Real-Time Detection of Compensatory Patterns in Patients With Stroke to Reduce Compensation During Robotic Rehabilitation Therapy

Siqi Cai, Guofeng Li, Enze Su, Xuyang Wei, Shuangyuan Huang, Ke Ma, Haiqing Zheng, and Longhan Xie

***Abstract*—*Objectives:* Compensations are commonly employed by patients with stroke during rehabilitation without therapist supervision, leading to suboptimal recovery outcomes. This study investigated the feasibility of the real-time monitoring of compensation in patients with stroke by using pressure distribution data and machine learning algorithms. Whether trunk compensation can be reduced by combining the online detection of compensation and haptic feedback of a rehabilitation robot was also investigated. *Methods:* Six patients with stroke did three forms of reaching movements while pressure distribution data were recorded as Dataset1. A support vector machine (SVM) classifier was trained with features extracted from Dataset1. Then, two other patients with stroke performed reaching tasks, and the SVM classifier trained by Dataset1 was employed to classify the compensatory patterns online. Based on the real-time monitoring of compensation, a rehabilitation robot provided an assistive force to patients with stroke to reduce compensations. *Results:* Good classification performance (F1 score $>$ 0.95) was obtained in both offline and online compensation analysis using the SVM classifier and pressure distribution data of patients with stroke. Based on the real-time detection of compensatory patterns, the angles of trunk rotation, trunk lean-forward and trunk–scapula elevation decreased by 46.95%, 32.35% and 23.75%, respectively. *Conclusion:* High classification accuracies verified the feasibility of detecting compensation in patients with stroke based on pressure distribution data. Since the validity and reliability of the online detection of compensation has been verified, this classifier can be incorporated into a rehabilitation robot to reduce trunk compensations in patients with stroke.**

***Index Terms*—Stroke, trunk compensation, pattern recognition, rehabilitation robot.**

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S. Cai, G. Li, E. Su, X. Wei, S. Huang, K. Ma, and L. Xie are with the Shien-Ming Wu School of Intelligent Engineering, South China University of Technology, Guangzhou, Guangdong Province 510460, P. R. China (e-mail: 2447379329@qq.com; megfli@mail.scut.edu.cn; enzesu@hotmail.com; 540321895@qq.com; mssyhuang@mail.scut.edu.cn; 843031001@qq.com; melhxie@scut.edu.cn).

H. Zheng is with the Third Affiliated Hospital of Sun Yat Sen University, and also with the South China University of Technology, Wushan Street, Tianhe District, Guangzhou, Guangdong 510640, China (e-mail: zhenghaiqing0909@aliyun.com).

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I. Introduction

STROKE is a leading cause of adult-acquired disability worldwide, and over a half of patients with stroke suffer from upper-limb impairments [1]. With limited upper limb motor function, patients with stroke usually use compensatory strategies during reaching tasks [2]. Compensation, described as incorporating additional degrees of freedom at new joints and body segments, are commonly employed to adapt to the loss of motor function [3]. Although motor compensation helps patients achieve an immediate improvement in function, it can impede progress toward recovery in the long term and introduce new orthopedic problems [4], [5]. Previous studies have demonstrated that reducing compensatory trunk movements may be helpful for the recovery [6]–[8]. Current approaches to reduce compensation relies on the supervision of and corrections by therapists. However, one-to-one manually assisted training is labor intensive, time consuming and expensive. There is a need for detecting and reducing trunk compensation of patients with stroke automatically to optimize the rehabilitation process.

A. Compensation Detection

Detecting compensation is important to ensure the quality of rehabilitation therapy. Existing detectors of compensatory motions mainly depend on wearable sensor and camera systems. In wearable sensor systems, accelerometers [9], inertial measurement units [10] or other sensors are placed on the patients with stroke to monitor the posture and upper limb motions during rehabilitation [11]. One limitation of wearable sensor-based systems is the probability of causing unnatural motions as a result of the attached sensors [12]. Finding an unobtrusive and easy-to-use solution is quite difficult. Camera-based detection systems, which include marker-based and markerless human motion capture technologies [13], [14]. Marker-based motion tracking systems can achieve accurate and robust results, however, suffer from complex setups [15]. Marker-free systems enable simple and time-efficient evaluation of human motions in clinics by eliminating the need for markers, however, the accuracy of markerless systems is still technically challenging [16], [17]. In addition, camera-based detection systems induced issues with respect to privacy and may cause unnatural behaviors in patients with stroke due to the discomfort of being monitored [18]. In general, detecting compensation in patients with stroke still lacks an appropriate method.

Recently, we addressed this important problem by presenting a compensation detection system using machine learning algorithms based on pressure distribution data [19]. Pressure distribution-based detection systems do not induce unnatural movements or the discomfort of being monitored [20], [21]. In our previous study, 15 healthy participants simulated common compensatory movements and several features were extracted from the pressure distribution data. Different classifiers were used to detect compensations and obtained good classification performance. However, compensatory patterns are more complex in patients with stroke [22], and classification performance in patients with stroke and in healthy people can be quite different [23]. Furthermore, since there is usually a gap between online and offline classification accuracies, the feasibility of detecting compensation in real time deserves further investigations. Therefore, we expanded on our previous study and provided additional details, results, and analyses in this work. First, we investigated whether the pressure distribution-based system can recognize compensatory patterns in patients with stroke during reaching tasks, and the existing approach was adapted to account for the variability in compensatory movements. Then, we tested this pressure distribution-based approach for the real-time monitoring of compensatory motions in patients with stroke in order to reduce compensation during robotic rehabilitation therapy.

B. Upper-Limb Rehabilitation Robot

Stroke rehabilitation is essential to all patients with stroke; however, many patients cannot receive rehabilitation training in a sufficient amount of time due to a lack of available therapists [24]. Rehabilitation robots, which can provide more effective and efficient rehabilitation, have the potential to improve stroke outcomes and have been increasingly used in rehabilitation training [25], [26]. Many different types of rehabilitation robots have been developed, and many studies have shown that robot-assisted training can significantly reduce upper limb impairments [27], [28]. Although the potential clinical efficacy of rehabilitation robots is promising, an important consideration is whether participants can correctly execute training exercises without the need for direct supervision by a therapist [29]. Specifically, patients with stroke often perform rehabilitation tasks with compensatory trunk movements when unsupervised. Therefore, there is a critical need to automatically detect and reduce such compensation in patients with stroke during robotic rehabilitation therapy.

In the past, our team developed an end-effector-based rehabilitation robot platform, ReRobot, which can provide the impaired arm with assistance in 3D space. To take full advantage of robot-assisted movement training, pressure distribution-based compensatory pattern recognition was integrated into the ReRobot system in this study. Thus, ReRobot provided an assistive force to patients with stroke as haptic feedback when trunk compensation was detected during reaching tasks.

TABLE I
DEMOGRAPHIC AND CLINICAL CHARACTERISTICS (N = 8)

Participant	Age	Sex	Weight (kg)	Affected Side	Months post stroke	FMA[a]
P1	54	F	60	Left	2	34
P2	45	M	54	Left	3	55
P3	68	F	39.5	Left	2	38
P4	52	M	65	Left	6	19
P5	37	M	72.5	Right	5	32
P6	65	M	65	Right	9	35
P7	65	M	51	Left	4	36
P8	66	M	65	Left	3	29

C. Objectives

In this study, we aimed to detect compensatory patterns in patients with stroke in real time based on pressure distribution data to reduce trunk compensation during robotic rehabilitation therapy. First, offline classification accuracy in detecting compensatory movements in patients with stroke was investigated. Second, online accuracy was investigated to assess the feasibility of our method for monitoring compensatory movements. Finally, based on the real-time monitoring of trunk compensation, the ReRobot provided assistance to patients with stroke to investigate whether haptic feedback is effective in reducing compensation during reaching tasks.

II. METHODS

A. Participants

Eight patients with stroke (P1-P8, 56.5 ± 10.6 years, 6 males, 2 females) were recruited from the Third Affiliated Hospital at SUN Yat-sen University in this study. These participants had a large variety of impairment severities; in the upper extremity, the Fugl-Meyer Assessment (FMA) scores ranged from 19 out of 66, which is indicative of a severe stroke, to 55, which is indicative of a mild stroke. Details of these participants are listed in Table I. All participants provided written informed consent, and the procedures were approved by the Guangzhou First People's Hospital Department of Ethics Committee.

Participants met the following inclusion criteria: 1) first ever stroke, 2) patients with stroke either in the subacute (between 1 to 6 months post stroke) or chronic (over 6 months post stroke) stage of recovery, 3) patients with stroke with a fair to good cognitive level (Mini Mental State Examination (MMSE) score $\geq$24 [30]), 4) patients with stroke with the ability to perform the required movements, and 5) patients with stroke with the ability to remain sitting. Exclusion criteria were as follows: 1) upper limb pain >4/10 on a Visual Analogue Scale (VAS) [31], 2) upper limb spasticity >2 on the Modified Ashworth

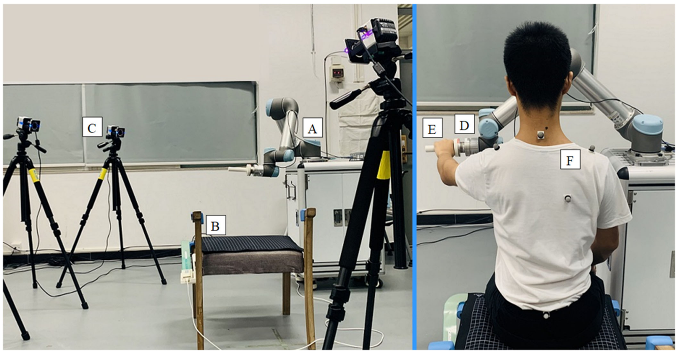


Fig. 1. The ReRobot system and the experimental setup. (A) ReRobot, (B) pressure distribution mattress, (C) 3D motion capture system (VICON, Oxford Metrics, UK), (D) six-axis force sensor, (E) handle of ReRobot and (F) reflective markers.

Scale (MAS) [32], and 3) visual spatial neglect based on clinical judgment.

B. Experimental Setup

1) ReRobot Platform: The ReRobot, designed for stroke rehabilitation training, was employed to assess the performance of real-time control driven by compensatory pattern recognition, as shown in Fig. 1. The ReRobot is set up to assist the movement of the impaired arm by using UR5 (Universal Robots Ltd, Odense, Denmark). UR5 is a lightweight, flexible and safe robotic arm with six degrees of freedom in cartesian space based on its six rotary joints [33]. A handle was attached at the end of UR5 for participants to hold. The ReRobot platform can be commanded to maintain the correct direction when the participant performs reaching tasks without compensation or provide haptic feedback in the form of assistive force to the participant when the participant performs the movements with compensation. An admittance control scheme [34], [35], which is a position controller with force feedback, was implemented and the assistive force was provided based on the 'assistance-as-needed' principle [28], [36]. A 6-DOF force sensor is attached to the end effector of the ReRobot, then the input from this sensor is used to produce velocity commands for the device. The transmission control protocol/internet protocol (TCP/IP) was used for communication between the ReRobot platform and the MATLAB (MathWorks Corp., Natick, MA, USA) user interface.

2) Pressure Measurement System: A pressure distribution mattress (Body Pressure Measurement System, Model 5330, Tekscan, Inc., South Boston, MA, USA) was used to measure and record the pressure distribution of patients with stroke during the seated reaching tasks, as shown in Fig. 1. A sampling frequency of 50 Hz was used in this study and these pressure distribution data were processed by using MATLAB software.

C. Experimental Procedures

Participants held onto the handle of the ReRobot while seated on a chair with the pressure distribution mattress mounted. If participants were unable to hold the robots' handle, they were provided with a strap. Every participant performed three forms of reaching motions which covered a wide range of movements of the upper limb. These reaching movements included (i) back-and-forth reaching (B-F reaching), (ii) side-to-side reaching (S-S reaching) and (iii) up-and-down reaching (U-D reaching). Reaching movements performed by the participants' healthy arm were labeled as noncompensation (NC) movements. And a therapist visually monitored these motions performed by the affected arm and labeled the compensatory motions.

Each experiment consisted of two sessions, including data recording for offline and real-time analysis. Participants were divided into two groups: Group 1 (P1-P6) and Group 2 (P7, P8). Several familiarization trials were performed to ensure these participants understand and feel comfortable with the experimental procedures. In this process, participants were also asked to perform reaching movements with their unaffected arm to set the required distance for each reaching task. In addition, each participant confirmed that he/she could sense the change in force when compensating and ensure the assistive force was suitable for him/her. To avoid fatigue, each participant was allowed 10 s of rest between two reaching motions and 3 min of rest after a certain type of reaching task.

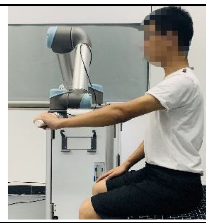
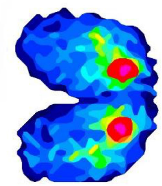
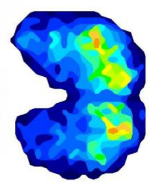
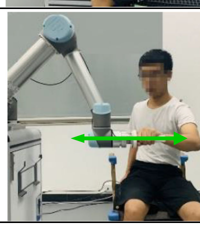
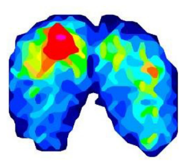
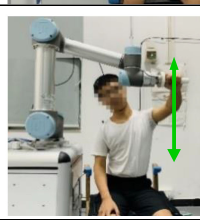
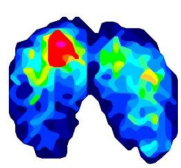
1) Session 1. Data Recording for Offline Detection of Compensation: Each participant in Group 1 performed B-F, S-S and U-D reaching tasks with his/her healthy arm and affected arm. Each task was repeated 30 times and the ReRobot platform was commanded to maintain the correct direction during the execution of each motion. Hence, each participant performed 180 motions in total, with 90 motions on each arm. This session lasted between 1 and 1.5 hr, including resting time. The pressure distribution data of the participants in Group 1 were recorded as Dataset1 for the training and testing of the classifier offline.

2) Session 2. Data Recording for Online Detection and Reduction of Compensation: Participants in Group 2 were involved in Session 2, which consisted of Phase A and Phase B. This session lasted 1 to 2 hr, including resting time.

Phase A (online detection of compensation): Each participant in Group 2 performed each reaching task with his/her healthy arm and affected arm 15 times at a self-selected speed. The pressure distribution data of the participants in Group 2 were recorded as Dataset2, and the classifier trained by Dataset1 was employed to detect compensation online. ReRobot was commanded to maintain the correct direction during the execution of each movement. A 3D motion capture system (VICON, Oxford Metrics, UK; 100 Hz) was used to track and record the participants' upper limb and trunk movements.

Phase B (online detection and reduction of compensation during robotic rehabilitation therapy): Each participant in Group 2 performed reaching tasks with his/her affected side. When the participant performed reaching tasks without compensation, the ReRobot platform was commanded to maintain the correct direction. When a compensatory motion was detected, ReRobot was then commanded to provide an assistive force to participants in the next movement. Each reaching task was completed 15 times in total, and the participant's kinematics were measured by the VICON system.

TABLE II
MOTION PRESSURE MAP IMAGES WITH MOVEMENT PATTERNS

Movement pattern	Motion image	Pressure map image
Noncompensation (NC)		
Trunk lean-forward (TLF, hip flexion angle less than 90° in the sagittal plane)		
Trunk rotation (TR, turning of the torso in the transverse plane)		
Trunk–scapula elevation (TSE, lateral inclination of the trunk and/or the scapula)		

D. Classification of Compensatory Movements

Three types of compensatory patterns were commonly elicited during reaching tasks, including excessive trunk lean-forward (TLF), trunk rotation (TR), and trunk–scapula elevation (TSE) movements [6], [37]. The details and pressure maps of NC, TLF, TR and TSE were shown in Table II. The pressure distribution data of Group 1 (P1-P6) were acquired, and each pressure map consisted of a 32 × 32-dimensional vector. The pressure sensor array is represented as a set of indexed sensors $\{P_1[t],\ P_2[t],\ \cdots,\ P_N[t]]\ \}$, where $N = 1024$ is the total number of sensors in the array. Each sensor is represented as a triple, $P_i[t] = (x_i,\ y_i,\ p_i(t))$, where x_i and y_i are the lateral and longitudinal coordinates of the ith sensor, respectively, and $p_i(t)$ is the sensor value at time t.

By reviewing previous research on pressure distribution mattresses [38], [39] and analyzing the pressure distribution data in this study, the following features were extracted to distinguish compensatory movements:

1) The average sensor values (AVE_{SSV}).

$$AVE_{SSV} = SSV/T \tag{1}$$

where T is the duration time and SSV is the summation of all sensor values, $SSV(t)$. $SSV(t)$ was gained by calculating the sum of $p_i(t)$ for all i at a given time t.

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

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

1) The maximum of the pressure sensor values.
2) The average values of the lateral and longitudinal center of pressure (AVE_{LatCOP} and AVE_{LonCOP}). The lateral center of pressure ($LatCOP$) and longitudinal center of pressure ($LonCOP$) can be calculated with (4) and (5), respectively.

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

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

3) The average ratio of the pressure on the left side to that on the right side ($AVE_{LRratio}$) and average ratio of the pressure on the anterior end to the pressure on the posterior end ($AVE_{APratio}$). The ratio of the pressure on the left side to that on the right side ($\mathrm{LRratio}$) and the ratio of the pressure on the front side to that on the back side ($\mathrm{APratio}$) were determined with (6) and (7), respectively.

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

$$APratio\,(t) = \sum_{x_i=1}^{x_i=16} p_i\,(t) \Bigg/ \sum_{x_i=17}^{x_i=32} p_i\,(t) \tag{7}$$

4) Standard deviation of the lateral and the longitudinal center of pressure (SD_{LatCOP} and SD_{LonCOP}). Standard deviation of the ratio of the pressure on the left side to that on the right side ($SD_{LRratio}$) and the ratio of the pressure on anterior end to the pressure on the posterior end ($SD_{APratio}$).

Support vector machine (SVM) [40] is widely used and one of the highest performing classifiers because of their high generalization performance [41]. Pervious study has demonstrated that the SVM classifier has achieved a higher classification accuracy in recognizing sitting postures from the pressure distribution data than other classifiers [42]. SVM classifier also showed a better classification performance in compensation detection in our previous study [19]. Thus, a SVM classifier was employed to recognize compensatory patterns in patients with stroke in this study. We trained an SVM classifier with a radial basis kernel function using LIBSVM in MATLAB [43]. The extracted features from pressure distribution data of all the participants in Group 1 were combined in a random order, and leave-one-subject-out (LOSO) cross validation was employed to evaluate the classification performance. With LOSO cross

TABLE III
OFFLINE CLASSIFICATION PERFORMANCE IN RECOGNIZING COMPENSATORY PATTERNS

Classifier	Posture	Precision	Recall	F1 score
SVM	TLF	0.939	0.994	0.963
	TR	0.990	1.000	0.995
	TSE	1.000	1.000	1.000
	NC	0.998	0.970	0.984

TABLE IV
OFFLINE CLASSIFICATION PERFORMANCE IN THREE TYPES OF REACHING

		B-F	S-S	U-D	Average
SVM	Precision	0.974	0.988	0.99	0.984
	Recall	0.972	0.991	0.992	0.985
	F1 score	0.973	0.989	0.991	0.984

B-F = Back-and-forth reaching, S-S = Side-to-side reaching, U-D = Up-and-down reaching.

validation, a model was trained on data from all subjects except one, who was "left out", and the data from the one subject was used as a test dataset. The process was repeated until the data from each subject was used as a test dataset, and can find the average recognition rate of the model. During online detection of compensation, the SVM classifier trained by using Dataset1 was applied to detect compensatory patterns of participants (P7, P8) based on the aforementioned pressure features.

E. Statistical Analysis

Statistical analyses were performed using SPSS 24.0 software (IBM Corp., Armonk, NY, USA). The descriptive statistics were used for means and standard deviations. The Kolmogorove-Smirnov test was used to confirm the normality of the distribution of the data, prior to selection of appropriate statistical tests. Friedman nonparametric tests were employed to analyze whether there were any significant differences in classification performance. When the test statistic was significant, Bonferroni post hoc tests were performed to determine if differences between each two conditions were significant. Wilcoxon rank sum test was used to analyze whether there were any significant differences in classification performance between patients with left-sided hemiplegia and right-sided hemiplegia. Paired t-tests were employed to analyze whether there were any significant differences in compensatory motions between ReRobot _OFF and ReRobot _ON conditions. Results were considered significant at $p < 0.05$ for all analyses.

III. RESULTS

A. Classification Performance in Offline and Online Detection of Compensation

Offline classification performance was assessed using Dataset1 by calculating precision, recall and F1 score. Precision measures the proportion of predicted observations that were correct while recall refers to how well the target objects are detected without being missed. F1 score combines precision and recall metrics and can be gained as:

$$\mathrm{F1} = (2 \times \mathrm{Precision} \times \mathrm{Recall})/(\mathrm{Precision} + \mathrm{Recall}) \quad (8)$$

The SVM classifier recognized compensatory patterns in patients with stroke with an average F1 score of 0.986 ± 0.014. As shown in Table III, TSE compensation was detected with excellent performance (F1 score $=$ 1.000), followed by TR compensation (F1 score $=$ 0.995), NC (F1 score $=$ 0.984) and TLF compensation (F1 score $=$ 0.963). F1 scores across different compensatory patterns showed a significant difference using the Friedman nonparametric test ($p = 0.032$). The post hoc analysis indicated that classification accuracies of TSE, TR and NC significantly outperformed of TLF compensation. Good classification performance (average F1-score > 0.95) was also achieved in detecting compensatory motions across B-F, S-S and U-D reaching tasks, as shown in Table IV. The best performance was obtained in U-D reaching, followed by S-S reaching and B-F reaching. No statistical significant differences were observed in the classification performance among different reaching motions ($p = 0.086$). Wilcoxon rank sum test was used to analyze whether there were any significant differences in classification performance between patients with left-sided hemiplegia and right-sided hemiplegia. There were no significant differences between these two conditions ($p = 0.109$). Offline classification performance of every class using the SVM classifier across all participants was shown in Fig. 2. The total F1 score of these four movement patterns in all participants ranged from 3.798 to 4.000. The classification accuracies for 5 of the 6 participants were greater than 95%, indicating that SVM-based pattern recognition could be a viable detector of compensation in patients with stroke.

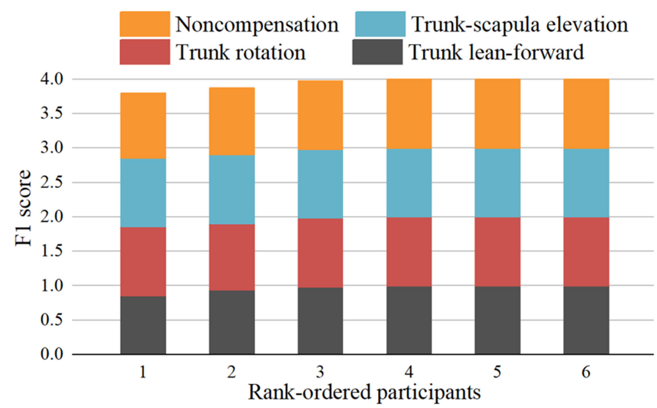


Fig. 2. Offline classification performance from the SVM classifier for all classes and participants. Participants were rank ordered based on the total value of the F1 score.

Online classification accuracy in categorizing compensatory movements of each patients with stroke was evaluated using Dataset2, as shown in Table V. The SVM classifier recognized compensatory patterns in patients with stroke with an excellent classification performance (average F1 score $=$ 0.985). This result indicates that the feasibility of applying compensation detection can be tested online in individual patient with stroke. The

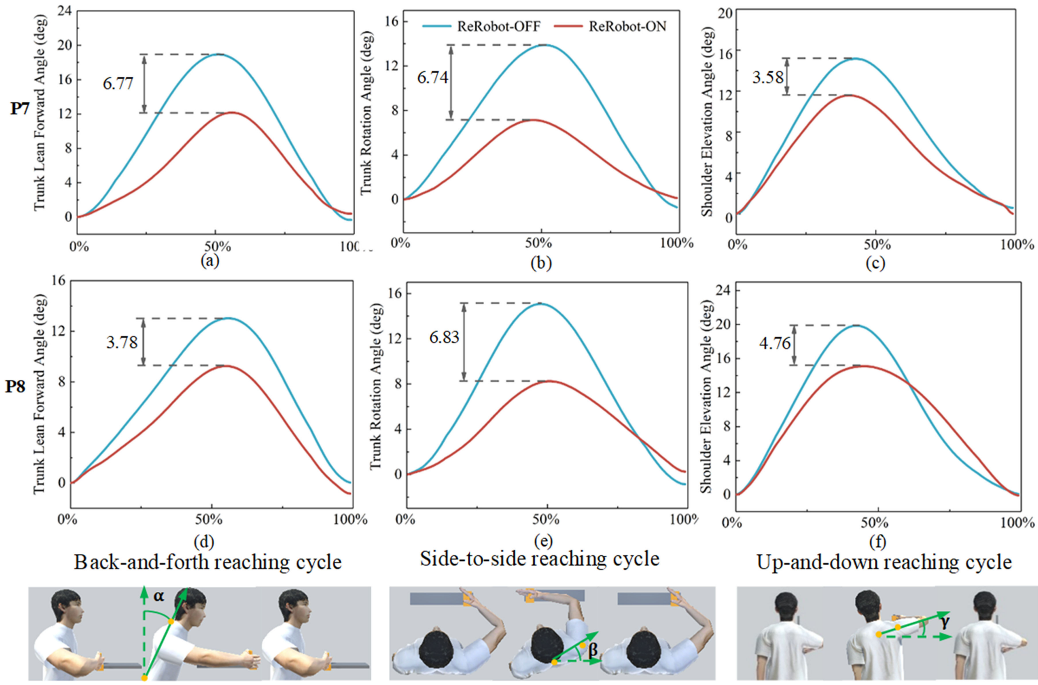


Fig. 3. Trunk compensation. Related trunk compensation angles are presented across the reaching cycle (B-F reaching, S-S reaching and U-D reaching). The curves represent the two different conditions: ReRobot_OFF (blue) and ReRobot_ON (red). Trunk compensation of P7 and P8 were compared.

TABLE V
ONLINE CLASSIFICATION PERFORMANCE IN RECOGNIZING COMPENSATORY PATTERNS

Participant	Posture	Precision	Recall	F1 score
P7	TLF	1.000	1.000	1.000
	TR	1.000	0.867	0.929
	TSE	1.000	1.000	1.000
	NC	0.957	1.000	0.978
P8	TLF	1.000	0.967	0.983
	TR	1.000	1.000	1.000
	TSE	1.000	1.000	1.000
	NC	0.989	1.000	0.994

classification accuracy was higher than 95% for both P7 and P8. Patients with stroke with high online classification accuracies are believed to be able to use a compensation detection-based control interface for rehabilitation training. Based on real-time monitoring compensatory patterns, the ReRobot platform can provide haptic feedback to patients with stroke and help them reduce trunk compensation.

B. Reducing Trunk Compensation Based on Online Detection and Assistance by ReRobot

Trunk compensation was represented by the angle of TLF (α), angle of TR (β) and angle of TSE (γ), as shown in Fig. 3. These three angles of P7 and P8 in the ReRobot_OFF and ReRobot_ON conditions were analyzed. ReRobot_OFF is condition in which ReRobot was commanded to maintain the correct direction during each reaching task. ReRobot_ON is the condition in which ReRobot provided an assistive force as haptic feedback to patients with stroke when compensation was detected. Mean values of these three angles of 15 motions during each reaching task were calculated and compared. Trunk movement angle analysis during the reaching tasks showed that patients with stroke moved their trunk significantly more in the ReRobot_OFF condition than in the ReRobot_ON condition. For P7, in the ReRobot_ON condition compared with the ReRobot_OFF condition, the angles of TR, TLF and TSE were reduced by 48.6%, 35.7% and 23.6%, respectively. The maximum amount of reduction, which was 6.74°, was obtained in the S-S reaching task. Similarly, P8 achieved a maximum reduction of 6.83° in the S-S reaching task. For P8, in the ReRobot_ON condition compared with the ReRobot_OFF condition, the angles of TR, TLF and TSE were reduced by 45.3%, 29.0% and 23.9%, respectively. As shown in Fig. 3, both patients reduced their compensation significantly in the ReRobot_ON condition compared with the ReRobot_OFF condition. The patients' trunk compensation movements occurred with lower variability in the ReRobot_ON condition, as demonstrated by small standard deviations. P7 and P8 showed an average reduction of $5.28 \pm 0.35°$ in the trunk compensation angle α, $6.79 \pm 1.20°$ in the trunk compensation angle β and $4.17 \pm 1.36°$ in the trunk compensation angle γ with the ReRobot_ON condition.

Paired t-tests were employed to analyze whether there were any significant differences between ReRobot _OFF and ReRobot _ON in terms of the three angles, as shown in Fig. 4. For P7, significantly lower peak trunk compensation angles were reported in the ReRobot _ON condition with respect to

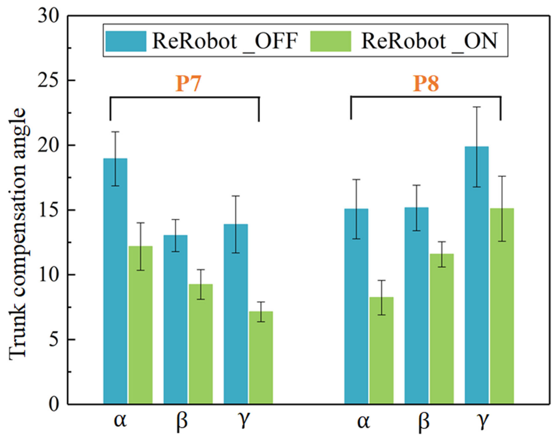


Fig. 4. Trunk compensation angles of patients with stroke under ReRobot_OFF and ReRobot_ON conditions.

the ReRobot _OFF condition ($\alpha,\ p < 0.0001$; $\beta,\ p < 0.0001$; $\gamma,\ p < 0.0001$). Similarly, P8 showed statistically significantly lower peak trunk compensation angles in the ReRobot _ON condition with respect to the ReRobot _OFF condition ($\alpha,\ p < 0.0001$; $\beta,\ p < 0.0001$; $\gamma,\ p = 0.001$).

IV. Discussion

This section first presents the discussion of classification performance in offline and online detection of compensatory patterns based on the pressure distribution data of patients with stroke. Subsequently, a discussion of real-time detection and reduction of trunk compensation during robotic rehabilitation therapy is provided. Finally, the advantages of integrating the online detection of compensatory patterns into a rehabilitation robot for reducing the trunk compensation of patients with stroke are emphasized, and future work is discussed.

To the best of ourknowledge, this is the first study to use machine learning methods for detection of compensations in patients with stroke based on pressure measurement. The pressure distribution-based system neither induced unnatural motions related to attached sensors like the sensor-based detection systems nor caused discomfort of being monitored like the camera-based detection systems. An SVM classifier was trained on features from the pressure distribution data of three reaching tasks (B-F reaching, S-S reaching and U-D reaching) that are routinely performed by patients with stroke. Three types of compensatory movements (TR, TLF and TSE) that are commonly utilized by patients with stroke and NC patterns were detected and categorized by our classifier. Good classification performance in offline and online detection of compensation were achieved, which verified the feasibility of applying the pressure distribution-based system in detecting compensatory patterns in patients with stroke.

Classification accuracies for most participants and classes were greater than 95%, indicating that the automatic detecting compensation by using the SVM classifier from pressure distribution data can be used as a viable monitoring system for patients with stroke. By comparison with the classification accuracies from wearable sensor data for B-F reaching (F1 score = 0.857) and U-D reaching (F1 score = 1.000) tasks in patients with stroke [18], our method exhibited an equal and even higher accuracy, with an average F1 score of 0.963 for S-S reaching and 1.000 for U-D reaching. Babak Taati *et al.* [12] employed a camera-based system for real-time compensation detection by a multiclass classifier and achieved an accuracy of 86% in healthy participants. However, the classification performance was worse in patients with stroke for TR (F1 score = 0.27), TLF (F1 score = 0.17), and TSE (F1 score = 0.07) [23]. Our classifier based on pressure distribution data achieves a better performance in recognizing compensatory motions, with an average F1 score of 0.992 for TLF, 0.964 for TR, and 1.000 for TSE. These results validated that our method can adequately recognize compensatory patterns and can be further applied in a rehabilitation robot to encourage patients with stroke to move into the correct pose when necessary.

In our previous work on healthy participants [19], fifteen people without motor impairments simulated common compensatory movement patterns during reaching tasks, and pressure distribution data were recorded. Classification algorithms were applied to detect compensation, and the classification performance was adequate for most participants (average F1 score > 0.9). Compared with the F1 scores in healthy participants, the F1 scores in patients with stroke with our method were higher (average F1 score > 0.95). This finding is consistent with the results in previous research [18], [44] in which a sensor-based system was developed to detect compensatory trunk movements in healthy participants (average F1 score = 0.907) and patients with stroke (average F1 score = 0.928). These results indicate that classifiers trained on data simulated by healthy participants also have the potential to be applied in detecting compensation in patients with stroke.

Since the validity and reliability of online detecting compensation movements in patients with stroke using our classifier from the pressure distribution data has been verified, a rehabilitation robot was incorporated to reduce compensation. The ReRobot provided an assistive force to patients with stroke as haptic feedback when trunk compensation was detected during reaching tasks. In terms of the trunk compensation angles, the angles of trunk rotation, trunk lean-forward and trunk–scapula elevation were reduced by 46.95%, 32.35% and 23.75%, respectively. This result demonstrates that the trunk compensation of patients with stroke can be decreased significantly by using both real-time monitoring of compensatory motions and haptic feedback provided by a rehabilitation robot.

Previous studies have shown that visual or auditory feedback can provide compensation information to patients with stroke and help them modify their movement patterns [45]–[49]. Little attention has been given to the role of haptic feedback in the reduction of compensation; however, haptic feedback can directly intervene in the physical movements of patients with stroke. Bulmaro Adolfo Valdés *et al.* [50], [51] investigated whether haptic feedback can reduce compensatory trunk movement and examined whether haptic or visual feedback is more efficacious in reducing compensation. Robot arms provided resistance to the participant's upper limb when anterior trunk displacement was detected during a reaching movement. The authors reported that trunk compensation was decreased based on haptic feedback, and no difference between haptic and visual feedback modalities was obtained. Given that providing resistance to the participant's limb movements makes tasks more difficult or challenging, providing assistive force instead of resistive force as feedback can help patients with stroke to move their affected limbs in desired patterns and reduce compensation more directly [28]. Meanwhile, actively assisted exercise is the primary control strategy in robotic therapy development [52]. Therefore, this study investigated whether compensation can be decreased by providing assistive force as haptic feedback. The experimental results verified the feasibility and validity of the proposed method, indicating its promising potential for reducing trunk compensation in clinical rehabilitation and clinical rehabilitation devices.

This study had several advantages. First, this study validated the feasibility of detecting compensatory motions of patients with stroke using pressure distribution data and a machine learning model. Second, both offline and online detection of compensatory patterns achieved excellent classification performance in patients with stroke. Third, a rehabilitation robot provided haptic feedback to patients with stroke and reduced compensation significantly based on real-time detection of compensatory motions. It is important to emphasize that combined real-time monitoring of compensatory motions and haptic feedback reduces the trunk compensation of patients with stroke during robotic rehabilitation therapy. Automated compensation detection has the potential to augment robotic stroke rehabilitation therapy and improve upper limb motor recovery.

This study is an early step in investigating the effects of real-time detection and reduction compensatory patterns in patients with stroke and there were several limitations in the current pilot study. Firstly, there were only eight patients with stroke participating in the current study. Though the results are well aligned, large sample populations of patients with different levels of upper limb impairment are needed in future research to draw stronger conclusions about the effects of detecting and reducing compensation using the proposed method. In addition, while trunk compensation was reduced by combining the real-time detecting of compensatory motions and haptic feedback of a rehabilitation robot, longitudinal studies are required to explore the long-term effects on patients with stroke. Clinical outcome assessments indexes on stroke should be included in the following studies. Finally, though we demonstrated that the compensatory patterns of patients with stroke can be decreased by providing real-time haptic feedback in form of assistive force, this result is only based on a robot-assisted platform. Considering that rehabilitation robots are relatively expensive and complex for using in home setting, the effectiveness of different types of feedback in reducing compensation will be investigated. We will further examine whether haptic feedback in form of assistive force is more effective than audiovisual feedback in reducing compensation for patients with stroke.

V. Conclusion

In general, this study investigated both offline and online compensatory pattern recognition analysis using an SVM classifier and pressure distribution data of patients with stroke. Good classification performance was achieved in the offline detection of compensation using leave-one-subject-out cross validation. Experiments on the real-time monitoring of compensation were performed, and high accuracy was obtained in the online detection of compensatory movements. These results verified the feasibility of detecting compensatory patterns in patients with stroke based on pressure distribution data. The method of monitoring compensation based on pressure distribution data is novel and has the advantages of being unobtrusive and easy to use and delivering steady performance. Furthermore, this method was integrated into a rehabilitation robot to reduce compensation by providing haptic feedback to patients with stroke. Trunk compensation was decreased significantly, which verified the effectiveness of combining the real-time monitoring of compensatory motions and haptic feedback of a rehabilitation robot.

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