Classification of Pathologies Using a Vision Based Feature Extraction

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Abstract. A lot of studies linking gait to different pathologies exists. However, few have addressed the automatic classification of such pathologies through computer vision. In this paper, a method to classify different gait pathologies is proposed. Using a smartphone camera, a sagittal view of the subject's gait is recorded. This record is processed by a computer vision algorithm that extract different gait parameters. These parameters are then used to perform a classification between 5 types of gait: normal, diplegic, hemiplegic, neuropathic and parkinsonian. Using a standard smartphone camera allows to simplify the data capturing step making this method suitable for Ambient Assisted Living. The experiments performed show an accuracy rate of 74% with a hierarchical classifier using Support Vector Machine combining Gait Energy Images and legs angle time series. The accuracy is improved to an 80% by applying data augmentation techniques during test, i.e., obtaining one sample per gait cycle and then combining the results to provide a more robust classification of the entire record.

Keywords: Gait analysis · Computer vision · Machine learning · Parkinson · Diplegia · Hemiplegia · Neuropathy

1 Introduction

The main objective of this work is to assess the suitability of a set of gait features based on computer vision to classify different gait pathologies. Physical activity is one of the main component involved in some syndromes evaluation like frailty [3,18], parkinson [6], neuropathy [21], hemiplegia [2] and diplegia [16]. Gait is identified as a high cognitive task in which attention, planning, memory and other cognitive processes are involved [4,11].

Through gait analysis, quantification of measurable information of gait and its interpretation [8,20], different syndromes and pathologies can be diagnosed. This process is carried out by specialist and is based on estimations through visual inspection of gait.

In this work we propose a feature set that could classify different gait pathologies and, thus, aid the specialists providing them with tool specialised in gait pathologies diagnosis.

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In our previous contribution [12,14] we proposed a method to obtain gait features using computer vision with smartphone cameras and a classifier able to determine if the gait was normal or not obtained more than 90% accuracy.

This paper is organised as follows. Section 2 describe related works. Section 3 presents the features used in the task of classifying different pathologies. Section 4 provides the experimentation performed and the obtained results. Finally Sect. 5 provides the conclusion.

2 Related Works

There are a great variety of proposals for human identification using gait analysis, however, few proposals exist for different gait pathologies classification.

Meyer et al. [10] proposed a method to classify gait between walking, hopping, running and limping, they track the head and trunk position and train some Hidden Markov Models (HMM). They obtained 62.2% accuracy rate between those four gait patterns.

To classify between normal and abnormal gait, Bauckhage et al. [1] proposed a homeomorphisms between 2D lattices and binary shapes to obtain a vector space where the silhouette is encoded. They performed successive bounding box splittings to obtain different lattices, then Support Vector Machine (SVM) was used for classification obtaining around 80% accuracy rate. For the same purpose, Wang [19] proposed a method based on optical flow to calculate a histogram of silhouette-masked flows, then an eigenspace transformation is performed. They compare with a normal gait template to calculate a deviation with which they obtain 90% accuracy rate.

An approach for parkinsonian gait recognition is presented by Khan et al. [5]. They use the silhouette to obtain the bounding box and fit a human model to find head, torso and legs segments. The skeleton is obtained by computing the mean points of each body segment. Following, they obtain legs movement and the posture inclination while the person is walking to get a particular score that it is compared with a normal gait model in order to get a similarity score. This approach provides 100% accuracy to detect parkinsonian gait through legs angle and posture inclination because there is a sufficient difference between normal and parkinsonian gait. To distinguish other gait types of pathological gait this approach could be insufficient but it provides a first approach. Similarly, Krishnan et al. [7] use lean and ramp angles to detect abnormalities such us postural instability and heel strike instability with satisfactory results.

3 Feature Selection

Although our previously proposed method [13,14] for gait feature extraction can work with both sagittal and frontal gait images, in this work we focus only in the sagittal ones as those provide more information for the classifier to discriminate the different classes.

For the purpose of classifying different gait pathologies we propose the use of leg angle time series as this feature was the most successful in our previous works classifying normal and abnormal gait patterns [14] were more than 90% accuracy was obtained. Leg-angle is obtained by computing the angle formed by the hip and each foot. In addition, we want to also assess the power of the Gait Energy Image (GEI) for classification. Using the heel strike (HS) we segment the gait sequence and obtain a GEI [9] for each cycle. A GEI is obtained by averaging all the silhouettes of the cycle aligned by the center of gravity of its bounding box. We compute a GEI for each cycle to obtain more samples to train and thus requiring HS to segment the cycle. The process to obtain HS can be avoided if we average all the silhouettes of a sequence simplifying the acquisition of the input, but we obtain one for each cycle to obtain a large amount of samples. We compute each GEI as described in Eq. 1.

$$GEI_i = \frac{1}{h_{i+2} - h_i} \sum_{k=h_i}^{h_{i+2}} s_k \tag{1}$$

Where s_k is the silhouette of frame k and $i = \{1, 2, \ldots, n-2\}$ the corresponding HS of the set of HS detected for the recording sample.

The main issue of GEI is the amount of dimensions it has to compare. For instance, we are using 50×50 pixels, that means we have to compare 2500 components for each sample. A large amount of pixels are empty so there are some pixels that are not necessary to compare so an optimization can be performed. We use Principal Components Analysis (PCA) to select the n main eigenvectors of all the training samples and then project all the samples into this new eigenspace. Now we only compare the n principal components instead of 2500 using SVM. This method is similar to the eigenfaces proposed by Turk and Pentland [17] and it is also applied by Man and Bhanu [9] for person identification using GEI.

Each recorded gait sample provides an average of 4 gait cycles. The training process usually needs a large amount of samples to obtain enough information

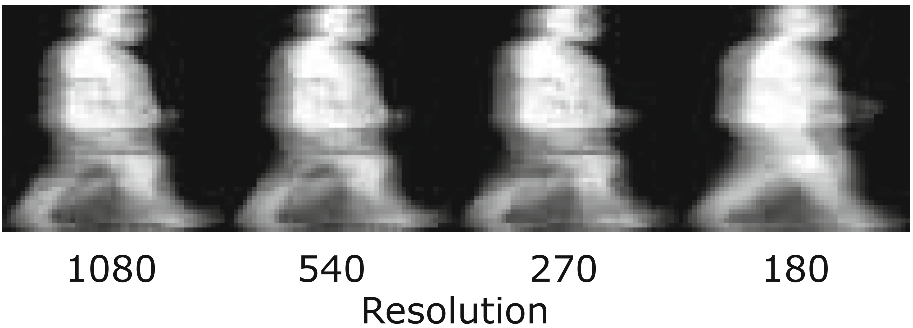


Fig. 1. This figure shows the different synthetic samples obtained from the original (left).

to perform a classification. That means we would have to record a great number of gait sequences to obtain a sufficient amount of samples. To solve this issue we propose the use of synthetic samples to increase the size of the training set.

For such purpose we use the multiresolution approach proposed in [15]. This method uses different resolutions to compute the silhouette providing a new synthetic sample for each subsampled resolution. By obtaining these samples, we provide robustness against scale variations.

This method transforms the original samples in new synthetic samples by adding artefacts that could be produced in reality. By using this method, we obtain 4 times more samples as shown in Fig. 1.

4 Experiments

For experimentation purposes, we recorded a dataset of subjects walking. We use healthy subjects feigning different pathologies due to having trouble finding real patient. However, we consider the feigned pathologies to be sufficient for our goal, which is to test if the proposed classifiers are capable of classifying between different pathologies. The data set is composed of samples of subjects walking over an 8 m hall. We set a camera perpendicular to gait direction at 4 m distance to record a side view of the person (around four steps). Figure 2 shows the set previously described.

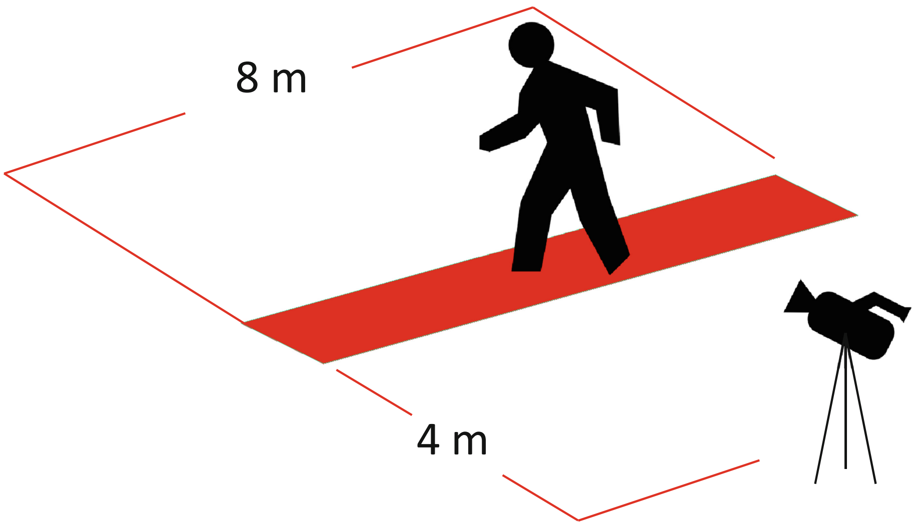


Fig. 2. Recording set up.

Table 1. Confusion matrix of legs-angle with DTW and KNN

		Actual				
		Normal	Diplegic	Hemiplegic	Neuropathic	Parkinsonian
Predicted	Normal	89,13%	0,00%	2,35%	18,45%	0,00%
	Diplegic	6,52%	47,27%	47,06%	4,85%	6,83%
	Hemiplegic	2,17%	14,55%	32,94%	7,77%	0,00%
	Neuropathic	2,17%	0,00%	12,94%	62,14%	0,00%
	Parkinsonian	0,00%	38,18%	4,71%	6,80%	93,17%

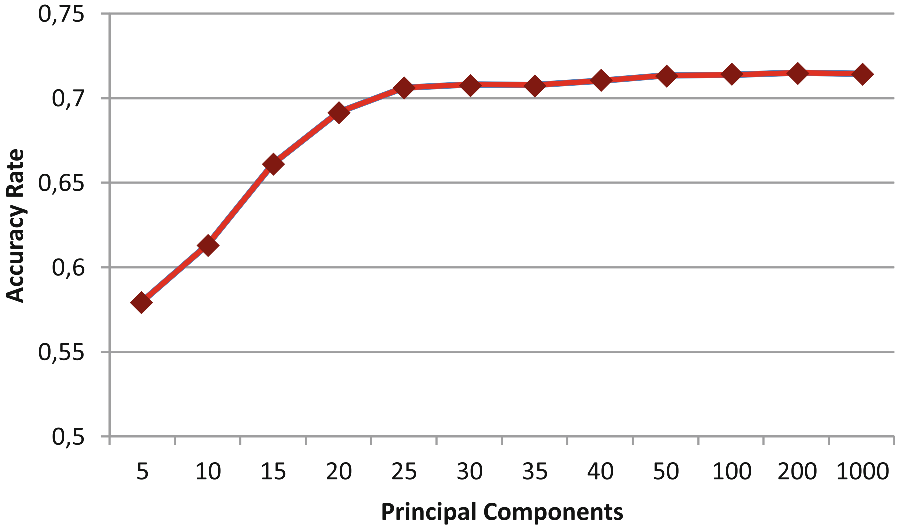


Fig. 3. Classification with different number of principal components

To perform the experiment we use this dataset with side view samples of five subjects feigning four different pathologies and normal gait. We recorded three samples of each subject and gait class which provided a total of 75 samples. The selected gait pathologies were diplegic, hemiplegic, neuropathic and parkinsonian.

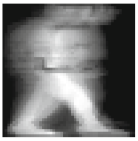
We processed the new dataset with the HSTOD algorithm [14] to obtain the HS to separate each gait cycle. We first tried the legs-angle time series with K-Nearest Neighbors (KNN) and Dynamic Time Warping (DTW) as distance function like in previous experiments [14]. Results, shown in Table 1, were not good as diplegic and hemiplegic are frequently confused and neuropathic is confused with normal gait because the pattern is similar between those classes and, thus, the DTW score is low. Normal gait and parkinsonian were successfully classified confirming the results of Khan et al. [5]. We then tried the GEI approach. For each gait cycle, a GEI is obtained as described in the previous section.

Figure 4 shows a GEI of each class. To assess the accuracy of the classifier we use 5-fold cross-validation using for each fold all the samples of one subject as test and the other subjects as training including synthetic samples in this case as well. This ensures that the subject silhouette has not been learned by the classifier. We apply PCA to reduce the dimensionality of the input images. Several classifications using SVM were performed with a different number of principal components as shown in Fig. 3. That allowed to determine that the optimal value is 50 which is the value where the curve stabilises. Therefore, 50 is the value used in the subsequent experiments.

(a) Normal gait

(b) Diplegic gait

(c) Hemiplegic gait



(d) Neuropathic gait

(e) Parkinsonian gait

Fig. 4. GEI image of each of the 5 different classes.

The confusion matrix in Table 2 shows an accuracy of 71.17%. It also show that hemiplegic and neuropathic gait are frequently confused between each other. Also diplegic is confused with parkinsonian, the other way around as well but in a lesser degree. Therefore, a new classifier capable of classifying neuropathic and hemiplegic and another for classifying parkinsonian and diplegic is needed. The fact that the couples hemiplegic-neuropathic and diplegic-parkinsonian are well distinguished provides a way of developing a hierarchical classifier, the first level classifies between normal, hemiplegic-neuropathic and diplegic-parkinsonian. Then in the next level two binary classifiers should deal with each couple. Observing Figs. 4b and e it can be seen the similarity between those two silhouettes. In the same way, Figs. 4c and d are also similar to each other.

Table 2. Confusion matrix of PCA with GEI and SVM

		Actual				
		Normal	Diplegic	Hemiplegic	Neuropathic	Parkinsonian
Predicted	Normal	89,13%	11,82%	3,53%	9,71%	0,00%
	Diplegic	0,00%	40,00%	1,18%	4,85%	7,45%
	Hemiplegic	2,17%	9,09%	62,35%	13,59%	0,00%
	Neuropathic	8,70%	1,82%	32,94%	71,84%	0,00%
	Parkinsonian	0,00%	37,27%	0,00%	0,00%	92,55%

That is the reason why the classifier is not capable of properly distinguish both couples using GEI.

Both couples cannot be classified with the first classifier because their shape is very similar. To differentiate hemiplegic from neuropathic we use the legs-angle time series because the results of Table 1 show that those two pathologies are well distinguished with legs-angle. In the case of diplegic and parkinsonian, we did not find a suitable classifier to deal with the problem, however, frontal view could provide a way to differentiate them. After applying the reclassification of hemiplegic-neuropathic, the resultant confusion matrix is as shown in Table 3 where the accuracy is slightly improved to reach 74.66%. This accuracy can be improved to 80.33% if for each GEI of each recording sample (there is one GEI images per gait cycle) we output the mode class, i.e., the class that is predicted in most cycles of the recording sample. E.g. assuming we have a recording sample which contains 5 gait cycles, we process each cycle with the classifier and obtains that parkinsonian is the output of 3 of the 5 cycles, then we assume that the whole recording sample output is parkinsonian (the class of most cycles). Diplegic is confused with parkinsonian in both GEI and legs-angle classifiers. As an example, removing diplegic from the dataset we obtain 86.52% accuracy reaching a 95% applying the mode as shown in Table 4.

Table 3. Confusion matrix of PCA with GEI and SVM after applying reclassification of hemiplegic-neuropathic with legs angle time series and KNN.

		Actual				
		Normal	Diplegic	Hemiplegic	Neuropathic	Parkinsonian
Predicted	Normal	89,13%	11,82%	3,53%	9,71%	0,00%
	Diplegic	0,00%	40,00%	1,18%	4,85%	7,45%
	Hemiplegic	2,17%	10,00%	78,82%	12,62%	0,00%
	Neuropathic	8,70%	0,91%	16,47%	72,82%	0,00%
	Parkinsonian	0,00%	37,27%	0,00%	0,00%	92,55%

Table 4. Confusion matrix of PCA with GEI and SVM after applying reclassification of hemiplegic-neuropathic with legs angle time series and KNN and removing diplegic gait.

		Actual			
		Normal	Hemiplegic	Neuropathic	Parkinsonian
Predicted	Normal	82,61%	2,35%	0,97%	0,00%
	Hemiplegic	4,35%	80,00%	15,53%	0,00%
	Neuropathic	13,04%	16,47%	83,50%	0,00%
	Parkinsonian	0,00%	1,18%	0,00%	100,00%

5 Conclusion

Using our feature extraction method based on computer vision we selected legs-angle time series and GEI as features to perform classification of different pathologies. The experiments performed with the recorded dataset show that both legs-angle and GEI features are capable of classify normal and abnormal gait patterns, however, legs-angle confuses hemiplegic with diplegic and neuropathic with normal gait because the pattern is very similar obtaining a low DTW score, while GEI confuses diplegic with parkinsonian and hemiplegic with neuropathic because the GEI silhouettes are very similar for those classes. The results are improved by combining both classifiers obtaining an accuracy of 74% by first classifying between normal, hemiplegic-neuropathic and diplegic-parkinsonian and then reclassifying both couples to improve the results. However, diplegic and parkinsonian are still not properly distinguished by the second level of the classifier.

As future work we will try to find a suitable feature set to classify between diplegic and parkinsonian to improve the results. We will also test the power of Convolutional Neural Network with the GEI because these neural network has proven to have great potential when applied to image classification as is our case.

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