# Audio based Relative Positioning system for a Swarm of Micro Air Vehicles

Meysam Basiri[1,2], Felix Schill [1], Pedro U.Lima[2] and Dario Floreano[1]

*Abstract*— **Employing a swarm of independently controlled flying micro air vehicles (MAVs) for aerial coverage missions, instead of a single flying robot, increases the robustness and efficiency of the missions. Designing a swarm of MAVs requires addressing new challenges, such as inter-robot collision avoidance and formation control, where individual's knowledge about the relative location of their local swarm members is essential. A relative positioning system for a MAV needs to satisfy severe constraints in terms of size, weight, processing power, power consumption, three-dimensional coverage and price. In this paper we present an on-board audio based system that is capable of providing individuals with relative positioning information of their neighbouring sound emitting MAVs. We propose a method based on coherence testing among signals of a small onboard microphone array to obtain relative bearing measurements; and a particle filter estimator to fuse these measurements with information about the motion of robots throughout time to obtain the desired relative location estimates. A method based on fractional Fourier transform (FrFT) is used to identify and extract sounds of simultaneous chirping robots in the neighbourhood. Furthermore, we evaluate our proposed method in a real world experiment with three simultaneously flying micro air vehicles.**

## I. INTRODUCTION

There has been a growing interest in the field of robotics in using multiple autonomous robots for achieving tasks in a collaborative manner. Teams of flying robots can accomplish aerial coverage tasks more robustly and more efficiently compared to a single flying robot. Possible applications include rapidly-deployable communication networks [1], environmental monitoring, aerial surveillance and mapping, traffic monitoring and search and rescue [2]. However, additional challenges are imposed on the design of MAV swarms that have so far prevented their use in real missions. Robots within an aerial swarm are required to interact with each other and to work together towards the achievement of a desired goal. This introduces new problems, such as inter-robot collisions and formation control. A common idea that has been addressed throughout both the natural and artificial swarms literature is that individual's knowledge about the relative location of other swarm members is essential for achieving successful swarming [3]–[5] . For example, awareness about the relative range and/or bearing of neighbouring robots can allow a robot to maintain formations [6] [7], and decrease the risk of collisions [8], with other swarm members.

*This work was supported by a doctoral grant from FCT (SFRH/BD/51070/2010), EC FP-7 research funding mechanism under grant agreement no. 266470 and FCT project [PEst-OE/EEI/LA0009/2011].

[1] Laboratory of Intelligent Systems, Ecole Polytechnique Federale de Lausanne, CH-1015 Lausanne, Switzerland (e-mail: meysam.basiri, felix.schill, dario.floreano@epfl.ch)

[2] Institute for Systems and Robotics, Instituto Superior Tecnico, Lisboa, Portugal (e-mail: pal@isr.ist.utl.pt)

A relative positioning system for a MAV needs to satisfy severe constraints in terms of size, weight, processing power, power consumption, three-dimensional coverage and price. These constraints prevent the current relative positioning systems designed for ground robots and large aerial vehicles to be used in MAVs. Inspired by the sense of hearing in animals, which provides them the ability of using sound for communication and localization; we propose an audio based positioning system for MAVs to allow them to obtain information about the position of their local swarm neighbours. Such a system could also possibly be used for perceiving other non-cooperative noise emitting aerial platforms. This paper is organized as follows: Section II describes the related works on relative positioning systems for MAVs. Section III describes the proposed method for our audio based relative positioning system and in Section IV results of real experiments with the proposed method is provided, where three flying MAVs are used in the experiment.

## II. STATE OF THE ART

Two main approaches for obtaining relative positioning information in multi-robot systems exist in the literature.

1) Using an absolute positioning system alongside a communication network, allowing robots to obtain relative positioning information by communicating their absolute locations with each other [9] [10]
2) Directly measuring the relative location of other robots using on-board exteroceptive sensors [11] [4]

A drawback with solutions based on the former approach, for relative positioning in MAV swarms, is that an external infrastructure, such as wireless positioning beacons or global positioning system (GPS) satellites, is required for acquiring the absolute positioning information. GPS technologies are vulnerable to jamming and interferences, have low resolution, and are impossible to use in cluttered terrains where there is no direct line of sight with the transmitting satellites [12]. Also, deployment of wireless positioning beacons in the environment in advance of each mission is both costly and time-consuming.

Due to disadvantages of the first approach, much effort has been put into the design of onboard relative positioning systems. In this approach, every individual robot measures the relative position of other robots using onboard exteroceptive sensors. Most current onboard relative positioning systems are developed for ground robots and mainly rely on sensors such as laser range finders, infrared sensors and cameras.

However, a relative positioning system for a MAV needs to satisfy constraints in terms of size, weight, processing power, power consumption, three-dimensional coverage and price. This prevents some of the successful sensor technologies implemented for relative positioning of ground robots to be used in MAVs. Despite this, some effort has been done in transferring these solutions from ground robots to MAVS. Mini laser range finders have been used [13] for detection of large static obstacles (trees and buildings) located in front of a MAV. These sensors provide accurate range measurements of obstacles directly located in front of the laser beam up to a few hundreds of meters away. A major drawback of such sensors is their single point/planar detection ability, which makes them a bad candidate for measuring the position of other MAVs in three-dimensional spaces. Few works also investigate the use of optical sensors for detecting the motion of other aircraft relative to the background scene, computing the relative azimuth and elevation [14]. Systems based on such sensors have a limited field of view and are highly dependent on light conditions and visual contrast. Furthermore, these systems greatly suffer from missed or false detections when the target is located on non-uniform or cluttered backgrounds and also in the presence of vibrations and adverse weather conditions. Small scale Doppler radar transducers are the basis of the sensor suite proposed in [15] for allowing a MAV to detect the presence and measure the relative bearing of colliding obstacles. The sensor suite has a small weight of about 300g and power consumption of 3.7 watts. However, small field of view (30deg), low resolution (15deg) and small range (10m) are some of the major drawbacks of this system. Infrared/ultrasound-based sensor suites have been shown in [11] [16] provide accurate relative range and bearing estimation in indoor flying platforms. However, they are not suitable sensors for outdoor MAVs due to their short working range.

Hearing has always been one of the key senses among humans and animals allowing them to use sound for attracting attention, communication and localization purposes. Despite this, audition in robotics has not received great attention compared to vision, and most studies on this focus on speech recognition and localization of talkers for home, office, and humanoid robots [17] In most works, a technique inspired by animal hearing called Inter-aural Time Difference (ITD) (also known as Time Difference of Arrival TDOA) is used for localizing sound sources. This method measures the time delay caused by the finite speed of sound between the signals received by two microphones. While the complex hearing capabilities of animals achieve good performance with only one pair of acoustic sensors, technical systems often use arrays of microphones for assisting robots in locating broadband sound sources in the environment [18]. Audio-based relative positioning for ground robots has not been favoured so far, due to the success of other available sensor technologies and because of the existing challenges in sound source localization inside reverberant and noisy domestic environments. In the case of underwater robotic swarms, the effectiveness of audio based relative positioning compared to other methods have been shown by some researchers [19]. In these systems, a pair of hydrophone sensors onboard a small submarine is used for measuring the relative bearing of other sound emitting submarines. Audio-based relative positioning for miniature aerial robots has not been addressed so far. However, existing natural swarms clearly show the success of such a system for achieving swarm behaviours. Flight calls of nocturnal migratory birds used for collision avoidance and coordinated migration during night [20], and phonotaxis behaviour among insect swarms for mating and predator avoidance [21] [22] are some of the many existing examples. Furthermore, in a recent work, an acoustic source localization system for MAVs was shown to be effective in locating the source of distress signals on the ground [2].Design of new acoustic sensors suitable for use on MAVs have been investigated in some recent works [23] [24].

An audio-based relative positioning system for swarm of MAVs will have several advantages. First of all, this system will be based on cheap, small size, passive and omnidirectional sensors which clearly satisfy the constraints of MAVs. The passivity of the sensors will result in low power consumption of the overall system, which is an important parameter for having longer swarm endurance. Also, this system will be independent of illumination and weather conditions, such as fog, dust and rain and will not require direct line-of-sight between robots for its operation. Such a system will also be potentially less computationally expensive compared to vision-based systems, as it will mainly rely on the available phase information in the sound waves rather than the need for extraction of features from sequence of images.

## III. Proposed Method

This section explains our method for relative positioning in a group of MAVs. Figure 1 presents the schematic diagram of this system. The overall system is divided in to two main parts of 'Target' and 'Perceiving robots' to illustrate the main units of the system involved at each state. In the target robot state, the robot generates chirps of predefined rate and frequency. In the perceiving state, sound waves are picked up by an on-board microphone array and are continuously checked by the Chirp Detection and Separation unit for existence of chirps in the sound mixture. When a full chirp is detected, it is filtered out from the sound mixture and is then passed to the coherence measuring unit. This unit cross correlates the signals from every microphone pair and obtains a measure of similarity between the signals as a function of time lag applied to one of them. This measure reflects the chirp's time difference of arrival (TDOA) likelihood for all possible time delays. This information along with knowledge of the microphone array's geometry is then used by the Relative Bearing Measurement unit to estimate a measure of the target's direction. Finally, a particle filtering unit is used to estimate more robustly the relative location of the target robot by fusing the noisy bearing measurements with information about the relative motion of robots throughout time. The relative motion between robots are computed using

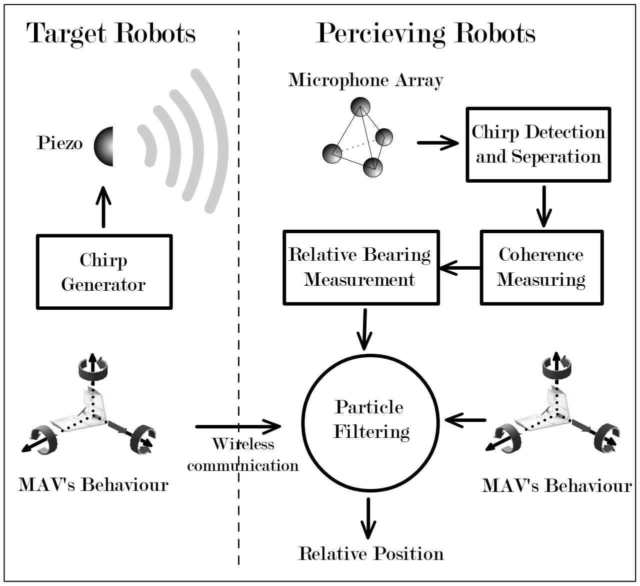


Fig. 1. Schematic diagram of the proposed relative positioning system illustrating main parts of the system

information from the on-board proprioceptive sensors and a communication network. A more detailed explanation of each unit is presented in the following sections.

### A. Chirp Generator

Piezo transducers are simple, inexpensive and lightweight devices that are suitable to be used on MAVs. These devices generate sound by converting electrical pulses into mechanical vibrations. The resulting sound can be very loud if the frequency of the vibrations are close to the resonance frequency of the piezo element. Hence, in order to generate a loud sound wave that is required here, narrowband sounds such as a pure tone or a band-limited chirp with frequencies close to the resonance frequency should be used. To avoid the problem of ambiguous bearing measurements, caused due to the repetitive nature of pure tone sounds, a band-limited chirp is used for the sound of the targets. The chirp generating unit of every target robot generates periodical linear chirps with a predefined and unique chirp rate. Figure 2 illustrates the sound wave and spectrogram of an in-flight sound recording involving one perceiving robot and two chirping MAVs.

### B. Chirp Detection and Extraction

This unit is responsible for the detection and extraction of a chirp in the perceived sound wave. Presence of a desired chirp in the sound mixture is initially detected by template matching technique, where a cross correlation of the sound mixture with a template of the desired chirp is used to find the existence and the time segment containing the chirp. After a chirp is detected, the Fractional Fourier transform (FRFT) [25] of the time window containing the entire chirp is computed with an FRFT order of $\alpha$ obtained by the following equation.

$$\alpha = \frac{2}{\pi} \tan^{-1}(a \times f_s) \tag{1}$$

where $f_s$ is the sampling frequency and $a$ is the chirp rate.

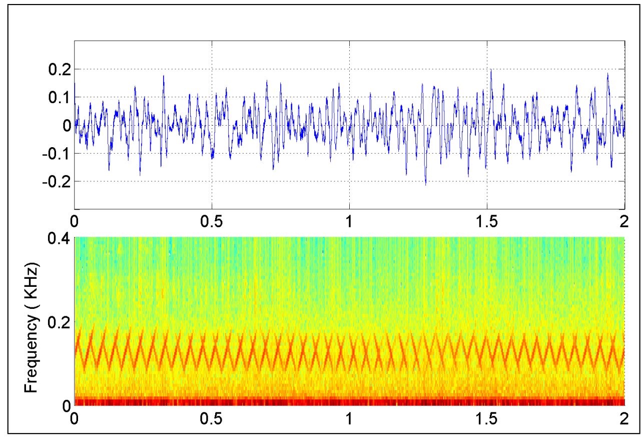


Fig. 2. Sound wave and spectrogram of an in-flight sound recording involving one perceiving robot and two chirping MAVs. The two linear chirps are in the same frequency band and have a different chirp rate.

First proposed by Namias [25], FRFT has been recently favoured in the field of signal processing [26], especially when dealing with chirp signals. The FRFT provides a compact representation of the chirp signal allowing us to extract the chirp corresponding to a desired target robot from other sounds. Figure 3 illustrate a comparison between the time, frequency and Fractional domain of a linear chirp signal.

The FRFT, computed by the Chirp detection unit, contains an Impulse shaped peak that corresponds to the desired chirp. This chirp is filtered out from other sounds by only retaining the bin with the highest peak along with its nearby bins and setting all other bins to zero. Furthermore, the filtered chirp in the FRFT domain is transformed back to the time domain by computing the inverse FRFT. The ratio of the peak value and the mean value of all zeroed bins prior to zeroing provides a good measure of the signal to noise ratio and is recorded and used later as a measure for the reliability of the bearing measurement.

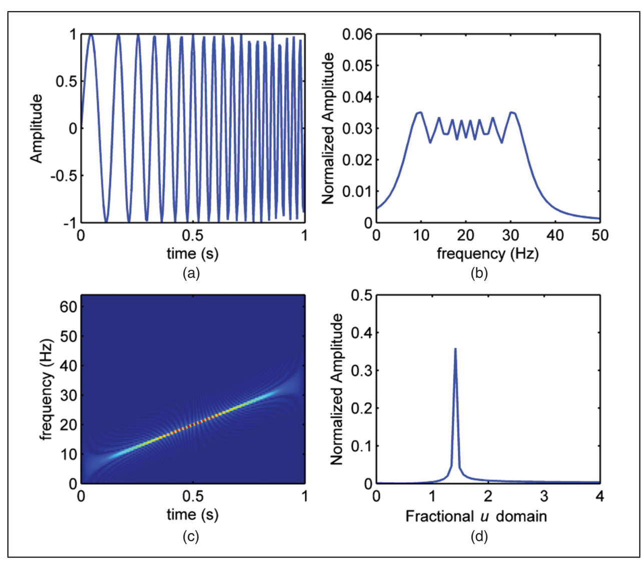


Fig. 3. A comparison between the time, frequency and Fractional domain of a linear chirp

### C. Coherence measuring

This unit compares the filtered chirp signals of all channels with each other and hence estimates a similarity degree for every pair of signals as a function of time-lag applied to one of them. Cross correlation is a commonly used technique for measuring the coherence between two signals. Cross correlation of two microphone signals each having a length of $N$ samples can be computed by

$$R_{ij}(\tau) = \sum_{n=0}^{N-1} p_i[n]\, p_j[n-\tau]$$

where $p_i[n]$ is the signal perceived by microphone $i$ and $\tau$ is the correlation lag in samples in the range expressed by

$$-\frac{d_m}{c} < \tau_d < \frac{d_m}{c} \tag{2}$$

where $d_m$ is the distance between the microphones and $c$ is the speed of sound. In order to reduce the computation time, the cross correlation function can be approximated in the frequency domain by computing the inverse Fourier transform of the cross spectrum:

$$R_{ij}(\tau) = \sum_{k=0}^{N-1} P_i[k]\, P_j^*[k] e^{i\frac{2\pi k\tau}{N}} \tag{3}$$

where $P_i(k)$ is the discrete Fourier transform of $p_i(n)$ and $P_j^*$ denotes the complex conjugate of $P_j$. This results in a reduction of complexity from $O(N^2)$ to $O(N \log N)$, hence making it more suitable for real time computations. A weighting function was introduced into equation (3) by [27] in order to solve the problem of wide cross correlation peaks.

$$R_{ij}(\tau) = \sum_{k=0}^{N-1} \frac{P_i[k]\, P_j^*[k]}{|P_i[k]|\, |P_j[k]|} e^{i\frac{2\pi k\tau}{N}} \tag{4}$$

This weighting function whitens the cross-spectrum of the signals allowing equal contribution of all frequencies in estimating the cross correlation and resulting in sharper peaks. This is only suitable when the desired sound is broadband, but for narrowband sounds it amplifies the background noise. Therefore, a modified version of equation (4) was used here instead to solve this problem.

$$R_{ij}(\tau) = \sum_{k=0}^{N-1} \chi \left[\frac{P_i P_j^*}{|P_i|\,|P_j|}\right] e^{i\frac{2\pi k\tau}{N}} \tag{5}$$

where

$$\chi = \begin{cases} 1 & f_{\min} < f < f_{\max} \\ 0 & \text{otherwise} \end{cases}$$

and $f_{\min}$ and $f_{\max}$ are the minimum and maximum frequencies of the chirp.

### D. Relative Bearing measurement

After obtaining $R_{ij}(\tau)$ from (5) for all microphone pairs $ij$, the Relative Bearing Measurement unit searches for the most likely sound source direction $\overrightarrow{b}_m$

$$\overrightarrow{b_m} = \arg\max_{\overrightarrow{b}} \sum_{i,j} R_{ij}(\tau_{\vec{b}ij}) \tag{6}$$

where time delay $\tau_{bij}$ corresponding to direction $\overrightarrow{b}$ and is computed from the coordinates of microphones $i$ and $j$ in the body fixed coordinate system. In this work a full direction grid search for all directions $\overrightarrow{b}$ around the robot is used for finding $\overrightarrow{b_m}$ . Other search methods exist in the literature that can reduces the cost of this search if necessary [28].

### E. Particle Filtering

The previous sections described methods of providing an instantaneous noisy information about the relative bearing of a target robot in the neighbourhood. It is now required to estimate more reliably this relative bearing and also obtain some information about the relative range of the target robot. This can be achieved by fusing all the available information together. Information from the on-board sensors reflecting the relative motion between the perceiving and the target MAVs throughout time along with all direction measurements available up to the current time could all be employed. For this purpose, we will use the particle filtering technique to recursively estimate the probability density of the target location. Using this method, all of the hypotheses about the target's position are represented as a set of particles with individual weights.

At time instant $t$, the direction to a target robot is modelled using a set of $N$ particles of vectors $p_i$ and weight $w_i$, where $p_i = (p_{xi}, p_{yi}, p_{zi})$ is a vector in the body-fixed coordinate system that starts at the origin and ends at a point in space. $p_i$ can also be described in the body-fixed spherical coordinate system $(\angle\phi, \angle\theta, r)$ by:

$$u_i = (\phi_i, \theta_i, r_i) \qquad i = 1, 2, ..N \tag{7}$$

where $\phi_i$ is the relative azimuth defined in the range $[-\pi, \pi]$ , $\theta_i$ is the relative elevation defined in the range $[-\pi/2, \pi/2]$ and $r_i$ is the relative range defined in the range $[R_{min}, R_{max}]$. $R_{min}$ and $R_{max}$ are dependant on the platform size and the sound power respectively. For the MAVs and the piezos that are used in this work the ranges are found approximately to be $[1, 250]$ meters.

A three dimensional state vector is specified for every particle:

$$S_i(t) = [\phi_i(t) \;\; \theta_i(t) \;\; r_i(t)] \tag{8}$$

The algorithm starts by forming an initial set of particles $\{S_i(0), i = 1 : N\}$. Particles either could be generated uniformly over the entire state space, or only over a desired part of the state space if some prior knowledge about the possible location of the target is available. In the proposed problem the initial state space is reduced to all vectors in the space having a small deviation from the first reliable bearing measurement.

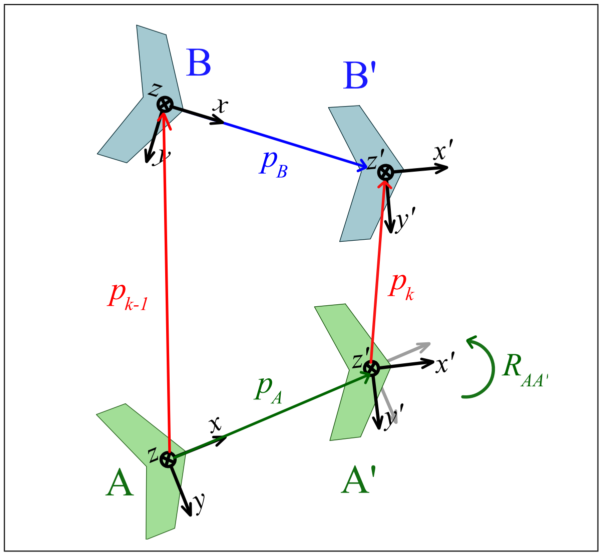


Fig. 4. Illustration of the motions of two robots in two successive time steps showing the vectors and coordinate systems

*1) Prediction:* In this work, we measure the change in roll and pitch of the MAVs using on-board gyroscopes and the airspeed and altitude using an absolute and a differential pressure sensor. As no compass is present on the MAV, the heading information is obtained from an on-board GPS sensor. The sensor readings of the target robot is communicated to the perceiving robot via a wireless communication network.

We use a simple model for the prediction step which assumes that the robot has only forward motion (i.e. along the $x$ axis on the body-fixed coordinate system). Figure 4 illustrates the motions of two robots for two successive time steps. From this figure and using linear algebra the following relationship between vectors can be described.

$$\vec{p}_k - R_{B'A'}.(R_{BB'}.\vec{p}_B) - R_{AA'}.\vec{p}_{k-1} + R_{AA'}.\vec{p}_A = 0 \tag{9}$$

where $R_{IJ}$ is a rotation matrix that rotates a vector from the coordinate system $I$ to the coordinate system $J$. This equation is used in the prediction step of the particle filter to predict the particles $\vec{p}_{ki}$ from there previous values $\vec{p}_{(k-1)i}$. For this, the vectors $\vec{p}_A$ and $\vec{p}_B$ are initially predicted from the speed sensor readings $V_{A(k-1)}$ and $V_{B(k-1)}$ at time $k-1$

$$\vec{p}_A = \begin{bmatrix} (V_{A(k-1)} + \xi_V)dt \\ 0 \\ 0 \end{bmatrix} \quad \vec{p}_B = \begin{bmatrix} (V_{B(k-1)} + \xi_V)dt \\ 0 \\ 0 \end{bmatrix}$$

where $dt$ is the time interval between the two time steps and $\xi_V = N(0, \sigma_V)$ is a random number generated with a normal distribution of mean zero and standard deviation $\sigma_V$. The value of $\sigma_V$ is chosen in relation with the reliability in the speed sensor reading measurements. Furthermore, the yaw $(\lambda)$, pitch $(\beta)$ and roll $(\alpha)$ readings from the on-board sensors at times $(k-1)$ and $(k)$ are used to predict the rotation matrices $R(\lambda + \xi_\lambda, \beta + \xi_\beta, \alpha + \xi_\beta)$ needed for the equation (9) with $\xi_\lambda = N(0, \sigma_\lambda)$, $\xi_\beta = N(0, \sigma_\beta)$ and $\xi_\alpha = N(0, \sigma_\alpha)$. Finally, equation (9) can be solved for the prediction $\vec{p}_{ki}$ of particle $i$.

Fig. 5. Picture of the MAV platform [29] used for experimenting the proposed algorithm. Four microphones and an on-board digital sound recorder is used for recording sounds during flight.

*2) Update:* As previously explained, an audio based relative bearing measurement is obtained at every time-step. In the update step, the likelihood of obtaining these measurements is investigated for every particle and particles are weighted based on this measure. For this investigation, we propose the likelihood function:

$$w_i = \frac{1}{\sigma_m \sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{\varepsilon_i}{\sigma_m}\right)^2} \tag{10}$$

where

$$\varepsilon_i = \angle(\vec{b}_{mk}, \vec{p}_{ki}) \tag{11}$$

is the angle between the measured bearing $\vec{b}_{mk}$ at time $k$ and the predicted vector $\vec{p}_{ki}$ of particle $i$. The value of $\sigma_m$ reflects the confidence of the bearing measurements and is found empirically.

*3) Relative Position Estimation:* The relative range and bearing of the target can be estimated at each time step from the probability density function represented by a particle set. For this, a weighted mean of all particles' positions could be employed. However, to avoid inaccurate estimations for situations with multi-modal distributions, a weighted mean of particles located in a local neighbourhood of the particle with the highest weight is used instead:

$$\bar{S}_T = \sum_{i=1}^{K} w_i S_i : \forall |S_i - S_{max}| < \xi \tag{12}$$

## IV. Experiments and Results

To test and verify the proposed algorithm, multiple real experiments were performed with three similar MAV platforms such as the one shown in figure 5. A microphone array consisting of four microphones is mounted on one of the robots along with a digital sound recorder for recording the microphone signals. The microphones are positioned in a way to form a regular tetrahedron of edge length 10 cm. The other two robots are equipped with a piezo and a micro controller programmed to generate chirps of different rate as shown in figure 2. All MAVs are equipped with an autopilot that allows it to fly fully autonomously to predefined way points. The orientation, altitude, air-speed and global positioning information of the MAVs are measured using on-board sensors and are transmitted and recorded on a ground station. The MAVs were controlled to fly within the

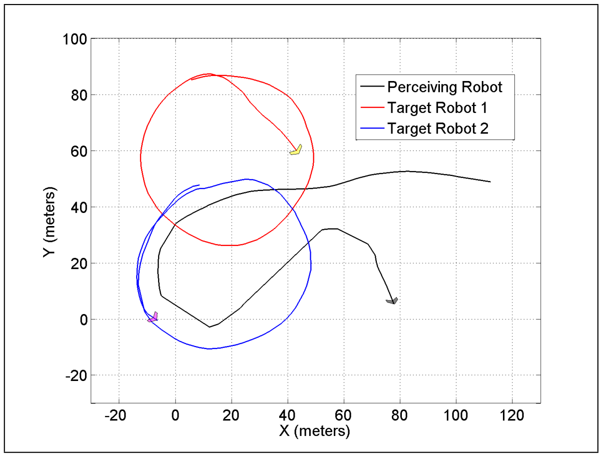


Fig. 6. The motion path of robots recorded by onboard GPS sensors, for 25 seconds of flight time in an experiment involving one perceiving robot and two target robots

visual range of a safety pilot while the engine power of the perceiving robot was occasionally reduced or even turned off to increase the detection range by increasing the signal to noise ratio. This reduction in the engine power is achieved automatically whenever the MAV is descending.

Figure 6 shows the path of all three robots, recorded by the GPS sensors, for 25 seconds duration of flight time. The relative azimuth estimations for this duration of time is shown in figure 7. These estimates are compared against the relative azimuth values that are computed from the GPS positions and the onboard IMU data and show a good correspondence at all times. Furthermore, the relative range estimations along with the particle distributions and GPS based range estimates are shown in figure 8. It can be seen that the particles gradually converge towards the correct relative range and furthermore track it with an acceptable accuracy. As expected, the speed of convergence and the accuracy in the relative range estimation is highly dependant on the motion and positions of the robots, as for some type of relative motions the inaccurate particles are eliminated faster than the others. Figure 8 shows that in the first few seconds where the perceiving robot is further away from the target robots and robots are moving towards each other, particles are still widely spread in relative range although they have converged to the correct bearing. As the robots get close and pass each other the disparity of particles is reduced.

## V. Conclusion and Future Work

This paper presents a solution to the problem of relative positioning for a group of micro air vehicles. The solution provided in this paper requires MAVs to be equipped with an on-board microphone array to measure the relative bearing to other sound emitting MAVs and on-board sensors to obtain information about the state of the MAVs. The particle filtering technique used in this paper was shown to be well-suited for fusing the relative bearing measurements with relative motion of the MAVs in order to achieve robust estimation of the relative range and bearing. In this work a communication network between the robots was needed for sharing sensor informations and computing the relative motion between the robots. Removing the need of a communication network, by considering some prior knowledge about the behaviours of robots, is an area of work we are currently pursuing. In this work a piezoelectric transducer was used on the robots as the target source. However as the engine of nearly all flying platforms generate sound when flying, this sound could possibly be used in the future for detecting other non-cooperative robots and aerial platforms.

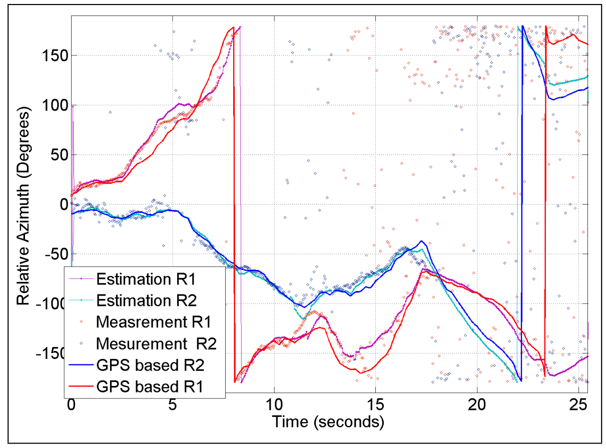


Fig. 7. The relative azimuth estimations along with the relative azimuth values computed form the GPS positions and the onboard IMU orientations

## References

[1] S. Hauert, S. Leven, J. Zufferey, and D. Floreano, "Communication-based swarming for flying robots," in *Proc. Intl. Conf. Robotics and Automation Workshop on Network Science and Systems*, 2010.

[2] M. Basiri, F. Schill, P. Lima, and D. Floreano, "Robust acoustic source localization of emergency signals from micro air vehicles," in *Intelligent Robots and Systems (IROS), 2012 IEEE/RSJ International Conference on*, oct. 2012, pp. 4737 –4742.

[3] C. W. Reynolds, "Flocks, herds and schools: A distributed behavioral model," *SIGGRAPH Comput. Graph.*, vol. 21, no. 4, pp. 25–34, Aug. 1987. [Online]. Available: http://doi.acm.org/10.1145/37402.37406

[4] J. Pugh and A. Martinoli, "Relative localization and communication module for small-scale multi-robot systems," in *Robotics and Automation, 2006. ICRA 2006. Proceedings 2006 IEEE International Conference on*, may 2006, pp. 188 –193.

[5] M. J. Mataric, "Behaviour-based control: examples from navigation, learning, and group behaviour," *Journal of Experimental and Theoretical Artificial Intelligence*, vol. 9, no. 2-3, pp. 323–336, 1997.

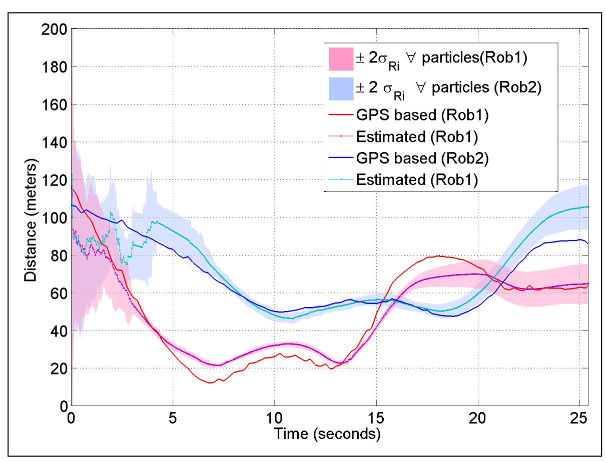


Fig. 8. The Relative range estimations, standard deviation of the relative range of all particles and GPS based range values

[6] M. Basiri, A. Bishop, and P. Jensfelt, "Distributed control of triangular formations with angle-only constraints," *Systems & Control Letters*, vol. 59, no. 2, pp. 147–154, 2010.

[7] N. Moshtagh, N. Michael, A. Jadbabaie, and K. Daniilidis, "Vision-based, distributed control laws for motion coordination of nonholonomic robots," *Robotics, IEEE Transactions on*, vol. 25, no. 4, pp. 851 –860, aug. 2009.

[8] R. Carnie, R. Walker, and P. Corke, "Image processing algorithms for uav "sense and avoid"," in *Robotics and Automation, 2006. ICRA 2006. Proceedings 2006 IEEE International Conference on*, may 2006, pp. 2848 –2853.

[9] P. DeLima, G. York, and D. Pack, "Localization of ground targets using a flying sensor network," in *Sensor Networks, Ubiquitous, and Trustworthy Computing, 2006. IEEE International Conference on*, vol. 1, june 2006, p. 6 pp.

[10] D. Pack, G. York, and R. Fierro, "Information-based cooperative control for multiple unmanned aerial vehicles," in *Networking, Sensing and Control, 2006. ICNSC '06. Proceedings of the 2006 IEEE International Conference on*, 0-0 2006, pp. 446 –450.

[11] J. Roberts, T. Stirling, J.-C. Zufferey, and D. Floreano, "2.5d infrared range and bearing system for collective robotics," in *Intelligent Robots and Systems, 2009. IROS 2009. IEEE/RSJ International Conference on*, oct. 2009, pp. 3659 –3664.

[12] R. Siegwart and I. Nourbakhsh, *Introduction to autonomous mobile robots*. MIT press, 2004.

[13] J. Saunders, B. Call, A. Curtis, R. Beard, and T. McLain, "Static and dynamic obstacle avoidance in miniature air vehicles," in *Proc. Infotech@ Aerospace Conf.* Citeseer, 2005.

[14] J. Utt, J. McCalmont, and M. Deschenes, "Development of a sense and avoid system," *AIAA Infotech at Aerospace*, 2005.

[15] A. Viquerat, L. Blackhall, A. Reid, S. Sukkarieh, and G. Brooker, "Reactive collision avoidance for unmanned aerial vehicles using doppler radar," in *Field and Service Robotics*. Springer, 2008, pp. 245–254.

[16] F. Rivard, J. Bisson, F. Michaud, and D. Létourneau, "Ultrasonic relative positioning for multi-robot systems," in *Robotics and Automation, 2008. ICRA 2008. IEEE International Conference on*. IEEE, 2008, pp. 323–328.

[17] Y. Matsusaka, T. Tojo, S. Kubota, K. Furukawa, D. Tamiya, K. Hayata, Y. Nakano, and T. Kobayashi, "Multi-person conversation via multi-modal interface-a robot who communicate with multi-user," in *Sixth Eu Conference on Speech Communication and Technology*, 1999.

[18] J. Valin, F. Michaud, J. Rouat, and D. Létourneau, "Robust sound source localization using a microphone array on a mobile robot," in *IROS-2003*, vol. 2. IEEE, 2003, pp. 1228–1233.

[19] N. Kottege and U. Zimmer, "Relative localisation for auv swarms," in *Underwater Technology and Workshop on Scientific Use of Submarine Cables and Related Technologies, 2007. Symposium on*. IEEE, 2007, pp. 588–593.

[20] A. Farnsworth, "Flight calls and their value for future ornithological studies and conservation research," *The Auk*, vol. 122, no. 3, pp. 733–746, 2005.

[21] G. Gibson, B. Warren, and I. Russell, "Humming in tune: sex and species recognition by mosquitoes on the wing," *JARO-Journal of the Association for Research in Otolaryngology*, vol. 11, no. 4, pp. 527–540, 2010.

[22] P. Muller and D. Robert, "A shot in the dark: the silent quest of a free-flying phonotactic fly," *Journal of Experimental Biology*, vol. 204, no. 6, pp. 1039–1052, 2001.

[23] F. Ruffier, S. Benacchio, F. Expert, and E. Ogam, "A tiny directional sound sensor inspired by crickets designed for micro-air vehicles," in *Sensors, 2011 IEEE*. IEEE, 2011, pp. 970–973.

[24] I. de Bree, I. Wind, and I. Druyvesteyn, "Multi purpose acoustic vector sensors for battlefield acoustics."

[25] V. Namias, "The fractional order fourier transform and its application to quantum mechanics," *IMA Journal of Applied Mathematics*, vol. 25, no. 3, pp. 241–265, 1980.

[26] H. Ozaktas, B. Barshan, D. Mendlovic, and L. Onural, "Convolution, filtering, and multiplexing in fractional fourier domains and their relation to chirp and wavelet transforms," *JOSA A*, vol. 11, no. 2, pp. 547–559, 1994.

[27] C. Knapp and G. Carter, "The generalized correlation method for estimation of time delay," *Acoustics, Speech and Signal Processing, IEEE Transactions on*, vol. 24, no. 4, pp. 320–327, 1976.

[28] J. Valin, F. Michaud, and J. Rouat, "Robust localization and tracking of simultaneous moving sound sources using beamforming and particle filtering," *Robotics and Autonomous Systems*, vol. 55, no. 3, pp. 216–228, 2007.

[29] S. Leven, J. Zufferey, and D. Floreano, "A simple and robust fixed-wing platform for outdoor flying robot experiments," in *International symposium on flying insects and robots*, 2007, pp. 69–70.