ON THE DISTRIBUTED ACOUSTIC SENSING BASED ON LOCAL TIME-FREQUENCY COHERENCE ANALYSIS

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ABSTRACT

This paper outlines novel approaches to design a new generation of distributed networks of acoustic sensors. The key-concept is marked by the use of time-frequency signal analysis tools directly embedded at the sensor node. The general framework for analysis at the acoustic sensor level is based on spectrogram which is very simple and easy to implement. The choice of the detection threshold in time-frequency domain is always a difficult task, even more complicated in the embedded computing configurations where eventual threshold adaptive selection algorithms might not have the required complexity. That is, the performances in terms of probability of detection classification and localization accuracy are generally strongly depending of the operational conditions. As such, this paper proposes a novel approach of local signal processing based on phase coherence criterion, designed to track the time-frequency multi-components and which is implemented in a distributed network with a minimum number of acoustic sensors.

Index Terms**—** distributed signal processing; time-frequency analysis; acoustic source localization.

1. INTRODUCTION

The conventional acoustic sensing arrays are generally composed of recording sensors and a real-time or offline data processing center. Here, operations such as detection and localization of the acoustic sources are made. The sensors generally include some simple detection algorithms based on the maximum signal power over a local window criterion. In the case when an event is detected, the sensor enables the execution of the next processing stages: storage of data and parameter extraction, transmission, etc. [1], [2]

While the signals transmitted by acoustic sources are generally non-stationary (for instance, acoustic signals generated by animals, underwater or aerial, sonar signals, etc.), the time-varying spectral analysis constitutes the major well-known technique to process them [3].

However, when computing a spectrogram (the most common time-frequency analysis tool), a time-frequency energy threshold must be set in order to detect the useful parts of the signals (in the time-frequency plane) that will be sent to the data processing center [7]. Despite the diversity of the interesting approaches of tracking using the spectrogram, the embedding of such approaches at a sensor level is always subjected to simplifications that reduce the required efficiency of the algorithms. Consequently, the signal processing at the sensor level is characterized by reduced performance, in terms of probability of detection vs. false alarm rate, with respect of the same algorithms that are not subject to embedding constraints.

This paper aims to introduce an alternative method for extracting the time-frequency parameters using the local phase information. The difference with respect of spectrogram-based processing is the use of the local phase coherence that decides if a time-frequency region of the observed data corresponds to the noise or to a signal of interest [4], [5]. That is, we replace the maximum power over a local window to decide if we detect the signal or not with a new time-frequency method which tracks the instantaneous phase of the local content of the signal provided by the High Order Ambiguity Function (HAF).

The tests performed for real data show the efficiency of this approach, with respect of the spectrogram-based approaches. From the implementing point of view, the proposed method has an attractive low complexity that makes it comparable with the existing embedded algorithms.

The paper is organized as follows. Some general aspects about the use of the time-frequency analysis in the context of the detection in distributed sensing array are discussed in the Section 2. Here, the proposed local phase-based tracking algorithm is compared to the generally used energetic-based tracking algorithm. In Section 3, the general features of the proposed distributed sensing array are presented and the global detection approach is described. Finally, the results obtained in some experimental underwater tests are presented in the Section 4. The Section 5 concludes with the theoretical and practical arguments for future developments.

2. TIME-FREQUENCY ANALYSIS IN DISTRIBUTED SENSING

2.1. The spectrogram method

In the context of distributed sensing of non-stationary signals, the time-frequency analysis offers the natural tool to deal with them. The most used methods are based on the spectrogram and the signal's detection and parameter extractions are done by thresholding the time-frequency energy.

From a mathematic point of view, for each analyzing window W_i, time-frequency coordinates belonging to the useful parts of the signals, or "tokens", are sent to the center of data processing (1).

$$(t_k, f_k) = \arg\max\{S(t,f) \,|\, S(t,f) \ge \alpha\} \Rightarrow (t_k, f_k)\ sent \quad (1)$$

where $S(t,f)$ is the spectrogram of the signal, defined as

$$S(t,f) = \left|\sum_{n=0}^{N-1} h(n)x(t+n-ol)e^{-2\pi jfn}\right|^2 \quad (2)$$

where x is the analyzed signal, h is the analysis window of size Wi, ol is the overlapping ratio and N is the number of FFT points. The choice of the constant time-frequency energy threshold α is very sensible to the nonlinear nature of the frequency estimation for sufficiently low signal-to-noise ratio (SNR) signals.

2.2. The high order ambiguity function based method

In order to reduce the sensitivity of the energy thresholding in the detection of the useful parts of the signal, we define the phase-coherence criterion for analyzing the time-frequency signature of an acoustic source is. This approach consists of estimating the polynomial phase form of a signal by applying the HAF algorithm over the local window of analysis. The mathematical modeling of a polynomial-phase signal (PPS) of the order 2 into a Linear Frequency Model (LFM) representation is described below.

For each window W_k of the signal $s(t)$, the local LFMs that fit the best the local signal's time-frequency behavior are estimated. For this purpose, the ambiguity function (AF) given by formula (3) is used.

$$AF_k(\tau; f_d) = \left|\int_{-\infty}^{\infty} s(t)\cdot s^*(t+\tau)\cdot e^{j2\pi f_d t}\,dt\right| \quad (3)$$

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

$$c_2 = \frac{1}{2\tau}\arg\max_f \left|AF_k(\tau, f)\right| \quad (4)$$

Once the chirp rate of the LFM is estimated, the demodulation operation will yield to a tone-like signal whose frequency (the central frequency of the LFM that locally models the signal) can be directly estimated by applying the Fourier transform.

This procedure of local window analysis is applied for the LFM in each local window, so, for the k^{th} analyzed windows W, the received signals in two overlapped windows are modeled locally as:

$$\begin{aligned} x_k(t) &\approx e^{j(c_{1,k}t + c_{2,k}t^2)}, t \in [W_k/2, W_{k+1}/2]\ ; \\ x_{k+1}(t) &\approx e^{j(c_{1,k+1}t + c_{2,k+1}t^2)}, t \in [W_{k+1}/2, W_{k+2}/2] \end{aligned} \quad (5)$$

Therefore, in order to be a useful signal, the two modeled LFM in (5) must be localized in the same time-frequency region on the signal spectrogram. This is the condition to transmit the corresponding LFM parameters to the center-level processing. If this similarity is not respected, the LFMs are considered to fit noisy parts of the acquired signal, so there will be no transmission further on. Mathematically, the detection based on the local time-frequency coherence is defined as:

$$\left\|(c_{1,k}, c_{2,k}), (c_{1,k+1}, c_{2,k+1})\right\| \le \beta \Rightarrow (c_{1,k}, c_{2,k})\ sent \quad (6)$$

The relation (6) is translated by the fact that the detection successfully takes place if the Euclidian distance between the set of two coefficients estimated in two adjacent time windows is inferior to a threshold β.

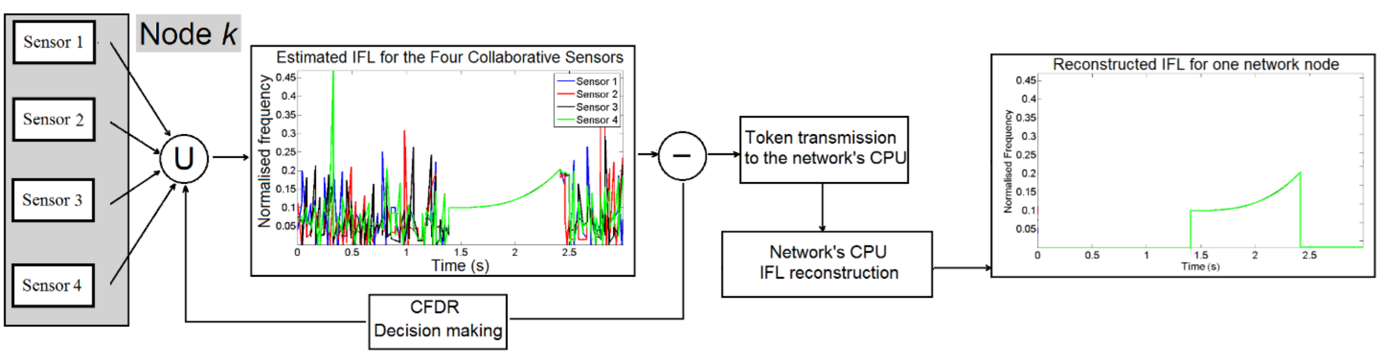

Fig. 1. Flowchart of the local detection by one network node composed by 4 sensors.

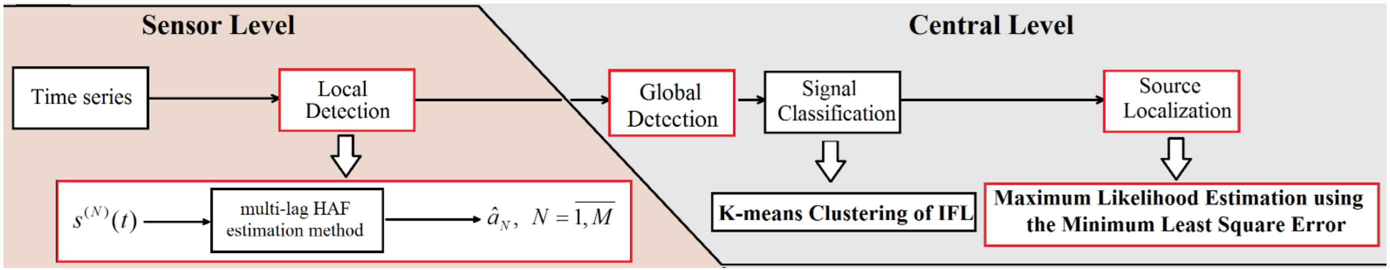

Fig. 2. Flowchart of the signal processing stages during one single cycle of the distributed network of acoustic sensors. The stages desribed in this paper are emphasized within the red color boxes.

3. OVERVIEW OF THE DISTRIBUTED NETWORK

3.1. Local distributed signal processing

As the "operational part" of the network, the sensors cover the area of interest, according to the operational purposes – detection, localization and tracking of the sources. The key element of each sensor is the embedded processing algorithm that allows the detection of a signal of interest and the extraction of the parameters describing the signal in an analysis window W.

The approach of using the time-frequency coherence-based method, already described in the Section 2.2, is to divide the signal in N windows and look over each local window for the local LFMs that fit the best the local signal's time-frequency behavior. The pair value (*coefficient*, *time*) which models the LFM is then grouped into the token of the k^{th} window. The condition that a "token" (7) is transmitted to the center of data processing is based on local coherence of the signals from two overlapped windows.

$$Tok = \left[c_{1k}\ c_{2k}\right] \tag{7}$$

Therefore, one can observe that the detection method consists of, instead using an energetic threshold as in the case of the spectrogram-based technique, but studying if the local LFMs x_k and x_{k+1} are in the same time-frequency region or not.

3.2. Global distributed signal processing

The functionalities of the sensing array are distributed between sensors and the center of the data processing. The key features of the applied signal processing in the design of the distributed network are synthetized in the flowchart of the Fig. 2. The center of data processing collects the tokens from which it reconstructs the instantaneous frequency law for each sensor, in a single local window W, as it is indicated in the formula (8).

$$IFL_m(t) = e^{c_{2,k} \cdot t^2 + c_{2,k} \cdot t},\ \ t \in \left[W_k, W_{k+1}\right] \tag{8}$$

After that, the IFL of each local window are merged in order to get a global IFL and to be used in the global detection part. Using the *IFLs* of all combinations of two sensors, the cross-correlations of IFLs are computed (9).

$$R_{mn}(\tau) = \langle IFL_m(t), IFL_n(t)\rangle = \int IFL_m(t) IFL_n(t-\tau)dt \tag{9}$$

where $\{m,n = 1 \ldots N_{sensors},\ m \neq n\}$. The global detection uses both the amplitude and the duration of the correlation between IFL_n and IFL_m of the sensors n and, respectively, m. Thus, the first test of global detection uses a trust index for detection formulated in (10).

$$N_{gd} \geq \gamma \cdot M \tag{10}$$

where $M = \{R_{mn}\}$ is the maximum of cross-correlation amplitude in a local window, N_{gd} is the number of good detections and γ is a threshold set to 0.8 during the tests.

The second test of global detection makes use of the duration of the $R_{mn}(\tau)$, as shown in the formula of (11).

$$R(\Theta) \geq \beta \cdot M \tag{11}$$

where

$$\Theta = \left[t_0 - \frac{D_{est}}{2}, t_0 + \frac{D_{est}}{2}\right],\ t_0 = \arg\max_{\tau} R_{mn}(\tau).$$

In the formula (11), the threshold is set to 0.5 during the tests. Therefore, if the conditions (10)-(11) are successfully achieved, then an event is globally detected and recognized by center of data processing and so it continues its computations for the localization and classification parts.

3.3. Acoustic localization

The cross-correlation between the every possible pair of sensors is computed is used to compute time delay of arrival (TDOA) as it is given by the formula (12). Therefore, three TDOA are obtained which it is enough to estimate a bi-dimensional spatial localization of acoustic source.

$$TDOA_{mn} = \arg\max_{\tau} \left|R_{mn}(\tau)\right| \tag{12}$$

where $TDOA_{mn}$ is the time delay of arrival between the m^{th} and the n^{th} sensor.

Then, the localization algorithm is implemented by simply applying a Maximum Likelihood Estimator (MLE) for the Minimum Least Square Error problem, as in [6].

4. EXPERIMENTAL VALIDATION

In order to study the operational interest of the proposed method, multiple experiments were conducted in sea trials. The underwater experiments were conducted on a distributed network contains three nodes, each of them with four vertically positioned sensors (hydrophones), and one PC acting as a center of data processing and data collector (CP).

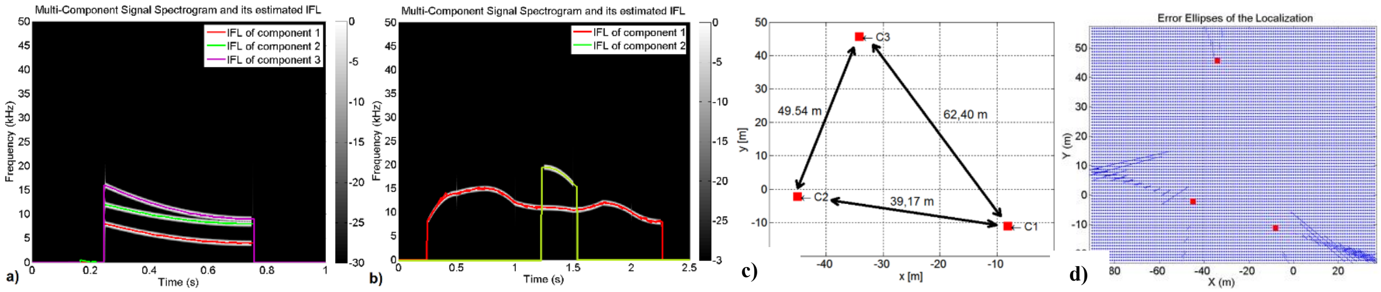

Fig. 3a-c. The signals used during the tests IV and the instantaneous frequency laws estimated with the time-frequency-phase approach: The signal during the tests: **a.** a 3-component signal and **b.** a longer 2-component signal; **c.** The positions of sensors; **d.** The error ellipses based on the Cramer-Rao bound of the ML estimator of the localization algorithm used in the experiments.

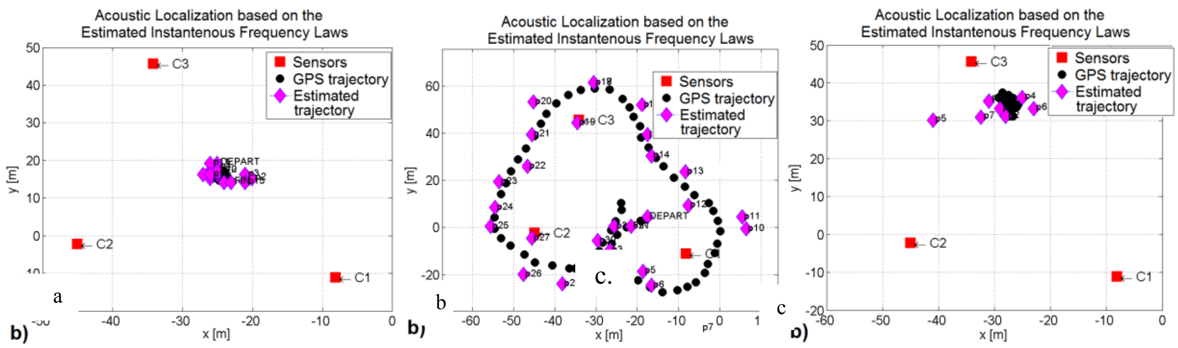

Fig. 4. Localization results during the emission of the waveform pictured in the *figure 9a-c*, for three types of trajectories: **a.** The source is static and emits 3-compoenents frequency modulated signals (dolphins' signals); **b.** The source took a tour of the sensor's perimeter static and emits 3-compoenents frequency modulated signals; **c.** The source is static and emits 2-compoenents frequency modulated signals (mammals' signals);

Acoustic emissions were made from a boat describing multiple trajectories in the perimeter of the sensors. Each hydrophone was equipped with pre-amplifying blocks with 40 dB the gain and DSP acquiring data with a sampling frequency of 100 kHz. Frequencies between 1.3 kHz and 48.8 kHz were selected using a band pass filter.

The spectrograms of the signal classes emitted during experiments are shown in the Fig. 3a-b and they represent:

- a 3-components quadratic frequency modulation (Fig. 3a), in the bands 16-10 kHz, 12-8 kHz and 8-4 kHz;

- a 2-component signal simulating a cetacean vocalization plus one more frequency-shifted reflection, in the bands 16-8 kHz and 16-20 kHz, (Fig. 3b).

The HAF algorithm uses 10 lags and it is designed to track a single time-frequency component by searching the best linear frequency modulations approximation within the local overlapping region.

The GPS trajectory positions described by the moving source are used to compute the averaged relative errors, presented in the Table I. The estimated trajectories by using the TDOA algorithm for localization are illustrated in the figures 4a-c. A higher error precision of localization, compared to the results of the matched filter, is observed for the local-phase coherence, algorithm explained mainly by the lack of informations about the signal's source.

TABLE I SOURCE LOCALIZATION AVERAGE PERFORMANCE [%]

Configuration	Time-Frequency-Phase method	Matched Filtering
Static position & 3-component signal	12,1%	0,8%
Triangle & 3-component signal	9,5%	1%
Static position & 2-component signal	7%	1%

Noise interference related errors are reduced due to the distinct shape of the signal's time-frequency content, as well as careful filtering and/or additional processing.

5. CONCLUSIONS

This paper addresses the problem of distributed processing in the context of acoustic sensor networks aimed to detect and to localize an unknown moving source. The classic approach based on local spectral analysis has been compared with a new concept that is based on the time-frequency information extraction that exploits the continuity of the received signal in the time-frequency plane. The results obtained for real data proved the benefits in terms of operational performances such as detection and localization. In addition, the time-frequency coherence makes a more relaxed assumption than the spectrogram: we look for linear time-frequency components rather than stationary ones, which allows us using longer windows than the spectrogram. Beside the quality of estimators that is improved, this fact conducts to a higher local compression ratio which reduces the quantity of information that we need to send from sensors to the center of data processing. Such property is helpful for ensuring autonomy and this aspect will be one of our further goal. In addition, the improvement of implementation in distributed configurations as well as the definition of algorithms for an improved localization and classification will be also part of our future work directions.

6. ACKNOWLEDGEMENT

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