Recognition Method for a Temporary Change in Walking based-on Anomaly Detection and Classification

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Abstract—**In recent years, the global population of the elderly has increased, and one of the challenges faced by this population is the increased vulnerability to falls. Two approaches to alleviate this problem are determining actions that cause these falls and preventing falls using the detection results. A temporary change in walking (i.e., stumbling and staggering) is a typical cause of a fall. However, existing studies do not focus on a temporary change in walking; they only distinguish between walking or other activities and recognize walking speed. In this paper, we propose a method to detect the change in walking using change point detection (i.e., anomaly detection for time series data) and a classification method for the multiple types of change. Moreover, we assume four cases classified using available data, and we propose the parameter setting of the proposed method for each case to be applied in diverse scenarios. During the evaluation, four anomalous walking videos (where, anomaly represents a temporary change) are used. Thus, the accuracy of the anomaly detection of the proposed method is up to 93.5%, and the four types of detected anomalous walking are classified into three clusters in 89.1% of cases based on each characteristic.**

Keywords–Walking recognition; Classification; Anomaly detection; Human activity recognition.

I. INTRODUCTION

This paper is an extended version of the paper presented at eTELEMED 2020 [1]; a summary of the major extension is presented below.

- We propose a method for parameter setting, which assumes four cases. The method is described in Section IV.
- We define a baseline method to compare the accuracy between the proposed and existing methods. The baseline method is described in Section V-C.
- The evaluations of the baseline method and new cases of the proposed method are added.

The global population of the elderly has grown in recent years, and one of the challenges faced by this population is an increased vulnerability to falls [2] [3]. Older people are more likely to be seriously injured by falls; further, falls lead to expensive hospitalization. In the USA, the cost for fall-related injuries was approximately $50 billion in 2015 [2]. Human activity recognition is a research field that focuses on addressing these problems [4]. The approaches for solving these problems using human activity recognition are divided into two types. The first approach is fall detection, which can detect falls soon after they occur. Several studies on this topic have already been conducted [5]. These studies indicate that this approach prevents fall-related injuries from becoming severe [6] [7]. The second approach is detection of actions causing falls, which can help reduce the incidence of such scenarios. These actions include stumbling and staggering, and they are caused by a temporary change in walking gait. Thus, it is necessary to recognize a change in walking. In addition, the change needs to be classified because it includes actions that are not related to falls, such as standing still. However, existing studies on walking recognition can distinguish between only walking and other activities [8], and they can recognize walking speed [9]; however, they do not focus on a temporary change in walking. Most of these studies recognize activity from common features among multiple persons if there is a clear difference between target activities (e.g., walking and sitting). Various methods can be used to identify these activities. However, detecting a change in walking is difficult because the difference in each person is larger than that in each action. In other research areas, a stumble detection system for powered artificial legs has been proposed [10]; however, its application is not possible in cases without artificial legs.

In this study, we propose a method to detect a change in walking using change point detection and anomaly detection for time series data. Change point detection is performed for each time series walking data. Although anomaly detection and parameter setting of the anomaly and change point detection methods require accumulated data, the effects of individual differences are mitigated. Moreover, the accuracy of the method depends on the parameters. Therefore, we propose a parameter setting method for multiple cases depending on the type of data accumulated data. In addition, the classification of multiple types of change using a method that clusters the results of the change point and anomaly detection is also proposed.

The rest of the paper is organized as follows. Section II presents related works. Section III presents our proposed detection and classification methods. Section IV presents the parameter setting method. Section VI evaluates our proposed method, and Section VII concludes the paper.

II. RELATED WORK

This section represents existing works of related research fields, viz., walking recognition and fall detection, and prerequisite technology of the proposed method, which is an image-based human posture estimation.

A. Walking Recognition

Walking recognition is one of the research fields of human activity recognition, which is human activity recognition is defined as the ability to recognize human activities using sensor data [4] [11] [12]. Each recognition method, including walking recognition, comprises two steps: data collection using sensors and human activity estimation based on the collected data. Some examples of sensors are cameras, wearable sensors,

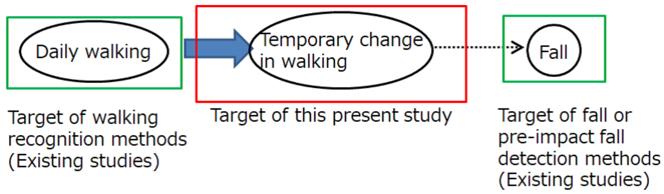

Figure 1. Relationship between this work and existing works.

and object-tagged sensors [13] [14] [15]. Walking recognition methods also employ these two steps.

Currently, several studies on walking recognition have been conducted; these studies focus on differences in sensors, target actions, and estimation methods. Khan et al. have detected walking and five other activities (i.e., sitting, standing, washing hands, driving, and running) using accelerometer data obtained via change point detection [8]. Further, they employ a genetic algorithm for the optimizing the parameters of change point detection to improve its accuracy. Thus, the accuracy of the detection is 99.4%–99.8% [8]. Trung et al. classified five types of walking (i.e., walking on a flat ground, upstairs/down stairs, and up/down a slope) with a 90.4% accuracy based on the accelerometer data using a support vector machine [16]. Davis and Taylor recognized walking speeds (i.e., normal speed, half the normal speed, and double the normal speed) and classified walking and 11 other activities (e.g., running, skipping) from the data of video-based four joint coordinates [17]. This classification is based on a threshold calculated statistically from the motion of the joint coordinates. Haescher et al. classified walking speed into four speeds (i.e., 1, 2.5, 4, and 5 km/h) based on the capacitive sensor data [9]. This walking recognition has numerous applications such as automated surveillance, monitoring systems to identify people that may be injured or require assistance, and estimation of the amount of activity [9] [17].

Unlike this study, the above mentioned studies do not focus on a temporary change in walking. However, this study can be used in combination with the previously mentioned studies to detect walking in several activities using the existing methods and to recognize a change in walking using our method.

B. Fall Detection

Fall detection is another research field in human activity recognition. Two approaches can be adopted to reduce the damage of a fall.

The first is fall detection, which detects a fall after or just before it occurs. It is classified into two types; the first one is fall detection, which refers to detection after a fall, and pre-impact fall detection, which refers to detection just before a fall [5]. There are several studies on fall and pre-impact fall detection, which focus on differences in sensors such as an accelerometer [18] (fall) [19] (pre-impact), a gyroscope [20] (fall), a video [21] (fall), and a depth sensor [22] (pre-impact).

The second one is detection of a temporary change in walking, which may cause falls. This approach helps to reduce the incidence of falls through detection and the provision of countermeasures to the temporary changes in walking. In this paper, we propose a detection method of a temporary change. Figure 1 presents the relationship between this study and the existing ones, as well as the flow from daily walking to fall. A temporary change is observed in daily walking if an incident occurs; some changes lead to falls. Existing studies on walking recognition target daily walking, and fall detection target falls or pre-impact falls. This study aims to detect the temporary change in walking. Therefore, existing studies and this present study do not exhibit a competitive relationship.

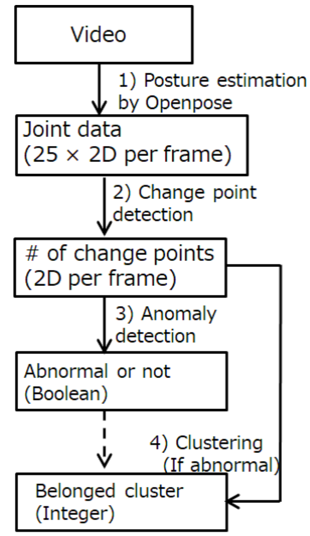

Figure 2. Overview of the proposed method using dataflow.

C. Image-Based Human Posture Estimation

In our proposed method, human joint coordinates are used as input for change point detection. These coordinates can be extracted using the existing methods. In this paper, OpenPose [23] is used to extract the coordinates. It outputs two-dimensional (2D) 25-joint data per image via deep learning-based posture estimation. Our proposed method is not constrained by OpenPose. If coordinates can be obtained, the output of other image-based posture estimation methods such as ArtTrack [24] and DeepCut [25] can be used. Our method can be applied in non image-based methods such as motion capture or depth sensor.

III. Recognition Method for a Temporary Walking Change

The input of the proposed method is the coordinate data of human joints during walking. This method comprises three steps: change point detection, anomaly detection, and clustering. It determines anomalous walking, which exhibits behavior that temporarily differs from daily walking. Anomalous walking detection can be employed to analyze the causes of falls. The input is obtained from videos using OpenPose. In this paper, we use a video ($1,920 \times 1,020$ resolution and 30-fps frame rate) of a person walking. The video of the person is captured from the front while the person is walking towards the camera.

Figure 2 presents the overview of the proposed method using the dataflow from the video data to determine anomalous walking. The preprocessing of the proposed method is the posture estimation performed by OpenPose. OpenPose has the ability to detect a human and estimate posture from the video.

Moreover, it outputs joint coordinates, which are 2D 25-point data obtained from one frame of the video.

The joint coordinate data are inputs of proposed method. The three steps of the method are presented below.

1) Change point detection determines whether each joint point or relationship between two joints is a change point. The output is the number of change points in each frame as detection is processed for each joint point and the relationship of each frame.
2) Anomaly detection detects anomalous walking using the number of change points. The result is output per overall walking data (data from one video).
3) Clustering classifies the anomalous walking detected by the second step. It is processed only if input walking data are detected as anomalies.

The processing of each step is performed via unsupervised machine learning. It means that manual data labeling is not required. However, the first and second steps need some preprocessing to determine the parameter of each machine learning algorithm. Preprocessing involves the preparation of the parameter determination standard. Thus, parameters are provided as a value relative to the standard. For example, when the parameter is three and if the result is greater than three times the standard, it is considered abnormal. About 1 or 2 min of walking data are required for each subject. In the evaluation, we use 20 videos of the daily walking data for each subject, with an average length of videos of approximately 3s. Thus, the total time of the walking data is approximately 1 min.

To distinguish daily walking, the terms “daily walking” and “normal walking” are utilized. “Daily walking” means input data given by a human as non-anomalous walking, and “normal walking” means output data detected by the proposed method as non-anomalous walking. In the next sections, the details of each step and each parameter are explained.

A. Change Point Detection for Human Joint Data

Change point detection is processed in each frame data using the target frame and previous frames consecutive to the target. The data format of the output data of OpenPose is 2D 25-point data per frame. Each data presents the 2D coordinate of the joint coordinate. Two methods can be employed to deal with the data; the data are treated as one 50-dimensional (50D) data or the data are treated as 2D 25-point data. The advantage of the method that uses it as 50D data, the relationship between each joint can be considered. As an example of the relationship, if the head position is lower than the shoulder position, the relationship is considered abnormal because the position of the head is higher than that of the shoulder in daily walking. However, when some joints significantly change, it affects the entire result. The effects may cause accuracy loss because the coordinates of a part of the joints are possibly changed significantly by the misestimation of OpenPose. Conversely, if the data are processed as 25-point data, the problem does not occur. Instead, the relationship cannot be considered. To solve this problem, we propose the use of difference data of all pairs of joints in addition to the 25-point data. This enables us to deal with the relationship using the sets of 2D data. In this method, the misestimation only affects a part of the difference and joint data, and not the entire result. Hereafter, the difference data of the pairs of joints are simply called “difference data.”

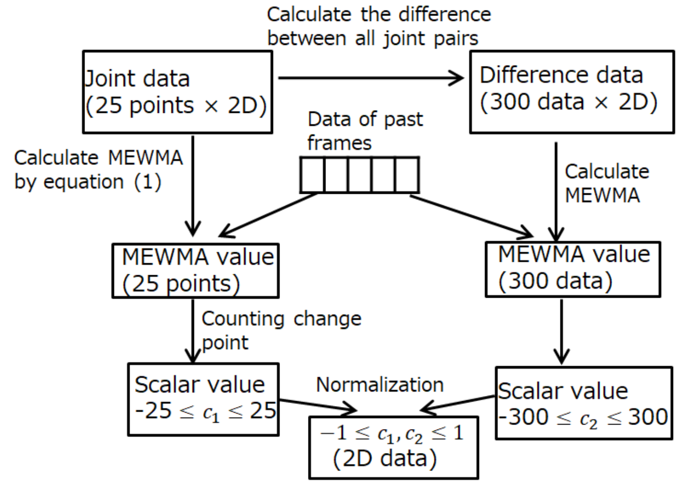

Figure 3. Dataflow of change point detection.

The total number of data is 325, which is obtained from difference data, which is 300 and joint data, which is 25. The result of change point detection from these data is output as the number of change points. In this method, we divide the result of the joint and difference data to distinguish a change in the movement of joints and the relationship between joints. Thus, the output is one 2D data per frame.

Figure 3 presents the change point detection flow as a dataflow. The input data are the joint data of 25 points, and the difference data consist of all pairs. We employ the multivariate exponentially weighted moving average (MEWMA) algorithm as the change point detection algorithm because it only uses target walking data and is not affected by individual differences [26]. The MEWMA algorithm uses data from the target frame and from previous frames consecutive to the target. If the number of frames is n (i.e., nth frame is the target frame), the MEWMA vector is defined as

$$Z_i = \lambda X_i + (1-\lambda)Z_{i-1} | i = 1, 2, 3, \ldots n, Z_0 = 0 \quad (1)$$

X_i denotes the input vector, which is the coordinate data of the joint or the difference data of each frame. The change point can be detected by utilizing the MEWMA vector as

$$T^1 < h_1, T^2 > h_2 | T^2 = Z_n^T \Sigma_n^{-1} Z_n \quad (2)$$

Z_n denotes the MEWMA vector and Z_n^T its transpose; Σ_n^{-1} denotes the variance-covariance matrix of Z_n; and h_1 and h_2 denote the thresholds ($0 < h_1 < h_2$): h_1 is the case, in which a change in the movement during walking becomes small, and h_2 is the case when a change in the movement during walking becomes large. The counter of the change point is decreased when $T^2 < h_1$, and the counter is increased when $T^2 > h_2$. This helps distinguish the cases, in which the movement becomes small or large.

Preprocessing is required to determine the thresholds (h_1, h_2). In preprocessing, the average value of T^2 is calculated using Equation (2) utilizing the data of several minutes of daily walking. h_1 and h_2 are calculated by *the average value of* $T^2 \times$ *constant value*. Thus, when the value is T_d^2, h_1 and h_2 can be represented as $\frac{T_d^2}{g_1}$ and $g_2 T_d^2$, respectively. g_1 and

g_2 are constant parameters and the determination method of g_1 and g_2 is described in Section IV.

Using the MEWMA algorithm for all joints and differences, the range of the counter value is $-25 < counter < 25$ (joints) and $-300 < counter < 300$ (differences). Finally, the counting results are normalized by dividing by 25 or 300. The outputs of change point detection are the 2D data, and the form is suitable for the anomaly detection mentioned in the next section.

B. Anomaly Detection for the Number of Change Points of Walking

The input data are 2D data per frame obtained from change point detection. Anomaly is defined as a temporary change in the movement in daily walking. Thus, the data of daily walking are required for each person. The data are prepared as a set of the result of change point detection for daily walking for a few minute; this set is called "normal data."

Anomaly detection is performed in each frame by comparing the normal data and target frame. Thus, anomaly detection is repeated in each frame by adding target frame data and removing it after the detection. We use a local outlier factor (LOF) for anomaly detection as it can be calculated in each data. Moreover, its feature is suitable for repetition [27]. LOF is calculated by comparing local densities. The local density is calculated using reachability distance (RD) expressed as

$$RD_k(p,q) = max(k - distance(q), d(p,q)) \tag{3}$$

where p and q denote the points of 2D data, d(p,q) is the Euclidean distance between p and q, and k-distance(q) denotes the Euclidean distance between q and the k-nearest neighbor of q. The local density, which is termed local reachability density (LRD), is expressed as

$$LRD(p) = \left(\frac{\Sigma_{q \in kNN(p)} RD_k(p,q)}{k}\right)^{-1} \tag{4}$$

where kNN(p) denotes the set of the k-nearest neighbor of p. Using the LRD, LOF is expressed as

$$LOF(p) = \frac{\Sigma_{q \in kNN(p)} \dfrac{LRD(q)}{LRD(p)}}{k}. \tag{5}$$

The value of LOF is large when the target is an outlier. LOF indicates whether the target frame is an anomaly; however, the result of the frame is not used to detect anomalous walking directly, because an anomaly frame may appear in the misestimation of OpenPose. Therefore, in this method, the condition of anomalous walking is the walk that includes two or more continuous anomalous frames. To distinguish anomalous walking, the walk characteristics are defined as the average number of change points of the continuous two or more anomaly frames.

Figure 4 presents an example of anomaly detection. There are 10-frame data, and the LOF is calculated for each frame. Figure 4 presents the case of frames 1 and 2. In the field of the LOF calculation, each frame data is deleted after calculation. The frames identified as outliers are collected if there are two or more continuous frames, and the walking including the frame considered as outlier is identified as anomalous walking. The characteristics of anomalous walking are the average values of the frames considered to be outlier, excluding the first frame of the continuous frame.

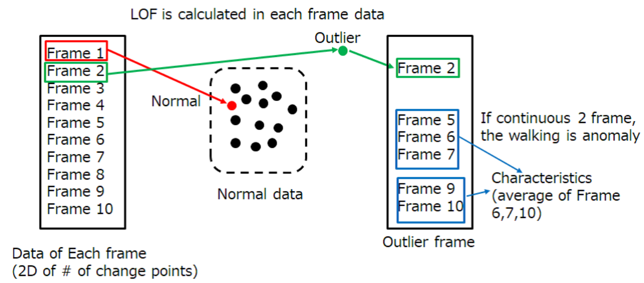

Figure 4. Example of the anomaly detection method.

C. Anomalous Walking Classification

The 2D characteristic data of anomalous walking are obtained from one video. When there are multiple anomalous walking videos, clustering algorithms can be used to identify the characteristics and walking can be classified. In this paper, we use K-means clustering, which is a typical clustering algorithm. In K-means clustering, the parameter given by a human is only the number of clusters k. In K-means clustering, each point, which means the characteristics of walking, is randomly classified into k clusters. Next, the following two steps are repeated until convergence.

1) The center of gravity of each cluster is calculated.
2) Each point is reclassified into the cluster, which has the nearest center of gravity from the point.

By clustering, the detection of anomalous walking and classification of the walks is completed from the walking videos. In this method, the longer the video, the higher is the probability of the video to include multiple instances of anomalous walking, because anomaly detection handles the video as one data unit. In classification, it is assumed that there is only one instance of anomalous walking per video. Thus, a long video should be divided per several seconds. However, videos that are too short are not suitable for the method. The minimum length of the video is two steps because walking has a periodicity of two steps.

IV. Parameter Setting Method in Various Cases

The accuracy of the proposed method largely depends on the parameter value. The optimal parameters depend on the individual and the type of temporary changes in walking. Therefore, parameters should not be set in advance, but instead be determined for the given data using an appropriate method. In this paper, we propose a method for the parameter setting for multiple cases, under the assumption that sufficient data are not available.

A. Common Parts of the Parameter Setting Method

In this method, parameters that need to be determined are as follows.

- n: The number of frames to calculate the MEWMA vector (Equation (1)).
- λ: The weight of the input vector in Equation (1) ($0 \leq \lambda < 1$).
- g_1, g_2: The parameters for determining the threshold value of change point detection. The parameters of

TABLE I. Assumed cases in the proposed method.

	Daily walking	Anomalous walking	Individual data
Case 1	○	○	○
Case 2	○	○	×
Case 3	○	△	×
Case 4	○	×	×

joint data are defined as gc_1 and gc_2, and the parameters of difference data are defined as gd_1 and gd_2.

- l: The threshold of anomaly detection of LOF. If the value of $LOF > l$, the frame is identified as outlier.

There are seven parameters, and it is impossible to find the best combination of these parameters because of the risk of combination explosion. Therefore, we use a greedy algorithm to determine the parameters. The greedy algorithm is used for repeating the two steps, which select a parameter and determine the best condition when only the selected parameter is changed. The repetition is performed until all parameters are determined. The order of the parameters to be changed is determined by the order of the calculations. The order is n, λ, gc_1, gc_2, gd_1, gd_2, and l.

The results vary depending on which indicator is targeted for optimization. In the next sections, the assumed cases and the indicators corresponding to the cases are explained.

B. Assumed Cases and Parameter Setting for the Cases

The available data for the parameter setting are different from the cases. The data required in this method are those of daily walking and anomalous (temporary change) walking for each individual. One of the requirements is the presence of sufficient data for each individual. Therefore, there are three requirements for the data. We assume five cases, depending on which requirements the data satisfy.

Table I represents the assumed cases. The requirement of anomalous walking is divided into three cases caused by the multiple types of anomalous walking. Anomalous walking is classified into two categories, in which the movement becomes small or large. The circle indicates that both data are available, whereas the triangle indicates that only one data point is available. The cross indicates that no data of anomalous walking is available. The requirements of daily walking and individual data are simply divided by whether the data are available. If the data are not available, the method is not applicable. Therefore, Case 4 has the smallest number of data.

Figure 5 presents the flowchart of the parameter setting. The indicator changes because of the requirement of anomalous walking. If data of anomalous walking are fully available, the F-measure is used as an indicator and calculated using precision and recall as expressed in Equations (6), (7), and (8):

$$precision = \frac{TP}{TP + FP} \tag{6}$$

$$recall = \frac{TP}{TP + FN} \tag{7}$$

$$F - measure = \frac{2 \times precision \times recall}{precision + recall} \tag{8}$$

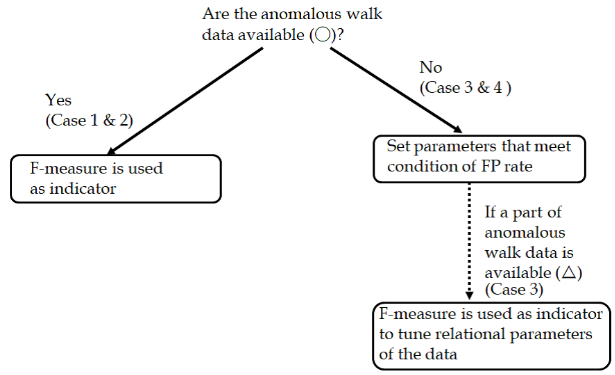

Figure 5. Flowchart of parameter setting.

where TP denotes true positive, FP denotes false positive, and FN denotes false negative. In other cases, the F-measure cannot be calculated because the calculation of TP requires data of anomalous walking. Therefore, in these cases, the FP rate is used. The FP rate is calculated using the ratio wherein daily walking is assessed as anomalous walking. The calculation of the FP rate is feasible because the data of daily walking are available in all cases. In general, the FP rate and TP rate are inversely correlated. A threshold is set for the FP rate, and parameters are selected such that the FP rate is below and closest to the threshold. Subsequently, if part of the data of anomalous walking are available, its relational parameters are (gc_1 and gd_1 or gc_2 and gd_2) changed so that the F-measure is maximized.

V. Evaluations

We evaluated the accuracy of the proposed method using four types of anomalous walking. Section V-A shows the detail of anomalous walking and subsequent sections show evaluation results.

A. Evaluation Method and Environment

In the proposed method, we evaluate the accuracy of the detection and classification of anomalous walking. Thus, it is important to prepare data of anomalous walking, for which the correct answer is known. We prepare the data of daily walking and change in walking from daily walking to anomalous walking. We included three adults as subjects. The detail of walking is presented in Figure 6. The walks start 6.6 m away from the camera and change to anomalous walking after reaching 2.4 m. The following are the four types of anomalous walking.

- Back: Go back one step and start walking again.
- Side: Walk 40 cm from side-to-side.
- Stop: Stop and start walking again.
- Wide: Take one large step (1 m).

The resolution of the videos is $1,920 \times 1,020$, and the frame rate is 30 fps. Each subject performs each type of walking (daily walking and four types of anomalous walking). Thus, the number of data of each type is 60. The average number of frames of each type of walk is presented in Table II.

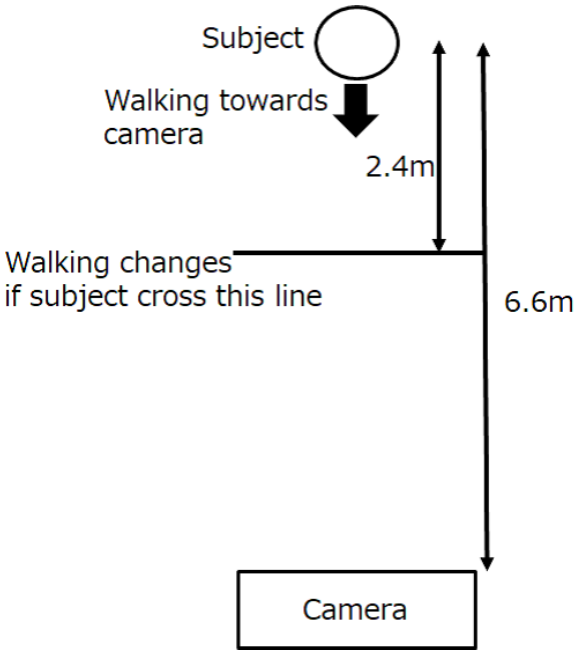

Figure 6. Walking during evaluation.

TABLE II. AVERAGE NUMBER OF FRAMES IN EACH WALKING TYPE.

Walking type	Daily walking	Anomalous walking
Daily	91	0
Back	49	83
Side	39	67
Stop	50	58
Wide	39	25

B. Transition of the Number of Change Points in Change Point Detection

In this section, the transition of the number of change points is presented. The transition of the number of change points was achieved using Case 2 to summarize the results of all subjects. It is an interim result of the proposed method; however, it presents an overall trend of each type of anomalous walking. The data of daily walking is used only when determining the parameters, and change point detection is performed for the four types of anomalous walking.

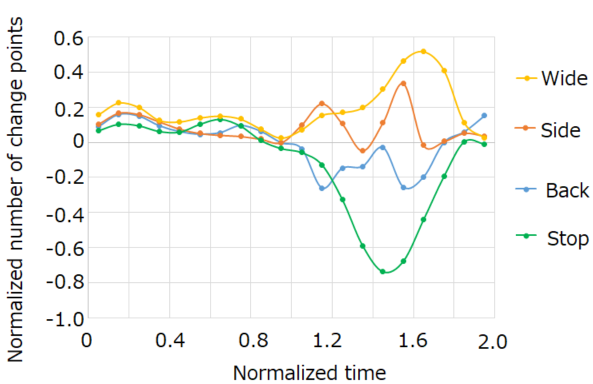

Figure 7. Transitions of the number of change points of joint data.

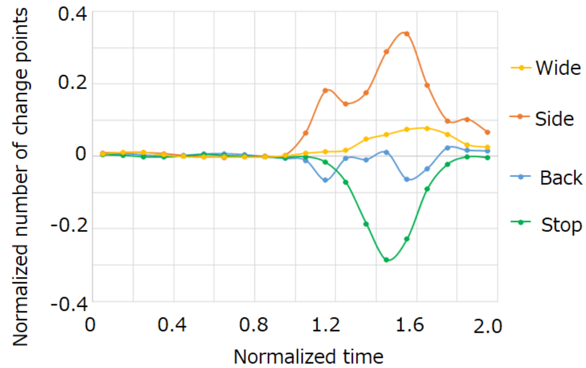

Figure 8. Transitions of the number of change points of difference data.

Transitions of the number of change points are presented in Figures 7 and 8. These figures show the average number of change points for 60 walks performed by three subjects. The x-axis indicates normalized time; 0-1 indicate daily walking, and 1-2 indicate anomalous walking. The boundary between daily walking and anomalous walking is determined by human confirmation in every frame. The y-axis shows the normalized number of change points. The data are plotted every 0.1 point on the x-axis as the average number of change points in the range. The positive values in the result indicate a change from walking movements to intense movements, whereas the negative values indicate a change in movements to small movements. Even for daily walking, the values of the joints are positive because of the periodic change in foot movement. However, the relationship between the joints does not change, and the values of difference are almost 0. Figures 7 and 8 demonstrates that the transition of the number of the change points changes between daily walking and anomalous walking; further, it is different in each type of anomalous walking. In Side and Wide, the values are both positive; however, a change in the difference in Wide is smaller than that in Side. The change in Wide is only a change in stride, and the change in the positional relationship between the joints of the body is smaller than that in Side. With regard to Stop and Back, the values of Stop are smaller than those of Back, and Stop is characterized by the temporal stopping of the movement of all joints. Thus, this method can detect the difference between each type of anomalous walking. Therefore, the proposed method can be used for analyzing the trend of each walking type. Moreover, the result of change point detection can be utilized for anomaly detection and classification. However, in the actual operation, the types are not provided. Thus, an analysis should be conducted after this classification if the method is used for the analysis.

C. Accuracy Evaluation of Anomalous Walking Detection by Comparison with the Baseline Method

We evaluate the accuracy of anomaly detection of the proposed method by performing a comparison between the proposed and existing methods. However, it is difficult to perform direct comparison as the existing methods for walking recognition do not target temporary changes in walking, as previously mentioned in Section II. Therefore, we define a statistics threshold-based method, which is one of the typical

TABLE III. Result of anomaly detection for each type of anomalous walking in the proposed method.

Walking type	Subject A		Subject B		Subject C		Total	
	TP	FP	TP	FP	TP	FP	TP	FP
Back	20	0	20	0	20	1	60	1
Side	14	1	16	1	19	1	49	3
Stop	20	0	20	1	20	2	60	3
Wide	16	2	20	1	16	2	52	5
Total	70	3	76	3	75	6	221	12

TABLE IV. Result of anomaly detection for each type of anomalous walking in the baseline method.

Walking type	Subject A		Subject B		Subject C		Total	
	TP	FP	TP	FP	TP	FP	TP	FP
Back	19	11	20	9	19	5	58	25
Side	17	4	20	16	20	2	57	22
Stop	13	5	18	9	14	4	45	18
Wide	13	6	13	5	15	7	41	18
Total	62	26	71	39	68	18	201	83

techniques in human activity recognition, including walking recognition [17] [28], as a baseline method and compare its accuracy with that of the proposed method.

1) Baseline method: In walking recognition, the data of waist movement are often utilized because waists are close to the center of gravity of humans. Moreover, the movements of the center of gravity are related to anomalous walking targeted in this study [28] [29]. Therefore, the baseline method uses the coordinate data of the waist for anomaly detection. The absolute coordinate data of the waist cannot be utilized as they are retrieved from the video. Therefore, the relative coordinate data from the neck are used because the coordinate data of the neck are on the central line of the body, and the change in the relative position between the neck and the waist is small in daily walking. It is divided by the ratio of the distance of each frame between the neck and the waist and the distance at the start of walking, because the size of the body is changed based on the distance from the camera. If the x-coordinate after the correction is significantly changed, walking is judged as anomalous walking. The average (m) and standard deviation (σ) of the x-coordinate are calculated, and if the x-coordinate is beyond the range of $m \pm 2.2\sigma$, the walking is judged as anomalous walking. The constant value “2.2”, which is the parameter of the baseline method, is determined so that the F-measure is maximized.

2) Comparison result: Tables III and IV present the result of the anomaly detection for each type of anomalous walking. In the proposed method, Case 1 is assumed, and the parameters are detected by the greedy algorithm described in Section IV. To avoid overfitting, cross-validation is performed by dividing the number of each type of data by 15 and 5, which are indicated as training and test data. Therefore, four sets of parameter exist. Table V presents all parameter sets; the parameters are of different combinations, even in the same subject. Therefore, multiple local solutions in the parameter setting algorithm exist.

In Tables III and IV, TP and FP denotes true positive and false positive respectively. The number of data of each walking type and each subject is 20. Thus, if TP is 20, the TP rate is 100%. FP indicates that daily walking is misjudged as anomalous walking. Each video includes daily walking because the walking is changed from daily walking to anomalous walking. Therefore, the number of data of daily walking is 20 in each walking type and each subject. Comparing each method, the precision is 94.8%, recall is 92.0%, and accuracy is 93.5% in the proposed method; the precision is 83.6%, recall is 70.8%, and accuracy is 74.6% in the baseline method. The accuracy is calculated using Equation (9)

$$accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{9}$$

where TN is the true negative. TN and FN are not shown in the table since they can be calculated by (240 (the total number of data) $- TP or FP$). All indicators show the performance of proposed method is above the baseline method. Moreover, the accuracy of the proposed method is high ($> 90\%$) according to the standards in [4].

The difference of FP between the proposed and baseline methods is larger than that of TP. As shown in Section V-B, there are periodical foot movement even in daily walking. The baseline method may misjudge such movements as anomaly. In contrast, the proposed method can avoid the misjudgement using both joint and difference data.

D. Accuracy Evaluation of Anomalous Walking Detection by Comparison between Each Case

Table VI lists the result of the anomaly detection of each case of the proposed method. In Case 4, the condition of the FP rate is $\leq 10\%$. Please note that the FP rate can be away from 10% because the used data of parameter setting and accuracy evaluation is different. In this evaluation, the initial value of parameter setting is randomly detected. In actual cases, the parameter of Case 2 is useful for the initial value. Therefore, the parameter sets are summarized in Table VII for reference. Please note that there are four sets because the evaluation is performed in cross validation.

The performance indicators are summarized in Table VIII. In comparison, accuracy decreases as the amount of available data type decreases. However, even in Case 4, the accuracy is higher than that of the baseline method. In Case 4, the TP rate is lower than that of the baseline method. The condition of FP rate should be higher than 10% to avoid it because the TP rate is inversely proportional to the FP rate.

The cases of the proposed method can be switched as data are collected. Therefore, in actual operation, the parameter setting method should be selected depending on the data available at the start, and it should be switched as data are collected.

Based on the comparison between Cases 1 and 2, the difference in accuracy is small. However, the difference is caused because a part of the accuracy of Case 2 is significantly low. Table IX shows the details of the results of Case 2. The TP of Wide of Subject C is 9, and the TP rate is 45%. The reason for the low TP is the unsuitability of the parameters for the subject because Case 2 cannot consider individual differences. To avoid this problem, the proposed method should be performed as Case 1, thereby collecting as much data as possible.

By comparing Cases 3 and 4, it can be inferred that the accuracy is improved not only by increasing the TP of Side and Wide but also by decreasing the FP of Stop as FP is

TABLE V. PARAMETER SETS OF CASE 1 IN THE PROPOSED METHOD

Parameters	Subject A				Subject B				Subject C			
n	31	36	32	34	38	32	31	38	31	35	36	31
λ	0.6	0.8	0.58	0.5	0.51	0.62	0.34	0.51	0.05	0.43	0.8	0.51
gc_1	1000	1000	100	1200	1200	100	1000	1200	80	1560	1000	100
gc_2	3.4	3	4.2	4.6	3	4.2	3.6	3	4.2	1.6	3	5
gd_1	820	900	300	1580	1160	1120	1260	1240	700	1260	680	1200
gd_2	5.4	8	4.4	4	8	4.4	4	8	4.4	5.2	7.2	4.2
l	2.3	4.2	2.2	3.1	3.8	2.2	3.2	3.5	2.8	3.1	4.2	2.2

TABLE VI. RESULT OF ANOMALY DETECTION IN THE PROPOSED METHOD FOR EACH CASE.

	Back		Side		Stop		Wide		Total	
	TP	FP	TP	FP	TP	FP	TP	FP	TP	FP
Case 1	60	1	49	3	60	3	52	5	221	12
Case 2	59	6	52	0	60	3	48	8	219	17
Case 3	60	8	50	4	60	4	32	1	202	17
Case 4	60	7	30	4	60	8	31	1	181	20

TABLE VII. PARAMETER SETS OF CASE 2

Parameters	Set 1	Set 2	Set 3	Set 4
n	15	31	34	35
λ	0.5	0.56	0.44	0.60
gc_1	800	1100	1400	1400
gc_2	2	4	4.2	4.2
gd_1	800	1260	1240	1120
gd_2	2	3.6	3.6	3.6
l	4.5	2	2.3	2.3

TABLE VIII. SUMMARY OF PERFORMANCE INDICATORS OF TABLE VI (%).

	TP rate	FP rate	Precision	Recall	Accuracy
Case 1	92.1	5.0	94.8	92.1	93.5
Case 2	91.2	7.1	92.8	91.3	92.0
Case 3	84.2	7.1	92.2	84.2	88.5
Case 4	75.4	8.3	90.0	75.4	83.5

TABLE IX. RESULT OF ANOMALY DETECTION IN CASE 2.

Walking type	Subject A		Subject B		Subject C		Total	
	TP	FP	TP	FP	TP	FP	TP	FP
Back	20	4	20	1	19	1	59	6
Side	16	0	18	0	18	0	52	0
Stop	20	1	20	0	20	2	60	3
Wide	19	3	20	1	9	4	48	8
Total	75	8	78	2	66	7	219	17

caused by the daily walking being misjudged as a temporary change. Therefore, a part of the data of anomalous walking can improve the accuracy of anomaly detection.

Comparing the results of each walking type, the TP of Back and Stop is 100% except for Case 2. This indicates that changes in movement that become small are easy to detect using the proposed method. This is because daily walking includes periodic foot movement and the feature prevents the detection of Side and Wide. Therefore, if you attach importance to the TP of Side and Wide, the indicator using parameter setting should be included in the conditions of the TP of Side and Wide. For example, the condition of the maximization of the F-measure while satisfying the TP rate of each type of anomalous walking is more than 90%.

E. Anomalous Walking Classification

Clustering is performed in the TP of Case 2 in anomaly detection. For accuracy evaluation, Case 2 is evaluated via cross-validation. However, the TP cases detected via cross validation are not suitable for clustering evaluation as the features of anomalous walking are calculated based on different parameter sets. Therefore, Set 1 of Table VII is used for all data to detect anomalous walking. Case 2 is used so that the same parameters can be used for all data of subjects.

Table X presents the result of clustering into four clusters. The number of clusters is the same as that of walking types. Each cluster is indicated by a number because of unsupervised clustering. In this result, clustering is performed separately for each subject, and we group each cluster of each subject with the highest match rate. Clustering does not classify four types of walks into four clusters. Back and Stop are grouped, and the clusters appear divided, such as Back and Stop, Side, Wide, and others. To explain this result, the characteristics of each walking type are plotted in Figure 9. Back and Stop overlap and create the same cluster, indicating that the movement tendencies of Back and Stop are the same, and that the difference is only the magnitude of the value. The trend is probably caused by the stopping motion because Back includes the motion of Stop. This is because stopping is required to switch the front step to the back step. The differences indicate the stopping time length.

We perform clustering into three clusters based on the grouping, and the result is presented in Table XI. In this result, the anomalous walking is classified into three clusters (Back and Stop, Side, and Wide), and the accuracy rate is 89.1%. The rate is medium as per the standard of [4], and it classified walks better than the existing method of walking recognition.

In terms of anomaly detection, clustering may exhibit

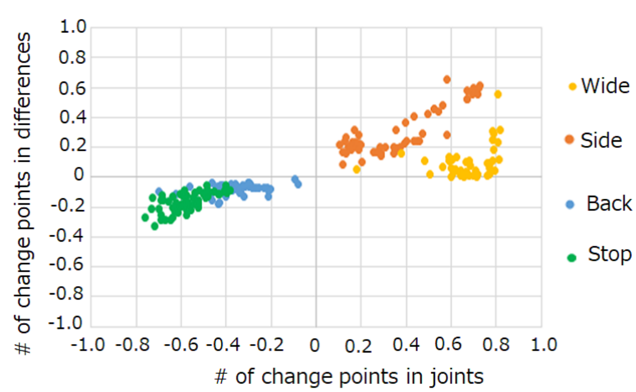

Figure 9. Characteristics of anomalous walks of each type of walking.

TABLE X. RESULT OF THE CLASSIFICATION INTO FOUR CLUSTERS FOR EACH TYPE OF ANOMALOUS WALKING.

Walking type	Cluster 1	2	3	4
Back	46	0	7	1
Side	0	52	4	2
Stop	50	0	10	0
Wide	0	2	13	33

TABLE XI. RESULT OF THE CLASSIFICATION INTO THREE CLUSTERS FOR EACH TYPE OF ANOMALOUS WALKING.

Walking type	Cluster 1	2	3
Back	46	0	8
Side	0	54	4
Stop	58	0	2
Wide	0	10	38

individual differences of walking. Figure 10 presents the plots of the same data in Figure 9, which are indicated by colors according to each subject. For Side and Wide, the figure indicates that the subjects have different tendencies of point distribution.

VI. DISCUSSION

According to the evaluation results, in the proposed method, the accuracy of detection and classification of anomalous walking is sufficient compared to other human activity recognition methods [4]. However, the proposed method requires the data of subjects to set parameters. Thus, it can be used to detect abnormal walking in a particular person. Therefore, the main application could be the reduction of incidents in nursing homes and companies that are repeatedly used by specific people. In this paper, we did not evaluate the accuracy in the elderly, and for practical use, future research will need to conduct experiments in the elderly.

VII. CONCLUSIONS

Detecting the temporary change in walking that causes falls can help alleviate problems such as expensive hospitalization and injury. However, existing methods only recognize the walking speed or whether a person is walking. In this paper, we proposed an anomalous walking detection and classification method that employs three processes: change point detection, anomaly detection, and clustering. Thus, instances of anomalous walking were detected in 92.1% of cases using 240 videos that included the change from daily walking to anomalous walking. Furthermore, in 89.1% of cases, the detected instances of anomalous walking can be classified into three clusters. The average length of the video is 87 frames (30 fps) for the longest motion. The result indicates that the proposed method can detect and classify a temporary change in walking. Moreover, this method can be used to the analyze the action that causes falling. We evaluated the method using video data, whereas the required input of the method is the coordinate data of the joints. Thus, the method has a wide range of application. For example, the method can be applied to wearable technology such as motion sensors if it can obtain the coordinates of a sufficient number of joints. In practical use, the application of the method will be expected for older people because they are vulnerable to falls. Thus, in future work, we will additionally perform evaluations for the elderly to verify the effectiveness of the method for elderly.

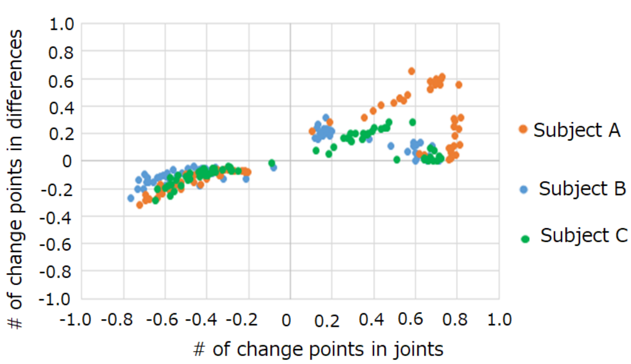

Figure 10. Characteristics of anomalous walks for each subject.

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