Which Gait Feature Is Effective for Impairment Estimation?

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To realize a system that can automatically estimate impairment from gait observation, we have to consider which features should be extracted from the gait. Gait Energy Image (GEI) is often used since GEI is well known as a feature which show high performance for personal authentication. GEI, however, does not preserve temporal information of gait, *i.e.*, a duration time of a walking period, and phase fluctuation, which may be effective for the impairment estimation but have not been investigated. In this paper, we thus evaluate performance of these temporal features as well as GEI. We prepare two kinds of impairment (leg impairment and visual impairment) and normal walking, and collect large number of subjects for each case. Experiment results confirm GEI is in fact the most reasonable feature for impairment estimation from the viewpoint of accuracy and robustness.

Keywords: gait feature, leg impaired walking, visual impaired walking

1. Introduction

People who have some impairments, such as a person whose leg is immobilized in a plastic cast, an elder person who cannot bend his/her knees, and a cataract patient has a weak sight view, show different walking styles comparing with people with no impairment. Indeed we can usually distinguish the differences quite easily just by observing their ways of walking. If we can realize a system that can automatically detect such impaired people from their walking styles, it could be very useful in many applications such as diagnosis of Parkinson's Disease, rehabilitation of injured people, and monitoring physical condition of elderly [5].

Existing related studies are broadly categorized into two categories; model-based and appearance-based methods. The model-based methods use pose of a walking person, which is usually measured by invasive sensors for accurate measurement. For example, Hallemans *et al.* [1] use Vicon motion capture system to measure a head orientation, a stride length, trunk flexion to classify normal person and person with visual impairments. Tao *et al.* [2] give a re-view about kinds of wearable sensors like accelerometers and pressure sensor for measuring temporal characteristics of gait, and goniometric measurements at the hip, knee and ankle joints for detection gait phases. Indeed, these invasive methods can achieve high accuracy in measurement, but they require cooperation of subjects; the subjects have to wear special clothes or devices. These ways are thus not be applicable to the system we would like to realize. Some other model-based methods [6]~[8] use movies captured by cameras and estimate the pose by fitting and tracking body components. In these methods subjects do not need to wear any special devices. These methods, however, usually suffer from difficulty and low quality of the pose estimation and quite far from practical use.

On the other hand, appearance-based methods use captured movies directly. They are thus suitable for our objective. Chen *et al.* [3][4] use binary silhouette extracted from color images to distinguish Parkinson's Disease from normal people. Other works [9]~[11] extract some features from the gait observation and use the features for gender recognition and human authentication. Among the features, Gait Energy Image (GEI) is often used since GEI is well known as a feature which show high performance for personal authentication from gait. It is another advantage of GEI that it does not require high quality silhouette extraction; it is quite robust against noise inevitably included in extracted silhouette images. Considering that GEI is defined as an average of sequential silhouettes in a walking period, GEI can well encode shape of a person, so that it must be effective for personal authentication. It does not, however, preserve temporal information such as duration time of a walking period, or phase fluctuation in the period. No one ever confirm how well these temporal information affect the performance of the impairment estimation.

In this paper, therefore, we list up features that can be extracted from gait image sequences and investigate how effective these features work for the impairment estimation. Indeed some works [3][4] partially report the effectiveness for Parkinson Disease, but they use so limited number of subjects so that they are not so reliable. In this paper, we pick up two kinds of impairments, *i.e.*, leg impairment like injured leg, and visual impairment like cataract, and collect image sequences of a large number of subjects as well as those of normal people. These different kinds of walking are then classified from the viewpoint of the duration time, GEI, and the phase change.

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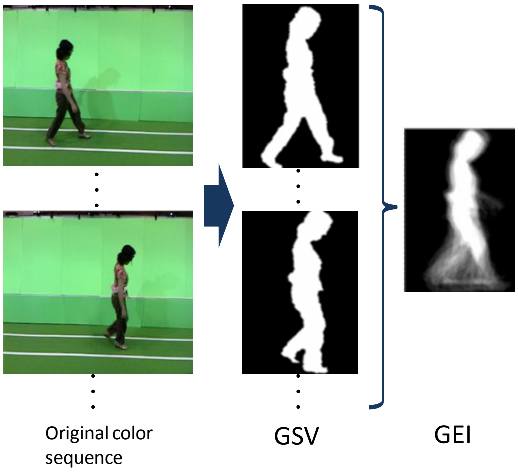


Fig. 1. Gait Energy Image (GEI).

2. Gait features

In this section, we list up features whose effectiveness we investigate in this study, and describe how to obtain these features.

From the original color image sequence, we firstly apply background subtraction to extract binary silhouette. The silhouette sequence after position alignment and size normalization are called Gait Silhouette Volume (GSV) [12]. With GSV, assuming periodicity of walking, we estimate a walking period length by calculating the normalized autocorrelation of the silhouette images in temporal axis. The gait period N_{period} is determined as the number of frames which makes the normalized autocorrelation maximum. As the sequence usually contains more than a period, we extract only a part $\{S_i\}(i = 1, 2, \cdots, N_{\mathrm{period}})$ that corresponds with a period, which we call "single GSV," Note that in our experimental setting, we pick up the period around the center of image. N_{period} denotes the number of frames in a period, which we call "duration time" in this paper.

Once we obtain GSV, GEI is calculated as follows. GEI was originally proposed by Han *et al.*to characterize human walking properties for individual recognition using gait data [11]. Given a detected walking period sequence $\{S_i\}$, GEI is the average of them, as defined as follow:

$$G(x, y) = \frac{1}{N_{\mathrm{period}}} \sum_{i=1}^{N_{\mathrm{period}}} S_i(x, y) \cdots\cdots\cdots\cdots\cdots (1)$$

Where i is the frame number in a period of walking silhouette sequence, and x, y is the coordinate in the image. An example of gait energy image is shown in Fig. 1.

GEI is well known as a feature which show high performance for personal authentication from gait. It is another advantage of GEI that it is reported that GEI is quite robust against noise contained in extracted silhouette sequences. Considering the above definition of GEI, which is in fact just an averaged image, we understand GEI can well encode shape of a person, so that it must be effective for personal authentication task. It does not, however, preserve temporal information such as the duration time, or phase fluctuation in the period. In this paper, therefore, we investigate discrimination ability of these temporal information as well as GEI. The duration time has already been obtained as N_{period}. The phase fluctuation is very difficult to be described as a feature vector. In this study, we implicitly cope with the phase change by regarding all the images included in a single GSV as a high-dimensional feature vector.

(a) (b) (c)

Fig. 2. Three types of walking; (a) leg impaired walking, (b) visually impaired walking, and (c) normal walking.

3. Experimental results

3.1 Data collection In our study, we pick up two kind of impairments; leg impairment and visual impairment. Injury on a leg is a typical case of the leg impairment. As an example of the visual impairment, cataract is well known. As you can image, however, it is hard to collect walking data of people who really have these impairments. One of the reasons is that it is difficult to find enough number of real patients. Moreover, even if we can find enough number of the patients, it is still difficult to ensure their safety in experiments. Considering these limitations, we thus use a simulation kits to help health people "act as" these two kinds of impaired walking. We then prepare three types of walking, as follows: 1) leg impaired walking by fastening leg supporters on both knees which restrict bending knee, 2) visually impaired walking by wearing goggle glasses which narrow sight field, and 3) normal walking with nothing fixed. Examples of these three kinds of walking styles are shown in Fig. 2 (a), (b) and (c), respectively. When collecting walking data, people walk on a straight path with a camera capturing from sideway. So all of the silhouette in our study is lateral. The numbers of subjects for these types are 186, 142 and 325, respectively.

In our experiments, the resolution of silhouette images is 128×88, so the dimension of GEI is also 128×88.

3.2 Classification method To evaluate performance of discrimination, we apply Linear Discriminant Analysis (LDA) to the collected data. Since our interest is how much each impaired walking is changed compared with normal walking, we apply two-class LDA between normal walking and that with leg/visual impairment.

In the case of GEI and single GSV, since these features are high dimensional vectors, we preliminarily ap-

normal vs. visual impairment	
normal	82.0%±2.5%
visual impairment	82.0%±2.3%

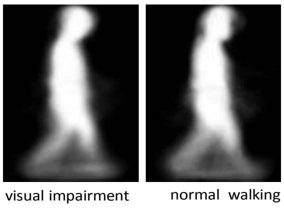


Fig. 3. Classification accuracy of normal walking and visually impaired walking.

normal vs. leg impairment	
normal	74.4%±2.2%
leg impairment	73.8%±2.3%

Fig. 4. Classification accuracy of normal walking and leg impaired walking.

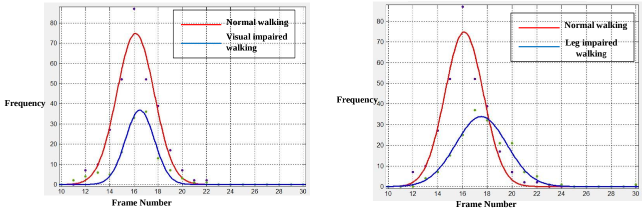
ply Principal Component Analysis (PCA) to compress them into a hundred dimensional vectors.

3.3 Discrimination ability of each feature

3.3.1 GEI We evaluate the performance of GEI in distinguishing impaired walking from normal walking. Table in left side of Fig. 3 shows the performance of normal walking and visual impairment. It says the accuracy is about 82%. Two images at the right side are the re-projection of most discriminative LDA direction. Comparing with these two images, we could find that a person with visual impairment tends to bend his/her head more to the front than a normal person. It sounds reasonable that people with lower visual ability need to be more careful about the road. As for the performance of leg impaired walking and normal walking, results are shown in Fig. 4. As it says, the classification accuracy is about 74%. The re-projection images on the right side show that leg impaired walking has a little smaller leg angle and lower head bending than that of normal walking.

3.3.2 Duration time Fig. 5 shows the distribution of duration time of normal walking and leg/visual impaired ones. The distribution of the normal and impaired walking are described by red and blue curves, respectively. In (a), the peaks of the two distribution are very similar to each other. It means that the visual impairment does not affect the duration time. In (b), on the other hand, we find that the leg impairment affects the duration time; the duration time of the leg impairment is obviously longer than that of the normal walking. We, however, have to focus on overlapped region of two distributions in each graph. In both graphs the overlapped region is very large. It means that the duration time is not so effective for accurate impairment estimation.

3.3.3 Single GSV Phase fluctuation in a walking period is also a feature that may be affected by impairments but is never preserved in GEI. To confirm the existence of the phase change, we use a single GSV. Each GSV is preliminarily normalized so as to have the same



(a) (b)

Fig. 5. Duration time distribution of normal/impaired walking.

number of frames and start with a frame corresponding with Double Support Phase (DSP). Frame with a certain index are then picked up and used as features for discrimination. If there is a certain consistent tendency in phase between the normal and impaired gaits, it is expected that the discrimination accuracy would be so different according to the index. And if the accuracy of a certain index is extremely higher than the others, we can say there would be a constant tendency of phase change around the index.

To prepare the normalized single GSV, we need to pick up the GSVs with the same number of frames in a period. Considering the distribution of the duration time, we determine the number should be 17. The numbers of subjects which fulfill the condition are 36, 37, and 52 for visual impaired, leg impaired and normal walking, respectively. We then manually select a DSP frame for each GSV to normalize the starting phase.

Fig. 6 overviews experimental results. We find that the DSP frames (first and ninth frames) give a little better performance than the others. This is, we guess, because DSP frames can express stride and contain less occlusion on arm and leg regions. But the most important point is that the performance is almost constant no matter which frame we choose. This means that there is very little phase fluctuation. The phase information is thus not effective for impairment estimation.

3.4 Discussion Among the features we pick up, GEI gives fine performance, but the others are not so effective. In the case of the duration time, although the statistical distribution is changed by impairment, it is not adequate for impairment estimation since the overlapped regions between the distributions are quite large. We also find the phase information is not effective. Impairment seems not to affect phase fluctuation of gait.

We have to point out, however, that the performances by GEI and a frame in GSV are very similar. This fact argues that if we can robustly extract a frame of a certain phase (DSP frame, for example) this frame has almost the same discrimination ability as GEI, which is calculated from all the frames in a period. This is very interesting discussion. In the practical use, however, choosing GEI is reasonable since GEI does not need the temporal normalization of GSV that cannot be achieved robustly.

4. Conclusion

In this paper, we evaluated effectiveness of features that can be extracted from gait image sequences to know

Frame Order	1st 	3rd 	5th 	7th 	9th 	11th 	13th 	15th 	17th 
Average accuracy Normal vs. visual impairment	**79.9% ±4.1%**	**76.8% ±4.5%**	**80.2% ± 4.1%**	**76.2% ±4.1%**	**80.8% ±5.1%**	**77.6% ±4.3%**	**76.9% ±3.8%**	**72.4% ±4.7%**	**71.5% ± 4.9%**
Average accuracy Normal vs. leg impairment	**74.3% ±4.7%**	**73.5% ±5.4%**	**72.4% ± 5.1%**	**67.6% ±5.1%**	**74.8% ±6.2%**	**69.1% ±6.8%**	**63.1% ±5.3%**	**63.9% ±4.5%**	**70.1% ± 6.4%**

Fig. 6. Classification accuracy for each frame of single GSV.

which feature should be used when we realize automatic impairment estimation. Among various gait features, GEI is often used since GEI is well known as a feature which show high performance for personal authentication from gait. GEI does not, however, preserve temporal information such as the duration time, or the phase fluctuation. No one has confirmed how well these temporal information affect the performance of the impairment estimation. In this paper, we thus evaluated the performance of these temporal features as well as GEI. From the experimental results using the large dataset, we found that these temporal features are not so effective as long as they are used for impairment estimation. Considering the performance and robustness, we finally found that using GEI is the most reasonable way.

Future work contains constructing a method for automatic impairment estimation. Moreover, we have to consider how similar walking wearing the simulation kits is to that of really impaired people.

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