game,  video) each having sub divided fields |
| 8 | 2015 | SVM(linear kernel) | 51 students(each subject  contributed around 800 touch-interaction operations) | FAR = 4.68%  FRR = 1.17%  Based on application | Position, Length, Angle, Temporal Features, Linear velocity, Linear Acceleration,Angular velocity, Pressure |
| 9 | 2014 | LibSVM(unary class) and BayesNet(multi class) | 20 participants from Georgia Institute of Technology | MultiUser(Accuracy = 97.78%)  SingleUser(Accuracy = 96.79%) | Radio Buttons, Checkboxes and Sliders |
| 10 | 2012 | Decision Tree, Random Forest, Bayes Net Classifier, FAST | 40 users | FAR = 4.66%  FRR = 0.13% | Touch Gestures, Virtual Typing and Touch Based Drawing |

GAPS IDENTIFIED

1. In this study, we report that combining multiple features gives better results than using each single feature alone[Elaine Shi]
2. Touch based results vary for different Mobile Model. For instance, the screen of different phones have slightly different dimensions.
3. Sometimes an impersonator might mimic the touch behaviour of another user.(For example, he can be a friend, coworker or a family member)
4. Increase the feature space by including a categorical variable that records values like ‘read e-mail’, ‘write e-mail’, ‘browse’, ‘control music player’.
5. Influence of sample size

WORKFLOW MODEL



IMPLEMENTATION

A Dataset consisting of various features such as Sliding on the screen, Handwriting and Pinching with their respective percentages on the touch screen recorded. The Dataset was taken in CSV format. Exploratory Data Analysis was performed on the data set. Followed by training and testing of the dataset to give accuracy. kNN and SVM Algorithm were the used to give the results.

1. Load the Dataset
2. Initialise the value of k
3. 3.For getting the predicted class, iterate from 1 to total number of training data points

* Calculate the distance between test data and each row of training data. Here we will use Euclidean distance as our distance metric since it’s the most popular method. The other metrics that can be used are Chebyshev, cosine, etc.
* Sort the calculated distances in ascending order based on distance values
* Get top k rows from the sorted array
* Get the most frequent class of these rows
* Return the predicted class

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