Deeper Insight Into Personal Running Pattern With The Assist Of Drones Through Artistic Representation

PENGPENG XU, University of Twente, The Netherlands

This paper explores the possibility of using drones to create visual feedback to help runners understand their running patterns better. Specifically, this paper presents a study modelled on top of our novel yet technical design and concludes with a functioning lo-fi prototype.

Using IMU which was onboarded on Crazyflie, measurement of human motion was done in this study. Following the data collection, motion design was completed employing Laban Motion Analysis before moving on to the final part of the study. In this part, the focus is on utilising drone motions to create artistic representations of runners' running patterns.

Evaluated on Technology Acceptance Model questionnaires collected from 6 runners. The outcome of this study measures the drone's efficiency and usefulness in helping runners gain insight into their running patterns.

Collaborators:
Reidsma, Dennis (Study Supervisor)
Balasubramaniam, Aswin (Technical and Design Advisor)

Additional Key Words and Phrases: Expressive Drones, Runner, Insight, Running pattern, Artistic representation

1 INTRODUCTION

Unmanned Aerial Vehicles (UAVs), commonly referred to as "drones," are versatile tools with a vast potential across civilian applications. Over recent decades, drone technology has revolutionized various industries, including aerial photography, agriculture [9], surveillance [6], and delivery services [1]. In the world of robotic development, drones have emerged as a new trend, indicating a promising future in Human-Robotic Interaction.

Similar to other robotic devices, drones can also be expressive in their interaction with humans. As stated by Cui et al. [4], expressive drones can indeed be created by employing Laban Motion Analysis which particularly focuses on the connection between human motion and its corresponding drone motion. Taken a step further, pioneers Sharma et al. [10] and Eriksson et al. [5] further enhance the adoption and uptake of the Laban Effort System. Their efforts contributed to revealing an opportunity – a drone that is capable of meaningfully expressing human emotions while flying.

Meanwhile, observed by Van Rheden et al. [13], running has witnessed a surge in popularity over recent decades, becoming one of the most widely practised forms of exercise worldwide. Moreover, being more than a sole exercise, running also forms the basis of many well-known sports events such as marathons. Having witnessed the competitive transformation of running, young athletes who strive to continually refine their running techniques are now in need of a new way of training - A way that should not only make running engaging for the runners but also motivate runners to actively participate in the run.

Interestingly, as proven by Balasubramaniam et al. [2], a well-designed drone can also be utilized as a potential running companion. Moreover, as demonstrated by Mueller and Muirhead [8] and Graether and Mueller [7], the utilization of drones in running certainly enables efficient communication between the runner and the drone through immediate feedback. By incorporating LED lights and dynamic mid-air movements, the feedback can also be upgraded to hold personal significance for the runner. Alternatively, grounded on the discovery provided by Cui et al. [4], the insights provided by Eriksson et al. [5] and Sharma et al. [10] align closely with the objectives of this study, showcasing the potential of drone technologies in enhancing user experiences and prompting deeper self-reflection and optimization of actions. In essence, just as the dancers adjusted their movements in response to drones[5]. In this study, we aim to empower individual runners to re-calibrate their running patterns through the interpretation of meaningful artistic drone representations.

Fig. 1. Expected Application of the Research.

1.1 Objective and goals

This study prioritises using Crazyflie drones [1] and the involvement of 5 runners as bridges to understanding runners' behaviour, while 6 other runners served as prototype testers. Based on different tasks, the study is divided into two different objectives.

The first objective of this study is to understand the runners' behaviour. The objective is composed of two parts. The first part is to investigate the runners' running habits and observations of drone presence during running activities. This process is done by conducting individual interviews with runners from different experience groups. The second part is carried out through numerous raw body-motion data collection using the installed IMUs on the human body.

Following the first objective, the second objective is to adapt drone motion based on human motion. This objective consists of two

[1](More information on https://www.bitcraze.io/)

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parts: Firstly, investigate methods which convert raw data collected in the first objective into meaningful information such as drone motion, etc. Secondly, to develop an interactive prototype using two Crazyflie systems (figure 8) and methods concluded from the previous step. One drone would be used as an IMU to track motion. The second drone will then adapt the recorded movements and illuminate accordingly, creating a synchronized motion and light display based on the captured human body movements.

Based on the objectives stated above, the final goal of the study is to conclude with a Human-Drone-Interaction prototype composed of two Crazyflie drones. The drone can transform the running pattern generated by the runner into meaningful artistic representation feedback. Upon observing the artistic representation, the runner should be able to quickly interpret the feedback and adapt their running patterns into a more optimized form.

1.2 Research Question

To achieve the objectives above, the following research questions require an answer: “How can we make an expressive drone system which provides intuitive feedback for the runner to understand their running patterns?".

In addition to the main research question, we also conclude several sub-research questions:

- Which variable provides the most information on the runner during running?
- Where to install the IMU drone to get the best reading?
- What are easy-to-understand artistic representations of different running patterns?
- What are the benefits that people expect from this artistic representation drone?

2 RELATED WORK

Our work is related to 1) technology-driven training, and 2) Human-Drone-Interaction Experience in Running.

2.1 Technology-Driven Training

Cesarini et al. [3] utilizes different sonification methods to assist in the refining of swimming techniques for swimmers. Similarly, the integration of drone technology across different activities has also resulted in enhanced performance and introspection for individuals engaging in physical exercise. Using the same sonification technique, Stienstra et al. [11] designed and developed a system that provides feedback on the technique of a professional speed-skater. This is done by visually mapping their skating skills to make the skater more aware of their form.

2.2 Human-Drone-Interaction Experienced in Running

Treurniet et al. [12] suggested numerous uses of expressive drones, specifically referring to emotional interaction between drones and humans. Such a study mentions potential bonds between the runner and the drone through effective communication during the run. Moreover, as proven in the previous section, smart interaction such as visual mapping can provide additional insight to athletes. Similarly, through the help of drones, the runner can visualize the running pattern objectively and directly through a series of mimicking movements expressed by the drone.

Referencing the study conducted by Eriksson et al. [5] regarding drones associated with performers on stage, dancers must adjust and refine their movements in response to drone cues. As highlighted by Balasubramaniam et al. [2] and reinforced in their related work of utilizing drones in detecting runners’ running pace, drones create a symbiotic relationship - A rhythm connecting the movements of a dancer’s body with the movements of a drone. Correspondingly, the dancers gain deeper insights into the performance. A similar symbiotic relationship could be represented in this study with the runner-drone interaction. This interaction helps runners gain awareness of their running patterns, subsequently aiding in improving their exercise routines and overall health by addressing nuances that may not be readily perceptible without technological assistance.

3 FROM HUMAN MOTION TO DRONE MOTION

In this section, we will provide a more detailed explanation of how human motion is translated to drone motion. This includes steps to collect, analyse, transform and convert motion from human to drone basis.

3.1 Human Motion Detection

Based on observation of runners’ lower-body motion during this study, human running gait is interpreted as two separate phrases in terms of calf swings: calf fully stretched, and calf full contraction. Each swing is composed of these two actions, which is also known as one stride. To accurately capture these aspects of human motion, the first step is to strategically place the IMU drone, the second step is to locate methods to capture human motions.

IMU drone positioning. IMU reading can vary in accuracy depending on where they are placed on the body. Insights from an online blog written by Ben Horsley [2] and experiments conducted by Watanabe et al. [15] emphasize the significance of human body parts such as feet, calf, thigh and hip during running. In particular, a technique referred to as "stride control" quantifies the leg swinging frequency and force exerted by runners during leg swings. Under inspiration from this technique, the "stride control" and the stride length of the runner are measured by attaching an IMU to the side of the calf.

Due to constraints related to the drone’s size and limited research time, as well as to mitigate potential issues arising from the drone’s physical structure, that could adversely affect the running experience. We chose to position the IMU drone on the outer side of the left calf. In this way, the weight of the drone can be ignored by the runner during running, and the physical frame of the drone will not easily collide with objects in the environment.

Variable Selection. The use of the stabilizer module onboard Crazyflie provided us with various choices in terms of variables which can be used to measure human running motion, running direction, including "pitch", "roll", "yaw", (figure 2).

[2](Article can be found in https://insidethenumbers.netlify.app/post/imu-placement/)

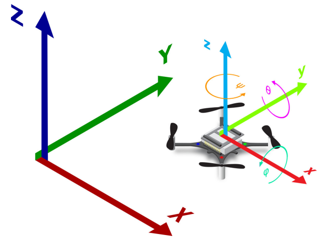

Fig. 2. Crazyflie sense of direction

We aim to align the onboard IMU with the level of the calf hence using either the stabilizer variable "pitch" or "yaw". To find out the best variable that can accurately track human motion, we ran 6 strides in a window of 200 seconds and collected the generated data.

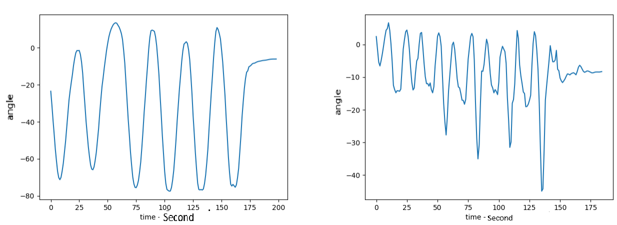

Fig. 3.
(Left): Result generated by "Yaw" Variable
(Right): Result generated by "Pitch" variable

As shown in both graphs (figure 3), there are multiple peaks with negative angles. This can be explained by the fact that human calves need to naturally stretch outwards during running. Thus, each negative peak indicates the completion of a stride.

Under comparison, pitch-generated data contains a large amount of noise peaks. While the yaw-generated data contains highly visible stride patterns with relatively less amount of noise. Thus, yaw rotation is the most suitable variable for revealing the angle at which human runners' calves rotate.

With certain angles set as thresholds, activation signals are released to indicate the completion of a counted stride. Consequently, such measurement also allows us to accurately track down the time interval between continuous strides. This not only pinpoints the striding frequency of the runner but also reflects the running pace of the runner.

3.2 Motion Design Based on Laban Motion Analysis

During this study, our drone motion design incorporates Laban Motion Analysis. As stated by von Laban [14], "Laban's complete framework, **Laban Motion Analysis (LMA)**", is a method for observing, describing, visualizing and notating human motions. This theory covers four different movement parameters - body, shape, space and effort. During this study, we adapt the **Laban Effort System(LES)** to the drone motion design during running, as it reflects a deeper insight into how the pattern of the target runner is constituted.

The Laban Effort System uses four parameters – Space, Weight, Time and Flow, to describe motion generated by the drone in a relatively closed space. Where each parameter can be two values. During this study, only three out of these four parameters are adapted in various contexts to describe the drone motion when representing the runner's movement.

Space: constituted of either "indirect" or "direct", defines the movement of the drone in the space. "Indirect" resembles a relatively relaxed drone motion with a larger swinging angle. While "direct" refers to a straightforward and aggressive drone motion with a smaller swinging angle.

Weight: defines the different impacts on drone body weight during a motion. This component is built on top of two extremes, "strong" and "light". Specifically, "strong" refers to a fast, forceful and powerful drone motion. While "light" explains the slow, relaxed drone motion that resembles the calm state of the runner.

Time: relates to the drone speed during the execution of motions. In terms of this study, two extreme cases are defined: "quick/sudden" which instructs the target drone with a fast, urgent movement in the least amount of time, and "sustained", which constitutes the opposite of the factor "quick/sudden", represents a slower-speed and relaxed motion.

With a clear understanding of LES parameters used during this study, here we visualize our design to transform human lower-body motions into drone motions. Based on the frequency of human strides, our motion design is divided into three different patterns:

Fast motion can be visualized by blinking Green LED and a set of "Direct", "Strong" and "Sudden" drone motions;

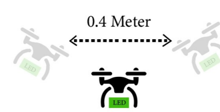

Fig. 4. "Direct", "Strong", "Sudden"

Moderate motion can be displayed by a blinking Yellow LED and a set of "Direct", "Strong" and "Sustain" drone motions.

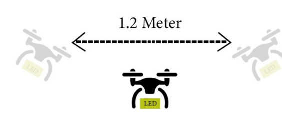

Fig. 5. "Direct", "Strong", "Sustain"

Slow motion can be showcased by a blinking Red LED and a set of "Direct", "Light" and "Sustain" drone motions.

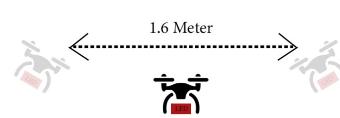

Fig. 6. "Direct", "Light", "Sustain"

3.3 "Talking" Drones

During this study, two Crazyflie drones(figure 8) were used: the wingless drone is used as an IMU sensor to detect calf movement and the airborne drone is used to mimic these movements based on the sensor's readings.

Communication between Crazyflie drones is achieved wirelessly through a designated radio firmware known as CrazyRadio[3]. But to maintain the communication between several Crazyflie drones, CrazyRadio would also require a base station. This base station can be implemented on any device using Crazyflie Python API while pairing with a CrazyRadio 2.0 dongle [4]. However, to ensure the mobility of this study, we chose a laptop running Windows 11 to serve as the base station. Additionally, to distinguish these two Crazyflie drones during communication, each Crazyflie drone was assigned a unique radio address and operated on a distinct radio channel with a transmission rate of 2 MB/s.

Upon establishing a connection from the base station to each Crazyflie drone, the base station will first request the sensor drone to pass the latest collected raw data. When the base station fully receives the raw data, it proceeds to analyse the data, and then process it into the corresponding set of drone motion controls using Crazyflie "MotionCommander"[5]. After transmitting the set of drone motion controls over to the airborne drone using CrazyRadio, the airborne drone is then directed to execute a series of drone motions. Sequentially, the runner should attempt to adjust their running pace based on the observed drone motions. Meanwhile, the sensor drone equipped by the runner collects the new measurement and sends it back to the base station to repeat the same procedure.(figure 7).

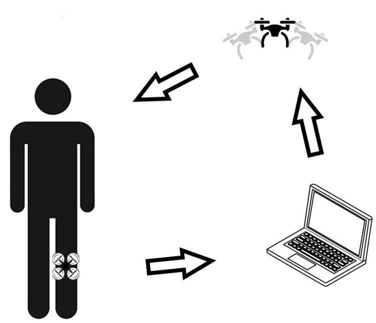

Fig. 7. Drone Wireless Communication

4 STUDY

To learn about runners' running technique and their thoughts on using drones to understand the human running pace, and to refine our motion design, we conducted several individual interviews and prototype tests. In the following subsections, we described the involved participant pool, the study design, the procedures and measurements followed throughout the study, and the data analysis conducted to evaluate the study outcomes.

[3](More information on https://github.com/bitcraze/crazyradio-firmware)
[4](CrazyRadio 2.0 dongle detailed in https://www.bitcraze.io/products/crazyradio-2-0/)
[5](Crazyflie API MotionCommander https://www.bitcraze.io/documentation/repository/crazyflie-lib-python/master/user-guides/sbs_motion_commander/)

4.1 Participant Pool

This study is composed of individual interviews with 5 (3 males, 2 females) participants and a prototype testing with 6(5 male and 1 female) participants, which added up to a total of 11 participants. All 11 participants in the study have identical ages in the range between 20 - 30 (Mean = 24.09; median = 24; std. dev. = 3.0), with different years of running experience (1-10 years, mean = 6.2 years). Specifically, 2 male and 1 female participant are experienced runners; 3 male and 1 female participant are intermediate runners; The other 3 male participants, and 1 female participant are beginners in running. All runners involved in the study ran outdoors 2-4 times every week with each run covering 5 - 8 km (Mean = 6.54 km; median = 6.75 km; std. dev. = 1.107). Experienced participants prefer to run outdoors, but beginners and intermediate participants tend to run indoors at a gym. The participants were recruited from local channels around the university and were compensated with snacks and water for their involvement in the study. Before the study, the participants had never used or operated a drone.

4.2 Study design

To fully answer our main research question, "How can we make an expressive drone system that provides intuitive feedback for the runners to understand their running patterns?", we split our study into two main activities: individual interviews and prototype testings.

In this study, individual interviews usually take place indoors in isolated meeting rooms of the Interaction Lab at the University, to use Crazyflie drone for visualising scenarios of running with drone presence. Moreover, to ensure a comfortable interview for the interviewee and a clear understanding of their valuable insights from various aspects, each interview is designed to last 1 hour or less. The conversation between the researcher and the interviewee is also relaxed and slow with short and simple but carefully clarified interview questions.

Similarly, prototype testing in this study also takes place indoors in meeting rooms of the Interaction Lab at the University, to prevent unexpected drone crashes caused by the outdoor environment. During each prototype test, two Crazyflie 2.0 drones are used, this includes a reaction drone and a sensor drone (Figure 8). To recreate the training environment for the runners, the participant equipped with a sensor drone is offered to run beside the reaction drone either with or without a treadmill.

To prevent damage from accidental crashes caused by drone malfunctions in the motors or propellers, the flight altitude is constantly maintained around 0.4 meters above the ground. Additionally, the reaction drone is also programmed with obstacle avoidance capabilities within a 0.5-meter range. In the event of an emergency or unforeseen collision, the user can hover their hand over the top of the drone, which will force it to land immediately. To ensure the safety of the participants in the experiment, the reaction drone is kept at least one meter away from the runner and the observer.

4.3 Procedure and Measurements

During the study, two main activities required the participation of human subjects – an individual interview and a prototype test.

Fig. 8. Reaction Drone(Left), Sensor Drone(Right)

Before the start of each activity, the participating runners were asked to sign a consent form and were briefed about the activity's objectives in the corresponding context.

Individual Interview: To avoid biases and potential misconceptions from group discussion, the interviews were conducted personally and sessions were separated. The interviewees were informed about the potential risks in the process, such as privacy leaks, and provided a clear explanation of the procedure for collecting personal information. Which can be rejected based on the interviewee's willingness. The interview occurred in separate sessions among 5 different interviewees, and they were grouped based on running experiences.

During the interviews, the interviewees were presented with different running scenarios, both with or without the involvement of drones. They were allowed to personally simulate these scenarios for a few minutes. Subsequently, interviewees were instructed to answer four different questions immersed in no-drone-presence running scenarios and another four different questions immersed in running scenarios with drone presences. By the end of the question discussion, the interviewees were also introduced to two unidentified drone motions that simulate the asynchronous running patterns. They were instructed to interpret the meaning behind the motion and explain how the representation related to the referred human body movement.

It is worth noting that responses gathered from individual interviews were influenced by the interviewee's personal running experience. This approach aimed to fulfil the first objective - to understand a runner's behaviour, which could be used as a reference for translating human motions to drone motions. Additionally, the result of the individual interview will also assist in a better understanding of runners' perceptions of drone presence.

Prototype Testing: Runners recruited for prototype testing were thoroughly briefed on the safety procedures and informed of their rights to withdraw from the study at any time. During the experiments, all runners were instructed to remain as close to the centre of the room as possible while facing the drone positioned one meter in front of them. Before each run, the sensor drone was safely attached to the outer side of the left calf using a black strap with buckles to prevent the drone from detaching. If the runner reported any discomfort caused by the frame of the sensor drone, it would be re-positioned to another spot on the outer side of the left calf. Once the runners were ready to begin the test run, they were given the option to run either with or without a treadmill.

Participants who chose to run without the treadmill were instructed to complete three separate runs at slow, moderate, and fast paces. Meanwhile, they were also instructed to maintain each pace for 2-3 minutes based on their interpretation of the drone's motions and onboard LED signals. For participants who chose to run on the treadmill, a treadmill set at slow, moderate, and fast pace would be provided to precisely control their running speed. In each of the three different paces, these runners were instructed to maintain their running patterns for 2-3 minutes, according to their interpretation of the drone's movements and the onboard LED.

Shortly after each run, runners were given time to rest and provide additional comments on the drone's expressions during the run. This was followed by a brief TAM (Technology Acceptance Model) questionnaire and an interview to learn about their experiences with the drone during the experiment.

4.4 Data Analysis

The measurement collected during prototype testing consists of the sensor data received from the onboard stabilizer which measures the angles of the calf movement, verbal descriptions from runners regarding their experience with drones during experiments, and runners' perceptions of the prototype gathered from the TAM questionnaire.

Using the TAM questionnaire, the participants can connect their running experience with the current prototype in the controlled environment and their past running experience in outdoor environments. Received responses are then grouped and evaluated in four dimensions related to runners' perceptions: Perceived Usefulness, Perceived Ease of Use, Attitude Toward Using, and Behavioral Intention to Use. The evaluations based on these four dimensions can not only help validate the usefulness of the prototype targeted by this study but also provide valuable feedback for future improvements.

Additionally, the raw sensor data collected from the stabilizer is refined into stride time intervals, step counts, and stride counts. These outputs help track down the running patterns of the target runners. The audio recordings of the individual interview before the technical development and the short interview after the prototype testing were manually transcribed and checked. Before being stored and archived, the audio and video collected during the study were anonymised and analysed.

The responses to the TAM questionnaires were evaluated following the instruction provided by the author of the questionnaires through email request. For each dimension of the questionnaires, the responses were associated with 4 different questions to the 5-item Likert scale (Strongly Disagree, Disagree, Neutral, Agree, and Strongly Agree), which is converted into data points that vary from 1 to 5, and visualized in Figure 9. To further analyse each dimension, a series of bar graphs are created and related descriptive statistics are calculated through an external website[6]. The series of bar graphs and their statistics were purposed to reflect the runners' responses to the TAM questionnaire (shown in Figure 10). In the following

[6]https://www.statskingdom.com/advanced-boxplot-maker.html

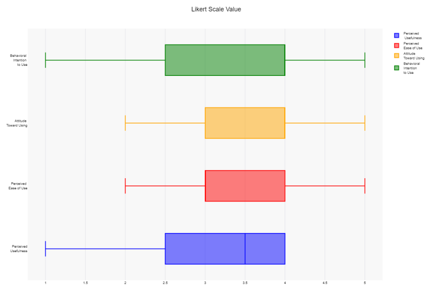

Fig. 9. Box Plot Illustrating Responses to the TAM Questionnaire, Providing Insights into the Runners' Experience of Running with a Drone.

section, we utilized the graphs and collected interview data to delve deeper into the experience of the runner running alongside a drone.

5 RESULT AND ANALYSIS: RUNNER'S PERCEPTION OF EXPRESSIVE DRONE

5.1 Interview feedback

Different interviewees proposed different types of artistic representation. The most commonly suggested type of artistic representation involved using the drone to simulate the runner's tempo during runs. Specifically, the drone's swing movement can be utilized to represent runners' strides, while the swing distance can indicate the strength of the runner's step and stretching angles of calves or legs. Additionally, some interviewees recommended employing abnormal drone movement to simulate unbalanced low-body movement. For instance, side-wiggling can signify asynchronous striding patterns and sudden altitude changes can indicate inconsistent leg-lifting.

80 per cent of the interviewees agree that our prototype will improve their running patterns by allowing runners to constantly observe their running patterns. 20 per cent of the interviewees disagree with the point stated above and continue to comment that the drone's presence may cause unnecessary disturbance to the run. Some interviewees also agree that our prototype has the potential to adjust their running habits, claiming that "constant training with drones seems fun and can encourage me to do more training".

5.2 Experiment feedback

5.2.1 Technology Acceptance Model Result. The summary of the calculated statistical values was as follows: Perceived Usefulness (Mean: 3.2; SD: 0.91); Perceived Ease of Use (Mean: 3.3; SD: 0.8975); Attitude Toward Using (Mean: 3.75; SD: 0.829) and Behavioral Intention to Use (Mean: 3.375; SD: 1.07). Combined with the result portrayed in figure 9, the cross-reference showcased noticeable results.

Summarized on the above bar graphs(10), positive acceptance can be spotted among most runners who participated in the test, especially in terms of ease-to-use and behavioural intention-to-use. Moreover, this result is interestingly coherent with runners' positive attitudes observed during interviews.

However, to gain a more comprehensive understanding of the runners' perspectives. We need to delve deeper into each bar graph(Figure 10).

Perceived Usefulness: In this dimension, the objective is aimed at evaluating runners' perception of the drone's usefulness during running. However, the overall mean (3.2) for perceived usefulness did not reflect a prominent positive trend nor fully portray runners' opinions toward drone usage. Supplement added by the bar graph(Figure 10) in graph(a) indicated that Our current design of drone motion as a representation of running patterns can be easily interpreted by most runners(Q1). But when it comes to portraying the striding frequency of the runners, participants reported that it is less obvious than expected(Q2). This can be explained by the latency accumulating whenever the reaction drone attempts to switch motions during the run. However, this defect did not necessarily force runners to have a negative image of the drone. Graph(a) also showcased that drone presence had raised motivation among runners to continue training for better performance(Q3). What's more, most runners comment on drone usefulness with a positive-neutral-trending after experiencing the prototype(Q4). This is evident from the possible fact that the current prototype may lack options to uniformly reflect human running patterns, but integrating drones can indeed elevate the running experience for participants, and motivate runners to participate in more training with the prototype.

Perceived Ease of Use: The objective of the dimension is aimed at evaluating the runner's perspective on how easily the prototype

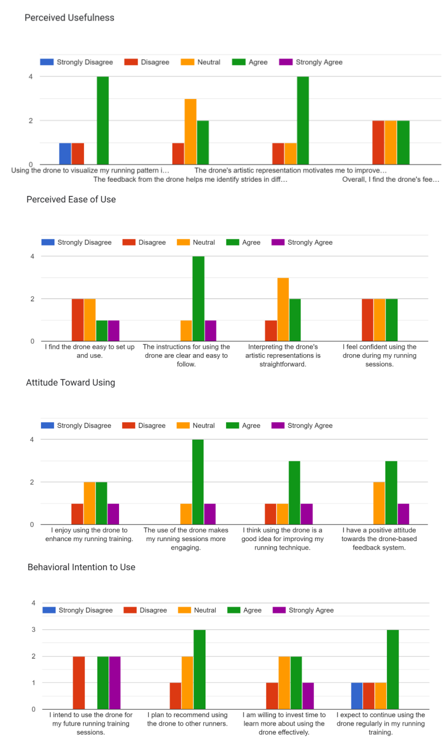

Fig. 10.
(a) "Perceived Usefulness"
(b) "Perceived Ease of Use"
(c) "Attitude Toward Using"
(d) "Behavioral Intention to Use"

can be set up and used. However, since the current implementation is merely an initial prototype, the startup sequence was commented by some runners as "over-complicated". Sequentially, as is shown in graph(b) in Figure 10, most runners during testing found start-up procedures hard to follow, and surprisingly, drones were also difficult to use(Q1). This difficulty can be explained by the participant's lack of drone experience and multiple Crazyflie sensor malfunctions. Moreover, we observed that without instructions, some runners can find it difficult to interpret certain patterns of drone motions (Q2, Q3), which leads to confusion and a lack of motivation on a personal basis (Q4).

Attitude Toward Using: The attitude of runners toward drone usage is one important piece of information that we must investigate in this study. Thus, we employed this dimension to extract the runner's perception of drone usage during running. Despite various defects existing in the prototype, the overall mean score(3.75) indicates a positive trend. What's more, as shown by graph(c) in Figure 10, most runners enjoy the drone presence(Q1) as well as finding drone usage creating engaging experiences during training(Q2). Moreover, most runners agree that the prototype can indeed provide various beneficial feedback to their running technique(Q3). Hence, these runners uniformly hold a positive attitude toward the drone feedback system(Q4). This result, explained by various participants, is a common agreement on the valuable potential of the conception behind the prototype.

Behavioral Intention to Use: Despite the positive attitude observed in the dimension "Attitude Toward Using", the prototype remains insufficient. As reported by a few runners, this prototype has negatively impacted their opinions regarding their potential future use of drones in running.

Nonetheless, the overall mean score(3.375) of this dimension was controlled near neutral evidently due to the presence of runners with extremely positive and extremely negative insight on the usage frequency and future usage. According to graph(d) in Figure 10, future usage of such a prototype was favoured by the majority, but a few participants explained that the usage of the prototype misaligned with their training (Q1). However, the graph also indicated a positive trend in possible future usages (Q4), this can be explained by the fact that most runners agree on the fact that frequent use of our prototype drone can encourage runners to do extra training, and positively improve their running experience.

5.2.2 *Runner's Additional Comment On Drone Experience.*

Pros. Runners who participated in testing reported that the expressive drone provided positive feedback on their running patterns. By using drone motion to recreate meaningful representations of the runners' movements from different perspectives, the system helped them improve their runs by giving a clear image of their own running pace. This motivated them to continue training to achieve a balanced running pace. In addition, the runners noted that this application could be useful for long-distance runners, as it can help identify abnormal or periodic stride frequencies during training. Furthermore, various experienced runners with a technical background reported that such a system seems to fit alongside a gamification design. They mentioned the joy of the drone's companion, which can merge into a sense of achievement when runners aim to reach a more balanced state of drone motion. Moreover, some runners also stated that such a prototype offers a greater amount of freshness and direct interaction compared to other existing technology as running assistants, such as VR, AR, etc.

Cons. However, the runners involved in the test also reported that the drone's motions could sometimes be outdated as the run progressed. For example, a runner might already be on their third stride while the drone is still executing motions for the second stride. This lag confused their current running patterns. Moreover, the prototype may not be beneficial for short-distance runners, like 100-meter sprinters, who maintain high to extremely high stride frequencies. Some runners also mentioned that this application might only be suitable for those with a strong awareness of their running patterns. Due to the previously mentioned latency, beginners might be confused by their running patterns and unsure of what to follow or how to optimize when observing the drone's motions. It is worth noting, that the attached sensor drone can also lead to potential physical damage through direct physical contact between the runners' calf and the sharp end of the drone frame.

6 DISCUSSION

Through the implementation of the Duel-Crazyflie prototype and runners' feedback in TAM questionnaires, this study explored the unknown potential of drones as running companions which positively enhances runners' understanding of their running patterns. In the following subsections, we discuss and conclude the limitation of this study, we also combined runners' suggestions alongside our observations into solutions which can be applied in the future.

Drone Communication: Initial testing indicates minor communication delays between two Crazyflie drones whereby the initialization of the program takes some time to complete, most likely due to threading in Python. During the prototype testing, such latency can be ignored, as interpreted by the runner. Nonetheless, during the communication, occasional lags exist for every 5-6 transmissions based on observation from LED changes and drone motions. But when monitored from the central hub, it particularly appears as freezing log output which assumes for 2 to 3 seconds, such latency is suspected to be related to the information processing handled by the central hub. According to the Crazyflie forum [7], the potential solution for such latency can be logging at 10Hz for future development.

Sensor Drone: Sensor drone performance did not reach our expected standard. The observation of collected data from the stabilize module embedded in the Crazyflie indicates unstable readings during several tests. Under heavy movement, sometimes the angle detected by the IMU did not display an obvious spike which is expected from the very specific patterns of movement. This problem has the potential fix of lowering the threshold values. On the other hand, enforcing lower threshold values could trigger the LED changes or movement signal earlier than expected, which caused unwanted confusion for the runner.

Moreover, during this study, we could only track one leg with our sole drone IMU, hence we focused our technical development around synchronised running. To simulate edge cases where asynchronous

[7] https://forum.bitcraze.io/viewtopic.php?t=4767

running patterns could have occurred, we simulated related drone movement to the participants and asked our participants if they could understand this movement. The result was that 80 per cent of our participants managed to correctly interpret the movement performed by the drone. Therefore, in terms of future development, the advice is to position another IMU/Drone IMU on the outer of the right calf to accurately track down and pinpoint the right leg movement. In this way, edge cases such as asynchronous running patterns can be resolved and maintain the least amount of confusion for the runner.

When the drone is positioned on the outer of the left calf, the strap with the buckle may exert excessive pressure on both the top and bottom of the drone. This can cause damage to the Crazyflie physical extension, such as the LED ring on the bottom of the drone. Future development should secure the sensor drone in the same position using alternative methods, such as a pouch that is as large as the Crazyflie drone itself. Moreover, attaching the sensor drone to the runner's calf may result in physical damage to the runner. It is therefore recommended to provide additional protection for future participants or to remove any sharp edges from the drone frame.

Data Processing: Various tests have proven, that sensor reading requires more calibrations and effective analyzing to be able to align closely to the runners' calf motions. Specifically, the raw data requires better sampling methods to avoid noise during data collection and to accurately track each stride.

It has come to our attention that the preset thresholds used to translate human motion to drone motion are not suitable for some runners. This has resulted in either overcounting or undercounting of steps and strides. Upon comparing different sets of running patterns collected during testing, we have observed that runners have different striding angles. However, the preset threshold does not account for these individual differences. As a temporary solution, an additional measurement run was included in the prototype testing to identify the specific striding angles of each runner. For future development, we recommend implementing methods that can automatically calculate the stride angles of different runners, taking into account individual factors such as height, stride length, and average stride time.

Python synchronization locks were used to transform human motion into drone motion one at a time, but this process prolonged the motion-to-motion transformation and led to gradual delays, resulting in visual latency discussed in the following sections.

Reaction Drone: Due to the accumulating latency caused by the reaction drone's efforts to connect multiple movements, the drone often fails to synchronise the corresponding drone motion with runners' strides. In some specific cases, the drone also fails at taking off either due to low thrust caused by a low battery or loss of control triggered by unknown disturbances from the environment. However, in the general case, the drone can perform as expected but its roll motion needs additional balancing for stabilization which could be achieved with a higher accuracy in the tracking of runners' lower-body motions. A more meaningful representation of the runner's running pattern can also be designed based on the more reliable reading of the runner's lower body motion, such as motions of ascending or descending in according to the height of lifted legs or a circling flight around the runner with drone speed as an indicator of runner speed.

On the other hand, due to the short battery life of the Crazyflie drone, the experiment can only last for up to 20 minutes before the power runs out. As the only airborne Crazyflie, the reaction drone is prone to losing power quickly. Therefore, it is recommended to find ways to extend the battery life of the Crazyflie drone or consider using similar drone products with longer battery life.

Population Sampling: Due to time constraints, the participant population was large enough to maintain the current study with a sufficient amount of information and insight during the individual interview, but not large enough to provide additional evidence of the efficiency of the prototype to extend the prototype testing nor allow the intake of additional insight during individual interviews. Therefore, it is recommended to introduce a larger population to the interview and testing of the prototype in future studies, which will not only prolong the study to contain information up to saturation but also introduce valuable insight within the target scope and aid in the future development of the prototype.

Future study design: The participant responses are promising and positive; However, the prototype remains incomplete compared to existing running technology. Therefore, despite the solutions mentioned above, the primary target of the future study should focus on the complete transformation from an indoor environment to an outdoor environment. This will include but not be limited to 1) Possible updates to the drone selection for achieving an optimised level of thrust and weight handling; 2) Optimized flight time introduced by a larger power supply; 3) Outdoor testing with carefully selected participants possessing various running experiences, etc. More importantly, 4) Properly captures the asynchronous movement patterns, such as using multiple sensors to pinpoint abnormal strides or utilizing better methods to support analysis on identifying abnormal strides.

7 CONCLUSION

In our study, we used two Crazyflie drones and a laptop as a base station to raise runners' awareness of their running patterns, achieved through a prototype with the potential to enhance runners' experience without significant side effects. Before developing the prototype, we conducted individual interviews to understand what factors runners consider important when running with or without drones. Aligned with perceived recommendations, we proceed to shape the initial prototype. We then rigorously validated the prototype across four dimensions - perceived usefulness, perceived ease of use, attitude toward using, and behavioural intention to use with a diverse group of runners. Similar to the outcome concluded by Balasubramaniam et al. [2], received responses provided valuable insights into potential drone roles and modifications, catering to runners with different purposes and experiences, and setting the stage for future research. Based on our findings and the discussion section, future studies will focus on enhancing the outdoor environment while capturing asynchronous movement patterns. This will further connect the prototype to the runner, providing greater motivation for training and a better understanding of their running pattern.

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[8]For software details, please visit "https://app.grammarly.com/")