Media Adaptation Framework in Biofeedback System for Stroke Patient Rehabilitation

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ABSTRACT

In this paper, we present a media adaptation framework for an immersive biofeedback system for stroke patient rehabilitation. In our biofeedback system, media adaptation refers to changes in audio/visual feedback as well as changes in physical environment. Effective media adaptation frameworks help patients recover generative plans for arm movement with potential for significantly shortened therapeutic time. The media adaptation problem has significant challenges – (a) high dimensionality of adaptation parameter space (b) variability in the patient performance across and within sessions (c) the actual rehabilitation plan is typically a non first-order Markov process, making the learning task hard.

Our key insight is to understand media adaptation as a real-time feedback control problem. We use a mixture-of-experts based Dynamic Decision Network (DDN) for online media adaptation. We train DDN mixtures per patient, per session. The mixture models address two basic questions – (a) given a specific adaptation suggested by the domain expert, predict patient performance and (b) given an expected performance, determine optimal adaptation decision. The questions are answered through an optimality criterion based search on DDN models trained in previous sessions. We have also developed new validation metrics and have very good results for both questions on actual stroke rehabilitation data.

Categories and Subject Descriptors

J.3 [**Life and Medical Sciences**]: Health; H.5.3 [**Group and Organization Interfaces**]: Computer-supported cooperative work; I.6.4 [**Simulation and Modeling**]: Model Validation and Analysis

General Terms

Algorighms, Experimentation, Human Factors,

Keywords

Biofeedback, Media adaptation, Dynamic decision network, Mixture of experts

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1. INTRODUCTION

The goal of this paper is to develop a Dynamic Decision Network (DDN) based media adaptation framework for use in a multi-modal biofeedback system [1] for stroke patient rehabilitation. Stroke rehabilitation is an important problem – every 45sec. someone in the United States suffers a stroke, often leading to physiological impairment. Effective media adaptation frameworks can potentially lead to significantly shortened therapeutic procedures (typically taking years). In this paper, media adaptation refers to changes in audio/visual feedback as well as changes in physical environment.

There has been prior work on biofeedback therapy. Virtual Reality (VR) is an emerging and promising technology for task-oriented biofeedback therapy to improve motor function in individuals with stroke [5]. VR can provide an effective human computer interface that allows users to interact with a complex, highly detailed and engaging multimodal feedback in response to physical action. This has significant potential in augmenting traditional task-oriented therapy training. It has been shown that task learning in a VR can be transferred into real world task performance [7]. Holden et al. [5] utilized VR to train reaching and hand orientation of stroke patients by developing a virtual mailbox environment with different slot height and orientation.

There has been extensive prior work on using dynamic models in multimedia (e.g. [12]) as well as in computer vision (e.g. [9]). However since our research is analogous to a real-time feedback control problem, the most relevant work appears in robotic control / planning problems using Partially Observable Decision Markov Processes [8,11]. There, Theocharous et al. [11] use hierarchical POMDPs to represent multi-resolution spatial maps for indoor robot navigation. This paper is motivated by these control problems and applies them to multimedia research.

The media adaptation problem has four significant challenges. (a) the joint subject movement and media adaptation is high dimensional, making model learning difficult (b) the patient performance across sessions is highly variable due to external factors such as medication, lack of proper sleep (c) the performance within session is affected by physiological factors such as being tired and (d) the physical therapist / doctors and artists plan two to three steps ahead – this is a non first-order Markov process, making the learning task hard.

The main contribution of this paper is in the development of a mixture-of-experts based DDN framework for online media adaptation. The subject functional task is to reach for a target. The decision network contains three types of nodes – adaptation decision (A_t, observable), state describing the movement plan (S_t, hidden) and subject movement observations (O_t, observable). The decision node A_t represents the media adaptation decision after

subject movement observations at time *t*. We make decision on *changes* rather than on values to make the DDN parameter learning problem tractable. The state node S_t represents the subject hidden state in reaching/grasping plan acquisition. The semantics of the hidden state represent the "goodness" of the body plan (in movement sequence) to reach the target. The observation node O_t represents the subject's reaching/grasping performance in the set *t*. We train DDN mixtures per patient, per session. In online adaptation, we dynamically search for a proper DDN model from all DDN models trained in previous sessions and use the selected model to give rehabilitation team adaptation recommendation.

Our framework addresses two issues – (a) given a specific adaptation suggested by the domain expert, predict patient performance and (b) given an expected performance, determine optimal adaptation decision. We have very good results for both questions on actual stroke rehabilitation data.

The rest of the paper is organized as follows. In the next section we overview the biofeedback system. In Section 3 discuss the media adaptation problem in biofeedback systems and present the key challenges. In sections 4, we present the adaptation model using DDN. We propose the performance prediction algorithm and adaptation recommendation algorithm in the section 5. In section 6, we show how to use DDN based adaptation in biofeedback system. We show the experimental results in section 7 and conclude this paper in section 8.

2. BIOFEEDBACK SYSTEM

In this section we summarize our current biofeedback environment for stroke patient rehabilitation [1] and discuss limitations for therapist decision making. Our system situates participants in a multi-sensory engaging environment, where physical actions of the right arm are closely coupled with audio/video feedback. Participants are guided by our system to explore the novel environment. Through exploration, the participants begin to discover rules embedded in the environment. Those rules have been designed to couple action to feedback, consistent with the functional task.

2.1 Functional Task

The functional task for our patients is *reaching out with the right arm and grasping the target*. This task was chosen because it is the basic arm movement for stroke patient rehabilitation. This function task includes three sub-goals: (a) reach – reach for and grasp the target successfully, (b) open – open the arm to reach for the target without shoulder and torso compensation, and (c) flow – reach for the target smoothly. Therefore, our biofeedback environment encourages the subject to achieve these three sub-goals through engaging and purposeful audio/visual feedback.

2.2 System Overview

We now summarize our current biofeedback system [1]. The system integrates seven computational subsystems (ref. Figure 1): (a) Motion capture; (b) Task control; (c) Motion analysis; (d) Visual feedback; (e) Audio feedback; (f) Media archival and (g) Visualization. All seven subsystems are synchronized with respect to a universal time clock. The motion capture subsystem we are using is produced by Motion Analysis Corporation. We use six near-infrared cameras running at 100 frames per second to track the three-dimensional position of reflective markers that are placed on the subject. The task control subsystem provides a parameter panel where we can adjust the parameters related with the reaching and grasping task. The real-time motion analysis subsystem smoothes the raw sensing data, and derives an expanded set of task specific quantitative features. It multicasts the analyzed data to the audio, visual and archival subsystems at the same frame rate. The audio and visual subsystems adapt their auditory and visual response dynamically to selected motion features under different feedback environments. The archival subsystem continuously stores the motion analysis as well as the feedback data for the purpose of annotation and off-line analysis. Visualization subsystem visualizes the analysis results of subject's performance [13].

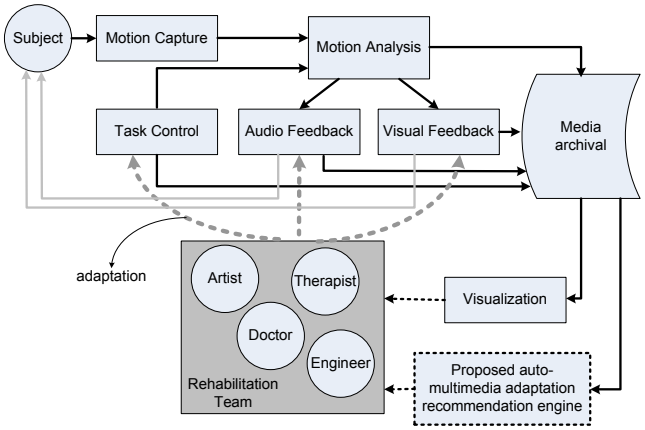

Figure 1. The flowchart of the biofeedback system.

The rehabilitation team includes therapists, medical doctors, artists and engineers. The visualization subsystem helps the rehabilitation team to make the decisions about how to change the environment for achieving a successful rehabilitation. The system can be fine-tuned through adjusting the parameters in task control, audio feedback engine and visual feedback engine. In this paper, we are proposing an automatic media adaptation recommendation engine (ref. Figure 1) that provides media adaptation recommendation to be used by the rehabilitation team.

2.3 Coupling Movement to Feedback

The structure of the feedback environment and its relationship to the achievement of the goals are based on well established principles regarding the role and function of art [4]. At the highest level of its structure the environment must communicate to the patient the messages that can encourage the accomplishment of the movement goals. These messages are: *reach*, *open*, *flow*.

The overall idea driving the mappings is that spatial and target information is better communicated through visuals and complex time series data is better communicated through audio. The movement parameters allowing successful manipulation of the environment are the key parameters of an everyday reaching and grasping movement. Thus, the environment can be easily connected in terms of action to its goal and does not require specialized movement training. Figure 2 shows visual feedback under four cases.

The mappings and content follow a similar structural hierarchy as the movement parameters and goals with sub-message levels supporting the communication of each larger message. As is the case of movement parameters, there are feedback parameters that

control the feedback generation. The subject can quickly understand the mapping from arm movement to feedback. Through practice, the subject can control the feedback by moving the right arm to achieve the goals. The detail of movement-feedback coupling is discussed in [1].

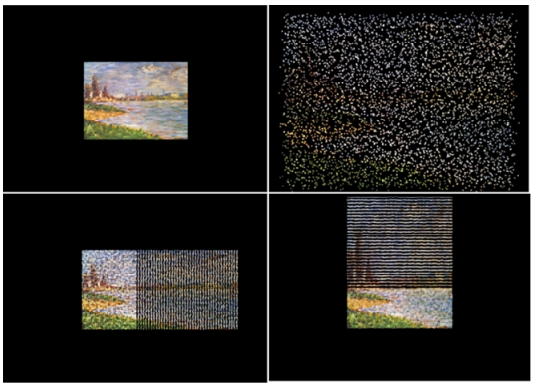

Figure 2. Visual feedback. Left-top: completion of image when subject grasps target successfully. Right-top: particles begin to form the image as the hand approaches the target. Left-bottom: Image pulled to the right when subject is off target. Right-bottom: Vertical bands appear when the subject has wrong target height.

2.4 Rehabilitation Procedure

We now introduce the rehabilitation procedure by using our biofeedback system. Let us denote every subject visit as *session*. For each session, there are several sets. In each set, the environmental condition (physical state, audio and visual parameters) remains fixed. Each set includes ten reaching trials. In each trial, the subject reaches out the right arm toward the virtual target, grasps the target and return back to the rest position.

The rehabilitation team (includes the therapists, doctors, artists and engineers) adapt the system during the short break (typically two minutes) between two consecutive sets. The team discusses the subject's movement performance through the visualization subsystem which shows the subject's performance for the previous sets. Then the group decides how to fine-tune the system (e.g. change musical instrument) to help the patient achieving a generative reaching/grasping plan.

2.5 Limitations of the current system

The major limitation of the current system [1] is that the media adaptation is totally done by the human expert (rehabilitation team) without accurate data driven analysis. The human expert may miss the information about the relationships between decisions on media adaptation and patient's movement. This is because the dimensionality of media parameters and movement parameters is very high (~100 parameters) and each rehabilitation takes long time (about 2 hours). Therefore, we are proposing an automatic media adaptation recommendation engine (ref. Figure 1) that suggests optimal media adaptation to be used by the team. Our proposed adaptation engine is data driven which analyzes the relationships between subject movement and media adaptation in previous rehabilitations. This adaptation recommendation subsystem will help the rehabilitation team to make correct adaptation decision.

3. MEDIA ADAPTATION

In this section, we shall discuss the media adaptation problem in our biofeedback system, present the key challenges of adaptation problem and finally propose our solution.

3.1 The Problem

The media adaptation problem is *how to adapt the biofeedback environment to help subject acquire a generative plan for reaching and grasping movement*. Mathematically, the problem is stated as follows: how to find optimal change in feedback space Δf which results in an expected change in the observation space (patient movement) ΔO (ref. Figure 3). Patient performance is variable both across subjects and within the same subject. The use of media adaptation allows the subjects under different conditions to successfully regain the generative plan for reaching / grasping the target.

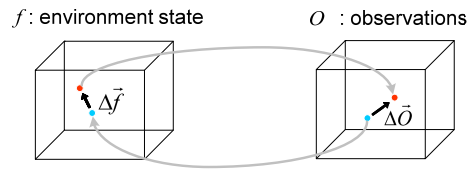

Figure 3. Diagram of media adaptation.

The environment adaptation includes five parts:

1. reaching/grasping task parameters (e.g. target position)
2. audio feedback parameters (e.g. musical instrument)
3. visual feedback parameters (e.g. the speed of image particles coming together)
4. physical environment parameters (e.g. table height)
5. therapist instruction (e.g. focusing on elbow extension)

We found that in patient rehabilitation, a combination of these five adaptations works well for subject to achieve good reaching/grasping plan. In this paper, we address the automatic data-driven recommendation for adaptation 1-3. We plan to address 4-5 in future work.

3.2 Why is it difficult?

The media adaptation is challenging because of four reasons:

1. *High dimensionality* – the dimensionality of the space for both subject's arm movement and environment parameters are very high. There are more than one hundred parameters related with multi-joint coordinated arm movement training and they are correlated. And there are five groups of environment parameters (ref. Section 3.1). The dimensionality of combination of environment change is very high and the relationship between the improvement of movement performance and environment change is complicated and needs to be learnt from the data.
2. *Consistency* – we have had over 30 sessions with the patients and a key observation of stroke rehabilitation is that the subject physiological condition is different for each session. This can happen due to many reasons including, taking of medication, not sleeping correctly (i.e. posture) the night before therapy. Hence the rehabilitation team can not make performance continuity assumptions (i.e. patient will move at

10cm/s etc); or make assumption on what specific environment condition is optimal.

3. *Engagement* – it is a challenge for the subjects to remain attentive and motivated during a long and tedious session and they easily become physically and mentally tired. Therefore, the media adaptation should also consider how to hold attention through engagement of subjects.
4. *Not 1st order Markov* – The artists and therapists do not only make changes for the next set, but may make plans for set groups (say next three sets). However, learning higher order Markov processes is severely constrained due to limited data. In this paper, we still use the first Markov process to approximate the real-world decision making process.

3.3 Our Solution

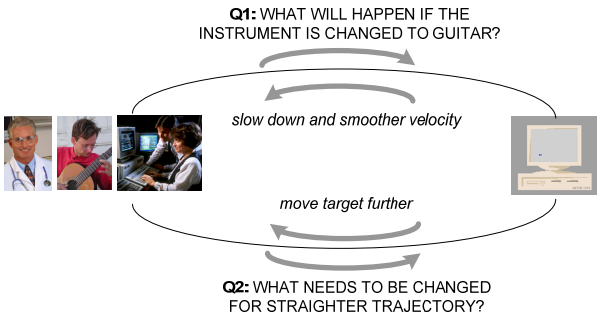

Figure 4. Diagram of automatic adaptation recommendation for queries of rehabilitation team.

We present a human-computer joint adaptation framework in our biofeedback system. Our idea is to compute the relationship between subject movement performance and environment change and provide useful suggestions for the rehabilitation team. Based on the automated suggestions and therapist domain knowledge, the rehabilitation team makes the decision for media adaptation. Figure 4 shows the interaction between the rehabilitation team and adaptation recommendation engine. The reason why a fully automated adaptation is not the attempted is that it is very difficult to account for the extensive experience of the therapist. For example, this experience is very valuable in assessing input at the beginning of the session when subject state is only available qualitatively e.g. "I do not feel too good today – I slept on my couch last night", "I took sleep medication last night". We propose to provide adaptation suggestions for the following:

Q1. *Performance prediction*: given the target environment adaptation, the algorithm provides expectation of subject movement performance for the next set. (e.g. what will happen if the instrument is changed to guitar?)

Q2. *Adaptation suggestion*: given the expected subject movement performance, computer adaptation provides the optimal change of the environment. (e.g. what needs to be changed for straighter hand trajectory?)

In this paper, computer adaptation only suggests which parameter should change, without considering the quantity of parameter change. The main reason is because of the high dimensionality of the media parameter space and not enough evidence to make accurate predictions. This suggestion by our system is valuable as it dramatically reduces the parameters of the therapist to consider. The rehabilitation team can then decide the exact quantity. In the following three sections, we discuss computer adaptation models.

4. DDN BASED ADAPTATION MODEL

In this section, we present the adaptation model based on Dynamic Decision Network (DDN) [10]. In Section 4.1 we show how a single DDN can be learned and used for media adaptation. In Section 4.2 we shall generalize the idea to a mixture of experts.

4.1 Adaptation Model

We use DDN to model the relationship between adaptation decision and subject's movement. We shall discuss three key components in adaptation model: DDN structure, observation prediction and DDN learning in this subsection.

4.1.1 DDN structure

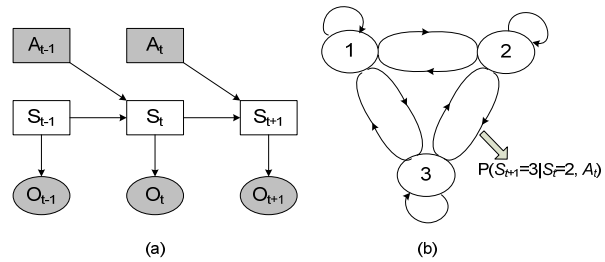

Figure 5 (a) Dynamic Decision Network structure for adaptation. A_t is the decision (i.e. environment change) at time slice t, S_t is the state of subject movement, O_t is the observation of subject movement. Shaded nodes are observable and blank nodes are hidden. Rectangular nodes are discrete and elliptical nodes are continuous. (b) Transition diagram for hidden node S_t. The hidden node has three values: 1, 2 and 3. The transition probability $P(S_t=3|S_{t+1}=2, A_t)$ represents the probability of transition from state 2 to state 3 under the decision A_t.

We now propose the general adaptation model in biofeedback system. Figure 5 shows the DDN structure for adaptation. The time slice in the DDN corresponds to the set (ref. Section 2.4). This is because we only change the environment (task, audio, visual, physical, and therapist instruction) between the sets and the environment is fixed for all trials within the set. At each time slice t, there are three nodes: (a) adaptation decision – A_t, (b) state – S_t, and (c) observation – O_t. For the sake of conciseness, we use the term *decision* to refer adaptation decision in rest of this paper. The decision and state nodes are discrete (rectangular nodes in Figure 5 (a)) and the observation nodes are continuous (elliptical nodes in Figure 5 (a)). The decision and observation nodes are observable (shaded nodes in Figure 5 (a)) and the state nodes are hidden (blank nodes in Figure 5 (a)). For example, let us assume the DDN model is used for hand velocity adaptation in biofeedback. The adaptation decision A_t could be the change of musical instrument. The hidden state S_t represents the goodness of the subject movement plan to achieve smooth velocity. The observation O_t is the average hand jerkiness over ten trials in set t. Hand jerkiness is a well defined measurement in bioengineering. We shall discuss hand jerkiness later in this paper (eq. <13> in Section 6.3).

We now discuss the nodes in the DDN (ref. Figure 5(a)) in detail:

- The decision node A_t represents the media adaptation between set t and set t+1. The change of media parameter is the decision. For example, assume that we consider the musical instrument and tempo as the media adaptation decision option.

Each parameter (instrument or tempo) is a binary variable: (no change/change). Therefore we have four possible decision values by combining these two musical parameters. We make decision on *changes* rather than on values to make the DDN parameter learning problem tractable.

- The state node S_t represents the subject hidden state in reaching/grasping plan acquisition. The semantics of the hidden state represent the "goodness" of the body plan (in movement sequence) to reach the target. We set three possible values for hidden state which indicate three different states in reaching/grasping plan acquisition. Figure 5 (b) shows the transition diagram between these three values. The transition probability $P(S_{t+1}|S_t, A_t)$ is represented as a conditional probability table (CPT): $R=\{r_{i,j,k}\}=\{P(S_{t+1}=k|S_t=i,A_t=j)\}$.
- The observation node O_t represents the subject's reaching/grasping performance in the set t. It is the observable output of hidden state node S_t. Since observation node is continuous, we use probability density p rather than probability P. We use Gaussian distribution for sensing probability density $p(O_t|S_t=i)=\mathrm{N}(\mu_i, \Sigma_i)$, where μ_i and Σ_i are mean vector and covariance matrix when the value of hidden nodes S_t equals to i.

4.1.2 Observation Prediction

In this section, we address the first question posed in Section 3.3. We show how to predict the subject movement performance in the set t+1 (i.e. $\tilde{O}_{t+1}$) given the decision and observation sequence for the pervious t sets using DDN model. Let us denote the decision and observation sequence from the first set to the set t as $A_{1:t}$ and $O_{1:t}$ respectively. The prediction includes three parts: (a) predict the probability of hidden nodes S_{t+1}: $P(S_{t+1}|O_{1:t}, A_{1:t})$, (b) predict the probability density of observation nodes O_{t+1}: $p(O_{t+1}|O_{1:t}, A_{1:t})$, and (c) predict the expected value of observation nodes: $\tilde{O}_{t+1}$. It is shown in [10] that $P(S_{t+1}|O_{1:t}, A_{1:t})$ can be computed as follows:

$$P(S_{t+1} \mid O_{1:t}, A_{1:t}) = \sum_{S_t} P(S_{t+1} \mid S_t, A_t) \cdot P(S_t \mid O_{1:t}, A_{1:t-1}), \qquad <1>$$

where $P(S_t|O_{1:t}, A_{1:t-1})$ can be computed iteratively as follows:

$$P(S_t \mid O_{1:t}, A_{1:t-1}) = \alpha p(O_t \mid S_t) \sum_{S_{t-1}} P(S_t \mid S_{t-1}, A_{t-1}) P(S_{t-1} \mid O_{1:t-1}, A_{1:t-2}) \qquad <2>$$

where $p(O_t|S_t)$ is sensing probability density (single Gaussian pdf), $P(S_t|S_{t-1}, A_{t-1})$ is transition probability, α is a normalization constant. Using eq<1>, we can predict the probability density $p(O_{t+1}|O_{1:t}, A_{1:t})$ as follows:

$$p(O_{t+1} \mid O_{1:t}, A_{1:t}) = \sum_{S_{t+1}} p(O_{t+1} \mid S_{t+1}) \cdot P(S_{t+1} \mid O_{1:t}, A_{1:t}). \qquad <3>$$

Therefore, we can compute the conditional mean of O_{t+1} as the prediction result:

$$\tilde{O}_{t+1}(O_{1:t}, A_{1:t}) = E(O_{t+1} \mid O_{1:t}, A_{1:t}), \qquad <4>$$

where $E(\cdot)$ is the expectation operator.

4.1.3 DDN Learning

There are four kinds of parameters that need to be learned:

(a) Probability of decision: $\eta_i=P(A_t=i)$.

(b) Initial probability of state: $\pi_i= P(S_1=i)$.

(c) Sensing probability density: $b_i(o_t)=p(O_t=o_t|S_t=i)$.

(d) Transition probability: $r_{i,j,k}=P(S_{t+1}=k|S_t=i,A_t=j)$.

We use the EM algorithm [2] to learn these parameters. We assume that we have L training data, $\{y_l\}$, l=1,…,L. Each training data is a temporal sequence of decision and observation ($y_l=\{a^l_{1:Tl},o^l_{1:Tl}\}$) where T_l is the length of the sequence for the lth training data. For the sake of simplicity, we do not discuss the details of EM learning in this paper. The details can be found in [2]. Note that we assume a uniform prior for transition probability (i.e. $P(S_{t+1}=1|S_t,A_t)=P(S_{t+1}=2|S_t,A_t)=P(S_{t+1}=3|S_t,A_t)=1/3$) if the decision A_t is not observed in the training data.

4.2 Mixture of Experts

In this section, we extend the basic DDN described in section 4.1 to a framework using mixture of experts. There are two key ideas: (1) In offline training, each session is considered separately. For each session, we use bagging to train K DDN models. (2) In online adaptation, we dynamically search for a proper DDN model from all DDN models trained in previous sessions and use the selected model to give rehabilitation team adaptation recommendation.

Figure 6 shows the diagram of offline training and online suggestions. We discuss the offline training in this section and present the online adaptation algorithm in the next section.

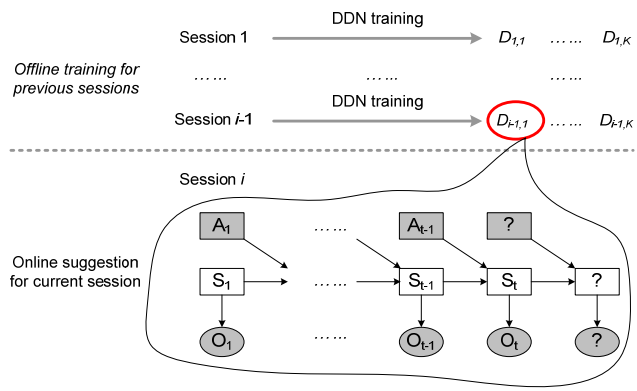

Figure 6. Diagram for offline training and online adaptation suggestion. We train adaptation models for session 1 to session i-1 separately and select a proper model for each set in session i to do online suggestion. $D_{i,j}$ is the jth DDN model for the ith session.

4.2.1 Why do we use mixtures?

We use mixture of experts (considering each session separately) because we find that the subject's performance is weakly correlated. The subject's performance is correlated across different dimensions over different sessions. This prevents a single model to give accurate prediction. We also find that there is *no* strong carry over effect even for two consecutive sessions conducted over consecutive days. By carry over we imply that the performance values of the previous session can *not* be assumed to continue to the current session. This is because subjects may have different amount of use of their impaired arm which results in different physical conditions of their arm ability. Therefore we train different sessions separately. We use bagging [3] to train K DDN models for each session as we have limited training data.

4.2.2 Offline Training

We now present the offline DDN training process using the data from previous sessions. The offline training includes two parts:

(a) bootstrap training dataset and (b) DDN bagging. For the sake of definiteness, we show the offline training process for one session. The process generalizes for all sessions.

We now show how we generate bootstrap training samples for DDN learning. Let us assume that we have T sets for current session and that each set has ten trials. We compute the observation measurement (e.g. hand jerkiness) for every trial. For each set, we use Huber's method [6] to compute robust mean and variance and detect outliers. Then we randomly select a trial from each set to construct an observation sequence $o^{l}_{1:T}$. We replace this selected trial back to the set and repeat this random selection until we have N observation sequences – ($o^{k}_{1:T}$, k=1,..,N). For each set, we use uniform distribution on non-outlier trials and zero probability on outlier trials prior to random selection. Figure 7 shows the diagram for generating N observation sequences. The decision sequence $a_{1:T-1}$ is the decision taken by the rehabilitation team in the session, where a_i represent the decision between set i and set i+1. Therefore, we combine the decision sequence and observation sequence to construct the N training samples $y_k=\{a_{1:T-1}, o^{k}_{1:T}\}$. Using EM algorithm (ref. Section 4.1.3), we can train an DDN model on these N training samples for the current session.

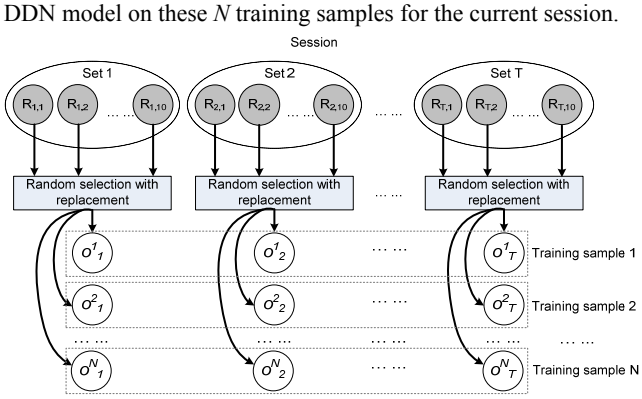

Figure 7. Construct N bootstrap training observation sequences. $R_{i,j}$ is the observation value for the jth trial in the ith set.

We repeat the process of generating N bootstrap training samples K times and hence create K training datasets. Each of these bootstrap datasets is used to train a different DDN adaptation model for the current session. Therefore, we train K DDN models for each session. The final online adaptation recommendation is done by selecting an optimal DDN model from K DDNs and using its adaptation suggestions. The DDN model is optimal in the sense that it has the closest relationship between adaptation decision and movement performance with the current session.

5. ADAPTATION RECOMMENDATION

We now present our online adaptation recommendation algorithm based on mixture of DDN experts to address online adaptation recommendation. We shall address both two questions presented in Section 3.3: (a) performance prediction and (b) decision suggestion.

5.1 Performance Prediction

The key idea of our performance prediction algorithm is that we first select an optimal DDN from all previous sessions dynamically, and use it to predict the performance for the next set in the current session. The DDN is optimal in the sense that it has the best prediction results prior to the current set. Let us assume that we have Q previous sessions. Each session has K trained DDN adaptation models. Let us denote the jth DDN trained for the ith session as $D_{i,j}$ (i=1,…,Q, j =1,…,K). For the current session, we compute the observation for each trial and compute robust mean [6] of observation for each set. Let us assume the current session has T sets. We denote the mean of observation of the tth set as o_t and the actual decision between the tth set and the t+1th set as a_t. Therefore the performance prediction is formulized as predicting the observation for the set t+1 (i.e. o_{t+1}) given Q*K DDN adaptation models for previous sessions and the decision and mean observation from set 1 to set t (i.e. $a_{1:t}$, $o_{1:t}$). We use the robust mean of observation over ten trials as the observation of the set because it is an important measurement for therapists to evaluate subjects. In this paper, we also refer the actual decision taken by the rehabilitation team and the mean observation of set (i.e. $a_{1:t}$, $o_{1:t}$) as *ground truth decision* and *ground truth observation* respectively.

The initial environmental parameters are set by the rehabilitation team based on observations of physical target reaching at the beginning of the session. At the end of the first set, therapist gives a decision query for the second set (i.e. a_1). Since this is the first prediction for the current session, we do not know which adaptation model can predict well. Hence, we use the median of prediction results of all DDN models as the prediction for the second set:

$$\tilde{o}_2(a_1) = \begin{cases} \underset{D_{i,j}\in\Omega(a_1)}{median}[\tilde{o}(2 \mid D_{i,j}, a_1)] & if\ \Omega(a_1) \neq \varnothing \\ \underset{D_{i,j}}{median}[\tilde{o}(2 \mid D_{i,j}, a_1)] & otherwise \end{cases}, \qquad <5>$$

where $\tilde{o}_2(a_1)$ is the expectation over the observation for the second set for decision a_1, $\tilde{o}(2|D_{i,j},a_1)$ is the prediction result for the second set for decision a_1 by using the DDN model $D_{i,j}$, $\Omega(a_1)$ is the set of DDN models $D_{i,j}$ that have decision a_1 in the training data. The idea is that when we predict the results for the decision a_1, we should use the previous sessions in which the same decision was taken. If this decision has not been used before (i.e. $\Omega(a_1)$ is empty), we assume uniform prior transition probability and to predict the observation. Since we consider all DDN models equivalently, the prediction results may be noisy. Hence, we inform the therapist that this result may not be very reliable.

We can use the previous prediction error to help us find a good DDN adaptation model starting from the third set. We select the DDN model with minimum prediction error before the current set as the adaptation model to predict the next set. The prediction error until the current set (t) using model $D_{i,j}$ (i.e. $\varepsilon(t|D_{i,j}, a_{1:t-1}, o_{1:t})$) is computed as follows:

$$\varepsilon(t \mid D_{i,j}, a_{1:t-1}, o_{1:t}) = \sum_{k=2}^{t} \| \tilde{o}(k \mid D_{i,j}, a_{k-1}) - o_k \|, \qquad <6>$$

where $\tilde{o}(k|D_{i,j},a_{k-1})$ is the prediction result for the kth set for decision a_{k-1} by using the DDN model $D_{i,j}$ using eq.<4>, o_k is the actual observation for the kth set. This equation computes the overall prediction error from the beginning of the session to the current set (set t) by using DDN $D_{i,j}$. Hence the optimal DDN model for the prediction of the t+1th set for the decision a_t – $D^*(t+1|a_t)$ is represented as follows:

$$D^*(t+1\,|\,a_t)=\begin{cases}\arg\min\limits_{D_{i,j}\in\Omega(a_t)}[\varepsilon(t\,|\,D_{i,j},a_{1:t-1},o_{1:t})] & \text{if } \Omega(a_t)\neq\varnothing\\ \arg\min\limits_{D_{i,j}}[\varepsilon(t\,|\,D_{i,j},a_{1:t-1},o_{1:t})] & \text{otherwise}\end{cases}\quad . \qquad <7>$$

Therefore, using eq.<4>, we can compute the prediction results for the t+1th set by using DDN model $D^*(t+1|a_t)$:

$$\tilde{o}_{t+1}(a_t)=\tilde{o}(t+1\,|\,D^*(t+1\,|\,a_t),a_t)\ , \qquad <8>$$

where $\tilde{o}_{t+1}(a_t)$ is the prediction result for the t+1th set for decision a_t, $\tilde{o}(t+1|D^*(t+1|a_t),a_t)$ is the prediction result for the t+1th set for decision a_t by using the DNN model $D^*(t+1|a_t)$.

5.2 Decision Suggestion

We now propose the decision suggestion algorithm. The idea is to find the decision whose prediction result is the closest to therapist's expectation. For example, a therapist might say if I want to improve hand trajectory straightness by 10%, what decision should I take? In this section, we first discuss a general decision suggestion framework by using utility function. Then, we apply a simple utility function to provide online decision suggestion for rehabilitation team.

Let us assume that the observation is scale variable in this section. It can be easily extended for vector variable. Let us assume that there are P possible decisions in the adaptation model which constructs an decision set $\mathbf{\Phi}=\{\alpha_1,\ldots,\alpha_P\}$. For the case of adaptation model for hand trajectory, we have 27 possible decisions (P=27). Let us denote $\mathbf{\Phi}_h$ as a subset of $\mathbf{\Phi}$ in which all decisions are taken in the previous sessions. We only suggest the decisions taken in the previous sessions, because the DDN adaptation models do not learn the cases of decisions that have not been observed and the suggestion may have large error. The optimal decision is the one that minimizes prediction error. This can be achieved by defining an appropriate utility function. In [10], it is shown that the optimal decision at time slice t is the decision that maximizes the expected utility:

$$\tilde{a}_t=\arg\max_{a_t\in\Phi_h}[u_a(a_t)]$$

$$u_a(a_t)=\sum_{S_{t+1}}U(S_{t+1})\left(\sum_{S_t}P(S_{t+1}\,|\,S_t,a_t)\cdot P(S_t\,|\,o_{1:t},a_{1:t-1})\right), \qquad <9>$$

where $u_a(a_t)$ is the utility of decision a_t, $P(S_{t+1}|S_t, a_t)$ is transition probability, $P(S_t|o_{1:t}, a_{1:t-1})$ can be computed using eq.<2>, $U(S_{t+1})$ is the utility function on the state nodes at time slice t+1. The utility function can be defined differently for different purposes by rehabilitation team. In this paper, we define the utility as a function of prediction error:

$$U(S_{t+1}\,|\,o^e_{t+1},a_t)=\lambda_{t+1}(E(O_{t+1}\,|\,S_{t+1})-o^e_{t+1})$$

$$\lambda_{t+1}=\begin{cases}1 & \text{if } \tilde{o}_{t+1}(a_t)<o^e_{t+1}\\ -1 & \text{otherwise}\end{cases} \qquad <10>$$

where $E(O_{t+1}|S_{t+1})$ is the expectation of observation at t+1th set given S_{t+1}, o^e_{t+1} is the rehabilitation team's expected observation for the t+1th set, λ_{t+1} is the sign indicator, $\tilde{o}_{t+1}(a_t)$ is the prediction results for the observation at the t+1th set for decision a_t using eq.<8>. The utility function is not only related to the state S_{t+1} but also related to the rehabilitation team's expected observation o^e_{t+1}, and the decision a_t. The utility is negative. The absolute value of the utility is the distance from the observation prediction $\tilde{o}_{t+1}$ to the rehabilitation team's expected observation o^e_{t+1}. The larger the utility (closer to zero), the smaller the prediction error. λ_{t+1} equals +1 when the predicted observation is less than the rehabilitation team's expected observation and equals -1 otherwise. Maximizing the utility is equivalent to minimizing the prediction error.

In practice, for each possible decision, we search for the DDN adaptation model to maximize the utility (or minimize the prediction error). Then we use the decision which maximizes the utility over all possible decisions as the recommended decision. We represent the decision recommendation in terms of minimizing the prediction error as follows:

$$\tilde{a}_t=\arg\min_{a_t\in\Phi_h}(|\,\tilde{o}_{t+1}(a_t)-o^e_{t+1}\,|)\ , \qquad <11>$$

where $\tilde{a}_t$ is the suggested decision between set t and t+1, $\tilde{o}_{t+1}(a_t)$ is the prediction result for the t+1th set for decision a_t (ref. eq. <8>), o^e_{t+1} is the therapist's expected observation for the t+1th set.

6. ADAPTATION IN BIOFEEDBACK

We now show how to use DDN based adaptation model in biofeedback system. We apply DDN model on three key aspects of subject movement performance: (a) spatial accuracy, (b) straightness of hand trajectory and (c) jerkiness of hand velocity. These three aspects are important for stroke patient rehabilitation as they are connected to the *reach*, *open* and *flow* sub-goals respectively (ref. Section 2.1).

In this paper, we consider these three adaptations separately. Each adaptation has a DDN adaptation model. For these three adaptations, we use the change of media parameter as the decision and we only consider the direction of the change (i.e. increasing/decreasing/no change). The exact quantity of parameter change is decided by the therapist. The domain experts (therapists and artists) suggested that the adaptation should be over three different media spaces: (a) reaching/grasping task control, (b) audio feedback and (c) visual feedback. For each adaptation, therapists determine the goal for stroke patient rehabilitation.

6.1 Adaptation for Spatial Accuracy

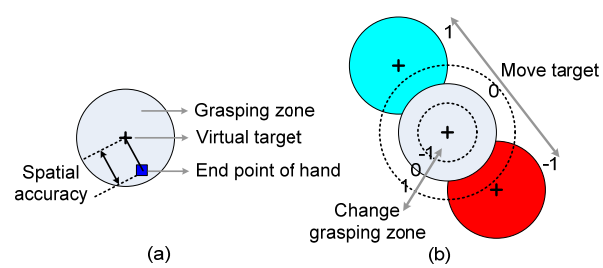

Figure 8. (a) Diagram for spatial accuracy, (b) diagram of adaptation decision for spatial accuracy.

We now propose the media adaptation for spatial accuracy. We describe the adaptation goal, the measure of the observation, the meaning of the state and the decision as follows:

- *Goal*: the goal is to help subject to reach close to the target.
- *Observation*: we use the distance from the subject hand to the virtual target during grasping as the measurement of spatial accuracy (Figure 8 (a)). The subject achieves grasping when his/her hand stay in the grasping zone (Figure 8 (a)) for

continuous 250ms. In this paper, we only focus on the grasping zone on the table plane.

- *State*: the state node has three values (1 – 3) that indicate three different body computational plans to reach for the target.
- *Decision*: we have nine possible decisions in the adaptation model for spatial accuracy. These are the combination of the change of grasping zone radius and virtual target position Figure 8 (b). The change of grasping zone has three values (i.e. -1: shrink, 0: no change, +1: enlarge). The change of target position also has three values (i.e. -1: move closer, 0: no change, +1: move further).

6.2 Adaptation for Hand Trajectory

We now present the goal, measure of the observation, the meaning of the state and the adaptation decision for hand trajectory.

- *Goal*: the hand trajectory adaptation is geared towards making the hand trajectory straight.
- *Observation*: The straightness of hand trajectory G is defined as follows:

$$G = \int_0^{\max(z)} |x(z)|\, dz \,, \qquad <12>$$

where x and z are x and z coordinates of subject's hand. The x and z axis is shown in Figure 9 (a). The straightness equals the area of trajectory region in Figure 9 (a). The smaller the area, the straighter the hand trajectory.

- *State*: In the similar to spatial accuracy adaptation, the state node in trajectory adaptation DDN has three values (1 – 3).

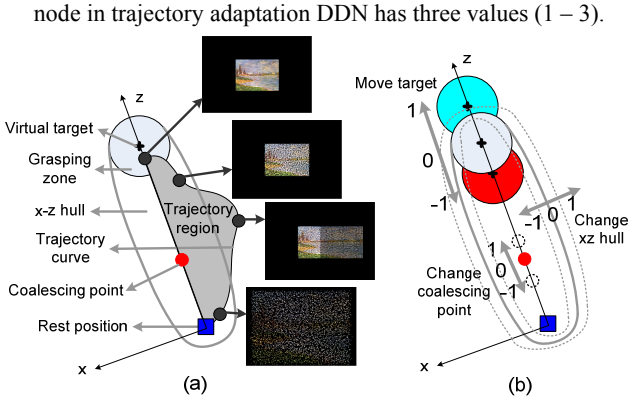

Figure 9. (a) Trajectory curve and trajectory region along table plane. Four pictures are visual feedback corresponding to four positions along the trajectory curve. (b) Adaptation decision for hand trajectory (change x-z hull, change coalescing point and move target position).

- *Decision*: We have 27 possible decisions hand trajectory adaptation which are the combination of change of the x-z hull parameter (size), coalescing point and target position (Figure 9 (b)). Each change has three values. The x-z hull is a forgiving region for subject hand movement related to the sensitivity of the image pulling in visual feedback (Figure 9 (a)). The coalescing point is a point on the z axis between the rest position and virtual target (Figure 9 (b)). It indicates the position where the image particles come together (coalescing) and controls the coalescing speed. The position of virtual target also has effect on trajectory.

6.3 Adaptation for Hand Velocity

We now discuss the goal, observation, state and adaptation decision for hand velocity adaptation.

- Goal: the hand velocity adaptation attempts to make the hand velocity smooth.
- Observation: We use a well understood measure (in Bioengineering) for velocity smoothness (Jerkiness) as the observation of DDN model for hand velocity. The jerkiness J is defined as follows:

$$J = \int_0^T \sqrt{\left(\frac{d^3x}{dt^3}\right)^2 + \left(\frac{d^3y}{dt^3}\right)^2 + \left(\frac{d^3z}{dt^3}\right)^2}\, dt \qquad <13>$$

where T is the time when grasping state is achieved, x, y and z are 3-D coordinates of subject's hand trajectory. The smaller the value, the smoother the hand velocity.

- State: In the similar manner, the state node in velocity adaptation DDN has three values (1 – 3).
- Decision: We have 12 possible decisions in velocity adaptation. They are related to the change of musical instrument, tempo, and task difficulty. Musical instrument has two values (i.e. 1: change, 0: no change). Tempo has three values (i.e. -1: decreasing, 0: no change, 1: increasing). Task difficulty has three values (-1: making task easier, 1: making task more challenge, 0: the difficulties of the consecutive sets are in the same level). The task difficulty is annotated by the therapist. It relates to multiple media parameters such as x-z hull, grasping zone, target position, etc.

7. EXPERIMENTAL RESULTS

We now discuss the experimental results. Our biofeedback system is in a state of continuous improvement. Three stroke patients and twelve non-impaired subjects are recruited to test the system (30 sessions, 60 hours). Their data is not used in this paper since we keep debugging and improving the system in these 30 sessions.

We recruited one stroke patient to use our biofeedback system for rehabilitation after the system is finalized. The recruited patient is middle aged female who suffered mild stroke in the right arm. The recruited patient was unfamiliar with the system prior to the rehabilitation. The patient did eight sessions in two consecutive weeks in January 2007. The eight sessions include one physical pre-test, one physical post-test and six sessions of rehabilitations using our biofeedback system. Each session lasted approximately two hours. The rehabilitations are lead by physical therapist that has one year experience of using our system. We use the six sessions of rehabilitation as the experimental dataset. These six sessions have 5, 7, 4, 7, 9 and 9 sets respectively.

7.1 Validation Measure

We now propose the validation measure for: (a) performance prediction and (b) decision suggestion. Let us denote M as number of sessions (M=6), T_m as number of sets for the mth session, a_t^m as the ground truth decision (rehabilitation team's decision) after the tth set in the mth session, o_t^m as the ground truth observation of the tth set in the mth session.

7.1.1 Validation of Performance Prediction

We use both mean of relative prediction error (e_m) and median of relative prediction error (e_{med}) to evaluate performance prediction algorithm. The e_m and e_{med} is computed as follows:

$$e_m = \left(\sum_{m=2}^{M} \sum_{t=2}^{T_m} \frac{| o_t^m - \tilde{o}_t^m(a_{t-1}^m) |}{| o_t^m |} \right) \Big/ \left(\sum_{m=2}^{M} (T_m - 1) \right)$$
$$e_{med} = \left(\sum_{m=2}^{M} (T_m - 1) \cdot \underset{2 \le t \le T_m}{Med} \frac{| o_t^m - \tilde{o}_t^m(a_{t-1}^m) |}{| o_t^m |} \right) \Big/ \left(\sum_{m=2}^{M} (T_m - 1) \right) \quad <14>$$

where $\tilde{o}_t^m(a_{t-1}^m)$ is the predicted observation of the tth set in the mth session given the decision a_{t-1}^m (ref. eq. <8>), Med(·) is median operator. e_m represents the average relative prediction error over all sets in all sessions. e_{med} averages the median of relative prediction error over all sessions using the weight (T_m–1). (T_m–1) indicates the number of sets for which we predict the performance.

7.1.2 Validation of Decision Suggestion

We use three validation measures to evaluate the decision suggestion: (a) average rank, (b) relative utility ratio and (c) difference of prediction error. As we discussed in Section 5.2, we need to know the rehabilitation team's expected observation before the decision suggestion. We use the actual observation o_{t+1}^m (ref. Section 5.1) as the expected observation and use the actual decision a_t^m as the ground truth decision. This is because the observation o_{t+1}^m is actually caused by the actual decision a_t^m.

The *average rank* is the average rank of ground truth decision (made by rehabilitation team) over all sets in all sessions. As we discussed in Section 5.2, we sort all possible decisions by the utility (ref. eq. <9>) in the descending order and select the first rank decision. We use average rank of ground truth decision to indicate the accuracy of our decision suggestion algorithm. If the ground truth decision has low rank, it has the large utility to achieve the rehabilitation team's expectation for the next set. The lower the average rank, the more accurate the decision suggestion. The ideal case is that the average rank equals to one. This means that all ground truth decisions are recommended. The average rank of ground truth decision is computed as follows:

$$r_{ave} = \frac{1}{M-1} \sum_{m=2}^{M} \frac{1}{T_m - 1} \sum_{t=2}^{T_m} rank(a_t^m \mid o_{t+1}^m) \quad <15>$$

where $rank(a^m_t|o^m_{t+1})$ is the rank of ground truth decision a^m_t over all possible decisions given the rehabilitation team's expected observation o^m_{t+1}.

However, the average rank does *not* consider the utility difference between the ground truth decision and our recommendation. For example, if ground truth decision has higher rank, its utility may be very close to the first rank decision. We should consider it differently with other high rank decision with much smaller utility. Therefore, we use the relative utility ratio (RUR) r_u to evaluate online suggestion:

$$r_u(\{a_t^m\}) = \frac{E_t[u_a(\hat{a}_t^m(1))] - E_t[u_a(a_t^m))]}{u_{\max} - E_t[u_a(\hat{a}_t^m(1)]}, \quad <16>$$

where $\{a^m_t\}$ is the set of ground truth decision, $u_a(\hat{a}^m_t(1))$ is the utility (eq.<9>) of the first rank decision after the tth set in the mth session, $u_a(a^m_t)$ is the utility of the ground truth decision a^m_t, $u_{\max}$ is the maximum of possible utility and E_t is expectation operator on set. In this paper, the maximum utility $u_{\max}$ is zero which means the predicted observation is exactly the same as the rehabilitation team's expected observation. For the ideal case in which all ground truth decisions are selected as the first rank decision, the relative utility ratio equals to zero. The smaller the relative utility ratio, the more accurate the online suggestion.

The difference of prediction error measures the difference between the ground truth decision and our suggested decision (first rank decision) in terms of prediction error. The difference of prediction error (DPE) is computed as follows:

$$d(\{a_t^m\}) = E_t \left(\frac{| o_t^m - \tilde{o}_t^m(a_{t-1}^m) | - | o_t^m - \tilde{o}_t^m(\hat{a}_{t-1}^m(1)) |}{| o_t^m |} \right), \quad <17>$$

where $\tilde{o}_t^m(a_{t-1}^m)$ is the predicted observation of the tth set in the mth session given the ground truth decision a_{t-1}^m (ref. eq. <8>), $\tilde{o}_t^m(\hat{a}^m_t(1))$ is the predicted observation of the tth set in the mth session given the recommended decision (i.e. first rank decision $\hat{a}^m_t(1)$) and E_t is expectation operator on set.

7.2 Results of Performance Prediction

We now discuss the experimental results of performance prediction. In the training phase, we train three kinds of DDN adaptation models for each session: (a) adaptation for spatial accuracy, (b) adaptation for hand trajectory and (c) adaptation for hand velocity. For each model, we train K=10 (ref. Section 4.2.2) different DDN models for each session. For each single DDN model training, we generate N=50 observation training sequences using bootstrap technique (ref. Section 4.2.2). In the prediction phase, the observation for each set is the robust mean observation over ten trials in the set. The adaptation decision is made by the rehabilitation team. Note that not all possible decisions are taken in the rehabilitation (ref. Section 6). We observe 5, 4 and 5 adaptation decisions taken for spatial accuracy, hand trajectory and hand velocity respectively.

We present two kinds of prediction result in this section: (a) online prediction and (b) offline prediction. In online prediction, we predict the observation for the session k using the DDN models for the session 1 to session k-1, and we do not predict the observation for the first session. In the offline prediction, we predict the observation for the session k using the DDN models for all sessions except the session k. While in practice, only online predictions are possible. The offline results are indication of the possible improvement of the results with more data. Figure 10 (a) (b) (c) shows the prediction results for spatial accuracy, hand trajectory and hand velocity respectively Table 1 shows the average prediction error over six sessions using eq.<14>**.**

Table 1. Online/offline prediction error (eq.**<14>**) for session 2–6

Adaptation Model	**Online prediction**		**Offline prediction**	
	mean	median	mean	median
Spatial accuracy	8.58%	7.32%	6.02%	3.56%
Hand trajectory	17.85%	14.02%	12.64%	9.27%
Hand velocity	13.76%	10.60%	8.00%	6.40%

We have two observations from the experimental results:

1. *Online prediction:* the online prediction error (both mean and median error eq.<14>) for three adaptations (spatial accuracy, hand trajectory and hand velocity) is low (less than 18%). This indicates that our DDN model works well to model the relationship between patient movement and media adaptation. This also indicates that the algorithm of mixture of experts works well for prediction. Note that compared to the single model, mixture of experts significantly reduces the prediction error. The results for single model prediction have been left out for the sake of brevity. We also observe the prediction error at the beginning of session is larger (especially for the second set) and the error decreases as the set number increases (Figure 10). This is because our expert selection is based on the prediction error of previous sets. The probability to find the proper DDN expert increases as more sets come. We also notice that predictions are not very good for some sessions (such as session 2, 4 in spatial accuracy, session 3, 5 in hand trajectory, session 4 in hand velocity). This is because the movement-adaptation relationship in previous sessions does not repeat in the current session.
2. *Comparison between online prediction and offline prediction*: The offline prediction has smaller prediction results for sessions 2-5 (the online prediction is equivalent to the offline prediction for session 6). This is because that we can only use early session to predict the late session in online prediction. While in offline prediction, the similarity between the early session and late session in terms of movement-adaptation relationship results in good prediction for both early session and later session. We can see the prediction results of session 2 and 4 for spatial accuracy, session 2 for hand trajectory and session 4 for hand velocity are improved significantly by using offline prediction. We understand that in practice, we can only do online prediction. We use the offline prediction to show that the online prediction results for some early sessions are not good because we do not have enough data. As we get more data, our algorithm provides more accurate prediction.

7.3 Results of Decision Suggestion

We now discuss the experimental results for online decision suggestion. Table 2 shows average rank (ref. eq.<15>), relative utility ratio (ref. eq.<16>) and difference of prediction error (ref. eq.<17>) for online decision suggestions for three adaptation models (spatial accuracy/hand trajectory/hand velocity). We can see that the average rank is close to one. This indicates that the ground truth decision has larger utility compared with other decision options. There are two reasons why some ground truth decisions are not chosen as the first rank decision. First, the performance prediction (related to the utility) for the ground truth decision is not accurate for some sets. Second, other decisions may result in similar performance to the ground truth decision.

We observe that the relative utility ratio (RUR) and difference of prediction error (DPE) of the ground truth decision are very close to zero for hand trajectory adaptation which means the ground truth decision and the first rank decision have very close utility and prediction error. The RUR for spatial accuracy adaptation and hand velocity adaptation are a little larger, but the DPE are very small. The small DPE means that although some ground truth decision are not rank first, their prediction error are very close to first rank suggestions. The RUR is a little larger because the prediction error of the first rank decision is close to zero which

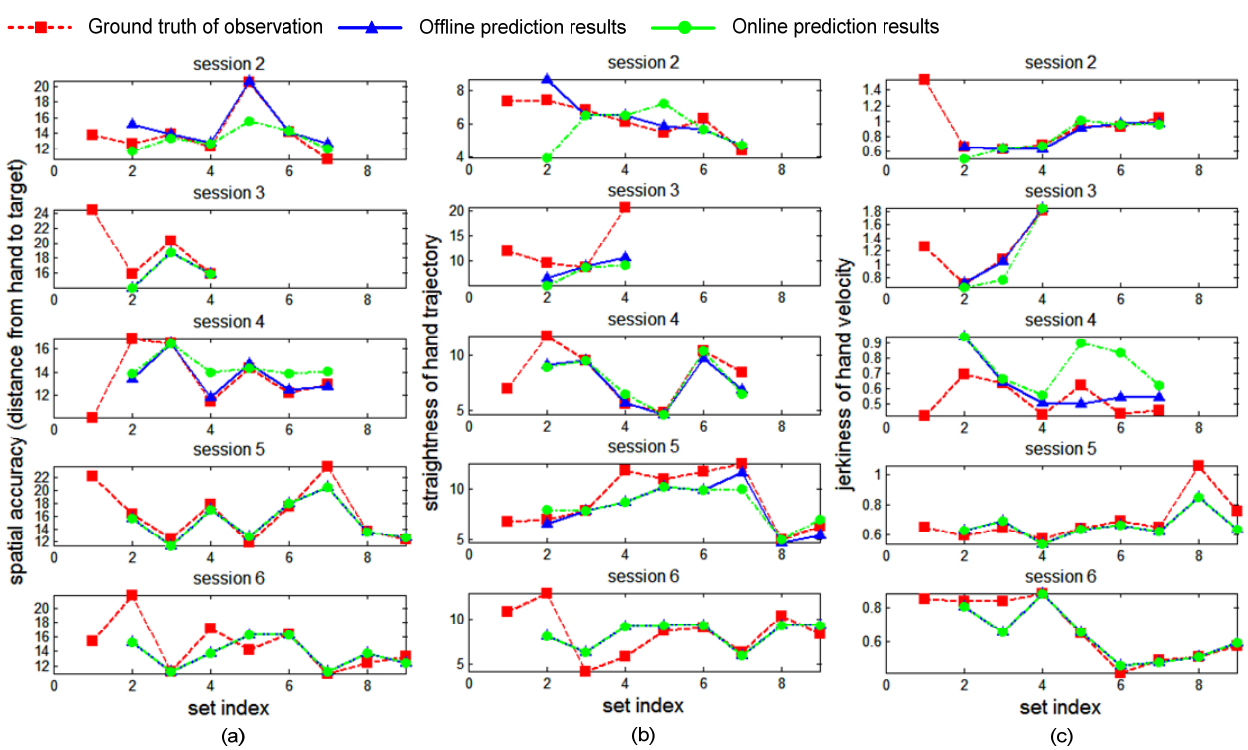

Figure 10. Experimental results for performance prediction. (a) Prediction results of spatial accuracy adaptation. The online prediction and offline prediction results overlap for session 3, 5 and 6. (b) Prediction results of hand trajectory adaptation. The online prediction and offline prediction results overlap for session 6. (c) Prediction results of hand velocity adaptation. The online prediction and offline prediction results overlap for session 5 and 6.

Table 2: Online suggestion results. The average rank is computed by using eq.<15>. The average rank for spatial accuracy 1.65/5 means the average rank is 1.65 and the number of observed decisions in rehabilitation is 5. In the last three columns, the first number (out of bracket) is the relative utility ratio (RUR) (ref. eq. <16>), the second number (in bracket) is the difference of prediction error (DPE) (ref. eq.<17>). We compare the RUR and DPE of ground truth decision and the second rank decision and the last rank decision.

Adaptation Model	Average Rank	Relative Utility Ratio (RUR) and Difference of Prediction Error (DPE)		
		Ground truth decision	*The second rank decision*	*The last rank decision*
Spatial accuracy	1.65/5	0.47 (1.78%)	1.31 (7.02%)	6.44 (35.63%)
Hand trajectory	1.48/4	0.12 (1.54%)	0.99 (16.83%)	2.76 (44.59%)
Hand velocity	1.77/5	0.92 (5.79%)	1.85 (11.19%)	6.86 (38.35%)

results in a small denominator in eq. <16>. We compare the relative utility ratio (RUR) and difference of prediction error (DPE) for ground truth decision with the second rank decision and last rank decision. The RUR and DPE for the second rank decision can be computed by using the second rank decision as the input eq.<16> and eq.<17> (i.e. $r_u(\{\hat{a}^m_t(2)\})$ and $d_u(\{\hat{a}^m_t(2)\})$). In the similar manner, we can compute the RUR and DPE for the last rank decision. We can see that both RUR and DPE for ground truth decision are significantly less than the second rank decision and the last rank decision. This indicates that our online suggestion algorithm works well.

8. CONCLUSION

This paper presented a new framework for media adaptation, for biofeedback rehabilitation. The problem was challenging for several reasons – (a) high dimensionality of parameter space, (b) within session and across session subject performance variation and (c) domain expert decision making was a non first order Markov process. Our key insight is to understand media adaptation as a real-time feedback control problem. We used a mixture-of-experts based Dynamic Decision Network (DDN) for online media adaptation. The mixture of experts model was adopted after we realized that patients exhibit significant variability across sessions. The expert mixture was trained using the familiar EM algorithm. The models were used to answer two basic questions – (a) given a specific adaptation suggested by the domain expert, predict expected patient performance and (b) given an expected performance, determine optimal media adaptation decision. The questions are answered through an optimality criterion based search on DDN models trained in previous sessions.

Our experiments on the real stroke patient data show excellent results on both performance prediction and adaptation decision recommendation. We plan to extend our research in several ways - (a) extend decision making to changes in the physical set-up, and suggestions on when the therapist should discuss with the patient. (b) joint decision making by incorporating the relationship between different aspects of patient's movements (e.g. combine spatial accuracy, hand trajectory and hand velocity), (c) prediction and decision suggestion for higher order Markov process rather than the first order Markov process. We also plan to continue our patient rehabilitation trials over the next few months.

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