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Investigating the use of motion-based features from optical flow for gait recognition

Zohra Mahfouf[a,b,*], Hayet Farida Merouani[a], Imed Bouchrika[b], Nouzha Harrati[b]

[a] Department of Computer Science, University of Annaba, 23000, Algeria
[b] Faculty of Science and Technology, University of Souk Ahras, 41000, Algeria

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ABSTRACT

Although numerous research studies have confirmed the potentials of using gait for people identification in surveillance and forensic scenarios, only a few studies have investigated the contribution of motion-based features on the recognition process. In this research paper, we explore the use of optical flow estimated from consecutive frames to construct a discriminative biometric signature for gait recognition. A set of experiments are carried out using the CASIA-B dataset to assess the discriminatory potency of motion-based features for gait identification subjected to different covariate factors including clothing and carrying conditions. Further experiments are conducted to explore the effects of the dataset size, the number of frames and viewpoint on the classification process. Based on a dataset containing 1000 video sequences for 100 individuals, higher recognition rates are achieved using the *Knn* and neural network classifiers without incorporating static and anthropometric measurements. This confirms that gait identification using motion-based features is perceivable with acceptable recognition rates even under different covariate factors. As such, this is a major milestone in translating gait research to surveillance and forensic scenarios.

1. Introduction

Because of the proliferating number of crimes and terror attacks that took place during the last decade across Europe, North Africa and the Middle East, a surge of concerns has emerged in many countries to ensure the safety of their citizens. Further to the unprecedented increase of surveillance CCTV cameras with the limited human resources to manually screen all monitored activities simultaneously, the uptake of biometric solutions within surveillance systems is considered a rudimentary factor for automating the process of security and forensic applications. The visual extraction of biometric data for identification can be poorly affected due to the crime scene, biometric modalities and image quality. Gait biometrics is argued to be suitable for visual surveillance mainly as the walking pattern can be recorded from a distance regardless of the low resolution of the camera. This is in contrast to other biometric modalities where their performance suffers severely in surveillance applications. Moreover, the attractive merit of gait recognition is the non-invasiveness nature and thus, there is no need or obligation for the candidate to interact cooperatively with the acquisition hardware for identification purposes. This sets gait biometrics more appropriate in cases such that direct contact with the offender is not an option. Moreover, the main objective of biometric systems is to be robust enough to prevent possible spoofing attacks and forgery, the biometric signature derived from gait which is constructed from the cyclic walking movement, is considered solely the optimal identity recognition method for covert scenarios.

Gait is defined as the way of the locomotion process characterized by successive periods of lifting and swinging the lower limbs. The word *Gait* refers generally to walking, hopping and running though the term gait is frequently used to describe the walking style of an individual. The human gait pattern is carried out in a characteristic, rhythmic and repeatable fashion [1] composed of consecutive cycles. In contrast to well-established biometric modalities including fingerprints and DNA being used in forensic investigations, security and surveillance applications, a wealth of research studies documented that the gait pattern can be affected by various factors which can influence the performance and evidence credibility within the identification process. Among such factors, psychological state of the person such as medical conditions, sobriety or anxiety. This is besides the appearance factors including load carriage, footwear and clothing in addition to the

* Corresponding author at: Faculty of Science and Technology, University of Souk Ahras, 41000, Algeria.
E-mail address: z.mahfouf@univ-soukahras.dz (Z. Mahfouf).

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acquisition settings as camera viewpoint, illumination and occlusion.

Due to the dearth of vision-based research studies which explore the contributions of motion-based features on the recognition process for gait biometrics, the use of optical flow features is investigated in this research paper for people identification via the way they walk. In fact, as early psychological and medical studies confirmed that the distinctive characteristics for the perception of human motion and people identification can be found mostly in the kinematic part of the gait pattern, the aim of this study is to confirm whether gait recognition is perceivable using features derived from the optical flow data using automated methods. A set of biometric descriptors derived from optical flow data are described accounting to the spatial, temporal and orientation aspects of the motion process. The gait signature is constructed purely from kinematic-based features without incorporating static or anthropometric cues. A set of experiments are carried out using the CASIA-B dataset to assess the discriminatory potency of motion-based features derived from optical flow for gait identification subjected to different covariate factors including clothing and carrying conditions. Further experiments are conducted to explore the effects of the dataset size, the number of frames in addition to the impact of viewpoint variation on gait biometrics. Comparative analysis is conducted against well-established methods including the Gait Energy Image descriptor. The attained results confirm that people identification using dynamic gait features is still perceivable with better recognition rates even under the influence of different covariate factors. As such, this is a major milestone in translating gait research to surveillance and forensic scenarios.

This paper is organized as follows. The next section outlines the previous approaches for gait biometrics using different types of features. The theoretical description of the presented motion-based method for extracting and constructing gait-based biometric signature is detailed in Section 3. Subsequently, the conducted experiments are discussed with the obtained results.

2. Related work

Early medical investigations conducted by Murray [2] in 1967 produced a standard gait pattern for normal walking people aimed at studying the gait pattern for pathologically abnormal patients. The experiments were performed on sixty people aged between 20 and 65 years old. Each subject was instructed to walk for a repeated number of trials. For the collection of gait data, special markers were attached on every subject. Murray [2] suggested that the human gait consists of 24 different components which render the gait pattern unique for every person if all gait movements are considered. It was reported that the motion patterns of the pelvic and thorax regions are highly variable from one subject to another. Furthermore, Murray observed that the ankle rotation, pelvic motion and spatial displacements of the trunk embed the subject individuality due to their consistency at different trials. In 1977, Cutting and Kozlowski [3] published a paper confirming the possibility of recognizing people by gait via observing moving lights mounted on the joints positions. Although, there is a wealth of gait studies in the literature aimed for medical use with a few referring to the discriminatory nature of the gait pattern, none is concerned with the automated use of gait for biometrics and recognizing people. The gait measurements and results introduced by Murray are to be of benefit for the development of automated gait biometric systems. For gait recognition using automated markerless approaches, various methods were surveyed in [4–6]. Based on the procedure for extracting gait features, gait recognition methods can be divided into two major types which are model-based and appearance-based approaches.

2.1. Appearance-based approaches

Appearance-based or model-free approaches for gait biometrics do not need a prior knowledge about the gait or model. Instead, features are derived from the whole body without the need to explicitly extract the human body parts. The majority of appearance methods depend on data taken directly from human silhouettes which are obtained via background segmentation. Appearance-based approaches rely pivotally on statistical tools to reduce or optimize the dimensionality of the feature space using methods such as Principal Component Analysis. In addition, advanced machine learning techniques are usually applied such as deep neural networks. Contentiously, investigations by Veres et al. [7] argued that most of the discriminative features for silhouette-based approaches are contributed from static components of the top section of the human body whilst the dynamic components generated from the swinging of the legs are ignored as the least important biometric data. There is a trending work on the use of deep learning for pattern recognition and image processing applications [8–10]. Yu et al. [11] considered the use of multi-modal features for the representation of images in order to ease the accurate retrieval based on specific queries. Their method is based on a newly presented deep multi-modal distance metric learning with a group of auto-encoders being applied. In [12], a new variant of generalized extreme learning auto-encoder for deep neural network for the extraction of features from unlabeled data. Baig et al. [13] proposed a boosting-based approach for learning a feed-forward artificial neural network with a single layer of hidden neurons and a single output neuron.

2.1.1. Silhouette-based methods

Silhouette-based methods work by separating walking people from the background. The simplest baseline method is to compute the similarity score between two synchronized sequences of concatenated silhouettes [14]. The *Gait Energy Image (GEI)* is another simple silhouette-based representation introduced by Han and Bhanu [15] in which the gait signature is constructed through taking the average of silhouettes for one complete gait cycle. Experimental results confirmed that higher recognition rates can be attained to reach 94.24% for a dataset of 3141 subjects [16]. However, such method performs poorly when changing the appearance and viewpoint. Xu et al. [17] proposed coupled locality preserving projections for cross-view recognition using GEI data. The *Motion Silhouette Image* (MSI) is a similar representation to GEI proposed by Lam and Lee [18] where each pixel intensity is computed as a function of the temporal history of motion for the corresponding pixels across a complete gait cycle. Experiments conducted on the large SOTON gait dataset using this descriptor showed that a success rate of 87% can be achieved. *Gait Entropy Image (GenI)* is a silhouette-based representation introduced by Bashir et al. [19] which is computed by calculating the Shannon entropy for each pixel achieving a correct classification rate of 99.1% on dataset of 116 subjects. The Shannon entropy estimates the uncertainty value associated with a random variable. Other similar representations include Motion Energy Image, Gait History Image, Frieze Patterns and Chrono-Gait Image [6]. Hayfron-Acquah et al. [20] introduced a method for constructing a gait signature based on analysing the symmetry of human motion. The symmetry map is produced via applying the Sobel operator on the gait silhouettes followed by the Generalized Symmetry Operator. On the use of deep learning with silhouette data, Hong et al. [21,22] proposed a multi-layered deep neural network for pose recovery to map 2D images into 3D poses. Yu et al. [23] employed deep learning on autoencoder for viewpoint invariant gait biometrics using Gait Energy Image. In [24], a framework based on subspace ensemble learning via totally-corrective boosting method is proposed to achieve competitive performance for gait recognition using appearance-based features.

2.1.2. Optical flow-based methods

Little and Boyd [25] were the first to use optical flow for gait recognition, they computed the dense optical flow from sequences containing 80 frames. Twelve types of statistical features from the horizontal and vertical components of the optical flow are extracted to compose a biometric signature. In their experiments, a recognition rate of 90.5% is achieved using the twelve features when applied on seven sequences for each of the six walking subjects. In [26], Huang used the temporal information from optical flow changes between two consecutive spatial templates of 70 to 80 frames spanning for about four walking cycles. They extracted a low dimension features space using a combination of the Eigenspace Transformation with canonical space projection. Using template matching for classification, a recognition rate of 100% was attained on a small dataset of five people using the magnitude of the horizontal optical flow components. Further, Bashir et al. [19] used the dense optical flow field computed using the method in [27] for each frame of the whole gait cycle to extract four different types of motion descriptors based on the horizontal and vertical optical flow components. Experiments on the CASIA and SOTON datasets with the clothing and bag carrying covariates outperform previous reported studies. Lam et al. [28] proposed the Gait Flow Image (GFI) descriptor computed as average of the binary flow images taken from silhouette data. In [29], the flow histograms were constructed by considering the polar components of the optical flow inside the bounding box. Since the length of the videos may be different due to varied walking speed, they applied a histogram matching method to find the gait cycle for each subject in order to obtain unbiased features. In [30], Hu et al. used the LBP descriptor to estimate the features from the horizontal and vertical components of the optical flow. Their experiments was aimed to explore the effect of covariates factors on the CASIA-B and CASIA-A datasets relatively to the frames number using incremental learning.

2.2. Model-based approaches

For the model-based approach, a prior model is established to match real images to this predefined model, and thereby extracting the corresponding gait features once the best match is obtained. Usually, each frame containing a walking subject is fitted to a prior temporal or spatial model to explicitly extract gait features such as stride distance, angular measurements, joints trajectories or anthropometric measurements. Although model-based approaches tend to be complex requiring high computational cost, these approaches are considered more suitable for human motion analysis due to their advantages [5]. The main merit of model-based techniques is the ability to derive detailed and accurate gait motion data with better handling of occlusion, self-occlusion and other appearance factors as scaling and rotation. The model can be either a 2 or 3-dimensional structural model, motion model or a combined model. Niyogi and Adelson [31] was perhaps the pioneer in 1994 to use a model-based method for gait recognition. The gait biometric signature is constructed from the spatio-temporal pattern using a five stick model. From a dataset of 26 sequences containing 5 different people, an encouraging recognition rate of 80% was reported. Wagg and Nixon [32] described a model-based approach for gait recognition based on the biomechanical analysis of walking people. Mean model templates are adopted to fit individual people. The anatomical knowledge of the human body are deployed to lessen the computational costs of the extraction process. The features vector is weighed using statistical analysis techniques to measure the discriminatory potency of each element. On the evaluation of this method, a correct classification rate of 95% is achieved on a large database of 2163 sequences containing 115 subjects.

3. Proposed approach

Vision-based systems for people recognition via the way they walk, are designed to extract gait features without the need to use special sensors or reflective markers to assist with the extraction process. In fact, all that is required is a video camera to stream images to a vision-based software for processing. Marker-less motion capture systems are more suited for scenarios where mounting sensors or markers on the person is not an option as the case of security surveillance. Typically, the gait biometric system consists of two main components: i) hardware platform dedicated for video acquisition. This can be a single CCTV camera or distributed network of cameras. ii) Software system for visual data processing and identification. The architecture of the software side for gait biometrics is composed broadly of three main stages:

i) Detection and tracking of the pedestrian: intra-camera tracking is performed to establish the correspondence of the same person across consecutive frames. For people detection, there are numerous robust and stable approaches for the automated detection of pedestrians in outdoor surveillance scenarios. The rhythmic gait motion can be exploited to further improve the detection accuracy [33]. As people usually walk slowly compared to the recording frame rate, the intra-camera tracking can be performed easily using a combination of basic low-level features including the size of the detected moving object, the centroid position, and the aspect ratio of height to width of the object bounding box.

ii) Feature extraction: in order to estimate a set of measurements either related to the configuration of the whole body or the configuration of the different body elements in a given scene and tracking them over a sequence of frames. For this research, the motion vectors from optical flow are considered as the main features extracted from consecutive frames.

iii) Classification stage: which involves matching a test sequence with an unknown label against a group of labeled references considered as the gallery dataset. This is a pattern recognition case to deduce or verify the identity of a given subject from the enrolled database. Fig. 1 shows the flow diagram for gait recognition outlining the different subsystems involved in the process of an automated people identification.

3.1. Optical flow estimation

The use of optical flow spans to a wide range of applications including video indexing, medical imaging, biometrics and automated video surveillance [34]. The proposed approach for people identification by gait encodes a sequence of frames into a feature vector describing the walking pattern from dynamic-based cues. The method does not depend on background subtraction for the derivation of motion features. This is because it is computationally expensive and complex to deploy background subtraction for real-time surveillance applications due the process of updating the background model which is influenced by a number of factors such as background clutter, weather conditions and other outdoor environmental effects. Inspired by the work of Kliper-Gross et al. [35] for proposing the Motion Interchange Pattern for action recognition together with the fact that local descriptors are known for their effectiveness and robustness for encoding texture for the human activity recognition. Provided that there is a motion of a small region within frame t to the next frame $t+1$, there is a high probability that a similar region would be induced inside the neighboring area of the original region position at the previous frame. The proposed descriptor is based on constructing a feature that reflects

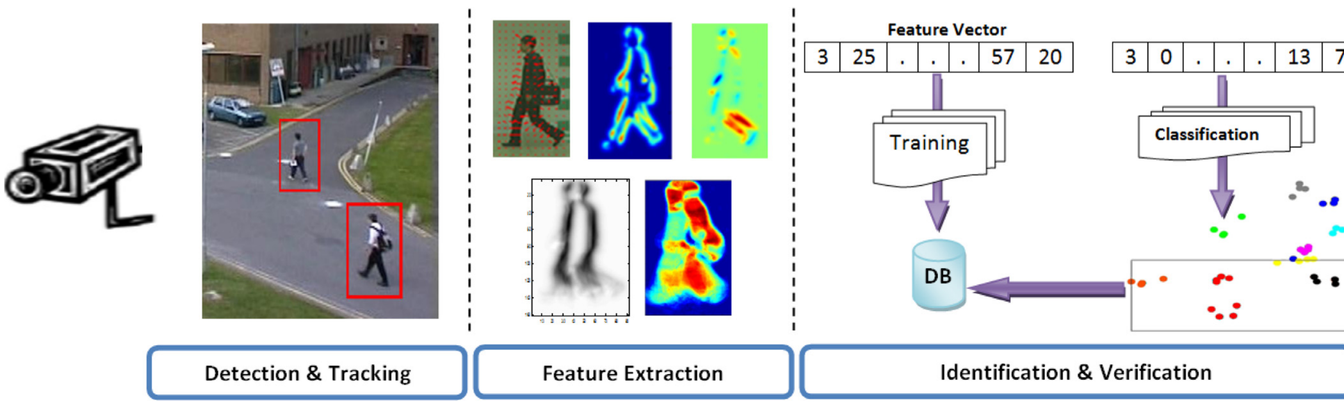

Fig. 1. Overview of gait biometric system.

the patch displacement from frame to frame. Optical flow is made from the vertical and horizontal components of the vector representing the orientation and velocity of the image's pixels between two consecutive frames. The estimation of optical flow is based on the brightness constancy constraint represented by the following equation:

$$I(x, y, t) = I(x + \Delta x, y + \Delta y, t + \Delta t) \tag{1}$$

Such that $I(x, y, t)$ represents the intensity of the pixel of coordinates (x, y) at the tth frame. The Taylor series is used to obtain a simplified equation expressed as:

$$\frac{\partial I}{\partial x}u + \frac{\partial I}{\partial y}v + \frac{\partial I}{\partial t} = 0 \tag{2}$$

where u and v are the horizontal and vertical components for the optical flow respectively. In order to deal with the aperture problem, considering the u and v variable values from Eq. (2), Horn and Schunck [36] proposed to minimize the following energy equation:

$$E = \iint \left(\xi_a^2 + \alpha^2 \xi_b\right) \mathrm{d}x\mathrm{d}y \tag{3}$$

While:

$$\xi_a = I_x u + I_y v + I_t \tag{4}$$

Where I_x, I_y, and I_t are the partial derivative of $I(x, y, t)$ with respect to x, y and t

$$\xi_b = \left(\frac{\partial u}{\partial x}\right)^2 + \left(\frac{\partial u}{\partial y}\right)^2 + \left(\frac{\partial v}{\partial x}\right)^2 + \left(\frac{\partial v}{\partial y}\right)^2 \tag{5}$$

Using the Euler–Lagrange method for the above minimization problem with the differentiation discretization, the case is converted to a fixed point solution. The Horn–Schunck derivation mask gives the following iterative system:

$$\begin{cases} u^{k+1} = \bar{u}^k + \dfrac{-I_x\left(I_x\bar{u}^k + I_y\bar{v}^k + I_t\right)}{\alpha + I_x^2 + I_x^2} \\ v^{k+1} = \bar{v}^k + \dfrac{-I_y\left(I_x\bar{u}^k + I_y\bar{v}^k + I_t\right)}{\alpha + I_x^2 + I_x^2} \end{cases} \tag{6}$$

Where the smoothing weight factor, $\alpha = 0.1$ and $k = 1 : n$ with n as the max iteration number which is set to 50 in our implementation. $\bar{u}^k$, $\bar{u}^k$ are the average of the forth adjacent u and v from the k precedent iteration.

3.2. Motion descriptors

Because of the paucity of research studies for exploiting the polar or Cartesian components of optical flow for gait recognition, we have explored in this paper various types of motion descriptors for people identification constructed from the optical flow vectors. The proposed descriptors are evaluated on different scenarios including the number of frames, increasing the dataset size and the viewpoint variation to analyze the discriminatory potency of the motion features under the influence of different factors. In contrast to previous studies which require a synchronizing point or impose the condition of detecting at least one full gait cycle, this assumption is relaxed to compose the gait signature from any random set of consecutive frames. Although, most studies affirmed that anthropometric measurements including the height and the different parts of the human body can boost the identification success rate, we have avoided using static features to explore solely the use of dynamic features derived from optical flow. (Fig. 2)

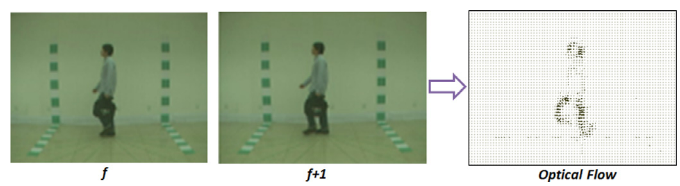

Fig. 2. Optical flow estimation.

3.2.1. Local optical flow features

The proposed descriptors are constructed from the optical flow features without the need to apply background subtraction to obtain silhouette data. This is because background subtraction is a difficult process to work for real surveillance scenarios. The main principle of this descriptor is to produce an averaged image based on superimposing images containing the individual on top of each other. Given two frames, optical flow using the Horn and Schunck method is applied to generate the motion flow image as shown in Fig. 3. Thresholding is app lied to remove flow vectors whose magnitude is less than a value of 0.001 which is determined empirically. The initial step is to enclose a bounding box around the walking subject consistently across all the frames. The height of the bounding box is determined from the optical flow vectors meanwhile the width is computed from the anatomical data reflecting the maximum distance when a person strikes their leg on the ground. The positioning of the bounding box across different frames is tuned by simple intensity matching of the top part of the human body as it is less susceptible to articulate and change. The naming is called local as the features are computed within the locality where the person moves ignoring the spatial displacement across the walking plane. The first descriptor is computed based on the magnitude of the optical flow vectors. For a point $p(x, y)$ at frame t, the magnitude of the optical flow computed between

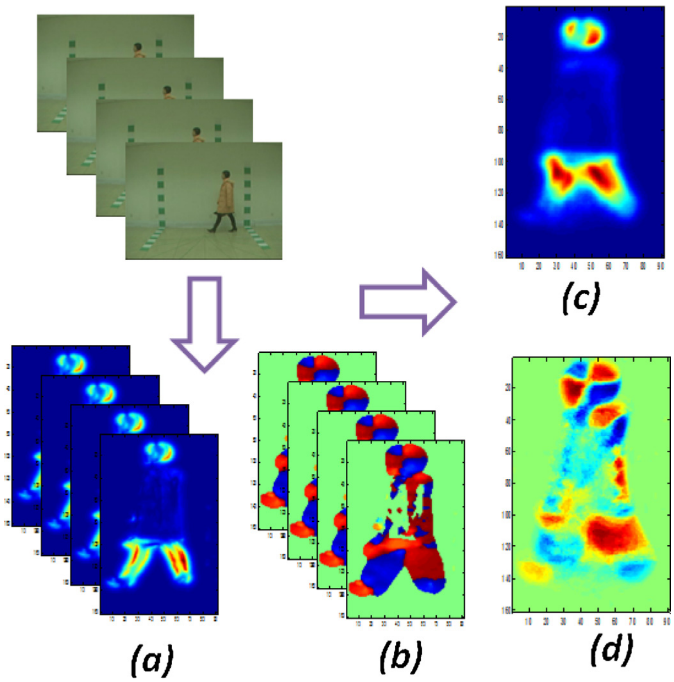

Fig. 3. Estimation of local optical flow descriptors: (a) Magnitude. (b) Angle. (c) Local averaged magnitude image. (d) Local averaged angle image.

frame t and $t+1$ is computed as given below:

$$mag_t(x, y) = \sqrt{u_t(x, y)^2 + v_t(x, y)^2} \tag{7}$$

Such that $u_t(x, y)$ and $v_t(x, y)$ are, respectively, horizontal and vertical Optical flow components in the point $p(x, y)$ at frame t. In order to produce the averaged magnitude image from the bounding boxes of all the frames which must all have the same size. The Local Flow Magnitude Image (LFMI) descriptor is computed using equation below:

$$LFMI(x', y') = \frac{\sum_{t=1}^{N-1} mag_t(x' + b_t^x, y' + b_t^y)}{N-1} \tag{8}$$

such that b_t^x and b_t^y are the (x, y) coordinates of the top left corner of the bounding box in the original frame meanwhile x' and y' are the new coordinates in the axis whose origin is the top left corner of the bounding box. For the angle of the optical flow vector at point $p(x, y)$, it is computed as shown in the following equation:

$$ang_t(x, y) = arctang\left(\frac{V_t(x, y)}{U_t(x, y)}\right) \tag{9}$$

In the same way as the local magnitude descriptor, the Local Flow Angle Image (LFAI) descriptor is based on the angle of the optical flow vector as described in equation:

$$LFAI(x', y') = \frac{\sum_{t=1}^{N-1} ang_t(x' + b_t^x, y' + b_t^y)}{N-1} \tag{10}$$

3.2.2. Global optical flow features

The global descriptor is constructed keeping into account the spatial and temporal property of the optical flow vectors as opposed to the local descriptors which averages the derived data. Instead, the area where the subject walks are superimposed on top of each other. The walking region is detected based on estimating the walking plane on the ground. This is done based on the extraction of the heel strikes position as described by the work of Bouchrika [37] where the striking points of the leg are detected based on the accumulation of points detected using the Harris corner detector. The height of the region is based on the same principle as described for the extraction of the bounding box for the local descriptors. For the descriptor related to the magnitude, it is computed as concatenating all the frames together and extracting only the regions related where the walking does occur. Given the walking region is having the top left corner at coordinates (x', y'), the Global Flow Magnitude Image (GFMI) descriptor shown in Fig. 4 is computed as:

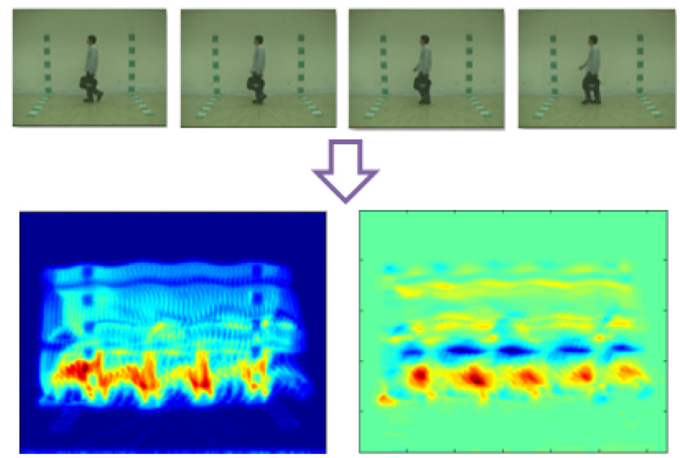

Fig. 4. Global optical flow descriptors: Angle (left). Magnitude (right).

$$GFMI(x', y') = \frac{\sum_{t=1}^{N-1} mag_t(x' + r_x, y' + r_y)}{N-1} \tag{11}$$

Meanwhile, the Global Flow Angle Image (GFAI) descriptor is computed as:

$$GFAI(x', y') = \frac{\sum_{t=1}^{N-1} ang_t(x' + r_x, y' + r_y)}{N-1} \tag{12}$$

3.2.3. Histogram-based optical flow features

Inspired from research studies on human activity recognition [38], we considered deriving features from the histogram of computed optical flow angles. The raw angles computed from Eq. (9) are discretized to a natural number enclosed between 0 and B. In this study, B is set to the value of 16. The zero value reflects the non-existence of motion such that the magnitude of the optical flow vector is less than the threshold $\tau = 0.001$. Based on the location of the angular values within the polar coordinate system which is equally divided into B numbered sections of $360/B$ degrees from 1 to B, the optical flow vector is converted into a number reflecting the order within the Bth circular portions. This is denoted using the function expressed in Eq. (13). Given the computed angle $ang(x, y)$ from optical flow ranging from π to $-\pi$, the descriptor value d at the point of coordinate (x, y) is determined as: (Fig. 5)

$$d_t(x, y) = floor\left(\frac{ang_t(x, y) \times B}{\pi}\right) + 1 \tag{13}$$

Having estimated the discretized value for every optical flow vector, two types of motion orientation histograms are computed. We first compute a local histogram without taking into account the temporal and spatial information from all the information in the frames as shown in Eq. (14). $LH(i)$ refers the local histogram bin of value i which is computed across all frames as illustrated in the following equation:

$$LH(i) = \sum_{t=1}^{N-1} h_t(i) \tag{14}$$

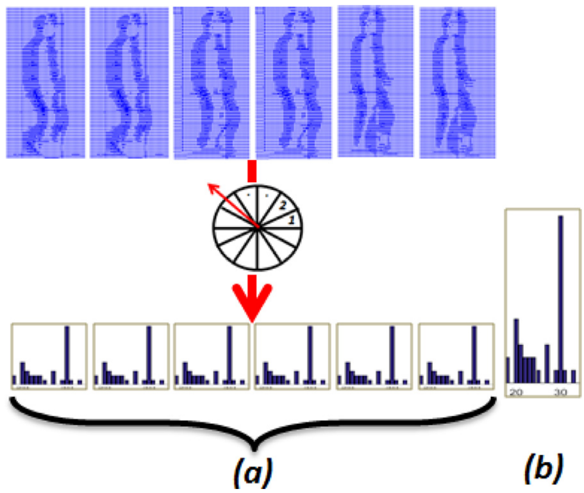

Fig. 5. Histogram-based descriptor: a) Global. b) Local.

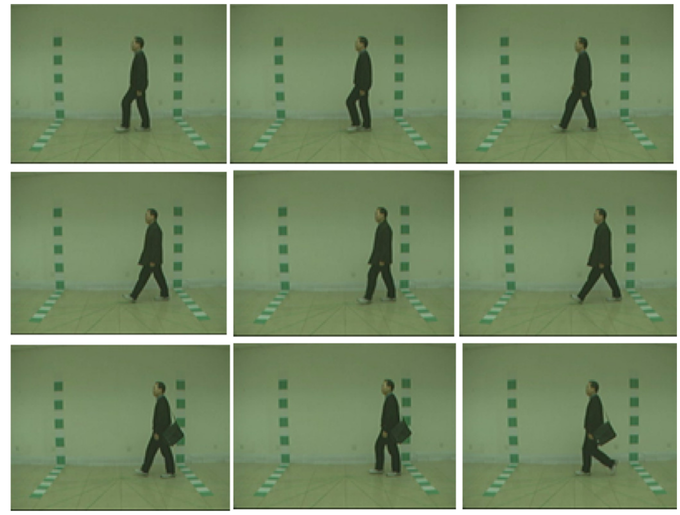

Fig. 6. Examples from the CASIA-B dataset.

such that the function h_t is to estimate the histogram at frame t defined in Eq. (15) where b is a Boolean function returning 1 for true cases and 0 otherwise:

$$h_t(i) = \sum_{x,y \in f_t} b(d_t(x,y) == i) \tag{15}$$

The global histogram which takes into account the temporal characteristics, is constructed via concatenating the histograms computed within every frame individually as shown in the following equation:

$$GH = [h_1 \quad h_2 \quad \ldots \quad h_{N-1}] \tag{16}$$

3.3. Gait recognition

For the identification of people from the computed descriptor derived using optical flow information, the *Knn* classifier is applied combined with the Euclidean distance metric. Normalization is applied for all instances to limit all the measurements between 0 and 1. The *Knn* rule is applied at the classification phase due to its simplicity and therefore fast computation in tandem with the ease to conduct comparative analysis against existing techniques being applied on the same dataset. To infer the identity of an unknown subject, a matching process is applied to find the nearest k instances from the training dataset. Further, the use of Deep Learning as a more advanced classifier is considered in this research. Neural networks are the basis of the classifier in order to learn a new representation from the raw data using multiple layers to learn new features. The autoencoder which is a special type of neural network, is deployed as a layer to extract lower number of new discriminative features in an unsupervised fashion separately from the other layers [39]. For gait biometrics using dynamic features, three layers of autoencoders are concatenated together to reduce the dimensionality of the biometric data followed with a softmax layer for the classification phase.

4. Experimental results

To demonstrate the efficacy of proposed method for gait recognition using dynamic features derived from optical flow, the system has been evaluated on a variety of scenarios and conditions. The CASIA-B database [40] has been considered as the real testbed of the proposed appearance-based method. The CASIA-B gait dataset shown in Fig. 6, contains 124 subjects recorded walking on a straight line using 11 different camera orientations (0°, 18°, 36°, 54°, 72°, 90°, 108°, 126°, 144°, 162°, 180°). The 90° corresponds to the side view walking direction. The video sequences have a spatial resolution and frame rate of 320×240 pixels and 25 fps respectively. The process of feature extraction method has been applied to a set of 1000 video sequences from the CASIA-B dataset for 100 different walking people with 10 sessions for every individual. The sessions for every subject include normal cases of a walking person, in addition to other covariate cases as clothing and load carrying. The lateral view corresponding to the 90° is considered for assessing the proposed approach meanwhile the other views are later used to test the viewpoint impact on the described biometric descriptors. For the computational time of estimating optical flow, the system was implemented using Matlab whilst all executions have been performed on an Intel Xeon server 2.4 GHz with 16 GB of RAM. The computation time to process dense optical flow is estimated as 3 fps (Frames per Second) without the use of any dedicated hardware (parallel computing, GPU, grid computing and FPGA) to boost the processing time. Although there are methods to estimate optical flow at real-time implemented on GPU [41], Zhu et al. [42] proposed an optimized implementation of dense optical flow capable of processing 10 frames per second without the use of parallel architectures.

4.1. Classification results

In order to compute the correct classification rate (CCR) for gait recognition using kinematic-based features, the leave one out cross validation method is applied with the *Knn* classifier on the set of 1000 video sequences taken from the CASIA-B dataset. In order to construct the gait biometric signatures, 24 consecutive frames are processed from each video sequence on the basis to include approximately one full gait cycle. Table 1 shows the classification results using the different types of the proposed descriptors from optical flow compared against the Gait Energy Image [15] being applied on the same collected dataset. Surprising, higher recognition rates are achieved using solely features describing purely the dynamics of the locomotion process. The Local Flow Angle Image (LFAI) is reported to offer better recognition rates compared to the Gait Energy Image and all other derived descriptors. Meanwhile, it is observed that the angular components of the optical flow vectors possess more discriminatory capability than the magnitude. Further, the histogram-based descriptors perform poorly compared to the local and global descriptors which retain the spatial and

Table 1
Classification results for gait biometrics.

		Knn		Neural
		$K=1$	$K=3$	networks
Local	LFMI	97.5	84.2	**95.0**
	LFAI	**97.8**	**89.0**	88.3
Global	GFMI	53.6	52.8	75.3
	GFAI	44.6	43.5	44.0
Histogram	LH	77.9	73.4	17.0
	GH	34.2	33.4	12.5
GEI		94.1	85.9	80.0
All features		50.5	40.9	–
Rida et al. [43]		88.7		
Jeevan et al. [44]		57.3		
Bashir et al. [45]		74.1		
Kusakunniran et al. [46]		69.4		
Medikonda et al. [47]		97.5		
Tang et al. [48]		95.1		

temporal information which are therefore considered vital for the recognition process. On combining all the features, a low recognition rate of 50.5% is attained using the *Knn* classifier. This is because the concatenated features may contain irrelevant and redundant elements that affect negatively the classification process. Feature selection can be considered in future work to determine the more discriminative elements.

Further, Deep Learning is applied on the same CASIA dataset with a three-fold cross validation. Training and test sets are composed of normal gait in addition to video sequences with covariate factors as clothing and load carrying. The architecture of the deep learning classifier is composed of three stacked autoencoders with a softmax network layer on top to classify the newly generated 100 features vector using the scale conjugate gradient training algorithm. The initial numbers of the raw features for the descriptors are 16, 64, 1461 and 8654 for LH, GH, LMFI/LAFI and GMFI/GAFI, respectively. As shown in Table 1, the local optical flow descriptors are observed to perform better reaching a CCR of 95% using the magnitude information. Although the obtained results are satisfactory using the local flow descriptors, the performance rates for the neural networks are less accurate than the simple *Knn* classifier. Poor results are reported for the histogram-based descriptors mainly due to the low size of the feature vectors. Comparative analysis is conducted using the Gait Energy Image (GEI) being tested on the same dataset using the same evaluation paradigm. Consistently with the results obtained using the proposed descriptors, the GEI achieved a higher CCR of 94.1% using *Knn* against 97.8% using the proposed LFAI descriptor. Furthermore, the obtained results are compared against recent and well-established methods being evaluated on the CASIA-B gait dataset using the *Knn* classifier with $k=1$ as depicted in Table 1.

The Cumulative Match Score (CMS) method introduced by Phillips et al. in the FERET protocol [49] is used to assess the identification performance of the proposed approach as shown in Fig. 7. The measure examines the ranking capabilities of the recognition system by producing a list of scores that indicate the probabilities that the correct classification for a given candidate is within the top n matched identities. In other words, The CMS curve provides a measure of the classification rate of data samples at different trials to be correctly classified. The scoring function employs the *Knn* rule with the value of $k=1$. It is worth noting that the CMS at rank $R=1$ is equivalent to the Correct Classification Rate. It is observed that a CMS score of 100% is achieved at rank $R=6$ for the LFMI descriptor meanwhile the same rate is achieved by the Gait Energy Image at rank $R=12$. All the global descriptors are observed to converge poorly reaching the CCR of 100% after a large number of iterations.

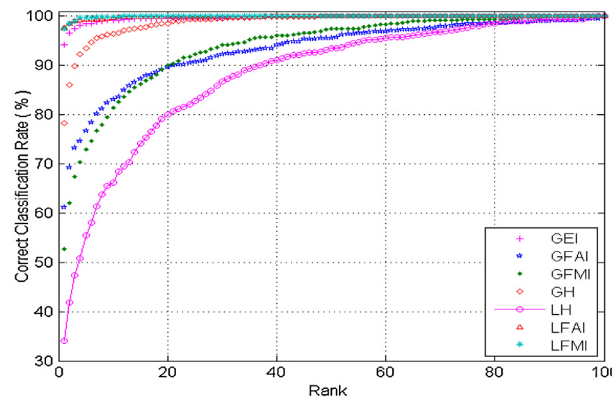

Fig. 7. Cumulative match score for gait biometrics.

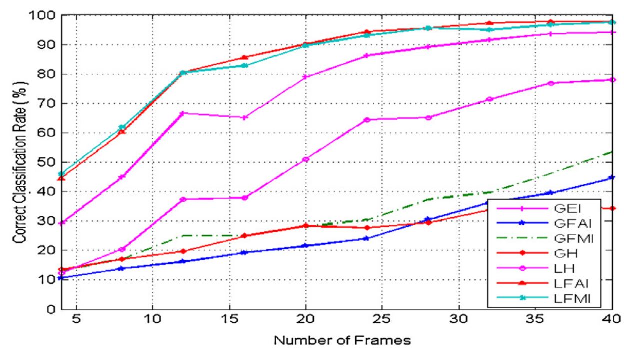

Fig. 8. Effect of frames number.

Table 2
Impact of the number of frames on gait biometrics.

FR	Local		Global		Hist		GEI
	FMI	FAI	FMI	FAI	LH	GH	
4	**46.0**	44.5	13.2	10.6	12.3	13.4	29.0
8	**61.9**	60.2	17.1	13.8	20.4	17.0	45.0
12	80.3	**80.5**	25.0	16.1	37.4	19.6	66.6
16	82.8	**85.6**	25.0	19.2	37.8	24.9	65.2
20	89.6	**90.1**	28.1	21.5	51.0	28.3	78.9
24	93.0	**94.3**	30.5	24.0	64.4	27.7	86.2
28	**95.6**	95.5	37.3	30.5	65.1	29.4	89.1
32	95.0	**97.3**	39.7	36.2	71.4	33.8	91.5
36	96.7	**97.8**	46.1	39.5	76.8	35.0	93.6
40	97.5	**97.8**	53.6	44.6	77.9	34.2	94.1

4.2. Effect of frames number

There is a limited number of research studies addressing how many frames are needed for gait recognition as the majority of approaches make use of one complete synchronized gait cycle for recognition. But cycle synchronization and having all frames of a complete gait cycle is not always an available option for real applications due to hardware failure or errors encountered during the detection and tracking phases. We analyze the effects of increasing or decreasing the number of frames from the constructed gait signature using optical flow and explore how the classification performance is affected. Martín-Félez et al. [50] studied the number of gait cycles required to derive a discriminant signature from averaged gait silhouettes. A number of extensive experiments are conducted in this study such that various gait signatures are constructed by considering a varying number of consecutive frames ranging from 4 to 40 as shown in Fig. 8. In contrast to previous studies, the gait signatures are not synchronized where the starting frame is totally selected at random. Table 2 shows the effects

Table 3
Cross-frame matching using the LFMI descriptor.

	Probes frames number							
		8	16	24	28	32	36	40
Gallery frames number	4	50.1	54.8	57.5	59.1	58.6	57.6	57.6
	8	60.2	74.6	78.2	79.8	81.5	81.2	80.7
	12	75.5	83.8	87.4	89.0	90.2	90.4	92.1
	16	73.6	85.6	90.6	89.6	92.2	92.7	92.6
	20	79.8	88.4	91.8	92.6	95.4	95.8	96.0
	24	81.2	92.0	94.3	93.8	95.3	95.7	95.9
	28	82.3	91.2	94.1	95.5	96.4	97.0	96.9
	32	82.7	92.6	95.3	96.6	97.3	97.5	97.3
	36	85.2	94.0	96.3	96.8	97.9	97.8	97.5
	40	85.3	93.6	95.9	97.3	97.5	97.7	97.8

of increasing the number of frames on the classification results for all the proposed optical flow descriptors in addition to the Gait Energy Image. The results are achieved on the same CASIA dataset using the Leave-out-one cross validation with the use of the *knn* classifier where $k = 1$. Overall, the classification results are consistent with the number of frames required to construct a gait signature. The more number of frames considered, the better achieved classification rate. The GEI descriptor requires 32 frames in order to achieve a CCR of 91.5% meanwhile the LFAI descriptor needs only 20 frames to attain a CCR of 90.1%. For the case of cross-matching signatures composed of different size of frames number, using the descriptors constructed from optical flow, 8 frames can be sufficient to achieve an acceptable recognition rate of 81% when proposed a dataset composed of 24 frames.

As a novel contribution in this paper, we have conducted cross-matching of biometric signatures composed of different number of frames using only the Local Flow Magnitude Image (LFMI) descriptor. The results for the cross-matching process is shown in Table 3. The purpose of this experiment is to examine the requirement of whether matching two biometric signatures need to have the same number of frames. From the attained results, it can be inferred that setting the number of frames for the gait signature has no major impact on the classification performance. The same conclusion applies to synchronizing the signatures to the same offset as higher CCRs are achieved without setting the gait signatures to start from the same time whilst probing signatures against signatures of different sizes. For instance, higher classification rates of over 90% are achieved when matching gait signatures consisting of 24 frames against galleries of signatures composed from at least 16 frames. Lower CCRs are reported when the signature is composed only from 4 or 8 frames.

4.3. Effect of database size

In order to analyze the scalability aspect of gait biometrics using the proposed descriptors from optical flow, we have performed another set of experiments on the CASIA dataset by varying incrementally the dataset size. Starting with an initial subset of 10 people picked up at random with 10 sequences for each person, the classification rate is computed using the leave-one-cross validation with the *Knn* classifier. Subsequently, 10 more people are added to the subset at every new iteration. Table 4 shows the computed results for the classification performance when increasing the dataset size. For a smaller dataset of 10 people, 100% is achieved for both local descriptors meanwhile using the GEI descriptor, 98% is attained. When augmenting the dataset to reach 100 subjects, the effect on performance is marginal for the LFAI and LFMI descriptors with a decrease of 2.2% and 2.5%, respectively, compared to 3.9% for the Gait Energy Image (GEI).

Table 4
Number of sequences effects on studies features.

Subj./	Local		Global		Hist		GEI
seq.	FMI	FAI	FMI	FAI	LH	GH	
100	**100**	**100**	74.0	65.0	93.0	48.0	98.0
200	**98.5**	**98.5**	67.5	62.5	92.5	49.0	95.5
300	97.6	**98.0**	64.0	55.0	88.6	47.3	95.3
400	97.0	**97.5**	56.7	47.5	85.2	43.0	95.2
500	96.8	**97.6**	56.0	48.2	82.0	39.4	95.0
600	97.0	**97.8**	54.3	46.1	80.1	38.3	94.8
700	96.8	**97.4**	50.5	44.8	79.1	36.4	93.8
800	97.1	**97.6**	50.8	44.5	79.0	35.1	94.0
900	97.2	**97.6**	51.3	44.0	77.6	35.0	94.1
1000	97.5	**97.8**	53.6	44.6	77.9	34.2	94.1

Table 5
Viewpoint effects on gait biometrics.

View	Local		Global		Hist		GEI
point	FMI	FAI	FMI	FAI	GH	LH	
36	100	100	80.8	76.6	50.8	85.8	61.6
54	100	100	83.3	80.0	43.3	92.5	76.6
72	100	100	82.5	78.3	58.3	92.5	98.3
108	100	100	85.0	78.3	49.2	85.8	100
126	100	100	70.8	75.0	25.0	67.5	93.3

Table 6
Cross viewpoint matching against 90° using LFMI.

Test	Local		Global		Hist		GEI
ang	FMI	FAI	FMI	FAI	GH	LH	
36	**28.3**	15.8	27.2	14.8	10.8	15.0	07.5
54	**85.0**	65.8	27.2	41.8	30.0	38.3	11.7
72	**98.3**	**98.3**	76.3	98.3	35.8	70.8	88.3
108	81.6	71.7	59.6	71.7	28.3	22.5	**86.6**
126	**32.5**	03.3	18.4	03.3	05.0	05.0	20.8

4.4. Effects of viewpoint

Changing the viewpoint is the most challenging covariate for gait recognition in particular for the case of appearance-based methods. We have conducted two experiments to explore the impact of viewpoint on the proposed descriptors considering only the following six different views from the CASIA dataset (36°, 54°, 72°, 90°, 108°, 126°). For the first experiment, smaller dataset of 20 people with 6 sequences per person are taken for each viewpoint and the classification results are estimated for every viewpoint separately using the leave-one-cross validation. The results are shown in Table 5. In alignment with other reported results, the local descriptors from optical flow including LFMI and LFAI are not affected when changing the viewpoint in contrast to the gait Energy Image which is susceptible to viewpoint variation. For the second experiment, the subsets constructed for different viewpoints during the first experiment are probed against a gallery database consisting only of people walking in the lateral view (90° viewpoint). The identification results for the viewpoint cross-matching is shown in Table 6 where it is shown that all appearance-based descriptors are prone to be affected highly by the viewpoint variation.

5. Conclusions

In this research paper, we have explored the use of kinematic-based features derived from optical flow for people identification by the way they walk. A set of biometric descriptors constructed from optical flow data are proposed accounting for the spatial, temporal and orientation aspects of the motion process of the gait pattern. The biometric signature is derived purely from kinematic-based features without incorporating static and anthropometric cues. A set of experiments are carried out using the CASIA-B dataset to assess the discriminatory potency of motion-based features subjected to different covariate factors including clothing and carrying conditions. The local features taken from the optical flow images are reported to achieve remarkable classification results compared to other appearance-based descriptors including the Gait Energy Image. Further experiments are conducted to explore the effects of the dataset size, the number of frames in addition to the impact of viewpoint variation on gait biometrics. The number of frames to compose the gait signature has a marginal impact on the classification performance using the proposed descriptors. Similar promising result are reported for the same descriptors when assessing the scalability aspect of gait biometrics. However, all appearance-based descriptors are prone to be affected highly by the viewpoint variation for the case f cross-matching. In conclusion, the attained results confirm that people identification using dynamic gait features is still perceivable with better recognition rates even under the influence of different covariate factors.

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Zohra Mahfouf is a research fellow at the University of Souk Ahras where she is also lecturing computer science courses within the Faculty of Science and Technology. Mahfouf graduated with Magister degree in 2011 from the University of Annaba, Algeria. Her research interests includes the deployment of human motion analysis and gait biometrics for visual surveillance applications.

Hayet Farida Merouani received her Eng. degree from Annaba University, Algeria in 1984, and the Ph.D. degree from Robert Gordon University, Aberdeen, UK. She is currently an associate professor with Badji Mokhtar University, Annaba. She also leads Research Group of Pattern Recognition. Her current work focuses on the computer vision, medical imaging, and biometry.

Imed Bouchrika received his B.Sc. and Ph.D. degrees in Electronics and Computer Science from the University of Southampton (United Kingdom) in 2004 and 2008, respectively. Since 2008, he has worked as a research fellow at the Information: Signals, Images, Systems Research Group of the University of Southampton. He is now a lecturer of Computer Science at the University of Souk Ahras. His research areas are human computer interaction, image processing and biometrics. He is the maintainer of the online research portal Guide2Research.com which is globally featured as the number one academic portal for various rankings including top scientists, conferences and journals within the arena of computer science.

Nouzha Harrati received her bachelor degree in computer science from the University of Annaba, Algeria, she obtained a Magister Degree in Computer Science from the University of Souk Ahras. She is an assistant lecturer of Computer Science. Her research includes human computer interaction, affective computing and automated classification of facial expressions.