Blind 3D Localization and Separation of Multiple Vibration and Acoustic Sources Simultaneously Active

Ruben Ruiz-Gonzalez, Jaime Gomez-Gil
Department of Signal Theory and Communications and Telematics Engineering
University of Valladolid
Valladolid 47011, Spain
rruigon@ribera.tel.uva.es; jgomez@tel.uva.es

Francisco Javier Gomez-Gil
Department of Electromechanical Engineering
University of Burgos
Burgos 09006, Spain
fjggil@ubu.es

Luis M. Navas-Gracia
Department of Agricultural and Forestry Engineering
University of Valladolid
Palencia 34004, Spain
lmnavas@iaf.uva.es

***Abstract*—Signal source localization and separation are key tasks for many applications. In this paper, a new deterministic method is proposed for estimating the 3D location and separating multiple acoustic or vibration sources, simultaneously active. The method is based on TDOA measurements obtained via cross-correlation. Then, with the information from the estimated locations, source separation is achieved. The performance of the method was evaluated, only through simulations, in terms of accuracy and computational load. The obtained results, with SNR=6dB, showed estimation errors for the localization method always bounded below 10 centimeters, obtaining the best results with a lower number of sources and a higher number of receivers. Furthermore, the computational load was substantially reduced as compared to exhaustive search, being the gain more noticeable for a higher number of sources. The corresponding error for the separation of the original source signals was bounded below 25%, for 2 sources and 6 receivers. Thus, there are strong evidences that the here-proposed method is accurate and robust enough, while being efficient in computational terms, so many applications can benefit from its use.**

***Keywords*—acoustics; blind source localization and separation; independent sources; single-path; Time Difference of Arrival (TDOA); vibration.**

I. INTRODUCTION

Source localization and separation of vibration and acoustic signals is widely recognized as a key task in many fields and applications [1-3]. One of those fields is predictive maintenance of agro-industrial equipment [4]. Being able to locate the source where vibrations are generated, altogether with source signal separation, can lead, in these cases, to more accurate fault identification and its prompt correction without needing further detailed inspections. Several methods have been deployed so far, using vibrations to identify the status of machinery components, but these methods still require quite a lot of prior knowledge and training in order to work accurately [5, 6]. Thus, source localization and separation techniques can be highly beneficial for this field, since they could limit, and even avoid, the need of a training stage, for each particular machine, before being able to operate. In this way, a higher independence is achieved and the techniques could readily work for any machine without needing further adjustments.

So far, many previous studies have tackled single source localization [1-3]. However, little progress has been made for locating multiple sources that are active at the same time [7]. In this paper, a new method for 3D location estimation and later separation of multiple vibration or acoustic sources is proposed (Section II). In addition to the proposal, its accuracy, robustness and computational load are assessed through simulations (Section III). To wrap up, some final remarks, conclusions and future lines are provided (Section IV).

II. PROPOSED METHOD

This section deals with the explanation of the proposed method for source location estimation and source separation.

A. Simplified Model: Assumptions

The underlying assumptions of the model, employed for signal generation and propagation, are that:

i. all the sources generate independent signals;
ii. there are no reflections, *i.e.* no multipath propagation;
iii. propagation is isotropic and at a known constant speed;
iv. the received signals are a superposition of the delayed-attenuated signals coming from each source;
v. additive Gaussian noise is added to each received signal.

B. Overview of the Simplified Model

Considering those assumptions, the employed model for the propagation of signals between sources and each receiver is exposed in this subsection. The scenario for the source localization and separation problem is illustrated in Fig. 1.

Assuming that there are N sources and M receivers (Fig. 1), let's denote each source signal as s_i, with $0 \leq i < N$, and each received signal as r_j, with $0 \leq j < M$. In this case, the received signals are, for all j such that $0 \leq j < M$, as shown in (1).

$$r_j(t) = \sum_{i=0}^{N-1} \frac{1}{\left\| \boldsymbol{x}_{s_i} - \boldsymbol{x}_{r_j} \right\|} s_i \left(t - \frac{\left\| \boldsymbol{x}_{s_i} - \boldsymbol{x}_{r_j} \right\|}{c} \right) + n_j(t) \qquad (1)$$

where $\boldsymbol{x}_{s_i}$ or $\boldsymbol{x}_{r_j}$ denote the spatial location of each source or receiver, respectively, c is the propagation speed of the signal, and n_j is the additive noise, superposed at each receiver, following a Gaussian distribution, *i.e.* $n_j \sim \boldsymbol{N}(\mu_j, \sigma_j)$.

Considering this model, the proposed method has three steps: (*i*) the calculation of the TDOA from all pairs of received signals; (*ii*) the calculation of the best location for each source based on the TDOA values computed in the previous step; and (*iii*) the solving of the source separation problem, considering as true locations the previously estimated ones.

C. Time Difference of Arrival (TDOA) Calculations

Based on all received signals r_j, with $0 \leq j < M$, the cross-correlation between all possible pairs is computed as in (2).

$$R_{i,j}(\tau) = r_i \star r_j, \forall\, i \in [0, M-2], j \in [i+1, M-1] \qquad (2)$$

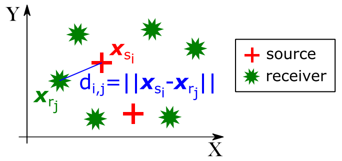

Fig. 1. Illustration of the 2D source localization and separation problem.

where the $\star$ operator denotes the cross-correlation function between r_i and r_j.

The N highest peaks in $R_{i,j}(\tau)$ are employed to estimate the TDOA for each source. From these TDOA, the equivalent distance difference can be calculated by multiplying the TDOA by c, the known propagation speed of the waves in the medium. Therefore, let's denote by $d_{i,j,k}$ the distance difference, corresponding to the kth peak, between receivers i and j. Negative $d_{i,j,k}$ distances mean that the distance from the source to the ith receiver is smaller than that to the jth receiver and *vice versa*. It is worth noticing here that, since one cannot distinguish which source the peak belongs to, exhaustive exploration should be used in the later steps to properly identify which source each particular peak belongs to. This uncertainty increases the required number of receivers in order to get a unique closed solution for the localization problem.

D. Sources Location Estimation

Assuming that the location for all the receivers ($\boldsymbol{x}_{r_j}$) is accurately known, one can try to solve the best locations for the unknown positions of the sources ($\boldsymbol{x}_{s_i}$). The estimation of the best location for all present sources is accomplished by searching for those locations that best fit, in a nonlinear least-squares sense, the system of nonlinear equations in (3).

$$\begin{cases} \vdots \\ \left\|\boldsymbol{x}_{s_k}-\boldsymbol{x}_{r_i}\right\| - \left\|\boldsymbol{x}_{s_k}-\boldsymbol{x}_{r_j}\right\| = d_{i,j,k}\,, & \begin{array}{l}\forall\, i \in [0, M-2],\\ j \in [i+1, M-1],\\ k \in [0, N-1]\end{array} \\ \vdots \end{cases} \tag{3}$$

The solutions for the system in (3) are the locations of all the sources, *i.e.* $\hat{\boldsymbol{x}}_{s_k}, \forall\, k \in [0, N-1]$. This solution can be straightforwardly found by using any of the widespread nonlinear techniques for solving it in a nonlinear least-squares sense, *e.g.* by employing the Levenberg–Marquardt algorithm.

1) Computational Load Reduction

Since there is no available way to distinguish the correspondence between the computed $d_{i,j,k}$ to each source, all possible permutations in k for the N values should be explored, *a priori*. However, it is worth noticing that not all the equations available in (3), $N \cdot \binom{M}{2}$, are required to completely determine a unique solution. These extra equations could, and should, be used for improving the robustness against noise.

So as to avoid the extra computing requirements the search for all permutations would lead to, the smallest subset of equations big enough to avoid uncertainties should be used. The remaining equations should be incorporated later, one by one, using the permutation of N estimated $d_{i,j,k}$, for this pair of receivers, that best fits the problem solved before.

Alternatively, even a fewer number of equations, less than the minimum required to fully determine a unique solution, can be used in the first step. In cases of ambiguity, if significant inconsistencies are detected later on, while adding the rest of the equations, other ordering can be used as initial hypothesis until the overall inconsistencies are minimized. By using this approach an even higher computational efficiency is reached, being more noticeable as the number of sources increases.

E. Source Separation

Once the locations have been estimated, and assuming the process was accurate enough, the original signals from each source can be recovered. The system of equations for the source signals, in the frequency domain, is as shown in (4).

$$\begin{cases} \vdots \\ \displaystyle\sum_{i=0}^{N-1} \frac{\exp\left(-j2\pi f \frac{\hat{d}_{i,k}}{c}\right)}{\hat{d}_{i,k}} S_i(f) = R_k(f), \forall k \in [0, M-1] \\ \vdots \end{cases} \tag{4}$$

where $\hat{d}_{i,k} = \left\|\hat{\boldsymbol{x}}_{s_i} - \boldsymbol{x}_{r_k}\right\|$ and, thus, the only unknowns are the N source signals, *i.e.* $S_i(f)$ for all $0 \le i < N$. The system is fully determined whenever there are at least N equations, *i.e.* if $M \ge N$. If extra equations are at hand, they are used to minimize the effects of the noise, by solving the system using the least-squares approach. Note that, in the transformation made from (1) into (4), the additive noise term was removed. Other more complete approaches can include the noise term in this stage and, thus, obtain a more statistically optimal estimate by characterizing the noise model and its parameters, instead of simply using a least-squares approach.

III. Evaluation through Simulations

In order to assess the performance of the proposed method, two kinds of evaluations were performed: (*i*) for the source localization problem, execution times and accuracy comparison as a function of the number of sources and receivers; and (*ii*) for the source separation problem, similarity of the estimated signals against the original ones. Each of these evaluations is explained in the subsequent subsections. In both cases, sources and receivers were randomly distributed along a 60m-side cube. All generated source signals were random, as well, with a unitary RMS value. Twenty repetitions were considered, for each case, so as to reduce the bias of the experiments and mean values are reported in this paper for the obtained results.

A. Execution Times and Accuracy for Source Localization

The source localization method was evaluated by executing it within the *MATLAB® R2015a* programming environment on a *Lenovo B560* laptop. The comparison, in terms of execution time (Table I) and accuracy (Table II), was made using a different number of sources and receivers. Great computational savings, reaching 99.99% for a high number of receivers, were obtained by avoiding brute-force exploration (Table I). The accuracy of the method was always bounded below 0.1 meters, as shown in Table II, with all standard deviations bounded below 0.03 meters. A sample graphical solution for 3 sources and 6 receivers is depicted in Fig. 2.

Table I. Execution Times for the Method (in Minutes) Varying the Number of Sources and Receivers (Needed Time Using Load Reduction Approach / Estimated Time Using Brute-Force).

		Number of receivers				
		4	**5**	**6**	**7**	**8**
Number of sources	**1**	~3·10⁻⁴ / ~3·10⁻⁴	~3·10⁻⁴ / ~3·10⁻⁴	~3·10⁻⁴ / ~3·10⁻⁴	~3·10⁻⁴ / ~3·10⁻⁴	~3·10⁻⁴ / ~3·10⁻⁴
	2	~0.09 / ~0.09	~0.09 / ~2.9	~0.10 / ~92.2	~0.11 / ~6·10³	~0.12 / ~7·10⁵
	3	~48.84 / ~48.84	~48.92 / ~6·10⁴	~49.07 / ~5·10⁸	~49.53 / ~2·10¹³	~50.78 / ~6·10¹⁸

TABLE II. MAXIMUM LOCATION ERROR (IN METERS) WITH SNR=6DB.

		Number of receivers				
		4	**5**	**6**	**7**	**8**
Number of sources	**1**	0.019	0.015	0.012	0.010	0.008
	2	0.029	0.019	0.014	0.013	0.012
	3	0.062	0.053	0.035	0.021	0.018

B. Similarity for Source Separation

For the case when $N = 2$ sources and $M = 6$ receivers, with an SNR of 6dB, the similarity between the estimated, $\hat{s}_i(t)$, and real, $s_i(t)$, source signals was calculated using (5).

$$S_{s_i,\hat{s}_i} = \sqrt{\frac{1}{T}\int_0^T (s_i(t) - \hat{s}_i(t))^2\, dt} \qquad (5)$$

Considering this, the average similarity obtained for the 20 trials was 0.2268±0.0453, *i.e.* always below 25% since source signals had a unitary RMS value. Notice that in (5), the greater the similarity among signals, the lower the value of $S_{s_i,\hat{s}_i}$. Sample original and estimated signals are depicted in Fig. 3.

IV. CONCLUSIONS

The results obtained in this preliminary study show the potential of the proposed method to accurately estimate the location and also to achieve the subsequent source separation. There are strong evidences that it is accurate and robust enough to noise interferences. Moreover, it is efficient in computational terms, since no exhaustive exploration of all the combinations is needed to estimate the best location.

From Table I, it can be seen that the computational load drastically increases as the number of sources grows, while slowly increasing as the number of receivers is incremented. From Table II, it can be observed that the accuracy of the method remains high enough irrespectively of the number of sources and receivers. Nevertheless, a higher immunity against noise is achieved as the number of receivers is increased. The location estimation also becomes a little bit less accurate when the number of sources is increased, as expected. From Fig. 3, it can be seen that a high accuracy for source separation is also achieved even with a relatively low SNR of 6dB.

Nevertheless, an important drawback is that the method still requires the number of active sources as prior knowledge to operate in a proper way. But this issue could be easily overcome by applying a threshold in cross-correlation to estimate the actual number of sources. The method also imposes certain assumptions that might not be valid in real environments, such as no reflections and the isotropic propagation. Therefore, future work should still tackle the extension of this method to other more realistic propagation models, *e.g.* with reflections and multi-path propagation. The evaluation of the method through experimental tests, apart from simulations, should be tackled as well, including the study of the influence of the SNR and the effects of having spread sources instead of idealized point sources. Moreover, it should also be investigated the mathematical determination of the minimum subset of equations that completely determines the solution of the problem posed in Section II.D, as a function depending on the number of sources and receivers.

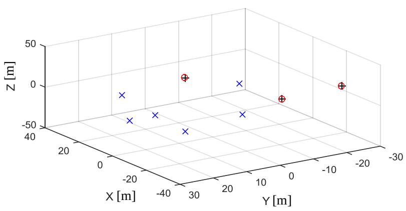

Fig. 2. Sample solution for the 3D source localization problem: 3 sources (real and estimated positions marked with red circles and black crosses, respectively) and 6 receivers (real positions marked with blue crosses).

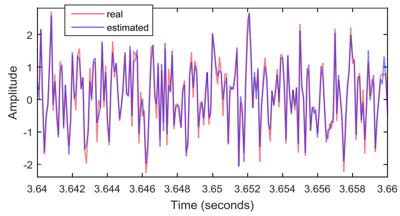

Fig. 3. One separated signal (blue) and the corresponding original one (red), for SNR=6 dB, M=6 receivers, and N=2 sources.

To wrap up, it is worth highlighting that the proposed method could be extended to other more complex geometries where no direct line of sight propagation exists, also having extra caution with several propagation paths causing echoes, such as in the case of typical machinery chassis. The authors are currently working on this last line and its validation with an agricultural harvester.

ACKNOWLEDGMENT

The first author’s work in this study was made possible thanks to a “*Formación de Personal Investigador*” doctoral program grant, financed by the *Universidad de Valladolid* (Spain) and co-financed by *Banco Santander*.

REFERENCES

[1] T. Kundu, “Acoustic source localization,” *Ultrasonics*, vol. 54, pp. 25–38, Jun. 2013.

[2] A. Nehorai and E. Paldi, “Vector-sensor array processing for electromagnetic source localization,” *IEEE Transactions on Signal Processing*, vol. 42, no. 2, pp. 376–398, Feb. 1994.

[3] C. Polprasert, P. Pongpaibool, P. Kukieattikuool, C. Vorakulpipat, and S. Siwamogsatham, “Sensor networks for acoustic source localization using acoustic fingerprint in urban environments and construction sites,” in *Proceedings of the 28th International Symposium on Automation and Robotics in Construction: ISARC 2011*, July 2011, Seoul, South Korea. pp. 581–586.

[4] C. Scheffer and P. Girdhar, Practical machinery vibration analysis and predictive maintenance, 1st ed. Newnes: Oxford, UK, 2004.

[5] S. Orhan, N. Aktürk, and V. Celik, “Vibration monitoring for defect diagnosis of rolling element bearings as a predictive maintenance tool: Comprehensive case studies,” *NDT & E International*, vol. 39, no. 4, pp. 293–298, Jun. 2006.

[6] R. Ruiz-Gonzalez, J. Gomez-Gil, F. J. Gomez-Gil, and V. Martínez-Martínez, “An SVM-based classifier for estimating the state of various rotating components in agro-industrial machinery with a vibration signal acquired from a single point on the machine chassis,” *Sensors*, vol. 14, no. 11, pp. 20713–20735, Nov. 2014.

[7] T. Kosel, I. Grabec, and F. Kosel, “Intelligent location of two simultaneously active acoustic emission sources,” *Aerospace Science and Technology*, vol. 9, no. 1, pp. 45–53, Jan. 2005.