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Development of Squat Posture Guidance System Using Kinect and Wii Balance Board

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Abstract

This study designs a squat posture recognition system that can provide correct squat posture guidelines. This system comprises two modules: a Kinect camera for monitoring users' body movements and a Wii Balance Board(WBB) for measuring balanced postures with legs. Squat posture recognition involves two states: "Stand" and "Squat." Further, each state is divided into two postures: correct and incorrect. The incorrect postures of the Stand and Squat states were classified into three and two different types of postures, respectively. The factors that determine whether a posture is incorrect or correct include the difference between shoulder width and ankle width, knee angle, and coordinate of center of pressure(CoP). An expert and 10 participants participated in experiments, and the three factors used to determine the posture were measured using both Kinect and WBB. The acquired data from each device show that the expert's posture is more stable than that of the subjects. This data was classified using a support vector machine (SVM) and naïve Bayes classifier. The classification results showed that the accuracy achieved using the SVM and naïve Bayes classifier was 95.61% and 81.82%, respectively. Therefore, the developed system that used Kinect and WBB could classify correct and incorrect postures with high accuracy. Unlike in other studies, we obtained the spatial coordinates using Kinect and measured the length of the body. The balance of the body was measured using CoP coordinates obtained from the WBB, and meaningful results were obtained from the measured values. Finally, the developed system can help people analyze the squat posture easily and conveniently anywhere and can help present correct squat posture guidelines. By using this system, users can easily analyze the squat posture in daily life and suggest safe and accurate postures.

Index Terms: Motion analysis, SVM, Naïve Bayes, Kinect, Wii Balance Board

I. INTRODUCTION

To maintain the healthier life, many people try to exercise at home. Among hands-free exercises, the squat is frequently performed during activities of daily living, and/or as part of an exercise routine. It requires adequate range of motion, giving insight on an individual's ability to effectively control whole body movements. Furthermore, for achieve effective squatting, maintaining a balanced and accurate posture is very important because it can reduce a possibility of serious injuries and increase effectiveness of squatting. The well-defined posture is important for individual's foot placement, upright posture, and knee flexion. Although, it is depending on the individual skills.

Most people who are unused to the squat posture take the same kind of wrong posture. Typically, they are in the wrong posture before and during exercise. The wrong posture before exercising is incorrect interval between both feet. The distance of both feet should be similar to shoulder spacing, but it is common for beginners to have narrow or wide

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spreads, or unbalanced. The wrong posture during exercising is when the knee is excessively protruded during the squatting. The knees should be the same or behind your feet when squatting. However, beginners are not accustomed to the squat posture, so they tend to take a position like almost sitting. It is the most common for beginners to have a knee protrude excessively. Measuring and assessing the identical squats posture can be challenges without guides or experts at home. Therefore, in this study we decided to study the posture before and during the exercise to correct the wrong posture that is commonly used by those who are not unused to the squat posture. Additionally, the posture before exercise was named “Stand Posture or State” and the posture during exercise was named “Squat Posture or State”.

The squat posture recognition system which designed in this study assist users with their squat posture. The proposed system utilizes Microsoft Kinect and the Nintendo Wii Balance Board (WBB) to analyze the user’s current squat posture and balance. Kinect and WBB were originally used as home-game devices and have good performance with low prices. Both devices make lower the accessibility of the equipment and enable anyone to use the developed system.

The difference between the shoulder width and the ankle width obtained by Kinect and the knee angle data is analyzed to determine the current posture of the user. Moreover, using the Center of Pressure (CoP) data acquired via WBB, the user’s balance is analyzed. In this study, SVM and Naïve Bayes were used for the classification of incorrect and correct postures. support vector machine (SVM) and Naive Bayes are powerful and accurate machine learning methods for data classification. And both methods are easy to implement. SVM is accurate for large amounts of data processing. Naive Bayes differs depending on the amount of feature but has fast performance.

Recently, with the rapid growth of motion capture and sensory technologies, there are many kinds of motion analysis system has been existing and a lot of related studies are also going on [1, 2]. But these devices are quite expensive and require complicated conditions. For this reason, these devices are rarely available to the ordinary people and there is a small chance for few people such as some athletes to use that.

In a recent study, there were few studies related to the “squat movement” itself. but these studies just focused only on the posture itself of the user in a squatting position [3-6] or effects and advantages of squat exercise [7-11]. In other words, these studies did not focus on the movement of the user when performing squats. In addition, the posture recognition systems developed in previous studies were difficult to use. Therefore, to address these challenges, we attempted to realize a more systematic and effective squat movement recognition system.

Thus, developed system helps people to analyze the squat posture easily and conveniently in anywhere. Moreover, the developed system can measure squat posture from Stand to Squat posture of expert and subjects, and it can present correct squat posture guidelines. With this system, user can easily analyze the squat posture at the gym or at home and suggest safe and accurate postures to users.

II. RELATED STUDIES

Previous posture analysis studies have been conducted was related to kinematics and anatomy as marker-based motion recognition system. However, due to the characteristics of marker-based motion recognition system, there are many disadvantages such as a large spatial restriction, the use of multiple cameras, and the inability to recognize a marker when the marker is covered by a part of the body.

The Kinect can recognize the joints of the human body [12]. We used Kinect’s depth camera to measure the depth data of each user’s skeleton. WBB was originally designed as a tool for Wii Fit, an exergaming system designed by Nintendo. However, given the utility of WBB, several studies have conducted studies pertaining human balance and control [13]. In a previous study, the validity of the WBB measurements in was 0.66-0.94 for the intra-device retest reliability (Intraclass Correlation Coefficients, ICC) and 0.77-0.89 for the inter-device retest reliability (ICC); when compared to the Force Platform, which is also a balance measurement device, the reliability of measurements taken using WBB was higher. Therefore, WBB is regarded an effective tool for evaluating the balance of effectiveness and reliability [13, 14].

Previous studies have used Kinect and WBB for posture recognition; however, most such studies have focused on the user’s posture or balance using either Kinect or WBB. Especially, Most of Kinect 's researches related to posture analysis were focused on only posture evaluation or recognition [15-17] and content development [18]. WBB was only used for evaluating and measuring user balance and for measuring ground reaction force. In other words, previous studies have used each device only as part of the measurement tool, and studies related to the actual user 's ability to exercise have rarely been done.

However, we utilize both Kinect and WBB to present the correct squat posture to the user. Kinect analyzes the user's posture and WBB analyzes the user's balance to determine a more accurate squat posture.

III. SYSTEM MODEL AND METHODS

A. System Design

1) Squat Posture Recognition Scenario

Fig. 1 is the overall procedure of the developed system in

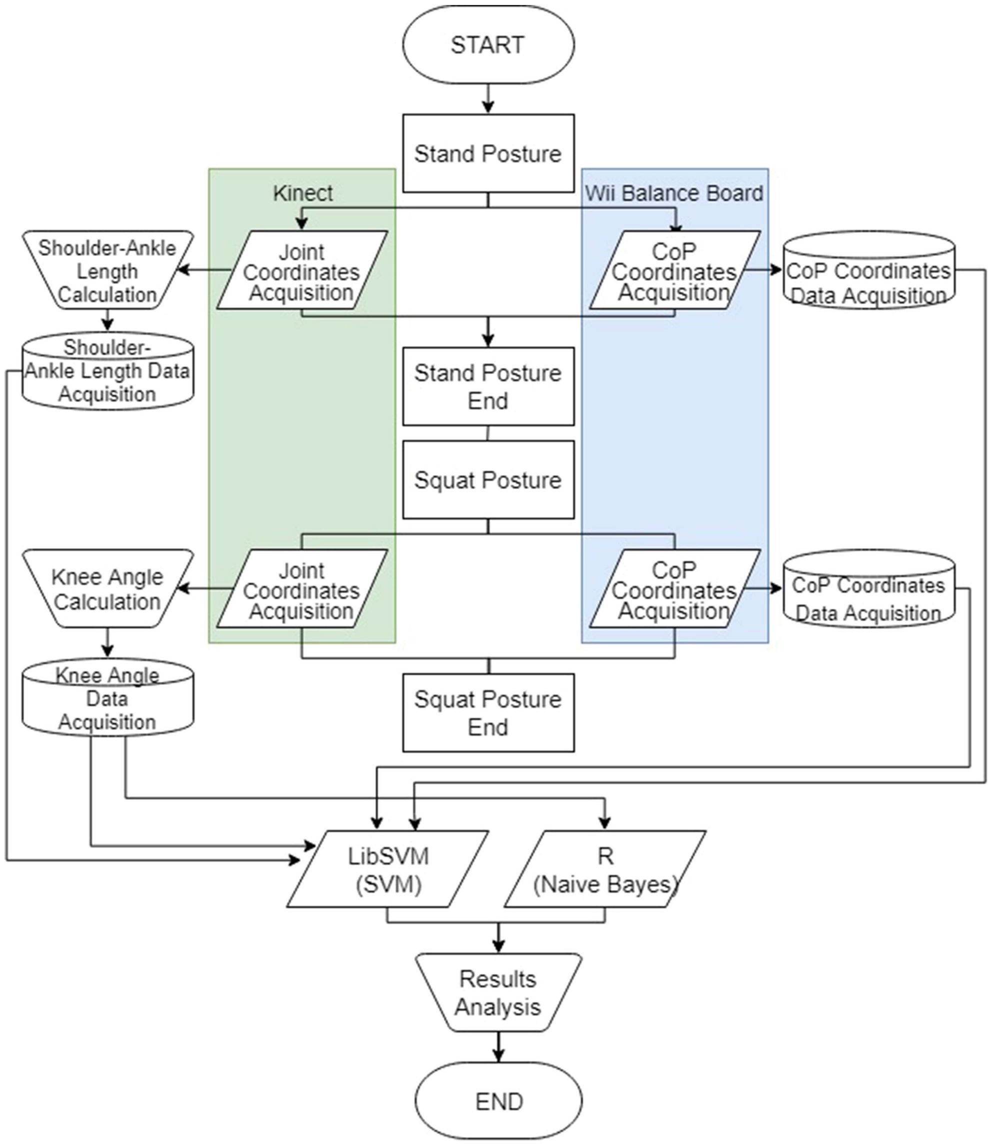

Fig. 1. Overall procedure of posture recognition system.

this study. In overall scenario, the first user steps up the WBB of the configured system, look at Kinect in front and take a Stand posture. After taking the posture, Kinect acquires the joint coordinates in the Stand posture. The acquired joint coordinates are used to obtain shoulder-ankle length data. At the same time, the WBB acquires the CoP coordinates of the Stand posture. Unlike Kinect, there is no need to do calculations in WBB. The balance analysis of the squat posture is carried out with the acquired joints coordinates.

When data acquisition is complete, end the Stand posture and take the Squat posture. When the user completes the squat movement, Kinect acquires the joint coordinates at the Squat posture. The acquired joint coordinates are used to acquire Knee Angle Data. At the same time, the WBB acquires CoP coordinates in a Squat posture. All acquired data are classified using LibSVM and R. LibSVM runs the SVM, Naïve Bayes runs the R. Verify the accuracy of the squat recognition system as a result of the classification process.

2) Development Environment

The configuration of the PC used in this study are CPU i7-4712MQ 2.3 GHz, RAM 8 GB, SSD 128 GB, NVIDIA GeForce 840M GPU. To measure the user's posture, Kinect for Windows v2 (Microsoft Corporation, WA, USA) and WBB for Nintendo Wii Balance Board (Nintendo Co., Ltd., Kyoto, Japan) were used. And to obtain and analysis the data we write the code in C# with Visual Studio 2015.

B. Experimental Method

1) System Implementation

a) Posture Recognition Design Using Kinect

We obtain the *x*-, *y*-, and *z*- coordinates of each joint recognized by Kinect to determine the shoulder width, ankle width, and knee angle. The measurements are identical for both right to left and left to right. Hereafter, we assume that both the right and the left parts of the body are identical, and we refer only to the right part of the body.

The difference between the shoulder width and the ankle width indicates the difference between the length of the right shoulder to left shoulder and the length of the right ankle to left ankle. The joints recognized by Kinect are termed SR to SL and AR to AL joints, as shown in Fig. 2. Fig. 2 shows how the difference between the shoulder width and the ankle width is calculated. The difference between the shoulder width and the ankle width is $\|\overrightarrow{SLSR}\| - \|\overrightarrow{ALAR}\|$ in this figure. Based on the coordinates of each joint obtained from Kinect, the distance between the two points in the space calculation function was used to determine the shoulder width and the ankle width.

The knee angle (θ) is determined from the brief expression of the user's profile when performing a squat movement, as shown in Fig. 3. In Fig. 3, the knee angle refers to the angle between the hip-knee-ankle sections. The joint is referred to as HR-KR-AR by Kinect. The coordinates obtained from Kinect can be used to determine the length of the user's hip-knee and knee-ankle. The law of cosines was applied to determine the angle made at the knee for each length.

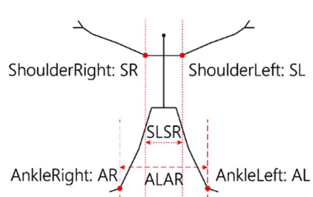

Fig. 2. Measuring difference between shoulder width and ankle width.

b) Balance Recognition Method Using WBB

The coordinates of the CoP can be obtained using the data from the four pressure sensors (F_{TL}, F_{TR}, T_{BL}, F_{BR}) in WBB shown in Fig. 4.

An Open source library, WiimoteLib, was used to acquire the data [19]. Then, the original code was modified according to (1) [20].

$$CoP_{WBB_x} = \frac{X}{2}\frac{(F_{TR}+F_{BR})-(F_{TL}+F_{BL})}{F_{TR}+F_{BR}+F_{TL}+F_{BL}}$$

$$CoP_{WBB_y} = \frac{Y}{2}\frac{(F_{TR}+F_{TL})-(F_{BR}+F_{BL})}{F_{TR}+F_{BR}+F_{TL}+F_{BL}} \quad (1)$$

In (1), X and Y are 433 mm and 238 mm in width and length, respectively [20, 21]. The *x*- and *y*- coordinates of CoP on the coordinate plane obtained through (1) are recorded for each frame.

Thus, Table 1 summarizes all measured values for classification in this study.

2) Experimental Evaluation

a) Squat Posture Configuration

A total of 11 subjects participated in the study. The participants comprised one expert and 10 subjects. All participants were asked to repeat postures (a)~(f) five times each.

In the Normal Stand posture, as shown in Fig. 5(a), the user prepares for squatting with both legs open with and shoulders wide open; the arms must be raised till the face, with palms facing front.

In the Narrow posture of Stand Posture, shown in Fig. 5(b), the user prepares for squatting with both feet close to each other. As regards the Wide Posture, shown in Fig. 4(c), the user readies to squat with both legs apart excessively; in the Unbalanced posture in Fig. 5(d), the user is ready to squat with both legs off the center of WBB.

In the Normal Squat posture, as shown in Fig. 6(e), the user performs a squat on the WBB such that the knee does not protrude beyond the foot.

In the knee protruding posture shown in Fig. 6(f), the

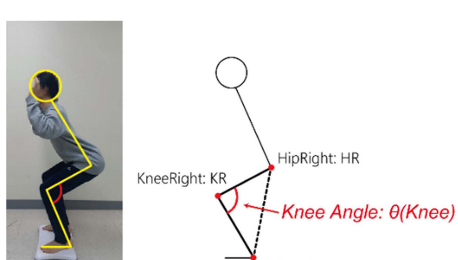

Fig. 3. Determination of knee angle: measuring the knee angle (θ) using coordinates of the three points.

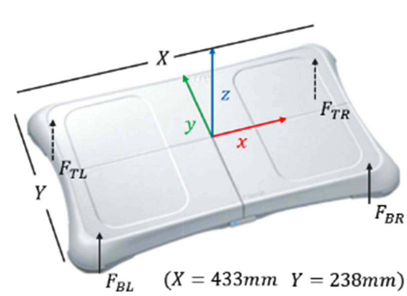

Fig. 4. Coordinate axis and pressure sensor recognized by Wii Balance Board.

Table 1. Items to be measured between experiments

Stand / Squat State	Correct / Incorrect Posture	(a) ~ (f) posture	Measurements values of Kinect	Measurements values of WBB
Stand State	Correct Posture	Normal Stand Posture: (a) posture	The difference between shoulder width and ankle width $\lVert\overrightarrow{SLSR}\rVert - \lVert\overrightarrow{ALAR}\rVert$	Center of Pressure **CoP(*x*, *y*)**
	Incorrect Posture	Narrow Stand Posture: (b) posture		
		Wide Stand Posture: (c) posture		
		Unbalanced Stand Posture: (d) posture		
Squat State	Correct Posture	Normal Squat Posture: (e) posture	Knee Angle $\theta(Knee)$	Center of Pressure **CoP(*x*, *y*)**
	Incorrect Posture	Knee Protruding Posture: (f) posture		

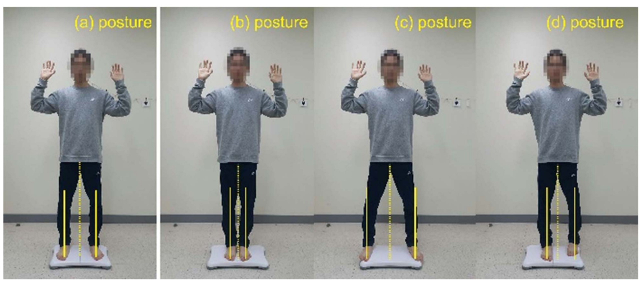

Fig. 5. Stand posture, Normal Stand posture: (a) posture, Incorrect Posture: (b)~(d) posture. (a), (b), (c) and (d) from the left. The solid line indicates the position of the user's feet, and the dotted line indicates the center of the body.

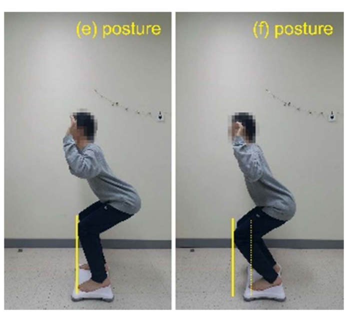

Fig. 6. Squat posture, Normal Squat Posture: (e) posture, Knee Protruding posture: (f) posture. (e) and (f) from the left. The solid line indicates the position of the user's knee, and the dotted line indicates the position of the knee in the correct posture.

user's posture during a squat is such that the knee protrudes excessively beyond the foot.

b) Squat Posture Classification

The developed system classified by using machine learning in order to check whether the accurate squat posture can be classified by $\lVert\overrightarrow{SLSR}\rVert - \lVert\overrightarrow{ALAR}\rVert$, $\theta(Knee)$, **CoP(*x*, *y*)** data of experiment participants. Classification proceeded to SVM and Naïve Bayes. SVM can be applied to various datasets, and it works well for data with low kinds of features.

It works well in binary classification, which classifies the posture of experts and subjects. And Naïve Bayes proceeds on the assumption that each feature is independent based on the conditional probability.

However, if there are too many features, Naïve Bayes takes complexity and have a long time to solve the problem because it considers the association between every feature.

However, in this study, Naïve Bayes was used because it predicted that there would not be many features to be applied to learning and that each feature would be simplified and classified quickly. Therefore, we classified the data into SVM and Naïve Bayes. Furthermore, the reason for using SVM and Naïve Bayes is because the two classification methods are different. Learning of SVM is based on geometric relationships between feature vectors which made input feature as a vector. But unlike SVM, Naïve Bayes is a probabilistic learning that classifies input features as independent based on conditional probability.

We tried to improve the reliability of the results by classifying them into two types of machine learning based on the geometric basis and stochastic basis.

IV. RESULTS

A. Posture Measurement Using Kinect System

The Kinect system was used to measure the $\lVert\overrightarrow{SLSR}\rVert - \lVert\overrightarrow{ALAR}\rVert$ and $\theta(Knee)$ values for both experts and the experiment subject. And a paired t-test was conducted to compare the mean of each values. The results of the paired t-test are shown in Table 2.

In (a) posture, the average of expert is 0.0380 and the average of subject is 0.0344. In (b) posture, the average of the expert is 0.0521 and the average of the subject is 0.0558. In (c) posture, the average of the expert is -0.0060 and the average of the subject is 0.0007. In (d) posture, the average of expert is 0.0260 and the average of subject is 0.0304.

The $\lVert\overrightarrow{SLSR}\rVert - \lVert\overrightarrow{ALAR}\rVert$ values for experts and experiment subjects for the four types of postures were statistically different at a significance level of 0.05 or less.

In (e) posture, the average of expert is 72.16 and the average of subjects is 104.81. In (f) posture, the average of the expert is 109.99 and the average of the subjects is 93.85.

The $\theta(Knee)$ values for experts and experiment subjects

Table 2. The paired t-test result of the difference in the $\|\overrightarrow{SLSR}\| - \|\overrightarrow{ALAR}\|$ values and $\theta(Knee)$ values for expert and subjects in (a)~(f) posture

95% confidence interval of the difference	$\|\overrightarrow{SLSR}\| - \|\overrightarrow{ALAR}\|$								$\theta(Knee)$			
	(a) posture		(b) posture		(c) posture		(d) posture		(e) posture		(f) posture	
	Expert's	Subject's	Expert's	Subject's	Expert's	Subject's	Expert's	Subject's	Expert's	Subject's	Expert's	Subject's
Mean	0.0380	0.0344	0.0521	0.0558	-0.0060	0.0007	0.0260	0.0304	72.16	104.81	109.99	93.85
Variance	1.52E-06	1.82E-07	1.6E-07	1.42E-07	9.62E-07	4.29E-07	2.24E-07	4.65E-06	976.3723	443.0337	430.1726	351.5689
standard deviation	0.001234	0.000427	0.000401	0.000377	0.000981	0.000655	0.000474	0.002157	31.24696	21.04836	20.7406	18.75017
Observations	250	250	274	274	279	279	279	279	225	225	206	206
Pearson Correlation	0.491099		0.1691		0.195329		0.273102		-0.2142		-0.07264	
df	249		273		278		278		224		205	
t Stat	53.2391		-120.843		-103.845		-35.7989		-11.8728		8.002593	
P(T<=t) one-tail	2.3E-138		2.4E-239		1E-224		2.1E-106		7.67E-26		4.45E-14	
t Critical one-tail	1.650996		1.650454		1.650353		1.650353		1.651685		1.652321	
P(T<=t) two-tail	4.6E-138		4.8E-239		2.1E-224		4.1E-106		1.53E-25		8.89E-14	
t Critical two-tail	1.969537		1.968692		1.968534		1.968534		1.970611		1.971603	

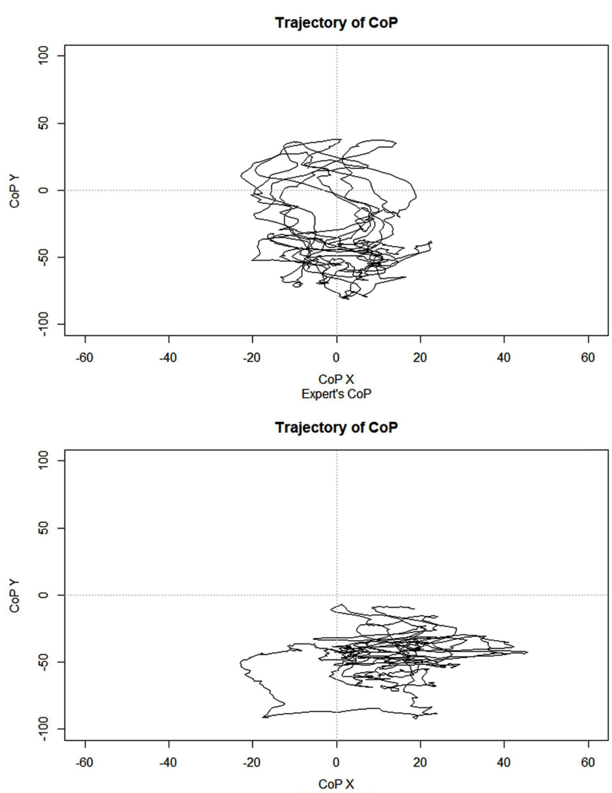

Fig. 7. Comparison of CoP trajectory between expert and experiment subject: (e) posture.

for the two types of postures were statistically different at a significance level of 0.05 or less.

B. Balance Measurement Using WBB System

The trajectory of the CoP coordinates of (e) posture for both the experts and the experiment subjects is shown in Fig. 7. The more stable the posture, the more the trajectory is drawn to the origin of the graph. Therefore, the Stand posture is drawn at the center of origin, and the Squat posture is drawn along the *Y*-axis.

Table 3. Mean values of CoP-Origin distance comparison between experts and subject

	Expert's mean	Subjects' mean
(a) posture	27.309	28.218
(b) posture	9.002	32.443
(c) posture	6.112	40.667
(d) posture	26.168	46.619
(e) posture	40.173	61.905
(f) posture	15.846	39.294

Next, we compared the difference in the CoP to origin for both experts and subjects in all posture ((a)~(f)) obtained through WBB. The CoP for the subjects was calculated by taking the average of the distances between the respective origins. Table 3 is the average of the distances between the respective origins.

In (a) posture, the average of expert is 27.309 and the average of subjects is 28.218. In (b) posture, the average of expert is 9.002 and the average of subjects is 32.443. In (c) posture, the average of the expert is 6.112 and the average of the subjects is 40.667. In (d) posture, the average of expert is 26.168 and the average of subjects is 46.619. In (e) posture, the average of expert is 40.173 and the average of subjects is 61.905. In (f) posture, the average of expert is 15.846 and the average of subjects is 39.294. In the six postures, the distance between the origin and the cop was smaller than that of the expert's posture. The fact that the distance of the CoP-origin is small means that the posture is stable.

Fig. 8. is the result of the difference in the CoP-origin for experts and experimental subjects and the result of Fast Fourier transform (FFT) it. To compare the instability of the posture, FFT was applied to the distance between the CoP and origin for all postures ((a)~(f)) which expressed in time series.

As a result, the FFT graph composed of frequency and amplitude was obtained. When comparing the FFT results of the expert and subjects, it can be seen that the expert's graphs are located below the subjects' in all positions. This means that the Amplitude of the Expert is smaller than the Amplitude of the subjects, and the smaller Amplitude means that the variation of the CoP trajectory graph of the body is relatively small. That is, when the squatting, the variation of the CoP is small, which means that the body oscillation itself is small. Thus, it can be confirmed that the posture of the experts is more stable than that of the subjects.

In addition, the system developed through this study correctly measures the squat posture and balance of the user. Thus, the system can acquire sufficient usable data for posture classification through machine learning.

C. Squat Posture Classification Using Machine Learning

SVM and Naïve Bayes for the classification of the squat postures performed by the expert and the subjects by using data obtained from Kinect and WBB. SVM was run on the SVM open source library LibSVM 3.22, while and Naïve Bayes was executed in a R 3.4.4 environment.

For the classification task, 80% of the total data were used as training data, and the remaining 20% of the data were used as test data. Table 4 presents the classification results obtained using SVM and Naïve Bayes.

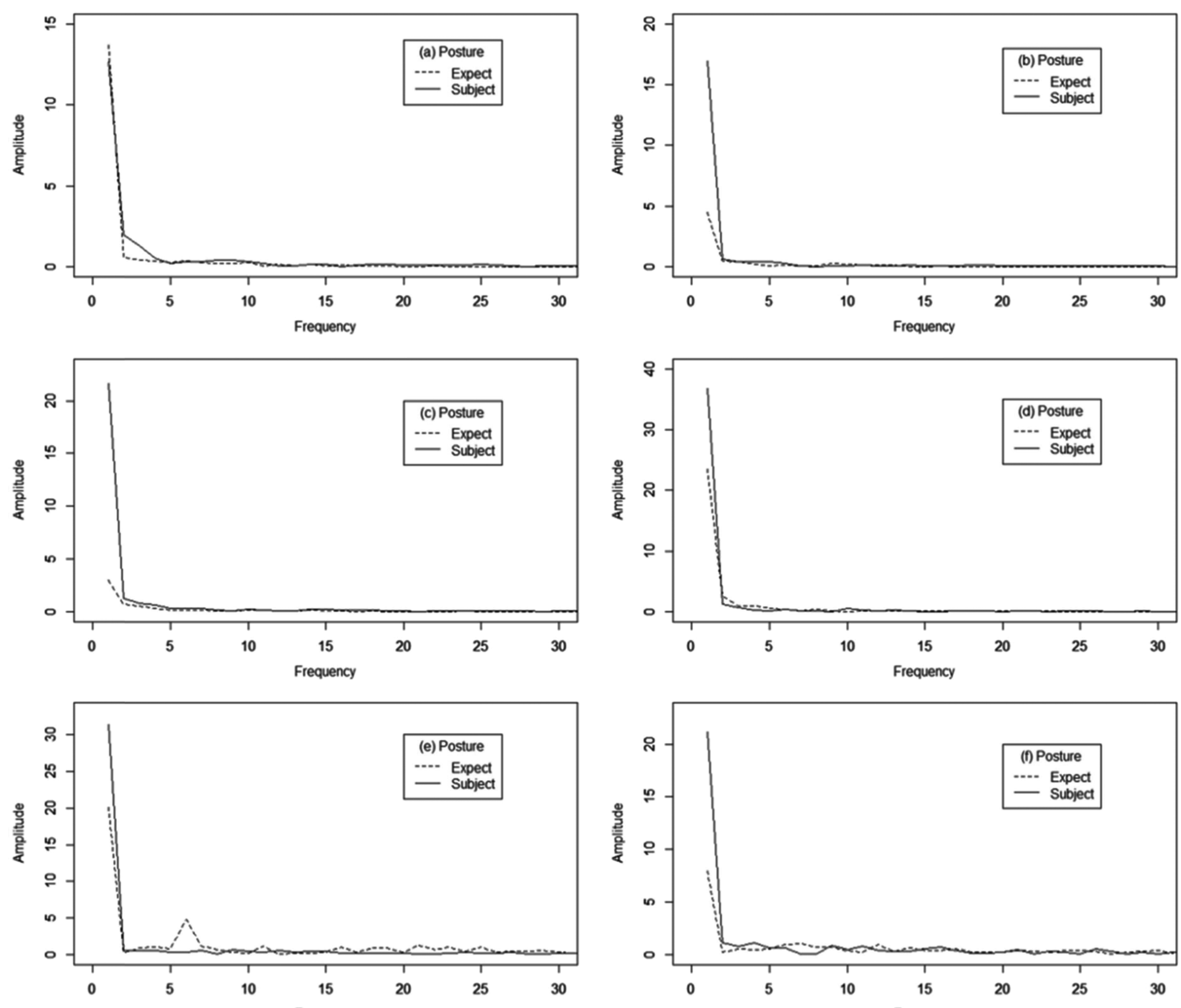

Fig. 8. FFT results of CoP-Origin distance comparison between experts and subject.

Table 4. Accuracy (%) of SVM and Naïve Bayes classification

Stand / Squat State	Correct / Incorrect Posture	(a) ~ (f) posture	SVM Classification		Naïve Bayes Classification	
			Kinect	WBB	Kinect	WBB
Stand State	Correct Posture	Normal Stand Posture: (a) posture	92.9	99.9	93.2	63.9
	Incorrect Posture	Narrow Stand Posture: (b) posture	98.3	99.9	99.3	79.3
		Wide Stand Posture: (c) posture	92.7	100	91.6	83.4
		Unbalanced Stand Posture: (d) posture	90.9	100	95.7	51.9
Squat State	Correct Posture	Normal Squat Posture: (e) posture	92.6	96.5	87.4	84.8
	Incorrect Posture	Knee Protruding Posture: (f) posture	89.1	94.5	86.1	65.2

The results of the classification showed that SVM classified the squat posture with an average probability of 95.61%, while the Naïve Bayes classifier classified the squat posture with an average probability of 81.82%.

V. DISCUSSION

In Posture measurement using Kinect system, $\|\overrightarrow{\boldsymbol{SLSR}}\| - \|\overrightarrow{\boldsymbol{ALAR}}\|$ values measured. In the (a) posture, the value of the expert was larger than that of the subjects. This means that subjects did not open their legs in Stand Posture. In the (c) posture, the value of the expert is negative $\|\overrightarrow{\boldsymbol{SLSR}}\|$ is smaller than $\|\overrightarrow{\boldsymbol{ALAR}}\|$ when calculating the $\|\overrightarrow{\boldsymbol{SLSR}}\| - \|\overrightarrow{\boldsymbol{ALAR}}\|$ value. This means that the subjects did not spread their legs much, which resulted in positive $\|\overrightarrow{\boldsymbol{SLSR}}\| - \|\overrightarrow{\boldsymbol{ALAR}}\|$ values for the subjects.

When the values of $\boldsymbol{\theta(Knee)}$ are compared, the values of $\boldsymbol{\theta(Knee)}$ of the subjects is higher than that of the expert $\boldsymbol{\theta(Knee)}$. This shows that the subjects have less knee flexion than expert when doing a squat exercise in the (f) posture, the $\boldsymbol{\theta(Knee)}$ value of the expert is larger than the $\boldsymbol{\theta(Knee)}$ value of the subjects.

As a result, the expert recognizes that knee protruding posture is not a squat movement, and it is judged that he cannot take a good squat posture. However, the subjects are expected to have a smaller $\boldsymbol{\theta(Knee)}$ value because the wrong squat posture is similar to sitting posture in daily life, allowing the knee to bend more.

In Balance measurement using WBB system, it can be seen that all the actions of Squat Posture in the trajectory are recorded. And trajectory is concentrated when it is maintained in one position. In the normal squat position, the trajectory is drawn long along the Y axis. Also, trajectory tends to concentrate on the negative direction of the origin and Y axis. This is because the trajectory is concentrated in the negative direction of the origin and the y-axis since the squat movement is normally performed, and the stance is maintained for the longest time when standing and bending the knee to the maximum. This means that the negative direction of the trajectory's y-axis is the user's hips

A small value at the distance between Cop to Origin means that the center of gravity is well-balanced and well-maintained. The distance between the CoP to Origin of the experts in all six postures was low. Thus, in every posture, expert can have a much more stable squat posture. FFT was also performed in six postures, which can be used to compare posture instability. After the application of Fourier transform, the obtained Fourier series can be regarded as a regression analysis of the magnitude of fluctuations in posture. Depending on the region of the lesion that causes the imbalance, oscillating of different frequencies is observed. At higher frequencies, the probability of a pathological condition existing at the site increased [22]. In this study, the higher the Fourier series was, the more unstable balance it was. When comparing the results of the FFT, we can confirm that the posture of the expert is more stable than that of the subjects. Based on the results, the comparison of the mean values and the results of the FFT, we can confirm that the posture of the expert is more stable and have low oscillation than the general posture.

In Squat posture classification using machine learning, SVM classifies the posture with an average probability of 95.61%, and Naïve Bayes classifies the posture with an average probability of 81.82%. The proposed system is more practical and usable than existing motion recognition systems, with no significant difference in accuracy. Moreover, the system is easy-to-use and can analyze squat posture and movement more conveniently than existing motion recognition systems. Moreover, the developed system can measure squat posture from Stand to Squat posture of expert and subjects, and it can present correct squat posture to ordinary people.

This simplicity of the system enables users to assess their squat motion at home with ease. It can be confirmed that the home devices (Kinect, WBB) can be used for motion analysis by utilizing only or all part of the system and performing balance analysis or motion analysis.

Previous studies related to motion recognition and motion capture using Kinect aimed at making content using the skeleton recognized by Kinect. Such studies merely apply the features of Kinect. However, this study obtained the spatial coordinates of the Kinect and measured the length of the body and obtained meaningful results from the measured values. This is a completely different type of motion recognition research from previous studies.

Finally, developed system helps people to analyze the squat posture easily and conveniently in anywhere and can present correct squat posture guideline. With this system, user can easily analyze the squat posture in daily life and suggest safe and accurate postures to users.

However, there exists certain considerations to the use and applicability of the proposed system. First, the Kinect sensor itself is confined; Kinect was built as a controller for the Xbox 360. Hence, it is not a conventional motion recognition device, and therefore, there are handicaps to its use as a motion recognition device. In particular, Kinect anatomically recognizes only the motion performed in the frontal plane. In fact, there is a lot of difficulties in doing limited exercise only on the frontal plane because of various actions when exercising. Thus, in this study, the participants performed squats by placing both arms placed raised towards the head instead of a more conventional general squat position, where both arms are extended forward. Therefore, in order to address these limitations, it is imperative to apply Kinect to various postures using multiple Kinect devices.

In addition, the dualized system is also limitation. The system developed in this study is driven by the dualization of Kinect and WBB. Therefore, there is a slight time difference when acquiring data, and hence, both devices must be calibrated separated prior to data collection. Therefore, in our future work, we intend to integrate Kinect and WBB.

The values of the accuracy difference between SVM and Naïve Bayes can vary depending on the type and amount of data and feature, but both methods are good classification methods. But it may be reduced by adjusting and tuning the hyper-parameter or kernel of the classifier. However, in this study, the accuracy of these two classifications is not the main research topic, thus it is that the constructed system classifies the posture with high accuracy. Therefore, the difference between SVM and Naïve Bayes is to be further investigated in subsequent studies on other topics.

VI. CONCLUSIONS

In this study, we developed a squat posture recognition system and it gives to present a correct squat posture guideline using Kinect and WBB. And we decided to study the posture before and during the exercise to correct the wrong posture that is commonly used by those who are not unused to the squat posture. And to make it easier for anyone to use the developed system, we conducted research using a home device.

Through the developed system, posture data and balance data of experts and subjects were collected and classified as SVM and Naïve Bayes which optimized for data classification and presented correct squat posture. SVM is accurate for large amounts of data processing. Naive Bayes differs depending on the amount of feature but has fast performance.

A total of 11 participants, one expert and 10 adults, participated in this study to compare the expert posture with the experiment. The participants measured the difference in shoulder width and ankle width and knee angle at every frame through Kinect and obtained CoP x and y coordinates through WBB.

The trajectory was drawn with the acquired data, and the data obtained as a result of the FFT were confirmed to be data suitable for the correct squat posture classification. As a result, the system developed in this study classified the correct squat posture as 95.61% for SVM and 81.82% for Naïve Bayes.

The posture and balance of the experts were more stable than the posture and balance of the subjects. The comparison of the average of each value, the comparison of the trajectory, and the comparison of the FFT results were found. Classification of posture and balance using machine learning also showed differences between the two groups.

Through experiments result, the system can be said to be more practical and more usable than the existing motion recognition system, while the accuracy is not significantly different from the conventional motion recognition system. In addition, it can be easily used by anyone and it can be confirmed that it is a system that can analyze squat movement more conveniently than previous motion recognition system. Furthermore, from these results, it will be suggested that this system can provide guidelines for the correct squat for the user.

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