An Intelligent Decision Support System for Stroke Rehabilitation Assessment

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ABSTRACT
Assessment of rehabilitation exercises is important to determine an adequate rehabilitation intervention. However, this assessment is costly as it requires the presence of a therapist. This paper presents an interactive multimodal approach that automatically assesses exercise performance, identifies salient features of assessment, and iteratively present user-specific analysis to support therapist's decision making on personalized rehabilitation assessment. This approach can achieve good agreement level with therapist's evaluation (i.e. an average of 0.8565 F1-scores on three upper-limb exercises), which is higher than non-interactive, unimodal models.

Author Keywords
Human-AI interaction, interactive machine learning, stroke rehabilitation assessment

CCS Concepts
•Computing methodologies → Intelligent agents; •Applied computing → Health care information systems;

INTRODUCTION
Physical rehabilitation is critical to regain functional ability of people with neurological and musculoskeletal disorders (e.g. stroke). To determine appropriate rehabilitation interventions, a therapist observes and assesses individual's rehabilitation exercises. However, this assessment is expensive and labor intensive as it requires the presence of a therapist. Due to the limited availability of therapists, an individual may not receive timely and comprehensive rehabilitation interventions.

Researchers have explored the feasibility of computer-assisted monitoring and assessment of chronic diseases [10]. One approach is called a rule-based model, in which domain experts are interviewed to elicit a set of rules to determine the correctness of a motion [2]. A rule-based model provides the modularization and flexibility of motion analysis. However, it is time consuming to determine the right threshold values of rules for individual's functional ability and experts might not articulate their decision making on a complex task. Another approach is called a statistical model that utilizes a supervised learning algorithm with labeled sensor data. This statistical approach processes complex data to automatically extract a meaningful function (e.g. Neural Network model) to classify the quality of motion [5]. However, a statistical model with a complex algorithm is limited to being a black-box system [1] that cannot explain its prediction on individual's functional ability to support therapist's decision making.

This paper describes an interactive multimodal machine learning approach that assesses exercise performance by integrating the benefits of both statistical and rule-based models. This approach can automatically identify salient features to assess the quality of motion and iteratively present user-specific analysis to elicit domain knowledge for personalized rehabilitation assessment (Figure 1a) [4].

INTERACTIVE MULTIMODAL MODEL TO ASSESS REHABILITATION EXERCISES
The proposed approach utilizes a weighted average, ensemble technique [8] to implement a Multimodal Modal (MM) that integrates two perspectives on assessment: Prediction Model (PM) that is driven by supervised learning algorithms and labeled data and Knowledge Modal (KM) that accommodates expert's knowledge with a set of rules. This approach identifies salient features for assessment using Sequential Forward Search with Neural Networks [6] and iteratively presents user-specific analysis by a web interface (Figure 1b) to elicit the inputs of an expert (i.e. feature relevance). Utilizing the relevant features and individual's held-out unaffected motions (*'User Data'*), this approach can automatically generate additional, feature-wise rules of assessment to update the KM for personalized assessment.

For the PM, Neural Network (NN) is trained while grid-searching various architectures (i.e. one to three layers with 32, 64, 128, 256, 512 hidden units) and learning rates (i.e. $0.0001, 0.005, 0.001, 0.01, 0.1$) using the *'Scikit-learn'* library [7]. *'ReLu'* activation and *'AdamOptimizer'* are applied and a model is trained until the tolerance of optimization is 0.0001 or the maximum 200 iterations.

For the KM, semi-structured interviews with two therapists were conducted to elicit their knowledge of stroke rehabilitation assessment, which is formulated as 15 independent *if-then* rules. Specifically, therapists focused on deriving rough threshold values on kinematic measurements for assessment. For

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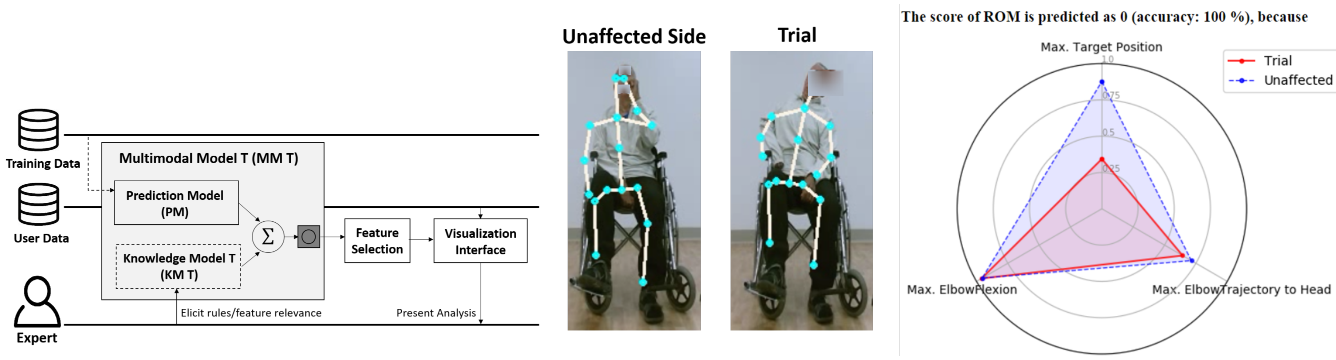

(a) (b)

Figure 1: (a) Flow diagram of the proposed interactive Multimodal approach. (b) Web-interface that presents user-specific analysis to an expert.

example, therapists check whether the maximum y-position of wrist ($wrist_y^{max}$) exceeds either the middle or top y-position of spine ($spine_y^{middle}$ or $spine_y^{top}$) to evaluate the range of motion, which can be expressed as the following rule:

$$Score_1 = \begin{cases} 2 & \text{if } wrist_y^{max} >= spine_y^{top} \\ 1 & \text{if } spine_y^{mid} < wrist_y^{max} < spine_y^{top} \\ 0 & \text{otherwise} \end{cases}$$

To predict the quality of motion, the KM computes an average score of rules:

$$Score = \frac{1}{N}\sum_{i=1}^{N} Score_i$$

where N is the number of utilized rules.

In addition, after reviewing user-specific analysis (Figure 1b), a therapist provided feature relevance to automatically generate additional rules (i.e. normalize the feature value of the affected side by that of unaffected side) and update the KM.

EXERCISE DATASET

For the validation, three upper-limb stroke rehabilitation exercises are recommended by therapists (*E1: 'Bring a cup to the mouth', E2: 'Switch a light on'*, and *E3: 'Move forward a cane'*) [3]. The exercise dataset is collected from 15 stroke survivors (37 ± 21 Fugl Meyer Scores [9]) and 11 subjects without motor impairment using a Kinect v2 sensor. A stroke survivor performed 10 repetitions of each exercise with both affected and unaffected sides. A subject without motor impairment performed 15 repetitions of each exercise with his/her dominant side. Two therapists watched recorded videos to annotate the collected dataset without reviewing user-specific analysis from the proposed approach.

Unaffected motions from 11 subjects without motor impairment (165 trials) and affected motions from 15 stroke survivors (150 trials) are utilized as *'Training Data'* for the Prediction Model (PM). Each stroke survivor's unaffected motions are held out as *'User Data'* for user-specific analysis.

RESULTS

The proposed interactive Multimodal (MM) approach is evaluated with Leave-One-Subject-Out cross validation on stroke survivors. The proposed approach has the following agreement levels with therapist's evaluation: average F1-scores of 0.8161 - 0.9041 on three exercises (Table 1). While interactively presenting user-specific analysis and accommodating therapist's inputs, the proposed achieves higher agreement level with therapist's evaluation than non-interactive, unimodal models (e.g. KM, PM, MM 1).

	Exercise 1 (E1)	Exercise 2 (E2)	Exercise 3 (E3)
KM 1	0.6148 ± 0.1702	0.6707 ± 0.1435	0.4626 ± 0.1716
PM	0.8806 ± 0.0502	0.8090 ± 0.0671	0.8115 ± 0.0436
MM 1	0.8504 ± 0.0584	0.7186 ± 0.1012	0.7446 ± 0.0538
MM 2	**0.9041 ± 0.0451**	**0.8161 ± 0.1088**	**0.8493 ± 0.0515**

Table 1: Agreement level with therapist's evaluation (F1-scores): interactive Multimodal modal (MM2), Unimodal models (KM 1, PM), and non-interactive Multimodal model (MM1)

CONCLUSION AND FUTURE WORK

The preliminary experiment shows that statistical and rule-based models complement each other to improve the performance of stroke rehabilitation assessment. Data-driven, user analysis of the proposed approach enables a therapist to understand post-stroke survivor's kinematic measurements and performance and elicit additional knowledge on feature relevance. While iteratively accommodating therapist's knowledge, a generic assessment model can be tuned into a personalized model with improved performance. In addition, this user analysis can be utilized to generate personalized corrective feedback for improvement to a post-stroke survivor instead of just reporting the correctness of a motion.

In future, an additional study will be conducted to analyze whether user analysis of the proposed approach is effective for therapists to gain new insights on post-stroke survivor's performance and facilitate the development process (e.g. annotation).

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