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A Non-GPS Return to Home Algorithm for Drones using Convolutional Neural Network

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ABSTRACT

The increasing vulnerability of Unmanned Aerial Vehicles (UAVs) in both military and civilian applications to Global Positioning System (GPS) spoofing attacks poses significant threats to security and safety like hijacking, collision, and potentially human casualties. Despite extensive research on countermeasures, existing solutions remain ineffective, as they rely on GPS data that is often the target of the spoofing to Return to Home (RTH) or the availability of ground sensors. This article proposes a drone's RTH mechanism based on non-GPS data utilizing Aerial Images and Convolutional Neural Network (CNN). The drone, as it flies, collects frames and the moving directions (degrees) to use it later for training the CNN model that will enable the drone to autonomously navigates back to its homebase (RTH). Several experiments have been conducted using the proposed method and it demonstrates promising results. The average distance of RTH distance to home base is 20 to 40 meters using 50 epochs only. The Mean Absolute Error (MAE) on the converted degrees (Cosine and Sin) reached below 0.02 during training. The findings not only offer a viable solution to the GPS spoofing problem but also significantly enhance the drone's RTH reliability and improve the robustness of the drone's ability to RTH.

1. Introduction

Unmanned Aerial Vehicles (UAVs), also known as Drones which are aircraft without a human pilot aboard, have been a part of our lives to solve a range of problems as discussed by Zaman *et al.,* [1] and by Mokhtar *et al.,* [2]. For safety reasons, such as running out of battery or lost connection to its homebase, the drone will go into Autopilot mode. When the drone initiates the Autopilot mode, it will totally rely on available sensors to return to home. This reliance on sensors immediately exposes the drone for a different range of attacks.

There are many types of hacks on the drones, and GPS Spoofing is one of the most common attacks on Drones. The goal of GPS spoofing is to intervene with valid GPS signals. The analysis conducted by Eason *et al.,* [3] focused on the GPS spoofing attack in the drone 3DR solo. According

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to their findings, drones offer significant benefits for companies and individuals; however, they can also pose a threat when their GPS signals are manipulated. In such cases, attackers exploit the opportunity to gain access to confidential information, violate people's privacy, or cause physical harm.

GPS is a very critical portion of the navigation and location of UAVs. As there is an open channel of communication for the GPS signals, the attacker's signals might take the form of real GPS signals for launching GPS spoofing attacks on real UAVs. The GPS spoofing attacks detection schemes are classified based on digital signatures and encryption and the UAV's external and GPS signal characteristics. Wang points out in [4] that GPS spoofing carries certain difficulties such as its restricted applicability, the complexity involved in modernizing the equipment, and insufficient computing performance. As mentioned before, when a GPS spoofing attack happens, the drone needs to be able to detect this attack, recover from it and return to home safely (RTH).

Many researchers solved the RTH problem using different methods such as OneM2M managing and controlling the drone, Adaptive Return-To-Home sensing mechanism that can carry out environmental sensing and reserves adequate energy to RTH, Intrusion Detection System (IDS) using Self-Taught Learning with multiclass SVM technology and Self- Healing approach for active learning of routes to ensure a safe RTH, Search Algorithm that uses previous flight data to determine the shortest distance safest path, Crowd- GPS-Sec based on Crowdsourcing, Visual Navigation Technique, Organized UAV Detection scheme through Radio Frequency (RF) that produces high power jamming signal that focuses towards the location of the drone and generates a strategy to RTH.

The above approaches are workable but still vulnerable to GPS spoofing due to either its continuous reliance on recalibrated GPS signals, ground sensors or equipment's. In this article, a UAV's Return to Home Algorithm without GPS based on Aerial Images using convolutional neural network (CNN) is proposed.

2. Related Work

A number for works has been identified for the RTH problems. For example, the system proposed by Choi *et al.,* [5], represents a one Machine-to-Machine (oneM2M) universal standard-based approach to drone management. This system, relying on the Interworking Proxy Entity, is designed for effective drone management and control. It facilitates the interoperability between machine-to-machine and Internet of Things (IoT) service platforms, leading to enhanced control and management of Unmanned Aerial Vehicles (UAV). The system primarily supports key drone control features such as Return to Home and waypoint navigation through a subscription and notification process embedded within oneM2M. However, a significant limitation is that this system does not incorporate a framework for video streaming.

An Adaptive Return-to-Home Sensing mechanism for a drone sensing framework in open environments has been developed, as detailed by Huang *et al.,* [6]. The framework is designed for tasks that require sporadic sensing of the environment. This unique system allows for multiple rounds of environmental sensing without severe fluctuation during consecutive sensing trials. Moreover, it ensures sufficient energy is kept in reserve for the drone to return home. It incorporates a budget function specifically for setting aside energy for the Unmanned Aerial Vehicle (UAV) to make its way back to the starting point, while the residual energy is utilized for additional sensing events.

As outlined by Arthur [7], a deep learning-based adaptive Intrusion Detection System has been conceptualized for drones. This system is designed to identify intruders and ensure the safe return-to-home (RTH) of the drone. Self-Taught Learning and multiclass Support Vector Machine (SVM) technology are employed within this system to maintain a high True Positive Rate (TPR) in intrusion detection, even in unfamiliar areas. During the recovery phase of the intrusion detection process, a self-healing strategy leverages the deep reinforcement learning method for active route learning, which further guarantees the safe return of the drone.

A search algorithm intended for network processing and finding the shortest and safest path is proposed, as reported by Morais [8]. This algorithm is part of a return-home protocol that aids in determining the shortest path back to the drone's point of origin. It accomplishes this by utilizing flight data from past missions to form secure path networks for the drone's return. However, this approach does not include a mechanism for sensing and dismissing redundant paths. Furthermore, it doesn't consider the potential for crashes resulting from altitude-related hazards.

As detailed by Hasan *et al.,* [9], a movable autonomous drone system has been introduced, primarily designed for use in agricultural applications. This system is equipped with a return-to-home feature, which is activated upon detecting a decrease in voltage or communication failure.

An organized UAV detection scheme has been developed, as documented by Abunada *et al.,* [10], which operates through Radio Frequency (RF) control signals exchanged between the remote controller and the drone. The framework emits a high-power jamming signal via the same carrier frequency as the detected drone. This signal is targeted at the drone's location to disconnect it from its controller, enabling it to make a safe landing or devise a return-to-home strategy. However, a limitation of this mechanism is that it only covers a limited area.

As noted by Jansen [11], a system called Crowd-GPS-Sec has been proposed. This system relies on crowdsourcing and uses parameters like advertisement messages, ADSB/Flarm Sensors, and GPS. It demonstrates capabilities such as detecting GPS spoofing attacks in less than two seconds, locating the spoofer's position, and facilitating Return to Home. Nevertheless, the system's operation is contingent on ground sensors.

The methodology presented by Bui *et al.,* [12] introduces a multi-task deep neural network for UAV flight control in indoor environments. This approach utilizes monocular camera images to enable UAVs to correct their self-position and direction, and it identify multiple movement directions. Despite its innovative use of multi-task learning for autonomous UAV systems, the system may face challenges in environments where more complex sensory inputs are necessary.

The study by Guo *et al.,* [13] presents an improved deep reinforcement learning approach for UAV navigation in dynamic environments. This method employs a distributed DRL framework that decomposes navigation tasks into simpler sub-tasks, each addressed using a Long Short-Term Memory (LSTM) based DRL network. Although effective in high dynamic settings with fast-moving obstacles, it might struggle in environments where real-time adaptation to more complex and unpredictable obstacles is required.

A deep reinforcement learning method for UAV navigation in unknown environments was introduced by He *et al.,* [14]. This method combines imitation learning and reinforcement learning, utilizing expert demonstration data to enhance the training process. While it demonstrates improved 3D UAV navigation performance, its reliance on pre-trained data may limit its adaptability in highly dynamic or novel environments.

Another deep reinforcement learning-based system for goal-oriented mapless navigation of UAVs was explored by Grando *et al.,* [15]. Utilizing sparse range data and localization, their approach showed effectiveness in UAV navigation and obstacle avoidance, comparing favourably to geometric-based tracking controllers. However, the performance might be challenged in environments where more comprehensive spatial mapping is crucial.

An integrated navigation system that combines GPS, Inertial Navigation System (INS), and vision sensors was mentioned by Wang *et al.,* [16]. Using a CCD video camera and a laser rangefinder, the system continuously monitors the UAV's ground-relative movements. Employing two Kalman filters, it offers robust navigation solutions even when GPS signals are unavailable.

A study about a GNSS/INS/LiDAR integrated navigation system was conducted by Ahmed *et al.,* [17]. They proposed to tackle the challenges posed by GNSS signal outages due to antenna malfunctions. The system takes advantage of LiDAR data processed through an optimized LOAM SLAM algorithm and camera images refined via Pix4D Mapper software.

The limitations of drones that rely solely on satellite navigation for their RTH functions were addressed by Blazhko *et al.,* [18]. By integrating on-board video cameras with existing Inertial Navigation Systems (INS), the paper explores feature-based methods for UAV navigation.

The focus on the complexities of UAV navigation in GPS-challenged environments was stated by Klavins *et al.,* [19]. The paper suggests a multi-sensor approach, incorporating Inertial Navigation Systems (INS) with computer vision techniques.

A novel approach to intelligent visual navigation for UAVs was proposed by Sineglazov *et al.,* [20]. Utilizing a combination of traditional visual navigation systems based on SURF and RANSAC algorithms, and CNNs, the system aims to enhance the accuracy of UAV position coordinates. It focuses on improving navigation through periodic correction of values and the use of an adjustment digital complex. Despite its advancements, one limitation of the proposed system is its potential difficulty in handling complex sensory inputs in varying environmental conditions.

A novel approach for autonomous UAV navigation in indoor corridors using a monocular camera was proposed by Akremi *et al.,* [21]. Their approach is based on a CNN named Res-Dense-Net, which combines the strengths of ResNet and DenseNet architectures. This CNN analyses images captured by the UAV's camera to predict its position and orientation. The method is validated on the NitrUAVCorridorV1 dataset and achieves high accuracy in UAV positioning even in challenging environments. While the approach shows promising real-time performance based on visual data, it may encounter limitations in more complex scenarios requiring additional sensory inputs or higher computational power.

An innovative framework for UAV visual localization was introduced by Ahn *et al.,* [22]. This framework uses a convolutional neural network-based Siamese Neural Network (CNN-SNN) with contrastive learning to match aerial and satellite imagery. By processing these images, the system accurately predicts the UAV's global coordinates. The framework efficiently handles visual discrepancies between aerial and satellite images due to factors like weather or lighting conditions. However, the paper acknowledges potential limitations in generalizing across different environments and suggests further research for optimization in various settings.

A route correction system for UAVs was explored by Truong *et al.,* [23]. They proposed an airborne radar-based method to adjust the UAV's flight path, especially in scenarios were active jamming renders radar imagery unusable for route correction. To address this, they suggested an onboard navigation system with an algorithmic correction. This system includes an error compensation scheme and a predictive model constructed using genetic algorithms and group method data handling. The paper evaluates the effectiveness of these algorithms through mathematical models, aiming to enhance the accuracy of autonomous UAV navigation systems in challenging interference conditions.

3. Methodology

In our work, we will be using the drone's capabilities to collect aerial images (frames) during the drone's flight and map them into the current moving degree. The CNN model is built and trained on this data to develop a model capable of returning home without any other sensor except the camera and compass.

Figure 1 below shows the research methodology of the proposed system here.

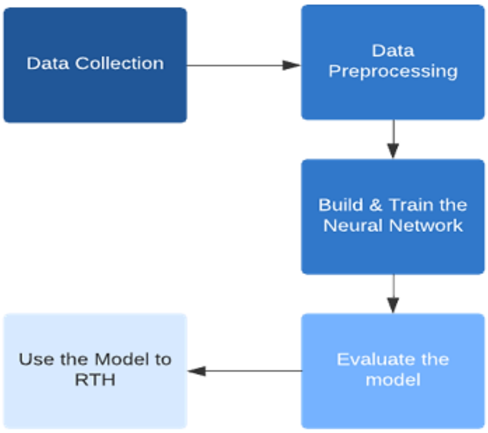

Fig. 1. Research Process

3.1 Data Collection

Data Collection is when the drone is flying, it is instructed to take a frame vertically to the ground and save it along with the current moving degree. Each frame corresponds to a moving degree. This will allow the CNN to learn the way to return home. For instance, Figure 2 shows a real drone's example image as a tangible demonstration.

Let us assume that the drone moving degree in respect to the north is 0°, and the image's top is the same as the north. Figure 3 shows the next frame that is taken.

Fig. 2. The First Aeriel Image was taken by a Drone

Fig. 3. The Second Aerial Image that was Taken by a Drone

3.2 Data Preprocessing

Data Preprocessing is when the raw image taken on each step during data collection, it is then resized to a reasonable resolution to fit the drone capabilities and the neural network conditions. And because the neural network only understands numbers, the drone's moving degree ranges from 0° to 360°, where 0° is the same as 360° and 0° is the opposite direction of 180°. As a result, this cyclical nature of the degree cannot be represented simply as a scalar number that ranges from 0 to 360. We need a way to represent the degree where 0° must have the same value as 360°, which must have an opposite value of 180°. The standard way to represent that is to transform them into two dimensions using sine and cosine transformation. So, the degree is transformed into two dimensions as sine and cosine following these two mathematical equations Eq. (1) and Eq. (2):

$$degree_{sin} = \sin\left(\frac{2*\pi*degree}{max\ (degree)}\right) \tag{1}$$

$$degree_{cos} = \cos\left(\frac{2*\pi*degree}{max\ (degree)}\right) \tag{2}$$

3.3 Build & Train the Neural Network

The process of training the Neural Network goes through four steps, we get an input image, apply convolution on it to obtain a convolution layer that extracts all the features in an image, then apply max pooling to get the most important features in an image. After that, flatten everything into a long vector which will be our input for the fully connected part of the network, and that is the last step called classification where we get the prediction output, Figures 4 and 5 illustrates the four steps:

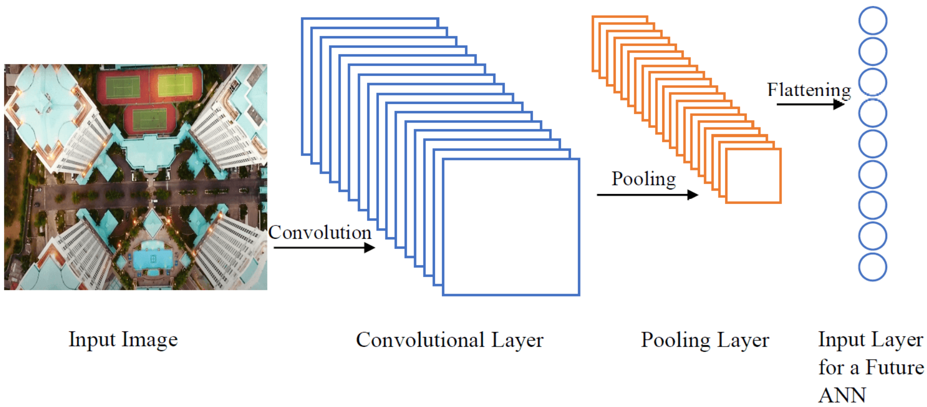

Fig. 4. The CNN part of the Neural Network

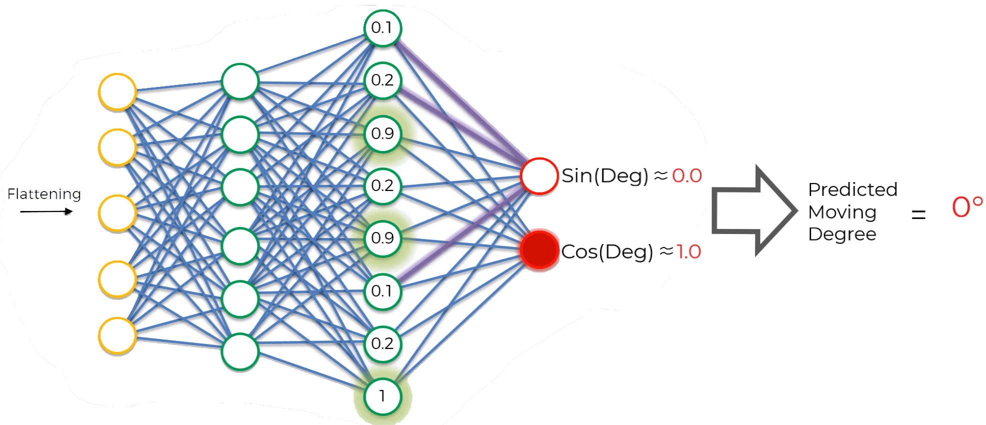

Fig. 5. The Fully Connected part of the Neural Network

i. We used Keras API in the TensorFlow framework in Python to build and train the CNN model.
ii. We trained the CNN on multiple epochs and used model checkpoints to save the model weights only when the metrics improve (mean absolute error).
iii. We also used TensorBoard to track how the metrics change during training.

3.4 Evaluate the Model

After the model is trained, the testing set is used to calculate the metrics for our final model and see how we can improve by tweaking the model's parameters and training. The metric used here are the Mean Absolute Error (MAE), and the Mean Square Error (MSE), MAE is simply the absolute difference between the actual degree and predicted degree averaged across all samples as shown in the following equation Eq. (3):

$$MAE = \frac{1}{N}\sum|y - \hat{y}| \tag{3}$$

MSE is the square difference between actual and predicted degrees across all samples as shown in the following equation Eq. (4):

$$MSE = \frac{1}{N}\sum(y - \hat{y})^2 \tag{4}$$

Here’s what each term represents:

i. N is the total number of data points or samples.
ii. y is the actual degree.
iii. $\hat{y}$ is the predicted degree.
iv. y - $\hat{y}$ is the absolute difference between the actual and the predicted degree.
v. $\sum$ Is the summation symbol, indicating that we sum over all data points.

3.5 Use the Model to RTH

After the drone gets GPS spoofed and the CNN model is successfully trained and tested, the drone takes frames of the ground, flip the resulting image by 180° since the model was trained on frames of the opposite moving direction, does the necessary preprocessing, and feed it to the CNN model and feed it to the CNN model to predict the moving degree. Figure 6 shows an example frame going in the opposite direction of Figures 2 and 3.

As discussed, since the CNN model was trained in the opposite direction of Figure 6, we must flip it 180° degrees (to get an image like in Figure 2 or 3) before we feed it to the model to use the same orientation that was trained on.

The resulting sine and cosine dimensions inferred from the model are converted back to a degree ranging from 0° to 360° excluding 360°. After we get the degree, we need to invert the degree too, as the drone must go the opposite way. The following equation Eq. (5) is responsible for inverting the moving degree:

$$degree_{inverted} = (degree + 180)\ mod\ 360 \tag{5}$$

This way, the drone gets home within the exact trajectory of the start. For example, if the drone was moving at a degree of 20°, the returning degree will be (20+180) mod 360 = 200° and so on.

Fig. 6. Aerial Image taken by a Drone in the Opposite Direction

4. Results and Discussion

4.1 The Trajectory

The drone flies following a trajectory written in the code using degrees, speed and duration. In the following Figure 7 is the trajectory of the flight in Green.

Fig. 7. Flight Trajectory of the Drone on the simulator AirSim

The drone saves images from the camera as it flies through the trajectory and stores it in a folder for the training, each image name has the image number and the degree as shown in Figure 8:

Fig. 8. Images taken by the drone in the folder

4.2 The CNN Training

The CNN uses the images taken by the drone in AirSim Simulator (CityEnviron) as Dataset and the degree assigned to each image to train. The images number range goes from 600 to 1000 images per experiment, depending in the computing power and the flight distance. These images get divided into 2 sets, one for training, which takes 75% of the collected data, and one for testing, which takes 25% of the collected data.

Even though the final CNN architecture is not determined yet, the CNN model that is used is a stack of three convolutional layers, each layer is followed by a max pooling and a ReLU activation function. After that, a layer that is a fully connected one preceded by a flattening layer, and finally the output layer that contain two output neurons for the x and y moving directions (cosine and sin).

The model is trained on multiple epochs (epoch is a hyperparameter to tweak), the model weights are saved on each epoch only when the metrics got improved, and these metrics (such as the MAE) are tracked using TensorBoard, the following figure shows the epoch_mae graph on TensorBoard.

In Figure 9 the diagram shows the Mean Absolute Error in our CNN that is been calculated in every epoch during training and every time the CNN adjust the weights slightly to find the lowest MAE possible during the training and then the lowest Mae model will be used in RTH

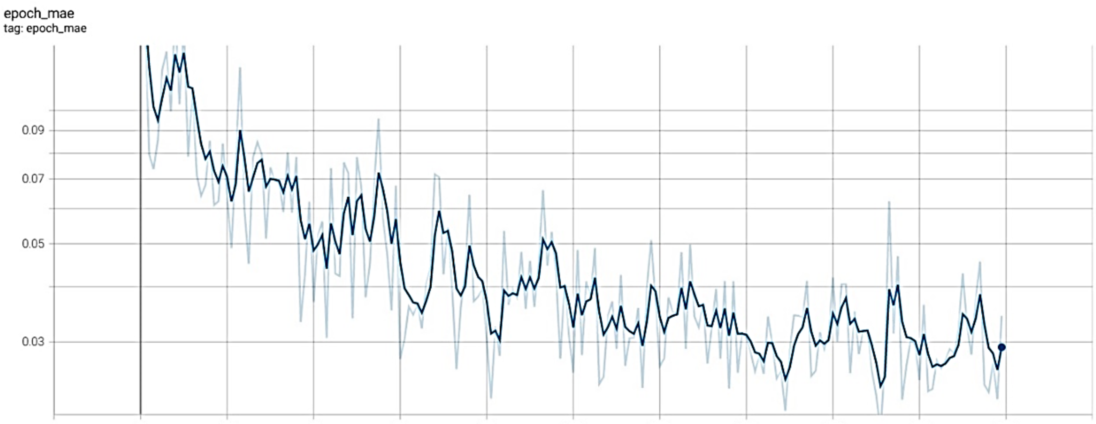

Fig. 9. Epoch_mae graph on TensorBoard

4.3 The Non-GPS Return to Home

After training, the CNN is able to predict the moving degrees. In Figure 10 the result of the non-GPS RTH shown in Red, the drone was able to get back to the starting point within the home range.

Fig. 10. Non-GPS Return-To-Home Trajectory

The following Figure 11 shows the result of 10 experiments on the drone to check its ability to Return to Home by calculating the distance from the starting point in a total flight time of 104.87 seconds and on the same flight trajectory, the results are in meters.

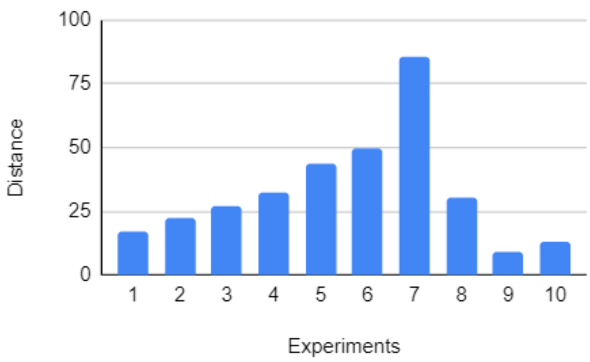

Fig. 11. Experiment of Distance to RTH

The following Table 1 shows the average training time, maximum distance, minimum distance and average distance for 100 experiments that were executed on each epoch 50, 100 and 200. Where The Average Training Time is the average time spent during training for 100 experiments, Maximum Distance is the furthest distance from home, Minimum Distance is the closest distance to home and Average Distance is the average distance of all the 100 experiments.

Table 1
The Results of Average Distance in Different Epochs

Epochs	Average Training Time	Maximum Distance	Minimum Distance	Average Distance
50	266.65 Seconds (04.44 Mins)	100.99 m	10.81 m	37.48 m
100	536.14 Seconds (08.93 Mins)	122.81 m	1.17 m	44.06 m
200	881.25 Seconds (14.69 Mins)	123.23 m	3.88 m	32.19 m

The following Figures 12, 13 and 14 are diagrams that show the results of the experiments conducted and discussed previously in Table 1 where you can see the distance obtained for each one of the 100 experiments and for each epoch separately 50,100 and 200:

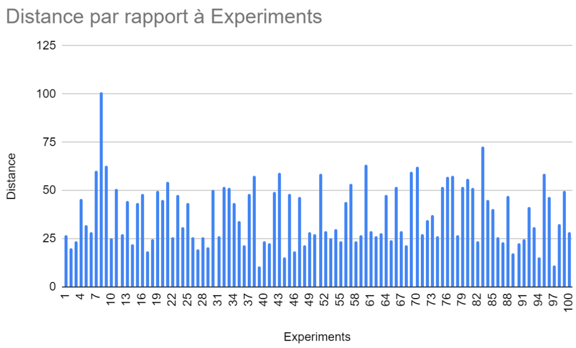

Fig. 12. Results of 100 Experiments on 50 Epochs

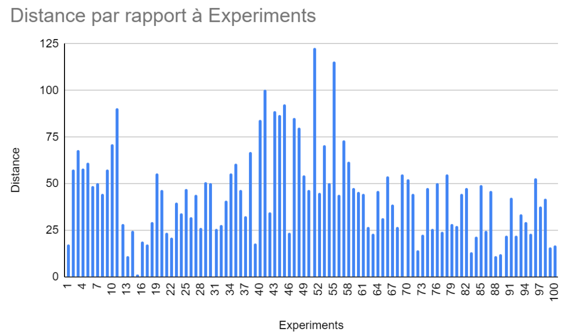

Fig. 13. Results of 100 Experiments on 100 Epochs

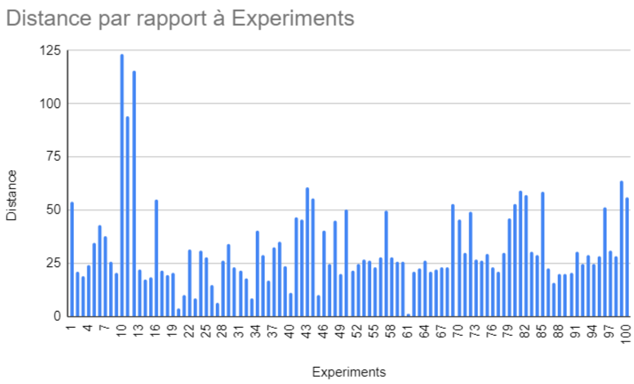

Fig. 14. Results of 100 Experiments on 200 Epochs

Similar work has been conducted by Warren *et al.,* [24], titled "Visual Teach and Repeat for Emergency Return of Multirotor UAVs During GPS Failure." They presented a vision-based route-following system using Visual Teach and Repeat (VT&R) algorithm to build a visual map of the environment during an outbound flight. It aims at autonomous return of UAVs under primary navigation failure, like GPS jamming. Our work focuses on enabling UAVs to autonomously navigate back to their starting point using a CNN model that processes images and moving directions collected during the flight. This method provides an alternative machine learning based to GPS-based navigation, addressing GPS spoofing attacks. Furthermore, we use CNN to analyse flight data (images and directions) for navigation, offering a robust solution against GPS vulnerabilities. On the other hand, the compared paper uses a gimbal-stabilized stereo vision and inertial sensing for localization and navigation without relying on external infrastructure like GPS. While our experiments demonstrate effective RTH with average distances of 20 to 40 meters using only 50 epochs, indicating a high degree of accuracy, Warren *et al.,* shows autonomous return at speed up to 15m/s at altitudes of 5-25 m. However, they did not report the RTH distance to homebase.

6. Conclusion

This article has presented the novel approach to address the problem of GPS spoofing in Unmanned Aerial Vehicles (UAVs) or Drones. The proposed solution utilized a Convolutional Neural Network (CNN) model to enable a drone to Return to Home without relying on compromised GPS data. The drone collected images of the ground and moving degrees during its flight, which are used to train the CNN model. The trained model guided the drone to Return to Home.

The results of the experiments conducted show that the proposed method is effective and robust. The average distance of the returning drone from home was found to be between 20 to 40 meters using only 50 epochs. This demonstrates the potential of the proposed method to improve the robustness of a drone's ability to Return to Home, even under GPS spoofing attacks.

However, it is important to note that the proposed method is not without its limitations. Further enhancement to the algorithm will be made to reduce the average distance of returning drone to less than 10 meters.

The novelty of using CNN for image processing and directional analysis in UAVs marks a significant advancement in the field, offering a fresh perspective on autonomous navigation systems and solid foundation for future enhancements.

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