A WIRELESS NETWORK OF ACOUSTIC MULTI MISSION SENSORS TO DETECT, LOCATE AND TRACK SIMULTANEOUSLY VARIOUS HELICOPTERS

David P. Cabo, Hans Elias de Bree
Microflown Technologies
cabo@microflown.com, debree@microflown.com,

Graciano Carrillo Pousa
Microflown Maritime
carrillo@microflown.com

Tivolilaan 205 6824 BV Arnhem (The Netherlands)

Manuel A. Sobreira Seoane
Atlantic Research Centre for Information and Communication Technologies
msobre@gts.uvigo.es
Telecommunication Engineering School, University of Vigo. 36310 Vigo (Spain)

Abstract

With the number of helicopter flights going up, also the need increases to monitor their trajectories in a 3 D space. For instance, in case of a disaster, where helicopters can bring in first responders, medical aid and food, and evacuate the injured, a rapid deployable air traffic control is a desirable matter. As an alternative to radar, a network of wireless distributed Acoustic Multi Mission Sensors (AMMSs) can be used to detect, locate and track helicopters.

Traditionally, arrays of sound pressure transducers have been used to obtain acoustic directional information, estimating the direction of arrival of a sound wave using relative phase differences, which requires spatial coherence. But apart from the fact that such an array obtains a difficult to handle size when trying to cover low frequencies, they need to exchange broad band signals in order to estimate the direction of the sound. It makes unfeasible to use arrays of sound pressure transducers to locate helicopters in long range and low frequency applications, as helicopter localization.

An Acoustic Multi Mission Sensor (*AMMS*) consists of a sensor unit (based upon two orthogonally placed acoustic particle velocity sensors and a collocated sound pressure transducer) that are connected to a Digital Signal Processor (DSP) and covered under a wind and rain resistant open foam wind cap. The 30 cm diameter device weighs around 2 kg and consumes around 2 W electrical power. Since wireless networks cannot handle raw data due bandwidth constrains, some kind of measurement model, source model and/or data compression is needed, i.e. the most important features of the acoustic signature of the detected sources must somehow be sent through the network in order to locate and track multiple sources.

Acoustic Multi Mission Sensors can provide a better and simpler measurement or source model than microphone arrays because the AMMS can measure the effective direction of the significant components of the sound at a single point. The distributed (pre)processing of the signals using the on-board DSP has quite some benefits.

In this paper a centralized algorithm is presented and tested by using realistic simulations. The signals are generated based on real GPS measurements and real acoustic measurements of two helicopters flying, recorded by a network of AMMSs. The goal of the measurements is to characterize and create a model of the noise of the bearing estimation that can be applied to the simulations. A realistic scenario which assumes that the number of acoustic sources is unknown and time-varying is considered for this research. Each Acoustic Multi Mission Sensor sends the source(s) or measurement model(s) parameters to a central node or main station. The main station or central node runs a centralized algorithm that combines all measurement or source models from all the AMMSs in the network in order to detect, locate and track the acoustic sources in the neighbourhood of the network. Since real sources in motion cannot move randomly with a random speed, some previous knowledge about the motion of the source can be used for tracking. The performance of the proposed system is studied under both single source and multisource scenarios using simulated signals based on real measurements. The results show that the proposed system can locate and track more than one source simultaneously.

1. INTRODUCTION

Acoustic source detection, localization and tracking in noisy environments are important and increasing in interest topics in signal processing and have many applications nowadays.

Traditionally, arrays of sound pressure transducers, as the one shown in Fig.1, have been used to obtain acoustic directional information, estimating the direction of arrival of a sound wave using relative phase differences[2,3,4]. On the one hand, such an array requires spatial coherence between microphones for all the frequency range of interest. However, it is well known that microphone array approach requires to increase the distance between transducers to cover low frequencies, getting a difficult to handle size and at the same time reducing the spatial coherence between them[5], mainly affecting high frequencies[7]. On the other hand, they need to exchange broad band signals in order to estimate the direction of the sound, which can be a challenging task if the distances between transducers increases to cover the low frequency range. All these features makes unfeasible to use arrays of sound pressure transducers to locate sound sources for long range and low frequency applications, as needed to perform helicopter localization and tracking. Moreover, different kind of flying vehicles have different spectral signatures and potentially disjoint frequency ranges (helicopters, planes, jets, UAVs, multicopters,...), it is difficult to get a microphone array geometry that works reasonably well for all the potential targets with an easy to handle size and a reasonable number of transducers. If the microphone array has a high density of transducers it becomes acoustically significant biasing the characterization of the sound field and also the estimation of the Direction Of Arrival (*DOA*).

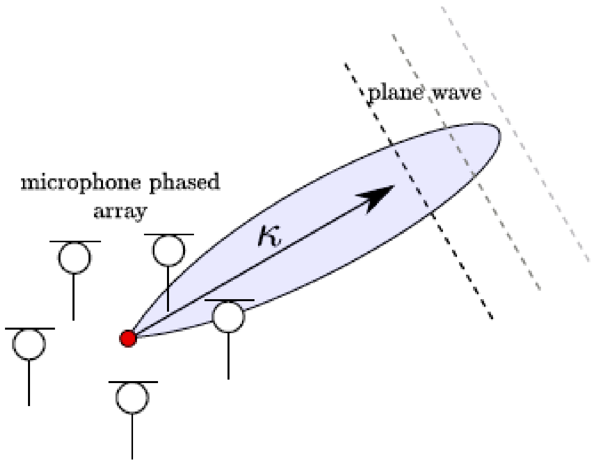

Figure 1. Microphone array example

In contrast, an Acoustic Vector Sensor (*AVS*) employs a sound pressure microphone and three orthogonally collocated particle velocity sensors, being capable of providing 2-D (azimuth and elevation) *DOA* information. The *AVS* behaviour, whose directivity diagram is shown in Fig. 2, is independent of frequency content of the source signal, which enhances its usage in wideband acoustic signal processing applications, including acoustic source detection[10], localization[9] and tracking[12,13,15], battlefield[8], room acoustics[11] and underwater communications[14]. The frequency-independent behaviour of the *AVS* makes it suitable for helicopter localization under long range conditions, because the attenuation of the sound in the atmosphere is way lower for low frequencies, for which microphone arrays tend to fail when trying to obtain directional information of the sound.

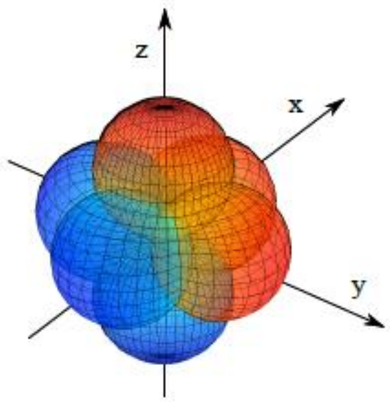

Figure 2. Directivity diagram of an acoustic particle velocity sensor

In aviation, acoustic measurements are expensive because it is very difficult to create “laboratory conditions” for flying aircrafts. Therefore, simulations and real measurements under un-controlled conditions must be used to develop and test the system.

This paper describes the status of the development of a wireless distributed network of *AVSs* that is able to measure and track the position of more than one aircraft simultaneously. The aircraft can be a propeller driven aircraft or a rotary wing aircraft including helicopters, planes and fixed wing UAVs. The rest of the article is organized as follows: The Acoustic MultiMision Sensor (*AMMS*), which is the key part of the proposed system, is introduced in the next section together with a brief explanation of the algorithms that are used in every sensor of the network. The central node or main station, which uses a random finite set framework and runs a centralized localization algorithm per source, is described in section 3. The simulations and the results are presented and discussed in section 4.

The conclusions of this research and suggestions for future work are presented in section 5.

2. ACOUSTIC MULTIMISION SENSOR (*AMMS*)

The Acoustic MultiMision Sensor is the basis of the proposed system. An *AMMS* consists of a sensor unit (based upon two orthogonally placed acoustic particle velocity sensors and a collocated sound pressure transducer) that are connected to a Digital Signal Processor (DSP), that is capable of processing the raw data for detecting, classifying and separating various sound sources. The *AMMS* readings are stored into a SD card with a maximum of 36 hours of continuous data, which is useful to process the data during the development stage.

The sensor and the electronics are covered by a wind and rain resistant open foam wind cap. The 30 cm diameter device weighs around 2 kg, consumes around 2 W electrical power and can be controlled remotely. The AMMS is powered by a battery and can be operational over a week approximately.

An *AMMS* is shown in Fig. 3. The *AMMS* is placed on a tripod which is oriented. As can be seen, an antenna is also connected to the battery box, which is used to send the source or measurement model(s) to the main station and makes it possible to communicate with the AMMS wirelessly to a computer to e.g. switch it on/off or to be able to monitor its status. Note that due bandwidth constrains it is not possible to download the acoustic recordings wirelessly.

Figure 3. An Acoustic Multi Mission Sensor (*AMMS*) with an antenna, a tripod and a battery

Since the goal of this research is to present and test the centralized network algorithm, no effort is done in this paper to explain in detail or test the algorithms at single sensor level. Only a brief explanation and some results are presented in the next subsection.

2.1. *AMMS* measurement model

The measurement model used here for the *AMMS* is the one presented by Hawkes *et al.*[9]. A single source located at position $\boldsymbol{x_s} \in \mathbb{R}^3$ that radiates bandlimited spherical waves into an isotropic field is assumed. We also assume that a network of N_S *AMMS*s is deployed on the ground, being $\boldsymbol{p}_i$, $i=1,\ldots, N_S$, the position of the sensors. Assuming far field for the whole frequency range of interest (plane wave front), we can relate the acoustic particle velocity and the acoustic pressure of the direct sound at any point of the space, $\boldsymbol{r}$, by using the Euler's formula.

(1) $$\boldsymbol{v}(\boldsymbol{r},\mathrm{t}) = p(\boldsymbol{r},\mathrm{t})\tilde{\mathbf{n}} \big/ (\rho_0 c)$$

Where $\boldsymbol{v}(\boldsymbol{r},\mathrm{t})$ is the acoustic particle velocity vector, $p(\boldsymbol{r},\mathrm{t})$ is the acoustic pressure, ρ_0 is the mean density of the medium, c is the speed of sound and $\tilde{\mathbf{n}}$ is a unit vector pointing from the source to $\boldsymbol{r}$. Thus, the output of an AMMS located at the position $\boldsymbol{r}$ can be written as follows.

(2) $$\boldsymbol{y}(\mathrm{t}) = \begin{bmatrix} y_p(t) \\ \mathbf{y}_u(t) \end{bmatrix} = \begin{bmatrix} 1 \\ \mathbf{u} \end{bmatrix} p(t) + \mathbf{e}(t)$$

Thus, the DOA measurement model for every single source can be modelled as a unit vector, $\boldsymbol{u}$, pointing from the sensor to the source position by normalizing the particle velocity vector multiplying it by $(\rho_0 c)$.

2.2. Detecting and modelling helicopter signals

With the aim of detecting and tracking the acoustic sources at single sensor level, a sinusoidal model is used to characterize the acoustic signature of the targets. The acoustic signature of the helicopter is assumed to be composed by tones being usually harmonic or quasi-harmonic (see Fig. 4). Thus, a model for the acoustic signature of the helicopter could be written as shown in Eq. 3,

(3) $$p_H(t) = \mathrm{Re}\left\{ \sum_i \alpha_i(t) \exp\left(j\int_0^t \omega_i(\tau) d\tau + \phi_i(t) \right) \right\}$$

where $\alpha_i(t)$, $\omega_i(t)$ and $\phi_i(t)$ are the arbitrary amplitudes, frequencies and phases of the i-th sinusoidal component respectively[16]. By using this model the source parameters are estimated for every tonal component whose level is above some threshold. After that the peak to peak matching algorithm is used to track the sinusoidal components, as explained in [16].

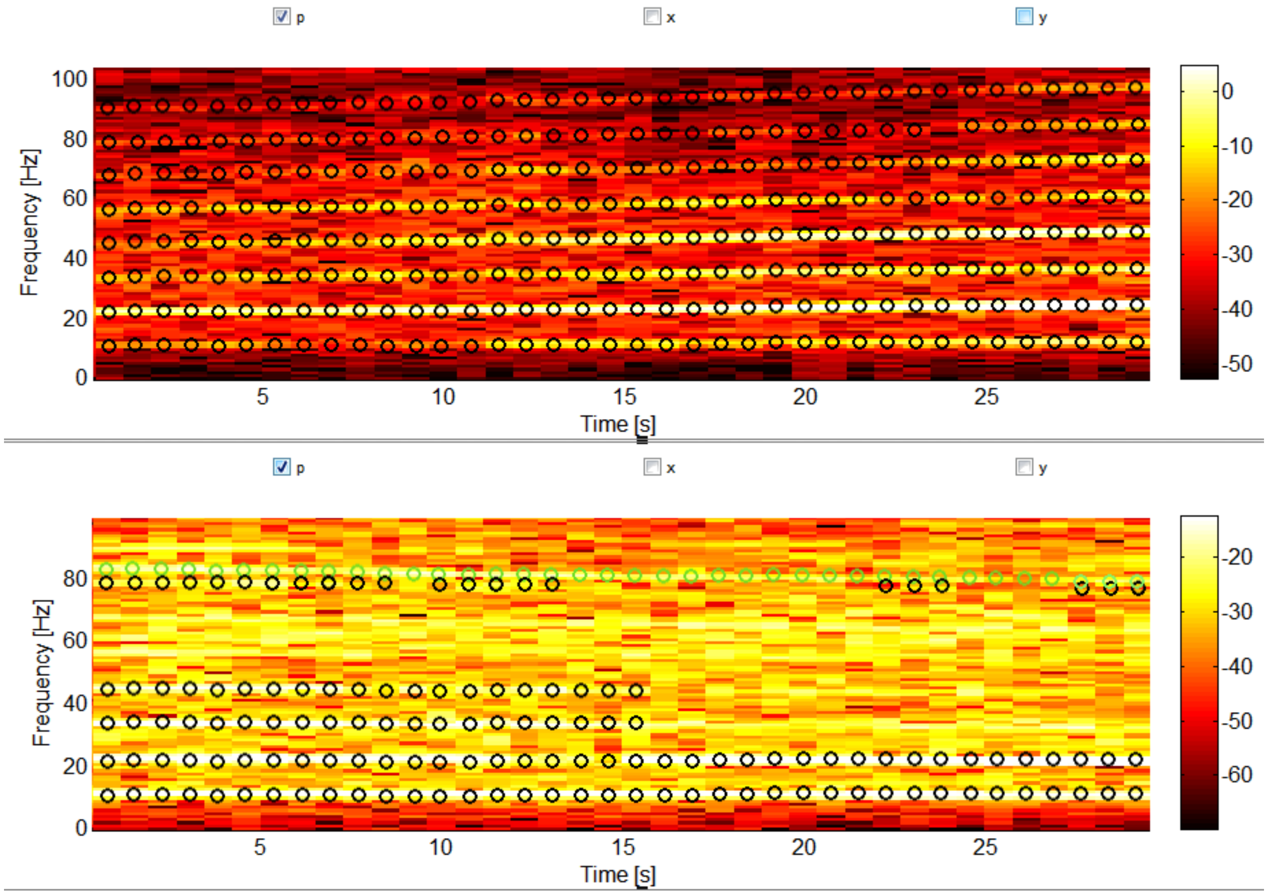

Figure 4. Spectrogram of the signals for two AMMS measuring a helicopter and results of the peak to peak matching algorithm (circles correspond to tracked tones and the and colors to tracked sources)

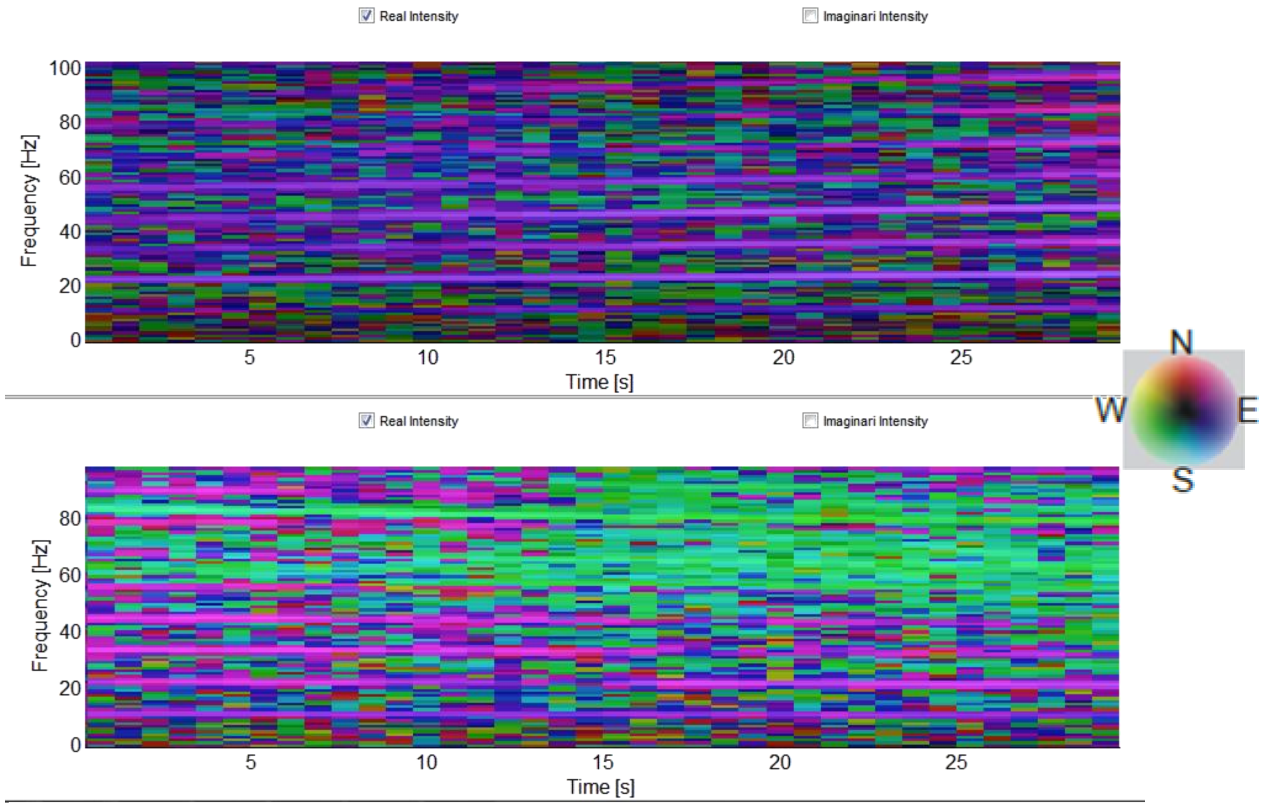

Figure 5. Time frequency Angle Spectrogram of the signals for two AMMS measuring a helicopter

In order to improve the tracking capabilities of the algorithm the *DOA* is used as an extra feature to match and also to combine tones into a source model. This way the source model(s) are detected, generated and tracked at single sensor level.

Fig. 4 and Fig. 5 show as an example a 30 seconds spectrogram and the corresponding time-frequency-angle spectrogram (respectively) for the signals recorded by two of the sensors in the network. The results of the before mentioned algorithm are also plotted. The horizontal distance between the helicopter and the first *AMMS* goes from 900m to 430 m approximately and the helicopter is flying towards the *AMMS*, while for the second *AMMS* the horizontal distance goes from 1.4 Km to 1.7 Km approximately. It is interesting to see that the second *AMMS* is detecting two sources, i.e. the helicopter and an unknown source in motion that looks like a Cessna-type plane (because of the frequency content and the Doppler shift), as can be derived by observing Fig. 4, where different colours of the circles mean different sources. In this case, the DOA of the tones is the key to separate the sources and to track the tones and the sources.

Note that due the frequency content of this kind of sources at the sensor positions and the long range (the atmospheric channel filters out the medium and high frequencies), it is not feasible to use a conventional microphone array for this application.

3. WIRELESS NETWORK OF $AMMS_S$

The proposed wireless networked system is presented in Fig. 6. It is composed by one command post or central node and N_S sensors (or sensor posts). As mentioned above, in this work every *AMMS* is assumed a black box that detects, generates and tracks source model(s), sending the source model(s) parameters periodically to the central node or main station, together with the identifier of the source, its position and a time stamp. The main station collects the source model(s) parameters received from all the sensors within the network and combines them in order to locate and track the potential targets.

3.1. Single Source Scenario

As commented by Cabo *et al.*[15], since the estimation of the azimuth using and ground based AVS placed is independent of the reflective properties of the ground[8,9], a simplified model can be used for the single source localization scenario in the 2D space. It can be thought as a set of 2D unit vectors pointing from every sensor position to the projection of the source position onto the horizontal plane, which we call $x_s(t)=[x(t)\ y(t)]^T$. Note that for a static source or a source that moves relatively slowly in comparison with the observation interval of the network $\mathbf{x_s}(t)=\mathbf{x_s}=[x\ y]^T$ and in absence of noise ($\boldsymbol{e}(t)=0$), the network measurement model is fully described by the next system of equations[9],

$$\mathbf{p}_\mathrm{i} + l_i \mathbf{u}_\mathrm{i} = \mathbf{x}_\mathrm{s} \tag{4}$$

where l_i is the norm of the projection of the vector from $\boldsymbol{p}_i$ to the actual 3D position of the source onto the horizontal plane. However, for most of the flying vehicles as helicopters or planes in a real application, for which the goal should be to increase the distance between sensors or reduce the density of sensors as much as possible for a given area, the motion of the source during the observation interval of the network should not be neglected[15].

Let us to define the maximum observation interval of a given network, $O_{i,max}$, as the difference between the maximum and the minimum delay of the sound wave going from the source positon to all the sensor positions, i.e. the maximum distance between sensors in the network, d_{max}, divided by the speed of sound.

$$O_{i,\max} = \frac{d_{\max}}{c} \tag{5}$$

Looking at Eq. 5, an assuming a network whose maximum observation interval is 3 seconds ($d_{max}=3c$) we can say that the observation interval is never short enough relative to the inverse of the speed of most of the flying targets and realistic networks of *AVSs*. For instance, if the source is moving at 15 m/s, the inverse of the source's speed is 0.067 s/m, that is 45 times less than $O_{i,max}$ in this case.

3.1.1. Modelling the motion off the source

Since the motion of the source within the observation interval of the network cannot be neglected for most of the potential flying targets, a possible solution to the problem explained above is to model the motion of the source.

Several motion models have been proposed in the literature[17]. One of the most used models is the Constant Velocity (CV) model, which can be written as shown in Eq. 6,

$$\boldsymbol{x}_{s,n+1} = \boldsymbol{x}_{s,n} + \Delta T \frac{d\boldsymbol{x}_{s,n}}{dt} \tag{6}$$

where $\boldsymbol{x}_{s,n}= \boldsymbol{x}_s(n{\cdot}\Delta T)$ and ΔT is the time between two consecutive snapshots. Such a CV model has been used to model the dynamics of flying vehicles even though more complicated models could be used for the same purpose[17].

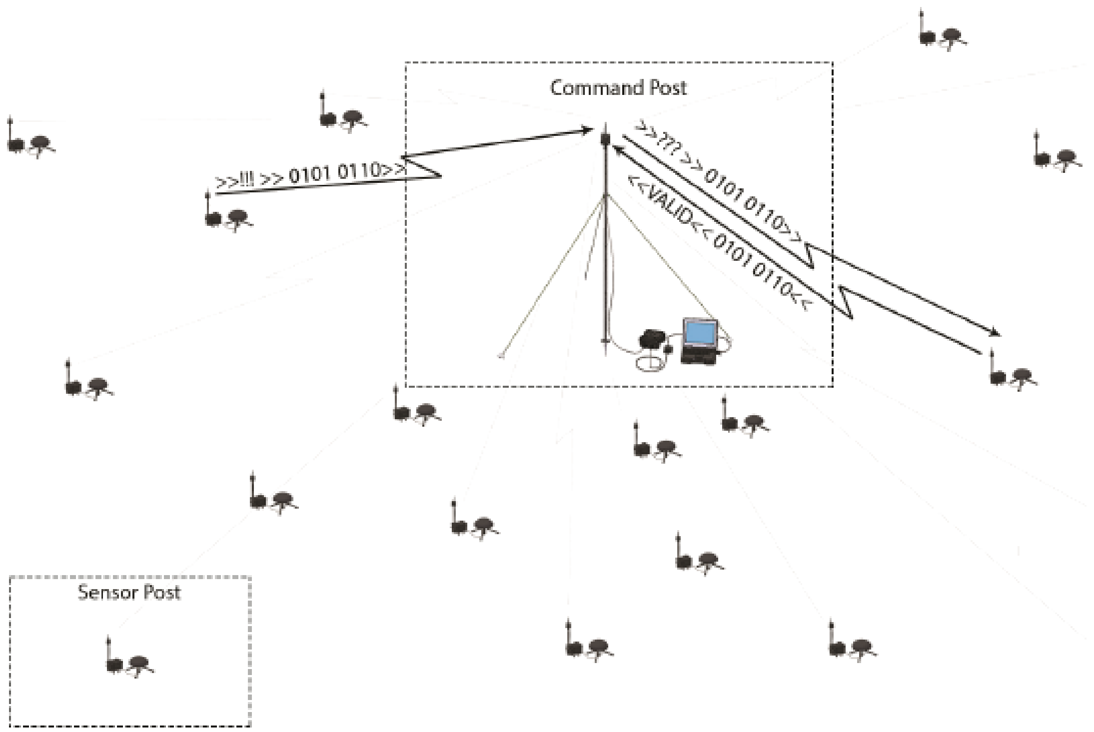

Figure 6. Wireless distributed network of Acoustic MultiMision Sensors

3.1.2. Single source localization algorithm

Now we consider the problem of how to combine the decentralized estimates of the target's bearings, given by the *AMMSs*, to obtain an estimation of the projection of its 3D position in the space onto the horizontal plane, in this case, taking into account that the source can move during the observation interval of the network.

Let us assume that every sensor periodically transmits its local estimate of the azimuth of the target to the central node of the network and that the central node knows an estimate of the position of all the sensors. Then, since in practice both the estimation of the position of the sensors and the estimation of the DOA performed by the sensors will contain errors, the estimation of the source's motion parameters (position and speed) should be done in some least squares sense. Thus, the problem here is to obtain estimates for the position and the speed vector that define a set of points in a straight line that best fit the estimates of the DOA given by the sensors, taking into account the delays caused by the propagation of the sound from the source to all the sensors, τ_i $i=1,\ldots,N_S$. With the aim of taking into account several snapshots, let us define $\tau_{i,m}$, $m=1,\ldots,N_T$, where N_T is the number of snapshots are considered at time step n.

Then, by including the delays, $\tau_{i,m}$, in Eq. 6, the CV model can be rewritten as follows,

$$\boldsymbol{x}_{s,m,i} = \boldsymbol{x}_{s,n} - (k \cdot \Delta T + \tau_{i,n-k})\frac{d\boldsymbol{x}_{s,n}}{dt} \tag{6}$$

where $k=[N_T-m]$, $m=1,\ldots,N_T$, being the delays given by Eq. 7.

$$\tau_{i,n-k} = \frac{\left\|\boldsymbol{x}_{s,m,i} - \boldsymbol{p}_i\right\|}{c} \tag{7}$$

The goal now is to estimate the position and the speed vector of the source at time step n by using the bearing estimates received from the sensors at time steps $n-k$, $m=1,\ldots,N_T$. With this aim, we propose the non-linear least squares (NL-WLS) optimization problem given by Eq. 8,

$$\hat{\boldsymbol{\theta}}_n = \underset{\boldsymbol{\theta}}{\arg\min} \sum_{m=1}^{N_T}\sum_{i=1}^{N_S} \left\| \boldsymbol{p}_i + (\hat{\boldsymbol{u}}_{i,n\text{-}k}^T(\boldsymbol{x}_{s,m,i} - \boldsymbol{p}_i)\hat{\boldsymbol{u}}_{i,n\text{-}k}) - \boldsymbol{x}_{s,m,i} \right\|^2 \omega_{i,k} \tag{8}$$

$$\boldsymbol{\theta}_n = \begin{bmatrix} \boldsymbol{x}_{s,n} \\ \frac{d\boldsymbol{x}_{s,n}}{dt} \end{bmatrix}$$

where the hat over a symbol indicates that it is an estimate of the actual quantity.

3.2. Multiple sources scenario

The capability of the system for locating multiple targets depends on the ability of the AMMS for separating and tracking multiple sources[9]. Since the *AMMS* is only looking for tonal or harmonic components, most of the interfering broad-banded or impulsive sources will not be detected. Therefore, broad banded or impulsive acoustic sources can be considered as an increase of the background noise that temporary masks some of the tonal components of the target of interest, as can be seen in Fig. 4 and Fig. 5.

On the one hand, a single *AMMS* will not consider detected tonal components with a wrong azimuth (relative to the tracked sources) to estimate the DOA of a tracked source, but it will create a new source. The *AMMS* will not track a source if its acoustic signature is not coming from a consistent direction within a time interval of several snapshots. This approach notably increases the robustness of the system by minimizing the number of false detections, and reduces the variance of the *DOA* estimates. As shown in Fig. 4, the AMMS is able to separate multiple sources even when one of the components of the helicopter noise is completely masked by a tonal component of the Cessna-type plane. Furthermore it finds the component again after some seconds and the tone is properly associated with the helicopter acoustic model.

On the other hand, it is well known that an *AVSs* can separate more than one stationary source at a single frequency[9]. Furthermore, since the single sensor algorithm is looking for flying vehicles in motion and the acoustic signatures of that sources are completely non stationary, mainly due the Doppler shift and the time-varying atmospheric conditions, it is almost impossible in practice to have overlap between all the components of two sources in motion for more than a few seconds (see Fig. 4). Non stationarity can be of help for separating more sources per frequency if several snapshots are taken into account at single sensor level, by using a Blind Source Separation technique[17].

Therefore, assuming that the number of tonal sources in motion is bounded to a realistic number and regarding the discussion above, the multisource scenario can be solved by combining properly the bearing estimates given by the sensors[9], and every source can be located and tracked by applying the NL-WLS algorithm presented in the previous subsection.

4. MEASUREMENTS

A network of 6 *AMMS* has been deployed close to an airbase. Fig. 7 shows the configuration of the network and its maximum observation interval, which is *3.9* Km. The temperature was around 8 degrees during the measurement campaign so the speed of sound was $c=336.1 \text{ m/s}^{1}$. Then the maximum observation interval for this specific network was 11.2 seconds.

Two helicopters were flying during a day and two GPS logger were used to estimate their position and their speed. One of them is shown in Fig. 8.

Figure 8. One of the helicopters used during the measurement campaign

The sensors recorded all the raw data into their SD card. All the data was collected to post-process it and to estimate the statistics of the error of the azimuth estimates given by the sensors and to know how those statistics were affected by the distance, i.e. the estimation of the azimuth has been compared with the *ground* truth in order to model the noise and apply such a model to the simulations. Since one of the helicopters was flying in circles it has been possible to get a good estimation of the statistics of the noise for different distances, which allow us to make quite realistic simulations based on measurements.

5. SIMULATIONS AND RESULTS

As mentioned before, the AMMS is assumed a black box that detects and track the harmonic source(s) and sends an estimation of the azimuth, the identifier of the tracked source and a time stamp of the detected source to the central node of the network. The main goal of the simulations performed during this investigation is to validate the proposed method and to compare it with other existent algorithms.

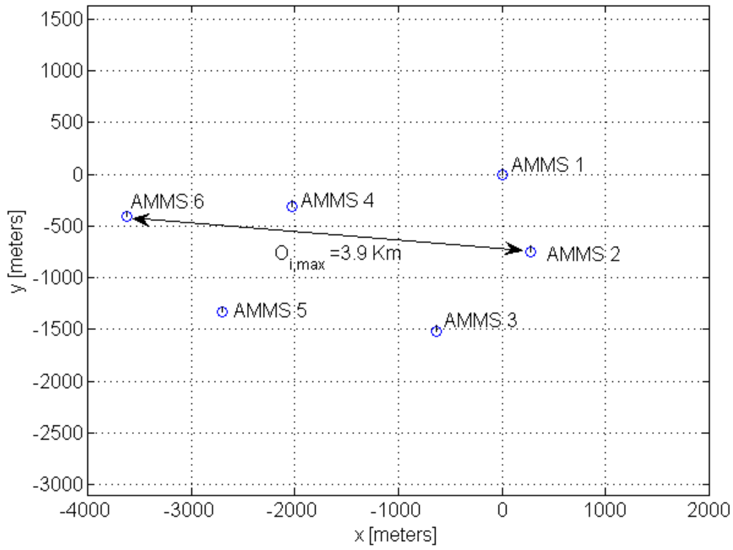

Figure 7. Wireless Network geometry for the measurements and some simulations

5.1. Ideal scenario – absence of noise

The goal of this simulation is to show the effect of the differential delays over all the proposed algorithms that assume that the source state remains invariant over several snapshots, neglecting the observation interval of the network. The proposed NL-WLS algorithm, the WLS and the RWLS algorithms[9] are compared using the *ground truth,* calculated during the post-processing stage to characterize the noise, as commented in the previous subsection. To fairly compare the algorithms, for the ideal scenario we only consider one snapshot, i.e. the same amount of information as the other two algorithms.

Fig. 9 and Fig. 10 show two examples of the localizing and tracking performance of the algorithms for the network shown in Fig. 7 and the same network but using 5 *AMMSs* respectively (*AMMS* 2 is not used). We have observed that the estimation of the position given by the WLS and the RWLS algorithms is extremely biased when the helicopter changes its state fast enough relative to the observation interval of the network even in absence of noise, as can be seen in Fig. 11 more in detail, meaning that the estimators proposed by Hawkes and Nehorai[9] are not suitable to locate flying sources in motion. Looking at the tracking capabilities of the proposed algorithm (NL-WLS) it is pretty clear that the problem is that WLS and RWLS are trying to solve a linear approximation of the underlying non-linear problem, which is not a good approximation for most of potential targets in aeroacoustics. However, it can be seen that the proposed algorithm approximates the problem much better by modelling the motion of the source within the observation interval of the network.

In order to get an estimation of the Root Mean Squared Error (RMSE) relative to the range, a reference point should be defined to compute the range. Since the error depends on the observation interval of the network, and it depends on the maximum and the minimum distance to the sensors, which are time-varying, the reference point used here is also time-varying. We decided to use as a reference midpoint of the line segment going from the closest sensor to the farthest one, that we call C_{ref}. Thus, we can express the localization error in terms of the range to a reference point.

Fig. 12 shows the evolution of the RMSE with the time for two circles of the helicopter path flying around the airbase. The distance to all the sensors is bounded between 200 meters and 6 Km in this case. On the one hand, it is shown that the localization error given by the WLS and the RWLS algorithms in absence of noise is too high. On the other hand, the localization performance of the proposed algorithm depends on the goodness of the approximation given by the CV model. As shown in Fig. 11, when the constant velocity vector is not close to be constant during the observation interval of the network the estimation of the position of the source is a bit biased, but the localization is still good.

The cumulative distribution function of the localization error given by the algorithms for this specific case is presented in Fig. 13. The NL-WLS algorithm clearly outperforms the algorithms proposed by Hawkes and Nehorai (2003)[9] even using 1 snapshot. It achieves an accuracy that is less than 2% of the range 90% of the time and less than 3% around 95% of the time, while the error given by the WLS algorithm and the RWLS algorithm is 6 and 5 times higher approximately.

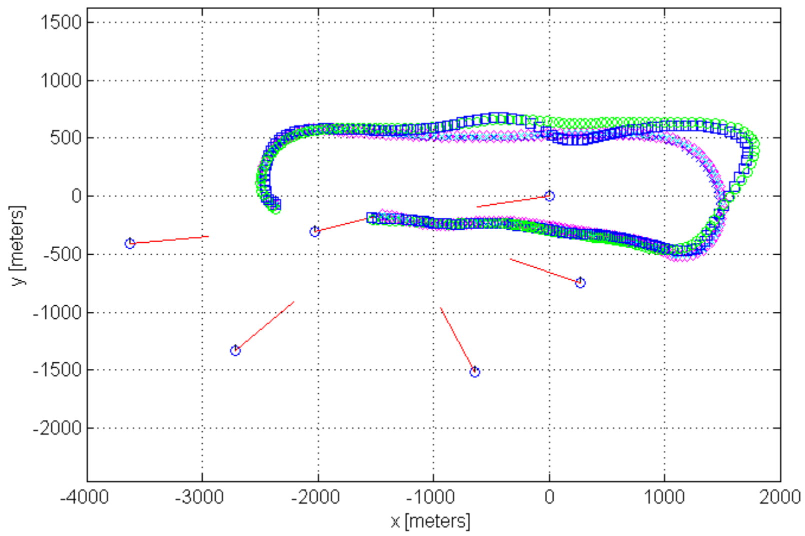

Figure 9. Tracking example for a network of 6 *AMMSs* in absence of noise
(WLS - green circles; RWLS - blue squares; NL-WLS magenta diamonds; GPS – blue crosses).

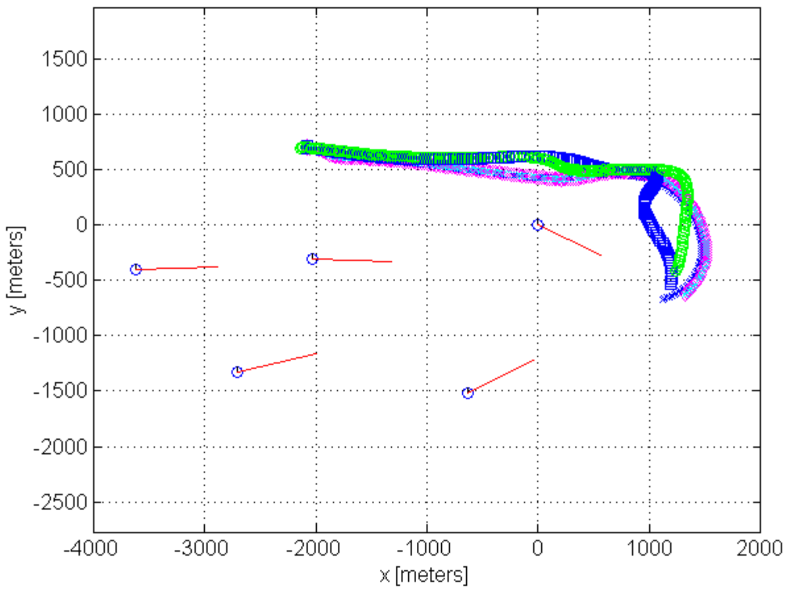

Figure 10. Tracking example for a network of 5 *AMMSs* in absence of noise for a different circle within the fligth path (WLS - green circles; RWLS - blue squares; NL-WLS magenta diamonds; GPS – blue crosses).

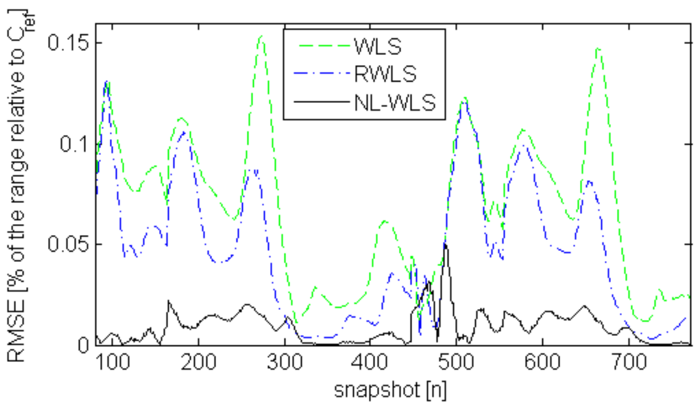

Figure 12. Evolution of the RMSE with the time for the first helicopter flying in circles around the airbase

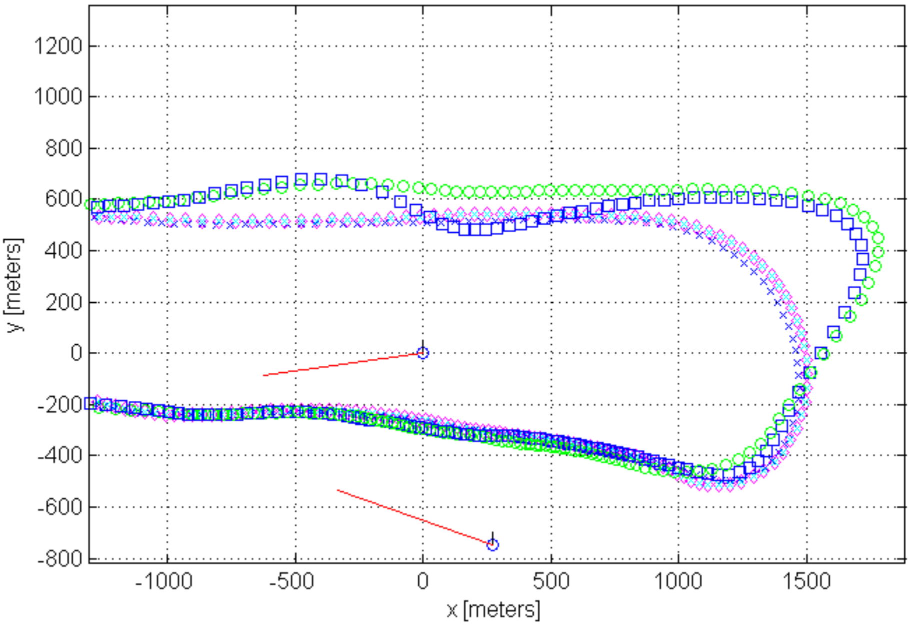

Figure 11. Tracking example for a network of 6 *AMMSs* in absence of noise (WLS - green circles; RWLS - blue squares; NL-WLS magenta diamonds).

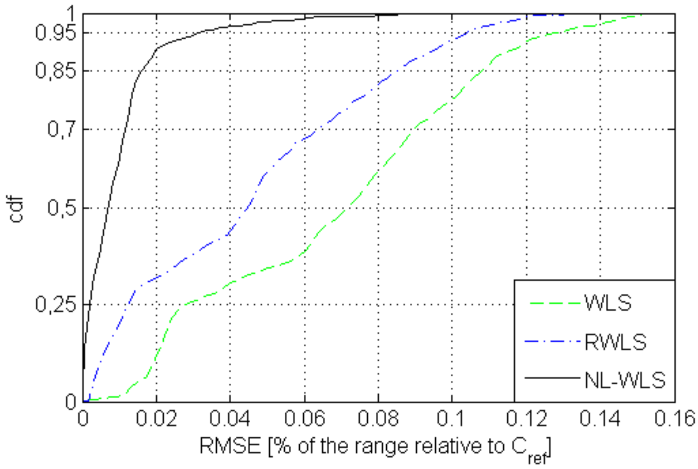

Figure 13.Cumulative distribution function of the RMSE Figure 11. Evolution of the RMSE with the time for the first helicopter flying in circles around the airbase in absence of noise

5.2. Including noise

As mentioned above, with the aim of making realistic simulations a statistical model of the error for the estimation of the azimuth relative to the range using an AMMS has been obtained using real measurements of two helicopters flying. Such a model has been applied to the simulations. This approach has quite some benefits, since it allows us to control the amount of noise we are using by increasing the variance of the error distribution.

Fig. 14 shows an example of the localization performance of the algorithms using the model obtained for the noise. Note that since the distribution of the noise for the estimated *DOAs* applied to the signals depends on the distance to every sensor, the noise is completely non-stationary, because the source is in motion and the distances to the sensors are time-varying. For this experiment N_T=10 snapshots are used to estimate the position of the target using the NL-WLS algorithm. The sensors send the source model parameters to the main station every 1 second. As can be seen, the NL-WLS algorithm outperforms WLS and RWLS algorithms even in presence of realistic noise. The key of its good performance is the fact that it takes the motion of the source over several snapshots, reducing the influence of the noise in the localization accuracy.

The cumulative distribution function (cdf) of the RMSE estimated over 50 MonteCarlo (MC) runs using 6.5 minutes of the flight path (helicopter making circles around the airbase) is shown in Fig. 15. As expected, the NL-WLS algorithm has better performance when realistic noise is applied to the simulation. The results are in good agreement with those presented by Cabo *et al.*[15] for real measurements using 2 RC aircrafts. Therefore, the algorithm is expected to work well also with real measurements.

5.3. Two sources scenario

To simulate the multisource scenario, the noise added to the signals has been notably reduced, in order to study the performance of the clustering algorithm that runs in the central node. During the measurement campaign only for a few minutes both helicopters were flying at the same time.

Fig. 16 shows the localization and separation performance of the system for that time interval. As can be see, the localization error increases in presence of low noise level in comparison with the single source scenario. It is caused by the fact that the clustering algorithm makes some mistakes when associating the received *DOAs* with the tracked sources. These association errors reduce the performance of the system, as expected, but it is unlikely for this specific case to make a mistake for more than one *DOA* at the same time step. Therefore, as can be seen in Fig. 16, the localization capabilities are still reasonably good.

In practice, the frequency content of both helicopters is not going to be exactly the same at the sensor positions, because of the Doppler effect, which depends on the state of every helicopter relative to all sensor positions, and the time-varying propagation condition. Hence, we believe that the single sensor algorithm is going to be able to separate the tonal components even though sometimes overlap between some components of the sources will exists. Fig. 17 shows the RMSE calculated for both helicopters. It is shown that in presence of low level noise the localization error of the multisource algorithm is still good, as commented above.

6. CONCLUSIONS AND FUTURE WORK

A wireless network of Acoustic MultiMision Sensors have been presented to solve the problem of locating and tracking multiple helicopters at the same time. The required bandwidth is low enough to make the system feasible for large networks with large number of sensors, because the potential target are detected and separated at single sensor level, i.e. in a distributed way. Since the system is focus on helicopters at long range, only the low frequency range is processed, allowing us to downsample the raw data considerably, reducing the processing time. Note that the proposed system is only feasible using *AVSs*, because conventional microphone arrays cannot get directional information at the frequency range of interest (10 – 150 Hz). Note that the low frequencies propagate farther away because medium-high frequencies are filtered out by the atmospheric propagation channel.

As a part of such a system, a centralized localization algorithm, that we call NL-WLS has been proposed and tested using simulated data based on real measurements of two helicopters flying. The proposed algorithm clearly outperforms other algorithms proposed in the literature for distributed networks of AVSs, even in presence of a considerable amount of non-stationary noise. Thus, further related work should be oriented to continue testing, developing and improving the system for the multisource scenario. It would be also interesting to try different dynamic models for manoeuvring target tracking. Source separation techniques for non-stationary sources under non-stationary conditions should be further investigated, in order to increase the number of sources that can be separated.

Acknowledgment: This research was partially funded by the JU Clean Sky Green Rotorcraft.

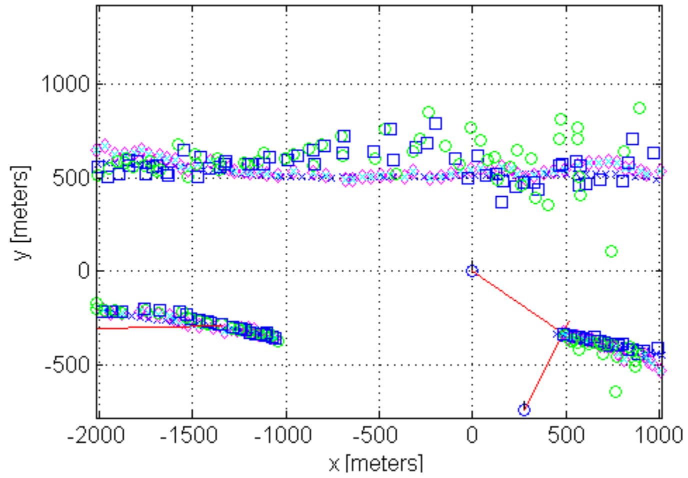

Figure 14. Tracking example for a network of 6 *AMMSs* in presence of noise
generated by a model obtained using real measurements of two helicopters flying
(WLS - green circles; RWLS - blue squares; NL-WLS magenta diamonds; GPS – blue crosses).

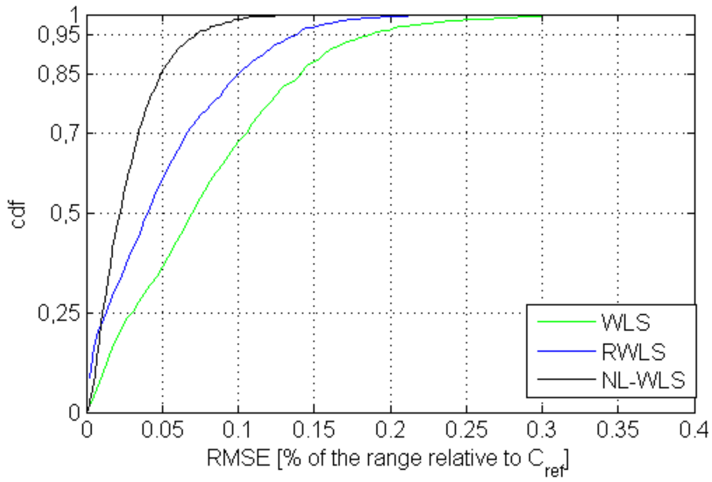

Figure 15.Cumulative distribution function of the RMSE Figure 11. Evolution of the RMSE with the time for the first helicopter flying in circles around the airbase in presence of realistic non-stationary noise

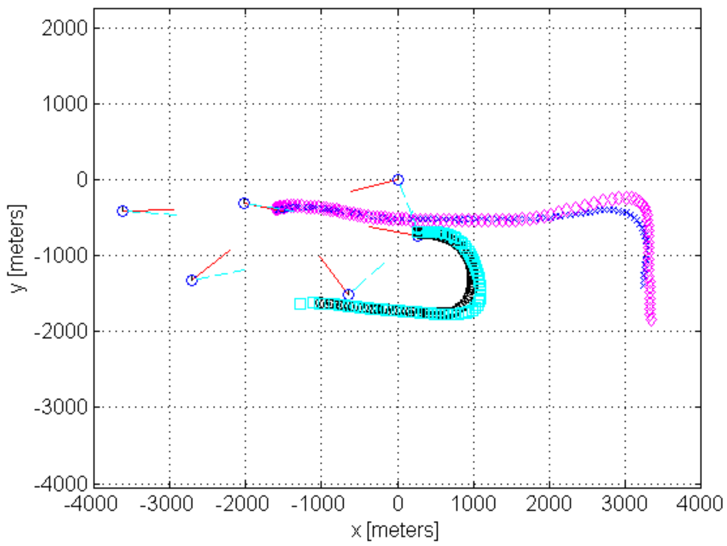

Figure 15.Separation of two simulated helicopters using the proposed system, real GPS data and a low amount of non-stationary noise (NL-WLS H1 magenta diamonds; GPS H1 – blue crosses; NL-WLS H2 cian squaress; GPS H2 – black cicles)

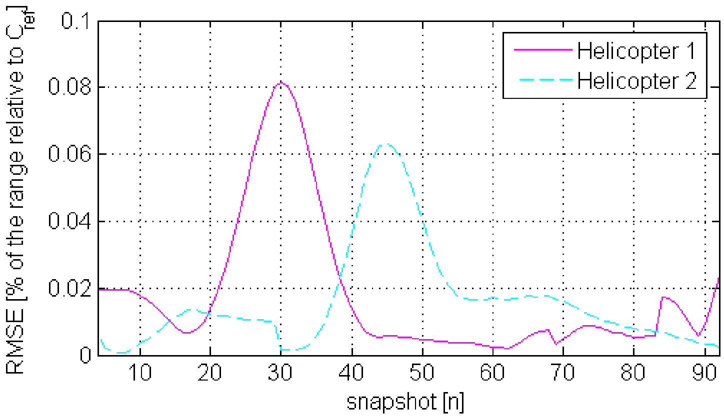

Figure 17. Evolution of the RMSE with the time for the localization of two helicopters under low noise conditions

7. REFERENCES

[1] Lawrence E. kinsler, Austin R. Frey, Alan B. Coppens, J. V.Sanders "Fundamentals of Acoustic" 4th edition, Chapter.8, p.p210-226, John-Wiley and Sons, INC (2005) USA.

[2] D. Khaykin, B. Rafaely,"Coherent signals direction of arrival estimation using a spherical microphone array: Frequency smoothing approach". Proc. IEEE WASPAA pp. 221-224. 2009.

[3] Dongwen Ying, Yonghong Yan,"Robust and Fast Localization of Single Speech Source Using a Planar Array". Signal Processing Letters, IEEE, pp. 909-912, june 2013.

[4] Osamu Hoshuyama, Akihiko Sugiyama, Akihiro Hirano, "A Robust Adaptive Beamformer for Microphone Arrays with a Blocking Matrix Using Constrained Adaptive Filters", IEEE Transactions on Signal Processing, Vol. 47, No. 10, October 1999.

[5] Brandstein M., Ward, D., Microphone arrays, Signal Processing Techniques and Applications. (Eds.) Springer, 2001

[6] Wind J., de Bree H. E., Buye Xu, 3D Sound Source Localization and SoundMapping using P-U Sensor Array, 16th AIAA/CEAS Aeroacustics Conference Stockholm 2010.

[7] Wen-Qian Jing, Daniel Fernandez Comesaña, David P. Cabo "Sound source localisation using a single acoustic vector sensor and multichannel microphone phased arrays". Inter-noise, Melbourne, November 2014.

[8] Hawkes, M., Nehorai, A.,"Battlefield target localization using acoustic vector sensors and distributed processing" in Proc. Meet. IRIS Specialty Group Battlefield Acoustics. Seismics (Invited), Laurel, MD, Sept. 1999, pp. 111Ð128.

[9] Hawkes, M., Nehorai, A.,"Wideband Source Localization Using a Distributed Acoustic Vector-Sensor Array". IEEE Transactions on signal processing, Vol. 51, NO. 6, pp. 1479-1491, June 2003.

[10] V. N. Hari, G. V. Anand, A. B. Premkumar, and A. S. Madhukumar, "Design and performance analysis of a signal detector based on suprathreshold stochastic resonance," Signal Process., vol. 92, no. 7, pp. 1745–1757, 2012.

[11] D. Levin, E. A. P. Habets, and S. Gannot, "On the angular error of intensity vector based direction of arrival estimation in reverberant sound fields," J. Acoust. Soc. Amer., vol. 128, no. 4, pp. 1800–1811, 2010.

[12] X. Zhong, A. B. Premkumar, and A. S. Madhukumar, "Particle filtering and posterior Cramér-Rao bound for 2-D direction of arrival tracking using an acoustic vector sensor," IEEE Sensors J., vol. 12, no. 2, pp. 363–377, 2012.

[13] X. Zhong and A. B. Premkumar, "Particle filtering approaches for multiple acoustic source detection and 2-D direction of arrival estimation using a single acoustic vector sensor," IEEE Trans. Signal Process., vol. 60, no. 9, pp. 4719–4733, 2012.

[14] A. Song, A. Abdi, M. Badiey, and P. Hursky, "Experimental demonstration of underwater acoustic communication by vector sensors" IEEE J. Ocean. Eng., vol. 36, no. 3, pp. 454–461, 2011.

[15] David P. Cabo, Hans-Elias de Bree, Daniel Fernández Comesana, Manuel A. Sobreira Seoane. "Real life harmonic source localization using a network of acoustic vector sensors" Euronoise 2015, Maastricht.

[16] Robert. J. Mcaulay, Thomas F. Quatiery, "Speech analysis/Synthesis based on a sinusoidal representation" IEEE Transactions On Acoustics Speech And Signal Processing Assp-34(4), pp. 744 - 754 · September 1986.

[17] X. Rong Li, Vesselin P. Jilkov. "A Survey of Manoeuvring Target Tracking: Dynamic Models". Proceedings of SPIE Conference on Signal and Data Processing of Small Targets, Orlando, FL, USA, April 2000. (4048-22)

[18] Ganesh Naik, Fernando J. Mato-Méndez, Manuel A. Sobreira Seoane. "Independent Component Analysis for Audio and Biosignal Applications. Chapter 1, pp. 4-22, Chapter 16, pp. 321-344, InTech, October 2012.