Analysis of 3D Trajectory-Based Modeling and Recognition

Deval Verma[1], Ajay Kumar[2]
[1]Lincoln University College,47301, Petaling Jaya, Selangor Darun Ehsan, Malaysia
[2] IILM University, Greater Noida, India
[1]Email ID: pdf.deval@lincoln.edu.my ; [2] Email ID: ajay.phdcse@gmail.com

Abstract: 3D trajectory-based recognition remains a challenging task in public authentication systems. Traditional authentication systems rely on memorized credentials, are susceptible to information leakage, and often depend on fingerprints, making them vulnerable to security breaches. Its capability to categorize attributes such as handedness, gender, and age groups highlights the uniqueness of this feature and its potential for further development in emerging applications. This work presents the utilization of feature extraction and selection techniques for recognition of online characters through the analysis of online data. Recognition has been carried out using various supervised machine learning models using Random Forest, Support Vector Machines, Hidden Markov Model (HMM), and deep learning models like CNN.

Experiments are carried out using performance criteria including accuracy and other parameters. This study demonstrates that ensemble methods such as Random Forest surpass alternative approaches, for early detection and public authentication.

Keywords: 2D handwriting systems; Authentication; Security Breaches; Human-computer interaction;

Introduction

These three-dimensional motion trajectories are records of moving objects that are kept in a computer as raw coordinate temporal sequence. [1].

The ability to recognize 3D motion trajectories involving human-computer interaction, it is crucial this includes language recognition, robotics control, gesture recognition, and action comprehension [1, 2, 5, 10]. The identification of 3D motion trajectories is fraught with difficulties.

The primary objective of this research is to detect unique characteristics in a person's handwriting and develop a text-independent method for nearly flawless user identification to remove the challenges given by the conventional approach. Machine learning and deep learning were among the methods employed to accomplish this goal. A digital pen tablet sensor's fine-motor numerical properties of human handwriting are used for feature extraction, feature selection techniques to extract and choose pertinent features, and user classification using those features. 3D motion trajectory recognition is a challenging task. These trajectories show how objects move, captured as unprocessed coordinates in computer-stored temporal sequences [6]. Human beings, robots, pen tip movements, and fingers are examples of moving objects. When describing these 3D trajectories with primitives rather than just raw data, efficiency can be greatly increased. [7-18].

Related work

Capturing a clear image depends on a number of factors, including lighting, image encoding, brightness, and image quality [2]. Additionally, preparation to improve the image increases computing expense and complexity. The key elements found in a person's handwriting's numerical values are overlooked by image-based models.

Guo et al. (2017) employed histogram of gradients (HOG) and double level kernel self-similarity matrices (DKSM) as features [16]. A user authentication system using digital pen-tablet sensor data is presented by Begum et al. [18]. It is observed that there is still a scope to work on using blends of features like slope, angular, z score statistical calculations features to maximize the accuracy.

The proposed framework's process flow is depicted in Figure 1.

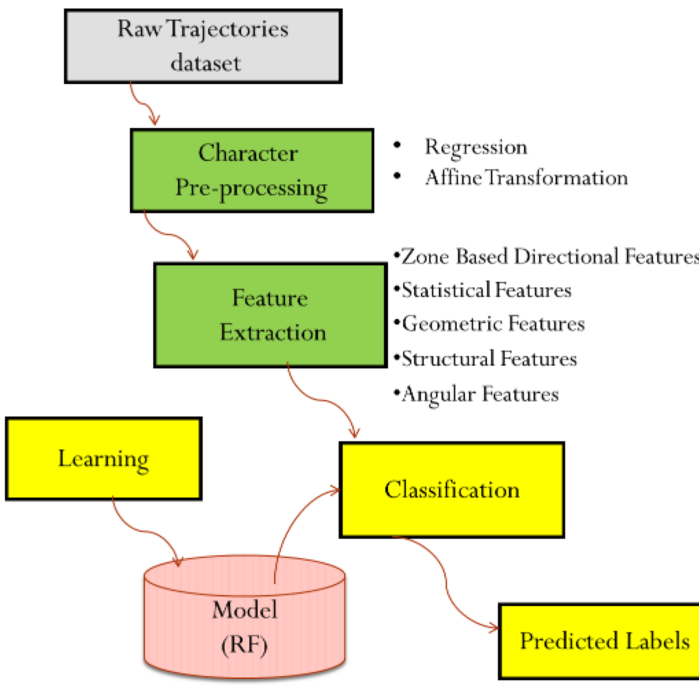

Figure 1. Proposed Methodology of framework.

Table 1. Compare the previous research by other researchers

Author	Year	Type (2D/3D)	Feature Extraction Method	Classification Method	Dataset / Characters	Output
Blumenstein et al. [19]	2003	2D	Geometric features	Neural network	English characters	80%
Lee et al. [20]	2004	3D	Contour-based features	Block-difference method	English characters (1248 samples)	-

Rani et al. [21]	2011	3D	Left diagonal line crossing and corner features	-	English characters	84.52%
Dinesh et al. [22]	2012	3D	Geometric and regional features	Neural network	English characters (650 images)	-

Key Contribution

To explore and compare the performance of various optimized set of discriminative features It is crucial for improving recognition performance while maintaining computational efficiency.

Experiments and Results

The handwriting data were collected using an external digitizing tablet, along with a cordless digital stylus pen. A graphical user interface (GUI)–based acquisition program was used, which displayed a writing box and additional control options on the screen. Participants were instructed to write only within the designated box. The program recorded the handwriting as a sequence of (X, Y) coordinate points using the pen position sensor, along with pen-up and pen-down signals. However, pressure information from the stylus was not captured.

The standard CHAR3D "mixout" character dataset consists of raw samples of 20 English 3D characters generated using a pen-tablet–based interface. Each character was repeated more than 100 times, resulting in a total of 2,858 recorded character samples. The collected data were processed using Gaussian smoothing and numerical differentiation. The character information is represented as sequences of (x,y,z) coordinate points. The Random Forest (RF) classifier is a supervised learning algorithm that operates using an ensemble of decision trees.

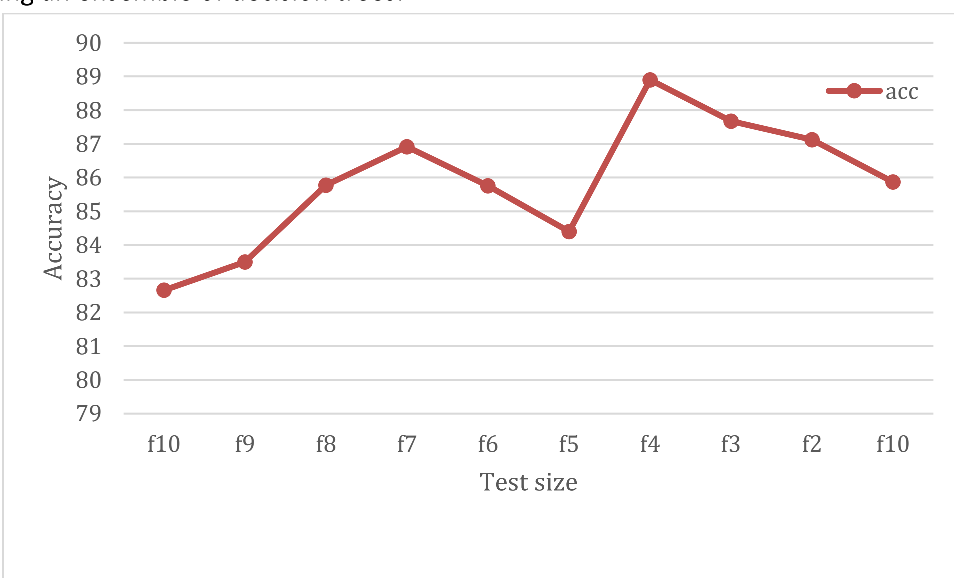

Figure 1. The Impact of RF classification over CHAR3D dataset.

Conclusions

The performance and efficacy of identifying 3D motion trajectories of lowercase alphabetic characters are assessed in this work using a ten-fold cross-validation technique, as shown in Figure 2. For the 3D motion trajectories of lowercase alphabetic characters, the maximum average recognition accuracy of 89% was attained. In order to enhance accuracy, it is noted that there is still room for improvement when utilizing a combination of features such as slope, orthocenter, GLCM, angular, and z score calculations.

References

1. X. Zhang, X. Zhang and L. Han, "An energy efficient Internet of Things network using restart artificial bee colony and wireless power transfer", *IEEE Access*, vol. 7, pp. 12686-12695, 2019. https://doi.org/10.1109/ACCESS.2019.2892798
2. J. Patvarczki, A. Kornafeld, and E. Tamas, “Method for image-based authentication,” U.S. Patent 12,753,225, Jan. 5, 2012.
3. D. Keysers, T. Deselaers, H.A. Rowley, , L.L. Wang, V. Carbune, “Multi-language online handwriting recognition”, IEEE transactions on pattern analysis and machine intelligence 39(6), 1180–1194 2016. 10.1109/TPAMI.2016.2572693
4. J.S. Wang, F.C. Chuang, ‘’An accelerometer-based digital pen with a trajectory recognition algorithm for handwritten digit and gesture recognition”, IEEE Transactions on Industrial Electronics 59(7), 2998–3007 (2011). DOI: 10.1109/TIE.2011.2167895
5. M.C. Shin, L.V. Tsap, D.M.B. Goldgof, "Gesture recognition using Bezier curves for visualization navigation from registered 3-D data." Pattern Recognition 37, no. 5, 1011-1024, 2004. https://doi.org/10.1016/j.patcog.2003.11.007
6. B. Williams, M.Toussaint, and A. Storkey, ‘’Extracting motion primitives from natural handwriting data’’. Artif.Neural Netw. ICANN 634–643., 2006. DOI: 10.1007/11840930_66, 2006,
7. B Williams, M Toussaint, A.J Storkey, "Modelling motion primitives and their timing in biologically executed movements." In Advances in neural information processing systems, pp. 1609-1616. 2008. http://papers.nips.cc/paper/3204-modelling-motion-primitives-and-their-timing-in-biologically-executed-movements.pdf
8. S. Wu, Y. F. Li, and J. Zhang, "Probabilistic cluster signature for modeling motion classes." In 2009 IEEE/RSJ International Conference on Intelligent Robots and Systems, pp. 5731-5736. IEEE, 2009. 10.1109/IROS.2009.5354142
9. J. Yang, Y. F. Li, and K. Wang. "A new descriptor for 3D trajectory recognition via modified CDTW." In 2010 IEEE International Conference on Automation and Logistics, pp. 37-42. IEEE, 2010. 10.1109/ICAL.2010.5585379
10. J Yang, Y.F. Li, K. Wang, Y. Wu, G. Altieri and M. Scalia. "Mixed signature: an invariant descriptor for 3D motion trajectory perception and recognition." Mathematical Problems in Engineering 2012 (2012). https://doi.org/10.1155/2012/613939

11. Z. Shao, Y. Li, “On integral invariants for effective 3-D motion trajectory matching and recognition”. IEEE transactions on cybernetics. Mar 3;46(2):511-23, 2015. 10.1109/TCYB.2015.2404828
12. M. Dahi, N.A. Semary and H.M. Mohiy "A comparative study of different approaches of primitive printed Arabic Optical Character Recognition." In 2015 11th International Computer Engineering Conference (ICENCO), pp. 105-110. IEEE, 2015. 10.1109/ICENCO.2015.7416333
13. J Grabocka, M Wistuba, L Schmidt-Thieme,"Fast classification of univariate and multivariate time series through shapelet discovery." Knowledge and information systems 49, no. 2, 429-454, 2016. https://doi.org/10.1007/s10115-015-0905-9
14. J Shen, K Lin, Y Wang, G Pan, "Character recognition from trajectory by recurrent spiking neural networks." In 2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 2900-2903. IEEE, 2017. 10.1109/EMBC.2017.8037463
15. Z. Yu, D. S. Moirangthem, M. Lee, "Continuous timescale long-short term memory neural network for human intent understanding." Frontiers in neurorobotics 11, 42, 2017. https://doi.org/10.3389/fnbot.2017.00042
16. Y. Guo, Y. Li, Z. Shao, "On double-level kernel self-similarities for 3D motion trajectory description and recognition." In 2017 IEEE International Conference on Real-time Computing and Robotics (RCAR), pp. 657-662. IEEE, 2017. 10.1109/RCAR.2017.8311938
17. M. Sanzari, V. Ntouskos & F. Pirri,"Discovery and recognition of motion primitives in human activities." PloS one 14, no. 4, e0214499, 2019. https://doi.org/10.1371/journal.pone.0214499
18. N. Begum, M. A. H. Akash, S. Rahman, J. Shin, M. R. Islam, and M. E. Islam, ‘‘User authentication based on handwriting analysis of pen-tablet sensor data using optimal feature selection model,’’ Future Internet, vol. 13, no. 9, p. 231, Sep. 2021
19. M. Blumenstein, B. Verma, and H. Basli, “A Novel Feature Extraction Technique for the Recognition of Segmented Handwritten Characters”, in Document Analysis and Recognition, 2003. Proceedings. Seventh International Conference on. IEEE, pp. 137–141, 2003.10.1109/ICDAR.2003.1227647.
20. H.J. Lee, S.Y. Chen, and S.Z. Wang, “Extraction and Recognition of License Plates of Motorcycles and Vehicles on Highways”, in Proceedings of the 17th International Conference on Pattern Recognition, 2004. ICPR 2004., vol. 4. IEEE, pp. 356359, 2004, 10.1109/ICPR.2004.1333776.
21. U.V. Marti and H. Bunke, “Text Line Segmentation and Word Recognition in a System for General Writer Independent Handwriting Recognition”, in Proceedings of Sixth International Conference on Document Analysis and Recognition. IEEE, pp. 159–163, 2001, 10.1109/ICDAR.2001.953775.
22. Dileep D. and Ramesh R., “A Feature Extraction Technique Based on Character Geometry for Character Recognition”, in arXiv preprint, arXiv, pp. 1202–3884, 2012, https://doi.org/10.48550/arXiv.1202.3884.