Passive source localization using power spectral analysis and decision fusion in wireless distributed sensor networks

Conference or Workshop Item

Passive Source Localization using Power Spectral Analysis and Decision Fusion in Wireless Distributed Sensor Networks

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Abstract

Source localization is a challenging issue for multisensor multitarget detection, tracking and estimation problems in wireless distributed sensor networks. In this paper, a novel source localization method, called passive source localization using power spectral analysis and decision fusion in wireless distributed sensor networks is presented. This includes an energy decay model for acoustic signals. The new method is computationally efficient and requires less bandwidth compared with current methods by making localization decisions at individual nodes and performing decision fusion at the manager node. This eliminates the requirement of sophisticated synchronization. A simulation of the proposed method is performed using different numbers of sources and sensor nodes. Simulation results confirmed the improved performance of this method under ideal and noisy conditions.

1 Introduction

Wireless Distributed Sensor Networks (WDSN) are a promising research topic in the literature due to their huge potential in different application areas from the monitoring to manipulation of physical world in a seamless fashion [6], [5], [8], [4]. WDSN comprise cheap nodes that have limited sensing, communication and computation capabilities. There are also some nodes designated as control nodes having powerful computational and communication ability. Each WDSN node can have different types of sensors such as acoustic, seismic and image. The fusion of data collected through sensor nodes to improve decision is a major research issue for WDSN.

Source localization is the most fundamental part of multisensor multitarget detection. The objective is to estimate the position of a source within the region covered by a WDSN.

Localization methods depend on three types of physical variables measured by or derived from, sensor readings: time delay of arrival (TDOA)[3], direction of arrival (DOA)[7] and received signal strength[9]. The source localization problem is solved by TDOA and DOA for WDSN using the same philosophy for localization as used in RADAR applications. This is not a suitable approach for WDSN since RADAR and WDSN nodes have fundamental differences in their sensing quality, computational ability and communication framework. The basic advantage of WDSN is that it has sufficient number of cheap and redundancy nodes that are feasible to deploy for tracking the source in close proximity. The critical issues in the application of WDSN to source localization are to cope with the efficient collaborative management specifically for decision fusion from readings of non-sophisticated nodes having scarce power, computational and communication resources. Only a selective subset of nodes should be allowed to communicate with the control node to reduce power consumption of individual nodes and the bandwidth overhead of the network.

A maximum likelihood(ML) source localization method using acoustic energy measurements from individual sensor in WDSN was presented in [9]. The ML method has several limitations for applications in WDSN. Specifically, it is sensitive to the parameter perturbation and computationally very expensive for multitarget location estimation [10]. These limitations made the ML estimation unsuitable for WDSN.

Particle filters were applied in [10] to overcome the limitations of ML estimation, by making an assumption about source dynamics such as source velocity and acceleration, which is not suitable for enemy/adverse situation surveillance.

To address these issues, this paper presents a novel method for source localization namely, passive source localization using power spectral analysis and decision fusion in wireless distributed sensor networks. The motivation behind using power spectral density (PSD) for source localization is that any rotating object emits its signal at a particular frequency. Analyzing this feature using PSD for a sample of a specific source helps identify the source.

Proceedings of the International Conference on Information Technology: Coding and Computing (ITCC'05)
0-7695-2315-3/05 $ 20.00 **IEEE**

The probabilistic localization is made from PSD analysis at each node. Statistical decision fusion of these estimates is made at a control node. The issue of accurate synchronization among the sensors is also resolved by their coarse time series data collection.

The paper is organized as follows: Section 2 gives a short overview on the PSD and its significance for source localization in WDSN. Section 3 provides a detailed description of the theoretical underpinning of the proposed method. Simulation results are described in Section 4, and finally some conclusions are presented in Section 5.

2 Power Spectral Density Analysis

The energy $\xi(t)$, of an arbitrary time varying signal $x(t)$ is represented in both time and frequency domains by Parseval's theorem as,

$$\xi(t) = \int_{\infty}^{\infty} x_1(t)x_2(t)dt = \int_{\infty}^{\infty} X_1(f)X_2(f)df \quad (1)$$

where $X(f)$ is equivalent Fourier transform representation of $x(t)$. Setting $x_1(t) = x_2(t)$, we get,

$$\xi(t) = \int_{\infty}^{\infty} x^2(t)dt = \int_{\infty}^{\infty} |X(f)|^2 df \quad (2)$$

$|X(f)|^2$ is known as the power spectral density function. The Wiener-Khintchine theorem proves that the spectral density $P(f) = |X(f)|^2$, of a stationary random process is just the Fourier transform of the autocorrelation function $R_{xx}(\tau)$ and is represented by the pair:

$$P(f) = \int_{\infty}^{\infty} R_{xx}(\tau)e^{-j\omega\tau}d\tau \quad (3)$$

and

$$R_{xx}(\tau) = \int_{\infty}^{\infty} P(f)e^{j\omega\tau}df \quad (4)$$

The periodogram is a commonly used PSD estimation technique using (3) [1]. Transforming from time domain to frequency domain for source localization is an integral part of signal analysis and hence periodogram for PSD estimation forms the fundamental basis for the proposed new algorithm. There are other methods for PSD estimation. Since, we are focusing on use of power spectral analysis for source localization we have chosen the simplest one to implement $i.e.$ periodogram.

3 Source Localization using Power Spectral Analysis and Decision Fusion

As alluded in Section 1, source localization using power spectral analysis and decision fusion is motivated by energy based source estimation algorithms [10], [12]. Using the formula for acoustic signal attenuation, it is possible to estimate the source location using redundant reading at different, known sensor locations.

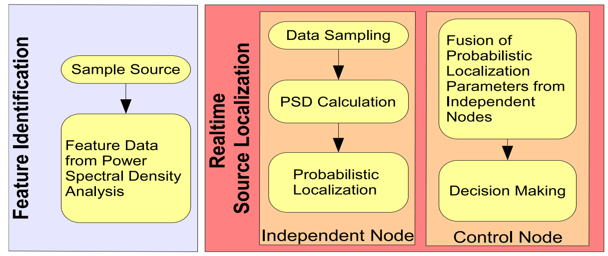

Figure 1. Block Diagram of Proposed Source Localization using Power Spectral Analysis and Decision Fusion

3.1 Feature Identification

As shown in Fig. 1, feature identification is one of the processing steps of source localization using power spectral analysis and decision fusion method. This can be obtained in different ways: - (1). collecting sampling data and (2). for a given set of features for a particular source. Sampling data can be collected for featured sources at ideal noise free condition at very short distance. The periodogram of a specific source signal at this condition gives the PSD estimation of the sampled data. The obtained PSD is then processed for power peak detection and corresponding frequency finding. The obtained peak power level and corresponding average frequency forms power-frequency pair $[\mathbf{P}, \mathbf{f}]$, where $\mathbf{P}$ represents the power level and $\mathbf{f}$ represents corresponding frequencies. This $[\mathbf{P}, \mathbf{f}]$ pair denotes the characteristic feature for the specific source.

3.2 Realtime Source Localization

The realtime source localization is the heart of the proposed source localization using the power spectral analysis and decision fusion method shown in Fig. 1. For the sake of the clarity , it is assumed that there are M sources and N sensors in a WDSN field. A node in the WDSN is modeled by $[x_i, y_i, \sigma_i]$, where (x_i, y_i) denotes the node position and σ_i its associated standard deviation of the estimation process for source localization. σ_i can be varied based on sensor quality measure or it can be estimated by an adaptive process. Assume that the signal received by the i^{th} node is the sum of attenuated signals emitted from each of these M sources. Thus, the signal energy received by the i^{th} node over a time interval t, denoted by $y_i(t)$, is expressed as follows:

$$y_i(t) = \gamma_i \sum_{m=1}^{M} \frac{s_m(t)}{\|\rho_m(t) - \mathbf{r}_i\|^2} + \varepsilon_i(t) \quad (5)$$

where $\varepsilon_i(t)$ is a perturbation term that summarizes the net effect of background additive noise and the parameter modeling error. γ_i and $\mathbf{r}_i$ are the gain factor and location of the i^{th} sensor respectively. $s_m(t)$ and $\rho_m(t)$ are the energy emitted by the m^{th} source and its location during the t^{th} time interval. The probability distribution of $\varepsilon_i(t)$ has been shown to be independent and identically distributed ($i.i.d.$) Gaussian random variable when the time period T for averaging the energy is sufficiently large [9].

Each node collects data for a specific T time period. The PSD estimation for i^{th} node $P_i(f)$ is made over the period T for each sampling time. The recent collected data over the period of T is used for PSD and hence location estimation. Sources are detected from the obtained PSD by matching with characteristic power-frequency pair. Due to the consideration of noise, the matching for particular frequency f is spread over within the range of $f \pm df$ frequencies, where $\pm df$ is the width of the variation of a particular frequency f caused by noise perturbation term $\varepsilon_i(t)$. The peak power within $f \pm df$ is used as detected power level.

For the j^{th} frequency component, $\hat{\rho}_m^{ij}$ represents the radial distance estimation of m^{th} source from i^{th} node using calculated PSD and characteristic power-frequency pair for individual sources, where $j = 1..k$ and k is the number of distinct features present in the power-frequency pair. The final estimation of ρ_m^i is found by averaging all $\hat{\rho}_m^{ij}$'s. This is derived from (5), considering the fact perturbation term $\varepsilon_i(t)$ is eliminated by PSD estimation and expressed as follows:

$$\rho_m^i = \frac{1}{k} \sum_{j=1}^{k} \left(\gamma_i \frac{SP_m}{RP_m^j} \right)^{\frac{1}{2}} \quad (6)$$

where SP_m denotes the signal power level at origin, RP_m^j denotes received signal power level for m^{th} source using j^{th} frequency feature component and γ_i is a constant.

The obtained ρ_m^i is transmitted to the control node for decision fusion. A 3D probability density function $p_m^i(x)$ having mean ρ_m^i and standard deviation σ_i is constructed for each node and source m at the control node through proper normalization. For location estimation from all supported data, all the probabilistic density functions from all nodes need to be fused together at the control node. Therefore, all probabilistic measures are fused together using weighting factor w_i for i^{th} node. This process generates an integrated 3D probability density function for the final decision making. This process for source m is formulated by the following equation.

$$p_m(x) = \sum_{i=1}^{N} w_i p_i^m(x) \quad (7)$$

To localize a source from this $p_m(x)$, a peak detection technique is employed in the $p_m(x)$. The locations of the detected peaks having probability estimation greater than a preset threshold h corresponds to detected source locations.

4 Simulation Results

The proposed algorithm was simulated using Matlab 6.5.1 (The Mathworks Inc.). For the simulation, three sources having characteristic frequencies at 200, 300 and 400 Hz and signal strength at source of 70, 75 and 80 dB respectively were used. The sound level and the dominant frequencies that have been used are in conformance with the power and frequency levels generated by conventional and military vehicles [11], [2]. The values of sampling frequency and σ_i were taken as 1000 Hz and 2 respectively. The weighting factors w_i are considered same for each node and set to $\frac{1}{5}$. The original node and source positions and the detected source positions are shown in Fig. 2.

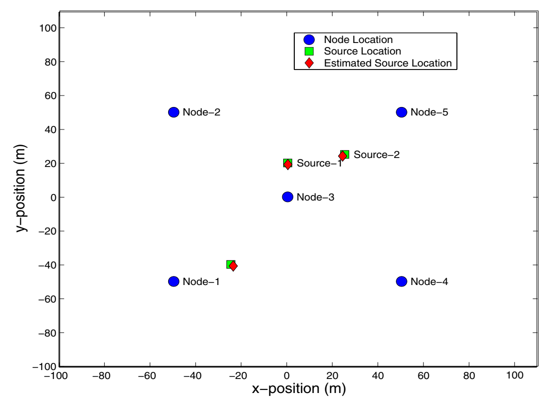

Figure 2. Ground Truth and Simulation Results for Three Sources

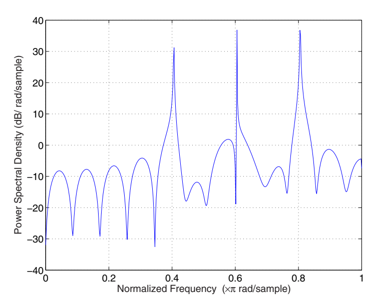

Figure 3. PSD Estimation at node 1

For better understanding of how a power level peak being generated for a particular source having a distinct frequency in the PSD, a representative sample of the estimated PSD from the simulation for node 1 is shown in Fig. 3. It is clear from this figure that representative frequencies for the three sources used here, generate distinct peaks in the PSD. These peak power levels provide the radial source distance by the use of the attenuation model described in Section 3.

The contribution of source 1 location estimation from individual node are fused together at the control node as shown in Fig. 4(a). The resulting 3D probabilistic estimation plot is shown in Fig. 4(b). The same results for source 2 are shown in Fig. 5.

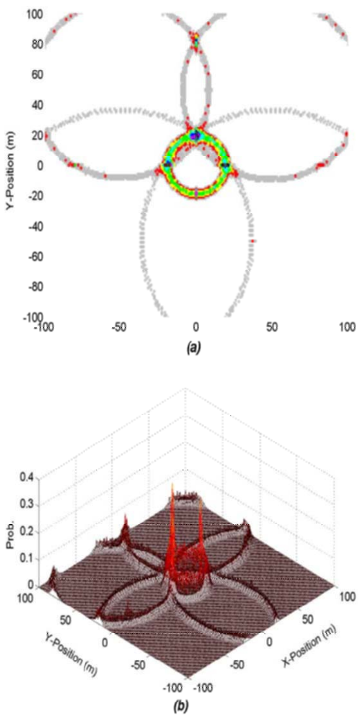

Figure 4. Source Localization Result for Source 1, a) A 2D radial basis location estimation for different nodes, b) A 3D probability space for source localization

From the obtained results in Fig. 2, it is shown that the proposed localization method can locate sources within the error range of 1 m. Also, due to radial estimation, it has been found that there are circular regions of a source location generated by different nodes. Fig. 4 and 5 show how the redundant information from the nodes play a role to make a decision for a source localization. The individual decisions from nodes are aggregated using (7). At the intersection of the circular regions the decision is strengthened to ultimately predict the source location estimation shown in Fig. 4 and 5 for Source 1 and 2 respectively. It is evident

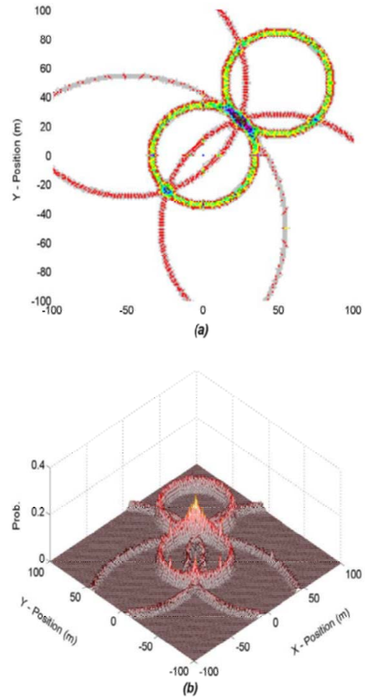

Figure 5. Source Localization Result for Source 2, a) A 2D radial basis location estimation for different nodes, b) A 3D probability space for source localization

from the obtained results that the decision fusion using the redundant information of the sensor nodes plays a vital role to make a decision for source localization.

Another experiment was conducted using the same ground truth information including addition of Additive White Gaussian Noise(AWGN) of 5 dB in order to simulate this method for testing its performance in a real-life context. Simulation showed exactly the same result as the AWGN is filtered out in frequency domain power spectral density estimation. It is clearly evident that the location estimation of the proposed method is not sensitive to AWGN and hence, suitable to determine the location of the source in a real-life environment.

5 Conclusions

In this paper, a novel energy based source localization using power spectral analysis and decision fusion method in WDSN has been introduced. A simulation has been conducted for multitarget location estimation for different levels of noise perturbation. The results have shown the accurate location estimation of the proposed method, which used the periodogram for PSD estimation. Other existing methods for PSD estimation could also be investigated and compared in future work.

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