Adaptive Mixed Reality Stroke Rehabilitation: System Architecture and Evaluation Metrics

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ABSTRACT

This paper presents a novel system architecture and evaluation metrics for an Adaptive Mixed Reality Rehabilitation (AMRR) system for stroke patient. This system provides a purposeful, engaging, hybrid (visual, auditory and physical) scene that encourages patients to improve their performance of a reaching and grasping task and promotes learning of generalizable movement strategies. This system is adaptive in that it provides assistive adaptation tools to help the rehabilitation team customize the training strategy. Our key insight is to combine the patients, rehabilitation team, multimodal hybrid environments and adaptation tools together as an adaptive experiential mixed reality system.

There are three major contributions in this paper: (a) developing a computational deficit index for evaluating the patient's kinematic performance and a deficit-training-improvement (*DTI*) correlation for evaluating adaptive training strategy, (b) integrating assistive adaptation tools that help the rehabilitation team understand the relationship between the patient's performance and training and customize the training strategy, and (c) combining the interactive multimedia environment and physical environment together to encourage patients to transfer movement knowledge from media space to physical space. Our system has been used by two stroke patients for one-month mediated therapy. They have significant improvement in their reaching and grasping performance (+48.84% and +39.29%) compared to other two stroke patients who experienced traditional therapy (-18.31% and -8.06%).

Categories and Subject Descriptors

C.4 [**Performance of Systems**]: Measurement techniques; J.3 [**Life and Medical Sciences**]: Health; H.5.2 [**Information Interfaces and Presentation**]: User Interfaces – auditory (non-speech) feedback, screen design, interaction styles

General Terms

Measurement, Design, Experimentation, Human Factors

Keywords

Mixed Reality Rehabilitation, Evaluation, Kinematic Deficit Index, Multimedia Feedback, Adaptation

1. INTRODUCTION

The goal of this paper is to propose a new system architecture and evaluation metrics for an adaptive mixed reality rehabilitation system for stroke patient. The problem is important – every 45 seconds, someone in the United States suffers a stroke, often leading to physiological impairment. Up to 85% of patients have a sensorimotor deficit in the arm, such as muscle weakness, abnormal muscle tone, abnormal movement synergies, and lack of coordination during voluntary movement [4]. Effective adaptive training using mixed reality rehabilitation can potentially lead to fuller and faster recovery [7,8,9,12]. Therefore, we develop this adaptive mixed reality rehabilitation system to help stroke patients recover the ability to form movement strategies for efficiently completing the reaching and grasping task.

There are three key problems that need to be addressed in an adaptive mixed reality rehabilitation system for stroke patient –

1. **Evaluating** the patient's movement performance computationally in real-time.
2. **Adapting** the system to customize the therapy based on the patient's ability and progress.
3. **Transferring** the movement knowledge from the virtual (or media) space to the physical space.

The computational evaluation for the patient's performance is important because it allows therapists to know the patient's status accurately in real-time without any additional test. This is very important for therapists to customize the training effectively. The computational evaluation also allows therapists to track the patient's entire improvement history. It is also important for the rehabilitation system to be adaptable to the patient's individual ability and progress, allowing for patients to be challenged physically and cognitively without frustrating them [9,12]. Finally, the system should be able to transfer the movement knowledge learned from the virtual space to the physical space. This is crucial because the rehabilitation goal is to improve the patient's daily life activities. These three problems are also limitations of our previous research on biofeedback system [1,2,18].

In this paper, we present an adaptive multimodal mixed reality rehabilitation system to address these three problems. *Firstly*, we present a computational kinematic deficit index to measure patient's movement performance and a deficit-training-improvement (*DTI*) correlation to evaluate the adaptive training strategy. The kinematic deficit index is a common, unified and subject-independent deficit measure for evaluating subject performance during reaching and grasping task. It is a computational indicator for the rehabilitation team to make adaptation decisions. The deficit-training-improvement (*DTI*) correlation tells us about the effect of the therapy by showing the patient's progress from pre-therapy to post-therapy, and the correlation between the improvement and training. *Secondly*, we present several adaptation assistive tools (e.g. central control, visualization, prediction and evaluation) that provide quantitative and informative analysis to help the rehabilitation team adapt the system and customize the training based on the patient's progress.

MMSys'10, February 22–23, 2010, Phoenix, Arizona, USA.

Finally, we integrate the interactive feedback environment with physical space by four environments (virtual, hybrid I, hybrid II and physical) to promote learning of generalizable movement strategies and transferring knowledge from media space to physical space. Our results for two stroke patients who used our system for mediated therapy strongly support that mediated therapy can lead to faster and more integrated recovery in terms of both activity accomplishment and performance. Both participants demonstrate greater significant improvement (+48.84% and +39.29%) in their performance of the reaching and grasping task after mediated therapy, as compared to two other stroke patients who experienced traditional therapy (-18.31% and -8.06%).

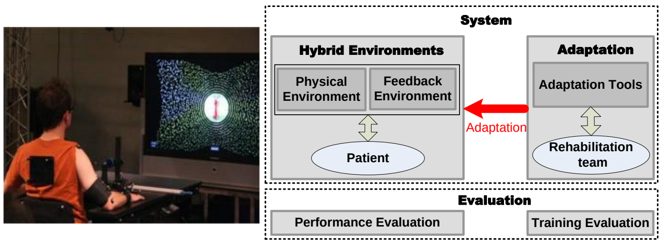

Figure 1. Adaptive mixed reality rehabilitation system. Left: physical setup, Right: system diagram.

The following sections of the paper are organized as follows. In section 2, we review the related work. In session 3, we present the architecture of our adaptive mixed reality rehabilitation (AMRR) system. In section 4, we discuss the multimedia feedback design. In section 5, we present the assistive adaptation tools that help the rehabilitation team adapt the system. We propose the evaluation for patient kinematic performance in section 6, and propose the evaluation for the adaptive training sequence in section 7. We describe the experimental results in section 8 and conclude the paper in section 9.

2. RELATED WORK

There has been extensive prior work on stroke rehabilitation using both mediated and non-mediated therapy. Improvements in kinematic or functional parameters of the upper extremity can be achieved through virtual reality therapy [8,12]. External feedback that augments the information gained from intrinsic sensory organs can offer guidance, motivation and encouragement. This can help stroke survivors to improve movements and gain confidence in the use of the affected limb [13,14]. Interactive environments can be used to encourage sensory-motor integration by providing feedback relevant to a specific function, and present this information in a meaningful and intuitive way [7,13,15]. The task and feedback should encourage active physical and cognitive participation by the patient to learn generalizable movement strategies [13]. The task and feedback must also be adaptable to the patient's individual ability and progress, allowing for patients to be challenged physically and cognitively without frustrating them [9,12]. These environments can provide accurate feedback on movement performance and record detailed kinematic parameters used for assessing functional recovery [5,12]. Patient interactions with such an environment have been shown to improve cognitive and physical function, increase self-esteem, and lead to feelings of greater self-efficacy and empowerment [9,15]. However, the existing systems do *not* provide real-time computational evaluation for kinematic movement or assistive adaptation tools based on data driven analysis. Thus, it is difficult for therapists to understand the patient's status accurately and customize the system based on patients' progress effectively.

There is also extensive prior work on qualitative and quantitative clinical measures for assessing a stroke patient's movement. The Motor Activity Log (MAL) [11] was developed to measure the improvement in the activities of daily living. The Wolf Motor Function Test (WMFT) [17] is a s series of functional tasks (arm movements, picking objects up, etc) that are timed and rated for quality by a trained therapist. Other measures such as the Arm Motor Activity Test [10], or the Fugl-Meyer Assessment Scale [6] are also used to evaluate a patient's movement pre and post therapy. However, these tests are based on questionnaires or movement assessment by a therapist. Thus they are sensitive to the subject's mood and individual interpretations by the different therapists conducting the evaluation.

Computational kinematic analysis using motion capture data provides reliable, repeatable, objective and quantitative measures of movement. It detects subtler changes in movements and provides specific quantities such as degree of elbow extension or hand velocity [5,16]. Recent rehabilitation studies have used kinematic measures resulting from motion capture to evaluate recovery in detail [12,16]. However these studies do not use a common, standard process to calculate the kinematics and thus they are hard to compare. Furthermore, they do not integrate the different attributes into a single deficit measure. Thus, we are not able to tell with confidence the overall performance improvement. Therefore, we are proposing a computational kinematic deficit index that integrates all key kinematic attributes into a single subject-independent deficit measure. This deficit index allows us to evaluate the patient's performance and to compare across patients in a standardized quantitative space.

3. SYSTEM ARCHITECTURE

We now present the system architecture of our Adaptive Mixed Reality Rehabilitation (AMRR) system. The primary goal of this system is the development of a real-time multimedia system that uses multimodal sensing to map structural representations of movement to interactive feedback. The environment provides a purposeful, engaging, visual and auditory scene in which patients can practice functional therapeutic reaching and grasping tasks, while receiving different types of simultaneous feedback indicating measures of both performance and results. Our system is an adaptive system that allows the rehabilitation team, consisting of a therapist and a media arts and sciences expert, to customize the training strategy by changing the system parameters. The system parameters include visual, audio, physical space and reaching task-specific parameters. Adaptation based on each patient's individual ability and performance is crucial for an effective rehabilitation. Our system provides an interface for changing the system parameters and several computational tools (such as visualization, prediction and kinematic assessment) to help the rehabilitation team make adaptation decision.

In this section, we first introduce the physical setup and functional tasks. Then we discuss the system structure and four training environments. Finally, we introduce the rehabilitation procedure.

3.1 Physical Setup and Functional Tasks

The patient is seated at a height- and position-adjustable table in front of a large screen display that provides visual feedback and two speakers that provide audio feedback. The table is placed to either fully support the affected arm or to leave the elbow of the affected arm unsupported. We use eight near-infrared cameras running at 100 frames per second to track the three-dimensional positions of reflective markers that are placed on the subject's back and affected arm. Figure 1-(left) shows the physical setup.

During training, patients perform a reaching task, either by reaching to a target, reaching to touch a target or reaching to grasp a target. The reaching task was selected because it is a widely used task for stroke patient rehabilitation. Reaching is a much needed functional task in everyday life, and the movement attributes of the task (i.e. bell like velocity profile) can easily generalize to performance of other functional tasks. Reaching movements start from a consistent rest position. The target can be physical (an object is placed in the space for the patient to touch or grasp with no feedback) or virtual (no physical object is present, with feedback) or hybrid (combined physical and virtual).

Patients are trained to reach towards four target locations that are placed according to each subject's body measurements and ability. The four target positions are determined by doctors and therapists. Two targets are on the table so the subject can use the table for support and two targets are placed 6 inches off the table so the subject must work against gravity to reach the targets. For both on-table and off-table, one target is positioned ipsilaterally and the other is placed in the midline. This results in four target locations:

1. Supported, Ipsilateral (SI) target: on the table and on the right.
2. Supported, Middle (SM) target: on the table and in the middle.
3. Against Gravity, Ipsilateral (AGI) target: off the table and on the right.
4. Against Gravity, Middle (AGM) target: off the table and in the middle.

3.2 System Structure

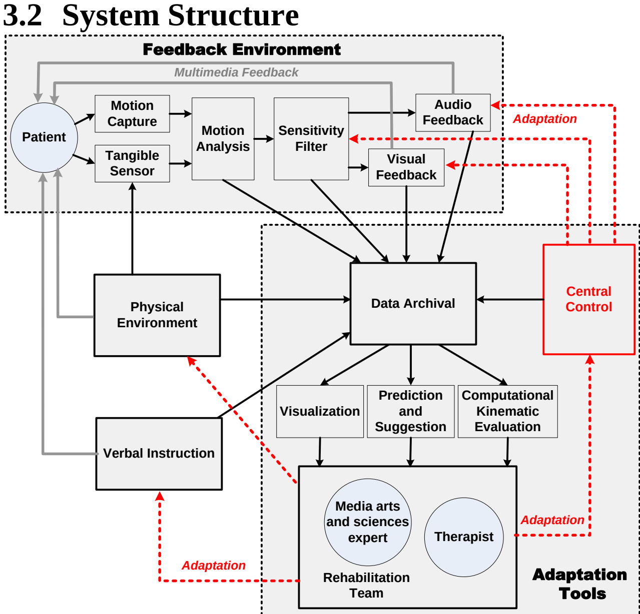

Figure 2. Adaptive mixed reality rehabilitation system structure.

We now discuss the structure of our adaptive mixed reality rehabilitation (AMRR) system. Figure 2 shows the system structure that integrates two major parts: (a) physical and feedback environments, and (b) adaptation tools. The physical and feedback environments are integrated into one multimodal interactive composition that (a) engages patients, (b) encourages patients to improve their performance of the training task, and (c) promotes learning of generalizable movement strategies. The adaptation tools help the rehabilitation team adapt the system to customize the training strategy. The rehabilitation team includes a therapist and a media, arts and sciences expert.

The physical environment includes a chair, a table and two physical targets (i.e. a push button and a 5-inch tall cone). The heights of the table and the chair are adjustable. The push button and the cone are used for training the push action and grasping action respectively. Force-sensing resistors are embedded in both the push button and the cone. The positions of these physical objects are measured physically and recorded in the data archival, in order to recover the same physical setup for a patient across visits.

In the feedback environment, the patient's arm movements are captured using multimodal sensing, analyzed, and then mapped as quantitative components of the action to the audio and visual feedback. Feedback communicates to the patient amount of error and direction for improvement and helps the patient learn a generative plan for reaching and grasping movement. We use OptiTrack motion capture system (including eight near-infrared cameras) to tracks the 3D positions of reflective markers that are placed on the subject at 100 frames per second. The tangible sensor tracks the touching and grasping movement of the patient's hand. The real-time motion analysis smoothes the raw sensing data, and derives an expanded set of task specific quantitative features. These features are normalized through the sensitivity filter. The motion analysis computation takes less than 5ms for each frame and results in zero latency (<10ms). It multicasts the analyzed data to the audio, visual and archival subsystems at the same frame rate. The analyzed data for each frame includes hundreds of parameters and takes 1408 bytes (binary format) which results in data transmission rate at 1.07M bps. Since this is the only data transmission in real-time and our system is built on a local wire network, we have not observed any delay and packet loss in our experiments. The audio and visual subsystems adapt their auditory and visual response dynamically to the normalized motion features under different feedback environments. The normalized and bounded movement error representation allows for feedback sensitivity to be adjusted by changing the control parameters in the sensitivity filter. The sensitivity filter, audio feedback and visual feedback can be adapted through the interface in the central control. The data archival subsystem continuously stores all types of the data streams (e.g. motion analysis data, sensitivity filter data, feedback data, etc.).

The adaptation tools allow the rehabilitation team to customize the training strategy by changing the system parameters. The rehabilitation team can change the system state by using the central control interface to operate the whole system such as calibration, start/stop of the training, changing the system parameters, and showing the selected motion features graphically in real-time. The visualization, prediction analysis and kinematic evaluation tools provide quantitatively helpful information for the rehabilitation team to make the decisions about how to adapt the rehabilitation process to meet the patient's needs and progress and enhance the rehabilitation outcomes. The visualization tool visualizes the analysis results of subject's performance. The prediction tool predicts the patient performance for the system adaptation query based on the mixture-of-experts based Dynamic Decision Network model [2]. The kinematic evaluation tool evaluates the patient's kinematic performance and the relationship between the training sequence and the patient's improvement.

3.3 Four Training Environments

In our adaptive mixed reality rehabilitation system, we organize the feedback into four different training environments:

1. Virtual – no physical target present, with interactive audio and visual feedback,
2. Hybrid II – a physical target present, with interactive audio and visual feedback.
3. Hybrid I – a physical target present, with interactive audio feedback only.
4. Physical – a physical target present, with no audio or visual feedback.

In the virtual environment, the patient learns the mappings between the feedback and his or her arm movements through exploring the action space and through experiencing the media environment. In the hybrid II environment, we help the patient transfer knowledge learned from the media interaction to physical space by integrating the multimedia feedback and physical target together in one environment. In hybrid I, we reduce feedback by only providing audio feedback to encourage transference and retention of knowledge gained from the media interaction. In the physical environment, we check if the patient successfully transfers knowledge from media space to physical space.

3.4 Rehabilitation Procedures

We now introduce the rehabilitation procedure by using our mixed reality rehabilitation system. Let us denote every subject visit as a *session*. For each session, there are several *sets*. Within each set, the environmental conditions (e.g. physical state, audio and visual parameters) remain fixed. Each set includes ten reaching *trials*. The rehabilitation team adapts the system during the short break (typically two minutes) between two consecutive sets. The team discusses the subject's movement performance, informed by the visualization, prediction analysis and kinematic evaluation tools, which illustrate the subject's performance for the previous sets. Then the rehabilitation team decides how to fine-tune the system (e.g. change musical instrument) to help the patient achieve a generative reaching and grasping plan. Again, the real-time aspect of the adaptation is crucial to this rehabilitation system, because immediate responses to patient performance greatly enhance the patient's ability to create and maintain a generative plan for movement [9,12].

4. MULTIMEDIA FEEDBACK DESIGN

We now present the design of the multimedia feedback within our AMRR system. Our system situates participants in a multi-sensory engaging environment, where structural components of physical actions by the right arm are coupled to audio and video feedback. Each key movement parameter of the affected arm's action is mapped to a feedback stream that is well suited to the intuitive display of the particular component of movement. Feedback streams are constructed based on multimodal arts composition principles, so as to intuitively communicate to the patient magnitude of error and direction for improvement. All feedback streams are integrated into one multimodal interactive composition that (a) engages patients, (b) encourages them to improve performance of the training task, and (c) promotes learning of generalizable movement strategies. An important measure of success of the feedback design is its ability to encourage participants to transfer the learned knowledge to interactions outside of the system in the physical world.

The feedback mapping has been presented in our previous work [1]. However, the previous system is not adaptable and has not been used for adaptive therapy for stroke patients. In this paper, we introduce a new component, feedback sensitivity filter, which normalizes the movement features. The normalized and bounded movement errors are dynamically mapped to the auditory and visual media. The normalized and bounded movement error representation allows for adjustment of feedback sensitivity by changing control parameters in feedback sensitivity filters. In this section, we first introduce specific features characterizing reaching and grasping movement. Secondly we discuss the feedback sensitivity filter. Finally, we review the design of the interactive feedback, the aspects of movement to which they are mapped, and the feedback adaptation.

4.1 Representing Reach and Grasp Action

We now discuss the key aspects of the reaching and grasping movement. We select four groups of features: (a) hand targeting and trajectory, (b) hand speed, (c) joint opening, and (d) compensation. Hand targeting, trajectory, and speed contribute strongly to the task completion, while joint opening and compensation focus on usage of key body structures to achieve task completion. The features of each group are listed in Table 1. We select these movement features because they can reflect non-impaired reaching movements, in which reaching for a target is efficiently accomplished with accuracy, natural speed, and joint extension without body compensation. These movement features can be derived from the 3D positions of reflective markers that are placed on the patient's affected arm and back of the torso [3]. We calculate these features every 10 milliseconds (i.e. at frame rate of 100fps). The data packet for each frame has 1408 bytes which results in data transmission rate at 1.07M bps.

The hand targeting and hand trajectory are represented by the hand marker position along the three directions in the local coordinate system X'Y'Z'. Let us denote the direction to the subject's left as X, the direction up to the ceiling as Y and the direction from the subject to the table as Z. Thus, we have a global 3D coordinate system. Based on the reaching task, we also have a local coordinate system X'Y'Z'. The Y' is the same as Y. We rotate the X and Z to X' and Z' such that the Z' direction is from the start position toward the target. Figure 3 (left) describes the global and local coordinate systems.

Table 1. Reaching and Grasping movement features

Group	Features
Hand targeting and trajectory	Hand maker position along three directions (X'Y'Z') in the local coordinate system.
Hand speed	Speed of the hand marker.
Joint opening	Shoulder flexion, Elbow extension and Forearm rotation
Compensation	Torso compensation (forward and twist Shoulder compensation (upward and forward) Elbow compensation (lift)

4.2 Feedback Sensitivity Filter

We now introduce the sensitivity filter. The basic idea is to filter the raw movement feature (finite or infinite) to a normalized and bounded movement error that is used by audio and visual feedback. This allows for (a) application of feedback design to any range of the movement features, and (b) adjustment of the feedback sensitivity by changing the filter parameters. In this section, we use the horizontal hand trajectory as an example to illustrate how to calculate the normalized feature error. In the similar manner, we can also compute the normalized error for joint opening and compensation.

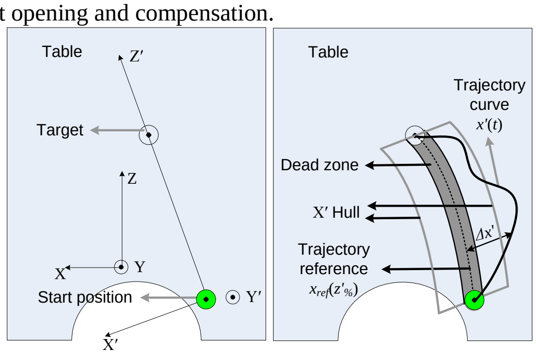

Figure 3. Hand trajectory along the table plane. Left: Global coordinate system XYZ and local coordinate system X'Y'Z'. Right: the reference trajectory, dead zone and the hull.

We denote the horizontal hand trajectory as $x'(t)$ (ref. Figure 3 right) that is along the X' direction in the local coordinate system. At every time stamp *t*, we compute the normalized horizontal trajectory error that is ranged from -1 to 1. Negative one and positive one means the hand is on the left and right respectively, very far away the reference trajectory (ref. Figure 3 right). The reference trajectory is extracted from averaging the reaching trajectory of non-impaired subjects. The normalized horizontal trajectory error is controlled by the two kinds of filter parameters: the dead zone and the hull (ref. Figure 3 right). The dead zone covers the non-impaired subject variation (3cm). The normalized error value is zero if the hand position is within the dead zone. The normalized error increases or decreases exponentially as the hand moves further from the dead zone toward the right or left respectively. The rate of the change is controlled by the size of the hull. The bigger the hull is, the slower is the rate of the error change. Thus loosening the hull provides a mechanism for lowering the feedback sensitivity. If the normalized error is less than -1 or bigger than 1, we cut it off to -1 or 1. Figure 4 shows how to normalize the error based on the dead zone and hull.

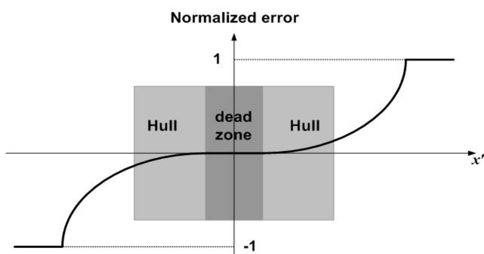

Figure 4. Sensitivity filter diagram

In the similar manner, we can also compute the normalized error for joint opening and compensation. For each feature of joint opening and compensation, we have a reference, a dead zone and a hull along the Z' direction.

4.3 Coupling Action Representation to Interactive Feedback

We now present how to couple our representation of a reach and grasp action to feedback generation. First, we discuss intuitions and principles guiding feedback design. Then, we follow with the audiovisual mappings and feedback adaptation.

4.3.1 Design of Interactive Feedback

Audiovisual feedback is mapped to key aspects of the user's action, with the purpose of directing his or her attention to how each aspect contributes to activity completion. The audiovisual media space is designed to recontextualize the reaching task, in that the mappings do not depict an arm reaching to grasp a target, but rather reflect an abstract audiovisual composition. The feedback environment therefore maps to any type of task or target location, and as a result, promotes learning that is generalizable beyond the rehabilitation training scenarios.

The interactive feedback must communicate a complex network of dynamic parameters in real time training. Thus intuitive communication to the user through the audiovisual media is crucial to meaningful understanding of his or her interaction with the system. Intuitive design of the feedback is based upon principles used within multimodal art forms, including music performance, dance, animation and film. The visual feedback communicates spatial aspects of the action relative to the target, while the auditory feedback communicates timing and event knowledge of specific aspects of action. The nature of the feedback highly correlates to the mapped action and thus is able to convey both magnitude of error and direction for improvement. Real time interactivity connects the user's action to immediate responses from the feedback environment that facilitates the action-feedback parallel. The user's active engagement within the integrated physical-digital space allows for training in the physical environment, while the media both (1) actively engages the user and (2) recontextualizes the reach and grasp to defuse frustrations associated with the difficulty of performing the task in daily life.

4.3.2 Feedback Mappings

In this section, we describe the specific audiovisual mappings used within our system. Goal accomplishment of the physical reach and grasp action is paralleled within the resolution of an audiovisual narrative, in which (1) an image that separates into particles is reformed, and (2) a musical progression initiated by reaching is resolved. The quality of the user's performance in physical space is manifested in the performance of the interactive media composition. A personalized image is presented on the screen before the user (Figure 5 a), and separates into hundreds of particles that expand to fill the screen (Figure 5 b). As the user's hand moves towards the target, he pushes the particles back to reassemble the image, while also driving the musical progression.

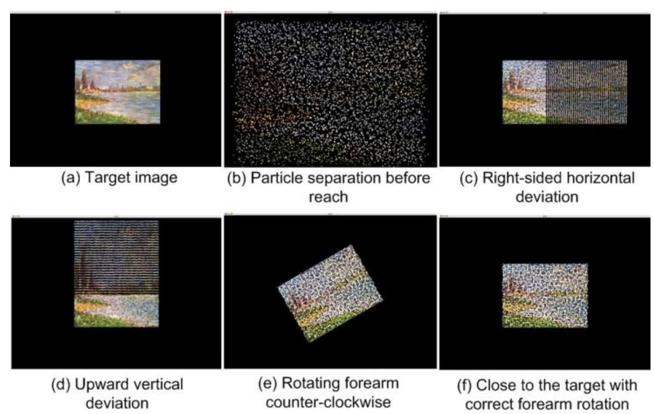

Figure 5. Visual feedback reflects spatial aspects of user's action

Reaching speed and duration, targeting, and trajectory accuracy are mapped to core aspects of the audiovisual narrative. As the most detailed, continuous feedback mappings, they draw attention to those aspects of movement that have the strongest integrated impact on completion of the action goal. When the user's hand deviates too far from an efficient trajectory path, the image particles sway in the direction of deviation (Figure 5 c, d). Thus the intuitive message is to move in the direction opposite of the particle sway to reassemble the image. Trajectory deviation is also reflected in the detuning of the harmonic progression within the audio feedback. Targeting is described by the coalescence of particles fitting into a white frame that appears near the end of the reach, as the user adjusts his hand position relative to the target. To communicate reach duration, each note of the harmonic progression is mapped along the normalized distance between the hand's start position and target. Reaching speed of the hand controls the rhythmic progression of the musical composition.

Joint function and compensatory movements are mapped to less detailed feedback that impart event knowledge amidst the more continuous feedback streams described above. Forearm rotation, if excessive or incorrectly timed, rotates the image in the direction of error (Figure 5 e). Magnitude of elbow extension is mapped to volume of orchestra strings that peak during full extension. Scraping or crackling sounds indicate compensatory body movements of the shoulder or torso, respectively. Finally, the communication of more complex, integrated descriptors of action performance emerges from the user's experience of multiple feedback mappings.

4.3.3 Feedback Adaptation

The feedback is adaptable in terms of feedback type, usage, and sensitivity. The rehabilitation team may select different training environments (see Section 3.3), enable or disable specific feedback mappings, adjust the media parameters in the audio and visual feedback (e.g. image set, musical instrument, sound volume), as well as change the sensitivity filter parameters to increase or decrease the feedback sensitivity (e.g. the width of dead zone, the width of hull). In the following section, we shall describe how we customize the feedback for each individual user by using assistive adaptation tools.

5. ASSISTIVE ADAPTATION TOOLS

In this section, we review the assistive adaptation tools that help the rehabilitation team to adapt the system. The prediction analysis, data archival, and visualization have been presented in [2,18]. However, we have not integrated these tools together for adaptive therapy for stroke patients. This is the first time that we integrate all these tools in our adaptive mixed reality rehabilitation system, which enables the rehabilitation team to adapt the mediated training based on the patient's progress. In addition, we develop two new tools – (a) central task control and (b) performance evaluation. The central task control provides a GUI for system adaptation and the performance evaluation provides the quantitative kinematic movement assessments for the patient.

5.1 Adaptive Training Sequence

We now discuss the adaptive training sequence. Training across all tasks and targets (ref. section 3.1) consists of approximately 14 sessions. Each session (ref. section 3.4) lasts for about 1.5 hours and includes about 120 reaches (12 sets of 10 reaches). Each session starts from the repetition of the last mixed reality set in the previous session. Depending upon patient needs, training starts with the easiest target location (supported ipsilateral ref. section 3.1) and gradually adjusts to the most difficult target location (against gravity at the midline).

The system supports an approach to highly customizable training. In the context of accomplishing the activity goal, the therapy may focus on any aspect of the reaching and grasping action, at the activity or body function level, or an integration of both. Within a single session, or across multiple sessions, the therapist may adapt the sequence and/or the weights of any aspect of the reach and grasp action. By enabling or disabling components of the feedback, or by increasing or decreasing feedback sensitivity, the therapist controls on which aspect of the feedback, and thus which aspect of the action, the patient should focus.

The training for each target includes a sequence of training sets (ref. section 3.4). Each set focuses on improvement of a set of movement parameters, while maintaining or further advancing gains in other parameters from previous sets. The rehabilitation team selects the focusing parameters for each training set and makes the adaptation decision between two consecutive sets based on task intensity and the movement assessment data. The task intensity refers to the number of sets remaining for training the current movement parameters. The adaptation decision-making includes four parts – (a) determine the focusing movement parameters, (b) select the appropriate training environment (virtual, hybrid I, hybrid II or physical), (c) select the feedback that relates to the selected movement parameters (e.g. enable image rotation for training the forearm rotation), and (d) adjust control parameters in the feedback sensitivity filters (e.g. width of the trajectory hull).

5.2 Central Task Control

The central task control provides a GUI to operate the whole system such as calibration, start/stop of the training set, changing system parameters. The rehabilitation team can use the central task control to change all feedback parameters that includes: (a) switch on/off of the specific feedback (e.g. torso compensation sound), (b) audio and visual feedback parameters (e.g. musical instrument and image set), and (c) the feedback sensitivity filter parameters (e.g. the trajectory hull or compensation hull). Figure 6 demonstrates the GUI of the central control. The central control also visualizes the motion features graphically in real-time, which allows the rehabilitation team to monitor the patient's movement during the patient's reaching.

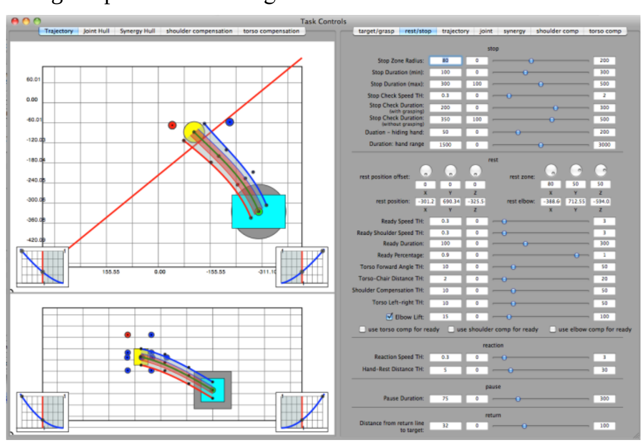

Figure 6. Central task control GUI.

5.3 Data Archival

The data archival subsystem continuously stores all kinds of the data streams for the purpose of annotation and off-line analysis. The data streams includes: (a) reaching and grasping movement features, (b) sensitivity filter control parameters, (c) audio and visual feedback parameters, (d) physical space measures, and (e) the verbal instructions and annotations of the rehabilitation team.

In addition, all rehabilitation sessions are videotaped. The recorded videos are important to help the rehabilitation team compare the patient performance perceptually and are also important for the offline analysis.

5.4 Visualization

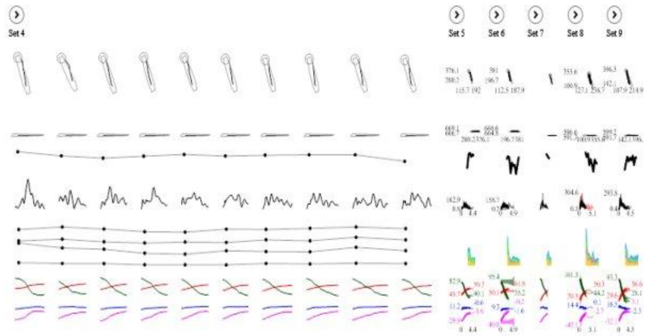

Figure 7. Screenshot of the visualization tool.

Visualization tool [18] summarizes the patient's kinematic performance in different temporal scales (session, set or trial). The fundamental challenge in visualization is that the rehabilitation team wants both the summary and the details at the same time. We organize the conceptual facets (i.e. kinematic features) vertically and the temporal faces hierarchically and horizontally. This organization reveals data trends within a conceptual facet and enables efficient data comparison across temporal facets. The visualization tool is very helpful for the rehabilitation team to track the patient's performance visually and adapt the training strategy efficiently.

5.5 Prediction and Suggestion

The prediction and suggestion tool addresses two basic questions based on data driven analysis:

Q1. *Performance prediction*: given a specific adaptation suggested Δf by the rehabilitation team (e.g. narrow the trajectory hull), the algorithm predicts the patient movement performance ΔO (e.g. trajectory error decreases by 1cm).

Q2. *Adaptation suggestion*: given an expected patient movement performance ΔO (e.g. increase the speed by 10%), the suggestion algorithm provides the optimal recommendation for the change of the environment Δf (e.g. increase the tempo).

We use a mixture-of-experts based Dynamic Decision Network (DDN) [2] for prediction and suggestion. We train DDN mixtures per patient, per session. The questions are answered through an optimality criterion based search on DDN models trained in previous sessions.

5.6 Performance Evaluation

The evaluation tool provides the quantitative kinematic assessments of the patient's movement to the rehabilitation team in real-time. This will help the rehabilitation team understand the patient's progress quantitatively. In addition, the evaluation tool can measure the correlation between the patient's improvement and adaptive training sequence. This allows the rehabilitation team to efficiently customize the training strategy for the therapy. Figure 8 shows a performance evaluation interface in our system. The details of algorithms to compute the kinematic deficit index and deficit-training-improvement correlation will be discussed in the next two sections.

Attribute	Mean	Std	deficit
reachingTimeConsistency	188.700	22.583	0.000
velocityPeak	4.261	0.388	0.037
velocityPeakConsistency	--	--	0.000
endPointCluster	--	8.533	0.000
endPointAccuracy	32.522	5.874	0.441
endPointErrorAtFivePercentVMax	35.306	9.619	0.322
trajectoryErrorX	38.022	8.474	0.243
trajectoryProfileConsistencyX	--	10.743	0.072
trajectoryErrorY	12.538	4.949	0.015
trajectoryProfileConsistencyY	--	2.906	0.000
velocityBellNormArea	0.517	0.153	0.921
velocityBellPhaseNumber	3.800	1.166	0.885
velocityBellCFE	0.391	0.095	0.574
velocityJerkiness	0.035	0.009	0.855
average deficit	--	--	0.293

Figure 8. Screenshot of the performance evaluation interface

6. KINEMATIC DEFICIT INDEX

In this section, we propose a common reference kinematic deficit index to measure patient performance during the reaching and grasping task. With this measure, we have a standard normalized space for all subjects. The deficit measure is important because: (a) It is subject-independent and allows us to compare the progress across patients, (b) the measure is bounded, so it is indicative of the room for improvement, and (c) it allows us to understand the rehabilitation progress quantitatively, and hence it is a computational indicator for the system adaptation.

A kinematic deficit index is computed for *a set* (ref. Section 3.4) of reaches (10 reaches) with respect to a reaching and grasping task. The basic idea is to use a normalized scalar between zero (implies no deficit) and one to evaluate the subject's kinematic movement. Zero deficit indicates that patient's movement is very close to non-impaired subject with respect to the reaching and grasping task. One means the patient's movement is very far away from non-impaired subject movement. Mathematically, the deficit measure can be formulated as a function of a set of reaches:

$$D = f(R_1, R_2, \ldots, R_N), \qquad \text{<1>}$$

where D is the deficit and R_i is the vector representation of the i^{th} reach. In our mixed reality rehabilitation, we evaluate the deficit for every set (ref. Section 3.4). Therefore N equals ten, since there are ten reaches within a set.

We develop the deficit measure in three steps. We first represent the subject's kinematic performance using 33 kinematic attributes. Then we map each kinematic attribute to a normalized attribute deficit number that is between zero and one. Finally we combine all attribute deficit numbers together to a single deficit number.

6.1 Kinematic Representation

We represent the kinematic movement during the reaching and grasping task by 33 attributes that are grouped into six groups. Each group has several related attributes. These six groups are shown in Table 2. The intuitions of these six groups come from the domain knowledge of therapists and bioengineering domain experts. The speed, time, targeting and trajectory are related to the simple reaching and grasping activity. The velocity bellness, jerk-cost and joint synergy are related to the reaching and grasping with good arm control. The velocity bellness refers to the bell shape of the velocity profile. The compensation and joint function are related to the body function.

Seven of these 33 attributes are in the set level (ref. Section 3.4). They are velocity peak consistency, time consistency, horizontal trajectory consistency, vertical trajectory consistency, shoulder flexion profile consistency, elbow extension profile consistency and forearm rotation consistency over ten reaching trials. The other 26 attributes are in the trial level. Each attribute is calculated per trial. For the sake of space limitation, we do not discuss the computation of these 33 attributes in this paper. The details of computation can be found in [3].

Table 2. 33 attributes for six groups.

Group	Attributes
Speed and Time	Speed (2 attributes), Time (1 attribute)
Targeting and trajectory	Targeting (3 attributes), Trajectory (4 attributes)
Velocity bellness and jerk-cost	Velocity bellness (3 attributes), Jerk-cost (1 attribute)
Joint synergy	pair-wise joint correlations (5 attributes)
Compensation	Torso compensation (2 attributes) Shoulder compensation (2 attributes) Elbow compensation (1 attribute)
Joint function	Shoulder flexion (3 attributes) Elbow extension (3 attributes) Forearm rotation (3 attributes)

6.2 Attribute Deficit

We now show how to compute the deficit for each attribute for *a set of reaches*. We treat the trial level attributes and set level attributes differently. For the trial level attribute (e.g. velocity peak), we first compute the deficit for every trial using the trial-level feature (e.g. velocity peak value of a trial), and then compute the average of ten trials as the deficit for a set. For the set level attribute (e.g. velocity peak consistency), we directly compute it using the set-level feature (e.g. velocity peak variance over a set).

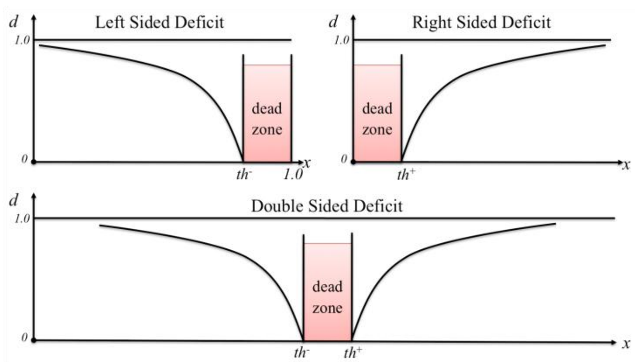

Figure 9. Three attribute deficit types. Top-left: left sided deficit. Top-right: right sided deficit. Bottom: double sided deficit.

The basic idea is to map each kinematic attribute range (infinite or finite) to a normalized range from 0 to 1. Zero deficit means that the subject performance is very close to non-impaired subjects in that attribute and one means the worst possible performance. Our intuition is that non-impaired subjects' performance for every kinematic attribute, results in a small value range for that attribute. In other words, unimpaired subjects performance for a specific task will show a small range of values, for each kinematic attribute. The more severe the stroke induced motor deficit, the further the patient performance will be from the non-impaired range. Therefore, we define a dead zone for each attribute that covers the non-impaired subjects' variation. The deficit value for an attribute is zero if the attribute value is within the dead zone. The deficit value increases exponentially as the attribute value moves further from the dead zone. The rate at which the deficit function increases is controlled by the sensitivity parameter. The values of dead zones and sensitivities [3] are determined from both kinematic literature and therapist domain knowledge. We classify the 33 attributes into three classes based on the shape of dead zone (shown in Figure 9):

1. Right sided deficit – The deficit range ($x>th^+$) is on the right of the dead zone.
2. Left sided deficit – The deficit range ($x<th^-$) is on the left of the dead zone.
3. Double sided deficit – The deficit range is on the both sides.

The deficit classes for all 33 attributes can be found in [3].

The right side deficit d for a *trial level* attribute (e.g. ending point accuracy in the targeting/trajectory group) is computed as follows:

$$d = \frac{1}{N}\sum_{i=1}^{N}\left(1 - e^{\frac{-h(x_i - th^+)}{\alpha^+}}\right), \quad h(x) = \begin{cases} x & if\ x > 0 \\ 0 & otherwise \end{cases}, \qquad <2>$$

where N is the number of trials in the set, x_i is the raw feature for the i^{th} trial, th^+ is the threshold and α^+ is the sensitivity parameter. The thresholds and sensitivity parameter for all 33 attributes can be found in [3]. They are determined from both kinematic literature and therapist domain knowledge. $h(\cdot)$ is a cut-off function. If the feature x is smaller than the threshold th^+, which means that the performance is within the dead zone, the deficit value is zero. If the feature x is larger than the threshold th^+ (right side), the deficit number increases exponentially to one. Slightly different with the trial level attribute, the *set level* attribute deficit (e.g. reaching time consistency in the speed and time group) is computed directly on the set level raw feature as follows:

$$d = 1 - e^{\frac{-h(x - th^+)}{\alpha^+}} \qquad <3>$$

where x is the raw feature (e.g. reaching time consistency) in the set level. In the similar manner to the right sided deficit, we can compute the left sided deficit for trial level attributes (e.g. joint synergy between shoulder flexion and elbow extension in the joint synergy group) and the double sided deficit. The mathematical details can be found in [3].

6.3 Computational Kinematic Deficit Index

Using the eq<2> and eq<3>, we can compute deficits for all 33 attributes. Therefore, we can construct a deficit vector using these 33 attribute deficit values:

$$\boldsymbol{d} = \left[d_1, d_2, ..., d_K\right]^T, K = 33, \qquad <4>$$

where d_k is the deficit of the k^{th} attribute for a set. Each element d_i is a scalar between zero and one. The overall deficit D for a set of reaching trials is computed as weighted summation over 33 attribute deficit values as follows:

$$D = \sum_{k=1}^{K} w_k^a d_k \Big/ \sum_{k=1}^{K} w_k^a, K = 33, \qquad <5>$$

where d_k and $w^a{}_k$ are the attribute deficit and the attribute weight for the k^{th} attribute. In our mixed reality rehabilitation for stroke patient with respect to the reaching and grasping task, we use the same attribute weights [3] for all patients. These attribute weights are subject independent and are determined by doctors and therapists based on their domain knowledge.

7. DEFICIT-TRAINING-IMPROVEMENT (DTI) CORRELATION

We now propose a computational algorithm for computing the deficit-training-improvement (*DTI*) correlation to evaluate the adaptive training (ref. Section 5.1) performed through our mixed reality rehabilitation system. This framework is based on calculating the correlations between the patient's initial movement deficit (D), the training implemented through our system (T), and the improvement in the patient's movement at the end of the therapy (I). The deficit-training-improvement correlation tells us about the effect of the therapy by showing the patient's progress from pre-therapy to post-therapy (DI), and the correlation between the improvement and training (TI). With this framework, we can evaluate and compare the different training procedures implemented through our mixed reality rehabilitation system.

7.1 Deficit-Improvement Correlation

The deficit-improvement correlation is the correlation between the deficit at the beginning and the improvement at the end. Therefore we need to compare the patient performance before the rehabilitation and after the rehabilitation fairly. In our mixed reality rehabilitation, the first session is the pre-test and the last session is the post-test. In both the pre-test and the post-test, the subject does four sets of reaches for four different targets. Each set has ten trials. The four targets in the pre-test and in the post-test are exactly same. These four targets are SI, SM, AGI and AGM (ref. Section 3.1). For each target, we can compute the deficit vector (ref. eq.<4>) and overall deficit value (ref. eq.<5>).

Let us denote the deficit for the k^{th} attribute for the m^{th} target for pre-test and for post-test as $d_{m,k}^{pre}$ and $d_{m,k}^{post}$ respectively. We defined the improvement from the pre-test to the post-test as the weighted average of deficit difference over all 33 attributes over all four targets. The overall improvement is computed as follows:

$$IMP = \frac{\sum_{m=1}^{M}\sum_{k=1}^{K} w_{m,k}^{a}(d_{m,k}^{pre} - d_{m,k}^{post})}{\sum_{m=1}^{M}\sum_{k=1}^{K} w_{m,k}^{a}}, \qquad <6>$$

where $w^{a}_{m,k}$ is the attribute weight for the k^{th} attribute for the m^{th} target, M is the number of targets and K is the number of attributes (M=4, K=33). Attribute weights are determined by doctors and therapists based on their domain knowledge. They are fixed for all subjects and can be found in [3].

We define the deficit-improvement correlation as the ratio between the improvement and deficit in the pre-test. The deficit-improvement correlation DI is computed as follows:

$$DI = \frac{IMP}{D_{pre}} = \frac{\sum_{m=1}^{M}\sum_{k=1}^{K} w_{m,k}^{a}(d_{m,k}^{pre} - d_{m,k}^{post})}{\sum_{m=1}^{M}\sum_{k=1}^{K} w_{m,k}^{a} d_{m,k}^{pre}}, \qquad <7>$$

where the IMP is the improvement (ref. eq.<6>) and the D_{pre} is the overall deficit value for the pre-test for reaching for four targets. The DI correlation tells us how much (in percentage) of the deficit in the pre-test is improved in the post-test.

7.2 Deficit-Training Correlation

We now propose the deficit-training correlation. The basic idea is to check if the attributes with high deficit value are more focused in the training. We address this problem by two steps: (a) representing the training as a training vector over 33 kinematic attributes, and (b) computing the cross correlation of training vector and deficit vector as the DT correlation.

7.2.1 Training Vector

We compute the training vector T using the task focus vectors $F_{i,j}$ of all training sets as follows:

$$T = \sum_{i=1}^{L}\sum_{j=1}^{J(i)} F_{i,j}, \qquad <8>$$

where L is the number of the training sessions, $J(i)$ is the number of sets in the i^{th} session, $F_{i,j}$ is the task focus vector (33x1) over the 33 attributes for the i^{th} session and the j^{th} set. The element $F_{i,j}(k)$ indicates if the k^{th} kinematic attribute (ref. Section 6.1) is directly trained in the i^{th} session and the j^{th} set. If yes, $F_{i,j}(k)$ equals one, otherwise, $F_{i,j}(k)$ equals zero. At the beginning of every training set, the rehabilitation team annotates the focusing attribute groups (ref. Table 2). If an attribute group is focused, all attributes in this group have value one on the corresponding elements of the task focus vector $F_{i,j}$. Therefore, the element of training vector $T(i)$ equals the number of sets in which the i^{th} kinematic attribute is directly trained. We normalize the training vector by dividing the maximum component. Thus, each component of the training vector represents the percentage of training efforts of the corresponding attribute compared to the most focusing attribute.

7.2.2 Computing Deficit-Training Correlation

We compute the cross correlation of training vector T and the average deficit vector over four targets in the pre-test as the deficit-training correlation:

$$DT = corr\left(\frac{1}{M}\sum_{m=1}^{M}\boldsymbol{d}_{m}^{pre}, T\right) = \frac{\sum_{k=1}^{K}\left[\left(\frac{1}{M}\sum_{m=1}^{M} d_{m,k}^{pre} - \mu_d\right)(T_k - \mu_T)\right]}{\sqrt{\sum_{k=1}^{K}\left(\frac{1}{M}\sum_{m=1}^{M} d_{m,k}^{pre} - \mu_d\right)^2 \sum_{k=1}^{K}(T_k - \mu_T)^2}},$$

$$\mu_d = \frac{1}{MK}\sum_{m=1}^{M}\sum_{k=1}^{K} d_{m,k}^{pre}, \quad \mu_T = \frac{1}{K}\sum_{k=1}^{K} T_k \qquad <9>$$

where $\boldsymbol{d}_m^{pre}$ is the deficit vector (ref. eq. <4>) for the m^{th} target in the pre-test and T is the training vector (ref. eq.<8>). $d_{m,k}^{pre}$ is the deficit for the k^{th} attribute for the m^{th} target for pre-test. T_k is the k^{th} element of the training vector (ref. eq.<8>). M is the number of the targets (M=4) and K is the number of attributes (K=33). If the deficit and training have the similar trend, the deficit-training correlation is close to 1. If they are in the opposite trend, the deficit-training correlation is close to -1.

7.3 Training-Improvement Correlation

The training-improvement (TI) correlation measures how much the training and the improvement align together. We use two measures – (a) observed expected improvement ratio (TI_R) and (b) observed expected improvement overlapping rate (TI_{OR}) to compute the correlation between training and improvement.

7.3.1 Observed Expected Improvement Ratio (TI_R)

The observed expected improvement ratio is the ratio of observed improvement and expected improvement. The observed improvement is computed using eq.<6>. The expected improvement is the expectation from the training that is computed by using the deficit in the pre-test and the training vector T (ref. eq.<8>). The expected improvement $E_{m,k}$ for the k^{th} kinematic attribute for the m^{th} target is computed as follows:

$$E_{m,k} = \alpha d_{m,k}^{pre} T_k, \qquad <10>$$

where $d_{m,k}^{pre}$ is the deficit for the k^{th} attribute for the m^{th} target in the pre-test, T_k is the k^{th} element of the normalized training vector. The element corresponding to the most focused attribute in the training vector has the maximum value – one. α is the expectation scalar that indicates the expected improvement percentage for the most focused attribute. In this paper, we select α = 0.65 from the therapist's intuition. For stroke patients, the most focused attribute (T_k=1) in the pre-test is usually further away dead zone by more than one time of sensitivity (e.g. $x>\alpha^+$+th$^+$ in the right sided deficit ref. Section 6.2). The therapist expects this attribute to be improved within quarter time of sensitivity close to the dead zone (e.g. $x<0.25\alpha^+$+th$^+$). Hence, α = 0.65.

The observed expected improvement ratio (TI_R) is computed as follows:

$$TI_R = \frac{IMP}{EXP} = \frac{\sum_{m=1}^{M}\sum_{k=1}^{K} w^a_{m,k}(d^{pre}_{m,k} - d^{post}_{m,k})}{\alpha \sum_{m=1}^{M}\sum_{k=1}^{K} w^a_{m,k} d^{pre}_{m,k} T_k}, \qquad \text{<11>}$$

where $d_{m,k}^{pre}$ and $d_{m,k}^{post}$ are deficits for the k^{th} attribute for the m^{th} target for the pre-test and the post-test respectively, $w^a_{m,k}$ is the attribute weight for the k^{th} attribute for the m^{th} target, T_k is the k^{th} element of the normalized training vector and α is the expectation scalar. If the observed expected improvement ratio is larger than one, the actual improvement is better than the expectation. Figure 10 (left) visualizes the computation of TI_R.

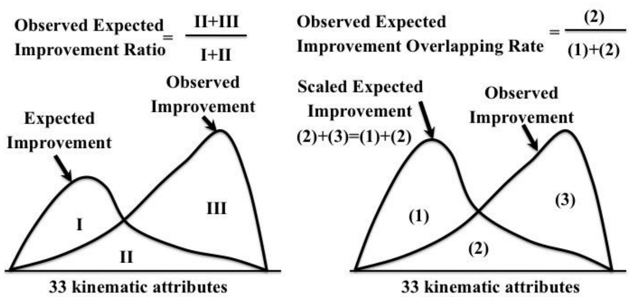

Figure 10. Training-Improvement (*TI*) correlation. Left: observed expected improvement ratio TI_R, Right: observed expected improvement overlapping rate TI_{OR}.

The observed expected improvement ratio tells us if the observed improvement is better than the expectation. However, it does not show if the observed improvement distribution over 33 kinematic attributes aligns to the expected improvement distribution. We shall address this using observed expected improvement overlapping rate (TI_{OR}) in the following section.

7.3.2 Observed Expected Improvement Overlapping Rate (TI_{OR})

We use the observed expected improvement overlapping rate (TI_{OR}) to measure the alignment between the observed improvement distribution and the expected improvement distribution over 33 kinematic attributes. The basic idea is to scale the expected improvement such that the overall expected improvement equals the overall observed improvement and to compute the overlapping between the observed improvement and scaled expected improvement over 33 kinematic attributes. Figure 10 (right) illustrates the computation diagram. The scalar is computed as follows:

$$\beta = \frac{\sum_{m=1}^{M}\sum_{k=1}^{K} w^a_{m,k}(d^{pre}_{m,k} - d^{post}_{m,k})}{\sum_{m=1}^{M}\sum_{k=1}^{K} w^a_{m,k} d^{pre}_{m,k} T_k}. \qquad \text{<12>}$$

where $d_{m,k}^{pre}$ and $d_{m,k}^{post}$ are the deficits for the k^{th} attribute for the m^{th} target for the pre-test and the post-test respectively, $w^a_{m,k}$ is the attribute weight for the k^{th} attribute for the m^{th} target and T_k is the k^{th} element of the normalized training vector. Then, we compute the overlapping rate (TI_{OR}) of observed improvement distribution and the scaled expected improvement distribution as follows:

$$TI_{OR} = \frac{\sum_{m=1}^{M}\sum_{k=1}^{K} w^a_{m,k} h[\min((d^{pre}_{m,k} - d^{post}_{m,k}), \beta d^{pre}_{m,k} T_k)]}{\beta \sum_{m=1}^{M}\sum_{k=1}^{K} w^a_{m,k} d^{pre}_{m,k} T_k}, \qquad \text{<13>}$$

where $h(\cdot)$ is a cut-off function (ref. eq.<2>). For the best case that the observed improvement and the expected improvement have the same distribution over 33 kinematic attributes, the overlapping rate equals one. For the worst case that attributes focused in the training have no improvement, the overlapping rate is zero.

8. EXPERIMENTAL RESULTS

We now discuss the experimental results. Our mixed reality rehabilitation system has been installed in the Banner Baywood Medical Center. Four stroke patients were recruited for the study. Two stroke patients (subject 1 and 2) experienced mediated therapy using our adaptive mixed reality rehabilitation system. They were unfamiliar with the system prior to the rehabilitation. The other two stroke patients (subject 3 and 4) are in the control group. They did traditional therapy. The age, sex and stroke severity for four subjects are listed in Table 3. All four patients were suffered stroke in the right arm. They did fourteen training sessions in one month. Each session lasted approximately 1.5 hours. The rehabilitations are lead by a therapist who has one year experience of using our system. For all four stroke patients, the first session is the pre-test and the last session is the post-test. In both pre-test and post-test, they have four sets of reaching for four different targets (i.e. SI, SM, AGI, AGM in section 3.1). For each subject, the four targets in the pre-test and the post-test are exactly same.

Table 3. Stroke patient information

Subject	Group	Age	Sex	Severity
1	mediated	aged	M	severe
2	mediated	Middle aged	F	moderate
3	control	aged	M	mild
4	control	aged	M	mild

8.1 Results of Computational Kinematic Deficit Index

We now show the deficit results for pre-test and post-test computed using eq.<5>. Table 4 shows the deficit results for the four subjects for four different targets (SI, SM, AGI and AGM ref. Section 3.1) for both pre-test and post-test. We can see that our deficit measure agrees with the stroke severity of the patients. In the pre-test, the severe stroke patient (subject 1) has higher deficit value 0.685, the moderate patient (subject 2) has the middle deficit value 0.201 and the two mild patients (subject 3 and 4) have lower deficit values 0.105 and 0.126. This shows that our deficit measure aligns to the clinical stroke severity.

We can also see that the two stroke patients experiencing the mediated therapy using our system have significant improvement (i.e. reducing deficit) in reaching and grasping movement for all four target positions. This indicates that our system helps them learn a generative movement plan for reaching and grasping task. We observe that two stroke patients who took traditional therapy improved in some targets but got worse in other targets. In average, their deficit values increase a little. This strongly supports the ability of adaptive mediated therapy using our system to lead to faster and more integrated recovery in terms of both activity accomplishment and performance.

Table 4. Deficit results for four subjects for pre-test and post-test for four targets (SI, SM, AGI and AGM) using eq.**<5>**. The deficit value for the subject 4 for the target SI in post-test is not available due to the system failure

Subject ID		SI	SM	AGI	AGM	Average
1	pre	0.716	0.627	0.658	0.740	0.686
(mediated)	post	0.258	0.294	0.416	0.432	0.351
2	pre	0.158	0.231	0.193	0.219	0.201
(mediated)	post	0.096	0.125	0.163	0.102	0.122
3	pre	0.087	0.121	0.100	0.111	0.105
(control)	post	0.127	0.138	0.075	0.156	0.124
4	pre	0.102	0.164	0.127	0.112	0.126
(control)	post	---	0.104	0.136	0.195	0.145

8.2 Results of Deficit-Training-Improvement (DTI) Correlation

We now discuss the deficit-training-improvement (*DTI*) correlation results. The *DI* correlation is computed for all four subjects and the *DT* and *TI* correlations are only computed for two subjects in the mediated group. This is because the two control subjects have no computational training representation *T* (eq.<8>) that is only available for mediated training. We first show the deficit-improvement correlation (eq.<7>). Then we present the deficit-training correlation results (eq.<9>) and the training-improvement correlation results (eq.<11> <13>).

8.2.1 Deficit-Improvement Correlation (DI)

Table 5 shows the deficit-improvement (*DI*) correlation results for four stroke patients. Figure 11 shows the deficit-improvement plot for the four sets of reaching for four different targets (i.e. SI, SM, AGI and AGM ref. Section 3.1). We observe that the two subjects in mediated group have significant improvement (*DI* values are more than +39%) and the movement performance of two subjects in the control group decreases (*DI* values are less than -8%). This indicates that our adaptive mixed reality system is very helpful and efficient for stroke patients to learn a generative movement plan for reaching and grasping task.

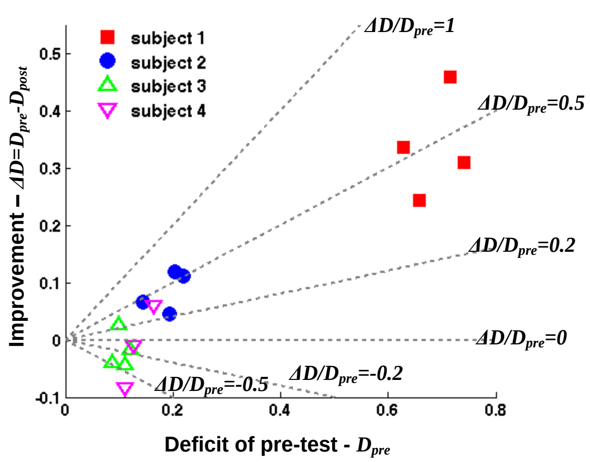

Figure 11. Deficit-Improvement plot.

Table 5. Deficit-Improvement (*DI*) correlation results for four stork patients. The improvement and *DI* correlation are computed using eq.<6> and eq.<7> respectively.

Subject	Improvement	Deficit-Improvement (DI)
1 (mediated)	+0.335	+48.84%
2 (mediated)	+0.079	+39.29%
3 (control)	-0.019	-18.31%
4 (control)	-0.011	-8.06%

8.2.2 Deficit-Training Correlation (DT)

The deficit-training (*DT*) correlation (ref. eq.<9>) results for subject 1 and subject 2 are 63.16% and 45.29% respectively. Figure 12 shows the average deficit vector (ref eq. <4>) in the pre-test and the training vector (ref. eq. <8>). We can see that the deficit and training are well correlated for both subjects. In practice, we understand the deficit and training are not fully aligned (100% correlated). This is because of two reasons:

1. The rate of improvement is different over kinematic attributes. Therefore the training efforts for different kinematic attributes might be different although they have the same deficit value in the pre-test.
2. The correlation between the 33 kinematic attributes is not known. It is very possible that when the training focuses on some attributes, other attributes are also improved accompany with the focusing attributes. It is also possible that the improvement of the attributes in focus in the current task makes worse the movement performance of other attributes.

Therefore, we expect the deficit training correlation to be high but not necessary to be perfect.

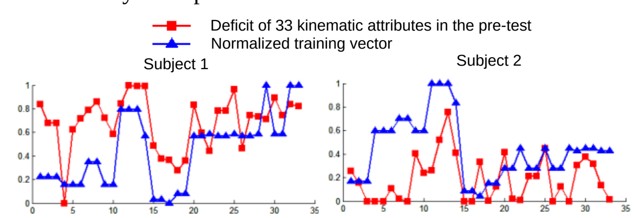

Figure 12. Deficit and training over the 33 kinematic attributes. The deficit vector is the average over four targets in the pre-test. The deficit vector for each target is computed using eq.**<4>**. The training vector is computed using eq. **<8>**.

8.2.3 Training-Improvement Correlation (TI)

We now show the training-improvement (*TI*) correlation results for two subjects in the mediated group. Table 6 shows the results for the observed expected improvement ratio (ref. Section 7.3.1) and observed expected improvement overlapping rate (ref. Section 7.3.2). We can see that the actual improvement is better than the expectation for both subjects (improvement expectation ratio TI_R is above one). We also observe that the actual improvement is well aligned to the expectation for the moderate stroke patient (subject 2). The overlapping rate is 69.66%. For subject 1, the overlapping rate is lower (53.39%). This is because for the severe stroke patient, it is difficult to improve some kinematic attributes such as velocity bellness (i.e. the bell shape of the velocity profile) within one month rehabilitation. For subject 1, although the velocity bellness is improved in the post-test compared to the pre-test, the velocity bellness value is still far from the dead zone. Therefore, the observed improvement cannot meet the expectation. However, for subject 1, some other attributes such as joint range of motion improve much more than the expectation.

When we compute the weighted summation over 33 kinematic attributes, subject 1 improves 1.545 times of expectation (improvement expectation ratio TI_R is 1.545).

Table 6. Training-Improvement (*TI*) correlation results for two subjects who did mediated therapy. The observed expected improvement ratio TI_R and the observed expected improvement overlapping rate TI_{OR} are computed using eq.<11> and eq.<13> respectively.

Subject	TI_R	TI_{OR}
1	1.545	53.39%
2	1.055	69.66%

Figure 13 compares the average improvement to the expectation over 33 attributes. We can see that the actual improvement for subject 1 is better than the expectation for most of the attributes except attribute 11–14. They are three velocity bellness measures and velocity jerk-cost. They are too hard for a severe stroke patient to improve close to the dead zone in one month therapy. For subject 2, the improvement and expectation are well aligned.

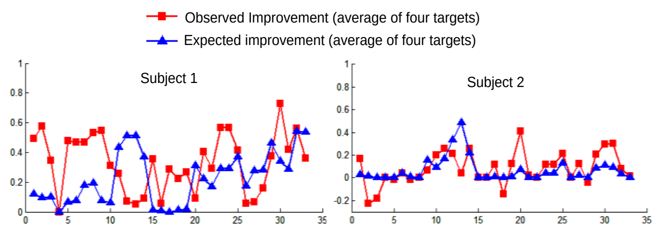

Figure 13. Observed improvement and expected improvement over 33 kinematic attributes. The observed improvement is the average improvement over four targets. The expected improvement is computed using eq. <10>.

9. CONCLUSION

This paper presents novel system architecture and evaluation metrics for an adaptive mixed reality rehabilitation (AMRR) system for stroke patient. Our system not only encourages stroke patients to learn a generative reaching and grasping movement plan, but also helps the rehabilitation team customize the training strategy. There are three contributions in this paper: (a) the computational deficit index for evaluating the patient's kinematic performance and deficit-training-improvement (*DTI*) correlation for evaluating the adaptive training strategy, (b) developing assistive adaptation tools in the system, and (c) integrating the interactive feedback environment with physical space to promote learning of generalizable movement strategies and transferring knowledge from media space to physical space. Results from our study show that the two stroke patients who experienced mediated therapy have greater significant improvement than the two stroke patients who experienced traditional therapy. This strongly supports the ability of mediated therapy to lead to faster and more integrated recovery in both activity accomplishment and performance. Future research includes (a) analyzing the correlation between different rehabilitation environments (virtual, hybrid and physical) and movement performance improvement, (b) discovering the structure in adaptive training and kinematic movement and their structural correlation, and (c) recommending the training sequence or strategy to the therapist.

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