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Walking Direction Estimation for Gait Based Applications

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Abstract

Gait has become a popular trait for biometric person recognition/re-identification. This is due to its advantage of being captured without any subject cooperation. This made it suitable especially for video surveillance applications. However, the gait features obtained in such scenarios depends on the observed walking direction of the subject. In this paper, we deal with the problem related to walking direction estimation in unconstrained environments. Covariates factors (*i.e.* carrying different types of bag, clothing) affect considerably the accuracy of walking direction estimation problem. Therefore, we have proposed a solution which is suitable for both real time application and unconstrained environment where the user walking direction is different and affected by covariates factors. The discriminative power of this solution is verified through experiments. The performance of this method was evaluated on the CASIA-B database. Experimental results prove the effectiveness of our proposed walking direction estimation method.

Keywords: Video Surveillance; Covariates factors; Walking direction; Gait

1. Introduction

Human gait is an important biometric feature which is able to identify a person at a distance. Gait based methods are typically applied to the side view[3,11,8]. Such methods cannot be applied when the user opts for a different walking direction, as it leads to a different observation viewpoint and a considerable change of person features. Therefore, a new research area is intersted with gait based application under different walking direction. This suppose to firstly recognize the walking direction before any other treatements. In fact, estimating direction of pedestrians walking from video is a crucial task for several applications: video surveillance, pedestrian protection using driver assistance systems, traffic control systems, improving people tracking and identification systems, monitoring high security areas including banks, airports, military bases, and railway stations, etc. Many contributions in this area have been proposed and challenges are still here, due mainly to internal and external conditions, which degrade the image quality especially covariate factors (*i.e.* carrying condition, clothing), low resolution,etc. Hence, to ensure gait based task in an unconstrained environment where the user walking direction is not predefined, a robust method to identify the

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walking direction is needed. In this paper, we propose a solution for walking direction estimation which overcomes the problem of covariates factors (*i.e.* carrying different types of bag, clothing). The rest of this paper is organized as follows. Section 2 summarizes some related works. Section 3 introduces the proposed method. Section 4 describes the evaluation protocol. Section 5 concludes this paper.

2. Related Work

Walking direction estimation is a crucial step for many video processing and computer vision-oriented tasks. It becomes mainly complicated by variations of clothing or by carrying some items. Methods that treat walking direction estimation can be classified into two groups: (i) Template based methods[15,10,6,4,1,17,16] and (ii) Silhouette based methods[22,9,7].

Template based methods rely on constructing a model representation over all the sequence or over one gait cycle. Model representation is classified into two groups which are GTI (Gait Texture Image) or GEI (Gait Energy Image). GTI can be obtained by vertically flipping the binary silhouette images and averaging all the resulting binary images over the entire gait sequence. Conversely, GEI is a spatio-temporal representation of a person's walking characteristic compacted into a unique image. It captures the changes in the shape of the silhouette over a sequence of images. In[15], authors build a GTI and estimate the viewing angle by analysing the spatio-temporal evolution of the user's feet position. User recognition is performed by applying LDA (Linear Discriminant Analysis) to dissimilarity vectors which represent a user. GEI based methods are generally applied over the leg region of the subject. Kusakunniran et al.[10] projects gait features extracted from GEI image into LDA in PCA (Principle Component Analysis) transformed space[19] in order to benefit from both PCA and LDA advantages. The work presented by Guan et al[6] has proposed two types of features, namely, global features (H) and local features (S) from GEI image. Global features are based on the entropy of GEI row entries. Standard deviation is employed to define the local features for each GEI row to describe the variations of the corresponding dynamic features. Based on H/S, PCA and LDA are employed for feature extraction. For a query gait in an unknown view, in terms of Euclidean distance, K nearest neighbors (KNN) are selected separately based on H and S to form a voting pool. A decision level fusion is then adopted to obtain the query gait view label by following the majority voting criterion. The example described in[4] uses the leg region of GEI to identify the walking direction since in general it is unaffected by variations in clothing and/or carrying conditions. It then computes the entropy of the cropped GEI followed by PCA for dimensionality reduction and data decorrelation. The entropy computed from the probe image is then matched against the gallery reference images to detect the probe walking direction. The work presented in[1] follows a similar approach by considering the cropped GEI and applying PCA for data decorrelation, but then uses a Gaussian process (GP) classifier for walking direction identification. Verlekar et al.[17,16] explore view estimation by computing a perceptual hash (PHash) over the leg region of the user from GEI image and comparing it against the PHash values obtained for training sequences. The PHash is a special type of hashing function that generates outputs that are comparable, as opposed to cryptographic hashing[23].

For the category of silhouette based methods, they rely on features extracted from silhouette images. Zhang et al.[22] present an idea of estimating the view angle automatically. They propose a view-sensitive feature to characterize the silhouettes from different views. The robust regression method is employed to estimate the viewpoint of gait. They proved that the regression model using pure cubic formulation is better than using linear or pure quadratic formulation to fit the training data generated by the proposed feature extraction method. Both the works of Jia et al.[9] and Issac et al.[7] use the positions and heights of the person at the beginning and at the ending points of a gait cycle. Considering the four quadrants of the camera's coordinate system, these parameters are used as features to identify the walking direction.

These methods are effective. However, some of these methods are computationally expensive, applicable to a limited range of walking directions and discard a lot of informations that can be useful for classification accuracy. Our proposed method overcomes these drawbacks by proposing a new method that benefits from the maximum of relevant informations while taking into consideration the covariate factors (*i.e.* carrying bag, clothing).

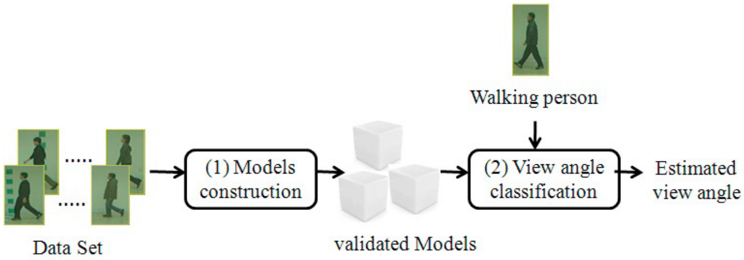

Fig. 1. Flowchart of the proposed walking direction estimation method.

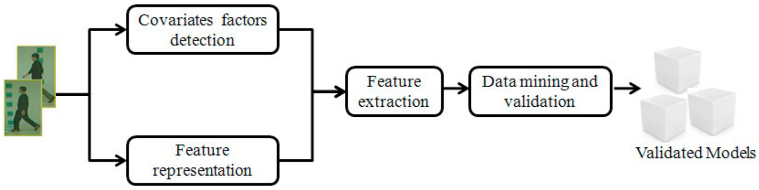

Fig. 2. Models construction step

3. Proposed Method

We propose to build an automatic walking direction estimation solution based on machine learning method. To classify each view angle into the corresponding class, we adopted a KDD process (Knowledge Discovery in Databases) for extracting useful knowledge from volumes data[30]. The total process of walking direction estimation is based on two steps which are (1) Models construction and (2) View angle classification. The output of the first step is the validated models that will be used further in the view angle classification step. Figure 1 shows the flowchart of the proposed walking direction estimation method.

3.1. Models Construction

The goal of the proposed method is to estimate the walking direction even in the presence of covariates factors. For thus, since covariates factors concern accessoires (bags) and clothing, we propose to generate different models dealing with the different covariates factors. Figure 2 describes the models construction step which consists in Feature representation, Covariates factors detection, Feature extraction and Data mining and validation.

3.1.1. Feature Representation

In this step, we opted for template based method like GEI (Gait Energy Image)[13]to represent the person gait. Firstly, we compute the gait cycle as the time between two successive strikes of the same foot. We adopt the method proposed in[18] based on aspect ratio for gait cycle estimation of arbitrary walking sequences. This method is used recently in the work of[21,20]. The aspect ratio of the silhouette over a sequence of frames is represented as a 1D temporal signal. The signal is z-normalized (subtracting the signal mean and dividing by signal's standard deviation) and smoothed using a moving average filter. After that, peaks in the aspect ratio signal are magnified by computing its auto-correlation sequence and the first derivative of the auto-correlation signal is used to identify zero-crossings. These positions of positive and negative peaks are used to compute distance between prominent peaks, average of distances between consecutive peaks result in the gait cycle in number of frames.
Secondly, we generate the GEI as a spatio-temporal representation of a person's walking characteristic compacted into a unique image. It captures the changes in the shape of the silhouette over a sequence of images. The GEI can be computed by averaging the silhouettes over a gait cycle (two stances). Figure 3 shows an example of silhouettes in one gait cycle and their corresponding GEIs for two subjects.

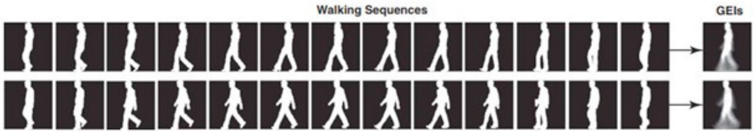

Fig. 3. The silhouettes in one walking cycle (left) and their corresponding GEIs (right) for two subjects.

3.1.2. Covariates factors Detection

Recently, semantic attributes which are human-understandable properties (*e.g.* "sunglasses", "headphones", "Age") are gained more and more interests. This interest is due to their ability to infer high-level semantic knowledge. Several methods[24,25,26,27] have proposed attributes like "sunglasses", "headphones", "is male", "Age" and "neckline shape". However, these attributes may not alter or affect the natural gait appearance and dynamic pattern of body motion. Therefore in a previous work[29], we have concentrated on covariates factors that can alter gait representation (*i.e.* Single Shoulder Bag, Back Pack, Hand Bag, Outerwear). These attributes can influence and occlude the gait based appearance of the body shape and consequently decrease accuracy of gait based application. We have considered four models (i.e. Outerwear model, carrying nothing model, Hand Bag model and Single Shoulder bag/Back pack model). We have constructed one model for single shoulder bag and back pack as they use same relevant parts. In our previous work[29], we have proposed to build an automatic semantic attribute classification solution which predicts the class of each semantic attribute from walking person image.

3.1.3. Feature Extraction

Once the class of semantic attribute is determined, the corresponding GEI image is divided into seven non-overlapping[5] parts which are: head, chest 1, chest 2, knee 1, knee 2, foot 1, foot 2. For each class of semantic attribute, parts that are affected are discarded. We adopt the relevant parts for the feature extraction sub-step. The extraction of the salient and suitable feature to successfully capture the gait characteristics is an important task. After an experimental study, we have adopted P_ LBP (Partial LBP). It is a modified LBP (Local Binary Pattern) introduced by[21]. The P_ LBP can be applied on GEI to extract meaningful texture features. P_ LBP takes the pixels of an image by thresholding the 3x3 neighborhood of each pixel with the center value and considering the result as a binary number (0 or 1) (*cf.* equations (1) and (2)). P_ LBP uses binary sequence as gait signature.

$$P\_LBP = (x_c, y_c) = \sum_{n=0}^{7} s(i_n - i_c)2^n \tag{1}$$

where i_c corresponds to the value of the center pixel (x_c, y_c), i_n to the value of the eight surrounding pixels, and function $s(x)$ is defined as:

$$s(x) = \begin{cases} 1 \ if \ x \geq 0 \\ 0 \ if \ x < 0 \end{cases} \tag{2}$$

3.1.4. Data mining and validation

Once the feature extraction is undertaken, our following sub-step is to perform machine learning using different classifiers in order to generate models. Further, trained models are tested and their corresponding results are presented in the experimental result section. We used two supervised algorithms from different families SVM (Support Vector Machines)[14] and KNN (K Nearest Neighbor)[31]. Finally, the best performer classifiers is chosen.

Support Vector Machine

Classification by SVM[14] is performed by constructing a model that iteratively separates the training data into two classes. $K(X_i, X_j) = \Phi(X_i)^T\Phi(X_j)$ is called the kernel function. In our work, we use a SVM using the histogram Intersection (HI) as kernel since our feature vectors are based on histograms, as formulated below.

$$K(X_i, X_j) = \sum_{k=1}^{n} min\left\{x_i, x_j\right\} \tag{3}$$

where: $X_i = \left\{x_1^i, ..., x_n^i\right\}$ and $X_j = \left\{x_1^j, ..., x_n^j\right\}$ are two histograms with n-bins (in $\mathbb{R}^n$). HI kernel has been demonstrated a positive result which makes it suitable as a discriminative classification kernel.

K Nearest Neighbor

In pattern recognition, the K-Nearest Neighbor algorithm (KNN)[31] is a non-parametric method used for classification and regression. KNN is among the simplest machine learning algorithm that uses existing database instances to classify new instance based on similarity measures (*e.g.* Euclidean distance, Hamming distance, Minkowski distance, Manhattan distance). The output is a class membership. KNN compares new input from existing instances from training set. In this classifier, k is the number of neighbors considered for classification of new instances. As the values of K is increased, and it approaches n (where n is the size of the instance base), the N neighbors will take part in the decision making for classification, hence an optimal value of K is desirable.

In order to guarantee the generality for future samples, we undertaken a validation step which measure the performance of the learned predictive model. Among the proposed metrics in the literature to evaluate the quality of the predictive model, we have opted for Correct Classification Accuracy (CCA) which denotes the ratio of correctly classified images with the total number of images. The output of the data mining and validation sub-step is four models (*i.e.* Coat model, carrying nothing model, Hand Bag Model and Single Shoulder bag/Back pack model). These models correspond to the number of semantic attributes class treated. We have constructed one model for single shoulder bag and back pack as they use same relevant parts.

3.2. View angle Classification

The second step of the process of walking direction estimation is view angle classification. This step is an online classification step. Given a sequence of testing image, gait cycle estimation is determined. Then, GEI image is generated. Depending on the semantic attribute class, feature extraction is undertaken then the suitable model (i.e. Outerwear model, carrying nothing model, Hand Bag model and Single Shoulder bag/Back pack model) is chosen for the classification step. Finally the correct view angle classification accuracy is determined.

4. Experimental Results

To validate our proposed method, we conduct three series of experiments on CASIA-B database[2]: The first one is realized in order to determine the most convenient descriptor for the walking direction estimation. The second series of experiments is about choosing the most performer classifier. The third series of experiments concerns validation and comparison of the proposed method with state-of-the-art methods notably the ones reported in[4,16]. Before presenting the results of the three series of experiments, we present in the next section a description of the CASIA-B database[2].

4.1. Database description

The proposed method is tested on CASIA database B[2,28] to evaluate its ability to handle the presence of covarites factors and view angle variations. CASIA database B is collected by the Institute of Automation of the Chinese Academy of Sciences. It is a large multi-view gait database containing 124 subjects captured from 11 different view angles using 11 USB cameras around the left hand side of the walking subject starting from 0°to 180°.

A step of 18°is between two adjacent views. View angles used are 0°, 18°, 36°, 54°, 72°, 90°, 108°, 126°, 144°, 162°, and 180°. Each subject is recorded six times under normal conditions (N), twice under carrying bag conditions (B) and twice under clothing variation conditions (C). Figure 4 shows several normal walking sequences from CASIA-B database with 18 degree interval and Figure 5 shows the three conditions that exist which are normal (Figure 5.A), carrying items (Figure 5.B) and with clothing (Figure 5.C) under 90°angle. The first four sequences of (N) are used for training. The two remaining sequences of (N) as well as (B) and (C) are used for testing normal, carrying and clothing conditions, respectively. For each sequence, GEI of size 64×64 is computed.

4.2. First Series of experiments

This section aimed to chose the most performer descriptor for walking direction estimation. For that, we have tried three descriptors which are: Partial_ Local Binary Pattern (P_ LBP), Histogram of Oriented Gradients (HOG) and

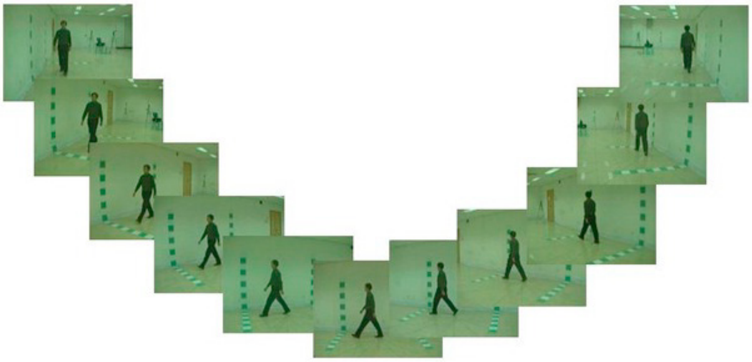

Fig. 4. Normal walking sequences from CASIA-B database with 18 degree interval.

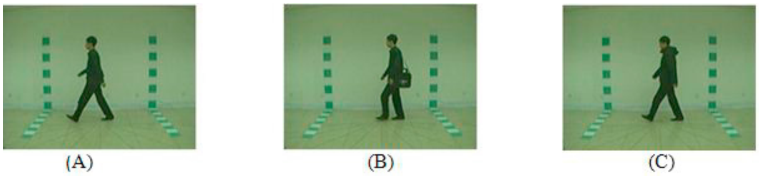

Fig. 5. (A) normal, (B) carrying conditions and (C) clothing at the angle of 90 degrees.

Local Binary Pattern (LBP). Train and test sets contain normal subjects. As shown in Table 1 providing comparative results for correct angle estimation using P_ LBP, HOG and LBP, P_ LBP outperforms the two other descriptors for the majority of view angles with an average of 95.48 %.

Table 1. Correct classification rate (%) against different descriptor using normal subjects

View	LBP based method	HOG based method	P_ LBP based method
000	71.138	93.495	95.528
018	58.704	81.781	85.829
036	78.861	89.430	90.650
054	82.186	98.380	97.975
072	87.441	98.604	99.069
090	81.300	95.934	95.528
108	65.587	96.761	98.380
126	76.612	97.983	98.790
144	88.663	97.570	98.785
162	75.609	94.715	94.308
180	62.753	95.546	95.951
Mean	75.205	94.519	95.488

4.3. Second Series of experiments

The second series of experiment aim to test several classifiers in order to choose the most performer one for walking direction estimation. For that, we have tried two classifiers which are: K Nearest neighbor (KNN) and Support Vector Machine (SVM). In this series of experiments, train and test set contain normal images. P_ LBP (Partial_ Local Binary Pattern) is used as descriptor as it is the most performer descriptor like shown in the previous series of experiments. Table 2 shows comparative results between KNN and SVM: SVM outperforms the KNN classifier for the majority of view angles.

Table 2. Correct classification rate (%) against different classifiers using normal subjects

view	K Nearest Neighbor	Support Vector Machine
000	93.089	95.528
018	72.983	85.829
036	87.449	90.650
054	95.967	97.975
072	93.951	99.069
090	96.356	95.528
108	95.141	98.380
126	98.387	98.790
144	98.387	98.785
162	91.056	94.308
180	94.736	95.951
Mean	92.500	95.951

4.4. Third Series of experiments

The purpose of this experimentation is to prove the effectiveness of our method for walking direction estimation in the presence of covariates factors. In addition, it presents a comparative study with two state-of-the-art methods reported in[4,16]. Choudhury et al.[4] and Verlekar et al.[16] have used the bottom leg region for their experiments. This is based on the hypothesis that this part is unaffected by clothing and carrying different types of bag. Choudhury et al.[4] computes the entropy followed by PCA for dimensionality reduction and data decorrelation. Verlekar et al.[16] computes a perceptual hash (PHash) function. As described above, in our method, in order to profit from the maximum of features, only parts affected by covariates factors are discarded for corresponding models construction step. For the experimental protocol, the first four normal walking sequences (N) of each user, in each walking direction are used for training. The remaining N, C (wearing of a coat) and B (carrying a bag) sequences are used for testing. The results in Table 3 show the superior average performance of our proposed method for normal (N) with an accuracy of 95.488 % of our proposed method, 92% for Verlekar et al. method and 86% for Choudhury et al. method. For carrying bags (B), our proposed method outperforms the Choudhury et al. method and Verlekar et al. method with a classification accuracy of 87.99%. It should be noted that for wearing clothes (C), the average classification accuracy of our proposed method is slightly lower compared to the method of Verlekar et al.[16]. This is due to the quality of generated GEI that depend on the existing silhouette. Bold value indicates that the accuracy of the view classification of our proposed method is better compared to the Choudhury et al. method and Verlekar et al. method.

Table 3. Correct classification rate (%) against state-of-art-methods

view	Choudhury et al. method[4]			Verlekar et al. method[16]			Proposed method		
	N	C	B	N	C	B	N	C	B
000	83	80	79	91	86	86	**95.528**	80.487	85.362
018	94	87	85	90	81	76	85.829	72.357	**83.262**
036	88	85	80	70	66	56	**90.650**	**77.235**	**81.25**
054	92	90	89	92	87	72	**97.975**	**93.495**	**95.736**
072	81	80	78	96	90	88	**99.069**	**90.725**	83.243
090	89	79	72	95	88	86	**95.528**	83.870	80.074
108	79	75	70	94	92	87	**98.380**	85.887	**92.403**
126	90	88	85	96	92	91	**98.790**	96.356	**97.122**
144	83	81	79	95	91	83	**98.785**	**94.308**	**95.736**
162	89	86	84	95	89	88	94.308	86.938	**91.314**
180	82	80	75	95	90	88	**95.951**	86.290	79.959
Mean	86	82	78	92	87	82	**95.488**	86.182	**87.99**

5. Conclusion

Using gait biometric is very effective in various tasks, because it can recognize people from distance, without their cooperation. However, gait based applications were always affected by covariates factors (*i.e.* carrying items and clothing). In this paper, a walking direction estimation method that takes into account these covariates factors is proposed. Parts that are affected by covariates factors are discarded while generating corresponding models. These models are used further for on-line classification of view angle for a new target. Our study shows the improvement in classification accuracy rate for the majority of view angle. Future work can be extended to develop gait based re-identification solution which deal with view angle change.

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