Distributed network of underwater sensors based on local time-frequency coherence analysis

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***Abstract* — Underwater acoustic sensor networks are an important element in a large number of applications such as surveillance, environment monitoring…The development of an autonomous sensor system imposes the distribution of the data processing at the level of sensors. This operation is subject to a trade-off between the processing efficiency and the algorithmic complexity that influences the power consumption. In the case of current networks, a common way to answer to this trade-off issue is to process data (detection, recording, transmission…) when the energy of the observed signal, in an arbitrary analysis window, exceeds a given threshold. In this paper, we propose an underwater network configuration that is composed of sensors implementing a different processing approach, based on the hypothesis of a local time-frequency coherence (FM sweep). The results obtained on real data illustrate the efficiency of this algorithm, in terms of signal's characterization and lower communication bit rates.**

Keywords—distributed signal processing; underwater source localization; time-frequency analysis

I. INTRODUCTION

The monitoring of the underwater environment must face different difficulties in terms of sensor network design and capabilities [1], [2]. Monitoring a large area requires a high number of sensors and complex communications channels, avoiding sometimes the use of wires. In such case, the wireless communications must be carefully designed in order to fulfill, in an optimal way, the requirements of bandwidth, energy consumption and to be robust to the propagation phenomena (multi-path, time-varying, etc). In this context, different interesting concepts are proposed to implement the distributed network in underwater environment [1], [2]. The sensors include some embedded algorithms that allow detecting the presence of *interesting* signals, mostly based on an energy criterion. Generally, the sensors "listen" to the acoustic signals in their neighborhood and, if the energy level in a time window exceeds some threshold (fixe or adaptive), an event is detected enabling the next processing stage : storage of data, signal analysis and parameter extraction, transmission, etc. From a mathematical point of view, this operation is equivalent to the detection in the spectrogram domain [3]. 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 rate. Another aspect related to the use of the spectrogram is the choice of window size, understanding that, fundamentally, the spectrogram is an appropriate analysis tool if the signal is stationary in the analysis window. In order to increase the efficiency of a distributed processing, this paper proposes an alternative to the time-frequency energy-based techniques. The hypothesis is to locally model the signal's time-frequency content with a second order frequency modulation (linear frequency modulation - LFM) and to call a detection when the LFM parameters provided by the modeling of the next analyzing window, half overlapped on the previous one, are *close* to the previous LFM estimates. Under these conditions, we say that the time-frequency coherence of the two windows is proved and it leads to the detection of an interesting event. Using this processing technique, each sensor of the network proceeds to the local LFM modeling and, for each analysis window, two parameters are extracted : the central frequency and the chirp rate modeling the local LFM. That is, at each sensor, the signal's samples corresponding to the analysis window are replaced by only two parameters, that approximate the signal's local time-frequency behavior, achieving also a high compression ratio of the information. These parameters are sent to the central processing unit that will reconstruct, for each sensor, the corresponding instantaneous frequency law (IFL). The localization is then possible as we will prove in this paper.

The paper is organized as follows. The general diagram of the network is discussed in the Section 2. The distributed processing methods are presented in the Section 3. Results on real data are the subject of the Section 4. The Concluding remarks will close this paper – in Section 5.

II. DISTRIBUTED NETWORK OF SENSORS

The acoustic network is composed by two main elements, defined in the Fig. 1 :

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- *The set of sensors* that covers the area of interest, according to the operational purposes – surveillance, monitoring, tracking,…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 the analysis window W. Thanks to this sensor-level processing, each signal is characterized by a much smaller number of parameters compared to the total number of samples. This considerably relaxes the communication constraints between sensor and the central processing unit, reducing the power consumption and increasing the communication range, thanks essentially to a reduced required bit rate.

In this paper, two classes of processing will be discussed, in the section 3 : the first one is based on the spectrogram and the second one is based on the local phase modeling using a second order modulation – linear frequency modulation. The common point is that the local time-frequency information is composed by only two parameters as it will be presented in the Section 3.

In terms of connection between sensors and central processing unit, each sensor has its own identifier and it transmits, for each time analysis slot W, the set of parameters that will represent the set of signal's samples.

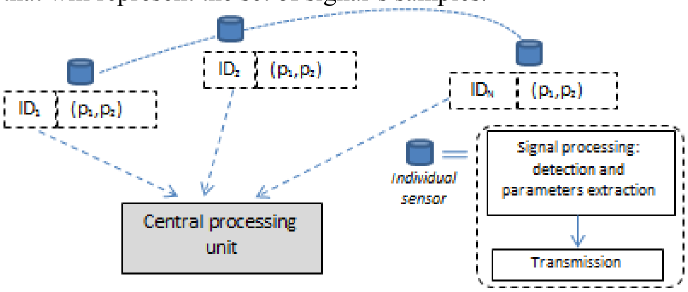


Fig. 1. Diagram of the network composed by several acoustic sensors

- *The central processing unit* is in charge to merge the information coming from all sensors. The combination of whole set of parameters allows the synthesis of the instantaneous frequency law of each signal detected by each sensor. More precisely, each pair (p_1,p_2) describes the local time-frequency behavior of the signal. The global IFL of the signal can be obtained by the interpolation of these parameters. Therefore, the global detection and localization will be possible by combining the IFLs corresponding

III. DISTRIBUTED SIGNAL PROCESSING

A. Sensor-level processing

At each sensor level, two processing algorithms can be implemented : the spectrogram, which is implemented for comparison purposes and the algorithm based on the time-frequency coherence analysis [4]. Each sensor detects and extracts, in each analysis window, two parameters that are transmitted :

- **Spectrogram** :

For each window W_1,

$$(t_k, f_k) = \arg\max_{t,f} S(t,f),\ S(t,f) \geq \alpha \Rightarrow (t_k, f_k) - \textit{transmitted} \tag{1}$$

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

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

where x is the analyzed signal, h is the analysis window of size W_1, ol is the overlapping length and N is the number of FFT points. The spectrogram parameters are illustrated in the figure 2.

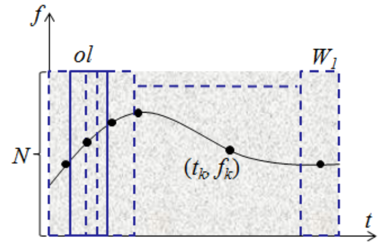


Fig. 2. Local time-frequency parameters extraction from spectrogram

The choice of α - the time-frequency energy threshold is very important since a low level will conduct to a high false alarm ratio and a high level will decrease the probability of detection. In our examples, we choose α as a half of the maximum amplitude of the signal. The choice of α is practically a difficult problem and the next section will present an alternative class of method.

- **Time-frequency coherence-based approach** [4] :

For each window W_2, we firstly look for the local LFMs that fit the best the local signal's time-frequency behavior. For this purpose, the ambiguity function (AF) is used :

$$AF_x(\tau, f) = \sum x(n) x^*(n-\tau) e^{-j2\pi\tau f} \tag{3}$$

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

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

Once this parameter estimated, the demodulation operation

$$x(t) \cdot e^{-j2\pi \cdot c_2 t^2} \tag{5}$$

will conduct to a tone-like signal whose frequency - the central frequency of the LFM that locally models the signal - can be estimated from the Fourier transform of (5).

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

$$\begin{aligned} x_k(t) &\approx \exp j\left(c_{1,k} t + c_{2,k} t^2\right), t \in [kW_2, (k+1)W_2]; \\ x_{k+1}(t) &\approx \exp j\left(c_{1,k+1} t + c_{2,k+1} t^2\right), t \in [(k+1)W_2/2, (k+3)W_2/2] \end{aligned} \tag{6}$$

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, as illustrated in the Fig. 3.

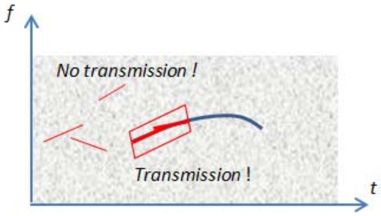


Fig. 3. Local parameters extraction by time-frequency coherence

Namely, we consider that the modeled LFM (6) correspond to a useful signal if they are in the same time-frequency region and we transmit the corresponding LFM parameters. 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 :

$$\begin{array}{l} If\ d\{(c_{1,k},c_{2,k}),(c_{1,k+1},c_{2,k+1})\}\leq \beta \Rightarrow (c_{1k},c_{2k})-transmitted \\ Else-no\ transmission \end{array} \quad (7)$$

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 coefficient sets are inferior to a threshold β.

At each sensor, independently of the processing method, the *local detection* is done. After the detection, each sensor transmits to the central processing unit, for each time analysis slot W_1 or W_2, two parameters that replace the set of signal's samples corresponding to the time slot. That is, at each sensor level, the compression ratio (CR) provided by the sensor-level processing is equivalent to $W_k/2; k=1,2$. This compression allows a significant bandwidth reduction as well as the power consumption required for the data transmission.

B. *Central-level processing*

At the central processing unit, the combination of the entire set of parameters allows the synthesis of the instantaneous frequency law for each signal detected by the field of sensors. The global IFL of the signal can be obtained such as :

$$\begin{array}{l} Spectrogram: IFL_1(t)=\{f_k | t\in[t_k-W_1/2, t_k+W_1/2]\} \\ Time-frequency\ coherence: \\ IFL_2(t)=\{c_{1k}+2c_{2k}t | t\in[kW_2,(k+1)W_2]\} \end{array} \quad (8)$$

In the rest of the paper, while the processing at the central level is the same for the both processing techniques, we do not index the IFL according to the sensor-level processing. Let note with IFL_n, n=1,.., N_s (N_s – the number of sensors of the network) the IFL synthetized from the parameters extracted and sent by the n^{th} sensor. Using the IFLs of all sensors, we compute the cross-correlations of IFLs as

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

where $m, n = 1,..,N_s$.

Using these functions, we can estimate the time delay of arrival (TDOA) between the sensors m and n via :

$$TDOA_{mn}=\arg\max_{\tau}|R_{mn}(\tau)| \quad (10)$$

With these values it is possible to localize the acoustic source and, computing the dynamic variation of these parameters, the source tracking can be done. The localization problem is defined in terms of the non-linear least-square problem [5]. In the context of a single source, its position (x_s,y_s) can be obtained from the equation system :

$$\left\{TDOA_{mn}=\frac{1}{c}(D_{s,m}-D_{s,n})\right\} \quad (11)$$

where c is the sound velocity in water and $D_{s,m}$ and $D_{s,n}$ are the distances between the source and the sensor m and n, respectively :

$$\begin{array}{l} D_{s,m}=\sqrt{(x_s-x_m)^2+(y_s-y_m)^2} \\ D_{s,n}=\sqrt{(x_s-x_n)^2+(y_s-y_n)^2} \end{array} \quad (12)$$

where (x_m,y_m) and (x_n,y_n) are the coordinates of the sensor m and n, respectively.

The optimal solution is obtained by solving :

$$(\hat{x}_s,\hat{y}_s)=\underset{(x_s,y_s)}{\arg\min}\sum_{m,n}\left[TDOA_{mn}-\frac{1}{c^2}(D_{s,m}-D_{s,n})\right]^2 \quad (13)$$

This optimization problem can be solved by searching, in a given domain, the coordinates of the sources that will conduct to a global minimal value of the quadratic error (13).

The distributed processing and the detection/localization at the central level will be illustrated, from real data, in the next section.

IV. RESULTS

In this section we present the detection and the localization results from real measurement campaigns that have been conducted in the Bay of Oursinières (Le Pradet, East of Toulon, France) on November 8th 2012 and March 7th 2013. In this experiment, three sensors have been placed as indicated in the Fig. 4 and a moving acoustic source. One of the recorded trajectories of the moving source is also plotted in the Fig. 4.

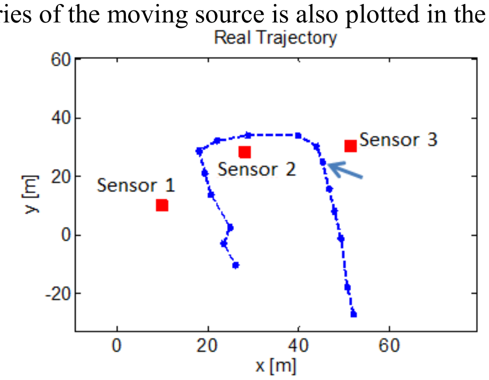


Fig. 4. Experimental setup of the measurement campaigns in the Bay of Oursinières - Toulon.

The next figure compares the two sensor-level signal processing methods. The analysed signal – a two chirp signal (Duration – 1 second and frequency support from 10 to 20 kHz), corresponds to one of the sea-trial data measured by one of the sensor – the spectrogram is plotted in the upper part of the Fig 1. The IFLs synthesized from the coefficients extracted by the two processing techniques are plotted in the bottom part of the figure.

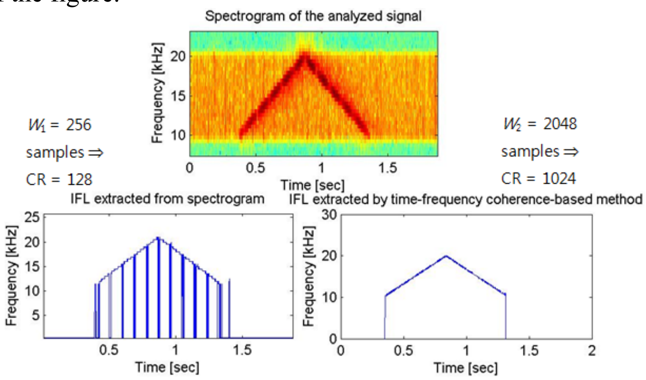


Fig. 5. Comparison of the IFLs synthetized at the central level for parameters sent by a sensor

As shown by this figure, the processing by time-frequency coherence allows, at the central level, a more accurate IFL estimation, in terms of IFL continuity and false alarms, which leads to better performances in terms of detection and localisation.

In terms of communication performances, the transmission of the entire signal, knowing that the minimal necessary sampling frequency is 40 kHz and assuming that we use 12 bit/sample, requires a bit rate of 480 kbits/sec. The use of the processing at the sensor-level significantly reduces the bit rate to 3.75 kbits/sec, for the spectrogram and to 0.46 kbits/sec, for the time-frequency coherence, respectively. Concerning the communication between the sensors and the central processing unit, the advantage of the time-frequency coherence is the use of longer time-windows than those of the spectrogram-based method : the stationarity, required by the spectrogram, is available for shorter window than the linear IFL model that is assumed by the proposed method.

The reduced amount of data that need to be transmitted (but significant with respect of the signal's time-frequency characteristics) allows reducing the power consumption, at the sensor level, and achieving, at the central level, fast time processing of data from all the sensors. In the case of our measurement campaign, the next figure plots the IFLs extracted by the three sensors and reconstructed at the central level. The received signals correspond to an emission of the acoustic source from the position indicated in the Fig. 4 by the arrow. The spectrograms of the signals received by each sensor are plotted in the Fig. 6.a and the IFLs extracted (and transmitted to the central level) from spectrogram and by time-frequency coherence technique are plotted in the Fig. 6.b and c, respectively. We can easily observe that the time-frequency coherence provides better estimations of the IFLs in terms of time-frequency support as well as the conservation of the time-frequency continuity.

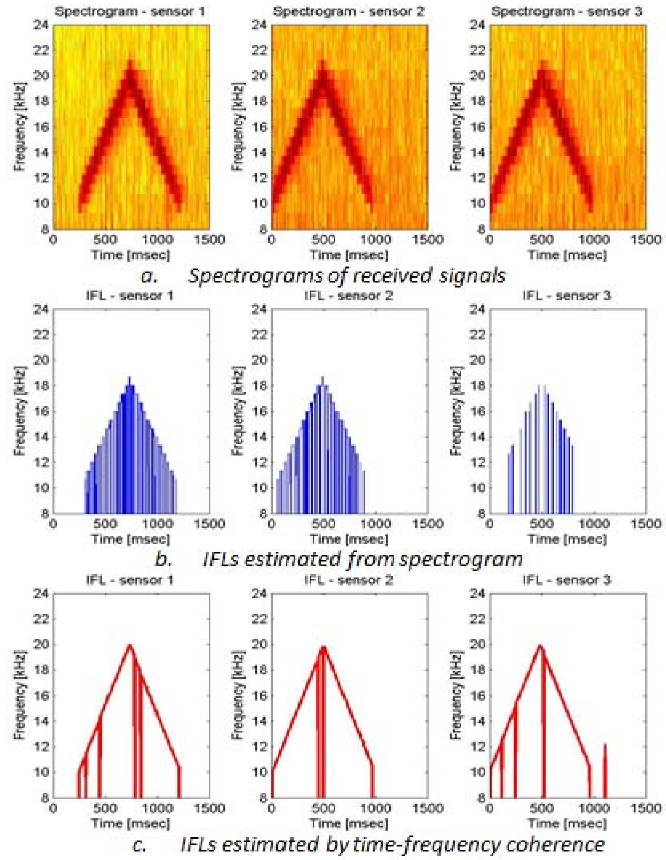
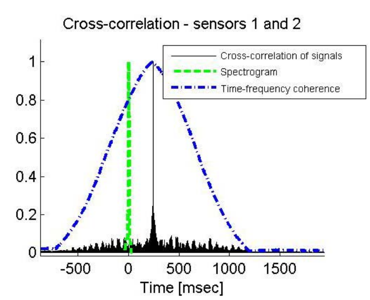


Fig. 6. Estimated IFLs for signals received by the three sensors – spectrogram and time-frequency coherence

The figure 7 shows the cross-correlations between the estimated IFLs, for both techniques. We compare these cross-correlations with the results of the cross-correlation between the received signals at the sensor level. Off course, this operation conducts to the most accurate estimator of the TDOAs but, in the context of the distributed processing, this operation is not possible while only the IFLs synthesized from local parameters transmitted from the sensors to the center are available. As we can observe, the cross-correlations of the IFLs extracted by the time-frequency coherence are close to the cross-correlations of the signals and, as we will see later, this conduct to better tracking performances.



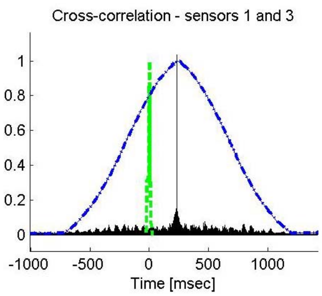


Fig. 7. Normalized Cross correlations of the estimated IFLs versus matched filter result

It is clear that the processing gain is better in the case of the time-frequency coherence and, in terms of the *global detection*, this is completely proved by the *Receiver Operating Characteristic (ROC)* plotted in the Fig. 8. These results have been obtained by processing 40 received signals collected during the measurement campaign. We compare the ROC from spectrogram and time-frequency coherence with the detection results obtained by matched filter, i.e., in such case the transmitted signal is supposed to be known (active context). For our context, while we work in passive configuration, the matched filter constitutes the "ideal" result.

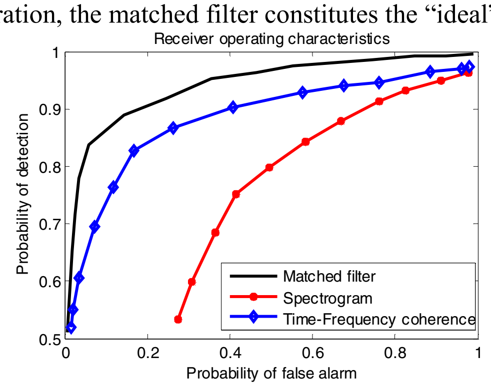


Fig. 8. Detection performances in terms of ROCs

This results show clearly that the detection based on the time-frequency coherence is better - the ROC curve is closer to the "ideal" one.

Finally, the last result concerns the *tracking* of the source whose real successive positions have been calculated from the GPS measurements. By processing the received signals with the matched filter, we get a close trajectory but this type of processing requires the knowledge of the emitted signal. The passive context and the distributed configuration are then considered, via the spectrogram and time-frequency coherence based processing. Using the cross-correlation of the synthesized IFLs issued from spectrogram and time-frequency coherence, we can estimate the TDOAs as the maxima of cross-correlation, as illustrated by the example of the figure 7. Using the TDOAs and the optimization procedure described in the section III, the trajectory can be estimated in the case of the both methods. Thanks to a more accurate estimation of the IFL, illustrated in the previous examples, the time-frequency coherence allows estimating better the trajectory, with respect of both real (GPS) trajectory and estimated from the TOAs provided by the matched filter – Fig. 9.

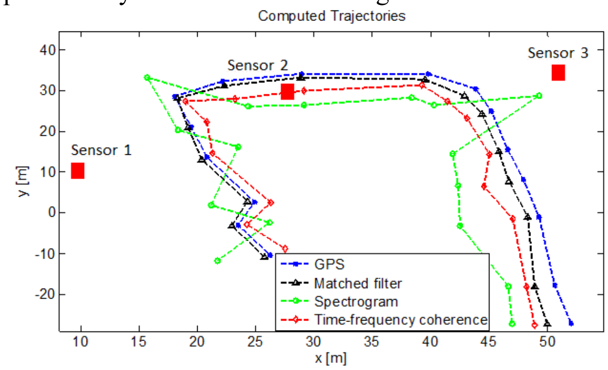


Fig. 9. Source tracking results

These results prove the interest of the distributed processing based on the time-frequency coherence, in terms of localization of acoustic sources in passive context.

V. CONCLUDING REMARKS

This paper addresses the problem of distributed processing in the context of underwater acoustic sensor networks aimed to detect and to localize an unknown moving source. The classical approach based on local spectral analysis has been compared with a new concept that is based on the time-frequency information extraction which exploits the continuity of the coherent acoustic emission. 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 central level. Such property is helpful for ensuring long consumption autonomy and this aspect will be one of our further goals. In addition, the improvement of implementation in distributed configurations and the definition of algorithms for improved localization and classification will be also part of our future work directions.

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