Assessment of Motor Compensation Patterns in Stroke Rehabilitation Exercises

Ana Rita Cóias
ana.coias@tecnico.ulisboa.pt
Alexandre Bernardino
alex@isr.tecnico.ulisboa.pt

Institute for Systems and Robotics
Instituto Superior Técnico, ULisboa
Lisboa, PT

Abstract

The increasing demand concerning stroke rehabilitation and in-home exercise promotion requires objective methods to assess patients' quality of movement, allowing progress tracking and promoting consensus among treatment regimens. In this work, we propose a method to detect diverse compensation patterns during exercise performance with 2D pose data to automate rehabilitation programs monitorization in any device with a 2D camera, such as tablets, smartphones, or robotic assistants.

1 Introduction

With the escalating demands towards stroke rehabilitation and the increase of in-home exercise recommendations [2], the need for new means to evaluate patients' motor performance has risen [4, 7]. In conventional assessment tests, therapists assess movement quality based on observation, thus being highly subjective [4]; with the degree of experience implying distinct treatment approaches [7]. Quantitative and objective methods allow patients' progress tracking, impaired movements' understanding, and formulation of standard therapy regimens [4, 6].

Patients' physically impaired often exhibit compensation behaviors to accomplish a task. Motor compensation is the presence of new movement patterns derived from the adaptation or substitution of old ones, which might help patients' execute a task [5]. New patterns can include the use and activation of additional or new body joints and muscles. Most typical compensation behaviors are trunk displacements, rotation, and shoulder elevation. These functional strategies are commonly observed in reaching and are highly related to severe impairment levels [5].

Early on the recovery process, the use of compensation strategies promotes patients' upper limb participation in task performance. However, their persistence may obstruct real motor function recovery and must be reduced during therapy through appropriate exercise instructions [5].

In this work, we present a method to assess quantitatively motor compensation from video frames during upper limb exercise performance. We have created a labelset (Table 2) for each video frame of the dataset regarding the observed compensation patterns. We then explore two methods to assess these patterns based on 2D pose data enabling this kind of analysis with widely available RGB cameras.

2 Related Work

When conceiving quantitative methods to assess movement quality, researchers carry out the kinematic study of 3D pose data to track patients' progress, enhance in-home therapy, and bring consensus among therapists' evaluation. Kinematics delineates body movements over space and time, giving information on linear and angular displacements. Prior works usually explore joint angular motion and trunk displacements. Some studies determined which kinematic variables better describe motor impairment and identify upper limb disability levels through PCA analysis [6]. Others assessed the quality of the upper extremity movement with machine learning methods [4, 7]. However, existing methods do not detect distinct compensation patterns and are based on 3D pose data, which limits its wide applicability in off-the shelf computational devices.

3 Learning to Assess Motor Compensation

Considering stroke survivors with one weakened side of the body, we assess motor compensation through individuals' body parts' 2D pose data extracted from video frames. To accomplish this task, we execute the following steps: body keypoints extraction and selection, data normalization, and multilabel classification to determine the compensation patterns observed among the video frames. We present a rule-based (RB) classification method, which works as our baseline approach and a Neural Network (NN) that assesses compensation through the body keypoints.

3.1 Feature Extraction and Selection

To extract the body joints' 2D pose data, we use the OpenPose [1], a software library that provides the location of 25 body keypoints in the image coordinate system. Each keypoint is denoted by $p_j^t = [x\ y]'$, where j denotes a body joint and t the frame number.

We consider two scenarios (S1 and S2) concerning patients' position in front of the camera: one facing the recording camera (S1) and the other with the patient's affected arm facing the camera (S2). According to [4], we select the joints shown in Figure 1 to describe patients' movements, which are held by the RB and NN methods. The head keypoints, $j \in [15, 18]$, are held for the RB method, in addition to the selected joints, to overcome the lack of 3D data by head size variation. Considering a multi-person setting (with the patient under evaluation and a caregiver), we select the patient assuming he/she is the closest person to the center of the image.

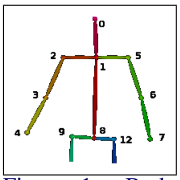


Figure 1: Body keypoints.

3.2 Data Normalization

In a real-world setting, subjects have body parts' of different sizes and are not placed at the same place regarding the camera. For this reason, we normalize the keypoints. First, we apply rigid body transformation from the image coordinate system, $\{I\}$, to the body coordinate system, $\{B\}$, in which the patient's joint 8 is the origin. This step considers the patients' affected side. For S1, the ^BX axis is directed to the affected side. For S2, the ^BX axis is directed to the patients' front. Additionally, we normalize each resultant keypoint coordinates to the spine length measured in $t = 1$. For the NN, to give the non-affected side as a reference, we mirror the joints to the ^BX axis positive side, aligning both sides. For RB, each keypoint moves regarding other specified keypoint.

3.3 Kinematic Variables

We compute kinematic variables for the RB approach to describe motion patterns similar to [4, 6]. However, as we work with 2D positional data, we do not have information about patients' movements in depth. This way, we formulate hypotheses to detect the different compensation patterns: trunk moving forward, trunk rotation, shoulder elevation, and other trunk displacements, such as trunk tilt and trunk moving backward. More specifically, for both scenarios S1 and S2 - the formulated hypotheses and respective kinematic variables are summarized as follows.

Trunk Forward/Backward: S1 - observed changes in patient's head size, ΔH^t (H^t - head area in $t > 1$); S2 - spine angular and linear displacements, $a^t(p_8^1, p_1^1, p_1^t)$ (a^t - angle between three joints) and $d_x^t(p_1^t, p_1^1)$ (d_x^t - displacement in X).

Trunk Rotation: S1 - simultaneous angular displacements of both shoulders, $a^t(p_2^1, p_1^1, p_2^t)$ and $a^t(p_5^1, p_1^1, p_5^t)$; S2 - absolute changes in the observed chest length, $|\Delta d^t(p_2^t, p_5^t)|$ (d^t - Euclidean distance between two joints) or[1] shoulder displacement regarding joint 1 in X, $d_x^t(p_{2/5}^t, p_1^t)$.

Shoulder Elevation: S1 - shoulder elevation angle $a^t(p_{2/5}^1, p_1^1, p_{2/5}^t)$; S2 - shoulder displacement regarding joint 1 in Y, $d_y^t(p_{2/5}^t, p_1^t)$ (d_y^t - displacement in Y).

Trunk Tilt: S1 - spine angular displacement $a^t(p_8^1, p_1^1, p_1^t)$; S2 - absolute changes in patient's head size, $|\Delta H^t|$.

[1] In S2 patients can show their chest or be completely aside

	Exercise	Scenario	P_{min}
$E1$	*'Bring a Cup to the Mouth'*	S1	83.83%
$E2$	*'Switch a Light On'*	S1	91.4%
$E3$	*'Move a Cane Forward'*	S2	98.15%

Table 1: The three exercises and percentage of single labeled frames.

Label	$IRLbl_{E1/E2/E3}$	Label	$IRLbl_{E1/E2/E3}$
'0: Trunk Forward'	-/-/3.54	*'3: Other'*	4.93/5.55/-
'1: Trunk Rotation'	16.23/19.25/-	*'4: Normal'*	1/1/1
'2: Shoulder Elevation'	2.15/3.03/15.77	-	-

Table 2: Considered labels and *IRLbl* metric for each one.

3.4 Classification Approaches

While exercising, a stroke survivor can describe multiple compensation moves. Thus, we consider this problem a multilabel classification problem and learn the different compensation patterns observed in a video frame. We explore two approaches: a RB method and a NN that learns the observed patterns based on the keypoints position.

The former method is a set of *if-then* rules (e.g. *'2'* if shoulder angle is above a threshold) applied to the kinematic variables and ending in the class labels [3, 8]. The latter is an ensemble of two classifiers seizing to respect label dependency and overcome label imbalance [8]. The first classifier (C1) executes binary classification, verifying compensation existence. If there is compensation, the second classifier (C2) performs multilabel classification to determine the pattern. Here we apply binary relevance *One-vs-Rest*, which considers each label independently. Afterward, we join the classification results into the multilabel output.

4 Method Validation

To validate our method, we use the rehabilitation exercise videos from Lee *et al*. work [4]. We validate the formulated hypotheses to assess compensation through the kinematic analysis and present the classification results with our baseline classifier. To validate the NN ensemble, we apply *Leave-One-Subject-Out* (LOSO) cross-validation (CV).

4.1 The Multilabel Dataset

The dataset consists of videos with 15 stroke survivors performing an average of 10 movement trials of three upper extremity exercises (E1, E2, and E3), detailed in Table 1. We assigned to every video frame multiple labels (Table 2). Label *'3'* includes trunk tilt and moving backward. Label *'4'* holds movements with no compensation or the resting state. As shown in Table 1, the dataset is almost single labeled - high percentage of single labeled frames, P_{min}. Regarding label imbalance, in Table 2, the *IRLbl* metric shows the ratio between the occurrences of the most frequent label and each label. We can see that, for the three exercises, label *'4'* is the most frequent, $IRLbl = 1$. For E1 and E2, *'1'* is poorly represented, $IRLbl \gg 1$, with only one patient exhibiting this compensation pattern. For E3, the less representative label is *'2'*.

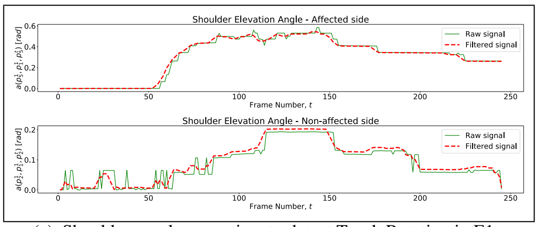
4.2 Kinematic Variables

We validate the hypotheses formulated to assess compensation from 2D positional data. Figures 2(a) and 2(b) show the variation over time of three kinematic variables used to assess compensation behaviors, without 3D data. In Figure 2.(b) trunk rotation is assessed in E1 with the simultaneous angular displacement of both shoulders. In Figure 2(b) shoulder elevation is detected in E3 through shoulder displacement in Y regarding joint 1.

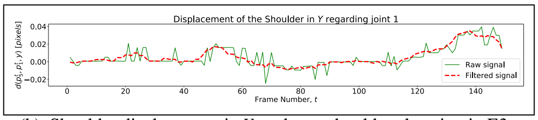
4.3 Classification Results

When applying the RB and performing LOSO CV to the NN approach, we obtained the average results given in Table 3. For the NN we explored one to two layers with 16, 64, and 96 hidden units with adaptive learning rate. We apply *'ReLu'* for C1 and *'Tanh'* for C2 activation functions and *'Adam'* optimizer with mini-batch size of 5.

As we can see in Table 3, the NN method performs better for the E2 and E3, with a higher P_{min} value, meaning the RB handles better E1. This suggests that the NN may work better in single labeled cases. Also, the high levels of standard deviation in both methods suggest that the approaches could benefit from more exercise examples from more patients to improve generalization ability.



(a) Shoulders angles over time to detect Trunk Rotation in E1.



(b) Shoulder displacement in Y to detect shoulder elevation in E3.

Figure 2: Examples of kinematic variables variation over time.

	Precision	Recall	$F1-score$	HammingLoss
$E1_{RB}$	**0.756 ± 0.14**	**0.783 ± 0.12**	**0.767 ± 0.12**	**0.11 ± 0.06**
$E2_{RB}$	0.555 ± 0.17	0.666 ± 0.17	0.602 ± 0.17	0.187 ± 0.08
$E3_{RB}$	0.697 ± 0.27	0.71 ± 0.26	0.701 ± 0.26	**0.126 ± 0.11**
$E1_{NN}$	0.692 ± 0.23	0.678 ± 0.25	0.679 ± 0.24	0.187 ± 0.15
$E2_{NN}$	**0.673 ± 0.21**	**0.675 ± 0.19**	**0.668 ± 0.19**	**0.182 ± 0.11**
$E3_{NN}$	**0.785 ± 0.22**	**0.783 ± 0.21**	**0.783 ± 0.22**	0.153 ± 0.14

Table 3: Average results for the rule-based (RB) and Neural Network (NN) methods.

5 Conclusions

We conclude that our method assesses distinct compensation patterns during upper extremity exercise performance pretty well from 2D pose data. In future work we want to leverage more data to achieve better label distribution and representativeness.

Acknowledgements

This work was supported by FCT with the LARSyS - FCT Project UIDB/50009/2020 and project IntelligentCare – Intelligent Multimorbidity Management System (Reference LISBOA-01-0247-FEDER-045948), co-financed by the ERDF – European Regional Development Fund through the Lisbon Portugal Regional Operational Program – LISBOA 2020 and by the Portuguese Foundation for Science and Technology – FCT under CMU Portugal.

References

[1] Z. Cao, G. Hidalgo Martinez, T. Simon, S. Wei, and Y. A. Sheikh. Openpose: Realtime multi-person 2d pose estimation using part affinity fields. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2019.

[2] T. M. Damush, L. Plue, T. Bakas, A. Schmid, and L. S. Williams. Barriers and facilitators to exercise among stroke survivors. *Rehabilitation Nursing*, 32(6), 2007.

[3] M. Kubat. *An Introduction to Machine Learning*. Springer, 2017.

[4] M. H. Lee, D. P. Siewiorek, A. Smailagic, A. Bernadino, and S. Bermúdez I Badia. Learning to assess the quality of stroke rehabilitation exercises. In *International Conference on Intelligent User Interfaces, Proceedings IUI*, pages 218–228. Association for Computing Machinery, 2019.

[5] M. F. Levin, J. A. Kleim, and S. L. Wolf. What do motor "recovery" and "compensation" mean in patients following stroke? *Neurorehabilitation and Neural Repair*, 23:313–319, 2009.

[6] M. A. Murphy, C. Willén, and K. S. Sunnerhagen. Kinematic variables quantifying upper-extremity performance after stroke during reaching and drinking from a glass. *Neurorehabilitation and Neural Repair*, 25(1):71–80, 2011.

[7] E. V. Olesh, S. Yakovenko, and V. Gritsenko. Automated assessment of upper extremity movement impairment due to stroke. *PLoS ONE*, 9(8), 2014.

[8] G. Tsoumakas and I. Katakis. *Multi-Label Classification*, volume 3. Springer, 2011.