# Dynamic Motor Skill Synthesis with Human-Machine Mutual Actuation

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## ABSTRACT
This paper presents an approach for coupling robotic capability with human ability in dynamic motor skills, called "Human-Machine Mutual Actuation (HMMA)." We focus specifically on throwing motions and propose a method to control the release timing computationally. A system we developed achieves our concept, HMMA, by a robotic handheld device that acts as a release controller. We conducted user studies to validate the feasibility of the concept and clarify related technical issues to be tackled. We recognized that the system successfully performs on throwing according to the target while it exploits human ability. These empirical experiments suggest that robotic capability can be embedded into the users' motions without losing their senses of control. Throughout the user study, we also revealed several issues to be tackled in further research contributing to HMMA.

### Author Keywords
Robotic device; Motor skill; Motion sensing; Human augmentation; Human-machine mutual actuation

### CCS Concepts
**•Human-centered computing → Human computer interaction (HCI); Interaction devices;**

## INTRODUCTION
Humans have extraordinary abilities for physical motions and dynamic movements. Athletes perform sophisticated motions, utilizing even slight information from sensory organs. Surprisingly, human motor skills can be controlled with millisecond order precision in some situations [6].

Recent improvements in computing powers, sensors, and actuators have allowed humans to perform closed-loop control of robotic systems at a sampling rate exceeding the nature of the human body. Thanks to the advancement of digital fabrication technologies, robotic systems have the feasibility to replace parts of a human's physical abilities and have started to provide physical augmentations not only for coping with disabilities [12, 28].

Technically, robots can perform motor skills that are comparable or superior to those of humans, although this is only in simple tasks or limited environments. However, when a robot needs higher power, its size and weight must be bigger. Therefore, it is almost impossible to keep its mobility; moreover, its costs should also be expensive. Overcoming these limitations, this research challenges to interweave robotic capability with human dynamic motions and offer an intuitive operation.

### Human-machine mutual actuation
*Human actuation* is a concept of using people as substitutions to motors and mechanical components, as proposed in previous research [2, 3, 4]. It is generally applied for large-scale force feedback to the users in immersive experiences. Similar approaches have also been proposed for large-scale objects in the digital fabrication field. In the approaches, humans provide mobility, and active tools perform cutting or additive manufacturing within a short-range [31, 44].

Inspired by previous works, we propose an approach called *Human-machine mutual actuation (HMMA)*, where robots act with human body actuation synchronously. Our key idea is applying the concept of human actuation to the robotics and human augmentation domain; a mobile (wearable) robot with a human body operates in its local coordinate system according to his/her motions that synthesize dynamic motor skills. HMMA couples human body actuation with dynamic motor skills instead of the conventional stand-alone robots. In our approach, a robot for completing a task exploits human actuator output power and synthesizes a motor skill. On the other hand, the human body exploits the robotic capability of performing motions. HMMA comprehensively allows humans to exploit robotic capabilities.

### Throwing motion as a case study
As a case study of HMMA, we propose a system illustrated in Figure 1. The system focuses on throwing motions, particularly throwing underhand, because it is a basic physical skill and requires dynamic movement with muscle force.

*Both authors contributed equally to this research



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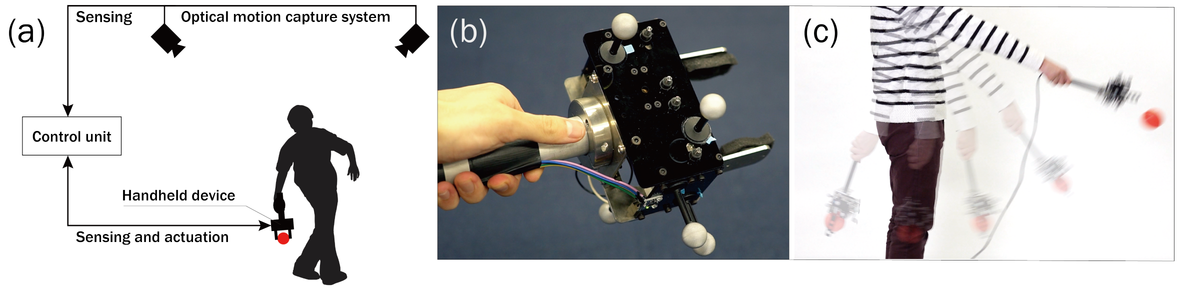


**Figure 1. (a) Framework of a system developed for a case study of HMMA. (b) A handheld device acting as a release controller. (c) The device is controlled by the computational process according to a user's motion.**

With our motivation in coupling robotic capabilities and human abilities, we present HMMA with the system focusing on the motion of throwing, leveraging *human actuation* concept. Our long-term goal is to develop the design guidelines for HMMA systems. This research investigates the feasibility of HMMA and explores how we can design human-machine relationships in the HMMA situation. Our computational processing system for throwing controls release timings according to human motions. It illustrates a concrete example of HMMA, preparing a robotic handheld device that acts as a release controller. We conducted user studies to verify our concept and investigate the users' subjective experiences. We also demonstrated the system at a public exhibition and observed the users' behaviors.

In summary, our contributions are as follows: 1) we propose a concept (human-machine mutual actuation: HMMA) utilizing the human body as an actuator for robotic motor skills, 2) we developed a system that consists of a simple handheld device and the framework tracking and predicting the device motions, 3) we conducted user studies to verify HMMA, revealing several key challenges throughout this research.

## RELATED WORK

This research is related to multiple fields. It mainly contributes to the human augmentation research community with our proposed system utilizing knowledge in the computational tool and device researches.

### Computational tool and device

#### *Handheld device*

Our system refers to previous works about human-machine hybrid systems using wearable devices. A handheld device is easy to install and is a familiar interface to users. For 2D digital fabrication, Rivers et al. proposed a human-machine hybrid approach where a human provides a wide range of mobility, and a tool adjusts the precise position [31]. Yoshida et al. also proposed an approach that utilizes human actuation for architecture-scale 3D printing with a handheld device [44]. Lafreniere et al. proposed a method using crowdsourced power for large-scale fabrication [13]. Yamaoka & Kakehi presented a system that provides the user with an augmented sketching experience by controlling the movements of a pen computationally [41]. FreeD is also a pen-like device to augment freehand sculpting of 3D shapes in a human-in-the-loop manner [47, 48]. These works focus on augmenting creativity with digital technologies. We also developed a similar device for performing dynamic motor skills.

In the areas of Augmented Reality and Virtual Reality, mechanical devices have been used as haptic displays in a human-in-the-loop manner. For example, handheld devices have been proposed for rotor thrust [42] and the gyro effect [5]. These devices are controlled according to human motion, whereas, their goal is to generate haptic sensations in AR or VR environments. Nojima et al. developed a system augmenting interactions connected with the environment via a mechanical device [24]. Referring to these works, we integrated computational fast-loops with slow-loops between human and machine.

#### *Digital technologies for human throwing*

Related with the throwing motion, researchers have applied technologies to sports including the throwing motion. Nitta et al. proposed a ball device that enhances the flying ability with a small quadcopter's thrust [22, 23]. Ohta et al. also developed a ball device that can change its trajectory with the emission of a gas-jet [25]. As another example, there is a moving target approach that allows a users to get a bulls-eye every time [32]. These works focus on applying the computational approaches to each projectile or target.

#### *Robotic exoskeleton and active prostheses*

Robotic exoskeleton is one of the ways of integrating robotic systems with human ability, e.g., by wearing on the hand [1, 43] or arm [8, 10]. These studies focus on rehabilitation or power assistance to increase load-bearing capabilities. As a case using robotic exoskeletons for dynamic motor skills, methods of minimizing human energy cost during walking or running have been proposed [46, 11]. These works deal with performing dynamic motions in lower body movements with robotic systems. In recent years, with the development of digital fabrication technologies, active prosthetic hands have become popular and some of them are available as open sources [12]. Humans have a remarkable ability to use these hands with dexterity, for instance, as shown in Cybathlon [30]. Our concept HMMA might fully exploit the ability of these hands and the abilities of the human body, and assist humans to complete tasks.

### Human augmentation

Human augmentation is an approach to enhancing and empowering human functions with information technologies utilizing robotics and sensing devices.

#### *Robotics*

Robotic systems commonly utilize sensors installed in the environment for a robot's motor skills. Senoo et al. proposed a method for robotic throwing [36, 39] and batting [37, 38] using high-speed cameras installed in the environment. Murakami et al. proposed a ball catching strategy with a robotic hand using high-speed visual feedback [20]. Our basic idea is designing these robotic motor skill techniques with human actuators. In the robotics field, the human-in-the-loop method has been investigated to deal with a dynamic task [27, 40]. Robots in these works are usually fixed to the environment while our scope of this paper is a wearable robot and the interaction between it and the user. Recently, extra robotic limbs have been proposed as approaches to enhance human manipulation ability or assist human works [15, 33, 34, 18]. For example, the Sixth-Finger is an extra-finger enhancing the wearer's manipulation dexterity [28]. Supernumerary Robotic Limbs were proposed for reducing the wearer's workload [26].

#### *Sensing and actuation*

Itoh et al. [9] and Sato et al. [35] developed systems visualizing the projectile trajectory or the landing position in the physical world. These works aim to augment a human's prediction skills and support appropriate responses using visualization of projectile trajectory. Our developed system includes a motion prediction to minimize effects by the system latency. Nishida et al. proposed a wired muscle system accelerating the human catching motion with electrical muscle stimulation [21]. It indicates that its actuation by a computational process can be perceived as a voluntary action. We also aim to evaluate not only the quantitative performances but also the qualitative aspects from the user's feedback.

### Our contribution

Robotic tools have been used as the devices for fabrication and the tools providing haptics in the HCI community. Recently, interactions with robotic devices and augmented bodies have been explored in the human augmentation field. However, we believe there is a frontier integrating the interaction with robotic devices with dynamic motor skills or high-speed movements. Based on the HMMA concept, we explore key elements of the interaction by the developed system. This research offers new insight into human augmentation researches. It also contributes to robotic technology researches, providing a direction for the human-robot interaction.

## SYSTEM DESIGN

### Overview of the system design

In this section, we describe the details of the developed system as a case study of HMMA. Figure 1 (a) shows an overview of the developed system framework. Our system consists of the handheld device holding and releasing an object, and the control architecture tracking the device's motion in real time and controlling the release timing. The handheld device has a gripper for holding and releasing a projectile with computational triggers. The device is tracked by external motion capture cameras. An onboard inertial measurement unit (IMU) sensor on the device consists of an accelerometer sensor and a gyro sensor. While the user is performing the throwing motion, the computation of the projectile trajectory is running based on the device motion in real time. At the timing when the computed trajectory passes through a defined target area, the gripper is opened with the trigger signal, and the projectile is thrown into the air. In other words, the object is not released while doing a motion that misses the target area. In this manner, the system allows the user to throw a projectile toward the defined target.

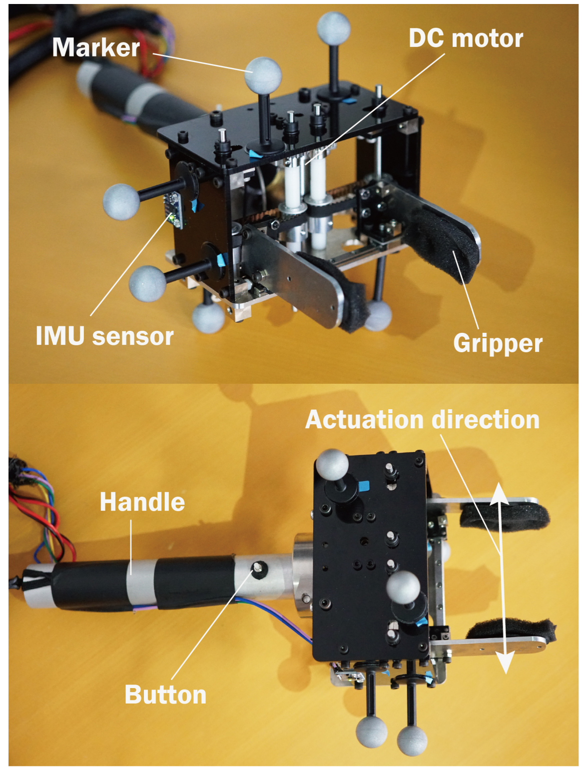


**Figure 2. The developed device employs one actuated degree of freedom (DoF) and acts as a release controller with an external trigger. This device has an onboard IMU sensor, and a button interface is installed to control the gripper's opening and closing manually.**

In the following section, we describe the handheld device and the motion tracking architecture in detail.

### Handheld device

Enabling the system with a human to throw in the arbitrary trajectory by only controlling the release timing according to the user's motion, we designed a robotic handheld device that can hold and release an object with a computational trigger (Figure 2). There were two key design criteria for this device: 1) holding an object without it slipping out, 2) releasing the object quickly from receiving the trigger to minimize the system latency. The device employs a gripper driven by a DC motor via a belt and pulley mechanism. The gripper has one actuated DoF. The gripper opens and closes in parallel and can hold an object by applying a force to both sides of the object.

The motor spec and gear ratio need to be selected carefully. For example, a high gear ratio can provide sufficient torque for holding an object while it usually gets high inertia and friction. The high inertia prevents the gripper from accelerating quickly. We chose a 10 W class coreless DC motor, MAXON DCX series, with a 21:1 ratio. The motor was controlled by the motor driver, ESCON 50/5, from MAXON. To control the force applied to the object, the motor driver controls the current going through the motor. An IMU sensor is installed on the device for using the position tracking described in the following section. The device also employs a button interface on the handle to control the gripper's open and close manually. The onboard IMU sensor and DC motor are connected to the external main controller and power supply by wire.

The total weight of the device is 1.0 kg, and the user grabs the handle and swings it. We attached a soft material to the gripper to adapt to the object to be grasped.

### Control architecture

To release an object at the optimal timing, we must detect the position of the device in real time. Since human throwing motion is a dynamic movement, the precision of the projectile trajectory can be affected by the difference of the release timing in a millisecond order. To this end, we developed a real-time position tracking workflow.

#### *Real-time position tracking*

Figure 3 shows the release control workflow of the developed system. We aim to track the position of the device by combining an external optical motion capture system and the onboard IMU sensor installed on the device. The motion capture can track the registered object accurately and precisely. However, we found that the frame rate was not fast enough for controlling the release timing in the human throwing movement. On the other hand, the onboard sensor can run at a high frame rate, although it is not suitable for estimating the absolute position accurately. Therefore, we designed the tracking workflow so that the current position of the device is estimated by sequentially integrating the data from the onboard sensor base on the position data obtained from the motion capture. We used a Madgwick filter [16] to estimate the orientation of the device from the raw values of the sensor.

The system computes a projectile trajectory in each time step based on the obtained current position data. This workflow includes the latency compensation process described in the following section. If the trajectory passes through the target area within the defined threshold, the trigger signal is sent to the motor driver and the object is released. The trajectory is computed using Newton's second law. We assumed that the force acting on the object was only gravity and the influence of air resistance was negligible.

#### *System architecture*

Figure 4 shows the system architecture. We used MAC3D systems including 8 cameras (Kestral 2200) for the optical motion capture systems, and it was run with a 300 Hz frame rate. For the onboard sensor, MPU 6050 was used, and it includes an acceleration and gyroscope sensor. We selected

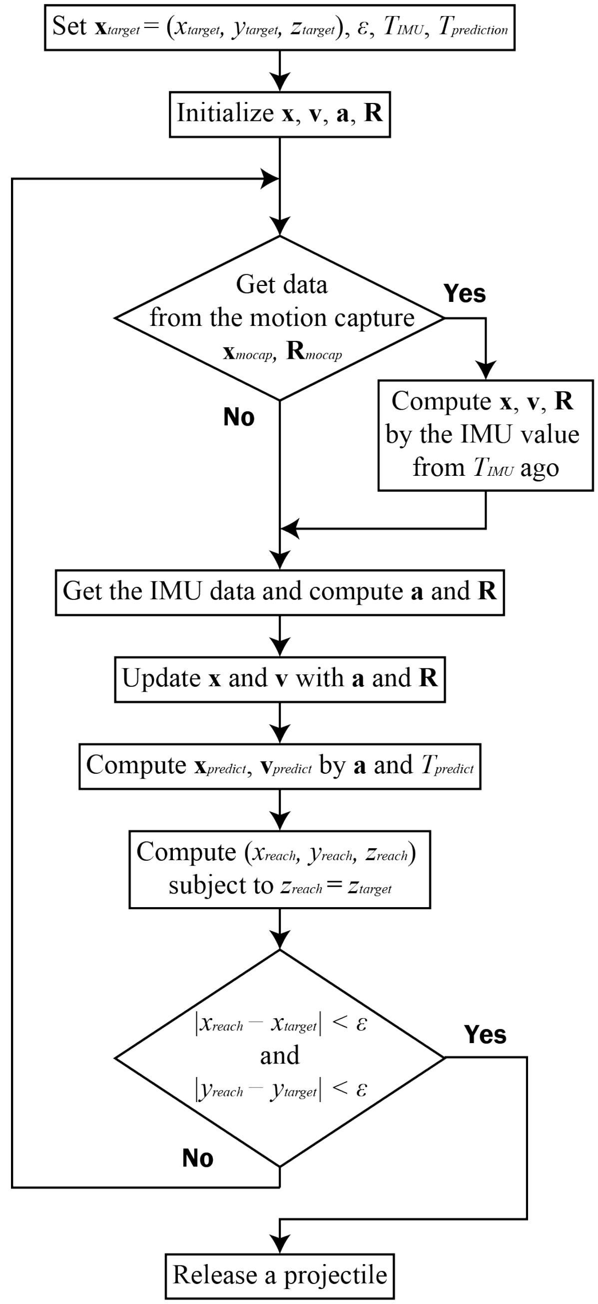


**Figure 3. Release control workflow (the X-Y plane target with the Z-UP world coordinate system example). $\boldsymbol{x}, \boldsymbol{v}, \boldsymbol{a}$, and $\boldsymbol{R}$ are the device's position, velocity, acceleration, and orientation in the world coordinate system respectively.**

the STM32 Nucleo-767ZI board, (which houses a Cortex-M7 clocked at 216 MHz) from STMicroelectronics, as the main controller. The controller and the motion capture system were connected through a Windows 10 PC with Intel Core i9-8950HK 2.90G Hz CPU and an NVIDIA Quadro P2000 GPU.

#### *Latency compensation*

Since human throwing motion is a dynamic movement, the device can move by an amount sufficient for the projectile

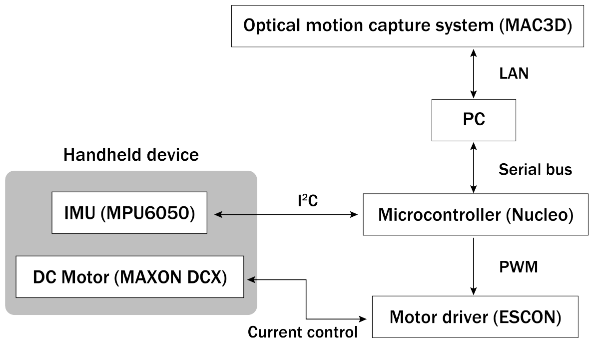


**Figure 4. The schematic diagram of the system architecture**

trajectory to change drastically within the system latency. In a preliminary study, we identified that the discrepancy of the position caused by the latency significantly degrades the system performance. To suppress the effect of the latency, we need to predict the user's motion.

We measured the duration from when the motion capture system acquired the position data of the object held by the gripper until the object was released. We defined this duration as the system latency. This latency was about 40–50 milliseconds with our setup. We concluded that this latency is composed mainly of two factors: 1) the duration required for the communication process between the microcontroller via the PC from the motion capture cameras and 2) the duration from when the trigger is received until the motor is accelerated and the object is released. In our setup, we compensated the device's movement in the former duration using the integrated value of the onboard acceleration sensor. The movement in the latter duration needs to be compensated by predicting future motion that has not yet occurred. We decided to predict the future motion based on the assumption that the user's arm movement can be regarded as constant acceleration motion in a short time. We tuned and determined the ratio of these two factors empirically.

## USER STUDY AND RESULTS

We conducted user studies to validate the feasibility of the proposed HMMA approach and to understand the users' subjective experiences. We evaluated the system by measuring the landing position of the projectile and collecting the users' feedback. First, in the situation where the user was aiming at the target, we compared the case where the user manually controlled the release timing and the case where the system controlled the release. We also analyzed the qualitative aspects based on the user's feedback in this study. In the second study, system performance was investigated in a situation where the user performed throwing without aiming at the target. We also demonstrated the system at an exhibition, observed the users' behaviors, and analyzed the users' feedback and experience.

All experiments complied with the safety standards approved by the Local Ethics Research Committee at the University of Tokyo, Japan. Moreover, all the participants signed a letter of consent after they were provided with an overview of the experiment and instructions. The study protocol was performed in accordance with the ethical standards provided in the Declaration of Helsinki.

### User study 1: With aiming at the target

The goal of this experiment is to evaluate the performance of the developed system in a situation where the user aims at the target, and investigate how the proposed system assists the user's performance. We also aimed at understanding and validating the user experience by analyzing the subjective reports from the users.

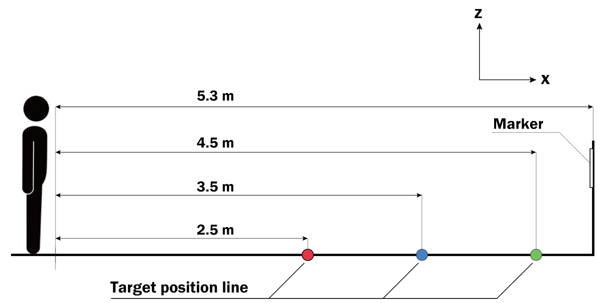


**Figure 5. The experimental setup for the system evaluation: we predefined three targets line depicted as three dots (red:** 2.5 m**, blue:** 3.5 m **and green:** 4.5 m**), and installed a marker for a guide in arm swing.**

#### *Setup*

The experimental setup is shown in Figure 5. The system described in the system design section was installed in an indoor room. We predefined three targets as shown in Figure 5. The threshold on the x-axis was set to 40 mm. In this study, since the accuracy in the y-axis direction was not considered, the threshold on the y-axis was set to 1000 mm. The system was set to select one of these targets for each trial in a randomized order. The projectile was a sphere ball with retro-reflective markers for the motion capture weighing about 170 g and about 68 mm in diameter.

The system has two modes: 1) auto mode and 2) manual mode. In the auto mode, the projectile was released automatically with the computational control according to the user's motion. In the manual mode, the projectile was released by pushing the device's button. In this study, we aim to investigate not only the performance but also the effect of adjusting the release timing by the system on the user experience. To this end, we asked the user to push the button in both modes and investigated how much the user could recognize the intervention of the computational process. In this study, 1) the release was executed after the computed optimal time if the user pushed a button in the auto mode, and 2) the release was executed after a fixed time if the user pushed a button in the manual mode. We introduced this fixed time aiming to make the conditions closer in the auto and manual modes. We set this time to 75 ms empirically and concluded that this delay was short enough such that the users were unaware of it and that it would not affect their sense and performance. In addition, we designed the system to not execute the release if the button was pushed at a timing when the projectile did not reach 1.5 m in the computation, or the button was pushed at a timing later than the computed optimal timing. In other words, it was designed not to be released if the button was pushed too early or too late during motion in both modes. This was designed to prevent the user from recognizing the current mode of the system due to a mistaken button push.

### *Participants*

We recruited nine participants (6 male, 3 female, *mean*=20.9 years old, *SD*=2.0). There were eight right-handed participants and one left-handed participant. No participants had any physical disability.

### *Procedure*

Before the experiment, we set up a training session to help participants become familiar with the system. The participants were asked to operate the device with their dominant hand. First, the experimenter demonstrated how to use the system and swing the arm. The participants were instructed to remain standing and to swing their arm holding the device without bending their elbow. Second, the participant swung the device repeatedly without setting the projectile in the gripper until the gripper was open in the auto mode. At this time, a marker position depicted in Figure 5 was set as the target. Finally, the participants actually performed throwing with the device five times each in the auto and manual modes. To ensure that the projectile obtained sufficient kinetic energy, the participants were instructed to follow through with the swing. In this actual throwing step, the target was selected in a randomized order. At these trials, participants were informed in which mode (auto mode or manual mode) the system was running.

We defined that one throwing action was one trial, and a set of 18 trials was one set. The participants performed three sets in manual mode and three sets in auto mode in a randomized order. For each trial, the participants were assigned one of three targets and instructed to aim at the target. In all trials, the participants were instructed to push the button aiming at the assigned target, whether in the auto or manual mode. The participants were instructed to push the device's button to release the projectile in all trials but they were not informed whether the current system was in the auto or manual mode. The landing position of the projectile was measured for each trial. To alleviate fatigue, the participants were allowed to take a break between each set. After each set, the participants were asked if they were able to recognize the mode in which the system was running in the final set. After all sets, we interviewed the participants about the experience.

## Results of User study 1

We collected 486 trials in each auto mode and manual mode from User study 1. The collected data are labeled into three types according to the assigned target. Figure 6 and Table 1 depict the collected results in User study 1. There are three peaks in the histograms of the trials in the auto mode (Figure 6 (a). The statistical significance $\alpha$ was determined at a two-sided p-value of $\leq 0.05$. The distances were significantly different according to the assigned target on both modes (Kruskal–Wallis test, $p < 0.01$). Significant differences are found in all combination of targets ($p < 0.001$) except between 3.5 and 4.5 m targets in manual mode ($p = 0.076$). We found that the system performs throwing selectively according to the assigned target. Compared with the auto mode result, the manual mode result has a larger variance, as shown in Figure 6 (b). The

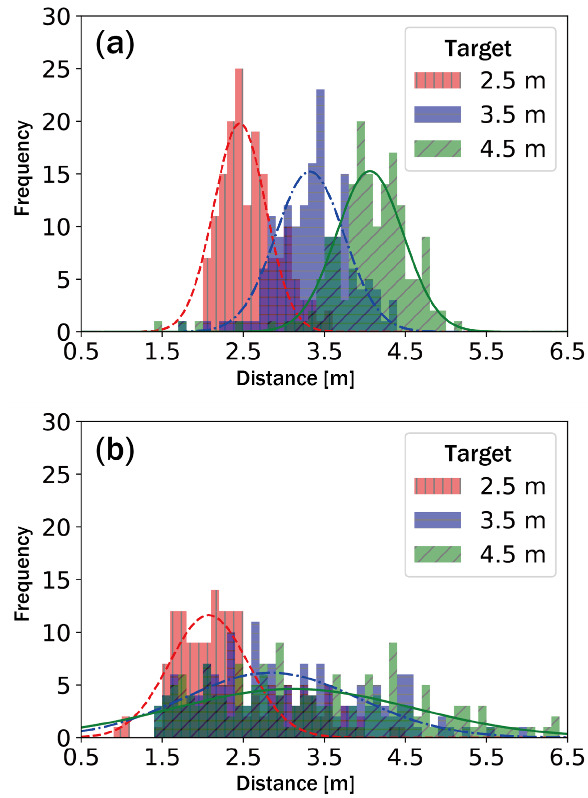


**Figure 6. Histogram and fitted Gaussian curves of the projectile landing position under conditions where the experiment participants aimed at the target (a) in the auto mode and (b) in the manual mode.**

difference in variance between the auto and manual modes was analyzed. The variances were lower with the auto mode than with the manual mode in all combinations of participants and targets. A significant difference in the variance between the auto and manual modes was found (Wilcoxon signed-rank test, $p < 0.001$). Although this result is not surprising given the fact that, in the manual mode, the users must perform all operations manually with the novel system. It indicates that the users may get used to the system immediately, and our method may assist the user's manual operation.

In addition, we observed that the projectile tends to land on the near side of the target positions. We concluded that one of the reasons for this can be errors of the model adopted in our system and hyperparameters in the prediction process. The results also indicate that the variance increases as the distance to the target increases. The cause for this is the fact that the influence of the initial state deviation increased in addition to the above errors due to the longer flight duration. As Table 1 shows, the variances of the results for each participant tends to be smaller than that from the total trials of all participants. We observe that the total variance becomes larger due to the differences among the means of each participant's result. It can be caused by the fact that the system developed in this paper was not optimized for each participant. We have identified that by introducing a calibration process for each individual,

| *ID* | *Mode* | *2.5 m* | *3.5 m* | *4.5 m* |
|---|---|---|---|---|
| 1 | A | $2.25 \pm 0.12$ | $2.89 \pm 0.15$ | $3.48 \pm 0.45$ |
| | M | $2.20 \pm 0.97$ | $3.55 \pm 1.23$ | $3.13 \pm 1.15$ |
| 2 | A | $2.46 \pm 0.18$ | $3.33 \pm 0.45$ | $3.96 \pm 0.58$ |
| | M | $2.40 \pm 0.65$ | $3.11 \pm 0.78$ | $3.79 \pm 1.25$ |
| 3 | A | $2.65 \pm 0.32$ | $3.55 \pm 0.36$ | $4.20 \pm 0.38$ |
| | M | $2.83 \pm 0.70$ | $3.22 \pm 0.70$ | $4.33 \pm 1.37$ |
| 4 | A | $2.41 \pm 0.18$ | $3.12 \pm 0.21$ | $3.86 \pm 0.34$ |
| | M | $2.69 \pm 0.91$ | $2.98 \pm 1.15$ | $3.19 \pm 1.23$ |
| 5 | A | $3.68 \pm 0.42$ | $3.35 \pm 0.54$ | $4.32 \pm 0.28$ |
| | M | $2.54 \pm 0.68$ | $3.15 \pm 0.76$ | $4.11 \pm 0.89$ |
| 6 | A | $2.70 \pm 0.40$ | $3.51 \pm 0.59$ | $4.02 \pm 0.94$ |
| | M | $2.30 \pm 0.53$ | $3.46 \pm 1.32$ | $3.27 \pm 1.56$ |
| 7 | A | $2.52 \pm 0.18$ | $3.44 \pm 0.16$ | $4.07 \pm 0.14$ |
| | M | $1.86 \pm 0.29$ | $2.13 \pm 0.80$ | $2.24 \pm 0.87$ |
| 8 | A | $2.97 \pm 0.38$ | $3.65 \pm 0.33$ | $4.38 \pm 0.26$ |
| | M | $2.26 \pm 0.42$ | $2.68 \pm 0.65$ | $3.01 \pm 1.03$ |
| 9 | A | $2.67 \pm 0.24$ | $3.46 \pm 0.47$ | $4.12 \pm 0.50$ |
| | M | $2.23 \pm 0.28$ | $3.09 \pm 0.53$ | $3.41 \pm 0.84$ |
| All | A | $2.59 \pm 0.34$ | $3.37 \pm 0.44$ | $4.05 \pm 0.53$ |
| | M | $2.38 \pm 0.69$ | $3.04 \pm 0.98$ | $3.39 \pm 1.27$ |

**Table 1. Means and standard deviations of the results in each participant and the total result of all participants in User study 1 (in the condition where the participants were aiming at the assigned target). A: auto mode, M: manual mode.**

this bias can be reduced, and the system performance can be improved.

### *Qualitative findings*

We describe the qualitative results based on the interview and the user's feedback, in User study 1. First, we asked the participants if they were able to recognize the mode (auto or manual mode) in which the system was running in each set. In most cases, the participants were aware of which mode the system was running in. We found that the users were able to judge the mode from the results of throwing. On the other hand, they could not judge from the release timing difference. For example, in the interview, User 6 reported, *"I thought it would be computer-controlled if the accuracy was good."* However, interestingly, there was a case where the user incorrectly answered the question about the mode. User 4 reported, *"I can't recognize it in the first set, but when I did the second set, it was clearly less accurate than the first set. So I thought the current mode was manual and the first set was in the auto mode."* This suggests that the user cannot perceive the computational process intervention on each trial alone. In other words, we found that the system can create a situation where the operation is performed by a computer process even though the users think that they are performing by themselves. In addition, unexpectedly, there was a trial where a user aimed at a position different from the assigned target. In the interview, User 3 reported, *"I tried to throw it to the target behind by mistake, but it was controlled and fell on the target in front! Amazing."* From this example, we found that the system might correct human errors.

## User study 2: Without aiming at the target

The goal of this study is to evaluate the feasibility of the developed system in a situation where the user does not aim at the target.

### *Setup*

The study setup is the same as User study 1. The system was executed in the auto mode in all trials.

### *Participants*

We recruited seven participants (7 male, *mean*=24.1 years old, *SD*=1.1). There were six right-handed participants and one left-handed participant. All participants did not have a physical disability.

### *Procedure*

The participants were instructed to operate the device as in User study 1. Each participant performed 3 sets, with 18 throwing actions as one set. To ensure that the projectile gets sufficient kinetic energy, the participants were instructed to swing their arm aiming toward a marker depicted in Figure 5 in all trials. The participants were not informed of the target position of the system aiming for each trial. As in User study 1, the projectile's landing position was measured, and the participants were allowed to take a break between each set.

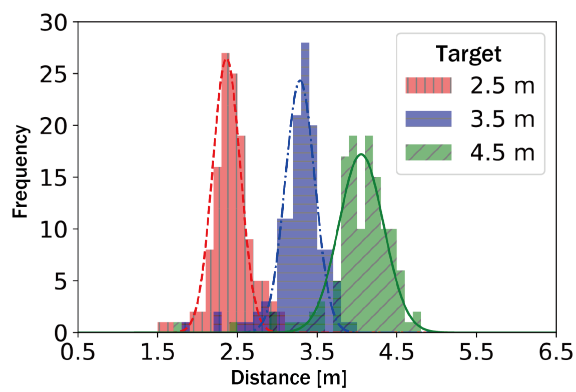


**Figure 7. Histogram and fitted Gaussian curves of the projectile landing position under the auto mode condition where the experiment participants did not aim at the target.**

## Results of User study 2

We collected 378 trials and labeled them into three types according to the assigned target. Figure 7 depicts the collected results in User study 2. There are three peaks similar to the result of the auto mode in User study 1. Significant differences are found in all combinations of targets ($p < 0.001$) with Steel–Dwass test. The results suggest that the system can perform throwing even if the user does not pay attention to the target or is in a blind condition. We observe a difference between the two results in auto mode. Unexpectedly, the group where the users did not aim at the target threw more precisely. This is probably because the constant acceleration model used in

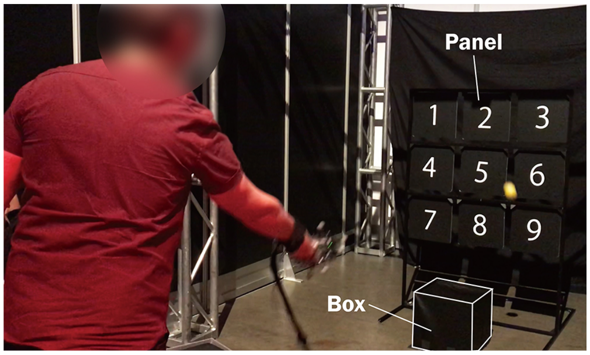


**Figure 8. Snapshot of the demonstration at an public exhibition. Two types of targets were installed (a box and nine numbers panels).**

this setup is better suited to swing aiming toward the far side of the target.

In the current system, the computed projectile trajectory and the actual trajectory do not match in the order of a centimeter accuracy. This can be caused by various factors such as measurement error, unexpected user movement, variations of the contact condition between the projectile and the gripper, and so on. For example, the system adopted a dynamic model where air resistance is ignored. Therefore, depending on the shape of an object and the flight duration, it will deviate significantly from the computed trajectory. It will be possible to improve accuracy by updating the current model to more detailed models with an object's physical properties.

### Demonstration at a public exhibition

For an informal validation study, we demonstrated the developed system at a public exhibition [17] to observe the users' behavior and obtain feedback.

As shown in Figure 8, two types of targets were set. All participants were given a brief overview of the system and were instructed on how to use the device. The participants were also instructed to hold the device with their dominant hand and to swing their arms like throwing underhand. In all trials, the system was executed in auto mode. The object to be thrown was a sphere ball with a diameter of about 65 mm and a weight of about 130 g. The target was chosen by the participant for each throwing, and they were allowed to interact with the system for as long as they liked. After the experience, with the consent of the participant, the following questionnaire in a 7-item Likert scale (from 1: "strongly disagree" to 7: "strongly agree"): Q1) I felt throwing ball with the handheld device was fun. Q2) I felt accomplishment by throwing the ball using the handheld device.

#### *Findings from the demonstration*

One-hundred thirty participants aged from under 20 to over 60 years completed the questionnaire. Most participants gave positive answers to the questions (*mean*=6.02, *SD*=1.24 for Q1, *mean*=5.58, *SD*=1.34 for Q2). Some participants reported that they felt as if they controlled the release timing while the system was run in auto mode. This fact indicates that the system can not only perform dynamic motor skills but can also enhance the subjective experience with the HMMA approach.

#### *Lessons learned*

When the user swung the device very quickly, we sometimes observed a case when the projectile was not released. We found that this could be caused by a spatial resolution of the trajectory step size. In the implemented system, the computed projectile trajectories were discretized with the sampling rate. When the device moves faster, the spatial step size between the trajectories become larger. As a result, the trajectory can jump over the target area in one timestep. To address this issue, we could enlarge the threshold; however, it has a trade-off for system accuracy. In other words, a significantly small threshold can cause the rare release while the system accuracy can be lower with a larger threshold. We consider that employing a higher sampling rate or a dynamic tunable threshold according to the step size will be a useful approach for this issue.

We observed several cases where the ball fell before the target at the early stage of the user's experience. We found that one reason for this can be that the kinetic energy of the users' motion was overestimated by the prediction process even though it did not have enough energy to obtain the desired flight distance. However, the number of such cases decreased after several trials, suggesting the possibility that the user can adapt to the system in a short time.

## DISCUSSION AND LIMITATION

Throughout the results, we revealed three key challenges to be tackled for designing HMMA systems.

First, we must consider how the HMMA system suppresses disturbances on computational processing caused by unintentional human motion (errors). For example, the developed device employs a gripper that moves only laterally in the local coordinate. When the user performed an arm-twisting motion to throw, we found that the gripper affected the behavior of the object being thrown out. This is because the object remains in contact with the gripper, although the system has released the object. The users can unintentionally disturb the system performance, even if the users recognize this phenomenon. For dealing with such human disturbance, active stabilization techniques will be effective (e.g., gimbal mehcanisms [29]).

Second, the HMMA system needs to particularly construct a model of each user's individual motions with an appropriate latency setting, which is the key element improving the system performance. With the current system, we struggled to suppress the effect of system latency. Through developing the system, we identified that humans can accurately perform their dynamic motor skills with their self-motion prediction models as much as possible. Therefore, a user-specific calibration will be highly required, utilizing advanced motion prediction models or machine learning-based techniques as [7, 19].

Third, we need to develop a method of inducing humans to move "correctly" as defined by the HMMA system. Our observations suggest that a user's undesired behaviors might lead to a significant decrease in system performance. We consider that one way to address this issue can be to design an incentive that occurs in the user experience. Our results indicate that the user's performance can be controlled without losing his/her sense of control. This suggests that a system (designed appropriately) can provide a sense of achievement or motivation to the users and induce them into doing desired behaviors defined by the system.

In this research, we developed a prototype system to perform throwing based on the HMMA concept. Through the development and user studies using the system, we have obtained some findings about interactions and challenges to address. Our research complements the findings for the interaction in human augmentation researches utilizing robotics techniques, which mainly have focused on static situations [28, 33]. We found that our proposed approach can also contribute to the robotics domain by compensating for the disadvantages of robots using human actuation. For example, object grasping is one of the challenging issues in robotics [14, 45] whereas, humans can recognize and grasp unfamiliar objects without prior knowledge. We observed that the users did not struggle to grab objects using the developed device. On the other hand, a robotic hand could manipulate objects that are dangerous for a human hand to touch directly.

## FUTURE WORK

Although we only focus on the throwing skill in this study, our idea can be applied to other motor skills, such as catching and kicking motions, and to using static tools as well. Furthermore, the idea will be expanded to situations that require more power and force by using multi-human actuation. Inducing multiple people's movements cooperatively will offer a new challenge.

Application to the robotic prosthesis will be one of the promising avenues. The experimental results indicate the possibility that the motor skill performance can be assisted via our proposed approach without losing the sense that the users are controlling the robotic hand themselves. By installing a computational environment, our approach can be used to augment the existing robotic limbs and provide an enhanced user experience.

## CONCLUSION

We proposed a new concept, HMMA coupling human actuation with robotic capability. Concretely, we investigated the feasibility of our concept and designing of particular interaction settings. Particularly focusing on the throwing underhand motion as a case study, we proposed a method to control the release timing in throwing using the computational process according to human motion. The developed system consists of a robotic handheld device that acts as a release controller and the control architecture to perform throwing. The handheld device has one actuated DoF and its gripper is controlled based on the computational process. The device position is tracked and estimated with the combination of the data from the motion capture system and the onboard IMU sensor. To validate the feasibility of the proposed concept and clarify the issues to be tackled, we conducted user studies. We found that the proposed system successfully performs throwing according to the assigned target with exploiting human ability. The results suggest that, in our approach, the robotic capability can be embedded into the user's motion without losing a sense of control. We hope that our work will lead to additional investigation for the human-robot hybrid system including overcoming disabilities and human physical augmentation.

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