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Person Identification Based on Euclidean Distance Transform

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Abstract: This study presents a method of person identification working on a sequence of 2D silhouettes. Inspired by the state-of-the-art gait signature gait energy image, we integrate a non-linear operation into the stage of feature extraction in order to enhance the obtained gait signature. Unlike related works, our method does not require the step of gait cycle separation. The accuracy of our approach was demonstrated by experiments on the CASIA-A gait dataset and was comparable with many related studies.

Key words: Person identification, distance transform, support vector machine, silhouette, gait, signature

INTRODUCTION

Computer vision is popularly integrated in many systems related to a wide variety of fields such as surveillance, human-machine interaction and communication. Person identification is one of the most common problems since, it has many practical applications. Researchers have dealt with this problem according to various input data such as 2D silhouette, skeleton and 3D Model. In this study, we present an approach dealing with a sequence of 2D silhouettes. The reason of our choice is the integration ability of our method when applying on typical surveillance systems without requiring specific and/or complicated devices.

Many gait signatures have been introduced to represent silhouette-based gait characteristics such as Gait Energy Image (GEI) (Han and Bhanu, 2006) and Motion History Image (MHI) (Ahad *et al*., 2012) in which the former was directly used for person identification and the latter is appropriate for action recognition. We perform a modification on GEI to improve the information representation and our method avoids the task of gait cycle separation that is required for GEI estimation. Our classification is performed using a typical Support Vector Machine (SVM).

MATERIALS AND METHODS

Pre-processing: Similarly to GEI, our gait signature is also estimated based on a sequence of consecutive input silhouettes. Normalization is thus necessary before performing the combination. First, every connected component in each binary silhouette is determined using a morphological operation with cross-shaped structuring element. The component of foreground pixels that has the largest number of points is considered as the subject silhouette while the others are discarded, since, they may be noise or bad segmentation results. The subject region is then cropped according to its boundary. This area is much smaller than the input frame.

The next step is to normalize cropped silhouettes to be the same size. In order to keep the overall shape of subject pose, we employ the method proposed in Vo *et al*. (2015). Given a cropped silhouette with the width w and the height, h the image is then padded twice to obtain a square image where the object of interest is aligned at the center. Concretely, the cropped silhouette of size $w \times h$ is respectively, padded by two regions of size $[0.5\ (h\text{-}w)] \times h$ and $[0.5\ (h\text{-}w)] \times h$. The square image is finally, scaled to a pre-defined size. The padding guarantees that all images have the same size after scaling while the object shape is still preserved. An example of the padding is presented in Fig. 1.

Gait signature calculation: Unlike popular gait signatures that are directly formed from a sequence of silhouettes, our method performs a transformation on the binary image before estimating a signature. Concretely, the Euclidean Distance Transform (EDT) Fabbri *et al*. (2008) is applied on the scaled square silhouette as illustrated in. In the original binary image, each pixel is independent with the others, there is thus no an overall relationship in the collection of points. The EDT, however, assigns to each pixel the spatial information related to the others. The obtained result can be considered as a skeletonized representation of the input 2D silhouette (Fig. 2).

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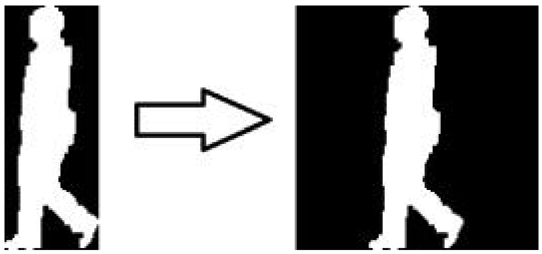

Fig. 1: Example of square image obtained by silhouette-based padding

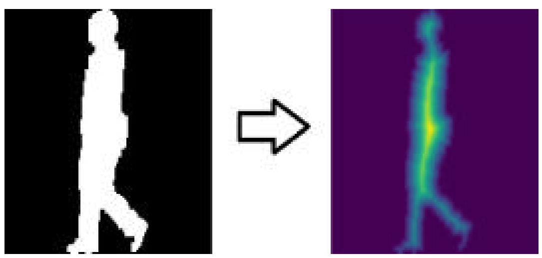

Fig. 2: Skeletonized representation of a 2D silhouette using EDT

Our gait signature is estimated according to a sequence of such EDT results. Differently from related studies where each gait cycle is employed as a gait unit (Nguyen *et al*., 2014), we calculate the signature on a fixed length of sequence of silhouettes with the support of a sliding window. The signature is simply the average EDT result as:

$$G(x,y) = \frac{1}{w}\sum_{i=1}^{w} E(x, y, i) \quad (1)$$

where, w is the width of a pre-defined sliding window and E is the EDT result obtained from a frame within the window. An example of our gait signature estimated from real data is shown in Fig. 3. It is obvious that our EDT-based signature is smoother than the one estimated directly from binary silhouettes. Besides, bad result of silhouette extraction significantly affects the silhouette-based signature [e.g., holes on the upper body in Fig. 3b while it almost does not appear in our proposed gait signature.

Person identification: In this stage, the input sequence of 2D silhouettes is represented by a collection of gait signatures. In order to determine the subject corresponding to the input sequence, we first attempt to assign a label to each signature, i.e., a short sequence of silhouettes within the sliding window. We employ a typical SVM to perform the classification. This model is considered as a collection of binary SVMs. In the feature, space, each elemental SVM attempts to separate data that belong to two subjects by a gap which is as wide as possible. If the training data cannot be linearly separated in the feature space, they are then projected onto a Hilbert space with a higher number of dimensions (Fukumizu *et al*., 2011).

After assigning labels (i.e., subject identity) to consecutive gait signatures belonging to an input sequence of silhouettes, the final identification is performed by selecting the statistical mode of labels. This operation comes from the assumption that some gait signatures may contain, noise, so that they become similar to other subjects while the remaining is still individually characterized. This non-linear operation is also employed in many recent studies to provide the final decision (Nguyen *et al*., 2016; Bauckhage *et al*., 2009).

RESULTS AND DISCUSSION

Experiments: In order to evaluate the proposed method, we performed the task of person identification on the CASIA-A gait dataset (Wang *et al*., 2003a, b). This dataset has been employed for the evaluation in many studies. The data contain walking gaits collected from 20 subjects under 3 different angles of view: 0° (literal), 45 and 90° (front). There are 4 walking sequences for each angle, the dataset thus has totally 240 sequences of silhouettes.

The experiments on the CASIA-A can be divided into two schemes. The first one is that the training and test sets are separated by the ratio 3:1. Concretely, the first three sequences corresponding to each angle of view are added to the training set, the remaining belongs to the test set. This evaluation scheme is not time-consuming but has a low generalization. The second scheme is leave-one-out cross-validation in which a sequence is considered as the test set and the remaining is used to train the model. By repeating this operation over every sequence in the dataset and calculating the average accuracy, the experiment provides the result with a high generalization. In this researcher, we focus on the latter evaluation scheme.

The hyper parameters were respectively 128×128 for the image size after normalization and for the width of the sliding window. Some gait signatures estimated from first 20 frames corresponding to different subjects in the dataset are shown in Fig. 4. The experimental results obtained from our method and the ones reported from related studies are provided in Table 1. According to Table 1, our method outperforms related studies in the task of person identification using the CASIA-A gait dataset. The table also shows that most silhouette-based classification approaches dealt with images captured from

Table 1: Identification accuracy (%) obtained by leave-one-out cross-validation

	Identification accuracy (%)		
Study	0° (Literal)	45°	90° (Front)
Ben Abdelkader *et al*. (2001)	72.50	-	-
Collins *et al*. (2002)	71.25	-	-
Phillips *et al*. (2002)	78.75	-	-
Ben Abdelkader *et al*. (2002)	82.50	-	-
Lee and Grimson (2002)	87.50	-	-
Wang *et al*. (2003a, b)*	65.00	63.75	77.50
Wang *et al*. (2003a, b)+*	65.00	66.25	85.00
Wang *et al*. (2003a, b)++*	75.00	81.25	93.75
Wang *et al*. (2003a, b)	82.50	-	-
Wang *et al*. (2003a, b)**	89.00	-	-
Ekinci (2006)	65.00	-	-
Lu and Zhang (2007)	92.50	-	-
Chen and Gao (2007)	92.50	95.00	65.00
Lee *et al*. (2009)	91.25	-	-
Zeng *et al*. (2014)	92.50	-	-
Liu *et al*. (2016)*	82.50	83.75	92.50
Liu *et al*. (2016)+*	85.00	87.50	95.00
Our method	93.75	96.25	98.75

*Results obtained with data augmentation by Liu *et al*. (2016); **Results reported by Zeng *et al*. (2014)

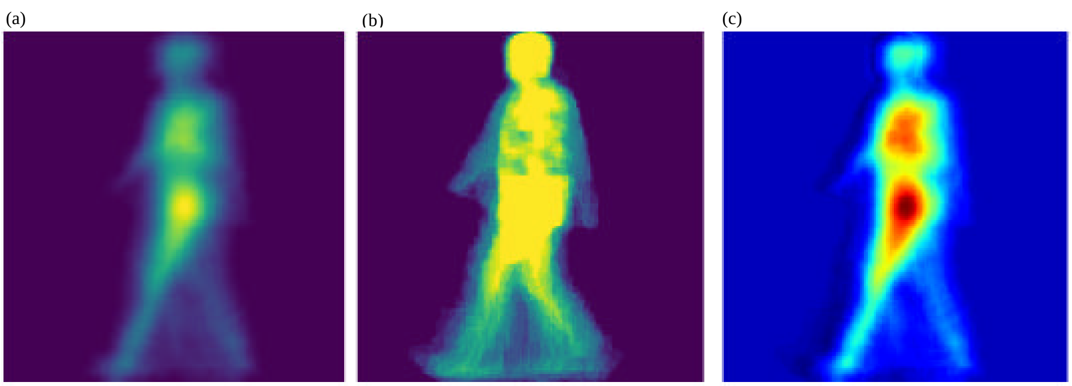

Fig. 3: a) Our gait signature estimated from a sequence of silhouettes; b) The corresponding GEI estimated on the same sequence. The last sub-figure and c) Visualizes the difference between the two signatures

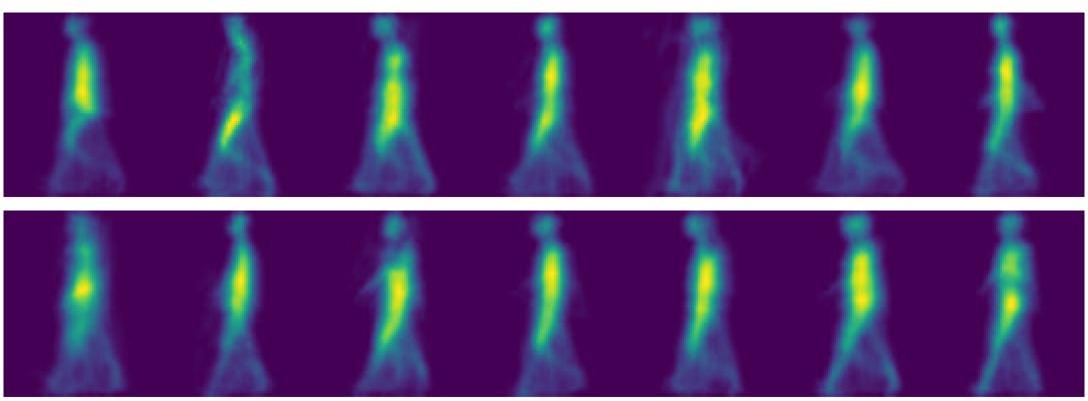

Fig. 4: Our gait signatures estimated for some subjects in the CASIA-A gait dataset

a side view. It is obvious that this view direction is appropriate for separating walking gait cycles as well as detecting the walking phase. Our approach, however, provided good results on all directions. Therefore, additional processing can be performed according to our method to improve the system when working on a specific camera view point. Notice that there are several deformed binary silhouettes in the CASIA-A gait dataset. Therefore, our system can be expected to get a better strength when working on good inputs.

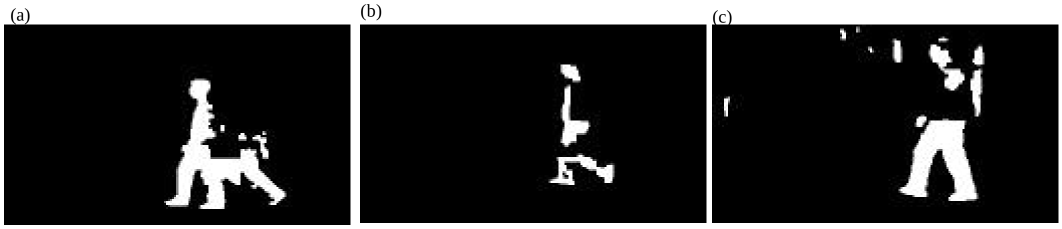

Fig. 5: a-c) Some bad 2D silhouettes in the CASIA-A gait dataset

CONCLUSION

In this study, we propose an approach for person identification based on a sequence of binary silhouettes. Differently from related studies on gait analysis, our method does not require a procedure of gait cycle separation. We instead employ a sliding window to embed the temporal factor into the stage of feature extraction. Another contribution of this research is the integration of Euclidean distance transform into the calculation of gait signature. The experiment on CASIA-A gait dataset showed that our method outperforms related studies while our system does not require any complicated operation. Besides, our method provided good results for all the three camera directions in the dataset.

RECOMMENDATION

In further researchers, the combination of recognition results obtained from different cameras will be considered to improve the ability of identification. That study would be applicable for large areas and is also appropriate to be used with existed surveillance systems.

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REFERENCES

Ahad, M.A.R., J.K. Tan, H. Kim and S. Ishikawa, 2012. Motion history image: Its variants and applications. Mach. Vision Appl., 23: 255-281.

Bauckhage, C., J.K. Tsotsos and F.E. Bunn, 2009. Automatic detection of abnormal gait. Image Vis. Comput., 27: 108-115.

Ben Abdelkader, C., R. Cutler and L. Davis, 2002. Motion-based recognition of people in eigengait space. Proceedings of the 5th IEEE International Conference on Automatic Face and Gesture Recognition, May 21, 2002, IEEE, Washington, USA., pp: 267-272.

Ben Abdelkader, C., R. Cutler, H. Nanda and L. Davis, 2001. Eigengait: Motion-based recognition of people using image self-similarity. Proceedings of the 3rd International Conference on Audio-and Video-Based Biometric Person Authentication (AVBPA), June 6-8, 2001, Springer, Halmstad, Sweden, Europe, ISBN:978-3-540-42216-7, pp: 284-294.

Chen, S. and Y. Gao, 2007. An invariant appearance model for gait recognition. Proceedings of the IEEE International Conference on Multimedia and Expo, July 2-5, 2007, IEEE, Beijing, China, pp: 1375-1378.

Collins, R.T., R. Gross and J. Shi, 2002. Silhouette-based human identification from body shape and gait. Proceedings of the 5th IEEE International Conference on Automatic Face and Gesture Recognition, May 21, 2002, IEEE, Washington, USA., pp: 366-371.

Ekinci, M., 2006. Human identification using gait. Turk. J. Elec. Eng. Comput. Sci., 14: 267-291.

Fabbri, R., L.D.F. Costa, J.C. Torelli and O.M. Bruno, 2008. 2D Euclidean distance transform algorithms: A comparative survey. ACM. Comput. Surv., 40: 1-44.

Fukumizu, K., G.R. Lanckriet and B.K. Sriperumbudur, 2011. Learning in Hilbert vs Banach Spaces: A Measure Embedding Viewpoint. In: Advances in Neural Information Processing Systems, Shawe-Taylor, J., R.S. Zemel, P.L. Bartlett, F. Pereira and K.Q. Weinberger (EdS.). Curran Associates, Inc., New York, USA., pp: 1773-1781.

Han, J. and B. Bhanu, 2006. Individual recognition using gait energy image. IEEE. Trans. Pattern Anal. Mach. Intelli., 28: 316-322.

Lee, H., S. Hong and E. Kim, 2009. Neural network ensemble with probabilistic fusion and its application to gait recognition. Neurocomputing, 72: 1557-1564.

Lee, L. and W.E.L. Grimson, 2002. Gait analysis for recognition and classification. Proceedings of the 5th IEEE International Conference on Automatic Face and Gesture Recognition, May 21, 2002, IEEE, Washington, USA., pp: 155-162.

Liu, D., M. Ye, X. Li, F. Zhang and L. Lin, 2016. Memory-based gait recognition. Proceedings of the International Conference on British Machine Vision (BMVC), September 19-22, 2016, BMVA Press, York, England, UK., ISBN:1-901725-59-6, pp: 1-12.

Lu, J. and E. Zhang, 2007. Gait recognition for human identification based on ICA and fuzzy SVM through multiple views fusion. Pattern Recognit. Lett., 28: 2401-2411.

Nguyen, T.N., H.H. Huynh and J. Meunier, 2014. Extracting silhouette-based characteristics for human gait analysis using one camera. Proceedings of the 5th International Symposium on Information and Communication Technology (SoICT'14), December 04-05, 2014, ACM, New York, USA., ISBN:978-1-4503-2930-9, pp: 171-177.

Nguyen, T.N., H.H. Huynh and J. Meunier, 2016. Skeleton-based abnormal gait detection. Sensors, Vol. 16, 10.3390/s16111792

Phillips, P.J., S. Sarkar, I. Robledo, P. Grother and K. Bowyer, 2002. Baseline results for the challenge problem of human ID using gait analysis. Proceedings of the 5th IEEE International Conference on Automatic Face Gesture Recognition (FGR), May 21-21, 2002, IEEE, Washington, USA., pp: 137-142.

Vo, D.H., T.N. Nguyen, H.H. Huynh and J. Meunier, 2015. Recognizing vietnamese sign language based on rank matrix and alphabetic rules. Proceedings of the International Conference on Advanced Technologies for Communications (ATC), October 14-16, 2015, IEEE, Ho Chi Minh City, Vietnam, ISBN:978-1-4673-8372-1, pp: 279-284.

Wang, L., T. Tan, H. Ning and W. Hu, 2003. Silhouette analysis-based gait recognition for human identification. IEEE Trans. Pattern Anal. Mach. Intell., 25: 1505-1518.

Wang, L., T. Tan, W. Hu and H. Ning, 2003. Automatic gait recognition based on statistical shape analysis. IEEE. Trans. Image Process., 12: 1120-1131.

Zeng, W., C. Wang and Y. Li, 2014. Model-based human gait recognition via deterministic learning. Cognit. Comput., 6: 218-229.