Kinematic Analysis and Quantitative Evaluation for Reach Movements in Stroke Rehabilitation

by

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ABSTRACT

In this thesis, quantitative evaluation of quality of movement during stroke rehabilitation will be discussed. Previous research on stroke rehabilitation in hospital has been shown to be effective. In this thesis, we study various issues that arise when creating a home-based system that can be deployed in a patient's home. Limitation of motion capture due to reduced number of sensors leads to problems with design of kinematic features for quantitative evaluation. Also, the hierarchical three-level tasks of rehabilitation requires new design of kinematic features. In this thesis, the design of kinematic features for a home based stroke rehabilitation system will be presented. Results of the most challenging classifier are shown and proves the effectiveness of the design. Comparison between modern classification techniques and low computational cost threshold based classification with same features will also be shown.

DEDICATION

To My family

ACKNOWLEDGEMENTS

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Chapter 1

INTRODUCTION

1.1 STROKE REHABILITATION

Stroke is a disease which affects the arteries leading to and within brain. It is the No.4 cause of death and a leading cause of disability in the United States [2]. Between 55% and 75% survivors remain to experience impairment on upper body movements [11]. Stroke rehabilitation aims to help patients who survive strokes return to normal life through systematic therapy and relearn the skills of everyday living [16]. Traditional stroke rehabilitation requires expensive facilities and intensive guidance from therapists, which is not affordable and accessible to many patients. To improve this condition, modern stroke therapy methods, such as combining training in virtual reality with traditional physical therapy, are currently growing as a hot spot in the field of physical therapy research.

Different from the traditional methods, each modern stroke rehab method comes with its own physical setup and functional task design. Robotic device which can provide real time interaction with patients have been designed [14]. Virtual reality along with haptics and modern sensing technique (VHS) [18] were developed in the University of Southern California. Customizable games are another modern aproach to stroke rehabilitation [1]. All these new techniques have their advantages. However, robotic devices are too expensive and so is VHS. Customizable games are a good low-cost solution to stroke rehabilitation, while it makes quantitative evaluation difficult due to lack of constraints.

The stroke rehabilitation research team in the School of Arts Media and Engineering in Arizona State University(ASU) has designed and implemented an adaptive mixed reality rehabilitation system for hospital use. This system, which was designed for a clinical setting, with high quality motion capture technologies with various markers and rigid-bodies attached to the wrist, arm, shoulder, torso etc, captured and computed very profound data about the human movement. The system provided an adaptive constraint induced movement therapy(CIMT) [12] with virtual and mixed reality environment [8]. This system has shown efficacy in helping to enhance the kinematic and functional performance [4].

A home-based adaptive mixed reality rehabilitation system for stroke survivors [3] has also been designed and implemented by the same research team in ASU. This system aims to provide assistance to stroke survivors to continue therapy at their homes. Low-cost sensing and fewer markers to be attached on the body are of special need in this situation.

In this thesis, I designed the kinematic features for the home system and compute the related quantitative evaluation. I also tested the features with experienced researchers in the field of stroke rehabilitation to ensure their validity.

1.2 PREVIOUS WORK

The quantitative evaluation and kinematic analysis during stroke rehabilitation are of cardinal significance. In traditional therapy, quantitative and qualitative clinical measures are used to access patient's movement quality [7]. The Motor Activity Log(MAL) [13] was designed and developed to provide measurement to progress in daily living activities. The Arm Motor Activity Test is another approach with high consistency and sensitivity to patient's change in performance [9]. The Wolf Motor Function Test(WMFT) [17] is a method to evaluate the upper extremity performance with insight to joint related and total limb movement. All these aproaches to stroke rehabilitation are based on the judgement of therapist, thus the results can be biased by:

- therapist's mood
- various individual interpretation by different therapists

In modern stroke rehabilitation systems, kinematic analysis is computational in nature by using of Mocap data. This makes the analysis reliable, repeatable and independent of human judgment. The Mocap data can reveal more subtle changes in movement with accurate detection and measures. Computational kinematic features using Mocap data have been used in stroke rehabilitation [15]. In our hospital and home system, a marker based Optitrack motion capture system has been used to provide accurate 3D position information [6]. A video based motion capture system using Kinect is introduced to the home system to provide additional motion information for analysis. The data collected by Mocap module is used to compute different features related to quality of movement. Reference data is computed from the data corresponding to non-impaired people. The reference data serves as baseline for later evaluation. How the reference data and the data collected with patents will be described in next Chapter. In the hospital system, a computational framework for quantitative evaluation is introduced. In this framework, kinematic features are designed in detail. A Kinematic Impairment Measure(KIM) method [5] is introduced to make the analysis results normalized and independent of specific kinematic features. In our home system, the evaluation structure is inherited from the evaluation structure in the hospital system, while the scale is reduced so that it can fit the need of fast and low-cost computation with fewer markers and sensors.

The evaluation and analysis of the movement are required mainly for two purposes, to drive the feedback on one hand and to support long term research on the other. The analysis to drive feedback desires high speed and low computation complexity. Coarse threshold measurement is implemented in this part. KIM provide a reliable , feature and task independent measurement to patients' movement after the therapy is completed and it is used for long term research.

1.3 OVERVIEW

This thesis is organized into five chapters. In Chapter 2, I will briefly present the system architecture, notations, concept and tools that will be used in the thesis. In Chapter 3, I will first briefly describe how the quantitative evaluation structure is designed in the hospital system and then present how the concept is inherited and developed in the home system. Then, I will present how the kinematic features are designed in the home system. The advantages and disadvantages of current design will be discussed with the previous work, KIM [5]. After that I will state the advantage of the combination of current design over the previous. Finally, I will discuss that how the modern classification techniques can be implemented in the evaluation system and the advantages and disadvantages. In Chapter 4, result of the evaluation system will be shown. The final chapter concludes the work and discusses the potential improvement of the analysis and evaluation system and future work.

Chapter 2

METHOD AND TOOLS

2.1 SYSTEM ARCHITECTURE AND PHYSICAL SET UP

2.1.1 SYSTEM ARCHITECTURE

The stroke rehabilitation system that our research group designed and developed is an adaptive mixed reality system. The system is composed of mainly five parts:

1. motion capture module
2. motion analysis module
3. adaptation module
4. feedback module
5. archive module

Data is first collected with motion capture module and passed to the motion analysis module. Motion analysis module computes features from the raw data, and then all the features are used by the classifiers which embedded in the motion analysis to classify the movement. Tangible objects on the table provide additional information to help the motion analysis. The classification result is then sent to the feedback module. Pre-designed and programmed visual and audio feedback is played after the classification result is received. The feature data is stored by archive module. All the other modules in the system are controlled by the adaptation module so that they work in a desired way. In this thesis, I mainly focus on the motion analysis module.

2.1.2 HOSPITAL SYSTEM

The hospital system is an adaptive mixed reality stroke rehabilitation system designed for hospital use. A adjustable table is provided to the patient so that he/she can sit comfortably. The table's surface extends out to support the patients affected arm [7]. Eight infrared-cameras are placed around and above the table. Reflective markers are placed on the affected wrist, elbow, shoulder as well as back of the patient during therapy. The infrared-cameras detect and capture the 3D position of each marker. A screen and a speaker is placed in front of the table to provide visual and audio feedback. Objects with tangible sensors embedded are placed on the table as the target in the task for the patient. The hospital system trains on the following:

- reach and grasp task
- against gravity task
- button box task

Therapist and technical support are required during the therapy. A novel kinematic analysis framework, Kinematic Impairment Measure(KIM), is introduced in this system and will continue to be used in the home system. I will describe the concept of KIM in the next section of this chapter.

2.1.3 HOME SYSTEM

The home system is an adaptive mixed reality stroke rehabilitation system designed for home use. The system structure inherits from the hospital system. We still have the adjustable table so that the patient can sit down with comfort. The motion capture module in the home system is significantly scaled down. This is due to the requirement that the system should be implemented in patients home with ease. The number of infrared-cameras is reduced to four. Instead of placing the cameras around and above the table, the cameras are placed above and behind the screen. Reflective makers are still used in the home system, but the number is reduced to one and it is placed on the patient's wrist. With this change, the patient can put on the marker by himself/herself at home. The disadvantage of this change is that the accurate Optitrack system now can only get the 3D position of the end point, the wrist, during the therapy. This leads to the change of design of kinematic features and classifiers in the motion analysis module. In compensation to this, a Kinect camera is introduced to the system to capture torso data. A screen and a speaker are placed in front of the table to provide visual and audio feedback and physical objects with tangible sensors embedded are placed on the table as the target in the task for the patient. The design of tasks in the home system has novel development. A three-level architecture is introduced in the system:

1. level one task contains simple tasks such as reaching and grasping, reaching and touching and provides detailed feedback
2. level two contains repetitive simple tasks and provides summary feedback
3. level three contains complex functional tasks and provides descriptive feedback

This three level design aims to help patients build relationship between therapy and everyday life. This requires the kinematic analysis and quantitative evaluation to keep in accordance to the information desired to convey to the patients. I will describe in detail how the kinematic features are designed for level two and three in Chapter 3. I will present the performance of the most challenging features and the related classifier in Chapter 4.

2.2 KINEMATIC IMPAIRMENT MEASURE

In greatly developed and diversified field of stroke rehabilitation research [10], kinematic analysis is designed in various ways. This raises several issues such as:

- comparison between different analysis architectures
- comparison between different tasks
- comparison between different kinematic features

KIM provides a standard evaluation architecture with consistent terminology and measurement [5] that can be applied to different stroke rehabilitation systems. This quantitative evaluation framework aims to provide task and feature independent evaluation result with long term and stable kinematic features data base.

2.2.1 CONCEPT AND COMPUTATION

Assume that we have a stable distribution of values of a specific feature and we have both distribution of non-impaired people and patients with different levels of impairment. The goal is to compute a score which is normalized between zero and one regardless of the distribution of the value of the feature is. Typically, we have three kinds of feature value distribution of non-impaired people and patients. Within each type of distribution, we need to find a normalize function $\varphi(x)$ to normalize the feature value x. Based on the three different types of distribution, the normalization is done in a similar way. How the KIM value is computed is described in [5].

2.2.2 BENEFITS AND LIMITS

KIM is of significant advantages for Kinematic evaluation for the following reasons:

1. All the evaluation result falls between zero and one, which makes further analysis easier.

2. The value of evaluation result is relevant only to the distribution feature value from patients and non-impaired people. The result of individual movement reveals how bad the quality of movement ranks among the all the data base. It is reasonable to compare the KIM value of different features while kinematic feature values can never be compared between different features. This makes the result feature independent.

3. For the same reason above, the value of the evaluation result is task independent, which means it is reasonable to compare KIM value between different tasks.

4. KIM value reveals subtle changes of quality of movement within the impaired range.

However, KIM also has disadvantages. To get reliable and robust KIM value, a stable data set with sufficient samples is required. Since the result of KIM is determined by the distribution of feature value from patients and non-impaired people, the result will be biased if the data set is biased. This effect is most obvious at the beginning of our research, data from each new patient influences KIM scores, which can not be ignored when the database doesn't contain enough samples. As a result, the distribution of feature values and the KIM values will not be stable. In our system, the data set keeps updating when the system is applied to more and more patients. The KIM result will be stable only after the research last for a adequate period of time.

2.3 CLASSIFICATION TECHNIQUES

In the home system, we design specific features to classify the movement to different inefficient categories. We are using simple low computation cost threshold based classifiers to give coarse classification result to drive feedback. The most challenging features for the kinematic analysis will be proven efficacy with modern classification techniques. In this thesis, I am using Weka tool box to classify the movement with the kinematic features.

Chapter 3

Design of Kinematic Features and Quantitative Evaluation

3.1 BASIC KINEMATIC FEATURES AND REFERENCE DATA

3.1.1 PRE-PROCESSING OF TRAJECTORY

The end point, which is the position of the marker that is placed on the patient's wrist, is used to build the baseline for all the kinematic computations. The raw data for the end point captured from motion capture system is the 3D global position data x, y and z with a time stamp. With the help of tangible data and calibration data, the starting point and ending point of a complete trial can be figured out within a sequence of continuous points. $p(t) = [X(t), Y(t), Z(t)], t = 0, \dots \tau$. In the hospital system, the motion capture system also captured the 3D positions of reflective markers which are placed on the affected elbow and should as well as the back of the patient during therapy. In total, twelve markers are used. Thus we have $p(t), p_1(t), \dots p_{11}(t)$, where $p_1(t), p_2, \dots p_{11}(t)$ are the marker positions of markers other than the one which is placed on the wrist of patient. The next step is to rotate the coordinate so that $p(0)$ is the origin of the new coordinate, the XZ plane is the horizontal plane and the straight line connecting $p(0)$ and $p(\tau)$ lies in the new YZ plane. The rotation is shown in fig 3.1

After the rotation, we now have a sequence of continuous points $p_{rotate}(t) = [X_{rotate}(t), Y_{rotate}(t), Z_{rotate}(t)], t = 0, \dots \tau$ to present the trajectory of end point during a single complete trial during the therapy. Then I normalize the range of z value to 0 and 1. This in effect re-parameterizes the trajectory $[X(t), Y(t), Z(t)], t = 0, \dots \tau$ to $[X'(z), Y'(z)], z = 0, \dots 1$. This re-parameterization works without introducing significant ambiguity in our case because of the strong directionality of the reach action as illustrated in the

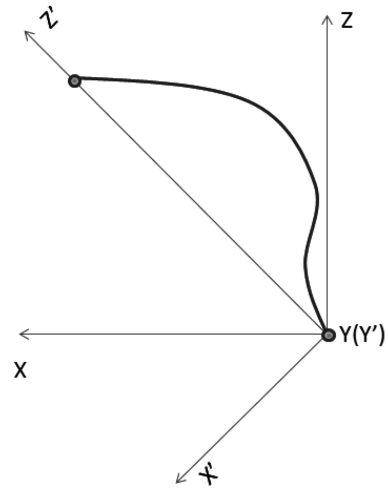

Figure 3.1: The rotation of the trajectory

above figure. After that, z-axis is further quantized into $N = 50$ bins. With this step, the trajectory is further transformed to $[X'(z), Y'(z)], z = 0, \ldots 1$ to $[X'(n), Y'(n)], n = 0 \ldots N - 1$. This transform to a simple vectorial representation makes it convenient for fast real-time comparisons and computation of reference data.

3.1.2 COMPUTATION OF REFERENCE DATA AND QUANTITATIVE EVALUATION FOR HOSPITAL SYSTEM

After the vectorial representation as described above, the next step is to compute the reference data for further evaluation. As we get the data from the twelve markers, we are able to compute the feature value $[f_1(t), f_2(t), \ldots f_M(t)], t = 0, \ldots \tau$, where $M = 33$ for the hospital system quantitative evaluation [6]. With the same re-parameterization as described in the last subsection, we can compute $[f_1(n), f_2(n), \ldots f_M(n)] n = 0, \ldots N - 1$. This transformation is done only with the data from non-impaired people. The strong directionality of the reach action does not hold for the movement of patients. After we have the discrete quantized feature value, we are able to compute the mean value and standard deviation of all the data collected from non-impaired people by feature $[f_1^{mean}(1), f_2^{mean}(2), \ldots f_M^{mean}(n)], n = 0, \ldots N-1$. By choosing a proper threshold $[Thre_1^{+}(1), Thre_2^{+}(2), \ldots Thre_M^{+}(n)], n = 0, \ldots N-1$ and $[Thre_1^{-}(1), Thre_2^{-}(2), \ldots Thre_M^{-}(n)], n = 0, \ldots N-1$, we are able to compute the zero zone, an area that any feature value falls inside will be considered as non-impaired movement[6]. The zero zone and mean value of features of non-impaired people are used as the reference data. When a new test sequence comes in, the 3D position X, Y, Z of all the sample points from the start of the movement to the end are first rotated from the global coordinate to the new coordinate system. Values of Z less than 0 or more than 1 are clamped at 0 and 1 respectively. From this rotated and normalized trajectory, one can now find the corresponding points in the reference trajectory. Thus we are able to find corresponding feature values according to Z.

3.2 KINEMATIC ANALYSIS DESIGN FOR HOME SYSTEM

In the home system, only one reflective marker is used and this marker is placed on the patient's wrist to track the end point. Other than the 3D position of the end point, the speed is computed as $speed(t), t = \ldots \tau$ and discretized to $speed(n), n = \ldots N-1$. So we have reference as $[X'(n), Y'(n), speed(n)], n = 0 \ldots N-1$.

3.2.1 THREE-LEVEL REHABILITATION

The assessment of end-point kinematics is divided into three levels with increasing abstraction. Below, we briefly describe the three levels of abstraction:

- Level 1 consists of simple tasks, such as reaching and grasping, reaching and touching. This level aims to provide both real time feedback during the task and detailed feedback after task completion. In this level, real time kinematic features, such as trajectory-error and speed-error, are computed from the three dimensional position and speed of the end-point and compared with a pre-defined reference trajectory and reference speed profile, obtained from a set of non-impaired subjects.

- Level 2 consists of multiple repetitions of level 1 tasks. This level provides summary feedback on a specific aspect based on evaluation of a set of repetitive level 1 tasks. Features are designed to evaluate the movement of patient along five aspects: curved/not curved, segmented/not segmented, too fast/not too fast, too slow/not too slow, smooth/not smooth.

- Level 3 consists of more complex *functional* tasks, such as transporting an object. Level 3 provides descriptive feedback on the overall quality of movement of the functional task. Descriptive evaluation results are computed based on completion time, path ratio and speed phases. These will be described in detail in the following section.

In the home system, rather than giving binary evaluation result, a confidence is computed for each feature in each task. Next, I will describe how the features are designed and how to use them for a rough evaluation to drive the feedback.

Level 1 Kinematic Features

Kinematic features for level one task are horizontal error, vertical error and speed deviation:

$$E_{hor}(i) = X(i) - X_{ref}(i), i = 0 \ldots N-1 \tag{3.1}$$

$$E_{vert}(i) = Y(i) - Y_{ref}(i), i = 0 \ldots N-1 \tag{3.2}$$

$$E_{speed}(i) = speed(i) - speed_{ref}(i), i = 0 \ldots N-1 \tag{3.3}$$

By comparing the feature value $E(i)$ to corresponding pre-designed threshold, $Thre_{zero}^{fea+}(i)$, $Thre_{zero}^{fea-}(i)$, $Thre_{hull}^{fea+}(i)$, $Thre_{hull}^{fea-}(i)$ for trajectory, wherefea can be X or Y, and $Thre_{zero}^{speed+}(i)$, $Thre_{zero}^{speed-}(i)$ for speed, the trajectory of current movement can be classified to three different categories in real time:

- non-impaired when $Thre_{zero}^{fea-}(i) < E(i) < Thre_{zero}^{fea+}(i)$
- mild-impaired when $Thre_{zero}^{fea+}(i) < E(i) < Thre_{hull}^{fea+}(i) || Thre_{zero}^{fea-}(i) > E(i) > Thre_{hull}^{fea+}(i)$
- severe-impaired when $E(i) > Thre_{hull}^{fea+}(i) || E(i) < Thre_{hull}^{fea-}(i)$

Where fea can be either X or Y when $E(i)$ is $E_{hor}(i)$ or $E_{vert}(i)$, and the speed of current movement can be classified in to three categories in real time:

- normal when $Thre_{zero}^{speed-}(i) < E_{speed}(i) < Thre_{zero}^{speed+}(i)$
- too fast when $E_{speed}(i) > Thre_{zero}^{speed+}(i)$
- too slow when $E_{speed}(i) < Thre_{zero}^{speed-}(i)$

Currently we are using a fixed number for the threshold, which means $Thre_{zero}^{+}$, $Thre_{zero}^{-}$, $Thre_{hull}^{+}$ and $Thre_{hull}^{-}$ are used instead of $Thre_{zero}^{+}(i)$, $Thre_{zero}^{-}(i)$,

$Thre^{+}_{hull}(i)$ and $Thre^{-}_{hull}(i)$. The threshold will be confined during the further study. The threshold will be listed in Chapter 4. The classification result is used to drive corresponding feedback.

Level 2 Kinematic Features

In level 2 task, rather than providing real time feedback to the patient during therapy, the feedback is conveyed to the patient after the completion of a set of tasks. Each individual movement during the set will be evaluated individually and all the individual results are used to compute the final result of the the set.

There are five classifiers in the motion analysis for the end point evaluation in the home system.

The curved/not curved classifier, is based on the deviation of the movement from the reference trajectory. For each point in the trajectory, we take use of the horizontal error E_{hor} and vertical error E_{vert} as $E_{hor}(i) = X(i) - X_{ref}(i), i = 0 \ldots N-1, E_{vert}(i) = Y(i) - Y_{ref}(i), i = 0 \ldots N-1$

A threshold error function is computed to only record those deviations that exceed a threshold. The threshold is the same as $Thre^{+}_{zero}(i)$ and $Thre^{-}_{zero}(i)$ in Level 1.

$$\hat{E}_{hor}(i) = \begin{cases} E_{hor}(i) & \text{if } (E_{hor}(i) > Thre^{X+}_{zero} || E_{hor}(i) < Thre^{X-}_{zero}) \\ 0 & \text{otherwise.} \end{cases} \tag{3.4}$$

Similarly,

$$\hat{E}_{vert}(i) = \begin{cases} E_{vert}(i) & \text{if } (E_{vert}(i) > Thre^{Y+}_{zero} || E_{hor}(i) < Thre^{Y-}_{zero}) \\ 0 & \text{otherwise.} \end{cases} \tag{3.5}$$

Confidence values of the movement being curved/not curved are estimated as

$$C_x^{curved} = \frac{\sum_{i=0}^{N-1} |\hat{E}_{hor}(i)|}{\sum_{i=0}^{N-1} |E_{hor}(i)|}, C_y^{curved} = \frac{\sum_{i=0}^{N-1} |\hat{E}_{vert}(i)|}{\sum_{i=0}^{N-1} |E_{vert}(i)|} \tag{3.6}$$

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

$$C^{curved} = \begin{cases} \lambda_1 & \text{if } \lambda_1 > 2\lambda_2 \\ min(1.5\lambda_1, 1) & \text{otherwise} \end{cases} \tag{3.7}$$

where $\lambda_1 = max(C_x^{curved}, C_y^{curved})$, and $\lambda_2 = min(C_x^{curved}, C_y^{curved})$.

By using the confidence of curved movement, we are able to classify the movement into three categories:

- non-impaired when $C^{curved} < 0.4$
- mild-curved when $0.4 < C^{curved} < 0.6$
- severe-curved when $C^{curved} > 0.6$

Confidence of fastness, which is used to classify a movement as too fast or not, uses speed profiles to compute its confidence values. For a given test data, first we perform a point-to-point comparison of speeds (much in the same way as the previous classifier). Let the speed vector for the reference and test data be denoted by $v_{ref}(i), v(i), i = 0 \ldots N-1$. Here too, we use a thresholded speed vector given by

$$\hat{v}(i) = \begin{cases} v(i) & \text{if } v(i) - v_{ref}(i) > Thre_{zero}^{speed+} \\ 0 & \text{otherwise} \end{cases} \tag{3.8}$$

The confidence of the action being too fast is computed as:

$$C^{fast} = \frac{\sum_{i=0}^{N-1} \hat{v}(i)}{\sum_{i=0}^{N-1} v(i)} \tag{3.9}$$

By using the confidence of too fast movement, we are able to classify the movement into three categories:

- non-impaired when $C^{fast} < 0.4$
- mild-fast when $0.4 < C^{fast} < 0.6$
- severe-fast when $C^{fast} > 0.6$

The slowness feature works similar to the too-fast classifier.

$$\hat{v}(i) = \begin{cases} v(i) & \text{if } (v(i) - v_{ref}(i) < Thre_{zero}^{speed-} || v(i) < Thre_{min}) \\ 0 & \text{otherwise} \end{cases} \tag{3.10}$$

The confidence of too slow movement is computed as:

$$C^{slow} = \frac{num(\hat{v}|(\hat{v}! = 0))}{num(v)} \tag{3.11}$$

where, $num()$ is an operator that counts number of points.

By using the confidence of too slow movement, we are able to classify the movement into three categories:

- non-impaired when $C^{slow} < 0.4$
- mild-slow when $0.4 < C^{slow} < 0.6$
- severe-fast when $C^{slow} > 0.6$

It can be noticed that, when we compute the confidence for too fast or too slow movement, I weigh the points differently. When computing the confidence for too fast movement, each point is weighed with its speed and when computing the confidence for too slow movement, each point is weighed with 1. This is because the system captured the points at a constant rate, which is 100 frames per second. By weighing the points with its speed would automatically draw more attention to those points which are too fast while equally weighing each point would automatically draw more attention to those too slow points.

When computing the feature for smoothness, we use the feature in speed profile and calculate J for jerkiness [6]. The mean value of jerkiness from non-impaired people is pre-computed as ref_{jerk}. For test data, we compute the jerkiness as J. Then the ratio of jerkiness can be computed as

$$r_{jerk} = \frac{J}{ref_{jerk}} \tag{3.12}$$

The confidence of not smooth movement is computed as

$$C^{unsmooth} = 1 - e^{-(a \cdot r_{jerk})^b} \tag{3.13}$$

Where the value of a and b are tuned so as to match the judgment of therapist.

By using the confidence of unsmooth movement, we are able to classify the movement into three categories:

- smooth when $C^{unsmooth} < 0.4$
- mild-unsmooth when $0.4 < C^{unsmooth} < 0.6$
- severe-unsmooth when $C^{unsmooth} > 0.6$

The segmented feature is used to measure whether the overall reach movement is performed using proper co-ordination of the wrist, elbow, shoulder joints. If a movement is 'segmented', usually it means that the elbow is not opening in synchrony with the shoulder moving forward. Instead, the movement of the shoulder forward and the openness of the elbow are done in sequence which results in a disjointed movement. An accurate analysis of this phenomenon requires us to track both the shoulder and elbow in addition to the wrist. In the proposed home-based system, this was deemed too cumbersome, instead we consider whether such movements can be described computationally using only the end-point trajectory. This is indeed challenging, and proved to be the hardest classification problem in this thesis. How does one measure movement segmentation simply from the end-point trajectory? After consultation with domain experts, it was found that segmented movements give rise to notches in the end-point trajectory. These notches can be quite subtle and often occur towards the end of the movement, making it hard to detect. We project the $3D$ trajectory onto the XZ and XY planes to detect the direction changes (notches) in both planes. The projection of the trajectory is down sampled, to ensure a distance of at least 2cm to its adjacent points. This is to ensure that direction change computations are meaningful. Then we compute three features to calculate the confidence of segmented movement in each projection:

1. The number of times that the movement changes its turning direction

2. The magnitude of absolute value of direction change

3. The ratio of magnitude of direction change

In the projection onto the X-Z plane, we first compute displacement vectors r(i) from the spatial locations. The direction change is quantified as the signed angle $\alpha_{XZ}(i)$ between successive displacement vectors (in the projected and down-sampled trajectory). The sign of the angle is defined as positive if it is clockwise from the previous displacement vector, and negative if it is counter-clockwise. The direction change in the $X - Z$ projection. Next, we compute the number of times, N_{change}, the movement changes its turning direction significantly and compute the corresponding confidence as:

$$C^{seg}_{XZ,feature1} = \begin{cases} 1 - e^{-(a_1 \cdot N_{change})^{b_1}} & \text{if } N_{change} > thre_{change} \\ 0 & otherwise \end{cases} \tag{3.14}$$

Where a_1 and b_1 are tuned to match the therapist's judgment. The magnitude of absolute value of direction change is computed by:

$$S = \sum_i |\alpha_{XZ}(i)| \tag{3.15}$$

This feature is used to compute the corresponding confidence:

$$C^{seg}_{XZ,feature2} = 1 - e^{-(a_2 \cdot \lambda_S)^{b_2}} \tag{3.16}$$

$$\lambda_S = \begin{cases} 1 - S/ref^{Dir}_{XZ} & \text{if } S < ref^{Dir}_{XZ} \\ 0 & \text{otherwise} \end{cases} \tag{3.17}$$

The ratio of magnitude direction change is defined as

$$\gamma = \frac{|\sum \alpha_{XZ}(i)|}{\sum |\alpha_{XZ}(i)|} \tag{3.18}$$

The corresponding confidence is computed as:

$$C^{seg}_{XZ,feature3} = \begin{cases} 1 & \text{if } \gamma < 0.3 \\ 1.47 * (1 - \gamma) & \text{otherwise} \end{cases} \tag{3.19}$$

The final confidence of segmentation of the projected movement on XZ plane is computed as :

$$C^{seg}_{XZ} = C^{seg}_{XZ,feature1} \cdot C^{seg}_{XZ,feature2} \cdot C^{seg}_{XZ,feature3} \tag{3.20}$$

. In the same manner, we can compute C_{YZ}^{seg} in the Y-Z plane. Let $\beta_1 = max(C_{XZ}^{seg}, C_{YZ}^{seg}), \beta_2 = min(C_{XZ}^{seg}, C_{YZ}^{seg})$. The final confidence of segmented movement is defined as

$$C^{seg} = \begin{cases} \beta_1 & \text{if } \beta_1 > 2\beta_2 \\ min(1.5\beta_1, 1) & \text{otherwise} \end{cases} \tag{3.21}$$

By using the confidence of segmented movement, we are able to classify the movement into three categories:

- non-impaired when $C^{seg} < 0.4$
- mild-segmented when $0.4 < C^{seg} < 0.6$
- severe-segmented when $C^{seg} > 0.6$

Level 3 Kinematic Features

The level three task contains:

- Combination of lower level tasks. e.g. Reaching different objects in sequence
- Transporting objects from one location to another

The level 3 tasks are functional tasks which aims to judge the overall quality of movement. The constraints during the therapy are reduced significantly than those in the lower level. We attempt to access the quality of the movement in three aspects:

1. Completion time
2. Path ratio

3. Speed phases

To access the quality of completion time, we compare the completion time$time_{total}$ of patient during each task to reference data ref_{time}, which is the mean value of completion time of non-impaired people. The confidence is calculate as:

$$C^{time} = \begin{cases} 0 & \text{if } time_{total} \leq ref_{time} \\ 1 & \text{if } time_{total} \geq \lambda_{time} \cdot ref_{time} \\ \frac{time_{total}/ref_{time}-1}{\lambda_{time}-1} & \text{otherwise} \end{cases} \tag{3.22}$$

Path ratio is the ratio between the length actual trajectory during a task and the length of straight line between the desired positions that the patient is expected to reach. The speed phases are the number of significant local minimums of speed during the task. In the same manner of C^{time}, we can compute $C^{PathRatio}$ and $C^{SpeedPhase}$. The confidence leads to following judgement:

- non-impaired when $C < 0.4$
- mild-impaired in the specific aspect when $0.4 < C < 0.6$
- severe-impaired in the specific when $C > 0.6$

After the confidence of each aspect is computed and the classification is done in every aspect, we categorize the movement into three descriptive categories, efficient, mild-inefficient and severe inefficient in the following manner:

- The movement is efficient if we have three non-impaired classification results or two non-impaired classification results and one mild-impaired classification result.

- The movement is mild-inefficient if 1)we get two or three mild-impaired classification results without any severe-impaired classification result, and 2)we get two non-impaired classification results and one severe-impaired classification result.

- The movement is severe-inefficient for other situations.

3.2.2 TRIAL EVALUATION AND SET EVALUATION

In both Level 2 and Level 3 therapy, there are repetitive tasks which are considered as a set. This is due to:

- The basic threshold classification with confidence that is implemented in the system is not reliable enough on individual task.

- The quality of movement varies with the same people and individual evaluation result is usually biased to rate the level of impairment.

The set evaluation would compensate to this lack of reliability. For any aspect, the set confidence is computed as:

$$C^{set} = \frac{\sum_i w(i) \cdot C(i)}{\sum_i w(i)} \tag{3.23}$$

where

$$w(i) = \begin{cases} 0.05 & \text{if } C(i) \leq 0.25 \\ C(i) - 0.2 & \text{otherwise} \end{cases} \tag{3.24}$$

3.2.3 EVALUATION ACROSS FEATURES

There are five aspects of interest in Level 2 and three aspects of interest in Level 3 as described above. Evaluation of individual aspect can be done properly. However, in some cases, evaluation across different features is required.

At this point, comparison of confidence across different features is conducted to decide the more significant factor. However, the validation of comparison of confidence across different features with current design is not guaranteed. KIM, as described in Chapter 2, is of significant advantages to compare between different features. It is believed that using the features designed above to compute KIM would help to figure out the aspect that is of most significance.

Chapter 4

EXPERIMENT AND RESULT

In this chapter, I will present experimental results which demonstrated the efficacy of the proposed features and classifiers.

4.1 EVALUATION RESULTS FOR HOSPITAL SYSTEM

Since the home system inherits many concepts from the hospital system, I would like to begin this chapter with some quantitative evaluation results from the hospital system and discuss the possibility that those evaluation methods affect the design of quantitative evaluation of the home system.

Comparing fig 4.1 and fig 4.2 it is not difficult to figure out:

- The same feature value varies when the location of objects in the task varies, while the KIM value is much more stable when with this variation.
- The KIM is more sensitive to subtle improvement of movement quality. There is very little change in button 8, group 2 in fig 4.1, which are plotted with the feature value. In fig 4.2 the difference between pre-task and post-task has been quite obvious with the same data set computed into KIM.

4.2 RESULTS FOR HOME SYSTEM

The prior goal of the design of kinematic features is to give coarse classification result to drive the feed back in the home system at this point. Most of the features are tested with experienced researchers in the field of stroke rehabilitation to ensure their validity. Various experimental thresholds and constants that are described in the Level 2 tasks in previous section are listed in table 4.1.

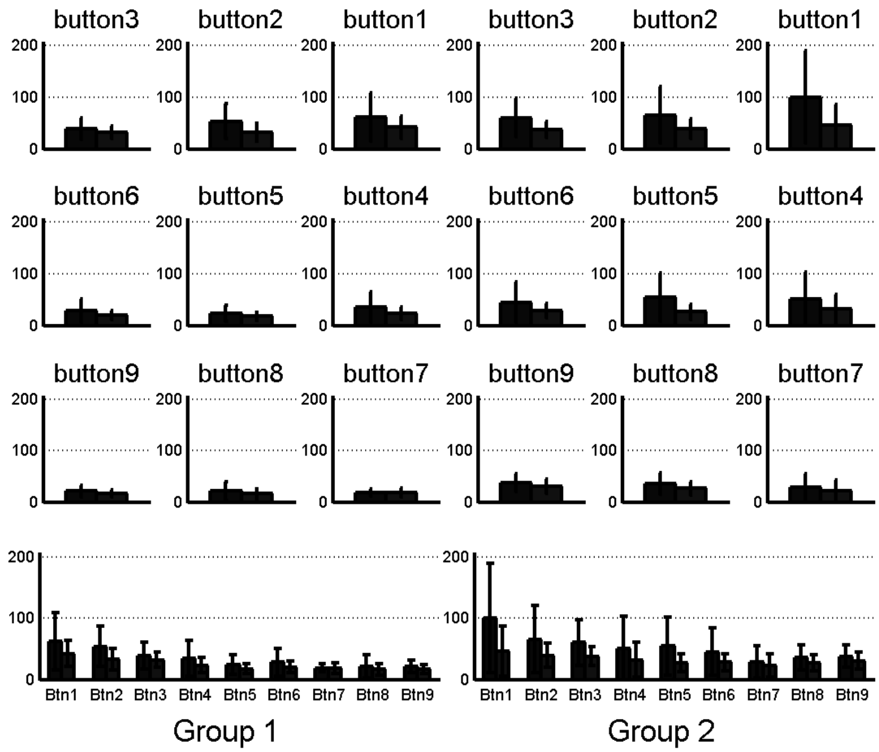

Figure 4.1: The distribution of vertical trajectory error in button box task. Group 1 are the distribution of a group which received the therapy without multimedia feedback. Group 2 are the distribution of a group which received therapy with multimedia feedback. Each error bar shows the mean value and standard deviation of the feature during the button box task. For every adjacent pair of error bars, the left present the data with pre-therapy task and the right present the data with the post-therapy task.

The sensitivity parameters in Level 3 tasks are listed in table 4.2

The segmented features and related classifier are the most challenging part in this thesis because there is no previous work on this problem with just end point information. How the features are designed has already been shown in Chapter 3. I will show how the features work with threshold based classification that is implemented in the system and how the features work with widely used modern classification tools. We have a training set with 10 segmented movements and 20 non-segmented movements and this set is used to design the features. We also have a testing set with 12 segmented movements

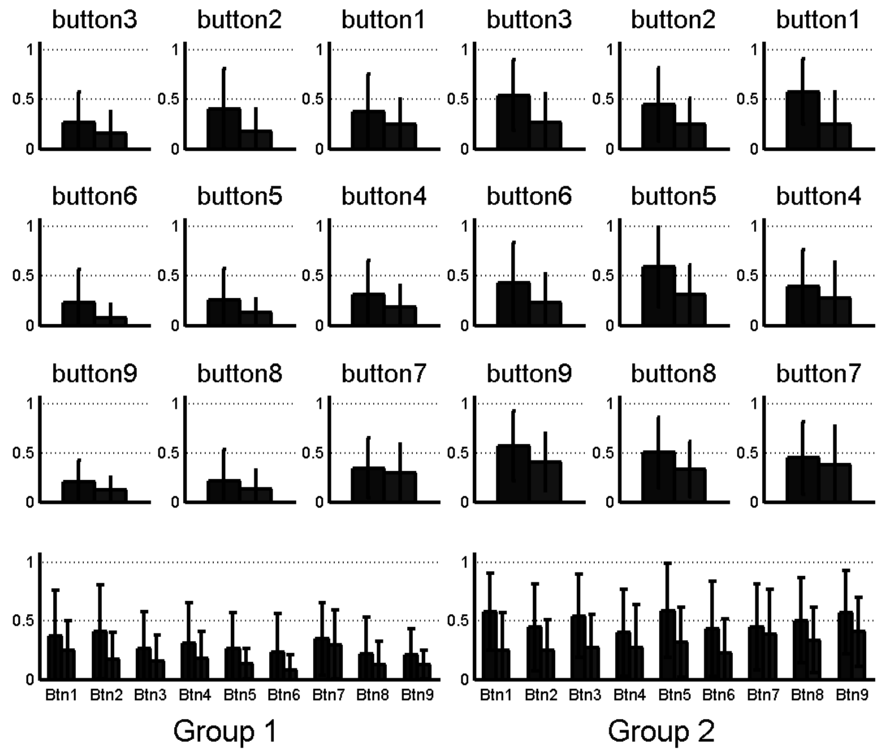

Figure 4.2: The distribution of KIM value vertical trajectory error in button box task.

Feature	Notation	Threshold	a	b
Curvedness	$Thre_{zero}^{X+}$	$20mm$	NA	NA
	$Thre_{hull}^{X+}$	$40mm$	NA	NA
	$Thre_{zero}^{X-}$	$-20mm$	NA	NA
	$Thre_{hull}^{X-}$	$-40mm$	NA	NA
	$Thre_{zero}^{Y+}$	$50mm$	NA	NA
	$Thre_{hull}^{Y+}$	$110mm$	NA	NA
	$Thre_{zero}^{Y-}$	$-50mm$	NA	NA
	$Thre_{hull}^{Y-}$	$-110mm$	NA	NA
Fastness	$Thre_{zero}^{speed+}$	$0.20m/s$	NA	NA
Slowness	$Thre_{zero}^{speed-}$	$-0.15m/s$	NA	NA
Smoothness	ref_{jerk}	$70000mm^2/s^2$	-0.693	1
Segmented	$thresh_{change}$	2	0.3046	-5.4449
	ref_{XZ}^{Dir}	$60°$	3.0908	-2.7530
	ref_{YZ}^{Dir}	$40°$	3.0908	-2.7530

Table 4.1: Threshold and parameters for Level 2 various features and confidence value estimation.

Feature	Notation	Value
Completion time	λ_{time}	2.5
Path ratio	$\lambda_{PathRatio}$	2.0
Speed phases	$\lambda_{SpeedPhase}$	2.5

Table 4.2: Sensitivity for Level 3 confidence estimation.

and 20 non-segmented movements. With the threshold based classifier which are implemented in the system, we classified 5 individual movements out of 12 as not segmented and 7 segmented. 1 of the 20 non-segmented movements is classified as segmented while the other 19 are correctly classified. By using the set evaluation, which is discussed in Chapter 3, we are able to get satisfactory results to drive the feedback. There are totally 62 movements, each presented by features that are discussed in the design of segmented features. Various combinations of features and classifiers, such as using just features obtained from $X - Z$ features, $Y - Z$ features, and a combination of both are tested. The results of 10-fold cross-validation are presented in tables 4.3 and 4.4. The results show that:

- Current design of segmented features leads to a satisfactory classification result.
- Modern classification techniques produce better results than threshold based classification which is implemented in the system.
- A combination of $X - Z$ and $Y - Z$ features leads to better results.

Classifiers	Naive Bayes	Nearest Neighbor	SVM
X-Z features	87.1%	96.77%	83.87%
Y-Z features	75.8%	98.38%	87.09%
Joint features	88.71%	98.38%	91.93%

Table 4.3: Results of cross-validation for classifying end-point trajectory into ‘Not Segmented’ and ‘Segmented’.

	Naive Bayes		Nearest Neighbor		SVM	
X-Z features	34	6	40	0	34	6
	2	20	2	20	4	18
Y-Z features	36	4	40	0	34	6
	11	11	1	21	2	20
Joint features	36	4	40	0	39	1
	3	19	1	21	4	18

Table 4.4: Confusion matrices for classifying end-point trajectory into 'Not Segmented' and 'Segmented'.

Chapter 5

CONCLUSION

Quantitative access to the quality of movement during stroke rehabilitation is discussed in this thesis. Current design of features for kinematic analysis is presented. The result of classification using these features currently meets the request of field experts. The validity of the design will be further tested in future research. The sensitivity and threshold will be refined in the future work. The need of evaluation across features requires feature independent analysis, and this would also be studied in the future work. KIM has shown its advantages in the hospital system, and will also be implemented in the home system after we collect enough data from patients.

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