# A Computational Framework for Quantitative Evaluation of Movement during Rehabilitation

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**Abstract.** This paper presents a novel generalized computational framework for quantitative kinematic evaluation of movement in a rehabilitation clinic setting. The framework integrates clinical knowledge and computational data-driven analysis together in a systematic manner. The framework provides three key benefits to rehabilitation: (a) the resulting continuous normalized measure allows the clinician to monitor movement quality on a fine scale and easily compare impairments across participants, (b) the framework reveals the effect of individual movement components on the composite movement performance helping the clinician decide the training foci, and (c) the evaluation runs in real-time, which allows the clinician to constantly track a patient's progress and make appropriate adaptations to the therapy protocol. The creation of such an evaluation is difficult because of the sparse amount of recorded clinical observations, the high dimensionality of movement and high variations in subject's performance. We address these issues by modeling the evaluation function as linear combination of multiple normalized kinematic attributes $y=\Sigma w_i\varphi_i(x_i)$ and estimating the attribute normalization function $\varphi_i(\cdot)$ by integrating distributions of idealized movement and deviated movement. The weights $w_i$ are derived from a therapist's pair-wise comparison using a modified RankSVM algorithm. We have applied this framework to evaluate upper limb movement for stroke survivors with excellent results – the evaluation results are highly correlated to the therapist's observations.

**Keywords:** Quantitative evaluation, Kinematic Impairment Measure (KIM), Rehabilitation.

## INTRODUCTION

The field of stroke rehabilitation research has recently begun to diversify. With the popularity of using virtual reality and robotics for stroke rehabilitation growing [9,13]**,** many disciplines have taken an interest in developing novel rehabilitation systems based on these technologies. Because the background and orientation of researchers may differ, thus resulting in varied outcome measures and terminology, transferring knowledge across research groups is often difficult and inefficient. There is a strong demand within the stroke rehabilitation community for a standardized way to describe disability and recovery, using consistent terminology and measurement. A standard evaluation system would allow for improved communication within the stroke rehabilitation community and allow for each patient to be assessed in a consistent manner.

While therapists have been providing useful and precise movement evaluations of people undergoing rehabilitation for decades, the problem lies in the fact that translation of these evaluations into detailed, standardized, quantitative measures has been difficult. Quantitative clinical scales [6,15] where the therapist rates aspects of an individual's movement ability or function have been successfully developed and employed, but each therapist approaches the ratings differently. Quantitative clinical scales [5,14] where the patient self-evaluates aspects of function or recovery have also been created, but each rating is made using the patient's own current frame of reference. The existing clinical measures generally use ordinal scales and only allow therapist to evaluate in a coarse scale.

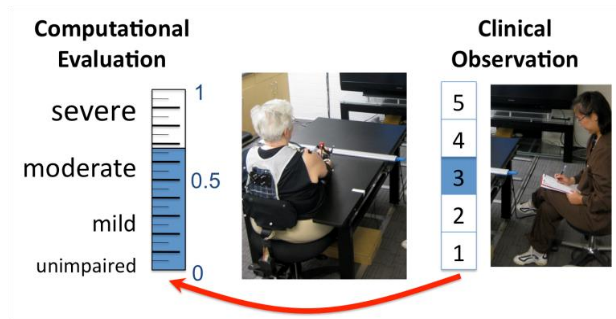


**FIGURE 1:** From clinical observation to computational evaluation.

New movement sensing technologies, such as optical motion capture systems, have the ability to detect movements of the human body in real-time at millimeter precision. The motion capture data can be used to calculate kinematic aspects of any movement, such as the velocity and spatial path of a body part. A kinematics-based measure would also allow for easier communication between research groups and has the potential to more easily predict future outcomes and effective therapy regimens [10]. Some groups [3,12] have begun using kinematic analysis, extracted from motion capture data, as a quantitative evaluation for patients before and after a therapeutic intervention, but there is no standard kinematic evaluation method to allow therapist to (a) compare across different movement aspects as well as across different patients, and (b) assess the potential room for patient to improve. The creation of a standard measure could provide useful supplementary information to existing therapist evaluation methods.

In this paper, we develop a generalized computational framework for quantitative evaluation of movement quality. This problem is challenging due to four reasons: (a) sparse clinical observations, (b) high dimensionality of movement variables, (c) high variation in performing a task for different subjects, and (d) high variation in clinician's observation across different clinicians. There are three contributions in this paper – (1) we model the evaluation function as a linear combination of multiple normalized kinematic attributes, (2) we estimate the attribute normalization function by integrating distributions of idealized movement and deviated movement, and (3) we modify the RankSVM algorithm [8] to learn the weights from therapist's pair-wise comparison. We have applied this framework to evaluate a reach and grasp task during stroke rehabilitation. The experimental results demonstrate that our algorithm is very consistent with the therapist's observations and standard clinical scales.

The rest of the paper is organized as follows. We first define the problem of quantitative evaluation of movement. Secondly, we present our framework of learning the evaluation function from clinical observations. Then, we apply the evaluation framework on a specific reach and grasp task. Finally, we show the experimental results and conclude this paper.

## PROBLEM STATEMENT

The general problem of Quantitative Evaluation of Movement is defined as follows:

> *Given a set of K movements $X^k$, $k=1,\dots,K$, each movement is represented by N continuous non-normalized kinematic variables $X^k = [x^k_1,\dots,x^k_N]^T$, and a set of sparse ordinal discrete clinical observations $z_j$, $j=1,\dots,M$, determine a continuous normalized kinematic measurement $y=f(X)$ to assess the overall movement quality which is consistent with clinical observations $z_j$.*

This is a general problem for quantitative evaluation for any specific movement task, even though the evaluation result is task dependent. The required inputs are non-normalized kinematic variables $x_1,\dots,x_N$ (e.g. hand speed 0.5m/sec), and the clinical observations $z_j$. The value of overall kinematic assessment $y$ is between zero and one. Zero indicates the *idealized movement quality* and one indicates the *maximal deviation from the idealized movement*. For example, in stroke rehabilitation, the idealized movement refers to unimpaired subjects' movement. Stroke patients with different levels of impairments have different deviations from the idealized movement. In this paper, the clinical observation $z$ refers to pair-wise comparison between two movements made by clinicians (e.g. a therapist compares two movement videos and determines which movement she believes to have a greater impairment). Let us denote $z_{k,l}$ as the comparison between movements $X^k$ and $X^l$. $z_{k,l}$ equals +1 if the clinician believes that $X^k$ is better than $X^l$, otherwise $z_{k,l}$ equals -1. We use pair-wise comparison because this type of rating is familiar to the therapist and has clinical relevance.

## SOLUTION: LEARNING THE EVALUATION FUNCTION

We formulate the solution to this problem by learning the function $y=f(X)$ such that the evaluation results for the movement pairs (e.g. $y^k=f(X^k)$, $y^l=f(X^l)$) agree on clinical observations (e.g. $z_{k,l}$). We consider the evaluation function in the following format:

$$y = \sum_{i=1}^{N} w_i \varphi_i(x_i) \ , \ \ s.t.\ w_i \geq 0, \sum_{i=1}^{N} w_i = 1, \quad 0 \leq \varphi_i(x_i) \leq 1 \qquad (1)$$

where $\varphi_i(\cdot)$ is a continuous function for normalizing individual kinematic variable $x_i$, and $w_i$ is the weight given to that variable. $\varphi_i(x_i)$ is close to zero if $x_i$ falls into the ideal range corresponding to the values seen in unimpaired movement and increases as $x_i$ move further from the ideal range. $\varphi_i(x_i)$ reveals the effect of individual movement components on the composite movement performance $y$. Since the $\varphi_i(x_i)$ is ordered in terms of quality of movement components, $w_i$ should be non-negative ($w_i \geq 0$). Therefore, the evaluation problem is to find the optimal weights $w_i$ and normalization functions $\varphi_i(\cdot)$ such that the difference between the computational evaluation of movement pair (i.e. $y^k - y^l$) and clinical observation $z_{k,l}$ is minimized. Mathematically, the problem is represented as follows

$$(w_1^*,\dots,w_N^*,\varphi_1^*,\dots,\varphi_N^*) = \min_{\binom{w_1,\dots,w_N}{\varphi_1,\dots\varphi_N}} \sum_{k,l} L\left(\sum_{i=1}^{N} w_i[\varphi_i(x_i^k) - \varphi_i(x_i^l)], z_{k,l}\right) \qquad (2)$$

where $L(\cdot)$ is a loss function. Searching for the optimal solution is difficult because the number of potential normalization functions is large, the movement contains a high number of dimensions (kinematic variables), and the clinical observation is sparse. In this paper, we simplify the problem by separating the weight determination from the selection of the normalization function. First, we estimate the normalization function for each kinematic attribute by integrating both idealized movement data and deviated movement data. Then, we fix the normalization function and find the optimal weights to minimize the loss function using modified RankSVM [8] algorithm.

## Normalization of Kinematic Attributes

There are two guidelines for choosing the normalization function $\varphi_i(\cdot)$: (a) $\varphi_i(x_i)$ should be close to 0 if the value of $x_i$ is close to the ideal range corresponding to the idealized movement, and (b) $\varphi_i(x_i)$ increases monotonically from zero to one as the value of $x_i$ move further from the ideal range to the maximum deviation.

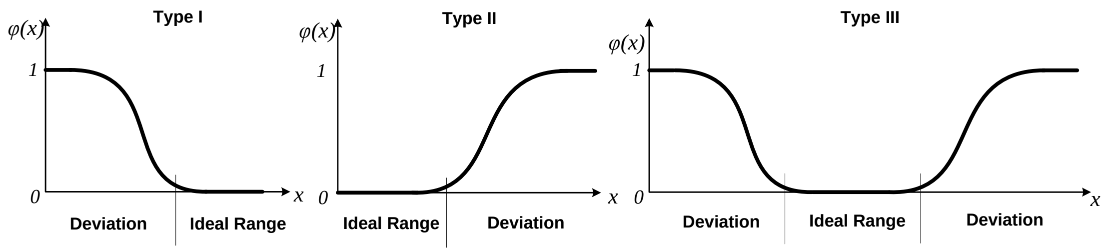


**FIGURE 2**: Three types of normalization functions.

Different kinematic variables have different normalization functions. In this paper, we consider three types of normalization functions (see FIGURE 2): (Type I) $\varphi_i(x_i)$ increases as $x_i$ decreases from ideal range, (Type II) $\varphi_i(x_i)$ increases as $x_i$ increases from ideal range, and (Type III) $\varphi_i(x_i)$ increases as $x_i$ increases or decreases from ideal range. The following section will use the Type II as an example to explain how to construct a normalization function. The other two types of normalization function can be computed in the same way. We determine the normalization function $\varphi$ by integrating the idealized movement dataset $D_+$ and deviated movement dataset $D_-$. Let us assume that the kinematic variable $x$ is positive and the ideal value is zero. The ideal range can be determined by the variations of idealized movement (i.e. unimpaired subject's movement) as $[0\ \mu_{x+}+a\cdot\sigma_{x+}]$, where $\mu_{x+}$ and $\sigma_{x+}$ are the mean and variance of $x$ in the idealized movement dataset, and $a$ is a constant scalar. Then we compute the cumulative distribution function $f(x)$ for $x$ outside of ideal range on the deviated movement dataset $D_-$. Finally, we determine the normalization function $\varphi(x)$ by fitting the

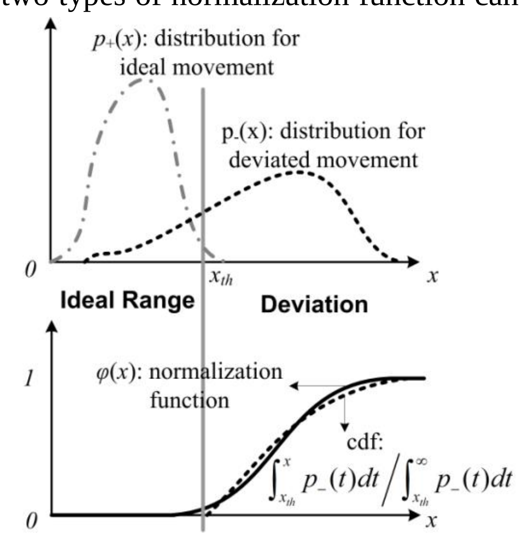


**FIGURE 3:** Diagram of computing normalization function.

cumulative distribution function using continuous exponential function $1 - e^{-(\frac{x}{a})^b}$. FIGURE 3 demonstrates how to compute the normalization function.

## Learning the Weights

Once the normalization function is chosen, we can determine the weights $w_i$ (Eq. (1)). Let us assume we have $K$ movements, each movement is represented by $N$ normalized kinematic variables – $\Phi(X)=[\varphi_1(x_1),\ldots, \varphi_N(x_N)]^T$. Let us also assume that the clinician compares $M$ pairs of movements ($M \leq K(K\text{-}1)/2$). Let us denotes each comparison as ($\Phi_j^{(1)}$, $\Phi_j^{(2)}$, $z_j$), $j=1,\ldots,M$, where $\Phi_j^{(1)}$ and $\Phi_j^{(2)}$ are normalized kinematic vectors for two movements and $z_j$ is the clinician's observation. $z_j$ equals +1 if the clinician believes that the former movement has better quality than the latter, otherwise $z_j$ equals -1. The optimal weights $W=[w_1,\ldots,w_N]^T$ for evaluation function $f(X)=\langle W, \Phi(X)\rangle$ (where $\langle\cdot,\cdot\rangle$ is inner product) are then set such that $\langle W, \Phi_j^{(2)}\text{-}\Phi_j^{(1)}\rangle$ matches $z_j$ (e.g. $z_j\langle W, \Phi_j^{(2)}\text{-}\Phi_j^{(1)}\rangle > 0$). Note that smaller value of evaluation measure $y=f(X)$ indicates better movement quality. The equivalent problem in web ranking has been solved by RankSVM [8]. The optimal weights are computed as follows:

$$W = \sum_{j=1}^{M} \alpha_j z_j \left(\Phi_j^{(2)}\text{-}\Phi_j^{(1)}\right), \tag{3}$$

where $\alpha_j$ are Lagrange multipliers that are solved by maximizing Lagrange function:

$$L_D = \sum_{j=1}^{M} \alpha_j - \frac{1}{2}\sum_{j=1}^{M}\sum_{k=1}^{M} \alpha_j \alpha_k z_j z_k \langle \Phi_j^{(2)}\text{-}\Phi_j^{(1)}, \Phi_k^{(2)}\text{-}\Phi_k^{(1)}\rangle, \tag{4}$$

subject to constraints $0 \leq \alpha_j \leq C_j$, where $C_j$ are positive constants. Compared to RankSVM [8], we have two additional constraints (see Eq.(1)): $w_i \geq 0$ and $\Sigma w_i=1$. $w_i \geq 0$ can be achieved by adding an inequality constraint $W=\sum_{j=1}^{M} \alpha_j z_j \left(\Phi_j^{(2)}\text{-}\Phi_j^{(1)}\right) \geq 0$ (ref. Eq.(3)) to maximize $L_D$ in Eq.(4) using quadratic programming. $\Sigma w_i=1$ can be easily achieved by updating $w_i=w_i/\Sigma w_i$ because scaling $W$ by a positive number does not change the sign of $\langle W, \Phi_j^{(2)}\text{-}\Phi_j^{(1)}\rangle$.

# APPLICATION: EVALUATING UPPER LIMB MOVEMENT DURING STROKE REHABILITATION

We apply the evaluation framework on a specific *reach and grasp task* performed during stroke rehabilitation. The framework is set up to assess the movement quality for ***a set of 10 reaches***, including the performance of each individual reach and the consistency over 10 reaches. Many therapies focus on teaching the stroke survivor not only a better way to move, but how to perform the better movement more consistently, which makes it an important aspect to rehabilitation. In the rest of this paper, '*trial*' refers to an individual reaching movement and '*set*' refers to a set of ten reaching movements. The result of this assessment is a continuous normalized measure – the Kinematic Impairment Measure (KIM). In this section, we first introduce the how the overall reaching action was broken down into aspects of the movement and then discuss how to compute these kinematic attributes from the motion capture data for this task. Finally, we apply the algorithm discussed in the previous section to determine the correct normalization functions and weights.

## Creating Simplified Action Representation

Based on the literature [2,7,11] and our experience [4], we describe the reach and grasp action as a manageable number of measurable kinematic features that collectively represent the entire action. TABLE 1 shows the kinematic attributes contained within the action representation. The action representation consists of 33 kinematic features, which are organized into seven categories based upon operational similarities within the reach and grasp action. Temporal profile, targeting, trajectory profile, and velocity profile are the four *activity level* categories that contain kinematic features derived from the endpoint activity (movement of the hand over space and time). Kinematic features within the four activity level categories are highly correlated and have the greatest influence on the efficient completion of the action goal. The remaining three categories, compensation, joint function, and joint synergy, are *body function level* categories, which include kinematic parameters that, when recovered, reflect pre-morbid movement patterns of specific body structures.

**TABLE 1** 33 kinematic attributes for evaluating reach and grasp movement performance, shown with their encompassing categories and their types of normalization function $\varphi_i$. The attributes marked by '*' (consistency) are measured at the set level (10 reaches) and other attributes are measured per trial. Because all consistencies are measured as variation magnitude, the increased raw value increases the attribute KIM. Therefore, their normalization functions $\varphi_i$ are Type II.

| **Activity Level** | | | **Body Function Level** | | |
|---|---|---|---|---|---|
| **Category** | **Kinematic Attribute** | $\varphi_i$ | **Category** | **Kinematic Attribute** | $\varphi_i$ |
| Temporal Profile | Reach time consistency* | II | Compensation | Torso flexion | II |
| | Peak speed | III | | Torso rotation | II |
| | Peak speed consistency* | II | | Preemptive elbow lift | II |
| Targeting | Initial spatial error | II | | Shoulder elevation | II |
| | Final spatial error | II | | Shoulder protraction | II |
| | Final spatial error consistency* | II | Joint Function | Shoulder flexion ROM | I |
| Trajectory | Horizontal trajectory error | II | | Shoulder flexion error | II |
| | Horizontal trajectory consistency* | II | | Shoulder flexion consistency* | II |
| | Vertical trajectory error | II | | Elbow extension ROM | I |
| | Vertical trajectory consistency* | II | | Elbow extension error | II |
| Velocity Profile | Phase number | II | | Elbow extension consistency* | II |
| | Phase magnitude | II | | Forearm supination ROM | I |
| | Bell curve fitting error | II | | Forearm supination error | II |
| | Jerkiness | II | | Forearm supination consistency* | II |
| '*': attribute is measured at the set level (10 trials). | | | Upper Extremity Joint Correlation | Shoulder flexion / elbow extension | I |
| | | | | Shoulder flexion / forearm supination | I |
| | | | | Shoulder flexion / shoulder abduction | I |
| | | | | Elbow extension / forearm supination | I |
| | | | | Elbow extension / shoulder abduction | I |

## Quantifying the Movement

We now discuss how to quantify these 33 attributes for evaluating a set of reaches. The movement evaluation relies on a real-time 3D motion capture system (OptiTrack system) that tracks the locations of fourteen markers located on the participant's right hand, arm and torso at a sampling rate of 100Hz. A set of motion features including *hand trajectory/velocity, shoulder joint angles (flexion/adduction), elbow joint angles (extension/supination), shoulder elevation and protraction, torso flexion and rotation* are derived from the 3D marker locations every 10ms. For each feature (except hand velocity), we compared the raw values to a reference curve from the start position to the target. The reference is derived from the idealized reach movement performed by unimpaired individuals. And we scale the reference curves to the participant-specific resting and reaching posture. The positions are consistently determined for each participant, with the reaching posture being an active reach, assisted by the therapist. Based on the raw motion capture data, we can compute the 33 kinematic attributes that are organized into the 7 categories noted below (see [1] for computational details).

In the *temporal profile category*, the reach time consistency is defined as the ratio between the standard deviation and the average of reach completion time over a set. The peak speed is the maximal hand speed during a trial. The peak speed consistency is computed as the standard deviation of the peak speed over a set.

In the *targeting category*, initial spatial error is the distance between the hand and the target at the moment the individual's hand speed drops below the 5% of the peak speed. This error represents the participant's initial hesitation when nearing the target. Final spatial error is the hand to target distance at the completion of the reach. Both values are computed per trial. Final spatial consistency is computed as a summation of endpoint variances along 3D directions across a set.

The *trajectory category* evaluates the hand's movement in planes parallel and perpendicular to the table surface. The horizontal and vertical trajectory errors are defined as the largest deviation from the reference trajectory (measured per trial). The trajectory consistency (horizontal or vertical) measures the variation of trajectory profiles over a set and is calculated using a profile variation function [1].

The *velocity profile category* evaluates the hand's velocity curve in terms of shape and smoothness at trial level. The phase number counts the number of acceleration/deceleration sequences beyond the first phase before completing a reach[4]. The phase magnitude is calculated as the ratio of the distance traveled after the first phase, during deceleration, to the distance over the deceleration after the velocity peak. Bell curve fitting error compares the velocity profile to a fitted bell-shape Gaussian curve. Jerkiness [7] measures the smoothness of the movement.

The *compensation category* measures excessive movements of the shoulder and torso [2] per trial. Torso flexion and torso rotation are calculated as the maximum deviation of torso flexion and rotation angle relative to the reference angular profile. Compensatory shoulder elevation and protraction is computed in a similar manner. Preemptive elbow lift measures the vertical elbow shift during movement initiation.

The *joint function category* focuses on shoulder flexion, elbow extension and forearm supination joint angles. The range of motion (ROM) measures the angular range per reach. The dynamic error is the maximum angular deviation from the reference angular profile per reach. The angular profile consistency measures the angular profile variations over a set in a similar manner to the trajectory consistency.

The *upper extremity joint correlation category* measures correlations between five joint angle pairs (see TABLE 1) during the reach and grasp. The joint correlation is defined as the absolute value of the cross-correlation of two angles during a trial.

## Learning the Kinematic Impairment Measure (KIM) Function

We learn the KIM function using the algorithm discussed in the Section "Solution: Learning the Evaluation Function". Assuming we collected reach and grasp movement data from $J_+$ unimpaired subjects and $J_-$ impaired subjects and computed the 33 kinematic attributes for each subject. For each kinematic attribute $x_i$, we determine the ideal range using unimpaired movement dataset, calculate the cumulative probability function of impaired movement data outside of the ideal range, and estimate the normalization function $\varphi_i(\cdot)$ using curve fitting (ref. Section "Normalization of Kinematic Attributes"). Hence, we can construct a normalized kinematic vector $[\varphi_1(x_1),\ldots \varphi_{33}(x_{33})]^T$ for any set of 10 reaches for each subject. Each component $\varphi_i(x_i)$ is referred to "Attribute KIM". Note that if $x_i$ is measured per trial, we first normalized every trial using $\varphi_i(\cdot)$ and then compute the average over ten trials (a set). TABLE 2 shows mapping examples from raw value to attribute KIM value for four attributes. Finally, we learn the weight $w_i$ using the modified RankSVM (ref. Section "Learning the Weights") from the clinician's pair-wise comparison of movement quality between impaired subjects. As a result, we obtain a composite KIM function $f(X)=\Sigma_i[w_i\varphi_i(x_i)]$.

**TABLE 2**. Correspondence between KIM values and raw values for 4 example attributes.

| Attribute KIM Value | Peak Speed (m/s) | Horizontal Trajectory Error (cm) | Torso Flexion Compensation (deg) | Upper Extremity Joint Correlation |
|---|---|---|---|---|
| KIM=0 | 0.42–0.60 | 0 – 1.5 | 0 – 3.1 | 0.95 – 1.0 |
| 0<KIM≤0.3 | 0.38–0.42 or 0.60–0.64 | 1.5 – 2.7 | 3.1 – 5.8 | 0.88 – 0.95 |
| 0.3<KIM≤0.7 | 0.35–0.38 or 0.64–0.67 | 2.7 – 3.7 | 5.8 – 8.2 | 0.80 – 0.88 |
| 0.7<KIM≤1.0 | <0.29 or >0.74 | >3.7 | >8.2 | <0.80 |

# EXPERIMENTAL RESULTS

We now discuss the experimental results. We recruited 7 unimpaired subjects and 17 stroke survivors for a study in which motion capture was used to collect data from reach and grasp tasks. All 17 stroke survivors had resultant right-sided hemiplegia in their arm: four had a severe level of impairment, six had a moderate level of impairment and seven had a mild level of impairment. The impairment level is determined by clinicians based on their observations and standard clinical assessments. Each subject (both impaired and unimpaired subjects) performed four sets of reaching and grasping tasks to four different targets, which were placed both on the table (the subject could slide his hand to reach the target) and off the table (the subject must move against gravity to reach the target). The four target positions were placed at a percentage of the subject's furthest reaching ability, which was an active assisted reach for the stroke survivors [4]. The 17 stroke survivors were also evaluated by the Wolf Motor Function Test (WMFT) [15]. We also recruited a therapist to compare the reach and grasp movement quality between any pair of stroke survivors. Overall there are 136 pairs for 17 impaired subjects. The therapist provided the comparison for 130 pairs and can't determine the order for other six pairs because these six pairs of subjects have almost the same quality of movement.

## Data Processing

We first calculated 33 kinematic attributes (ref. TABLE 1) for each subject (both unimpaired and impaired), for all reaches to each target position. Then, for each kinematic variable, for each target position, we determine the ideal range and the normalization function $\varphi_i(\cdot)$ by integrating the unimpaired movement data and impaired movement data (ref. Section "Normalization of Kinematic Attributes"). Therefore, we have four attribute KIM vectors $[\varphi_1(x_1),\ldots \varphi_{33}(x_{33})]^T$ (corresponding to four target positions) for every subject and we compute the average of these four vectors. Finally, we apply the modified RankSVM (ref. Section "Learning the Weights") to determine the weights for 33 kinematic attributes and compute the composite KIM for every subject.

## Kinematic Impairment Measure (KIM) Results

We first present the composite KIM values for all subjects. TABLE 3 shows the mean and the standard deviation of composite KIM value for both unimpaired subjects and stroke survivors for evaluating the reach and grasp task. We can see that the KIM value is highly correlated to the impairment levels (mild, moderate, severe). We also validate our KIM function by comparing to the Wolf Motor Function Test (WMFT) [15]. We selected 14 tasks in the WMFT that are highly correlated to the reach and grasp tasks. The average functional activity score (FAS) and completion time for these 14 selected tasks are shown in TABLE 3. The Pearson correlation between the KIM and the FAS from the WMFT across 17 impaired subjects is 0.882 and the Pearson correlation between the KIM and the completion time from the WMFT is 0.887. The high correlation between the KIM and the WMFT may indicate that the KIM values measure impairment in a similar way to a widely used clinical scale.

TABLE 3. The composite KIM value, FAS and time from the Wolf Motor Function Test (WMFT) for unimpaired subjects and stroke survivors with different impairment level (Mild, Moderate, and Severe)

| | Number of Subject | KIM | | FAS from WMFT | | Time from WMFT (sec) | |
|---|---|---|---|---|---|---|---|
| | | mean | std | mean | std | mean | std |
| Unimpaired | 7 | 0.031 | 0.005 | -- | -- | -- | -- |
| Mild | 7 | 0.107 | 0.023 | 3.85 | 0.21 | 4.01 | 1.17 |
| Moderate | 6 | 0.258 | 0.058 | 3.50 | 0.32 | 5.69 | 2.14 |
| Severe | 4 | 0.533 | 0.212 | 2.86 | 0.38 | 19.02 | 16.04 |

We also use the leave-one-out-cross-validation to validate our KIM function. We pick one impaired subject for testing and use other 16 impaired subjects for training to learn the KIM function. Then we compare the KIM value of the testing subject with other 16 subjects and check how many pairs match therapist observations. "Match" refers to that the KIM difference $y^{(2)}$-$y^{(1)}$ between the two subjects has the same sign as the therapist comparison $z$. We repeat this until every impaired subject is selected as the testing subject and compute the overall percentage of subject pairs on which the computational evaluation results match therapist observations. The match percentage of leave-one-out-cross-validation for our algorithm is 90.38%.

We can also identify the key kinematic attributes that the therapist used for evaluating the movement quality because the key kinematic attributes are associated with higher weights than other attributes. The top 5 kinematic attributes are: (1) torso flexion compensation ($w$=0.128), (2) forearm supination ROM ($w$=0.116), (3) horizontal trajectory error ($w$=0.098), (4) phase number of velocity profile ($w$=0.093), and (5) vertical trajectory error ($w$=0.073). We understand these results are biased to the recruited therapist and different therapists might have different preference on kinematic attributes. But our algorithm is still useful to discover therapist's evaluation preference and identify the key kinematic attributes.

## CONCLUSION AND FUTURE WORK

This paper presents a computational framework to learn a continuous normalized kinematic evaluation function from the clinician's pair-wise comparison between two movements. The resulting evaluation measure allows clinicians to assess patient's movement quality in a finer scale and in real-time. This problem is challenging because of sparse clinical observations, high dimensionality of movement variables and high variations in subject's performance. We solve this problem by two steps – (a) normalizing each kinematic variable by curve fitting the cumulative distribution function, and (b) determining the optimal weights using the modified RankSVM algorithm. We have very good results on applying this framework for evaluating the reach and grasp task. The evaluation results are highly correlated to the clinical observations. Future work includes applying this framework on multiple tasks and determining correlations between kinematic variables.

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