Feasibility of Measuring Shot Group Using LoRa Technology and YOLO V5

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***Abstract*—Shooting is a common activity all over the world for both military and recreational purposes. Shooting performance can be measured from the size of the shot group (grouping). Shooters have been calculating the size of the group by measuring the distance between bullet impacts using their hands. This paper aims to create a reasonable automated shot grouping size measuring module that is available from several kilometers away. It includes an IoT(Internet of Things) system and a mobile application that users can access. LoRa technology is adopted for covering long distances, and YOLO V5 is implemented to detect bullet impacts. Mathematical methods for calculating accurate distance and engineering techniques to fill the needs are described with experiments on various parameters and conditions. The proposed module showed that indoor tests measured the shot group with a mean accuracy of 91.8%. For future work, outdoor tests, which were affected by environmental control variables, are expected to give better accuracy.**

***Index Terms*—Shot Group, LoRa, YOLO V5, Bluetooth, Edge Computing, IoT**

I. Introduction

In recent years, shooting has become a popular hobby forming a large industry as well as being one of the core activities in the military. Approximately American civilians own 393 million guns, and the Gun & Ammunition market size has reached 15 billion dollars in 2021 [1], [2]. Naturally, there is a high demand for measuring shooting performance to improve one's shooting skills. A shooter's performance can be derived from the Shot Group. The term 'Shot Group' is generally understood to mean the pattern of bullet holes fired on a target in one shooting session. How closely the impacts are clustered is an indicator of the precision of a weapon and shooter, whereas how close the bullet impacts are to a specific point is an indicator of the accuracy [3], [4].

One of the current limitations of gauging shooting performance is that shooters have to use their hands to measure their group size. It means they have to go all the way to their target to retrieve it, then measure the size of their shot group or count up their scores manually. Technology can overcome this limitation, particularly by using long-range networking and object detection, as this allows the shooter to check their target, regardless of distance. Specifically, long-range networking allows shooters to get the bullet impact coordinates with actual target images, while object detection yields the location of bullet impacts. Despite there being various methods to get the locations (e.g., acoustic nodes and impact sensors), they have their limitations. Acoustic nodes can have difficulty detecting subsonic rounds and are liable to experience damage from gunshots. Impact sensors are accurate and durable, but expensive.

This paper proposes a shooting performance measuring module, which scores a user's performance based on the tightness of their shot group. The proposed module focuses on LoRa as a wireless network, coordinates, and image transmission protocol for the privilege of long-range covering and low-power consumption. Bluetooth is used for near data-sharing giving bullet impact coordinates and actual target images to the user application. In order to get the coordinates of bullet impacts, this module includes YOLO V5 customizable object detection model. OpenCV is applied to make the target image upright, while the user application does mathematical work to calculate the shot group size. Putting all these together, the system allows shooters to automatically measure their shot group from a distance without the need to retrieve targets. Moreover, it also gives the actual target image with substantive bullet impacts to help the shooters.

II. Related Work and Motivation

Several systems such as Shot Marker, Ballistic Precision, and Kongsberg targets have emerged to overcome the limitations of shot group measuring, yet all have their shortcomings or are expensive. This section describes the brief motivations for LoRa, Object Detection, and Bluetooth technologies by comparing existing systems with the proposed approach.

Shot Marker is an interactive feedback system on the mobile device at any range, giving shooters the impact points and shot group size [5]. This system is composed of a LoRa module, acoustic nodes, and an access point that uses local Wi-Fi. LoRa module is for its low battery consumption and ability to transmit data several kilometers. Acoustic nodes are 8 high-precision microphones installed on the frame to

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find the locations of bullet impacts. Although an error range of sensors is less than 1 mm in ideal conditions, it highly depends on external physical factors such as the straightness of the frame, the movement of the sensors, and the winds [5]. Also, this system requires the user to manually zero their shots before a shooting session in order to adjust the acoustic nodes. Moreover, if the bullet is slower than a gunshot sound (subsonic), the acoustic nodes cannot detect the impact points due to the interference between gunshot and passing sound. Power consumption is another limitation of this system. This system utilizes local Wi-Fi at the access point which consumes lots of power. In comparison to Shot Marker, the proposed system uses Custom YOLO V5 to find the bullet impacts, regardless of bullet speed, while taking the advantages of LoRa long range. Bluetooth is used at the access point instead of Wi-Fi in order to reduce power consumption.

Ballistic Precision provides real-time streaming video up to 1.6 km with Wi-Fi [6]. The system consists of a camera for video streaming and two semi-directional antennas using Wi-Fi for communication. However, a distinct disadvantage is that Wi-Fi uses more power between the target and user. Also, this product lacks a module for detecting bullet impacts, only streaming the target image from distances. Ballistic Precision, however, shows the actual target with substantive bullet impacts. This approach is similarly applied to the proposed system, enabling users to check their genuine target from distances.

Kongsberg targets is an electronic target system that uses impact sensors. It includes an electronic target, a monitor, a signal distributor, and a power supply [7]. With the impact sensors, this product gets the most accurate impact points among all of the existing systems. Also, impact sensors handle both super and subsonic ammunition as the proposed system does. Yet, Kongsberg targets cannot cover a wide range and requires stable power. Above all, it is expensive as impact sensors cost more than one thousand U.S. dollars.

Previous works suffer from high-power consumption by using Wi-Fi. One system meets difficulty detecting subsonic ammunition, while others lack a shot group measurement module.

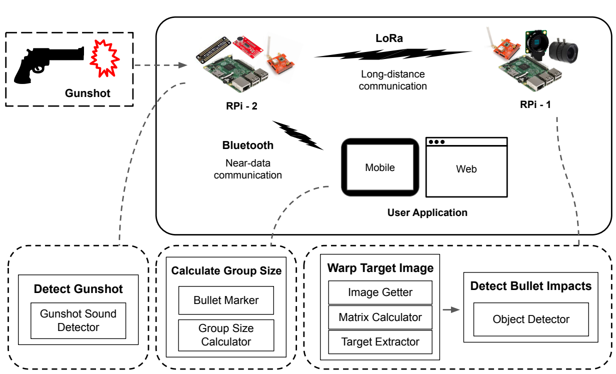

Fig. 1. Block Diagram of Proposed Module

III. Proposed System

A. Hardware Devices

The proposed system as shown in Fig. 1 contains the following components: 2 Raspberry Pi 4 B 4GB, Android Device, 2 Dragino LoRa/GPS Hats, HQ Raspberry Pi Camera Module with a Wide Angle CS-Mount lens, LMV324 Sound Detector Sensor. One of the two Raspberry Pis has a Pi Camera attached for capturing target images, referred to as RPi-1. The other Raspberry Pi is connected to a sound sensor to detect gunshots while connecting with a user application via built-in Bluetooth, referred to as RPi-2. Each LoRa Hat acts as a point-to-point transceiver for signals, target numbers, coordinate data, and images. A nano hacker is inserted between RPi-2 and LoRa Hat in order to connect the sound sensor directly to RPi-2.

B. LoRa

Since the proposed model plans for shootings from any distance, it was necessary to have a wireless network that replaces cabled networks. LoRa is a wireless network protocol that is designed for the low-power transmission of small IoT sensor data over distances. Adopting this network technology enables the system to efficiently transmit and receive small data (e.g., signals, coordinates) from distances.

Despite its long-range coverage and low-power consumption, LoRa suffers from major drawbacks: low data rate, payload size, and duty cycle limit [8]–[10]. Accordingly, the proposed system overcomes the downsides of LoRa technology by using compression to reduce the size of the transmitted data as much as possible. Applying image warping and compression shrinks the image to be at most 150 times smaller than before, enabling faster image transmission. In addition, this system sends the actual image only at the end of the shot session, reducing the burden of LoRa. While several wireless network protocols can cover long-range with minimal power, LoRa became the most feasible technology for this application.

C. Bluetooth

Bluetooth is used as the shooter's end of the proposed system. While most user devices such as smartphones and laptops lack a LoRa module, Bluetooth is a common feature. This allows Bluetooth to be the bridge between RPi-2 and the user device. Bluetooth consumes low battery power, making IoT systems with limited batteries last longer [11]. This paper attempted to maximize its power efficiency even more by minimizing the idle time of the Bluetooth socket. For each distinct communication between RPi-2 and the user application, a new socket connection is established to reduce the idle time of the Bluetooth socket, reducing power consumption.

D. Edge Computing

Since cloud computing requires the target image to be sent to the cloud server for each bullet impact detection, the need for edge computing emerged in order to reduce the burden of LoRa's low data rates. In this study, RPi-1 acquires the image of the target. It then arranges the image and runs the object detection program without the need to send the actual target image to a cloud server. In order to do this, the 64-bit Raspbian Operating System, PyTorch, and OpenCV are installed on RPi-1.

E. OpenCV

Not only are there targets of different sizes and ranges that can be selected for shooting, but also the images of the target from the camera are warped depending on the location and the angle of the camera. The camera is installed next to the target and takes photos at an angle making the image to be oblique. When measuring the size of a shot group, there should be a consistent coordinate calculation standard, such as a clear, direct reference photo of the target taken directly in front of it. In order to make a frontal image, computer vision techniques are used for image feature matching, such as Oriented FAST and Rotated BRIEF (ORB) and Random Sample Consensus (RANSAC).

ORB finds the key points and descriptors using feature matching, which is faster than Speeded Up Robust Features (SURF), and over twice as fast as Scale Invariant Feature Transform (SIFT) [12]. The key points and descriptors found from the two images are matched using a brute force algorithm. The RANSAC algorithm for object tracking and video stabilizing chooses maximum consensus by random sample methods [13]. This system computes the matrix that transforms the captured image to match the reference image since image warping requires only one matrix as shown in Fig. 2.

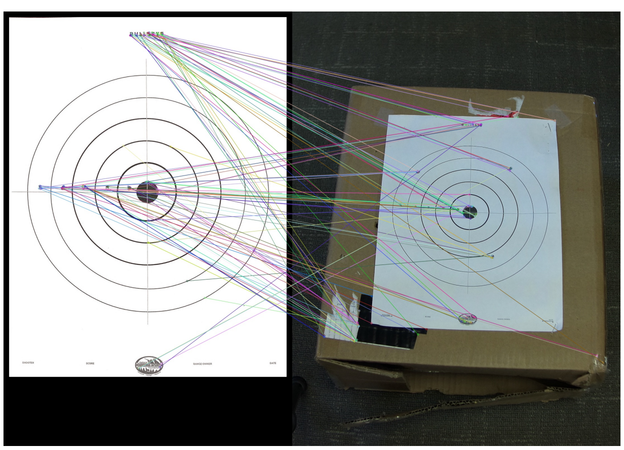

Fig. 2. Feature Matching Result of Reference and Captured Images

F. YOLO V5

Existing target systems based on electronic sensors and acoustic nodes both have their shortcomings. Electronic sensors have a high price, usually more than one thousand dollars, with sound sensors having difficulties detecting subsonic shots and lacking visual feedback. While requiring some tuning to get precise results, object detection with a camera can be a fine alternative to detect bullet impacts.

In the area of object detection, the YOLO series has proved an improvement in speed and accuracy. YOLO V5 achieves 140 FPS compared with the 50 FPS of YOLO V4 [14], [15]. It can train the new model to detect bullet impacts using a customized Common Objects in Context (COCO) dataset. YOLO V5 has several models, among which the nano model has fast speed and low accuracy compared to other models. Because the proposed system utilizes a Raspberry Pi with low processing power to run YOLO V5, it uses the nano model. YOLO V5 finds the coordinates from the warped image by processing it with computer vision techniques.

G. Extreme Spread Measure

There are several methods to calculate group sizes, such as the extreme spread, the figure of merit, the diagonal, the mean radius, and the radial standard deviation [16]. Among all of them, the extreme spread method is the most widely used measure of shot group dispersion [16]. This method calculates the size of the group using the maximum distance between the center of any two shots within the group.

IV. Implementation

A. Data Communication

1) Signal Transmission: Signals are triggers to activate the features of the proposed system. The signals include capture signals, finish session signals, and shutdown signals. The capture signal makes RPi-1 activate the camera and start bullet impact detection, while the finish session signal requests RPi-1 to capture and send the image of the actual target. The shutdown signal turns off the power of both RPi-1 and RPi-2. When every gunshot is heard, a capture signal is sent from RPi-2 to RPi-1. Other signals are sent from the user application and are relayed from RPi-2 to RPi-1.

2) Coordinate Transmission: Coordinate data are produced in RPi-1 as the result of bullet impact detection. They are sent to RPi-2 in a single byte string form through LoRa. RPi-2 then transmits the coordinates to the user application in the form of ASCII encoded bytes. ASCII encoding makes the application easy to parse the received coordinate data into each coordinate. In order to help the user application indicate the end of coordinate data, an exclamation mark is appended at the end of the transmitted data.

3) Image Transmission: Prior to actual target image transmission, RPi-1 warps and compresses the image. The compressed image file is read and then encoded into the Base64 format, representing a compressed binary image file in an ASCII string format [17]. It is chosen as the encoding method for its compatibility with the format of LoRa transmission [18]. The encoded data is fragmented into packets with 253-byte payloads. While RPi-1 sends the packets, RPi-2 receives each packet in sequences. After transmitting the final packet, RPi-1 sends an extra packet containing the EOF flag. RPi-2 indicates the end of transmission through the EOF flag, after which it starts to reconstruct the image by decoding the given data. Considering the possibility of the EOF packet loss, RPi-1 sends ten equal packets while RPi-2 only needs to receive one of them. For image transmission from RPi-2 to the user application, it utilizes ObexFTP for the convenience of file image transfer.

B. Image Processing

1) Image Capturing: RPi-1 takes a picture of the actual target whenever the gunshot occurs. To remove unnecessary color channels when finding the warping matrix, RPi-1 converts the color space of both the target and reference image from BGR to gray.

2) Image Warping: With the target image taken, and the reference image stored, ORB extracts the features of the images. Then, RANSAC is applied to find the matrix for image warping. The image of the actual target is warped using the matrix.

3) Bullet Impact Detecting: In order to train the new model, the dataset is built with 260 target images (214 for training and 46 for validation) and 2,578 labels. The trained nano model achieved 0.62 mean Average Precision (mAP).

Algorithm 1 Shot Group Size Calculation Algorithm

Require: $n \geq 2$
Ensure: $dmax \leftarrow 0$

```
for i = 0 → Points.length − 2 do
    for j = i + 1 → Points.length − 1 do
        (x_i, y_i) ← Points[i]
        (x_j, y_j) ← Points[j]
        d ← sqrt((x_i − x_j)^2 + (y_i − y_j)^2)
        if d > dmax then dmax ← d
        end if
        i ← i + 1
        j ← j + 1
    end for
end for
```

$$d \leftarrow \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$$

C. User Application

1) Bullet Impact Drawing: During the shooting session, the user application receives ASCII encoded coordinates of bullet impacts in String format. It then parses the received String data into each coordinate. From the parsed coordinates, the user application draws bullet impacts on the reference target image, as well as displays the total number of shots fired in the current session.

2) Group Size Measuring: The proposed system uses the extreme spread method to compute the size of the shot group. The result of object detection, which is the coordinate information, is sent to a user device through the LoRa and Bluetooth network every shot. When the shooter finishes their set, the user application applies Euclidean distance among every point, as shown in Algorithm 1. It finds the maximum Euclidean distance by traversing a double loop.

3) Scale Conversion: Since RPi-1 provides coordinates as pixel units, there is a difference between the distance from the actual target image and the distance calculated from the two coordinates. In order to find the actual distance between the two coordinates, Scale Conversion is applied by using a letter-size target image that is already registered in the user application. It has its own height and width measured as pixel units. As the actual height and width, the ratio of centimeters per pixel can be calculated automatically, by multiplying the distance by the actual ratio. The end-users get the centimeter values of the measured shot group.

V. Results and Discussion

In order to prove the proposed system's functionality, several tests have been conducted indoors and outdoors. The assumption of the indoor experiments includes the constant brightness of light with a fixed target, stable room temperature, and tranquil surroundings (i.e., A frequent recommendation is a stable temperature no higher than 70°F and a tranquil relative noise level no higher than 30 dB).

A. Test Scenario

The target images used for reference are stored on an Android device as well as RPi-1 in order to utilize image warping. When the shooter selects the target image on the Android device, a message including the reference image's ID is sent to RPi-2 through Bluetooth networking. The message is then transferred using LoRa from RPi-2 to RPi-1 to set the reference image in RPi-1. If the signal arrives at RPi-1, it sends back an ACK message to the Android device via RPi-2. The ACK activates the sound sensor in order to detect gunshot sounds.

Once the ACK passes RPi-2, it detects a number of sounds equal to the specified rounds in the set. Whenever the sound sensor detects a gun firing, RPi-2 sends a capture signal, the image processing signal, to RPi-1. Upon receiving the signal, RPi-1 starts the procedures to compute the coordinates of bullet impacts. Detecting the impact points proceeds in the order of taking a picture, warping the image, and applying object detection to the warped image. Then, RPi-2 receives the calculated coordinates through LoRa, relaying the information to the Android device through Bluetooth. On the mobile device screen, it draws the bullet marks using received data.

When the shooter has fired all rounds, the shooter clicks the finish button to measure the shot group. The Android device finds the maximum distance line between all of the bullet coordinates and displays the computed extreme spread length. Also, Android sends a finish session signal to RPi-1, asking for the warped actual target image. The warped image is compressed and then broken down into tiny packets so that it can be sent by LoRa. The scenario ends when the user receives the image sent from RPi-1 to the Android device.

B. Indoor Tests

The RPi-1 made up of the camera and LoRa was installed in front of the target to take a picture of the letter size (21.59 x 27.94 cm) target. The RPi-2, including the sound detector and LoRa, was placed next to the shooter in a straight line with RPi-1. These two Raspberry Pis were set 15 m apart. In the experiments, a screwdriver was used to make bullet impacts on the target, making holes similar to the ones of 5.6 mm caliber bullets. Similarly, a hand clap was used to simulate

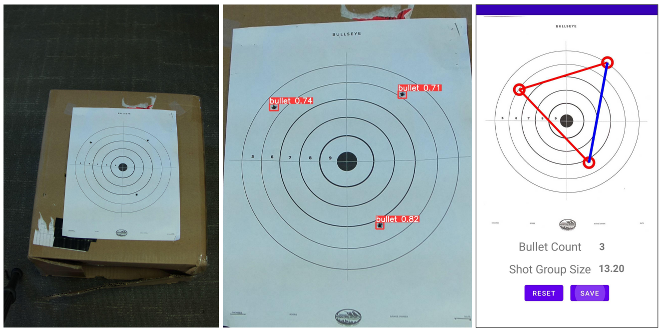

Fig. 3. Results of Indoor Tests

gunfire, activating the sound detector. Fig. 3 shows one of the results of indoor tests, displaying a captured image, an image detected bullet hole after warping, and an application page after one shooting session.

As indoor tests were conducted in a stable test environment, there were no interrupts such as other image features and shadows making the target image to be warped unexpectedly, nor winds and shot impacts moving the targets from their origin placement. The sound detector intentionally triggered RPi-1 via hand clap.

Fig. 4. RPi-1 (left) & RPi-2 (right)

C. Outdoor Tests

The outdoor tests were conducted on a tree farm in Romney, Indiana, USA, from 4:00-6:00 PM EST. The proposed module was set as shown in Fig. 4. The Raspberry Pis and the target settings of outdoor tests were the same as the indoors. The distance between two Raspberry Pis was 15 m. In these tests, 9 mm bullets were fired from 15 m away.

In the first outdoor experiment, we found that the sound detector was more sensitive than expected. Without adjustment, various noises (e.g., reload noise, conversation noise) could activate RPi-1 accidentally. To alleviate this, resistors are utilized to lower the gain of the sound detector in order to make it less sensitive. The sound detector with a 10kΩ resistor installed detected the gunshot with and without a silencer, whereas a 2.2kΩ resistor only detected the gun without a silencer. By populating a 10kΩ resistor, surrounding noises were filtered while suppressed shots were accepted. Also, the target had a background that confused the image matching algorithms. Due to the features behind the target, the captured image warped poorly, detecting none of the bullet impacts. YOLO V5 couldn't detect bullet holes and calculate coordinates from the mess image. As a result, the mobile application didn't draw any impact.

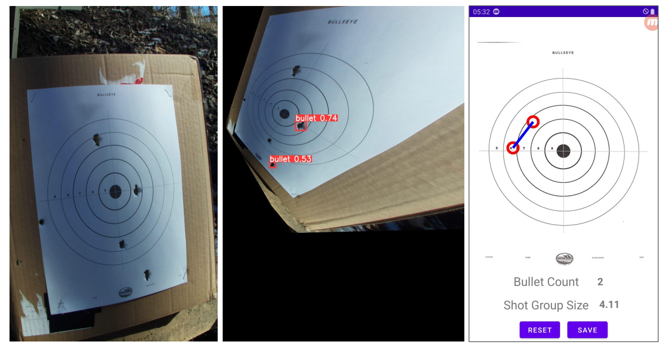

Fig. 5. Results of the Second Outdoor Test

We removed the object behind the target to make the system work properly in the second outdoor test. However, there were several unconsidered control variables such as tree shadows, irregular wind directions, or target moves after shot impacts, making unintended results. Due to the branches swaying in the wind, image processing was imperfect. Instead of a frontal image, the warped image was sheared, producing the wrong coordinates. Fig. 5 shows the overall results of the outdoor test, with the imperfectly warped image.

D. Percent Accuracy

For the evaluation of conducted tests, the Percent Accuracy (PA) formula was used to prove the accuracy of the proposed system. The measured and actual shot group size was noted as $Dist_{Result}$ and $Dist_{Actual}$, respectively. Percent Accuracy of the test results was derived by Percent Error (PE), while PE was calculated as below:

$$PA(\%) = 100 - PE \tag{1}$$

$$PE(\%) = \frac{|Dist_{Result} - Dist_{Actual}|}{Dist_{Actual}} \times 100 \tag{2}$$

Applying the percent accuracy formula, the best result of indoor tests gave a percent accuracy of 99.8%, meaning that the percent error of actual and result distances is only 0.2%. The accuracy of these indoor experiments is described with mean and standard deviation (SD) in Table I.

Unfortunately, the first outdoor test had difficulties getting a well-warped image, which affected the trained YOLO V5 model detect none of the two bullet impacts. Two bullet impacts out of five were detected in an imperfect warped image on the second outdoor test. The YOLO V5 gave incorrect coordinates

TABLE I
ACCURACY TABLE OF INDOOR EXPERIMENTS

Trial	$Dist_{Result}(cm)$	$Dist_{Actual}(cm)$	$PA(\%)$
1	13.2	11.2	81.8
2	14.7	14.4	98.4
3	10.5	10.8	97.4
4	12.4	12.4	99.8
5	8.84	9.88	89.5
6	11.2	10.4	92.5
7	13.5	13.0	96.3
8	8.59	9.80	87.6
9	11.7	10.9	92.3
10	10.6	12.9	82.4
Mean	11.5	11.6	91.8
SD	1.97	1.53	6.42

of the detected bullet holes, leading to a meaningless value of percent accuracy.

E. Discussion

Given the results of indoor tests, the proposed system proved to measure shot group size with a high mean accuracy of 91.8%. Although the first trial (Trial 1) gave the least-accurate results, the cause was found to be the margin on the top of the warped image as shown in Fig. 3, and is expected to give better results with a fully warped image. It is especially notable that the trained object detection model succeeded in recognizing bullet holes with high accuracy despite the image distortion caused by feature matching.

Additionally, the outdoor test results required improvements in the test environments. Several factors disturbing the target image from being warped upright were found to be as follows: tree shadows, features behind the target, movements of the target, winds, and noises. Tree shadows found to disturb both image warping and bullet impact detection. Outdoor tests with controlled variables are expected to give better results with high accuracy.

VI. CONCLUSION

This paper presents a long-range accessible, long-lasting shot group measuring IoT system to check the shooter's performance from distances. By adopting LoRa and Bluetooth technologies, we successfully fulfilled the initial system requirements. We detected the bullet impacts of the target using YOLO V5 by making the oblique target image upright with computer vision techniques such as ORB and RANSAC. With several tests from various environments conducted, we showed the feasibility of an accurate shot group measuring system.

However, there were several limitations to our research. In this system, the camera is set up fixed in front of the target. With indoor tests that target distances differ by some rounds, this system would have difficulty matching the target features, leading to inaccurate detection. Unfortunately, the student group working on the system had to return to their home country at the end of their time as visiting scholars, so test results and system improvements were not feasible.

For future works, additional tests that are conducted outdoors in an as similar environment as indoors are recommended to increase the accuracy of image warping and ultimate shot group measurement. While this system is only in the scope of LoRa peer-to-peer communication, it could expand to a large-scale network (e.g., LoRaWAN). As scaling up the network, we expect our systems to be connected to a central server, storing and comparing each shooter's performance with analysis.

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