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One-Step Gait Pattern Analysis of Hip Osteoarthritis Patients Based on Dynamic Time Warping through Ground Reaction Force

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Abstract: Osteoarthritis (OA) of the hip is a degenerative joint disease, which means it causes gradual damage to the joint, and its incidence rate continues to increase worldwide. Degenerative osteoarthritis can cause significant pain and gait disturbance in walking, affecting daily life. A diagnosis method for hip OA includes questioning and various walking movements to find abnormalities of gait patterns based on human observation. However, when multiple gait tests are performed to notice the gait, it can cause pain continuously, even during the examination. Suppose hip OA could be diagnosed with only a one-step gait; both patients and medical doctors would be benefited because the diagnosis time can be reduced and the burden on the patient is decreased dramatically. Therefore, in this paper, we aimed to propose a method to recognize the abnormality of the hip OA patient with a one-step gait pattern based on a dynamic time warping (DTW) algorithm through three directional ground reaction forces (GRFs). After a force plate measured three directional GRFs, the data of twenty-three hip OA patients and eighteen healthy people were classified using supervised machine learning algorithms. The results of the classification showed high accuracy and reliability. Then, the DTW algorithm was applied to compare the data of patients and healthy people to find out when patients may feel pain during the gait. By applying the DTW algorithm, it was possible to find out in which gait phase the patient's gait showed the difference, such as when the heel first contacted the ground, in the middle of walking, or when the toe came off the ground. Through the results, the data of the one-step gait on the force plate enabled us to classify patients and healthy people with a high accuracy of over 70%, recognize the abnormal gait pattern, and determine how to relieve the pain during the gait.

Keywords: abnormal detection; dynamic time warping; hip osteoarthritis; one-step gait pattern

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1. Introduction

The hip joint is one of the largest weight-bearing joints in the body and is commonly affected by arthritis after the knee joint. Among hip arthritis, degenerative osteoarthritis is the most common form of arthritis. It can occur when the joint is deformed or damaged due to congenital or acquired disease or trauma or when it appears with age without a specific cause. The global incidence rate of hip osteoarthritis (OA) has increased from 740,000 to 1.58 million between 1990 and 2019. This trend is likely to continue due to the rapid aging of the world population, increased lifespan, and prevalence of arthritis and obesity [1]. Thus, the importance of early treatment and continuous disease management is essential.

OA in hip joints induces pain in the gait process, thus limiting the range of movement. While pain and weakened muscles cause abnormal gait on the affected side, the non-affected side also shows an abnormal gait caused by compensatory motions in other joints. From these, hip OA patients have a slower gait speed when compared to healthy subjects. The stride length of the affected side is shortened, the stance duration is lengthened, and the swing duration is quickened. When comparing the patient's affected and non-affected sides, the stance duration of the affected side was shorter. Thus, although there is no severe problem in classifying the difference in gait pattern between hip OA patients and healthy subjects, the current methods for evaluation or diagnosis still give patients a high burden.

When diagnosing such hip OA in general, medical doctors ask the patient about the onset of symptoms, progression pattern, and medical history. Then, they request the patient to walk in various postures along a line to record the gait pattern based on human observation. Existing methods for diagnosing degenerative hip arthritis include the gait in various motions. For example, the squat test can be used to see the patient's ability to squat, and the hip flexion and hip scour tests can be used to test the range of motion of the hip and knee [2]. In addition, the TUG test is an abbreviation of the time up to the test. It is an evaluation that measures exercise ability and static and dynamic balance ability when walking for 6 m [3]. However, according to studies, when comparing affected and non-affected sides, the results of swing duration and step length were inconsistent.

Patients may have different gait patterns despite the same hip OA. For example, some studies reported the existence of different gait patterns in patients with the same disease for hereditary spastic paraparesis. Furthermore, these existing methods are problematic because they can continuously cause pain during diagnosis. It causes pain continuously, even while examining people with pain. Despite the same patient with hip OA, it is possible to show a different gait pattern according to the pain symptom at that time. That means deciding on the kinematic solution with measured angles and angular velocities seems complicated.

Suppose hip OA could be diagnosed with only a one-step gait. This would be is excellent for both patients and medical doctors because it would not only reduce the diagnosis time but also decrease the burden on the patient dramatically. Thus, we aimed to propose a method to recognize the abnormality of the hip OA patient with a one-step gait pattern based on a dynamic time warping (DTW) algorithm through three directional ground reaction forces (GRFs).

2. Human Subjects and Methods

2.1. Human Subjects

The human subjects were twenty-three hip OA patients (eleven female, twelve male) with a history of previous surgery and eighteen healthy people (nine female, nine male) without any symptoms. In Table 1, the subjects' gender, age, height, weight, and BMI (=body mass index) are shown as average values for each gender. The mean and standard deviation (SD) are expressed to summarize by gender. For the patients, the average age is fifty-six years and the SD is thirteen years, and for healthy people, the average is fifty-six years and the SD is ten years.

Table 1. Human subject (patients with hip osteoarthritis (OA) and healthy subjects (Normal)) information in this experiment: gender, age, height, weight, and body mass index (BMI).

Class	Gender	Number	Age	Height [cm]	Weight [kg]	BMI [kg/m^2]
Patient	female	11	60.2 ± 14.2	159.7 ± 10.1	65.2 ± 9.7	25.72 ± 4.2
	male	12	52 ± 10.3	164.8 ± 8.2	68.8 ± 8.3	25.35 ± 2.9
mean ± SD			55.7 ± 12.5	162.6 ± 9.2	67.2 ± 9.2	25.5 ± 3.4
Normal	female	9	55.8 ± 8.4	161.0 ± 4.5	57.1 ± 6.3	22.0 ± 1.7
	male	9	55.8 ± 11.9	167.1 ± 5.6	71.4 ± 8.3	25.6 ± 3.5
mean ± SD			55.8 ± 10.0	164.1 ± 5.8	64.3 ± 10.3	23.8 ± 3.2

For the patients, the average BMI is 25.51 kg/m^2 and the SD is 3.42 kg/m^2, and for healthy people, the average is 23.81 kg/m^2 and the SD is 3.25 kg/m^2. There is no statistically significant difference in BMI between the patient and control groups ($p > 0.05$).

All subjects gave their informed consent for inclusion before participating in the study. The study was conducted under the Declaration of Helsinki. The Ethics Committee of the Clinical Trial Center at the Kyungpook National University Hospital in the Republic of Korea approved the study protocol.

2.2. Construction of Dataset

2.2.1. Experimental Environment and System

Figure 1 shows an overview of the experimental environment. All participants walk indoors at the usual speed on the force plate that can measure three directional ground reaction forces (GRFs) and moments. Because of the size limitation of force plate hardware specification, the plate allowed us to measure only one-step gait in this experiment. Thus, wooden blocks of the same height were placed around the force plate. There was no inconvenience to the force plate in measuring the subjects' natural gait. About seven times per human subject were stored as gait data to determine the gait pattern's mean and standard deviation (SD) for each participant.

Figure 1. An overview of the experimental environment: Participants walk on the force plate, which can measure three directional ground reaction forces (GRFs) and moments. Because of the limitation of force plate hardware specification, the force plate allows us to measure only one-step gait in this experiment.

The force plate, in general, is an instrument that measures three directional GRFs and moments generated by a body standing on or moving across them to quantify balance, gait, and other biomechanics parameters. The force plate (2EA, AMTI, Watertown, MA, USA) is utilized to measure GRFs and moments of the human subject's gait. We used Python (version 3.8.8, 64bit) with NumPy 1.20.1, Matplotlib 3.3.4, Pandas 1.2.4, and Scikit-learn 0.24.1 API packages for gait data analysis.

2.2.2. Flow Chart

Figure 2 shows a three-step flow chart for rehabilitating patients after the surgery. The rehabilitation requires personalized training to improve the patient's gait pattern closer to the standard group after the surgery. The first step is the data acquisition to measure data with the force plate. The gait pattern of the healthy group is set to the standard. Then the second is the data analysis to classify whether the patient's gait pattern is close to the standard group and recognize in which step the abnormality has occurred. The machine learning model can discriminate between the normal and the patient groups. The DTW algorithm can make clear in which step the patient feels inconvenient during the gait. The final is personalized training to improve the gait pattern. Although the training is outside the scope of this study, the proposed method supports the medical service provider in evaluating the gait pattern for personalized training.

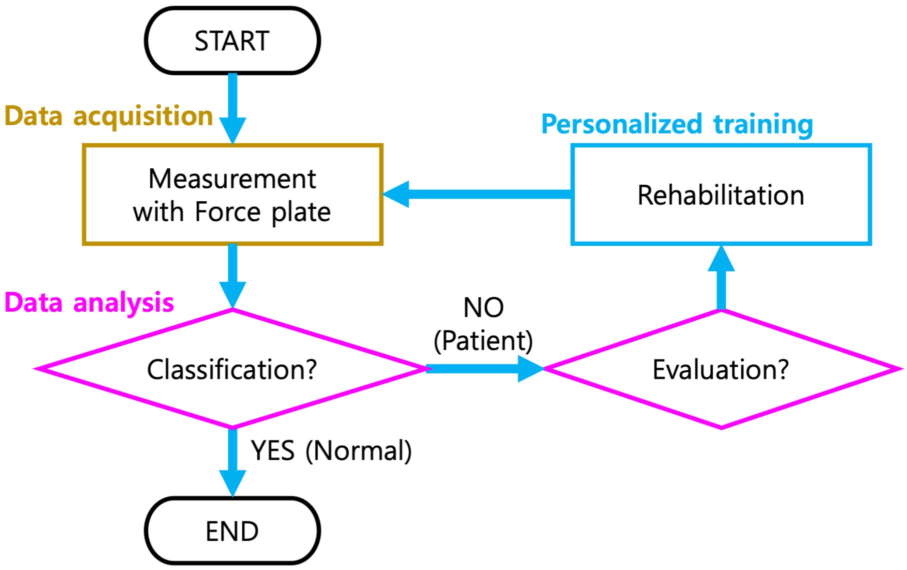

Figure 2. A three-step flow chart for the rehabilitation of patients after the surgery: first, data acquisition to measure data with the force plate, then data analysis to classify whether the gait pattern of the patient is close to the standard group or not and to recognize in which step the abnormality has occurred, and finally personalized training to improve the gait pattern.

2.3. Analysis

2.3.1. Classification through Machine Learning

Machine learning is a method of measurement data analysis that automates analytical model building. It is one kind of artificial intelligence based on the concept that systems can learn from data, determine patterns, and make decisions with minimal human intervention. Machine learning algorithms are mainly divided into four types: supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning. A machine learning technique is used to classify data from patients with hip OA and healthy people. We use SVM (support vector machine) [4], LDA (linear discriminant analysis) [5], KNN (K-nearest neighbor) [6], and random forest [7], which are supervised-learning algorithms that can be used for classification tasks [8–13].

2.3.2. Similarity through Dynamic Time Warping Algorithm

Figure 3, reproduced with permission from [14], copyright from Professor Romain Tavenard 2023, shows a comparison between DTW [15] and Euclidean distance. Dynamic time warping is a method of calculating a more accurate distance than Euclidean distance. It has an advantage over Euclidean distance if the data points are shifted between each other, and we want to look instead at its shape. Thus, two time series do not have to be equal in length. The Euclidean distance takes pairs of data points and compares them. The DTW calculates the smallest distance between all points, enabling a one-to-many match. Since the Euclidean distance matches the timestamp regardless of the feature values, we should note DTW, a method for matching distinctive time-series patterns.

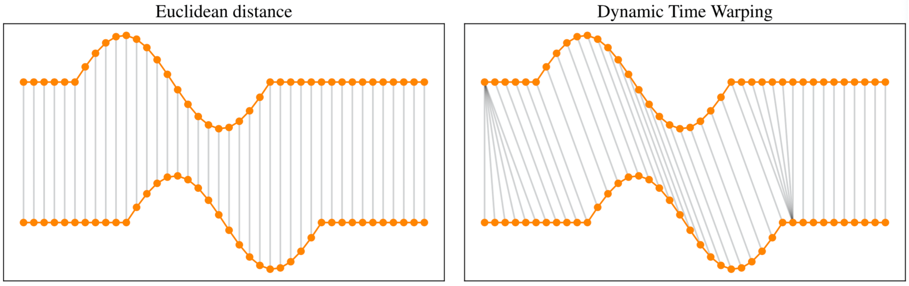

Figure 3. A comparison between dynamic time warping (DTW) and Euclidean distance, reproduced with permission from [14], copyright from Professor Romain Tavenard 2023. Note that the two time series have a similar overall shape but are not aligned on the time axis. Euclidean distance, which assumes the ith point in one sequence is aligned with the ith point in the other, may produce a pessimistic dissimilarity measure. The non-linear dynamic time warped alignment allows a more intuitive distance measure to be calculated.

More formally, the optimization problem writes:

$$DTW_q(x, x') = \min_{\pi \in A(x,x')} (\Sigma_{(i,j)\in\pi} d(x_i, x'_j)^q)^{\frac{1}{q}}. \tag{1}$$

Here, an alignment path π of length K index pairs $((i_0, j_0), \cdots, (i_{K-1}, j_{K-1}))$ and as $A(x, x')$ is the set of all admissible paths, a path should satisfy the following conditions in order to be considered admissible:

- Time series are matched at the beginning:

$$\begin{aligned} \pi_0 &= (0,0) \\ \pi_{K-1} &= (n-1, m-1) \end{aligned} \tag{2}$$

- The sequence is monotonically increasing in both i and j, and all time-series indexes should appear at least once, which can be written as:

$$\begin{aligned} i_{K-1} \leq i_K \leq i_{K-1} + 1 \\ j_{K-1} \leq j_K \leq j_{K-1} + 1 \end{aligned} \tag{3}$$

Another method, the warping path to minimize the cumulative distance between two time-series paths is to use a binary matrix whose non-zero entries correspond to matching between time-series elements. That means that the simple method is to compare the two paths.

$$(A_\pi)_{i,j} = \begin{cases} 1 & if(i,j) \in \pi \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

Equation (4) is illustrated in Figure 4, reproduced with permission from [14], copyright from Professor Romain Tavenard 2023, where the dots represent non-zero entries in the binary matrix, and the plot on the right in Figure 4 is generated using the matched equivalent sequence.

Using matrix notation, DTW can be written as the minimization of a dot product between matrices:

$$DTW_q(x, x') = \min_{\pi \in A(x,x')} < A_\pi, D_q(x, x') >^{\frac{1}{q}} \tag{5}$$

where $D_q(x, x')$ stores distances $d(x_i, x'_j)$ at the power q.

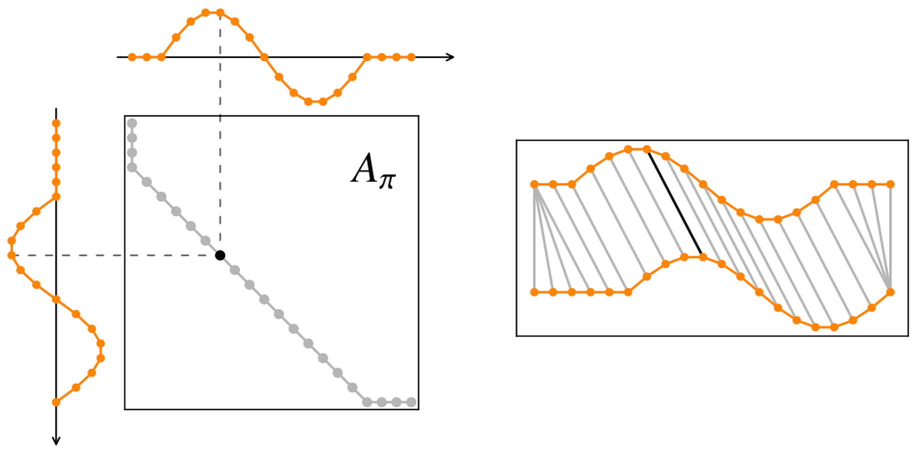

Figure 4. The warping path to minimize the cumulative distance between two time series is determined by the dynamic time warping (DTW) in the n-by-m matrix, reproduced with permission from [14], copyright from Professor Romain Tavenard 2023. The dot on A_π indicates the optimal alignment of an element in x with an element in x'.

The gait data used in this experiment are time-series data obtained during the stance phase. The DTW algorithm was applied to these data to compare patients' and healthy people's data to confirm whether there was a difference between the two data. For the patient's data, the distance values obtained by applying the DTW per patient data based on the average value of the entire data set of healthy people were obtained and averaged. For the healthy person's data, the distance value was obtained by applying DTW to the average of the rest of the healthy people's data except for each healthy person's data was averaged. The difference between the two data sets was seen by applying the DTW algorithm to the average of the patient's data and the average of the healthy people's data. Furthermore, the DTW cost matrix can represent in which phase the data of each patient differed from the average data of healthy people.

3. Results

3.1. Results of Measured Time-Series Data

Figure 5 shows the results of the measured time-series data using the force plate. The data from the stance phase in the gait cycle are measured during the one-step gait cycle, and those of the swing phase are not recorded in the experiment. The normalized time for 0∼25% expresses the initial contact, 25∼80% expresses the midstance, and 80∼100% expresses the propulsion. The body weight of the participant normalizes the value of GRFs. The x-axis represents the normalized time for the stance phase, and the y-axis represents the measured values. The three plots on the top side are three directional ground reaction forces (GRFs), and the three at the bottom are three directional moments. Blue-colored curves indicate the patient data, and orange-colored indicate those of the control group. Soft shades of blue and orange show the standard deviation distribution, and heavy curves show the mean values.

By visualizing the data as mean and standard deviation, it was found that there was no significant difference in the measured time-series data between the two groups. However, we could see a tiny difference when the stage in the stance phase was changed around the normalized time of 25% and 80%.

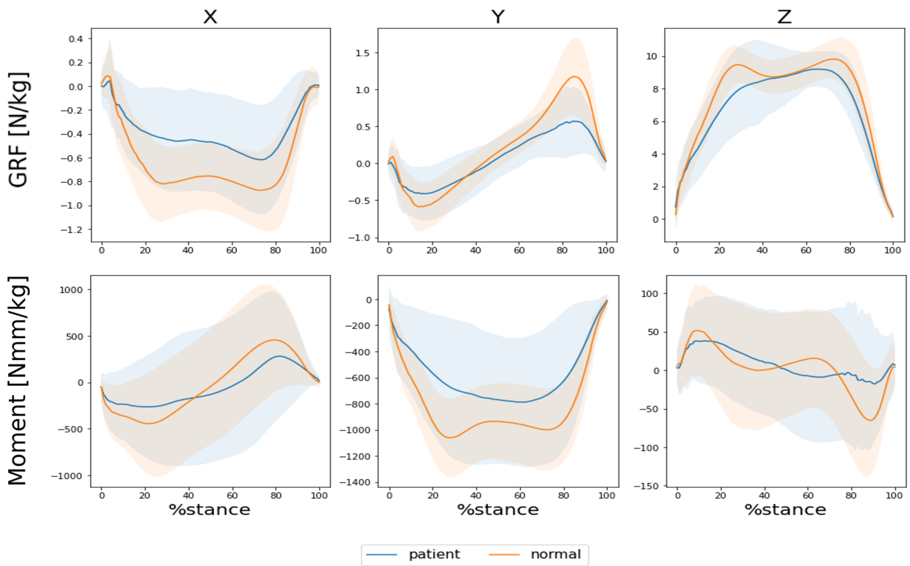

Figure 5. Results of measured time-series data using the force plate. Data from the stance phase in the gait cycle are measured during the one-step gait cycle, and those of the swing phase are not recorded in the experiment. The normalized time for 0∼25% expresses the initial contact, 25∼80% expresses the midstance, and 80∼100% expresses the propulsion.

3.2. Results of Classification through Machine Learning

Data on the x, y, and z axes of the GRF are classified through the machine learning algorithm. Table 2 shows the accuracy, sensitivity, and specificity obtained through five-fold cross-validation. The accuracy is how close a given set of measurements are to their actual ground true value. Comparatively, the results show a high performance. The sensitivity, the probability of a patient conditioned on being an actual patient, is averaged for each algorithm to obtain 0.63 in SVM, 0.72 in LDA, 0.69 in KNN, and 0.67 in random forest. The specificity, the probability of a healthy person conditioned on an actual healthy person, is averaged to obtain 0.87 in SVM, 0.77 in LDA, 0.83 in KNN, and 0.91 in random forest.

Table 2. Human subject classification results through machine learning.

Model	GRF	Accuracy	Sensitivity	Specificity
SVM	x	0.785	0.700	0.826
	y	0.741	0.588	0.814
	z	0.850	0.600	0.970
LDA	x	0.753	0.738	0.760
	y	0.733	0.688	0.754
	z	0.773	0.725	0.796
KNN	x	0.753	0.700	0.778
	y	0.733	0.625	0.784
	z	0.874	0.755	0.922
Random Forest	x	0.818	0.662	0.892
	y	0.810	0.637	0.892
	z	0.862	0.700	0.940

The classification results showed good performance, only possible with a one-step gait. However, the classification results did not tell us at which stage patients' gait differs from that of healthy people.

3.3. Results of Similarity through Dynamic Time Warping

Figure 6a describes the GRFs and each stage in the stance phase with the normalized time. Figure 6b,c show the results of the accumulated cost matrices for patient A (b) and patient B (c) and the warping path, which is expressed by pink-colored curves for each plot. If there is no difference in the gait cycle between patients with hip OA and healthy participants, the warping path draws a diagonal line. However, if there is some difference during the gait, the warping path has curves at different stages.

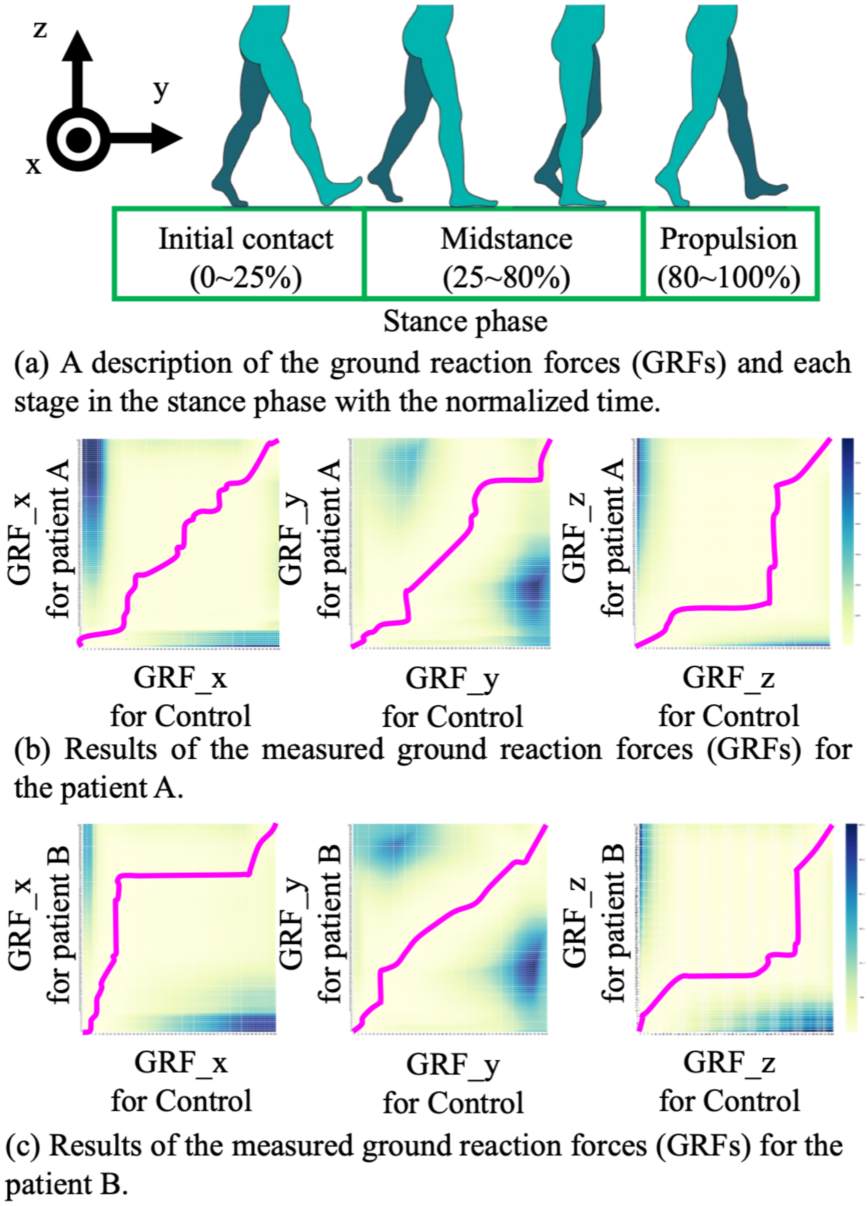

Figure 6. Results of accumulated cost matrices for patient A (**b**) and patient B (**c**) and the warping path, which is expressed as pink-colored curves for each plot.

We applied the DTW algorithm to see the gait cycle similarity between the two groups. From the left for each person, three examples are shown along the x, y, and z axes of the GRF values of the foot of one patient. We can see the description of these directions in Figure 6a. Looking at the direction in which the subject is walking, the x-axis represents the medial–lateral direction, the y-axis represents the anterior–posterior direction, and the z-axis represents the vertical direction, which is the gravity direction. The horizontal axis of each matrix in Figure 6b,c is the average value of healthy people's data, and the vertical axis is the value of one patient. In the DTW matrix, a lower the cost is represented by a brighter yellowish color, and the higher the cost, the darker the indigo-based color. Furthermore, the pink line represents the minimum path in the DTW matrix. This path is a diagonal line as the two GRF data sets are similar.

The stance phase is divided into three parts, as shown in Figure 6a. Looking at the GRF_x plot of patient A in Figure 6b, there is a slight difference from a healthy person in the medial–lateral direction in the initial contact stage and a little difference in the midstance phase as well. The GRF_y plot shows a difference in the anterior–posterior part in the initial contact and propulsion stages. Finally, the GRF_z plot shows a big difference in the midstance. This means that differences in the gait originated from unconscious avoidance motions to alleviate the produced pain.

In the case of patient B in Figure 6c, it can be seen that the GRF_y plot is similar to that of healthy people, and the GRF_x plot has much difference overall, with a significant difference present in the midstance stage. Furthermore, looking at the GRF_z plot, we can see a significant difference in the midstance stage.

In the GRF_z plot of both patients, the midstance stage is the most different from the data of healthy people. Unlike the other phases, the midstance stage supported the body weight with only a single limb. Thus, the midstance, which felt much weight, differed significantly. All patients walked with reduced body weight in the midstance stage. Data with reduced body weight came from limping movements to avoid pain.

Figure 7 shows the results of the accumulated cost matrices for all patients, and the warping path, which is expressed by dark-blue-colored curves: (a) represents the results of GRF_x, (b) represents that of GRF_y, and (c) represents that of GRF_z. Although a clear difference exists, it is not easy to find a clear pattern. This means that the pattern of relieving pain during the gait is expressed in many ways.

Through the DTW algorithm, it was possible to determine which stage differed from healthy people. However, the most challenging thing in this study was the various abnormalities according to each patient. For example, despite the same hip OA, the various abnormalities from that difference in gait originated from unconscious avoidance motions to alleviate pain.

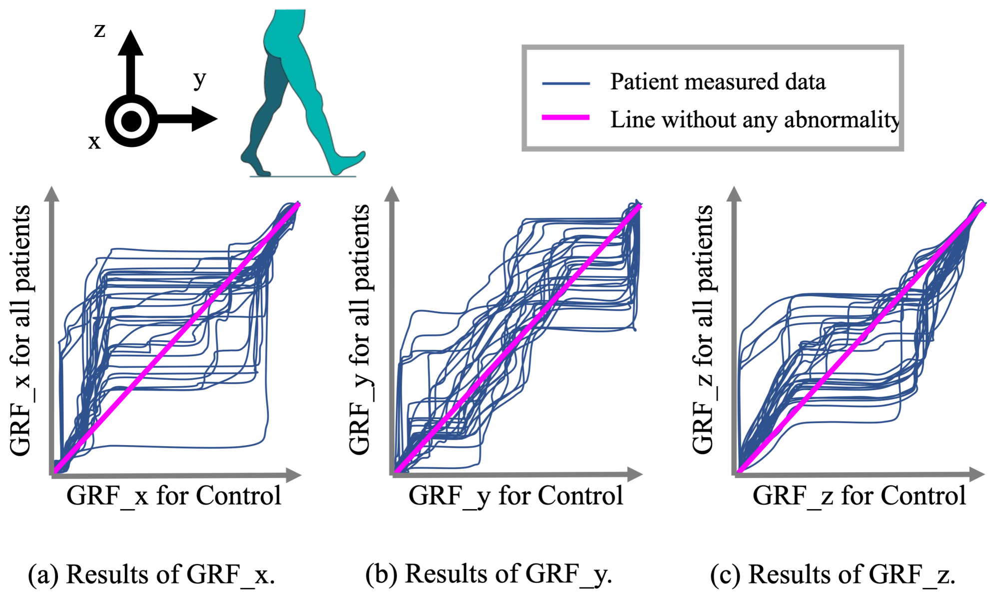

Figure 7. Results of accumulated cost matrices for all patients and warping path, which is expressed by dark-blue-colored curves: (**a**) represents the results of the x-axis ground reaction force (GRF_x), (**b**) represents that of the y-axis GRF_y, and (**c**) represents that of the z-axis GRF_z.

4. Discussion

■ Advantages

This study proposed a method to recognize the abnormality of the hip OA patient with a one-step gait pattern based on the DTW algorithm through three directional GRFs. The experimental results enabled us to verify the usefulness of showing the recognition of the abnormal gait pattern and how to relieve the pain during the gait. The proposed method of one-step gait pattern analysis has two main advantages: relief from the burden of participating and a response to the randomly expressed abnormality.

Most studies have investigated the effect of walking speed on differences in kinematic trajectories between patients with hip OA and control participants using a wearable sensor system [16,17]. Data for multiple walking trials at a self-selected speed for 6∼20 m in a flat corridor are measured for the experiment. If the step length for the one-step gait is 0.5 m, patients should walk for approximately 40 steps. The maximum force of the hip joint varies from 1.8 times to 4.3 times the body weight during walking, and so does the maximum pressure that the hip joint receives from the initial contact with the heel strike to the early midstance [18]. The experiment, in terms of kinematics, must cause pain to the patient. Thus, the proposed method of one-step gait pattern analysis enabled patients with hip OA to relieve the burden of participating in the experiment or medical examination.

Arthritis in the lower part of the body, whether OA or inflammatory arthritis, can change the gait or how we walk. To understand how arthritis affects the gait, first, we need to consider the biomechanics of walking. The gait is a complex process in which well-coordinated mechanical movements occur simultaneously in various joints of the lower limbs to gently switch the center of gravity of the body, enabling us to move. Medical doctors instruct that arthritis in the hips and knees affects the gait because of pain, stiffness, and weakness. Although there are many abnormal gaits, when it hurts to put weight on the hip or knee, we often unconsciously spend less time bearing weight on that extremity during the gait cycle, shortening the stance phase, which is usually 60% of the gait. This is called an antalgic gait. Furthermore, patients with arthritis often have a lot of muscle weakness around the hip and knee. For example, it is common for patients with OA to have poor balance and be unable to stand on one leg without pain. Since single-limb support occurs during the gait, this poor balance affects the gait, often resulting in a waddling pattern called a Trendelenberg gait. This muscle weakness causes the pelvis to drop on one side when the opposite leg is lifted. Finally, arthritic joints can lead to a loss of flexibility or stiffness in the body, changing the way we normally move. Arthritis patients tend to walk slower due to all these additional challenges. Thus, the proposed method of DTW-based analysis enabled us to cope with many types of abnormal gait patterns according to the patient's symptoms.

In addition, it is possible to numerically compare the patient's degree of rehabilitation and postoperative recovery through the DTW matrix, even without professional engineering knowledge. This is also an advanced point in that it fills the point where previous studies [19] could not perform more detailed analysis in walking by comparing only data values, and it allowed us to know in which phase there was a difference.

■ Limitations

It is possible that the normalized time can lose the information on the shortened stance phase under the x-axis condition. Then, one step cannot analyze asymmetries in the step time between affected and non-affected hips. Two points can be the limitation of this approach. However, the gait step can be divided into the fixed gait phase despite the different duration to move the body weight. When we know the body weight, it is possible to calculate the ratio of the body weight. That means that it is possible to evaluate the different gait phases with different body weight ratios even though it is difficult to evaluate the exact duration.

5. Conclusions

Using machine learning algorithms, we classified the one-step gait data of hip OA patients and healthy people. Then, we analyzed the patients' one-step gait data by finding the difference between each patient's gait and that of healthy people using the DTW algorithm. With the classification results through machine learning, we concluded that it could be discriminated with only a one-step gait. This finding could shorten the time compared to conventional diagnosis, even for patients with pain, reducing the burden on the patient and allowing doctors to follow up more quickly. Therefore, it was adequate for both doctors and patients. In addition, in the DTW matrix, it was possible to check at which stage the patient's data differs significantly from that of healthy people.

As a result of the analysis, the gait patterns of patients with hip OA were slightly similar to or significantly different from those of healthy people according to their abnormalities so that we could see various data different from those of healthy people. If doctors see a patient's data using this method, it can be used for examination and gait patterns. It is also possible to numerically compare the degree of recovery through rehabilitation training to see if the training is going well. Several studies have shown that the pain and function reported by patients following surgery are better in patients who receive early referral and treatment before the joint's functional limitation and pain are severe [20,21]. Accordingly, if a one-step gait reduces the burden on the patient and allows for a quick diagnosis of hip OA, inducing early treatment, prevention, and early management is possible before the symptoms worsen, which will help the patient's recovery. The values allowed us to know in which phase there was a difference.

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Institutional Review Board Statement: All subjects gave their informed consent for inclusion before participating in the study. The study was conducted under the Declaration of Helsinki. The Ethics Committee of the Clinical Trial Center at the Kyungpook National University Hospital in the Republic of Korea approved the protocol.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: You can download the dataset at https://drive.google.com/drive/folders/1aijKxEaLrzbDUV-qwCAPVbcmUfoDB1mx?usp=share_link (accessed on 5 April 2023).

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Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

GRF	Ground Reaction Force
hip OA	Hip osteoarthritis
DTW	Dynamic Time Warping

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