Distributed Array of Cooperating Acoustic Sensors using Local Time-Frequency Coherence Analysis

Cornel Ioana, Ion Candel, Angela Digulescu-Popescu
University of Grenoble-Alpes, GIPSA-lab
Saint Martin D'Heres, France
E-mail: [cornel.ioana, ion.candel, angela.digulescu]@gipsa-lab.grenoble-inp.fr

Abstract—**The distributed array of sensors is an interesting concept in the context of underwater environment monitoring. The signal processing distributed at sensors level has to have a low consumption (much less than the data transmission) and, in the same time, the processing efficiency needs to be satisfactory compared with a processing without any algorithmic complexity constraint.**

In this paper, we define a network of sensors which individually detect signals of interest based on the concept local time-frequency coherence analysis. This concept consists of estimating, in each analysis window, the local linear frequency modulation that matches the best the analyzed signal. This concept is much less sensitive to the time-varying energy of the signals, providing better detection performances than an energy-based detector. In addition, the sensors are organized in local sub-networks that will provide a joint detection stage. This operation consists in comparing the local time-frequency information obtained by the sensors of the sub-network and if they are the same, at the sub-network level, we decide that the detected signal is a useful one and its parameters has to be sent to the central processing level. This cooperating capability improves the performances as it is proved by the results on real data and quantified in terms of receiving operating characteristics.

Keywords— distributed sensors, time-frequency analysis, detection, localization

I. INTRODUCTION

The distributed sensing array are currently of great importance in the monitoring of underwater environments. In this context, different interesting concepts are proposed to implement the distributed network in underwater application [1], [2]. In order to proceed to the distributed signal processing, the sensors include some embedded algorithms that allow detecting the presence of *interesting* signals, mostly based on an energy criterion applied in short analysis windows – *spectrogram-based detectors.* Indeed, the automatic choice of the detection threshold is very important because of its influence on the probability of detection and on the false alarm ratio. In order to increase the efficiency of a distributed processing, we introduced in [3] an alternative to the time-frequency energy based techniques. The idea is to locally model the signal's time-frequency content as a linear frequency modulation (LFM). In addition to this single-sensor detection level, we organize the sensors in sub-networks, formed by the sensors located at the same node. The detection is then done by the group of sensors analyzing the coherence of the signal's time-frequency contents. As we will show on real data, this cooperation between sensors will conduct to an increasing of sensors autonomy and, in the same time, to a reduce level of the false alarm ratio.

The paper is organized as follows. The section 2 recalls the principle of non-stationary signal analysis in distributed context, based on the concept of time-frequency-phase analysis. In the section 3 the concept of cooperating sensors is defined and the results will be presented in section 4. Finally, the concluding remarks and some considerations on further works are presented in the section 5.

II. NON-STATIONARY SIGNAL ANALYSIS IN DISTRIBUTED CONTEXT

In order to increase the robustness of the detection at the sensor-level, the non-stationary signal analysis technique employed is time-frequency-phase method. Rather than relying on an energetic criterion, as it is the case of the spectrogram method, the method used a phase-coherence one [3], [6]. For each analysis window of received signal *s*, *W*, we first look for the local linear frequency modulations (LFMs) that best fit the signal's local time-frequency behavior. For this purpose, the ambiguity function (*AF*) is used:

$$AF_s(\tau, f) = \int s(t)s^*(t-\tau)e^{-j2\pi \cdot ft}dt \qquad (1)$$

where τ is the lag used for the *AF* computation. The chirp rate of the LFM that approximates the signal *x* is computed as:

$$c_2 = \frac{1}{2\tau}\arg\max_f \left|AF_s\ (\tau, f)\right| \qquad (2)$$

Once this parameter estimated, the demodulation operation:

$$s(t)\cdot e^{-j2\pi \cdot c_2 t^2} \qquad (3)$$

leads to a sinusoidal signal whose frequency - the central frequency of the LFM that locally fits the best the signal's time-frequency shape - can be estimated from the Fourier transform of (3).

978-0-933957-43-5 ©2015 MTS

The interest for LFM signal types is related to the fact that any arbitrary time-frequency component can be linearly approximated with linear frequency modulations that can have particular orientation (chirp rate) and center in frequency (central frequency). The local piecewise linear approximation is more flexible than the approximation with local sinusoids, thanks to the chirp rate that help to orient the LFM according to the approximated part of the time-frequency structure.

Applying this method in the analysis windows half overlapped so, for k^{th} and $(k+1)^{th}$ analyzed windows, the received signal is modeled locally as:

$$x_k(t) \approx \exp j\left(c_{1,k}t + c_{2,k}t^2\right); t \in \left[k \cdot W, (k+1) \cdot W\right] ;$$
$$x_{k+1}(t) \approx \exp j\left(c_{1,k+1}t + c_{2,k+1}t^2\right); t \in \left[(k+1) \cdot W/2, (k+3) \cdot W/2\right] \tag{4}$$

The detection method consists now, instead to compare the time-frequency information with an energetic threshold, as in the case of the spectrogram-based technique, in studying if the local LFMs x_k and x_{k+1} are in the same time-frequency region or not. More precisely, we consider that the modeled LFM (4) corresponds to a useful signal if they are in the same time-frequency region. If not, the LFMs correspond to noise and there is no transmission. Mathematically, the detection based on the local time-frequency coherence is defined as:

$$\begin{aligned} &if\ d\left\{\left(c_{1,k}, c_{2,k}\right), \left(c_{1,k+1}, c_{2,k+1}\right)\right\} \le \beta \Rightarrow \left(c_{1k}, c_{2k}\right) - sent \\ &Else - not\ sent \end{aligned} \tag{5}$$

where d is the Euclidian distance between the set of two coefficients estimated in two adjacent time windows. The detection is called when the distance between both coefficients sets are inferior to a threshold β.

Irrespective of the processing method used, a sensor level *local detection* is done. Each sensor transmits to the central processing unit, for each time analysis slot, two parameters that replace the set of signal samples corresponding to the time slot. This compression allows a significant bandwidth reduction as well as the power consumption reduction required for the data transmission.

Once an event detected, at the central processing level, we compute the cross-correlation functions $\{R_{mn}(\tau)\}_{m,n=1..N_s-1}$ (N_s is the number of network sensors) between the synthesized instantaneous frequency law (IFL). The time coordinates corresponding to the maxima of these cross-correlation functions are the estimations of time difference of arrival (*TDOA*) between each pair of sensors:

$$TDOA_{mn} = \arg\max_{\tau} \left|R_{mn}(\tau)\right| \tag{6}$$

Having computed these values, it is possible *to localize* the acoustic source and, computing the dynamic variation of these parameters, *track the source's trajectory*. The localization is achieved by using a Maximum Likelihood Estimator (MLE) of the Minimum Least Square Error, as it is defined in [5]. For a single position of the source, its coordinates (x_s, y_s) can be obtained by solving the optimization problem defined by :

$$\left(\hat{x}_s, \hat{y}_s\right) = \arg\min_{(x_s, y_s)} \sum_{m,n} \left[TDOA_{mn} - \frac{1}{c^2}\left(D^{\alpha}_{s,m} - D^{\alpha}_{s,n}\right)\right]^2 \tag{7}$$

where

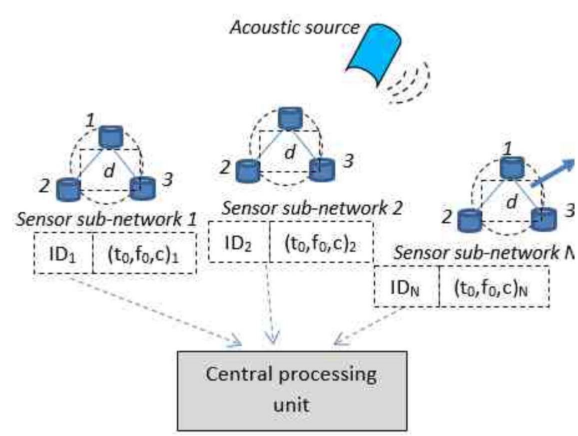
$$TDOA_{mn} = \frac{1}{c}\left(\underbrace{\sqrt{\left(x_s - x_m\right)^2 + \left(y_s - y_m\right)^2}}_{D_{s,m}} - \underbrace{\sqrt{\left(x_s - x_n\right)^2 + \left(y_s - y_n\right)^2}}_{D_{s,n}}\right) \tag{8}$$

where c is the sound velocity in water and $D_{s,m}$ and $\underline{D_{s,n}}$ are the distances between the source and the sensor m and n, respectively, and (x_m, y_m) and (x_n, y_n) are the coordinates of the sensor m and n, and $D^{\alpha}_{s,m}$, $D^{\alpha}_{s,n}$ are the respective distances to the possible positions of the source.

This optimization problem can be solved by searching, in a given domain, the coordinates of the sources that will conduct to a minimum distance error.

III. DISTRIBUTED SIGNAL ANALYSIS IN THE CONTEXT OF COOPERATING SENSORS

The general overview of the distributed array of cooperating sensors is presented in the figure 1. The array is composed by N sub-networks, each of them composed by three sensors wire-connected and disposed at equal distance d. The signals received continuously by the sensors are analyzed in the time windows and the linear frequency modulations that match the local signals are obtained, as presented in the previous section. The parameters of a LFM detected at one of the sensors of the sub-network, f_0 - central frequency and c – chirp rate, are sent to the other sensors of the sub-network. Each sensor compares, in a ***matching search window***, the similarity between the received LFM's parameters and the own estimated ones. The principle here is to consider that if one coherent signal has been firstly received by the closest sensor to the source, **an *almost* similar** LFM component will be received later by the other sensors of the sub-network. The maximum delay, that defines the size of search window, is d/v where d is the distance between sensors and v is the sound velocity – see the figure 1, where a useful signal is represented, as a time-frequency component (solid curve) at different time of arrival, according to the range source-sensors.



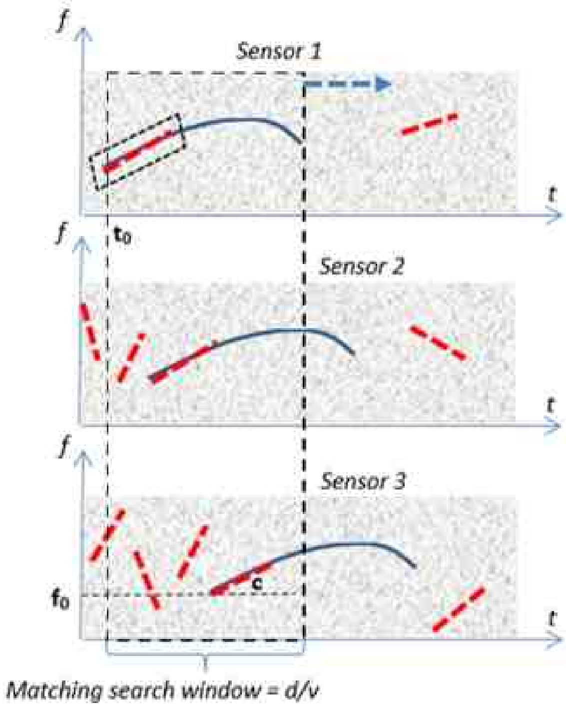


Figure 1. Distributed array of cooperating sensors and illustration of processing at sub-network level.

The first LFM will define a time-frequency mask that will serve to identify the close LFMs in the matching searching windows defined for the other sensors. If the same structure is detected by the three sensors (the dashed line matching the first part of the solid curve), we decide to send the corresponding parameters (t_0 – the first time of arrival, f_0 and c) to the central processing level (with the identifier *ID*). If there is no similarity between the components (dashed lines appearing after the component in figure 1), there is no any detection.

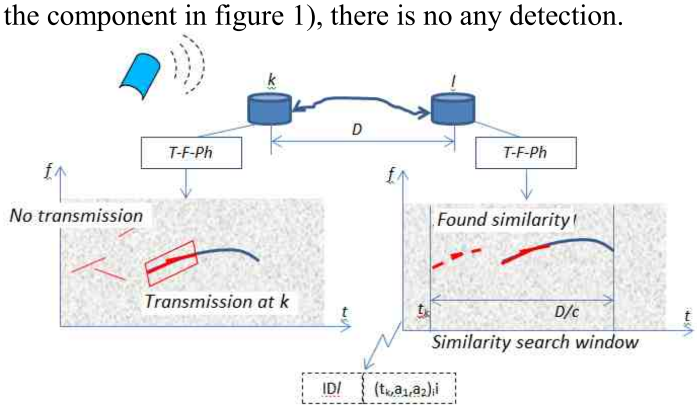


Figure 2. Configuration of two cooperating sensors that use the time-frequency coherence to detect jointly the presence of a source

The principle of this configuration, in the case of two sensors *k* and *l*, is illustrated in the figure 2:

1. The two sensors run the time-frequency-phase(T-F-Ph) algorithm described in the section 2; as long as there is no a coherent emission, the phase continuity yields theoretically nothing.
2. Once a coherent emission took place, it will reach first sensor *k* for example. The T-F-Ph algorithm applied on successive windows will detect a coherence and will send, using a wired connection, the polynomial coefficients to the sensor *l*.
3. Having received these coefficients, the T-F-Ph algorithm embedded in sensor *l* searches for linear frequency modulations similar to the ones detected by sensor *k* in the time window d/v (d – distance between the sensors, v – the sound velocity in water) that correspond to the relative propagation delay between the two sensors. If this similarity is found, sensor *l* sends to the central processing unit the correspondent coefficients, as well as the receiving time of the first coefficients, t_k, from sensor *k*.
4. If no similarity is found in the search window, no coefficient will be sent, a false alarm will be associated to the detection occurred at sensor *k*.

The main advantages of this cooperating sensors network are related to the high probability of detection and a reduced level of the false alarm ratio. These operational advantages, that will be shown in the next section, are completed by a reduced power consumption while the transmissions will be done only by one sensor of the sub-network.

IV. Results

In this section, we prove the performances of the distributed sensing using cooperating sensors, first, in terms of detection capabilities.

The next figure gives an overview of the interest of the proposed technique that provides a ROC close to the matching filter that is the current method used in active context. This method cannot be imagined in passive configurations since the reference of the transmitted signal is not available.

In a passive and distributed context, the cooperating sensors leads to very good detection results, much better than the case of independent sensors, performing the local time-frequency coherence [6] ("Individual sensors") and the spectrogram [4], respectively. These results have been obtained for real data, obtained in our reduced scale experimental capabilities, characterized by a SNR bellow 0. In terms of autonomy, we measured that the cooperation between sensors increases by a factor of 3 the power consumption autonomy, compared with the method proposed in [6]. This is explained by the decreasing of the information quantity to be sent while the false alarms are drastically reduced thanks to the cooperation between sensors.

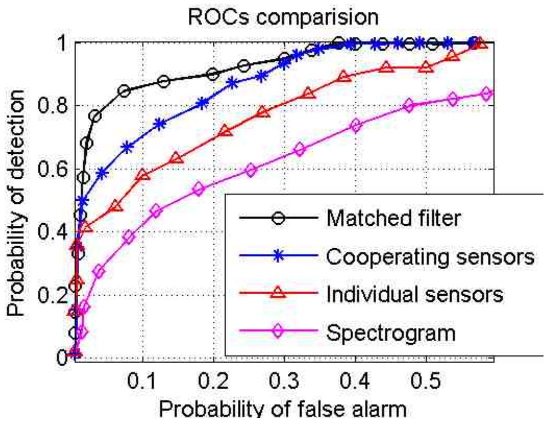


Figure 3. Comparative results in terms of ROC.

The next example concerns the results in terms of localization, considering an acoustic source transmitting a sinusoidal frequency modulation: The experimental trials have been organized using the reduced-scale thank facility existing with GIPSA-lab in Grenoble. The figure 4 shows this experimental facility and the organization of distributed sensing network.

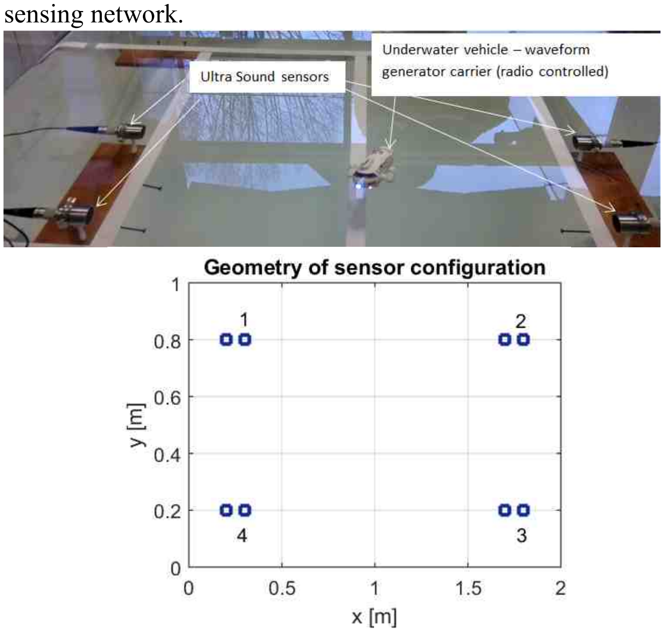


Figure 4. Illustration of GIPSA-lab's experimental setup, composed by eight ultrasound sensors at 1 MHz, organized in four sub-networks

The water thank is of 2×1×1 meters size and the sensors of 1 MHz are placed as shown in figure 4. The four pairs of sensors placed at 10 cm each other form the four sub-network of the distributed sensing configuration. The acoustic source has been moved according to different trajectories, one of them being illustrated in figure 5. The comparison in terms of source trajectory estimation is made between the real trajectory, the ones estimated using matched filtering, spectrogram-based method and time–phase–frequency method with sensor cooperation (T-F-Ph).

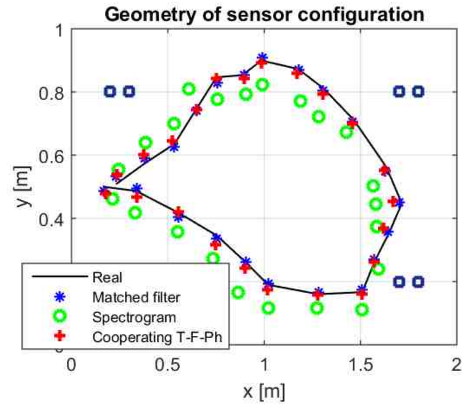


Figure 5. Source tracking/localization results

The tracking results show that the system has good performance: localization errors, with respect of matched filter, are situated around 5.8 % for the spectrogram based detection. For the time-phase-frequency method, thanks to the both time-frequency-phase technique and sensor cooperation, the errors are situated around 1.2 %.

V. CONCLUDING REMARKS AND PERSPECTIVES

In this paper, we addressed the problem of the underwater distributed sensing using local coherence analysis and the cooperation between local sensors. The idea is to proceed to the detection at local level, by comparing the time-frequency-phase information provided by sensors that are part of the same sub-network. A detection is decided if the same component are present in the time-frequency-phase domains of all sensors of the sub-network. As shown by the results, these cooperation between sensors improves considerably the detection performances in terms of ROCs. Also, the localization is much more accurate as we shown for real dataset.

In our further works, we will concentrate on the dynamic definition of the local sub-network, helping us to improve the trajectory estimation, especially in the case of multi sources.

REFERENCES.

[1] H. Qi, S. Iyengar and K. Chakrabarty (2001, Sept.). Distributed sensor networks–a review of recent research. *Journal of the Franklin Institute 338(6)*, pp. 655—668.

[2] I. Akyildiz, D. Pompili, T Melodia (2005, Jan.). Underwater acoustic sensor networks: research challenges. *Ad hoc networks*, *3(3)*, pp. 257—279.

[3] C. Ioana; J.I. Mars, A. Serbanescu and S. Stankovic, "Time – Frequency – Phase Tracking Approach: Application to Underwater Signals in a Passive Context", in *Proc. of ICASSP Dallas*, USA, 2010, pp. 5634-5637.

[4] T. A. Lampert, S. E. M. O'Keefe (2010, Feb.). A Survey of Spectrogram Track Detection Algorithms. *Journal of Applied Acoustics 71(2)*, pp 87-100.

[5] F. Gustafsson, F. Gunnarson, "Positioning using time-difference of arrival measurements" in *Proc. of ICASSP Hong Kong*, China, 2003, vol. VI, pp. 553-556.

[6] Dadouchi, F.; Ioana C.; Gervaise C.; Mars J. I.; Mauuary D.; Mallet J.; Philippe O.; Jespers S. "Distributed network of underwater acoustic sensors based on local time-frequency coherence analysis", *IEEE OCEANS 2013*, San Diego, CA, USA, 2013.