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Knowledge discovery, rehabilitation robotics, and serious games: examining training data

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Abstract— **In this paper, we present an initial attempt to apply Knowledge Discovery techniques over real performance data from patients enrolled in robotic therapy in order to explore how to better optimize therapy. Performance data sets encompass measurements such as position, velocity and force, as well as final performance measures. We apply the Principal Component Analysis method in an attempt to reduce the dimensionality of the problem, molding subsets that were the input into a Multilayer Perceptron Artificial Neural Network which would carry out data mining with the purpose of discovering the relative significance of each field, in relation to a performance measure. It was possible to notice the impact caused by the lack of each field in terms of specific performance measures, indicating which data are more relevant to use in further experiments.**

I. INTRODUCTION

Life expectancy of the world population is increasing as is the percentage of its elderly population, placing more demands for rehabilitation services. The increase in the demand for rehabilitation services is in part due to stroke. According to the World Health Organization (WHO), every year 15 million people worldwide suffer a stroke. Two thirds of this population will survive but will be left with significant residual impairments and in need for rehabilitation [1].

Motor impairment is susceptible to treatment and rehabilitation [2]. Rehabilitation, in essence, consists of repetitive exercises that might be tiresome and boring and negatively affect patient's performance [3] [4]. Despite the existence of traditional rehabilitation methods, patient's motivation can significantly contribute to ultimate outcomes. In contrast, the use of robots in rehabilitation [5] affords a significantly higher number of repetitions per treatment session as well as proper evaluation of patient’s performance [6] [7] and, moreover, the ability to interact and motivate patients using game-based approaches [8]. In such treatments, robots serve as an interface to a computer game environment. This gaming environment enhances patient's attention, potentially transforming a taxing exercise into an engaging activity.

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II. RELATED WORK

A. Robotic Therapy and Data Collection

Robots also allow the collection of patient's performance data. This information can serve as input to afford additional insights into the outcomes, enabling the grounding for future guidelines to be used by clinicians. In spite of several ways to analyze data [15], it is important to check the quality of the raw data to generate relevant outcomes (from clinical perspective), prompting better acceptance of as well as reliability on measurement accuracy of each involved aspect [6] [7] [9].

The collected and analyzed data can inform researchers and clinicians on how to conduct and improve therapy methods. In [12], Krebs and colleagues describe the way that some performance data collected by robots and games in robotic therapy can indicate the progression of some patients during their sessions. There, four performance measures were derived from big data sets collected during robot-interactive games’ runtime. This performance data was used as a gain scheduler to modify the next batch of games. Other works, such as [23] and [24], go towards the same goals, developing strategies to measure performance in robot-aided therapy, analyzing the results that were obtained during the therapy procedure, and making use of analyzed data to learn more about how to develop new protocols to be used in this kind of robot-aided therapy.

In order to interpret this new big collection of data, there are several machine learning techniques for mining and analyzing data that have been used to discover new information and knowledge with this rehabilitation robotics method [7][11][13][14].

B. Paper Contribution

This paper focuses on the development of an efficient and more reliable method to extract valuable knowledge for clinicians.

III. KNOWLEDGE DISCOVERY AND DATA MINING

This section describes the role of the main assets of the rehabilitation robotics scenario and the format of the collected input used to perform an initial assay.

The rehabilitation robotics scenario, illustrated in Fig. 1, is comprised of two main assets: a robotic device to interact with the patient as well as collect runtime performance data, and a performance analysis that seeks knowledge, employing performance data as input. The robotic device in this scenario, already used in clinics and hospitals, is an InMotion ARM from Interactive Motion Technologies (Watertown, MA, USA) [19]. This device is provided with a screen to

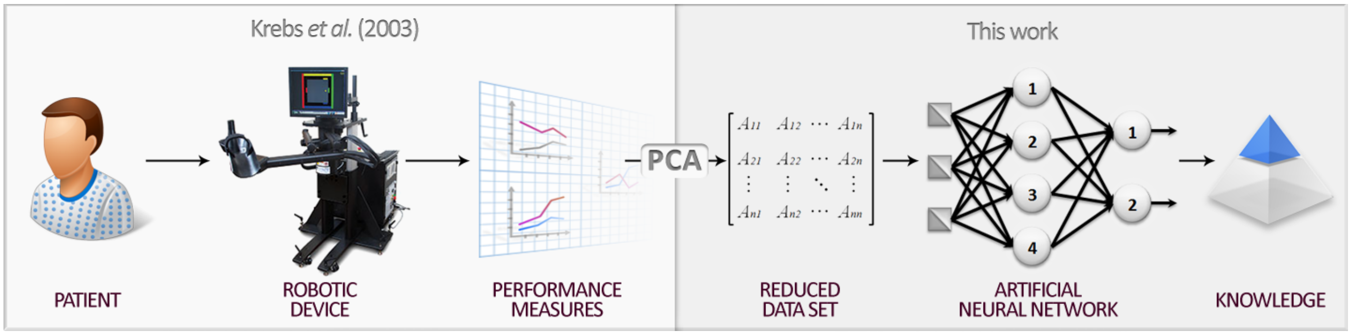

Figure 1. Rehabilitation Robotics Scenario.

display the gaming environment (for example: a serious game), which updates its runtime logic according to the patient's effort that is reproduced through a three active degrees-of-freedom robotic arm. Here we will use only the data collected in two of these degrees corresponding to the arm and forearm movements. Measures of the end-point position (x and y axes, in meters), velocity (x and y axes, in meters per second) and force (x, y and z axes, in Newtons) compose a data array that is collected every 5 milliseconds (200Hz). Performance data of a whole session are stored in files that represent individual movements or aggregated data.

One of the serious games included with this robotic device is called Clock game. It displays a clock-like circle, having eight targets arranged, as illustrated in Fig. 2. The goal is to make a reaching movement towards a target currently indicated by a red circle, and then backwards, towards center, making a star-like pattern.

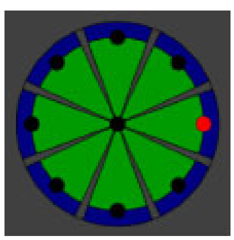

Figure 2. Clock Game.

At the end of every 5 repetitions around the 8 targets (total of 80 movements), performance metrics are properly calculated and stored. Here we will use three of these metrics. The first measure is the "Distance from Target," indicating in millimeters the distance between the patient's hand and the target at the time the robot stops assisting. The optimum outcome for this metric is when the value is zero. The second measure is called "Robot Power." It indicates, in milliwatts, the mean assistance the robotic device has delivered in order to support the patient, ranging from a lower bound of zero to an unbounded maximum power necessary to assist. The optimum outcome for this metric is also zero. The third measure is called "Motion Jerk." It measures, in meters per second cubed, the jolt performed by the patient when moving towards a target. Given the acceleration, one calculates its derivative (Jerk), and then calculates the square root of the sum of the squares of Jerk. The optimum outcome for this metric is derived from the minimum-jerk profile [21].

Having collected performance data during a certain number of sessions, we will attempt to extract patterns from this large data set. Knowledge Discovery in Databases (KDD) describes a step-by-step approach [16] to search for patterns through three major steps. Preprocessing takes place first by filtering the raw data and attempting to reduce it dimensionally to a smaller subset. Data mining comes second, done by employing methods such as clustering and pattern recognition to search for patterns. The final step is Postprocessing, which consists of adjustments (if necessary) and evaluation of the result as a whole in lieu of our objectives [16].

This paper describes our first attempt in building an assay from the performance results of a patient during the 38 sessions that were provided by Instituto Lucy Montoro [18] for analysis.

A. *Principal Components Analysis (PCA)*

The first KDD step requires the preprocessing of the raw data. Notwithstanding the initial steps that eliminate unnecessary data, the dimensionality of the resulting data set needs to be reduced. Here we employed the Principal Components Analysis [17]. We applied the PCA over the 38 subsets of data, considering each rehabilitation session data as an individual sample for further steps of KDD.

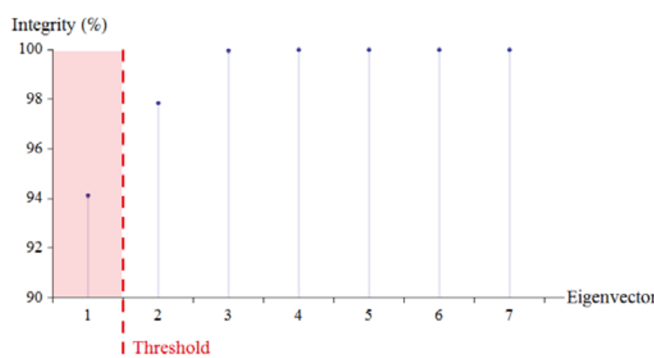

Figure 3. Cumulative Mean Significance of the Principal Components.

The principal components are the eigenvectors of the covariance matrix, calculated from the original data set with the mean of every dimension subtracted. The choice of how many principal components should be used relies on the level of significance required to maintain data integrity. The eigenvector with the highest eigenvalue is the most significant principal component, whereas the eigenvector with the lowest eigenvalue indicates less significance.

Cumulatively, principal components can be used to perform a more integral data reduction. Fig. 3 indicates the cumulative mean significance (from all samples) of each principal component.

Note in Fig. 3 that the most significant principal component accounts for over 90% of the content variance. Thus, only the first principal component will be used to summarize data.

B. Data Mining and Artificial Neural Networks

The data mining is the next step. From a relatively small data set, it is now possible to extract patterns in order to turn quantitative results into knowledge. Here data mining seeks the relevance of each field initially collected. To gain the information, a Multilayer Perceptron (MLP) Artificial Neural Network [20] was trained using Levenberg-Marquardt back propagation learning algorithm.

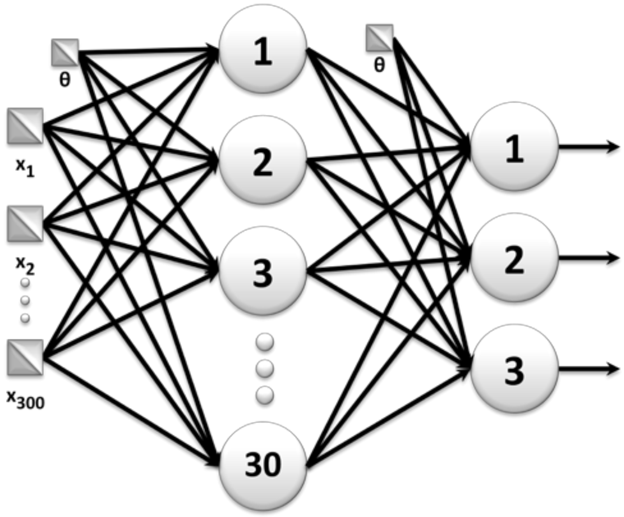

Figure 4. MLP Artificial Neural Network Topology.

Considering MLP architecture has supervised training (a desired output for each input is required), three evaluations were joined as output for each input sample. Such evaluations were represented numerically, varying from 0 to 1, being assigned to Distance From Target, Robot Power and Motion Jerk. For each performance measure, maximum and minimum values were considered for normalization, as defined in (1).

$$\begin{cases} a \cdot x_{max} + b = 0 \\ a \cdot x_{min} + b = 1 \end{cases} \tag{1}$$

It is possible to notice a high amount of neurons in the hidden layer (Fig. 4) of the MLP neural network, inducing an overfitting. The purpose is to use several decision boundaries to narrow every area that a normal topology (normal, in this case, refers to the non proneness to overfitting) would surround for a wider generalization. These conditions might enable us to analyze the relevance of each collected field in terms of the final evaluations, so by weighting a field in less than 100%, it is possible to verify whether or not the pattern is still surrounded by the same decision boundaries, which might indicate its significance in relation to a specific final evaluation [7]. It is important to point out that the topology of Figure 4 was obtained empirically, having its outputs satisfactorily fitted to the expected results.

The samples used in training mode were used 7 times as inputs into the trained MLP neural network. Each time a different column was entirely set to zero (before PCA) aiming to obtain the affected final evaluations as the result of this assay, which is also the output for the last step of KDD: Interpretation.

IV. RESULTS AND DISCUSSION

This section clarifies the initial set of results obtained during KDD process, providing a graphical interpretation. First notice the behavior of the trained artificial neural network compared to the original/desired behavior. Figures 5 and 6 indicate, respectively, the behaviors of the normalized Robot Power and Motion Jerk evaluations in the course of 38 sessions.

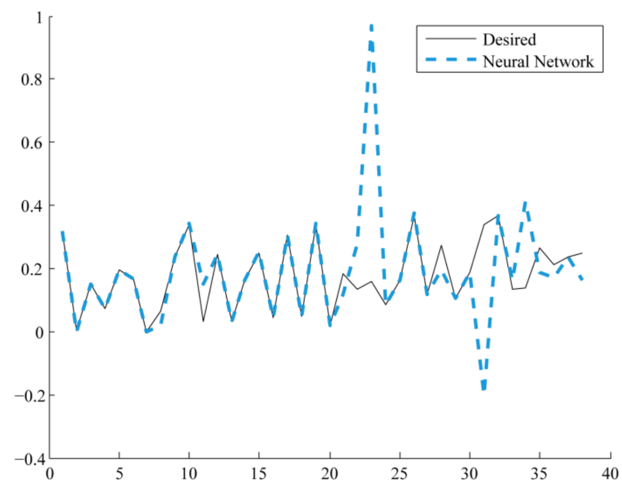

Figure 5. Desired and Neural Network Outputs for Robot Power.

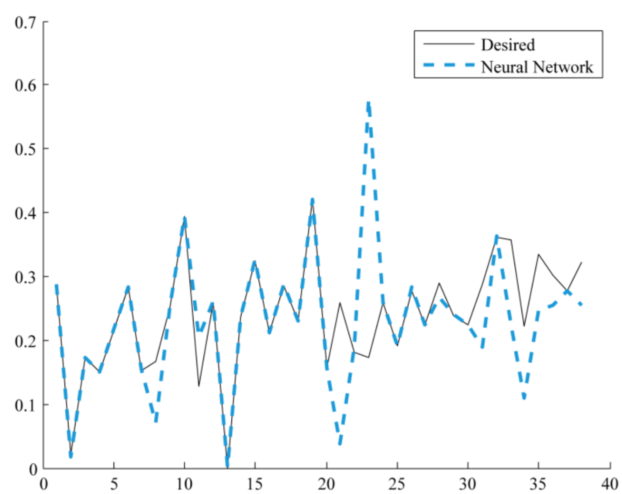

Figure 6. Desired and Neural Network Outputs for Motion Jerk.

One can notice that regardless the induced overfitting, there are still some outlier data (see for example the 23^{rd} session). This discrepancy can be interpreted either as improper use of the robotic device or as an unusual session.

Patient may present signs of local physical tiredness, such as fatigue, or general health disorders that strongly influence motor behavior. Here we will ignore this kind of outlier session. Regarding the significance of the collected fields, Figures 7 to 13 delineate the results of the used approach (inspired in jackknife [22]) and the most affected evaluations.

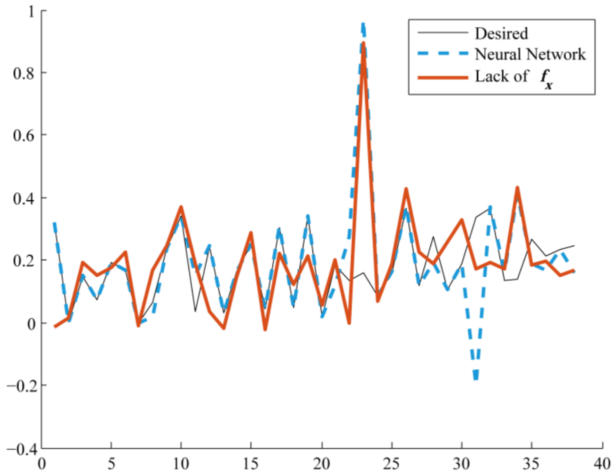

Figure 7. Robot Power Behavior without f_x.

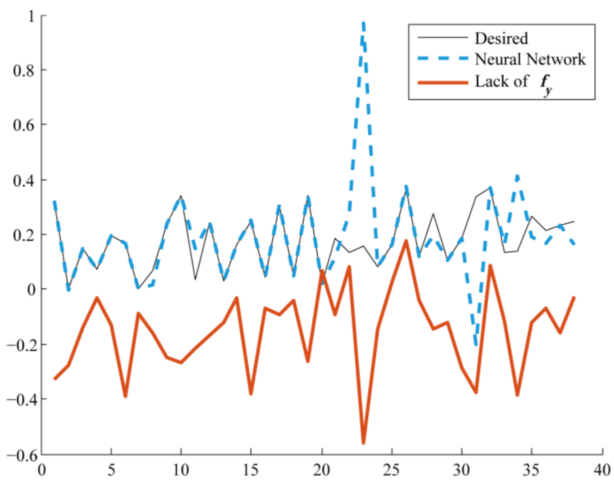

Figure 8. Robot Power Behavior without f_y.

Figures 7 and 8 show that certain data are not correlated to a particular performance measure. As an example, for the Robot Power the force along x axis (f_x) is the side force applied in order to keep patient's movements straighter towards a target, and its absence minimally affects the outcome. In contrast and having quite a different affect, the force along y axis (f_y, orthogonal to f_x) is the force minimally applied towards the true straight path to a target of the game. Therefore, comparing the affected behaviors due to the lack of each field, one can conclude that f_x is not as relevant as f_y for this performance measure.

Still, regarding Robot Power, it is also pertinent to mention the relevance of other fields besides force, such as Velocity along y axis (v_y). Illustrated in Fig. 9, the lack of v_y also strongly affects the final evaluation.

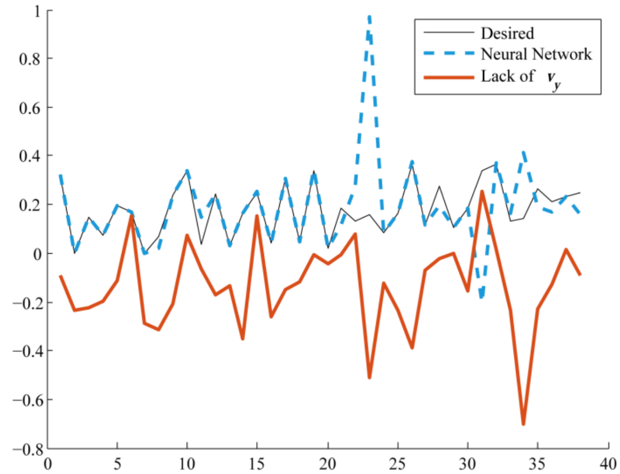

Figure 9. Robot Power behavior without v_y.

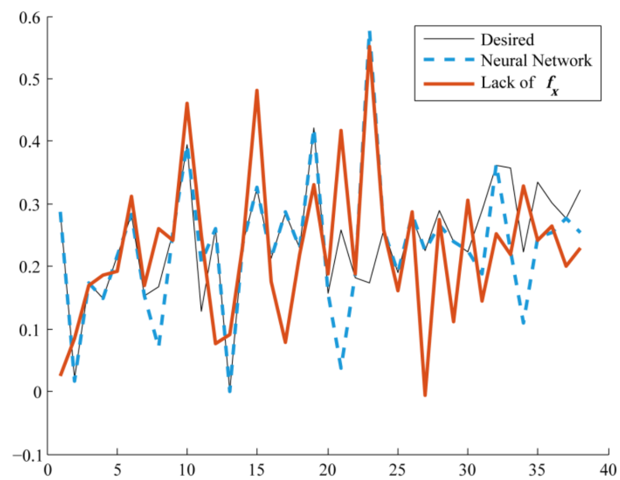

Figure 10. Motion Jerk Behavior without f_x.

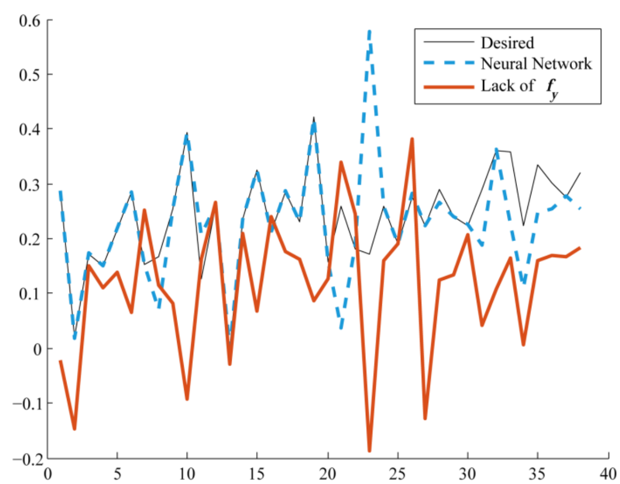

Figure 11. Motion Jerk Behavior without f_y.

Final evaluations are not always directly related to collected fields, such as the relation between Robot Power and Force fields (f_x and f_y). Concerning Motion Jerk, f_x (in Fig. 10) is not as irrelevant as in Robot Power perspective and, in addition, f_y continues to be significant for this evaluation as well, as shown in Fig. 11.

In this assay, not every performance measure did fit in this KDD strategy. Distance from Target measure afforded an interesting outcome: as expected, the lack of any field resulted in a significant change in final evaluation's behavior. Even considering position fields as the most expressive data of this performance measure, neither omitting Position along x axis (p_x), nor Position along y axis (p_y), nor both, it was still possible to cause satisfactory changes, as indicated in Figures 12 and 13.

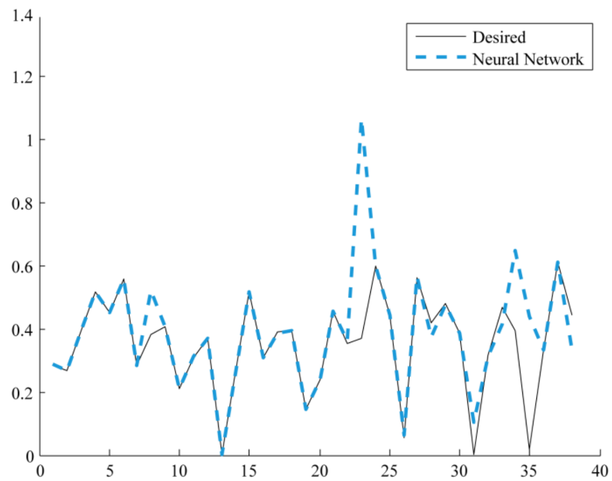

Figure 12. Desired and Neural Network Outputs for Distance From Target.

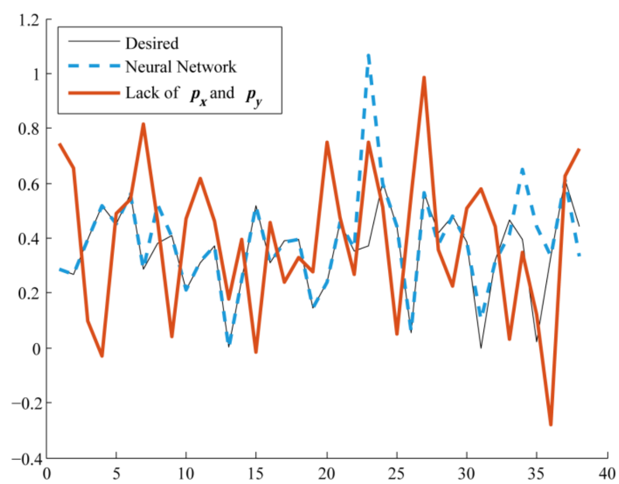

Figure 13. Distance From Target Behavior without p_x and p_y.

Completing this discussion, we could simulate, through the linear regression defined in (1), what would be an evaluation subjectively assigned by therapists, so as to comprise a model that analyzes patient's performance during the usage of the robot-assisted system. Through machine learning mechanisms, this system enabled the development of an initial and cohesive method to evaluate the relevance of performance measures, inspiring future KDD strategies and aiming future methods with a runtime that no longer lean on subjective evaluations, once these were initially fed to the KDD process.

V. Conclusion

This pilot effort represents our initial efforts to implement KDD techniques in data being collected with stroke patients at Rede Lucy Montoro in order to enhance our understanding of what might constitute optimal therapy and new knowledge discovered from the collected data. We employed PCA techniques for dimensionality reduction and artificial neural networks for function approximation and demonstrated their potential as useful ways to select the most important variables. We employed a jackknife-inspired approach to probe the significance of each of the collected fields in terms of measured performance. Of course, one must take the results with the appropriate caveats, but the approach was able to catch the lack of correlation of the Distance From Target to any of the measurements, hence confirming the potential of the KDD method in handling big data, as well as predicting trends.

We expect to learn more about the interaction between human and robot using KDD techniques, what might improve the whole robot-aided therapy approach.

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