

Benchmark RGB-D Gait Datasets: A Systematic Review

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Abstract. Human motion analysis has proven to be a great source of information for a wide range of applications. Several approaches for a detailed and accurate motion analysis have been proposed in the literature, as well as an almost proportional number of dedicated datasets. The relatively recent arrival of depth sensors contributed to an increasing interest in this research area and also to the emergence of a new type of motion datasets. This work focuses on a systematic review of publicly available depth-based datasets, encompassing human gait data which is used for person recognition and/or classification purposes. We have conducted this systematic review using the Scopus database. The herein presented survey, which to the best of our knowledge is the first one dedicated to this type of datasets, is intended to inform and aid researchers on the selection of the most suitable datasets to develop, test and compare their algorithms.

Keywords: Gait Datasets · Depth Sensors · Systematic Review.

1 Introduction

The analysis of human motions has been a very active research topic, with a manifold of potential applications. Some of them have already been discussed in reviews like [22,27,20,30]. Particularly, gait, as a specific type of human movement, has been used for a wide range of applications, either as a data source or simply as a way to interact with them. For example, in healthcare, gait data has been used i) for geriatrics assistance (elderly fall prevention [15,19], mobility assessment, and home monitoring [8]); ii) to conduct orthopedic studies [4,28]; and iii) to neurological and chronic disorders assessment [9,12,32]). In the sports domain, gait patterns have been used to assist athletes so they can perform better and safer [26,13]). In smart surveillance systems, gait signatures are used

as a new type of biometric authentication [6,7]). And also, in human-computer interaction, where gait has been used to interact in video-game environments [3] or to animate virtual characters [14].

Several methodologies for a detailed and accurate gait analysis have been proposed, including computer vision-based, inertial sensors-based or other based approaches. Simultaneously, dedicated gait datasets have appeared almost in a proportional way. The relatively recent arrival of depth sensors, like Microsoft Kinect, Intel RealSense or Asus Xtion, capable of tracking humans in real-time without the need to wear special suits or markers, contributed to an increasing interest in this research area leading also to the emergence of a new type of motion datasets. A detailed description of a widely used depth sensor functionality is given in [34]. These depth-based datasets, besides the RGB data, also include raw depth data and in some cases also the 3D coordinates of a set of points that in general, correspond to human body joints.

Regardless the methodologies nor the technologies used, it is very important for the scientific community to use common input data, enabling coherent comparisons of performances and results. For that reason, and focusing specifically on the human gait, we have conducted this systematic review, whose primary goal is to identify all the existing, freely available, depth-based datasets containing human gait information, whose applicability encompasses person recognition and/or classification purposes. Consequently, we are assisting researchers by presenting an updated framework, easy to analyse, useful to identify existing datasets, and suitable to compare them, avoiding, eventually, the creation of new (and sometimes redundant) datasets.

2 Related Work

Several human motion-based datasets reviews can be found in the literature. Some examples are presented in [24,21,17,29]. It is evident the diversity between datasets in terms of their applicability, the acquisition environment conditions, the number of participants, the number of sequences, etc. However, none of those reviews have been presented in a simple form, easy to analyse and to compare datasets. In most of the reviews each dataset is described without any formal organization or structure. Moreover, in the examples previously identified, the revised datasets do not include depth data. Nevertheless, in [10], it is presented a revision of depth-based datasets within eight categories: semantics, object pose estimation, camera tracking, scene reconstruction, object tracking, human actions, human faces and human identification. The latter encompasses four datasets, in which two of them are also present in our study.

3 Systematic Review

The protocol that was used to locate, gather and evaluate the datasets under study is described in this Section. The review took place in the first quarter of 2019 and it was conducted using the Scopus database. The criteria defined for the

selection of articles were as follows: Domain (Gait Analysis); Purpose (Person Recognition and/or Gender Classification); and Dataset (Depth-Based).

Thus, the searched terms used in the Scopus database were: (“gait recognition” OR “gait identification” OR “person recognition” OR “person identification” OR “gender identification” OR “gender recognition”) AND (“depth sensor” OR “RGBD” OR “RGB-D” OR “Kinect” OR “RealSense” OR “Xtion” OR “ToF”) AND (“dataset” OR “database” OR “data set”). These terms were searched in the title, abstract and keywords of the indexed articles in Scopus database and were refined by: Publication types = (ALL) AND Languages = (ENGLISH). This search resulted in 58 articles.

Every resulting article was analysed and both self-constructed and referenced depth-based gait datasets were included in the first set of articles. From among the 58 articles retrieved, we were able to identify 10 freely available datasets, which are described in Section 4. A newly created dataset that was developed by us was also included in the list, thus resulting in a total of 11 datasets reviewed.

4 Framework for Datasets Comparison

For a simple and easy way to analyse and also to compare datasets we decided to present them in form of a table, describing each dataset based on a set of generic features. In this Section the features used to describe each dataset are listed, and then the selected datasets are identified. The proposed framework is presented in Table 1.

4.1 Features Description

The selected features were the following:

- *applicability*: the context for which the dataset was created;
- *subjects*: number of participants, and if possible, their description regarding gender and age;
- *sensor*: number and type of sensors used, and how they were placed on scene;
- *trajectories*: number of different defined trajectories;
- *sequences/subject*: number of sequences performed per subject;
- *covariates*: list of existing variations between sequences (e.g.: walking styles, clothing, etc.);
- *collected data*: list of data that was collected and made available to download;
- *additional data supplied*: list of additional data that was made accessible, like code/applications to manipulate data.

A few other features were initially included in the datasets description structure proposal, however, given that their values were constant between all datasets, we have decided to omit them. Those features included information about the environment where the sessions took place (indoor laboratories), about the frame rate of used sensors (30 fps) and about whether the participants were aware that they were being filmed (all participants were conscious that they were being observed).

Selected Datasets The datasets that were part of our study, whose selection procedure was explained in Section 3, and that consequently are present in our proposed framework are the following: Depth-Based Gait Dataset [?], DGait [5], GRIDDS, [11], Kinect Gait Biometry Dataset [1], RGB-D Person Re-identification Dataset [2], SAIVT-DGD [25], SDUgait [31], SZU RGB-D Gait Dataset [33], TUM-GAID Database [16] and UPCV Gait Dataset [18].

5 Conclusions

The importance of human gait is quite evident, considering its wide range of application domains. Systems that are able to recognize humans and to classify human attributes like gender, age or mood may have a great impact in our society. In the last decade, the dissemination and availability of RGBD sensors (depth + image) prompted the development of new methods and the availability of datasets including depth information beyond the objects represented in the images. This work, to the best of our knowledge, is the first systematic review dedicated to depth-based gait datasets, whose purpose is person recognition and/or classification, covering a total of 11 datasets, of which 72% were acquired between 2011 and 2015, using the first version of the Kinect sensor, whilst 18% were acquired between 2016 and 2018, using the second version of Kinect. Concerning the original context that they were created for, 81% aimed to recognize persons by their gait, while for the remaining 19% their goal was to classify people’s gender. As an outcome of this work, we introduce our perspective on how these datasets can be classified and compared and a logical, structured and feature oriented classification framework is presented.

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Table 1. The proposed framework used to describe each dataset.

identification	year	applicability ¹	#subjects	#sensors	#trajectories ²	#sequences/subject ²	covariates ³	collected data ⁴	extra data
BVH MoCap Database [11]	2010	PR	6 + 4 static + moving sessions	Kinect v1 static or in motion	5 (2S+F+B+MS)	IN	SP	SK	c# code + matlab scripts
Depth-Based Gait Dataset [?]	2013	PR	29	2×kinect v1 fixed at 2.5m high	2(F+B)	4 (2F+2B)	VP, OC, FR, WC (NW+FW)	D, SK, T	-
DGait [5]	2012	GR	55 36♂+19♀	kinect v1 fixed at 2m high	8 (F+B+2S+2D45+2D-45)	11 (2F+B+4S+2D45+2D-45)	VP	C, D, SK	start-end frame/gait cycle
GRIDDS [23]	2018	PR + GR	35 11♂+24♀	kinect v2 fixed at 1.8m high	2S	10 (5S+5S)	-	C, D, SK, T, DS, S	start-end frame/gait cycle + matlab scripts
Kinect Gait Biometry Dataset [1]	2014	PR	164 17-35 years old	2×kinect v1 in motion	1SC	5SC	-	SK	-
RGB-D Person Re-identification Dataset [2]	2012	PR	79	kinect v1 fixed	2(F+B)	4 (3F+1B)	T, C, WC (SW+NW)	C, SK, S, 3DM, EF	matlab scripts
SAIVT-DGD [25]	2011	PR	15	kinect v1 fixed	1F	20F	WC (NW+FW), CC (BC+SC+FC) + S	D, DS, 3DV	matlab scripts + documentation
SDUgait [31]	2015	PR	52 28♂+24♀	2×kinect v2 fixed at 1m high	Kinect1: 5 F+B+S+D45+A Kinect2: 5 F+2S+D-45+A	5	VP	DS, SK	C# code
SZU RGB-D Gait Dataset [33]	2013	PR	99	ASUS Xtion PRO LIVE fixed at 0.8m high	4 (2S+2D30)	8 (4S+4D30)	VP	D, DS	-
TUM-GAID Database [16]	2012	PR	305	kinect v1 fixed at 1.9m high	2S	10 ⁵	CC, S, T ⁶ , C ⁶	C, D, A	-
UPCV Gait Dataset [18]	2013	GR	30 15♂+15♀ 23-55 years old	kinect v1 fixed at 2m high	1S	5S	-	SK	matlab scripts

1 PR: Person Recognition; GR: Gender Recognition.

2 F: Frontal; B: Backwards; S: Side (Left-to-Right and/or Right-to-Left); Dxx: Diagonal at xx Degrees; SC: Semi-Circular; MS: Moving Sensor; A: Arbitrary; IN: Irregular Number.

3 VP: Viewpoint; WC: Walking Conditions (SW: Slow Walk, NW: Normal Walk, FW: Fast Walk); C: Clothing; S: Shoes; FR: Frame Rate; OC: Occlusions; CC: Carrying Conditions (BC: Back Carrying, SC: Side Carrying, FC: Front Carrying); T: Time; SP: Sensor Position.

4 SK: 3D Skeleton Coordinates; T: Time; C: RGB data; D: Depth data; A: Audio; S: Silhouettes; 3DM: 3D Mesh; EF: Estimated Floor; 3DV: 3D Volumes; DS: Depth Silhouettes.

5 10 sequences for 273 subjects and 20 sequences for 32 subjects.

6 Only applied to 32 subjects.

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A Datasets’ URLs

- BVH MoCap Database
<https://github.com/trafbarak/Database-for-gait-recognition-research->
- Depth-Based Gait Dataset
<http://www.facweb.iitkgp.ac.in/~shamik/Gait/Dataset1.html>
- DGait
<http://www.cvc.uab.es/DGaitDB>
- GRIDDS
<http://gridds.ipvcc.pt>

- Kinect Gait Biometry Dataset
<https://bit.ly/2QbDu6U>
- RGB-D Person Re-identification Dataset
<https://bit.ly/2HLXZU7>
- SAIVT-DGD
<https://research.qut.edu.au/saivt/databases/saivt-dgd-database>
- SDUgait
<https://sites.google.com/site/sdugait>
- SZU RGB-D Gait Dataset
<http://yushiqi.cn>
- TUM-GAID Database
<https://www.mmk.ei.tum.de/en/misc/tum-gaid-database>
- UPCV Gait dataset
<http://www.upcv.upatras.gr/personal/kastaniotis/datasets.html>