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BODY PARTS DYNAMICS AND GEOMETRY FOR AUTOMATIC GENDER CLASSIFICATION

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Abstract

Gender classification has become one of the most exciting research areas because of its numerous applications in computer vision. Most of the researches utilize facial images for automatic gender classification. However, the facial image based gender classification techniques suffer from pose, rotation, illumination and size of the faces. As a result, some gait-based gender recognition techniques have been introduced. These gait-based gender classification techniques use only the geometrical features from the gait images. Hence, in this article, we have introduced a novel gait-based gender classification technique namely Body Parts Dynamics and Geometry (BPDG). BPDG is able to capture temporal dynamics as well as geometry of head and chest in gait sequence, which have more distinguishing power and less computational complexity. The experiments on CASIA(B) dataset show that BPDG outperforms state of the art gait based gender classification techniques.

Keywords: BPDG, Gait, Gender Classification, Temporal Information.

Introduction

Gender classification is one of the most emerging research areas of computer vision. Both facial images (Rahman et al., 2015; Rahman et al., 2017; Rahman et al., 2018) and gait sequences (Li et al., 2008; Hu et al., 2011; Wang et al., 2015) are used for automatic gender classification. In recent days, gait-based gender and person identification techniques have gained popularity because of being unobtrusive and accessible from any distance (Li et al., 2008; Hu et al., 2011; Wang et al., 2015). Most of the existing gait based gender classification approaches generate gait energy image (GEI) from a sequence of images and divide the body into several parts such as head, chest, thigh, leg, feet, etc. Afterwards, the appearance information is extracted by fitting ellipses in these parts (Lee et al., 2002; Huang et al., 2007). These techniques are computationally expensive because

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of ellipse fitting. Li et al., (2008) and Yu et al., (2006) segment the silhouette into seven and five parts respectively, and find control points of those parts. However, both of these techniques can be affected by the carrying conditions and clothing as these approaches consider lower parts of the silhouette. Moreover, temporal dynamics and geometric information of body parts cannot be effectively captured by these techniques due to using GEI. Different model based techniques such as hidden Markov model (HMM) (Lee et al., 2002; Cheng et al., 2008) and conditional random field (CRF) (Hu et al., 2011) are also used for gait based gender classification. Still these techniques are computationally cost-intensive for calculating several parameters. Hence, a computationally efficient discriminative feature descriptor is a growing demand for human gender classification.

In this article, we consider the gait sequence for gender classification, where features are extracted only from head and chest parts. We discard the features from lower parts of the body as it poses little information related to gender (Yu et al., 2009). Further, these parts sometimes create ambiguity due to the presence of cloth, bag and other staffs.

BPDG

Like other gait based gender classification approaches, BPDG first extracts the region of interest (ROI) (as shown in Fig. 1 (b)) from Fig. 1 (a). Different from Li et al., (2008) and Yu et al.(2009), we consider only head (h) and chest (c) parts (as shown in Fig. 1 (c)) from the ROI and discard other parts because these two parts provide significant discriminatory information for classifying male and female which is shown in Fig. 2 and Fig. 3. The aforementioned graphs are generated by considering 50 frames from each sequence and averaging over 310 sequences of CASIA(B) (Yu et al., 2006) dataset for each of the genders. For each part, four extreme points are calculated representing minimum top, maximum bottom, maximum right and minimum left as shown in Fig. 1 (d). Furthermore, we calculate intersection points (x_h, y_h) and (x_c, y_c) for head and chest part respectively. The final feature vector V is constituted by considering the intersection points of both head and chest from each gait frame. So, the size of the feature vector will be 4n for a sequence where n is the number of frame. The whole process is demonstrated in Algorithm 1.

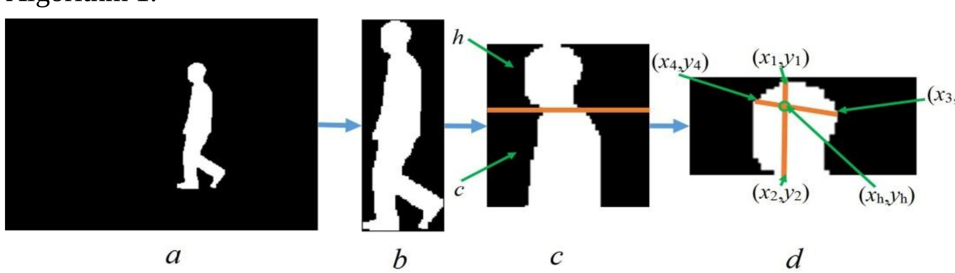

Fig. 1. Feature extraction process, (a) Binary image, (b) ROI from the silhouette, (c) Head and chest part, (d) Feature extraction from head.

Justification of BPDG Feature

We consider the intersection points as features because these points provide temporal dynamics, direction of movements and the geometry of body parts with respect to ROI which are different for male and female. For example, the intersection point for male head (x_{hm},y_{hm}) in general has lower value compared to that of female (x_{hf},y_{hf}) as shown in Fig. 4. Similar thing can also be observed for chest part but in this case male has higher value compared to the female. Furthermore, the nature of motion of these points are also different for male and female. These issues offer BPDG to provide very low cost solution. To validate our observation, we plot the average intersection points of head, and find that on an average *X* and *Y* coordinates of the intersection point of male head are lower than that of female as shown in Fig. 2.

Algorithm 1. Feature Vector Creation

Input: Sequence of gait frames F

Output: Feature vector V

$V \leftarrow \emptyset$

for each $f \in F$ **do**

 Extract ROI of f

 Segment the ROI into h and c parts

 Assuming (x_1, y_1) - min top, (x_2, y_2) - max bottom, (x_3, y_3) - max right, (x_4, y_4) - min left points for h

 $x_h = \frac{(x_2y_1 - x_1y_2)(x_3 - x_4) + (x_3y_4 - x_4y_3)(x_1 - x_2)}{(y_1 - y_2)(x_3 - x_4) - (y_3 - y_4)(x_1 - x_2)}$

 $y_h = \frac{(x_h - x_1)(y_1 - y_2)}{(x_1 - x_2)} + y_1$

 $V \leftarrow V \cup \{x_h, y_h\}$

 Assuming (x_5, y_5) - min top, (x_6, y_6) - max bottom, (x_7, y_7) - max right, (x_8, y_8) - min left points for c

 $x_c = \frac{(x_6y_5 - x_5y_6)(x_7 - x_8) + (x_7y_8 - x_8y_7)(x_5 - x_6)}{(y_5 - y_6)(x_7 - x_8) - (y_7 - y_8)(x_5 - x_6)}$

 $y_c = \frac{(x_c - x_5)(y_5 - y_6)}{(x_5 - x_6)} + y_5$

 $V \leftarrow V \cup \{x_c, y_c\}$

end for

Moreover, the male head movement is slower compared to that of female. Except the case of average Y coordinate (i.e., higher for male and lower for female), similar types of observation can also be found for chest part which is shown in Fig. 3. All of these characteristics of BPDG features help to better classify human gender.

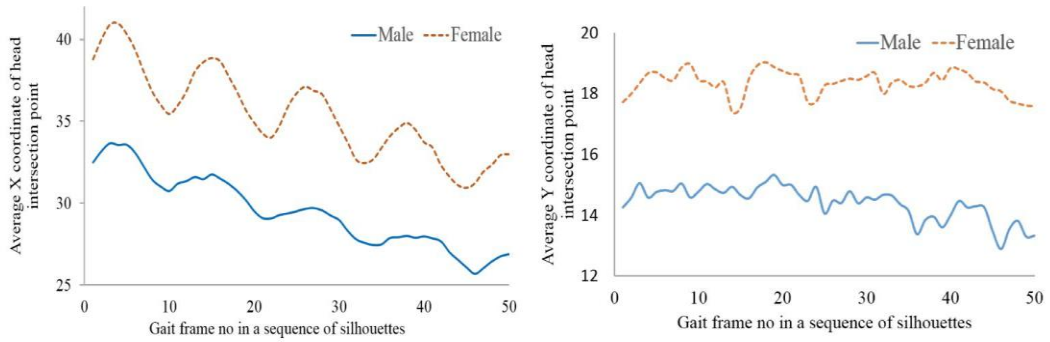

Fig. 2. Change of head intersection points in a sequence of silhouettes (left X coordinate, right Y coordinate).

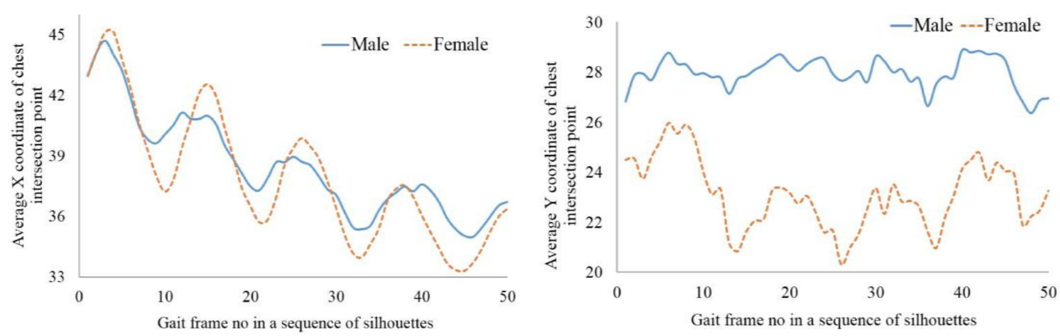

Fig. 3. Change of chest intersection points in a sequence of silhouettes (left X coordinate, right Y coordinate).

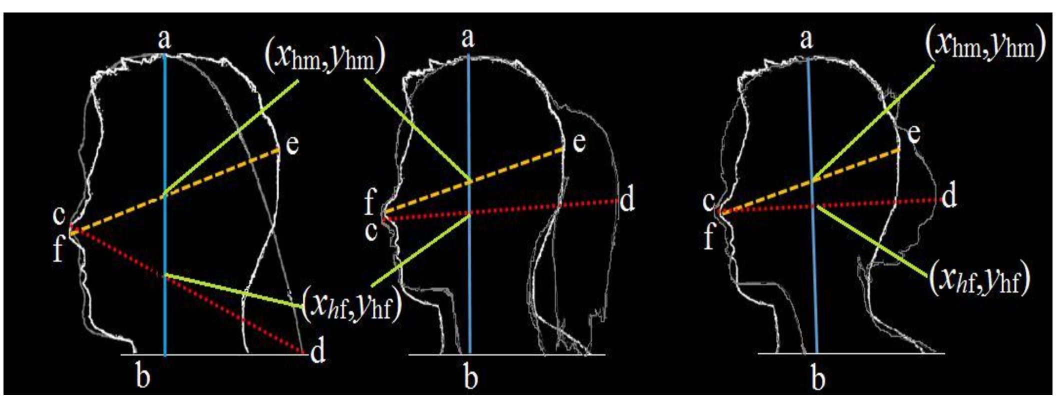

Fig. 4. Variation of head center for male and female in three different scenarios.

Experimental Results

A comparative experimental evaluation of BPDG with the existing gait based gender classification techniques is performed on CASIA(B) dataset (Yu et al., 2006). In this study, 31 subjects are taken from each of the male and female classes. Experiments have been performed in two different settings to demonstrate the impacts of bag and cloths on gender classification. In the first setting, we consider only the six normal sequences (named as nm), while all ten sequences including bags and cloths (named as nm-bg-cl) are considered in the second setting. We have performed a subject independent leave-one-out cross validation in first and second experiments with total of 1,116 and 1,860 sequences respectively for view 72, 90 and 108. Support vector machine with linear kernel is employed for classification which is also used in most of the studies (Li et al., 2008; Yoo et al., 2005). Table I presents the accuracy of different techniques showing that BPDG achieves the highest performance in both experiments. It is noteworthy that few methods consider bag and cloth due to the difficulty of identifying gender for the presence of bag and cloth (Yu et al., 2006; Shan et al., 2007; Hu et al., 2010). However, we have achieved better performance with much lower computation in this case.

Table 1. The correct classification rate (CCR) of different techniques in CASIA (B) dataset.

Method	Condition	Dataset	CCR (%)
Lee et al., 2002	nm	25 M and 25 F	85.00
Yu et al., 2006	nm	93 M and 31 F	96.80
Yu et al., 2006	nm-bg-cl	93 M and 51 F	72.21
Shan et al., 2007	nm-bg-cl	31 M and 31 F	94.20
Yu et al., 2009	nm	31 M and 31 F	95.97
Li et al., 2008	nm	31 M and 31 F	93.28
Hu et al., 2010	nm	31 M and 31 F	96.77
Hu et al., 2010	nm-bg-cl	31 M and 31 F	89.78
Hu et al., 2011	nm	31 M and 31 F	98.39
Wang et al., 2015	nm	31 M and 31 F	97.31
BPDG (Proposed)	nm	31 M and 31 F	**98.81**
BPDG (Proposed)	nm-bg-cl	31 M and 31 F	**95.32**

*nm includes only normal gait sequences and nm-bg-cl includes the gait sequences with normal, bag and cloth.

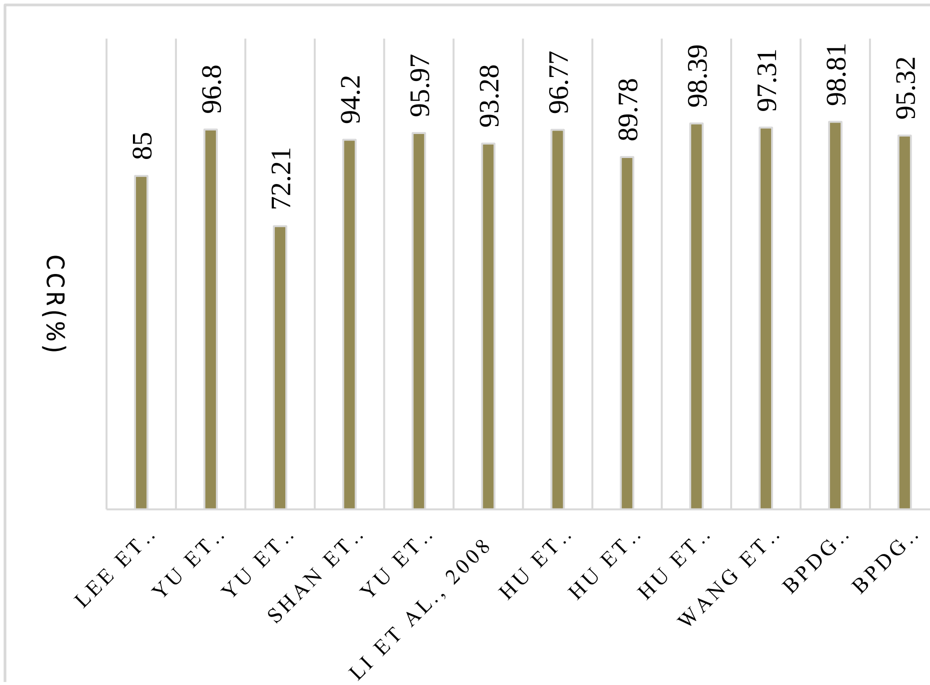

Fig. 5. The correct recognition rate (CCR) of different techniques.

Conclusion

We have proposed a low cost gait based gender classification technique. The proposed technique calculates the feature set corresponding to an input in a single scan, whereas the other approaches are more computationally expensive due to the ellipse fitting or calculating HMM. Hence, several important engineering applications such as surveillance systems, marketing research and social networking may be benefited by adopting the proposed gait based gender classification technique.

References

Rahman, M. M., S. Rahman, M. Kamal, M. Abdullah-Al-Wadud, E. K. Dey, and M. Shoyaib. 2015. Noise adaptive binary pattern for face image analysis.18th International Conference on Computer and Information Technology (ICCIT), Dhaka, Bangladesh, IEEE, pp. 390-395.

Rahman, M. M., S. Rahman, E. K. Dey, and M. Shoyaib, 2015. A gender recognition approach with an embedded preprocessing. International Journal of Information Technology and Computer Science (IJITCS). **7**:19-27.

Rahman, M. M., S. Rahman, R. Rahman, B. M. Hossain and M. Shoyaib, 2017. DTCTH: a discriminative local pattern descriptor for image classification. EURASIP Journal on Image and Video Processing. **2017**:30-53.

Rahman, M. M., S. Rahman, and M. Shoyaib. 2018. MCCT: a multi-channel complementary census transform for image classification. Signal, Image and Video Processing. **12**: 281-289.

Li, X., S. J. Maybank, S. Yan, D. Tao, and D. Xu. 2008. Gait components and their application to gender recognition. IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews. **38**:145–155.

Hu, M.,Y. Wang, Z. Zhang, and D. Zhang. 2011. Gait-based gender classification using mixed conditional random field. IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics. **41**:1429–1439.

Wang, Y., Y. Chen, H. Huang, K. Fan. 2015. Local block-difference pattern for use in gait-based gender classification. Journal of Information Science and Engineering. **31**:1993-2008.

Lee, L. and W. E. L. Grimson. 2002. Gait analysis for recognition and classification. Fifth IEEE International Conference on Automatic Face and Gesture Recognition, Washington, DC, USA,IEEE, pp. 148–155.

Huang, G. and Y. Wang. 2007. Gender classification based on fusion of multi-view gait sequences. 8thAsian Conference on Computer Vision (ACCV), Tokyo, Japan, Springer, pp. 462–471.

Yu,S., T. Tan, K. Huang, K. Jia, and X. Wu. 2009. A study on gait-based gender classification. IEEE Transactions on Image Processing. **18**:1905–1910.

Cheng, M.H., M.F. Ho, and C.L. Huang.2008. Gait analysis for human identification through manifold learning and hmm. Pattern recognition. **41**:2541–2553.

Yu, S., D. Tan, and T. Tan.2006. A framework for evaluating the effect of view angle, clothing and carrying condition on gait recognition.18th International Conference on Pattern Recognition (ICPR), Hong Kong, China, IEEE. **4**:441–444.

Shan,C., S. Gong, and P. W. McOwan. 2007. Learning gender from human gaits and faces. IEEE Conference on Advanced Video and Signal Based Surveillance (AVSS), London, UK, IEEE, pp. 505–510.

Hu,M., Y. Wang, Z. Zhang, and Y. Wang. 2010. Combining spatial and temporal information for gait based gender classification. 20th International Conference on Pattern Recognition (ICPR), Istanbul, Turkey, IEEE, pp. 3679–3682.

Yoo, J.-H., D. Hwang, and M. S. Nixon. 2005. Gender classification in human gait using support vector machine.7th International Conference on Advanced concepts for intelligent vision systems (ACIVS), Antwerp, Belgium, Springer, pp. 138–145.