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Human Sitting Postures Classification Based on Angular Features with Fuzzy-Logic Labeling

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Abstract – Musculoskeletal disorders (MSDs) are generally associated with sitting postures. Assessing and ensuring healthy sitting posture are indispensable aspects of reducing the occurrence of MSDs. This study aims to develop a system that allows office workers' body postures to be contactless and recognized by different classification methods while sitting on a chair and can be used for health applications. Five different sitting body postures have been determined within the scope of medical and health literature studies and relevant standards. Thirty subjects were asked to sit in these body postures for 30 seconds. While the subjects were sitting, skeleton point position defined as a pose data of the subjects were obtained from the Kinect device simultaneously. Five angles that are thought to distinguish sitting positions according to different joint positions were determined and calculated. The angle values that can take in the standard sitting position in the literature have been determined. According to these values, the angle values in other postures were determined. A rule-based fuzzy inference system was designed using angle values for labeling sitting posture data. Angle values were calculated to classify the labeled depth values, and an artificial neural network classifier was designed according to these angle values. As a result, five different sitting body postures were classified with KNN (K-Nearest Neighbours) and Neural Network (NN), respectively, with 98.9% and 97% overall accuracy values. The study was compared with other studies in the literature. In this context, a high-performance system design that can improve healthy sitting behaviors for office workers that can be used in both health applications and robot vision is presented.

Keywords – Sitting Posture, Angular Features, Fuzzy-Logic Labeling, Classification, Depth-Based Sensor, Kinect

I. Introduction

Today, most people work sitting in their work environment. Sitting in the same position for a long time or wrong sitting can be caused unhealthy body posture, skeleton point and low back pain, disorders, muscle, and heart disorders, etc., leading to disadvantageous situations. [1], [2] According to the European Agency Safety and Health at Work [3], around 60% of all workers in the EU with a work-related health complaint identify Musculoskeletal Disorders (MSDs) as their most serious problem. MSDs cause 58% of work-related diseases, deaths, and permanent incapacity from work. 75% of these are the actions of sitting in the wrong position for a long time. Globally, the number of people suffering from MSD has increased by 25% over the past decade, accounting for 2% of the global disease burden [4]. Therefore, MSDs are an increasingly crucial work-related health issue in contemporary workplaces. Although, as some suggest, eliminating the necessity of sitting down would be better for human health [5], [6] it is obvious that it is inevitable to take measures such as correcting sitting postures and not sitting for a long time working. An intelligent workplace environment with an automatic sitting posture tracking system is presented as a potential solution to save the high cost of health problems. In previous related studies, sitting poses were determined using certain skeleton point positions, and these were generally classified by machine learning methods using different features. In this context, in this study, a contactless measurement system proposal was presented for the problem of recognizing the specified postures in line with the recommendations of health institutions and experts. For this purpose, the Kinect v2 device was used. Thanks to the depth sensor and camera of the Kinect device, it can obtain the width, height, and depth location information of 25 joint positions. In an office environment, this can provide contactless access to sitting posture information without affecting employees. In this direction, how different sitting poses should be classified using depth-based angular features and methods with more effective performance than the studies in the literature were investigated in this study.

II. Related works

Paliyawan et al. [7] proposed classifying office workers' sitting on the real-time skeleton data stream captured by a Kinect camera in an office work area. They collected 397800 poses compiled from 10 body skeleton point belonging to 28 different subjects to create the dataset. The performance of several classification methods such as Decision Tree, (DT) Neural Network (NN), Naive Bayes (NB), and k-Nearest Neighbors (KNN) have been compared. They achieved to classify one postures class with 98% accuracy. Thus, real-time feedback based on the three levels of health in ergonomics has been given to subjects. Pal et al. [8] researched occupational hazards from prolonged sitting in a particular employee posture. Sitting posture recognition has been achieved using seven similarity measures. Using city-block distance, they classified two sitting body posture types with a high accuracy of 94.29% in 3.83 milliseconds. Therefore, the 6500 sitting poses containing the 16 different body skeleton points from 20 subjects have been collected to create the dataset. Bei et al. [9] present a sitting posture classification method based on a Kinect device depth sensor. The dataset, which contains 16200 poses compiled from six body skeleton points, has been used to classify the nine postures belonging to 18 subjects. According to the experimental results, the accuracy value of 95.8 has been achieved using the fusion of the body skeleton point features and the KNN method. Li et al. [10] proposed a method involving BP (backpropagation) neural network. The BP network used the skeleton data captured by the Kinect depth sensor to classify postures. They utilized eight skeleton points to recognize the sitting posture of 100 subjects. While they recognized four types of body posture, they achieved 97.77 accuracy for sitting posture. Ray et al. [11] proposed an automated approach to classify construction workers' postures as ergonomic or non-ergonomic. The dataset, which contains 22226 poses compiled from twelve joint body points, has been used to classify the four postures belonging to 8 subjects. According to the experimental results, the accuracy value of 94.8 has been achieved using the linear discriminant analysis (LDA) method in real-time. The literature makes it unclear how different sitting postures are defined or based on which medical studies or standards. Therefore, the relevant medical and health literature was examined, and the standard sitting posture was defined with precise expressions and angle values in this study. This study determined four different sitting postures to distinguish the standard sitting posture from others. Besides, the difference between the sitting posture, which the subjects feel comfortable with, and the standard sitting posture was revealed due to classification. In some studies, it has been mentioned that body posture classes are determined by observation. The Kinect-based angular features method is proposed in this study to eliminate the lack of observational studies has qualitative features. In most studies in the literature, instead of classifying the data obtained with more than one method, a single method has been proposed. Being dependent on one method has limitations for the generalization of the study. In order to eliminate this deficiency, five different sitting poses created with angular features obtained from the Kinect device were classified with eight different classifiers, and the classification results were compared with the studies in the literature. According to the comparison results, higher accuracy values were obtained by using fewer joint points.

III. Materials and Method

A. *Determination of Sitting Postures*

The suggestions of the studies in the literature [12]–[16] and definitions in ISO 7250-1:2017 [17] have been referred to for the determination of sitting postures. One is a healthy and standard body posture defined as to suggestions in the literature and ISO 7250-1 standard. A sample drawing of a healthy and standard body posture determined according to these suggestions in [12], [16], [17] is given in Figure 1 [13]. The determined five different positions are given in Table I.

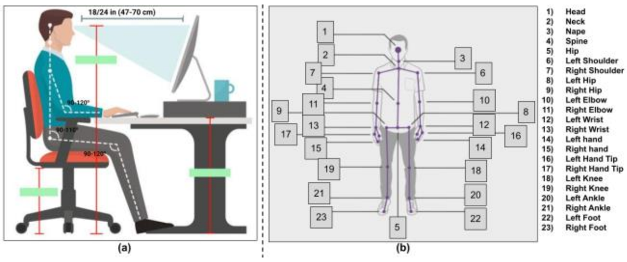

Figure 1 Standard sitting illustration (a), Kinect skeleton points (b)

In order to ensure that the sitting postures of the subjects are correctly changed during the experiment to apply the sitting positions specified in Table I, a presentation containing the positions in Figure 4 was prepared. The subjects were asked to follow their sitting postures via this presentation throughout the experiment.

Table I. Definitions of sitting postures used in experiments

#	Position	Description	Ref.
1	Standard sitting	The hands were asked to sit on both armrests with the back fully leaned back and knees bent 90 degrees straight.	[12], [16], [17]
2	Leaning to the front side	They were asked to sit, so they bent forward as much as possible, avoiding contact with the back.	[12]–[18]
3	Leaning to the left side	It was requested that the body be bent to the left by placing the right foot on the left foot and leaning the left arm on the armrest, and the contact with the right sitting area was cut as much as possible.	[12]–[18]
4	Leaning to the right side	It was requested that the body be bent to the right by placing the left foot on the right foot and resting the right arm on the armrest, and the contact with the left sitting area was cut as much as possible.	[12]–[18]
5	Leaning to the backside	They were asked to sit and slide in the seat by creating a triangular gap in this area, in the form of cutting contact with the lower back and sitting back area.	[12]–[18]

B. *Experimental Setup and Software*

Depth sensor-based data used for this study were collected with a Kinect camera. By using the depth camera, monitoring can be done without the user needing to install any equipment. An experimental setup was set up to create a depth sensor-based sitting posture database. In this setup, the subjects sit on a chair 1.5 meters from the Kinect device. They were requested to exhibit the postures defined in Table I.

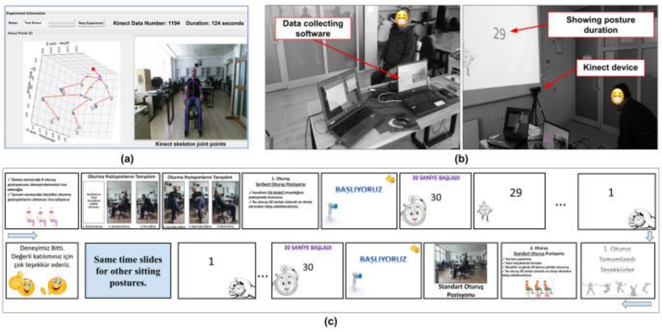

Figure 2 (a) Data collection software, (b) experimental setup, and (c) guide presentation

Subjects waited for 30 seconds for each posture. The real-time data collection and recognition software (a) developed by Python, experimental setup (b), and presentation samples (c) are shown in Figure 2. The recognition software uses the TensorFlow machine learning library to create classification models.

C. *Algorithms for Calculating Joint Angles to Label Body Posture Data*

The skeleton point positions were used to exclude body posture transition values from the data set and to label skeleton point data according to the definitions in Table I. Each posture's specific angle values were selected to label using the skeleton points data.

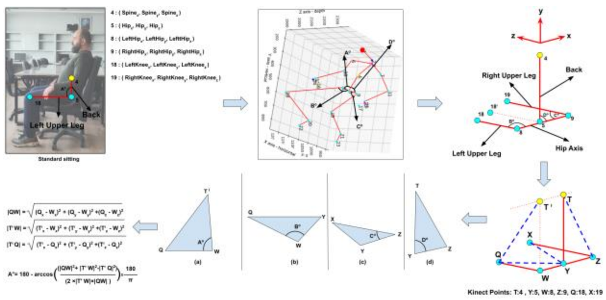

Figure 3 The skeleton points and the angles for standard posture

An example drawing and angle representation of skeleton point position data of standard sitting position is given in Figure 3. These angles are had been defined respectively as the angle of the back with the left upper leg axis in the sitting position (A), the angle of the hip axis with the left upper leg (B), the angle of the hip axis with the right upper leg (C), and the left angle of the back with the hip axis (D). It was decided that these angles are the least number of angles that can represent incorrect sitting postures according to suggestions in [12], [16], [17]. Skeleton point location data is used as unit length, not actual length measures such as meters or inches. In order to calculate the angles A, B, C, and D, four triangles given in Figure 3 were formed, and the lengths of the sides forming these triangles were calculated. Since skeleton point coordinate information was obtained from the Kinect device in 3D space, the edge lengths of the triangles were calculated according to Equation 1 [19].

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2 + (z_2 - z_1)^2} \qquad (1)$$

For a triangle whose sides are A, B, and C, respectively, and each side has interior angles with the same name, angle A is calculated by Equation 2 [19]. According to the example triangle (a) given in Figure 3, whose side lengths were calculated with Equation 1, the value of angle A was calculated with Equation 2. Likewise, Equation 2 calculates the angles B, C, and D.

$$A° = 180 - arccos\left(\frac{|AB|^2 + |AC|^2 - |BC|^2}{2 \times |AC| \times |AB|}\right) \times \frac{180}{\pi} \qquad (2)$$

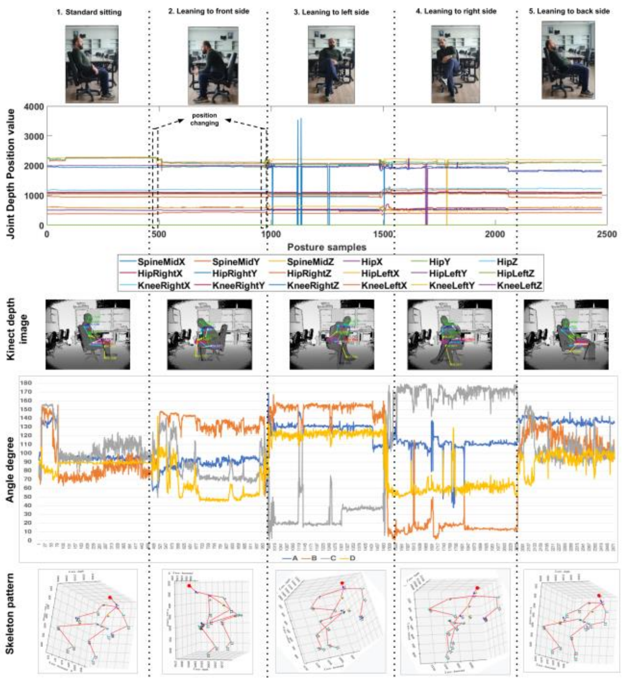

Figure 4 A subject's Kinect raw data as to sitting postures (between 1 and 2477 of supplementary data)

During the experiment, raw data on the x (horizontal), y (vertical), and z (depth) axes of the 25 joint points of the subjects were obtained. The sample raw data of a subject and images of the skeletal pattern are presented in Figure 4. In Figure 4, the changes in the regions of the joint positions corresponding to the sitting positions for different axes values can be observed. The aim here is to determine the positions of the skeleton points of the subjects in the sitting position and to observe the proper sitting behavior with mathematical values instead of qualitative observation. The drawings were created as a result of axis rotation processes in order to make the skeleton point position drawings look more understandable in Figure 4. According to the angle range values determined by the recommendations in the literature in [12], [16], [17], the average angle values of the postures are given in Table II; it is seen that angle values are suitable for the postures in Table I.

Table II. Angle values of sitting postures

Posture	1	2	3	4	5
Angle A	104.3	68.8	88.2	80.4	118.2
Angle A Range	95-105	60-90	80-90	80-90	110-120
Angle B	101.3	121.5	47.1	41.4	115.3
Angle B Range	95-105	110-125	40-55	40-55	110-125
Angle C	104.2	125.7	44.2	50.5	118.2
Angle C Range	95-105	105-125	40-55	40-55	110-125
Angle D	92.1	88.2	76.2	72.4	88.4
Angle D Range	95-105	85-100	70-80	70-80	80-90

Since the sides forming the B and C angles represent the upper legs mutually, these values should be close to each other. When the values are examined in Table II, it is seen that this situation is achieved. At the same time, angle A is an angle that should decrease when leaning forward and increase when leaning back. Therefore, when the values are examined, they are calculated correctly, especially in the second and fifth sitting postures. It is also seen that the D angle values should not change much since there is not much bending to the right and left in the second and fifth sitting postures. For each pose recorded in the dataset, the angle values were calculated using the joint points in Figure 3.

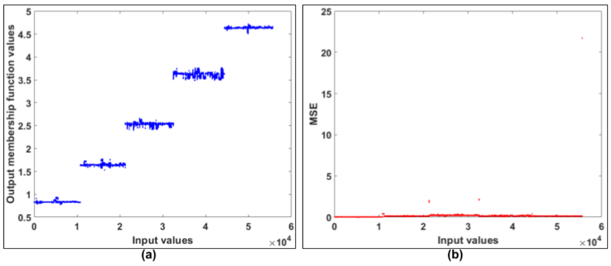

Figure 5 Fuzzy inference evaluation

Using SQL stored procedures, the sitting postures were labeled according to the angle ranges. Mamdani's fuzzy inference system is used in the fuzzy logic-based labeling approach. Four inputs are specified for each angle value. According to the angle ranges in Table II, the Gaussian membership functions and the range of output variables for each class are defined as [0 5]. As the output variable membership function rules, range [0 1] for grade 1, range [1 2] for grade 2, range [2 3] for grade 3, range [3 4] for grade 4 and [4 5] range is determined for the 5th grade. The output results and MSE (Mean squared error) values after the designed fuzzy inference system's evaluation of the angle values are presented in Figure 5. When the charts are examined, it is seen that the classes are separated from each other due to the evaluation, and the MSE value is quite low. Therefore, the fuzzy inference result labeled angle values clustered around their own class as belonging to that class.

D. *Preparing the Dataset and Machine Learning Methods*

After the fuzzy-rule-based labeling process, different machine learning methods classified the angular features whose class information was assigned. The labeling and classification diagram is given in Figure 6. The depth sensor-based data of sitting body posture were obtained with an average 100 ms cycle (10 Hz). The field of view is 84.1 and 53.8 for horizontal and vertical, respectively. The depth distance is 3 meters.

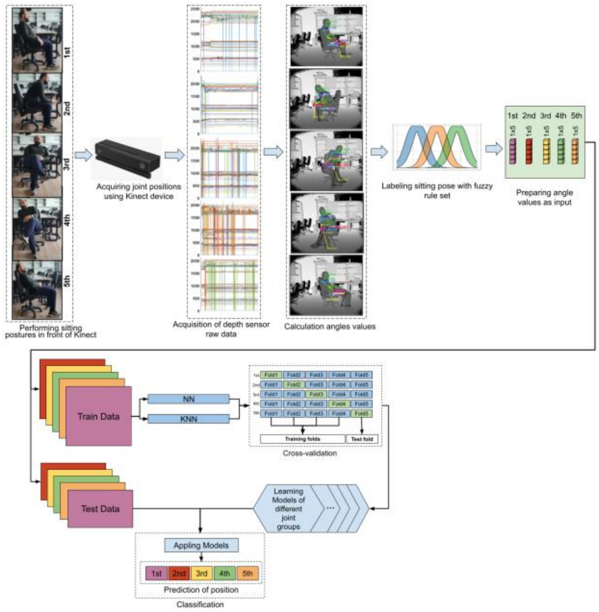

Figure 6 The labeling and classification diagram

49580 sitting body posture poses were obtained for 30 subjects in 5 classes. Since some subjects corrected their sitting positions during the experiment, the angle values obtained from the skeleton point data were not at the desired values. Therefore, angle-based labeling could not label these data for the determined sitting position. Since data obtained from different subjects were used with Kinect-based labeling, different numbers of data were obtained for each class. The data set has 9827, 9617, 9778, 10553, and 9805 records for the First, second, third, fourth, and fifth postures. For all classifiers, 15% of the data was used as validation and test data. The training model has been tested with data not previously used in training. Therefore, test data is entirely different from training data. To recognize sitting body posture, shallow machine learning algorithms, the most widely used in the related literature, were used, and results were evaluated with performance indicators. Although deep learning methods gradually become overwhelming, shallow classifiers remain preferred because training time is shorter than deep learning methods [20]–[22]. NN and KNN classifiers were designed and utilized to classify sitting posture. The classification models with different parameters have been evaluated for the best performance. The network has 2 inputs, 100 hidden layers, and five output layers. Data division feature random, training function scaled conjugate gradient (SCG), Levenberg-Marquardt optimization method, and cross-entropy are used in the networks. The activation function is tan-sig, and 234 epochs were used to train. The error goal has been limited to 0.001 [23], [24]. The weights and biases are initialized using the Nguyen-Widrow method. For the KNN, model flexibility parameters such as the number of neighbors, distance metric, and distance weight have been chosen as 3, Euclidean, and Uniform, respectively. All models were validated through a 5-fold cross-validation (cv) process to evaluate the predictive ability as it allows the classifier to operate without bias and avoids the overfitting problem. The cv was performed without data sharing between training and validation data to avoid overtraining. In order to measure the performances of each model, a multi-class confusion matrix which is defined in [25] and the ROC curve, is created, and Accuracy (A), Recall (R), precision (P), F1-score (F), AUC (Area Under Curve), LogLoss (LL-logistic loss) and Specificity (S) indicators are calculated to evaluate performance [25].

IV. Results and Discussion

For the classification of body postures, confusion matrices for the models of NN, KNN, and classifier methods with the highest accuracy are presented in Figure 7. Both training and testing processes were performed on the same computer. When the confusion matrices are examined, it is seen that the samples are mainly classified according to their classes.

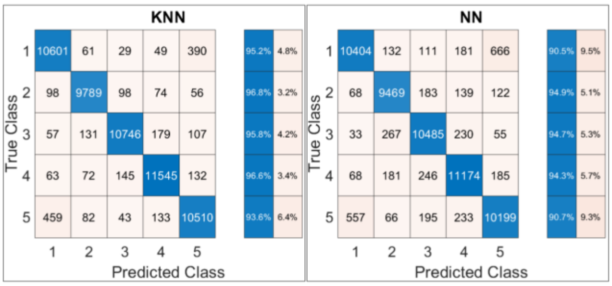

Figure 7 Confusion matrices of classifiers

It is seen that the first-class labeled samples are mainly classified as 5th class apart from their groups and vice versa. Next, it is seen that the samples labeled as 3rd class are mainly classified as 4th class and 2nd, except for their groups, and the samples labeled as 4th class are mainly classified as 3rd class, except for their groups.

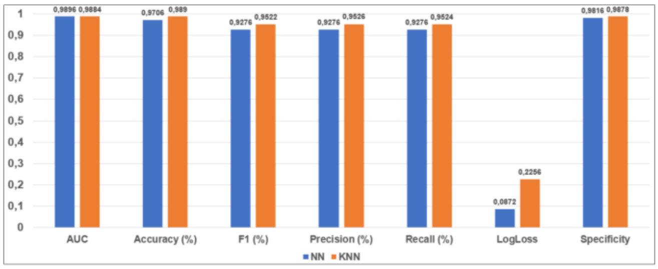

Figure 8 Performance indicators of all classifiers

Finally, it is seen that the samples labeled as 5th class are mainly classified as 1st and 4th class, except for their groups. When the performance of the classifiers is evaluated, if Figure 7 and Figure 8 are examined, it is seen that the classification accuracy of the KNN classifier is higher than the NN classifier.

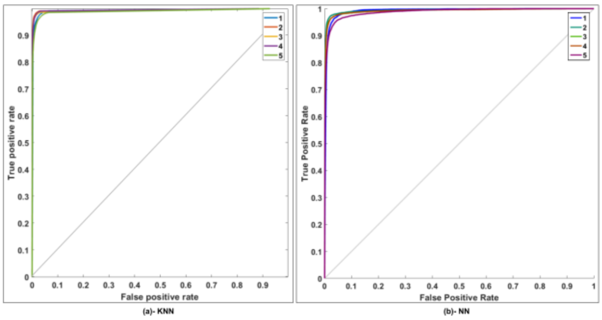

Figure 9 ROC curves of classifiers

The ROC curves belonging to the models with the highest accuracy values for interpreting the accuracy values are presented in Figure 9. When the ROC graphs are examined, it is seen that all models are very close to the upper left corner point (0,1); therefore, the ability of the models to diagnose classes fits quite well. Different studies classify the data from different skeleton points in the related literature. However, in these studies, data acquired from the specified skeleton points were classified at once, and the data from different skeleton points were not separated and classified same time. Therefore, when True Positive Rates (TPR) in confusion matrices and Table III are examined, the best and worst overall accuracy classes are the second and fifth classes.

Table III. Performances of classification methods for all posture classes

Model	Posture	AUC	A (%)	F1 (%)	P (%)	R (%)	LL	S
NN	1	0.991	0.969	0.924	0.912	0.935	0.089	0.977
	2	0.992	0.977	0.939	0.938	0.940	0.068	0.986
	3	0.989	0.974	0.935	0.939	0.932	0.086	0.984
	4	0.989	0.970	0.931	0.937	0.926	0.090	0.983
	5	0.987	0.963	0.909	0.912	0.905	0.103	0.978
KNN	1	0.988	0.986	0.941	0.932	0.951	0.268	0.982
	2	0.991	0.987	0.964	0.965	0.964	0.162	0.992
	3	0.988	0.993	0.961	0.968	0.955	0.221	0.992
	4	0.991	0.991	0.961	0.960	0.962	0.192	0.989
	5	0.984	0.988	0.934	0.938	0.930	0.285	0.984

In order to visualize the sitting posture data, the data in each sitting class and sample 3D drawings of them are given in Figure 10. When these drawings are examined, it is seen that the TP, FP, and FN groups differ.

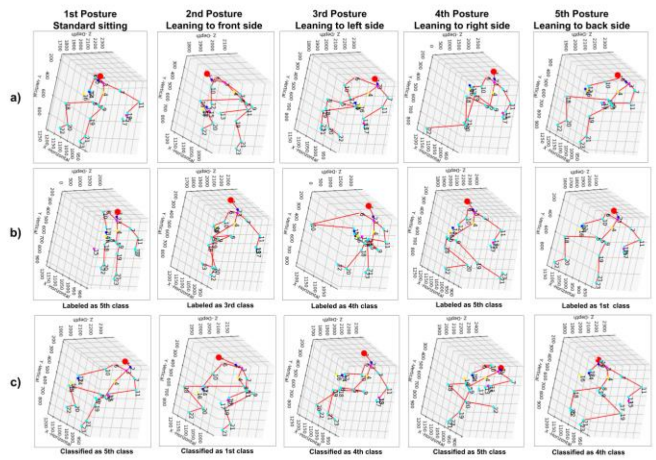

Figure 10 a) TP sitting posture, b) FP sitting posture, c) FN sitting posture

When the joint points are examined, it is seen that most of the joint points are distinctive according to the sitting positions for the true positive samples. It is seen that the 5, 8, and 9 joint points, which are mostly fixed, are insufficient to distinguish the class samples from each other. The use of other joint points that are thought to be distinctive, such as joint no. 4, may not be included in the data set because it is difficult to obtain in terms of office workers' current positions (desk, computer, etc.). In this context, classification accuracy values and other features obtained in studies in the relevant literature were compared with the results of this study and presented in Table IV. The feature extraction method involves extracting more meaningful core data from raw data. The angular calculation method is used for labeling sitting poses, and angular features are used for classification.

Table IV Comparison of studies in the related literature

Study	Pal [8]	Ray [11]	Bei [9]	Paliyawan [7]	Li [10]	*This Study*
Accuracy	94.29	94.80	95.80	98.19	98.85	**98.9**
Labeling Method	Angular calculation	Angular calculation	Angular calculation	Automatic Time-based	Geometric shape calculator	**Fuzzy rule set**
Feature Method	Angular feature	Grayscale image	Local contour - topological	Statistics features	Human body physical features	**Angular Features**
Classifier	City-Block Distance	LDA	KNN	NB	BP NN	**KNN**
Joint Point	16	12	6	10	8	**6**
The Number of Classes	2	4	9	2	2	**5**
Pose Number	5600	22226	16200	397800	55080	**49580**
The Number of Subjects	20	8	18	28	100	**30**

Dataset volume represents the total number of postures used as training and test data. The number of subjects indicates how many were collected while the data set was created. Joint Point is the skeleton point value used to classify sitting positions. When Table IV is examined, it is seen that the highest accuracy value for the models was reached in this study. While there are studies [7] and [10] with datasets more extensive than the dataset volume in this study, other studies used smaller-volume data. As a result, high accuracy values were obtained from studies [7] and [10] with a larger volume than the dataset volume used. The highest classification accuracy value was obtained compared to the study [9], with the most minor joint points in the literature. Using the same labeling and classification method (KNN), a feature set with more joint points (6) and a data set with more posture class types (9) were used, and higher accuracy was obtained compared to the other study [9]. A higher validation success was obtained compared to the other study [10], whose data set used the same classification method (NN), with more total joint points (8) and fewer posture class types (2) used. According to the sitting posture class type, this study has more class types than half of the studies [7] [8] [10] [11] in the literature. Therefore, higher accuracy values were obtained compared to studies with the same or lesser class types. The fact that the subjects are different people means they have different body characteristics. This may cause more separation of the classes representing the sitting posture data obtained from each other. This situation directly affects the classification success. The subjects in the experiments of this study are fewer than the only one studies [10] in the literature. However, it is close to one study [7] and considerably higher than the other [11].

V. CONCLUSION AND FUTURE WORKS

Developing new, low-cost, accessible technologies is an essential step towards facilitating the assessment of sitting postures as office workers sit for extended periods. In this direction, standard sitting posture has been determined within the scope of relevant medical and health studies and standards to carry out the tests of the proposed system. Depth sensor-based 49580 sitting pose data were obtained from 30 subjects for five different sitting positions, including the standard sitting posture. A fuzzy-logic labeling method with depth-based angular features for sitting position labeling data has been proposed for the first time in the related literature. This method calculates the angle values between the body parts according to the sitting postures. In order to obtain the best classification accuracy, the sitting poses dataset with the most minor joint points was classified with two different classification methods. A high classification accuracy value was obtained in most of the methods. In order to determine the relationship between emotional states and sitting postures, simultaneous data can be obtained by methods such as EEG [26], [27] and emotion detection-recognition, and their similarities can be investigated. The ability of the Kinect device to detect the skeletal points of up to 6 people creates a very reasonable amount in terms of system design when a single device can be used to evaluate the body postures of office workers. The presentation of a depth sensor-based system prepares the infrastructure for a system that can be used in intelligent robot assistants, especially in robot vision. The system is thought to recognize sitting or other postures (bending, lifting, etc.) for those working in other fields. The proposed system is thought to be innovative and promising for detecting the sitting postures of office workers and presenting meaningful suggestions.

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