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Abstract: Human often cross their legs unconsciously while sitting, which can lead to issues like shifting the center of gravity, lower back pain, decreased blood flow and pelvic distortion. Detecting unconscious leg-crossing is important for maintaining correct posture. In this study, we explored the detection of leg-crossing postures using machine learning on data from body pressure distribution sensors. Collected 180 seconds of pressure data from 4 male subjects (25.8 ± 6.29 y.o.) in three conditions: no leg crossing, right leg crossed, and left leg crossed. Seven classifiers, including SVM and RF, were evaluated using Accuracy, Recall, Precision, and Specificity. As a result, SVM was difficult to classify.

Keywords: pressure distribution sensor, leg-crossing, machine learning, posture estimation

1. Introduction

It is known that many people unconsciously cross their legs in everyday life. However, maintaining the leg-crossing posture for long periods of time can have a variety of negative effects on the body. For example, if the center of gravity of the body shifts to one side or the other due to leg-crossing, the pelvis will become distorted, causing lower back pain and twisting of the body. It has also been pointed out that a decrease in blood flow can cause coldness and circulatory disorders in the lower limbs [1-4]. For this reason, it is important to detect the unconscious act of crossing legs at an early stage and encourage improvements in posture in order to maintain good health.

In addition, people today spend a lot of time sitting, which is a factor that increases health risks. Japanese people in particular spend a lot of time sitting, and a survey of 20 countries around the world found that the average amount of time Japanese people spend sitting on weekdays is 7 hours (420 minutes) per day, the longest in the world. This is about three times longer than the 2.5 hours (150 minutes) spent sitting in Portugal, which is the shortest [5]. It has been pointed out that sitting for long periods of time can lead to a reduction in muscle metabolism and blood flow, and an increase in obesity, diabetes, cancer, cerebrovascular disease, and dementia, which can shorten life expectancy. In particular, it is well known that leg-crossing while sitting can cause high blood pressure [6-15].

The reason that blood pressure rises when you cross our legs is because the blood vessels that run through the hip joint are compressed. Also, the peroneal nerve, which controls the sensation of the leg, branches off at the back of the knee, and when you cross our legs, this nerve is compressed. When you cross our legs, your heart will think that there is a lack of blood in every part of your body, and your heart rate will increase and your blood pressure will rise. If you sit with your back straight, it will not have a negative effect on your posture, but if we cross our legs, your posture will lean forward. For this reason, it is desirable to be able to detect unconscious leg-crossing.

In previous research on posture estimation, the main methods used were those that used cameras and image analysis [16,17]. While these methods can analyze the position and posture of the skeleton using image processing technology, they have the problem that it takes time to perform advanced image processing and load model data. In addition, there are environments where it is difficult to use cameras from the perspective of protecting human privacy.

In this study, we focus on a non-contact body pressure distribution sensor that enables immediate data processing, and evaluate the accuracy of leg posture detection using this sensor. Specifically, we propose a method for detecting leg posture with high accuracy by applying machine learning to the data acquired from the body pressure distribution sensor. The aim of this research is to provide the basis for a system that can detect the leg-crossing posture in real time and contribute to improving the sitting posture.

2. Materials and Methods

2.1. Data collection

In this data measurement, we will verify the extent to which it is possible to detect leg-crossing postures using pressure distribution sensors.
We measured seat pressure using a pressure distribution sensor (Azwil, Takano Corporation, Japan), and obtained data on three patterns of leg positioning (with no leg positioning, with the right leg on top, and with the left leg on top) for more than 120 seconds of sitting pressure distribution data for at least two male subjects (25.8 ± 6.29 years old) in each case. The pressure distribution sensor is in the shape of a seat, with 16×16 pressure sensors built in, for a total of 256 sensors. The external size of the sensor is 600mm square, and the detection area is 397mm square. The sensor is capable of detecting pressures up to 200 mmHg, and the data is sampled at 5Hz. In this study, the pressure data acquired from each sensor was recorded as a heat map showing the change in pressure distribution over time. The three different sitting postures recorded (center position (without legs crossed), right leg crossed, left leg crossed) were labeled as "C", "R" and "L", respectively.

.2. Data Analysis

The collected data was analyzed using seven different classifiers. The classifiers used were Support Vector Machine (SVM), Random Forest (RF), K-neighbors (KNN), Multi Layer Perceptron (MLP), AdaBoost (ADB), ⑥Quadratic Discriminant Analysis (QDA), ⑦Naïve Bayes (NAB). And we calculated the pressure data obtained from the 256 pressure sensors as features and performed classification for each posture. The features were classified into three categories in advance: C (center position, no leg crossing), R (right leg crossed over left leg), and L (left leg crossed over right leg). To evaluate the accuracy of the classification, we performed K-fold cross-validation. First, we trained the classifier using 90 seconds of data for each posture, and then we verified the accuracy using 10 seconds of test data. As evaluation metrics, we calculated Accuracy (percentage of correct answers), Recall (reproduction rate), Precision (accuracy), and F-score, used Python 3.6.5 to compare the performance of each classifier.

Machine learning was performed in Python (Ver 3.6.5) using Spyder (editor, Ver 3.2.8) obtained from the open data science platform Anaconda. The machine learning library used was scikit-learn. Table 1. shows the hyperparameters for each classifier. *n_estimators* and *max_depth* for RF are the number of decision trees and the maximum depth of decision trees, respectively. *n_neighbors* for KNN is the value of k, and is an odd number. The *max_iter* of MLP is the maximum number of iterations, and the *n_estimators* of ADB is the maximum number of estimators when boosting is finished. The hyperparameters of QDA and NAB are the default values. We changed the hyperparameters using grid search, and calculated the AUC of the ROC curve for Accuracy, Precision, Recall, F-score, True positive rate and false positive rate, and the AUC of the Precision-Recall curve (PR curve) for the optimal hyperparameters. These six indices were used as the accuracy indices. Accuracy, Recall, Precision and F-score are defined by the following equations (1) to (4).

$$Accuracy = (TP + TN) / (TP + TN + FP + FN) \qquad (1)$$

$$Recall = TP / (TP + FN) \qquad (2)$$

$$Precision = TP / (TP + FP) \qquad (3)$$

$$F\text{-}score = 2* Recall* Precision \,/\, (Recall + Precision) \qquad (4)$$

The feature values used 196 pressure values (100 seconds each) for each of three postures for each person (196 x 100 x 5Hz = 98,000 pressure values for each posture). In addition, the first 10 seconds of measurement and the last 10 seconds before the end of measurement were removed.TP, TN, FP and FN are true positive, true negative, false positive and false negative, respectively. In addition, the average value of the discrimination accuracy index was calculated for each value of k using the k-fold cross-validation method (k=2,5,10) for each subject.

k=2 (150 seconds learning, 150 seconds testing)

k=5 (240 seconds learning, 60 seconds testing), and

K=10 (270 seconds learning, 30 seconds testing)

The accuracy evaluation metrics were Accuracy, Precision, Recall, F-score, AUC-tpfp, and AUC-pr.

Table 1. Hyperparameters for each classifier.

Classifier	Hyperparameter	
SVM	C	0.001, 0.01, 0.1, 1, 10, 100, 1000
	gamma	0.001, 0.01, 0.1, 1, 10, 100, 1000
RF	*n_estimators*	16, 32, 64, 128, 256, 512, 1024
	max_depth	16, 32, 64, 128, 256, 512, 1024
	criterion	gini
KNN	*n_neighbors*	3, 5, 7, 9, 11, 13, 15, 17, 19, 21
MLP	*alpha*	0.001, 0.01, 0.1, 1
	max_iter	16, 32, 64, 128, 256, 512, 1024
ADB	*n_estimators*	16, 32, 64, 128, 256, 512, 1024
	algorithm	SAMME.R
QDA	Default	
NAB	Default	

* In Secondary discriminant analysis (QDA), no regularization is applied and 'full' was used for the covariance matrix estimation. Naive Bayes (Gaussian naive Bayes), smoothing parameter var_smoothing = 1e−9 (default setting).

2.4. Ethics Review Committee

This research was conducted after receiving approval from the Ethics Review Committee of the Graduate School of Information Sciences, Tohoku University (approval date: November 27, 2003, approval number 85: 5-2).

3. Results

3.1. Pressure distribution heat map

The pressure distribution heat map used to detect the leg-crossing posture is shown in Figure 1. The changes in pressure distribution are shown visually for each of the three postures: C (center position, no leg-crossing), R (right leg crossed over), and L (left leg crossed over). In particular, when the legs are crossed, the pressure on the left and right sides changes markedly, and the bias in the center of gravity can be confirmed.
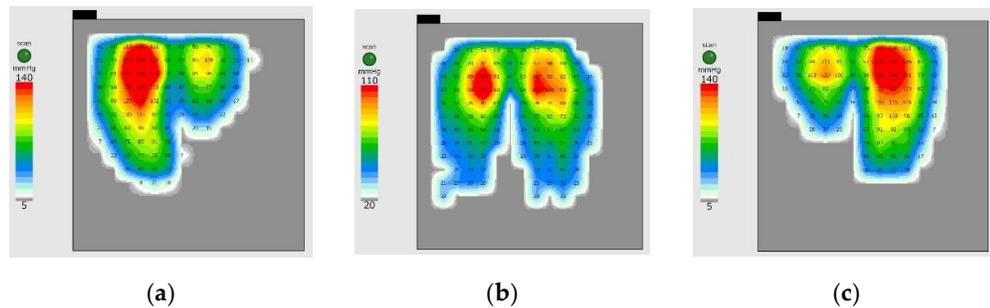

(a)   (b)   (c)

Figure 1. Heat map of pressure distribution in the leg-crossed posture.

Figure (a) shows the heat map for L (left leg crossed over), (b) for C (center position), and (c) for R (right leg crossed over). When the left leg is placed on the right leg, the right isthmus bears the weight, so the heat map on the right side is displayed more intensely.

3.2. Comparison of Accuracy Evaluation Metrics

ROC curves (true positive rate and false positive rate) to evaluate the performance of the seven classifiers (Figure 2 and Table 2). And we calculated the evaluation index for each subject and then expressed the results as the average value for all subjects. As a result, the evaluation index for all classifiers except SVM was 99% or more when k was 5 or more. The discrimination accuracy improved as the training time increased. Therefore, a training time of around 240 seconds (80 seconds for each; center, right and left) is appropriate. In addition, SVM proved to be difficult to classify, in particular, the Center position was difficult to misclassify for SVM.
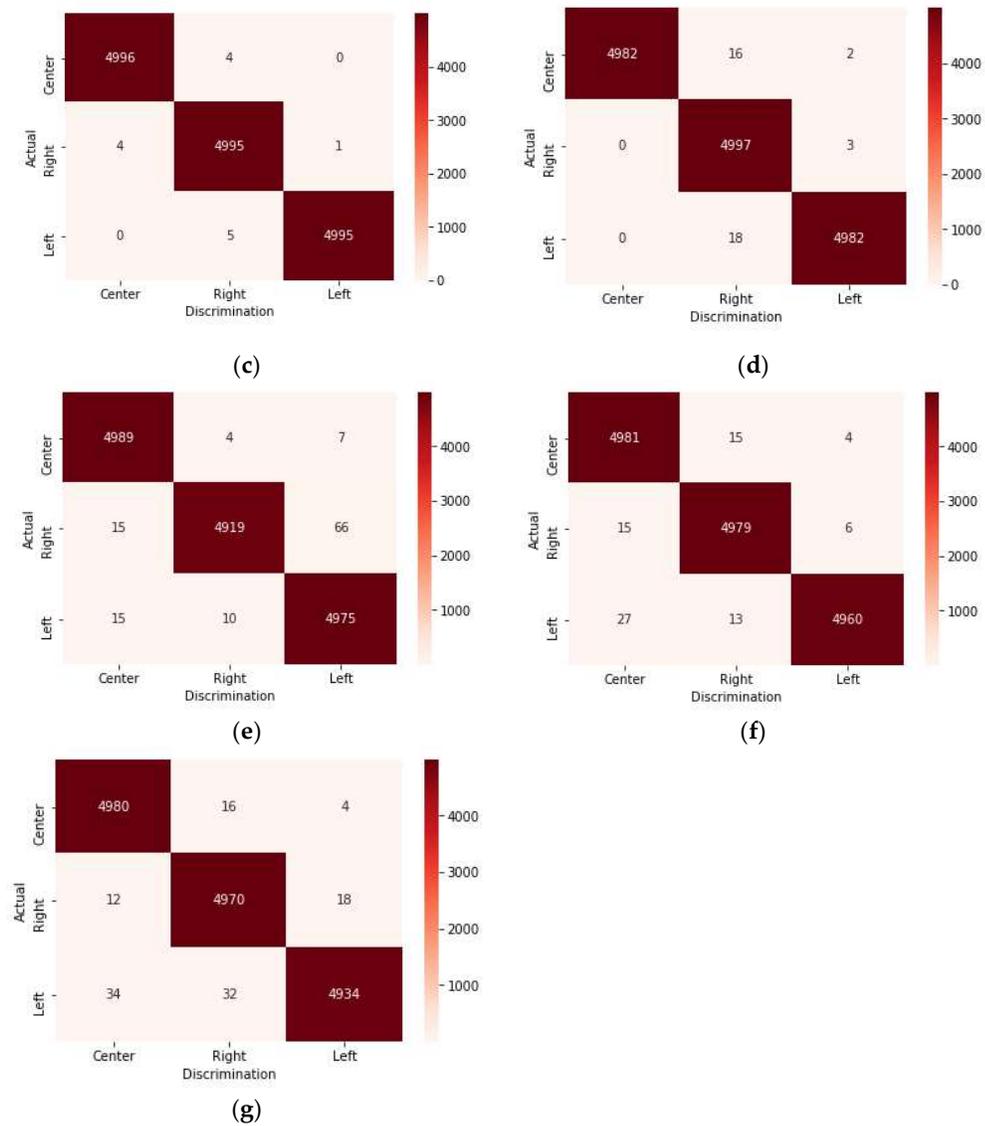

(a)   (b)
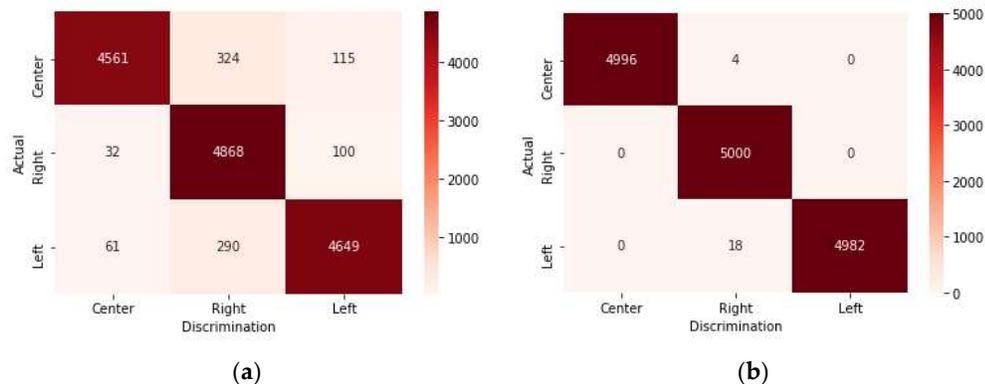
Figure 2. Confusion Matrix by Classifier.

Figure show the total sum of the confusion matrices for all subjects. The confusion matrices for each classifier are (a) SVM, (b) RF, (c) KNN, (d) MLP, (e) ADB, (f) QDA, and (g) NAB.

Table 1. Performance indicators for each classifier.

Accuracy

Classifier	k-value		
	2	5	10
SVM	0.698 ± 0.039	0.881 ± 0.025	0.939 ± 0.010
RF	0.980 ± 0.009	0.996 ± 0.003	0.999 ± 0.001
KNN	0.992 ± 0.005	0.998 ± 0.002	0.999 ± 0.001
MLP	0.988 ± 0.007	0.993 ± 0.003	0.998 ± 0.001

	0.983 ± 0.007	0.998 ± 0.002	0.992 ± 0.004
ADB	0.983 ± 0.007	0.998 ± 0.002	0.992 ± 0.004
QDA	0.946 ± 0.014	0.995 ± 0.002	0.995 ± 0.002
NAB	0.962 ± 0.013	0.991 ± 0.004	0.992 ± 0.002

Precision

Classifier	k-value		
	2	5	10
SVM	0.853 ± 0.015	0.910 ± 0.020	0.947 ± 0.011
RF	0.983 ± 0.007	0.997 ± 0.003	0.999 ± 0.001
KNN	0.993 ± 0.004	0.998 ± 0.001	0.999 ± 0.001
MLP	0.990 ± 0.005	0.995 ± 0.003	0.998 ± 0.001
ADB	0.986 ± 0.006	0.999 ± 0.001	0.995 ± 0.003
QDA	0.961 ± 0.010	0.996 ± 0.002	0.996 ± 0.001
NAB	0.971 ± 0.010	0.993 ± 0.003	0.994 ± 0.002

Recall

Classifier	k-value		
	2	5	10
SVM	0.698 ± 0.039	0.881 ± 0.025	0.939 ± 0.010
RF	0.980 ± 0.009	0.996 ± 0.003	0.999 ± 0.001
KNN	0.992 ± 0.005	0.998 ± 0.002	0.999 ± 0.001
MLP	0.983 ± 0.007	0.993 ± 0.003	0.998 ± 0.001
ADB	0.983 ± 0.007	0.998 ± 0.002	0.992 ± 0.004
QDA	0.946 ± 0.014	0.995 ± 0.002	0.995 ± 0.002
NAB	0.962 ± 0.013	0.991 ± 0.004	0.992 ± 0.002

F-score

Classifier	k-value		
	2	5	10
SVM	0.659 ± 0.046	0.853 ± 0.027	0.931 ± 0.012
RF	0.980 ± 0.009	0.995 ± 0.004	0.998 ± 0.001
KNN	0.992 ± 0.005	0.997 ± 0.002	0.999 ± 0.001
MLP	0.988 ± 0.007	0.992 ± 0.003	0.998 ± 0.001
ADB	0.983 ± 0.007	0.997 ± 0.002	0.991 ± 0.005
QDA	0.942 ± 0.016	0.995 ± 0.002	0.994 ± 0.002
NAB	0.961 ± 0.013	0.989 ± 0.004	0.992 ± 0.003

AUC_tpfp

Classifier	k-value		
	2	5	10
SVM	0.788 ± 0.003	0.927 ± 0.017	0.959 ± 0.007
RF	0.991 ± 0.004	0.998 ± 0.002	0.999 ± 0.001
KNN	0.998 ± 0.001	1.000 ± 0.000	1.000 ± 0.000
MLP	0.996 ± 0.002	0.998 ± 0.002	0.999 ± 0.001
ADB	0.989 ± 0.005	0.999 ± 0.001	0.994 ± 0.003
QDA	0.954 ± 0.016	0.995 ± 0.004	0.995 ± 0.004
NAB	0.971 ± 0.015	0.993 ± 0.004	0.992 ± 0.004

AUC_pr

Classifier	k-value		
	2	5	10
SVM	0.797 ± 0.037	0.937 ± 0.015	0.964 ± 0.007
RF	0.989 ± 0.005	0.998 ± 0.002	0.999 ± 0.001
KNN	0.997 ± 0.001	0.999 ± 0.001	1.000 ± 0.000
MLP	0.996 ± 0.002	0.997 ± 0.002	0.999 ± 0.001
ADB	0.985 ± 0.008	0.998 ± 0.002	0.993 ± 0.003
QDA	0.953 ± 0.015	0.995 ± 0.003	0.995 ± 0.003
NAB	0.970 ± 0.014	0.994 ± 0.003	0.992 ± 0.003

Evaluation index was calculated for each subject, and the average value for all subjects was shown. Each subject was measured 10 times (S.E. indicates the standard error.).

4. Discussion

In this study, we attempted to detect leg positioning posture using a body pressure distribution sensor, and evaluated the accuracy of the detection using machine learning. As a result, the classifier other than SVM showed high classification, and was confirmed to be effective for detecting leg positioning posture. The main points of the results obtained are discussed below.

First, regarding the result that the SVM results are significantly lower than those of other classifiers; SVM is an algorithm that classifies and performs regression by determining boundaries and hyperplanes that divide the data groups of two classes, it was considered that it was basically for two class classification, that preprocessing of data was necessary, that there were few parameters, but that it was difficult to adjust the parameters and interpret the results.

Next, the body pressure data acquired by the pressure sensor provided sufficient information to identify the leg crossing posture even at a sampling rate of 5 Hz. Not only could the heat map visually confirm that the pressure distribution on the left and right sides of the body changed significantly when crossing the legs, but it was also demonstrated that this change in pressure was effective as a feature quantity for machine learning. In contrast to conventional posture estimation methods using depth cameras, which suffer from a delay when tracking posture changes in real time, the body

pressure sensor can acquire data in real time without contact, and so was considered to be superior in terms of efficiency and privacy protection.

In comparison with other classifiers, RF, KNN and MLP also showed high accuracy and were to some extent effective in identifying leg-crossing postures. These classifiers have the ability to capture complex data patterns, showed stable performance in identifying different pressure distributions. On the other hand, ADB and NAB showed a little poorer performance than the other classifiers excluding SVM. This is thought to be because these methods have specific assumptions about the distribution of data, and so they may not have been able to fully reflect the nonlinear and complex changes in pressure data.

The results of this study demonstrate the effectiveness of posture detection using body pressure distribution sensors. However, there are still further issues to be addressed before practical application. For example, the experiment classified static postures, but in real-life sitting postures, dynamic changes occur frequently. In order to be able to detect dynamic sitting postures in real time, it is necessary to collect more diverse data and improve the classification algorithm. In addition, since the number of subjects is limited, it is necessary to collect data from more subjects and improve the generality of the algorithm. For example, it is possible that elderly people and female subjects may show slightly different pressure distributions, so it is necessary to verify the effects of gender and age differences on the data. In our preliminary experiments, even for women and the elderly, the heat map displays a load on the ischium of the leg that is on top (right side if it is the right leg), and there is no significant difference in the shape of the ischium of healthy people, so we can predict that there will be no significant difference [18], but it is also necessary to analyze the chronological changes due to long-term leg-crossing. In recent years, some studies have suggested that the crossed leg sign may indicate a good outcome after a severe stroke [19]. In addition, research is being conducted on applying the comfort of leg-crossing to interior design[20], and there are various potential applications for detecting the action of crossing one's legs from the pressure of sitting.

5. Conclusions

In this study, we attempted to detect the leg-crossing posture in a sitting position using a body pressure distribution sensor, and evaluated its accuracy using machine learning. As a result of comparing seven different classifiers, it was found that classifiers other than SVM can identify with high accuracy when the K value (number of clusters) is 5 or more, with an evaluation index of 95% or more. It was also shown that the accuracy of identification improves as the learning time increases. This study demonstrated excellent performance in detecting the leg-crossing posture. In addition, RF, KNN and MLP exhibited high classification accuracy, demonstrating that body pressure distribution data is an effective feature. The results of this research will contribute to the development of a system that can detect unconscious leg-crossing posture in real time in everyday life. Since leg-crossing posture can cause a shift in the center of gravity of the body and back pain, the detection method verified in this research can detect posture without using a camera, taking privacy into consideration, and it is expected that this detection will encourage posture improvement.

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