Social Behavioral Biometrics

Subjects: Computer Science, Information Systems | Computer Science, Cybernetics
Contributor: Marina L. Gavrilova

Social Behavioral Biometrics (SBB) is a novel biometric category. This innovative field of study investigates a person’s social interactions and communication patterns to ascertain their identity.

natural language processing | social behavioral biometrics | biometric identification

1. Introduction

Biometric methodologies are recognized for their ability to confirm an individual’s identity by analyzing unique physical or behavioral attributes [1][2]. In the realm of physiological biometrics, the physical characteristics of a person are coded to form a distinctive profile that can later be used for identification [3]. This category of biometrics frequently incorporates fingerprint, iris, palm, face, and hand geometry analysis [1][3]. In contrast, behavioral biometrics focus on an individual’s unique patterns of behavior, including distinct ways of speaking, walking, typing, and signature writing [4][5].

Emerging from the rapid expansion of social media, Social Behavioral Biometrics (SBB) is a novel biometric category. This innovative field of study investigates a person’s social interactions and communication patterns to ascertain their identity [6]. Given the dramatic growth in social media users, Online Social Network (OSN) platforms have become data-rich environments, providing valuable insights into user behaviors. With this wealth of data, SBB has found successful applications across a range of fields, such as person authentication, anomaly detection, behavioral analysis, risk assessment, and situation awareness [6][7][8].

A burgeoning area of research within the field of social behavioral biometrics is the utilization of behavioral traits for biometric identification. Recent scholarly endeavors have delved into various aspects of social behavior, such as retweet networks, Uniform Resource Locator (URL) networks, reply networks, hashtag networks, temporal networks, linguistic profile, and human micro-expression from text as potential biometric identifiers [9][10][11]. Harnessing these social behavioral biometrics offers potential avenues for bolstering cyberspace security and surveillance [12]. Moreover, SBB traits have found diverse applications in areas such as digital banking [13], spam detection online [14][15], assessing trustworthiness in social media [16][17], identifying sexual predators [18], detecting cyberbullying [19], exploring psychological states [20], predicting mental health conditions [21], and facilitating the early detection of depression [22].

2. Social Behavioral Biometrics

The concept of Social Behavioral Biometrics (SBB) was first unveiled in 2014 [6]. Subsequently, there has been a growing interest and surge in advancements within the SBB discipline. Sultana et al. [6] introduced the framework for both unimodal and multi-modal SBB systems based on user social patterns. They discussed Dunbar's number theory [23], which suggests cognitive limits to the number of stable social connections a person can maintain, thereby providing a basis for user identification [23]. Despite the proliferation of online social networks allowing thousands of connections, studies assert that cognitive thresholds still apply [24][25], reinforcing the idea that a person's primary circle of friends, exhibiting distinct behavioral patterns, can be used to identify them.

Later, the research in [9] introduced key SBB traits, including the reply and retweet networks. Both networks serve as social behavioral biometrics and are generated based on how often a user responds to or retweets content from their digital acquaintances [9]. They represent social interactions as network structures, with nodes being users and edges denoting interactions [9]. They differ in their data sources, with the reply network focusing on user responses and the retweet network revolving around content redistribution. Logarithmic frequency of weights is assigned to the edges in these networks to establish them [9]. Among these two, the reply network exhibited superior performance in identifying individuals.

Further, the trendy topic profile captures users' hashtag usage behaviors to understand topic-wise interests and preferences, and the URL network maps users' domain preferences and sharing patterns in online social networks [9]. Additionally, a temporal profile was designed to capture the temporal information regarding an individual's online activity [26]. The temporal profile yields a wealth of data, including the average daily probability of tweeting, average hourly tweet frequency, patterns of tweeting across seven-day intervals, specific times of tweeting throughout the week, and others, while offering statistical data-rich insights. The temporal profile demonstrates lower performance in comparison to other SBB traits [26].

Language-based identification was also explored by Sanjida et al. [10][27]. They designed linguistic profiles as an SBB trait for online user authentication to identify writing style, vocabulary, and other language attributes. A Term Frequency-Inverse Document Frequency (TF-IDF) technique was utilized to extract the linguistic profiles of OSN users. The method was validated with machine learning classifiers, demonstrating a high degree of accuracy in recognizing users through linguistic attributes [10].

SBB features have been applied to enhance online safety lately. A sexual predator detection system is introduced in [18] that extracts SBB features from textual conversations to build user profiles, and by focusing on specific features, the system was able to detect potential threats with high accuracy. In [28], an innovative method was proposed to improve both personalized services and the security of Internet of Things (IoT) devices by leveraging SBB features. By incorporating continuous verification intelligence into smart devices, a high user verification rate was reported. In addition, personality traits were explored as a form of SBB features to evaluate user trustworthiness online [16], demonstrating the potential of SBB traits in fostering trust in online interactions. Lastly, Saleema and Thampi [29] put forth an innovative approach to user identification in online social networks, using behavior modeling based on cognitive psychology. This approach amalgamated user-generated content with social interaction data, taking into account aspects like memory, learning, and perception, thereby achieving a comprehensive understanding of user behavior [29]. The model was able to discern between authentic and fake users, indicating the potential of cognitive psychology-based behavior modeling for user identification in online social networks [29].

In the latest advancement of SBB, Zaman et al. [11] introduced human micro-expression as a novel social behavioral biometric. This method transforms users' microblogs into emotion signals by leveraging Parrott's [30] six primary emotions [11]. An emotion detection model was developed to extract these six fundamental emotions from the user-generated content [11]. Later, the emotion signals and their corresponding mappings are constructed using an original technique proposed in [11]. Dynamic Time Warping (DTW) algorithm [31] was subsequently employed to extract emotion-progression features within pairs of emotion signals, leading to the creation of a comprehensive human micro-expression profile for users on online social networks. A rank-level fusion with weighted Borda count technique [32] is used to generate the final decision score for user identification. The identification of users based on solely human micro-expression biometrics demonstrated promising results.

One of the key limitations of the recent SBB trait is that while the standalone identification performance is reasonably good, the identification process is not comprehensive, resulting in underperformance when compared to existing multimodal SBB systems. Furthermore, the compatibility of human micro-expression for comprehensive user identification by looking at several SBB traits is still unknown. Therefore, the incorporation of human micro-expression not only reveals the integration capacity of the emotion-based SBB features with the network, temporal, and linguistic-based SBB features but also demonstrates the potential ability to improve the existing identification performance in a multimodal framework. This aspect necessitates further research to bridge the gap between individual SBB traits and a comprehensive, multimodal user identification approach.

References

1. Abdulrahman, S.A.; Alhayani, B. A comprehensive survey on the biometric systems based on physiological and behavioural characteristics. Mater. Today Proc. 2021, 80, 2642–2646.
2. Unar, J.; Seng, W.C.; Abbasi, A. A review of biometric technology along with trends and prospects. Pattern Recognit. 2014, 47, 2673–2688.
3. Jain, A.K.; Flynn, P.; Ross, A.A. Handbook of Biometrics; Springer Science & Business Media: Berlin/Heidelberg, Germany, 2007.
4. Liang, Y.; Samtani, S.; Guo, B.; Yu, Z. Behavioral biometrics for continuous authentication in the internet-of-things era: An artificial intelligence perspective. IEEE Internet Things J. 2020, 7, 9128–9143.
5. Revett, K. Behavioral Biometrics: A Remote Access Approach; John Wiley & Sons: Hoboken, NJ, USA, 2008.

6. Sultana, M.; Paul, P.P.; Gavrilova, M. A concept of social behavioral biometrics: Motivation, current developments, and future trends. In Proceedings of the International Conference on Cyberworlds, Santander, Spain, 6–8 October 2014; IEEE: Piscataway Township, NJ, USA, 2014; pp. 271–278.
7. Gavrilova, M.L.; Anzum, F.; Hossain Bari, A.; Bhatia, Y.; Iffath, F.; Ohi, Q.; Shopon, M.; Wahid, Z. A multifaceted role of biometrics in online security, privacy, and trustworthy decision making. In Breakthroughs in Digital Biometrics and Forensics; Springer: Berlin/Heidelberg, Germany, 2022; pp. 303–324.
8. Rayani, P.K.; Changder, S. Continuous user authentication on smartphone via behavioral biometrics: A survey. Multimed. Tools Appl. 2023, 82, 1633–1667.
9. Sultana, M.; Paul, P.P.; Gavrilova, M.L. User recognition from social behavior in computer-mediated social context. IEEE Trans. Hum.-Mach. Syst. 2017, 47, 356–367.
10. Tumpa, S.N.; Gavrilova, M. Linguistic profiles in biometric security system for online user authentication. In Proceedings of the IEEE International Conference on Systems, Man, and Cybernetics, Toronto, ON, Canada, 11–14 October 2020; IEEE: Piscataway Township, NJ, USA, 2020; pp. 1033–1038.
11. Wahid, Z.; Bari, A.H.; Anzum, F.; Gavrilova, M.L. Human Micro-Expression: A Novel Social Behavioral Biometric for Person Identification. IEEE Access 2023, 11, 57481–57493.
12. Yang, Y.; Guo, B.; Wang, Z.; Li, M.; Yu, Z.; Zhou, X. BehaveSense: Continuous authentication for security-sensitive mobile apps using behavioral biometrics. Ad Hoc Netw. 2019, 84, 9–18.
13. Sahdev, S.L.; Singh, S.; Kaur, N.; Siddiqui, L. Behavioral Biometrics for Adaptive Authentication in Digital Banking-Guard Against Flawless Privacy. In Proceedings of the International Conference on Innovative Practices in Technology and Management, Noida, India, 17–19 February 2021; IEEE: Piscataway Township, NJ, USA, 2021; pp. 261–265.
14. Chu, Z.; Gianvecchio, S.; Koehl, A.; Wang, H.; Jajodia, S. Blog or block: Detecting blog bots through behavioral biometrics. Comput. Netw. 2013, 57, 634–646.
15. Awad, A. Collective framework for fraud detection using behavioral biometrics. In Information Security Practices; Springer: Berlin/Heidelberg, Germany, 2017; pp. 29–37.
16. Granatyr, J.; Gomes, H.M.; Dias, J.M.; Paiva, A.M.; Nunes, M.A.S.N.; Scalabrin, E.E.; Spak, F. Inferring trust using personality aspects extracted from texts. In Proceedings of the IEEE International Conference on Systems, Man and Cybernetics, Bari, Italy, 6–9 October 2019; IEEE: Piscataway Township, NJ, USA, 2019; pp. 3840–3846.
17. Parmentier, A.; Cohen, R.; Ma, X.; Sahu, G.; Chen, Q. Personalized multi-faceted trust modeling to determine trust links in social media and its potential for misinformation management. Int. J. Data Sci. Anal. 2022, 13, 399–425.

18. Wani, M.A.; Agarwal, N.; Bours, P. Sexual-predator detection system based on Social Behavior Biometric (SBB) features. Procedia Comput. Sci. 2021, 189, 116–127.
19. Wahid, Z.; Al Imran, A. Multi-feature Transformer for Multiclass Cyberbullying Detection in Bangla. In Proceedings of the IFIP International Conference on Artificial Intelligence Applications and Innovations, León, Spain, 14–17 June 2023; Springer: Berlin/Heidelberg, Germany, 2023; pp. 439–451.
20. Ren, Z.; Shen, Q.; Diao, X.; Xu, H. A sentiment-aware deep learning approach for personality detection from text. Inf. Process. Manag. 2021, 58, 102532.
21. Guntuku, S.C.; Yaden, D.B.; Kern, M.L.; Ungar, L.H.; Eichstaedt, J.C. Detecting depression and mental illness on social media: An integrative review. Curr. Opin. Behav. Sci. 2017, 18, 43–49.
22. Tadesse, M.M.; Lin, H.; Xu, B.; Yang, L. Detection of depression-related posts in Reddit social media forum. IEEE Access 2019, 7, 44883–44893.
23. Dunbar, R. How Many Friends Does One Person Need? Dunbar’s Number and Other Evolutionary Quirks; Faber: London, UK, 2010.
24. Gonçalves, B.; Perra, N.; Vespignani, A. Modeling users’ activity on Twitter networks: Validation of Dunbar’s number. PLoS ONE 2011, 6, e22656.
25. Mac Carron, P.; Kaski, K.; Dunbar, R. Calling Dunbar’s numbers. Soc. Netw. 2016, 47, 151–155.
26. Sultana, M.; Gavrilova, M. Temporal Pattern in Tweeting Behavior for Persons’ Identity Verification. In Proceedings of the IEEE International Conference on Systems, Man, and Cybernetics, Miyazaki, Japan, 7–10 October 2018; IEEE: Piscataway Township, NJ, USA, 2018; pp. 2472–2477.
27. Tumpa, S.N.; Gavrilova, M.L. Template aging in multi-modal social behavioral biometrics. IEEE Access 2022, 10, 8487–8501.
28. Anjomshoa, F.; Aloqaily, M.; Kantarci, B.; Erol-Kantarci, M.; Schuckers, S. Social behaviometrics for personalized devices in the internet of things era. IEEE Access 2017, 5, 12199–12213.
29. Saleema, A.; Thampi, S.M. User recognition using cognitive psychology based behavior modeling in online social networks. In Proceedings of the Advances in Signal Processing and Intelligent Recognition Systems: 5th International Symposium, SIRS 2019, Trivandrum, India, 18–21 December 2019; Springer: Berlin/Heidelberg, Germany, 2020; pp. 130–149.
30. Parrott, W.G. Emotions in Social Psychology: Essential Readings; Psychology Press: London, UK, 2001.
31. Berndt, D.J.; Clifford, J. Using Dynamic Time Warping to find patterns in time series. In Proceedings of the Knowledge Discovery in Databases Workshop; ACM: Seattle, WA, USA, 1994; Volume 10, pp. 359–370.

32. Li, S.Z. Encyclopedia of Biometrics: I-Z; Springer Science & Business Media: Berlin/Heidelberg, Germany, 2009; Volume 2.