Intelligent Seat: Tactile Signal-Based 3D Sitting Pose Inference

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Abstract

Owing to people spending a large portion of their day sitting while working, commuting, or relaxing, monitoring their sitting posture is crucial for the development of adaptive interventions that respond to the user's pose, state, and behavior. This is because posture is closely linked to actions, health, attention, and engagement levels. The existing systems for posture estimation primarily use computer vision-based measurements or body-attached sensors; however, they are plagued by challenges such as privacy concerns, occlusion issues, and user discomfort. To address these drawbacks, this study proposed a posture-inference system that uses high-density piezoresistive sensors for joint reconstruction. Tactile pressure data were collected from six individuals, each performing seven different postures 20 times. The proposed system achieved an average L2 distance of 20.2 cm in the joint position reconstruction with a posture classification accuracy of 96.3%. Future research will focus on the development of a system capable of providing real-time feedback to help users maintain the correct sitting posture.

CCS Concepts

• **Human-centered computing → Ubiquitous and mobile computing**.

Keywords

Tactile Sensor; Human Pose Reconstruction; Sitting Posture;

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1 Introduction

Sitting is the dominant posture adopted during various daily activities, such as working in an office, commuting in a vehicle, or relaxing on a sofa. This sedentary lifestyle can directly affect productivity by contributing to various health issues, including musculoskeletal disorders and decreased cognitive function [2]. Consequently, maintaining proper posture is crucial for physical well-being and enhancing productivity. Thus, monitoring sitting postures can be an effective method to encourage healthier habits [6].

In such situations, the posture constantly changes based on the task being performed. Moreover, the posture adopted can be influenced by actions, health states, attention, and engagement levels. For example, a desirable posture enhances work efficiency and productivity [5, 8]. In addition, individuals may move from a comfortable and natural posture to another, indicating an increased difficulty in performing the required task [3]. Thus, the relationship between posture and these factors is bidirectional, with each element having the potential to impact the other. Consequently, tracking the sitting pose can provide a basis for monitoring the actions and other states while working and relaxing in our daily lives.

Similarly, in vehicular contexts, driver posture can be affected by fatigue, which consequently influences driving performance

[22]. In automated vehicle contexts, driver posture monitoring can be used to assess the readiness to take control of the vehicle [19]. Considering these relationships, the monitoring and tracking of sitting postures can provide important insights for the development of adaptive interventions that respond to a user's pose, state, and behavior.

This study proposed a tactile-sensing-based approach to classify a user's sitting posture and reconstruct joint-level motion for unobtrusive monitoring, facilitating such interventions. The main contributions of this study are as follows:

- The development of a high-density piezoresistive sensor system integrated into a seat, enabling unobtrusive pressure data capture.
- The implementation of a robust system that combines high-accuracy posture classification with detailed motion analysis, achieved through 3D joint position reconstruction.

2 Related Work

The continuous sensing and monitoring of user posture, particularly in indoor environments, are considered essential for providing adaptive and proactive interactions tailored to user posture and behavior. Camera-based approaches are widely used for tracking user poses at the joint level, classifying joint positions, and reconstructing poses while seated [10, 12]. However, these methods are plagued by privacy and occlusion concerns in crowded or cluttered indoor environments [15, 16].

As alternatives to vision-based approaches, tactile sensor-based methods have been proposed to preserve user privacy by reducing the amount and type of data collected [25]. For example, load cells [20] and pressure sensors [1, 4, 13, 23] installed on the backrests and seat plates of chairs can be used to classify sitting postures. Recent advancements in piezoresistive sensors with wider resolutions have facilitated the capture of richer features regarding user postures from pressure sensing. This has facilitated accurate three-dimensional (3D) reconstruction and analysis of standing postures [7, 17]. Consequently, this study is aimed to unobtrusively classify user postures and reconstruct sitting postures at the joint level using piezoresistive signals from sensors installed on the backrest and seat of chairs. The proposed method facilitated an approach for continuously monitoring and analyzing user sitting postures while preserving user privacy.

3 System Overview

3.1 Tactile Seat

To collect tactile data, we developed and utilized a custom high-density piezoresistive pressure-sensing seat (Figure 1). The tactile pressure seat featured 32×32 metal contact points on each side, totaling 1024 sensing points for detecting pressure through electrical signals. These metal contact points were orthogonally arranged on piezoresistive films, which changed resistance upon the application of pressure at the intersection of the conductive threads. The pressure on the seat altered the resistance between the conductive wire arrays, thereby changing the voltage output and facilitating the identification of tactile readings from each pressure point. These tactile readings from each point on the grid were sent to a computer via a microcontroller. Each sensor could measure pressures of up to 14 kPa, with the highest sensitivity of 0.3 kPa [17]. The tactile data were collected at a frequency of 6 Hz.

Figure 1: Hardware setup and data collection process. The left image shows the custom, high-density piezoresistive pressure sensing seat. The right image depicts a participant wearing the Perception Neuron Studio motion capture system, which provides the ground truth for three-dimensional skeleton data.

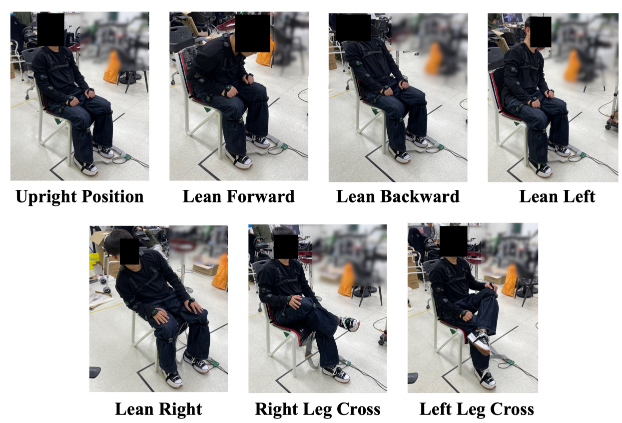

Figure 2: Illustration of the seven sitting postures used in our study.

3.2 Dataset

We utilized the IMU-based motion capture system called Perception Neuron Studio to establish the ground truth for 3D skeleton data. These data were collected at a frequency of 43 Hz. The x-, y-, and z-coordinates of 21 global joint data points were collected, resulting in 63 features. To simultaneously collect data from both the tactile sensor and skeleton data, we used the ActionSense framework [9], which was modified to include Perception Neuron Studio [21] and tactile seat [14]. This framework concurrently stored data from the tactile seat and the Perception Neuron Studio in separate threads.

We gathered data on seven types of sitting postures from six participants, with each participant repeating each posture twenty

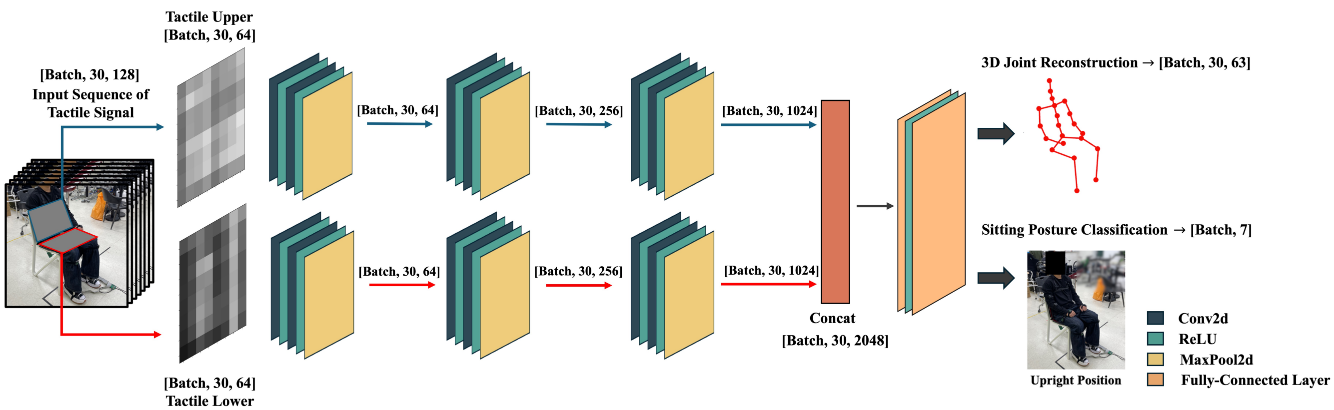

Figure 3: Model architecture for 3D posture reconstruction and classification

times (see Figure 2). These postures were specifically selected to represent common sitting behaviors frequently observed in office environments [1, 11, 18, 24]. The participants held each posture for approximately 2 seconds. We annotated the start and end times and guided the participants to assume the posture correctly. This ensured that the central 2-second window used for training accurately represented the intended posture. We did not provide specific guidance such as exact angles to move for each posture; instead, we allowed the participants to assume the sitting pose based on the posture type.

3.3 Preprocessing

The preprocessing stage involved the application of a low-pass filter with a cutoff frequencies of 2 and 5 Hz for the tactile and Perception Neuron Studio data, respectively, to remove high-frequency noise. To ensure consistency and improve the model performance, the data were normalized. In case of the tactile sensor data, normalization was conducted by subtracting the mean sensor value obtained during an initial 30-s calibration period from each data point and then scaling the data to the range of (-1, 1) using the minimum and maximum values from each data collection session. Further, the dimensionality of the tactile sensor data (originally read as a 32 × 32 grid) was reduced via the application of pooling to downsample the grid to an 8 × 8 resolution by averaging the values of all four adjacent sensors.

To address the differing sampling rates of the tactile sensor and Perception Neuron Studio, all data were resampled to a uniform rate of 15 Hz over 2-s intervals. This preprocessing yielded a final dataset with a shape of (840, 30, 191), where 840 corresponded to six participants, seven types of actions, and 20 repetitions per action. The 191 features represented the combined data from 128 tactile sensor data points (64 each from the upper and lower sensors, respectively) and 63 Perception Neuron Studio data points. The tactile input sequence had a shape of (840, 30, 128), and the ground truth data of the joint positions had a shape of (840, 30, 63).

3.4 Proposed Architecture and Model Training

We designed an architecture that stacks multiple Conv2D layers, as illustrated in Figure 3. The input sequence, comprising tactile data from both the upper and lower sections of the seat, was processed separately through Conv2D layers. Initially, the tactile sensor data were provided in a 32 × 32 grid, which was reduced to an 8 × 8 grid by averaging the values of every four adjacent sensors. Features from the upper and lower data were extracted using Conv2D layers with ReLU activation and MaxPool2D layers. The architecture started with a Conv2D layer with 32 filters, followed by layers with 64, 128, 256, 512, and 1024 filters, each followed by ReLU and MaxPool2D layers. The extracted features from both sections were concatenated into a single feature map, which was then processed using fully connected layers to reconstruct a 3D skeleton sequence. The fully connected layers included a linear layer with 2048 input and 512 output features, followed by ReLU and a final linear layer. For the reconstruction task, the final layer had 512 input features and an output size of (30, 63), while for classification, the output size was 7.

The choice of filter sizes and the number of layers was guided by the need to capture both simple and complex features from pressure image maps. MaxPool2D layers were used to reduce spatial dimensions while retaining essential features, and ReLU activation functions were chosen to introduce non-linearity and mitigate the vanishing gradient problem. Although extensive hyperparameter tuning was not performed, the chosen architecture was based on established deep learning practices for image data and validated through preliminary experiments [1, 17].

4 Results

4.1 3D Pose Reconstruction

To assess the accuracy of the proposed 3D joint reconstruction, we calculated the L2 distance, which measures the Euclidean distance between the predicted and ground-truth coordinates for each joint. This provides a direct measure of the deviation of the predicted 3D skeleton joints from their actual positions. Before calculating the L2 distance, the predicted and ground-truth sequences were aligned by matching the initial coordinates of the hip joint. Subsequently, the L2 distance was computed for each joint using the X, Y, and Z coordinates between the aligned predicted and ground truth coordinates, thereby measuring the discrepancy in the 3D joint positions. The results are summarized in Table 1.

Table 1: L2 distance (in cm) between predicted and ground truth coordinates for each joint.

Joint	L2 (cm)	Joint	L2 (cm)
Middle Hip	2.1	Neck1	21.2
Right Hip	5.7	Head	22.4
Right Knee	29.2	Right Shoulder	17.7
Right Ankle	37.9	Right Arm	19.9
Left Hip	5.9	Right Forearm	20.6
Left Knee	36.7	Right Hand	26.2
Left Ankle	41.5	Left Shoulder	18.3
Spine	4.2	Left Arm	22.2
Spine1	9.9	Left Forearm	21.9
Spine2	13.7	Left Hand	27.6
Neck	19.9	**Average**	**20.2**

As presented in Table 1, the L2 distance of each joint ranged as 2.1–41.5 cm, indicating variations in the accuracy across different joints. In general, the joints closer to the sensor (e.g., hip and spine) exhibited higher accuracy than those farther away (e.g., feet and hands). These observations aligned with the intuition that the pressure map changed most significantly with movements of the spine and upper leg. This trend indicated that the accuracy decreased for joints farther from the hip.

4.2 Sitting Posture Classification

To classify the seven sitting postures, we utilized accuracy, balanced accuracy, F1 score, recall, and precision as evaluation metrics. Our dataset consisted of 840 instances, with each of the seven postures represented by 120 instances, recorded for approximately 2 seconds each. To ensure model generalization, we combined the data from all six participants and split it into a 4:1 ratio for training and testing. We employed stratified 5-fold cross-validation on this mixed dataset to ensure that each fold maintained the same class distribution as the original dataset. By averaging the metrics across the five stratified folds, we obtained a robust estimate of the model's performance.

To prevent overfitting, we applied several strategies during training and network design. Early stopping monitored validation loss, halting training if no improvement occurred over 10 epochs, thus avoiding excessive adaptation to training data. Dropout layers in the fully connected layers randomly set a fraction of input units to zero during training to reduce neuron dependency. These strategies collectively improved the model's generalization, ensuring reliable performance on unseen data.

For hyper-parameter tuning, we experimented with learning rates of 0.0001, 0.0003, and 0.0005. We selected the model configuration that achieved the highest accuracy. Based on this optimal configuration, we conducted an ablation study to assess sensor importance by using only one sensor at a time.

We compared the results of our CNN-based model with two baseline methods: major class voting and random voting. Since our dataset had an equal number of instances for each class (120 instances per class), in major class voting, the model always predicts the most frequent class, which we chose to be class 0 for consistency. In random voting, it randomly assigns one of the seven class labels to each instance. The classification results are presented in Table 2.

Table 2: Evaluation metrics for sitting posture classification.

Model	Acc.	Bal. Acc.	Precision	Recall	F1-score
Major Voting	14.4%	14.3%	2.1%	14.4%	3.6%
Random Voting	15.7%	15.7%	15.6%	14.4%	15.5%
Only Upper	86.5%	86.5%	87.6%	86.5%	86.5%
Only Lower	97.7%	97.7%	97.9%	97.7%	97.7%
All Sensors	96.3%	96.3%	96.8%	96.3%	96.2%

An accuracy of 96.3% and a balanced accuracy of 96.3% demonstrated the overall effectiveness of the model in classifying various sitting postures when using all sensors. Further, the F1 score of 96.2%, recall of 96.3%, and precision of 96.8% indicated the robustness of the model, demonstrating balanced performance with minimal trade-offs between false positives and negatives. The model using only the lower sensors also showed remarkable performance, with an accuracy and balanced accuracy of 97.7%, precision of 97.9%, recall of 97.7%, and F1 score of 97.7%, indicating that the lower sensors play a crucial role in posture classification. The model using only the upper sensors achieved an accuracy and balanced accuracy of 86.5%, precision of 87.6%, recall of 86.5%, and F1 score of 86.5%, showing lower performance compared to the models using all sensors or only the lower sensors. The baseline methods, major voting and random voting, showed expectedly lower performance, with accuracies of 14.4% and 15.7% respectively, consistent with the expected performance of random guesses given a balanced dataset with 7 classes. In contrast, our CNN-based model demonstrated robust and effective classification performance across all metrics, significantly outperforming these baselines and highlighting the model's capability in accurately classifying sitting postures.

In addition, we present the confusion matrix for sitting posture classification in Figure 4. The confusion matrices for models using only the upper sensor, only the lower sensor, and all sensors are displayed. The model using only the lower sensor and all sensors showed the highest classification accuracy with minimal misclassification across all postures. The model using only the upper sensor, while still effective, showed more misclassifications compared to the other configurations, particularly between "Lean Forward" and "Upright Position", and between "Lean Right" and "Lean Left".

These misclassifications can be attributed to the nature of the pressure distributions for certain postures. For example, the confusion between "Lean Forward" and "Upright Position" when using only the upper sensor can be explained by the fact that both postures involve similar upper body pressure patterns, making it difficult for the model to distinguish between them. Similarly, the confusion between "Lean Left" and "Lean Right" can be attributed to the fact that these postures produce subtle pressure changes in the upper sensors, which are not distinctive enough for accurate classification.

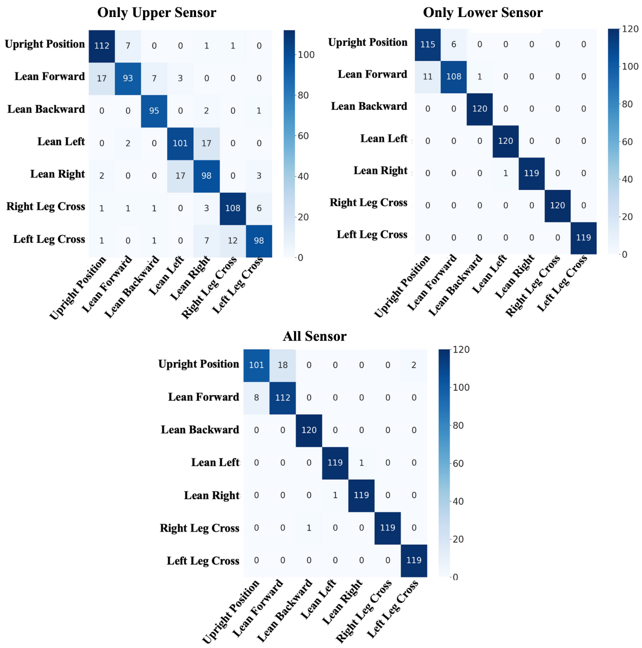

Figure 4: Confusion Matrix for the sitting posture.

Additionally, the "Right Leg Crossed" and "Left Leg Crossed" postures primarily affect the lower body pressure distribution, leading to misclassification when only upper sensor data is used.

These observations imply that for the classification of the seven sitting postures we analyzed, using only the lower sensors is sufficient to achieve high accuracy. Overall, our evaluations demonstrated that the proposed system effectively classified the sitting postures with high accuracy. These results validate the feasibility of using pressure sensors for posture analysis and provide a foundation for developing real-time posture monitoring and intervention systems.

5 Limitations and Future Work

Although our proposed system showed promising results in posture classification and joint reconstruction, several limitations must be addressed for practical applicability and robustness.

First, the data collected in experimental scenarios need validation in natural settings using more complex ground-truth methods like cameras and depth sensing. Second, the wired sensor design limits user convenience and complicates installation, suggesting a need for wireless sensor technology to improve usability and scalability.

Furthermore, the pose classification tasks used in this study were relatively simple, which may not fully challenge the model's capabilities. Future research should consider incorporating more complex and contextually rich sitting postures to better evaluate the model's robustness. For instance, predicting sitting postures not only based on position but also in the context of different activities, such as reading a book or typing on a keyboard, would provide a more comprehensive assessment of the system. Such complex tasks would demand the model to understand and classify sitting postures in varied and realistic scenarios, reflecting real-world usage more accurately.

Additionally, adjusting skeletons only at the hip position without correcting for key rotational axes may lead to larger errors for joints farther from the hip. Skeletal dimensions could also affect error metrics, with taller individuals potentially showing larger positional errors for the same joint angle error.

To address these issues, future work will involve defining and analyzing essential joint angles for seated posture, expanding our dataset, and incorporating these angles into our reconstruction methods to deliver detailed feedback on seated posture. Moreover, the system's real-time capabilities have not yet been tested. Future work will also include usability testing to evaluate if the system operates effectively in real-time and if users perceive it as functioning accurately.

6 Conclusion

This study developed a pressure-based posture estimation system using high-density piezoresistive sensors for accurate 3D joint reconstruction and posture classification. The system reconstructed joint positions with an average L2 distance of 20.2 cm and classified sitting postures with 96.3% accuracy. Integrated with real-time feedback, it can help users maintain healthy sitting habits by encouraging posture adjustments. Combining this system with visual or depth sensors could enhance accuracy and robustness, especially for joints less influenced by seat pressure, such as the foot and hand positions, which are crucial for understanding user behavior.

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