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Developing and Evaluating a Mixed Sensor Smart Chair System for Real-time Posture Classification: Combining Pressure and Distance Sensors

Haeseok Jeong and Woojin Park

***Abstract*— A novel sensor-embedded smart chair system was developed to monitor and classify a worker's sitting postures in real time. The smart chair system was a mixed sensor system utilizing six pressure sensors and six infrared reflective distance sensors in combination. The pressure sensors were embedded in the seat cushion to gather seat cushion pressure distribution data. The distance sensors were placed in the seatback to measure seatback-trunk distances at different locations in the frontal plane. The use of the seatback distance sensors represented a unique design feature, which distinguished the mixed sensor system from the previous posture monitoring systems. Employing a k-Nearest Neighbor algorithm, the mixed sensor system classified an instantaneous posture as one of posture categories determined based on an analysis of the ergonomics literature on sitting postures and sitting-related musculoskeletal problems. The mixed sensor system was evaluated in posture classification performance in comparison with two benchmark systems that utilized only a single type of sensors. The purpose of the comparisons was to determine the utility of the design combining seat cushion pressure sensors and seatback distance sensors. The mixed sensor system yielded significantly superior classification performance than the two benchmark systems. The mixed sensor system is low-cost utilizing only a small number of sensors; yet, it accomplishes accurate classification of postures relevant to the ergonomic analyses of seated work tasks. The mixed sensor system could be utilized for various applications including the development of a real-time posture feedback system for preventing sitting-related musculoskeletal disorders.**

***Index Terms*—Ergonomics, k-nearest neighbor algorithm, musculoskeletal disorders, posture classification system, smart chair**

I. INTRODUCTION

Working in stressful sitting postures has been associated with physical discomfort in the upper body areas [1]–[3] and increased risks of work-related musculoskeletal disorders (WMSD) [4]–[7]. Much research has been conducted to determine and characterize high- and low-risk sitting postures [8]–[18]. Existing studies and recommendations generally portray stressful, high-risk sitting postures as possessing some of the following characteristics: lumbar lordosis with excessive anterior pelvic tilt, sideward bending of the neck or trunk, convex low back, excessive trunk inclination, trunk unsupported by seatback, twisted trunk, and unbalanced postures [8], [9], [11], [12]. On the other hand, low-risk, recommendable postures were typically described in terms of normal lumbar lordosis with lower back support, normal thoracic kyphosis, and lateral symmetry [8]–[10], [13]–[18].

Working in high-risk sitting postures for prolonged durations must be avoided. However, most individuals find it difficult to avoid adopting high-risk sitting postures because it requires continually monitoring one's own posture and making corrective adjustments upon detecting the occurrence of undesirable postural changes while simultaneously conducting one or more primary cognitive tasks. The postural task and the primary cognitive tasks would compete for a limited attention capacity [19]–[21]. As the worker directs attention to the primary cognitive tasks at hand, the postural task may become unattended, and, adverse postural changes may occur without the worker's awareness.

A promising solution to the above-mentioned problem is to develop an external posture feedback or warning system, which continually monitors the worker's posture, detects the occurrence of a stressful posture, and, provides a warning through an effective yet non-distracting display. Such a feedback/warning system would help workers easily detect and correct stressful postures with minimal distractions, and, therefore, would help reduce prolonged use of high-risk postures. Creating it, on the other hand, requires developing a sub-system capable of monitoring and classifying a seated worker's postures in real time.

Multiple research studies have developed systems for monitoring and classifying a seated worker's postures in real time. These existing systems may be categorized into three types according to the type of sensors employed: the wearable, image-based, and pressure sensor-embedded systems [22]–[44].

The wearable systems typically employed acceleration sensors and/or optical fibers – these sensors were adhered to the skin or were sewn into a garment. These systems classified upper body postures based on the measurement data from the body-worn sensors representing the orientations of the body

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segments [22]–[25]. The image-based systems analyzed video images of a seated worker to classify instantaneous sitting postures [26]–[28]. One or multiple cameras were placed to capture the sagittal and/or frontal plane images of the seated worker. Some of these image-based systems were designed to classify the worker's head postures [26], [27].

The pressure sensor-embedded systems typically utilized a large array of pressure sensors or a pressure mat placed inside the seat cushion of an office chair to classify a worker's sitting postures. Many of the recent sitting posture monitoring and classifying systems belonged to this category [29]–[44]. The pressure sensor-embedded systems have been referred to as "smart chairs." They typically employed machine-learning models, such as k-Nearest Neighbor (kNN), neural network, Naïve Bayes, and support vector machine classifiers, for real-time posture classification [29], [30], [37]–[39].

Each of the existing systems mentioned above has been reported to successfully classify seated working postures within its own set of pre-defined posture categories. These systems, however, have some limitations. The wearable systems require the users to wear them, and, thus, are perceived as invasive and inconvenient. The invasiveness and inconvenience can make it difficult for the system to gain a wide user acceptance. The image-based systems could not serve their purpose when the worker is out of the camera view or obstacles occlude the worker's body parts. In addition, the image-based systems require the user to be exposed to the cameras at all times; this could cause psychological discomfort, which can hinder user acceptance.

The pressure sensor-embedded systems are free from the invasiveness and inconvenience of wearable systems, and the occlusion and psychological discomfort problems of image-based systems. However, these systems relying solely on pressure sensors seem to have some limitations in the posture classification capability – for example, none of the existing systems has been shown to be capable of accurately recognizing trunk rotation, which is important for the ergonomics evaluation of sitting postures. Also, many of these systems require integrating a pressure mat or utilizing a large number of pressure sensors, which makes them rather expensive for wide-spread use.

The long-term goal of our research is to develop an effective real-time posture feedback system that contributes to reducing sitting-related discomfort and musculoskeletal problems. As an initial effort towards this goal, the purpose of the current study was to: 1) develop a novel, affordable, sensor-embedded smart chair system that is capable of monitoring and correctly classifying an instantaneous sitting posture as one of the major sitting posture categories discussed in the ergonomics literature while not suffering from the limitations of the previous posture monitoring and classification systems, and, 2) empirically validate its posture classification performance. Eleven posture categories relevant to the ergonomics analyses of seated work tasks were identified through an analysis of the ergonomics literature on sitting postures and sitting-related musculoskeletal problems. They included both high- and low-risk sitting postures.

To accomplish the research objectives of the current study, this study adopted a new design strategy of utilizing a small set of infrared reflective distance sensors in combination with a small number of pressure sensors – the distance and pressure sensors were embedded in the seatback and cushion areas, respectively. Thus, the resulting smart chair system was termed the mixed sensor system. The mixed sensor system utilized a kNN algorithm for posture classification - for a given set of sensor measurements, it classified the corresponding posture as one of the predefined posture categories on the basis of a training dataset.

The mixed sensor system was empirically evaluated in posture classification performance in comparison with matching smart chair systems that utilized only a single type of sensors - a pressure sensors only system and a distance sensors only system. The two benchmark systems were identical to the mixed sensor system except that each of them utilized only a single type of sensors; also, they employed a kNN classifier. The comparative evaluation was intended to confirm the utility of the unique design feature of the mixed sensor system, that is, combining seatback distance sensors and seat cushion pressure sensors, in terms of posture classification performance. In particular, the comparative evaluation was focused on examining if the two sensor clusters (the 6 pressure sensors and the 6 distance sensors) both contribute significantly to the overall performance of the mixed sensor system. 10-fold cross-validation was conducted for the comparative evaluation.

The rest of this article is organized as follows. Section II describes the design of the mixed sensor system, and, the methods for the comparative evaluation. Section III describes the results of the posture classification performance evaluation. Finally, Section IV provides a discussion of the study findings.

II. Materials and Methods

This section describes the design and development of the mixed sensor system, and, the methods for evaluating its posture classification performance.

A. *Predefined posture categories for the mixed sensor system*

The mixed sensor system was intended to classify an instantaneous sitting posture as one of the predefined posture categories relevant to the ergonomics evaluation of seated work tasks. A total of eleven posture categories were considered in this study (Fig. 1). They were identified through a review of the existing ergonomics literature on sitting postures and sitting-related musculoskeletal problems, including low back pain, shoulder and back disorders [8]–[18].

The eleven posture categories (Fig. 1) included both high- and low-risk postures. Posture categories 1 and 2 are considered low in the level of bodily stresses and have been recommended for office workers [10], [13]. The other posture categories have been associated with increased risks of WMSD. Forward trunk flexion characterizing posture category 3 has been shown to increase the compression forces on the intervertebral discs [45]. Increased loads on the intervertebral discs have been related to low back pain [46].

Trunk lateral bending depicted in posture categories 4 and 5

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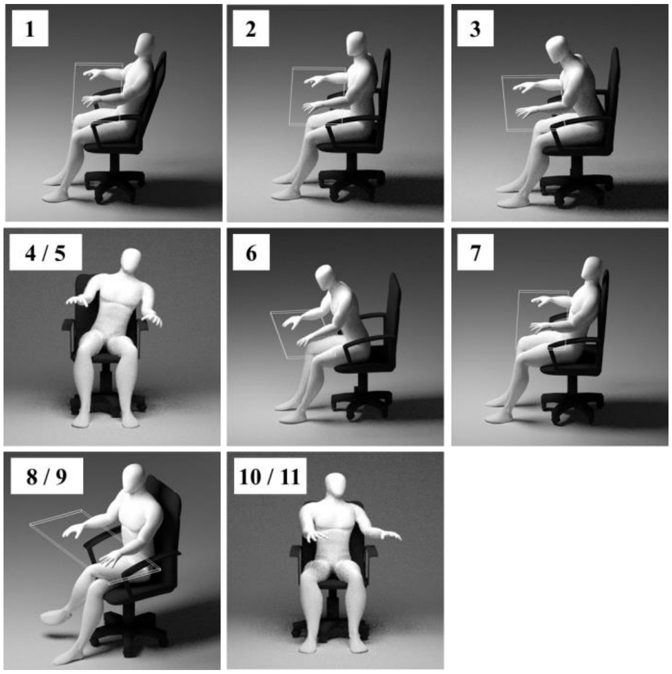

Fig. 1. Eleven sitting posture categories: (1) Leaning on the seatback while keeping the back straight, (2) detaching the back from the seatback and keeping the trunk erect, (3) flexing the trunk forward about 45 degrees (slouch), (4) leaning against an armrest with lateral bending (left), (5) leaning against an armrest with lateral bending (right), (6) sitting on the leading edge with convex trunk, (7) leaning back with hips slightly forward (slump), (8) legs crossed (left), (9) legs crossed (right), (10) rotating the trunk about 20 degrees (left), and (11) rotating the trunk about 20 degrees (right)

generates asymmetrical compressive loadings on the intervertebral discs. During trunk lateral bending, the trunk is maintained by imbalanced activities of the erector spinae muscles of the ipsilateral and contralateral sides [47]. Trunk lateral bending during sitting increased antagonistic contractions in the trunk muscle activity and resulted in increased stress concentration in the intervertebral discs [48]. Repetitive lateral bending and unequal stress concentration in the intervertebral discs have been associated with increased risks of low back pain [49].

Posture categories 6 and 7 are characterized by the lack of lumbar support use. The use of a lumbar support reduces the loads exerted on the ischial tuberosities; such off-loading was found to be beneficial to individuals with low back pain [50]. The lack of lumbar support, on the other hand, is known to flatten the lumbar spine, cause tension on the ligaments and other connective tissues in the spine area, and, lead to excessive loads on the discs [51].

The "legs crossed" postures (posture categories 8 and 9) are known to create asymmetric high-pressure regions and increase peak pressures in the hips and thighs, resulting in pain and discomfort [52]. Also, unbalanced gluteal pressure distributions could cause trunk forward leaning during prolonged sitting [53].

Posture categories 10 and 11 involve trunk rotation. Prolonged twist of trunk increases passive resistance that needs to be overcome [18] and has been associated with increased risks of low back pain and WMSDs [14], [54]. The existing smart chair studies did not consider identifying trunk rotation

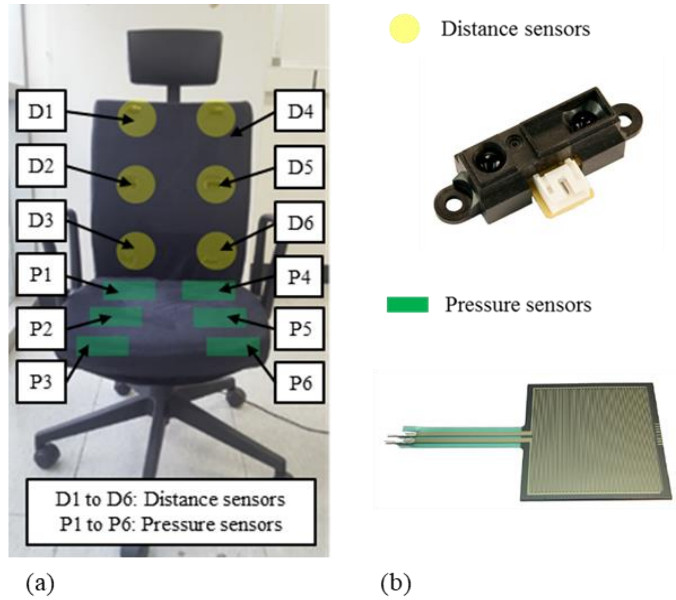

Fig. 2. Physical construction of the mixed sensor system: (a) placement of sensors, and (b) distance and pressure sensors.

despite its relevance to the ergonomics evaluation of seated work activities [22]–[44].

B. *Physical construction of the mixed sensor system*

The proposed mixed sensor system utilized sensor measurements of seat cushion pressure distribution and seatback-trunk distances to classify sitting postures. A typical height-adjustable office chair with armrests and a headrest was adopted to develop the system (Fig. 2(a)).

The seat cushion and seatback were equipped with six force sensing resistors (FSRs; "P1" to "P6") and six infrared reflective sensors ("D1" to "D6"), respectively (Fig. 2(b)). Each batch of six sensors was arranged in two columns of three. The FSRs embedded beneath the seat cushion surface were to gather the seat cushion pressure distribution data. Each FSR measured the pressure applied to an active surface of a 3.8 cm × 3.8 cm square. One FSR could stably measure up to 10 kgf. The infrared reflective sensors were embedded into small pits created in the seatback cushion in advance. They were to determine the horizontal distances between the seatback and the trunk at different heights for both the left and right sides of the back; therefore, they reflected the upper body posture of the seated worker. The infrared reflective sensors provided stable measurements from 2 cm to 50 cm.

The infrared reflective sensors in the seatback represented a novel design feature, which was not considered in the previous smart chair studies [22]–[44].

The locations of the FSRs and the infrared reflective sensors were determined to ensure that all of the twelve sensors produce valid measurements for at least 99 percent of the Korean adult population – to do so, the anthropometric dataset of the SizeKorea survey was utilized [55]. The SizeKorea survey was conducted on the basis of ISO 7250 (1996) and ISO 8559 (1989), and the survey participants consisted of 2,196 males and

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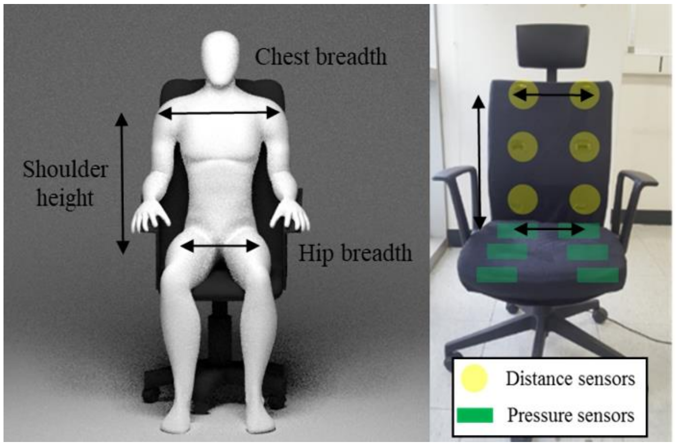

Fig. 3. Anthropometric dimensions considered for the sensor placement

2,293 females aged between 20 and 69 years. The anthropometric dimensions considered for the determination of the sensor locations were: shoulder height, chest breath, and hip breadth in sitting position (Fig. 3).

C. Posture classifier design for the mixed sensor system

The mixed sensor system employed a kNN classifier for posture classification. It classifies an instantaneous sitting posture as one of the eleven posture categories in Fig. 1, on the basis of the corresponding sensor measurements.

The kNN algorithm is simple and intuitive, and is widely used for various engineering applications that require pattern classification [56]–[58]. A kNN classifier stores a set of training set (training cases and their classes). Each case is a vector in a feature space.

A test case (a new observation to be classified) is classified based on the classes of the k most similar cases (the k nearest neighbors) found in the training dataset - the class of the test case is determined by a majority vote among the classes of the k nearest neighbors.

A weighted Euclidean distance shown in (1) was used as the distance function for the kNN classifier; it represents how close the i-th training case $\mathbf{x}_i$ is to the test case $\mathbf{x}_t$. In Equation (1), $\mathbf{x}_i$ represents the normalized N-dimensional feature vector of the i-th training case, and $\mathrm{x}_{i,j}$ denotes its j-th element. Similarly, $\mathbf{x}_t$ and $\mathrm{x}_{t,j}$ denote the normalized feature vector of the test case and its j-th feature value, respectively. The feature vectors were normalized by min-max normalization. w_j is the weight assigned to the j-th feature. The weight w_j reflects the relative importance of the j-th feature [59], [60].

$$d(\mathbf{x}_i, \mathbf{x}_t) = \sqrt{\sum_{j=1}^{N} w_j(\mathrm{x}_{i,j} - \mathrm{x}_{t,j})^2} \ \ with \ \sum_{j=1}^{N} w_j = 1 \tag{1}$$

The feature vector elements, that is, the features, were selected from a set of candidate features. The candidate features included the normalized pressure and/or distance sensor measurements and the pairwise differences of the normalized sensor measurements within each sensor type. The normalized pressure sensor measurements were obtained by dividing each of the original pressure sensor measurements by their sum. The candidate features utilized in the classifier is shown in Table I – the features are grouped into laterally symmetric pairs.

TABLE I
LIST OF CANDIDATE FEATURES

	Candidate features
Pressure-related	P1 & P4, P2 & P5, P3 & P6, P1-P3 & P4-P6, P1-P2 & P4-P5, P2-P3 & P5-P6, P1-P4, P2-P5, P3-P6
Distance-related	D1 & D4, D2 & D5, D3 & D6, D1-D3 & D4-D6, D1-D2 & D4-D5, D2-D3 & D5-D6, D1-D4, D2-D5, D3-D6

TABLE II
PARTICIPANT DEMOGRAPHIC INFORMATION

Gender	N	Age [a] (year)	Height (mm)	WEIGHT (KG)
Male	21	26.7±2.0	175.9±6.4	77.1±15.0
Female	15	25.0±2.3	162.8±4.6	51.4±4.3

[a]Mean±Standard deviation

Feature selection was performed utilizing the domain knowledge-guided forward selection method [61]. The feature weights, w_j, in (1) were optimized using the grid search method [62], [63] - the model parameters, the feature weights and the number of nearest neighbors, were determined to maximize the match between the class of each case in the training dataset and the class determined through majority voting of k nearest neighbors excluding itself. The weights of the laterally symmetric features were constrained to be identical. The hyperparameter k was determined within the range from 2 to 15. Each weight w_j was determined within the grid range from 0 to 2 with the increment of 0.02, and, was divided by the total sum of the weight.

D. Data collection for training and testing the posture classifier of the mixed sensor system

Data collection was conducted to gather labeled sensor measurement data for training and testing the kNN classifier of the mixed sensor system. A total of thirty-six individuals participated in the data collection. The demographic information of the participants is summarized in Table II. The participants performed a single posture measurement trial for each of the eleven posture categories shown in Fig. 1. In each trial, the participants were asked to maintain the corresponding posture for 10 seconds while sitting on the chair of the mixed sensor system. The order of the eleven posture categories was randomized for each participant. In order to help the participants correctly adopt and maintain the postures shown in Fig. 1, the experimenters utilized external visual references (markings on the side wall and the desktop) depicting the trunk forward flexion angle (45 degrees) for posture category 3 and the trunk rotation angle (20 degrees) for posture categories 10 and 11. For the rest of the posture categories, the participants

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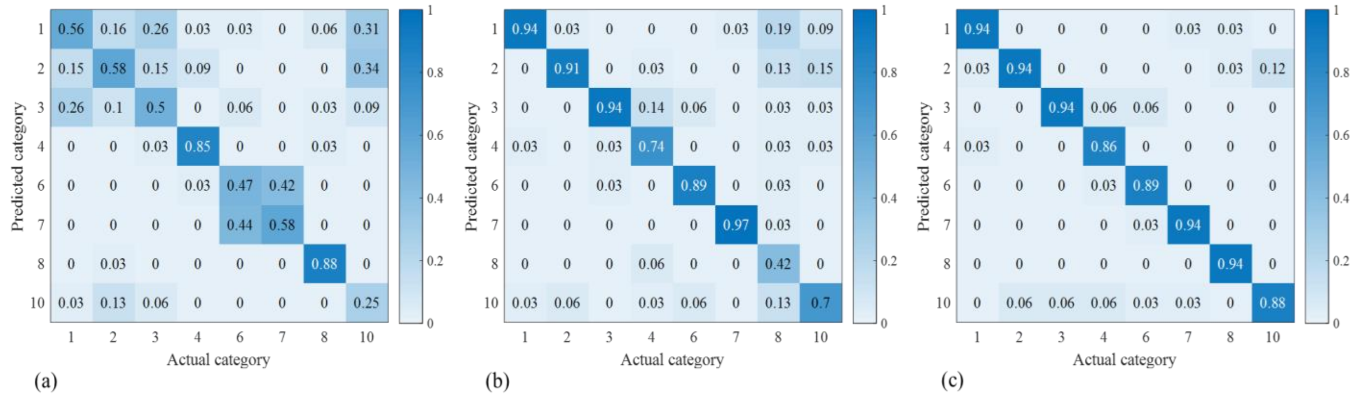

Fig. 4. The confusion matrices of the posture classification results: (a) the pressure sensors only system, (b) the distance sensors only system, and (c) the mixed sensor system

and the experimenters relied on the visual images shown in Fig. 1 and the associated verbal descriptions. In each trial, the measurements from the twelve sensors were collected at a sampling frequency of 10Hz, and, their median values were transformed to the corresponding SI units of distance or pressure. For each trial, the distance and pressure values along with the posture category label were recorded. The data collection protocol was approved by the Institutional Review Board of Seoul National University (IRB No. 1605/003-008).

E. Comparative evaluation of posture classification performance

The posture classification performance of the mixed sensor system was evaluated in comparison with those of two benchmark systems. The benchmark systems employed only a single type of sensors. They were: the pressure sensors only and the distance sensors only system. This comparative evaluation was aimed at quantifying the effectiveness of combining seatback distance and seat cushion pressure sensors, which was the unique design feature of the mixed sensor system.

The pressure sensors only system chosen for the comparative evaluation consisted of an office chair and an array of six FSRs embedded inside the seat cushion, which were identical to those of the mixed sensor system – in other words, the pressure sensors only system was the same as the mixed sensor system with the distance sensors deactivated. In the same way, the distance sensors only system was identical to the mixed sensor system with the pressure sensors deactivated. Thus, the pressure and distance sensors measurement data contained in the dataset for training and testing the posture classifier of the mixed sensor system (Section II.D) were utilized to build and evaluate the kNN classifier for each of the two benchmark systems - the entire dataset was utilized for the mixed sensor system. The subset of the entire dataset containing the FSR measurement data was utilized for the pressure sensors only system; and, the subset containing the distance sensors measurement data, for the distance sensors only system.

While all of the eleven posture categories were considered in training and testing the classifiers, for each of the left and right posture pairs in Fig. 1 (posture categories 4 & 5, posture categories 8 & 9, and posture categories 10 & 11), only the left one (posture categories 4, 8 and 10) was considered in describing the performance of the classifiers. In other words, the right postures (posture categories 5, 8 and 11) were removed from the confusion matrices constructed for the three classifiers. This was to avoid double counting identical evaluation results - for each of the three posture category pairs, the classifier performance evaluation results were almost identical for the left and right postures as the two (left and right) postures as well as the sensor placements were bilaterally symmetric and also the instructions for the two postures were identical except for the asymmetry.

For each of the three systems, the posture classifier performance was evaluated through stratified 10-fold cross-validation. For each system, the corresponding sensor measurement dataset collected from the thirty-six individuals was divided into ten equal-sized partitions. In one iteration of the cross-validation process, the classifier was trained utilizing nine of the partitions as the training dataset, and was validated using the remaining partition as the test dataset. Ten iterations of this procedure were performed, each time using a different partition as the test dataset. The kNN classifier classified a test case (to be classified) utilizing its nearest neighbors within the training dataset – in other words, the test dataset served as an independent, unseen dataset for cross validation.

In order to evaluate the classification performances of the

TABLE III
MODEL PARAMETERS AND FEATURES

System	Number of nearest neighbors	Feature (weight)
Pressure sensors only	9	P1 & P4 (0.20), P2 & P5 (0.14), and P3 & P6 (0.15)
Distance sensors only	5	D1 & D4 (0.19), D2 & D5 (0.16), and D3 & D6 (0.15)
Mixed sensor	3	P1 & P4 (0.16), P2 & P5 (0.07), D2 & D5 (0.06), D1-D3 & D4-D6 (0.14), and D1-D4 (0.15)

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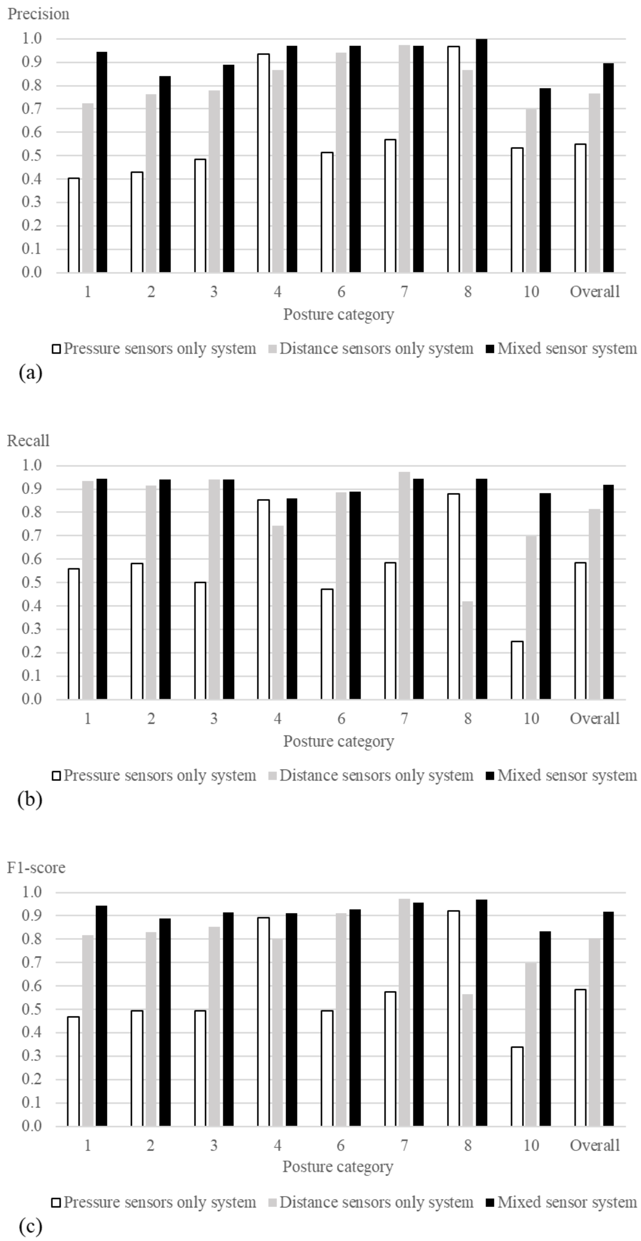

Fig. 5. Posture classification performance of the three smart chair systems for each posture category: (a) precision, (b) recall, and (c) F1-score

smart chair systems, four performance measures for multi-class classification were employed: overall accuracy, precision, recall, and F1-score. Overall accuracy is the ratio of the number of correctly classified cases to the number of test cases. Precision is the ratio of the number of correctly classified cases to the number of cases labeled by the system as positive. Recall is the ratio of correctly classified cases to the number of positive cases in the data. F1-score is the harmonic mean of precision and recall.

III. Results

A. Model parameters and features

For each of the three smart chair systems, the set of model parameters and features trained on the entire dataset collected from the thirty-six individuals is shown in Table III.

B. Posture classification performance

For each of the three smart chair systems, the normalized confusion matrices for the 10-fold cross validation results is provided in Fig. 4(a)-(c). Each confusion matrix was normalized by the number of cases in each class - sum of the values in a column is equal to one. The overall accuracies of the pressure sensors only, distance sensors only and mixed sensor systems were 0.59, 0.82 and 0.92, respectively. Fig. 5(a) provides the mean precision values of the three smart chair systems for each posture category. Similarly, Fig. 5(b) and 5(c) provide mean recall and mean F1-score values.

IV. Discussion

This study developed a novel mixed sensor smart chair system for monitoring and classifying a worker's sitting postures in real time. The mixed sensor system performed posture classification by combining information from six seat cushion-embedded pressure sensors with that from six seatback-embedded distance sensors. It utilized a kNN algorithm for posture classification - for a given set of sensor measurements, it classified the corresponding posture as one of the eleven predefined posture categories, on the basis of a training dataset. The eleven posture categories were determined based on analyzing the relevant ergonomics literature.

The mixed sensor system was evaluated comparatively against two benchmark systems in posture classification performance. The benchmarks were: the pressure sensors only and distance sensors only systems. They were identical to the mixed sensor system except that they employed only a single type of sensors. An independent, unseen test dataset was utilized for the comparative evaluation.

The mixed sensor system was found to achieve a high overall posture classification accuracy (0.92). On the other hand, the overall accuracies of the pressure sensors only and the distance sensors only system were much lower – they were only 0.59 and 0.82, respectively. Also, it was found that the mixed sensor system was able to perform accurate classifications robustly across all of the posture categories considered (Fig. 4 and Fig. 5) - the F1-score of the mixed sensor system ranged from 0.83 to 0.97 (Fig. 5(c)). Its performance was better than or comparable to those of the benchmarks consistently across the posture categories considered (Fig. 5).

The excellent posture classification performance of the mixed sensor system observed in this study is thought to result from combining the two types of sensors - the two sensor types seem to be complementary. In what follows, the impacts of the sensor combination are described focusing on the limitations of the pressure sensors and the roles of the distance sensors.

The mixed sensor system showed far more accurate classification performance than the pressure sensors only system for posture category 10 labeled "Rotating the trunk and keeping the trunk erect." Recall for the posture category 10 was 0.88 and 0.25, respectively (Fig. 5(b)). The poor performance of the pressure sensors only system is thought to result from the fact that in the upright sitting posture, trunk rotation around the

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vertical axis by itself does not affect the position of the upper body center of mass (CoM) position or its projection on the seat cushion surface. Therefore, the pressure sensors alone cannot detect or differentiate trunk axial rotations. The distance sensors embedded in the seat back, on the other hand, provide information directly reflecting trunk axial rotations; thus, combining them with the pressure sensors results in improved posture classification performance.

The mixed sensor system was far superior to the pressure sensors only system in differentiating posture categories 1, 2 and 3, and, posture categories 6 and 7 for which different degrees of trunk flexion account for much of the differences (Fig. 4(a) and 4(c)). The result seems to reflect the difficulties in differentiating different trunk configurations using only the pressure sensor measurements. One possible scenario in which the pressure sensor measurements would not be able to differentiate trunk configurations is when the back of the thighs does not make a full contact with the seat cushion surface and the weight of the upper body is concentrated on a small area around the ischial tuberosities. For example, if the back of the thighs does not make a contact with the pressure sensors embedded in the front and middle parts of the seat cushion (“P2”, “P3”, “P5” and “P6”), then the pressure would be concentrated on the rear part of the seat cushion (“P1” and “P4”) regardless of trunk configuration. In such situation, only the distance sensors embedded in the seat back would provide information useful for discerning different degrees of trunk flexion.

Another reason why the pressure sensors only system could not accurately classify different trunk configurations is the redundant degrees of freedom of the spinal column. The spinal column consists of twenty-three intervertebral discs with each joint having six degrees of freedom. Consequently, different spinal curvatures may result in the same CoM projections on the seat cushion surface and the same seat cushion pressure distributions. Therefore, the CoM projection alone is not enough to determine the spinal curvature or differentiate different trunk configurations due to trunk flexion or axial trunk rotation, and, neither are the pressure sensor measurements. Again, the distance sensors are free from this problem and reflect the curvature of spine in a relatively direct manner.

The impacts of the sensor combination could also be described in terms of the roles of the pressure sensors, in other words, how they complemented the distance sensors only system. One observation concerning the distance sensors only system was that it did not accurately classify posture category 10 (labeled “Rotating the trunk and keeping the trunk erect”). Recall for posture category 10 was only 0.7 (Fig. 4 and Fig. 5). This is possibly because 1) left trunk rotation occurred simultaneously with some trunk flexion due to the interference between the left shoulder and the seatback, and 2) some participants did not sit exactly in the center of the seat cushion. Sitting off the center of the seat cushion could made deviations of the distance sensor measurements and worsen classification performance. The pressure sensor measurement data may have captured and contributed to correcting such offsets.

The distance sensors only system showed relatively better performance than the pressure sensors only system except for posture category 8 labeled “Legs crossed.” For posture category 8, recall of the distance sensors only system was only 0.42 while that of the pressure sensors only system was 0.88 (Fig. 4 and Fig. 5). This is not surprising, as the distance sensors could not provide information about the user’s leg posture. It is thought that the information from the pressure sensors complemented that from the distance sensors to correctly portray posture category 8 “Legs crossed.”

It may be worth providing some discussion on the hyperparameters of the kNN classifiers. First, regarding the results on the hyperparameter k (the number of nearest neighbors of a kNN algorithm), the optimal k value was the smallest for the mixed sensor system; and, between the two benchmark systems, it was smaller for the distance sensors only system than for the pressure sensors only system (Table III). In general, the optimal k value of a kNN classifier is known to increase as the boundaries between the classes become less obvious [64]. The observation is thought to confirm the strength of the design strategy combining the two types of sensors.

Second, for each smart chair system considered in this study, the feature weights help determine the relative importance of the sensors located at different locations [59], [60], [65]. As shown in Table III, the pressure sensor measurements near the hip segment (“P1” and “P4”) had larger feature weights than those near the knees (“P3” and “P6”) and thighs (“P2” and “P5”) in the systems that adopted pressure sensors. This suggests that the pressure sensor measurements of the hip region were more important than the rest. In the mixed sensor system and the distance sensors only system, the uppermost of distance sensor-related feature (“D1-D4”) had the largest feature weights among the distance-related features. This implies that the position of the upper part of the trunk played a major role in posture classification. It may be that the sensors involving large feature weights are the targets for design changes when attempting to optimize the sensor placement.

Overall, this pilot study demonstrated the feasibility and utility of a novel, non-invasive, chair-based posture monitoring system, which combined the pressure distribution and the seatback-trunk distances data. The results of the posture classification performance evaluation (Fig. 4 and Fig. 5) revealed that: 1) the mixed sensor system was capable of accurately classifying sitting postures robustly across major posture categories that are ergonomically relevant, and, 2) the excellent performance of the mixed sensor system was attributable to the design strategy of combining pressure and distance sensors. The proposed mixed sensor system is considered an improvement over the existing pressure sensor-based smart chair systems in that it enables classifying a wide variety of ergonomically important sitting postures, economically using a small number of sensors.

The mixed sensor system presented in this study may have various applications. The mixed sensor system could be combined with a real-time feedback/warning system to help the users adjust their postures and thereby contribute to reducing the risk of WMSDs. Another possible application of the mixed sensor system currently under our consideration is estimating

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the seated worker's mental workload from conducting a cognitive task on the basis of real-time posture measurements. Such mental workload estimation could serve as a basis for optimizing job scheduling.

Further research may be conducted to improve the current mixed sensor system. It is expected that posture classification accuracy is affected by the locations of the pressure and distance sensors [40]. By exploring different sensor placement possibilities, it may be possible to identify new designs that achieve equivalent or enhanced performance with a smaller number of sensors. Also, a future study is warranted to compare the mixed sensor system of the current study against smart chair systems that employ the same number of sensors of a single type, that is, a pressure sensors only system with 12 pressure sensors and a distance sensors only system with 12 distance sensors. Such a study may provide additional information regarding the benefits of combining different types of sensors.

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