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Automatic Detection of Compensatory Movement Patterns by a Pressure Distribution Mattress Using Machine Learning Methods: A Pilot Study

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ABSTRACT For stroke patients with hemiplegia, reaching with the paretic arm is often associated with compensatory movements due to limited active arm movement and a loss of interjoint coordination. Detecting common compensatory movement patterns, such as excessive trunk displacement and scapular elevation, is critical for improving the motor function of the paretic arm. Existing compensatory movement pattern detection methods, including sensor-based systems and camera-based systems, suffer from object obstruction and require complex setups. In this paper, a compensatory movement pattern detection system using a pressure distribution mattress is presented. This method is a novel approach to detect compensations and has observed advantages; it is simple, unobtrusive and low cost. Fifteen healthy participants with no motor impairments performed three reaching tasks (back-and-forth, side-to-side, and up-and-down reaching) in a normal pattern and in compensatory movement patterns (trunk rotation and lean-forward, and scapular elevation). Pressure distribution data of all motions were recorded and processed to generate a group of features (average sensor values, the lateral center of pressure, longitudinal center of pressure, the ratio of left-side to right-side pressure, and the ratio of front-side to back-side pressure) reflecting the information of each predefined pattern. Four machine learning methods were implemented to detect compensatory movement patterns and showed good reliability and precision. Both k-nearest neighbor (kNN) and support vector machine (SVM) classifiers have achieved an excellent classification performance (F1-score = 0.934) in detecting compensation during all reaching tasks. For the multiclass classification of compensatory movement patterns, the SVM classifier exhibited a good classification performance for trunk lean-forward (F1-score = 0.933), scapular elevation (F1-score = 0.881), and trunk rotation (F1-score = 0.854) and outperformed previous reports. The study results provide initial evidence of a pressure distribution mattress for detecting compensatory movement patterns. Future work needs to test the approach on stroke survivors to verified the feasibility and validity.

INDEX TERMS Compensation detection, machine learning, classification, pressure measurement.

I. INTRODUCTION

Stroke is a leading cause of adult disability around the world [1], and up to 80% stroke survivors may suffer from upper-limb impairments that have a severe impact on a person's ability to perform daily activities and influence their quality of life [2]. Compensatory strategies, described as incorporating additional degrees of freedom at new joints and body segments, are commonly employed by stroke survivors to adapt to the loss of motor function [3].

As for the upper limb, compensations mainly include the use of movement patterns that incorporate a forward trunk lean, trunk rotation and scapular elevation compensation [4]. Although compensation may help patients complete tasks in the short term, motor function improvement by compensation is limited, and the presence of compensation may be

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associated with long-term problems such as a reduced range of joint motion and pain [5], [6]. Compensatory strategies could lead to a pattern of learned nonuse [7] and prevent patients from attempting to generate more 'normal' motor patterns in daily activities that may ultimately limit the final functional outcome of the impaired arm [8]. Moreover, there is also evidence that reducing compensatory movements, for instance using a trunk restraint [9] or providing a visual feedback [10] to stroke survivors, is beneficial for improving arm function. This evidence highlights the need to monitor compensation automatically to optimize rehabilitation for stroke survivors.

Current approaches for detecting compensatory movements have focused on sensor-based systems and camera-based technology. Sensor-based systems are mostly used for monitoring and providing feedback on posture and upper extremity movements in stroke rehabilitation [11]. Generally, accelerometers [12], inertial measurement units (IMUs) [13]–[16], sensing garments [17], torso harnesses [18] or other sensors are placed on the patients to monitor trunk and/or shoulder compensatory movements. Such sensor-based approaches often require careful engineering [19], and these sensor suites are difficult to put on [20]. It is difficult to find an unobtrusive and easy-to-use solution. Moreover, wearable sensing systems may hinder user acceptance and induce unnatural movements owing to the attached sensors. The validity and reliability of outcome estimates from these wearable sensors for stroke rehabilitation is a daunting challenge for researchers [21], [22].

Other works on detecting compensatory movements in rehabilitation have relied primarily on camera-based technology [23], [24] and included marker-based human movement tracking and markerless tracking. Marker-based motion capture technologies require that retroreflective markers be placed on the body, whose three-dimensional (3D) locations are subsequently recorded by multiple cameras. This method can obtain more accurate and robust 3D tracking results compared with the markerless tracking method [21]. However, marker-based tracking systems require expensive specialized hardware and an elaborate setup. The laboratory environment and the attachment of markers can cause unknown experimental artifacts and make marker-based tracking systems inappropriate for use in clinical settings [25]. By eliminating the need for markers, marker-free methods have been developed to reduce patient preparatory time and enable simple, time-efficient, and potentially more meaningful assessments of human movement in clinical practice [26], [27]. However, the accuracy of movement tracking without markers is still technically challenging and leads to markerless methods that are not widely available [28]. Moreover, camera-based technologies, both marker-based and markerless-based methods, are not particularly well suited outside the lab environment since camera-based systems are not portable and require a space with clear line-of-sight for the cameras. The camera-based system also raises privacy concerns and could cause unnatural behaviors owing to negative feelings caused by being monitored [29].

Therefore, it is critical to develop a simple, unobtrusive, low-cost and adaptable method to detect compensations in clinical practice. Considering that stroke survivors generally sit and perform upper-limb rehabilitation training, trunk compensation can inform proximal arm use because the hand is the end effector of the kinematic chain formed by the trunk, arm and forearm [30]. Assessing the pressure distribution in a chair can reflect upper-limb movement behaviors of stroke survivors and serve as a compensation-detection method. Pressure distribution mattresses are matrices of usually piezoresistive effect-based sensors. In previous studies [31]–[34], pressure distribution mattresses have been employed to classify the sitting-upright posture in which the waist is straight, and the feet are placed flat on the floor, the postures in which the upper body is tilted forward, backward, left, or right, and the postures in which the left or right leg is crossed. The classification process was performed by various methods, including the naïve Bayes classifier [35], the k-nearest neighbor (kNN) classifier [31] and support vector machine (SVM) [36], and the classification results demonstrated sufficient accuracy and precision.

While compensation detection in stroke survivors still lacks a suitable measurement system, the proposed pressure measurement have not yet been used for such analysis. The main contributions of this paper are as follows:

- A compensation-detection method based on pressure measurement is proposed.
- Compensations are classified using machine learning algorithms with satisfactory accuracy (F1-score > 0.9).
- A convenient, practical and cost-effective system can be used to monitor compensations and refine the assessment of rehabilitation training, which is suitable for clinical and home use.

The rest of this paper is organized as follows. Section II describes the participants, the experimental setup and the measurement procedure. Section III presents the sensor data processing, the pressure-feature extraction and the classification algorithms for compensation detection. In Section IV, the performance of the proposed approach is evaluated using standard performance metrics, and the results are compared with previous state-of-the-art works. Finally, Section V concludes this paper.

II. METHODS

A. PARTICIPANTS

Fifteen healthy participants with no history of neurological or mobility impairments participated in the experiments. All participants provided informed consent, and the procedures were approved by the South China University of Technology Research Ethics Board (SCUTREB). Table 1 provides summary information for all participants.

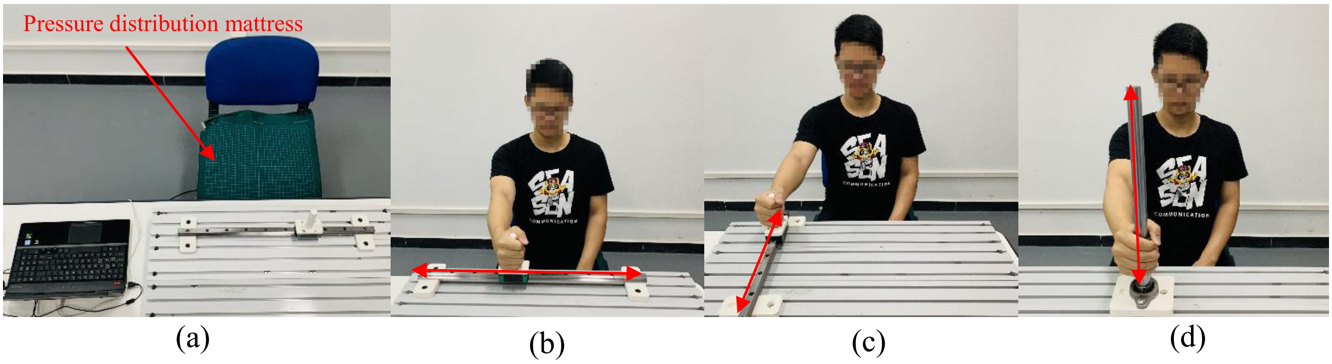

FIGURE 1. Experimental setup and three types of reaching tasks. (a) Experimental setup for the reaching tasks. (b) Side-to-side reaching. (c) Back-and-forth reaching. (d) Up-and-down reaching.

TABLE 1. Basic parameters of participants.

Characteristics	Mean±SD
N	15
Male	12
Age (years)	23.5±1.7
Weight (kg)	64.8±10.5
Height (cm)	173.5±7.2
Right-hand dominance	15

TABLE 2. Description of movement tasks and compensations.

Type	Motion	Description
Normal	Back-and-forth reaching	Move back and forth on the transverse and sagittal planes.
	Side-to-side reaching	Move side-to-side on the transverse and coronal planes.
	Up-and-down reaching	Move up and down on the sagittal and coronal planes.
Compensatory	Trunk rotation	Turning of the torso in the transverse plane
	Trunk lean-forward	Hip flexion angle less than 90° in the sagittal plane
	Scapular elevation	Unilateral scapular raise in the coronal plane

B. EXPERIMENTAL SETUP AND MEASUREMENT PROCEDURE

The movements of the trunk were recorded during seated tasks with a commercially available pressure distribution mattress (Body Pressure Measurement System (BPMS), Model 5330, Tekscan, Inc., South Boston, MA, USA). This soft mattress is 0.2 mm thick, with 1024 (32 × 32) piezoresistive pressure sensors covering approximately 471 mm × 471 mm of total pressure-sensitive area. It enables the precise measurement of the pressure distribution between the human body and the chair, including the location of pressure, magnitude of peak pressures, and overall pressure distribution patterns. The sensor is read sequentially by driving one of the rows and sensing one of the columns. The microprocessor selects the row and column to be read by identifying the proper location for each intersecting row and column. The pressure distribution data were recorded at a measurement frequency of 50 Hz.

Subjects sat comfortably in front of a table on an adjustable chair with a back support that did not restrict trunk movements. The pressure distribution mattress was mounted on the chair. The chair height was adjusted to the length of the legs of the subjects so that their feet were flat on the floor. Each subject performed three types of reaching tasks that were selected to cover a wide range of movements of the arm at the shoulder and elbow. These tasks were (i) side-to-side reaching (Figure 1b), (ii) back-and-forth reaching (Figure 1c), and (iii) up-and-down reaching (Figure 1d).

During reaching motions, three types of poststroke compensatory synergies were commonly elicited, including excessive axial trunk rotation, trunk lean-forward [37], [38] and scapular elevation movements [21], [22]. The details of the motions are shown in Table 2.

All subjects performed three types of reaching motions with their dominant hand. Each reaching task was repeated 3 times as a group at a self-selected speed. In addition, each subject was asked to simulate common poststroke compensatory movements, which included trunk lean-forward, trunk rotation, and scapular elevation. The raw data of all participants were recorded for training and testing the pressure sensor-based detection method of compensation in upper-limb movements.

III. COMPENSATION DETECTION

This section is organized as follows. Initially, the sensor data processing method of the pressure distribution mattress is presented. Next, the 5-dimensional feature vector is extracted from the pressure distribution data to represent the different movement patterns. Then, four machine learning methods are implemented to automatically classify the compensatory movement patterns. Finally, the training and testing procedure is described, and the accuracy metrics for judging the classification performance are given.

A. DATA COLLECTION AND PROCESSING

The pressure distribution data of 270 motions (216684 frames with a 32 × 32-dimensional vector in each frame) were acquired using the BPMS software and exported into ASCII format for postprocessing in MATLAB (MathWorks Corp., Natick, MA, USA). The pressure maps of four typical postures, including sitting up straight, sitting with the trunk leaning forward, sitting with trunk rotation and sitting with scapular elevation, were presented as a color-coded real-time display (Figure 2). The pressure sensor values were preprocessed before calculating the features. Since pressure mattress modules have a unique default offset level, a bias value matrix was recorded on a regular basis and used for offset data removal. Five pressure features were calculated for classification, and four different classification algorithms were applied to compare and determine which algorithm gave the best classification accuracy.

B. FEATURE EXTRACTION

The pressure sensor array is represented as a set of indexed sensors $\{\boldsymbol{P_1}[\boldsymbol{t}], \boldsymbol{P_2}[\boldsymbol{t}], \cdots, \boldsymbol{P_N}[\boldsymbol{t}]\}$, where $\boldsymbol{N} = 1024$ is the total number of sensors in the array. Each sensor is represented as a triple $\boldsymbol{P_i}[\boldsymbol{t}] = (\boldsymbol{x_i}, \boldsymbol{y_i}, \boldsymbol{p_i}(\boldsymbol{t}))$, where $\boldsymbol{x_i}$ and $\boldsymbol{y_i}$ are the lateral and longitudinal coordinates of the ***ith*** sensor, respectively, and $\boldsymbol{p_i}(\boldsymbol{t})$ is the sensor value at time $\boldsymbol{t}$. Considering the characteristics of compensatory and noncompensatory movements, the following features have been tested for classification.

- Average sensor values (ASV).

$$\mathrm{ASV} = \mathrm{SSV}/\mathrm{T} \tag{1}$$

where T is the total time and *SSV* is the sum of sensor values $SSV(t)$. $SSV(t)$ was obtained from the sum of $p_i(t)$ for all i at a given time t.

$$SSV(t) = \sum_{i=1}^{N} p_i(t) \tag{2}$$

$$SSV = \sum_{t=1}^{T} SSV(t) \tag{3}$$

- Lateral center of pressure (LatCOP).

$$\mathrm{LatCOP(t)} = \sum_{i=1}^{N} x_i p_i(t)/SSV(t) \tag{4}$$

- Longitudinal center of pressure (LonCOP).

$$\mathrm{LonCOP(t)} = \sum_{i=1}^{N} y_i p_i(t)/SSV(t) \tag{5}$$

- Ratio of left-side to right-side pressure (LRratio).

$$\mathrm{LRratio(t)} = \sum_{y_i=1}^{y_i=16} p_i(t) / \sum_{y_i=17}^{y_i=32} p_i(t) \tag{6}$$

- Ratio of front-side to back-side pressure (FBratio).

$$\mathrm{FBratio(t)} = \sum_{x_i=1}^{x_i=16} p_i(t) / \sum_{x_i=17}^{x_i=32} p_i(t) \tag{7}$$

These five features (the average sensor values (ASV), the lateral center of pressure (LatCOP), the longitudinal center of pressure (LonCOP), the ratio of left-side to right-side pressure (LRratio) and the ratio of front-side to back-side pressure (FBratio)) were extracted and supplied to train the different classifiers.

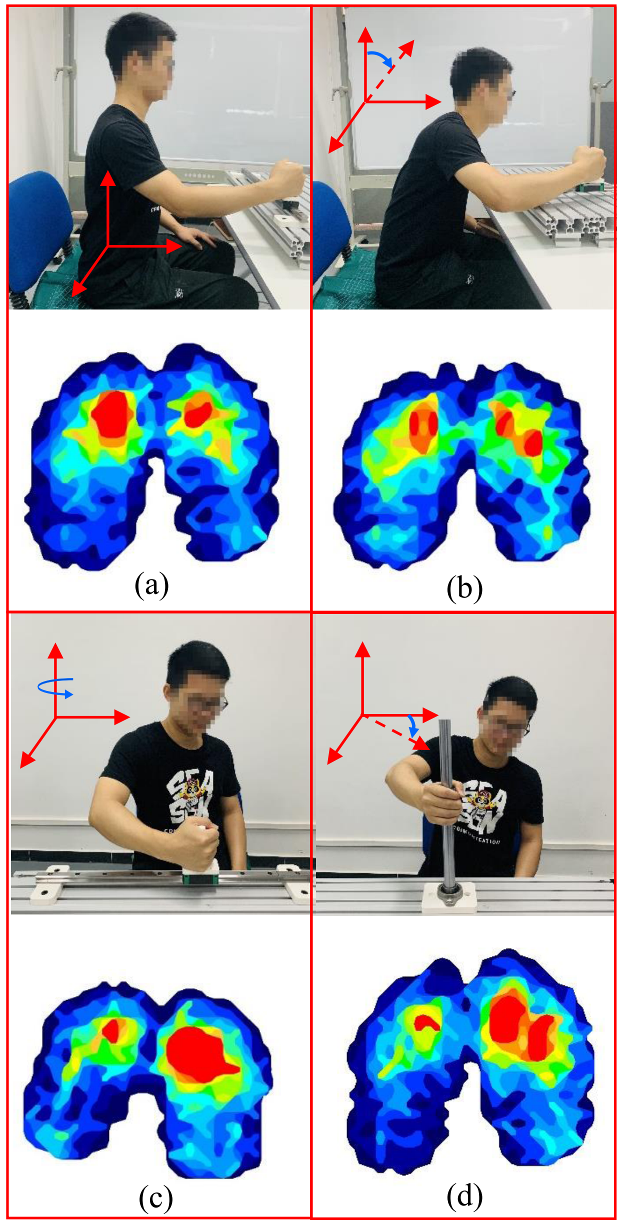

FIGURE 2. The pressure map of the four postures. (a) Sitting straight; (b) Sitting with the trunk leaning forward; (c) Sitting with trunk rotation; (d) Sitting with scapular elevation.

C. CLASSIFICATION

Different machine learning algorithms, including linear discriminant analysis (LDA) [39], the k-nearest neighbor (kNN) classifier [40], the naïve Bayesian classifier [41], and a support vector machine (SVM) [42], were used to classify the posture of the participants. Each algorithm is briefly described below.

LDA was evaluated as a representative example of a linear classifier in this study. It is much simpler to implement and much faster to train than other types of classifiers. The linear classifier can trace the hyperplane that best separates the data distributions of compensation and noncompensation.

The kNN classification algorithm is a nonparametric classification method, which is simple but effective in many cases [43]. The kNN training sample consists of feature spaces containing K different tags. Training classifications were obtained by using majority voting from the distance between the feature space and the given object. In this study, the distance is measured using the Euclidean distance. The Euclidean distance between n-dimensional attribute vectors $X = (x_1, x_2, \ldots, x_n)$ and $Y = (y_1, y_2, \ldots, y_n)$ can be defined by equation (8). To determine the k value, the kNN algorithm was run with different k values, and the one with the best performance was chosen.

$$\mathrm{dist}\,(\mathrm{X},\,\mathrm{Y}) = \sqrt{\sum\nolimits_{i=1}^{n} (x_i - y_i)^2} \tag{8}$$

The naïve Bayesian classifier is a supervised machine learning classifier, which is a probabilistic classification algorithm based on Bayes' theorem. Suppose we have a set of training tuples and a corresponding set of class labels. Each tuple is represented by an n-dimensional attribute vector $X = (x_1, x_2, \ldots, x_n)$ in the form of K class labels $\{C_1, C_2, \ldots, C_k\}$.

For a given tuple X, the naïve Bayesian classifier can predict which category it should belong to. Assuming that all attributes are independent of each other, the classification rule for the new input data can be represented by equation (2).

$$P\,(X|C_i) = \prod\nolimits_{k=1}^{n} P\,(x_k|C_i) \tag{9}$$

A SVM is a machine learning method based on statistical learning theory. It constructs a high-dimensional hyperplane for small samples and nonlinear models and classifies samples by calculating the maximum distance between training data points on the hyperplane [44]. A SVM has the advantages of higher stability and fewer training parameters [42], [45]. The equation solved by the SVM algorithm from the Lagrange operator can be expressed as:

$$\begin{cases} min\dfrac{1}{2}\,\|w\|^2 + C\sum_{i=1}^{N}\xi_i \\ s.t.\; y_k\left(w^T x_k + b\right) \geq 1 - \xi_i, \quad k = 1, \ldots N \end{cases} \tag{10}$$

The SVM classifiers were configured using a radial basis kernel function, and the cost parameter was optimized by using cross-validation.

To compare and determine the most suitable classifier, these four machine learning methods were implemented to detect and categorize compensatory movement patterns.

D. TRAINING AND TEST PROCEDURE

The five extracted features, including the ASV, LatCOP, LonCOP, LRratio, and FBratio, were supplied to the LDA, kNN, naïve Bayesian and SVM classifiers, respectively. A five-fold cross-validation method was used to divided the feature data and action labels into five equal groups. Four groups were used to train the classifiers, and the other group was used to verify the accuracy of the classifiers. The process is repeated until each participant has been used as a test dataset, and the results are aggregated to verify the models to find the average recognition rate of the system [46].

TABLE 3. Confusion matrix.

		Actual Class	
		Positive	Negative
Predicted class	Positive	True positive (TP)	False positive (FP)
	Negative	False negative (FN)	True negative (TN)

The confusion matrix displays information about the actual and predicted classifications performed by a classifier and is a convenient tool for evaluating the classification performance [47]. For binary classifications, the confusion matrix contains true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN), as shown in Table 3.

Based on the confusion table, three accuracy metrics (precision, recall and F1-score) can be obtained [48]. Precision describes the accuracy of the detection and can be calculated with equation (11). Recall is the detection rate, which refers to how well the target objects are detected without being missed and can be calculated with equation (12). The F1-score combines the precision and recall and provides a single measure of quality that is easy for end-users to understand, which can be calculated with equation (13).

$$Precision = \frac{TP}{TP + FP} \tag{11}$$

$$Recall = \frac{TP}{TP + FN} \tag{12}$$

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{13}$$

IV. RESULTS AND DISCUSSION

A. RESULTS

The classification accuracies for each type of reaching—back-and-forth reaching, side-to-side reaching, up-and-down reaching—are shown in Tables 4-6, respectively. The classification performance was better in the back-and-forth reaching tasks with high F1-score (>0.90) for all classification algorithms. Each classification algorithm had a higher F1-score in the up-and-down reaching tasks compared to the side-to-side reaching tasks. Differences in F1-scores were tested for statistical significance using the Friedman nonparametric test [49]. An alpha level of 0.05 was used as the level of significance. For the LDA ($F_{2,11} = 9.58$, $p = 0.008$), kNN ($F_{2,11} = 10.00$, $p = 0.007$), naïve Bayesian ($F_{2,11} = 10.00$, $p=0.007$) and SVM ($F_{2,11} = 9.33$, $p = 0.009$) algorithms,

TABLE 4. Classification performance -back-and-forth reaching.

	LDA	kNN	Naïve Bayesian	SVM
Precision	0.958	0.986	0.924	0.993
Recall	0.978	0.993	0.952	0.996
F1-score	0.968	0.989	0.938	0.994

TABLE 5. Classification performance -side-to-side reaching.

	LDA	kNN	Naïve Bayesian	SVM
Precision	0.891	0.905	0.859	0.908
Recall	0.837	0.844	0.872	0.874
F1-score	0.863	0.873	0.865	0.891

TABLE 6. Classification performance –up-and-down reaching.

	LDA	kNN	Naïve Bayesian	SVM
Precision	0.895	0.895	0.891	0.933
Recall	0.864	0.886	0.862	0.894
F1-score	0.879	0.890	0.876	0.913

TABLE 7. Classification performance - compensation.

	LDA	kNN	Naïve Bayesian	SVM
Precision	0.903	0.927	0.895	0.921
Recall	0.914	0.941	0.901	0.948
F1-score	0.908	0.934	0.898	0.934

the Friedman nonparametric test provided evidence of a statistically significant difference in average F1-scores across the three reaching tasks. For each reaching task, back-and-forth reaching ($F_{3,15} = 14.02$, p=0.003), side-to-side reaching ($F_{3,15} = 12.70$, $p = 0.005$), and up-and-down reaching ($F_{3,15} = 10.59$, $p = 0.014$), the Friedman nonparametric test provided evidence of a statistically significant difference in average F1-scores across the four classification algorithms. The SVM algorithm showed the highest average F1-score in each reaching task.

The performances of the four different classification algorithms in detecting compensations during all reaching tasks (back-and-forth, side-to-side, and up-and-down reaching) are shown in Table 7. Good classification performance was achieved by both the k-NN and SVM (F1-score = 0.934), followed by the LDA and naïve Bayesian methods. The Friedman nonparametric test provided evidence of a statistically significant difference in average F1-scores across the four classification algorithms ($F_{3,15} = 12.60$, $p = 0.006$).

The average F1-score performance for each classification algorithm is displayed in Figure 3. For LDA, the minimum and maximum values of the F1-score in all reaching tasks were 0.898 and 0.926, respectively. The average value was 0.908 (Std. = 0.010). The F1-score of the kNN algorithm ranged from 0.911 to 0.949, with an average value of 0.934 (Std. = 0.014). For the naïve Bayesian algorithm, the minimum and maximum values of the F1-score were 0.871 and 0.924, respectively. The average value was 0.898 (Std. = 0.022). For the SVM, the F1-score ranged from 0.922 to 0.941. The SVM exhibited a higher average F1-score (0.934±0.007) than the other classifiers.

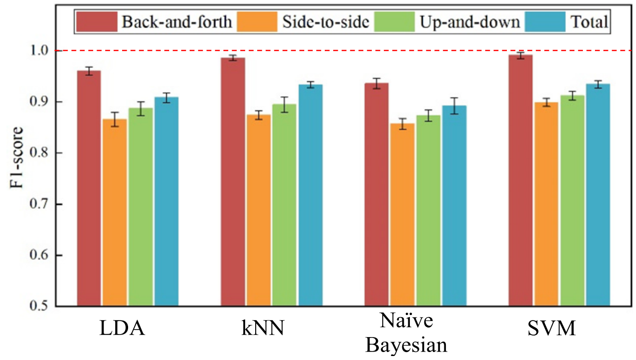

FIGURE 3. F1-score performance for the kNN, naïve Bayesian and SVM classifiers. LDA = linear discriminant analysis, kNN = k-nearest neighbor, SVM = support vector machine. Total = all reaching tasks.

The LDA, kNN, naïve Bayesian and SVM algorithms were used to classify four different postures, including three types of compensatory motions (trunk lean-forward, trunk rotation, and scapular elevation) and no compensatory motion. The precision, recall and F1-scores of each classification algorithm were calculated to evaluate the classification performance, as shown in Table 8. The SVM classifier showed a better performance in detecting no compensatory motion (F1-score = 0.953) and three types of compensatory motions—trunk lean-forward (F1-score = 0.933), scapular elevation (F1-score = 0.881) and trunk rotation (F1-score = 0.854). The highest average F1-score of four different postures was 0.905 by using the SVM algorithm, followed by the kNN, Naïve Bayesian and LDA algorithms. Figure 4 shows how each class performs using the SVM classifier across all participants (N = 15). The SVM-based classifier generally classified well (F1-score>0.9) for 10 of the 15 participants. The minimum and maximum F1-scores of the four postures in all subjects were 3.353 and 3.873, respectively. The Friedman nonparametric test provided evidence of a statistically significant difference in F1-score across the fifteen participants ($F_{14,59} = 60.707$, $p<0.0001$).

B. DISCUSSION

To our knowledge, this is the first study to develop and test machine learning models for the automatic identification of compensatory movements based on pressure measurement. Five features were extracted from the pressure distribution data, including the average sensor values, the lateral center of pressure, the longitudinal center of pressure, the ratio of left-side to right-side pressure and the ratio of front-side to back-side pressure. Four different classification algorithms, including the linear discriminant analysis (LDA), k-Nearest Neighbor (kNN), naïve Bayesian and support

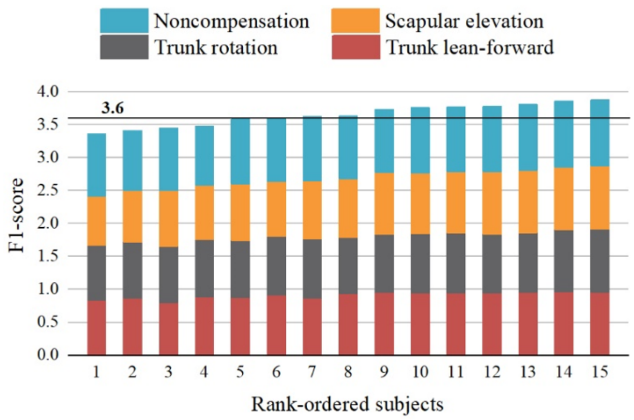

FIGURE 4. Stacked bar graph of F1-scores from the SVM classifier for all classes and subjects. Participants were rank ordered based on the total value of the F1-score in the presented classes. The black horizontal line represents a general cutoff for highly functional levels of classification performance (average F1-score>0.9).

TABLE 8. Classification performance - three types of compensatory motions.

Classifier	Posture	Precision	Recall	F1-score
LDA	TR	0.814	0.795	0.804
	TLF	0.887	0.905	0.896
	SE	0.854	0.822	0.838
	NC	0.906	0.971	0.937
kNN	TR	0.857	0.818	0.837
	TLF	0.949	0.902	0.925
	SE	0.905	0.844	0.873
	NC	0.918	0.964	0.940
Naïve Bayesian	TR	0.835	0.778	0.805
	TLF	0.913	0.906	0.909
	SE	0.902	0.815	0.856
	NC	0.922	0.945	0.933
SVM	TR	0.881	0.829	0.854
	TLF	0.925	0.942	0.933
	SE	0.904	0.859	0.881
	NC	0.936	0.971	0.953

TR= Trunk rotation, TLF= Trunk lean-forward, SE= Scapular elevation, NC= No compensation.

vector machine (SVM) algorithms, were trained and achieved good classification performances when detecting compensatory movements during three types of reaching tasks performed by fifteen participants. Furthermore, different classifiers were developed for the multiclass classification of three types of compensatory strategies (trunk rotation, trunk lean-forward, scapular elevation) which are commonly utilized by stroke patients with hemiplegic upper limbs. The pressure distribution-based system is capable of automatically detecting and categorizing compensatory movements during reaching tasks and displays comparable classification performance with sensor-based and camera-based systems.

In terms of compensatory movement detection, the F1-scores of the LDA, kNN, naïve Bayesian and SVM algorithms ranged from 0.898-0.934. The high precision and recall values indicate that the pressure distribution-based system can reliably detect compensatory movements. Compared with the classification performance from wearable sensor data for the two reaching tasks (back-and-forth and up-and-down reaching) combined using 10-fold cross-validation (F1-score= 0.893-0.964) [50], our method exhibited an equal and even higher F1-score (0.907-0.954). A better classification performance was achieved when detecting compensation in tasks that required a larger scale elbow extension. This finding is consistent with the results of a study involving four tasks, in which the classification accuracy is lower for tasks where elbow extension was not a primary motion [29]. These results are also consistent with the biomechanical perspective of compensatory movements [6], [30]. Since the elbow extension of the hemiplegic upper limb was limited, trunk motions as a compensatory strategy are commonly used by stroke patients. Greater trunk displacement was induced in tasks that require a larger scale elbow extension. Therefore, detecting compensation in these tasks could result in a higher classification accuracy.

Regarding the multiclass classification of compensatory postures, our classifiers exhibited excellent classification performances for trunk lean-forward (F1-score = 0.896-0.933), scapular elevation (F1-score = 0.838-0.881) and trunk rotation (F1-score = 0.804-0.854). Compared with the classification performance from a camera-based system (trunk rotation F1-score = 0.53-0.57, trunk lean-forward F1-score = 0.81-0.82, and scapular elevation F1-score = 0.07-0.27) [4], we provide a more reliable method of categorizing compensatory motions based on a pressure distribution system. In addition, both pressure distribution-based and camera-based compensatory posture categorization systems showed good classification performances for the trunk lean-forward compensation. This result is consistent with the kinematic data of trunk movement from stroke patients [51], [52]. It demonstrated that substantial trunk sagittal displacement was used by stroke patients to complete reaching tasks.

Most participants had an adequate classification performance (average F1-score>0.9) in this study, and different features and other classification algorithms were not used to explore the possibility of classification accuracy improvement. Furthermore, we think the loss of accuracy was due to these participants completing the movements in a different way rather than any deficit in the classifiers' abilities. Specifically, some healthy participants may complete the reaching tasks with abnormal synergy patterns since they do not have motor impairments and subjectively simulate compensatory motions. Considering that the lack of elbow extension is a main reason for trunk and shoulder compensations, a protocol has been proposed to simulate elbow contracture in a previous study [53]. We will use an elbow brace to limit the arm function of participants to induce compensatory movements in a follow-up experiment.

This study had a number of advantages. This study is the first to detect compensatory movement patterns based on pressure distribution data. Second, machine learning methods were implemented to detect and categorize different types of compensatory movements during reaching tasks and exhibited excellent classification performances. Third, a pressure distribution mattress is portable and convenient to use in clinical and home settings, and it will not induce unnatural movements owing to attached sensors or negative feelings caused by being monitored. The pressure distribution-based compensation-detection method is more practical and cost-effective than sensor-based and camera-based detection systems. In addition to the automatic detection of compensatory movement patterns, the system can also provide feedback to the participants to modify his/her interjoint coordination to restore normal motor control strategies [54], [55].

One limitation of the study is that our classifiers trained and tested on the simulated data of healthy participants instead of data acquired from stroke survivors. Though common compensatory movement patterns were simulated by healthy participants in this paper, compensatory movement patterns may be more variable in stroke survivors at different phases of recovery and with different levels of upper limb impairment. Babak Taati et al. [4] applied a camera-based system to identify and categorize compensatory movements by a multi-class classifier. F1-score in stroke survivors was worse than in healthy participants, which indicated the challenges of adapting classifiers to account for the variation in compensatory movements of stroke survivors. Limited number of compensations in stroke survivors is the main cause of bad classification performance and the experimental design need further improvement. However, Rajiv Ranganathan et al. employed a sensor-based system to detect compensatory movements and good classification accuracy was achieved in both stroke survivors [29] and healthy participants [50]. These results indicated that simulated motions by healthy participants provide a valuable source of data to train the classifiers and can be further used to detect compensations in stroke survivors.

Future work will explore the classification performance in compensation movements of patients with hemiparesis. Since different patients use different patterns of joint recruitment with different scaling rules, the classifier needs to be adaptive to the variation in compensatory movements. Examples of noncompensatory and compensatory motions of stroke patients for training an accurate posture detection classifier are key issues.

V. CONCLUSION

Compensatory movements are commonly employed by stroke patients with hemiplegia during seated reaching. Currently available sensor-based and camera-based systems are obtrusive and require complex setups and operational expertise to detect compensations. In this paper, we proposed and tested the use of a pressure distribution mattress to detect compensatory movement patterns automatically. This method is novel and has observed advantages; it is simple, unobtrusive and low cost. Fifteen healthy subjects performed reaching tasks in normal and compensatory movement patterns, including trunk rotation, trunk lean-forward and scapular elevation. The binary and multiclass classification processes were performed by linear discriminant analysis, k-nearest neighbor, naïve Bayesian and support vector classifiers. Automated compensation detection achieved an excellent performance (F1-score = 0.934) in all reaching tasks using both the SVM and kNN algorithms. The SVM classifier exhibited a good performance in multiclass classification with the trunk lean-forward (F1-score = 0.933), scapular elevation (F1-score = 0.881) and trunk rotation (F1-score = 0.854) motions. Experimental results show that detecting compensatory movement patterns using machine learning methods from pressure distribution data has good reliability and precision.

In follow-up studies, clinical trials are needed when expanding the compensatory movement pattern detection of stroke patients. Furthermore, visual and written feedback to stroke patients will be added so that patients can reduce compensations and improve the quality of rehabilitation.

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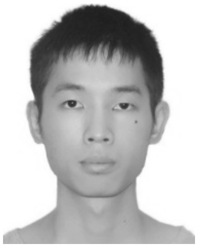

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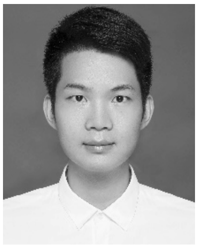

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