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A Computational Framework for Constructing Interactive Feedback for Assisting Motor Learning

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***Abstract*—New motion capture technologies are allowing detailed, precise and complete monitoring of movement through real-time kinematic analysis. However, a clinically relevant understanding of movement impairment through kinematic analysis requires the development of computational models that integrate clinical expertise in the weighing of the kinematic parameters. The resulting kinematics based measures of movement impairment would further need to be integrated with existing clinical measures of activity disability. This is a challenging process requiring computational solutions that can extract correlations within and between three diverse data sets: human driven assessment of body function, kinematic based assessment of movement impairment and human driven assessment of activity.**

We propose to identify and characterize different sensorimotor control strategies used by normal individuals and by hemiparetic stroke survivors acquiring a skilled motor task. We will use novel quantitative approaches to further our understanding of how human motor function is coupled to multiple and simultaneous modes of feedback. The experiments rely on a novel interactive tasks environment developed by our team in which subjects are provided with rich auditory and visual feedback of movement variables to drive motor learning. Our proposed research will result in a computational framework for applying virtual information to assist motor learning for complex tasks that require coupling of proprioception, vision audio and haptic cues. We shall use the framework to devise a computational tool to assist with therapy of stroke survivors. This tool will utilize extracted relationships in a pre-clinical setting to generate effective and customized rehabilitation strategies.

I. Introduction

Smart, Evidence Based, Neurorehabilitaiton involves the well-informed selection and continuous customization of therapy for each patient based on the best available evidence [1]. Relevant information from scientific research must be combined with the following features: (a) a well-grounded prognosis of functional improvement for each patient, (b) holistic understanding of patient preference and learning approaches and (c) continuous integrated monitoring of patient progress across the key domains of the World Health Organization International Classification of Functioning model (ICF). The ICF places influences on disability into four distinct categories: Patho-physiology of the Health Condition, Impairment at the Body Function/Structure level, Disability at Activity level and Handicap in the Participation level [2]. There are a number of validated clinical measures for assessing (monitoring) impairment at the body function/structure level [2]. For example, the Fugl-Meyer scale [3] measures strength of limb parts, isolated joint motion, spasticity, and other motor aspects that influence the movement of stroke survivors. There are a considerable number of clinical measures for evaluating disability at the activity level. For example the TEMPA scale [4] measures the ability of stroke survivors to complete a selection of indicative functional tasks (key turning, jar opening etc). New embedded technologies are making possible the increased monitoring of daily life activities (Participation) [5]–[7]. Advances in brain imaging are improving monitoring options of relevant brain activation patterns (Health Condition) [8]–[10].

However, *there does not exist* a framework for integrating the outcomes of these measuring instruments into a holistic assessment of the effect of a chosen movement therapy on a patient. Integrative evaluation of body function/structure (movement impairment) and activity (task completion) must be the first step towards holistic movement rehabilitation assessment. Integrated understanding of movement impairment and task completion will allow clinicians to determine whether motor relearning is based on reacquisition of elemental motor elements (recovery) or adaptation of remaining motor elements (compensation) [2]. The need for integrative evaluation has recently lead to the creation of clinical measures that evaluate both task accomplishment and movement impairment (i.e Wolf Motor Function test [11]).

A. The Need for Integrated Computational Assessment

Established and newer clinical assessment measures rely on human observation. However, it is impossible for even an experienced human expert to monitor in real time (while the patient is performing a task) all aspects of movement quality and their interactions with precision. This leads to coarse, imprecise and incomplete measurements of movement impairment [1], [2], [12]. New motion capture technologies are allowing detailed, precise and complete monitoring of movement through real-time kinematic analysis. However, a clinically relevant understanding of movement impairment through kinematic analysis requires the development of computational models that integrate clinical expertise in the weighing of the kinematic parameters [12], [13]. The resulting kinematics based measures of movement impairment would further need to be integrated with existing clinical measures of activity disability. This is a challenging process requiring computational solutions that can extract correlations within and between three diverse data sets: human driven assessment of body function, kinematic based assessment of movement impairment and human driven assessment of activity.

The challenge is made harder by the large variance in patient populations and differences in assessor approaches.

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Neurological disorders (resulting from disease or injury) vary in terms of severity and effects on patients' body function and activity. Different patients also have different therapy preferences, learning styles and learning rates. This means that the hierarchy and weights of movement elements to be treated for each patient will vary and learning progress may also vary. Therefore, the network of correlations within and between assessment measures will also vary for each patient. Furthermore, human driven clinical assessments shows the typical small variances that result from the training and preferred methodology of each assessor [14].

B. *Our Approach*

We propose to identify and characterize different sensorimotor control strategies used by normal individuals and by hemiparetic stroke survivors acquiring a skilled motor task. We will use novel quantitative approaches to further our understanding of how human motor function is coupled to multiple and simultaneous modes of feedback, just as humans experience the physical world. The experiments rely on a novel interactive tasks environment developed by our team [15], in which subjects are provided with rich auditory and visual feedback of movement variables to drive motor learning (ref. Fig. 1). The system is capable of providing concurrent online information about errors in both extrinsic (spatial) and intrinsic (joint) coordinates. Our pilot studies have shown that such augmented feedback can substantially enhance recovery of motor function in stroke survivors [16], [17].

We propose to determine the relative contribution of several sensorimotor control strategies used in developing skilled motor behavior (e.g. how particular sensory channels conveying feedback signals are used to minimize intrinsic and/or extrinsic errors, which characterizes learning) first in normal controls then in stroke survivors. We will then determine whether different training regimens, for example engaging one or another previously identified sensorimotor strategy, are optimal for different subjects or subject groups. We will finally develop a general computational framework for extracting specific sensorimotor strategies employed to perform the task in each subject and for providing each subject with customized multisensory and multidimensional information to assist motor learning of complex motor tasks and operational demands.

Our proposed research will result in a computational framework for applying virtual information to assist motor learning for complex tasks that require coupling of proprioception, vision audio and haptic cues. We shall use the framework to devise a computational tool to assist with therapy of stroke survivors. This tool will utilize extracted relationships in a pre-clinical setting to generate effective and customized rehabilitation strategies. These strategies will then be applied in clinical and home-based settings. In general, the framework will facilitate the development of intelligent interactive environments where virtual information assists the learning of challenging movement tasks (i.e. telecontrol, rehabilitation).

II. Context: An Interactive Multimodal System

We have determined a set of high-level design guidelines for the construction of interactive feedback for assisting motor learning. The guidelines incorporate important principles of information processing used in the arts (visual arts, music and dance), cognitive science and in neural control. The guidelines assist the specification of appropriate sensory modality (visual, auditory, haptic) for both explicit and implicit cues and the integration of multiple concurrent sensory streams. The guidelines allow for manipulation of the time structure (synchronous or asynchronous, discrete or continuous) of subject interactivity and provide the ability to define usage goals for the information stream (e.g. for feedback or feed-forward adjustments, contextual switching). The guidelines promote the creation of coherence between movement and digital feedback through an action representation and the balancing of representational and abstract digital feedback elements to achieve various levels of distancing during training. Finally, the guidelines provide rules for online changes (adaptation) of the interactive feedback so as to maintain interest, avoid forming of dependencies and promote customized learning.

Fig. 1: A subject interacting with our system

We have developed an interactive system that applies these principles and have successfully used the system in the specific scenario of upper extremity stroke rehabilitation. The system provides multiple concurrent feedback streams allowing for integrated training of multiple movement components. The feedback denotes performance error and direction for improvement and can be provided over single task trials or multiple epochs. We are able to use consistent feedback mappings across different tasks thus promoting generalized learning. The virtual feedback elements have intrinsic reward value to motivate users. Furthermore, we have developed an innovative computational framework to support our interactive system. The computational framework currently has two key components: a computational index to measure learning in terms of kinematic performance and, algorithms to extract correlations between significant variables of kinematic performance and feedback. We are currently extending the latter by monitoring brain activity patterns through EEG during the interactive learning process though in anticipation of adding this as a third class of variables.

Our full-scale, stroke patient rehabilitation system works in real-time, using an array of 11 high-speed infrared cameras that track reflective markers on the patients arm. We have dedicated sub-systems for motion analysis, audio and visual feedback, system adaptation and archiving. This system has been successfully set up in Banner Baywood Hospital since spring 2009, and is being used to train patients. Eleven stroke survivors have been trained using our system and have shown substantial improvement in movement quality [16], [17]. Our system demonstrated improvement in both movement quality and clinical scores [16]. Furthermore, larger improvements in movement quality are seen during tasks where feedback is present when compared to tasks for which no feedback is provided [18], [19].

In this paper, we propose a computational framework for constructing interactive feedback via an integrative assessment of movement impairment, body function and activity. The two key components of the framework will be the kinematics based evaluation of movement impairment and the extraction of correlations between the computational assessment of movement impairment and the human expert (clinician) assessment of body function and activity. In recent work, we have developed a computational assessment of movement impairment [20].

III. Learning Higher-Order Relationships

We propose to identify effective sensorimotor control strategies being used by each subject through the extraction of ternary relationships amongst sustained kinematic performance improvement indicative of motor learning, specific combinations of audio visual feedback and brain reorganization patterns monitored through EEG. We propose to learn higher order relationships between these multiple variables via sparse inverse covariance estimation. Sparse inverse covariance estimation technique has been successfully applied for learning biological and brain networks [21]–[23]. However, it assumes a Gaussian distribution of the data, which may not be the case in our data. We propose to employ the sparse regression approach for estimating the relationships and their strengths. A linear regression model estimates the interaction between a specific variable and the remaining variables.

Estimating invariant relationships and their strengths is inherently ill-posed; an infinite number of solutions exist. This is a fundamental challenge in regression-based models. We hypothesize that a variable interacts with a small number of variables in the sparse high-dimensional data. This suggests that the variables are sparsely connected. A sparsity constraint, imposed by applying an appropriate regularization, leads to sparse solutions. In particular, it has been shown that L_1-norm regularized regression model leads to sparse solutions [24]. Furthermore, with the sparse regression model for inferring relationships, it has been recently shown that consistent neighborhood selection can be obtained under certain mild conditions [25], [26]. In this research, we plan to solve sparse regression using our SLEP package (Sparse Learning with Efficient Projections) [27]. The algorithms in SLEP achieve the optimal convergence rate among all first-order methods and scale to high-dimensional data.

IV. Learning Strategies for Interactive Learning

Developing an interactive and computational training strategy requires us to use the higher order relations indicative of effective sensorimotor control strategies (via sparse inverse covariance estimation), and training sequences developed by a domain expert (instructor).

Our methodology for developing training sequences will use a tree representation that establishes a hierarchy of components of the task. The tree representation denotes the interrelationship of the components and their relationship to the task goal. We turn this representation into a learning methodology by applying the principles of methods for learning musical instruments (Arban, Suzuki etc). We develop an exercise per task component, which requires a certain level of mastery of that component before the learner can advance. We combine lower-level exercises to create higher-level exercises, which are more complex. We do so, until the full complex task is learned. Alternative types of exercises are given for each task component since each learner is different. The possible interactive feedback combinations for each exercise are selected based on our established guidelines. All exercises and tasks teach skills which generalize across different task contexts. During the experiments for developing computational training strategies the domain expert (instructor) will utilize the rate of change of the indicative relationship strength to adapt the feedback elements for each exercise and the sequences of exercises (tree path) to facilitate learning for each subject.

The resulting training sequences, including adaptations to the interactive feedback and rates of change of relationship strengths, will help develop the computational strategy. Developing a computational strategy is challenging due to three reasons: (a) the number of variables in the strategy space is very large; (b) the training data is sparse; (c) human subjects can vary, often significantly, in their motor learning patterns. We propose to tackle the computational challenges in the following ways. The sub-task training sequence can be modeled as a Conditional Random Field [28]–[30], where the transition to the next training sub-task depends upon prior sub-task as well as fully observable ternary relationships, including the rates of change for each relationship. We shall also investigate the use of Boosted Random Fields [31], and other dynamic Bayesian representations that incorporate context [32]. Learning to adapt the environment, given a sub-task, involves determining the interactive feedback parameters. We plan to improve upon our previous work dynamic decision networks [33] and related work on Partially Observable Decision Markov Process [34], [35]. We plan to address dimensionality and data sparsity challenges in two ways: clustering adaptation variables and developing Dynamic Decision Networks (DDN's) for each cluster, developing a utility function for choosing amongst several adaptation candidates.

V. Conclusions and Future Work

The resulting computational framework will have significant impact on advancing smart neurorehabilitation. The framework will allow computer assisted, continuous customization of therapy based on the best available evidence. Since the framework can be applied across many studies, it will promote comparative evaluation of the results of the studies, facilitate communication amongst researchers and establish a significant body of common evidence that can be used for the selection and customization of therapy. Currently, different types of clinical scales are being used across the many rehabilitation studies making it hard to produce common evidence [1].

The network of correlations within and between the three types of assessments measures is large and complex. We plan to develop, as part of future work, computational methods to extract and present only significant correlations and changes for each patient. A useful framework must offer relevant summarizations of changes in the assessment network over multiple time-scales. Finally, the framework requires an interactive visualization interface that allows the therapist to easily access relevant assessment information for each patient at multiple time scales, within and across measures.

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