# A functional analysis-based approach to quantify upper limb impairment level in chronic stroke patients: a pilot study

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***Abstract*— The accurate assessment of upper limb motion impairment induced by stroke - which represents one of the primary causes of disability world-wide - is the first step to successfully monitor and guide patients' recovery. As of today, the majority of the procedures relies on clinical scales, which are mostly based on ordinal scaling, operator-dependent, and subject to floor and ceiling effects. In this work, we intend to overcome these limitations by proposing a novel approach to analytically evaluate the level of pathological movement coupling, based on the quantification of movement complexity. To this goal, we consider the variations of functional Principal Components applied to the reconstruction of joint angle trajectories of the upper limb during daily living task execution, and compared these variations between two conditions, i.e. the affected and non-affected arm. A Dissimilarity Index, which codifies the severity of the upper limb motor impairment with respect to the movement complexity of the non-affected arm, is then proposed. This methodology was validated as a proof of concept upon a set of four chronic stroke subjects with mild to moderate arm and hand impairments. As a first step, we evaluated whether the derived outcomes differentiate between the two conditions upon the whole data-set. Secondly, we exploited this concept to discern between different subjects and impairment levels. Results show that: i) differences in terms of movement variability between the affected and non-affected upper limb are detectable and ii) different impairment profiles can be characterized for single subjects using the proposed approach. Although provisional, these results are very promising and suggest this approach as a basis ingredient for the definition of a novel, operator-independent, sensitive, intuitive and widely applicable scale for the evaluation of upper limb motion impairment.**

## I. Introduction

Human upper limb movements require an extraordinary coordination of numerous degrees of freedom (DoFs). Based on neuroscientific literature, this coordination is supposed to be organized according to covariation patterns – the so called *synergistic control*, which allow a successful interaction with the environment [**?**], [**?**], [**?**], [**?**]. After stroke, these upper limb movements can be affected by different types of sensorimotor impairments, such as weakness or loss of inter-joint coordination resulting in deficits ranging from paralysis, abnormal movement patterns or pathological synergies (e.g. coupling of shoulder abduction and elbow flexion) to a certain degree of inter-joint coordination [**?**], [**?**]. In consequence, stroke subjects with arm impairments can show a reduced adaptability to task demands [**?**], inefficient movement trajectories [**?**], higher energy and force-consumption [**?**] (when for example trying to perform goal-directed reaching movements), and the increased risk of frustration in case of unsuccessful movement attempts [**?**], [**?**]. Hence, these impairments lead to long-term disabilities contributing in making stroke one of the main causes of disability world-wide, with a tremendous socio-economic impact [**?**]. Being able to evaluate stroke-specific upper limb movement patterns with sufficient detail is critical to properly monitor upper limb impairments after stroke, the recovery thereof and determining the effectiveness of different treatment approaches [**?**]. There exist multiple different standard clinical upper limb assessments in stroke research, among which the Fugl-Meyer Assessment of the Upper Extremity (FMA-UE) [**?**] is widely used to describe voluntary movement control [**?**]. This is assessed in a hierarchical structure; from within to out-of synergistic movements and from proximal to distal upper extremity segments. Despite the satisfactory measurement properties [**?**], [**?**], most of these clinical assessments exhibit floor and ceiling effects [**?**] and heavily rely on subjective observer scoring on broad ordinal scales (such as: 0=not, 1=partially, 2=fully possible).

Novel technologies for kinematic signal detection and processing provide the opportunity for an objective and accurate motion analysis, which allow to overcome the limitations of standard clinical assessments in stroke research and rehabilitation [**?**]. Among the different approaches, it is worth mentioning (i) device-based assessments [**?**], [**?**] and (ii) less interfering wearable systems for bio-signal and motion capture processing [**?**], [**?**]. However, although promising, the state-of-the-art solutions need to face with important issues, such as operator and patient safety and costs of the procedure (i). Bio-signal measurements, especially kinematic recordings (ii), can offer a reliable way for motion evaluation during a set of natural movements. In particular, the wearable sensor-based approach has shown to be applicable to a variety of movement tasks and expendable to daily-living tasks [**?**], which increases

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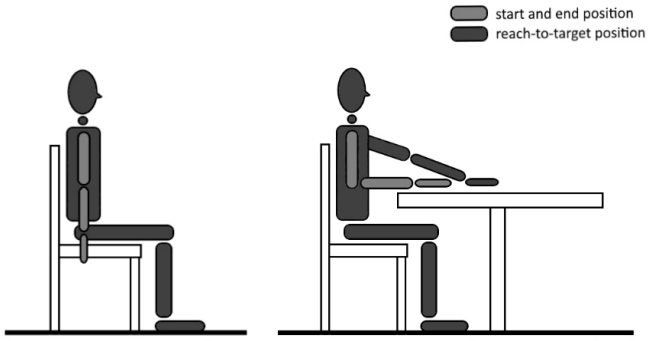


Fig. 1. Overview of the experimental setup for the intransitive task (left) and transitive and tool-mediated task (right).

the relevance of the assessment compared to the more abstract and stringent nature of movements performed during standard clinical assessments. Though some characteristics such as longer movement times and higher trunk displacement were described in stroke subjects [**?**], an exhaustive mathematical characterization on the level of loss of inter-joint coordination or pathological synergies after stroke still lacks in literature [**?**]. The most common way to quantify synergies is through Principal Component Analysis (PCA), a statistical method that allows the identification of dominant variation patterns in the data [**?**], [**?**]. Using this approach in a single-case study, fewer combinations of joint motions were identified in one stroke subject [**?**] as well as stronger synergistic coupling between shoulder, elbow and wrist motions in contrast to a healthy subject [**?**]. In [**?**], the authors applied a PCA on a larger dataset of stroke subjects (n=46) to investigate the components of linear relations between the upper limb joints and the trunk at the end of reaching movements. However, a common drawback of applying PCA is the underlying hypothesis of temporal uncorrelation of upper limb poses in time [**?**]. Consequently, the dynamic aspects of upper limb motion including the temporal evolution of upper limb joint trajectories are neglected. To overcome this issue, in [**?**] the authors proposed functional Principal Component Analysis (fPCA) as a technique to investigate the dominant modes of time-dependent variation upper limb movements on a comprehensive set of upper limb daily-living activities in healthy subjects. The main advantage of this analysis is that, while classical PCA-based analysis consider single kinematic postures, with fPCA all the temporal evolution of the movement is considered (thus intrinsically including the dynamic aspects). Results showed that a reduced number of functional Principal Components (fPCs) can be used to describe and accurately reconstruct the complexity of upper limb activities in healthy subjects, at joint level. The authors also pointed to the possibilities of an automatic recognition of physiological and pathological movements in stroke research and rehabilitation by analyzing fPCs variations between the affected and non affected upper limb [**?**].

In the present study we investigate whether the outcomes discussed in [**?**] can be effectively exploited to characterize upper limb motor impairment in chronic stroke subjects. For that purpose, four chronic stroke subjects with moderate arm and hand impairments performed the same 30 tasks of daily

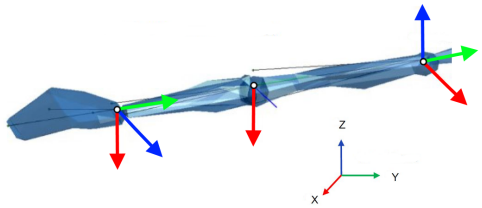


Fig. 2. Kinematic model used in this work. Three rigid links are connected by seven joints. Picture adapted from [**?**].

living activities [**?**] with both arms (affected and non-affected) and a functional PCA analysis was applied. Based on this data set, we evaluated whether the set of fPCs and the associated approximation error in reconstructing joint trajectories are appropriate outcome measures to differentiate i) between the affected and the non-affected arm across stroke subjects and ii) between different levels of upper limb impairments of the single subjects.

## II. Experimental Protocol and Setup

### A. Set of daily living tasks

In [**?**], the authors discussed a large set of tasks (i.e., 30 different actions), which were selected to excite the whole upper limb work-space [**?**], [**?**], [**?**] and to span all the major hand configurations, e.g. referring to the most common hand grasping taxonomies [**?**], [**?**]. Leveraging on this, we employed here the same protocol, with the twofold goal to: i) provide a comparison between different groups of populations, including chronic stroke subjects in this case, and ii) contribute to building up a large experimental data set of upper limb motion (acquired using different acquisition modalities), to enable comparison and benchmarking in future works. Under this regard, the possibility to publicly share collected data is envisioned and already under evaluation. The task-set is divided in three sub-groups of ten actions each: intransitive, transitive and tool-mediated tasks. Actions included in the first group are gestures with no contact with the external environment (i.e., requiring movement of the proximal part of the upper limb), while the second group contains actions that involve interaction with an object. The third group implies tasks in which one external object is used to act on the environment. A detailed description of the task-set can be found in [**?**], [**?**]. In contrast to standard clinical scales that mostly consist of abstract movement executions and postures, the execution of a set of daily living tasks increases the meaningfulness of arm and hand movements, and thereby the ecological validity of measurements.

### B. Experimental setup for data acquisition

The data were recorded with a full-body worn IMU-based system sensor suit (Xsens technologies B.V., Enschede, The Netherlands). The system consists of 17 inertial measurement units (IMUs) placed symmetrically on predefined body positions and fixed with Velcro straps and a size-fitting T-Shirt. The IMUs provide 3D angular velocity using rate gyroscopes, 3D acceleration using accelerometers, 3D earth magnetic field

| Subject ID | Age | Diagnose | AS | DS | Month since stroke | FMA Total NA | FMA Total AS | FMA Arm | FMA Wrist, Hand | FMA coord. |
|---|---|---|---|---|---|---|---|---|---|---|
| P05 | 73 | Dorsal-stream left, TOAST2 | Right | Right | 18 | 62 | 40 | 23 | 14 | 3 |
| P16 | 61 | CVI left, corona radiata | Right | Right | 108 | 66 | 38 | 23 | 11 | 4 |
| P17 | 59 | CVI right, MCA | Left | Right | 20 | 63 | 46 | 25 | 18 | 3 |
| P20 | 42 | CVI right, MCA | Left | Right | 12 | 65 | 39 | 25 | 10 | 4 |
| Median (IQR) | 60.00 (54.75;64.00) | | | | 20 (16;64) | 64.00 (62.75;65.25) | 39.50 (38.75;41.50) | | | |

Fig. 3. Legend: FMA-UE, Fugl-Meyer Assessment of the Upper Extremity; IQR, Interquartile Range; Max., Maximal; MCA, Middle Cerebral Artery; *, Subscale of the FMA-UE.

using magnetometers, as well as atmospheric pressure using the barometer in an operating frequency 2405-1475 MHz [**?**].

A calibration procedure was required to evaluate sensors drifts and internal parameters. This was achieved using information related to subjects' body dimensions and through data fusion. The calibrated model was then used to reconstruct the whole body kinematic description. In particular, 23 links (or segments) connected through 22 spherical joints are used to model the human body. Several relevant motion-related quantities are then calculated and provided as output with a recording frequency of 60 Hz, such as segments and joint position, velocities, and accelerations (see Fig. 2). More details can be found in [**?**]. Once the system is calibrated, the experimental procedure established the repetition of each task of the protocol three times. All measurements were performed in upright sitting position on a chair. Subjects were instructed to perform each movement task at comfortable speed, first using the non-affected and then the affected upper limb. Task actions including grasping and manipulating objects (e.g. transitive and tool-mediated task group, see [**?**], [**?**] for more details) were performed in front of an height-adjustable table (at forearm height in 90 elbow flexion and neutral shoulder position) with the targets placed at about 90 percent of the arm length (shoulder joint-axis until line of proximal interphalangeal joints).

### C. Study information

In this work, we use data recorded from a subset of four chronic stroke subjects, which are part of the observational study *"Assessing pathological synergies of upper limb function and the relationship to visuospatial function after stroke"*. All subjects gave written consent in accordance with the current version of the Declaration of Helsinki and the Swiss regulatory authority requirements. The protocol was approved by the Cantonal Ethics Committee Northwest and Central Switzerland (BASEC-ID: 2016-02075) and registered on ClinicalTrials.gov (Identifier: NCT03135093). Subject-specific characteristics are reported in Fig. 3.

## III. Data Analysis

### A. Modeling and Pre-processing

We decided to use the XZY Euler parametrization to represent the data. In this way, we obtained nine angles in total to describe upper limb kinematics, three for the shoulder, three for the elbow and three for the wrist. Additional details on angles identification are provided in [**?**]. Without any loss of generality and to allow future comparisons, we chose to represent data with a 7 DoF model coherent with [**?**]. For these reasons, we considered only one DoF out of the three provided for the elbow (i.e. flexion-extension), three DoFs for the shoulder, and three DoFs for the wrist (of which one is related to forearm pronation-supination) (See Fig. 2). Recorded data were manually segmented, meaning that for every data stream, we selected initial and final frames of each task repetition. Then, we linearly warped in time all the segments through a re-sampling procedure with respect to a fixed number of time frames ($T = 300$). This was made to enable time-comparison of different movements and allow a proper implementation of functional analysis (see [**?**]).

### B. Evaluation-index of motion complexity

After the pre-processing phase, for each task, we got the temporal evolution of each joint normalized in time. To quantify the complexity of these movements under a functional point of view, a possible strategy is to evaluate how many basis functions are required to reconstruct the specific joint trajectories. Functional Principal Component Analysis (fPCA) represents a classic approach to identify the main modulating functions of one data set, and to order these in a descending order related to the explained variance. fPCA is a functional extension of Principal Component Analysis (PCA), typically used in several research fields to analyze multi-dimensional time series [**?**]. More recently, this technique has

**Algorithm 1** General procedure to calculate Reconstruction Error Plots and Dissimilarity Index ($I_D$)

**procedure** FUNCTIONALPCA
    Resample Signals to $T$ time frames;
    Calculate $fPCs$ (ref. [**?**]);
**end**
**procedure** GETRECONSTRUCTIONERROR
    Load $Dataset$;
    $N \leftarrow$ NumElements($Dataset$);
    $fPCs \leftarrow$ FunctionalPCA($Dataset$);
    $M \leftarrow$ MaxNumfPCs($fPCs$);
    $k \leftarrow 0$;
    **while** $k \leq M$ **do** ▷ For each fPC
        **while** $i \leq N$ **do** ▷ For each element in $Dataset$
            Load $Dataset(i)$;
            $Approx(i) \leftarrow$ Approximate $Dataset(i)$ using the first $k$ fPCs [1];
            $error(k,i) \leftarrow$ rms($Dataset(i) - Approx(i)$);
            $i = i + 1$;
        **end**
        $k = k + 1$;
    **end**
    $GlobalError \leftarrow$ rms($error$) ▷ rms per columns
**end**
**procedure** CALCULATE DISSIMILARITY INDEX ($I_D$)
    Load $Dataset1$;
    Load $Dataset2$;
    $MeanError1 \leftarrow$ GetReconstructionError($Dataset1$);
    $MeanError2 \leftarrow$ GetReconstructionError($Dataset2$);
    $I_D \leftarrow$ norm($MeanError1 - MeanError2$);
**end**

been profitably applied in [**?**] to identify the main functions that modulate human movements.

In the following, we will briefly describe the main idea behind fPCA and how it has been applied for motion description. Let us assume, without any loss of generality, a 7 DoF kinematic model to represent upper limb joint trajectories $q(t) : \mathbb{R} \to \mathbb{R}^7$ where $t \in [0,1]$ is the normalized time. In these terms, generic upper limb motion $q(t)$ can be decomposed in terms of the weighted sum of base elements $S_i(t)$, or functional synergies

$$q(t) \simeq \bar{q}(t) + S_0(t) + \sum_{i=1}^{s_{\max}} \alpha_i \circ S_i(t) \,, \tag{1}$$

where $\alpha_i \in \mathbb{R}^{\mathrm{k}}$ is a vector of weights, $S_i(t) \in \mathbb{R}^{\mathrm{n}}$ - in our case $n$ equals to 7 - is the i$^{\text{th}}$ basis element or synergy and $s_{\max}$ is the number of basis elements. The operator $\circ$ is the element-wise product (Hadamard product). and $\bar{q} \in \mathbb{R}^7$ is the average posture of $q$

$$\bar{q} = \int_0^1 q(\tau) \mathrm{d}\tau \,, \tag{2}$$

while $S_0 : \mathbb{R} \to \mathbb{R}^7$ is the average trajectory, also called *zero-order* synergy. The output of fPCA is a basis of functions $\{S_1, \ldots, S_{s_{\max}}\}$ that maximizes the explained variance of the movements in the collected dataset. Given a dataset with $N$ elements, the first fPC $S_1(t)$ is the function that solves the following problem

$$\begin{aligned} \max_{S_1} \quad & \sum_{j=1}^{N} \Big( \int S_1(t) q_j(t) dt \Big)^2 \\ \text{subject to} \quad & ||S_1(t)||_2^2 = \int_0^1 S_1^2(t) dt = 1 \,. \end{aligned} \tag{3}$$

Subsequent fPCs $S_i(t)$ are the functions that solve the following:

$$\begin{aligned} \max_{S_i} \quad & \sum_{j=1}^{N} \Big( \int S_i(t) q_j(t) dt \Big)^2 \\ \text{subject to} \quad & ||S_i(t)||_2^2 = 1 \\ & \int_0^1 S_i(t) S_p(t) dt = 0 \,, \, \forall p \in \{1, \ldots, i-1\} \,. \end{aligned} \tag{4}$$

A detailed implementation of this method - which bypasses the solution of the minimization problem - is discussed in [**?**]. In this paper we used $s_{\max} = 15$.

It has been proved that the higher is the number of fPCs used to reconstruct a signal, the lower is the error obtained for reconstructing the real data. This observation implies that also the complexity of a sample could be quantified in terms of the number of functional components needed to provide reliable reconstruction. Indeed, given an arbitrary reconstruction error threshold, the higher is the variability of a time series, the higher is the number of fPCs required to approximate the signal with an error lower than the threshold.

In this paper, we propose to exploit these characteristics to quantify the differences, in terms of functional complexity, between two different physical conditions, i.e. non-affected vs. affected upper limb movements. The main hypothesis is that an affected motion, due to the loss of inter-joint coordination or - in other words - increased joint coupling, leads to more simple and less variable joint contributions than the normal condition [**?**], when analyzed on the same task-set of upper limb activities. In our analysis, this should be reflected in the fact that, given a specific number of fPCs used to reconstruct a signal, the reconstruction error will be lower in case of pathological movements. Given $d_i$ as the $i^{th}$ element of the dataset, and given the first $k$ synergies, the approximation error is evaluated as

$$e_k(i) = \min_{\alpha_{j,i}} \quad [\mathrm{rms}(q_i(t) - \hat{q}_i^k(t, \alpha_{j,i}))], \tag{5}$$

where $\hat{q}_i^k(t, \alpha_{j,i})$ is the approximation of $q_i(t)$ using the first $k$ synergies, calculated as

$$\hat{q}_i^k(t) = \bar{q}(t) + S_0(t) + \sum_{j=1}^{k} \alpha_{j,i} \circ S_j(t) \,, \tag{6}$$

and $\alpha_{j,i}$ are the optimal weights associated to the element $d_i$. Representative error values for each $k$ are then calculate as the average $\bar{e}_k = mean([e_k(1), \ldots, e_k(N)])$ and collected in a vector $E = [\bar{e}_1, \ldots, \bar{e}_{s_{\max}}]$.

A schematics of this idea is depicted in Fig. 4, where the red plot refers to affected motion, while the green plot refers to the non-affected motion. The blue area within the two

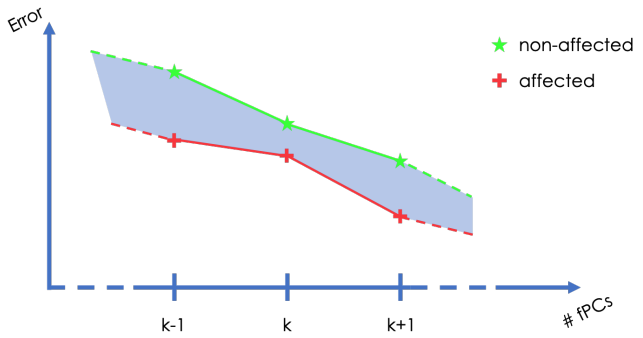


Fig. 4. Typical profiles of reconstruction error w.r.t. the number of fPCs enrolled. Red and green lines are the expected shapes in case of affected and healthy motion, respectively. The area between the two curves can be intended an an index of dissimilarity between the two conditions.

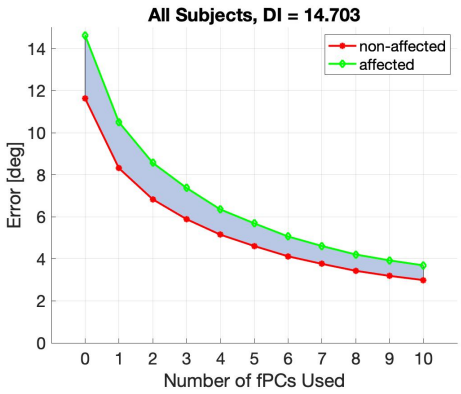


Fig. 5. Root Mean Square of reconstruction error vs. number of fPCs used. All subject are considered for this analysis. $I_D = 14.703$

profiles can be regarded as an index of dissimilarity between the two conditions. The dissimilarity index ($I_D$) can be easily calculated as:

$$I_D = \sum_{i=1}^{s_{\max}} E_H(i) - \sum_{j=1}^{s_{\max}} E_S(i) = \sum_{i=1}^{s_{\max}} (E_H(i) - E_S(i)), \quad (7)$$

where $E_H$ is the vector of reconstruction error for the healthy case, $E_S$ is the vector of reconstruction error for the stroke case.

The procedure to obtain the plots theorized in Fig. 4 and to calculate $I_D$ is reported in Alg 1. Please note that under a theoretical point of view, this methodology could be generalized to the analysis of different types of motion datasets with multiple subjects, and applied to intra-subject analysis.

## IV. Results and Discussions

To verify whether our main hypothesis holds true, we calculated the dissimilarity index ($I_D$) defined in the previous section between the whole data-set of non-affected arm motions and the whole data-set of affected arm motions. Results are depicted in Fig. 5 for all the stroke subjects. It is possible to observe that the reconstruction error is lower for the affected upper limb, as per research hypothesis discussed in the previous section. The blue area can be used as a gross difference index between the affected and non-affected conditions for all stroke subjects in the whole data sample ($I_D = 14.703$). This result supports our assumption that analysis of movement variability can be used to effectively distinguish between non-affected and affected conditions due to stroke.

To further characterize the proposed $I_D$ as index of the impairment level, we performed the same analyses on a single-subject-level. In order to evaluate whether our approach is able to differentiate between subjects and their individual impairment severity, we repeated our procedure to each single-subject's data-set. Results, reported in Fig. 6, illustrate differences in terms of movement variability between the affected and non-affected side of each subject. While our main hypothesis of lower reconstruction errors in the affected arm holds true for S1, S2 and S3 ($I_D$ ranging from 12.12 to 27.31), higher reconstruction errors are visible in the affected arm of S4 when compared to the non-affected side leading to a negative $I_D$ equal to -6.91. We believe that, this higher variability in the affected arm is related to extra-movements, which S4 performed to compensate for the diminished grasp function (FMA-UE hand score: 4 out of 14) when performing the transitive and tool-mediated task actions. To verify this hypothesis, we performed the same approach for the subset of intransitive task actions, where finger and hand functions are not crucial for the task accomplishment, for all the considered subjects. Almost equal variability profiles between the affected and non-affected arm and a $I_D$ of 1.27 were found in S4, supporting the idea of approximately normal movement behavior as long as no hand or finger function is needed, whereas the movement variability seems to be comparably diminished in S1 ($I_D$ of 11.65), S2 ($I_D$ of 24.33) and S3 ($I_D$ of 12.60). Illustrations of these analyses are omitted for sake of space.

## V. Implications and Conclusions

In this proof-of-principle work, we demonstrated how stroke subjects' level of impairment may be assessed through the quantification of upper limb movement variability, in terms of the resulting root mean square of reconstruction error using a fPCs based description. The $I_D$ calculated upon the whole dataset revealed differences in terms of motion variability between the two upper limb conditions. In this manner, novel measurement outcomes are provided to describe stroke-related upper limb movement impairments, such as the loss of inter-joint coordination, commonly associated with reduced variability of motion elements, when performing a comprehensive set of daily living activities. This opens fascinating perspectives toward the usage of this methodology as a tool for assessing motor impairment after a stroke, herein defined as reduced movement variability, in a quantitative, sensitive and operator-independent fashion. Although only preliminary, results seems confirming our hypothesis of generally lower profiles of reconstruction errors in the affected compared to the non-affected upper limb (as shown in Fig. 5 by comparing both conditions for the whole set of four subjects as shown in Fig. 6). The single-subject analysis revealed a $I_D$ ranging from 27.31 in S2 to -6.91 in S4, that can partially be explained by clinical assessment outcomes as shown in

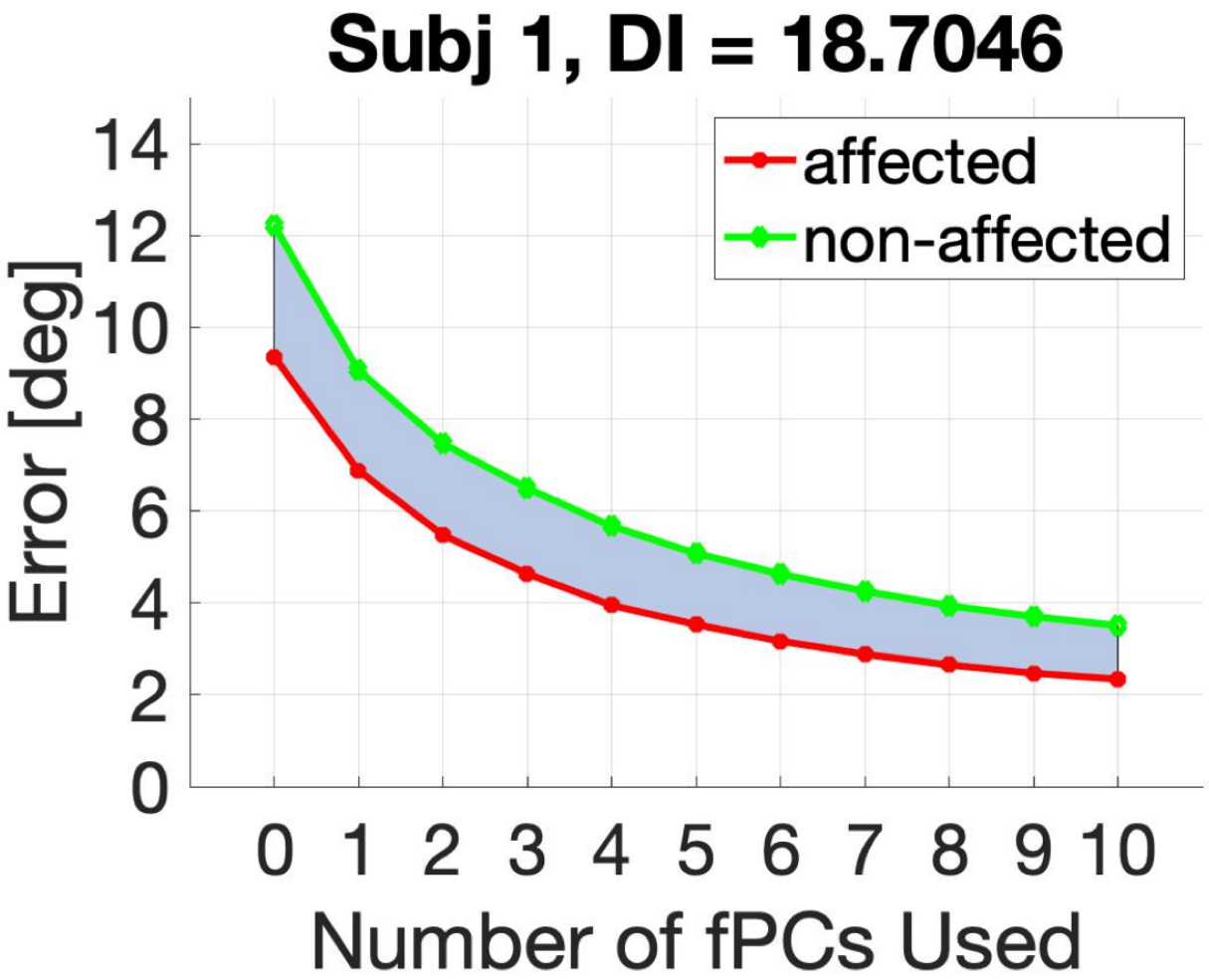


Fig. 6. Root Mean Square of reconstruction error vs. number of fPCs used. Each sub-plot reports the analysis subject-specific. From top-left to bottom-right results for Subjects from 1 to 4 are considered. Correspondent $I_D$ is reported in figure headings.

Fig.3. Studies on a larger data set are needed to confirm these preliminary findings, also including other motor impairments, such as ataxia, which would likely influence the results and interpretation of the presented outcomes. These findings suggest the usefulness of fPCA to study the motion variability and provide implications for sensitive outcomes of post-stroke upper limb impairment, which may be effectively used as suitable biomarkers to discriminate between pathological and physiological movement behaviour in stroke research and rehabilitation [**?**]. In [**?**] the authors similarly found correct predictions of the presence or absence of basic limb synergies (defined by FMA-UE $\geq 34$ and FMA-UE $< 34$) for 38 of 46 patients (82.6%) using PCA on endpoint reaching kinematics. Here, we extend the PCA to the whole time set of motion data using shape analysis described in functions, which enables the investigation of dynamic aspects of movement behavior, including the spatio-temporal evolution of joint trajectories to precisely describe pathological joint coupling or pathological synergies due to stroke. However, we acknowledge that, in contrast to the classical PCA performed at one point in time, direct coupling between joints are not explicitly considered with our approach. As another limitation, we acknowledge that limiting the application of the approach to the upper limb except for the hand and fingers could lead to erroneous assessment and interpretation of the results. For this reason, model extensions to hand and finger motions will be considered to additionally include relevant kinetic information for grasping activities. Finally, our future works will also take into account possible deficits in the non-affected arm. Considering previous works on physiological movement datasets [**?**], here, we could broaden the analysis to pathological movement data from mildly to moderately affected stroke subjects, when performing a set of daily living tasks. In a next step, differences between specific single task-items will be investigated using the same methodology. Finally, this methodology could be further exploited for an automatic recognition of physiological and pathological movements through machine learning and in terms of online evaluations of improvements related to rehabilitation procedures.