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Development of a relative localization scheme for ground-aerial multi-robot systems

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***Abstract*— In this paper we demonstrate a design and experimentation of a relative localization solution for a multi robot team involving both ground and aerial robots. The relative localization method proposed in this paper has the ability to localize a dynamic agent with respect to only one leader ground robot in a GPS denied environment. The sensor solution proposed in the study employs a combination of an acoustic sensor and an infra-red(IR) based vision sensor for relative range and bearing estimations respectively. An extended Kalman filter performs the sensor fusion using a four degree of freedom kinematic model. Numerical simulations validate the sensor fusion scheme for both ground and aerial robotic relative localization. An experimental test-bed of the system with the hardware implementation of the sensors were developed. For comparison purposes the self localization modules of the robots are further integrated into the experimental setup. Realtime experiments were performed where 5-10 cm mean accuracy of pose estimation was achieved in multiple experiments.**

I. INTRODUCTION

A robotic multi-agent system is a collection of autonomous agents designed for cooperative mission execution. The team-based approach is preferred in robotics due to its robustness to failure, wide coverage and efficiency in missions. In many applications it is common for robot teams to exhibit heterogeneity among agents, in terms of perception capabilities, processing power, locomotion or domain of operation among many other differentiating factors. In this setting the fundamental problem of localization is more complex with the anonymity in measurements and asynchronous updates of multiple observations. The design of multi-agent systems should ensure that the system is fully observable by either empowering agents with sufficient self localization ability or establishing relative localization schemes between agents.

The ground and aerial indoor multi-robot team considered in this research is a sample configuration of a heterogeneous multi-agent system. The ground and aerial agents possess complementary unique characteristics which are highly advantageous for team-based indoor mission execution. Micro aerial vehicles (**MAV**), the aerial agents, allow navigation in cluttered indoor settings with the ability to maneuver through multi-floor buildings. The dynamic nature of MAVs do not allow accurate localization, thus require high cost payload and processing dedicated to localization. The MAV hardware platforms also have limited flight times making them incapable of continuous practical mission execution. In contrast, ground robots have higher payload, processing power, long range sensing and ability to provide accurate localization. Therefore the combined team mission execution would enhance their relative capabilities.

Simultaneous localizing and mapping (**SLAM**) methods remain the popular choice for robot localization in indoor environments. Although laser-based and vision-based realtime SLAM implementations are reported [1], [2], [3], [4] for MAVs, successful implementation of such filters require considerable processing and payload requirements. It is advantageous for multi-robot system designs to reduce the application of SLAM to strategically selected agents while establishing relative localization schemes for the rest of the agents. This also applies to similar ground agents in the team with inferior localization ability due to limited exteroceptive sensing.

Therefore, to develop simpler multi-robot systems in terms of cost and processing capability, we identify the requirement of a scalable relative localization method. Previous studies on developing spatial relative localization methods include vision based or acoustic based solutions [5], [6], [3] [7], [8]. Vision-based techniques require higher computational overhead for depth perception and agent identification, while relative bearing estimation capability is a strong aspect of the solution [5], [6], [3]. Completely acoustic-based solutions require multiple geometrically conditioned observations for applying lateration techniques for localization [7], [8]. Range perception is a strong aspect of the acoustic solution while accurate bearing estimation require computationally demanding acoustic array signal processing techniques [9].

In this study we assess an acoustic and vision based hybrid solution for spatial relative localization, exploiting their relative capabilities. The following main contributions of our work can be identified. 1) A relative localization method for both ground and aerial agents with the requirement of only one perceiving leader robot. 2) A scalable architecture which enables simultaneous localization of multiple "pod" agents. 3) Realtime hardware implementation of the system employing low cost, low payload hardware and computationally efficient measurement equations.

Validation of the method is presented with numerical simulations and experimental results. The conceptual design of the sensor solution exhibits capability of localization up to 10m range with a mean accuracy of 5-10 cm. The architectural aspects which should complement this relative localization method are discussed along with the required modifications for robust implementation.

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II. BACKGROUND

Multi-agent localization generally employs probabilistic methods to localize the agents via stochastic filtering of robot states [10] [11]. Often ground-aerial teams are localized using the self localization ability of agents to ensure robustness of the system. Outdoor implementations employ GPS-based localization of agents which suffer from poor accuracy and unavailability in indoors and in urban canyons. Laser-based SLAM, tend to be the popular choice reported for GPS denied MAV pose estimation [1], [2]. Separate studies focus on employing vision-based methods due to the expensive hardware and payload requirement of the laser-based solution. Stereo vision [3] , monocular vision [4] and appearance-based [12] implementations are some of the reported methods. Fixed camera system-based implementations are also reported for multi-agent ground-aerial team localization in both indoor [13][6] and outdoor settings [5]. This solution confines the team operation to a limited workspace observable from the fixed camera system.

Recent literature addresses indoor relative localization using different measurement sources. Stereo vision-based visual 3D tracking solutions are reported with accuracies of 5 to 10 cm over 4m range [6]. The method requires different color markers placed at four corners of each agent, compromising the practical scalability of the system. Similarly visual servos for relative localization is also reported [14], but experimentation was only successful with the MAV hovering closely over the ground robot. Therefore a solution primarily based on vision tends to degrade the scalability and range. Recent studies report the application of custom built acoustic sensor nodes for indoor relative localization of MAV agents [7]. The method performs relative localization by lateration techniques. Thus require line of sight between at least three agents with a geometrically appealing configuration for accuracy.

Candidate indoor positioning systems are reported for the purpose of relative localization in ground aerial robot teams. RF, WiFi and WLAN based methods have not achieved acceptable accuracy for robot implementations [15]. Active BAT system [16] and Cricket systems [17] are early laboratory level full implementations of acoustic localization using ultrasonic transducers. More recent studies proposes code division multiple access (**CDMA**)[8] and frequency hopping spread spectrum (**FHSS**) [9] methods for simultaneous and robust localization of acoustic sources. The spread spectrum techniques allows simultaneous localization capability and better noise immunity, but additional hardware overhead is introduced with wideband transducers, demodulators, and higher sampling rates for application in robotics.

III. METHODOLOGY

Fig. 1 illustrates the robotic arrangement used in the relative localization sensor solution. The robots which posses self localization capability are termed “leaders” and other ground and aerial robots without this capability are termed as “pods”. We attempt to exploit the strong aspects of the two widely reported relative observation solutions. The bearing estimation is dedicated to a vision sensor and the range estimation is primarily supported by an acoustic ranging method. In the proposed method the height estimates of the MAVs in team are taken as an additional observation, mainly to support measurement correspondence when multiple pods are perceived by the camera.

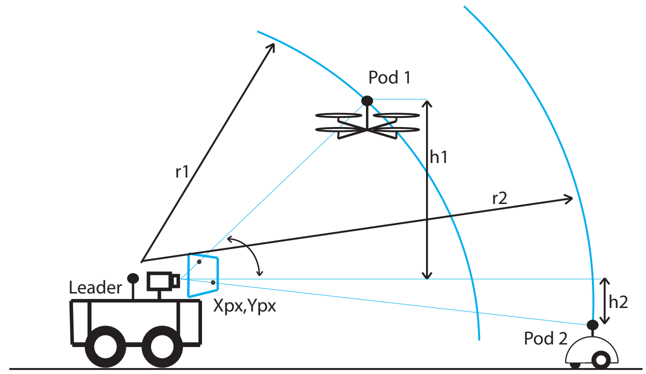

Fig. 1. Ground aerial multi-robot relative localization method

A. Bearing sensor

The vision sensor, which estimates the bearing of the required agent, locks on the visual features of the agent to measure the pixel position of the desired target in the image plane. A perfect pinhole camera model is assumed with $(0, 0)$ image center equal pixel scaling factors and focal length of f_c. The projection of the relative position $[x, y, z]'$ relative to camera coordinate system is projected to the image plane $[x_{px}, y_{px}]'$ (in pixels) using equation (1). Corresponding measurement errors of the measured pixel position in the image plane is identified using the noise terms $\nu_{x_{px}}$ and $\nu_{y_{px}}$.

$$\begin{bmatrix} x_{px} \\ y_{px} \end{bmatrix} = \begin{bmatrix} \frac{y}{x}.f_c \\ \frac{z}{x}.f_c \end{bmatrix} + \begin{bmatrix} \nu_{x_{px}} \\ \nu_{y_{px}} \end{bmatrix} \tag{1}$$

The height information h can be incorporated in to the measurements to arrive at a vision only localization solution as given in equation (2). However, this solution imposes an additional requirement for the leader and pod agents to share a common ground reference. This would be highly disadvantageous in practical localization tasks.

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} \frac{h}{y_{px}}.f_c \\ \frac{h}{y_{px}}.x_{px} \\ h \end{bmatrix} \tag{2}$$

B. Ranging sensor

The ranging sensor in this study is an acoustic time of flight (**TOF**) sensor. The measurements correspond to the shortest distance between an acoustic source and a sensor. Sensor parameters include the speed of sound C_{air}, a bias term b_{T_d} which include biases introduced by clock synchronization, and a noise term ν_{T_d} introduced by timer resolution and multi-path effects. The measured time delay T_d between the two agents is given by equation (3).

$$T_d = \frac{\sqrt{x^2+y^2+z^2}-b_{T_d}}{C_{air}} + \nu_{T_d} \tag{3}$$

C. System model

The kinematic model of the agent which is to be localized is simplified based on assumptions related to hover conditions. A four degree of freedom (**DOF**) model is assumed for dynamic tracking. A full 6-DOF kinematic model is not required for localization since MAVs have sufficiently accurate low-level control loops to stabilize the pitch and roll angles at low velocity movements. The kinematic model in equation (4) has an eight dimensional state vector $\mathbf{x}$, which carries the three dimensional position x, y, z, heading θ relative to a leader and body fixed velocities v_x, v_y, v_z, ω_z of a pod. A vector ν introduces noise due to modeling error and environmental disturbances. The inputs to the model include the linear velocities v_{Lx}, v_{Ly}, v_{Lz} and angular velocity ω_{Lz} of the leader. $f(\mathbf{x})$ defines the nonlinear state transformation function of the state vector $\mathbf{x}$.

$$\dot{\mathbf{x}} = f(\mathbf{x})$$

$$\begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{z} \\ \dot{\theta} \\ \dot{v_x} \\ \dot{v_y} \\ \dot{v_z} \\ \dot{\omega_z} \end{bmatrix} = \begin{bmatrix} v_x \cos\theta - v_y \sin\theta - v_{Lx} + \omega_{Lz} y \\ v_y \cos\theta + v_x \sin\theta - v_{Ly} - \omega_{Lz} x \\ v_z - v_{Lz} \\ \omega_z - \omega_{Lz} \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} + \nu \tag{4}$$

For ground robots, equation (4) omits the position state z and velocity states v_y, v_z to satisfy the two dimensional constraints of the system.

The measurement model defined by $g(\mathbf{x})$ combines the previously discussed sensor options used in the study.

$$\mathbf{y} = g(\mathbf{x})$$

$$\begin{bmatrix} h \\ x_{px} \\ y_{px} \\ T_d \end{bmatrix} = \begin{bmatrix} z \\ \frac{y}{x} \cdot f_c \\ \frac{z}{x} \cdot f_c \\ \frac{\sqrt{x^2+y^2+z^2}-b_{T_d}}{C_{air}} \end{bmatrix} + \begin{bmatrix} \nu_h \\ \nu_{x_{px}} \\ \nu_{y_{px}} \\ \nu_{T_d} \end{bmatrix} \tag{5}$$

D. Sensor fusion

Fusion of the available information for dynamic tracking of the desired target is achieved employing an extended Kalman filter (**EKF**). Other probabilistic non-gaussian estimators are suitable for a general approach. The EKF prediction correction structure used for sensor fusion of the system follows equations (6) and (7). The matrices F and H are the linearized nonlinear state transformation $f(\mathbf{x})$ and measurement $g(\mathbf{x})$ models. The matrices P, Q and R carries the state, process noise and measurement noise covariances respectively. The filter performs an estimation of the states $\hat{\mathbf{x}}$ using the knowledge of the nonlinear model and the measured outputs $\mathbf{z}$.

$$\begin{array}{lcl} \multicolumn{3}{l}{\mathit{Prediction}} \\ \dot{\hat{\mathbf{x}}}^- & = & \bar{f}(\hat{\mathbf{x}}) \\ F & = & \frac{\partial}{\partial \mathbf{x}} \bar{f}(\mathbf{x})|_{\mathbf{x}=\hat{\mathbf{x}}} \\ \dot{P} & = & FPF^T + Q \end{array} \tag{6}$$

$$\begin{array}{lcl} \multicolumn{3}{l}{\mathit{Correction}} \\ \hat{\mathbf{y}} & = & \bar{h}(\hat{\mathbf{x}}) \\ H & = & \frac{\partial}{\partial \mathbf{x}} \bar{h}(\mathbf{x})|_{x=\hat{\mathbf{x}}} \\ K & = & PH^T(HPH^T + R)^{-1} \\ \hat{\mathbf{x}}^+ & = & \hat{\mathbf{x}}^- + K(\mathbf{z} - \hat{\mathbf{y}}) \\ P & = & P - KHP \end{array} \tag{7}$$

The main limitations of the proposed approach are; a) Robots in the team satisfy the field of view constraint imposed by the camera. This constraint can be relaxed using an omnidirectional vision apparatus. However, it is still required to maintain line of sight between leaders and pods. b) The pods operate within the acoustic range of the ultrasonic relative ranging sensor. Similar to our experimental system, these sensors can be designed with sufficient range for indoor applications. c) The leaders traverse on a flat ground plane. To relax this assumption additional sensors should be introduced to estimate the roll and pitch of the leader and to compensate for the undesired effect.

IV. Experimental setup

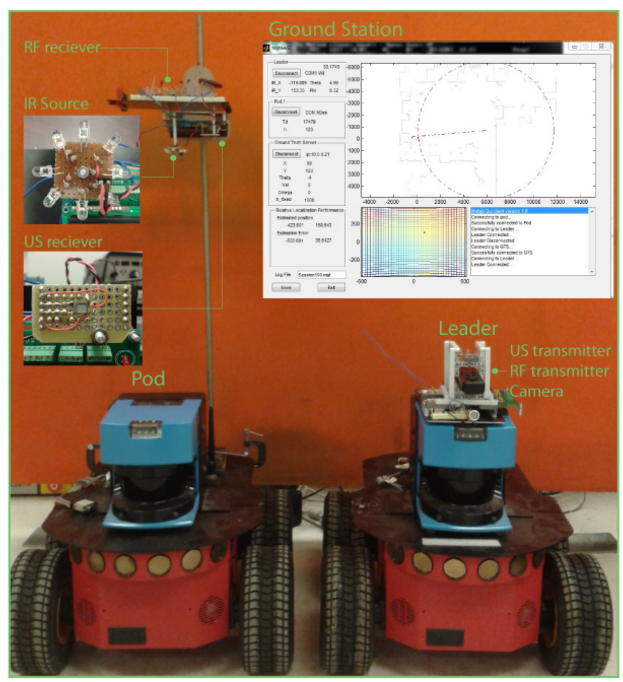

Fig. 2. The test bed used for experiment which includes the relative localization sensor nodes attached on mobile robots and a Matlab GUI application for establishing connection and visualization

An experimental validation of the relative localization accuracy of the proposed sensor solution was performed.

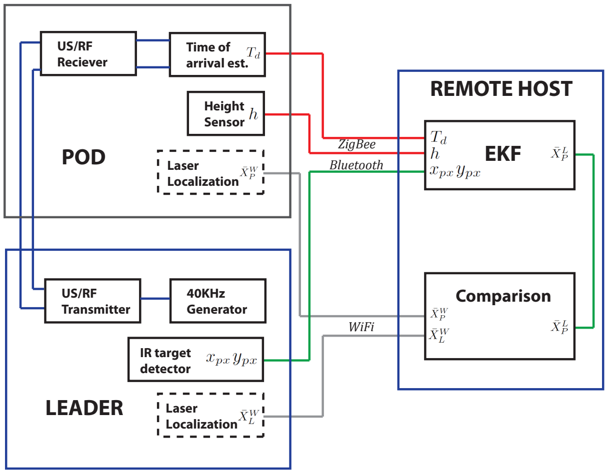

Fig. 3. System architecture of the relative localization scheme

The experimental test bed comprises of sensor nodes having camera-based bearing estimation, ultrasonic three dimensional ranging setups and support mobile robots to test relative localization. The architecture of the experimental test-bed is illustrated in Fig. 3.

The vision sensor used in the study is a PixArt computer vision IR sensor commonly seen in commercial Wii remotes. The sensor performs embedded image analysis and target detection tasks to output the pixel position of up to four perceived IR sources. An omnidirectional IR source was employed using a circular array of IR LEDs as the tracked target. The sensor successfully tracks the beacon up to 10m range in the lab environment. The limitation of the image sensor option lies in its range and number of IR sources that can be simultaneously tracked. Although for illustration of the relative localization scheme this option meets the requirements as a bearing estimation sensor.

The ranging sensor design, which follows [18][16], performs omnidirectional ultrasonic ranging from a transmitter to a receiver where the transmitter receiver pair is detached for relative ranging. This sensor was developed using an array of ultrasonic transmitters (PROWAVE 400ST160) and an omnidirectional micro electro mechanical system (**MEMS**) ultrasonic receiver (KNOWLESS ACOUSTICS SPM0404UD5). The transmitters have limited bandwidth of about 2 KHz whereas the receivers are wide band which is bandpass filtered to operate at the frequency of 40KHz. The method used for ranging is termed "tone burst", where a tone of 40 KHz is sent from the transmitter at a known time and the TOA of the signal is calculated at the receiver. The 5 Vpp signal generated from a micro controller was amplified up to 20Vpp to achieve a measurement range of 10m. The clock synchronization was established using a RF link with no protocol handling layers. This ensures a clock synchronization of +/- 5μs which corresponds to a ranging error of about 2 mm. The calibration parameters of the sensor were identified by logging measurements of the sensor at known range values. A height measuring device is assumed in this study which would include an infrared, ultrasonic ranging device or a air pressure sensor. Use of multiple ultrasonic height sensors and relative ranging sensors require proper time domain, frequency domain or code division multiple access (TDMA, FDMA, CDMA) methods to overcome issues related to interference and noise.

Pioneer P3AT robots were used as experimental platforms for the sensor node accuracy measurement. To simulate a robot hovering at a set height the sensor node is attached at a fixed height on one robot. The laser localization capability of the robots are used to find the map based localization of each robot. All data of sensors and robots are transferred to MATLAB realtime using the COM port, bluetooth and TCP/IP interfaces for analysis. A graphical application in MATLAB visualizes the positioning of each robot, measurements given from different sensors and the EKF sensor fusion.

The proposed architecture for multi-robot relative localization posses scalability in terms of the number of pods. An expert system should perform measurement correspondence of the IR detector when multiple pods are perceived. In the current architecture, increasing the number of leaders without hardware modifications is possible by establishing time domain multiple access methods where sequential ultrasonic transmission is performed. Hardware modifications are necessary to introduce simultaneous transmission with CDMA or FDMA methods.

V. Results

A. Simulation results

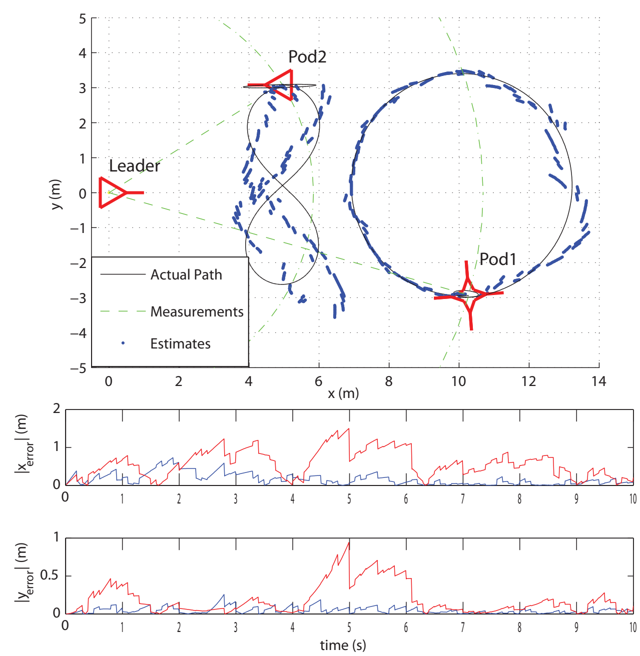

Fig. 4. Relative localization accuracy with measurement updates of vision and height only

The relative localization scheme along with the proposed sensor fusion was numerically simulated for performance evaluation. The process noise figures which correspond to external disturbances and robot modeling inaccuracies were identified through low acceleration variances. The measurement noises were set to correspond to realistic values. An experimentally evaluated measurement model of the ranging sensor was used to set the ranging noise variances of $20\mu s$. The height measurement noise was set to $5mm$ and the visual tracking variance was set to $5px$.

The simulation was set up with one ground leader robot, one ground pod robot and one aerial pod robot. The measurement frequency was set to 10 Hz, while the kinematic model runs at 100 Hz. Ground pod robot movement was at a plane 0.1 m below the level of ground leader sensors node, while the aerial pod agent moved in a plane 2m elevated from the leader. Two experiments were simulated where the robots follow the same path while changing the available sensors for the fusion scheme. The performance of different sensor combinations for the purpose of localization was evaluated.

The sensor fusion scheme was first performed with only vision and height measurement updates (Fig. 4). In the simulation only the aerial pod agent localization was successful, while the filter was unable to estimate the position of the ground pod agent to acceptable accuracy. The vision only solution degenerates as the height of the agent approaches the elevation of the leader robot. Thus unsuitable for localization of pod agents closer to ground plane. Furthermore the solution tends to be significantly sensitive to errors in the height estimate and require a strict constraint of a common ground reference.

The next experiment was performed employing the ranging and vision-based bearing measurements Fig. 5. Significant improvement was observed where sufficient localization and tracking was achieved while overcoming the undesirable constraint in the previous method. The height sensor is a redundant measurement source which is used for data correspondence of the anonymous bearing measures perceived by the image sensor. Simple nearest neighbor data correspondence method was sufficient for the purpose.

B. Experimental results

Experiments were performed to asses the realtime localization accuracy of the system. A "pod" robot was driven along a defined path with the sensor node attached at a elevation of 1 m. The robot's self localization estimates were used for verification of the estimates received from the relative localization solution. The pod agent tracking accuracy was assessed across two measurement combinations which were 1) vision and height 2) vision and ranging only measurement updates of the filter (Fig. 6 and 7). Results congruent with simulation were achieved where the vision only relative localization solutions is unstable due to degeneration as relative height approaches zero and the relative range grows. Furthermore, the vision-based ranging estimate was particularly sensitive to the errors in height of the pod and the position of the leader.

It is important to note that the EKF has some stability issues when the filter encounters poor initialization and outliers in this experiment. Fine tuning of process noises

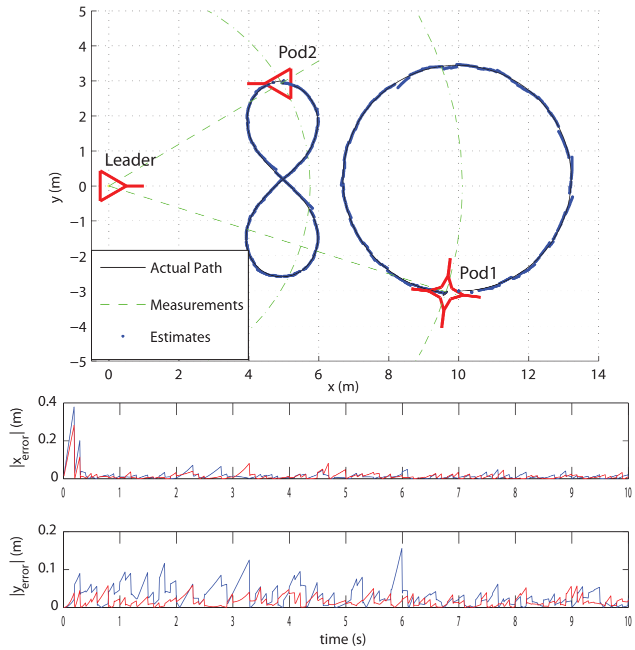

Fig. 5. Relative localization accuracy with measurement updates of vision and ranging only

were necessary for acceptable tracking of the robot. The initial tuning of the parameters were sufficient for all the experiments performed including different sensor update combinations, tracking close to ground plane and increasing the speed of the robot.

The actual measurements were not ideal due to outliers in measurements and field of view, line of sight constraints. The error plots in Fig. 6 and 7 highlight the corresponding error growth during non field of view operation and ultrasonic measurement outliers. Interested readers are directed to the multimedia attachment of the paper for a video presentation of the main results.

VI. Conclusion

This paper presented the development and performance evaluation of a relative localization sensor solution suitable for multi-agent relative localization in indoor environments. The solution is particularly unique in its ability to accurately localize agents in field of view up to 10 m range using only one observer. Further there is no strict requirement of a common ground plane thus the approach is suitable for practical indoor ground aerial multi-robot localization.

Numerical simulation of ground and aerial agent localization was performed for verification of the localizing scheme and the data fusion scheme. The experimental results suggest that the vision only solution produces poor results and requires a strict constraint of a common ground reference. The proposed sensor solution overcomes these issues with the addition of a ranging measure and further carries redundant information for the purpose of data correspondence. The method was successfully able to localize with 5-10 cm mean accuracy during multiple dynamic tracking experiments. Work is ongoing to improve the proposed method for practical realtime implementation for indoor missions and to relax the main constraints in the current system.

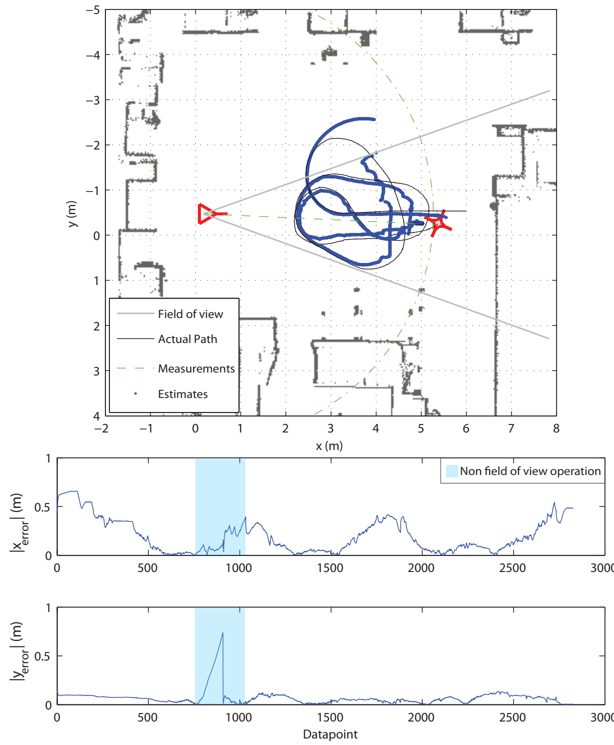

Fig. 6. Relative localization accuracy with measurement updates of vision and height only (actual data)

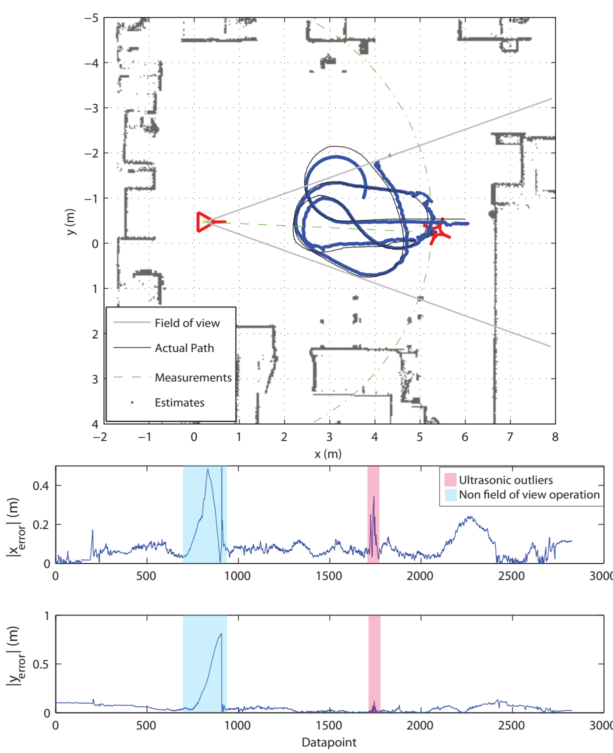

Fig. 7. Relative localization accuracy with measurement updates of vision and ranging only (actual data)

REFERENCES

[1] S. Shen, N. Michael, and V. Kumar, "Autonomous Multi-Floor Indoor Navigation with a Computationally Constrained MAV," in *IEEE International Conference on Robotics and Automation*, pp. 20–25, 2011.

[2] A. Bachrach, S. Prentice, and N. Roy, "RANGE - Robust Autonomous Navigation in GPS-denied Environments," *Journal of Field Robotics*, vol. 28, no. 5, pp. 644–666, 2011.

[3] L. Heng, L. Meier, P. Tanskanen, F. Fraundorfer, and M. Pollefeys, "Autonomous Obstacle Avoidance and Maneuvering on a Vision-Guided MAV Using On-Board Processing," in *IEEE International Conference on Robotics and Automation*, pp. 2472–2477, 2011.

[4] M. Achtelik, M. Achtelik, S. Weiss, and R. Siegwart, "Onboard IMU and Monocular Vision Based Control for MAVs in Unknown In- and Outdoor Environments," in *IEEE International Conference on Robotics and Automation*, pp. 3056–3063, 2011.

[5] M. Matsuoka, a. Chen, S. P. N. Singh, a. Coates, a. Y. Ng, and S. Thrun, "Autonomous Helicopter Tracking and Localization Using a Self-surveying Camera Array," *The International Journal of Robotics Research*, vol. 26, pp. 205–215, Feb. 2007.

[6] M. Achtelik, T. Zhang, K. Kuhnlenz, and M. Buss, "Visual tracking and control of a quadcopter using a stereo camera system and inertial sensors," in *International Conference on Mechatronics and Automation*, pp. 2863–2869, Ieee, Aug. 2009.

[7] J. Eckert, R. German, F. Dressler, and S. Member, "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.

[8] J. C. Prieto, A. R. Jiménez, J. Guevara, J. L. Ealo, F. Seco, J. O. Roa, and F. Ramos, "Performance Evaluation of 3D-LOCUS Advanced Acoustic LPS," *IEEE Transactions on Instrumentation and Measurement*, vol. 58, no. 8, pp. 2385–2395, 2009.

[9] J. R. Gonzalez and C. J. Bleakley, "High-Precision Robust Broadband Ultrasonic Location and Orientation Estimation," *IEEE Journal of Selected Topics in Signal Processing*, vol. 3, no. 5, pp. 832–844, 2009.

[10] D. Fox, W. Burgard, H. Kruppa, and S. Thrun, "A Probabilistic Approach to Collaborative Multi-Robot Localization," *Autonomous Robots*, vol. 8, no. 3, pp. 325–344, 2000.

[11] S. Roumeliotis and G. Bekey, "Distributed multirobot localization," *IEEE Transactions on Robotics and Automation*, vol. 18, pp. 781–795, Oct. 2002.

[12] M. J. Milford, F. Schill, P. Corke, S. Member, and G. Wyeth, "Aerial SLAM with a Single Camera Using Visual Expectation," in *IEEE International Conference on Robotics and Automation*, pp. 2506–2512, 2011.

[13] B. Y. N. Michael, D. Mellinger, and Q. Lindsey, "Experimental Evaluation of Multirobot Aerial Control Algorithms," *IEEE robotics & Automation Magazine*, no. September, pp. 56–65, 2010.

[14] W. Li, T. Zhang, and K. K, "A Vision-Guided Autonomous Quadrotor in An Air-Ground Multi-Robot System," in *IEEE International Conference on Robotics and Automation*, pp. 2980–2985, 2011.

[15] H. Liu, H. Darabi, P. Banerjee, and J. Liu, "Survey of Wireless Indoor Positioning Techniques and Systems," *IEEE Transactions on Systems, Man and Cybernetics, Part C (Applications and Reviews)*, vol. 37, pp. 1067–1080, Nov. 2007.

[16] N. B. Priyantha, A. Chakraborty, and H. Balakrishnan, "The Cricket location-support system," in *Proceedings of the 6th annual international conference on Mobile computing and networking - MobiCom*, vol. 2000, (New York, New York, USA), pp. 32–43, ACM Press, 2000.

[17] M. Hazas and A. Ward, "A Novel Broadband Ultrasonic Location System," in *Ubiquitous Computing*, vol. 2498, pp. 264–280, 2002.

[18] J. Eckert, K. Koeker, P. Caliebe, F. Dressler, and R. German, "Self-localization capable mobile sensor nodes," in *IEEE International Conference on Technologies for Practical Robot Applications*, pp. 224–229, Ieee, Nov. 2009.