

PAPER

Design and Implementation of Sensor-Embedded Chair for Continuous Sitting Posture Recognition

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SUMMARY In this paper, we design and develop a sensor-embedded office chair that can measure the posture of the office worker continuously without disturbing their job. In our system, eight accelerometers, that are attached at the back side of the fabric surface of the chair, are used for recognizing the posture. We propose three sitting posture recognition algorithms by considering the initial position of the chair and the difference of physique. Through the experiment with 28 participants, we confirm that our proposed chair can recognize the sitting posture by 75.4% (algorithm 1), 83.7% (algorithm 2), and 85.6% (algorithm 3) respectively.

key words: *internet of things, posture sensing, smart chair, posture recognition*

1. Introduction

Most office workers usually work sitting down. It is said that sedentary behavior may cause diabetes, cardiovascular disease, and weight gain. In addition, sitting with an undesirable posture is considered to be a cause of burden on the shoulders and waist, including physical burdens such as low back pain and stiff shoulders. To maintain health and improve working efficiency, it is necessary for the worker to understand both the current posture and the ideal posture for working. Also, the suggestion of correct posture while working with the same posture for a long time is helpful for solving the problems.

However, it is hard to recognize the sitting posture continuously because of the following reasons. (1) privacy intrusion due to the utilization of high privacy-invasive devices like cameras; (2) deterioration of the original performance of a chair due to attachment many sensors to a chair; (3) user discomfort due to the need to attach a sensor to the body; (4) the limited number of recognizable sitting postures; (5) uncertainty in recognizing the posture of people

with various physiques due to the lack of experiment participants.

In this paper, we address all the above problems, propose a sitting posture recognition method and develop a sensing chair that can continuously observe the sitting posture. To solve problems (1) (2) (3), the sensing chair is equipped with eight accelerometers attached at the back of the chair, and the sitting posture is recognized using the tilt angle of the accelerometer. Sensing chair recognizes 18 types of sitting posture.

Each sitting posture is defined by the combination of three main features. The first feature is selected from three types of inclination; whether the upper body is centered or leaning to the left or to the right side. The second group is chosen among three kinds of inclination; whether the upper body is upright or leaning forward, or leaning back. The third group is determined from two types of sitting depth on the chair; either deep or shallow. In addition, it can identify if an office worker is seated or not, which can be used to measure sitting duration. To solve problem (4), the sensing chair can recognize more postures than previous studies. There are 3 kinds of proposed sitting posture recognition methods, (1) using the tilt angle of accelerometer as feature, (2) using a change in the relative tilt angle from the time of seat movement as a feature, (3) a method based on relative angle change from standard posture as a feature.

In order to evaluate the accuracy of the proposed sitting posture recognition method, and to solve the problem (5), 28 participants of various physiques were recruited. We evaluated the recognition methods using the Leave-One-Participant-Out Cross-Validation using various machine learning techniques. As a result, the recognition using neural network was the most accurate out of all proposed sitting posture recognition methods, 75.4% for method 1, 83.7% for method 2, and 85.6% for method 3. In addition, the positions of the accelerometer sensors were examined using random forest, the result was that the sensors attached on the center of the chair provided the most important features. Using only the four center sensors, the sensing chair still had a 78.6% accuracy in recognizing sitting posture.

2. Related Work

Many methods with various sensors have been proposed to recognize sitting posture.

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2.1 Pressure-Based Recognition

Pressure-based recognition methods use pressure sensors [1], [2] or seat pressure sensors [3]–[6], to collect pressure values. These methods build a classification model recognizing 7 to 10 types of sitting postures with about 80% to 94% accuracy by using pressure features such as 64 to 4023 features from seat pressure sensor, 14 to 54 features from pressure sensors. However, the pressure-based recognition methods where the pressure sensors are embedded on the surface of the chair lead to spoiling the performance of the office chair designed based on Ergonomics.

2.2 Temperature Sensor-Based Recognition

Rusell et al. [7] have proposed a method to distinguish an upright posture, a posture tilting to the left, a posture inclining to the right, and a standing posture by observing the temperature. They installed multiple temperature sensor arrays on the seat, the back, and the left and right armrests of the chair. They observe the phenomena that the temperature sensed by the temperature sensor increases exponentially when the user sits on the chair, but the temperature is attenuated exponentially when the user does not sit on a chair.

The problem of this method is a possibility that the temperature sensor might be influenced by the ambient temperature, and the author was experimenting in the temperature controllable laboratory. In order to cope with this, a sensor for measuring the ambient temperature is additionally required, and correction for the ambient temperature becomes necessary. The authors also pointed out that the response of the sensor is influenced by the thermal characteristics of the chair.

2.3 Depth Sensor-Based Recognition

Grafsgaard et al. [8] estimated the depth position of the learner's head, upper torso and lower torso using Kinect to investigate the correlation between the posture of the person sitting on the chair and the cognitive load at the time of learning. And they reported that they observed the relationship between posture and emotional state. Kinect is inexpensive and can measure the posture of a person sitting using the depth information. However, when the subject moves the head or torso from the frame of Kinect or covers the torso or lumbar region with the arm and hand, an error occurs. Also, it is vulnerable to occlusion.

2.4 Wearable Sensor-Based Recognition

Sangyong et al. [9] used the 3-axis accelerometer sensor attached to the neck of the user, and identified the 5 types of the sitting postures by SVM and k-means learning algorithm with the acceleration features applied principal component

analysis (PCA). They reported that they achieved the classification accuracy of 95.53% for the SVM and 89.35% for k-means model. However, these wearable-based approaches enforce the user to continuously wear and maintain the device to the body only to identify the sitting posture, which may place on a burden to the office worker and disturb concentration for the work.

3. Sitting Posture Recognition Using Sensing Chair Embedded Accelerometer

The existing methods about sitting posture recognition has the following problems: (i) privacy intrusion due to high privacy-invasive devices such as camera or microphone; (ii) deterioration of the original performance of office chair designed based on Ergonomics due to attachment of many sensors; (iii) user discomfort due to the need to attach a sensor to the body anytime; (iv) the limited number of recognizable sitting postures; (v) uncertainty in recognizing the posture of people with various physiques due to the lack of experiment participants.

In this study, we developed a novel sensing chair to continuously monitor the sitting posture of office worker. To solve the problem (i), (ii), and (iii), We used only 3-axis accelerometer sensors without high privacy-invasive devices and attached the sensors to back side of the fabric surface of the chair to prevent the deterioration of the chair performance and the user's discomfort. In addition, to solve the problem (iv) and (v), we constructed the recognition model that can recognize various kinds of postures by using data of different physiques than other methods.

3.1 Target Sitting Postures

In this study, we focused to recognize the 18 types of sitting postures that combine two types sitting positions, three types of sitting postures for leaning forward-backward, and three types of sitting postures for leaning left-right, as shown in Fig. 1. These sitting postures are defined based on the research that monitored the sitting postures of office workers [10], conducted by OKAMURA CORPORATION. In addition to the above sitting postures, we also targeted to recognize the non-sitting condition.

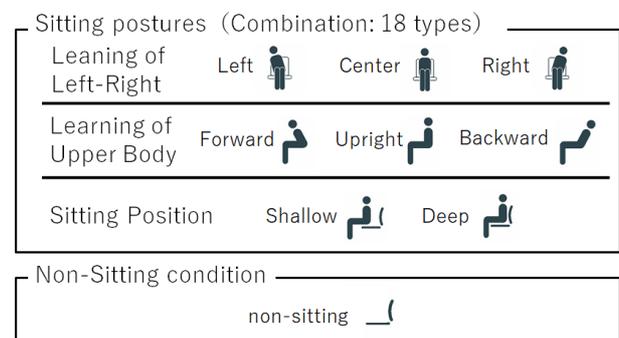


Fig. 1 Target sitting postures



Fig. 2 Implementation of sensing chair

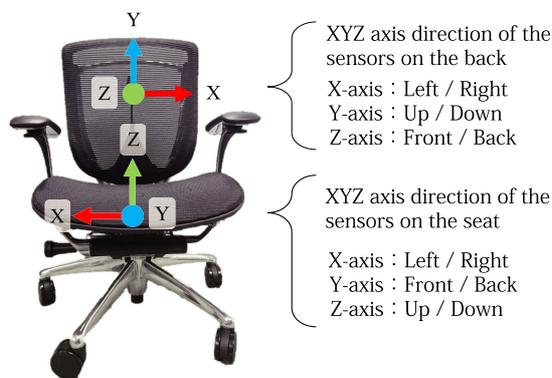


Fig. 3 Direction of acceleration on back and seat

3.2 Accelerometer-Based Sensing Chair

Figure 2 shows the implementation of the sensing chair. Our target sensing chair is an ergonomic mesh office chair in which the seat and back are made of mesh fabric and fits to body depending on the posture and physique. The sensing chair has two accelerometer sensors to the back and six accelerometer sensors on the seat, with total eight accelerometer sensors, placed to the positions, as shown with read boxes in Fig. 2. We attached each accelerometer to the back side of the mesh fabric surface not to deteriorate the chair performance due to body touch.

We decided these sensor positions that important for sitting posture recognition, based on the knowledge of OKAMURA CORPORATION, an office furniture manufacturing company. An accelerometer sensor measures the acceleration for the 3-axis (X, Y, Z) as shown in Fig. 3. The accelerometer sensors on the back measure acceleration about left-right direction as the X-axis direction, up-and-down direction as the Y-axis direction, and front-back direction as the Z-axis direction. On the other hand, the accelerometer sensors on the seat measure acceleration about left-right direction as X-axis direction, front-back direction as Y-axis, and up-and-down direction as Z-axis direction.

Accelerometer sensors send acceleration to Raspberry Pi that are placed at the bottom space of the seat through the transmission cable. The Raspberry Pi continuously collects the acceleration from each accelerometer sensors and recognizes the sitting postures by using the sitting posture

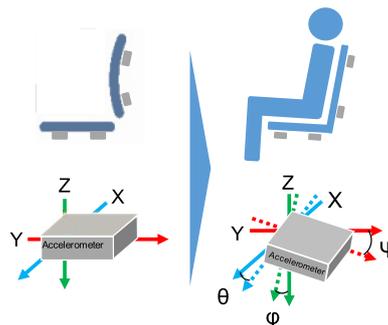


Fig. 4 Change of tilt angle of accelerometer

recognition model as described in Sect. 3.3.

3.3 Sitting Posture Recognition Methods

In this study, we propose three types of the recognition methods to realize the sitting posture recognition which is independent of the individual differences in physiques and chairs. In our basic principle to recognize the 18 types of sitting postures and the non-sitting condition, the methods use the tilt angles of the accelerometers as the input features to the recognition model. The tilt angles θ , ψ , and ϕ for each accelerometer change because the mesh fabric of the chair fits the physique and the sitting posture of the office worker, as shown in Fig. 4. Specifically, our methods recognize the sitting posture based on the difference of change of tilt angles by postures and physiques. Difference between our three methods is the calculation method of the tilt angle. Method 1 uses the tilt angles as the input features. Method 2 uses the relative tilt angles between the tilt angles of the sitting posture and the tilt angle of the non-sitting condition. Finally, method 3 uses the relative angle between the tilt angles of the sitting posture and the standard sitting posture that represents the center position for the left-right direction of the body, the upright position for the forward-backward direction of the body and deepness of the sitting position on the seat.

3.3.1 Method 1: Tilt Angle of Accelerometer

Method 1 recognizes the 18 types of sitting postures and non-sitting condition by the tilt angles calculated using the sensor values for xyz axis Acc_{xt} , Acc_{yt} , and Acc_{zt} from eight accelerometers as the input features. For the calculation of features, we collect Acc_{xt} , Acc_{yt} , and Acc_{zt} by 10Hz, then, calculates the averages in one second of the xyz-axis tilt angles θ , ψ , and ϕ for each accelerometer by Eqs. (1)(2)(3). Consequently, we use a set of the total 24 tilt angles as the input features, x_a , shown in Eq. (4). We collect the features for every sitting posture and non-sitting condition and build the sitting posture recognition model by the machine learning algorithm with the features.

$$\theta = \frac{1}{10} \sum_{xt, yt, zt=1}^{10} \tan^{-1} \left(\frac{Acc_{xt}}{\sqrt{Acc_{yt}^2 + Acc_{zt}^2}} \right) \quad (1)$$

$$\psi = \frac{1}{10} \sum_{xt, yt, zt=1}^{10} \tan^{-1} \left(\frac{Acc_{yt}}{\sqrt{Acc_{xt}^2 + Acc_{zt}^2}} \right) \quad (2)$$

$$\phi = \frac{1}{10} \sum_{xt, yt, zt=1}^{10} \tan^{-1} \left(\frac{\sqrt{Acc_{yt}^2 + Acc_{zt}^2}}{Acc_{xt}} \right) \quad (3)$$

$$\mathbf{x}_a = [\theta_1, \psi_1, \phi_1, \theta_2, \psi_2, \phi_2, \dots, \theta_8, \psi_8, \phi_8] \quad (4)$$

3.3.2 Method 2: Relative Tilt Angle from Non-Sitting

To reduce the effect due to the sensor position, method 2 uses the relative tilt angles between the sitting condition and non-sitting condition as the input features to the machine learning algorithm.

For the calculation of the features, we collect the initial tilt angles θ_{ini} , ψ_{ini} , and ϕ_{ini} on the non-sitting condition, then, calculate the relative tilt angles θ' , ψ' , and ϕ' with the tilt angles on the sitting condition by calculating difference between θ , ψ , and ϕ and θ_{ini} , ψ_{ini} , and ϕ_{ini} with Eqs. (5)(6)(7). Consequently, we use a set of the total 24 tilt angles as the input features, \mathbf{x}_b , shown in Eq. (8).

$$\theta' = \theta - \theta_{ini} \quad (5)$$

$$\psi' = \psi - \psi_{ini} \quad (6)$$

$$\phi' = \phi - \phi_{ini} \quad (7)$$

$$\mathbf{x}_b = [\theta'_1, \psi'_1, \phi'_1, \theta'_2, \psi'_2, \phi'_2, \dots, \theta'_8, \psi'_8, \phi'_8] \quad (8)$$

3.3.3 Method 3: Relative Tilt Angle from Standard Sitting Posture

To reduce the effect due to the physique of the worker, method 3 uses the relative tilt angles between the sitting posture and the standard sitting posture as the input features to the machine learning algorithm. For calculation of the relative tilt angles θ'' , ψ'' , and ϕ'' , we collect the tilt angles θ_{std} , ψ_{std} , and ϕ_{std} on the standard sitting posture, then, calculate difference between the tilt angles θ , ψ , and ϕ of the sitting posture and θ_{std} , ψ_{std} , and ϕ_{std} with Eqs. (9)(10)(11). Here, the standard sitting posture represents sitting 'Deep' on the seat of the chair, 'Upright' of the body for forward-backward direction, and 'Center' of the body for left-right direction. Consequently, we use a set of the total 24 tilt angles as the input features, \mathbf{x}_c , shown in Eq. (12).

$$\theta'' = \theta - \theta_{std} \quad (9)$$

$$\psi'' = \psi - \psi_{std} \quad (10)$$

$$\phi'' = \phi - \phi_{std} \quad (11)$$

$$\mathbf{x}_c = [\theta''_1, \psi''_1, \phi''_1, \theta''_2, \psi''_2, \phi''_2, \dots, \theta''_8, \psi''_8, \phi''_8] \quad (12)$$

4. Experiment

The purpose of this experiment is to verify the most accurate method among the three proposed methods and confirm the most suitable machine learning algorithm. We asked experimental subjects of various physiques to cooperate with data collection and adopted various machine learning algorithms to the collected data for investigating the accuracy of each method.

The machine learning algorithms used in this experiment are six: logistic regression, k neighborhood method, decision tree, random forest, SVM, and neural network. We use Python 3.5.2 scikit-learn 0.19.0 [11] for the implementation, and the parameters of each machine learning are the default setting of scikit-learn [12].

4.1 Data Collection

First, we explain the data set used in this evaluation.

We collected sensing data (θ_{std} , ψ_{std} , ϕ_{std}) in 18 sitting types from 28 subjects. Because it is assumed that various workers with different physiques work in the actual office, we invited various experimental subjects whose physique is between 150 [cm] to 180 [cm] in height, 40 [kg] to 90 [kg] in weight. Figure 5 shows the distribution of subjects' physiques.

In order to collect the sensor data of each seated posture, we asked the experimental subjects to change their seating posture in order of the seating postures from No. 1 to No. 18 shown in Table 1, and stand up (No. 19) at the end. At each posture, we record the sensing data when the subject is in a stationary state. Each subject did this loop five times. Finally, we collected 2,660 data sets (28 subjects \times (18 seating postures + leave) \times 5 times measurement) in total.

Table 2 shows variances for the data sets every method. Overall, the variances of ψ on the center part of the seat (accelerometer 2, 5), θ and ϕ on the rear both sides of the seat (4, 6), ϕ on the bottom part of the back (7) are large. Moreover, the rear part of the seat tends to be a larger variance than the front part. Method 2, which calculates features based on relative tilt angle from non-sitting, is smaller overall variances than other methods. On the other hand, Method 3, which calculates features based on relative tilt angle from the standard posture, is more variances for the center part

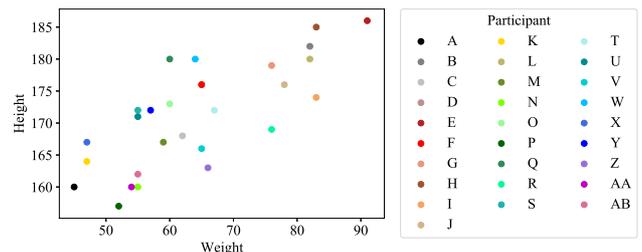


Fig. 5 Distribution of height and weight of participants

of the seat, where come under pressure in any postures than other methods; conversely, variances for both sides of the seat is less than Method 1. We assume that such different features between methods affect posture recognition accuracy.

The office chair *Contessa* used in this experiment has a function to adjust various parts of the chair. For example, the seating surface can slide from 425 to 475 mm with 10mm interval (6 steps). The back reclining tilts backward from the upright position to 26 degrees (5 steps). The range of seat height is 420-520 mm. In this experiment, the position of the seating surface is fixed at 425 mm, the back reclining was fixed with a single step backward from the upright, and the seat height was adjusted to the appropriate height of each experiment subject.

4.2 Evaluation Method

We evaluate the performance of each proposed method by using precision, recall, and F-value. A precision means the probability that identified sitting posture matches the actual sitting posture. A recall is a ratio that the sitting posture is

correctly identified. A F-value is calculated from the harmonic mean of precision and recall, and is expressed by the expression (13).

$$F - measure = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{13}$$

We conducted Leave-One-Participant-Out Cross-Validation where only one of the experimental subject as test data and the remaining 27 subjects' data as learning data. In addition, we calculated precision, recall, and F-value by macro mean after collecting each subjects' results.

4.3 Experiment Result

In this section, we explain the accuracy of seating posture identification of three proposed methods by applying six machine learning algorithms respectively. In the following part of this paper, we classify our proposed method as follows. Method 1: a seating posture identification method using an absolute tilt angle of the acceleration sensor. Method 2: a seating posture identification method using a relative tilt angle of the acceleration sensor from the default position (no sitting). Method 3: a seating posture identification method using a relative tilt angle of the acceleration sensor from the initial position in sitting.

4.3.1 Results of Method 1

Table 3 shows the results of Method 1 with 6 machine learning algorithms. From the viewpoint of F-value, it is found that the seating posture can be identified accurately in the order of neural network, support vector machine, logistic regression, random forest, k-neighbor method, and decision tree. The most accurate neural network identifies 18 sitting postures and absences with 75.4%.

Table 1 Target sitting postures (19 types)

Posture	Sitting position	Leaning of upper body	Leaning of left-right
1	Deep	Upright	Left
2	Deep	Upright	Center
3	Deep	Upright	Right
4	Deep	Forward	Left
5	Deep	Forward	Center
6	Deep	Forward	Right
7	Deep	Backward	Left
8	Deep	Backward	Center
9	Deep	Backward	Right
10	Shallow	Upright	Left
11	Shallow	Upright	Center
12	Shallow	Upright	Right
13	Shallow	Forward	Left
14	Shallow	Forward	Center
15	Shallow	Forward	Right
16	Shallow	Backward	Left
17	Shallow	Backward	Center
18	Shallow	Backward	Right
19		non-sitting	

Table 3 Method 1 with 6 machine learning algorithms

Learning Algorithm	Precision	Recall	F-measure
Logistic Regression (LR)	0.711	0.704	0.705
k-Nearest Neighbor (k-NN)	0.673	0.667	0.667
Decision Tree(DT)	0.601	0.601	0.601
Random Forest (RF)	0.673	0.669	0.669
Support Vector Machine (SVM)	0.734	0.732	0.730
Neural Network (NN)	0.755	0.754	0.754

Table 2 Variance for data sets

Accelerometer	Method 1			Method 2			Method 3		
	θ	ψ	ϕ	θ'	ψ'	ϕ'	θ''	ψ''	ϕ''
1	14.02	15.15	14.55	13.40	14.14	13.98	13.01	15.11	13.46
2	13.86	33.44	15.18	13.86	32.13	17.26	13.75	35.38	17.84
3	12.96	14.22	13.62	10.53	13.22	11.05	10.19	14.37	10.70
4	24.26	11.21	23.31	20.03	9.06	21.84	20.63	10.57	20.07
5	15.87	37.53	13.03	15.97	37.21	14.03	16.75	43.59	13.50
6	26.83	9.52	25.56	22.23	9.21	22.09	23.66	11.40	22.36
7	0.21	6.94	3339.64	0.13	6.25	3349.74	0.13	6.63	3737.05
8	3.42	7.55	7.88	0.77	4.30	4.44	0.77	4.71	4.85

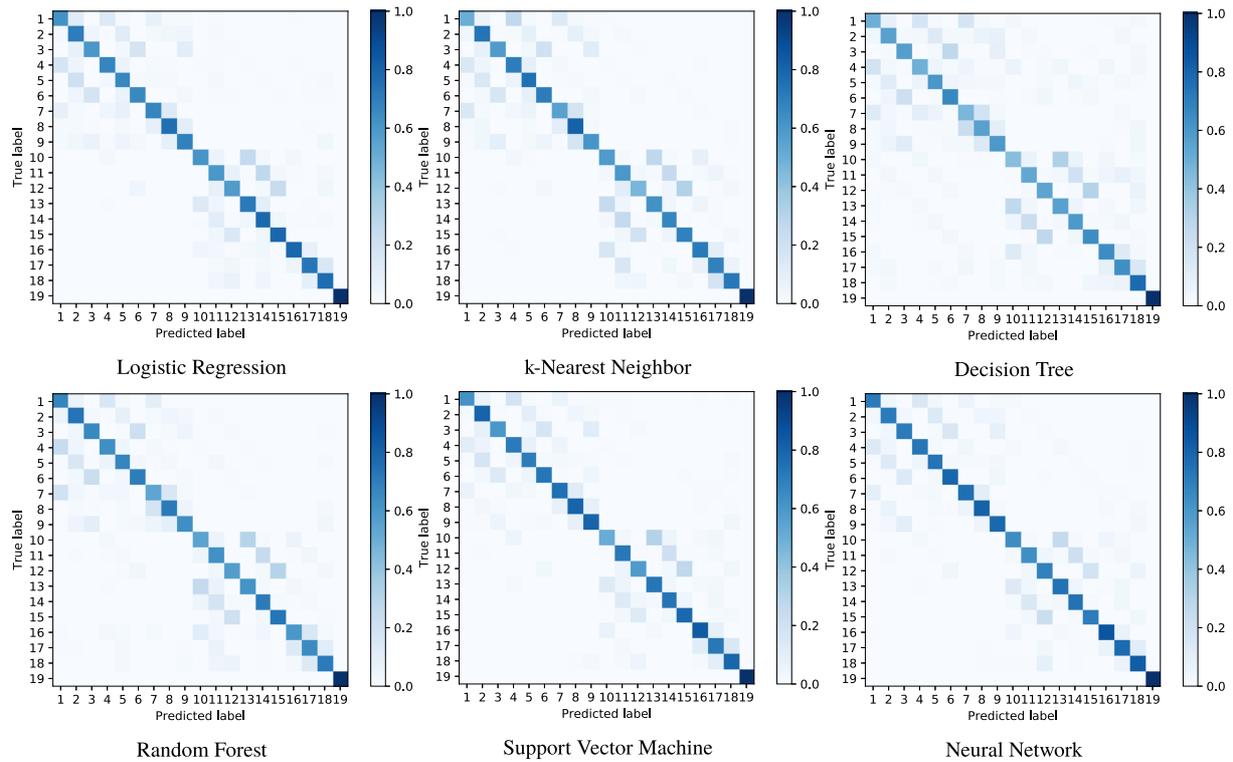


Fig. 6 Confusion matrix for each learning algorithm on Method 1

Table 4 Method 2 with 6 machine learning algorithms

Learning Algorithm	Precision	Recall	F-measure
Logistic Regression (LR)	0.786	0.779	0.780
k-Nearest Neighbor (k-NN)	0.778	0.771	0.772
Decision Tree (DT)	0.743	0.741	0.741
Random Forest (RF)	0.792	0.791	0.791
Support Vector Machine (SVM)	0.819	0.815	0.815
Neural Network (NN)	0.838	0.837	0.837

Figure 6 shows the confusion matrix of the identification accuracy of each sitting posture for 6 machine learning algorithms. In each machine learning algorithm, the confusion between No.1 and No.4, No.2 and No.5, No.3 and No.6, No.10 and No.13, No.11 and No.14, No.12 and No.15 often occur.

4.3.2 Result of Method 2

Table 4 shows Precision, Recall and F-value of Method 2 with 6 machine learning algorithms. From the viewpoint of F-value, it is found that the seating posture can be identified accurately in the order of neural network, support vector machine, random forest, logistic regression, k-neighbor method, and decision tree. The most accurate method, neural network, identifies 18 sitting postures and absences with 83.7%.

Figure 7 shows the confusion matrix of the identification accuracy of each sitting posture by Method 2 with 6 machine learning algorithms. In each machine learning al-

Table 5 Method 3 with 6 machine learning algorithms

Learning Algorithm	Precision	Recall	F-measure
Logistic Regression (LR)	0.798	0.791	0.792
k-Nearest Neighbor (k-NN)	0.816	0.804	0.806
Decision Tree (DT)	0.749	0.746	0.747
Random Forest (RF)	0.800	0.799	0.799
Support Vector Machine (SVM)	0.835	0.830	0.831
Neural Network (NN)	0.857	0.855	0.856

gorithm, as same as Method 1, the confusion between No.1 and No.4, No.2 and No.5, No.3 and No.6, No.10 and No.13, No.11 and No.14, No.12 and No.15 often occur.

4.3.3 Result of Method 3

Table 5 shows Precision, Recall and F-value of Method 3 with 6 machine learning algorithms. From the viewpoint of F-value, it is found that the seating posture can be identified accurately in the order of neural network, support vector machine, k-neighbor method, random forest, logistic regression, and decision tree. The most accurate method, neural network, identifies 18 sitting postures and absences with 85.6%.

Figure 8 shows the confusion matrix of the identification accuracy of each sitting posture by Method 2 with 6 machine learning algorithms. In each machine learning algorithm, as same as Method 1, the confusion between No.1 and No.4, No.2 and No.5, No.3 and No.6, No.10 and No.13, No.11 and No.14, No.12 and No.15 occur. However, the

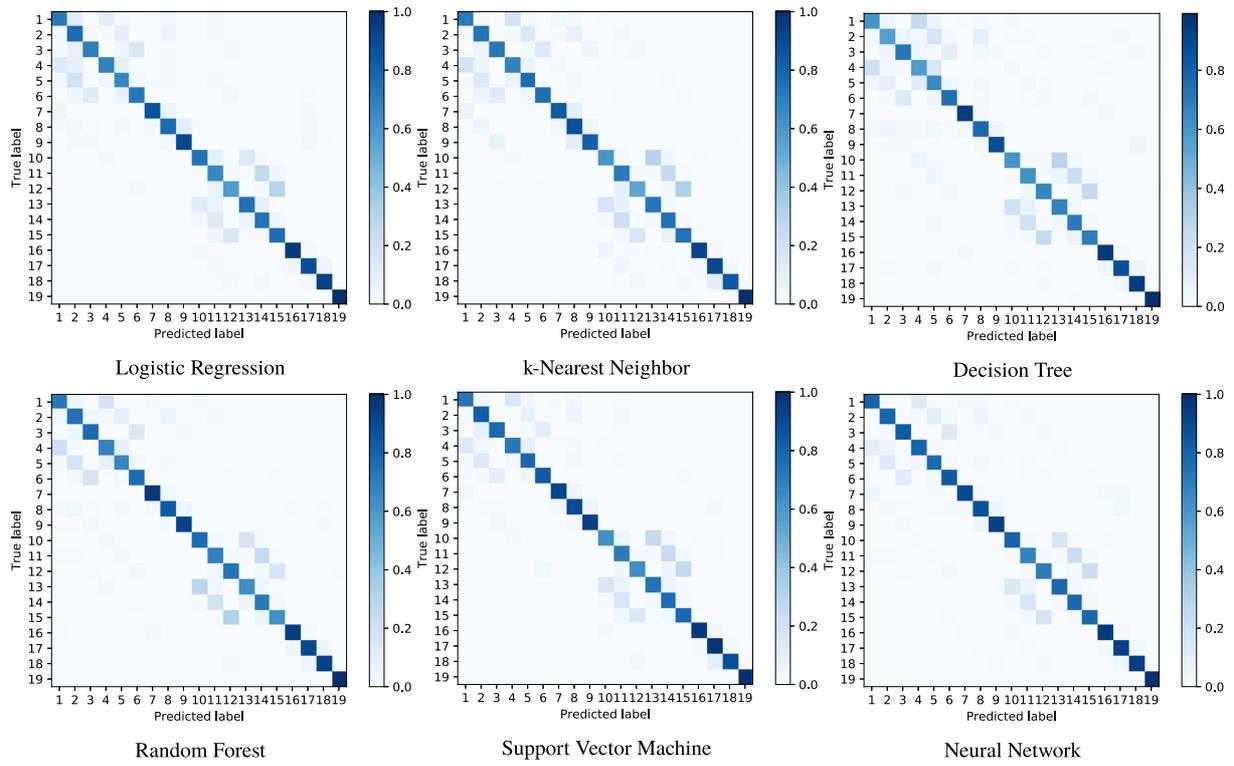


Fig. 7 Confusion matrix for each learning algorithm on Method 2

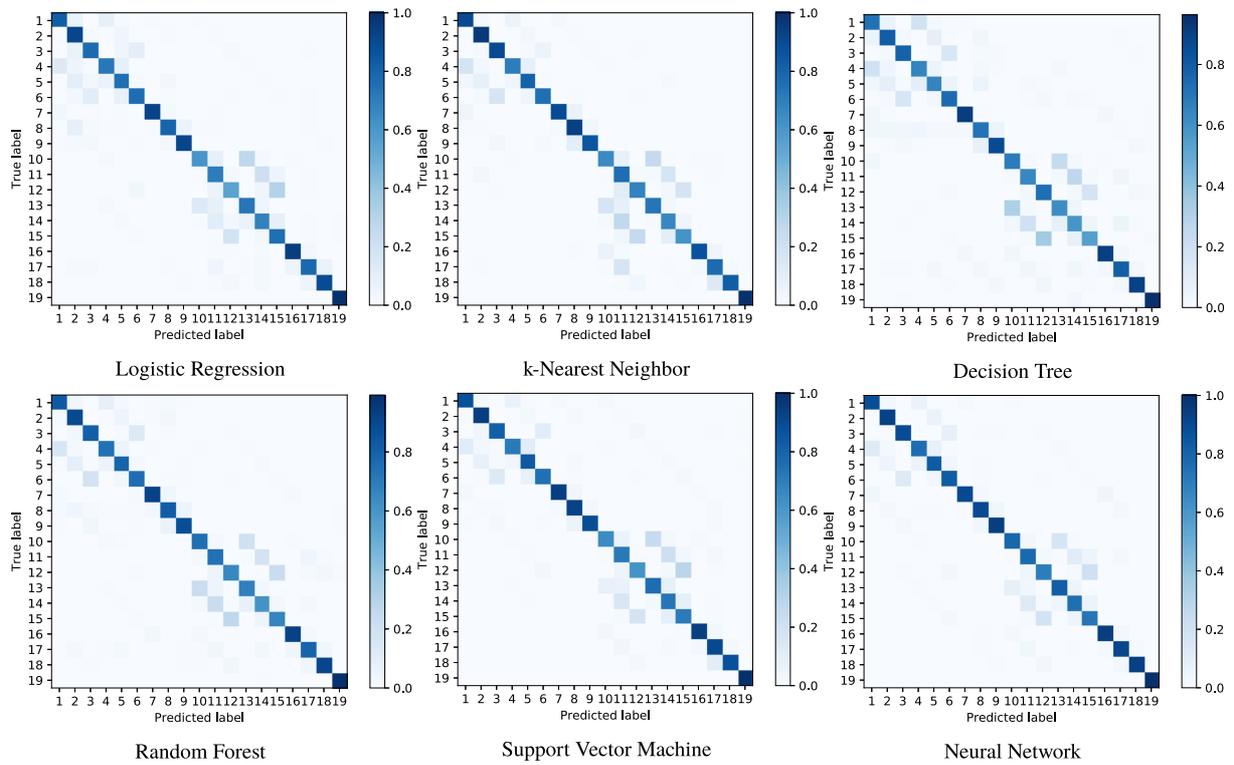
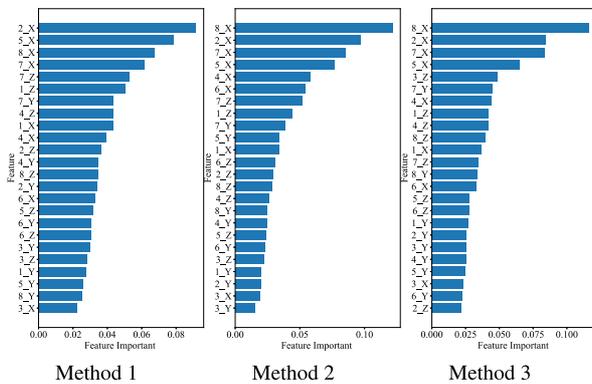


Fig. 8 Confusion matrix for each learning algorithm on Method 3

Table 6 Result for combination of accelerometers

Combination	Description	Precision	Recall	F-measure
8	Using the highest important feature	39.4	39.8	38.8
8,2	Using Top 2 important features	69.4	69.6	69.4
8,2,7	Using Top 3 important features	72.9	73.0	72.8
8,2,7,5	Using Top 4 important features	78.6	78.6	78.6
7,8	Using accelerometers on backrest	54.3	54.3	54.0
1,2,3,4,5,6	Using accelerometers on seat	66.0	66.2	65.9
1,3,4,6,7,8	Using backrest and four corners of seat	80.1	80.0	80.0
1,2,3,7,8	Using backrest and front of seat	81.0	80.9	80.9
4,5,6,7,8	Using backrest and back of seat	77.8	77.8	77.7
All	Method 3	85.7	85.5	85.6

**Fig. 9** Feature importance for each method

total number of confusion is lower than other methods.

4.4 Evaluation of the Sensor Position Based on Feature Selection

The installation position of the acceleration sensor attached to the sensing chair has been decided from the knowledge obtained by Okamura co., Ltd. We use a random forest for the feature selection and clarify the best position to achieve the highest accuracy in the posture sensing.

Figure 3 shows the position and the direction (x , y , z) of eight acceleration sensors attached to the sensing chair. Those are numbered from 1 to 8 for to ease the following explanation.

The back face sensors: The X-axis is the left and right direction against the back face, the Y-axis is the up and down direction against the back face, and the Z-axis is the front-back direction.

The seat face sensors: The X-axis is the left and right direction against the seating face, the Y-axis is the front-back direction, the Z-axis is in the vertical direction.

Figure 9 shows the result of feature selection in a random forest, where more important features are described in the upper part.

In all the methods, we can observe that X-axis of the sensor No.2, No.5, No.7 and No.8 contribute the accuracy of posture recognition. These sensors are attached on the center line of the chair (see Fig. 2) and those X-axis repre-

sents the movement or tilt of right and left direction. As a result, we can confirm that it is important to measure the movement or tilt of right and left direction for achieving accurate posture recognition.

4.5 Comparison between Combinations of Accelerometers

In this section, we evaluate the combination of accelerometers to confirm how many sensors are required for achieving a certain accuracy.

Based on the result of previous evaluation about the importance of each sensor, we pick up 10 combinations shown in Table 6, where numbers in the column “Combination,” represent the number assigned to each sensor in Fig. 2. “All” means the case where all the sensors are used for recognition. We adopted a method 3, with a neural network, that achieved the highest accuracy as shown in Sect. 4.3. Also, we used all the values of x , y , z axis of each sensor.

Table 6 shows the result of Precision, Recall and F-value of each combination. In the case of one sensor, we selected the accelerometer No.8 based on the result of Sect. 4.4. The result of F-value changed to 38.8%. Next, we add features one by one in ascending order of importance of the feature. In the case of combination No.8 and No.2, the accuracy changed to 69.4%. Adding No.7, the accuracy changed to 72.9%. If we used four sensors (No.8, No.2, No.7, and No.4), the accuracy was improved to 78.6%. This result shows that accuracy increases as the number of sensors increases, and especially the contribution of No.2 is high. The combination of No.7 and No.8 is the case where we used only the sensors on the backrest. In this case, we observed to be 54.0%. On the other hand, the combination of No.1 to No.6 is case where we used only the sensor attached on the seat surface. In this case, the accuracy changed to 65.9%. Since the combination of No.8 and No.2 achieves higher accuracy, we can say that the sensor should be attached on both the seat surface and the backrest. Finally, we investigate the combination of sensors on the seat in case we assume to use backrest sensors. In the case of using four sensors at the corner of seat, the accuracy changed 80.0%. In the case of using two sensors at the front or back of seat, the accuracy changed to 80.9% and 77.7% respec-

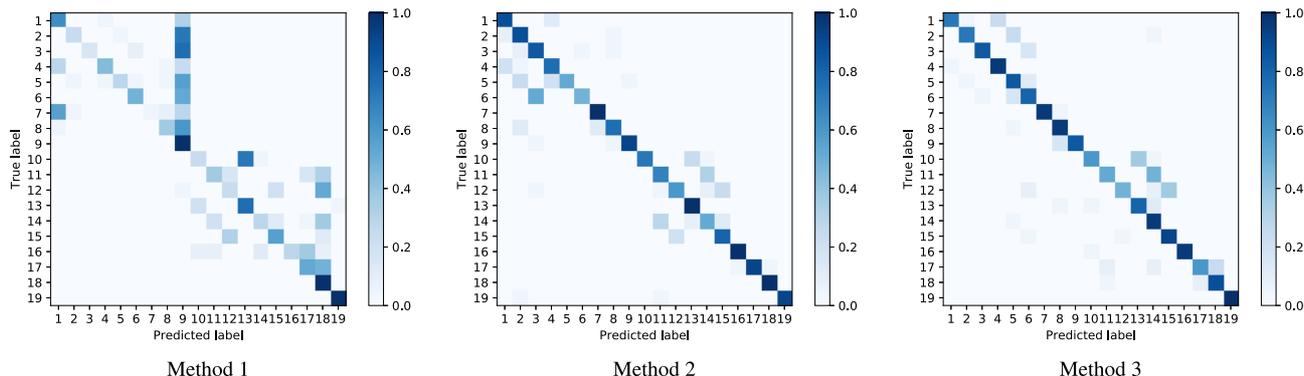


Fig. 10 Confusion matrix for each method with the reproduced sensing chair

Table 7 Result for each method with the reproduced sensing chair

Method	Precision	Recall	F-measure
1	65.9 (75.5)	46.7 (75.4)	45.8 (75.4)
2	82.3 (83.8)	80.0 (81.5)	79.8 (81.5)
3	83.9 (85.7)	80.8 (85.5)	80.7 (85.6)

tively. This result shows that the sensor in the front part is more effective for improving the accuracy. Also, the difference between the highest accuracy (85.7%) achieved when all the sensors are used is just 4.7%.

4.6 Sitting Posture Recognition Using a Reproduced Sensing Chair

Although we reproduce the same sensing chair by using the same commercial chair, the tension of the mesh fabric of the seat surface is slightly different. Also, even the same sensors have different measurement errors. Therefore, even we set the sensor almost the same position, we assume that the accuracy will be affected. In this section, we evaluate the posture recognition accuracy using the reproduced sensing chair.

First, we develop a new sensing chair with the same way shown in Sect. 3.2; and then we collect new data from 5 subjects by the same method conducted in Sect. 4.1. The reproduced sensing chair is implemented the same product sensors to the almost same positions on the same commercial chair; the position errors and the angle errors between the reproduced chair and the chair that used in Sect. 4.1 are approximately 1-2 millimeters and 1-2 degrees, respectively. The algorithm used in posture recognition is neural network because it achieved the highest accuracy. To generate the test data, we selected the subjects' data from previous experimenter who didn't attend this experiment.

Table 7 shows the accuracy of posture recognition with the reproduced sensing chair. The result shows that the accuracy of Method 1 becomes worse drastically because the absolute data of accelerometers may a different chair by chair. The reason why we proposed Method 2 and Method 3 is that we assumed it before developing the chair. As we expected, Method 2 and Method 3 achieved near 80% ac-

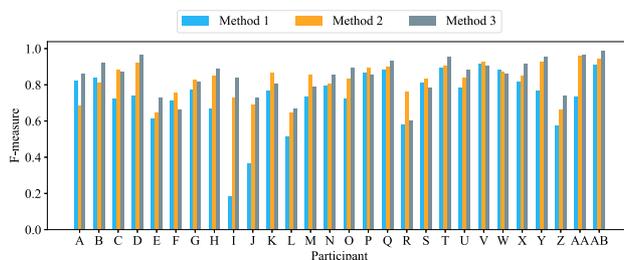


Fig. 11 Per-subjects F-values for our proposed methods (A-C: underweight, D-W: normal, and X-AB: overweight)

curacy. We can say that by using the relative data from the initial position, those methods can avoid the affect of the difference of sensor position.

Figure 10 shows the confusion matrix for each method with the reproduced sensing chair. The label show the posture type shown in Table 1. From this figure, we can observe that Method 1 often fails to recognize the posture 9 and 19. On the other hand, Method 2 and Method 3 succeeded to recognize almost all the posture accurately.

4.7 Comparison between Physiques

In this section, we evaluate the influence on posture recognition accuracy by the physiques of subjects.

First, we calculate Body Mass Index (BMI) for the 28 participants based on height and weight by the following equation.

$$BMI = Weight(kg) / Height(m)^2 \tag{14}$$

BMI can be classified by the following types: Underweight (BMI < 18.5), Normal (18.5 – 25), Overweight (25 – 30), and Obese (BMI > 30). As a result, the number of participants of each type are 3, 20, 5, respectively.

Figure 11 shows per-participant F-measure of our three proposed methods by leave-one-person-out cross-validation with Neural Network algorithm. Method 2 and 3 improve F-measure for 20 participants against Method 1; moreover, Method 3 can achieve better performance for 16 participants than Method 2.

Table 8 Result for each body type on Method 3

Body Type	Precision	Recall	F-measure
Underweight	0.918	0.888	0.885
Normal	0.853	0.834	0.821
Overweight	0.934	0.922	0.913

Table 9 Result for gender difference on Method 3

Gender	Precision	Recall	F-measure
Men	0.875	0.856	0.846
Women	0.879	0.842	0.827

Table 8 shows the precision, recall, and F-measure averaged for each body type on Method 3. Both of underweight and overweight are achieved higher classification metrics than Normal; especially, overweight is over 0.91 every metrics. The reason for lower metrics on normal is that the model classified most 10, 12, 13, 14, 15 (Upright or Forward on Shallow) to 11 (Shallow, Upright, and Center) for four participants.

We assume that gender difference also affects recognition accuracy because the physique is different between man and woman. Table 9 shows the precision, recall and F-measure averaged for gender difference on Method 3. As a result, it appears that the influence of gender difference is smaller than those of BMI.

5. Conclusion

To classify the sitting posture of office workers, this research developed a sensor-embedded chair that attaches eight accelerometers to the ergonomic mesh office chair. We collected the acceleration data for 18 types of sitting postures for 28 participants with various physiques, then, evaluated the three kinds of the our sitting posture recognition methods using Leave-One-Participant-Out cross-Validation. As the result, the proposed methods achieved 75.4% to 85.6% recognition accuracy.

For future work, we plan to implement a notification function to improve undesirable posture and sitting position for office workers who suffer from problems caused by long time sitting.

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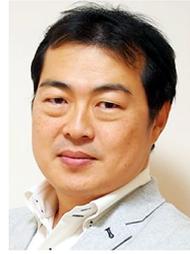
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