Automatic enrolment for gait-based person re-identification under various view angles

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Abstract: Automatic enrolment constitutes a demanding decision-making practice for person re-identification task but rarely considered in the literature. This paper introduces a new method for automatic enrolment relying on gait analysis. The enrolment problem involves that the gallery database is automatically fed as a new subject is presented. The originality of the proposed method is that in the gallery, a given subject may be represented by several samples. This will improve the re-identification under various view angles. Experiments on CASIA-B database based on accuracy, sensitivity and specificity proved the performance and flexibility of the proposed method.

Keywords: gait; automatic enrolment; person re-identification; view angles.

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1 Introduction

The exponential growth of camera networks in public places has attracted the attention and whetted the interest in automatic video analytics techniques. When multiple non-overlapping cameras are jointly operating, a useful function is to keep the track of the same subject across several places covered by different cameras. This challenging problem is known as person re-identification (Liu et al., 2017). Several domains such as video surveillance or marketing can benefit from this functionality. For example, the re-identification of a subject visiting the same place at different times might suggest a suspicious behaviour or a remarkable interest in some products in a shop. In fact, re-identification is based on matching a new person (probe) with a set of persons in the gallery set which contains gait patterns from known subjects. For a real-time application, the gallery set must be fed up automatically. In other words, a comprehensive re-identification system should dynamically enrol new subjects in order to re-identify them later.

A pure online enrolment strategy consists in determining whether a new probe sample belongs to any known (enrolled) subject in the gallery set or it is the first occurrence of a new subject. This is of critical importance to the re-identification performance process because wrong decisions could induce other types of error. For instance, two situations may occur and do involve errors:

1. misclassification of a sample from the enrolled subject class where a redundant class is created for a previously enrolled person, which can be considered as a minor error because it does not contaminate any existing class
2. misclassification of a sample from the new subject class while assuming that the sample is used to update the class supporting its acceptance which may lead to the corruption of a wrong person's data.

This situation can exhibit a major error. The enrolment method depends on the feature representation adopted for re-identification.

In the literature, there are several representations for person re-identification such as the face (Choi, 2018; Wu et al., 2018b), the gait (Chi et al., 2018; Xu et al., 2018) and the appearance (Liu et al., 2015; Wu et al., 2018a; Fendri et al., 2018). Among these feature representations, gait is a behavioural biometric modality that is widely accepted to extract a signature for person re-identification in uncontrolled scenarios. This modality is invariable over time, does not require the cooperation of the target subject and can be extracted from low-resolution images. In the literature, the majority of gait-based re-identification techniques assume that target subjects are already enrolled and achieve their experimentation on existing databases (Yu et al., 2006).

In this paper, we presented a gait-based method for automatic person enrolment for re-identification purposes. Unlike the work of Ortells et al. (2015), this method is able to handle target with multi-view angles. The basic merit of this solution is that in the gallery, a given subject may be represented by several samples in different view angles. This minimises the large transformation errors. Throughout the experiments, a random flow of people was simulated in which each person may appear and re-appear in different view angles or within the same view angle. The rest of this paper was organised as follows. Section 2 provided a formal definition of the automatic enrolment problem. The related works were reviewed in Section 3. The proposed method was detailed in Section 4. The experimental evaluation were presented in Section 5. Finally, Section 6 summarised the main conclusions and proposed some future research perspectives.

2 Formalisation of the automatic enrolment problem

This section handled the problem of automatic enrolment within the context of person re-identification. Enrolment can be viewed as a two-class classification problem aiming to classify the probe into either new subject or already enrolled subject. Given a probe sample as input, a basic online enrolment method should determine whether that sample is sufficiently similar to any gallery sample or not. In this case, it is considered as being a previously enrolled subject (no matter who). Otherwise, it is labelled as a new subject. The probe sample can be added to the gallery set in both cases. The position of the samples in a given sequence affects these class labels: the first sample of someone should be considered as a new subject, while the rest should be labelled as enrolled subject samples. Therefore, enrolment efficiency relies heavily on the sequential order of probe samples. A simple operational scope of the online enrolment strategy can be defined by the following elements (Ortells et al., 2015):

- *Distance or score function s(.):* it is assumed to measure dissimilarity or distance between two samples (a probe sample p and a gallery sample g) through a match score $s(p, g)$ and thus, generate a matching hypothesis $h(p, g)$ representing if the probe sample is in the gallery set or not. $s(.)$ is assumed to measure dissimilarity or distance between two samples.
- *Numerical threshold* γ *:* a match score $s(p, g)$ is compared to γ to make a decision on the acceptance or rejection of $h(p, g)$. The determination of the gamma threshold was detailed in the experimental section.
- *Gallery set G:* it holds the samples from the enrolment process. Given a (probe) sample p, the enrolment method searches for the gallery sample $\hat{g}$ most similar to p, and the associated match score $\hat{s}(p) = s(p, \hat{g})$ is used to make a decision.

A matching takes place if $\hat{s}(p) \le \gamma$, while a non-matching occurs when $\hat{s}(p) > \gamma$. The fact that $\hat{s}(p)$ omits $\hat{g}$ means that only the minimum score is required. At the beginning of the enrolment process p is directly added to G since the gallery set is empty.

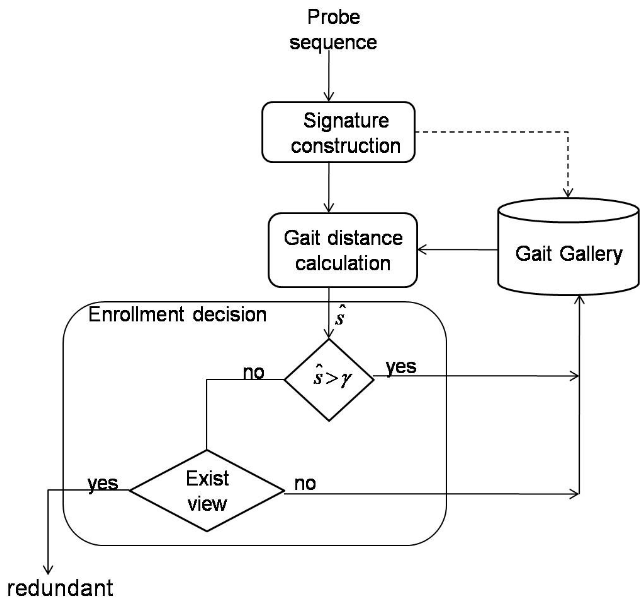
- *Enrolment decision:* for each matching process a decision will be taken either to enrol or not the probe subject. We can distinguish two types of errors and two types of success:
  a *False acceptance (FA):* a matching decision is incorrectly made, $\hat{s}(p) \le \gamma$, with p being the first appearance of a person, i.e., a sample from the new person class is misclassified. Assuming that a sample was wrongly accepted in a certain class, this would result in a major error.
  b *False rejection (FR):* a non-matching decision is incorrectly made, $\hat{s}(p) > \gamma$, with p being not the first appearance of a person, i.e., a sample from the enrolled person class is misclassified. A redundant class is created for a previously enrolled person, which can be considered as a minor error because it does not contaminate any existing class.
  c *True acceptance (TA):* a matching decision is correctly made, $\hat{s}(p) \le \gamma$, with p being a sample of any previously enrolled subjects (no matter who). Note that no condition is imposed on the gallery sample $\hat{g}$ that supports the decision. That is, p and $\hat{g}$ could belong to different identities.
  d *True rejection (TR):* a non-matching decision is correctly made, $\hat{s}(p) \le \gamma$, with p being the first sample of a subject.

3 Related works

The interest in an automatic person enrolment for re-identification as part of intelligent video surveillance systems recently begin to draw attention. In this section, a literature review that tackles the enrolment issue is presented. The problem of enrolment concentrates, essentially, on the modality of the re-identification (face, gait, etc.) and the enrolment algorithm. In the literature, automatic enrolment has been addressed based on either face (Wheeler et al., 2010; Dadgostar et al., 2011) or gait (Roy et al., 2012; Ortells et al., 2015).

On the one hand, dealing with faces, a fully automated system for recognising faces at a distance was discussed in Wheeler et al. (2010), where recognition exploits face images stored in a gallery set or captured by manual or automatic enrolment processes. The subject's face image with the highest quality score is enrolled in the face gallery set. For automatic enrolment and subsequent re-identification of faces on a network of cameras, an architecture for a video analytics framework was exposed by Dadgostar et al. (2011). The goal of this architectural design was scalability and real-time performance (Dadgostar et al., 2011). Mogelmose et al. (2013) developed a system that automates the subject enrolment, while building a gallery set of known people. A confidence measure, computed by fusing three modality scores, is compared to two thresholds so as to determine whether a subject is a new or a known person. A subject classified as a new one is enrolled, while a known person is re-identified. This solution is a tri-modal re-identification system, based on RGB, depth, and thermal descriptors (Mogelmose et al., 2013).

Figure 1 Flowchart of the proposed method for automatic enrolment for gait-based person re-identification



On the other hand, dealing with gait, Roy et al. (2012) determined an approach which is based on a combination of phase of motion, gait, and spatiotemporal model. The re-identification of each observed subject entering a camera spectrum is based on the set of all candidates previously observed in other cameras, which can be considered as a spatio-temporal collection of enrolled subjects (Roy et al., 2012). Ortells et al. (2015) addressed the problem of person enrolment for gait-based biometric re-identification. The enrolment problem has been characterised as a two-class problem. Both short and long-term enrolment processes were tested using a random flow of people. Two classification schemes which are ranking support vector machine (RankSVM)-based model and traditional 1-nearest neighbour (1NN) are used. The results were presented in terms of receiver operating characteristic (ROC) curve showing high area under the curve (AUC) values for both experimental scenarios, mainly when using the RankSVM. Only the 90° view angle was used for both short and long-term enrolment processes (Ortells et al., 2015). However, methods in the literature (Ortells et al., 2015; Roy et al., 2012; Mogelmose et al., 2013; Wheeler et al., 2010) do not take into account the problem of varying view angles. Indeed, the latter considerably affects both the re-identification and the automatic enrolment of the gallery database. In this paper, an automatic enrolment solution is proposed for the context of gait-based person re-identification under various view angles. The main originality of our solution is that it differentiates a given subject with diverse view angles from others in the gallery set. This fact provides more features for a gait-based re-identification context.

4 Proposed enrolment method

The multi-view angle variation is a challenging problem which may affect accuracy. From this perspective, a new gait-based enrolment method was proposed. The advantage of our proposed method lies in the fact that it provides a new representation of the gallery set. The gallery set may contain several view angles for one subject. This offers richer feature information for further steps. Given a probe gait sample, the goal is to determine whether it is in the gallery or not, regardless of its identity. In the best case, the probe will be re-identified. The proposed method involves three major steps which are signature construction, gait distance calculation and enrolment decision (c.f. Figure 1). Algorithm 1 depicts the proposed method's steps.

4.1 Signature construction

The signature construction step is an important step. In fact, gait (Ghaeminia and Shokouhi, 2018; Dehache and Souici-Meslati, 2017) is one of behavioural biometrics that can be captured and perceived from a distance thanks to its non-invasive and less intrusive nature. Thus, we opted for a gait-based person re-identification method (Fendri et al., 2019) relying on a dynamic selection of human parts from the gait energy image (GEI) (Han and Bhanu, 2005). It consists in computing a new person descriptor from relevant selected human parts. Concerning the descriptor, the P-LBP (Kusakunniran et al., 2009) on the relevant parts was used. As for the selection of the most informative parts, it was achieved depending on the presence of semantic information (Layne et al., 2014; Chtourou et al., 2017; An et al., 2013). For that, we have divided the GEI image into seven parts $\{G_{H1}(x, y), \ldots, G_{H7}(x, y)\}$. The set of relevant parts V is determined as follows:

$$V = \{c_1.G_{H1}(x, y), \ldots, c_i.G_{Hi}(x, y), \ldots, c_7.G_{H7}(x, y)\}$$
$$\begin{cases} c_i = 0 & \text{if} \quad \textit{semantic attribute exist in part } c_i \\ \textit{otherwise} & c_i = 1 \end{cases} \tag{1}$$

where i is the index of part $G_{Hi}(x, y)$, $i \in [1 \,..\, 7]$ and c is the coefficient related to each part.

4.2 Gait distance calculation

The gait distance calculation requires two steps which are view angle estimation and distance computation. Each step will be detailed in the following sections.

4.2.1 View angle estimation

To tackle the multi-view context, a sub-step of view angle estimation of the probe sample is needed. Many contributions in this area were forwarded. Yet, there are still some challenges which refer to internal and external conditions, that degrade the image quality especially the covariate factors (i.e., carrying condition, clothing), low resolution, etc. To classify each view angle into its corresponding class, we adopted a knowledge discovery in databases (KDD) process for extracting useful knowledge from a huge data volume. The total process of walking direction estimation is based on two steps which are:

1 models construction

2 view angle classification.

The output of the first step is the validated models that would be used further in the view angle classification step (Chtourou et al., 2018). The general principle of the classification method is the following: let *I* be the population of images to be classified. For each image *i* of *I* one can associate a particular view angle, namely, its class label *C*. *C* takes its value in the class of labels [cf. equation (2)] corresponding to the eleven view angles {0, 18, 36, …., 180}.

$$C: I \rightarrow \Gamma\{000, 018, 036, ..., 180\} \quad (2)$$

$$i \in I \rightarrow C(i) \in \Gamma \quad (3)$$

The observation of *C*(*i*) is not easy; therefore we are looking for constructing a prediction model to describe each class *C*.

4.2.2 Distance computation

The distance computation step involves the determination of the smallest distance between the probe image and gallery images. However, the accuracy is considerably affected if observation views of matching pairs of images are at different view angles. In order to avoid the accuracy degradation, we will adopt the view transformation models (VTMs) where a gait feature from one view is transformed to another different view so as to match the gait features under the same view. If gallery and probe images are in the same view angles, we will calculate a distance between them. If they are in different view angles, we will use VTM in order to transform probe view angle into the same view angle as gallery image.

4.3 Enrolment decision

The enrolment decision is the third step in the process of our proposed method. In fact, the smallest distance obtained is compared to a threshold gamma γ which is empirically determined. More details about the determination of the threshold gamma are presented in the first series of experiments. As we are interested in the multi-view re-identification context, as a consequence in this paper, we deal also with automatic enrolment under various view angles. In the case that the image is not enrolled (i.e., the first presence of the person), we add it to the gallery set. In the other case where the image is already enrolled, according to its view angle, two treatments can be considered: label the image as redundant or add its new representation to the gallery set. The fact that a given person may be represented by images under several view angles offer the possibilities to compare it with the closest one and consequently reduce errors due to transformation.

4.4 Enrolment algorithm

In this section, we detailed the enrolment algorithm. The algorithm is divided into three parts which are signature construction, gait distance calculation, enrolment decision. The role of each function is detailed below.

- *Feat_rep* is a function for feature representation. It includes the application of the P-LBP descriptor on the GEI image.
- *ViewAngle* is a function that determines the view angle of the input image.
- *UnifyAngles* is the function that transforms the probe view angle into the same view angle as the gallery image. A VTMs is adopted in order to suppress the degradation of accuracies when the probe and gallery image are not in the same view angles.
- *dist_EU* is the function that computes the distance between the probe image and the gallery image.
- *add* is the function that adds the view angle.
- *Create_g* is the function that appends the image to the gallery dataset with the label of new image and the view angle.

Algorithm 1:

Require: *Gamma threshold* = γ

Gallery = if empty add the first sample of the probe

Probe = random flow of images

$i \leftarrow 0$

for *each image p from Probe set P* ***do***

/* ***Signature construction*** */

$p \leftarrow Feat\_rep(p)$

for *each image g from Gallery set G* ***do***

/* ***Gait distance calculation*** */

$\theta_p \leftarrow ViewAngle(p)$

$\theta_g \leftarrow ViewAngle(g)$

$(p_1, g_1) \leftarrow UnifyAngles(p, g)$

$d \leftarrow dist\_EU(p_1, g_1)$

$v[i] \leftarrow d$

$i{+}{+}$

end for

Sort (v, ascendant)

$\hat{s} = v[1]$

/* ***Enrolment decision*** */

if $\hat{s} > \gamma$ ***then***

$Create\_g(G, p, \theta_p)$

end if

if $\hat{s} < \gamma$ **then**
  if *the* θ_p *exist* **then**
    Label it as redundant image
  end if
else
  if *the* θ_p *does not exist* **then**
    add (G, p, θ_p)
  end if
end if
end for

5 Experimental evaluation

In this section, we will present the performance assessment and the experimental results.

5.1 Performance assessment

In order to evaluate our proposed method, we adopted the confusion matrix, also known as an error matrix (Stehman, 1997) which is a specific table layout that allows the visualisation of an algorithm's performance. The instance of a predicted class is represented in each row of the matrix while the instance of an actual class is denoted in each column (or vice versa). Table 1 summarises the four possible decisions as a 2 × 2 confusion matrix, where columns represent the predicted class and rows indicate the real class.

Table 1 Example of confusion matrix

		Predicted class	
		A	*B*
Real class	A	TR	FA
	B	FR	TA

From the confusion matrix, we have computed the accuracy (ACC), the sensitivity: true positive rate (TPr), and the specificity: false positive rate (FPr) which are defined as follows:

$$ACC = \frac{TR + TA}{TR + FR + FA + TA} \tag{4}$$

$$TPr = \frac{TR}{TR + FA} \tag{5}$$

$$FPr = \frac{TA}{TA + FR} \tag{6}$$

where

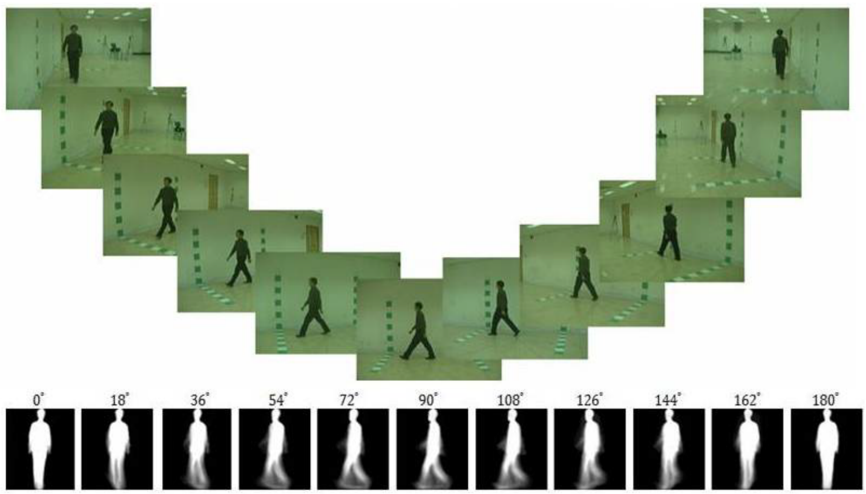
TR number of truly classified new subjects (TR)

FA number of new subjects classified as enrolled subject (FA)

FR number of enrolled subjects classified as new subject (FR)

TA number of already enrolled subjects truly classified (TA).

Figure 2 Normal walking sequences from CASIA-B database and their corresponding GEIs (see online version for colours)



Source: Yu et al. (2006)

5.2 Experimental results

In this section, we described the adopted database, then we detailed the three series of experiments. The first series of experiments was carried out in order to determine the value of the threshold gamma. The second series of experiment was undertaken in order to compare our proposed method with the work of Ortells et al. (2015). The third series of experiments was performed to show the accuracy of our proposed method within different view angles.

5.2.1 Database description

The performance of the proposed algorithm was evaluated on the benchmark CASIA-B gait database (Yu et al., 2006) proposed by the institute of Automation, Chinese Academy of Sciences (CASIA). CASIA-B is a multi-view database which is the referenced database for a gait-based re-identification task. It contains the gait sequences of 124 subjects captured using eleven different viewpoints: 0°, 18°, 36°, …, 180°. Figure 2 displayed normal walking sequences from CASIA-B database with 18-degree interval and their corresponding GEIs. Six walk sequences are recorded for each subject with normal walk. Cross-view gait recognition on this dataset is quite challenging owing to the large cross-view angles.

Table 2 The gamma value reported for each probe view angle

View angle	*Gamma*
000	4.695809e+02
018	5.458098e+02
036	5.934189e+02
054	5.355305e+02
072	4.077859e+02
108	4.504675e+02
126	5.155681e+02
144	5.953280e+02
162	5.848505e+02
180	6.350482e+02

Table 3 Accuracy reported for each gamma value independently of the probe view angles

Gamma	*ACC (%)*
4.695809e+02	81.012
5.458098e+02	81.416
5.934189e+02	81.719
5.355305e+02	81.416
4.077859e+02	80.911
4.504675e+02	81.012
5.155681e+02	81.113
5.953280e+02	81.719
5.848505e+02	81.719
6.350482e+02	*81.921*

5.2.2 First series of experiments: determination of gamma value

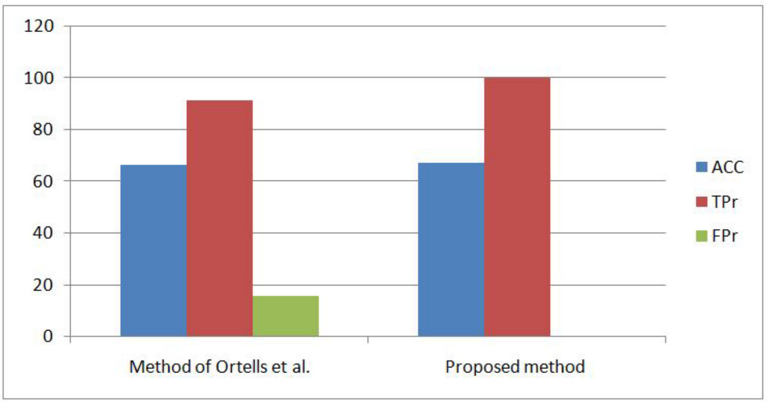
The first series of experiments aimed to determine the best value of the threshold gamma γ which will be used for our further work. This series of experiments included two evaluations. The first evaluation intended to determine the gamma value in the same view context (i.e., the probe and gallery are in the same view angles). Thus, for each view angle, we have chosen the minimum distance among distances where the label of a predicted person is the same as the real one of the person. Table 2 shows the different values of the gamma where the probe/gallery view angle varies from the view angle 000° to the view angle 180°.

The purpose of the second evaluation was to choose the most suitable gamma value independently of the probe view angles. In other words, we determined the best threshold while probe and gallery samples may be with different view angles. Thus, we randomly chose 100 samples for the probe set with various view angles from 000° to 180°. The gallery database is automatically fed as the image probe is presented. This process is repeated ten times with different image combinations. The gamma value corresponding to the best accuracy was further adopted. Table 3 shows that the best accuracy is 81.921% reported for the gamma value 6.350482e+02.

Table 4 State-of-the-art comparison under the same view angle

Experiments	*ACC*	*TPr*	*FPr*
Method of Ortells et al. (2015) with KNN	66.165%	91.278%	15.42%
Proposed method	67.175%	100%	0%

Figure 3 Chart of state-of-the-art comparison (see online version for colours)



5.2.3 *Second series of experiments: comparison with the method of Ortells et al. (2015)*

In this series of experiments, we evaluated our proposed method using the view angle 90°. We compared our proposed method to the work of Ortells et al. (2015) due to the lack of studies that deal with automatic enrolment for gait-based person re-identification. We implemented the method of Ortells et al. (2015). We used normal walking GEI images under the 90° view angle for gallery and probe set from CASIA-B database. A continuous flow of 100 probe samples was simulated so that each subject might randomly appear several times along the flow by chance. Thus, the process of enrolment is repeated ten times in order to ensure reliability. Ortells et al. (2015) addressed the problem of person enrolment for gait-based biometric re-identification. The authors used a classification scheme in order to validate their method based on the traditional 1NN. Table 4 and its corresponding chart (cf. Figure 3) reveals that our proposed method outperforms the method of Ortells et al. (2015). This confirms the advantage of using the P-LBP descriptor on the GEI image for the feature representation step as well as the effectiveness of the chosen gamma threshold.

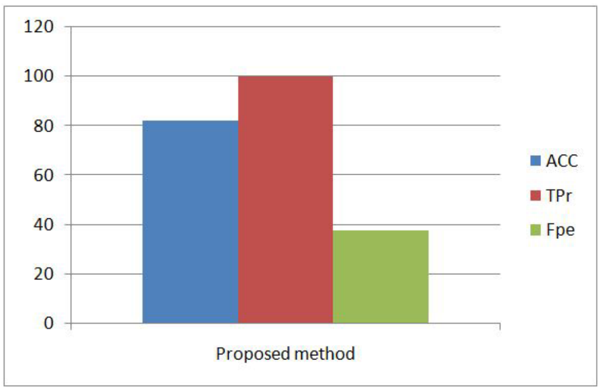
5.2.4 *Third series of experiments: accuracy of our proposed method*

The third series of experiments was performed to check the performance and the efficiency of our proposed method in the context of the presence of several view angles. In this series of experiments, we used different normal appearances and various view angles. We randomly chose 100 samples for the probe set. Each experiment was repeated ten times in order to guarantee the performance reliability of the proposed method. Owing to the fact that there are no previous works that dealt with different view angles, Table 5 and its corresponding chart (cf. Figure 4) highlights the average accuracy (ACC), sensitivity (TPr) and specificity (FPr).

Table 5 ACC, TPr and FPr of the proposed method under various view angles

Experiment	*ACC*	*TPr*	*FPr*
Proposed method	81.921%	100%	37.624%

Figure 4 Chart of the proposed method under various view angles (see online version for colours)



6 Conclusions

This paper dealt with the problem of person enrolment for gait-based biometric re-identification. Enrolment has been characterised as a two-class problem with two error types. The novelty of our proposed method lies in the fact that it offers a new representation for the gallery set. This provides richer information about the subjects as a given subject may be represented by several samples. Consequently, the accuracy of re-identification rate will increase. Realistic experiments were designed to simulate random flows of people under several view angle variations. The experimental results illustrate the promising performance of our proposed method. As a future perspective, we intend to incorporate such method in a complete re-identification system based on both appearance and gait.

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