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Utilizing Unsupervised Learning to Create Privacy-Preserving Gait Biometrics

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Introduction

The use of biometrics on mobile devices for authentication has already been demonstrated in a number of studies published in the literature. However, it has been demonstrated that biometric system-associated learning processes may reveal sensitive personal information about subjects. A novel mobile gait biometrics verification method that provides accurate authentication results while safeguarding the subject's sensitive information, is the idea presented in this study.It is made up of two convolutional autoencoders with shared weights that turn the biometric raw data into a new privacy-preserving representation of things like gender and activity;and ii) a Siamese-architectured mobile gait verification system built on a Siamese architecture of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs).The fact that the first module of GaitPrivacyON—convolutional autoencoders—is trained without supervision and without specifying the subject's sensitive characteristics is the main benefit.

Description

The databases for MotionSense and MobiAct;and) the database OU-ISIR. The obtained experimental results indicate that GaitPrivacyON may be able to maintain user authentication results above 96.6% AUC while significantly enhancing the subject's privacy. This is, to our knowledge, the first mobile gait verification method that takes into account privacy-preserving techniques trained unsupervisedly .One of the most common methods of authentication for mobile devices is the use of biometrics. Particularly, smart devices, such as accelerometer and gyroscope data, make passive recognition possible with behavioural biometrics, which are based on how subjects perform actions like writing and walking. Even though mobile behavioral biometrics are becoming increasingly popular, the data that is collected may contain a substantial amount of personal and sensitive information, such as demographics or the subject's activity. As a result, it's possible that this technology amounts to an invasion of personal privacy.

The recent European Union's General Data Protection Regulation (GDPR) is one example of a concept that has been defined in numerous ways. "Any information relating to an identified or identifiable natural person" is the definition of personal data in this. "racial or ethnic origin, political opinions, religious or philosophical beliefs, trade union membership, genetic data, biometric data for the purpose of uniquely identifying a natural person, health data or data concerning the individual's sex life or sexual orientation" are all examples of sensitive data in this set. It is against the law to use automated means to process these kinds of data for any purpose at all without the explicit consent of the subject. A brand-new method for verifying mobile gait biometrics, safeguards the subject's privacy while providing precise authentication results. Because of the particular arm swing amplitude, step frequency, and length, it is unique to each individual. There are a number of ways to easily identify this trait. One of them comes from Inertial Measurement Units (IMUs), such as accelerometers and gyroscopes, which allow mobile devices to use gait biometrics for authentication. The accelerometer's gait biometrics data were used in a cross-correlation and template matching framework to achieve 7% of the Equal Error Rate (EER).According to the review by, many researchers used this approach to propose new studies in the literature.

Due to their ability to extract more discriminative and robust features, Deep Learning (DL) methods have dominated the field of gait recognition in recent years. One of the first systems based on DL that utilized CNNs was developed. For the purpose of recognizing gait biometrics, the authors used universal feature extractors with 0.15 percent misclassification rates. Their findings demonstrated that CNN-based systems outperform previous approaches with pre-defined and frequently arbitrary features because they learn more useful statistical features. RNNs are also one of the most effective DL methods for temporal sequences. Ackerson, otherspropposed another methodology in which the OU-ISIR dataset was utilized. Long Short-Term Memory (LSTM) was one of the first RNN methods developed by the authors, with an EER of 7.55 percent.

For more robust features, a hybrid DL model incorporating CNNs and LSTM was developed. CNNs, which extract convolutional maps with more discriminative features, and RNNs, which process features as temporal sequences, were combined in the proposed model. With 118 subjects and data extracted from the accelerometer and gyroscope, mobile devices in the wild were considered, with an accuracy of 93.7 percent. New privacy laws and regulations are making privacy concerns even more pressing in today's world. As a result, a lot of researchers have done extensive research on the topic over the past ten years [1-5].

Conclusion

Their system, which was based on Generative Adversarial Networks (GANs), achieved a 45.8% accuracy reduction in the gender classification task while only a 1.37 percent accuracy reduction in the activity recognition task. For model training, the authors wanted to avoid having to collect a lot of sensitive data. Unsupervised learning training for the privacy-preserving task was carried out for this purpose. Data transformation and noise addition using an Autoencoder and a CNN were used to treat the framework.While the activity recognition task remained virtually unchanged, gender classification yielded results with an accuracy of 56.79 percent.

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Conflict of Interest

The Author declares there is no conflict of interest associated with this manuscript.

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