DEVELOPMENT OF AN INDOOR LOCALIZATION SYSTEM FOR AN UNMANNED AERIAL VEHICLE

Tyler Cove[1], Scott B. Nokleby[1], Remon Pop-Iliev[1]
[1]*Faculty of Engineering and Applied Science, University of Ontario Institute of Technology*
tyler.cove@uoit.ca,scott.nokleby@uoit.ca,remon.pop-iliev@uoit.ca

ABSTRACT

Presented is the development of an indoor localization system for an Unmanned Aerial Vehicle. A new system was created using a pre-existing localization testbed. The previous testbed was used in the development of ground-based robots. The measurements provided by the existing testbed are used in conjunction with newly available measurements from an Inertial Measurement Unit. These sources are fused using an Extended Kalman Filter, a method of estimating the current position and orientation using a state model based on the previous position, as well as new measurements. This new system was tested on a quadrotor: a four-bladed aerial robotic platform. Test results are presented.

Keywords: Quadrotor; Extended Kalman Filter; Localization.

DÉVELOPPEMENT D'UN SYSTÈME DE LOCALISATION D'INTÉRIEUR POUR UN VÉHICULE AÉRIEN AUTOMATISÉ

RÉSUMÉ

Le développement d'un système de localisation d'intérieur pour un véhicule aérien sans pilote (drone) est présenté. Un nouveau système a été créé en utilisant un banc d'essai de localisation pré-existant utilisé précédemment dans le développement de robots terrestres sans pilote. Les données fournies par le banc d'essai existant sont utilisées avec celle d'une unité de mesure inertielle indépendante du banc d'essai pré-existant. Ces sources sont fusionnées en utilisant un filtre de Kalman étendu, un procédé pour estimer la position et l'orientation à l'aide d'un modèle d'état à base de la position précédente, ainsi que des nouvelles mesures. Ce nouveau système a été testé sur un quadrirotor : une plate-forme robotique aérienne à quatre rotors. Les résultats des épreuves sont présentés.

Mots-clés : Quadrirotor ; Filtre de Kalman étendu ; Localisation.

1. INTRODUCTION

Discussed is a method of localization for an aerial robot using an Extended Kalman Filter (EKF). The research and design was carried out at the Mechatronic and Robotic Systems (MARS) Lab at the University of Ontario Institute of Technology. Previous research in the MARS Lab has yielded the Modified Cricket Localization System (MCLS) [1]. The MCLS has been used for ground-based robots but not with aerial platforms. This new application of the indoor localization system will verify its practicality for indoor three-dimensional tracking. The intended purpose of this aerial robotic platform is the maintenance and repair of high-voltage transmission lines. The historical way of accomplishing these tasks involves the use of a helicopter equipped with an onboard maintenance worker. After approaching the work site, the worker will disembark from the helicopter directly onto the power lines. This is hazardous due to both the high voltage and fall potential. In lieu of this method, an aerial robotic platform is desired to take over such tasks.

As part of the development of this system, an indoor test facility is being developed that will allow the testing of scaled-down prototypes. This paper will describe one of the most critical components to the design of this test facility, namely the localization system. An engineering design process was used to select and design the system described in the next sections. Although the proposed system has been designed for indoor use, it is anticipated that it would be readily adapted to outdoor use by replacing the localization data provided by the testbed with GPS data.

Several works have been published by others seeking to use localization in mobile robot platforms. Eckert et al. [2] described a system which uses an ultrasonic system to determine position based on time-of-flight trilateration. A lack of payload capacity and desire for privacy necessitated the usage of a distributed passive sensor network. Abas, et al. [3] realized that algorithms such as those based on Kalman Filters (KF) can benefit from a system model, but physical parameters are not always easily available. For example, a flight vehicle's moment of inertia will vary when the payload changes. Overcoming this is possible, and knowing the control inputs is beneficial to a Kalman Filter and can be factored into the position calculation. Inertial Measurement Unit (IMU) data supplied to the EKF permits calculation of the moments of inertia and velocities. Roumeliotus [4] discusses a method to circumvent dynamic modeling on mobile platforms using an Indirect Kalman Filter (IKF). Instead of using a direct state model based on physical variables and sensor measurement, a model containing error of the state is used instead.

Achtelik [5] developed a system for testing a host of flight strategies on a quadrotor platform. Seeking a cost-effective and simple to set up vision tracking system, cameras were used to track uniquely-coloured spheres on the aerial platform. Control of the quadrotor was also simplified by assuming control inputs were linear, which is practical for non-acrobatic flight. Bachrach [6] and Zhang [7] similarly describe methods used to relate assumed linear control inputs to acceleration. Bachrach used this as part of an EKF to create a mapping system to explore an unknown area. Zhang performed pose (position and orientation) estimation based on the position of a ground robot. Herisse, et al. [8] achieved localization using optical flow: the relative movement of an image captured by a camera as the camera itself moves. This was tested on an existing quadrotor platform and additionally permitted a way to perform obstacle avoidance. Caron, et al. [9] described using a multisensory Kalman Filter with fuzzy rules to weigh the competency of GPS and inertial measurement data. For example, erroneous data such as an incorrect GPS signal could be flagged if the environment where the measurement was taken is known to be unreliable. Tanigawa, et al. [10] described using a fusion of vertical acceleration and barometric pressure measurements to compute relative rather than absolute altitude using a Kalman Filter. The filter permits velocity to be derived as part of the state model as well. Grisetti, et al. [11] described a hybrid system where a Kalman Filter is used to estimate altitude, but what is unique is shared control with a human operator. The software-controlled position is less favoured when human input is present.

Figure 1 shows the existing testbed of the MARS lab, where the primary component is the Modified

Fig. 1. The existing MCLS testbed showing the listener Crickets

Cricket Localization System (MCLS). The system was based on the Cricket Localization System originally developed by the Computer Science and Artificial Intelligence Laboratory (CSAIL) at the Massachusetts Institute of Technology (MIT). The general functioning of the Cricket system is akin to that of the widely known Global Positioning System. The MCLS is comprised of twenty fixed position *listener* Crickets, and two platform-mounted *beacon* Crickets. Each Cricket is composed of an ATmega128 micro-controller, ultrasonic transmitter and receiver pair, radio-frequency transceiver, and a serial data interface. The method of operation has been used on previous mobile robot platforms in the MARS lab, and the localization method presented here could be considered the next generation of this system.

The objective of this work was to modify the current terrestrial localization system to permit functionality for aerial robotic systems.

2. LOCALIZATION USING EXTENDED KALMAN FILTER

What follows is a brief description of what the Kalman Filter is and its implementation on the robotic system.

The purpose of the Kalman Filter is to estimate the state of the platform at time *t* given knowledge of the previous state at *t-1*. This is accomplished by using two models: a *system* model and a *measurement* model. Both the system and measurement model are assumed to have a certain amount of noise. The Kalman Filter performs best when the noise is Gaussian distributed. The state representing the system model is an 18 element vector **x**, and the measurement model is represented by a 14 element vector **z**:

$$\mathbf{x} = \begin{bmatrix} \mathbf{p} & \mathbf{v} & \mathbf{a} & \boldsymbol{\theta} & \boldsymbol{\omega} & \boldsymbol{\omega_b} \end{bmatrix}^T, \tag{1}$$

$$\mathbf{z} = \begin{bmatrix} \mathbf{p_0} & \mathbf{p_1} & \mathbf{a} & \boldsymbol{\omega} & \boldsymbol{\theta} \end{bmatrix}^T \tag{2}$$

with the linear vectors position $\mathbf{p}$, velocity $\mathbf{v}$ and local acceleration $\mathbf{a}$, followed by angular orientation $\boldsymbol{\theta}$, and rotational velocity $\boldsymbol{\omega}$. Linear values each comprise of Cartesian coordinates *x*, *y* and *z*, whereas angular values each comprise of roll α, pitch β, and yaw γ. Additionally there is the angular velocity bias $\boldsymbol{\omega_b}$: a reading of the initial angular velocity measured when the filter initializes, and is subtracted from $\boldsymbol{\omega}$ during runtime. The measurement vector contains the three-dimensional coordinates of two Crickets $\mathbf{p_0}$ and $\mathbf{p_1}$, the local acceleration $\mathbf{a}$ measured by the onboard accelerometer, local angular velocity $\boldsymbol{\omega}$ via the gyroscope, and the roll and pitch angles $\boldsymbol{\theta}$ which have been previously calculated by the onboard stabilization software. A typical Kalman Filter works best when both the system and measurement models are comprised of linear functions. Conversely, this is not the case for the aerial robot presented here where both models contain nonlinearities. The KF operating under these circumstances will not perform well. In lieu of this, the Extended Kalman Filter (EKF) can be employed. The EKF is a modification of the KF that performs linearization before applying the filter. For a more detailed understanding the reader is encouraged to review [12].

The filter loop starts by estimating the platform's initial position using the mean of the onboard Crickets' positions. Once the filter is initialized a *prediction step* is performed. Using previously gathered data one time step is taken in the system model. The duration of this period without measurement depends on the robustness of the filter, as each time step introduces a new amount of uncertainty to the system. If new measurements are available, a *measurement step* can be taken. A large amount of uncertainty in the previous prediction will favour the new measurement more. This is also true vice-versa: a confident prediction of state will favour a new measurement less so. If no new measurement is available, the algorithm simply returns to taking a prediction step.

3. TESTING PLATFORM

What follows is a brief overview of the quadrotor platform, a Vertical Take-Off and Landing (VTOL) type of aerial vehicle. While quadrotors are the most common type of multiple-rotored research platform, it is possible to have any even number of rotors if more lift or redundancy is required.

The prevalence of quadrotors in research today can be attributed to a few benefits. Where applications requiring stationary flight would have used a helicopter previously, the quadrotor provides an ample alternative. Mechanical complexity can be substituted for electrical complexity: the complex mechanical linkage with one large variable-pitched rotor can be removed for four smaller, static-pitched rotors. Since fewer parts are necessary, the manufacturing cost is reduced. The factor of safety is also increased, as the smaller rotors possess less kinetic energy than one single rotor. This is desirable, should the blades come into contact with operators or equipment.

3.1. Quadrotor platform

The MARS Lab quadrotor, as shown in Figure 2, is a mobile platform with four rotors spaced equally at a 50 cm distance rotor-to-rotor. The four blades are counter-rotating 25.4 cm length plastic with a 12 cm pitch. The platform has an overall mass of 1.54 kg and typically carries a 0.43 kg 5,000 mAh lithium polymer battery, usually giving 10-15 minutes of flight time. This battery can be exchanged for others of more or less capacity for different flight scenarios. Four three-phase motors with individual Electronic Speed Controllers (ESCs) provide the lift required for flight. The front and back arms have been extended for attaching the beacon-mode Crickets by 25 cm each such that the ultrasonic signals are not interfered with by blade motion.

For onboard control the quadrotor is using AeroQuad, a hardware and software package based on the Arduino microcontroller. Aeroquad was selected since a controller was required that could be easily augmented with additional sensors and programming modifications. AeroQuad's open-source nature permitted both of these activities.

The functioning of the software is shown in Figure 3. The process for Cricket localization is as follows: The quadrotor controller first requests that one Cricket in beacon mode transmits a "chirp", consisting of a simultaneously transmitted ultrasonic and radio-frequency signal. The listener Crickets will receive this signal almost instantaneously, triggering an event. If any listener is within range, it will receive the ultrasonic signal soon after. The time-of-flight can then effectively determine the distance between the listener and the beacon. This distance, along with the listener ID, is returned to the beacon. This in turn is communicated to the quadrotor controller.

Fig. 2. The quadrotor platform

Once this has been received by the quadrotor controller, the sensor data is transmitted to the ground station during the next communication cycle. Stabilization is done onboard of the quadrotor, so a brief loss of communication will not affect flight operation. Additionally, any available inertial sensing data from the IMU is transmitted back to the base station as it becomes available.

3.2. Ground Station

The ground station, shown in Figure 4, is comprised of a System76 Lemur laptop. The laptop is running Ubuntu Linux 11.10 and Robotic Operating System (ROS). Additionally an XBee Pro modem connected via USB provides wireless connectivity to the onboard controller. ROS allows program function to be split into modules called *nodes*. The modular nature of ROS permits programming functions to be added, modified, or removed without having to modify other parts of the system.

The ground station sequence of operations occurs as follows: Communication is established using the *marslab-quadrotor* package. This package negotiates serial communication between ROS and the quadrotor, decodes commands received from the quadrotor into sensor-based *topics*, which are used by the nodes to communicate with each other. The data gathered here is passed to *kfilter-wrapper* which takes the Cricket measurements and IMU data into the EKF filter developed with the KFilter library. Once processed, the filtered pose is sent to *starmac-ros-pkg*, a ROS package developed by UC Berkeley. This package serves as a platform-agnostic control system which uses the current pose in conjunction with a desired pose to calculate flight commands. These commands are then sent back to *marslab-quadrotor*, which finally dispatches the command over XBee to the quadrotor. In addition to logging the position of the quadrotor there is visual feedback given though the ROS package *RViz* as shown in Figure 5.

4. SYSTEM EVALUATION

How well the localization performed was evaluated in the following manner: Two recordings of the current position of the quadrotor in the testbed were taken. A ground-truth measurement using an Optitrack optical motion capture system would concurrently record the quadrotor's position. This would be assumed to be the actual position. An additional ROS package was created to log both positions to a file for analysis.

A stationary position was first measured for 60 s to determine the static error between the EKF-estimated

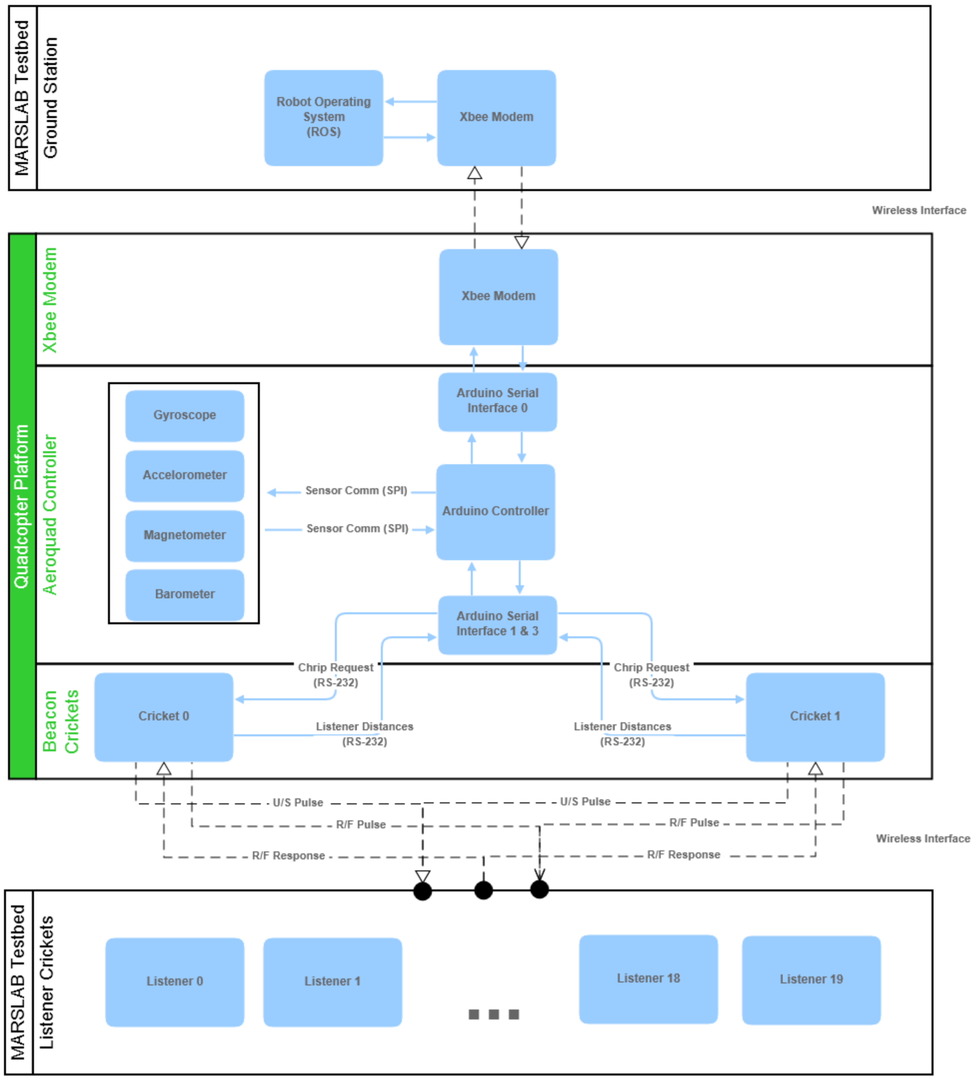

Fig. 3. Localization Schematic

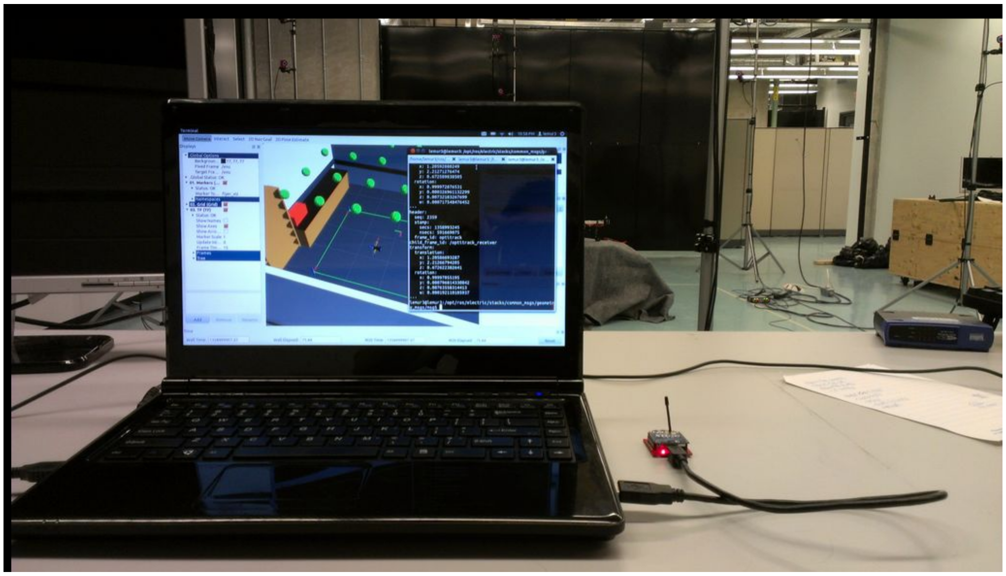

Fig. 4. The quadrotor ground station

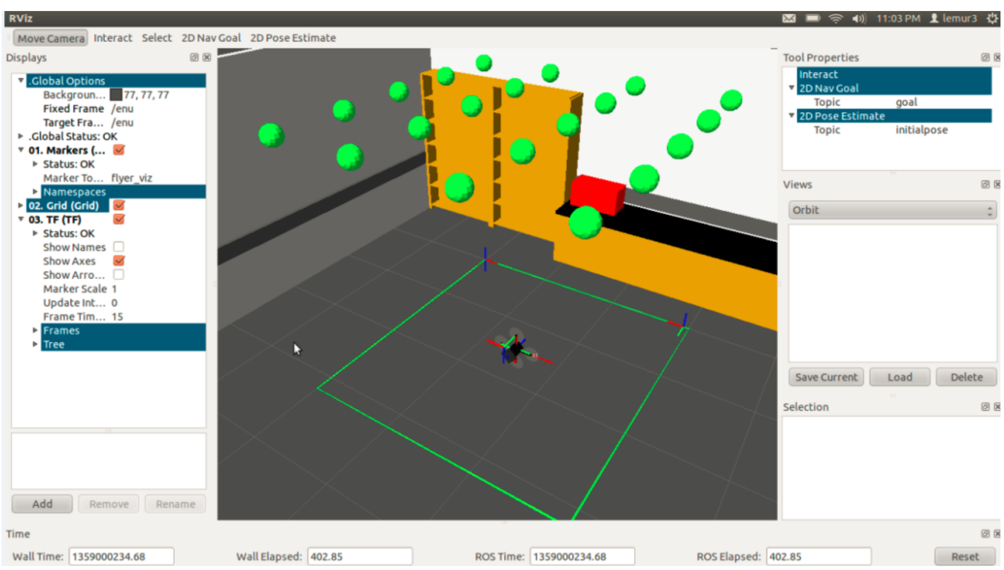

Fig. 5. RViz visualisation running under ROS

pose and ground truth. The orientation was also corrected in the motion capture system's software. To correct the static error an additional translation was added to the ROS software between the world origin and Cricket origin. The results of this test are shown in Figure 6. What can be seen here is that while there is a large deviation within the first two seconds of axes X and Y, the estimation settles near the actual position after five seconds. Along X any Y it can be noted that there are three larger deviations from ground truth between 13 s and 18 s. During these times it was likely that an absolute position measurement from the Crickets would have been missed, and estimation was performed using only the inertial sensors. Over the duration of the test these sensors will gain bias and the estimate will become less accurate until a Cricket measurement is taken again.

A second trial was performed by manually moving the quadrotor from a ground position to approximately 1 m off the ground, moving in a circular pattern, and then returning to the ground. The results are shown in Figure 7. The movement of the quadrotor is shown to have an effect on the estimation of the EKF, especially for the Y axis. Time to approach the actual position is similar to the previous test, however deviation from ground truth has increased. This can be attributed to the inertial sensor bias that differs as time passes. This is apparent in the position along the X axis. Both tests also exhibited a static error in the Z direction, which can likely be attributed to the difference in height between the Cricket beacons and the optical tracker beacon.

What these results show is that the inertial bias can have an effect on position estimation if very frequent position updates are required, such as for acrobatic flight. For such usage a higher accuracy would be required. However, since the goal of this research is non-acrobatic yet stable position estimation this EKF implementation should be suitable.

5. CONCLUSIONS AND FUTURE WORK

In this paper the implementation of an Extended Kalman Filter and how it is used in the localization of an aerial robotic system is presented. Using the previous work done with the Modified Cricket Localization System and ground-based robots, the MARS Lab testbed was modified to enable three-dimensional localization. The EKF is used to make a prediction of the robot's next state based on the previous state and newly available measurements. The aerial platform took the form of a quadrotor, transmitting gathered measurement data back to a ground station for computation. The localization system was evaluated using a ground-truth system to accurately track the actual quadrotor pose and compare it to the estimated EKF-determined pose.

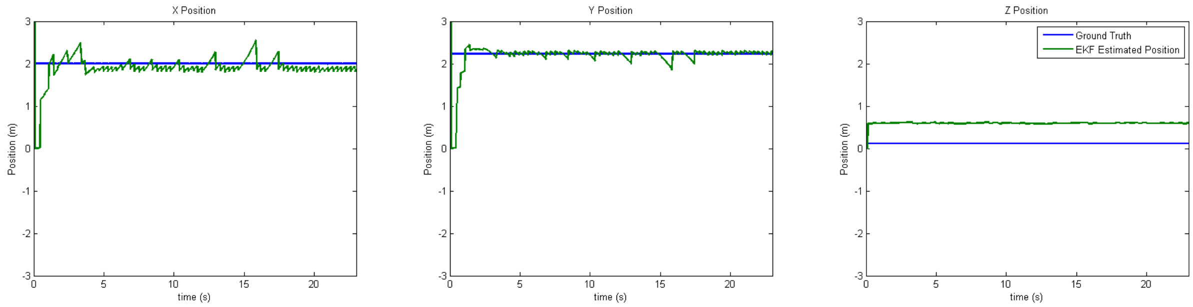

Fig. 6. Static quadrotor EKF Estimation vs. Ground Truth

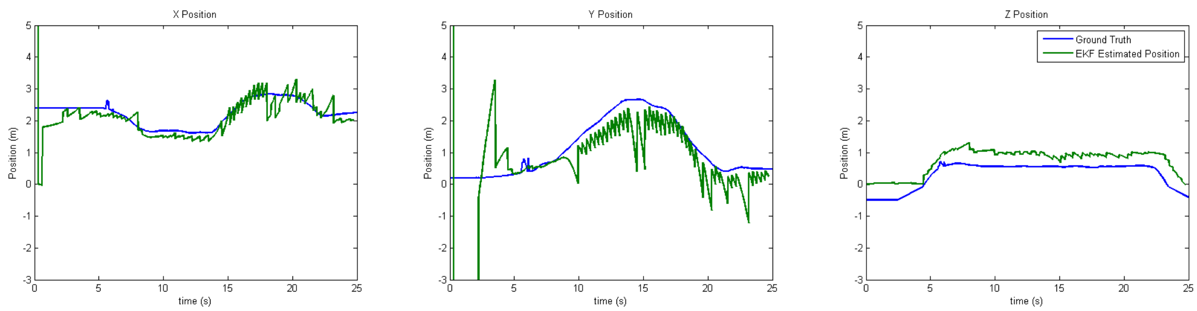

Fig. 7. Moving quadrotor EKF Estimation vs. Ground Truth

REFERENCES

1. Ginzburg, S., Frankenberg, F.V. and Nokleby, S. "Design and Implementation of an Indoor Localization System." *Transactions of the Canadian Society for Mechanical Engineering*, Vol. 33, No. 4, pp. 715–729, 2009.
2. Eckert, J., German, R., Dressler, F. and Member, S. "An Indoor Localization Framework for Four-Rotor Flying Robots Using Low-Power Sensor Nodes." *IEEE Transactions on Instrumentation and Measurement*, Vol. 60, No. 2, pp. 336–344, 2011.
3. Abas, N., Legowo, A. and Akmeliawati, R. "Parameter Identification of an Autonomous Quadrotor." In "2011 4th International Conference on Mechatronics (ICOM)," May, pp. 17–19, 2011.
4. Roumeliotis, S., Sukhatme, G. and Bekey, G. "Circumventing Dynamic Modeling: Evaluation of the Error-State Kalman Filter Applied to Mobile Robot Localization." *IEEE International Conference on Robotics and Automation*, Vol. 2, pp. 1656–1663, 1999.
5. Achtelik, M., Zhang, T., Kiihnlenz, K. and Buss, M. "Visual Tracking and Control of a Quadcopter Using a Stereo Camera System and Inertial Sensors*." In "IEEE International Conference on Mechatronics and Automation," pp. 2863–2869, 2009.
6. Bachrach, A., He, R. and Roy, N. "Autonomous Flight in Unstructured and Unknown Indoor Environments." pp. 2–9, 2009.
7. Zhang, T., Li, W., Achtelik, M., Kuhnlenz, K. and Buss, M. "Multi-Sensory Motion Estimation and Control of a Mini-Quadrotor in an Air-Ground Multi-Robot System." In "IEEE International Conference on Robotics and Biomimetics (ROBIO)," pp. 45 –50, dec. 2009.
8. Herisse, B., Russotto, F.X., Hamel, T. and Mahony, R. "Hovering Flight and Vertical Landing Control of a VTOL Unmanned Aerial Vehicle Using Optical Flow." pp. 801 –806, sept. 2008.
9. Caron, F., Duflos, E., Pomorski, D. and Vanheeghe, P. "GPS/IMU Data Fusion Using Multisensor Kalman Filtering: Introduction of Contextual Aspects." *Information Fusion*, Vol. 7, No. 2, pp. 221 – 230. ISSN 1566-2535, 2006.
10. Tanigawa, M., Luinge, H., Schipper, L., Slycke, P. and Technologies, X. "Drift-Free Dynamic Height Sensor

using MEMS IMU Aided by MEMS Pressure Sensor." *5th Workshop on Positioning, Navigation and Communication, 2008.*, pp. 1–6, 2008.
11. Grisetti, G. "Towards a Navigation System for Autonomous Indoor Flying." *IEEE International Conference on Robotics and Automation*, pp. 2878–2883, 2009.
12. Negenborn, R. *Robot localization and kalman filters*. Ph.D. thesis, Citeseer, 2003.