IEEJ TRANSACTIONS ON ELECTRICAL AND ELECTRONIC ENGINEERING
IEEJ Trans 2015; **10**(s1): S69–S76
Published online in Wiley Online Library (wileyonlinelibrary.com). DOI:10.1002/tee.22166

Paper

Detection of Gait Impairment in the Elderly Using Patch-GEI

Chengju Zhou[a], Non-member
Ikuhisa Mitsugami, Non-member
Yasushi Yagi, Non-member

We propose a novel method for estimating physical impairment of elderly people using gait. To achieve this, we first investigate which gait feature is effective for this purpose among gait energy image (GEI), duration time, and phase fluctuation as dynamic features. GEI is a popular appearance-based feature showing high performance in human authentication. By comparison, we find that it is the most reasonable feature. In real situations, however, GEI is easily affected by clothes variations or carrying conditions, so that the use of whole body results in decreasing performance. Considering this problem, we thus propose to use only the GEI features of the most discriminative body patches. From the experiments that evaluate the contribution of various sizes of body patches, we find that head and chest regions perform better than the whole body with the classification accuracy improved from 80.93% to 83.17% for the visual impairment discrimination case. As for the leg impairment detection case, the leg region performs better than the whole body by an accuracy increased from 69.30 to 75.05%. These results confirm the effectiveness of patch-GEI for impairment detection. © 2015 Institute of Electrical Engineers of Japan. Published by John Wiley & Sons, Inc.

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

Received 22 October 2014; Revised 28 April 2015

1. Introduction

Walking is one of the indicators of human health. Normal walking requires the coordination of the cerebellar, sensory, visual, vestibular, muscular, basal ganglia, and auditory systems, so any abnormality in these systems can result in gait disorder [1]. With aging, those functions degenerate, which results in abnormal walking style. Indeed, adult people who have some impairments, such as poor binocular visual acuity, weak inter-joint coordination ability, and loss of hearing, show different walking styles in postural and dynamic aspects compared to people with no impairments [2–4]. We, humans, can usually distinguish the differences quite easily just by observing their ways of walking. If we design a system that can automatically detect such impaired people from their walking styles, it would be very useful in elderly care [5] and in many other gait-related applications such as the diagnosis of diseases like Parkinson's disease [6–9].

Existing studies related to gait analysis are separated into two categories: model-based and appearance-based methods. Model-based methods usually apply a motion capture system [2,3,10–12] or wearable sensors [6,13,14] to capture accurate pose parameters. For example, Hallemans *et al.* [10] used a 3-D motion capture system to measure head orientation, stride length, and trunk flexion to verify whether poor vision affects dynamic stability of walking. Other model-based studies [15–20] use movies captured by cameras and estimate the pose parameters by fitting and tracking body components. Taha *et al.* [17] fitted a skeleton model to binary human silhouettes to calculate their posture lean and stride cycles for detecting Parkinsonian gait. From the promising results of these two model-based approaches, we confirm that the walking posture, the temporal cue, and the stability property are important for disorder gait detection. In fact, model-based approaches can measure precise trajectories of moving joints and body components, but they require laboratory environment settings and cooperation of the subject; the subjects have to wear special clothes or devices. Further, they usually suffer from low quality of the pose estimation and high computation cost. These methods are thus not applicable to the scheme we would like to achieve.

On the other hand, appearance-based methods use captured movies directly, so subjects do not need to wear any special devices. Chen *et al.* [7,8] used binary silhouettes extracted from color images to distinguish people with Parkinson's Disease from normal ones. Their study used the binary images directly for classification, and hence the results heavily depend on the quality of each silhouette. Other works [21–24] have tried to extract some features from the gait observation and use them for gender recognition and human authentication. Among those features, gait energy image (GEI) [23] was often used since it is well known to show high authentication performance for individuals from their gait. Another advantage of GEI is 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, it can encode the shape of people very well, so that it must be effective for personal authentication. It does not, however, preserve temporal information such as the duration a walking period. Therefore, besides the GEI, we still investigate the effectiveness of the duration, which is relative to the walking speed. Considering that both GEI and duration time describe properties within a period, we further study phase fluctuation [25] between the neighboring walking periods. This phase fluctuation is used for estimating the walking stability, which is considered to be an important cue for assessing the ability to walk. We extract those gait features and use them to distinguish two common forms of impaired walking (leg and visual) from normal walking using linear discriminant analysis (LDA). From the evaluation results, we find that GEI is the most reasonable gait feature to describe

[a] Correspondence to: Chengju Zhou.
E-mail: zhou@am.sanken.osaka-u.ac.jp

The Institute of Scientific and Industrial Research, Osaka University 8-1 Mihogaoka, Ibaraki, Osaka 567–0047, Japan

the differences between the two walking categories. As Cho *et al.* [26] have pointed out that for healthy adults gender would affect their walking styles in some aspects, we also discuss the influence of gender on impairment detection among those gait features.

GEI mainly encodes the shape information of a human body. Even if we include a size normalization step before extracting GEI, it is still more or less affected by individual shape differences. To eliminate the influence of body parts other than the relevant region, we propose using only the most effective GEI patch for classification. Two works give detailed analysis of body components in gender recognition [27,28]. Li *et al.* [27] segment the averaged gait image into seven components: the head, the arm, trunk, the thigh, the front leg, the back leg, and the feet. The different contributions of human components for human authentication and gender recognition are analyzed. In addition, Yu *et al.* [28] point out that hair style and chest are two important body components for gender classification. Those components therefore should not be separated. In their paper, they have a different segmentation approach for human components: head and hair style, chest, back, waist, buttocks, and legs. This segmentation improves their performance. Experimental results vary with the change of the criteria for the segmentation of human body parts. Even though disorder gait is quite different from normal walking in gender classification, walking posture will change according to different illnesses. It is hard to decide what kind of body component segmentation will be suitable for our purpose. Therefore, we apply several grid patch sizes of the human silhouettes for evaluation. We present the effectiveness of our method by comparing the performance of patch-GEI with full-body GEI in impairment detection. Considering realistic applications of distinguishing multi-class impairments simultaneously, we also provide a solution strategy.

The rest of this paper is organized as follows. In Section 2, we first describe gait features extraction, and then introduce experimental data collection. Finally, we show the performance of three different gait features in detecting impairment and identifying the influence of gender. Section 3 is concerned about the contribution of body patches and an attempt to provide a solution to a real-life application. Conclusions are drawn in Section 4.

2. Gait Features and Their Performance

2.1. Gait features extraction

In this section, we describe how to extract the shape, temporal, and stability information features of walking subjects. From the original input color image sequence, we first apply background subtraction to extract binary silhouettes. After position alignment and size normalization, the binary silhouette sequences are called "gait silhouette volumes" (GSVs) [24].

With GSV, assuming periodicity of walking, we estimate a walking period length by calculating the normalized autocorrelation of the silhouette images in the temporal axis. The gait period N_{period} is determined as the number of frames that makes the normalized autocorrelation maximum. As the sequences usually contain more than a period, for duration time and GEI, we extract only the part $\{S_i\}(i = 1, 2, \cdots, N_{\text{period}})$ that corresponds to a period. Note that in our experimental setting, we pick up the period around the center of the image. N_{period} denotes the number of frames in a period, which we call "duration time" in this paper. Once we obtain GSV, the GEI feature is calculated as follows:

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

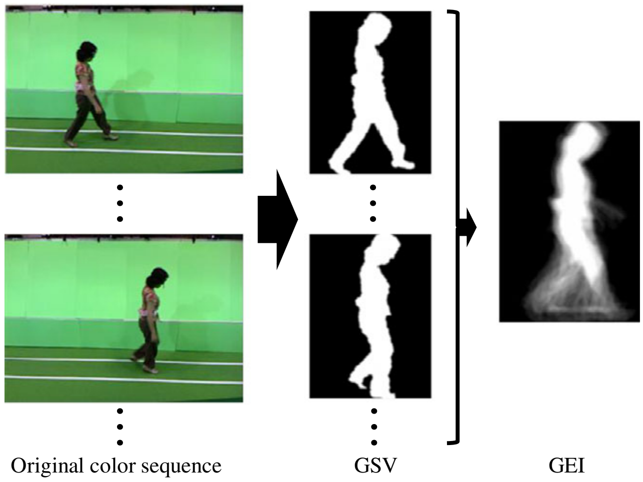


Fig. 1. Gait energy image (GEI)

where i is the frame number in a period of walking silhouettes, and x, y is the coordinate in the image. An example of the GEI is shown in Fig. 1. In the GEI image, the pixel intensity corresponds to the frequency about the human body appearance. A brighter intensity indicates a human body part that has less motion, such as the head and torso. On the other hand, gray parts correspond to regions with a lot of motion, like legs. Black means no body parts appear at the corresponding place.

We now briefly introduce the main processing steps for calculating phase fluctuation using the method that was proposed by Makihara *et al.* [25]. Based on the prior known relation between time and phase, and given a quasi- periodic sequence (GSV in this study), we can estimate a phase evolution sequence in an optimization framework with the help of instantaneous period estimation using short-term period detection (STPD) and self-dynamic time warping (DTW). This is the problem of phase registration. However, because of the existence of the combination ambiguity included in the quasi-periodic signal, the combination of the phase evolution function and the normalized periodic signal is not fixed. Thus, the phase evolution function linearization process is still needed. The procedures are mainly separated into three steps [29]: (i) period segmentation, (ii) reconstruction of the time warping function (TWF), and (iii) linearization of the TWF. Here, the TWF is about the relationship between linearly evolved phase and estimated relative phase in a period. As Makihara *et al.* [26] pointed out that their proposed method reconstructs TWFs from a single quasi-periodic signal through a bias estimation process, the variance in the reconstructed TWFs can be used as a kind of phase evolution instability measure. For more processing details, we refer the reader to [25–29].

2.2. Experimental data collection

In our study, we pick up two categories of commonly seen impairments among senior people: leg impairment and visual impairment. Stiff knee is a typical leg problem in the elderly. The reason for that problem is that joints become stiffer and less flexible with aging. In addition, old people are prone to have some lesions on the eye lens or retina, which results in visual impairments with symptoms of blur and tunnel view. 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 numbers of real patients. Moreover, even if we can find sufficient number of patients, it is still difficult to ensure their safety in experiments. Considering these limitations, we use an age simulation kit to help healthy people "act as" these two kinds of commonly seen impaired people. As the simulation kit, we adopt a product of

(a) (b) (c)

Fig. 2. Three types of walking. (a) Leg-impaired walking. (b) Visually impaired walking. (c) Normal walking

Sanwa Manufacturing Co., Ltd [30]. Since it is a popular one that has been used in many fields, it is reasonable for us to assume that it simulates well real elderly walking. We then prepare three types of walking, as follows: 1. leg-impaired walking by fastening leg supporters on both knees, which restricts knee bending, 2. visually impaired walking by wearing glasses that blur the sight and narrow the view field, and 3. normal walking without anything fixed. Examples of these three kinds of walking styles are shown in Figs 2(a)–(c), respectively. When collecting walking data, people walk on a straight path with a camera capturing sideways, so all of the silhouettes in our study are lateral. In our experiments, the resolution of silhouette images is 120×80, so the dimension of GEI is also 120×80. [1]

The number of subjects for leg impaired walking, visually impaired walking, and normal walking were 186 (71 female, 115 male), 142 (73 female, 69 male), and 325 (148 female, 177 male), respectively. Note that every participant in the data collection was instructed to finish two categories of walking: one type of impaired walking, and normal walking. So number of subjects with normal walking is much larger than that of impaired walking. The age range of participants was 4–78. By wearing the simulation kits, they were all recognized as same-age group "old adults". Some situations, such as calculating phase fluctuations, required the walking sequence to contain more than one walking periods, hence the number of subjects decreased.

2.3. Classification method To evaluate performance of discrimination, we apply LDA to the extracted gait features. Since our interest is in how much each impaired walking is changed compared to normal walking, we apply two-class LDA between normal walking and that with leg/visual impairment. Note that, because the subject number is not balanced for each class, we choose the same subject number for the two classes. In total, we make 30 times selection, and the results are the average of those 30 times and also their standard deviation. In the case of GEI, since the feature is high-dimensional vectors, we preliminarily apply principal component analysis (PCA) to compress them into the dimension number that preserves around 90% of the original energy. Each selection randomly chooses GEI from different subjects to compose the input features for PCA. As a result, the number of components and distribution of principal component scores vary among between selections. So instead of a specific number of components, a range is given. Take the whole body GEI as input feature, for example. Considering the situation of compressing features of subjects with normal and visual impairments, the range of component numbers corresponding to 90% of the original energy is 50–52. For case of normal between-leg impairment, the range is 54–56. One example for the distribution of each principal component score is shown in Fig. 3.

[1] As is well known, nowadays we have to obtain and manage such image data including personal information with extreme discretion. We consulted a lawyer about procedure to obtain and manage the data and about how to get agreement from subjects, and we carefully followed the procedure. Moreover, in the case of a child subject, who is not regarded to be responsible for the agreement, we ask his/her parent to give the agreement on his/her behalf. Owing to this procedure, images in this dataset can be pasted on this paper, and can be analyzed for our research purpose.

2.4. Discrimination ability of each feature

2.4.1. GEI We evaluate the performance of GEI in distinguishing impaired walking from normal walking. The table in left side of Fig. 4 shows the performance of normal walking and visually impaired walking. It shows the accuracy is about 81%. The two images at the right side are the re-projections of the most discriminative LDA direction. Comparing these two images, we can find that a person with visual impairment tends to bend his/her head more to the front than a normal person. It sounds reasonable because people with lower visual ability need to be more careful about the road. As for the performance of the leg-impaired walking and normal walking, theresults are shown in Fig. 5. As the figure shows, the classification accuracy is about 69%. The re-projection images on the right side show that leg-impaired walking has a slightly smaller leg angle and lower head bending than normal walking. The performance of GEI shows that impairment affects the walking posture.

2.4.2. Duration time Fig. 6 and Fig. 7 show the distribution of the duration time of normal walking and leg/visually impaired walking and also their classification accuracy. The distributions of the normal and impaired walking are shown by red and blue curves, respectively. In Fig. 6, the peaks of the two distribution are remarkably aligned. It means that visual impairment does not affect the duration time. In Fig. 7, on the other hand, we find that leg impairment affects the duration time; the duration time of the leg impairment is obviously longer than that of normal walking. However, the large overlapped region of two distributions in each graph means that the duration time is not very effective for accurate impairment estimation and the classification results also prove that point.

2.4.3. Phase fluctuation Phase fluctuation of a neighboring phase estimated sequence is used to estimate the stability of a walking style. It is measured by the variance of the reconstruction of TWFs. The smaller the variance, the more stable the phase evolution between neighboring periods. That also means the walking style of the subject is more stable. We note here that to calculate the phase fluctuation, a walking sequence should contain more than two periods. The numbers of subjects who fulfill this condition are 198, 92, and 66 for normal walking, leg-impaired walking, and visual-impaired walking, respectively.

Fig. 8 and Fig. 9 show the distribution of variance of reconstruction DTW of normal walking and leg/visual-impaired walking and also their classification accuracy. The distributions of the normal and impaired walking are shown by the red and blue curves, respectively. In both Fig. 8 and Fig. 9, the peaks of the two distribution are aligned. It means that the stability of the walking style is different between individual people, but not affected by the physical impairment. The classification accuracy also proves this point.

2.5. Influence of gender on gait features The paper of Cho *et al.* [26] proves the assumption that healthy adults walk

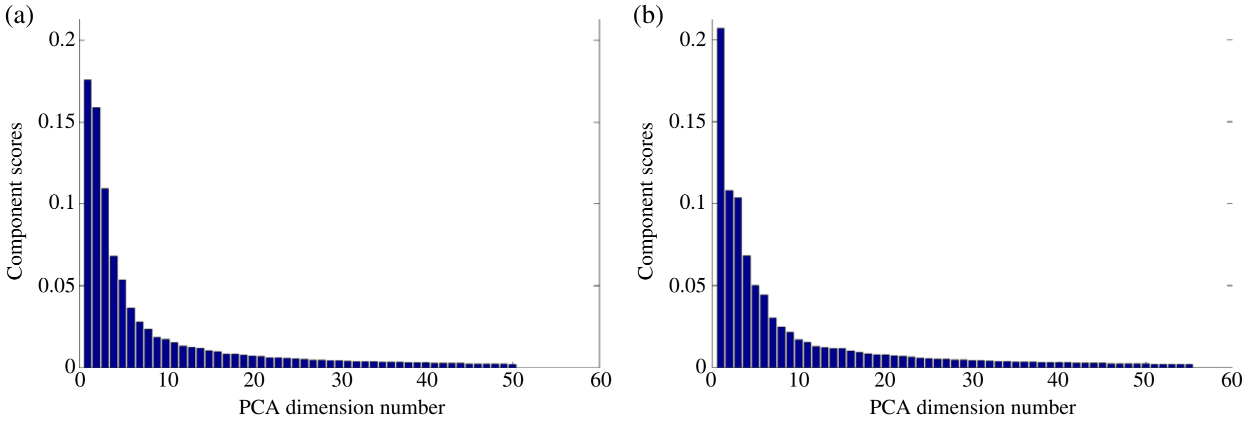


Fig. 3. Distribution of the principal component scores for GEI of subjects from (a) normal and visual impairment, and (b) normal and leg impairment

Normal vs. Visual impairment	
Normal	81.17 ± 2.84%
Visual impairment	80.68 ± 1.99%
Average accuracy	80.93 ± 1.90%

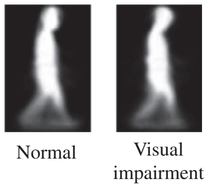


Fig. 4. Accuracy and re-projection of normal and visually impaired walking

Normal vs. Leg impairment	
Normal	70.27 ± 2.00%
Leg impairment	68.33 ± 1.99%
Average accuracy	69.30 ± 1.47%

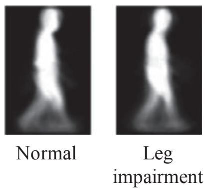


Fig. 5. Accuracy and re-projection of normal and leg-impaired walking

differently according to their gender, based on some aspects. After normalization, which was used to avoid the body size effect, the authors reach the following conclusions: (i) no gender differences were found in walking speed and also in the durations of the stance phase and the double support period; (ii) some differences were discovered in postural aspects. Females walked with their pelvis tilted more anteriorly, more up and down oblique motion, hip joints more flexed rotated, knee joint in more valgus angles, and narrower step widths. Considering the property of the three gait features in this paper (namely GEI, duration time, and phase fluctuation), GEI, which describes the body shape of the walking subjects, is probably affected by gender. We verify the assumption by comparing among the detection results using GEI from subjects of mixed gender, same gender, and cross-gender, which are shown in Fig. 4 and Fig. 5, Table I and Table II. Note that mixed gender means subjects used without considering gender, mixed together for training and testing, while cross-gender means using male (female) subjects for training but female (male) subjects for testing.

From these figures, we find that the results change when applying different gender conditions, which means that both categories of impairment detections are affected by the gender. Leg impairment classification is further affected. This may be due to the fact that more obvious differences exist in gait-related anatomy in leg rather than neck between genders. Since the results decrease in most of the classification in same gender cases and in all cross-gender situations, and also gender information always lacks in the real scenarios, using the strategy of classification without considering gender factor is more robust.

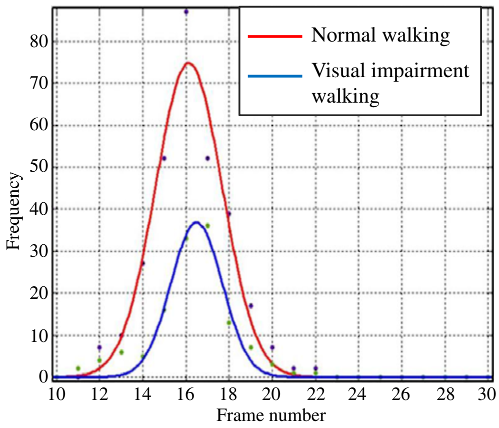
2.6. Discussion Among the features we picked up, GEI gives fine performance, but duration time and phase fluctuation are not very effective. In the case of the duration time, although the statistical distribution is changed by impairment, it is not adequate for impairment estimation since the overlapped regions between the distributions are quite large. We also found that the phase information is not effective. Walking stability is not affected by the physical impairment, but rather by the individual differences. So GEI is chosen to present the discriminative information of different walking styles. Even though gait is affected by gender, GEI evaluation results show that classification without considering gender is more feasible in real scenarios.

3. Performance and Real Application of Patch-GEI

3.1. Performance of patch-GEI As discussed in Section 2, it appears that GEI is the best feature to detect impaired walking, because posture difference between different walking styles can be described by this feature. In other words, walking shape contains the discriminative ability for impairment detection. On the other hand, however, the shape is usually affected by clothing, carrying, and so on, in real situations. Considering this problem, we thus propose to use only effective parts to decrease negative influence of the other parts of the body.

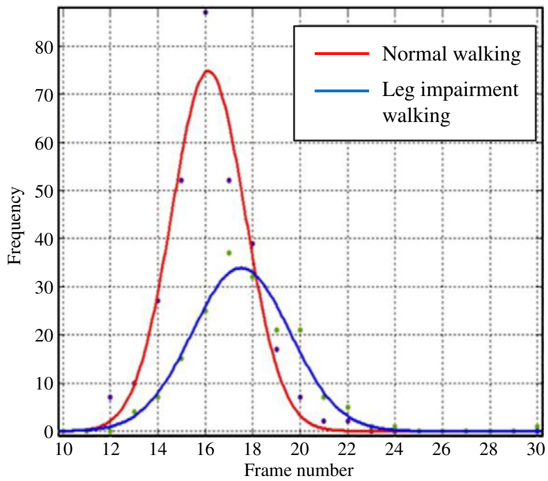
To decide which body patches contain the most discriminative information, we first need to determine the criterion for segmenting the whole GEI into patches. As mentioned previously, two works give detail analysis of contribution of body components for gender recognition [27,28]. From their experiments, we found that results become different with the change of criterion for the segmentation of human component. Since our scenario is, of course, different from those studies, we have to find a new rule (the most discriminative patches) for our scenario. To do this, we apply various grid patch sizes of human body, and evaluate performance.

In this study, we evaluate the performance of five levels of patch sizes, they are 5×5, 10×10, 20×20, 30×30, and 40×40. From the whole-body GEI, we extract the region corresponding to the patch size with row scanning order and with the skipping step of 5 pixels. For each patch region, we also use the same processing flow with whole GEI, first PCA for compressing into the dimension which preserves about 90% energy of the original one, and then LDA for classification. Their performances are shown in Fig. 10 and Fig. 11.



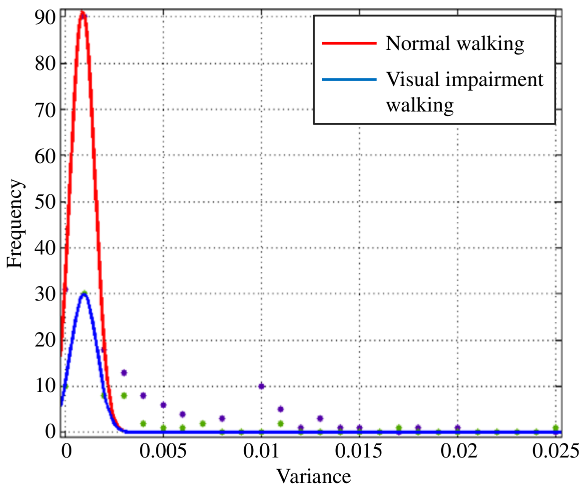
Normal vs. Visual impairment	
Normal	50.77 ± 10.11%
Visual impairment	47.68 ± 9.43%

Fig. 6. DT distribution and accuracy of normal and visually impaired walking



Normal vs. Leg impairment	
Normal	55.87 ± 2.01%
Leg impairment	73.97 ± 4.90%

Fig. 7. DT distribution and accuracy of normal and leg-impaired walking

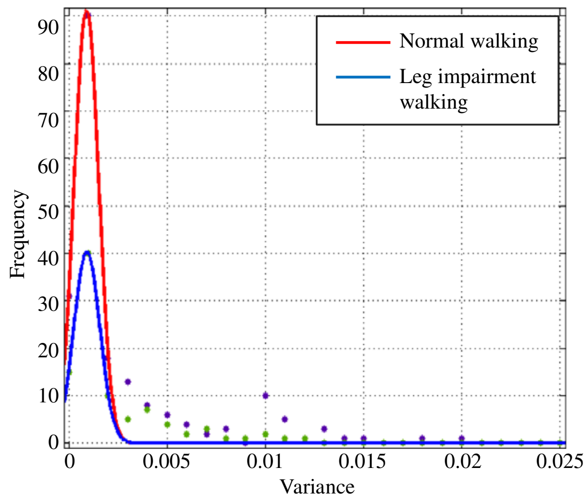


Normal vs. Visual impairment	
Normal	37.02 ± 20.70%
Visual impairment	65.20 ± 21.18%

Fig. 8. Phase fluctuation distribution and accuracy of normal and visually impaired walking

In Fig. 10 and Fig. 11, "classification accuracy" is the performance of patch shown in the third row, which is the best performance of the same patch size for a whole GEI. And the gray human images in the these rows are the averages of GEI from all the leg-impaired subjects and all the visual-impaired subjects for Fig. 10 and Fig. 11, respectively. The figures on the fourth row of each figure are the performance of all the patches of the same size. The points in the image are located on the center of the patches. And color of the points is relative to the classification accuracy using that corresponding patch GEI; color closer to blue means lower accuracy and color closer to red means higher accuracy. Also note that the rightmost column is the performance of the whole GEI.

From the results shown in Fig. 10, we found that patch with size of 30×30 positioning at the head and breast gave the best performance with the classification accuracy of 83.17%. Comparing with the average accuracy of whole GEI of 80.93%, using only patch around the head and breast region can improve the accuracy by 2.24%. This result proves our assumption that other parts of the human body will influence the discriminative ability



Normal vs. Leg impairment	
Normal	30.33 ± 8.80%
Leg impairment	68.33 ± 9.04%

Fig. 9. Phase fluctuation distribution and accuracy of normal and leg-impaired walking

Table I. Accuracy of same gender classification. (a1),(b1) Female subjects training and testing; (a2),(b2) male subjects training and testing

normal vs. visual impairment (female training, female testing)	
normal	79.41% ± 3.27%
visual impairment	76.80% ± 3.41%
average accuracy	78.11% ± 2.81%

(a1)

normal vs. leg impairment (female training, female testing)	
normal	65.40 %± 4.66 %
leg impairment	62.30 %± 3.42 %
average accuracy	63.85 %± 3.42 %

(b1)

normal vs. visual impairment (male training, male testing)	
normal	77.29 %± 2.67 %
visual impairment	78.26 %± 2.50 %
average accuracy	77.78 %± 1.93 %

(a2)

normal vs. leg impairment (male training, male testing)	
normal	80.52 %± 2.36 %
leg impairment	84.61 %± 2.25%
average accuracy	82.57 %± 1.8%

(b2)

Table II. Accuracy of cross-gender classification. (a1),(b1) Male subjects training and female subjects testing; (a2),(b2) female subjects training and male subjects testing

normal vs. visual impairment **(male training, female testing)**	
normal	63.09%± 11.26%
visual impairment	72.42%± 7.60%
average accuracy	67.75%± 4.11%

(a1)

normal vs. leg impairment **(male training, female testing)**	
normal	68.17%± 7.21%
leg impairment	42.77%± 5.38%
average accuracy	55.47%± 1.70%

(b1)

normal vs. visual impairment **(female training, male testing)**	
normal	77.74%± 6.39%
visual impairment	78.16%± 8.77%
average accuracy	77.95%± 3.13%

(a2)

normal vs. leg impairment **(female training, male testing)**	
normal	48.40%± 9.63%
leg impairment	70.64%± 8.39%
average accuracy	59.52%± 2.79%

(b2)

when using GEI is reasonable. Note that, though the other sizes of patches perform a little worse, all color closer to red appears at the upper region and all the highest accuracy appears at the head regions. This once again confirms the fact that people with visual impairments need to bend their heads to pay more attention to the condition of roads. And still, when we check the lower part of the color points image, we find that they are near to the blue color, which means impairment on eyes have little influence on the lower body.

Fig. 10 shows the performance of patch-GEI in detecting leg-impaired walking. The patch size of 40×40 shows the most discriminative ability at the accuracy of 75.05%, which is an improvement of 5.75% compared with the performance of whole GEI. All the best performances at the leg region also confirm the fact that people with leg impairments walk with smaller stride lengths. And about the color point distribution, the red closer color points also appear at the head region, but they are not so obvious. This means that the leg impairment makes the subject walk with a smaller leg angle, and at the same time, makes the balance of the moving body, so the subjects have a little front lean. But this "front lean" is less effective than the leg change, so using only the leg region is enough. From the analysis mentioned above, patch-GEI can decrease the influence of the other parts of the human body. It also can solve the problem of sharp shape change due to carrying baggage. Using only the effective patch, like only head or leg regions can avoid the shape change around baggage regions.

3.2. A solution to a real application of patch-GEI

Besides exploring the difference between impaired walking and normal walking, we go further to solve another issue that makes our research more practical, namely distinguishing multi-type impairments simultaneously. Considering that visual impairment and leg impairment are independent of each other, a subject might suffer from both visual and leg impairments at the same time. To label the subject as either visually impaired or leg impaired only is not very reasonable; therefore such kind of compound visual and leg impairment is considered as a new impairment type.

The direct multi-class classification would get confused in distinguishing pure impairment and compound impairment. We thus provide the classification strategy of using a binary classifier to detect one type of impairment, one type of impairment vs. the other types of impairments (including normal). In detail, we employ the strategy of visual impairment vs. non-visual impairment (including normal and leg impairment) to diagnose whether the subject suffers from visual impairment, and use the method of leg impairment vs. non-leg impairment (including normal and visual impairment) to detect leg impairment. In our experiment, the accuracy of visual impairment detection is 77.82% and that of leg impairment detection is 72.65%.

4. Conclusion

In this paper, we developed a scheme for impairment detection in elderly people through camera-captured walking sequences. We first listed three gait features: GEI, duration time, phase fluctuation, which cover the posture, temporal, and dynamic aspect of walking. Next, we used a two-class LDA for classification.

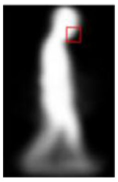
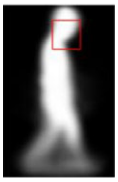
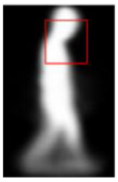
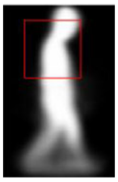
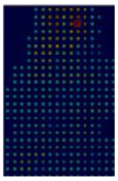
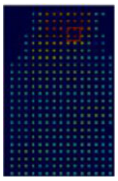
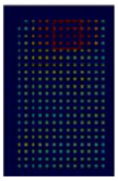
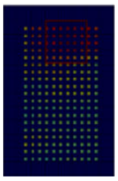
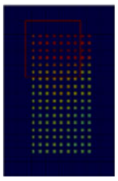
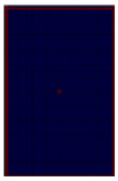
Patch size	5*5	10*10	20*20	30*30	40*40	120*80
Average accuracy	76.26 ± 1.40%	75.79 ± 1.18%	81.20 ± 1.61%	83.17 ± 1.36%	82.31 ± 1.75%	80.93 ± 1.90%
Most effective patch						
Patch accuracy of the whole image						

Fig. 10. Classification accuracy of normal walking and visually impaired walking

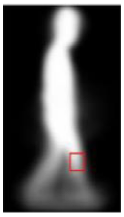
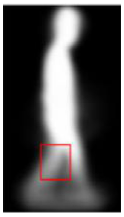
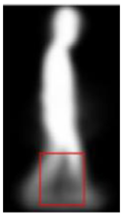
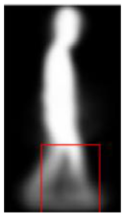
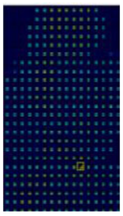
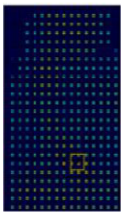
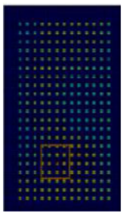
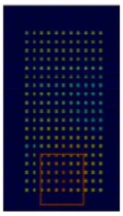
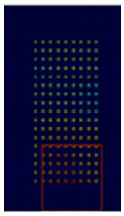
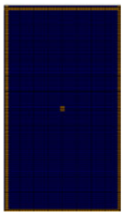
Patch size	5*5	10*10	20*20	30*30	40*40	120*80
Average accuracy	62.24 ± 1.59%	66.01 ± 1.49%	69.87 ± 2.05%	72.68 ± 1.38%	75.05 ± 1.60%	69.30 ± 1.47%
Most effective patch						
Patch accuracy of the whole image						

Fig. 11. Classification accuracy of normal walking and leg-impaired walking

From the experimental results, we confirmed the discriminative ability of GEI over the three features. We also discussed the influence of gender in GEI. Further, considering that GEI is mainly about shape information, it must be affected by the other parts of the human body except the effective part for detecting impairments. We thus proposed using only the effective patch GEI for classification. We could improve the performance by 2.24 and 5.75%, respectively, for detecting visual and leg impairment compared with whole GEI. This proves the effectiveness of patch-GEI. Based on this fact, we considered the real application of distinguishing multiple impairments simultaneously using binary classification. The accuracy of detecting visual impairment was 77.82% and that of leg impairment detection was 72.65%.

Future work consists of constructing an automatic impairment estimation system based on the patch-GEI method. Moreover, we also have to consider how similar it is to walk wearing the simulation kits when compared to the walking of actually impaired people.

References

(1) Ali A, Sundaraj K, Ahmad B, Ahamed N, Islam A. Gait disorder rehabilitation using vision and non-vision based sensors: a systematic review. *Bosnian Journal of Basic Medical Sciences* 2012; **12**(**3**):193–202.

(2) Shin S-S, An D-H, Yoo W-G. The effect of navigating obstacles when walking with deficient (inappropriate, deprived, limited) foot sensory input on spatiotemporal gait parameters of elderly individuals with different visual acuities. *European Geriatric Medicine* 2015; **6**(**1**):1–6.

(3) Chiu S, Chou L. Variability in inter-joint coordination during walking of elderly adults and its association with clinical balance measures. *Clinical Biomechanics* 2013; **28**:454–458.

(4) Lia L, Simonsickc EM, Ferruccic L, Lin FR. Hearing loss and gait speed among older adults in the United States. *Gait & Posture* 2013; **38**(**1**):25–29.

(5) Uddin MZ, Kim T-S, Kim JT. Video-based human gait recognition using depth imaging and hidden Markov model: a smart system for smart home. Proceedings of 3rd International Symposium on Sustainable Healthy Buildings, Seoul, Korea,2010.

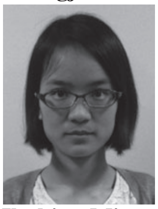
(6) Salarian A, Russmann H, Vingerhoets FJG, Dehollain C, Blanc Y, Burkhard PR, Aminian K. Gait assessment in Parkinson's disease: toward an ambulatory system for long-term monitoring. *IEEE Transactions on Biomedical Engineering* 2004; **51**(**8**):1434–1443.

(7) Cho C-W, Chao W-H, Lin S-H, Chen Y-Y. A vision-based analysis system for gait recognition in patients with Parkinson's disease. *Expert Systems with Applications* 2009; **36**:7033–7039.

(8) Chen Y-Y, Cho C-W, Lin S-H, Lai H-Y, Lo Y-C, Chen S-Y, Chang Y-J, Huang W-T, Chen C-H, Jaw F-S, Tsang S, Tsai S-T. A vision-based regression model to evaluate Parkinsonian gait from

monocular image sequences. *Expert Systems with Applications* 2012; **39**:520–526.
(9) Khan T, Grenholm P, Nyholm D. Computer Vision Methods for Parkinsonian Gait Analysis: A Review on patent. *Recent Patents on Biomedical Engineering* 2013; **6**:97–108.
(10) Hallemansa A, Ortibusc E, Meired F, Aertsa P. Low vision affects dynamic stability of gait. *Gait & Posture* 2010; **32**(**4**):547–551.
(11) Fang W.Stone E. Gait analysis and validation using voxel data, Proceedings of 31st Engineering in Medicine & Biology Society, 2009
(12) Mostayed A. Abnormal gait detection using discrete fourier transformation. Proceedings of International Conference on Multimedia and Ubiquitous Engineering, 2008.
(13) Baker R. Gait analysis methods in rehabilitation. *Journal of NeuroEngineering and Rehabilitation* 2006; **3**(**4**), doi:10.1186/1743-0003-3-4.
(14) Tao W, Liu T, Zheng R, Feng H. Gait analysis using wearable sensors. *Sensors* 2012; **12**:2255–2283.
(15) Okusa K, Kamakura T. Normal/Abnormal Gait Analysis based on the Statistical Registration and Modeling of the Frontal View Gait Data. Proceedings of World Congress on Engineering and Computer Science, 2012.
(16) Yoo J-H, Hwang D, Moon K-Y, Nixon MS. Automated human recognition by gait using neural network. First Workshops on Image Processing Theory, Tools and Applications, 2008; 1–6.
(17) Khan T, Westin J, Dougherty M. Motion cue analysis for Parkinsonian gait recognition. *The Open Biomedical Engineering Journal* 2013; **7**: 1–8.
(18) Lee H, Guan L, Lee I. Video analysis of human gait and posture to determine neurological disorders. *EURASIP Journal on Image and Video Processing* 2008; **2008**:1–12.
(19) Lee L, Grimson WEL. Gait analysis for recognition and classification. Fifth IEEE International Conference on Automatic Face and Gesture Recognition, 2002; 148–155.
(20) Wang L, Tan T, Ning H, Hu W. Silhouette analysis-based gait recognition for human identification, *IEEE Transactions on Pattern Analysis and Machine Intelligence* 2003; **25**:1505–1518.
(21) Hu M, Wang Y. A new approach for gender classification based on gait analysis. Fifth International Conference on Image and Graphics, 2009; 869–874.
(22) Yang X, Zhou Y, Zhang T, Shu G, Yang J. Gait recognition based on dynamic region analysis. *Signal Processing* **88**(**9**):2350–2356.
(23) Han J, Bhanu B. Individual recognition using gait energy image. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 2006; **28**(**2**):316–322.
(24) Makihara Y, Sagawa R, Mukaigawa Y, Echigo T, Yagi Y. Gait recognition using a view transformation model in the frequency domain. *9th European Conference on Computer Vision* 2006; **3**:151–163.
(25) Makihara Y, Aqmar MR, Ngo TT, Nagahara H, Sagawa R, Mukaigawa Y, Yagi Y. Phase estimation of a single quasi-periodic signal. *IEEE Transactions on Signal Processing* 2014; **62**(**8**):2066–2079.
(26) Cho SH, Park JM, Kwon OY. Gender differences in three dimensional gait analysis data from 98 healthy Korean adults. *Clinical Biomechanics* 2004; **19**(**2**):145–152.
(27) Li X, Maybank SJ, Yan S, Tao D, Xu D. Gait components and their application to gender recognition. *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews* 2008; **38**(**2**):145–155.
(28) Yu S, Tan T, Huang K, Jia K, Wu X, Study A. on Gait-based gender classification. *IEEE Transactions on Image Processing* 2009; **18**(**8**):1905–1910.
(29) Ngo TT, Makihara Y, Nagahara H, Sagawa R, Mukaigawa Y, Yagi Y. Phase registration in a gallery improving gait authentication, Proceedings of the International Joint Conference on Biometrics (IJCB), 2011.
(30) http://www.sanwa303.co.jp/products/medicare/teaching-material/104-990.

Chengju Zhou (Non-member) received the B.S. degree in Electronic and Information Engineering and the M.S. degree in Signal and Information processing from Dalian University of technology, China, in 2008 and 2010, respectively. Since 2012, she has been pursuing the Ph.D. degree in Computer Science at Osaka University.



Ikuhisa Mitsugami (Non-member) received the B.S. degree in Engineering from Kyoto University in 2001, and M.S. and Ph.D. degrees in Engineering from Nara Institute of Science and Technology in 2003 and 2007, respectively. He is currently an Assistant Professor with the Institute of Scientific and Industrial Research, Osaka University. His research interests include geometry in computer vision, detection and tracking, and gait analysis. Dr Mitsugami is a member of the IEEE, IEICE, IPSJ, RSJ, and VRSJ.

Yasushi Yagi (Non-member) received the Ph.D. degree from Osaka University in 1991. In 1985, he joined the Product Development Laboratory, Mitsubishi Electric Corporation, where he worked on robotics and inspections. He became a Research Associate in 1990, a Lecturer in 1993, an Associate Professor in 1996, and a Professor in 2003 at Osaka University. He is currently the Director of the Institute of Scientific and Industrial Research, Osaka university. He has served as Chair in various international conferences, including FG1998 (Financial Chair), OMINVIS2003 (Organizing chair), ROBIO2006 (Program co-chair), ACCV2007 (Program chair), PSVIT2009 (Financial chair), ICRA2009 (Technical Visit Chair), ACCV2009 (General chair), ACPR2011 (Program co-chair) and ACPR2013 (General chair). He has also served as the Editor of IEEE ICRA Conference Editorial Board (2007–2011). He is an Editorial Board member of IJCV and the Editor-in-Chief of IPSJ Transactions on Computer Vision & Applications. He was awarded ACM VRST2003 Honorable Mention Award, IEEE ROBIO2006 Finalist of T.J. Tan Best Paper in Robotics, IEEE ICRA2008 Finalist for Best Vision Paper, MIRU2008 Nagao Award, and PSIVT2010 Best Paper Award. His research interests include computer vision, medical engineering, and robotics. Prof. Yagi is a fellow of IPSJ and a member of IEICE, RSJ, and IEEE.