CHAPTER 16

Gait Recognition

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CONTENTS

16.1 DATASETS

Gait analysis databases are used in a myriad of fields that include human motion study, kinesiology, and surveillance, which are typically based on vision. These gait data are mostly collected by camera in a laboratory that has a specially designed walking belt. However, the available data acquired from mobile devices are still very limited. Gait authentication from a wearable sensor is still a rather new research area and thus not many datasets are available yet. In recent years, as more researchers show interest exploring gait on mobile devices and conduct experiments, we are fortunately able to find the following public databases for gait research:

1. University of California—Irvine released their gait database on their website. Twenty-two participants walk in the wild over a predefined path with their Android smartphone positioned in their chest pockets. Accelerometer data are collected for motion patterns research and authentication.
2. Another database was collected by Dr. Jordan Frank at McGill University. In this case, HTC Nexus One and HumanSense open-source Android Data Collection Platform were used for gait data acquisition. Twenty participants performed two separate 15-min walks on two different days with the mobile phone in their pockets.

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3. The OU-ISIR (Osaka University—I Research) Gait Database was collected by using one smartphone (Motorola ME860) with accelerometer and three inertial sensors with each embedded with a triaxial accelerometer and triaxial gyroscope. In all, 744 volunteers participated in this experiment. Three sensors are positioned in the back, center and left, and right of the subject's waist. Each subject walked in and out on the level path and upslope and downslope.

4. Pattern Recognition Lab in University Erlangen—Nuremberg used two sensors for gait data acquisition. Each sensor node was equipped with a triaxial accelerometer and a triaxial gyroscope. Data were sampled with 200 Hz and stored on an SD card. Fifteen participants performed seven daily life activities: sitting, lying, standing, walking outside, jogging outside, ascending stairs, and descending stairs.

   Study Cases
   Gait authentication using a cell phone-based accelerometer sensor offers an unobtrusive, user-friendly, and periodic way of authenticating individuals on their cell phones. Here, we present three study cases for gait authentication on a mobile platform.

5. Case 1: Unobtrusive User-Authentication on Mobile Phones Using Biometric Gait—In 2010, researchers from the Norwegian Information Security Lab in Gjovik University in Norway did an experiment on 51 participants carrying Google G1 mobile phones equipped with accelerometers to record their gait data. The mobile phone was placed on the belt on the right-hand side of the subject's hip. The phone's screen pointed to the subject's body and the top pointed to the walking direction, which means the phone was in the same direction as the person who was walking.

   The G1 has an integrated sensor (AK8976A) for measuring accelerations in three axes. The sensor is a piezoresistive micro electro mechanical system (MEMS) accelerometer. Accelerations in all directions can be collected with three sensors perpendicular to each other that represents x, y, and z directions, respectively. The accelerometer can obtain 40–50 samples per second.

   A total of 51 subjects performed two sets of walking, each of two walks, that is a round trip of 37 m of flat carpeted hall. The author defines a cycle as two steps because every a person repeats the same walking every two steps. Notice from all four walks, the first one is used as a template and only the other three are used as test data.

The x-axis data have the best performance among all three (x, y, z), from the gait data obtained and thus x-axis is used as the measurement in this case. To extract features, the author preprocessed the data by interpolating time and filtering data, and then performed cycle estimation and detection.

Since the accelerometer only detects when there is motion change, the data interval is not always equal. Time interpolation is necessary in order to fix this problem. For filtering, apply a weighted moving average [1] filter to remove noise of the data.

From the data, we observed a cycle length is about 40–60 samples per second. The average cycle length is computed based on the distance scores from the small subset to the center of the data.

Cycle detection is conducted after computing the cycle estimate. A cycle starts with the minimum point, which is set as the starting point and goes to both directions by the length of the average cycle length that is computed from the last step. Instead of specifying a particular point, a 10% positive and negative estimation around that point is applied for accuracy and robustness.

As to the average cycle, the authors first drop out the irregular cycles and then use the dynamic time warping (DTW) [2] algorithm to calculate the distances between all cycles and deleting the ones which have an unusually large distance to the other cycles. The cycle with the lowest average DTW distance to the remaining cycles will be used as the average cycle. Average cycle is a feature vector (of real values) of an average length of around 45 samples.

This experiment and algorithm resulted in 20.5% equal error rate [3]. It is not 50% higher than the one using a more advanced sensor that is capable of obtaining twice the data samples.

6. Case 2: Orientation Independent Cell Phone-Based Gait Authentication—The previous research experiment was conducted under a nearly perfect situation where the mobile phone was stably positioned. However, this is not close to a real-life situation at all. People usually put their phone in their pocket and the orientation of the phone-based accelerator continuously changes. This author conducted a research experiment under a more realistic scenario, contributed in compensating the orientation error, and showed the

authentication results by using the modified cycle length estimation and detection algorithm he proposed.

In this research, 35 participants' gait data are collected using the Google Nexus Android phone. An Android application is developed to record three-dimensional accelerometer data at a sampling rate of 100 Hz, and a text file with timestamps is written out. Participants were asked to put their phone in the pant's right-hand side front pocket and walk two round trips in a 68 m long straight corridor at their normal pace.

From the subject's gait data, a total of four walks are observed and each walk roughly lasts 50 s. The walking activity data vary person to person. To separate each walk, the author monitored the variances of data along one axis and examined the variances for every second and compared the data variances with the predefined threshold. If the data variances are above the threshold, it is set as the start of a walk. If the data variances are below the threshold, then it is set as the end of the walk. After all the walk cycles are marked, the walk that is longer than 10 s was selected and the Euclidean resultant vector computed.

A few preprocessing procedures are applied including reshaping of the data for equal time interval, and rescaling the feature with zero normalization and the wavelet-based noise removal modules. It was the same with the last study case, since the data are collected only when the sensors detect the motion change, the time interval between every two input data is not equal. Therefore, the author applied interpolation to reshape the data in equal time intervals.

Data normalization is necessary before any furthering gait analysis. In this case, the author simply obtained the new acceleration data by subtracting the mean acceleration for each axis. The multilevel Daubechiess orthogonal wavelet (db6) [4] with level 3 and soft thresholding is used to eliminate the noise from the walking signal.

In this example, the cycle length estimation is based upon the assumption that the center of the walk is the most stable data. So, it starts with extracting 80 small sets of walk data as samples around the center of the walk, and stores them in a reference window. Compare the reference window with the rest of the data subset to get the difference vector. Then, store the minimum indices found from it which results in a new vector. Compute every two adjacent values in the new vector and the mode, which is the most frequent data of the resultant set of numbers, is used to estimate the cycle length. However, if the mode does not exist, it means that every step of the subject varies and the cycle length can be computed by averaging the values of the difference vector.

To reduce the risk of picking the wrong minimum, the author takes a segment of the size twice of the estimated cycle length in the center of the walk, therefore obtaining two minima. The smaller minima is picked and used as the start of a cycle. Similarly with the last study case, the cycle's ending is obtained by adding and subtracting a cycle length time. Since not all the minimas in the walk occur in the equal interval, applying an offset (0.2*estimated cycle length) helps to increase the accuracy. Finally, all the gait cycles are normalized and unusual cycles are removed by computing the pairwise distance using DTW.

Once the references and the probe cycles are generated, they are compared against each other to compute the intraclass (genuine) and interclass (imposter) distances. If 50% cycles of a walk have distances below the threshold value, it is considered as genuine, and vice versa.

The author compares the gait analysis on the same day and cross-days and found big differences. Since people's gait changes over time, he points to an online learning method to cope with the aging factor as future work.

7. Case 3: Secure and Privacy Enhanced Gait Authentication on Smartphone—In this paper, the author proposes a gait biometric cryptosystem (BCS) using a fuzzy commitment scheme on mobile platform. The gait features are used to biometrically encrypt a cryptographic key which acts as the authentication factor. Gait signals are acquired by the mobile phone-based triaxial accelerometer. Error correcting codes are adopted to deal with the natural variation of gait measurements. The gait sample is merely used to retrieve the cryptographic key and then discarded.

   The author collected 34 participants' gait data. Each subject walked with the Google Nexus One smartphone inside the front pant pocket. The experiment achieved the lowest false acceptance rate and the false rejection rate of 3.92% and 11.76%, in terms of key length of 50 bits.

There are two phases in this gait BCS, namely enrollment and authentication. In the enrollment phase, a user's gait features are collected. Similarly with the previous two examples, the acquired gait data are preprocessed in a few steps: data interpolation to achieve equal time interval and noise filter using Daubechie orthogonal wavelet (db6) [4] with level 2. Feature vectors are extracted in both time and frequency domains. Euclidean distance in 3D space is calculated for measurement. Then, the vectors are binarized. A reliable binary feature vector w is extracted based on the user's gait. Meanwhile, a randomly generated cryptographic key m is encoded to a codeword c by using error correcting codes. The fuzzy commitment scheme F computes the hash value of m and a secured δ using a cryptographic hash function h and a binding function. The helper data which are used to extract reliable binary feature vectors and values of h(m), δ are stored for later use in the authentication phase.

In the authentication phase, the user provides a different gait sample. It is also preprocessed to extract a feature vector and a reliable w' is extracted by using helper data which is stored in the enrollment phase. The decoding function f computes the corrupted codeword c' via binding w' with δ and then retrieves a cryptographic key m' from c' using the corresponding error correcting code decoding algorithm. Finally, the hash value of m' will be matched with h(m) for authentication decision.

There is good potential to construct an effective gait-based authentication system. Design and construct better discriminant feature vectors (using global feature transformations), finding optimal quantization scheme for binarization can help to achieve better performance.

16.2 CONCLUSION

Humans walk in their own unique style with a natural repetitive mode. A mobile-based accelerator is able to collect the gait data. A gait cycle which is the time interval between two successive occurrences of one of the repetitive events when walking is used to study and analyze the characteristics of the gait. The key of the gait analysis lies on a good algorithm for cycle length estimation and cycle detection—points where a cycle starts and ends.

Under the realistic situation where the phone's positions change all the time, the orientation of the sensor changes frequently and much noise is created by random motions of the mobile phone. The human gait can be affected by clothes, weight lifting, carrying burdens, etc., besides the fact that the human gait may change with aging. All these factors affect accuracy recognition and pose challenges. More work may be needed in improving the cycle extraction algorithms and exploring various walking environment settings.

Regardless of a number of challenges, gait authentication on mobile devices is a feasible and promising field. The three case studies detailed here achieved good results and meanwhile indicate that there is more that can be done. In order to improve gait authentication performance, we need a continuous research effort in developing a more robust cycle estimation and detection algorithm and a sophisticated adaptive learning system to compensate the constant position changes with mobile devices.

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