2018 7th IEEE International Conference on Biomedical
Robotics and Biomechatronics (Biorob)
Enschede, The Netherlands, August 26-29, 2018

Position Error-Based Identification of Subject Participation in Robotic-Rehabilitation*

Shrey Pareek[1], Pramod Chembrammel[2], John K. Nguyen[3], and Thenkurussi Kesavadas[1]

Abstract— **In this paper, we present a haptics-based rehabilitation system that uses kinematics of a haptic device to monitor a subject's participation in therapy. In robot-assisted therapy, it is crucial to monitor if the patient is actively performing the rehabilitation task and is not just passively following the robot's motions. In this paper, we have used position-tracking error patterns as a metric for identifying whether the subject is actively participating in the therapy. Using a single feature identification scheme, our method demonstrated a real-time classification accuracy of 80.04% in separating active and passive participation during a therapy session.**

I. INTRODUCTION

Stroke has been identified as the leading cause of disability in the United States. An estimated 800,000 people suffer from stroke each year [1]. Even mild motor impairments can be disabling as they slow down functional activities such as dressing and walking. These impairments manifest themselves as inhibitors to the patient's ability to carry out activities of daily living (ADL) such as writing, using cutlery, knife etc. In order to regain functional control via neuroplasticity, stroke patients participate in rehabilitation programs.

Current stroke rehabilitation paradigms are primarily hospital-centric and involve an occupational therapist and a doctor working in close conjunction with the patient. As the therapy progresses, a transition in rehabilitation goals from gross motor skills to fine motor skills is observed [2]. Fine motor skills are fine movements that require the control of the smaller muscle groups of the fingers or wrists. Gross motor skills refer to larger movements that use the muscles in the arms, legs or torso.

However, owing to the time-consuming and expensive nature of physical therapy aggravated by the disability of stroke patients to easily travel to the therapy center; patients are sent home after a few sessions to continue therapy on their own accord [3]. In such situations, home-based therapy presents itself as a viable alternative. Incidentally, this form of therapy is amiable to the rehabilitation of ADL skills. However, due to the lack of a human chaperone in home-based therapy, patients seldom practice the recommended therapy. Recent years have seen the advent of tele-rehabilitation systems to address the challenges of home-based therapy [2], [4]. These tele-rehabilitation systems allow the therapist to remotely monitor the patient's progress and suggest required changes to therapy.

Most tele-rehabilitation systems [5]–[11] allow the therapist or technician to manually adjust the difficulty levels of the tasks and/or the stiffness of the haptic device. These manual adaptations are based on off-line analysis of patient data during post-therapy sessions. The effects of instantaneous patient performance and/or mental engagement are seldom factored into these analyses; which may be inhibitory to therapy. In addition, while these studies have implemented technologies aimed at boosting patient engagement, little or no resources have been allocated towards monitoring these parameters.

Active mental engagement of the patient toward therapy is imperative to the success of any rehabilitation paradigm [4]. In case of conventional hospital-centric therapy, the therapist ensures patient engagement and motivation; and enforces the required modifications. The lack of this active patient-therapist interaction inhibits the efficacy of robotic-rehabilitation systems over traditional therapy [12]. While various attempts have been made to study human-robot engagement in the fields of social robotics [13]–[19] and robotic-rehabilitation [4], [20], these techniques require significant pre-deployment and calibration, which has limited their efficacy and scalability in different settings.

Peters et al. [14] used eye gaze and head direction information to evaluate a user's engagement while interacting with a virtual agent. Use of facial expressions to quantify engagement had been explored by [19]. Use of electromyography (EMG) is yet another technique for quantifying subject engagement [20]. Also, recent years have seen the advent of non-invasive brain computer interfaces (BCI) [21], [22] to study and quantify the cognitive states of subjects. Use of BCI to quantify task engagement and mental workload has been demonstrated by [23]–[26]. While these techniques have demonstrated efficacy in quantifying user engagement in human-machine interactions, they may not be feasible in tele-rehabilitation systems. BCI and EMG sensors need a considerable amount of time to set up and usually require the assistance of another person in doing so. Further, stroke patients might not be receptive to these technologies due to their cumbersome form factors. Use of cameras for facial

*We acknowledge the support from NSF IIS 15-02339 grant award towards the funding of this study.

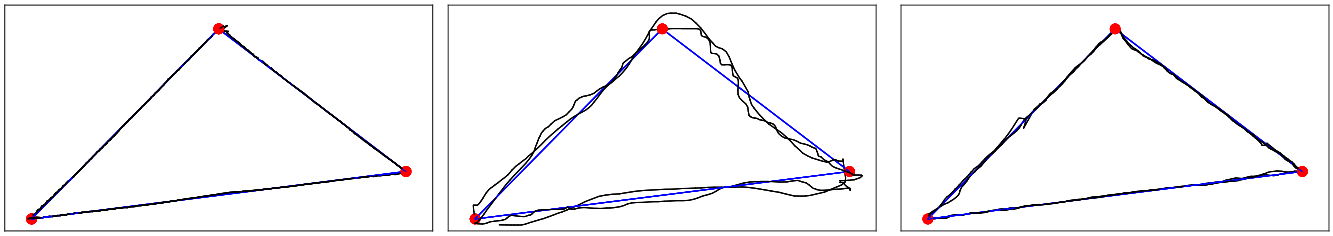
[1]Shrey Pareek is with the Department of Industrial and Enterprise Systems Engineering, University of Illinois at Urbana Champaign, IL-61820 spareek2@illinois.edu

[2]Pramod Chembrammel is with Health Care Engineering Systems Center, University of Illinois at Urbana Champaign, IL-61820 pramodch@illinois.edu

[3]John K. Nguyen is with the Illinois Informatics Institute, University of Illinois at Urbana Champaign, IL-61820 jknguye2@illinois.edu

[1]Thenkurussi Kesavadas is with the Department of Industrial and Enterprise Systems Engineering, University of Illinois at Urbana Champaign, IL-61820 kesh@illinois.edu

978-1-5386-8183-1/18/$31.00 ©2018 IEEE



(a) Case A - Only robot applies force. (b) Case B - Only user applies force. (c) Case C - Shared-control.

Fig. 1: Trajectories generated during the three test cases.

feature recognition may not require any significant pre-deployment, but these devices involve continuous recording of the subject; raising privacy concerns, particularly in the home setting. Auditory feedback systems [27] suffer from similar challenges.

In this paper, we present a human-robot symbiotic rehabilitation system, that identifies subject's engagement and provides motivation towards therapy. We use the term symbiotic to describe our system as it ensures that the human and robot work together to attain the therapy goals. We exclusively use joint rates from the proprioceptive sensors of the robot to identify user engagement/participation. The system does not require the use of any additional hardware or manual calibration. Using data-analytics, our system can monitor whether a user is actively participating in the therapeutic exercises and adapt accordingly. The robot-assisted therapy task described in this paper requires the subject to track reference trajectories by controlling the position of a cursor on the computer screen using a haptic device. The system has been designed to imitate a massed practice therapy regime that benefits from the inherent advantages of implicit therapy [28]. Implicit learning refers to skill acquisition without awareness or not directed at a conscious level [28]. For instance, in the current scenario, implicit learning is incorporated by programming the trajectory tracking task into a handwriting simulation game. Studies have demonstrated the efficacy of implicit learning paradigms over explicit ones [29], [30].

Traditionally, position error is used as a metric to evaluate patient performance - low position error is indicative of superior performance and vice-versa. We hypothesize, test and prove that this error may also be used as a real-time indicator of the subject's participation in the therapy task. Consider three cases of straight line tracking tasks between two points as shown in Fig. 1 performed by a healthy subject. The user is required to control the position of an on-screen cursor using the robot's end-effector to follow the straight lines between the two points (red circles in the figure). Case A involves the autonomous operation by the robot; in case B, the user performs the experiment without any assistance from the robot; case C is a shared-control scenario in which the user is assisted by the robot in tracking (haptic assistance). The blue line in the figure is the straight line trajectory to be followed, and the black line is the actual

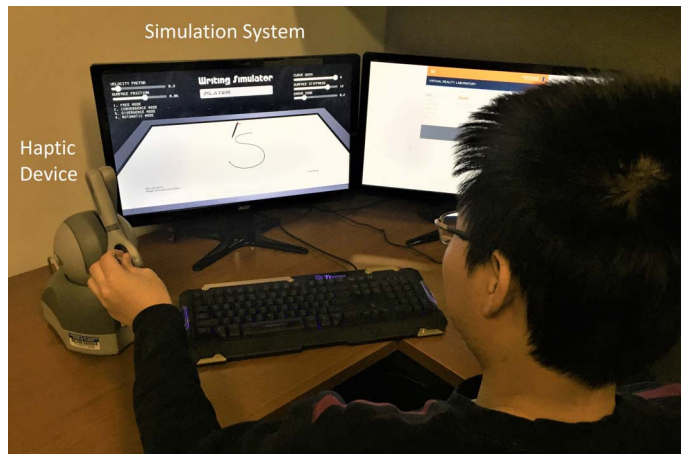


Fig. 2: Experimental setup.

trajectory traversed by the user/robot. It is evident that case A has the lowest error, followed by case C and case B. However, in case A, only the robot tracks the trajectory (without any patient participation) and hence, no patient recovery of any form will be observed. For rehabilitation, case B is also undesirable since there is no assistance or any correcting agent. Shared-control demonstrated by case C serves as the best approach wherein force applied by the user is augmented by the robot for any deficit force. While a therapist can easily differentiate the above cases (autonomous control, no assistance, shared-control) on the basis of the position tracking; a robotic system cannot separate these cases explicitly. Further, the therapist usually analyses the data in an off-line environment after the therapy session. This off-line analysis ignores the real-time force-interaction[1] of the user with the robot, and may render the therapy session ineffective. This calls for the development of real-time algorithms to classify the user responses and to enable the robot to share the control accordingly. This is the major contribution of this paper.

The rest of the paper is organized as follows. We describe the system architecture in the following section. Section III describes our signal processing and classification regime; our experimental evaluations and results are discussed in Section IV and V, respectively. We conclude in Section VI.

[1]Force-interaction refers to the active or passive participation of the patient.

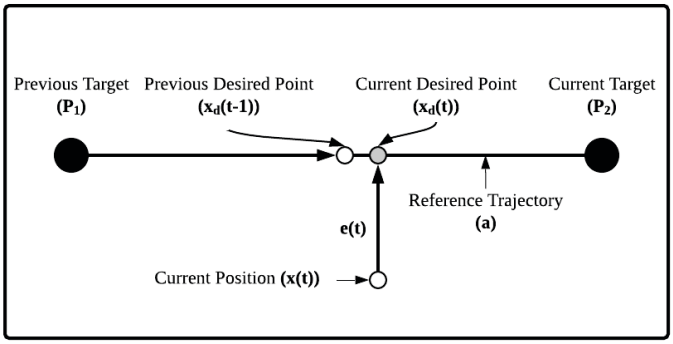


Fig. 3: Schematic representation of the tracking task.

II. SYSTEM DESCRIPTION

The system comprises of two main components - (1) a haptic device, and (2) a simulation system (Fig. 2). The haptic device used in this study is a 6 degrees-of-freedom (DOF) Geomagic Touch [31]. The device has 6 revolute joints which include 3 actuated joints and 3 passive joints. The actuated joints provide force feedback to the user. While the Geomagic Touch is limited by its force feedback capability ($3.3N$ saturation), it's small form factor, lower cost and 3 dimensional workspace make up for it's viability for home-based fine motor skill rehabilitation.

The simulation system is a Writing Simulator game (WS) (see Fig. 2). The game is developed using the Unity3D interface and C# programming. The end-effector of the robot acts as the game controller.

WS involves a trajectory tracking task wherein a symbol or an alphabet drawn by the therapist on the screen is used as the reference trajectory for the user to follow. The game operates in two modes - (1) Free Mode - the haptic device does not apply any assistive force; and (2) Assistive Mode - the haptic device assists the user in following the trajectory. Robot states such as the joint position and velocities and game data such as cursor position, cursor velocity, position error, velocity error, elapsed time, and robot joint angles are measured at a sampling rate of 100 Hz and are used for real-time data-analytics. The system comprises of two parallel processes; graphical rendering (sampling rate 100 Hz) and haptic rendering (sampling rate 1000 Hz). Since the higher sampling rate of 1000 Hz is not required for evaluation, we log these states only during the graphical rendering process.

A. Haptic Rendering

The haptic interaction with the simulation environment (haptic rendering) is modeled as a mass-spring-damper system. The robot provides an assistive force as the subject is playing the game. In other words, the robot assists the user as they guide the end effector from one point to another. The assistive force command is generated based on the PID control law given by,

$$\mathbf{u}(t) = K_p\mathbf{e}(t) + K_i\int_0^t \mathbf{e}(\tau)d\tau - K_d\dot{\mathbf{x}}(t) \tag{1}$$

where, K_p, K_i and K_d[2] denote the proportional, integral and derivative gains respectively; **e** represents the difference between the desired position ($\mathbf{x}_d$) and the actual robot position ($\mathbf{x}$) at time t (see Fig. 3); and **u** is the control input provided to the robot to generate the haptic feedback. The gains determine the degree of robotic assistance and can be adjusted based on the subject's response to therapy. The derivative gain term (K_d) is set to a small positive value to simulate the sensation of moving through a lightly viscous environment.

The control law (1) has been designed to guide the subject along the trajectory from one point to the next at a predefined speed (s). The desired position is calculated as follows -

$$\mathbf{x}_d(t) = \mathbf{x}_d(t-1) + s(t)\hat{\mathbf{a}} \tag{2}$$

where,

$$\hat{\mathbf{a}} = (\mathbf{p}_2 - \mathbf{p}_1) \,/\, \|\mathbf{p}_2 - \mathbf{p}_1\|_2 \tag{3}$$

where, $\mathbf{p}_1$ and $\mathbf{p}_2$ are the position vectors of the previous and current point, respectively; $\mathbf{x}_d(t-1)$ refers to the desired position at the previous time-stamp; $\hat{\mathbf{a}}$ is the unit vector along the line connecting the two targets; and $\mathbf{x}_d(t)$ serves as the desired position in (1). The predefined speed ($s(t)$) is varied to mimic the original velocity profile generated by the therapist.

B. The Writing Simulator

For our study, we have used the example of handwriting rehabilitation. To regain writing skills, an agent who can kinesthetically assist the patient is required. In current rehabilitation programs, a therapist acts as the agent by assisting the patient to regain his or her writing skills. As the patient's skills improve, the assistance is relaxed. We have adopted the same approach for home-based robotic-rehabilitation to regain a subject's writing skills.

Evaluation of handwriting patterns of experts reveal consistent force and velocity patterns [32], [33]. Experts tend to have higher smoothness in their handwritten symbols when compared to novice subjects (Fig. 4). Thus, to achieve a truly assistive system, we have programmed WS to assist the user in position as well as velocity tracking.

To achieve a high fidelity haptic rendering and hence better haptic assistance, the sampling rates of the simulation system (SS) and the robot are synchronized by interpolating the expert data recorded by the SS. The therapist draws a symbol on the writing interface (Fig. 2) that we have developed in Unity programing environment. We use a cubic B-spline interpolation between the sampled points, which are sampled at a rate of 100 Hz. The B-spline allows for parametrization of handwriting trajectory required for the interpolation of data points for the higher sampling rate (1000 Hz) of the robot. The velocity of the demonstrated writing, ($s(t)$), is given by the time derivative of the B-splines.

[2]The negative K_d term in (1) is obtained by setting the $\dot{\mathbf{x}}_d(t)$ term to zero in the derivative law $K_d(\dot{\mathbf{x}}_d(t) - \dot{\mathbf{x}}(t))$.

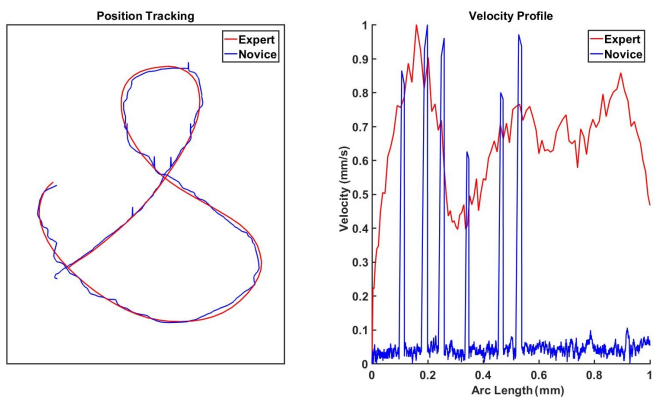
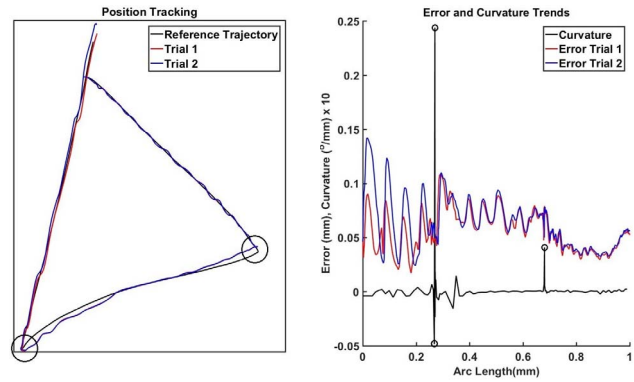


Fig. 4: Left: Point to point position tracking using the subject's non dominant hand, Right: Velocity Tracking. Since the subject concentrated on tracking each point on the curve as opposed to the overall trajectory profile, we observed sharp jumps in the position tracking and the velocity profile.



(a) (b)

Fig. 5: (a) Position tracking of the robot over two autonomous runs, (b) Curvature (Black) of the reference trajectory and error profiles generated during these runs (Red and Blue). The regions with high errors (black circles) are associated with very high curvatures.

III. IDENTIFYING SUBJECT PARTICIPATION

During its autonomous operation, the robot tracks the reference trajectory with relatively small errors in position (Fig. 1 - Case A). Application of force by the subject induces disturbances leading to larger deviations from the desired trajectory, thus magnifying these errors (Fig. 1 - Case C). We use these deviations as a metric to determine whether or not the patient is actively participating in therapy. If the deviations are large, it is identified as a patient force on the robot. Conversely, smaller deviations are identified as robot-applied forces without patient participation. A small error-zone around the reference trajectory is used for identifying autonomous operation by the robot (no patient force), as the tracking error by the robot is small but never zero. Anything outside this error-zone is considered as a user applied force.

In order to determine the error-zone, the variability of the tracking error of the robot is estimated. The magnitude of tracking errors are not same across different runs of the robot. Although their trends tend to be similar (Fig. 5), minor variations in the position tracking are observed even for same control parameters. It is also observed that the error tends to be higher around regions with large curvature (for eg. sharp corners, black circles in Fig. 5-(b)). As a result, a varying error-zone is used along the reference trajectory. This is called the *baseline error*.

Data-analytics is used to determine whether the patient is applying force. Dissimilarity between error profiles of robot and subject is used as the indicator of the user force. The schematic of our approach is given in Fig. 6. The trajectory data of tracking by the subject is sampled with an experimentally determined moving time window of size 500 ms. A 500 ms window allows for a balance between computation time and classification accuracy. A smaller window would result in faster computation at the expense of classification accuracy, and vice-versa. Both the baseline and the real-time data are filtered using an exponential smoothing filter [34]. This reduced the sensitivity of the system to inadvertent hand motions and also improved overall system performance in separating cases of active participation from passive ones[3].

The data within the window are iteratively compared with the baseline using the dynamic time warping (DTW) algorithm [35]. The goal of the DTW algorithm is to perform a non-linear mapping of one signal on to another by minimizing the euclidean distance between the two. DTW allows us to determine the optimal alignment between two time-series data. If the distance between the data and the chosen baseline segment is less than a threshold, that would indicate robot-applied forces. Conversely, a larger value would indicate patient-applied forces.

An obvious shortcoming of using the above approach is the case with an ideal subject (who perfectly executes the trajectories). Such a subject would also be mis-classified as the robot. While such an ideal subject may perform better tracking than the robot, this scenario is highly unlikely. In our experiments, we observed that even for healthy subjects using their dominant hand, the deviations are large enough for the system to recognize user-applied force. The robot exhibited a mean lowest error of 0.029 mm, while healthy subjects demonstrated a mean lowest error of 0.149 mm. These observations reaffirm our claim regarding the tracking limitations of human subjects. We explain these results in detail in Section IV. On the flip side, intentional large errors may be interpreted as subject-applied force since the system has been designed to identify when a subject is applying force, and not whether the applied force is in the desired direction.

A. Threshold Determination

The performance of DTW algorithm depends on the selection of the distance threshold. Fig. 7 shows a cumulative distribution function (CDF) of the DTW distance across two

[3]We observed a ~3% improvement in the classification accuracy when using exponential smoothing.

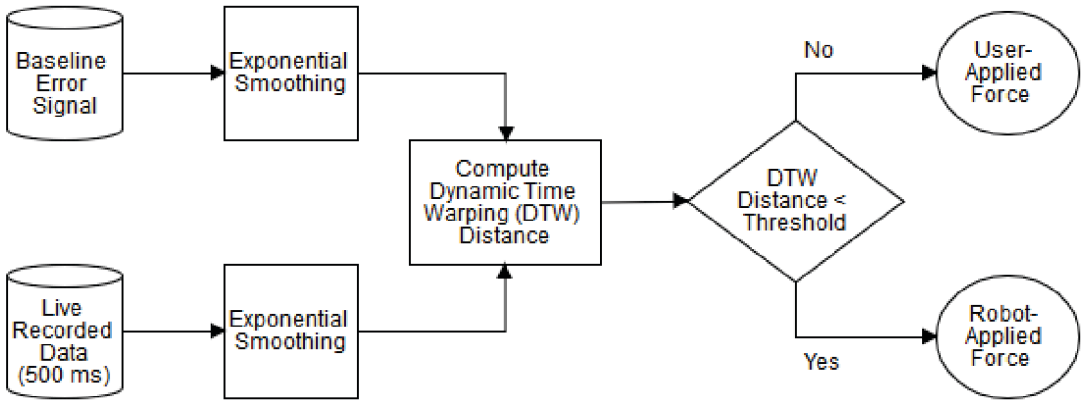


Fig. 6: Schematic representation of our data-analytics based approach.

experimental trials - the red curve represents an autonomous robot control and the blue curve represents shared-control. A low threshold (dotted black line) would make the system very sensitive to noise, classifying most cases as the user-applied force condition (blue), and a large threshold (dotted green line) would bias the system towards identifying it as autonomous operation of the robot (red). Selection of an intermediate threshold (solid black line) allows for a well balanced trade-off between these two cases. However, manual determination of this threshold can be cumbersome and exhaustive. The therapist may draw a variety of symbols, and thresholds for each of these symbols need to be uniquely determined. Storing these thresholds into the database is not a viable choice, as even for the same symbols, these thresholds would differ across different trials, subjects and robots. To overcome this challenge, dynamic threshold determination which computes the distance threshold for each trajectory is employed. Further, the patient may prefer a different speed (slower or faster depending on degree of impairment) than that defined at the beginning of the session. Use of DTW ensures robustness to differences in the predefined speed ($s(t)$) and the actual speed demonstrated by the patient.

1) Automatic Calibration: Once a hand stroke is drawn by the therapist, the robot automatically traverses the trajectory *twice*. The baseline error is recorded during the first-run. During the second-run, the system computes the DTW distance for each data point in the stroke. The DTW distance is calculated between a 500ms window for the second-run data, and 1000ms for the baseline data. Since DTW is an expensive operation ($O(N^2)$), comparing the 500ms window to a 1000ms reduces computation time. This also ensures more accuracy in the computation of the distance threshold because a larger window may contain more noise. n^{th} percentile of DTW values for each window is selected as the threshold for data belonging to that window. These thresholds are used for classification.

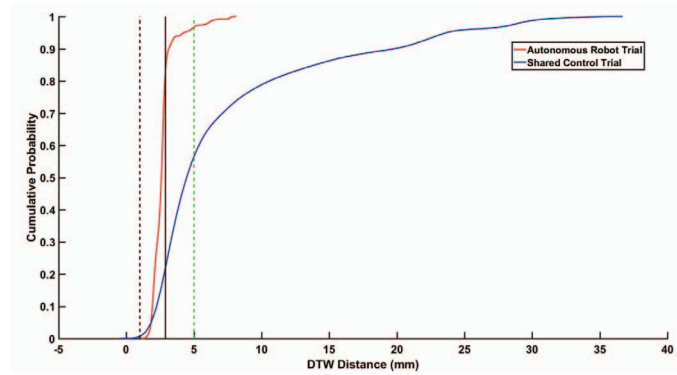


Fig. 7: Cumulative Distribution Function of distance threshold. Observations to the left of the selected threshold are classified as robot-applied forces and those to the right are identified as user-applied forces.

IV. EXPERIMENTAL EVALUATION

The performance of our system is evaluated by conducting a set of experiments involving the Writing Simulator (WS) game. The algorithm is implemented in C# and all computations are done in real-time. Five healthy subjects (average age of 27.8 years; age range from 24 to 33) were recruited for a single-session study. All subjects were right-handed males. The subjects reported no history of any motor impairments. Each subject played the game under two conditions - (1) Active Subject Participation (ASP) - during which the subject applied force along with the robotic assistance; and (2) Passive Subject Participation (PSP) - during which the subjects either just held the end-effector of the robot without applying any force or they completely let go of it. The K_p, K_i and K_d gains of (1) were chosen as 6.0, 0.01 and 0.06, respectively. These gains were selected experimentally, as they provided adequate assistance without causing instability in the system.

As mentioned in Section III, an ideal subject who tracks the trajectory perfectly will be mis-classified as the robot.

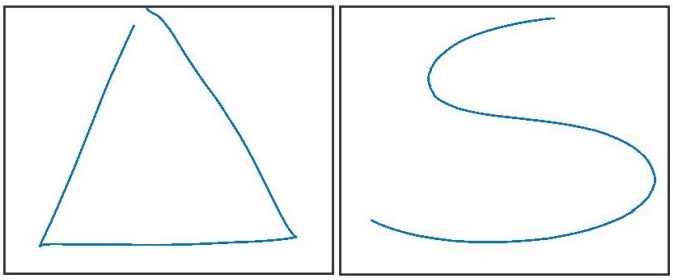


Fig. 8: Test trajectories used for the case study.

We argue that such an ideal tracking is highly improbable. In order to quantify the above claim, we extract the mean of the lowest 1st to 5th percentile error exhibited by the robot and the subjects across all runs. The lowest mean error exhibited by the robot was 0.029 mm (range of 0.00 mm to 0.09 mm), while that for the healthy subjects was 0.149 mm (range of 0.04 mm to 0.26 mm). These observations reaffirm our claim that even for healthy subjects, it is nearly impossible to obtain a better tracking than the robot. While it is certainly possible that some humans might defeat the system; addressing these issues is beyond the scope of this paper.

The subjects were required to track the trajectories described in Fig. 8. The trajectories were first drawn by an expert (in this case one of the authors). Once the trajectories are drawn, the robot performs the calibration step, following which the subjects used their dominant hand to mimic the trajectory profile. Each trajectory was drawn two times; once without any human force (PSP) and once with shared-control (ASP). For the experiment, we use the 80th percentile value as the threshold criteria.

V. RESULTS AND DISCUSSIONS

We obtained a mean classification accuracy of 80.04% across all subjects. It should be noted that this is the best accuracy demonstrated by the system irrespective of the percentile value chosen. Increasing or decreasing the percentile only affects the false positive and false negative rates, with the over all accuracy remaining around 80%. Choosing the 80th percentile value provided a balance between the false positive and false negative rates. The system demonstrated a mean accuracy of 82.92% in identifying the ASP condition (Class Label - 1) and 77.17% in identifying the PSP case (Class Label - 0) (see Table. I). It should be noted that in case of the PSP, the subjects held on to the end-effector of the robot without applying any forces. The system demonstrated robustness in identifying and eliminating these pseudo-force conditions.

TABLE I: Confusion matrix

Class Label	0 (Predicted)	1 (Predicted)
0 (Actual)	77.17%	22.83%
1 (Actual)	17.08%	82.92%

While most robotic-rehabilitation systems involve the adjustment of the system gains based subject performance, distance threshold can be used as an additional tunable parameter. In the early stages of therapy, the subject would exhibit weaker motor control and would mostly rely on the robot for assistance. This condition manifests itself as high robot gains and a lower distance threshold. A lower threshold would bias the classification regime toward the ASP condition (Class Label - 1). Thus even a low force applied by the patient will be detected by the system. As the subject progresses in therapy, the threshold can be increased to motivate the patient to apply more force while maintaining sufficient tracking accuracy. As a proof of concept, we implemented a real-time adaptive control algorithm, wherein the results from the classifier are used to adapt the robot states. When the robot detected the PSP condition (Class Label - 0) for ten consecutive 500 ms windows, we displayed a message urging the subject to apply more force. However, if no change in the force condition is detected, the robot came to a halt and did not resume until enough force was applied. If this pattern continued, the distance threshold was reduced iteratively until either consistent performance was observed, or the threshold reached its lower bound. The system demonstrated a similar classification accuracy (around 80%) in the online proof of concept scenario.

VI. CONCLUSION AND FUTURE DIRECTIONS

In this paper, we have demonstrated that measurements by the proprioceptive sensors of a robot can be used as determinants of patient engagement. Using time-stamped position error signals as a performance metric, a subject's participation (active or passive) in the therapy could be detected. The system operates in real-time and does not require any pre-deployment or manual calibration. By developing a novel threshold determination algorithm, we highlight the robustness and adaptability of our system as a rehabilitation tool. Using classification results obtained from our algorithm, we have developed an adaptive control strategy that motivates active subject participation during therapy. In our experimental evaluation, the classification algorithm demonstrated a mean accuracy of 80.04% in separating the active and passive participation of the subjects.

We are working towards the development of environments that simulate several ADL tasks. The system was tested with healthy subjects, and needs to be studied with stroke patients to obtain a true measure of efficacy and usability. A key criterion to measure the efficacy of any learning paradigm is the transfer of learning to perform daily activities. It is important to study how the patients use the skills gained from this system in actual practice; as this transfer of learning is the goal of any therapy regime.

REFERENCES

[1] CDC, "http://www.cdc.gov/stroke/," 2015.

[2] P. Langhorne, J. Bernhardt, and G. Kwakkel, "Stroke rehabilitation," *The Lancet*, vol. 377, pp. 1693–1702, 2011.

[3] S. Rosewilliam, C. A. Roskell, and A. D. Pandyan, "A systematic review and synthesis of the quantitative and qualitative evidence behind patient-centred goal setting in stroke rehabilitation." *Clinical rehabilitation*, vol. 25, pp. 501–514, 2011.

[4] E. T. Esfahani, S. Pareek, P. Chembrammel, M. Ghobadi, and K. Thenkurussi, "Using Brain Monitoring for Adaptive Human Robotic Interaction in Robotic Rehabilitation," in *ACM/IEEE International Conference on Human-Robot Interaction*, 2015, p. (Submited).

[5] D. J. Reinkensmeyer, C. T. Pang, J. A. Nessler, and C. C. Painter, "Web-based telerehabilitation for the upper extremity after stroke," *Neural Systems and Rehabilitation Engineering, IEEE Transactions on*, vol. 10, no. 2, pp. 102–108, 2002.

[6] H. Sugarman, E. Dayan, A. Weisel-Eichler, and J. Tiran, "The jerusalem telerehabilitation system, a new low-cost, haptic rehabilitation approach," *Cyberpsychology & behavior*, vol. 9, no. 2, pp. 178–182, 2006.

[7] J. Broeren, A. Bjorkdahl, L. Claesson, D. Goude, A. Lundgren-Nilsson, H. Samuelsson, C. Blomstrand, K. S. Sunnerhagen, and M. Rydmark, "Virtual rehabilitation after stroke." *Studies in health technology and informatics*, vol. 136, p. 77, 2008.

[8] A. Alamri, M. Eid, R. Iglesias, S. Shirmohammadi, and A. El Saddik, "Haptic virtual rehabilitation exercises for poststroke diagnosis," *Instrumentation and Measurement, IEEE Transactions on*, vol. 57, no. 9, pp. 1876–1884, 2008.

[9] R. Huq, E. Lu, R. Wang, and A. Mihailidis, "Development of a portable robot and graphical user interface for haptic rehabilitation exercise," in *Biomedical Robotics and Biomechatronics (BioRob), 2012 4th IEEE RAS & EMBS International Conference on*. IEEE, 2012, pp. 1451–1457.

[10] P. Lam, D. Hebert, J. Boger, H. Lacheray, D. Gardner, J. Apkarian, and A. Mihailidis, "A haptic-robotic platform for upper-limb reaching stroke therapy: Preliminary design and evaluation results," *Journal of NeuroEngineering and Rehabilitation*, vol. 5, no. 1, p. 1, 2008.

[11] S. Pareek, P. Chembrammel, and T. Kesavadas, "Development and evaluation of haptics-based rehabilitation system," in *Medical Robotics (ISMR), 2018 International Symposium on*. IEEE, 2018, pp. 1–6.

[12] A. C. Lo, P. D. Guarino, L. G. Richards, J. K. Haselkorn, G. F. Wittenberg, D. G. Federman, R. J. Ringer, T. H. Wagner, H. I. Krebs, B. T. Volpe, C. T. Bever, D. M. Bravata, P. W. Duncan, B. H. Corn, A. D. Maffucci, S. E. Nadeau, S. S. Conroy, J. M. Powell, G. D. Huang, and P. Peduzzi, "Robot-Assisted Therapy for Long-Term Upper-Limb Impairment after Stroke," *New England Journal of Medicine*, vol. 362, no. 19, pp. 1772–1783, may 2010.

[13] J. Sanghvi, G. Castellano, I. Leite, A. Pereira, P. W. McOwan, and A. Paiva, "Automatic analysis of affective postures and body motion to detect engagement with a game companion," in *Proceedings of the 6th international conference on Human-robot interaction - HRI '11*. New York, USA: ACM Press, 2011, p. 305.

[14] C. Peters, S. Asteriadis, and K. Karpouzis, "Investigating shared attention with a virtual agent using a gaze-based interface," *Journal on Multimodal User Interfaces*, vol. 3, no. 1-2, pp. 119–130, mar 2010.

[15] R. Vertegaal, R. Slagter, G. van der Veer, and A. Nijholt, "Eye gaze patterns in conversations: There is More to Conversational Agents Than Meets the Eyes," in *Proceedings of the SIGCHI conference on Human factors in computing systems - CHI '01*. New York, USA: ACM Press, 2001, pp. 301–308.

[16] Q. Xu, L. Li, and G. Wang, "Designing engagement-aware agents for multiparty conversations," in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems - CHI '13*. New York, USA: ACM Press, 2013, p. 2233.

[17] J. Hall, T. Tritton, A. Rowe, A. Pipe, C. Melhuish, and U. Leonards, "Perception of own and robot engagement in human–robot interactions and their dependence on robotics knowledge," *Robotics and Autonomous Systems*, vol. 62, no. 3, pp. 392–399, mar 2014.

[18] Y. I. Nakano and R. Ishii, "Estimating user's engagement from eye-gaze behaviors in human-agent conversations," in *Proceedings of the 15th international conference on Intelligent user interfaces - IUI '10*. New York, USA: ACM Press, 2010, p. 139.

[19] L. Kessous, G. Castellano, and G. Caridakis, "Multimodal emotion recognition in speech-based interaction using facial expression, body gesture and acoustic analysis," *Journal on Multimodal User Interfaces*, vol. 3, no. 1-2, pp. 33–48, mar 2010.

[20] L. Zimmerli, M. Jacky, L. Lünenburger, R. Riener, and M. Bolliger, "Increasing Patient Engagement During Virtual Reality-Based Motor Rehabilitation," *Archives of Physical Medicine and Rehabilitation*, vol. 94, no. 9, pp. 1737–1746, sep 2013.

[21] T. O. Zander, C. Kothe, S. Jatzev, and M. Gaertner, "Enhancing Human-Computer Interaction with Input from Active and Passive Brain-Computer Interfaces," 2010, pp. 181–199.

[22] T. O. Zander and C. Kothe, "Towards passive brain-computer interfaces: applying brain-computer interface technology to human-machine systems in general." *Journal of neural engineering*, vol. 8, no. 2, p. 025005, apr 2011.

[23] C. Berka, D. J. Levendowski, M. M. Cvetinovic, M. M. Petrovic, G. Davis, M. N. Lumicao, V. T. Zivkovic, M. V. Popovic, and R. Olmstead, "Real-Time Analysis of EEG Indexes of Alertness, Cognition, and Memory Acquired With a Wireless EEG Headset," *International Journal of Human-Computer Interaction*, vol. 17, no. 2, pp. 151–170, jun 2004.

[24] J. Nakamura and M. Csikszentmihalyi, "The concept of flow," in *Flow and the foundations of positive psychology*. Springer, 2014, pp. 239–263.

[25] C. Berka, D. J. Levendowski, M. N. Lumicao, A. Yau, G. Davis, V. T. Zivkovic, R. E. Olmstead, P. D. Tremoulet, and P. L. Craven, "EEG Correlates of Task Engagement and Mental Workload in Vigilance, Learning, and Memory Tasks," *Aviation, Space, and Environmental Medicine,*, vol. 78, pp. B231—-B244, 2007.

[26] S. Pareek, "Cognitive adaptation for human computer interaction," Ph.D. dissertation, State University of New York at Buffalo, 2015.

[27] R. Secoli, M.-H. Milot, G. Rosati, and D. J. Reinkensmeyer, "Effect of visual distraction and auditory feedback on patient effort during robot-assisted movement training after stroke." *Journal of neuroengineering and rehabilitation*, vol. 8, p. 21, jan 2011.

[28] B. R. Brewer, S. K. McDowell, and L. C. Worthen-Chaudhari, "Poststroke upper extremity rehabilitation: a review of robotic systems and clinical results," *Topics in stroke rehabilitation*, vol. 14, no. 6, pp. 22–44, 2007.

[29] P. S. Pohl, J. McDowd, D. Filion, L. Richards, and W. Stiers, "Implicit learning of a motor skill after mild and moderate stroke," *Clinical rehabilitation*, vol. 20, no. 3, pp. 246–253, 2006.

[30] J. L. Patton and F. A. Mussa-Ivaldi, "Robot-assisted adaptive training: custom force fields for teaching movement patterns," *IEEE Transactions on Biomedical Engineering*, vol. 51, no. 4, pp. 636–646, 2004.

[31] (2016). [Online]. Available: http://www.geomagic.com/en/products/phantom-omni/overview

[32] G. Srimathveeravalli and K. Thenkurussi, "Motor Skill Training Assistance Using Haptic Attributes," in *First Joint Eurohaptics Conference and Symposium on Haptic Interfaces for Virtual Environment and Teleoperator Systems*. IEEE, 2005, pp. 452–457.

[33] G. Srimathveeravalli, V. Gourishankar, and K. Thenkurussi, "Haptic Attributes and Human Motor Skills," in *2006 14th Symposium on Haptic Interfaces for Virtual Environment and Teleoperator Systems*. IEEE, 2006, pp. 453–459.

[34] E. S. Gardner, "Exponential smoothing: The state of the art," *Journal of forecasting*, vol. 4, no. 1, pp. 1–28, 1985.

[35] D. J. Berndt and J. Clifford, "Using dynamic time warping to find patterns in time series," AAAI, Tech. Rep., 1994.