The Toronto Rehab Stroke Pose Dataset to Detect Compensation during Stroke Rehabilitation Therapy

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ABSTRACT

Stroke often leads to upper limb movement impairments. To accommodate new constraints, movement patterns are sometimes altered by stroke survivors to use stronger or unaffected joints and muscles. If used during rehabilitation exercises, however, such compensatory motions may result in ineffective outcomes. A system that can automatically detect compensatory motions would be useful in coaching stroke survivors to use proper positioning. Towards the development of such an automated tool, we present a dataset of clinically relevant motions during robotic rehabilitation exercises. The dataset is captured with a Microsoft Kinect sensor and contains two groups of participants – 10 healthy and 9 stroke survivors – performing a series of seated motions using an upper-limb rehabilitation robot. Healthy participants performed additional sets of scripted motions to simulate common post-stroke compensatory movements. The dataset also includes common clinical assessment scores. Compensatory motions of both healthy and stroke participants were annotated by two experts and are included in the dataset. We also present a preliminary evaluation of the dataset in terms of its sensitivity and specificity in detecting compensatory movements for selected tasks. This dataset is valuable because it includes clinically relevant motions in a clinical setting using a cost-effective, portable, and convenient sensor.

Author Keywords

Automated coaching; Upper Body Motion; Benchmarking; Kinect; Stroke Rehabilitation; Compensatory Movements.

ACM Classification Keywords

I.2.9.

INTRODUCTION

Diminished upper-limb movement control is common after stroke and can affect daily activities profoundly. Chronic stroke survivors can benefit from ongoing intensive upper-limb rehabilitation to gain motor function [3]. Robotic stroke rehabilitation, which may include robot-assisted therapy and gaming technology, has the potential to augment treatment and improve stroke outcomes, thereby allowing for more effective and efficient rehabilitation. Literature reviews indicate that robotic therapy for the upper-limb can help motor recovery for stroke survivors in the subacute and chronic recovery stages [4, 5]. Despite the potential benefits, a major concern regarding robotic rehabilitation technology, especially with end effector robots, is the stroke survivor's ability to perform exercises as intended. The underlying mechanisms of motor recovery are very complex and inappropriate movements may compromise the efficacy of the therapy. Therefore, effective training requires patients to reproduce upper-limb movements using the joints and muscles targeted in the therapy [6].

Therefore, there is a need for a tool to ensure the correct completion of the prescribed exercises for stroke patients (i.e. using the targeted joints and muscles, rather than compensating with other stronger muscles). Preferably, the system will be automated to allow stroke survivors to complete their exercises without constant therapist supervision. The automated tool should be able to detect inappropriate postures or other compensatory upper-limb positions. Feedback (e.g. auditory or visual cues) could then be delivered through the system interface to coach stroke survivors to correct their body position. In our earlier work, we presented proof-of-concept results for such a system with simulated data from healthy participants [7]. A record of the stroke survivor's posture, upper-limb movement deviation, and adherence to feedback will also help therapists to optimize their treatment plans, e.g. changing the exercise set-up to minimize compensation.

However, there is a lack of established benchmarking for monitoring pose and motion impairments related to conditions such as stroke. Typically, each research group tests and reports the performance of their algorithms on either their own datasets or non-clinical datasets (healthy participants). As a result, it is difficult to develop, evaluate, and compare algorithms for the study of human upper body mobility during rehabilitation following stroke.

The Toronto Rehab Stroke Posture (TRSP)[1] dataset is meant to aid research in the general area of developing and evaluating algorithms for the monitoring of post-stroke upper-body posture and motion. This paper describes the dataset containing upper-limb rehabilitation with associated ground truth that can be used to develop algorithms to automatically detect various characteristics using visual and depth information processing. Some of these characteristics and applications include: (1) the range of motion, (2) complicated mobility impairments such as combined joint movements and incoordination in body structures or (3) the most common types of compensation movements performed during simple scripted tasks such as reaching for a point or pushing a robotic end effector (hand hold) back and forth.

[1] http://www.cs.toronto.edu/~taati/TRSP.html

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PervasiveHealth '17, May 23–26, 2017, Barcelona, Spain

ACM ISBN 978-1-4503-6363-1/17/05…$15.00
https://doi.org/10.1145/3154862.3154925

We hope that the creation of TRSP dataset will advance the state of the art in the study of human upper body mobility and impairments during rehabilitation.

RELATED WORK

A number of human activity benchmarking datasets have been previously reported. They were mostly captured in two modalities: marker-based human movement tracking and vision-based (markerless) tracking. Marker-based motion capture (MoCap) technologies entail retroreflective markers to be placed on the key body parts, whose three-dimensional (3D) locations are subsequently recorded by multiple cameras. This approach yields accurate and robust 3D tracking results. For that reason, the most popular datasets, such as HumanEva [8], CMU MoCap [9] and HDM05 [10], are based on this method. However, MoCap systems can cause user discomfort [11], are prohibitively expensive, and require elaborate setup [12]. Due to these reasons, MoCap is not appropriate for use in clinical settings. On the other hand, vision-based technologies, e.g. using the Microsoft Kinect sensor for Windows (k4W), while less accurate, can collect and analyse human movement without the constraint of markers. Therefore, they can easily blend into individual environments and do not intrude in participants' activities. Additionally, because only one camera is used, the system can be affordable, easy to set up, and operate with little or no perceived effort for researchers. As such, vision-based systems have a high potential for clinical applications.

Using the k4W, the human pose can be extracted from depth and video sequences captured by an infrared camera and a color camera. The k4W has been validated by several research groups against standard motion capture systems, other vision-based tracking algorithms, and wearable sensors [13-15]. In our previous work, we have validated the k4W with the a portable gait analysis walkway system (GAITRite®) on spatiotemporal measures [16]. In those studies, the k4W's performance and reliability have been thoroughly analysed, rendering the k4W a promising tool for assessing gait and posture in the clinical setting.

To date, several k4W-based motion capture databases are available to the public. The UTKinect-Action3D Dataset is composed of ten healthy participants performing ten types of actions ranging from walking, sitting down to waving hands and clapping hands [17]. Color images, depth images, and tracked skeleton joints were recorded, along with matching labels for the actions that were performed. Another dataset (CAD-60 and CAD-120) contains the same data formats, but has a different number of participants, environments, and sets of activities [18]. Although these datasets contribute to research in human action recognition, the data were from healthy participants, without the movement activities of clinical populations such as stroke survivors.

To obtain actions relevant to studying clinical populations, the K3Da dataset included three groups, namely twenty six young (<=59 years of age), fourteen old (=>61 years of age), and fourteen athletic old (=>61 years of age) participants [19]. By comparing inter-group differences, the dataset aimed to elucidate the effects of ageing on body movements. This dataset is the first k4W-based benchmarking dataset in a healthcare setting based on common clinical assessments of gait and balance such as the Short Physical Performance Battery and the Timed-Up-And-Go [20, 21]. Nevertheless, the overall health status of each participant was not disclosed. Therefore, it would be difficult to determine if the impact on mobility was in fact due to ageing or any pathological conditions.

To account for these limitations, our dataset contains both mobility-impaired stroke survivors (who were clinically assessed and diagnosed) and healthy participants performing the same actions. This is the first dataset, to our knowledge, that documented the movements of participant groups both with and without a clinical condition. This dataset is especially valuable because it promotes mobility-related rehabilitation research using k4W as a cost-effective, portable, and convenient means.

TRSP DATASET

This section describes the protocol and rationale for how the dataset was created. It describes the hardware setup and the participants included in the dataset. This study was approved by the Research Ethics Board at the Toronto Rehabilitation Institute – University Health Network (TRI-UHN) University Centre. All participants provided written informed consent.

Participants

The dataset contains data from two groups of participants:

Group 1: Stroke survivor participants

Ten stroke survivors with varying degrees of upper-limb mobility impairment were recruited from a rehabilitation hospital in the greater Toronto area (TRI-UHN). They were recruited by therapist referral and through the central recruiting process at the hospital. However, data from one participant was not recorded properly due to software issues and data from nine stroke survivors are included in the dataset. Participants met the following criteria:

Inclusion Criteria

- stroke survivor either in subacute (between 1 to 6 months post stroke) or chronic (over 6 months post stroke) stages of recovery;
- right or left upper-limb impairment as a result of stroke, stages 2 to 6 on Chedoke-McMaster Stroke Assessment (CMSA) [2];
- physically and cognitively able to participate in an approximately 30 minutes session moving upper-limbs (according to therapist, if involved in active rehabilitation), total session duration 30 to 90 minutes; and
- able to understand English (e.g. follow simple directions in English)

Participants	Age mean ± std	Gender # woman	Hand dominance right (#)	Mobility status (%)		
				No gait aid (#)	# using cane/walker (always)	# using cane/walker (occasional)
Group 1 Stroke (N = 9)	52 ± 13.58	5	9	4	4	1
Group 2 Healthy (N = 10)	31 ± 9.48	5	8	10	0	0

Table 1. Summary of participants included in dataset.

<u>**Exclusion Criteria**</u>

- history of physical aggression, agitation, and/or exit-seeking behavior; and
- significant upper-limb joint pain on affected side that limits movement in transverse or sagittal planes

Group 2: Healthy participants

Ten healthy adults with no mobility impairments were recruited. The healthy participants were matched approximately in height and body size with the stroke survivor participants.

Participants' age at the time of the study, gender and hand dominance were collected at the beginning of the session. Table 1 provides summary information of all 19 participants.

Experimental set-up

The robotic rehabilitation system used in Figure 1 was a tabletop, 2-degree of freedom haptic robot that provided assisted and resisted shoulder and elbow movement therapy [22]. The manipulator is specifically designed for adaptive post-stroke rehabilitation exercises. To use the robot, participants were seated in front of the table. The K4W version 2 (v2) was mounted on a wall, behind the table with the sensor facing the subject. The K4W v2 sensor was adjusted to be less than three meters away from the participants. A recording application based on the K4W v2 SDK 2.0 was developed and used to detect, track, and record motions.

The application tracked and recorded 3D locations, i.e., x, y, and z coordinates, and orientations of 10 body parts (upper body) and joints relative to the depth sensor (e.g., head, shoulders, elbows, hands, etc.) at 30 frames per second.

Qualified stroke survivors were invited to the Rocket Family Upper Extremity Clinic at TRI-UHN. First, a researcher inquired about their demographic and health history information (i.e., gender, age at time of study, hand dominance, date of stroke, affected side, mobility status, clinical diagnoses affecting mobility) and a therapist clinically assessed the stroke survivors' affected upper limb using the Fugl-Meyer Assessment Upper Extremity (FMA-UE) [1] and CMSA. If the stroke survivor met the inclusion criteria, another session was scheduled for motion data collection. The stroke survivors' weight and height were measured with consent during the data collection session.

The two sessions took approximately an hour and a half on average for each stroke survivor. All participants wore their own clothing for the duration of the study.

Motion data collection

All participants were given a brief description of the purpose of the study, the robot, and the equipment used for data collection. The participants were then asked to perform a series of short scripted motions, each consisting of five repetitions. All scripted motions were executed at a pace and movement range that was comfortable for the participant. Each motion was performed with the left arm, and then followed by the right arm for consistency. Participants took breaks between repetitions if needed. A researcher collecting the data counted each repetition and signaled to the participant when to start a repetition.

Stroke survivors were asked to perform two types of scripted motions using the robot with both upper limbs as they were able. Namely, they were the Reach-Forward-Backward and the Reach-Side-to-Side motions. These motions were intended to reveal the active upper-limb range of motion in the shoulders and elbows and elicit common compensatory movements and limb synergies associated with stroke.

Healthy participants completed the same scripted motions with additional sets to simulate common post-stroke compensatory movements, which included lean-forward, trunk rotation, and shoulder elevation.

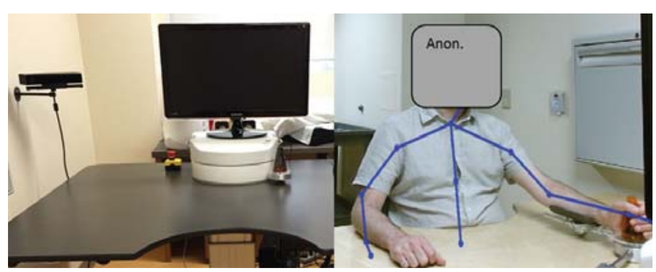

Figure 1. (Left) the haptic robot and Kinect sensor set up. (Right) a participant operating the haptic robot.

Type of motions		Upper limb sitting motions using robotic device
Details of captured data	Joint position	The 3D locations (x,y,z) of 10 upper body joints in centimeters in world coordinates, at 30 frames per second (fps). Each joint is marked as tracked, inferred, or not tracked.
	Joint orientations	The absolute orientations of 10 upper body joints in the form of quaternion, at 30 fps. Each joint is marked as tracked, inferred, or not tracked.
	Timestamps	In milliseconds
Background information	Demographic information	Age, Height, Waist Diameter, and Hand Dominance
	Clinical history of stroke survivors	Days/Month/Years post stroke, affected side, mobility status, CMSA, and FMA-UL
Annotations	Labels	Labels (from 1 to 4) showing the type of compensatory movements (at 1 fps)

Table 2. Summary of data released in TRSP Dataset

Lean-forward happens when a person moves their upper body forward while reaching forward (either bending at the hips or flexing their spine). Trunk rotation happens when a person rotates their upper body while moving the exercised arm from side to side. Shoulder elevation happens when people raise their shoulder (on one side) while reaching forward. Table 2 summarizes the data which is released in TRSP Dataset.

DATASET ANALYSIS

Annotations

The motion data collected from both healthy participants and stroke survivors were annotated by two expert raters using a software application developed in house for the purpose of this study. The data were annotated at roughly one frame per second to identify movements while performing scripted movements. The compensatory movements were categorized and labelled as *1. No Compensation*, *2. Lean-Forward, 3. Shoulder Elevation*, *4. Trunk Rotation*. For example, if a participant did not have any compensation while performing a scripted movement, the movement was labelled with 1. If a participant had multiple compensatory movements while performing a scripted movement they were labelled concurrently. There was no priority sequence of the compensatory movements. The label was only to indicate the type of the compensation. If there were other compensatory movements that were not included in the pre-set categories, they were recorded as *Other* in a field box in the software.

Calibration

The skeletal information was recorded in the coordinate frame of the sensor. However, analyzing the data in this coordinate frame was dependent on the placement of the sensor (position and orientation) relative to the room, and also relative to the sitting position of the subject. It was therefore necessary to perform a pre-processing step to express the joint information in world coordinates, independent of the mounting position and orientation of the sensor and its relative placement to the subject.

The skeletal trajectories from the depth coordinates were mapped to the world coordinate using the intrinsic and extrinsic parameters of the K4W v2 through the following steps: (1) we retrieved the calibration data for the depth camera of the K4W v2 using the SDK 2.0 interface. Using this information, all points were mapped from depth camera coordinates to the color camera coordinates; (2) we then formed a rotation-translation homogeneous transformation matrix (a 3x3 rotation matrix and a 3x1 translation vector) to transform the points from camera coordinates to real world coordinates [23]. The rotation-translation matrix was created from two orthogonal planes of the scene (the wall and the floor) for each session of data collection [23, 24]. For this purpose, we created a 3D point cloud using a single depth map of the scene of the clinic and used to compute the two orthogonal planes. The surface normal of the orthogonal planes were computed to form the K4W v2 extrinsic parameter that aligns the camera coordinates with the world frame. Under the transformed world coordinates, the y axis is aligned with the room vertical pointing upward (the surface normal of the floor), the participant faces the camera along the z axis (the surface normal of the wall, explicitly made perpendicular with the y axis), and the x axis, which defines the left and right direction, is computed as a cross product of the y and z axes to form a right-handed orthonormal frame. The transformation also ensures that the floor is at height y = 0 m.

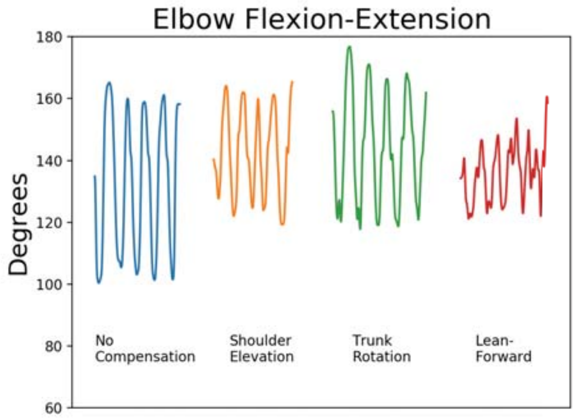

Figure 2. flexion/extension angle of the right elbow joint during robot use by a healthy participant.

Dataset evaluation

In addition to the dataset and annotations, we also provide a toolkit and baseline algorithms in Python for (1) viewing and working with the dataset, and (2) testing the sensitivity and specificity of the TRSP dataset in identifying compensatory movements. The toolkit includes Python scripts for retrieving and illustrating trajectories of the joint positions and hierarchical joint orientations.

For the toolkit, the skeleton is represented by 10 points (upper body) with the root of the Cartesian 3D coordinate system positioned in the spine base and oriented in alignment with the sensor. Figure 2 illustrates an example of the flexion/extension of the right elbow joint during robot use plotted using the toolkit. The trajectories belong to a healthy participant operating the robot without any compensation, as well as when simulating shoulder elevation, trunk rotation and lean forward compensations while performing Reach-Forward-Backward motions. It can be observed in the Figure 2 that the range of motion for compensatory movements, particularly shoulder elevation and lean-forward, are shorter than no compensation movement.

In order to examine how well the dataset can be used to discriminate among alternative states of compensation, we examined the performance of a simple binary thresholding method and we report sensitivity and specificity in identifying compensatory motions. Since Kinect posture tracking is prone to noise and occasional unstable tracking, this simple approach does not always work. To illustrate, we present an example showing good performance and another example showing poor performance for each of the three compensatory motions investigated here. The receiver operating characteristic (ROC) curve and the area under the ROC curve (AUC) are reported in each case.

The angle between the trunk vector and the y-axis (α) was used to assess the degree of lean-forward compensation; the angle between the shoulder vector and the x-axis (β) was used to examine the degree of shoulder elevation compensation; and the angle between the shoulder vector and the z-axis (ϒ) indicated the degree of trunk rotation compensation. Figure 3 illustrates these angles. The trunk vector is defined as the line from middle of the spine to spine at the shoulder. The shoulder vector was defined as the line from the left shoulder to the right shoulder.

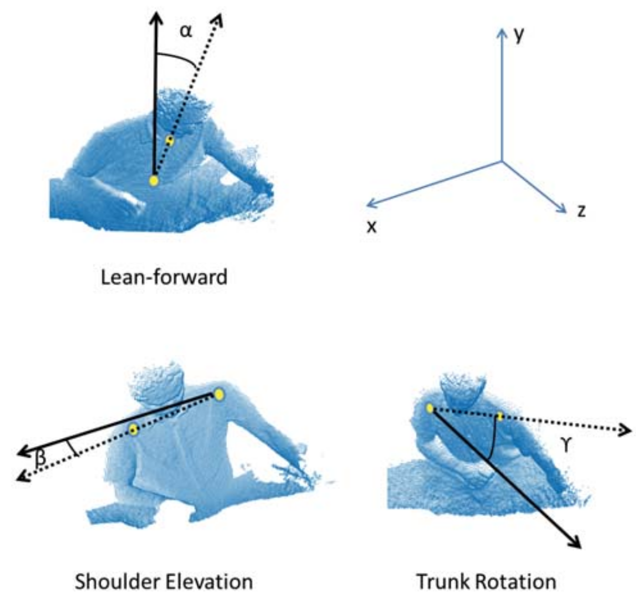

Figure 3. α is the angle between the trunk vector and the y-axis; β is the angle between the shoulder vector and the x-axis; ϒ is the angle between the shoulder vector and the z-axis.

Figure 4 illustrates both good and poor examples of when using α, β and ϒ trajectories to detect shoulder elevation, trunk rotation and lean-forward compensations respectively. All trajectories in Figure 4 belong to stroke (i.e. not healthy) participants. In addition, Table 3 reports the AUC values in binary classification of shoulder elevation, trunk rotation, and lean-forward compensations (vs. no compensation), when using the α, β, and ϒ angles, respectively.

Feature (input of binary classifier)	**Type of compensation** (output of binary classifier)	**AUC**	
		Good Example	**Poor Example**
α	Lean-Forward	0.92	0.52
β	Shoulder Elevation	0.94	0.37
ϒ	Trunk Rotation	0.97	0.63

Table 3. Area under the ROC curve (AUC) values in the good and poor examples shown in Figure 4.

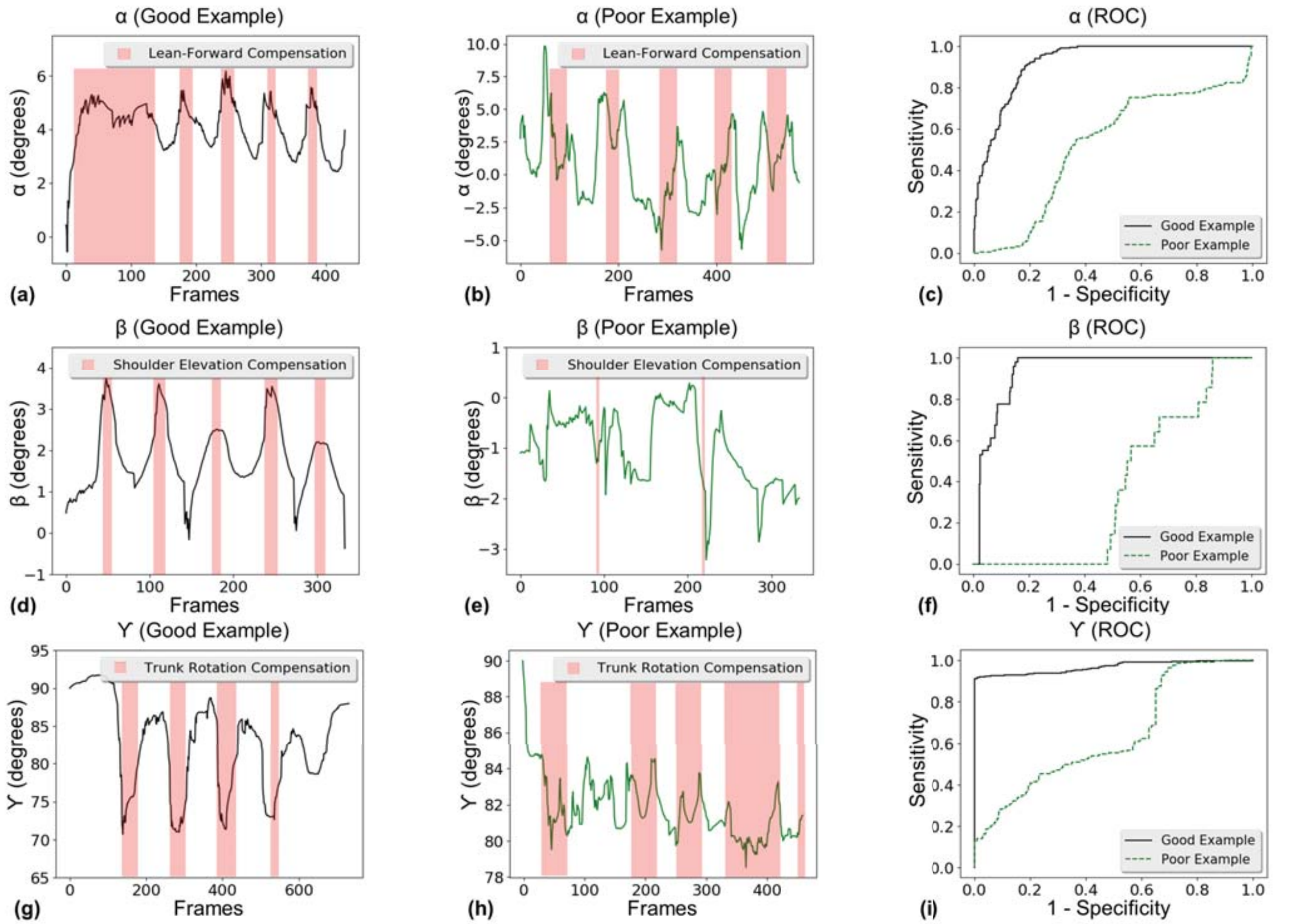

Figure 4. (a) Good and (b) poor examples of α for a stroke survivor while performing reach-side-to-side with the right arm, (c) ROC curve for both the good and the poor examples, (d) good and (e) poor examples of β for a stroke survivor while performing reach-forward-backward with left arm, (f) ROC curve for both the good and poor examples, (g) good and (h) poor examples of ϒ for a stroke survivor while doing reach-side-to-side with left arm, and (i) ROC curve for both good and poor examples. Highlighted regions indicate the compensated movements labelled by an annotator.

CONCLUSION

We have introduced the TRSP dataset for benchmarking algorithms to detect and categorize mobility compensatory movements during upper-limb stroke rehabilitation exercises. Such algorithms can then be used to provide real-time automated coaching during therapy sessions. The dataset could also be used in the kinematic analysis of the upper limb motor strategies in stroke survivors.

The TRSP dataset is the result of the availability of an affordable and easy to use K4W v2 compared to complex marker based motion capture systems. This is a comprehensive dataset that contains a series of scripted motions performed by both healthy participants and stroke survivors when using a robotic therapy device. In addition to the motion data, the dataset includes demographic information and clinical assessments for participants, as well as annotations of common compensatory motions. We also presented a baseline method to demonstrate the usefulness of the dataset. The baseline algorithm examines the associations between compensatory movements and the angle of the trunk vector or that of the shoulder vector. The specificity and sensitivity of the classification in both well performing and poorly performing examples were shown.

We anticipate that supervised machine learning algorithms considering the position (and/or orientation) of all upper body joints will have better sensitivity and specificity in identifying compensatory motions.

ACKNOWLEDGEMENTS

We would like to thank Jyoti Mann, Christopher Welton, Michelle Lukasik and Trina Mitchell for assistance with data annotations. Data collection from individuals with stroke for this project was generously funded by a grant from the Heart and Stroke Foundation Canadian Partnership for Stroke Recovery. We would also like to thank NSERC and AGE-WELL for partially supporting the HQP working on this project.

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