2024 IEEE International Conference on Robotics and Automation (ICRA)
May 13-17, 2024. Yokohama, Japan

Towards Robot to Human Skill Coaching: A ML-powered IoT and HRI Platform for Martial Arts Training

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2024 IEEE International Conference on Robotics and Automation (ICRA) | 979-8-3503-8457-4/24/$31.00 ©2024 IEEE | DOI: 10.1109/ICRA57147.2024.10610291

***Abstract*— Advances in human sensing and machine learning are paving the way for new applications of robotics in sports and fitness, making skill coaching smarter, easier and more accessible. Physical and social human robot interaction in particular has received special attention as a feedback mechanism for human performance augmentation. A core challenge in deploying robots that interact physically with humans in dynamic environments such as sports, relates to modeling human skills and designing appropriate interaction schemes. We present the first ML-based HRI platform for physical robot to human skill coaching in real-time in Martial Arts which can be extended to various sports. Our system comprises of the Sawyer robot, our specially developed IoT katana and a skill-training program for the Martial Art of Iaido. We built and deployed in real-time a ML-based Iaido strike recognition model trained on expert and beginner data, and achieved accuracies ranging between 94.8% and 99.97%. We assessed the system's effectiveness in coaching skills through robot interaction in a sparring experiment and a survey involving 12 participants practicing key Iaido techniques with guided training from Sawyer. Our results demonstrated improvement in all participants' Iaido strike skill after training with Sawyer, and they responded positively to robot-assisted skill coaching.**

I. INTRODUCTION

Emerging technologies in human sensing and machine learning are paving the way for creative new applications of robotics in sports and fitness, making skill coaching smarter, easier and more accessible. Notably, physical and social human robot interaction (HRI) has received special attention as a feedback mechanism for human performance augmentation in sports and fitness settings [1], [2], [3], [4]. A core challenge in deploying robots that interact physically with humans in dynamic environments such as sports, relates to modeling human skills for skill transfer and designing appropriate interaction schemes. Previous works have largely focused on using vision and user-worn inertial sensors data for human action detection. However, these modalities alone are limited in their suitability for designing a real-time and adaptable model of human skill and for designing scalable interaction paradigms. This work investigates skill transfer between a robot and a human in training Iiado, the traditional Japanese martial art of swordsmanship, through physical human robot interaction (pHRI) using machine learning-based human action recognition and an IoT katana.

There has been no previous research investigating the use of a robot coach for the purpose of skill coaching in sword-based martial arts. Additionally, there has been no research that uses a robotic coach powered by ML-based human action recognition for training beginners in martial arts with the purpose of skill acquisition. In designing the target activity for the ML-powered robotic coach, it was important to define a clear, feasible and effective target for robot-assisted skill transfer for training beginners to acquire a skill. We performed pilot studies across various sports (e.g. Martial Arts, baseball, weight-lifting) and interviewed expert practitioners to identify key criteria for the target activities.

Martial Arts and Iaido in particular, with its emphasis on precision in strikes, deflections, and sheathing, presents an ideal target for developing a machine learning-powered robotic coaching platform. Its diverse styles cater to various learner levels and physical abilities, with the globally recognized Katana as a fundamental Martial Arts weapon. Additionally, Iaido's rich historical significance extends from folklore to modern fiction and art, making it a culturally significant martial art. Its motions are conducive to modeling through sensing data and activity recognition, particularly in hand-held tool manipulation skills, which can be applied to robots like manipulators and cobots. These factors underscore Iaido's suitability as a model for exploring robot-human physical skill coaching, which can be potentially extended to other sports.

Iaido can be practiced with a foam sword, a *bokken* (wooden sword), *iaito* (unsharpened katana) or *shinken* (live-blade katana). Our research involved the use of a foam-based katana, chosen for its suitability for beginners and safety during interaction with the robot. We focus on introductory level strikes, including kesa-migi (falling diagonal strike to the right) and kesa-hidari (falling diagonal strike to the left), along with corresponding parries known as overhead blocks, where the sword is drawn upwards above the head with the blade pointing towards the incoming strike direction.

Our main contributions in this research are:

- We develop a human robot interaction framework for Iiado skill coaching using a sword fighting robot, an IoT sword, and ML-based human action recognition.
- We develop and demonstrate the deployability of the first ML-based Iiado strike model for sword techniques with accuracies ranging between 94.8% and 99.97% performance accuracy.

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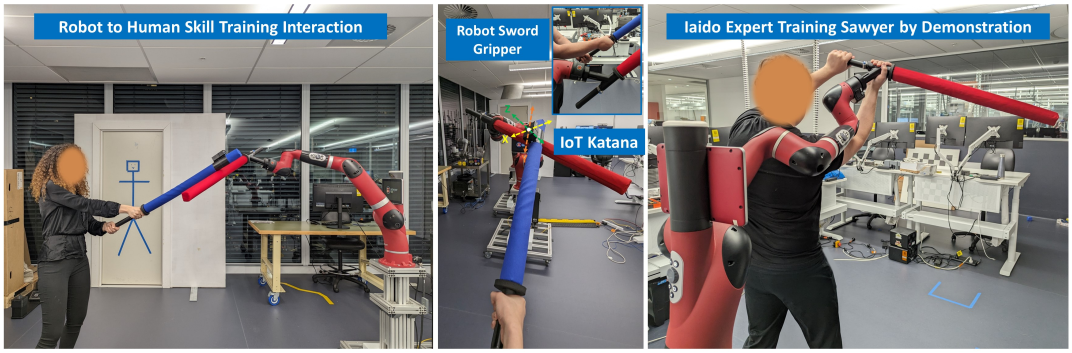

Fig. 1. Robot to Human skill training system: ML-based sword training (left), IoT Katana device with specialized developed sword mount end effector for Sawyer (mid) and Robot learning Iaido from expert by demonstration (right).

- We show initial results on a robot to human interaction platform for skill acquisition in Iaido with scalability to other physical sports.
- Development of an IoT sensing sword that can be used for real-time sensing of human and robot skill and wireless real-time interactions with a robot.

II. RELATED WORKS

We discuss in this section related works in pHRI and cobots, HRI in Martial Arts, and IoT physical human sensing.

A. Human Robot Interaction and Cobots

Collaboration between humans and robots encompasses various interaction styles, including human-led, robot-led, or autonomous, depending on the task. A significant part of Human Robot Collaboration literature is centered around its application in manufacturing [5], [6]. HRC in fitness and sports is a much less explored area rife with opportunity for innovation and research.

[7] identified two main paradigms of robots for fitness, namely robots as coaches or instructors and robots as motivational aids. They conducted a preliminary survey on the adoption of a robot as a coach or as a companion during training using a child-sized robot (NICO, Neuro-Inspired Companion) [7]. In the last 5 years, a growing body of literature investigated how robots can be used as coaches for elderly fitness [1], [2], [3], training partners in jogging [8], underwater guidance coaches in swimming [4], volleyball motion correction [9], dancing [10], swing motion coaches in tennis [11], badminton training robot partner [12] and home-based exercise guides [13].

The research in [14] demonstrated that social robots were effective in improving intrinsic motivation in sports coaching applications. Research in [15] found that participants who exercised at home with a co-located robot for for correcting exercises made fewer mistakes.

[16] developed a framework for tele-operated robot coaching for mindfulness using a virtual reality system. The social robot approach presented mixed results when compared to a human-coaching system for mindfulness training.

These works remain preliminary and share common limitations in terms of their feasibility and effectiveness in real-world scenarios, with many still relying on human coach interventions to operate. These works explore proof-of-concept systems with no concrete deployment strategies. Additionally, they rely on outdated human activity modelling schemes and robot learning strategies. In our proposed system, the robot can perform coaching independently using AI when a human coach is not present.

B. Human Robot Interaction in Martial Arts

The feasibility of accelerometer-based trackers in Iaido has been verified in previous research [17], [18] but there is no research to our knowledge, based on specific techniques and skill-transfer in Iaido. Furthermore, previous research lacks the use of machine learning procedures which allows for versatile assessment against expert motion. The research in [19] explored a sword fighting robot but focused primarily on reactive sword fighting. The system uses a camera based approach which may be subject to occlusion and environmental issues depending on lighting in the space which restricts the usability of the system. Sword-based martial arts, including Iaido, require very fine and precise high-speed movements which are difficult to observe using vision-based sensors. The work in [20] also investigated the feasibility of camera-based sensing for detecting motions in Kenjutsu, another similar type of Japanese swordsmanship. It concluded that camera sensing is not enough to capture accurate sword motions, which are needed for robot skill transfer to humans.

C. IoT Physical Human Sensing

We have previously investigated the use of IoT sensing interfaces for posture training and developed a machine learning classifier that demonstrated over 98% accuracy [21], [22]. In another related work we investigated the effectiveness of an IoT-based sensing system and Serious Game for skill transfer in martial arts [23]. The study demonstrated that all participants had improved skill performance when receiving feedback from a virtual coach and were motivated to use the system for long-term training. Additionally, we have previously explored the use of a social emotive robot in improving the posture of people in the workplace in real-world office settings [24]. Participants responded positively towards interacting with a desktop-based robot for skill

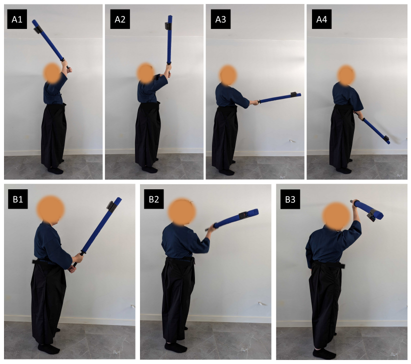

Fig. 2. Example of kesa-hidari strike i.e. falling diagonal strike to the left (A1-A4) and upper-migi i.e. upper-right block (B1-B3) used in experiments.

training. These works provided promising results towards the possibilities of using an IoT device and a real robot system for skill-transfer in sports and martial arts settings.

III. Proposed System for ML-powered Human-Robot Swordsmanship Skill Coaching

Our system is comprised of the Sawyer robot by Rethink Robotics [25], our developed IoT katana, foam katana for Sawyer, specialized sword mount end effector for Sawyer, and our custom training software with our skill classification model. The system components are illustrated in Fig. 1.

A. IoT Sword

We developed an IoT sensor sword (IoT Katana) for tracking the motion of Iaido techniques in real-time. In this research we have used a foam sword (bokken style) for safety and teaching introductory techniques since the target user of our system is a beginner. The sword is 147cm long, with the handle length approximately 30cm, tsuba length 17cm and blade length 70cm. The weight of the sword is 290g.

The IoT katana electronics are packaged and attached at the back of the sword near the end tip. The device is composed of an AVR-based microcontroller, BMI270 6-axis IMU (accelerometer and gyroscope), buttons for input and RGB (red-green-blue) leds for system status indicators. It communicates wirelessly using Bluetooth Low Energy 5.0 (BLE) through an nRF52840 chip. The package is powered by a 3.7V lithium-polymer battery. It includes a USB-A type charging port to recharge the sword. The package was attached to the sword using adhesive fittings. The IMU is positioned to be flat against the sword and located at the section of the sensor package that directly touches the sword. The orientation of the IMU axes are displayed in Fig. 1.

Two identical foam swords were used for this study. The IoT Katana was given to the participants (beginner and expert) and the other foam sword was given to the robot Sawyer. Since we mainly focused on the skill level progression of the user, they were equipped with the IoT Katana. When the user swings the sword, the IMU sensors output the changes in acceleration and angular velocity wirelessly to the main program at a sampling rate of 104Hz. The time-series sensor values provide indication into which type of technique the user is most closely performing based on an Iaido skill classifier described later in this section.

B. Sensor Configuration

The sensor was attached to the back tip of the sword, the IMU axes and sensor position are depicted in Fig. 1. In this configuration the x-axis relates to tilt, y-axis to roll and z-axis to yaw. The position of the sensor was chosen because that part of the blade hardly makes contact during Iaido motions. It is also ideal for Iaido analysis since it provides insight into the trajectory of the blade during techniques. Previous research investigated placing the sensor on the wrist, but had mentioned that it is difficult to translate the wrist motion to the exact blade trajectory [18].

The accelerometer 3D accelerations are denoted by a_x, a_y and a_z and the gyroscope angular velocities are denoted by ω_x, ω_y and ω_z. BMI270 settings are configured as accelerometer range $\pm 4g \pm 0.122mg$ and gyroscope range $\pm 2000dps \pm 70mdps$.

C. Sawyer Robot Configuration

For this research we use the Sawyer Robot by Rethink Robotics [25]. Sawyer is a 7 DoF cobot designed to work closely with human operators. Sawyer has been used in various industrial and research applications ranging from manufacturing to education. For this research we developed a special sword gripper end-effector for the robot to ensure the stability of the sword when making contact with the participants sword. The sword gripper comprises of a base plate which mounts directly to Sawyer and a mechanism for holding the sword in place which supports a sword of handle diameter 20mm-40mm to be inserted into the tube and fixed with a screw or clamp. The base cylinder extends out from the plate to allow for enough clearance during sword techniques so not to make contact with the Sawyer arm, mirroring proper Iaido form. The sword gripper is slotted into our base plate and fixed with an M6 hex screw for additional stabilisation. Fig. 1 shows the sword gripper end-effector.

In this research Sawyer acts as a coach and training partner that performs the appropriate blocks for the beginner's sword strikes. The data from the beginner's sword is transmitted using BLE to a program running on the main computer system that also controls Sawyer. The program reads in sensor data of the sword, performs real-time filtering and smoothing then outputs the data to a ML-based classifier. The classifier then outputs the detected motion or technique of the user. Based on this label, Sawyer then performs the appropriate action to counter the technique of the user. This happens in real-time as soon as the user begins to move the IoT Sword. The system control diagram for the human and robot skill training interaction system is illustrated in Fig. 3 where the 3 key phases are highlighted.

D. Skill Acquisition and Iaido Motion Recognition Model

After consulting with Iaido experts on the appropriate techniques for a beginner to learn, we confirmed that the system should focus on teaching the right diagonal strike

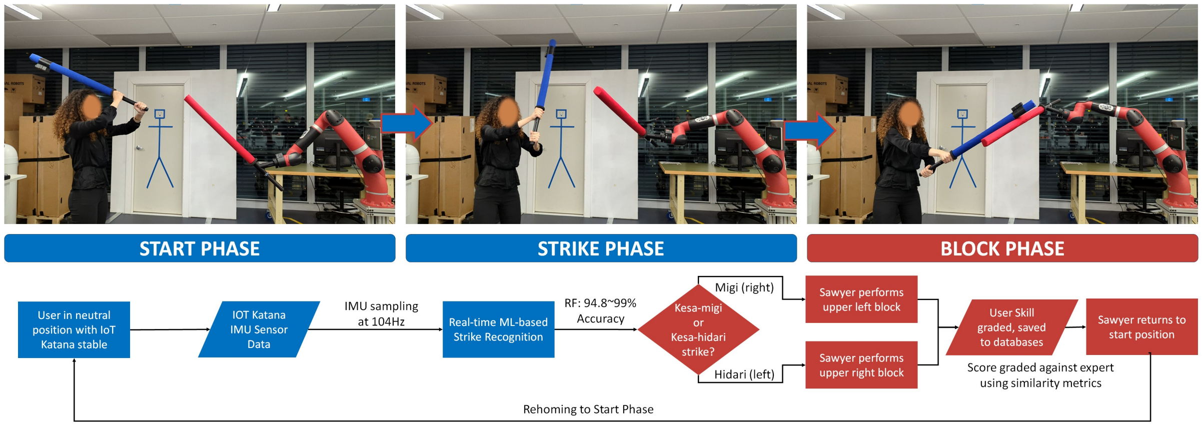

Fig. 3. System control diagram for the human and robot skill training system.

(kesa-migi) and the left diagonal strike (kesa-hidari) as well as the respective blocks for each motion. In the case of a kesa-migi strike, the training partner should defend with an overhead block with the sword tip pointing to the same direction as the incoming attack in a slight downward tilt so that the incoming attack's momentum slides off to the side of the defending blade. The same is repeated for kesa-hidari. Examples of the described strikes and blocks performed by the Iaido expert are depicted in Fig. 2. Each technique in Iaido emphasizes precision and is comprised of very fine, sharp and quick motions that involve precise kinetic chains of the three external forms (elbows, hips, knees) and intricate wrist motions. This makes it difficult for a camera-based system to analyze, as mentioned in previous research [17], [20]. Our sensor package is capable of real-time precision sensing and is unaffected by vision issues. In this research, the participants focus on striking with the correct technique to improve their skill level, and the Sawyer robot focuses on classifying the incoming strike and performing the appropriate block in real-time. We consulted with different Iaido experts on how to correctly perform the selected strikes and parries. For this study we recruited an Iaido expert with 15 years of martial arts experience, to perform a total of 78 strikes and blocks with the IoT katana we developed. We recorded the timestamped IMU data (accelerometer, gyroscope) for each sample at a sampling rate of 104Hz. In addition to this data, we also collected the IMU data of over 200 beginner strikes.

To communicate the different sword strikes to Sawyer in real-time, we built a machine learning classifier for sword action recognition. The model was trained on a dataset comprising of IMU data (6 features: the accelerations a_x, a_y, a_z and the angular velocities ω_x, ω_y and ω_z) of both expert- and beginner-level strikes for kesa-migi and kesa-hidari. We compared the performance of several machine learning classifiers for sword action recognition. Specifically, we targeted recognising action intention by focusing on the early stages of the strike to ensure the system is deployable in real-time. The investigated models were: Logistic Regression (LR), Linear Discriminant Analysis (LDA), k-Nearest Neighbours (KNN), decision trees (DT), Random Forest (RF), Naive Bayes (NB), Support Vector Machines (SVM), Multi-layer Perceptron (MLP).

IV. EXPERIMENTS

We conducted experiments to investigate ML-based sword strike recognition, skill coaching using a robot as a sparring guide, and HRI feedback. All experiments were approved by the UTS Human Research Ethics Committee, University of Technology Sydney (ETH22-7457).

1) Participants: The robot interaction experiment was conducted with 12 healthy adult participants (age 18-34; 9M, 3F). In a pre-experiment survey, participants were asked to evaluate their self-perceived skill level on swordsmanship, experience with robot and Sawyer. The questions were answered using a Likert Scale from 1 to 5 where 1 is 'no experience' and 5 is 'expert'. The mean skill level in swordsmanship was 1.17 (SD=0.58), the mean experience with robots was 3.33 (SD=0.65) and the mean experience with Sawyer was 1.92 (SD=0.79).

2) Experiment Procedures: The experiment consisted of each participant firstly completing a signed consent form and pre-experiment demographic survey. Next, each participant was guided on the basics of Iaido and instructions for the experiment through a 5 minute video. The video included information on how to perform each strike and

TABLE I
CLASSIFICATION PERFORMANCE OF THE DIFFERENT ML CLASSIFIER IN THE SWORD STRIKE RECOGNITION TASK

Model	Accuracy	F1
Logistic Regression (LR)	90.31	90.30
Linear Discriminat Analysis (LDA)	88.97	88.96
K-Nearest Neighbours (KNN)	94.70	94.70
Decision Trees (DT-CART)	90.00	89.99
Random Forest (RF)	94.81	94.20
Naive Bayes (NB)	87.08	87.04
Support Vector Machines (SVM)	93.27	93.27
Multi-layer Perceptron (MLP)	93.58	93.39

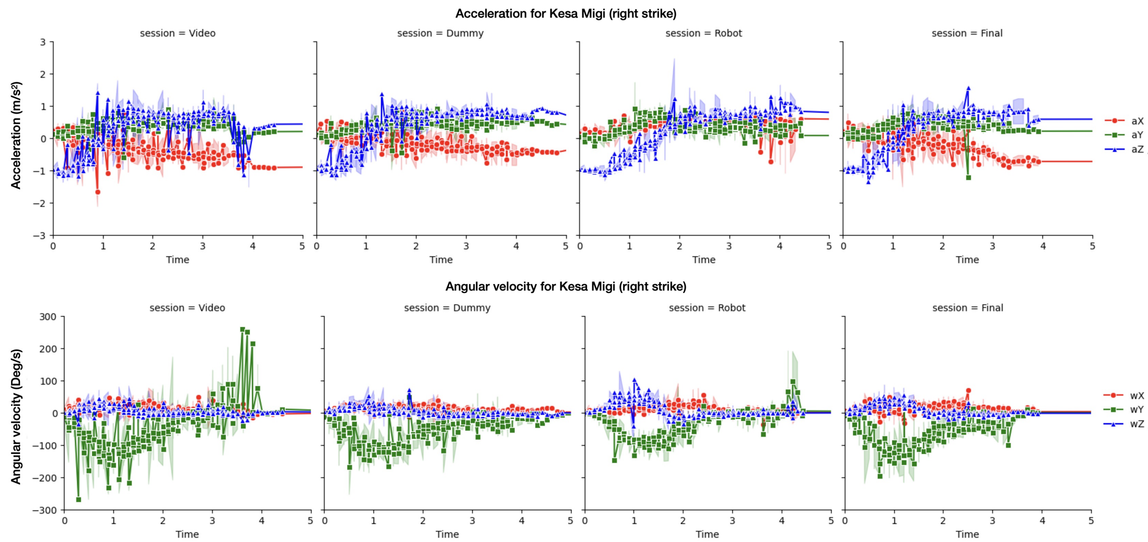

Fig. 4. Sword swing acceleration (top) and angular velocity (bottom) for the Kesa-migi strike i.e. falling diagonal strike to the right in the different experiment conditions. Left to right: baseline video, interaction with a dummy, interaction with Sawyer, and the final grading swing.

safety information when interacting with Sawyer. Then each participant was asked to perform 3 kesa-migi and 3 kesa-hidari strikes freely to obtain a baseline of their motions. They would then begin training with either the (a) physical dummy or (b) Sawyer robot. During experiments, the order of conditions was randomized between participants so that some participants would begin training with the physical dummy and others would begin with training with Sawyer. For both conditions, the participants are asked to perform 3 kesa-migi strikes and 3 kesa-hidari strikes. After completing training with both conditions, the participant is asked to perform a final 'grading' strikes. The participants were given a 30s-1min break between performing each sword technique.

When training with Sawyer, the goal was to perform the kesa-migi and kesa-hidari techniques precisely so that the participants sword meets atop Sawyer's sword at the centre in a perpendicular-like formation. If the strike is performed correctly, both the user and Sawyer should make first contact at this point. In this configuration, Sawyer is training the user to perform the strike with the correct angle, timing and distance to the target. Sawyer is also using the sword skill classifier to detect the incoming strike and move to the appropriate block in real-time. Participants were required to stand in the same marked position (based on). When training with the physical dummy, participants were instructed to perform their sword techniques while facing a dummy target which acts as a visual guide for the strike.

V. Results

A. Sword Motion Recognition and Assessment

We first compared the performance of several classifiers for Iaido sword techniques based on expert and beginner data. Table I shows the accuracy and F1 score of the different ML classifiers in the sword strike recognition task. The best performing model was Random forest with an accuracy of over 94.8% (cross-validation). This model lends favourably to real-time deployment for applications such the one investigated in this research. We thus deployed the Random Forest model to recognise the initial phase of the sword strike as the user engages in a strike. After deployment, the real-world classification accuracy was 99.97% with 5 miss-classification over a total of 240 strikes. We observed that the mis-classified strikes were the one where the user hesitated between engaging to strike right or to strike left before committing to a strike.

We secondly sought to investigate the effectiveness of using robot to human skill coaching in training a user to learn an Iaido skill through physical human robot interaction. Fig. 4 shows the average acceleration and angular velocity for the kesa-migi strike for all participants in the different sessions of performing the strike alongside the video, against the dummy, against sawyer and a final strike with no feedback (with the shaded area representing the 95% confidence interval). Similar patterns have also been observed for the kesa-hidari strike. Interestingly, the data recorded in the session where participants interacted with Sawyer showed a more stable acceleration and angular velocity profile. Empirically, this is consistent with the observation during the experiments that participants took more care in the robot session to hit the correct target on the robot sword.

Fig. 5 shows the Fretchet distance between the different strikes performed by all participant in the different session and that of the expert. A higher Fretchet distance value indicates a greater dissimilarity between the strikes.

B. Participant Interaction Survey

We conducted a post experiment activity survey that has been adapted for our application from [26]. The survey was given to participants immediately after completion of the experiment, and the key survey questions and results are listed in Table II. The survey uses a 5 point Likert Scale where

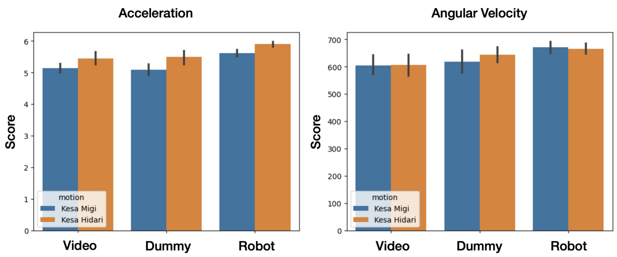

Fig. 5. Fretchet Distance between the beginner strikes and the expert strikes for acceleration (left) and angular velocity (right) in each session

1 equates to strongly disagree and 5 is strongly. Notably, participants responded very positively to using a robot for coaching as evident in responses to Question 1 (Mean=4.50, SD=0.71) and Question 5 (Mean=4.50, SD=0.53) which demonstrates implementation feasibility.

VI. Discussion

The sword motion recognition results showed that ML-powered action recognition is a viable and reliable method for modelling actions in Iiado. This is promising for future work with our system as we designed the IoT sensing component to be modular, making it suitable for applications in different target activities. In deployment, the selected model (RF) performed well in real-time, as observed during the live experiments and further corroborated by the participant interaction survey on how the ML-enabled robot performed.

The accelerometer profile of the sword strikes in the different conditions showed that practising the sword strike skills with the robot as a training partner led to a smoother and more controlled acceleration and velocity profiles during their swing, indicating better control over the sword movement. The trends in the final sword session also showed visible improvement from the initial baseline strikes. In these experiments, the Fretchet distance metric was not conclusive in identifying the differences between the different feedback conditions that the HRI survey identified. A limitation and a challenge of our study relates to obtaining more expert data in Iiado to have a diverse reference profile for validation.

TABLE II
Post experiment Activity Survey

Question	Mean (SD)
1. I think using a robot is a good idea	4.50 (0.71)
2. I could learn a skill from the robot	4.30 (0.48)
3. My skill improved after using the robot	3.90 (0.88)
4. I am afraid to make mistakes while using the robot	2.60 (1.17)
5. I could do activities with this robot	4.50 (0.53)
6. I feel threatened by the robot	1.70 (0.67)
7. This robot could support me	3.90 (0.32)
8. I feel understood by the robot	3.70 (0.82)
9. I feel comfortable while interacting with the robot	4.50 (0.53)
10. I trust the robot	4.30 (0.82)
11. I would follow the example of the robot	4.30 (0.67)
12. How safe did this robot behavior seem?	4.30 (0.67)
13. How much did you enjoy this set of interactions?	4.60 (0.70)
14. How engaged did you feel throughout this set of interactions?	4.20 (0.63)
15. How well did you perform during this set of interactions?	4.10 (0.74)
16. How well did the robot perform during this set of interactions?	4.30 (0.67)

The overall positive survey response to Question 2 (Mean=4.30, SD=0.48) indicated that all participants felt like they had learned a skill through interacting with Sawyer in the experiment. Additionally, the results for Question 3 (Mean=3.90, SD=0.88) highlighted that overall participants experienced a self-perceived improvement in their swordsmanship skill after using the robot. The responses to Question 11 (Mean=4.30, SD=0.67) were also very promising for scalability of the system to be used long-term and for training other skills. The results from Question 2, 3 and 11 in particular demonstrate the effectiveness of our proposed system for skill acquisition from a robot to a human.

In terms of system performance, results from Question 12 (Mean=4.30, SD=0.67) show positive response to robot safety and responses to Question 16 (Mean=4.30, SD=0.67) highlight that participants felt the robot performed well during interaction experiments. These were important design criteria when developing the system as we had hypothesized that the user should always feel safe when interacting with the robot to allow them to focus on the skill training aspect of the interaction. Furthermore, responses to Question 6 (Mean=1.70, SD=0.67) shows that the participants did not feel threatened by the robot and felt trust towards the robot based on results in Question 10 (Mean=4.30, SD=0.82).

The mixed responses to Question 4 (Mean=2.60, SD=1.17) indicate that some users were afraid to make mistakes while using the robot. This could be due to self-perceived safety or hesitation in damaging the robot during interaction. Increased system familiarity or additional safety features may assist in improving this issue but it remains a point of important future research interest for pHRI in skill training in relation to (1) robot control and (2) human data modelling.

Future work will target diverse skill assessment metrics to capture key human motion characteristics in the targeted sword strikes. Additionally, we aim to investigate and compare different HRI paradigms for our application. System enhancements will focus on boosting perceived confidence during training and examining how user comfort with the robot influences skill acquisition. Furthermore, we are exploring different feedback modalities, including visual, haptic, audio, physical sensing, and gamification, to assess their effectiveness in the training process.

VII. Conclusion

We presented the first ML-based pHRI platform for physical robot to human skill coaching in real-time in Iiado which can be extended to various sports. Our system comprised of a sword fighting robot, an IoT sword, and ML-based human action recognition. We achieved over 94.8-99.9% in recognising the main Iiado strikes in real-time. Strikes performed with the robot demonstrated a smoother acceleration and angular velocity profile compared to the baseline of learning from a video and learning with a dummy. Survey results highlighted that participants experienced an improvement in their Iaido skill after training with Sawyer and responded positively towards training with a robot for skill coaching.

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