MODERN METHODS OF HUMAN IDENTIFICATION USING GAIT CHARACTERISTICS

Review Article

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Saša Mićin[1]
Danijela Tatić
Milica Hrvač
Faculty of Security Studies, University of Banja Luka

Abstract: Automatic systems for personal identification based on gait occupy an important place among biometric identification systems. The development of information technologies has enabled a very intensive development and application of these systems in criminal and security sciences. This paper presents the systems of biometric personal identification using gait characteristics based on input data collected using different techniques, algorithms for extracting and selecting characteristics, different classifiers in the classification process, including databases used to evaluate and compare the efficiency of the system.

Keywords: biometric characteristics, gait recognition, identification

INTRODUCTION

Biometric recognition is one of the most important methods of personal identification, which has been frequently been used in various fields, especially criminal and security sciences, and forensics (Jain, Ross, & Nandakumar, 2011). Developed systems are based on the measurement and analysis of various unique physical and behavioral characteristics of a person. The most commonly used characteristics are papillary lines, iris and retina, face, handwriting, and voice (Takemura, Makihara, Muramatsu, Echigo, & Yagi, 2018). Personal identification based on gait patterns is a more recent method.

Gait is one of the basic human activities and represents the basic way people move. It is classified as a complex biometric behavior characteristic that is based on Newton's third law – the principle of action and reaction (Whittle, 2007). Studies have shown that human gait is characterized by 24 different components, that is, that each person has a specific musculoskeletal structure, which is the basis for identification (Kale, Sundaresan, Rajagopalan, Cuntoor,

1 Corresponding author: Saša Mićin, Assistant Professor, Faculty of Security Studies, University of Banja Luka. E-mail: sasa.micin@fbn.unibl.org.

Roy-Chowdhury, Kruger, & Chellappa, 2004). Research has confirmed the possibility of recognizing people and a person's gender based on human gait patterns (Cutting & Kozlowski, 1977). The influence of various factors (gender, body weight, feeling, emotion) on human gait patterns was analyzed (Troje, 2002).

The beginning of the development and application of automatic systems for personal identification based on human gait patterns can be linked to the study by Niyogi and Adelson, which was based on a database with a small amount of data (Niyogi & Adelson, 1994). Further research was mainly carried out using video recordings, where the so-called model-based approach involving the formation of a model of the human body based on video recordings and extraction of the features that correspond to the physical model of the human body was mainly used (Wang, Ning, Tan, & Hu, 2004). In order to research, test and verify the proposed methods, the authors created input data databases with different covariance.[2] The first publicly available gait recognition database was released in 2005 as a part of the *HumanID* program developed by the Defense Advanced Research Projects Agency – DARPA[3] (Sarkar, Jonathon Phillips, Liu, Vega, Grother, & Bowyer, 2005). The development of a model-free approach based on extracting a person in motion from the background and deriving a human silhouette began in 2006 (Man & Bhanu, 2006). Further development of algorithms for data processing has enabled the recognition of human gait, which is used to identify the emotions of the observed person (Mathivanan & Perumal, 2021).

Some characteristics of biometric identification based on human gait patterns, such as the possibility of recognizing a person at greater distances between the object of identification and the identification system, the use of several different simple recording devices with low resolution, recognition without the cooperation of a person (Kim, & Paik, 2010), difficult imitation of gait patterns and movement, give this method an advantage over other biometric methods (Nixon & Carter, 2004).

MODERN METHODS OF PERSONAL IDENTIFICATION BASED ON GAIT PATTERNS ANALYSIS

In general, the basic elements of a biometric system for gait-based personal recognition are data collection, feature extraction, feature selection, and classification (Wan, Wang, & Phoha, 2018).

2 Covariance is a measure of the relationship between two random variables and to what extent they change.

3 DARPA is an agency of the United Statets Department of Defense responsible for the development of emerging technologies for use by the military.

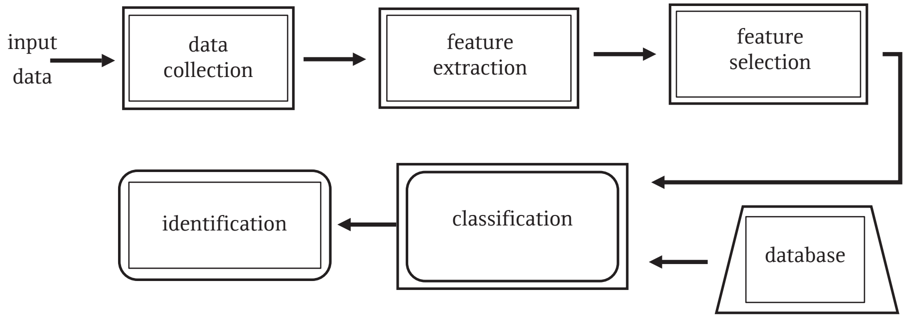


Figure 1: Block diagram of the biometric system for gait-based person recognition

A similar block diagram of a biometric system for gait-based person recognition was proposed by Kastaniotis et al., which contains a preprocessing module, a feature extraction module, a pattern classification module, and a result module (Kastaniotis, Theodorakopoulos, Economou, & Fotopoulos, 2016).

Data Collection

The data collection module includes the acquisition of spatiotemporal data related to human gait. The data was collected using video cameras, accelerometers, floor sensors and continuous-wave radar (Wan et al., 2018). One or more RGB cameras are often used. The use of one camera enables identification based on the so-called 2D gait signature in contrast to the use of multiple synchronized cameras, which significantly increase the possibility of applying input data (3D gait model creation, 2D gait signature creation with additional elements (the so-called 2.5D gait signature), invariant gaze tracking) (Makihara, Nixon, & Yagi, 2021; Santos, Tavares, & Rocha, 2022).

Similar results can be achieved by using the so-called depth sensors of which the most famous is Microsoft Kinect[4] (Khoshelham, 2012), on the basis of which several gait recognition systems have been developed (Dikovski, Madjarov, & Gjorgjevikj, 2014).

4 Kinect is a line of motion detection input devices manufactured by Microsoft, which was released in 2010. These devices generally contain RGB cameras, infrared projectors, and detectors that map depth through structured light or time-of-flight calculations, which in turn can be used to perform real-time motion recognition and body skeleton detection, among other capabilities. They also contain microphones that can be used for speech recognition and voice control.

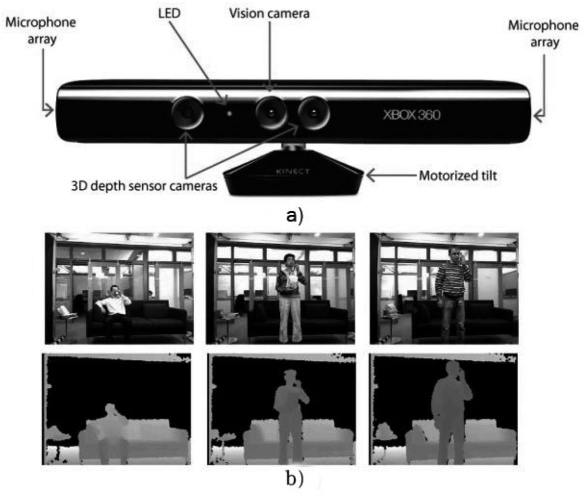


Figure 2: Presentation of 3D camera and input RGB-D data a) Microsoft Kinect device b) input RGB-D data (images) captured by Microsoft Kinect device (Ly Quoc Ngoc, Vo Hoai Viet, Tran Thai Son, & Pham Minh Hoang , 2016).

The input data collected by the accelerometer[5] was used to develop biometric identification systems based on gait (Derawi & Bours, 2013). In general, the accelerometer-based systems are placed on the human body, recording the three-dimensional accelerations of characteristic points on the body during walking, which represent the input data for the given system (Semwal, Gaud, Lalwani, Bijalwan, & Alok, 2021).

When walking, people produce different intensity of pressure on the surface on which they move, which provides the possibility of identification. On the basis of input data obtained by means of floor sensors, walking pattern is modeled and then the person is identified (Nakajima, Mizukami, Tanaka, & Tamura, 2000). The classification algorithm for processing steps called Distinction Sensitive Learning Vector Quantization (DSLVQ) was developed (Suutala & Röning, 2004). It has been shown that the impact of footwear on input data can be reduced (Orr & Abowd, 2000). The floor sensors used include OR6-7 force plate, a sensor mat, load cells, and electro-mechanical film (EMFi)[6] (Wan et al., 2018).

5 Accelerometers are sensors that measure acceleration, that is, inertia force. They can measure acceleration in one or more directions, where those directions are perpendicular to each other.

6 A thin, flexible material, which consists of cellular, biaxially oriented polypropylene film coated with metal electrodes. An external force affecting the surface of the EMFi causes a change in the thickness of the film, resulting in an electric charge between the conductive metal layers. It can be detected as a voltage, which describes changes in the pressure affecting the film.

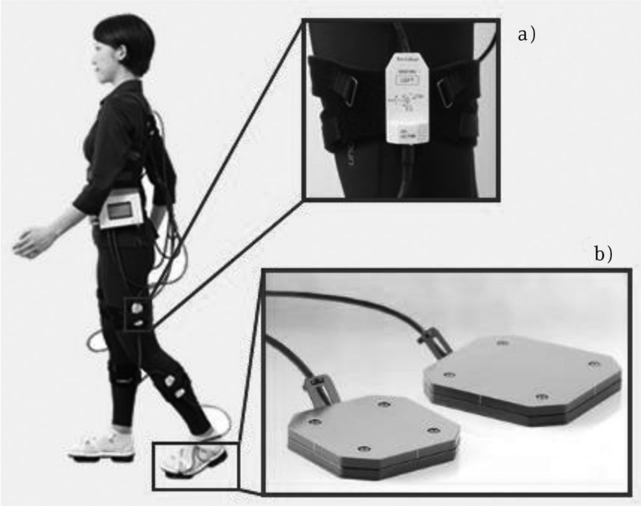


Figure 3: Wearable sensor system a) inertial sensor (accelerometer) b) floor sensors (Muro-de-la-Herran, Garcia-Zapirain, & Mendez-Zorrilla, 2014).

In addition to the previously mentioned ways of collecting input data, research was carried out related to the use of radar systems for the purpose of identifying persons based on human gait. The system functions based on the Doppler effect using a continuous spectrum radar[7] with electromagnetic waves characteristic of the microwave region of the spectrum of electromagnetic radiation. Tests were also conducted using ultra-wideband Doppler radar[8] and micro-Doppler effect in the radar[9] (Wan et al., 2018). Based on previous research, Yamada et al. presented a biometric identification method for gait recognition using real-time multi-line LiDAR[10] (Yamada, Ahn, Martinez Mozos, Iwashita, & Kurazume, 2020) to collect input data.

Extracting gait characteristics

Gait characteristics used in gait recognition systems can be classified into two groups, static and dynamic (Rao, Sahu, & Parida, 2021). Static character-

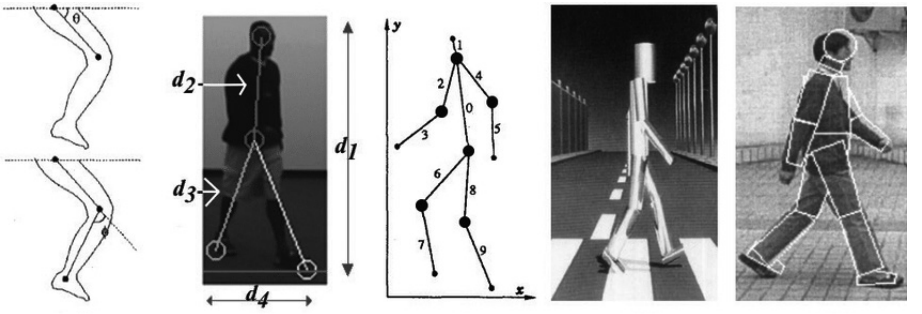
7 A continuous wave or continuous waveform (CW) is an electromagnetic wave of constant amplitude and frequency, typically a sine wave, which, for mathematical analysis, is considered to be of infinite duration.

8 Ultra-wide-band (UWB) radars produce very short radio-frequency (RF) pulses in the range of a sub-nanosecond and are used for sensing and imaging applications.

9 If the observed/recorded subject has mechanical vibrations or rotations, modulation frequencies can be induced on the return signal that generate sidebands spaced at the Doppler frequency of the observed subject.

10 LiDAR (Light Detection and Ranging) – an optical system that emits laser beams to an object and detects the beams reflected back.

istics refer to the anthropometric parameters, while the dynamic parameters are related to the trajectory of individual elements of the skeletal system. These two approaches have been developed for processing input raw data and presenting the processed data collected through video cameras. The model-based approach represents movement modeling and calculation of gait characteristics based on a created movement model based on spatial and temporal data (Lee & Grimson, 2002). The structure of the human body is used, mainly the kinematic characteristics of the human locomotor system. It requires higher resolution input data (images) and is conditioned by higher computer processing costs (Makihara et al., 2021). After the formation of the movement model, the characteristics are extracted from the given model. In the model-based approach, the extracted characteristics predominantly include the distance and angles of individual points on the human body.



a) b) c) d) e)

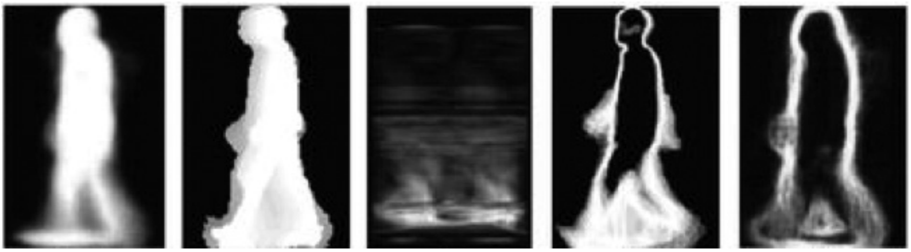
Figure 4: Input data processing using the model-based approach a) joint model; b) static human parameters; c) stick model; d) volumetric model; e) static and dynamic characteristics (Sun, Wang, & Li, 2017).

Several biometrics personal identification systems based on gait, which are based on different models, have been presented (Table 1).

Table 1: Models used to create the movement model (Makihara et al., 2021; Wan et al., 2018)

Model	
Single oscillator	Joint Model
Ellipsoidal fits	Dual oscillator
Kinematic features	Linked features trajectories
Stride parameters	Stick model
Human parameters	Layered deformable model
Joint trajectories	Marionette mass-spring model

Model-free approaches use the whole motion pattern of the human body, that is, the input data are taken directly from the movement sequence of the observed subject without fitting a model (Makihara et al., 2021).



a) b) c) d) e)

Figure 5: Input data processing using a model-free approach a) gait energy image; b) motion silhouette image; c) shape variation-based image; d) gait entropy image; e) compressed silhouettes image; (Sun et al., 2017)

During the extraction and presentation of the characteristics of human gait, different algorithms were used for the processing of individual characteristics (Table 2).

Table 2: Model for representing and extracting gait features based on a model-free approach (Makihara et al., 2021; Wan et al., 2018)

Model
Silhouette similarities
Motion-history image, MHI
Motion-energy image, MEI
Gait History Image, GHI
Gait Energy Image, GEI
Gait energy volume, GEV
Frame Difference Energy Image, FDEI
Gait Gaussian Image, GGI
Gait Entropy Image, GEI
Flow Histogram Energy Image, FHEI
Gradient Histogram Gaussian Image, GHGI
Active energy image, AEI
Distance-based features
Gabor filter
Learned features using a convolutional neural network, CNN
Hidden Markov model

The methods of extracting features based on the input data collected by means of the accelerometer can be divided into two groups. Gait-cycle-based features are based on the average gait cycle, which is the basis for the classification procedure (Wan et al., 2018). Frame-based feature extraction and representation divides the input data into multiple individual groups, from which a feature vector is extracted for each group. The set of extracted vectors is the basis for classification (San-Segundo, Cordoba, Ferreiros, & D'Haro-Enriquez, 2016). Previously, the development of biometric identification systems based on gait using multiple accelerometers was started, that is, the merging of isolated features using multiple accelerometers simultaneously (Chen, Liang, Zhao, Hu, & Tian, 2009).

The features extracted from floor sensor data include body mass, cadence, and stride length (Jenkins & Ellis, 2007).

Doppler frequency shift is the basis for extracting features when using radar biometric personal identification systems based on gait (Wan et al., 2018).

The selection (reduction) of features

The selection (reduction) of features previously extracted represents the extraction of irrelevant and bad features by means of appropriate algorithms. There are different approaches to feature reduction: a) the filter-based approach,[11] b) the wrapper-based approach,[12] c) the embedded-based approach[13] (Jović, Brkić, & Bogunović, 2015).

The most commonly algorithms used to select and extract features are the principal component analysis (PCA), Linear Discriminant Analysis (LDA), a combination of the principal component analysis and the linear discriminant analysis, and Piecewise Linear Representation (PLR) (Rao, et al., 2021), Discrete Cosine Transform (DCT) (Fan, Jiang, Weng, He, & Liu, 2016), and I-vector (San-Segundo, Echeverry-Correa, Salamea-Palacios, Lutfi, & Pardo, 2017).

In addition to the aforementioned algorithms used for feature selection, the existing studies also mention the application of the Gabor features and General Tensor Discriminant Analysis, Modified Independent Component Analysis (MICA), Discrete Wavelet Transformation (DWT), Fourier descriptors, Canonical Analysis, Sparse Bilinear Discriminant Analysis (SBDA), General Tensor Discriminant Analysis (GTDA) and Discriminant Analysis with Tensor Representation (DATER) (Wan et al., 2018).

In this module, in addition to the feature selection (reduction) process, which mainly refers to the removal of irrelevant features, modern biometric recognition systems based on gait also remove bad quality outliers. Bad quality outliers include outliers in one frame, outliers in datasets, outliers in one gait video, and outliers caused by cloths (Wan et al., 2018).

11 The filter-based approach.

12 It evaluates attribute sets using a learning scheme. Cross-validation is used to eestimate the accuracy of the learning scheme for a set of attributes.

13 Embedded methods combine the qualities of filters and wrapper methods. It is implemented by algorithms that have their own built-in feature selection methods

Classification

The classification procedure means a comparison of the collected and pre-processed features (through the feature collection, extraction and selection module) with the features collected in the databases. Distance, correlation, machine learning, the Hidden Markov model and Bayesian classification were used for the classification procedure (Rao, et al., 2021).

A distance-based classification method calculates the distances from collected gait data to the gait pattern in the database. The methods used to calculate differences include Euclidean distance,[14] Manhattan distance,[15] dynamic time warping (DTW) distance,[16] and the K-Nearest Neighbor (K-NN)[17] (Wan et al., 2018).

Correlation is a statistical relationship involving dependence, or the degree to which two variables move in coordination with each other. Studies have been conducted using Pearson's correlation coefficient (Khurelbaatar, Kim, Lee, & Kim, 2015).

Machine learning classifiers[18] use different algorithms for data processing, which include Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), Decision Tree Ensemble Classifier (DTEC)[19], Neural Network Classifier,[20] and the so-called Deep Learning in Gait Recognition[21] (Wan et al., 2018).

Hidden Markov Model[22] is widely used in biometric gait recognition systems. Different variations of this algorithm have been used, such as Full Hidden Markov Models (FHMM) and Parallel Hidden Markov Models (PHMM) (Chen, Liang, Zhao, Hu, & Tian, 2009b).

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14 The Euclidean distance between two points in the Euclidean space is defined as the length of the line segment between two points.

15 The Manhattan distance is a metric distance between two points in an N dimensional vector space. It is defined as the sum of the lengths of the projections of the line segment between the points on the coordinate axes. Simply put, it is the sum of absolute difference between coordinates of corresponding dimensions.

16 Dynamic time warping is an algorithm used to measure similarity between two sequences which may vary in time or speed.

17 K-NN is a non-parametric algorithm used for classification and regression.

18 Machine learning (ML) is a type of artificial intelligence (AI) that allows software applications to become more accurate at predicting outcomes without being explicitly programmed to do so. Machine learning algorithms use historical data as input to predict new output values.

19 Ensemble methods which combine several decision tree classifiers to produce better predictive performance than a single decision tree.

20 A neural network consists of units (neurons), arranged in layers, which convert an input vector into some output vector. Each unit takes an input, applies a (often non-linear) function to it and then passes the output on to the next layer.

21 Deep learning (also known as deep structured learning or hierarchical learning) is part of a broader family of machine learning methods based on data representation learning, as opposed to algorithms based on lists of commands.

22 A hidden Markov model (HMM) is a statistical Markov model in which the system being modeled is assumed to be a Markov process with unobservable (hidden) states.

The Bayesian classifier is based on the Bayesian Theorem,[23] which is used to calculate the probability that the processed characteristics match the data in the database (Bazin, & Nixon, 2005).

To evaluate and compare the efficiency of gait recognition systems, several specific databases have been developed for with different methods of collecting input data.

Table 3 shows the available databases used in the classification process of recognition systems based on input data collected by video cameras (Wan et al., 2018; Rao, et al., 2021; Makihara et al., 2021).

Table 3: Databases used in the classification process

Databases			
CMU MoBo	SOTON Temporal	OU-ISIR, Treadmill B	WOSG
Georgia Tech	USF HumanID	OU-ISIR, Treadmill C	AVA
HID-UMD	CASIA A	OU-ISIR, Treadmill D	AVAMVG
SOTON Small Database	CASIA B	OU-ISIR, LP	OU-ISIR MVLP
SOTON Large Database	CASIA C	TUM-IITKGP	NIST
SOTON Multimodal	OU-ISIR, Treadmill A	TUM-GAID	KY 4D

Databases used in the evaluation of biometric systems based on the input data collected through accelerometers are the Speed Dataset, the Motion-Recording-Sensor-Based Dataset, the Walking Pattern Dataset, the Android phone Google G1 Dataset, and the Human Activities and Postural Transitions Dataset (Wan et al., 2018).

A number of databases used in gait recognition systems based the input data collected through floor sensor have been presented and radar systems (Jenkins & Ellis, 2007; Middleton, Buss, Bazin, & Nixon, 2005).

CONCLUSION

Biometric gait recognition systems are novel systems characterized by intensive development with the application of appropriate information technologies. The advantages of these systems are reflected in the possible use of larger distances between the subject and the identification system, the use of several different simple recording devices with low resolution, recognition independent of the cooperation of the observed person, as well as a reduced possibility of imitating gait characteristics and masking movements. The development of software and hardware has enabled the application of complex mathematical algorithms, resulting in a high degree of reliability of the developed systems.

23 It describes the probability of an event, based on prior knowledge of the conditions that might be related to the event.

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