**Smartphone Authentication using Soft Biometrics**

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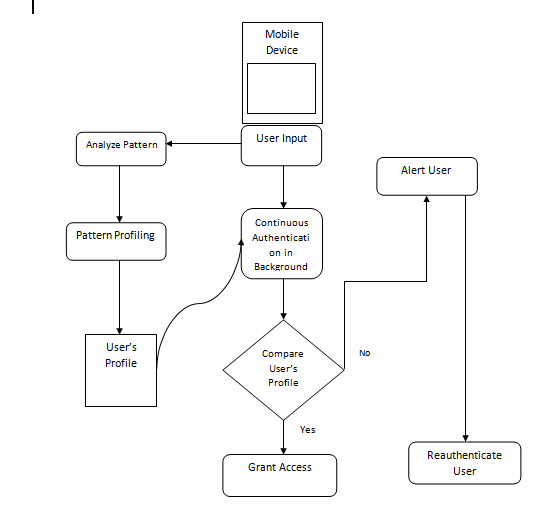
COMPARATIVE ANALYSIS

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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 Algorithm was the classifier used to give the results.

1. Load the Dataset
2. Initialise the value of k

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

REFERENCES

1. L Li,X Zhao and G Xue,”Unobservable Reauthentication for Smartphones”,NDSS Symposium 2013
2. J. Angulo and E. W’astlund,”Exploring touch-screen biometrics for user identification on smart phones”, In Privacy and Identity Management for Life, pages 130–143. Springer, 2012
3. E Shi,Y Niu, M Jakobson and R Chow,”Implicit Authentication through Learning User Behavior”,Springer,2011
4. H Xu, Y Zhou and M Lyu,“Towards Continuous and Passive Authentication via Touch Biometrics: An Experimental Study on Smartphones”,Proceeding SOUPS '14 Proceedings of the Tenth USENIX Conference on Usable Privacy and Security,10th Symposium,USENIX,2014
5. M. Frank, R. Biedert, E. Ma, I. Martinovic, and D. Song.,”Touchalytics: on the applicability of touchscreen input as a behavioral biometric for continuous authentication,”IEEE Trans. on Information Forensics and Security, 8(1), Jan. 2013.
6. M Antal and L Szabo,”Biometric authentication based on touchscreen swipe patterns”, 9th International Conference Interdisciplinarity in Engineering, INTER-ENG 2015, 8-9 October,2015
7. K Leyfer and A Spivak“Continuous User Authentication by the Classification Method Based on the Dynamic Touchscreen Biometrics”, PROCEEDING OF THE 24TH CONFERENCE OF FRUCT ASSOCIATION, 2019
8. C Shen, Y Zhang,Z Cai, T Yu and X Guan,“Touch-Interaction Behavior for Continuous User Authentication on Smartphones”,IEEE,2015
9. P Saravanan, S Clarke,“LatentGesture: Active User Authentication through Background Touch Analysis”,Proceeding Chinese CHI '14 Proceedings of the Second International Symposium of Chinese CHI,2014
10. T Feng, Z Liu, K Kwon, W Shi, B Carbunar, Y Jiang and N Nguyen,”Continuous Mobile Authentication using Touchscreen Gestures”,2012 IEEE Conference on Technologies for Homeland Security (HST), 15 Nov. 2012
11. A. De Luca, A. Hang, F. Brudy, C. Lindner, and H. Hussmann, “Touch me once and I know it’s you!: implicit authentication based on touch screen patterns,” in ACM Conference on Human Factors in Computing Systems, 2012
12. N. SaeBae,K. Ahmed, K. Isbister, and N. Memon,”Biometric Rich Gestures: a novel approach to authentication on multitouch devices”,In Proc. of the SIGCHI Conf. on Human Factors in Computing Systems, 2012.
13. H. Seo, E. Kim, and H. K. Kim, “A novel biometric identification based on a users input pattern analysis for intelligent mobile devices,” 2012
14. Z Ali, J Payton and Sritapan,”At Your Fingertips: Considering Finger Distinctness in Continuous Touch-Based Authentication for Mobile Devices”, IEEE Security and Privacy Workshop,2016
15. C Bo, L Zhang, X Li, “SilentSense: Silent User Identification via Dynamics of Touch and Movement Behavioral Biometrics”, MobiCom '13: Proceedings of the 19th annual international conference on Mobile computing & networking, 2013
16. K Niinuma, U Park and A K Jain, “Soft Biometric Traits for Continuous User Authentication”, IEEE TRANSACTIONS ON INFORMATION FORENSICS AND SECURITY, VOL. 5, NO. 4, DECEMBER 2010
17. Z Sitova, J Sedenka, Q Yang, G Peng, G Zhou, P Gasti, K Balagani, “HMOG: New Behavioral Biometric Features for Continuous Authentication of Smartphone Users”, DARPA, IEEE, 2013
18. S. Thomas. ,”Touchscreen handsets dominanting uk mobile market!” http://www.3g.co.uk/PR/Nov2012/touchscreen-handsets-dominanting-uk-mobile-market.html, 2012
19. Symantec (2011) A window into mobile device security – examining the security approaches employed in Apple’s IOS and Google’s Android. Available: <http://www.symantec.com/content/en/us/about/media/pdfs/symc_mobile_device_security_june2011.pdf>
20. R. Yampolskiy and V. Govindaraju,”Behavioural biometrics: a survey and classification”, International Journal of Biometrics, 1(1):81–113, 2008