Component-Level Tuning of Kinematic Features from Composite Therapist Impressions of Movement Quality

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***Abstract*—In this paper, we propose a general framework for tuning component-level kinematic features using therapists' overall impressions of movement quality, in the context of a Home-based Adaptive Mixed Reality Rehabilitation (HAMRR) system. We propose a linear combination of non-linear kinematic features to model wrist movement, and propose an approach to learn feature thresholds and weights using high-level labels of overall movement quality provided by a therapist. The kinematic features are chosen such that they correlate with the quality of wrist movements to clinical assessment scores. Further, the proposed features are designed to be reliably extracted from an inexpensive and portable motion capture system using a single reflective marker on the wrist. Using a dataset collected from ten stroke survivors, we demonstrate that the framework can be reliably used for movement quality assessment in HAMRR systems. The system is currently being deployed for large-scale evaluations, and will represent an increasingly important application area of motion capture and activity analysis.**

***Index Terms*—Stroke rehabilitation, movement quality assessment, kinematic features.**

I. Introduction

STROKE is the most common neurological disorder worldwide [1] leaving behind a significant number of survivors every year disabled with chronic impairments such as problems with vision, difficulty to formulate or understand speech, or inability to move limbs. Even with persistent efforts to lower blood pressure and reduce smoking, the incidence of stroke remain high due to the ageing population, with nearly three-quarters of stroke related events experienced by people over the age of 65 [2], [3]. This increasing demand for rehabilitation facilities has been seen as a significant healthcare problem worldwide [4], [5]. In addition, studies indicate that the increasing healthcare costs paired with insufficient coverage by insurance for long-term therapy treatment has often left impairments untreated [6]. Hence, it is important to have well-thought-out strategies to manage these stroke survivors by providing low-cost long-term rehabilitation therapy for their recovery.

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Traditional rehabilitation therapy is usually composed of repetitive movement tasks such as reaching and grasping an object. A participant performs these movement tasks in a hospital under the supervision of a physical therapist, who visually monitors the quality of movement over time to provide personalized rehabilitation therapy. This laborious and expensive process has motivated researchers to invent novel strategies to accelerate hospital discharge without compromising on clinical outcomes.

Challenges in Developing Component-level Kinematic Features: Therapists are trained to assess the overall performance of a task, which can also be achieved through existing validated clinical measures such as the Wolf Motor Function Test (WMFT) [7] and the Fugl-Meyer Assessment (FMA) [8]. Such clinical measures do not provide enough information about the component-level impairments, which will be useful in providing focused rehabilitation. The motivation of our research was to develop a computational framework for component-level tuning of kinematic features such as trajectory error, speed profile deviation, jerkiness, and segmentation using the composite (overall) therapist impressions of movement quality to drive the feedback module in the HAMRR system.

One recurring problem in the stroke rehabilitation community is the general lack of consensus among physical therapists in defining an ontology of component level labels for movement quality, thereby leading to lack of training datasets to develop algorithms for movement quality assessment. In addition, therapists only provide composite assessments indicative of quality of overall movement without any information about components such as deviation in speed profile, leading to a challenging problem to train the component-level kinematic features, which are required to provide personalized rehabilitation and facilitate active learning without therapist supervision. An illustration of the above concept is shown in Fig. 1, where the aim is to induce active learning by providing auditory and visual feedback implying the impairments in low-level components such as trajectory inaccuracy, tremor, and segmentation [9]. In Fig. 1, (a) and (c) represent the

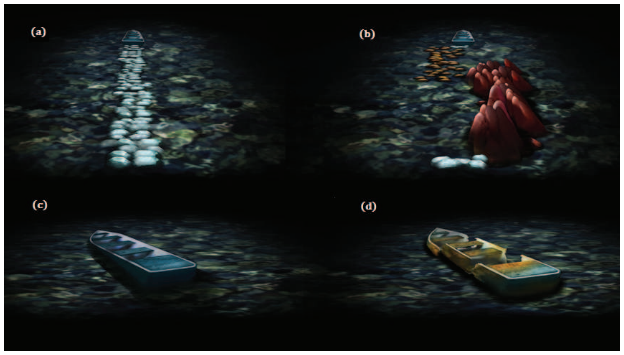


Fig. 1: Exemplar visual feedback summaries based on low-level kinematic analysis. (a) represents an efficient reach, (b) represents trajectory error to the right. (c) is a representation of an efficient and consistent task completion and (d) represents segmented movement.

Fig. 2: The Home-based Adaptive Mixed Reality Rehabilitation (HAMRR) system designed for stroke survivors. The system uses four OptiTrack cameras to track the wrist movements as well as a computer and speakers to provide audio and visual feedback during therapy treatment. The table is designed to accommodate custom touch and grasp objects for training reaches in different orientations. In the inset, we see the placement of a wrist marker on a participant performing reaching tasks to a cone. The system design is discussed in detail in [9].

visual feedback seen during an efficient reach (reach trajectory without any impairments) marked by a straight path of rocks or a complete boat, while (b) represents a reach with trajectory error on the right marked by curved path of rocks (in red), and (d) represents a reach with segmentation error marked by a broken boat.

Towards Home-based Rehabilitation Systems: Clinical intervention alone is not completely effective for restoring daily activity functionality in a stroke survivor [10]–[13]. A comprehensive study involving 1277 stroke survivors has reported that an early hospital discharge and home-based rehabilitation strategy resulted in reduced length of stay by 13 days, and overall mean costs being 15% lower compared to standard care, without any significant effect on mortality or clinical outcomes [14]. A similar long-term study has reported significant reduction in hospital stay without any change in health outcomes in stroke survivors who experienced home-based rehabilitation compared to traditional rehabilitation care [15].

Interactive neurorehabilitation systems which computationally evaluate and deliver feedback based on a subject's movement performance have been utilized to provide home-based rehabilitation care. With advances in 3D motion capture and wearable sensor technology, researchers from various backgrounds have developed objective measures for movement quality assessment during and following rehabilitation [16]–[20]. Virtual and mixed reality environments have been employed in novel stroke rehabilitation strategies [21]–[24]. In this direction, Adaptive Mixed Reality Rehabilitation (AMRR) system which integrates rehabilitation and motor learning theories with motion capture, activity analysis, and multimedia feedback [25], [26], has been shown as an effective rehabilitation system in helping improve the kinematic and functional performance of a stroke survivor's upper extremity in a hospital setting. Examples of visual feedback for active learning using the home system are shown in Fig. 1. In addition, accommodating heavy marker-based systems in a home-based setting is unrealistic, as inaccurate placement of markers can negatively affect the movement quality assessment framework and place a heavy burden on the stroke survivor and/or caregiver. In recent years, the focus of rehabilitation research has been towards devising multi-modal interventions and accompanying tools to assist home-based therapy [9], [25], [27], thereby supplementing traditional therapy received in the hospital. A solution to this was proposed in [9], where a single reflective marker was placed on the participant's wrist to track the movement (see Fig. 2). A recent study has shown that a single marker-based system (marker on the wrist) can achieve comparable performance levels of movement quality assessment to a heavy marker-based system [17].

In this paper, our aim is to use the composite labels provided by therapists' impressions to learn the underlying movement components. We propose several kinematic features and learn the associated thresholds and weights using composite labels for reach data. This research facilitates better understanding of the underlying components defining movement quality and also the generation of a '*cumulative score*' for movement quality, which can aid physical therapists in visual monitoring during supervised rehabilitation therapy.

Contributions: Our aim is to decompose the movement quality score (given by therapists) into its constituent kinematic components. We assume a linear relation between kinematic features and composite movement quality score. This paper has two main contributions: 1) propose component-level kinematic features for movement quality assessment of wrist movement, 2) propose a generic framework for tuning the thresholds and weights associated with each of these kinematic features using movement quality labels provided by therapists.

II. Related Work

Quantifying movement quality is useful for physical therapists to provide improved and personalized rehabilitation therapy. Several quantitative scales for movement quality assessment have been proposed, including the FMA [8] and the WMFT [7]. For example, the WMFT has been used to quantify the upper extremity motor ability through timed and functional tasks [28]. However, these methods rely on visual monitoring of movements by experienced and trained physical therapists. Hence, these methods can be subjective, as a therapist will apply their individual training and impressions when evaluating a participant's movement quality. Developing an objective computational framework for movement quality assessment will be beneficial, thereby minimizing the influence of a therapist.

The focus of existing approaches for movement quality assessment has been towards finding typical patterns in kinematic attributes which differ between healthy and impaired participants. Kinematic Impairment Measure (KIM) proposed by Chen *et al.* [16] employs 33 kinematic attributes derived from a heavy-marker based system in a hospital setting to quantitatively evaluate the movement quality. This study showed that the weighted average of individual kinematic attributes was strongly correlated with the WMFT scores. Similar work using kinematics to model the smoothness of the movement have also been explored [29], [30]. In a similar study, it was shown that features derived from wearable sensor data can be used to estimate the FMA score [31].

Rehabilitation robotics has gained a lot of attention in quantification of motor functionality due to its ability to offer objective and repeatable therapy treatment [32]–[38]. Linear regression model-based kinematic scales were developed using the MIT-Manus robot to achieve highly a repeatable and high resolution framework for quantification of motor performance [39]. Another robotics-based rehabilitation technique proposed four measures showing correlation with clinical measures such as FMA, MAL, Action Research Arm Test, and Jebsen-Taylor Hand Function Test [40]. A recent work using movement time, trajectory length, directness, smoothness, and mean and maximum velocity claims that such kinematic features can be effectively used to assess upper limb motor recovery and is linked to FMA score [41].

Nonlinear dynamical analysis methods have been employed to model the variability in repetitive movements, which are an integral part of rehabilitation therapy [18], [42]. To address the drawbacks of traditional nonlinear dynamical measures, a shape theory based dynamical analysis framework for movement quality assessment was proposed [17]. This study also demonstrated that the information contained in a single marker on the wrist is sufficient to achieve comparable performance levels to a heavy marker-based system in movement quality assessment.

The outline of the paper is as follows: The design of the home-based rehabilitation system and protocol for collecting reach data from stroke survivors are discussed in sections III and IV, respectively. In section V, we propose component-level kinematic features and a framework to tune the associated thresholds and weights using overall therapist impressions for movement quality. The results of the proposed frameworks in section V on data collected from ten stroke survivors are discussed in section VI.

III. System Design

The HAMRR system has four Natural Point Opti-Track cameras facing down on a table to track a single reflective marker placed on the participant's wrist (wrist marker). The selection of the wrist marker was motivated by previous investigations indicating that the wrist trajectory is the most informative joint about the reach trajectory [16], [17], [23], [43], [44]. The system also tracks torso movement using four reflective markers attached to a badge worn on the left side of the participant's chest. Effective upper extremity rehabilitation requires monitoring of such aspects of the body movement to evaluate the extent participant's compensation while performing a task. In this study, we focus solely on the data collected from the wrist marker.

The table houses a contact switch rest position pad and can accommodate a target location of the cone object based on the participant's reaching ability. While we only consider reaching tasks for the cone object located on the left of a participant, the system was designed to accommodate custom touch and grasp objects for training reaches in different orientations. The system is shown in Fig. 2 and detailed information of the system design can be found in [9]. The main objective of this design was to be able to install the system in a participant's home for long term therapy treatment, which prohibits the use of a heavy marker-based system.

IV. Data Collection

Therapists undergo training to assess both the overall performance of a task and monitor some individual coarse aspects of movement for a set of reaches. While validated clinical measures exist for assessing overall task performance, no such measures currently relate these to performance of component-level kinematic attributes for an individual reach. Therefore, in this study we have collected therapist ratings for quality of wrist trajectory for each reach in an attempt to build a computationally generated component-level assessment that correlates with therapist impressions.

The dataset consists of reaching tasks performed by a total of ten participants (refer to Table I for demographics) to an on-table cone left of the participant's rest position. Each participant performs five reaches in each of four sessions. An iPad application was developed to assist therapists in administering the system experience questionnaire, recording videos of reaching tasks, and providing movement quality labels. These videos were later segmented to contain individual reaches, which were randomized across participants and provided to two physical therapists (each therapist would rate a reach movement which was not repeated by the other therapist) to rate each reach in terms of overall performance of the task. Overall reaching performance was rated on a scale from 1-5 based on the therapist's impression of the participant's performance, where a 1 denotes that the participant could

Name	Age	Gender	Time since stroke*	Lesion Location	FMA Score(/66)
S1	63	Male	14	Left posterior frontal ischemic	37
S2	69	Male	44	Left ICH (fronto-parietal)	50
S3	65	Male	31	AVM rupture	47
S4	47	Male	26	Left pontine infarct	47
S5	56	Male	28	Left Internal Capsule	44
S6	49	Male	18	Left MCA (Middle cerebral artery)	37
S7	64	Female	6	Unknown	28
S8	27	Male	12	Unknown	26
S9	50	Male	15	Left basal ganglia hemorrhage	30
S10	44	Female	13	Ischemic left pons	29

TABLE I: The demographics and FMA score of the stroke survivors who participated in our study and have experienced the HAMRR system. All participants had impairment in their right hand with one stroke event. *Time since stroke event is in months.

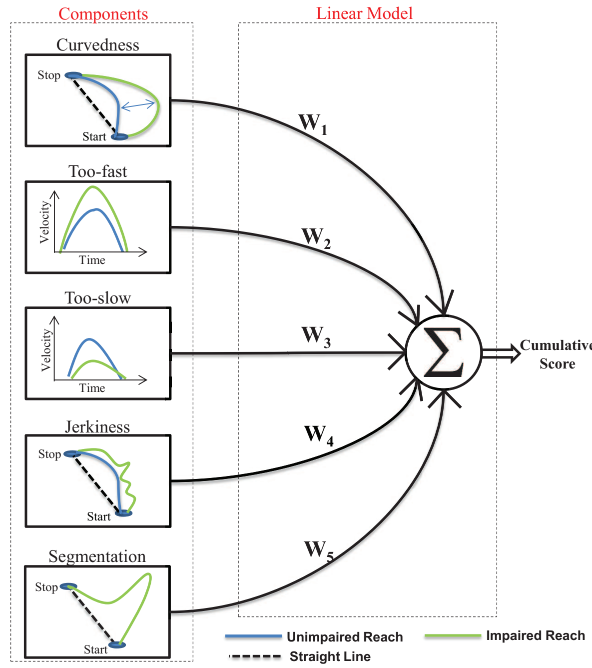


Fig. 3: The proposed linear model of kinematic features extracted from the wrist marker. The weights (W_1, W_2, …, W_5) and a unique threshold associated with each kinematic feature (T_1, T_2, …, T_5) were estimated by minimizing the L_1 norm between *cumulative score* and *therapist rating* (R_j^w).

not complete the task and a 5 denotes that the participant performed the task with the same quality of performance as the therapist if he/she were to perform it. This rating scale was adapted from the WMFT Functional Assessment Score [7] by rehabilitation experts who collectively created a rubric for the purposes of this study.

V. Quality Assessment of Wrist Trajectory

In this section, we introduce the framework for quantitative assessment of quality of wrist trajectory using kinematic analysis. We learn kinematic features using composite movement quality labels provided by therapists. The proposed kinematic features were designed to evaluate the movement along five aspects of impairment with respect to hand trajectory performance: *curvedness, fastness, slowness*, *smoothness* and *segmentation* (see Fig. 3 for pictorial representation of these features). Each of these kinematic features have a unique threshold (T_i) which is difficult to define, and hence we use optimization theory to estimate these values. We also learn the weights in our proposed linear model using the same framework which is discussed in section V-G. The steps involved in feature extraction are explained below.

A. Choice of Kinematic Features

The movement during reach and grasp action is thought to be controlled by considering the end-point (wrist) as the guiding reference [23], [43], [44]. Hence, the end-point acts as the interactor between the environment and the action goal to reach the target. Further, studies indicate that the end-point trajectory data from multi-joint movement such as reach and grasp (e.g., movements utilizing both shoulder and elbow) consistently have nearly invariant kinematic characteristics, such as straight-line trajectory paths and bell-shaped velocity profiles [45]–[47]. The findings from these studies have motivated our selection of kinematic features to represent the reach and grasp action focusing significantly on the end-point using trajectory error, velocity profile deviation, jerkiness and segmentation.

B. Pre-processing of Trajectories

The three-dimensional positions of the wrist marker $p(t) = [\mathbf{x}(t), \mathbf{y}(t), \mathbf{z}(t)], \quad t = 0, \ldots, \tau$ were recorded from the start of the movement to the target grasp state. The coordinate system was rotated such that $p(0)$ was the origin, $\mathbf{X} - \mathbf{Z}$ plane was the horizontal plane and the straight line connecting $p(0)$ and $p(\tau)$ lies along the new $\mathbf{Z}$-axis. This in effect re-parameterizes (after normalization) the trajectory $[\mathbf{x}(t), \mathbf{y}(t), \mathbf{z}(t)], \quad t = 0, \ldots, \tau$ to $[\mathbf{x}'(\mathbf{z}), \mathbf{y}'(\mathbf{z})], \quad \mathbf{z} = 0, \ldots, 1$. This re-parameterization works without introducing significant ambiguity in our experiments due to the strong directionality of the reach action. The $\mathbf{Z}$-axis was further quantized into $N = 50$ bins, thereby transforming the trajectory to $[\mathbf{x}'(n), \mathbf{y}'(n)], \quad n = 0, \ldots, N-1$. We now have a vector representation of the trajectory suitable for real-time comparisons. For every new sequence, the 3-D positions from the start of the movement to the end were rotated from the global coordinate to the new coordinate system. This rotated and normalized axes facilitates easier calculation of deviation of kinematic features from a reference trajectory (efficient reach trajectory collected from mean-age matched unimpaired participants).

C. Trajectory Error

Trajectory error is a measure of spatial deviation of the wrist trajectory from the reference trajectory. For every point in the reach trajectory, horizontal error (E_{hor}) and vertical error (E_{vert}) were defined as

$$E_{hor}(i) = \mathbf{x}(i) - \mathbf{x}_{ref}(i), \quad i = 0, \ldots, N_s - 1 \tag{1a}$$

$$E_{vert}(i) = \mathbf{y}(i) - \mathbf{y}_{ref}(i), \quad i = 0, \ldots, N_s - 1 \tag{1b}$$

where N_s is the number of points in the reach trajectory. A thresholded error function was calculated as

$$\hat{E}_{hor}(i) = \begin{cases} E_{hor}(i) & \text{if } E_{hor}(i) > T_1 \\ 0 & \text{otherwise.} \end{cases} \tag{1c}$$

Similarly,

$$\hat{E}_{vert}(i) = \begin{cases} E_{vert}(i) & \text{if } E_{vert}(i) > T_1 \\ 0 & \text{otherwise.} \end{cases} \tag{1d}$$

Confidence values for the movement being curved were estimated as

$$C_{\mathbf{x}}^{curved} = \frac{\sum\limits_{<i>} |\hat{E}_{hor}(i)|}{\sum\limits_{<i>} |E_{hor}(i)|} \tag{1e}$$

$$C_{\mathbf{y}}^{curved} = \frac{\sum\limits_{<i>} |\hat{E}_{vert}(i)|}{\sum\limits_{<i>} |E_{vert}(i)|} \tag{1f}$$

The final confidence of curved movement was a combination of the above two confidences,

$$C_{T_1}^{curved} = \begin{cases} \lambda_1 & \text{if } \lambda_1 > 2\lambda_2 \\ min(1.5\lambda_1, 1) & \text{otherwise} \end{cases} \tag{1g}$$

$$\text{where } \lambda_1 = 1 - max(C_{\mathbf{x}}^{curved}, C_{\mathbf{y}}^{curved}),$$
$$\lambda_2 = 1 - min(C_{\mathbf{x}}^{curved}, C_{\mathbf{y}}^{curved}).$$

D. Speed Profile Deviation

It is a measure of deviation of the speed profile from the reference speed profile (speed profiles collected from 10 unimpaired participants to generate a reference). For a given reach trajectory, a point-to-point comparison of speeds with the reference speed profile was calculated. The speed vector for the reference and test data are denoted as $v_{ref}(i)$ and $v(i)$ respectively and was calculated as the first derivative of the position vector. The thresholded speed vector for *fastness* feature was calculated as

$$\hat{v}_f(i) = \begin{cases} v(i) & \text{if } v(i) - v_{ref}(i) > T_2 \\ 0 & \text{otherwise} \end{cases} \tag{2a}$$

The confidence score for movement being too-fast was computed as C^{fast} given by

$$C_{T_2}^{fast} = 1 - \frac{\sum\limits_{<i>} \hat{v}_f(i)}{\sum\limits_{<i>} v(i)} \tag{2b}$$

Similarly, the thresholded speed vector for *slowness* feature is given by

$$\hat{v}_s(i) = \begin{cases} v(i) & \text{if } v(i) - v_{ref}(i) < T_3 \\ 0 & \text{otherwise} \end{cases} \tag{2c}$$

The confidence score for movement being too-slow was calculated as C^{slow} given by

$$C_{T_3}^{slow} = 1 - \frac{\sum\limits_{<i>} \hat{v}_s(i)}{\sum\limits_{<i>} v(i)} \tag{2d}$$

E. Jerkiness

The jerkiness (or smoothness) feature is a measure of variations in the velocity profile. An '*efficient*' reach movement should have a smooth velocity profile with an accelerating pattern followed by a decelerating pattern without any jerks. Jerkiness of a movement was calculated using the method described in [16] (similar to [29]) and is given by

$$J = \int_{t_{som}}^{t_{eom}} \sqrt{\left(\frac{d^3\mathbf{x}}{dt^3}\right)^2 + \left(\frac{d^3\mathbf{y}}{dt^3}\right)^2 + \left(\frac{d^3\mathbf{z}}{dt^3}\right)^2} dt \tag{3a}$$

where $\mathbf{x}, \mathbf{y}$ and $\mathbf{z}$ are 3-D coordinates of the position of participant's wrist. t_{som} is the time index corresponding to the start of the movement and t_{eom} is the time index of the end of the movement. The thresholded jerkiness function was calculated as

$$\hat{J}(i) = \begin{cases} J(i) & \text{if } J(i) > T_4 \\ 0 & \text{otherwise} \end{cases} \tag{3b}$$

The confidence score for movement being jerky was calculated as

$$C_{T_4}^{jerk} = 1 - \frac{\sum\limits_{<i>} \hat{J}(i)}{\sum\limits_{<i>} J(i)} \tag{3c}$$

F. Segmentation

A movement is termed as '*segmented*' if the elbow does not open in synchrony with the shoulder moving forward. Instead, the forward movement of the shoulder and the opening of the elbow happens in sequence, resulting in a disjointed movement (or presence of submovements). Rohrer *et al.* [48] have shown how paretic movement can be represented by submovements using MIT-MANUS and InMotion2 robots, which allows motion within a horizontal plane. An accurate analysis of this phenomenon (presence of submovements) requires tracking of both shoulder and elbow in addition to the wrist. In the proposed home-based rehabilitation system, this was not possible with the one marker sensing solution, and we wanted to learn if such movements can be described computationally using only the wrist marker.

After consultation with domain experts, it was found that segmented movements give rise to notches (sudden change in direction) in the wrist trajectory. These notches can be quite subtle and often occur towards the end of the movement. We quantify segmented movements by calculating the following:

1) The number of times the movement changes its turning direction

2) The magnitude of direction change
3) The ratio of the magnitude of direction change

We project the 3D trajectory onto the **X-Z** and **Y-Z** planes to detect the direction changes (notches). In the projection onto the **X-Z** plane, we first compute displacement vectors from the spatial locations. The direction change was quantified as the *signed angle* ($\alpha_{\mathbf{xz}}(i)$) between successive displacement vectors. The sign of the angle is positive if the displacement is clockwise from the previous displacement vector and negative if it is counter-clockwise. Using this, the number of significant changes in turning direction of the movement is calculated (N_C), and the corresponding confidence is calculated as

$$C_{seg1,\mathbf{xz}} = \begin{cases} 1 - e^{-(a \cdot N_C)^b} & \text{if } N_C > N_{ref} \\ 0 & \text{otherwise} \end{cases} \tag{4a}$$

The magnitude of direction change is computed as $S = \sum_{<i>} |\alpha_{\mathbf{xz}}(i)|$, and the corresponding confidence score was given by

$$C_{seg2,\mathbf{xz}} = 1 - e^{-(a \cdot \lambda_S)^b} \tag{4b}$$

$$\lambda_S = \begin{cases} 1 - S/ref_{\mathbf{xz}} & \text{if } S < ref_{\mathbf{xz}} \\ 0 & \text{otherwise} \end{cases} \tag{4c}$$

The ratio of magnitude of direction change is defined as $\gamma = \frac{|\sum \alpha_{\mathbf{xz}}(i)|}{\sum |\alpha_{\mathbf{xz}}(i)|}$, and the corresponding confidence score was computed as

$$C_{seg3,\mathbf{xz}} = \begin{cases} 1 & \text{if } \gamma < \gamma_{ref} \\ 1.47 * (1 - \gamma) & \text{otherwise} \end{cases} \tag{4d}$$

The final confidence for segmentation of the projected movement on $\mathbf{X} - \mathbf{Z}$ plane is computed as

$$C_{\mathbf{xz}} = C_{seg1,\mathbf{xz}} \cdot C_{seg2,\mathbf{xz}} \cdot C_{seg3,\mathbf{xz}} \tag{4e}$$

Similarly, we can compute $C_{\mathbf{yz}}$ in the **Y-Z** plane. Let $\beta_1 = 1 - max(C_{\mathbf{xz}}, C_{\mathbf{yz}}), \beta_2 = 1 - min(C_{\mathbf{xz}}, C_{\mathbf{yz}})$. The final confidence of segmented movement is given by

$$C^{seg}_{T_5} = \begin{cases} \beta_1 & \text{if } \beta_1/\beta_2 > T_5 \\ min(1.5\beta_1, 1) & \text{otherwise} \end{cases} \tag{4f}$$

The thresholds $T_1, \ldots, T_5$ were difficult to define and hence optimal values for these thresholds was estimated using movement quality label provided by therapist. Thresholds such as $N_{ref}, ref_{\mathbf{xz}}, \gamma_{ref}$ were determined from the data collected from unimpaired participants. The constants a and b were selected through empirical observation. The confidence scores range from 0 to 1, with 0 indicating maximum impairment and 1 indicating movement being similar to an unimpaired participant's reach.

G. Estimation of Optimal Weights and Thresholds

A physical therapist rating the quality of reach trajectory will pay careful attention to many kinematic attributes, including speed, trajectory and jerkiness. We believe that a linear combination model of the non-linear kinematic features will be correlated with the therapist rating. In this paper, we propose a linear model of kinematic features for movement quality assessment by posing an optimization problem to determine the thresholds and weights associated with each kinematic feature in the linear combination model. Hence, the equation for the linear model for movement quality assessment for the wrist trajectory can be written as

$$\Big\{ w_1 C^{curved}_{T_1} + w_2 C^{fast}_{T_2} + w_3 C^{slow}_{T_3} + w_4 C^{jerk}_{T_4} + w_5 C^{seg}_{T_5} \Big\} \approx R^w_j \tag{5}$$

where, $w_1, \ldots, w_5$ are weights for each of the confidence scores of kinematic attributes *curvedness, fastness, slowness, jerkiness and segmentation*, respectively. R^w_j is the therapist rating for quality of wrist trajectory. The thresholds $T_1, \ldots, T_5$ bound a region called 'zero-zone' where the attribute value is termed '*efficient*' (indicating a reach movement without any impairments). For example, eq. (2a) has a threshold T_2 which represents a 'zone' of ideal speed profiles. Eq. 5 is pictorially depicted in Fig. 3. The aim here is to minimize the error between cumulative score and therapist rating in L_1 sense to estimate thresholds and weights associated with each kinematic feature. The cost function can be written as

$$\begin{aligned} P1 : \{w_1, \ldots, w_5, T_1, \ldots, T_5\}^{opt} = \\ \underset{w_1,\ldots,w_5,T_1,\ldots,T_5}{\arg\min} \sum_{<j>} | \sum_{i=1}^{5} w_i C^i_{(T_i)} - R^w_j | \\ \text{subject to} \quad w_i \geq 0, \\ 0 \leq T_i \leq 10. \end{aligned} \tag{6}$$

This cost-function is difficult to optimize, and is non-convex. In order to solve this optimization problem, we use the active-set method [49], because of its reduced complexity of the search, as the algorithm uses a subset of inequalities while searching the solution. We use the implementation of the active-set method available in Matlab.

VI. Experimental Results

In order to measure the efficacy of the proposed optimization procedure, we look at the output (cumulative score) generated by the forward-model in eq. 5. The results of our analysis using the linear combination of kinematic features for movement quality assessment of the wrist trajectory are shown in Fig. 4. The information about participants who experienced our system is tabulated in Table I. Each participant performed 20 repetitions of reach and grasp to a cone target, except participants $S7, S8$, and $S10$ who performed 5, 5, and 15 repetitions, respectively. Fig. 4 shows the comparison between the movement quality scores provided by a trained physical therapist against the cumulative score predicted by our proposed framework. If the feature thresholds and combination weights were tuned, we expect the cumulative predicted scores to be correlated with the therapist ratings. The Pearson correlation coefficient between the cumulative scores and the therapist ratings was found to be 0.6 with a significant p-value ($p < 0.001$). The results of our analysis using the linear combination

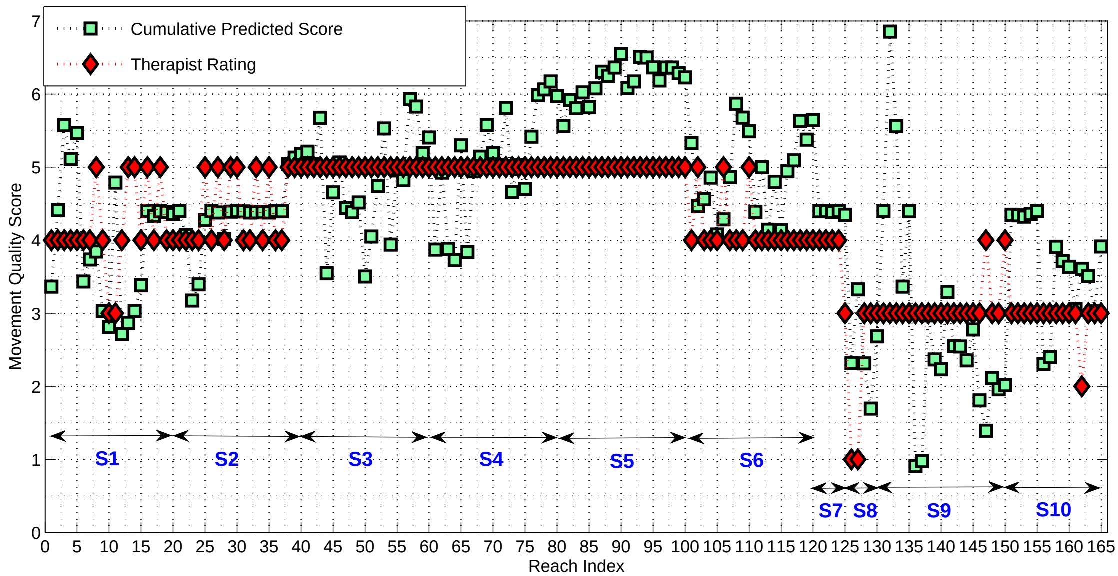
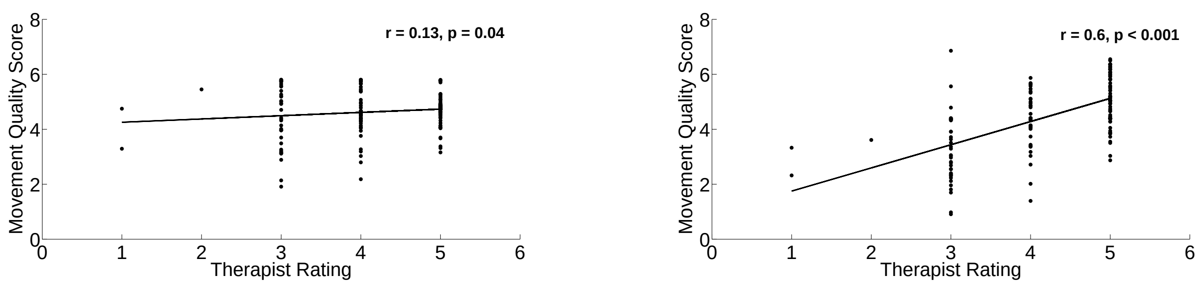


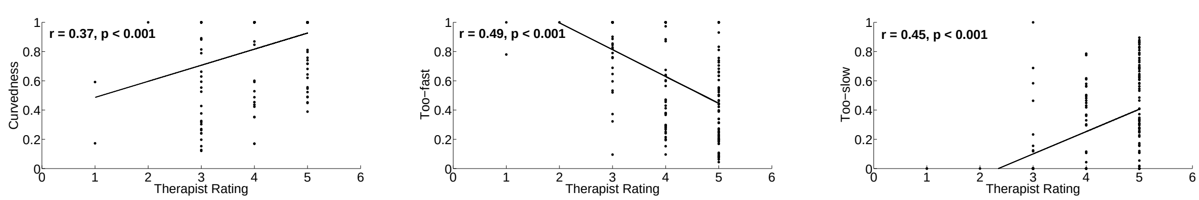
Fig. 4: Comparison between the predicted cumulative score and therapist rating for movement quality. Each of 10 participants performed 20 reach and grasp to cone tasks except subjects S7, S8, and S10. The demographics and FMA score for each subject is tabulated in Table I. A correlation of 0.6 exists between the predicted cumulative score and therapist rating for movement quality.



(a) Before Optimization

(b) After Optimization

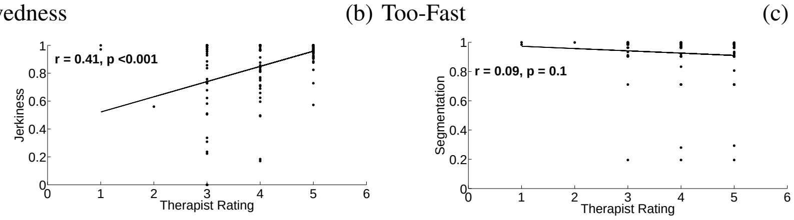
Fig. 5: Comparison of cumulative score and therapist rating before and after optimization procedure. A linear regression plot between cumulative score and therapist rating indicates that correlation coefficient increases from 0.13 to 0.6 with a significant p-value and increased slope.



(a) Curvedness

(b) Too-Fast

(c) Too-Slow



(d) Jerkiness

(e) Segmentation

Fig. 6: Linear regression plots for various low-level kinematic features used in our linear model for movement quality assessment with estimated thresholds. (a) Curvedness, (c) Too-slow and (d) Jerkiness show positive and significant correlation with therapist rating. (b) Too-fast shows a negative and significant correlation. (e) Segmentation shows a weak correlation with therapist rating.

Parameter	Optimized Value
T_1	$0.13m$
T_2	$0.2m/s$
T_3	$0.1m/s$
T_4	$2.5m/s^3$
T_5	0.99
w_1	2.5
w_2	2.5
w_3	1.8
w_4	0.05
w_5	0.05

TABLE II: The optimized values for thresholds and weights in the proposed linear model for movement quality assessment.

of kinematic features for quality assessment of wrist trajectory before and after optimization is shown in Fig. 5. We see that before optimization, the predicted movement quality scores of all classes (therapist ratings from 1 to 5) are overlapping (Fig. 5a). The use of optimized weights and thresholds resulted in an increased correlation between cumulative predicted score and therapist rating from 0.13 to 0.6. The contribution of each of the low-level kinematic features with optimized threshold towards movement quality assessment is shown in Fig 6. A linear regression analysis between each kinematic feature and therapist rating shows that curvedness, too-slow and jerkiness show a significant positive correlation, while too-fast and segmentation respectively show negative and weak correlation. The weak correlation between segmentation and therapist rating could be due to the fact that the segmentation feature needs data from elbow and shoulder joints, which is not available in our single marker-based system. The obtained values for thresholds and weights after solving the optimization problem $P1$ are listed in Table II. Kinematic features curvedness and too-fast have the highest weight of 2.5 in our linear model, with jerkiness and segmentation having lowest weight. It is evident from these results that the estimation of weights and thresholds of linear model using the proposed framework provides a novel methodology to combine low-level kinematic features to generate a cumulative score for movement quality of wrist trajectories. Furthermore, the cumulative score aligns with the ratings given by a therapist, which makes it a suitable tool to assist physical therapists in assessing the movement quality during supervised rehabilitation, leading to better evaluation and adaptation of therapy. The estimation of thresholds for low-level kinematic features facilitates better evaluation of components of movement (e.g., curvature, segmentation), thereby improving the efficacy of audio and visual feedback in our home-based rehabilitation system.

VII. Conclusion and Future Work

In this paper, we have introduced the problem of developing a computational framework for movement quality assessment suitable for home-based rehabilitation systems using kinematic analysis. We have proposed and evaluated a linear model of component-level kinematic features for movement quality assessment of the wrist. We propose a framework to learn these component-level kinematic features indicating impairments in underlying movement components using composite therapist impressions of movement quality. Our results indicate that the proposed framework can be used to provide improved and efficient audio and visual feedback indicative of the impairments in component-level kinematics of a participant's reach. Further, this framework can be used to generate a cumulative score indicative of overall reach quality, which can be used to aid therapists during supervised rehabilitation. It should be noted that kinematic analysis of movement has an inherent requirement of "reference" trajectory data, which is difficult to define for complex movements (e.g., lift and transport an object) due to variability. Since we are interested in analyzing such complex movements of stroke survivors, our future directions will be focused towards developing suitable quantitative frameworks for modeling such complex movements.

Monitoring body movement during upper extremity tasks is necessary to determine the extent to which the stroke survivor is using body compensation. Preliminary work using the data collected from the marker plate worn by the participant (not presented here due to scope) is promising for applying similar methods to aspects of movement beyond wrist trajectory performance. However, the consistent marker placement on the torso requires assistance from a caregiver, and we believe markerless solutions for monitoring the torso movements, such as using the Kinect, could provide a robust alternative. This points to several interesting directions of future work. From a sensor fusion perspective, one can explore the utility of multiple Kinect sensors and study the effects on obtaining high fidelity tracking results. Such efforts are already underway, with early commercial systems that are limited to a few gestures [50]. Accuracies of such multi-Kinect systems and its efficacy for rehabilitation systems are still unknown. We are currently working on pilot experiments with Kinect and mono-vision systems.

For the computer vision and machine learning communities, this application area opens up several interesting questions related to the design of robust features for movement quality analysis. Significant research in computer vision has been focused on activity and gesture recognition and not much on measures for '*quality*' of the movement. While this problem is traditionally addressed in the bio-mechanics community, the tools developed there are based on precise clinical measurements of biomechanics. These tools have limited applicability in home-based deployments, where data is of significantly lower quality. Thus, one needs to rely on larger datasets and advanced feature selection and machine learning tools to design movement quality measures. This can form the basis of several interesting research questions in the future.

VIII. Acknowledgments

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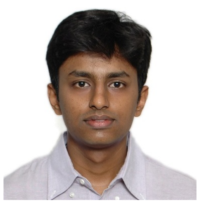

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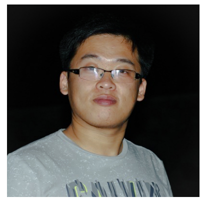

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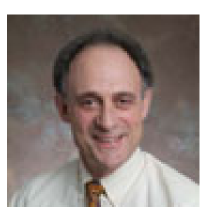

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