Real Life Harmonic Source Localization Using a Network of Acoustic Vector Sensors

David Pérez Cabo, Hans Elias de Bree, D. Fernandez Comesaña
Microflown Technologies, Tivolilaan 205, 6824 BV, Arnhem, The Netherlands

Manuel A. Sobreira Seoane
AtlantTIC, Atlantic Research Center for Information and Communication Technologies. Telecommunication Engineering School, University of Vigo. 36310 Vigo-Spain.

Summary
Using networks of acoustic vector sensors for sound source localization and tracking has become of research interest given its importance in a great variety of applications. An Acoustic Vector Sensor (AVS) consists of two or three orthogonal particle velocity sensors in combination with a sound pressure microphone. In several publications it has been proven that multiple sources can be located in three dimensions with a single AVS. Furthermore, it has been demonstrated that ground-based two-dimensional acoustic vector sensors can be used to estimate the elevation of a single source. Two different algorithms for harmonic source localization using a distributed and synchronized network of 2-D AVS are presented and tested in this work. Both algorithms are based on the Direction Of Arrival (DOA) estimate performed by each sensor in the network for every dominant component of the source. Localization and tracking results based on simulations and two extensive measurements of flying aircrafts are also presented and discussed. Some of the main factors that affect the detection and the localization range are pointed out.

PACS no. 43.60.Jn, 43.60.Fg

1. Introduction

With the number of flying vehicles going up, as helicopters, planes, Radio Controlled (RC) aircrafts or Unmanned Aerial Vehicles (UAVs) , also the need increases to monitor their trajectories in the 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 system 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 aircrafts.

Traditionally, arrays of sound pressure transducers have been used to obtain acoustic directional information by estimating the direction of arrival of a sound wave using relative phase differences [2, 3, 4]. However, such an array obtains a difficult to handle size when trying to cover low frequencies and it requires spatial coherence between transducers for the whole frequency range of interest. It is well known that the spatial coherence between transducers decreases as the size of the array increases [5], specificaly for high frequencies [7]. Therefore, any attempt to cover lower frequencies by increasing the spacing between transducers will lead to a reduction of the performance of the system at higher frequencies due to aliasing [6, 7] and the lack of cross-correlation or coherence between receivers [5]. Furthermore, since different kind of flying vehicles have different spectral signatures and potentially disjoint frequency ranges, it is a challenging task to get a microphone array geometry that works reasonably well for all the potential targets with an easy to handle size. Moreover, the acoustic pressure transducers of the array need to exchange broad band signals in order to estimate the direction of the sound. It should be noted that the complexity and the price of the system increase with the size of the array. All this makes no feasible to use arrays of sound pressure transducers to locate all kind of flying targets.

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 windcap. The 30 cm diameter compact device weighs around 2 kg and consumes around 2 W electrical power. 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.

Since the particle velocity vector was invented some decades ago, some algorithms for acoustic source localization using a distributed network of AVSs have been proposed, but no one has been tested in real life. Nehorai and Hawkes [9] proposed two different algorithms to estimate the position of a single source in the space: The Weighted Least Squares (WLS) algorithm and the ReWeighted Least Squares (RWLS) algorithm. Both are referred in the literature as triangulation methods because the estimation of the position of the source is made using only the DOA of the sound at every sensor position. A 2-D version of both algorithms together with a simple Kalman filter have been used for this investigation. Recently, a distributed particle filter based approach was proposed with the aim of solving the multi-source scenario [10]. It should be noted that the multi-source localization problem could also be solved by using the WLS and RWLS algorithms, as commented in [9].

The rest of the article is organized as follows. The measurement model is described in the next section and the source localization algorithms have been used in this work are described in section III. The simulations and the measurements are briefly explained in section IV. The results of the simulations and the measurements are presented in section V together with a brief discussion about the main factors that can affect the performance of both algorithms. Finally conclusions and future related work are discussed in section VI.

2. Measurement model

The measurement model used here is the one presented in [9]. A single source located at the position $\mathbf{\Theta} \in \mathbb{R}^3$ that radiates bandlimited spherical waves into an isotropic homogeneous field is assumed. We also assume that a network of N_s AMMSs is deployed on the ground, being $\mathbf{p}_1, ..., \mathbf{p}_{N_s}$ the position of the sensors. Assuming far field for the whole frequency range of interest (plane wave front), we can relate the particle velocity and the pressure of the direct sound at any point $\mathbf{r}$ using the Eulerńs formula.

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

where $\mathbf{v}$ is the velocity vector, p is the pressure, ρ_0 is the density of the medium and c is the speed of sound, and $\tilde{\mathbf{n}}$ is a unit vector from the source to $\mathbf{r}$. Thus, in the free space, the output of a 3D AVS located at $\mathbf{r}$ can be written as follows.

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

Since for the ground scenario the estimation of the azimuth of the source is independent of the reflective properties of the ground where the sensor is deployed [8, 9], a simplified measurement model for the single source localization scenario in 2D can be derived. It can be thought as a set of unit vectors in 2D, $\hat{\mathbf{u}}_i$, pointing from every sensor position to the projection of source position onto the horizontal plane, which we call $\boldsymbol{\theta}(t)$. Then, for a fixed $\boldsymbol{\theta} = [x\ y]^T$ and in absence of noise ($\mathbf{e}(t) = \mathbf{0}$), the measurement model is fully defined by the next system of equations,

$$\mathbf{p}_i + l_i \hat{\mathbf{u}}_i = \boldsymbol{\theta} \tag{3}$$

where l_i is the norm of the projection of the vector from $\mathbf{p}_i$ to the actual 3D position of the source onto the horizontal plane.

3. 2D position estimation of the source

Let us assume that every sensor periodically transmits its local estimate of the azimuth of the source $\hat{\mathbf{u}}_i$ to the central node of the network and that the central node knows an estimate of the position of all the sensors. As commented in [9], in practice both the estimation of the position of the sensors and the bearing estimate performed by every sensor will contain errors. Hence the estimation of the position should be made in some least squares sense by taking as a solution the closest point to all the lines from the sensor position in the direction of the source. Thus, the closed form estimate of the position proposed by Nehorai and Hawkes, called WLS algorithm is shown in Eq. 4,

$$\hat{\boldsymbol{\theta}} = \left[\left(\sum_{i=1}^{N_s} w_i \right) I - \hat{U} W \hat{U}^T \right]^{-1} A\mathbf{w} \tag{4}$$

where w_i is the weight corresponding to the accuracy of each $\hat{\mathbf{u}}_i$ given by the $i-th$ sensor, $\hat{U} = [\hat{\mathbf{u}}_1, ..., \hat{\mathbf{u}}_{N_s}]$, $\mathbf{w} = [w_1, ..., w_{N_s}]^T$, $W = diag(\mathbf{w})$, I is the identity and

$$A = \left[(I - \hat{\mathbf{u}}_1 \hat{\mathbf{u}}_1^T) p_1, ..., (I - \hat{\mathbf{u}}_{N_s} \hat{\mathbf{u}}_{N_s}^T) p_{N_s} \right].$$

The second algorithm proposed in [9] is called RWLS, because the weights are recalculated after getting a first guess of the position of the source. Since the errors in the estimation of the azimuth from sensors far from the source have a greater effect upon x_s than those from sensors nearby, the weights w_i are divided by the square of the distance from the sensor to the estimation of the source position. In our case, it is the distance from the sensor to estimation of the projection of the source position onto the horizontal plane, $\hat{l}_i$.

$$w'_i = w_i/(\hat{l}_i^2) \tag{5}$$

Therefore, the RWLS estimator for the source position can be written as shown in Eq. 6.

$$\hat{\boldsymbol{\theta}}_R = \left[\left(\sum_{i=1}^{N_s} w'_i \right) I - \hat{U} W \hat{U}^T \right]^{-1} A\mathbf{w} \tag{6}$$

It should be noted that both algorithms are not made for locating all kind of vehicles in motion, because the differential delays between sensors and the observation interval of the network are assumed negligible relative to the inverse of the speed of the target [9]. It can be a quite realistic assumption for underwater acoustics but it is simply not true for most flying and ground vehicles. Hence, both WLS and RWLS may be seen as a linearization of the underlying non-linear problem that can work well when the mach number of the source, $M_s = c_s/c$, is much less than 1, where c_s is the speed of the target.

3.1. Tracking

Assuming that is the case and that $\hat{\boldsymbol{\theta}}_R$ is an unbiased estimator of $\boldsymbol{\theta}$, some information about the dynamics of the process (a real source in motion) should be used in order to get a smoother estimation of the path. A basic direct Kalman filter can be used for this purpose. It is a common filter in control theory that implements a predictor-corrector type estimator that is the optimal recursive filter in the sense that it minimizes the estimated error covariance [12]. A constant velocity model is assumed for the source, and therefore, the state vector of the Kalman filter for the $k-th$ snapshot is a 4x1 dimensional vector containing the 2D coordinates of the source and their derivatives with respect the time.

$$\hat{\boldsymbol{\theta}}_k = \left[x_k \ \frac{dx_k}{dt} \ y_k \ \frac{dy_k}{dt} \right]^T \tag{7}$$

The discrete Kalman filter time update equations are [11],

$$\hat{\boldsymbol{\theta}}_k^- = M\hat{\boldsymbol{\theta}}_{k-1} + Bv_k \tag{8}$$

$$P_k^- = MP_{k-1}M^T + Q \tag{9}$$

and the Kalman filter measurement update equations are,

$$K_k = P_k^- H^T (HP_k^- H^T + R)^{-1} \tag{10}$$

$$\hat{\boldsymbol{\theta}}_k = \hat{\boldsymbol{\theta}}_k^- + K_k(z_k - H\hat{\boldsymbol{\theta}}_k^-) \tag{11}$$

$$P_k = (I - K_k H)P_k^- \tag{12}$$

where the matrix M relates the state in the previous step to the state at the current step, the matrix B is an optional control input, P_k^- is the *a priori* estimate error covariance, P_k is the *a posteriori* estimate error covariance, Q is the covariance matrix of the process noise, H is a matrix that relates the previous state with the $k-th$ observation, called here $\mathbf{z_k}$, which is the output of the WLS or the RWLS algorithm, K_k is the Kalman filter gain at the $k-th$ snapshot and R is the covariance matrix of the measurement noise. For this investigation, both the covariance matrix of the measurement and the process noises are estimated via forgetting factor (as in the Recursive Least Squares Algorithm [11]) and both transition matrices can be written as shown in Eq. 13 and Eq. 14.

$$H = \begin{bmatrix} 1 & \Delta t & 0 & 0 \\ 0 & 0 & 1 & \Delta t \end{bmatrix} \tag{13}$$

$$M = \begin{bmatrix} 1 & \Delta t & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & \Delta t \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{14}$$

4. Simulations and Measurements

During this paper the AMMS is assumed a black box that detects the harmonic source and sends an estimation of the azimuth 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 method and also to know if the 2D localization and tracking of flying vehicles is feasible when the altitude of the source is unknown and time-varying.

4.1. Simulations

To model this, the simulations were performed by using the GPS data of the track of a RC flying aircraft. Then the time signals (pressure and particle velocity) were generated at every sensor position using the measurement model in Section II, taking into account the actual 3D position, the speed and the direction of the target and the time that the sound takes to travel from the source position to every sensor position.

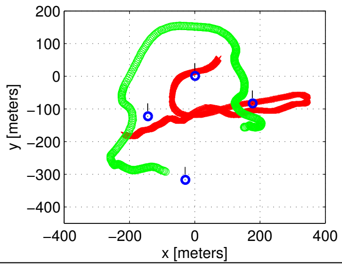

Figure 1. 2D tracks used to simulate the source localization problem.

Figure 2. Pusher UAV used for the measurements.

The tracks used in the simulations are shown in Fig. 1. As can be seen, both test tracks include changes in the trajectory of the RC aircraft. In the simulations the source is assumed harmonic. Several harmonics are generated assuming a constant ground frequency and applying the corresponding Doppler shift based on the velocity and the direction of the target. At single sensor level the Capon method is used to estimate the DOA of the source (azimuth) [7]. The background noise is simulated by adding complex circularly white Gaussian noise with constant variance to the received signal in order to achieve a SNR of 0 dB 100 meters away from the source for the ground tone, and the signals are attenuated using the quadratic law and the atmospheric attenuation [13]. Note that the SNR of every harmonic is time-varying and it depends on the distance from the sensor to the source. As shown in Fig. 1, four sensors are used during the simulations. Then, the algorithms explained in the previous section are used to get the estimation of the position of the target in the horizontal plane.

With the aim of estimating the error, a reference time is needed. The time when the sound reaches the farthest sensor is taken as a reference time to estimate the error at every instant. It makes difficult to simulate the problem because the reference sampling rate is not constant. Since we are tracking source in motion an estimation of the Root Mean Square Error (RMSE) for the whole track can be a good indicator of the average performance [10] of the algorithm, but

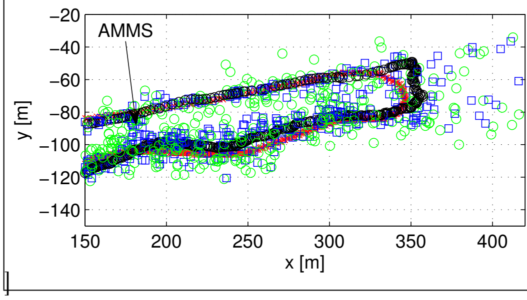

Figure 3. Results of the tracking for a small part of the first track. Red crosses - GPS 2D position of the source, green circles - WLS, blue squares - RWLS, black stars - direct KF

it is meaningless if the goal is to know the evolution of the performance with the time and the position of the source. It would be interesting to observe the evolution of the statistical properties of the error with the time. The evolution of the error with the time was studied by performing 100 Monte Carlo repetitions for each track and estimating the RMSE per frame. The Cumulative Distribution Function (CDF) of the RMSE is then obtained by averaging also over the time.

4.2. Measurements

As commented before, two measurements were performed using two small RC aircrafts (Fig. 2) using a synchronized network of AMMSs. The weight of both aircrafts is less than 500 grams and the size of the propeller is small. Because of that, the signal to noise ratio at the sensors is extremely poor (between -40dB and 3 dB for all the sensors all the time). Furthermore, the pilot referred to a turbulent flight conditions, so extremely hard propagation conditions are expected. The same algorithms used in the simulations were applied to the measurements. Some localization results are presented and commented in the next section.

5. Results and discussion

The results of the localization for a small part of the first simulated track and a single MC run are shown in Fig. 3. As can be seen, for low SNR conditions and sources in motion both WLS and RWLS are extremely noisy estimators of the position, as expected. However, the standard Kalman filter is able to minimize the estimation error by modeling the dynamics of the process and its estimation is in good agreement with the actual path of the target. It is easy to see that the error notably increases when the aircraft change 180 degrees the direction relatively fast and close to one of the sensors. Note that in this case the differential time delays and the observation interval of the network are not small relative to the inverse of the speed of the target, i.e. the source is

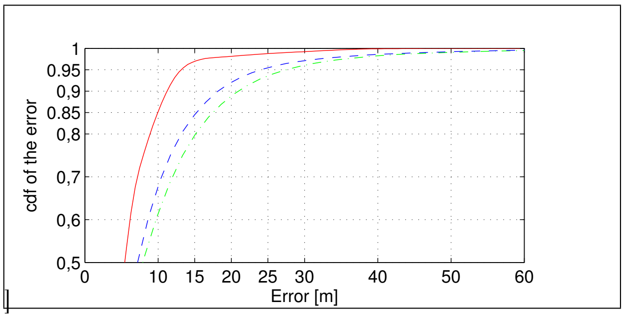

Figure 4. Cumulative Distribution Function of the RMSE. green dash-dotted line - WLS, blue dashed line- RWLS, red line - standard KF

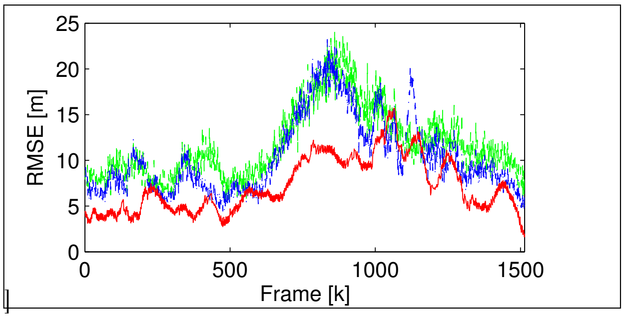

Figure 5. RMSE vs Time for the second track. green dash-dotted line - WLS, blue dashed line- RWLS, red line - standard KF

notably moving within the observation interval.

Fig. 4 shows the CDF of the RMSE averaged over all the MC runs, over the time and over the simulated tracks. As can be seen, the RWLS outperforms the WLS algorithm in mean, as expected. On the other hand, it is shown how much the estimation can be improved by modeling the motion of the source. The exact values are not important because they depend on the number of sensors, the geometry of the network, the propagation conditions and so on. However, it is shown that for any high percentage of the time (80%, 90%, 95%) the RMSE is considerably reduced under the simulation conditions. In order to know how the RMSE depends on the source position (on the time) the RMSE is averaged over the MC runs only. Thus an estimation of the RMSE for every source position is obtained. The results are shown in Fig. 5. It is worth it to mention that the error is higher when the speed of the target increases and it is close to one AMMS, because in this case the observation interval of the network is close to its maximum and it is not short enough relative to the inverse of the speed of the target.

The results of the localization for a small part track of one of the RC aircrafts are shown in Fig. 6. As can be seen, for this part all the approaches are giving as a result a reasonably good estimation of the flight track. It is seen that the RWLS algorithm outperforms the WLS algorithm, as expected in view of the results of the simulations.

The results of the localization for a small pice of the track of the other RC aircraft are presented in Fig. 7. It is easy to see that both algorithms fail in this case because the target is passing over one AMMS at more than 60 km/h and the observation interval reaches its maximum for the given network configuration (around 1 second). It causes the WLS algorithm estimation to be dominated by the farthest sensors whose azimuth estimates are more noisy due the SNR. It is seen that the RWLS algorithm notably improves the estimation of the position, but it does not seem an unbiased estimator of the actual 2D position of the aircraft when it is approaching the sensor. Because of that, the smoother is not estimating the path properly, but still it outperforms the noisy estimation of the path given by WLS and RWLS.

5.1. Some factors that can affect the detection and the localization range

Based on the measurements using the RC small aircrafts, a list of some of the factors that can affect the detection and the localization range using the algorithms tested during this investigation is presented in this section. As mentioned along the paper, the speed of the source relative to the observation interval of the network and the differential relative delays, beside the geometry of the network and the number sensors notably affect the localization range for a given network [9].

The detection range is affected by the directivity of the source and the attenuation of the sound traveling through the atmosphere from the source position to the sensors. In free field this attenuation is well defined by the quadratic law [1]. It can be a good approximation under some controlled measurement conditions or for relatively short ranges outdoors, but it is not for medium or large ranges. Due the fact that the propagation of the waves from flying aircrafts to ground sensors is not parallel to the ground and that the range may be large for realistic applications, better attenuation models can be used in practice, which take into account the lack of homogeneity of the medium. The most used one is the Excess of Attenuation Model [13] that accounts for several attenuation effects. The most important factors of that model regarding this investigation are:

- Atmospheric attenuation that depends on the frequency, temperature and humidity. It is measured in $dB/(100m)$.
- Weather conditions as the effects of the wind, temperature effects. Note that both kind of effects are frequency dependent.

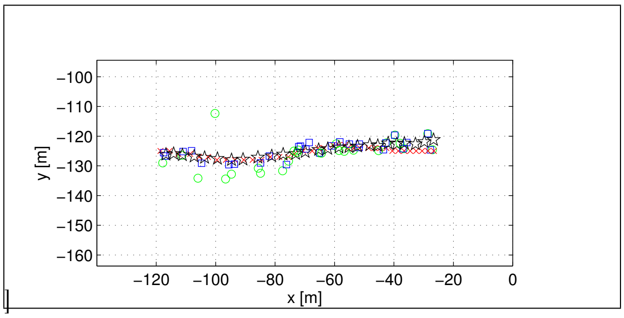

Figure 6. 2D Localization and tracking of a real flying aircraft. Red crosses - GPS 2D position of the source, green circles - WLS, blue squares - RWLS, black stars - direct KF

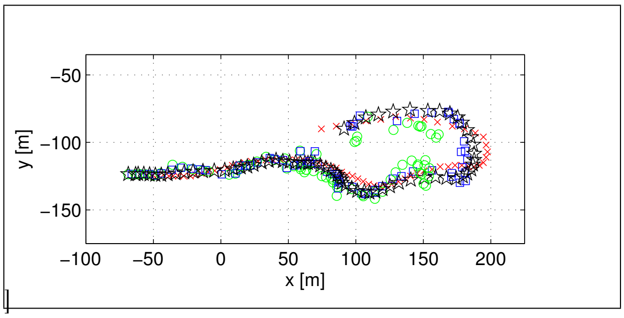

Figure 7. 2D Localization and tracking of a real flying aircraft. Red crosses - GPS 2D position of the source, green circles - WLS, blue squares - RWLS, black stars - direct KF

- Ground effects as reflections or absorption due the ground propagation. Both are related to the acoustic reflective properties of the ground, which also depend on the frequency.
- Atmospheric turbulence, caused by random fluctuations of the wind and the temperature, that randomly changes the amplitude and the phase of the sound.
- Vegetation and foliage close to the sensors provides a small amount of attenuation only if it is sufficiently dense.

Note that all the mentioned factors are frequency dependent. It makes difficult to predict the attenuation of sources in motion because all this effects are time varying and the frequency of the sound received at every sensor may be different.

6. Conclusions

A 2D version of the two algorithms proposed in [9] and described in section 3 for broadband source localization using acoustic vectors sensors have been presented and tested using realistic simulations of flying aircrafts and real measurements. It is shown that the RWLS algorithm clearly outperforms the WLS algorithm also for real measurements. A standard Kalman filter was applied to the estimates of the RWLS algorithm with the aim of modeling the motion of the source and smoothing the 2D flight path estimation. It has been proven that reasonably good results can be obtained by modeling the dynamics of the problem, mainly in low SNR conditions. Since both algorithms will not be able to track any kind of flying aircrafts, further related work should be oriented to derive and test algorithms that can track faster aircrafts. Another important issue to be investigated is the feasibility of a 3D localization using 2D acoustic vector sensors.

References

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

[2] D. Khaykin, B. Rafaely, Coherent signals direction-of-arrival estimation using a spherical microphone array: Frequency smoothing approach. *IEEE Workshop on Applications of Signal Processing to Audio and Acoustics WASPAA* pp. 221-224. 2009

[3] Dongwen Ying, Yonghong Yan, Robust and Fast Localization of Single Speech Source Using a Planar Array. *IEEE Signal Processing Letters* , 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] M. Brandstein, D. Ward, *Microphone arrays, Signal Processing Techniques and Applications.* (Eds.) Springer, 2001

[6] J. Wind, H. E. de Bree, Buye Xu, 3D Sound Source Localization and Sound Mapping using P-U Sensor Array, 1*6th AIAA/CEAS Aeroacustics Conference.* Stockholm 2010.

[7] Wen-Qian Jing, D. 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] M. Hawkes, A. Nehorai, Battlefield target localization using acoustic vector sensors and distributed processing. *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] Xionghu Zhong, A. Mohammadi, A. B. Premkumar, A. Asif, A distributed particle filter for acoustic source tracking using an acoustic vector sensor network. *IEEE International Conference on Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP)* , pp. 1-5 April 2014

[11] Haykin, S., *Adaptive Filter Theory* , 1996. Third Edition, Englewood Cliffs, NJ: Prentice-Hall.

[12] G. Welch and G. Bishop. An introduction to the Kalman filter. *Association for Computing Machinery (ACM) SIGGRAPH.* Course Notes, 2001.

[13] J. S. Lamancusa, Penn State. *Noise Control* . Chapter 10. Outdoor Sound Propagation. Course Notes, 2009.