

# Deep Learning Based to Bridge GPS Denied Area with Fusion Tracking Camera Navigation

Muhammad Wicaksono, Silvianti, Soo Young Shin\*

Email: ([muhammadwicak97](mailto:muhammadwicak97@kumoh.ac.kr), [silvirianti93](mailto:silvirianti93@kumoh.ac.kr)\*, [wdragon](mailto:wdragon@kumoh.ac.kr) \*)@kumoh.ac.kr

Department of IT Convergence engineering  
Kumoh National Institute of Technology

## Abstract

In this paper, a Deep Learning based method is proposed to bridge GPS denied areas with fusion tracking camera navigation. This fusion tracking method is for navigating in GPS-denied areas using a camera and an inertial measurement unit (IMU). The fusion approach integrates visual and inertial information to estimate the position and orientation of the camera in real-time, even in GPS-denied areas. To achieve this, a neural network-based architecture that fuses the visual and inertial data using a set of convolutional and recurrent layers is proposed. This method has the potential to enable a wide range of applications, including robotics in autonomous aerial vehicles or autonomous ground vehicles, in which reliable pose estimation is crucial.

keywords : Fusion, Tracking Camera, GPS, Deep Learning

## I . Introduction

Unmanned vehicles, also known as drones, have seen significant growth in recent years, with applications in a wide range of industries including agriculture, construction, delivery, inspection, and surveillance [1]. There are several key challenges that need to be addressed in order to enable autonomous navigation such as sensing, localization, and Mapping. Another method is used fusion techniques, some common fusion techniques include Kalman filtering which a recursive estimation method that combines a model of the system's dynamics with measurements from sensors to produce an optimal estimate of the system's state [2]. Another method was Particle filtering, it is a Monte Carlo method that represents the state of the system as a set of random samples, or particles, which are updated based on the measurements from the sensors [3]. However using multiple sensors typically increases the cost of the system, fusion techniques often require the use of complex algorithms inside system to combine the

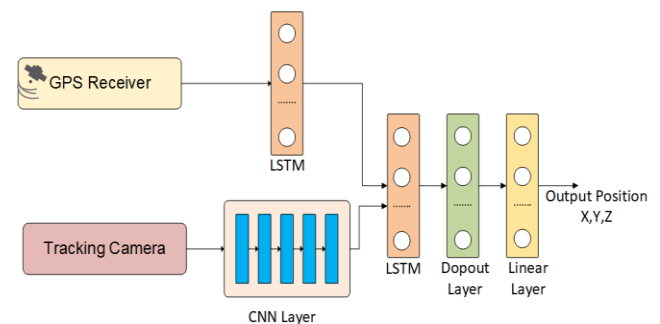


Figure 1. System Model of Fusion Tracking Camera with GPS receiver

measurements from the sensors, and integrating multiple sensors and fusion algorithms can be a complex and time-consuming process. To address the challenges of integrating GPS and tracking camera data for autonomous navigation, this paper aims to improve the accuracy and robustness of the navigation system. The way to do this is by combining tracking camera data with GPS data. This is achieved by using a convolutional neural network (CNN) and a long short-term memory (LSTM) network.

## II . Method

In this system model ROS is utilized as middleware to subscribe and publish odometry of

simulation devices. This simulation is applied to UAV simulation in gazebo. A system model is proposed to use CNN for visual-inertial navigation with tracking cameras, to know the position of object. The CNN is trained to recognize specific landmarks or features in the camera's field of view, as shown in Fig.1. The CNN will detect the features in the current image and match them with the features detected in the previous image. This estimates the motion of the camera between the two images by using the relative positions of the matched features.

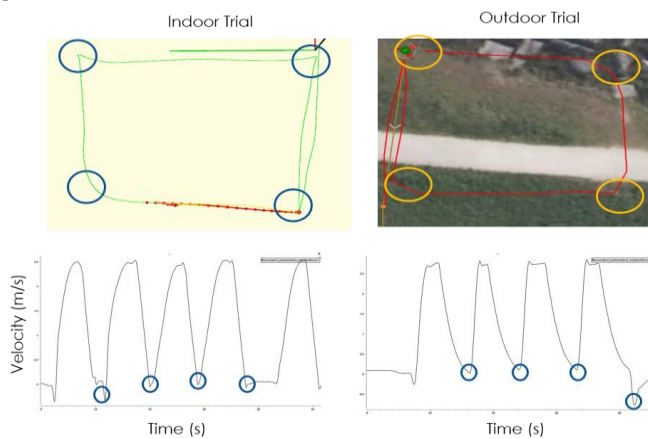


Figure 2. Result data preprocessing of GPS navigation in outdoor and Visual odometry in indoor simulation by subscribe ROS topic local velocity.

To ensure the trajectory is working correctly, the GPS signal receiver is forwarded to be processed by LSTM. In cases where the GPS receiver is unreliable or unavailable, the visual odometry becomes the primary source of navigation and the fusion approach relies on it, and the fusion approach can then rely on the visual odometry output. It's also important to take into account the accuracy of GPS to prevent errors or drift. LSTM is employed to combine the GPS trajectory for sequential processing, this integration is done with results from CNN features of the tracking camera for motion estimation. This motion estimate, derived from combining CNN features of the tracking camera with LSTM fused GPS trajectory, can then be utilized to adjust the device's position and orientation, and this refined location and direction is subsequently broadcasted as the device's local position, together with providing the information

of the local position in geocentric coordinates, by the publisher.

### III. Conclusion

A deep learning-based method was proposed to use fusion tracking camera navigation to bridge GPS-denied areas. This fusion tracking method navigates in GPS-denied areas by using a camera and an IMU sensor. This fusion approach combines visual and inertial information to estimate the camera's position and orientation in real-time, including in GPS-denied areas. As illustrated in Fig.2, the trial results confirm that, in the indoor scenarios, the visual odometry technique was adopted to navigate, whereas for the outdoor experiments, the GPS navigation system was utilized, in order to thoroughly evaluate and contrast the capabilities and effectiveness of these two navigation methods. Based on this conclusion, future work could involve further developing the CNN-LSTM part to improve device positioning in GPS-denied areas.

### ACKNOWLEDGMENTS

This research was supported by the MSIT(Ministry of Science and ICT), Korea, under the Grand Information Technology Research Center support program (IITP-2023-2020-0-01612) supervised by the IITP(Institute for Information & communications Technology Planning & Evaluation) and by Priority Research Centers Program through the National Research Foundation of Korea(NRF) funded by the Ministry of Education, Science and Technology"(2018R1A6A1A03024003).

### REFERENCES

- [1] Nguyen, A. M. and Nguyen, D. T. and Pham, V. Q. and Nguyen, H. T. and Tran, D. T. et al "Real-time ROS Implementation of Conventional Feature-based and Deep-learning-based Monocular Visual Odometry for UAV," 2022 11th ICCAIS, Hanoi, Vietnam, 2022, pp. 436-441
- [2] C. Chu and S. Yang, "Keyframe-Based RGB-D Visual-Inertial Odometry and Camera Extrinsic Calibration Using Extended Kalman Filter," in IEEE Sensors Journal, vol. 20, no. 11, pp. 6130-6138,
- [3] H. Yu, W. Longsheng and Y. Yunzhi, "A video tracking algorithm for UAV based on differential evolution particle filter," Proceedings of the 31st Chinese Control Conference, Hefei, China, 2012, pp. 3955-3959.