# Assessment of Motor Compensation Patterns in Stroke Rehabilitation Exercises

Ana Rita Cóias
ana.coias@tecnico.ulisboa.pt

Alexandre Bernardino
alex@isr.tecnico.ulisboa.pt

VisLab, Institute for Systems and Robotics, Instituto Superior Técnico, Lisbon, Portugal

## 1. Motivation

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 (CP)** 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.

## 2. Learning To Assess Motor Compensation

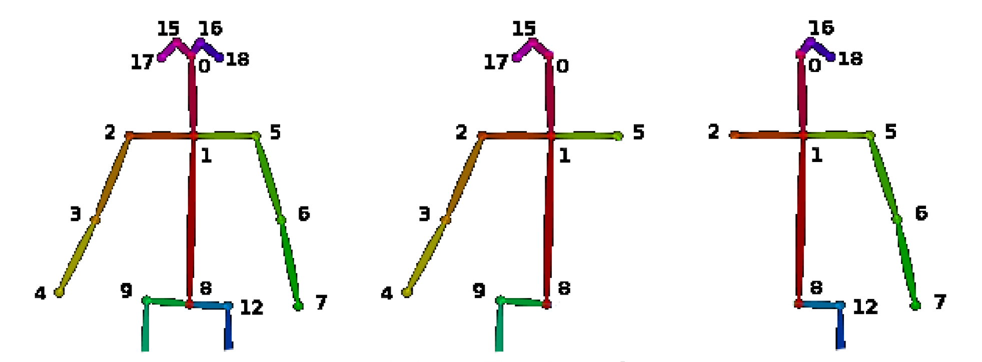
**Keypoint Extraction from Video Frames** → **Keypoint Selection** → **Data Normalization** → **Kinematic Variables** → **RB Definition**

**Data Normalization** → **NN Definition**

We present a **Rule-Based (RB)** classification method and a **Neural Network (NN)** that assesses compensation through the body keypoints.

## Feature Extraction and Selection

We extract 2D pose data with **OpenPose** software library.
Body keypoint: $p_j^t = [x \quad y]'$ - $j$ denotes a body joint and $t$ a frame number. Head joints $j \in [15,18]$ only are included for the RB method to overcome the lack of 3D data.



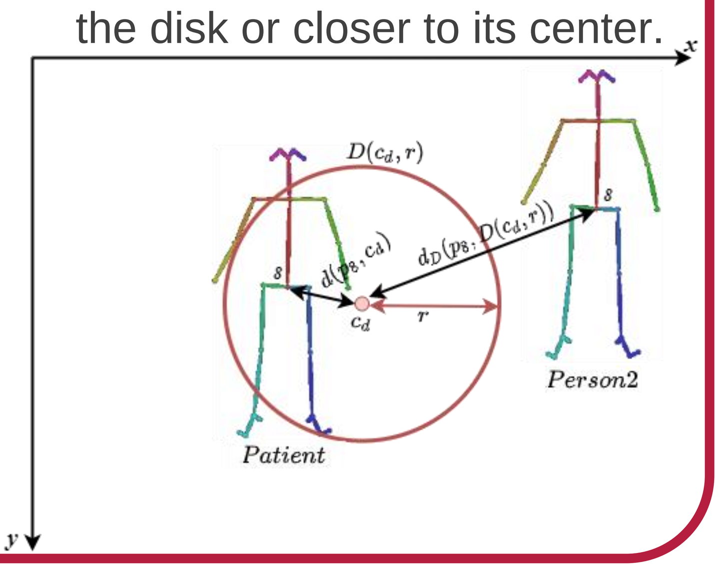
S1 – Patient facing the camera

S2 – Patient's affected arm facing camera (left)

S2 – Patient's affected arm facing camera (right)

**Selected body joints**

Subject selection in a multi-person setting. Patient is inside the disk or closer to its center.




## Data Normalization

$$ {}^B_I R = \begin{bmatrix} x_B^x & x_B^y \\ y_B^x & y_B^y \end{bmatrix} $$

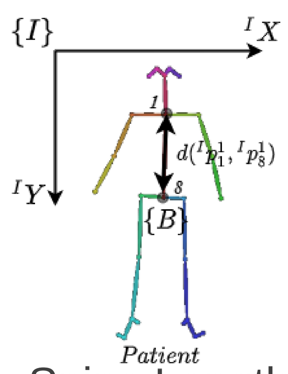
$$ {}^B P_I = {}^B_I R . (-p_8^1) $$

- Rigid body transformation: ${}^B p_j^t = {}^B_I R.\ {}^I p_j^t + {}^B P_I$

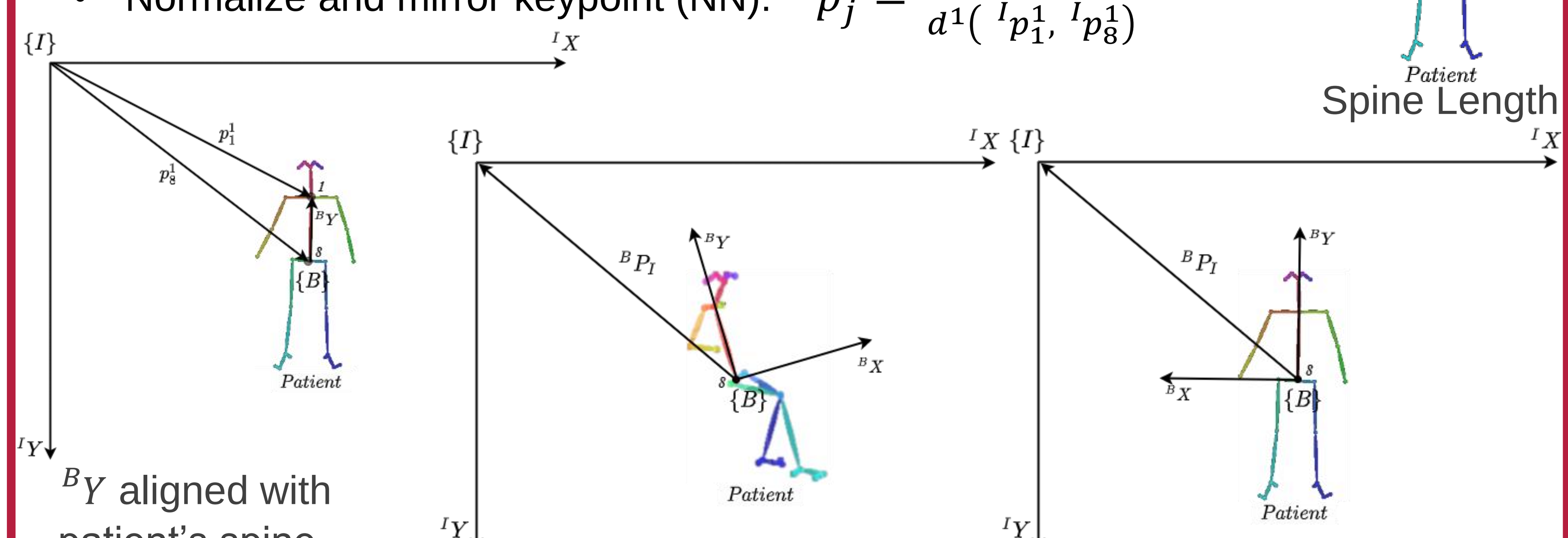
$$ {}^B Y = \frac{p_1^1 - p_8^1}{\|p_1^1 - p_8^1\|},\ {}^B X.\ {}^B Y = 0,\ \|{}^B X\| = 1 $$

- Normalize keypoint (RB): ${}^B \hat{p}_j^t = \dfrac{[{}^B x_j^t \quad {}^B y_j^t]'}{d^1({}^I p_1^1, {}^I p_8^1)}$

- Normalize and mirror keypoint (NN): ${}^B \tilde{p}_j^t = \dfrac{[-{}^B x_j^t \quad {}^B y_j^t]'}{d^1({}^I p_1^1, {}^I p_8^1)}$




Spine Length




${}^B Y$ aligned with patient's spine.

${}^B X$ axis direct to the affected side (S1) or patient's front (S2) and translation vector.

## Classification Methods

- Rule-Based (RB): *if-then* rules applied to kinematic variables.
- Neural Network (NN): binary and multilabel classifiers with body keypoints as input.

**Normalized Keypoints** → **Kinematic Variables** → **Rules** → **Type of Compensation**

**Normalized Keypoints** → **(mirror)** → **C1 Binary Classifier** → **Frames with Compensation** → **C2 Multilabel Classifier** (*One-vs-Rest*) → **Type of Compensation**

## Kinematic Variables for the RB Method

| CP | Kinematic variables & Rules |
|---|---|
| Trunk Forward (TF) | **S1:** Observed changes in patient's head area: $Hypothesis$: $\Delta H^t = \begin{cases} H^t - H^1, & if\ t > 1 \\ 0, & otherwise \end{cases}$ - **Rule:** *If* $\Delta H^t > threshold \rightarrow TF$ <br> **S2:** Spine angular and linear displacements: $a^t(p_8^1, p_1^1, p_1^t) \wedge d_x^t(p_1^t, p_1^1)$ - **Rule:** *If* $a^t > threshold \wedge d_x^t > 0 \rightarrow TF$ |
| Trunk Rotation (TR) | **S1:** Simultaneous angular displacements of both shoulder: $Hypothesis$: $a^t(p_2^1, p_1^1, p_2^t) \wedge a^t(p_5^1, p_1^1, p_5^t)$ - **Rule:** *If* $a^t(p_2^1, p_1^1, p_2^t) > threshold1 \wedge a^t(p_5^1, p_1^1, p_5^t) > threshold2$ and $threshold1 \approx threshold2 \rightarrow TR$ <br> **S2:** Absolute changes in the chest length: $Hypothesis$: $\lvert\Delta d^t(p_2^t, p_5^t)\rvert$ or shoulder displacement regarding joint 1 in $X$: $Hypothesis$: $d_x^t(p_{2/5}, p_1)$ - **Rule:** *If* $\lvert\Delta d^t\rvert > threshold$ or $d_x^t > threshold \rightarrow TR0$ |
| Shoulder Elevation (SE) | **S1:** Shoulder elevation angle: $a^t(p_{2/5}^1, p_1^1, p_{2/5}^t)$ - **Rule:** *If* $a^t > threshold \rightarrow SE$ <br> **S2:** Shoulder displacement regarding joint 1 in $Y$: $Hypothesis$: $d_y^t(p_{2/5}, p_1)$ - **Rule:** *If* $d_y^t > threshold \rightarrow SE$ |
| Other (TI or TB) | **S1:** Trunk Tilt – spine angular displacement: $a^t(p_8^1, p_1^1, p_1^t)$; Trunk Backward – observed changes in patient's head area: $Hypothesis$: $\Delta H^t = \begin{cases} H^t - H^1, & if\ t > 1 \\ 0, & otherwise \end{cases}$ - **Rule:** *If* $a^t > threshold$ or $\Delta H^t > threshold \rightarrow O$ <br> **S2:** Trunk Tilt – absolute changes in patient's head area: $Hypothesis$: $\lvert\Delta H^t\rvert = \begin{cases} \lvert H^t - H^1\rvert, & if\ t > 1 \\ 0, & otherwise \end{cases}$; Trunk Backward – spine angular and liner displacements: $a^t(p_8^1, p_1^1, p_1^t) \wedge d_x^t(p_1^t, p_1^1)$ - **Rule:** *If* $\lvert\Delta H^t\rvert > threshold$ or $a^t > threshold$ and $d_x^t > 0 \rightarrow O$ |

## 3. Method Validation

To validate our methods we use a **dataset of rehabilitation exercise videos** from 15 stroke survivors and apply ***Leave-One Subject-Out*** **(LOSO) cross-validation**.

## The Multilabel Dataset

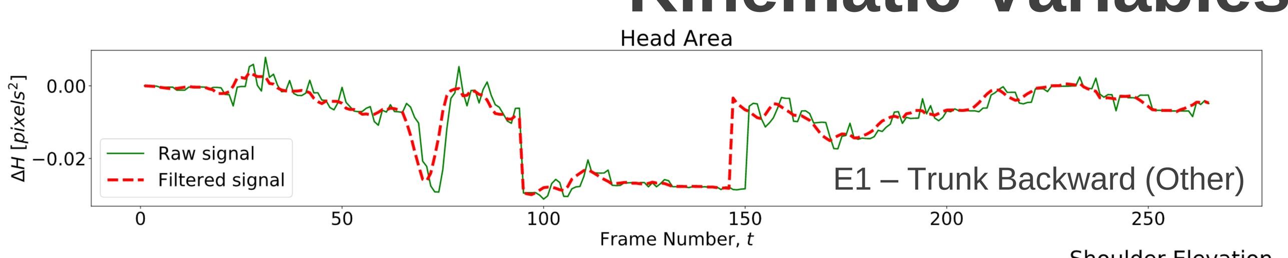
Three **upper extremity** exercises: E1, E2, and E3. We assigned **labels** to the dataset video frames indicating the observed compensation patterns. $P_{min}$ and $IRLbl$ metrics characterize the dataset.

These metrics indicate that the dataset is mostly single labeled.

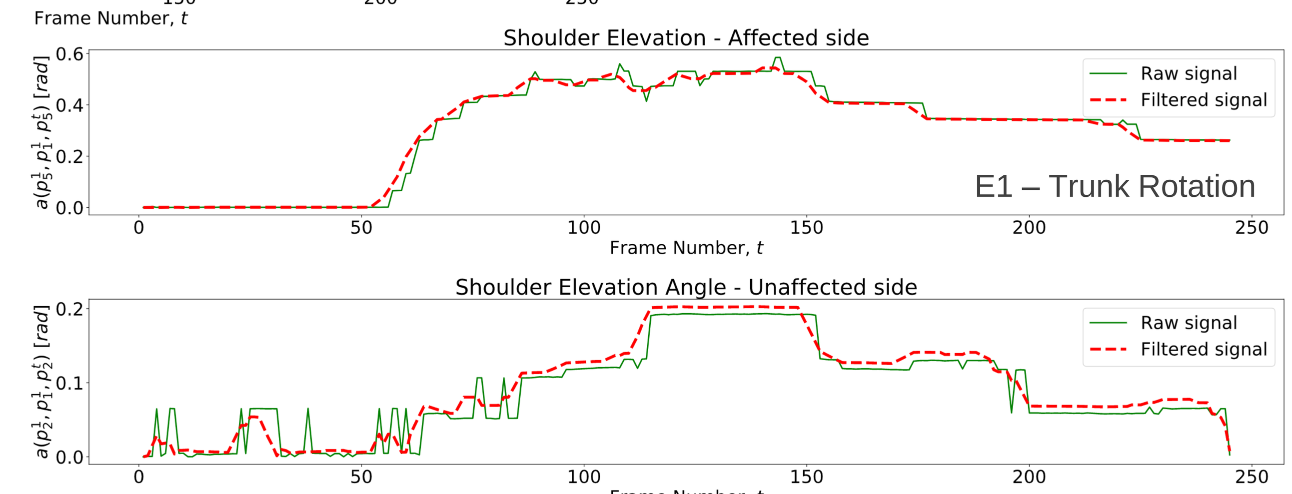
| | Exercise | Scenario | $P_{min}$ |
|---|---|---|---|
| **E1** | *'Bring a Cup to the Mouth'* | S1 | 83.83% |
| **E2** | 'Switch a Light On' | S1 | 91.4% |
| **E3** | 'Move a Cane Forward' | S2 | 98.15% |

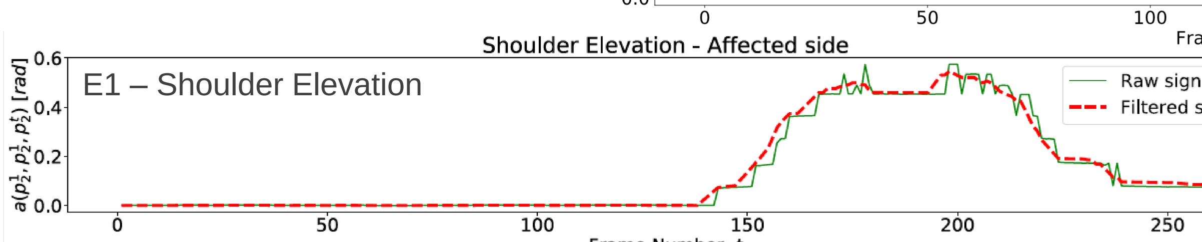
| | $IRLbl$ | | |
|---|---|---|---|
| **Label** | **E1** | **E2** | **E3** |
| *'0: Trunk Forward'* | - | - | 3.54 |
| *'1: Trunk Rotation'* | 16.23 | 19.25 | - |
| *'2: Shoulder Elevation'* | 2.15 | 3.03 | 15.77 |
| *'3: Other'* | 4.93 | 5.55 | - |
| *'4: Normal'* | 1 | 1 | 1 |

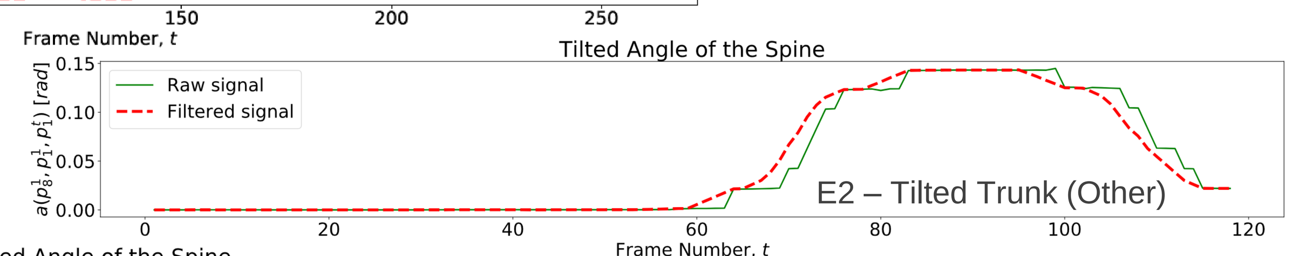
## Kinematic Variables

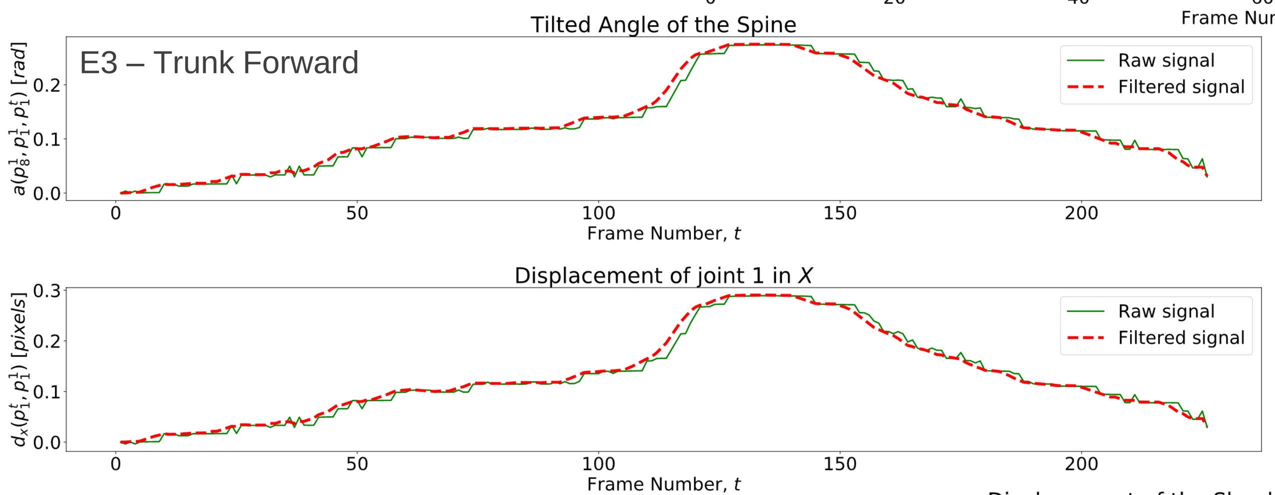



We observe the behavior of **kinematic variables over time** to validate the validate the formulated **hypotheses** to assess motor compensation from **2D data**.

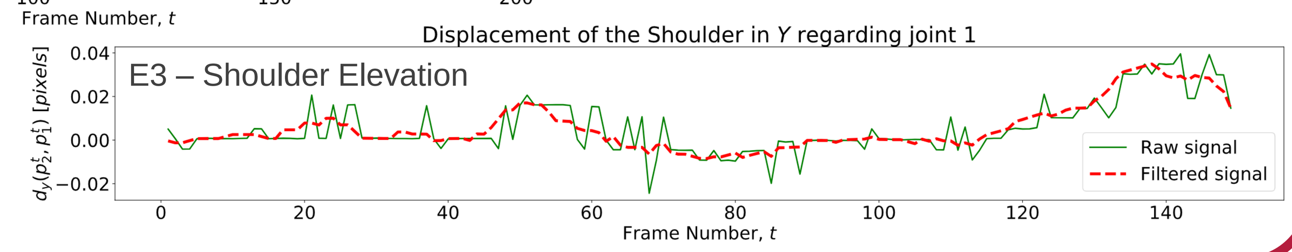



Observing the presented plots, we can conclude with our formulated hypothesis we can assess motor compensation by applying the established rules.




## Classification Results

**NN method**

| | |
|---|---|
| Layers | One to Two<br>16, 64, and 96 hidden units |
| Learning rate | Adaptive |
| Activation Function | C1 - *'ReLu'*; C2 – *'Tanh'* |
| Optimizer | *'Adam'* with mini-batch of size 5 |

| RB | Precision | Recall | F1 – Score | Hamming Loss |
|---|---|---|---|---|
| ***E1*** | $\mathbf{0.765 \pm 0.14}$ | $\mathbf{0.783 \pm 0.12}$ | $\mathbf{0.767 \pm 0.12}$ | $\mathbf{0.11 \pm 0.06}$ |
| ***E2*** | $0.555 \pm 0.17$ | $0.666 \pm 0.17$ | $0.602 \pm 0.17$ | $0.187 \pm 0.08$ |
| ***E3*** | $0.697 \pm 0.27$ | $0.71 \pm 0.26$ | $0.701 \pm 0.26$ | $\mathbf{0.126 \pm 0.11}$ |

| NN | Precision | Recall | F1 – Score | Hamming Loss |
|---|---|---|---|---|
| ***E1*** | $0.692 \pm 0.23$ | $0.678 \pm 0.25$ | $0.679 \pm 0.24$ | $0.187 \pm 0.15$ |
| ***E2*** | $\mathbf{0.673 \pm 0.21}$ | $\mathbf{0.675 \pm 0.19}$ | $\mathbf{0.668 \pm 0.19}$ | $\mathbf{0.182 \pm 0.11}$ |
| ***E3*** | $\mathbf{0.785 \pm 0.22}$ | $\mathbf{0.783 \pm 0.21}$ | $\mathbf{0.783 \pm 0.22}$ | $0.153 \pm 0.14$ |

The NN deals better with singles labeled frames. RB handles better with more multilabeld samples. Both methods could benefit from more data samples.

**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.