Kinematic Covariance Based Abnormal Gait Detection

Margarita Khokhlova, Cyrille Migniot, Albert Dipanda

Kinematic Covariance Based Abnormal Gait Detection

Margarita Khokhlova
Le2i, FRE CNRS 2005,
Univ. Bourgogne Franche-Comté, France
margarita.khohklova@u-bourgogne.fr

***Abstract*—This paper proposes an approach for automatic detection of abnormal human gait. We use an improved skeleton data covariance based gait assessment approach. Low-limbs flexion angles are derived using skeletons computed from data acquired by the Kinect sensor. Then for each gait sequence, we calculate a covariance matrix from the obtained angles data. The matrices are used as features for two classification schemes: a normal gait model-based and a k-NN-based. The resulting descriptor is compact, does not require prior temporal segmentation and shows competitive results on available pathological gait datasets.**

***Index Terms*—covariance features, abnormal gait, gait assessment, skeleton data**

I. Introduction

Gait is a manner of walking naturally composed by repetitive parts - gait cycles, and deviations in normal gait pattern can signal different diseases. Traditional measures used to analyze gait parameters in clinical settings are semi-subjective. Medical specialists monitor the quality of the patient's walk and note their observations. Such gait assessment does not guarantee accuracy, repeatability and reproducibility, which adversely affect the diagnosis, supervision and treatment of gait pathologies.

To make gait analysis more qualitative, floor sensor-based (ground force platforms) and marker-based (Vicon, Optotrac) solutions exist. These systems provide accurate and reliable data for gait assessment and are considered as the golden-standard, but pose a significant cost burden for clinics. Moreover, the setup of such systems for each patient is time costly[1]. Machine Vision based gait analysis approaches gained popularity as alternatives to subjective gait analysis and costly marker-based or floor sensor based methods.

Abnormal or pathological gait deviates from normal gait patterns. There could be many different reasons for such a deviation, the most common are different neurological diseases, amputations or age-effects. The effect of these pathologies on the gait can be very different, affecting various gait parameters. The fact that each persons gait is unique makes the gait assessment task even more challenging. One of the first steps in gait analysis is the binary classification, detecting the presence or absence of deviations in patient's gait pattern.

RGBD sensors and the skeleton data they provide, are often used in gait analysis. Skeletons are composed of body joint locations in 3D, similar to the ones obtained by the Mocap system Vicon. Previous studies had shown that Microsoft Kinect sensor can be exploited to examine gait. The validity of skeletons from the Kinect was assessed in [1]. Many researchers proposed gait-related studies based on the Kinect skeleton data.

Some researchers directly estimated different commonly used gait parameters from skeleton sequences [2]–[5]. The analysis system based on skeleton joints was proposed by Gabel et al. [2]. Using regression models, the authors successfully estimated the stride duration and arm angular velocity from the joints data. Rocha et al. [3] evaluated the possibility to use skeleton joints data from the Kinect v.1 sensor for gait assessment. The acquired gait sequences were temporally segmented in cycles. Joints' velocities, accelerations and intra-distances and angles were used as gait features. The mean, median and variance of these values were calculated, resulting in a total of 136 parameters. Then the most characteristic features for Parkinson patients were identified. The proposed research approach is interesting, however, the used test data was quite small - just 3 training and 3 testing subjects. Devanne et al. [4] segmented the skeleton sequences in separate steps and analyzed the motion trajectory for each step. Full body posture described by all joints positions was used for the analysis. The trajectory made by the skeleton joints during each step was obtained by concatenating all the feature vectors with joints of the corresponding time intervals. A custom distance metric was then used to compare different gait sequences and remove the outliers. A statistical model of the normal distribution in a Riemannian shape space was build by analyzing shape variations among all samples belonging to left and right steps. New gait sequences were evaluated using the two learned normal step models. Experimental results demonstrate the effectiveness of the proposed approach in the context of asymmetric gait detection. However, the resulting trajectory feature relies on prior segmentation and can be affected by the arms motions and erroneous estimations of the feet joints.

Other researchers choose to use skeleton joints to model gait without estimating intermediate gait parameters [6]–[8]. Paiement et al. [6] targeted abnormal gait detection by analyzing the skeleton data coming from the Kinect v.1 sensor. A non-linear manifold learning technique was employed to reduce the dimensionality of the noisy skeleton data. Then a

[1]According to the clinical staff of the CHU Dijon, the time to place Vicon markers and calibrate the system takes at least 15 minutes per patient.

statistical model was learned from the normal gait sequences and the detection is performed based on matching the new observations to the model following Markov assumptions. This model was then applied to detect simulated gait anomalies on subjects which are climbing a flight of stairs. The authors performed both event-based and frame-based classifications. The event-based abnormal gait sequences were considerably better detected with 2 false alarms and 2 missed anomalies in a total of 58 sequences. Chaaraoui et al. [7] performed abnormal gait detection with using the Kinect v.2 device based on so called Joint Motion History (JMH) features. All joints from skeletons were used to track motion over a segment of frames in 3D volume. Each skeleton (obtained by a Kinect v.2 sensor) was normalized for location, size of body parts and rotation. The skeletons were accumulated using a sliding window approach. For each window, all skeleton joints were considered as 3D coordinates of a volume, and by the occupancy of this volume voxels, the final JMH was described. The Bag-of-Key-Poses (a variation on the bag-of-words model and represents the most common feature instances present in the learning data) was used to detect abnormal behaviour based on JMH features. The temporal relation was obtained via learning templates of sequences of key poses, which indirectly captures the gait events. The method is original, but it is complicated and doesn't identify the source of the gait pathology. The datasets used are not large enough to generalize the results.

The two works that are most closely related to that proposed were presented by Nguyen et al. [5] and Li et al. [8]. Nguyen et al. [5] proposed a normal gait model built on selected skeleton joints to detect abnormal human gait. The authors decomposed each gait sequence in cycles. Each frame of a skeleton sequence was represented by a feature vector which describes relationships between pairs of lower body bone joints. The selected features were: hip angles, knee angles, ankle angles, and two feet angles. The angles corresponding to flexion angles (one for each joint) were calculated via two planes computed with the three joints of each leg. The feature vectors were then converted into codewords representing different postures using a clustering technique. The normal human gait model was created based on the multiple sequences of codewords corresponding to different gait cycles. A Left-to-Right Markov chain was used to model the gait data. In the detection stage, a gait cycle with a normality likelihood below a pre-selected threshold estimated in the training step, was assumed to be an anomaly. The method shows state-of-the-art results, however, we are not sure that with the current difficulties for the Kinect sensor to detect low-limbs joints and, particularly, ankles and feet joints, it is sufficiently reliable to base a feature vector on them. Many researchers report the inaccuracy of feet position estimations and corresponding angles [9] coming from Kinect v.2. Available gait datasets [10], [11] also suffer from this issue. Li et al. [8] proposed a method to classify normal and abnormal gait based on skeleton data. The researchers focused on the group of motion anomalies characteristic for Parkinson and Hemiplegia (tremor, partial paralysis, gestural rigidity and postural instability). At the heart of their descriptor laid 2 covariance matrices. One for 24 mutual joint positions and another one for the motion rate of the same 24 joints. A K-NN based classifier and a custom covariance distance metric were used. Sequences were temporally segmented using the sliding window approach. A distinctive classifier was learned for the time windows to yield an importance weight assignment. The method gives good results with an average accuracy 80 %. However, the custom dataset used is not publicly available. Although the full list of body joints is commonly used to compose a covariance matrix, we believe that in many cases upper joint motion can be a source of ambiguity for the gait assessment task. In our work we propose to use compact covariance features based on low-limbs flexion angle data only. We choose to use angles over joints directly because they are more robust and vary less between individuals: hip and knee skeleton joints. The scheme of the proposed method is shown in Figure 1.

The contributions of this work may be summarized as follows. We propose to use a limited set of joints to calculate kinematic gait parameters. We combine the low-limbs flexion evaluation and the representativeness and compactness of covariance matrices to propose a novel gait assessment feature, which describes the symmetry of a gait. We create a kinematic based normal gait model. We demonstrate that it is not necessary to use temporal information for the gait symmetry assessment task. The proposed method is effective, simple and can be used for real time gait analysis. The remainder of this article is organized as follows. Section II describes the proposed covariance gait features. The dataset used in our work are listed in section III. Experiments to validate our approach are described in Section IV. Finally, Section V concludes the paper, where we highlight the outcomes of this research and propose our outlook for the future work.

II. Kinematic Covariance Based Gait Feature

We propose to use angle-based covariance matrices as the features for binary gait assessment. Kinematic parameters are reported to be widely used for gait analysis [12]. In application to the angle data, covariance captures the information about the gait symmetry: the diagonal of the matrix captures the angle amplitude, and other entries show how the hip and knee kinematics are related between the left and right foot.

A. Flexion angles

We selected to use hip and knee flexion angles to describe the patient's gait. The Cosine Rule was used for the triangles formed by triplets of skeleton joints: hip-knee-ankle and mid spine-hip-knee. The result are the kinematic parameters of a gait sequence.

B. Covariance matrices

Covariance matrices are discriminative features for action recognition as shown by [13]. Lately they were also successfully exploited for gait assessment by [8]. One of the advantages of the covariance matrices is the fact that they

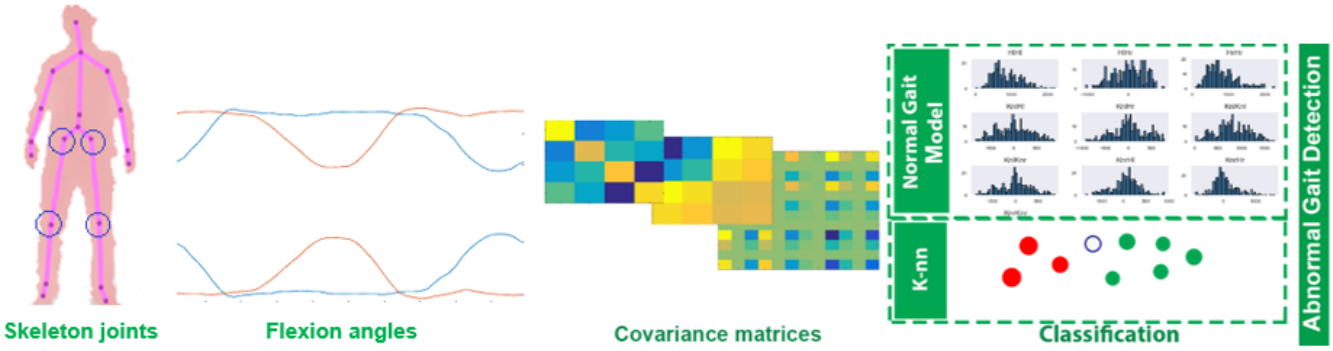

Fig. 1. The proposed binary gait assessment pipeline. We select the most stable among low-limbs skeleton joints to calculate flexion angles. Then the angles-based covariance features are used for gait assessment in different scenarii.

provide a feature representation which is not time dependent. It allows to obtain a constant sized gait feature, independent of the speed variations in a subjects' walking manner.

Flexion angles are known and widely used features for gait analysis in clinics and hospitals. We combine the compactness and representativeness of the covariance matrices with the highly relevant flexion angles features to propose a new gait assessment method. A covariance matrix summarizes the relations between the hip and knee flexion angles for a gait sequence.

We use traditional variance-covariance matrices (Equation 1) and covariance matrices as described in [13] (Equation 2).

$$cov = \frac{1}{(T-1)} \sum_{t=1}^{T} (P_a - \mu)(P_a - \mu)^T \tag{1}$$

$$cov = \frac{1}{(T-1)} P_a (\frac{1}{T} I_T - 1_T) P_a^T \tag{2}$$

where μ is the mean of P_a, T is the number of frames, I_T is the identity matrix, $1T$ is the $T \times T$ unity matrix and P_a contains Knee and Hip angles coordinates for the time frame.

$$P_a = \begin{bmatrix} KL_1 & KR_1 & HL_1 & HR_1 \\ \vdots & \vdots & \vdots & \vdots \\ KL_T & KR_T & HL_T & HR_T \end{bmatrix} \tag{3}$$

KL_i, KR_i are knee flexion angles and HL_i and HR_i are hip flexion angles for each frame i. Note that the obtained matrices should not be further normalized since the flexion angles are already within the same scale.

In this work we mostly use hip and knee flexion angles to compute a 4×4 covariance matrix using the formula 1.

III. Skeleton Gait Data

The absence of data is a big issue in gait clinical studies. Normal gait is more prevalent, since we can use data from the gait recognition domain. However, there are very few examples of the abnormal gait publicly available. We use the following datasets: UPCV Gait K2 [11] contains data from 30 persons performing normal walking 10 times. DAI dataset [7] contains 7 actors performing normal and abnormal gait. The SPHERE-Walking2015 dataset [6] contains normal and abnormal gait sequences by an RGBD sensor. There are 21 normal sequence and 20 sequences of patients with Parkinson and Stroke diseases. The walking gait dataset [10] was recently proposed by Nguyen et al. It has been established to enable comparative studies on gait analysis, especially the problems of gait index estimation and abnormal gait detection. The dataset includes 9 normal gaits and 8 simulated abnormal (asymmetric) ones performed by 9 individuals on a treadmill. Abnormal gaits were simulated by attaching a weight to a foot and padding a sole. In one of the experiments we also used 22 normal sequences acquired by a Kinect v.2 camera in our lab with a setup similar to the one in [11].

The [7] and [10] datasets perfectly suit the proposed algorithm specifics, since actors imitate different anomalies affecting the similarity of the gait. However, the number of sequences is small. We enlarged the normal dataset with data coming from a gait recognition dataset, assuming that the people do not have a pathological gait, and by adding the Sphere dataset and the data acquired in our lab. We provide the results obtained on the [7] and [10] datasets separately and also perform some experiments on a mixed dataset as it was previously done by [5]. Information about the employed datasets is grouped in Table I.

We prepare the data from all datasets in the following way. We apply a low-pass filter to the joints data. A standard normalization is then done by subtracting the center of the spine joint from other joints for each frame as in [13].

IV. Experiments

We performed a serie of experiments to validate the proposed approach. The experiment design is conditioned by the nature of the datasets. Cross-dataset evaluations are made in order to show that our method can be generalized towards different data. Due to the different purposes of the datasets used, we had to elaborate different testing protocols for the cases when a) there are pathological data in training and testing

TABLE I
DATASETS USED IN THIS WORK

Dataset	Normal seq	Abnormal seq	Normal cycles	Abnormal cycles	Data	Comment
DAI [7]	28	28	28	55	25 joints	Normal/abnormal sequences performed by actors
UPCV Gait K2 [11]	300	na	1555	na	25 joints and 20 orientations	Gait recognition, 30 subjects, 10 trials
SPHERE-Walking2015 [6]	21	20	65	162	15 joints	Normal, PD and stroke patients
Walking gait dataset [10]	9	72	17047	1405	25 joints, point clouds	A treadmill is used, padding sole and attaching weight to simulate the pathological gait
Ours	22	n/a	64	na	25 joints and orientations	Normal subjects, clinical conditions

part of the dataset; b) there are pathological data in the testing part only. We use statistical normal gait modeling when the training part of the dataset contains only one type of data (i.e normal gait samples), and a k-NN classifier otherwise.

In all reported tests we used a covariance matrice for 2 low-limbs angles coming from the left and right feet. We compare our method with state-of-the-art methods [4], [5], [7] on the available datasets and perform a generalization of the results on custom dataset similar to [8]. We used the whole sequences in case when each gait example contains small number of frames (the datasets [6], [7], [11] and window-based segmentation of the gait sequences in case when continuous shooting is provided (the dataset [10]).

A. The normal gait model

We represent normal poses by their probability density function (pdf) $f(cov)$. We obtain this pdf from training data. Then we evaluate each train sample by the model to obtain a negative log likelihood ($nlogL$) as the measure of similarity. The threshold for the normal sequence is estimated as a $\mu \pm 3\sigma$, where μ is the mean and σ is the standard deviation of the normal $nlogL$ data. For the test set, all the sequences with the log-likelihood according to the normal model higher than this threshold were considered as abnormal. Results for the test schemes proposed by [7] are summarized in Table II. The DAI dataset [7] design requires one to use only the normal examples for training and then detect the outliers (i.e pathological gait sequences) during the test. We developed a normal gait model based on the training data.The first scenario uses all the actors while the second leaves 3 unseen actors for the test.

Our results are less accurate than the results published by [4], [7], however, we believe our method to be more general and simple, and working well when there is more data available.

B. K-NN classification

For the second group of experiments, we used Walking Gait dataset [10]. In this dataset both training and testing parts contain normal and abnormal gait samples. We used the division scheme proposed by the authors when 5 subjects are used for training and the other 4 for testing. Each sequence has 1200 frames, so to increase the number of samples, we use the window approach to segment the data. We opted to use non-overlapping windows, in order to have independent data for the experiment. Training and testing data are segmented with window size of T frames. Earlier we estimated that the cycle length in this dataset is between 15 and 25 frames. The optimal window size was selected experimentally. T is equal to 90 frames.

TABLE II
NORMAL GAIT MODEL RESULTS, DAI [7]

method	scenario 1	scenario 2
[7]	0.98	0.85
[4]	0.98	**0.96**
ours	0.90	0.86

Since our goal is to detect abnormal gait samples and the dataset contains more abnormal (positive) than normal (negative) examples, we construct the abnormal part of our test in the following way. The total number of positive examples is equal to the number of the negative examples. The positive examples part is equally divided to contain the same number of sequences from each pathology. The pathological sequences are assigned randomly. The procedure of the test construction is performed 20 times in order to cover the dataset. Each time we calculate the precision, recall and F-measure based on the number of K neighbors in the k-NN algorithm. The correlation distance is used and the concensus model is employed as the parameters of the k-NN algorithm. We also tested the eigenvalues based distance between matrices as [8], but it was outperformed by the Euclidean and Correlation distance. We then take the mean value of all the trials as the final F-measure value, and report corresponding precision, recall and accuracy.

We also compared the angle-based covariance matrices with standard joint-based matrices as in [8] calculated by Equation 1 from 24 joints, and the covariance features proposed in [13] calculated by Equation 2 from 24 joints. In first case the final

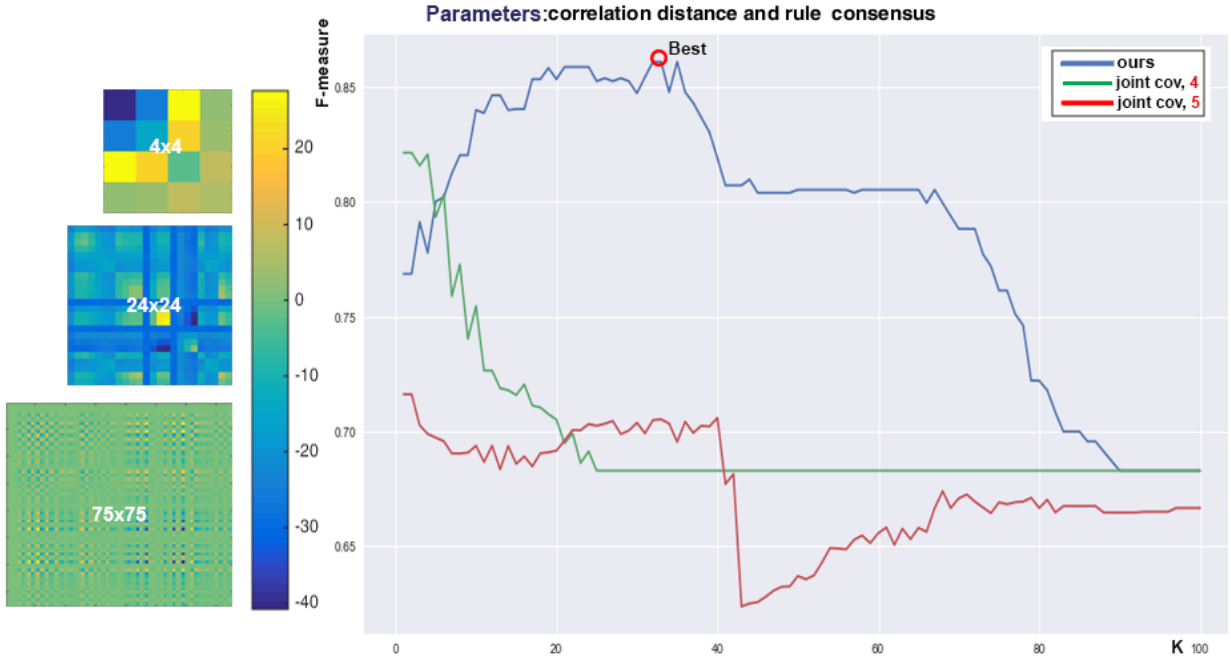

Fig. 2. Curves for results summarized in Table III and corresponding covariance matrices.

feature is 24×24 and in the second 75×75. We use the same window size as for our angle-based data equal to 90 frames. Optimal number of K = 2 and K=1 correspondingly. Results are presented in Table III. Our simple feature outperforms the algorithm [5] in terms of recall and accuracy (however, note that the authors report the score for an unbalanced dataset partitioning; we provide here an average F-measure, precision, accuracy and recall reported by the authors) and joint-based matrices. Resulting F-measure curves and covariance matrices are shown in Figure 2.

TABLE III
RESULTS ON [10] WITH K-NN

method	F-measure	precision	recall	accuracy
[5]	**0.87**	**0.96**	0.80	0.83
ours	0.86	0.76	**0.99**	**0.84**
joint cov by Eq 1	0.82	0.95	0.73	0.79
joint cov by Eq 2	0.69	0.55	0.90	0.13

C. Cross-datasets analysis

In order to show that the proposed approach can be also applied to entire normal/abnormal sequences and is not limited to a given dataset, we arranged a simple test. The data from [11] was used to train to create a normal gait model. The distribution of each covariance feature follows a multivariate normal model. All the sequences from the DAI gait dataset were used as test data. In this test we do not pre-segment the data into cycles and use all the sequences. We evaluated

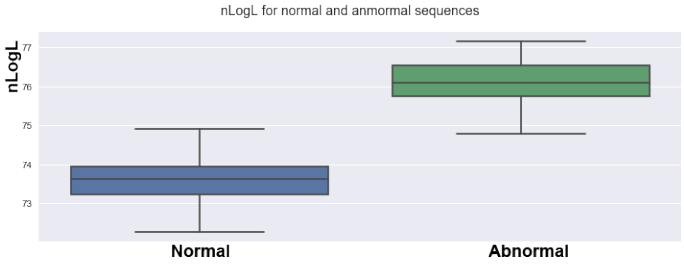

Fig. 3. The $nlogL$ for normal/abnormal gait sequences from [7] by the $pdf(cov)$ build on the [11] dataset. The resulting distribution and confidence intervals show that the data are easily separable.

the Normal negative loglikelihood for each test sequence and then compared the distribution of the values. The distribution is shown on Figure 3. It can be seen that the normal sequences can be easily separated from the abnormal ones based on the likelihood value. The test shows the generality and descriptiveness of the proposed gait correlation feature. It also confirms that accurate cycles segmentation is not necessary for this gait assessment task.

We also evaluated the possibility to combine the DAI and Sphere datasets together with our K-NN classifier. The data were pre-segmented in gait cycles by the method proposed in [5]. The segmentation was necessarily due to the fact that the Sphere joints are extremely noisy, and our correlation matrix design is affected by the noise. We added 64 normal

TABLE IV
GENERALIZATION ON DATA [7] [6]

F-measure	precision	recall
0.76	0.60	0.96

cycles acquired in our lab to the test data. The resulting set contains 162 abnormal and 104 normal cycles. The Sphere dataset contains the gaits of patients with Parkinson Disease and Stroke. We aim to see if the proposed method can be used to detect this type of gait pathology and compare it with the algorithm [8], where researchers use a covariance based approach to detect Hemiplegia and Parkinson gaits on a proprietary dataset. We used the DAI dataset [7] as a training dataset for our K-NN classifier and Sphere dataset for the test. The test set contains equal number of normal and abnormal cycles as in the previous experiment, and same parameters for the K-NN are used. The results of this test are summarized in Table IV. The best parameters were obtained with K=12. We have lower accuracy then the one reported by [8], where the authors obtained around 80% of correct classifications on the average. This experiment shows the limits of our method, which is more suited to detect gait asymmetry and not able to detect 'static' abnormalities characterizing Parkinson or Stroke patients.

V. CONCLUSION

In this paper we propose an enhanced gait representation for abnormal gait detection. Our approach tackles the problem of low-limb kinematic symmetry description. Experimental results demonstrate the effectiveness of the proposed covariance based approach in the context of abnormal gait detection. The low-limb gait feature is compact and representative for gait symmetry assessment. It also has a physical sense, since it is constructed in way to capture the covariance of the flexion angles during locomotive motion. We do not explicitly use temporal information and achieve close to the state-of-the-art performance on the datasets available.

It has been shown that the Kinect v.2 sensor has potential for abnormal gait detection. However, the number of publicly available datasets is very small which makes it difficult to generalize the results and compare the existing algorithms. Therefore, as a future work, we intend to propose a publicly available dataset of normal and abnormal gait samples. The possibility to make a continuous measure of movement quality and not a binary classification is aimed. We also see potential to work towards the recognition of a particular gait pathology automatically. For this task the proposed covariance feature will be used as a part of a multipurpose gait assessment descriptor.

REFERENCES

[1] S. Springer and G. Yogev Seligmann, "Validity of the kinect for gait assessment: A focused review," *Sensors*, vol. 16, no. 2, p. 194, 2016.

[2] M. Gabel, R. Gilad-Bachrach, E. Renshaw, and A. Schuster, "Full body gait analysis with kinect," in *Engineering in Medicine and Biology Society (EMBC), Annual International Conference of the IEEE*. IEEE, 2012, pp. 1964–1967.

[3] A. P. Rocha, H. Choupina, J. M. Fernandes, M. J. Rosas, R. Vaz, and J. P. S. Cunha, "Parkinson's disease assessment based on gait analysis using an innovative rgb-d camera system," in *36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, 2014, pp. 3126–3129.

[4] M. Devanne, H. Wannous, M. Daoudi, S. Berretti, A. Del Bimbo, and P. Pala, "Learning shape variations of motion trajectories for gait analysis," in *23rd International Conference on Pattern Recognition (ICPR)*. IEEE, 2016, pp. 895–900.

[5] T.-N. Nguyen, H.-H. Huynh, and J. Meunier, "Skeleton-based abnormal gait detection," *Sensors*, vol. 16, no. 11, p. 1792, 2016.

[6] A. Paiement, L. Tao, S. Hannuna, M. Camplani, D. Damen, and M. Mirmehdi, "Online quality assessment of human movement from skeleton data," in *British Machine Vision Conference*, 2014, pp. 153–166.

[7] A. A. Chaaraoui, J. R. Padilla-López, and F. Flórez-Revuelta, "Abnormal gait detection with rgb-d devices using joint motion history features," in *11th IEEE International Conference and Workshops on Automatic Face and Gesture Recognition (FG)*, vol. 7. IEEE, 2015, pp. 1–6.

[8] Q. Li, Y. Wang, A. Sharf, Y. Cao, C. Tu, B. Chen, and S. Yu, "Classification of gait anomalies from kinect," *The Visual Computer*, vol. 34, no. 2, pp. 229–241, 2018.

[9] M. Eltoukhy, J. Oh, C. Kuenze, and J. Signorile, "Improved kinect-based spatiotemporal and kinematic treadmill gait assessment," *Gait & posture*, vol. 51, pp. 77–83, 2017.

[10] T.-N. Nguyen and J. Meunier, "Walking gait dataset: point clouds, skeletons and silhouettes," DIRO, University of Montreal, Tech. Rep. 1379, April 2018.

[11] D. Kastaniotis, I. Theodorakopoulos, and S. Fotopoulos, "Pose-based gait recognition with local gradient descriptors and hierarchically aggregated residuals," *Journal of Electronic Imaging*, vol. 25, no. 6, pp. 063 019–063 019, 2016.

[12] M. Roberts, D. Mongeon, and F. Prince, "Biomechanical parameters for gait analysis: a systematic review of healthy human gait," *Physical Therapy and Rehabilitation*, vol. 4, no. 1, p. 6, 2017.

[13] J. Cavazza, P. Morerio, and V. Murino, "When kernel methods meet feature learning: Log-covariance network for action recognition from skeletal data," in *Proceedings of the 2017 IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), Honolulu, HI, USA*, 2017, pp. 21–26.