Gait Analysis Parameter Study Using Xbox Kinect Aimed at Medical Rehabilitation Tool

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Gait Analysis Parameter Study Using Xbox Kinect Aimed at Medical Rehabilitation Tool

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Abstract: There are various methods of rehabilitation to restore disabled gait, one of which is gait analysis. However, some gait analysis systems have shown drawbacks for clinical use, such as system complexity and the high cost of gait equipment. A Kinect sensor could be used as an alternative for gait analysis and is studied in this research. The accuracy of a Kinect in calculation of kinematic gait parameters was computed during normal gait. The gait analysis was processed with Matlab and data was acquired by recording multiple subjects' gait with different Kinect position. Subjects' the right knee was calculated and the results shown the best position of Kinect to capture gait is 45º towards motion path with errors of detecting gait parameters about 7%. Hence, Kinect sensor is capable of doing gait analysis for further pre-clinical applications.

Keywords: gait analysis; gait classification; gait parameters; Kinect; Matlab

1. Introduction

Analysis of gait in humans is one of the important and growing sciences in understanding the human body. This makes gait analysis as one of the methods for treating or rehabilitating human body movement[1]. There are several reasons for the use of gait analysis in the clinical world, namely as a diagnosis between disease entities, severity, monitoring progress in the presence or absence of intervention, predicting the outcome of interventions in human movement[2]. These reasons can make gait analysis as an application of diagnosis, monitoring, treatment, and rehabilitation, and even home remedies to direct treatment optimization[3]. As in the research conducted by Clark et al.[4], gait analysis is able to provide an overview of specific motor function impairment so that it can be useful in clinical diagnosis.

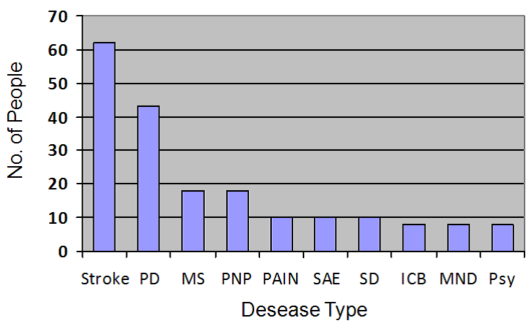

Fig.1: Disease related data or patients with gait disturbance[4]

PD, Parkinson's disease; MS, multiple sclerosis; PNP, polyneuropathy; SAE, subcortical arteriosclerotic encephalopathy; SD, spinal disorders; ICB, intracerebral bleeding; MND, motor neuron disease; PSY, psychogenic gait disorders. PD, Parkinson's disease, Figure 1 shows data on the number of patients with gait disorders in a study conducted by H Stolze et al.[5]. The data were collected at the University Hospital Department of Neurology, Kiel, Germany. The number of participants from the study was 493 people and 292 of them had a gait disorder.

Calculation of kinematic and kinetic parameters of gait based on three-dimensional (3D) motion capture equipment information is frequently used in evaluation of gait disorders[6], knee amputation[7], and to design a industrial robot hand[8]. Despite the high accuracy of commercial motion capture equipment, most of them are expensive and not widely used in clinical gait analysis.

Microsoft Kinect is an affordable, portable motion capture system consisting of an infrared (IR) projector, RGB camera, and IR camera. The Kinect sensor does not have the problems of commercial systems and does not need to be calibrated, therefore this system is a great choice for clinical and home-based motion assessment. With Kinect, tracking and recording 3D movements of skeletal joints is feasible without using any markers on anatomical landmarks. If the sensors' inaccuracy is acceptable, the Kinect sensor is a suitable choice for in-home or clinical gait.

Generally, gait is adapted to ease the pain of diseased limb[9] thus home or clinical gait assessment using Kinect can be proposed as one of the solutions to the problem of expensive and complex systems of commercial motion capture equipment. Using Kinect as in-home or clinical gait analysis, patients can do rehabilitation more often without having to spend more money. Furthermore, by using machine learning technology (in this study, we use classification learning), patients can see changes in gait recording results whether they are normal or still in abnormal conditions. With Kinect, in-home or clinic gait assessment will be easier or even can be done anywhere. The gait parameters such as stride length, stride time, and lower extremity angle acquired from patients' gait records can be processed by using Matlab and then classified by classification learner for further analysis.

Limited gait parameters have been calculated in studies using the Kinect sensor for gait analysis, and there has not been any comprehensive study of the sensor's position relative to the motion path. The sensor positions that have been studied are in front of the subject[10], perpendicular to the motion path[11]. Mostly, the studies in gait using Kinect involve another Vicon system. There is a lack of a comprehensive study on the parameters that are likely to affect the accuracy of the Kinect sensor when measuring gait parameters.

The purpose of this study is determining the Kinect position in gait analysis for medical rehabilitation application. The error calculation method used in this study was placing Kinect sensor in two different positions towards the motion path. In each position, the data was recorded by only one Kinect and further compared in a qualitative way with other research.

2. Methods

2.1 Study of Literature

Prior to this research, there was also notable research regarding the use of Kinect with its motion capture capability in doing a gait analysis. It is unclear about the exact year of the first research that use Kinect as a tool for gait analysis, but the study of Kinect as a tool for gait analysis has begun since the release of Kinect V1 and the study continues as the newer Kinect version has better component and more efficient programs.

There are some studies to validate the use of Kinect in gait analysis and test the accuracy of Kinect itself compared to the other motion capture equipment. A study of concurrent validity of the Kinect for assessment of spatiotemporal gait variable was done by testing the Kinect with a marker-based three-dimensional motion analysis (3DMA) system by Clark et al.[4]. Twenty-one healthy adults were performed in normal walking trials while being monitored using both systems. The outcome measures of gait speed, step length and time, stride time and length. The study found that Kinect possesses concurrent validity with a 3DMA system for some spatiotemporal components of gait, however Kinect does possess limitations.

Morten Kolbjrnsen et al.[12] also conducted a study in which he compared the motion sensing capabilities of the Kinect, Nintendo Wii, and PlayStation Move. According to the study's findings, each device has its own advantages in detecting, but the Kinect camera has the most advantages, including the shortest delay value, the highest connectivity value, the best documentation results, and the best motion sensing quality.

Similar to this study, Preis et al.[13] and Zahra et al.[14] shows the accuracy of Kinect alone[13] and Kinect compared with commercial motion capture camera[14]. Preis et al. used 13 biometric features such as the height, length of limbs, and step length which then are computed from the skeleton frames generated by Kinect. The placement of Kinect itself in Morten Kolbjrnsen research was perpendicular to the motion path. Zahra et al. did a research that examines the Kinect placement position. A gait analysis was performed on a healthy man in the study, with a Kinect and a Vicon camera used as a comparison. According to the study, the best location for Kinect to perform gait analysis was directly in front of the subject.

Gait analysis is a measure that can be easily translated from animals to humans, especially in the case of motor diseases[15]. Mostly, gait analysis approach relies on an analysis of the binary silhouette of walking persons for identification[16]. Existing approaches are classified as model-based and model-free. Model-based approaches attempt to simulate the human body and its movement. The stick-figure model, in which the human body is represented by sticks and joints, is the most common option[17]

As the model-based become the most common option for gait analysis, it also becomes one of the easiest ways to display detection of human body movement. Such an approach was then also implemented in a gaming sensor known as Kinect. Kinect is a sensor that consists of two cameras and an infrared projector. The cameras that Kinect use are a color camera and a depth camera. The operative measuring range of Kinect is from 0.5 m to 4.5 m[17]. Kinect uses speckle pattern of infrared laser light which then combined with two classic computer techniques: depth from focus and depth from stereo. Subsequently, Kinect will implement machine learning to infer body position[14].

A research was done by Chambers et al.[18] reported the accuracy of Kinect depth camera. The research was performed using 3 Kinect at the same time and they recorded a stationary object and used trilateration method to calculate the optimal depth camera detection. They concluded that the optimal recording is 3 to 4 meters away from the Kinect placement. Things to be noted from this research are the position of Kinect which must be in triangle shape to avoid IR interruption between each Kinect.

There was also an evaluation done by Erik et al.[19] using the depth camera of Kinect for passive in-home fall risk assessment. The research purpose was to validate the useability of Kinect camera, especially the depth sensor, ability to detect the movements of a person. Their research method was also using another two web cameras as a comparison The result showed that Kinect V1 had a valid recording ability compared to the web cameras. The depth cameras in Kinect also helped reducing the computational requirements necessary for robust foreground extraction.

We have also considered and researched the factors that can affect the accuracy of Kinect. A study was conducted by Latore et al.[20]. The research was carried out in several scenarios where Kinect recording was carried out in indoor and outdoor areas. Based on their research, the object worn by the subject and sunlight can affect the model recorded by Kinect.

One of the steps taken by Kinect to infer body position is machine learning. As a result, in this study's data analysis stage, we used classification learning to determine the value of Kinect detection accuracy. Because the training dataset for creating a classification model requires labels to categorize the instances in the dataset, classification learning is termed as supervised machine learning[21]. In this study, we used the ensemble bagged trees and k-Nearest Neighbor methods, which are both used in classification learning.

The definition of ensemble learning is a method that combines or combines several decision tree classifiers to produce better predictive performance than a single decision tree classifier[22].

Bagging predictors are a way to generate multiple versions of predictors and use them to get aggregated predictors. Aggregates across versions are averaged when predicting numerical results, and a majority vote is performed when predicting classes[23]. In ensemble learning, bagging or bootstrap aggregation is used to reduce the variance value of the decision tree classifier. Decision trees itself consist of a series of “if-else” statements performed in a specific order to predict an outcome of an input.

k-Nearest Neighbors (k-NN) classification is part of the lazy learner, so the process carried out on k-NN starts with storing training data in algorithm memory which then new instances will be classified based on the training data. Each instance in the dataset will have a distance between each other, the instance will be classified based on the number of k nearest neighbors. The distance between instances can be measured using the Euclidean distance[24].

2.2 Data Collection

This research method is started from a study of related works from the previous research that covers utilizations of Kinect in gait analysis and its comparison to other gait equipment. Types of literature materials used are gathered from scientific journals, books, and other scientific articles.

We propose a model-based approach for gait analysis based on the skeleton provided by Kinect, using data captured from a color and depth camera. As previously stated, Kinect creates a high-quality skeletal model of up to two users in a Cartesian coordinate system in front of the Kinect sensor.

Our system consists of two components: the first component records the skeletal information offered by Kinect which is then processed by the second component. The second component is Matlab software where we extract the features and then we use the classification learner in Matlab to classify the data into the extracted features.

The method of this research is summed up in the diagram as shown Fig. 2.

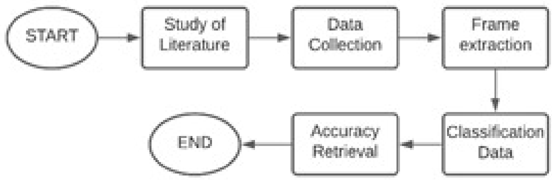

Fig.2: Research method diagram

This study's gait analysis consisted of two scenarios for the placement of the Kinect camera, that was 45 and 90 degrees to the walking path. As earlier stated in Section II, the research that has been carried out on several scenarios by Preis et al.[13] and Zahra et al.[14] involves scenarios 0º, 30º, 60º, 90º to the walking path. There has been no research that has tested at a 45º position to the walking path, besides that the selection of this position is also a comparison to the 90 degrees position of the walking path. Logically, the position of the Kinect camera 45 degrees to the walking path can provide more accurate detection results.

First, research subjects will be directed to stand at the starting line of the walking path. Then, the research subject will follow the cues from the examiner to start walking on a predetermined walking path and also stop when the subject reaches the finish line of the walking path. This is then repeated at a different Kinect position. Fig. 3 shows illustration of gait data collecting for frame selection.

2.3 Gait Parameter Design, Classification Learner

In this study, the data processing process begins with the selection of gait recording frames that represent the best stance and swing phases. Based on the selected frame, the gait analysis parameter will be calculated which is then followed by classifying the data into two classification models, namely stance and swing phase classification; and classification of walking methods, using the ensemble bagged tree and k-NN methods. Fig. 4 shows illustration of data processing diagram.

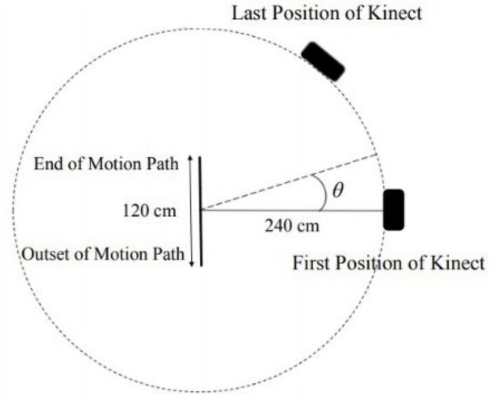

Fig.3: Illustration of data collecting scheme

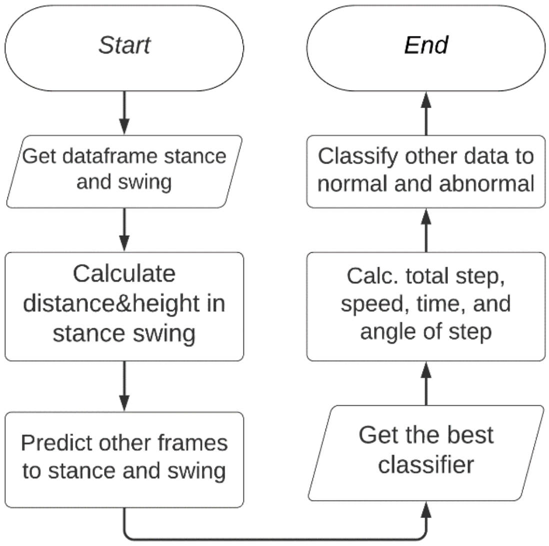

Fig.4: Flow chart of gait data processing

As mentioned earlier, we use skeletal data stream provided by Kinect. This skeleton model has 25 joints with each number correspond to the detected human body. Fig. 5 shows the illustration of Kinect skeletal model.

We calculated gait analysis parameters based on several studies, such as the research of Oberg et al.[25] and S. Chauhan[26] who performs a temporal-spatial gait analysis with parameters of stride length, stride frequency, and stride speed, and in his research has provided reference data for gait analysis parameters for ages 10-79 years.

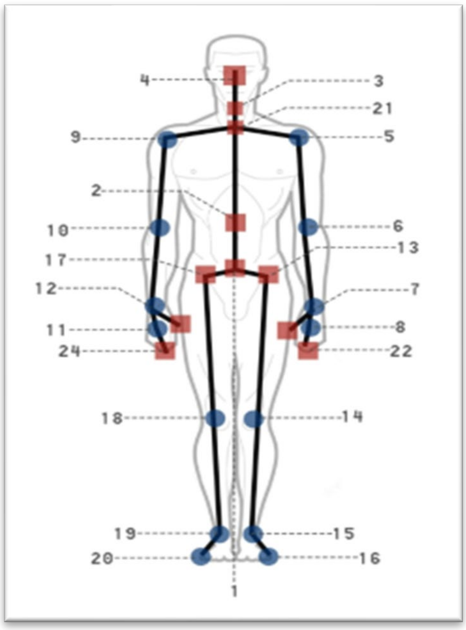

Fig.5: Kinect skeleton model

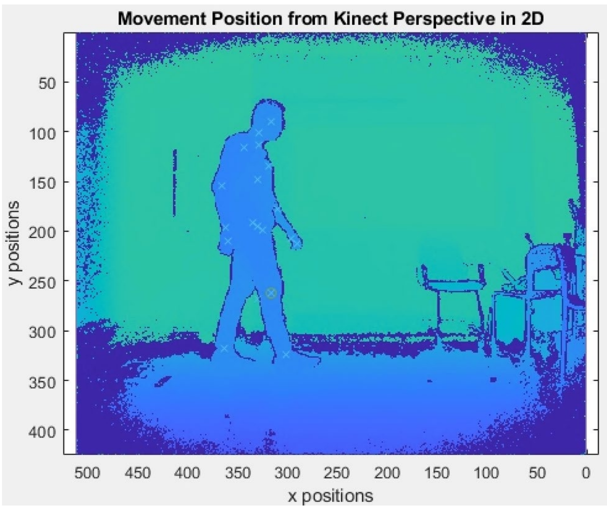

Fig.6: Visualization of data collection using Matlab

Fig. 6 is an image that shows the visualization of the gait recording on each subject. Fig. 7 is used to validate the suitability of the data obtained and is also used to select the frame that represents the best stance and swing phases when processing the data frame to create a dataset.

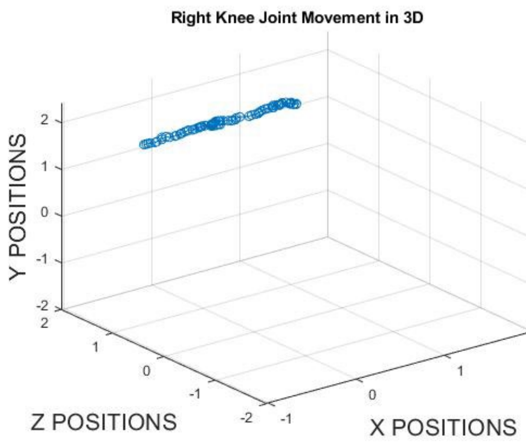

Fig.7: Visualization of right knee joint in XYZ plane using Matlab

Fig. 7 shows a visualization image of the gait recording on each subject's right knee joint. This is used to provide a clearer image of the movement of the right knee of each subject and is also used to match the movement of the right knee according to the visualization of the gait recording results.

The calculation of the change in joint movement is carried out for joints 18, 19, and 20. The following is the change equation used to measure joint movement:

$$Movement\ X = x(t+1) - x(t) \quad (1)$$
$$Movement\ Y = y(t+1) - y(t) \quad (2)$$
$where:$
$t = frame\ number$

The calculation of the number of steps starts from the first frame to the last frame. The result will be divided by two because one step contains one stance and swing phase on the same foot.

After getting the value of the number of steps, the next step is to calculate the distance of the steps. Calculating the step distance can be done with the equation below:

$$Step\ distance = (x(n) - x(1)) \div total\ steps \quad (3)$$
$where:$
$n = frame\ number$

Then, to calculate other gait parameters such as stride length, step time, step speed, and joint movement in Z axis, we can use the equation below:

$$Stride\ L = (Mov\ X + Mov\ Y) \div total\ steps \quad (4)$$
$$Step\ T = (t(n) - t(1)) \div total\ steps \quad (5)$$
$$Step\ speed = Stride\ L \div Step\ T \quad (6)$$
$$Mov\ Z = Z(t+1) - Z(t) \quad (7)$$
$where:$
$t = frame\ number$
$L = Length\ \&\ T = time$

Then, the calculation to get the angle value at joint number 18 and joint number 19 is done by calculating the root of the difference in the squares of joints number 17,18 and 19 and joints number 18,19, and 20.

To summarize the above calculations, the gait analysis parameters used in this study are the number of steps, changes in distance and height, step frequency, step speed, movement of joints 18 in the *Z*-plane, angles at the knee and ankle joints.

3. Results and Discussion

From the results of calculations that have been carried out in section IV, classification is carried out based on the values that have been obtained for each parameter. As already mentioned, there are two classifications for each Kinect camera placement scenario. Figs.8 and 9 show the results of the classification of stance and swing phases:

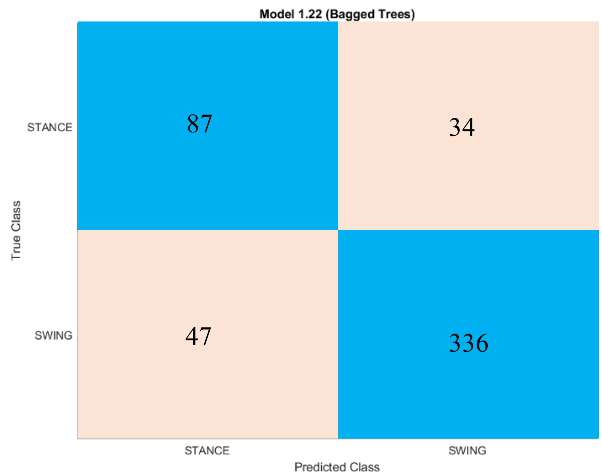

Fig.8: Classification of stance and swing phases in scenarios of 45° to the walking path using the ensemble bagged trees method

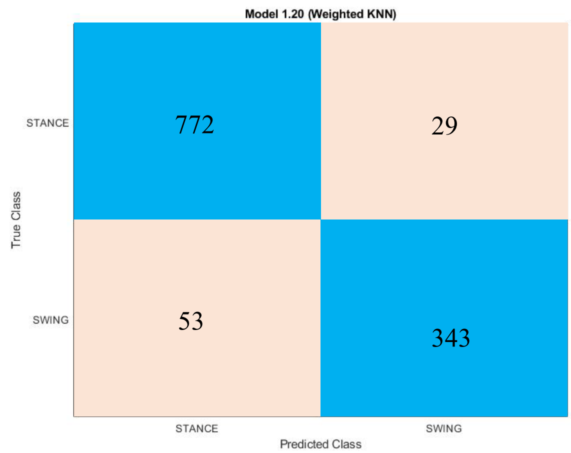

Fig.9: Classification of stance and swing phases in scenarios of 90° to the walking path using the weighted k-NN

We can see in Figs.8 and 9 show the classification results in scenario 45º produce an accuracy of 93.7% with an error value of 6.3% using the ensemble bagged trees method, while in scenario 90º the classification results have an accuracy of 93.1% and an error value of 6.9% by using the weighted k-NN method. The accuracy that has been obtained in both scenarios indicates that the detection results are quite sufficient. The 45º scenario produces better detection results than the 90º scenario because the 45º scenario provides clearer recording coverage. When recording a 90º scenario, the Kinect camera can only detect the right side of the body (the location of the Kinect camera is on the right side of the walking path) while the left side of the body cannot be detected clearly so that it causes an inaccurate joint detection process, such as right knee detection error as left knee or variable knee detection position. Meanwhile, in the 45º recording scenario, the subject's body can be recorded in its entirety, so the Kinect camera does not make as many detection assumptions as it did in the 90º scenario.

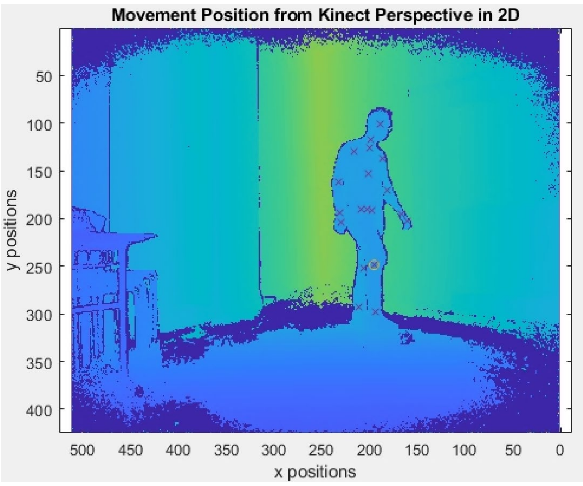

Fig.10: Kinect camera recording coverage in 45º scenario

As shown in Fig. 10, all joint detection positions are in the correct position. If all joint positions can be detected correctly, it will describe the shape of a skeleton.

The error value in the classification can be caused by several things, such as the value of changes in knee distance and height when doing a gait cycle is not much different so that there are similar data between changes in the stance phase and changes in the swing phase. Variations in the size of the subject's feet that are too slender can give detection errors, the intensity of sunlight can interfere with the speckle pattern emitted by the Kinect camera so that the detection is less accurate. The use of loose pants can also reduce the accuracy of detection because the waving of the pants when walking gives the Kinect the wrong perception of the shape of the foot.

In the research conducted by Preis et al.[13] several results were obtained using three classification methods, namely 1R with 62.7% accuracy, C4.5 decision tree with 76.1% accuracy and Naive Bayes with 85.1% accuracy. Research by Preis et al. also was conducted using only one Kinect camera (no other Vicon camera) as in this study. Ifwe compare with the results of the 90-degree recording scenario of that study, our study produces better detection results, which is 93.1% using the k-NN classification method. This could be because in this study has a larger number of subjects, thus providing more data variants.

After getting the classification model for each scenario, the next step is to predict the same data into the classification of the way of walking. This classification classifies the data into two classes, i.e. normal and abnormal way of walking. The classification is also carried out in both scenarios. Figs.11 and 12 show the results of classifying gait using the weighted k-NN method.

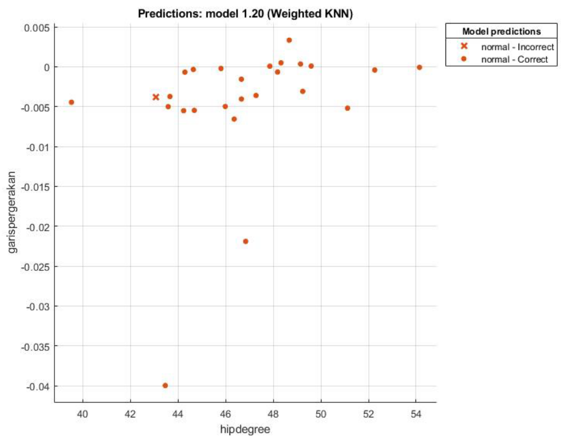

Fig.11: Gait classification in 45º to the walking path using the weighted k-NN

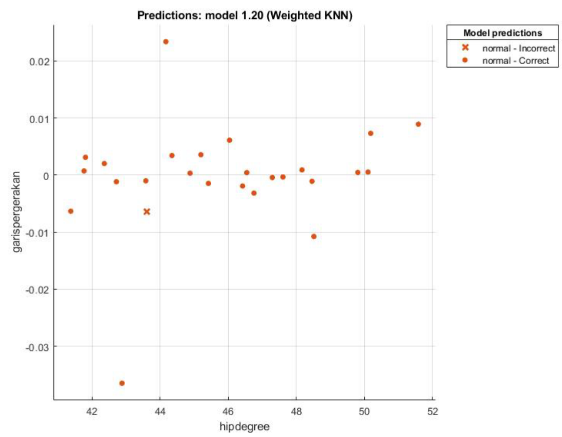

Fig.12: Gait classification in 90º to the walking path using the weighted k-NN

As we can see in Figs.11 and 12, both produce the same accuracy of 96.2% and the error value of 3.8%. This accuracy indicates Kinect detection is quite good.

As earlier explained, the error value in Figs. 11 and 12 can be caused by several things, namely the value of changes in the distance and height in the stance and swing phases which are not much different; variations in the shape of the subject's lower extremities also cause some wrong detection. This happened to subjects who have slender legs so gait recording must be done several times to be detected, the use of loose pants and the intensity of sunlight that can interfere with Kinect's infrared emission. Another thing that needs to be known in this study is the number of subjects were 26 people where 25 people had normal walking conditions and only 1 person had abnormal walking conditions. This could be the cause of imbalance in the dataset so that this factor can also be considered as an error value analysis.

4. Conclusion

This study succeeded in recording gait analysis using one Kinect camera with two different Kinect placement scenarios, namely 45º and 90º to the walking path and classifying the data into two classification models with the aim of finding the accuracy of the Kinect recording results. Based on the results of the study, the position of 45º to the walking path resulted in the best accuracy which is 93.7% in classification of stance and swing; 96.2% in classification of way of walking. The 90º scenario gives 93.1% of accuracy in the classification of stance and swing; 96.2% of accuracy in classification of way of walking. In this study, which observes the accuracy of Kinect and its placement in performing gait analysis, Kinect can become a tool in gait analysis as a medical rehabilitation application tool. We provide suggestions for such research in the future, such as the number of subjects more than the number of subjects in current study, a place for gait analysis recording that is not exposed to sunlight at all and increasing the number of subjects who have abnormal gait.

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