Online Dynamic Time Warping Algorithm for Human-Robot Imitation

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Abstract— **In this paper, we propose a novel online algorithm for motion similarity measurements during human-robot interaction (HRI). Specifically, we formulate a Segment-based Online Dynamic Time Warping (SODTW) algorithm that can be used for understanding of repeated and cyclic human motions, in the context of rehabilitation or social interaction. The algorithm can estimate both the human-robot motion similarity and the time delay to initiate motion and combine these values as a metric to adaptively select appropriate robot imitation repertoires. We validated the algorithm offline by post-processing experimental data collected from a cohort of 55 subjects during imitation episodes with our social robot Zeno. Furthermore, we implemented the algorithm online on Zeno and collected further experimental results with 13 human subjects. These results show that the algorithm can reveal important features of human movement including the quality of motion and human reaction time to robot stimuli. Moreover, the robot can adapt to appropriate human motion speeds based on similarity measurements calculated using this algorithm, enabling future adaptive rehabilitation interventions for conditions such as Autism Spectrum Disorders (ASD).**

I. Introduction

Human motion assessment is an important part of many clinical evaluations and rehabilitation therapies for conditions such as stroke [1], cerebral palsy [2], spinal cord injuries (SCI) [3], Parkinson's disease [4], and many others. Technology for analyzing human motion has advanced dramatically in recent years, enabling researchers and engineers to develop tools and methods to support patients and clinicians for both diagnostic and treatment purposes [5].

For example, Wei and colleagues [6] created a system to prevent Parkinson's disease patients from performing incorrect repetition grading exercises at home. Their system includes a Microsoft Kinect V2 for motion performance capturing paired with a machine learning-based task recommender model to enable on-demand and personalized task recommendations for patients. Zunino and colleagues [7] proposed an autism diagnosis method using video sequences of grasping gestures of individuals with Autism Spectrum Disorder (ASD). They report that the grasping behavior of ASD children is significantly different by analyzing data from 40 subjects. These results support the hypothesis that the motion performance can be used to quantify autism severity and evaluate interventions.

Robotic devices also have the capability to assist patients and clinicians in various rehabilitation protocols [8]. Methods and algorithms have been developed for humanoid robots to imitate their human teachers [9, 10]. These robots can be used as socially assistive robots to encourage patients to imitate a motion and learn specific motor skills. Fitter and colleagues [11] demonstrated that the humanoid robot Nao can encourage infants to perform a motion like kicking a ball through imitation. This system can help an infant with motor delay to practice a motion at early age which can be a preventative measure from later developmental impairment.

To understand human motions, biomechanical factors such as limb kinematic variables are captured and analyzed by using both inertial and biological signal tracking systems. The outputs of these systems are usually in the form of time series. Mathematical and statistical analysis of sequence similarities of these time series data can be useful to understand movements, detect abnormalities in motions, and reveal specific patterns [12]. There are several algorithms available to measure the similarity between two time sequences, such as: the Euclidean distance [13], longest common subsequence [14], nearest neighbor distance [15], Frechet distance [16], SpADe [17], and Dynamic Time Warping (DTW) [18]. The DTW algorithm for signal similarity measurements was first introduced by Berndt and Clifford [18]. It is a dynamic programming algorithm that iteratively calculates the similarity of time series data. The advantage of DTW over other methods includes good accuracy for two sequences with different lengths, high computer calculation speed, and not being sensitive to time delays and uneven sampling time. Wang and colleagues [19] proposed a method based on DTW for monitoring gait joint angle trajectories in patients with Parkinson's disease.

Another factor reported in the literature related to the motor performance of patients with disabilities, is the reaction time of these individuals to stimuli such as visual cues [20]. Studies by Inui and colleagues [21] showed that subjects with Down syndrome and ASD have longer simple reaction times than neurotypical subjects.

For rehabilitation purposes, real-time feedback to the patient about their motion performance is an important factor. Lieberman and colleagues [22] developed a system that

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featured a wearable vibrotactile suit. A student wearing the suit, received feedback based upon the quality of their motion performance when mimicking a teacher. The input to the system is optically tracked trajectories of the student and their teacher recorded by a VICON vision system. The trajectories are compared to generate feedback for the student in real-time.

In our previous work, Wijayasinghe and colleagues [23] recorded sequences from hand joint angles of autistic and non-autistic subjects while they imitated the upper arm motions of social robot Zeno. They calculated the DTW cost to compare the similarity of motions between the subject and the humanoid robot. They showed that the DTW cost was higher for interaction with ASD children and concluded that this algorithm could be used to design robotic autism intervention. One of the drawbacks of this work was that the data was collected and processed off-line, and that the time-series had to be truncated in length and shifted in time by a human researcher based on visualized waveform similarity.

The contribution of this paper is to develop an online algorithm that does not require the subjective visual inspection of collected waveforms in order to measure the similarity between a subject's imitation motion performance and a reference trajectory of a robot. The resulting online SODTW algorithm is also able to measure the reaction time of the subject and consolidate both numbers into a weighed metric. The metric was validated using off-line interaction data collected from a cohort of 55 subjects interacting with Zeno. It was then used to provide on-line feedback during interaction and design adaptive human-robot imitation sessions that encourage a subject to perform upper limb imitation motions with higher precision and speed. A second set of experiments was conducted with 13 human subjects to validate Zeno's adaptive behavior.

The paper is organized as follows: in section II we present the SODTW algorithm; in section III we use data collected from human subjects to validate the algorithm and collect HRI statistics; in section IV we implement SODTW on social robot Zeno along with adaptive behaviors and discuss our experimental results. Finally, section V presents our conclusions and discusses future work.

II. Segment-based Online Dynamic Time-Warping Algorithm

Our proposed method works for calculating a similarity measurement of any two time sequences when the reference trajectory is cyclic. Fig. 1 shows a sample model for a representative wave pattern from the robot and human joints during HRI, consisting of a cyclic reference trajectory and a time sequence that is measured in real time. The measured time sequence looks dissimilar to the cyclic reference at first, but after approximately 250 seconds, as marked by the circular dot in Fig. 1, the measured trajectory becomes cyclic and appears similar to the reference trajectory. The goal of our SODTW algorithm is to detect the starting point, where the most similarity occurs between our data-streamed time sequence and the reference trajectory. SODTW cost to compare the interaction performance will then be calculated only based on the similar part of the sequence, which in this case is one cycle.

In this algorithm, one cycle of the reference trajectory initiated by a robot limb can be divided into several segment sequences with predefined length, as well as a segment interval that is the distance between start and end points of two consecutive segments. In Fig. 1, two sample segments on the reference trajectory from the robot and one segment on the measured trajectory from the human have been highlighted. The algorithm selects segments on the measured trajectory with the same length as reference trajectory segments. Each segment of the measured trajectory is compared with all segments of the reference trajectory by calculating a DTW cost between two segments.

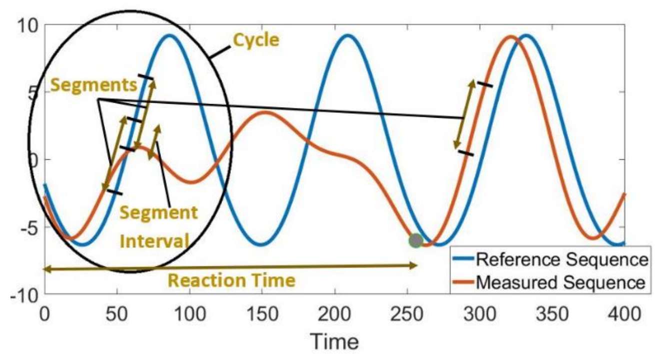


Figure 1. An example of a reference (from robot joint) and measured (from human joint) time sequences indicating the point where the two start looking similar.

The DTW cost for any two sequences $X=x_1, x_2, \ldots, x_m$ and $Y=y_1, y_2, \ldots, y_n$, with lengths m and n respectively, can be calculated from the following dynamic program:

$$D(i, j) = d\,(x_i, y_j) + min\,\{D(i\text{-}1, j\text{-}1), D(i\text{-}1, j), D(i, j\text{-}1)\} \quad (1)$$

where $d\,(x, y)$ is Euclidean distance between x and y, $i = 1,\ldots, m$, $j = 1,\ldots,n$ and $D(m, n)$ is the DTW cost.

When the smallest DTW cost is found, the algorithm saves the segment index on the reference and sequence index on the measured trajectories and calculates the DTW cost for the sequences on reference and measured trajectories with the length of one cycle starting from those indices on both trajectories. Next, the calculated DTW cost is compared with the DTW calculated from the previous cycles. If the new DTW cost is smaller than the previous cost (with an added error tolerance), the algorithm substitutes this new DTW as the total DTW for one cycle and saves the sequence index on the measured trajectory when the cycle started. This index is in fact the time in Fig. 1, where the best cycle on measured trajectory has started. The error tolerance can be determined for each specific application to cover normal inaccuracy in human motions. The process of searching and updating the DTW cost is continued until the end of the data measurement and the DTW cost for the most similar cycle which is the SODTW cost of measured sequence is calculated.

The SODTW algorithm finds the best similarity cost for one cycle for any measured sequence. If the measured trajectory is completely dissimilar, the algorithm still finds the most similar part of the sequence, however, it reports a large number for SODTW cost which shows the dissimilarity. The algorithm is independent of the length of measured sequence. The SODTW algorithm is summarized below.

Algorithm 1. SODTW algorithm

Part 1: Initialization

1. Nseg ← Number of segments for one cycle
2. segLen ← Length of each segment
3. segInter ← Segment interval
4. Time ← Elapsed time/measured sequence indices
5. Q ← One dimensional reference trajectory with fixed length
6. S ← One dimensional measured streaming data sequence (of changing length)
7. cycleLen ← Length of one cycle sequence calculated as (Nseg-1)*segInter+segLen
8. DTW_O ← A large default number
9. DTW_N ← 0
10. Error_Tolerance ← Error tolerance for SODTW cost

Part 2: Dividing one cycle of reference trajectory into segments

11. Seg ← Segments created from Q (Seg is a matrix with Nseg row and segLen column)

Part 3: Finding the segment index and DTW cost between segments on reference and measured sequences

12. SWindow ← Segment on measured trajectory, S, with the same length of the segLen
13. for i ← 1 to Nseg
14. SEG ← Seg(i,:)
15. DTW_S_W(i) ← *D*(SEG, SWindow) (Equation (1))
16. end for
17. I ← Index of the segment on reference trajectory for the minimum of DTW_S_W
18. D ← Minimum DTW cost in DTW_S_W
19. T ← Time/index on the measured trajectory

Part 4: DTW cost calculation for one cycle

20. Scycle ← Cycle on S started from T and included Nseg segments
21. Qcycle ← Cycle on Q started from I and included Nseg segments
22. DTW_N ← *D*(Qcycle, Scycle) (Equation (1))
23. if DTW_N <= DTW_O – Error_Tolerance
24. DTW_O ← DTW_N
25. Reaction_Time ← T
26. end if

III. Validation with Human Subjects

In this section, we discuss our methods and experiments to validate the SODTW algorithm during HRI. All the participants in this study were physically healthy adults over the age 18, who signed an IRB-approved consent form prior to admission.

A. *Offline Validation from HRI data with Zeno*

For validation of the SODTW algorithm, we set up a series of imitation experiments with social robot named Zeno and adult human subjects. Zeno (Fig. 2) is a two foot tall humanoid robot originally developed by Hanson Robotics and Robokind. The robot has an expressive face with movable eye lids and lips. It has four degrees of freedom in each arm, one degree of freedom for torso movement, and rigid legs attached to a base. Dynamixel® RX-28 servo motors are present at each joint of the robot. Unlike the original Robokind unit, our laboratory version has been upgraded to be controlled externally using a Dell Quad core laptop, and a MyRIO controller running LabVIEW ®.

During experiments depicted in Fig. 2, Zeno was used to perform a waving hand motion, while subjects were asked to imitate the performed Zeno gestures under two different conditions. For the first condition, 55 healthy adults without previous experience with the robot performed imitation trials without holding a weight. In the second condition, 44 of the same subjects performed imitation trials while holding a 15 pounds weight in their hand. Carrying a weight makes motion performance difficult and simulates conditions similar to neuro-motor impairments. In each trial, three cycles of motion separately recorded. Using a Kinect® motion capture system, the hand motion of the subject mimicking the hand movements of the robot were recorded and saved for further numerical investigation offline.

The SODTW algorithm was implemented offline using MATLAB®. Fifty five subjects completed the first condition trials. Forty four of these subjects successfully completed the second condition trials as well. We recorded hand motions of all the subjects and produced time series for cyclic elbow joint angles with the sequence length of $n=279$. Then we compared these time sequences with a pre-recorded sequence applied to the elbow joint angle of Zeno using the SODTW algorithm.

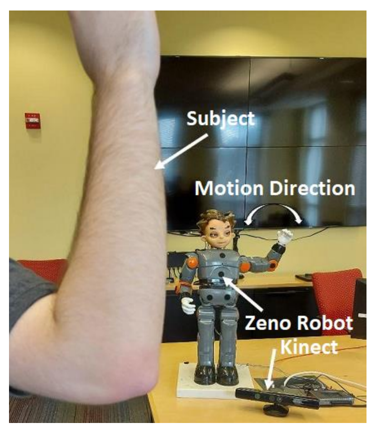


Figure 2. Experimental setup for offline validation of SODTW algorithm.

There are two important notes in our measurements and calculations. First, the pre-recorded motion was sent to the Zeno as input which was used for our similarity calculations. There is a time delay between the sent input and performance of Zeno which is seen and imitated by the subject. Second, the Kinect sensor sampling also suffers from measurement time

delays. These delays combine to affect the accuracy of the reaction times that our algorithm measures. In our experiments, we find the sequence index in the measured time series where the best performance of the subject starts, which we call Reaction Sequence Index (RSI), instead of reaction time. This helps in investigating the effects of a human learning a task and impairment on reaction time indirectly by comparing RSIs calculated for two mentioned conditions while not confusing readers about human reaction time, which has a specific medical and physical meaning.
Table 1 lists all the initial values and tuned parameters for the calculation of the SODTW cost and RSI for our experiments.

TABLE I. LIST OF SODTW ALGORITHM TUNED PARAMETRS AND THEIR VALUES

SODTW Parameters	Values
Nseg	52
segLen	6
segInter	1
cycleLen	57

Fig. 3 shows the SODTW costs for 55 adult subjects when they imitate the robot without carrying weights. The costs were calculated with an error tolerance of 0. By visualizing the statistics in Fig. 3, the average SODTW cost for these 55 subjects is $\mu=5.85$ with minimum $m=2.03$, maximum $M=27.1$ and standard deviation $\sigma=4.7$.

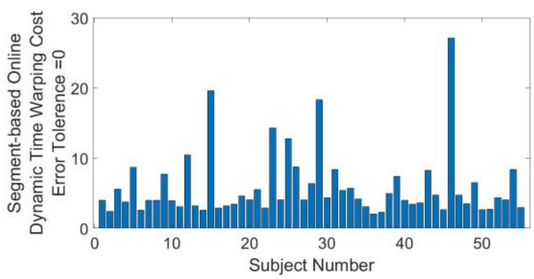


Figure 3. SODTW cost across 55 subjects.

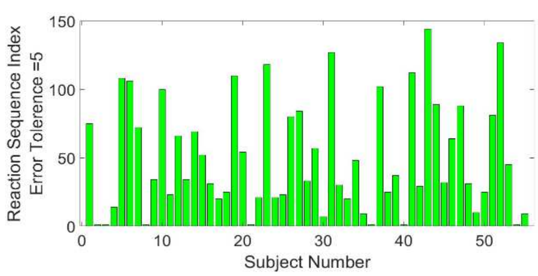


Figure 4. Reaction Sequence Indices (RSI) for 55 subjects.

Since the standard deviation is around 5, we have selected an error tolerance of 5 to calculate the RSIs. Even neurotypical subjects cannot imitate the robot perfectly without some errors after they react to the robot motions. The tolerance of 5 covers these inaccuracies and gives a smaller average RSI for 55 subjects in comparison with 0 tolerance RSI calculations. Fig. 4 shows the RSIs for 55 subjects and error tolerance of 5. The average of these numbers is approximately 50. Fig. 5 shows the histogram plot for RSIs of these 55 subjects. Thirty of these 55 subjects (more than half of them), have RSI less than 40. We call this normal RSI since subjects did not carry any weights.

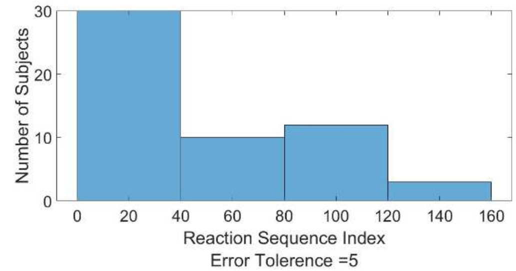
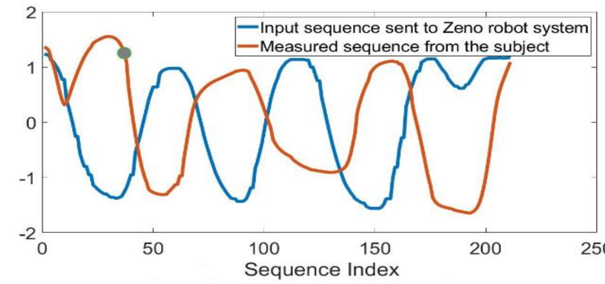
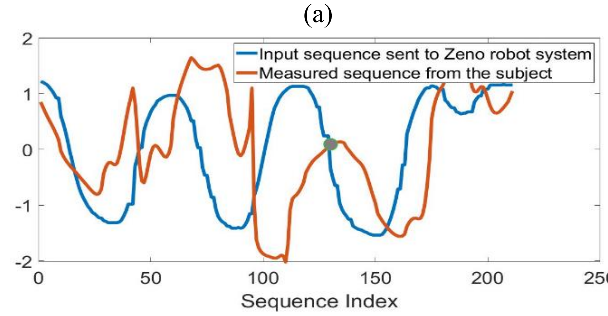


Figure 5. Reaction Sequence Indices (RSI) histogram for 55 normal subjects.



(a)



(b)

Figure 6. Measured sequence for a normal subject in comparison with Zeno input sequence a) first condition: first trial without carrying weight b) second condition: second trial with subjects carrying 15 pound weights.

Fig. 6 Shows the Z-normalized measured sequences from a subject for both experimental conditions. The circle dot shows the RSI. When the subject does not carry a weight, their performance is similar to the robot motion with a small $RSI=38$ (Fig. 6 (a)). The SODTW cost with zero tolerance, which is the similarity cost for the best performance of the subject, was calculated as $SODTW=3.22$ using our SODTW algorithm. When subject carries 15-pound weight, (Fig. 6 (b)), it affects the normal performance of the subject, increases the cost to $SODTW=9.98$ and $RSI=131$.We calculated SODTW cost and RSI for 44 subjects for the second condition when subject carries weight. SODTW cost for 22 of these subjects were higher than average SODTW cost for the normal subjects calculated for the first condition. The average SODTW cost for these 22 subjects is $SODTW=10.49$ and the average RSI for these subjects are $RSI=66$, which is significantly higher than the average RSI for 55 subjects in the normal model condition. These results show that carrying a 15-pound weight affects the physical performance of these subjects to imitate the gestures of Zeno. This can be immediately detected by SODTW cost. However, carrying a weight also affects the RSI of the subjects which is detected by the SODTW algorithm.

For the other 22 subjects, carrying a weight did not affect the quality of their motion performance which shows the strong physical ability of these subjects that they are capable of easily imitating the robot while they carried the 15-pound weight. Because of their physical abilities, the average SODTW cost for these subjects is *SODTW=3.98* and the average *RSI =39*. By comparing these numbers with the average SODTW cost and RSI we found from the 55 subjects, we conclude that practicing a motion performance increased the performance quality of these subjects caused a decrease in both average SODTW cost and RSI for these subjects.

Our simulation and experimental results show that our SODTW algorithm can determine two important motion features. The first feature is the quality of the motion imitation, which can be assessed by calculating SODTW cost, and the second one is the reaction time of the subject. These two features can help diagnose or monitor neuromuscular impairments including tracking the improvements of the patients after physiotherapy. A metric for evaluation of these patients can be proposed based on the following formulation:

$$M = c_1\,(SODTW/SODTW_{av}) + c_2\,(RSI_r/RSI_{rav}) \qquad (2)$$

in which *SODTW* is the SODTW cost of the subject, and RSI_r is the reaction sequence index. The $SODTW_{av}$ is the average of SODTW cost obtained from control subject, RSI_{rav} is the average reaction sequence index for these control subjects. c_1 and c_2 are gain constants, that can be tuned for each specific application.

B. Online Validation of SODTW on Zeno Robot

To prove the effectiveness of the SODTW algorithm in real time systems, we developed an experimental setup to implement the SODTW algorithm in our social robot, Zeno. We programmed the robot using the LabVIEW environment to evaluate the subject performance and calculate SODTW cost and RSI in real time. The procedure is as follow:

1. The robot performs a special hand motion, a hammer, by sending the pre-recorded joint angle commands to the robot joint motors.
2. Time series from hand joint angles of the subject imitating the robot hand motion is obtained using the Kinect sensor and data is streamed into the robot system for real-time calculation of similarity using the SODTW algorithm.
3. Using the SODTW algorithm, the robot system calculates the SODTW cost as well as RSI of the subject by comparing the elbow joint angle data from the subject and pre-recorded data sent to the robot system.

Thirteen subjects participated in this study. The subjects were invited to the social robotics lab at the Next Generation System Group and asked to imitate hand motion of Zeno. The subjects completed motions with and without carrying a 15-pound weight to model normal and impaired subjects. Fig. 7 shows the SODTW cost for a subject calculated by Zeno robot system in real time during the experiment. This figure shows that the system updates the SODTW cost while the subject performs the motion.

We exported the SODTW cost and RSI calculated by system of Zeno for these 13 subjects after 279 sequence data point from the subject captured and checked the accuracy of the reported SODTW costs and RSIs offline using our MATLAB code. We found the exact same numbers from our MATLAB code that shows the accuracy of our real time calculations. The average SODTW cost when subjects did not carry a weight was *SODTW=7.23* for this motion which increased to *SODTW=9.5* when subjects carried 15-pound weight. The average normal RSI was *RSI=107* which decreased to *RSI=103* when subjects performed their motion with a 15-pound weight. We noticed that impairment modeled by carrying weights did not significantly affect the RSI for these subjects. Decrease in RSI can be due to learning the imitation task by subjects after their first trial which causes faster reaction to the robot in the second trial of the experiments.

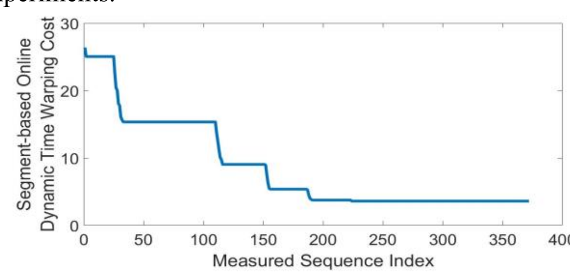


Figure 7. SODTW calculation in real time performed by Zeno robot system.

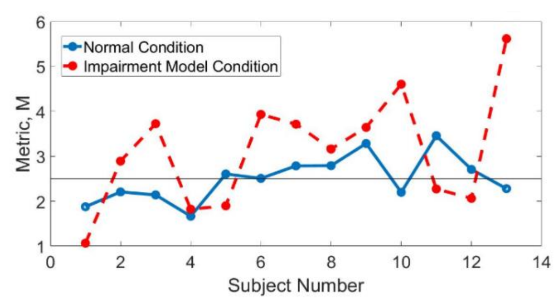


Figure 8. Metric, *M*, for normal and impairment model conditions.

We developed our metric, *M*, by assigning $SODTW_{av} = 7.23$ and $RSI_{rav} = 107$ for this motion. Since we found a small effect of RSI in our impairment model in comparison with SODTW cost, we selected c_2 as 0.5 while c_1 was chosen as 2. Fig. 8 shows the calculated metrics for 13 subjects for normal and impairment model conditions. For nine subjects, we see an increase in the metric values when the subject carries the weight during the experiments. A metric of 2.5 is the normal line in these experiments which is calculated by substituting $SODTW=SODTW_{av}$ and $RSI_r= RSI_{rav}$ in Equation (2). Smaller metric reflects a higher quality of performance of the subject.

IV. Adaptive Imitation

SODTW algorithm can be used to assess the human

performance and adapt the robot motion to the user by calculating the similarity measurement costs in real time. In this section, we discuss the application of the SODTW algorithm to design an adaptive interactive behavior on Zeno for practicing a hammering motion with subjects.
Specifically, we have programmed Zeno to change the speed of the motion based on the speed of the hand movements of the subject. This was done by comparing the streamed data from the subject for the cyclic elbow joint angle with reference time series of three similar motions and different speed levels. In an initial experiment, we defined three speed levels including slow, normal, and fast. The Zeno robot performs one cycle of the motion in 0.9s, 1.71s, and 3.51s for fast, normal and slow speed levels respectively. The robot system calculates the SODTW cost comparing these three reference trajectories for the cyclic elbow joint angle and data streamed from the subject. Then the robot selects the reference trajectory time series with the smallest SODTW cost to perform next. If the subject imitates the motion slower than the robot, the robot will select the slow level motion performance since this trajectory gives the smallest SODTW cost. If the hand motion of the subject is faster than the robot, the fast level motion is selected by the system since it gives the smallest SODTW cost.

To test our adaptive algorithm, we asked the 13 subjects to perform the hammering motion with normal speed and let the robot to follow their motion. Simultaneously, our system calculated the SODTW costs for all three speed levels. Fig. 9 shows the online similarity measurements comparing subjects elbow joint angle data with, fast, normal, and slow reference trajectories. When subjects perform the motion with normal speed, the SODTW cost for normal trajectory is smaller than both fast and slow SODTW costs.

Figure 9. SODTW costs comparing the subject normal speed trajectory with three different speed levels.

As the last part of our experiments, we asked subjects to imitate motion of Zeno; however, they performed the motion faster or slower based on our instructions. We observed that the Zeno robot switched the motion to the faster or slower speed level based on the performance of the subject. Fig. 10 shows the SODTW costs calculated by system of Zeno when it changes the speed of the motion in comparison with the SODTW cost of a normal speed level. When the subject performs with slow speed, the SODTW cost with respect to slow reference trajectory is smaller than SODTW cost of normal trajectory (Fig. 10 (a)). When subject is fast, the SODTW cost with respect to fast reference trajectory is smallest (Fig. 10(b)).

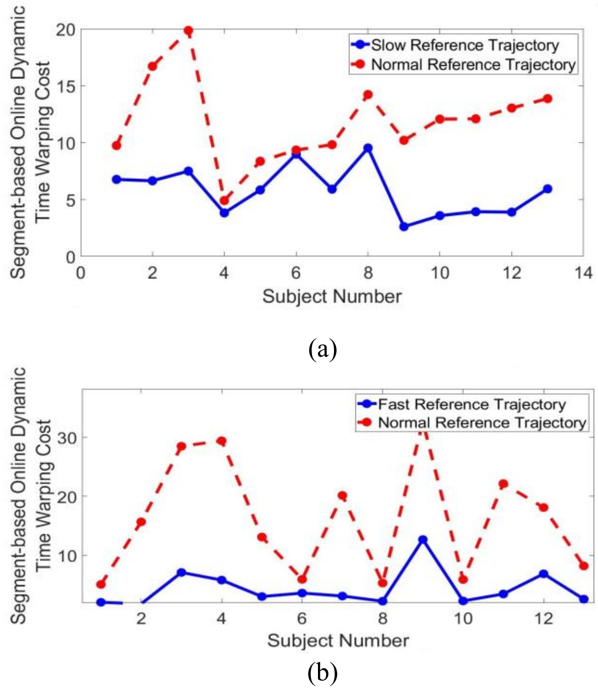


Figure 10. SODTW costs for adaptive robot a) subject performs slowly, b) subject performs fast.

V. Conclusions and Future Work

In this paper, we proposed a new algorithm, SODTW, for online calculation of joint trajectory similarities during HRI, as well as the human subject's imitation reaction time. These numbers are then aggregated into a HRI quality metric and used to adapt robot motion speed. Results from our experiments of interaction by social robot Zeno and approximately 70 subjects prove that the SODTW algorithm can suitably work for online applications and can be used to design adaptive robotic therapies. The system can adapt to human performance during imitation by adjusting upper arm cyclic motion speeds. As a result, the robot can be programmed to play the role of a teacher motivating subjects to perform a special physical motion. It also encourages the patient to perform movements with higher quality and faster speeds until imitation performance deteriorates.

In the future, the resulting metric incorporating SODTW will be used to diagnose the severity of neuromotor conditions of patients such as children with ASD.

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REFERENCES

[1] T.-W. Lu, H.-C. Yen, H.-L. Chen, W.-C. Hsu, S.-C. Chen, S.-W. Hong, and J.-S. Jeng, “Symmetrical kinematic changes in highly functioning older patients post-stroke during obstacle-crossing,” *Gait Posture*, vol. 31, no. 4, pp. 511–516, Apr. 2010.

[2] B. Lofterod, T. Terjesen, I. Skaaret, A.-B. Huse, and R. Jahnsen, “Preoperative gait analysis has a substantial effect on orthopedic decision making in children with cerebral palsy: comparison between clinical evaluation and gait analysis in 60 patients,” *Acta Orthop.*, vol. 78, no. 1, pp. 74–80, Jan. 2007.

[3] K.-H. Lin, T.-W. Lu, P.-P. Hsu, S.-M. Yu, and W.-S. Liao, “Postural responses during falling with rapid reach-and-grasp balance reaction in patients with motor complete paraplegia,” *Spinal Cord*, vol. 46, no. 3, pp. 204–209, Mar. 2008.

[4] A. P. Rocha, H. Choupina, J. M. Fernandes, M. J. Rosas, R. Vaz, and J. P. Silva Cunha, “Kinect v2 based system for Parkinson’s disease assessment,” presented at the 37th Conf. Proc. IEEE Eng Med Biol Soc (EMBC), pp.1279–1282. Milan, 2015.

[5] N. Taghavi, G. R. Luecke, N. D. Jeffery, “A neuro-prosthetic device for substituting sensory functions during stance phase of the gait,” *Appl. Sci.*, vol. 9, no. 23, pp. 5144. Nov. 2019.

[6] W. Wei, C. McElroy, and S. Dey, “Towards on-demand virtual physical therapist: machine learning-based patient action understanding, assessment and task recommendation,” *IEEE Trans. Neural Syst. Rehabil Eng*, vol. 27, no. 9, pp. 1824–1835, Sep 2019.

[7] A. Zunino, P. Morerio, A. Cavallo, C. Ansuini, J. Podda, F. Battaglia, E. Veneselli, C. Becchio, and V. Murino, “Video gesture analysis for autism spectrum disorder detection,” presented at the 24th International Conference on Pattern Recognition (ICPR), pp. 3421–26, Beijing, 2018.

[8] J. Skidmore, and P. Artemiadis, “Leg muscle activation evoked by floor stiffness perturbations: a novel approach to robot-assisted gait rehabilitation,” presented at the IEEE Int. Conf. Robot Autom. (ICRA), pp. 6463–6468, Seattle, WA, USA, 2015.

[9] M. Riley, A. Ude, K. Wade, and C. G. Atkeson, “Enabling real-time full-body imitation: a natural way of transferring human movement to humanoids,” presented at the IEEE Int. Conf. Robot. Autom. (ICRA), pp. 2368–2374, Taipei, Taiwan, 2003.

[10] J. Koenemann, F. Burget, and M. Bennewitz, “Real-time imitation of human whole-body motions by humanoids,” presented at the IEEE Int. Conf. Robot. Autom. (ICRA), pp. 2806–2812, Hong Kong, China, 2014.

[11] N. T. Fitter, R. Funke, J. C. Pulido, L. E. Eisenman, W. Deng, M. R. Rosales, N. S. Bradley, B. Sargent, B. A. Smith, and M. J. Mataric, “Socially assistive infant-robot interaction: using robots to encourage infant leg-motion training,” *IEEE Robot Autom. Mag*., vol. 26, no. 2, pp. 12–23, June 2019.

[12] H.-S. Lee, “Application of dynamic time warping algorithm for pattern similarity of gait,” *J. Exerc. Rehabil.* , vol. 15, no. 4, pp. 526–530, August 2019.

[13] C. Faloutsos, M. Ranganathan, and Y. Manolopoulos, “Fast subsequence matching in time-series databases”, *ACM SIGMOD Record.*, vol. 23, no. 2, 1994.

[14] M. Vlachos, M. Hadjieleftheriou, D. Gunopulos, and E. Keogh, “Indexing multi-dimensional time-series with support for multiple distance measures”, in Proc. *9*th ACM SIGKDD *I*nt. *C*onf. on Knowledge discovery and data mining, 2003, pp. 216–225.

[15] A. M. Qamar, E. Gaussier, J. Chevallet, and J. H. Lim, “Similarity Learning for Nearest Neighbor Classification,” *8th* IEEE Int. Conf. on Data Mining, Pisa, Italy, 2008, pp. 983–988, 2008

[16] H. Alt, “The computational geometry of comparing shapes”, in Efficient Algorithms*. Lecture Notes in Computer Science*, vol 5760, Springer, Berlin, Heidelberg, 2009, pp. 235–248.

[17] Y. Chen, M. A. Nascimento, B. C. Ooi, and A. K. H. Tung, “SpADe: On Shape-based Pattern Detection in Streaming Time Series,” IEEE 23rd Int. Conf. on Data Engineering, Istanbul, Turkey, 2007, pp. 786-795.

[18] D. Berndt, J. Clifford, “Using dynamic time warping to find patterns in time series,” presented at the AAAI workshop on knowledge discovery in databases, pp 229–248, 1994.

[19] X. Wang, M. Kyrarini, D. Ristic-Durrant, M. Spranger, and A. Graser, “Monitoring of gait performance using dynamic time warping on IMU-sensor data,” presented at the IEEE International Symposium on Medical Measurements and Applications (MeMeA), pp.1–6. Benevento, Italy, 2016.

[20] A. A. Baumeister, and G. Glus, “Reaction time and mental retardation,” in *N. R. Ellis (Ed.), International review of research in mental retardation*., Vol. 3. New York, 1968, pp. 163-193.

[21] N. Inui, M. Yamanishi, and S. Tada, “Simple reaction times and timing of serial reactions of adolescents with mental retardation, autism, and down syndrome,” *Percept. Mot. Skills*, vol. 81, no. 3, pp. 739–45, December 1995.

[22] J. Lieberman, and C. Breazeal, “Development of a wearable vibrotactile feedback suit for accelerated human motor learning,” in *Proc. IEEE Int. Conf. Robot. Autom. (ICRA)*, Rome, Italy, 2007, pp. 4001–4006.

[23] I. B. Wijayasinghe, I. Ranatunga, N. Balakrishnan, N. Bugnariu, and D. O. Popa, “Human–robot gesture analysis for objective assessment of autism spectrum disorder,” *Int. J. Soc. Robot.*, vol. 8, no. 5, pp. 695–707, November 2016.