Unsupervised GEI-Based Gait Disorders Detection From Different Views

Amr Elkholy[1], Yasushi Makihara[2], Walid Gomaa[1,3], Md Atiqur Rahman Ahad[2], Yasushi Yagi [2]

***Abstract*— Early detection of gait disorders may provide a safer living for elderly people. In this paper, we propose an automatic method for detecting gait disorders using RGB or RGBD camera (e.g., MS Kinect, Asus Xtion PRO). We use Gait Energy Image (GEI) as our main feature that can be computed from different views. Our method depends on computing GEI, learning the representative features from the GEI using convolutional autoencoder, and using anomaly detection method for detecting abnormal gait. We applied the proposed method on two different public datasets that include normal and abnormal gait from different views. Experimental results show that our method achieves high accuracy in detecting different gait disorders from different views, which makes it general to be applied to home environment and adds a step towards convenient in-home automatic health care services.**

I. INTRODUCTION

Gait is one of the common daily activities that can be unobtrusively observed. Normal gait is an indicator for a healthy person; on the contrary, abnormal gait is an indicator for a number of neuromusculoskeletal disorders, e.g., Parkinson's disease (PD), stroke. The phenomenon of living alone is increasing among the elderly worldwide [1], [2], [3], which makes them vulnerable to falling risk or suffering an injury. Hence, early detection of abnormal gait can provide a safer and independent living by preventing more serious developments.

The currently used approaches for gait assessment are taking place at medical facilities, where a specialist observes the subject gait, measures the gait parameters and manually scores gait disorders using a number of rating scales, e.g., Gait Assessment Rating Scale (GARS) [4], Rating Scale for Gait Evaluation (RSGE) [5]. Hence, the patient is required to visit the clinic periodically, which represents a burden on him/her. Several sensor-based methods have been proposed for assessing human gait [6], [7], [8]. However, these methods represent an obtrusive way for gait assessment as some wearable sensors may cause inconvenience, and need frequent battery charging.

On the contrary, vision-based approaches offer unobtrusive techniques for detecting gait disorders. Different vision-based methods have been proposed for detecting gait disorders. The proposed methods can be broadly classified into two classes, i.e., model-based methods, and model-free methods.

Model-based methods depend on using articulated body pose model such as the 3D skeleton data provided by the SDK of MS Kinect. Li et al. [9] proposed a method that computes two covariance matrices, one for the 3D skeletal joints positions and the other for joints speed, then uses a classifier to classify gait into Parkinsonian, Hemiplegia and normal. Meng et al. [10] proposed a method that computes inter-joints distances, then uses the random forest classification method to classify gait into normal or abnormal.

Both methods, similar to other model-based methods, are computationally intensive and require high-resolution images. Moreover, depth sensors suffer from the limited range for detecting the skeletal data of the moving subject (e.g., 0.5–4.5 m for MS Kinect V2) and the optimal tracking of joints is accomplished when capturing the subject from a frontal-view; otherwise, the skeleton data may be noisy.

On the contrary, model-free methods act directly on the video sequence by extracting the subject's binary silhouette from a color/depth video sequence. Zhou et al. [11] proposed a method that detects abnormal gait by computing three features, i.e., gait cycle duration, phase fluctuation, and patch-GEI. The best accuracy is achieved by using a specific patch-GEI that depends on the type of abnormal gait (i.e., visually impaired gait, and leg-impaired gait). In [12], Ortells et al. proposed a method for detecting gait impairment by computing a number of side-view gait features (e.g., stance phase, swing phase, step length, and GEI intensity). All these features are calculated from the lower body part silhouette, while this method cannot be applied to detect upper body part abnormalities and requires high-quality silhouettes. Both methods depend on extracting features from side-view gait and cannot be applied to gaits captured from other views.

In contrast to the above methods, our method can be computed from different views, which makes it more applicable to real life situations where the subject can move freely in different directions.

In this paper, we propose a robust method for detecting gait disorders from different views (e.g., frontal-view, and side-view). Our method depends on computing the GEI of the moving subject using color/depth image sequence. After that, we learn the representative features from GEI using convolutional autoencoder (CAE). Finally, we model the normal representative features and detect the abnormal gait using an anomaly detection method. We applied and compared different anomaly detection methods, i.e., One-Class Support Vector Machine (OC-SVM), and Isolation

[1]Cyber-physical Systems Lab, Egypt-Japan University of Science and Technology (E-JUST), Alexandria, Egypt, {amr.elkholy; walid.gomaa}@ejust.edu.eg

[2]The Institute of Scientific and Industrial Research, Osaka University, Osaka 567-0046, Japan, {makihara; ahad; yagi}@am.sanken.osaka-u.ac.jp

[3]Faculty of Engineering, Alexandria University, Alexandria, Egypt

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Forest [13]. We tested the proposed method on two different public gait datasets containing normal and abnormal gait from different views (i.e., frontal-view, and side-view).

Besides this introduction, our proposed method is illustrated in Section II. In Section III, the experimental results are presented. Finally, the paper's conclusion is drawn, and future work is outlined in Section IV.

II. Proposed Method

In our proposed method, we generate the GEI of the moving subject from an input gait sequence as our feature, and then, we learn the representative features from the GEI. Finally, we model the normal learned representative features and detect abnormal gait using an anomaly detection method as illustrated in Fig. 1.

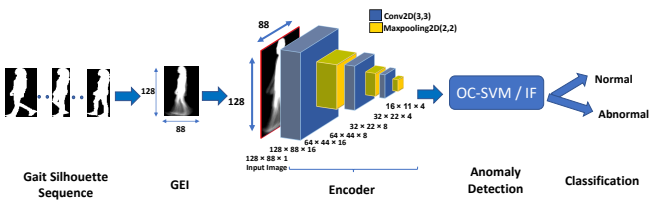


Fig. 1: Proposed Method.

A. Gait Energy Image (GEI) Generation

GEI [14] is an appearance-based gait feature that can preserve the static and dynamic information of a gait sequence. GEI is well known for its high performance in person authentication and robustness against low-quality silhouette extraction. It is computed by averaging the normalized subject silhouette over a gait cycle. To compute the GEI, we start by extracting the subject binary silhouette from an original color/depth image sequence using background subtraction based on Gaussian mixture model (GMM) per pixel and refined by selecting the largest blob. After that, we align and normalize the silhouettes using the method proposed in [15]. After silhouette alignment and normalization, we extract one gait cycle using the normalized auto-correlation of silhouette images in the temporal axis. Here the gait cycle N_{cycle} is estimated as the point where the normalized auto-correlation of silhouette images is maximum as illustrated by the following equations:

$$C(N) = \frac{\sum_{x,y}\sum_{n=0}^{K} S(x,y,n)S(x,y,n+N)}{\sqrt{\sum_{x,y}\sum_{n=0}^{K} S(x,y,n)^2}\sqrt{\sum_{x,y}\sum_{n=0}^{K} S(x,y,n+N)^2}}, \quad (1)$$

$$N_{cycle} = arg\ max\ C(N), N \in [20, 60], \quad (2)$$

where $C(N)$ is the autocorrelation for N frame shift, N value was selected empirically to cover all abnormal gait cycles exist in the tested datasets, $K = N_{Total} - N - 1$, N_{Total} is the total number of frames in the sequence, and $S(x, y, n)$ is the pixel value at position (x, y) of silhouette frame n.

Finally, we compute the GEI as the average of the normalized and aligned silhouettes over a gait cycle using the following equation:

$$G(x,y) = \frac{1}{N_{cycle}} \sum_{i=1}^{N_{cycle}} S_i(x,y), \quad (3)$$

where N_{cycle} is the number of frames in a gait cycle, S_i is the silhouette at frame i, and x, y are pixel coordinates.

B. Extracting Representative Features from GEI

The computed GEI is of a height of 128 pixels, and a width of 88 pixels, which represents a high dimensional feature vector, i.e., 11264 feature vector. Hence, we first learn the representative features from the computed GEI, then we model the normal representative features and detect abnormal gait using an anomaly detection method.

To extract the representative features from GEI, we use convolutional autoencoder (CAE) as a deep learning architecture that can learn the high representative features from images. The architecture of the convolutional autoencoder consists of encoder and decoder. The encoding part consists of several stacked 2D convolutional layers, each followed by a max pooling layer. In contrast, the decoder is used to reconstruct the original input GEI by using the compressed representation, i.e., code. The decoder consists of 2D deconvolutional layers, each followed by up-sampling layer, where ReLU activation is used, and the loss is the reconstruction error. The architecture of the proposed autoencoder, including the number of filters used in each layer and the dimension of each layer, is illustrated in Fig. 2. We used mean squared error as a cost function for training the autoencoder.

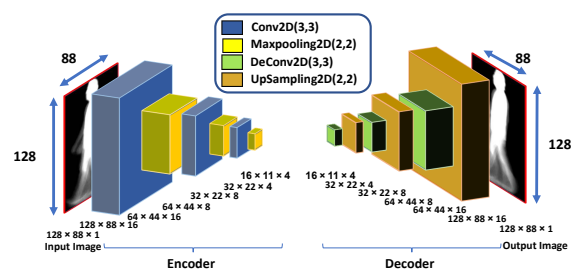


Fig. 2: Proposed Convolutional Autoencoder (CAE) Architecture.

We conducted unsupervised training of the convolutional autoencoder using "OU-ISIR Gait Database, Multi-View Large Population Dataset" [16] as a large different-views normal gait dataset. Then, we used the encoder of the pre-trained auto-encoder as a high representative feature extractor to reduce the high-dimensional GEI feature vector before the anomaly detection step. The encoder part is used to reduce the GEI feature vector from 11264 to 704, i.e., $R^{11264} \rightarrow R^{704}$.

C. Anomaly Detection

To detect abnormal gait, we model the normal learned feature representation. Thereafter, abnormal gait can be detected as an anomaly using an anomaly detection technique. In our experiments, we tested two different anomaly detection models, i.e., OC-SVM, and Isolation Forest (IF).

1) One Class-Support Vector Machine (OC-SVM): The first model we used is OC-SVM. We model the normal learned feature representation using OC-SVM with radial basis function (RBF) kernel. The idea of OC-SVM is to find the hyperplane that maximizes the gap which separates the data from the origin by solving the following equation:

$$\begin{aligned} \text{minimize} \quad & \frac{1}{2}||W||^2 + \frac{1}{vN}\sum_{i=1}^{N}\xi_i + b, \\ \text{subject to} \quad & \vec{w}.\vec{x} + b \geq -\xi_i, \\ & \xi_i \geq 0 \\ & \text{for } i = 1, \ldots, N, \end{aligned} \tag{4}$$

where w is the perpendicular to the hyperplane, v is a constant that controls the number of allowed false positives, b is the intercept, and ξ_i is a slack variable. v was set empirically to 0.1, which means that 90% of the training samples are within the boundary.

2) Isolation Forest (IF): Isolation Forest (IF) [17] is a model-based anomaly detection method. IF depends on isolating anomalies, instead of profiling normal points. IF consists of an ensemble of isolation trees where each tree is a binary tree and built by recursively partitioning a given training set. Each partition is generated by selecting a random attribute and then selecting a random split value to split the data until either: the tree reaches a height limit, or instances are isolated. Finally, anomalies are those points which have short average path lengths on the isolation tree (i.e., closer to the root of the tree).

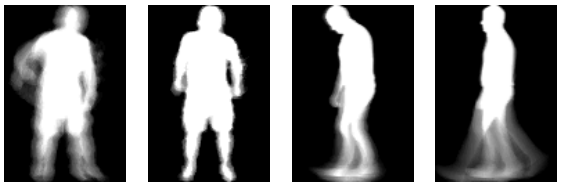
III. Evaluation and Results

A. Datasets

To evaluate the proficiency of the proposed abnormal gait detection method, we tested our method on two different public datasets. The datasets contain normal and abnormal gait sequences with different neuromusculoskeletal disorders from frontal-view and side-view. Abnormal samples include imitation of different neuromusculoskeletal disorders (e.g., Parkinsons disease, stroke). Table I illustrates the counts of normal and abnormal sequences exist in the two datasets.

ID	Dataset	View	Sequences Count
1	SPHERE-Walking [18]	Frontal	18 / 17 [1]
2	INIT-Lower Abnormality [12]	Side	20 / 60

TABLE I: Employed Datasets for Normal/Abnormal Sequences.



(a) (b) (c) (d)

Fig. 3: Some examples of abnormal GEIs (a) Stroke, (b) Parkinson, (c) Full body affected, (d) Half right step.

1) SPHERE-Walking Dataset [18]: We first tested our method on a public frontal-view gait dataset, released by the University of Bristol. The dataset was collected from normal people imitating several shapes of gait abnormalities, i.e., Parkinson, stroke, as illustrated in Fig. 3 (a) and (b), respectively. This dataset was collected using MS Kinect V2 depth sensor with a frame rate of 30 fps. The dataset consists of 3D skeleton data and depth images, where the depth images are used in our experiments.

2) INIT Gait Dataset [12]: INIT Gait dataset consists of side-view gait sequences of binary silhouettes. It was collected from normal people simulating several abnormal gait styles, e.g., left/right leg half step, full body abnormal gait. For more details about the dataset, the reader is referred to read the original paper [12]. Fig. 3 (c) and (d) represent full body abnormal gait and right leg half step, respectively.

B. Evaluation and Discussion

The convolutional autoencoder was trained using a large multi-view normal gait dataset, i.e., OU-ISIR Gait Database. We trained two autoencoders, one for frontal gait using frontal-view GEI, and the other for side-view gait using side-view GEI. Thereafter, to train the anomaly detection methods, we exploited 100 disjoint samples from the OU-ISIR Gait Database. Finally, to evaluate our proposed method we tested the pre-trained models on the two datasets. We used the Area Under the Curve (AUC) of the Receiver Operating Characteristics (ROC) curve of sequence classification as our evaluation metric.

For the SPHERE-Walking dataset [18], the proposed method achieved AUC of 1 using both models, where the method was able to classify all the SPHERE dataset sequences correctly. In SPHERE dataset, healthy people imitated the abnormal gait sequences of this dataset. Hence, the abnormality in this dataset was exaggerated and can be detected clearly. The method proposed by [18] tested different models and parameters, and the best AUC achieved is 1. Table II illustrates both results and the best model/parameters used by [18]. Despite achieving the same AUC as the SPHERE method [18], the proposed method is general enough to be applied on gait sequences captured from different views, while the SPHERE method is applied only to the 3D Skeletal data from frontal-view.

[1]Samples count that we were able to extract a complete gait cycle, where the original count is 23/17.

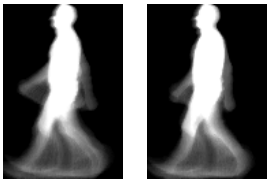
Our Results		Results of [18]	
AUC	**Model**	**Best AUC**	**Model**
1	CAE + OC-SVM	**1**	λ_c (JP/2D)
1	CAE + IF		

TABLE II: Comparison with SPHERE Method [18] (AUC).

Method	OC-SVM	IF
INIT Method [12]	**0.99**	**0.99**
Proposed Method	0.91	0.94

TABLE III: Comparison with INIT Method [12] (AUC).

For the INIT dataset [12], we implemented the INIT method to compare with our results. Table III describes the results of both methods using OC-SVM and IF. We can observe that the INIT method achieves better results than ours. The reason behind that, the INIT method depends on computing the distance between feet over gait sequence by computing the width of the 33% lower body part of the silhouette. Then, divide the gait cycles into two groups (i.e., A, and B), where A is the odd half cycles, and B is the even half cycles. After that, the method measures the asymmetry between both groups, which gives this method the ability for better detection of the abnormal gait due to asymmetric motion between both legs. This gait pattern represents most of the samples that exist in the INIT dataset (i.e., a half motion of left/right leg, while the other leg moves normally). On the other hand, while GEI was able to capture abnormal pose and severe-to-medium abnormal gait dynamics, it failed to detect some subtle abnormal gait dynamics (e.g., some samples with a half motion of left/right leg). Despite achieving little lower results, the INIT method depends on extracting high-quality silhouettes from side-view only. Hence, it cannot be applied to any other view. On the contrary, our method is general enough to be applied to different views and robust against low-quality silhouettes. Fig. 4 illustrates normal vs. misclassified abnormal GEI for the same person, where the abnormality is very subtle and cannot be captured by the GEI.



(a) (b)

Fig. 4: Abnormal GEI (a) similar to normal GEI (b).

IV. Conclusion

In this paper, we propose and evaluate a method for gait disorders detection. The method depends on generating the Gait Energy Image (GEI) from color/depth image gait sequence, and learn the representative features from the GEI using convolutional autoencoder. After that, we model the normal GEI representative features and detect abnormal gait by exploring two anomaly detection techniques. We tested the proposed method on two different benchmark datasets. The results indicate that the proposed method can present a general method that can detect abnormal gait from different views with high accuracy. This work can be extended by considering the conditions that affect the accuracy of abnormal gait detection using GEI, e.g., subtle abnormal gait dynamics, clothes variation, etc. One of our extensions in this regard is to propose one more feature that can concentrate on gait dynamics to be used along with GEI for more robust gait disorders detection and assessment.

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