HUMAN-CENTRIC CO-ADAPTATION FOR OPTIMAL HUMAN-MACHINE COORDINATION

A Thesis

by

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Submitted to the Office of Graduate and Professional Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

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August 2020

Major Subject: Electrical Engineering

ABSTRACT

In this paper, we investigate the optimal co-adaptation strategy between humans and machines in order to maximize the performance outcome in completing a coordinated task. Although prior works identified the optimal machine adaptation for human's specific condition, it is still not clear how to design an optimal co-adaptation strategy which enables the machine to adapt to the human concurrent with human adaptation. To achieve the optimal co-adaptation between human and machine, the adaptation strategy should maximize the immense potential of the human adaptation while minimizing the resources required of the machine. To accomplish this, we propose a novel human-centric co-adaptation strategy of the machine.

In our strategy, the machine initially waits for the human to adapt to machine. Once human adaptation arrives to the plateau, the machine starts to adapt. Rather than addressing the error fully on its initial adaptation, the machine still provides headroom for the human to adapt further, since the changed condition might augment the capability of human adaptation. We call this strategy human-centric co-adaptation, as the machine adapts based on the human's capability. We implemented the test setup by measuring the step distance of a human using a treadmill alongside an optical tracking system. We tested our strategy alongside two other adaptation strategies: single sided adaptation, where only the human adapts to the machine, and co-adaptation without a strategy, where both human and machine concurrently adapt to each other without priority.

Our results indicate that, with an accuracy task, machine co-adaptation did not reduce the error in easy target. However, if the target became challenging for the human, machine co-adaptation successfully lowered the error. When the human-centric strategy was applied to the co-adaptation, the error was not further reduced but the dependency to the machine was reduced.

ACKNOWLEDGEMENTS

I would like to thank my committee chair, Dr. Park, for helping me throughout my project as well as believing in my capabilities as a researcher. I would also like to thank the other committee members for their support.

CONTRIBUTORS AND FUNDING SOURCES

This work was supervised by a thesis committee consisting of Professor Hangue Park (committee chair), Dr. Raffaella Righetti of the ECEN department, Dr. Jun Kameoka of the ECEN department, and Dr. Vladislav Yakovlev of the BMEN department.

All work conducted for the thesis was completed by the student independently. Graduate study was supported by the student himself.

NOMENCLATURE

HMI	Human-Machine Interaction
CA	Co-Adaptation
HCCA	Human-Centric Co-Adaptation
SSA	Single-Sided Adaptation
GUI	Graphical User Interface

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1. INTRODUCTION

From the more simple tasks of text messaging to the more complex tasks of assisted driving and robotic surgery, human-machine interaction (HMI) either helps humans to overcome their limited capability or promotes convenience in their lives. When machines did not have the capability to adjust to humans, HMI basically consisted of a human adapting to machine to optimize the coordination between the two. Therefore, the conventional design of machines focused on maximizing the human's ability to adapt to the machine. However, as the physical and intellectual capabilities of machines approach or even exceed their human counterparts, machines are taking the role of adaptation from humans in these interactions [1], [2], [3]. For example, human gesture recognition software adjusts the required human gesture according to each person's characteristics [4], and myoelectric-controlled active prosthesis adjusts the required muscle activation pattern for active joint control [5]. A lot of machine learning algorithms are in development to improve the adaptation ability of the machine. However, machine adaptation should be carefully designed because excessive machine adaptation can limit the human adaptation and degrade the HMI performance in the long run. Note that, although machines have become smarter and more dexterous, many of the human's unique abilities could not be still imitated by the machine.

As all interactions require at least one party to adapt and interact with the other, adaptations in HMI can be largely categorized by two kinds: single-sided adaptation (SSA) and co-adaptation (CA). Single-sided adaptation, or SSA, is the interaction between two parties where only one side adapts to the other. In case of SSA, only one side adjusts their operating parameters to fit to the other side, while both sides pursue the same objective. Although SSA can be applied to either side, in most cases the human is the sole party which adapts, since machines in HMI application usually does not have capability to adapt to the human. An example of SSA would be a human interacting with an automatic paper towel dispenser. The machine is designed to dispense paper towels whenever it detects an object, in its vicinity. Although the machine dispenses a towel whenever a hand is detected, the machines function involves no adaptation to the human, since it is not able to adjust its activation range to fit to the human's traits. The human, on the other hand, adapts to the machine by placing their hand in the specified activation range of the dispenser.

Co-adaptation (CA), on the other hand, is where both parties are adapting to each other while performing a given task. Both sides still have a main task they aim to perform, however they adjust their methods of performing their task according to the performance of the other party. Co-adaptation can be either one-time change in an entity's routine or an evolving mechanism based on the subsequent adaptations in both parties. Essentially, co-adaptation of each party is determined based on the outcome of the other party, with pre-defined algorithm of co-adaptation at the machine side and natural adaptation ability at the human side.

Many human-machine interactions that appear to be CA are in fact SSA. For example, in the paper towel dispenser example, although it may appear that the dispenser is adapting to the human by dispensing a paper towel whenever the human is in its vicinity, this notion is false. Adaptation requires a change in routine or function to fit the other party, as the adaptive human gesture recognition software [4].

In conventional CA strategies, machines only consider how the human performs (*i.e.,* outcome of the human) and not how the human adapts. Because of this, the conventional co-adaptation is concluded to a machine-leading co-adaptation rather than the coordinated co-adaptation, which limits the huge potential of the human adaptation, as described in the left side of Fig. 1. To secure the human adaptation and maximize the effectiveness of co-adaptation in HMI, the machine should consider the trait and direction of human adaptation, instead of just monitoring the performance of the human. Having a well-defined co-adaptation strategy will not only make the HMI more effective and efficient, but also make the human operator feel more comfortable and arrive at the optimal solution that values human's trait and direction of the adaptation.

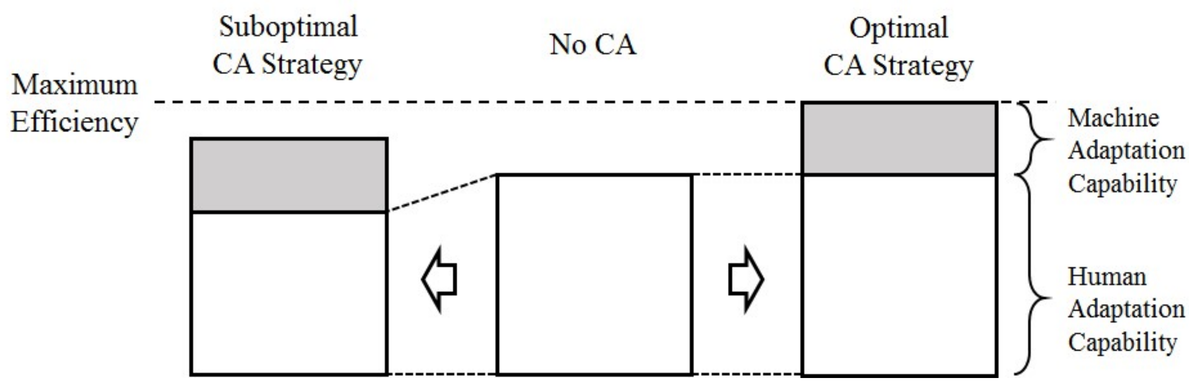


Figure 1. Conceptual description showing the importance of utilizing an optimal strategy when applying co-adaptation. With no co-adaptation at machine, the human cannot accomplish challenging task beyond their capability. Co-adaptation at the machine can improve the result but co-adaptation may limit the human capability in adaptation if the suboptimal strategy is applied (left side). For the human-machine coordination to achieve maximum capability for both parties, co-adaptation should be applied with optimal strategy that secures the capability of the human adaptation.

To maximally use the capability of both the human and the machine, the co-adaptation will play an essential role for the future HMI [6]. Studies have been done to model how machine interaction could be introduced into HMIs [7], [8]. From there, co-adaptation methods have also been analyzed. Many attempts have been made to identify the optimal co-adaptation as a closed-loop operation [9], [10]. Leader-follower strategies have also been investigated and applied to HMI [11], [12]. Most of the co-adaptation studies focused on how the machine better co-adapts to human interactions [13-15], but the importance of investigating how the machine should adapt to any human adaptation has been underrepresented. To preserve the immense potential of the human adaptation, as described in the right side of Fig. 1, it is important to adjust the degree of the co-adaptation according to the progress of the human adaptation. Paolo et al have identified that the machine should predict the traits of human motor learning and change the co-adaptation strategy according to the evolution of human skills and performance (*i.e.,* progressive co-adaptation strategy) [16]. However, it was a conceptual study and the applicability of the progressive co-adaptation strategy has not yet been tested in actual applications of HMI. So long as the effort to find proper implementation details and verification of their efficacy remains absent, the promise of optimal coordination between the human and the machine will remain uncertain.

If CA is not properly designed, it often produces even worse performance outcome than SSA, particularly when the human can perform the given task with ease. Let’s assume a task of human throwing a dart in a short distance. Most of the humans will quickly learn how to hit the center with minimal error. If the machine attempts to co-adapt to the human, by controlling the position of dart board, then it would rather confuse the user instead of helping the user. In this case, CA (human and dart board adapting to each other) may produce worse performance outcome than SSA (no machine adaptation). In other words, for cases where the human is skilled enough to perform a task with decent accuracy and precision, SSA is the superior adaptation method. Any machine interference would hurt the user’s performance more than help it.

Although less efficient in some situations, CA has clearly the potential to outshine its single-sided counterpart (*i.e.,* SSA), particularly in scenarios where the human loses their accuracy, but keeps their precision. Using the same dart example, if the human is inaccurate at throwing darts but is still precise, the machine can co-adapt and move the dart board in the general direction of where the darts land. Having a higher precision allows the actions of the human to be much more predictable and allows the machine to adapt much more consistently to the human. Essentially, the human’s role in CA is to be as precise as possible, and the machine’s role is to turn their precision into accuracy. If the human is not able to maintain precision when performing a task, the machine will have a much harder time adapting to the human's abilities, and the potential for the machine and human to adapt to each other will severely be hindered.

However, most of the cases are not in the extremes and contain the traits suited for both SSA and CA. Therefore, it is necessary to design CA utilizing a smart strategy, to make it outperform SSA. In this paper, we proposed and tested a human-centric co-adaptation (HCCA) approach. The basic idea of the HCCA approach is machine adapting according to the human adaptation ability to secure the human adaptation ability. Previous studies have shown the need for HMIs to be centered around the human's capabilities [2], [16], [17]. Co-adaptation between humans and machines should be human-centric, focusing on maximally using the human adaptation ability and at the same time, minimizing the potential discomfort of human caused by machine adaptation. At the same time, machine should be ready to assist the human if the human is not skillful enough to address the problem. Simply put, in our HCCA approach, if the human is skilled enough, the machine will not interfere with their adaptation, whereas if the user needs assistance, the machine will adapt based on the skill level of the human. A conceptual graph of the efficiencies of each adaptation method are shown in Fig. 2 for both skilled and unskilled humans. As the uses of individual machines varies greatly, the ability to adapt to both skilled and unskilled users is necessary for the advancement of different types these interactions. Machines which propagate rehabilitation may be used by those who are dysfunctional or lower skilled [18-20], whereas humans that are highly skilled may be handling equipment such as robotic surgery devices.

In this paper, we compared the efficacy of SSA and CA, with and without the proposed human-centric strategies, using a challenging walking task on a treadmill to identify which adaptation method is best in different scenarios. The following sections are composed of experimental design, experimental result, discussion, and conclusion.

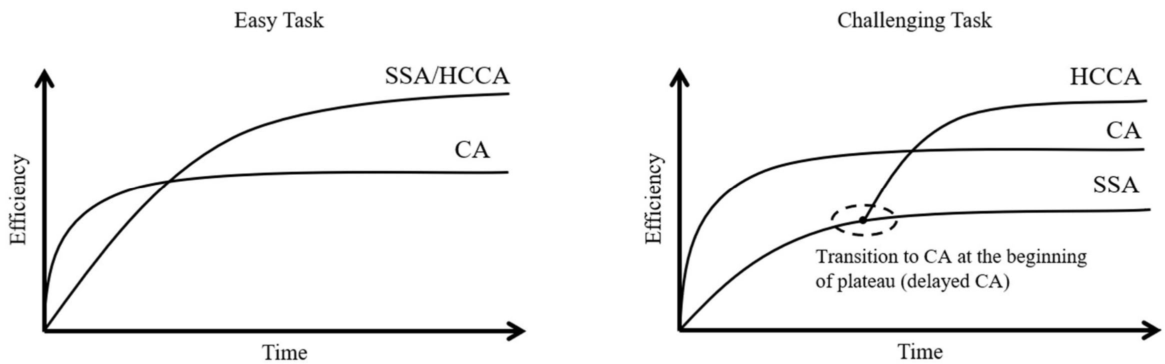


Figure 2. Conceptual graph of the efficiencies of multiple adaptation methods. For a skilled human, Co-adaptation is faster to adapt initially since there are two parties working rather than one, however it saturates at a lower efficiency rate than SSA/HCCA. For an unskilled human, CA both saturates and adapts at a quicker rate than SSA. Once HCCA is introduced, however, it saturates at a much higher efficiency rate than CA alone.

2. EXPERIMENTAL DESIGN

2.1 Human Subject Recruitment

The experiments in this study were performed in accordance with relevant guidelines and regulations, according to the procedure described in the protocol approved by the Institutional Review Board of Texas A&M University (IRB2019-1585D). Informed consent was collected from all subjects. Three healthy human subjects participated in the experiments in this study. The subject group consisted of three males. All subjects were over the age of 18, and the mean age of subjects was 23.

2.2 HCCA was implemented by two co-adaptation strategies

In this study, we implemented the HCCA strategy as a combination of two separate methods: 'Delayed co-adaptation' and 'Threshold-based co-adaptation'. The aim for both methods is for the machine to regulate its adaptation according to the human's ability to adapt. First, the machine holds off its adaptation for a certain interval until the human adaptation ability saturates (*i.e.,* delayed co-adaptation). The purpose of this delay is to maximally utilize the human resources for the adaptation. After the delay, the machine adaptation was applied to further improve the new performance level (see Fig. 2). The machine determines when the human becomes saturated in their ability to adapt through a differential reading. As the human saturates in their adaptation, the difference in their current step and last step will become smaller over time. This difference is calculated for the human's last three steps and is averaged. Once saturated, the user's difference between steps can be positive or negative, and when these numbers are averaged, the average value of a user with saturated adaptation is considerably smaller than that of a user who is still adapting. Once this average value has become sufficiently small, the machine will begin to adapt.

Once the machine has recognized the human is saturated in its adaptation, it may begin to adapt. The machine starts adaptation if the humans error if larger than the intrinsic variation of the human (*i.e.,* threshold-based co-adaptation), and stops once the humans error is smaller than the same threshold. The intrinsic variation of the human was measured ahead with easy objective. This threshold-based co-adaptation was designed to minimize the potential confusion of human, potentially caused by excessive machine adaptation. Similar to delayed co-adaptation, the average error of the last three steps are compared to the threshold, so as to prevent the machine from co-adapting to any errors the user makes in their footsteps.

By delayed co-adaptation, we allow the humans to exhibit their adaptation ability unrestrained, allowing the machine to add value onto the human ability. At the same time, the machine is ready to assist the human if the human is not skillful enough to address the problem. For example, machine co-adaptation can begin very early if the human is novice on the given task. Additionally, the machine stops adaptation if the error is within the range of intrinsic human variation. These two methods also work independently, meaning that even if the machine has recognized the human has saturated their adaptation, it will not adapt if it recognizes the human is skilled enough.

2.3 Treadmill walking task utilizing blocked vision and a posterior target line

Note that, the task should be difficult enough for the humans not to easily accomplish the goal. In this regard, we selected a treadmill walking task with a posterior target line. Foot placement on the treadmill can be hardly accurate with intrinsic visual-proprioceptive mapping error [21], [22], especially when the target footstep location is located at the posterior side of the belt. Additionally, another reason we selected the treadmill walking is that, humans lose their sense of accuracy but retain their precision when visual-proprioceptive mapping is involved in the motor task [21]. If the human performance shows high level of precision, the co-adaptation at the machine can be very effective as it can turn the precision into accuracy. As for the task itself, subjects were asked to walk on a treadmill, and the location of their footstep was calculated with each step. Subjects were asked to match the location of their footsteps with a posterior line shown on a graphical user interface. We will further expand upon this in later sections.

2.4 Optical motion capture system to capture the location of the forefoot

To measure the location of each footstep from the front end of the belt, an optical-tracking system (Prime 41, Motive: OptiTrack) was utilized. These motion capture cameras were placed around the ceiling in the room where the experiment was being held (8 in total). The cameras have the ability to track the 3D orientation of any object by detecting any retro-reflective spheres placed on them. To detect the footstep distance of the users, the retro-reflective spheres were placed on both the subject's dominant foot as well as the head of the treadmill, as shown in Fig. 3. We used MATLAB to read the real-time coordinates of the treadmill and footsteps and detected the peak distance of these footsteps by finding the magnitude of the distance away from the two bodies, with a precision of 0.8 mm. Since the markers can only detect the center of the foot instead of the tip of it, the subjects placed their dominant foot at the base of the treadmill to determine the offset distance needed to find the correct position of their footstep relative to the treadmill. Readings were taken every 0.011 seconds (90 samples per second).

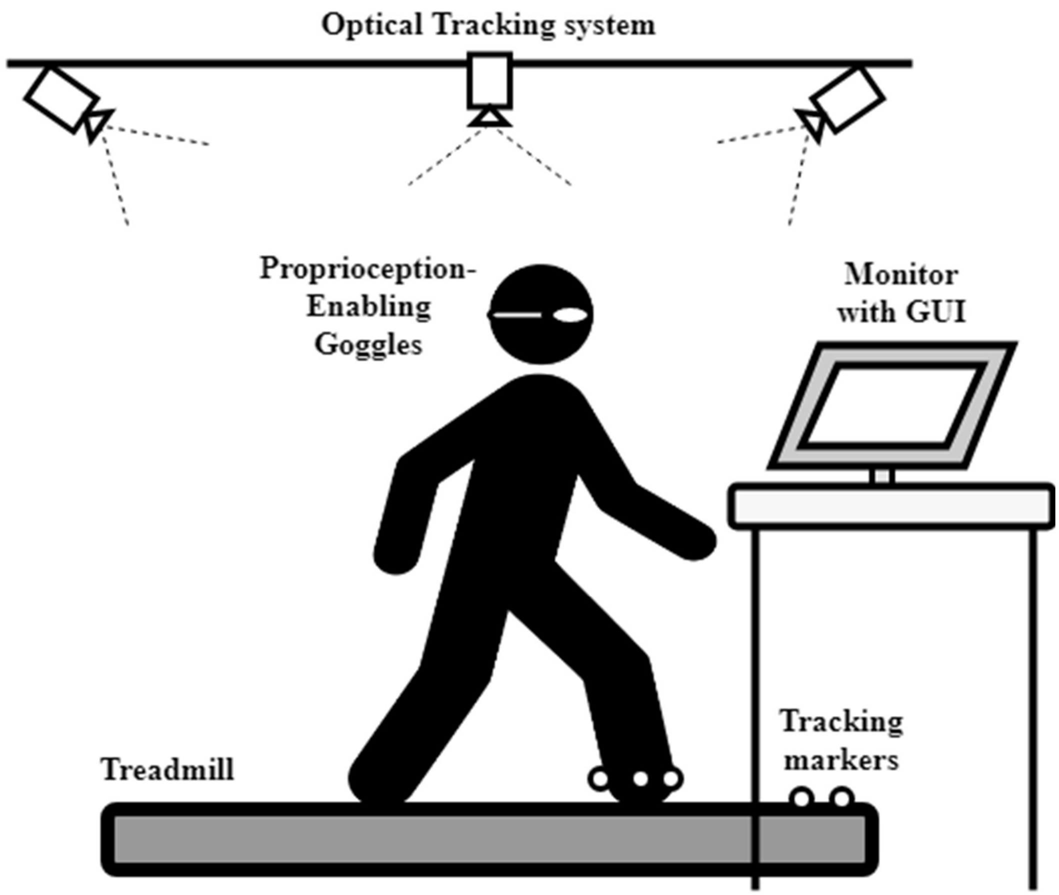


Figure 3. Overall experimental setup. The subject will perform the experiment while being tracked with an optical tracking system which detects the retro-reflective orbs placed on the feet and treadmill. The subject will perform the experiment while wearing proprioception-enabling goggles, looking only at the monitor with GUI running to allow for visual proprioception.

2.5 Signal processing to update the target line

The machine changed the distance of the target line based on the selected co-adaptation strategy: SSA, CA, and HCCA. Additionally, we will have a control test which consists of a target that does not change, located at a distance in which the user will have an easier time matching their footsteps to. Before each of the other three strategies, the subject initially walked for 10 steps on the treadmill, matching the same easier control target line, so as to keep the initial position as consistent as possible between tests and between subjects. The new target line then appeared on the screen and was updated to a new, more difficult location according to the co-adaptation strategy. 1) In case of SSA, the target line shifted backward to a more difficult location, then remained stagnant. 2) In case of CA, the target shifted backwards after 10 steps and for every step from 11^{th} step, the target line was changed to the halfway location between the previous target line and the last forefoot line. We use the halfway mark (50% tolerance) simply to implement a low pass filter rather than a strategy. 3) In case of HCCA, the target shifted after 10 steps and did not change until the subjects did not make any more significant improvements in their footsteps. The machine determined if the human adaptation was saturated by comparing the change in the last step with the standard deviation of the subject's step measured with the easy target line. The target line was then changed to the halfway location (similar to CA) between the previous target line and the last forefoot line. Subjects then adapted to the new target line. The machine also tracks the average change in the last three steps and compares it with the standard deviation of the subject's step measured with the easy target line. If the average change in the last three steps is smaller than the standard deviation of the subject's step, the machine stopped applying co-adaptation and target line will stay the same. We apply the same 50% tolerance of CA to HCCA to keep the filter consistent across tests. This filter does not apply to SSA, however, since the target line does not move in this scenario.

2.6 Installation of treadmill, desk, and monitor with graphical user interface (GUI)

A motorized treadmill 1 meter long was installed onto the ground and portable desk was positioned on top of the treadmill. To make sure the visual-proprioceptive error is engaged in the experiment, we blocked users' vision on their feet by placing a desk between users' vision and the treadmill belt. In addition, goggles were given to the user which blocked the vision of the lower half of their body. On top of the desk, monitor was located to provide a display of graphical user interface (GUI) to the subjects. The overall description of experimental setup is shown in Fig. 3.

The GUI was created by open-source graphical library “Processing”. The GUI showed two pieces of information by solid lines: the actual location where their forefoot stepped on, and the target location their forefoot needs to step on. Fig. 4 shows an image of the GUI and how the information was presented to subjects.

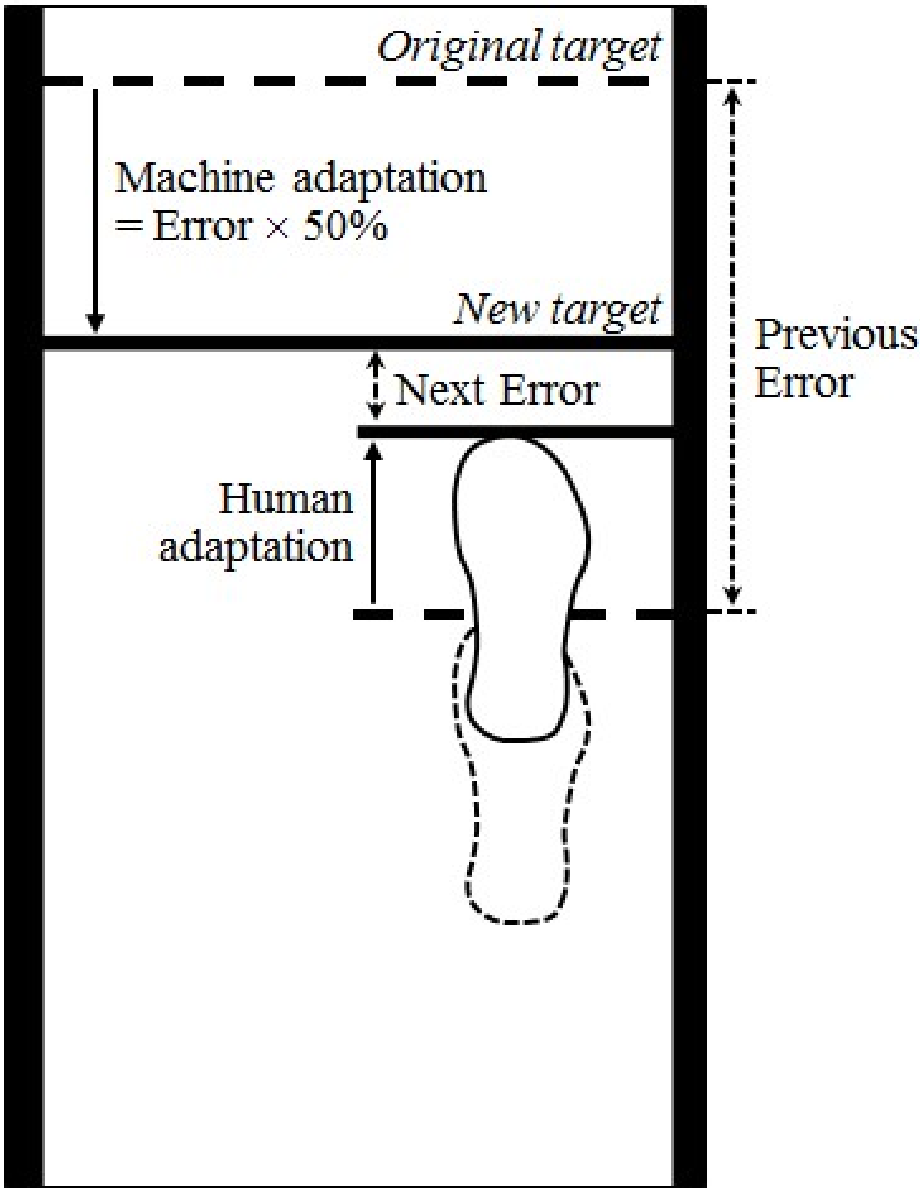


Figure 4. Image of the Graphical User Interface to display the subjects step distance. A scaled model of the treadmill is shown in background, while the footsteps and the target line is shown on top of the treadmill. The horizontally dashed line represents the previous target. The footprint shows the GUI creating the step at the tip of the foot, while the vertically dashed lines show the error margins for the current and previous steps.

2.7 Test procedure to compare the performance with SSA, CA, and HCCA

Subjects were initially standing on the treadmill and the operator increased the speed of the treadmill to 3.5 mph and subjects were asked to talk until the operator gave the verbal stop signal. The operator gave the verbal stop signal when subjects walked 50 steps with their dominant foot. Considering the initial 10 steps used for the subjects to adapt to the speed, subjects were asked to walk total 60 steps on the treadmill. The speed of 3.5 mph was maintained till the end of the trial, consistently for all subjects. Note that 3.5 mph is 12.9% faster than the normal human walking speed of 3.1 mph, which means the treadmill walking at 3.5 mph is challenging for most of the people. Subjects were asked to place their foot as closely as possible to the target line, which was provided at GUI on the monitor. Note that, to eliminate any discrepancy between the dominant and non-dominant foot in each user, only the user's dominant foot was tracked in this co-adaptation process.

The experiment itself consisted of the human trying to match the target line while three different adaptation methods were implemented on the machines side, being SSA, CA, and HCCA. For each of these adaptation methods, the test was conducted with the target line at two separate locations, resulting in a total of six tests for the experiment.

In the 1st trial (control test), the subject walked on the treadmill matching an easy forefoot target line, located at the 15% (0.15 meter) position from the front end of the belt (0.85 meters from the back). No co-adaptation was applied at the first trial. In the 2nd, 3rd, and 4th trials (SSA, CA, and SBCA respectively), subjects walked on the treadmill with challenging forefoot target line, located at 60% position (0.6 meters from front of the treadmill, 0.4 meters from the back) from the front end of the belt. In the 2nd trial, no co-adaptation was applied. In the 3rd trial, co-adaptation was applied without strategy (*i.e.,* CA). In the 4th trial, co-adaptation was applied with strategies of delayed co-adaptation and threshold-based co-adaptation (*i.e.,* SBCA).

The 1st trial provided a baseline variability of the subject, which was used to determine the skill level of the human by finding the standard deviation of their steps. The following trials added difficulty on the task, so that the human cannot achieve the goal without the help from the machine. The 2nd trial tested the ability of human adaptation to achieve the goal without the help from the machine. The 3rd trial tested the basic effect of the co-adaptation without any strategy. The 4th trial tested the efficacy of the co-adaptation strategies on achieving the goal by HMI, and utilized the skill level from the 1st trial to achieve this.

2.8 Data analysis

To evaluate the efficacy of the strategies of co-adaptation, we used three kinds of measures and compared them among three adaptation strategies: SSA (no adaptation from machine), CA with no strategy (machine does its best to adapt), and HCCA (machine adapts based on human adaptation). First, we evaluated the accuracy of stepping (*i.e.,* how close the forefoot step is to the target line). Second, we evaluated the machine resource usage by finding the distance between the original target line and the final target line (*i.e.,* how much the machine must adapt to the human). Third, we evaluated the speed of adaptation by calculating how many steps were needed to reduce the variation within the standard variation. By this measure, we can evaluate the effect of the strategies of HMI in adaptation speed.

3. EXPERIMENTAL RESULTS

3.1 Stepping Accuracy

To evaluate the speed of accuracy of stepping, we calculated the distance between the target line and the forefoot location. Since the initial few steps have an exponentially larger error than the rest of the steps, we have only calculated the accuracy after stabilizing, which is determined by the first step the users take which is within the standard deviation of the entire experiment. The mean and standard error are shown for both sections of this experiment, as well as their absolute values. The results for experiment A are shown in Fig. 5, and an example of experiment over time for is shown in Fig. 6.

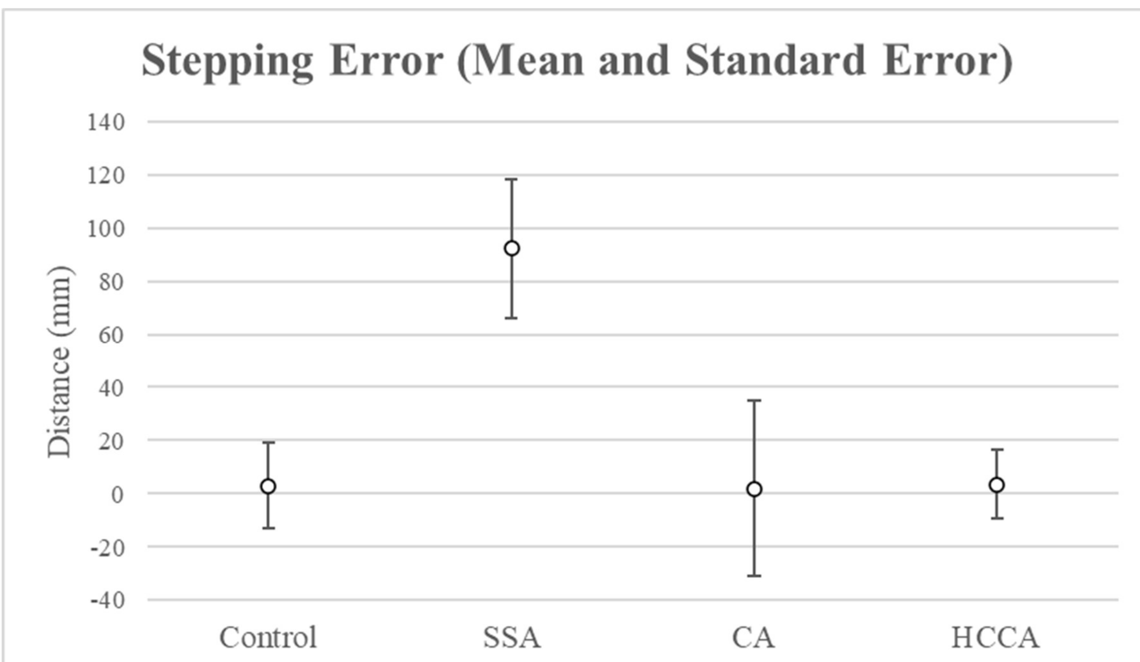
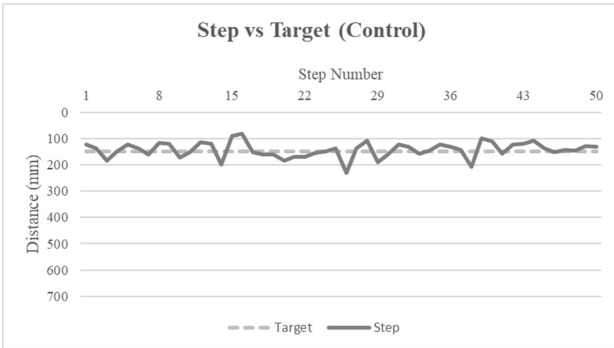


Figure 5. Results for Experiment A, stepping accuracy. The mean and standard error are shown for each adaptation in the graph above. The mean is shown by the dots on the graph, and the lines represent one standard error above or below the mean.



(a)

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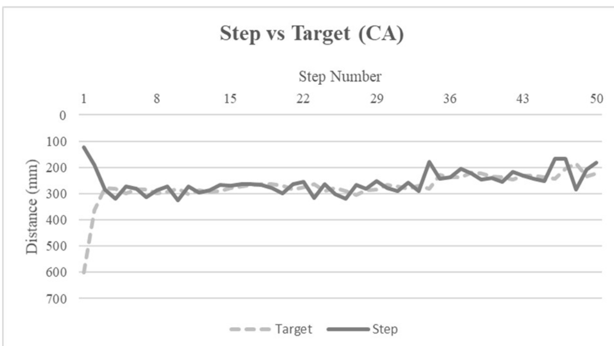

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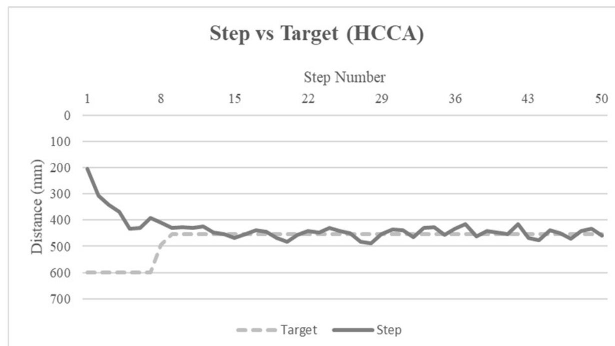


(d)

Figure 6. Graph of each adaptation method over time from multiple subjects. A distance of 0 marks the very front of the treadmill, and an increase in distance represents movement towards the back of the treadmill, simulating a top-down view of the machine. (a) shows the control test, where the target line is at a comfortable position for the user does not move at all. The SSA target line in (b) similarly does not move for the user, however it begins at a more difficult position towards the back of the treadmill. (c) shows the tests for CA, in which case the target line moves to the halfway distance between the previous target and the current step, and (d) show the tests for HCCA, which implement both the delayed adaptation and threshold-based adaptation methods.

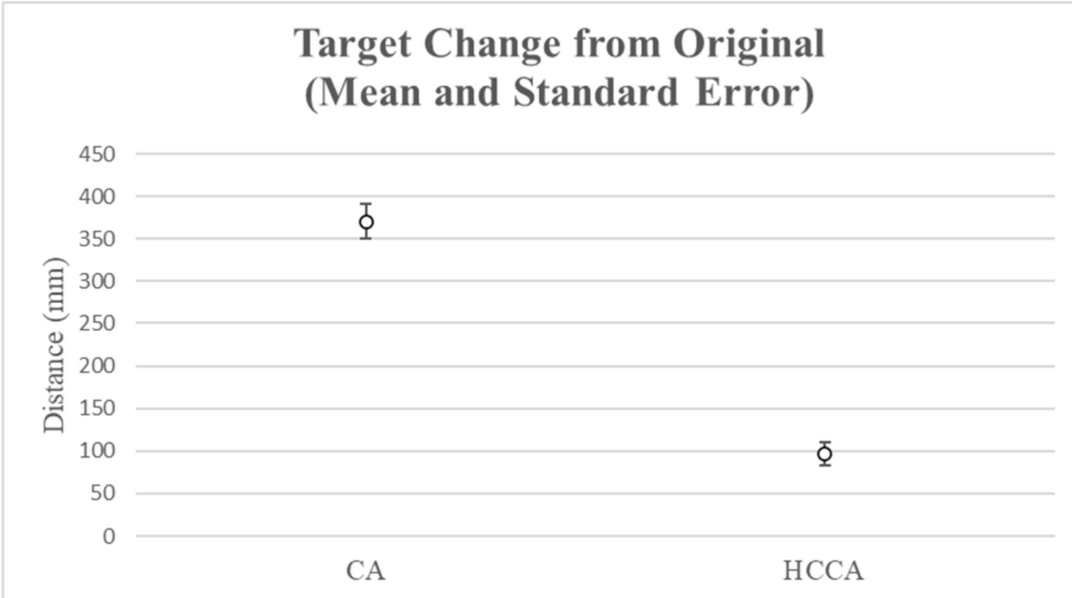
3.2 Machine Resource Utilization

To evaluate the how much the machine needs to adapt to the human, the average distance between the original target line and the final target line was calculated for all trials. Additionally, the standard error was calculated for both CA and HCCA. As there is no target change in the control and SSA tests, the average target change is not shown for these tests. The results for experiment B are shown in Fig. 7.

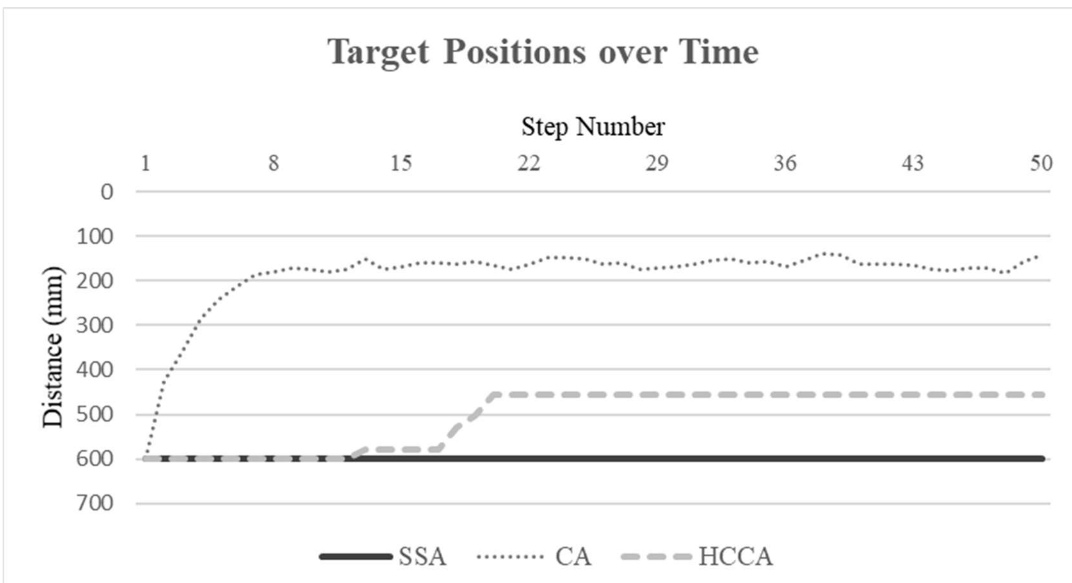
3.3 Speed of Adaptation

To evaluate the speed of adaptation, we calculated how many steps were needed to reduce the variation within the standard variation. The results for experiment C are shown in Fig. 8.
The results for each experiment are shown in the figures below. The values for Experiment A and Experiment B are in millimeters, while the values for Experiment C are in number of steps. For Experiment A, positive values indicate the error is in front of the target (human steps too far forward), while negative errors indicate the error is behind the target (human does not step far enough).

Fig. 6 shows the step and target values over the entire experiment for one subject. A distance of 0 indicates the very front of the treadmill. Step values lower than the target line (above the target line graphically), indicate that the step is in front of the target, and step values higher than the target line (below the target line graphically) indicate the step is behind the line. The control test stayed at a constant target of 150 (0.15 meters from the front of the treadmill) throughout the entire test, whereas the other three tests began at a target of 600 (0.6 meters from the front). The other three tests were additionally prefaced by a ten step target line 150mm from the front of the treadmill. This was done to keep the starting point consistent between tests, and the ten prefaced steps were not recorded.



(a)



(b)

Figure 7. Results for Experiment B, machine resource utilization. (a) shows a graph of the mean and standard error of target changes for each adaptation method. As the target does not change for the SSA tests, their tests are not considered when determining machine resource utilization. To give a better perspective on how these target lines change, (b) shows a graph of the target changes over time for one subject. SSA remains stagnant throughout the experiment. CA stabilizes quickly but never fully stabilizes to one point. While HCCA adapts much more slowly, once it has stabilized it does not change.

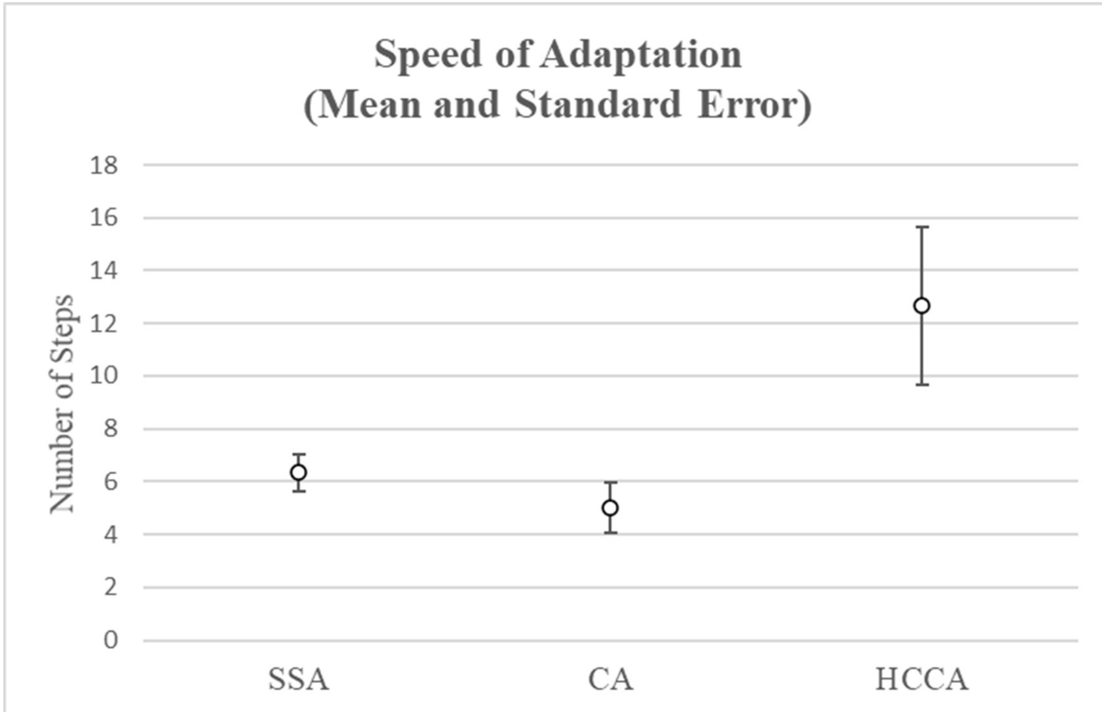


Figure 8. Results for Experiment C, speed of adaptation. The average number of steps for each adaptation method are shown above. The mean is shown by the dots, and the standard error is shown by the lines.

4. DISCUSSION

4.1 Machine co-adaptation enhances the human performance

The results for multiple subjects over time are shown in Fig. 6. Since each subject has a different performance level, the graphs from the figure were cherry picked from subjects to give the best representation of how each test performs over time. For the control test, the average mean error was 3.07 mm and the absolute mean was 22.64 mm. Despite the challenges presented for the human, including the use of proprioception and walking at a relatively fast speed, under normal circumstances the subjects were able to be accurate in their footsteps. The low value of the standard deviation further indicates the human was able to be precise as well as accurate, having a normal standard deviation of less than 3 centimeters.

By comparison, SSA has an exponentially larger mean error. We can see the mean error is around and standard deviation have both increased by a significant margin. By moving the target line back from the easy control target line to the harder SSA target line, the human becomes unable to perform the task as well. Additionally, the normal mean error and the absolute mean error are less than three percent different than each other after stabilization, indicating the vast majority of the steps for the SSA line are in front of the target. This indicates that the humans have an inability to reach the target line, and on average, walk around 9 cm in front of the designated target line due to their inability. Although the standard deviation also drastically rose, it did not rise nearly as much as the mean error, especially after the humans have stabilized. This indicates that although the humans have some inability to perform this task, they still retain most of their precision when attempting to reach the target line.

Our third test involved bringing machine adaptation into the mix. In this test, the machine continually adapted to the halfway point between the human's steps and the previous target line. By introducing co-adaptation to the system, we can see the mean and absolute error have drastically decreased, indicating the machine has helped bring the user error down. After stabilization, the absolute mean decreased from 91.34 mm to 40.95 mm, almost half of the error margin of SSA. This drastic decrease, alongside the very low normal mean of 1.97 mm, shows by adding machine adaptation alongside the human's adaptation, the human can become much more accurate in performing their task. Contrary to the mean, the normal standard deviation of CA is larger than the standard deviation of SSA. Paired with the change in the mean, this indicates that although CA assists the human in reaching their goal, their accuracy is still low due to the fact that although the machine adapts to the user's shortcomings, the machine also adapts to the user's errors, amplifying them further.

By introducing our two methods (delayed adaptation and threshold-based adaptation) to CA, we were able to create a new co-adaptation technique, HCCA. Testing HCCA, the results of the test turned out to be better than not only SSA and CA, but also the control test. After stabilization, the normal mean is very near the CA test, however the absolute mean error is less than half of that of CA, indicating that utilizing HCCA, the human is able to reach the target both accurately and precisely. This is further confirmed by the low standard deviation, which is lower than that of the control test, even though the task is still moderately harder than the control test. This is likely due to the subjects being much more focused while performing a harder task than performing an easier one.

Overall, when testing single-sided adaptation, the subjects had a difficult time matching the target line due to their inability to reach the target. This inability is able to be corrected when co-adaptation is introduced, allowing the user to reach the target, however, using CA without any sort of strategy still retains the accuracy error of the subjects and does not preserve the human's accuracy. By introducing a strategy to CA in our final test, the human's intrinsic traits are preserved in this adaptation method, even when compared to the control method, indicating that although the task was more difficult, a more smart implementation of co-adaptation can preserve the human's adaptation traits even performing a more difficult task.

4.2 HCCA achieves the best accuracy and the best achievement level

The achievement level is indicated by how much the target line changes with each test. Ideally, we would want the achievement level as high as possible, which is achieved by changing the target line as little as possible. A higher achievement level indicates that less resources are used on the machines side and is therefore more beneficial to the interaction.

Utilizing SSA, although the achievement level is the highest since the machine does not change its target distance, the user error is significant enough to where introducing co-adaptation is beneficial. In the CA test, the target line eventually regressed from the initial position to around the same control location. Beginning at 0.6 meters from the front of the treadmill, the target line moved up to a final location of 0.182 meters from the front, 70.3% of the distance from their original location. This high change in the target line, paired with the fact that the target changes with every step, indicates a low achievement level for the system when utilizing CA.

In the case of HCCA, however, the target line changed on average to 96.67 mm from the initial target line, with an average final target of 123.67 mm. Additionally, the target line changes very few times in the beginning of the test then ceases any changes for the remainder, due to the human's newfound ability to reach the target. The lower average and final target change indicate a significantly higher achievement level for HCCA than for CA.

4.3 Speed of adaptation was not much sacrificed by HCCA

The speed at which co-adaptation was determined by the moment the error fell within the standard deviation for SSA and CA, and the moment when the machine stopped adapting for HCCA. From the results in Fig. 8, we can see CA is the fastest to adapt, with an average of 5 steps needed to fully adapt. SSA requires an average of 6.33 steps to adapt, slightly higher than CA, and HCCA needs an average of 12.67 steps to adapt, more than twice the number of CA. Although CA and SSA both adapt and stabilize much faster than HCCA, the human will have an easier time adjusting to the system once stabilized in HCCA, whereas there is still an everlasting difficulty of not being able to reach the target line in SSA, and continually having to change your adaptation to a target line that hardly stays still in CA. This downside to HCCA is very much worth the tradeoff of maintaining better accuracy, especially interactions over long periods of time where the time to initially adapt is negligible compared to the time the interaction is stable. If strategies of delayed co-adaptation and threshold-based co-adaptation were applied, the human adaptation could be secured and synergistic with the machine adaptation. One thing to note, the average change in the final target line of 123.67 mm is fairly close to the average SSA error of 92.22 mm. These two numbers indicate that most of the adaptation on the machines part in HCCA is simply used to correct any inability on the users part. Paired with the low mean error and standard deviation of HCCA, overall the machine is able to preserve the human adaptation trait and allow them to perform their task freely without any unnecessary interference.

5. CONCLUSION

Utilizing a treadmill and a GUI, subjects were able to accurately perform an easy walking task by matching their step distance to a static target line during a control test. Three adaptation methods were then tested using a more difficult target line and compared to one another as well as the control method. The three methods are single-sided adaptation, which consisted of a static target line, co-adaptation without a type of strategy, in which the machine constantly moved the target line closer to the humans steps, and co-adaptation utilizing a strategy, dubbed human-centric co-adaptation, which consisted of the machine waiting for the human to fully adapt to the machine before adapting back to the human, as well as holding off any sort of adaptation while the human is performing on par to their general level of skill, so as not to confuse the user with any sort of unnecessary movements.

Compared to an easy control test, the introduction of a challenging task made users unable to efficiently reach the target line in the SSA test. This inability was rectified by introducing co-adaptation on the machines part, however the results were still inefficient; Without introducing a strategy to co-adaptation, the machine introduces unnecessary interference while adapting, and the user must continually adapt to this unnecessary interference, further propagating error. Experiment A, B, and C demonstrated by introducing a type of strategy to co-adaptation, in our case HCCA, any unnecessary adaptation is removed from the machines side, thereby saving the machines resources while increasing the accuracy of the user.

Different machines have different ways of interacting with humans, and even though a human-centric strategy may not be the most optimal strategy to utilize in every single case, utilizing a strategy when attempting to co-adapt is necessary for both saving the machines resources as well as preserving the humans ability to adapt to any system and keeping them comfortable even when performing difficult tasks. Furthermore, these optimal strategies may be able to be varied from machine to machine, depending on the needs of the human, machine, or outcome objective.

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