The AVA Multi-View Dataset for Gait Recognition

D. López-Fernández, F.J. Madrid-Cuevas, A. Carmona-Poyato, M.J. Marín-Jiménez, and R. Muñoz-Salinas

24 August - 2014
Stockholm, Sweden

2nd Workshop AMMDS - ICPR 2014
Activity Monitoring by Multiple Distributed Sensing

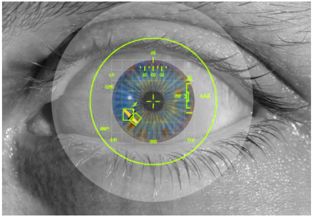
Content index

Introduction

Gait Recognition

Human gait as a biometric for identification.

- Non invasive way to identify people without requiring their cooperation.



Applications [1]

- Automation of surveillance,
- Access control,
  - Military bases,
  - Government facilities,
  - Smart areas,
  - Bank offices.
- Human-machine interface,
- Crowd flux statistics,
- Detection of anomalous behaviours.

Gait recognition methods

- Most gait recognition methods require gait sequences captured from the side view or from the front view of a walking person. [2-6]
- New challenges in the topic of gait recognition, such as achieving the independence from the camera point of view, usually require multi-view datasets. [7-11]

Current datasets

- Single view datasets.
- Multi-view datasets:
  - They were recorded in controlled conditions,
  - Some of them made use of a treadmill,
  - Most of them lack calibration information.


Figure : Samples from CMU Motion of Body (MoBo) [14] and CASIA Dataset B [17].

Current publicly available datasets

Database	Subset	Type of problem	Subjects	Sequences	Source	Treadmill	Views	Path	Year
UCSD [12]	N.A	Shaded scenes	6	7	Outdoor	No	Side	Circular	1998
HID-UMD [13]	N.A	Undetermined	25	1	Outdoor	No	Front, side	Straight	2001
MoBo [14]	N.A	Multi-view recognition	25	4	Indoor	Yes	Six views	Straight	2001
SOTON [15]	Large	Multiple purposes	100	6	In-outdoor	Some seq.	0, 45, 90	Straight	2002
	Small	Diff. walk. cond.	12	15	Indoor	No	0, 45, 90	Straight	
CASIA	A [16]	Undetermined	20	12	Outdoor	No	0, 45, 90	Straight	2001
	B [17]	Multi-view recognition and diff. carrying cond.	124	10	Indoor	No	11 views	Straight	2005
	C [18]	Diff. walk. cond.	153	10	Outdoor	No	Side	Straight	2005
USF Human ID [19]	N.A	Covariate conditions	122	Up to 5	Outdoor	No	Side	Elliptical	2005
TUM-IITKGP [20]	N.A	Occlusions	35	1	Indoor	No	Side	Straight	2011
OU-ISIR [21]	A	Speed variation	34	68	Indoor	Yes	Side	Straight	2012
	B	Clothes variation	68	Up to 32	Indoor	Yes	Side	Straight	
	D	Gait fluctuation	370	185	Indoor	Yes	Side	Straight	
AVA	N.A	Multi-view recognition	20	10	Indoor	No	Six views	Curved and straight	2013

Figure : **Summary of existing datasets**. Some of the current databases are divided into other subsets, to deal with specific challenges, as clothes variation, carrying conditions, or multiple view gait recognition.

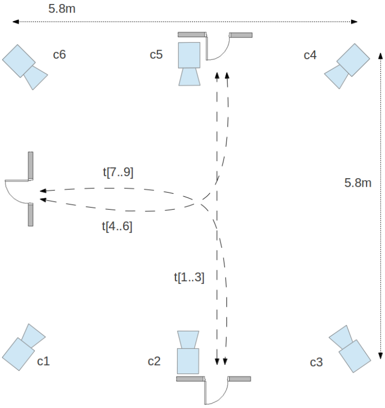
AVAMVG Multi-View Dataset for Gait Recognition

Features:

- 20 subjects.
- 10 sequences by each one.
- Curved and straight trajectories.
  - Three straight trajectories.
  - Six curved trajectories.
  - A figure-eight trajectory.
- Was recorded on May 2013.

Workspace setup for dataset recording

- 6 IEEE 1394 cameras at a height of 2.3m.
- Capture volume dimensions $5m \times 5m \times 2.2m$.
- Coverage of a 360 degrees.
- $4 : 3$ format with 640×480 at 25Hz.



Calibration

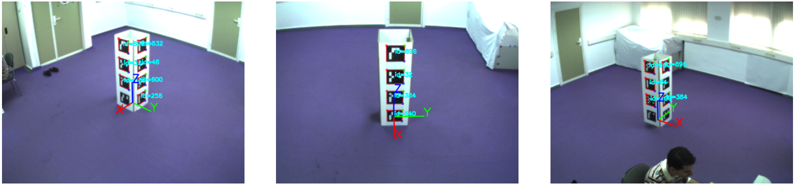


Figure : **3D artifact with Aruco [22] board of markers**, used for getting the pose and orientation of each camera.

Sample sequences

Figure : **Example of our multiview dataset.** People walking in different directions, from multiple points of view.

Preprocessing

We have used Horprasert's algorithm [23] to obtain the silhouettes of actors.

- Is able to detect moving objects in a static background that contains shadows on color images.
- Is able to deal with local and global perturbation such as:
  - Illumination changes,
  - Casted shadows,
  - Lightening.

Applications

Shape from Silhouettes [24]

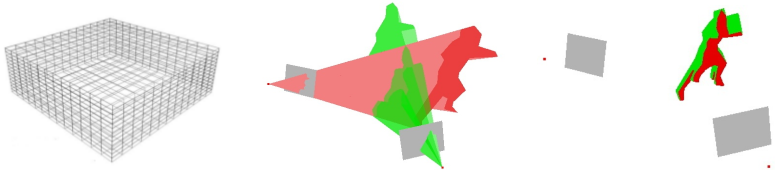


Figure : **Voxelset, silhouette cones, and Visual-Hull**

Shape from Silhouettes

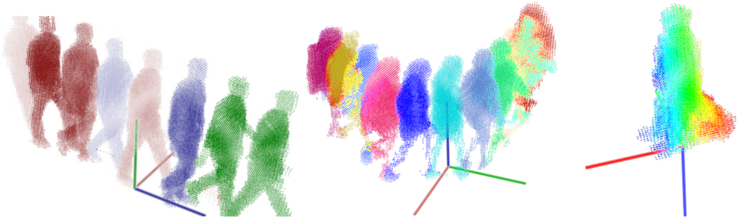


Figure : **3D straight sequence, 3D curve sequence, 3D aligned gait sequence**

Method to test 2D view-dependent gait recognition algorithms on any kind of path

1. Reconstruct all gait sequences by SfS algorithm.
2. Align and centre them respect to a global reference system.
3. Use rendered projections of 3D volumes to test 2D-based gait recognition algorithms.

- By this way, we can test view-dependent gait recognition algorithms on any kind of path, either curved or straight.

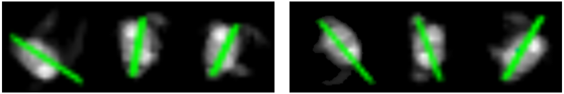


Figure : **Principal axis**

Gait recognition based on rendered side images

- GEI: Gait Energy Image [3], which consists in an average on pixel level of the entire gait sequence.
- GEnI: Gait Entropy Image [5], which encodes in a single image the randomness of pixel values in the silhouette images over a gait cycle.

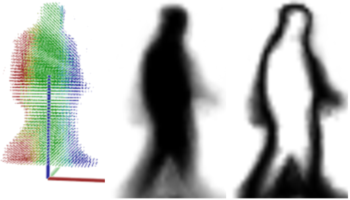


Figure : The reconstructed volumes are aligned along the gait sequence. The two last images show the GEI and GEnI computed over rendered images of the aligned sequence, respectively.

Gait recognition based on frontal-rendered gait images

- Hold-out experiment.
  - Gallery set composed by the 1st, 2nd, 4th, 5th, 7th and 8th sequences.
  - Probe set composed by the 3rd, 6th and 9th sequences.
- Direct template matching based classifier.

Database	GEI	GEnI
AVA Multiview Dataset	94.6	98.1

Figure : Results of the algorithms proposed in [3] and [5] on the AVA Multi-View datasets. We report the recognition rate in %, comparing GEI with GEnI, by direct template matching.

Gait recognition based on frontal-rendered gait images

- Video cameras are placed in hallways to capture longer sequences from the front view of walkers rather than the side view.
- Cover by Rectangles (CR) [6], defined as the union of all the largest rectangles that can fit inside a silhouette. This approach is view-dependent.
- We can use front-rendered projections of the aligned volumes to compute the CR, and test the method proposed in [6] in a view invariant way.
- We use a leave-one-out cross-validation, and SVM with Radial Basis Functions.

Gait recognition based on frontal-rendered gait images

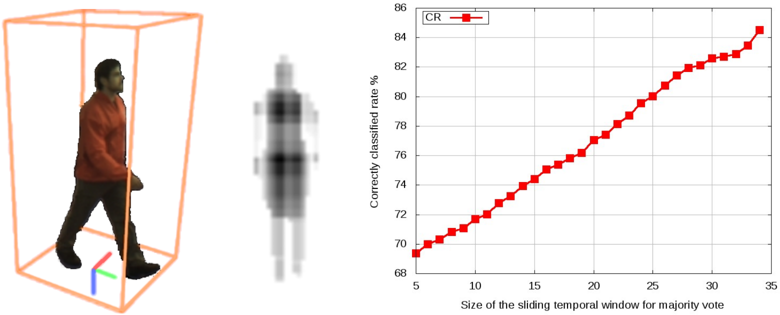


Figure : Cover by Rectangles descriptor. Bounding box of a walking human (left), Cover by Rectangles descriptor (center). Recognition rate obtained with the application of the appearance based algorithm proposed in [6] (right). We show the effect on the classification rate of using a sliding temporal window for voting.

Conclusions

Conclusions

- We have presented a new multi-view database containing gait sequences of 20 actors that depict ten different trajectories each (curved and straight)
- This database has been specifically designed to test multi-view and 3D based gait recognition algorithms.
- Calibration information and binary silhouettes are also provided.

Conclusions

- To validate our database, we have carried out some experiments.
  - 3D reconstruction of volumes of walking people. Then, we aligned and centred them respect to a global reference system.
  - We used rendered projections of these volumes to test some appearance-based algorithms that work with silhouettes.
- The dataset is free only for research purposes.

Questions time

1. Hu, W., Tan, T., Wang, L., Maybank, S.: A survey on visual surveillance of object motion and behaviors. IEEE Transactions on Systems, Man, and Cybernetics 34 (2004) 334-352
2. Lee, C.P., Tan, A.W.C., Tan, S.C.: Gait recognition via optimally interpolated deformable contours. Pattern Recognition Letters 34 (2013) 663-669
3. Han, J., Bhanu, B.: Individual recognition using gait energy image. Pattern Analysis and Machine Intelligence, IEEE Transactions on 28 (2006) 316-322
4. Zeng, W., Wang, C.: Human gait recognition via deterministic learning. Neural Networks 35 (2012) 92-102
5. Bashir, K., Xiang, T., Gong, S.: Gait recognition without subject cooperation. Pattern Recognition Letters 31 (2010) 2052-2060
6. Barnich, O., Van Droogenbroeck, M.: Frontal-view gait recognition by intra- and inter-frame rectangle size distribution. Pattern Recognition Letters 30 (2009) 893-901
7. Iwashita, Y., Ogawara, K., Kurazume, R.: Identification of people walking along curved trajectories. Pattern Recognition Letters (2014)
8. Kusakunniran, W., Wu, Q., Zhang, J., Li, H.: Gait recognition under various viewing angles based on correlated motion regression. IEEE Transactions on Circuits and Systems for Video Technology 22 (2012) 966-980
9. Krzeszowski, T., Kwolek, B., Michalczuk, A., Switonski, A., Josinski, H.: View independent human gait recognition using markerless 3D human motion capture. In Bolc, L., Tadeusiewicz, R., Chmielewski, L.J., Wojciechowski, K., eds.: Computer Vision and Graphics. Number 7594 in Lecture Notes in Computer Science. Springer Berlin Heidelberg (2012) 491-500
10. Lu, J., Tan, Y.P.: Uncorrelated discriminant simplex analysis for view-invariant gait signal computing. Pattern Recognition Letters 31 (2010) 382-393
11. Kusakunniran, W., Wu, Q., Li, H., Zhang, J.: Multiple views gait recognition using view transformation model based on optimized gait energy image. In: 2009 IEEE 12th International Conference on Computer Vision Workshops (ICCV Workshops). (2009) 1058-1064
12. Nixon, M.S., Tan, T.N., Chellappa, R.: Human identification based on gait. Volume 4. Springer (2006)

13. Chalidabhongse, T., Kruger, V., Chellappa, R.: The umd database for human identification at a distance. Technical report, University of Maryland (2001)
14. Gross, R., Shi, J.: The cmu motion of body (mobo) database. Technical Report CMU-RI-TR-01-18, Robotics Institute, Pittsburgh, PA (2001)
15. Shutler, J., Grant, M., Nixon, M.S., Carter, J.N.: On a large sequence-based human gait database. In: Proc RASC, Springer Verlag (2002) 66-72
16. Wang, L., Tan, T., Ning, H., Hu, W.: Silhouette analysis-based gait recognition for human identification. Pattern Analysis and Machine Intelligence, IEEE Transactions on 25 (2003) 1505-1518
17. Yu, S., Tan, D., Tan, T.: A framework for evaluating the effect of view angle, clothing and carrying condition on gait recognition. In: Pattern Recognition, 2006. ICPR 2006. 18th International Conference on. Volume 4. (2006) 441-444
18. Tan, D., Huang, K., Yu, S., Tan, T.: Efficient night gait recognition based on template matching. In: Pattern Recognition, 2006. ICPR 2006. 18th International Conference on. Volume 3. (2006) 1000-1003
19. Sarkar, S., Phillips, P.J., Liu, Z., Vega, I.R., Grother, P., Bowyer, K.W.: The humanid gait challenge problem: Data sets, performance, and analysis. IEEE Transactions on Pattern Analysis and Machine Intelligence 27 (2005) 162-177
20. Hofmann, M., Sural, S., Rigoll, G.: Gait recognition in the presence of occlusion: A new dataset and baseline algorithm. In: Proc. 19th Intern. Conf. on Computer Graphics, Visualization and Computer Vision (WSCG), Plzen, Czech Republic. (2011) 31.01.-03.02.2011.
21. Makihara, Y., Mannami, H., Tsuji, A., Hossain, M., Sugiura, K., Mori, A., Yagi, Y.: The ou-isir gait database comprising the treadmill dataset. IPSJ Trans. on Computer Vision and Applications 4 (2012) 53-62
22. Garrido-Jurado, S., Muñoz-Salinas, R., Madrid-Cuevas, F., Marín-Jiménez, M.: Automatic generation and detection of highly reliable fiducial markers under occlusion. Pattern Recognition 47 (2014) 2280-2292
23. Horprasert, T., Harwood, D., Davis, L.S.: A statistical approach for real-time robust background subtraction and shadow detection. In: Proc. IEEE ICCV. (1999) 1-19
24. Díaz-Más, L., Muñoz-Salinas, R., Madrid-Cuevas, F., Medina-Carnicer, R.: Shape from silhouette using Dempster-Shafer theory. Pattern Recognition 43 (2010) 2119-2131