

FLIPPED PARAMETER TECHNIQUE APPLIED ON SOURCE LOCALIZATION IN ENERGY CONSTRAINT SENSOR AR-RAYS

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Abstract. *In this paper novel flipped parameter technique (FPT) for time delay estimation (TDE) in source localization problem is described. We propose passive source localization technique based on the development of an energy efficient algorithm that can reduce intersensor and interarray communication. We propose a flipped parameter (FP) which can be defined for any sensor in distributed sensor subarrays during the observation period. Unlike classical TDE methods that evaluate cross-correlation function, FPT requires evaluation based upon single sensor signal. The computed cross-correlation between a signal and its analytic "flipped" pair (flipped correlation) is a smooth function which peak (time delay) can be accurately detected. Flipped parameters are sufficient to determine all differential delays of the signals related to the same source. The flipped parameter technique can be used successfully in two-step methods of passive source localization with significantly less energy in comparison to the classic cross-correlation. The use of FPT method is especially significant for the energy con-strain distributed sensor subarrays. Using synthetic seismic signals, we illustrate the error of the source localization for classical and proposed method in the presence of noise. We demonstrate the performance improvement in noise environment of the pro-posed technique in comparison to the classic methods that use real signals. The pro-posed technique gives accurate results for both coherent and non-coherent signals.*

Key words: *source localization, time delay, cross-correlation, wireless sensor networks, analytic signal*

INTRODUCTION

The signal source localization is one of problems that has been explored for a long time. [1]-[3]. Algorithms for source localization are applied in seismics, acoustics, SONAR, RADAR, microphone array processing and speech recognition. Active [4], [5] and passive localization systems [6], [7] are described in literature. Two-step localization

methods are based on computation of differential delays between sensor signals, in the first step, and estimating source location using spherical interpolations (circle for 2-D space) or hyperbolic intersections in second step [8]. Accurate the time delay estimation (TDE) for the signals originated from the same source [9] is one of essential problems in signal processing and source localization problem. Depending on the type of application, two different types of TDE can be distinguished. Time of Arrival (TOA) is the time delay between the transmitted signals and received its echo. TOA assumes knowledge of the waveform of the transmitted signal, such that a signal from only one sensor is necessary in order to compute differential delay. TDOA is the other type of TDE applied in passive systems where the waveform of the transmitted signal is not known. At these systems, differential delay is computed for signals acquired from two spatially separated sensors. In the presence of noise, reliability of differential delay computation decreases which is a major issue TDE algorithms should deal with.

In algorithms for passive source localization [10]-[12], that are the subject of our interest, the differential delay among sensor signals is used as a computation parameter. The sensor signals are acquired from spatially separated sensors and contain information about the source location. As sensors, radio antennas, sensitive microphones, geophones or hydrophones can be used. To provide identification and accurate source localization, the collaborative sensor networks are formed out. Thus, reliable sensor localization is in principle possible with at least three sensors. Depending on the application requirements, the sensor networks can contain from a few to even hundreds of sensor elements [13]. When the sensor network consists of a large number of sensor elements, it is usually divided into sensor subarrays [14]. The collaborative sensor network designs [15], in addition to central intelligence (the fusion center) often contain local intelligence (a local processor) which combines and controls work of several sensor modules. A sensor module is a basic hardware for acquisition and processing data coming from a sensor. To make possible efficient localization using distributive sensor networks, it is necessary to accomplish mutual communication (usually wireless) between the fusion center and local processors. Due to the necessary communication of the network elements in order to implement localization algorithms, such networks are referred as collaborative sensor arrays. Modern integrated circuits technology makes possible inexpensive design of sensor modules and sensor networks, with standardized structure of wireless communications [16]. In addition to the localization, which is the main subject of our interest, sensor networks with such a design can accomplish several other tasks, such as detection, tracking and source identification in the sensor field.

Energy consumption is one of fundamental design constraint when designing distributed sensor networks. The energy consumption of the collaborative distributed sensors networks can be minimized using several techniques [17]. In this paper, we propose passive localization technique based on the development of an efficient algorithm that can reduce intersensor and internetwork communication. Main purpose of the analyzed distributed sensor network is localization and tracking of passive seismic source. Using the flipped parameter technique (FPT), the intersensor communication is minimized with direct effects on the energy consumption of communication modules in the fusion center or in a local processor.

Classic algorithms for passive localization based on cross-correlation require the availability of two sensor signals samples in order to compute the differential delay between two spatially separated sensors. Therefore, this condition implies that at least one

sensor should transmit samples of the acquired signal to corresponding sensor, local processor or even the fusion center. Subsequently, cross-correlation is computed in a local processor or in the fusion center, with necessary time synchronization of acquired sensor signal samples. Differential delay is determined by identifying the peak of the cross-correlation function, and such determined delay is an input for two-step algorithms for source localization. In addition, the two-step methods require the knowledge of the wave propagation velocity in the real medium. Unlike propagation of acoustic waves through air, the propagation velocity of seismic waves through real geological medium is unknown. Due to the fact that the seismic wave propagation velocity is extremely dependent on the geological medium, an efficient technique to determine propagation velocity of surface seismic waves is proposed in [18]. In [19] are present the concept of the time delay estimation based on the transformation of real sensor signal into analytic ones. The difficulties to select a peak of cross-correlation function are significantly reduced if analytic signals are applied. The application of the flipped parameter technique consists of assigning a corresponding FP to each sensor module, which corresponds to the acquired sensor signal. To compute differential delay between sensor signals, it is necessary to compute the value of the FP and to communicate the value to the local processor/the fusion center. Subsequently, the fusion center computes the difference between appropriate flipped parameters and this way computes the differential delay between corresponding sensor signals. Hence, the amount of information that should be transmitted through the wireless communication channel in order to compute differential delay and to perform localization is significantly decreased [20]. As a direct consequence, the energy consumption is reduced.

In the remaining parts of the paper, we discuss fundamental methods of passive source localization using the energy constrain distributed sensor networks and proposed flipped parameter technique.

NETWORK LOCALIZATION METHODS

Essentially, localization methods can be categorized into one-step parametric and two-step non-parametric. One-step methods can compute the source location in one computational step. Parametric ML methods maximize the probability density function based on raw signal data, and do not require computation of differential delays between signals. Two-step localization methods are based on computation of differential delays between sensor signals, in the first step, and on subsequent determination of the source location using the least squares technique. These two-step methods require the knowledge of exact sensor locations, i.e. inter-sensor distances and waves propagation velocity in a real medium [18]. With these parameters known, based on differential delays, a system of non-linear equations is formulated. The system of equations can be made inconsistent if additional sensor data are joined to the basic system. Equations that link geometric characteristics of the two dimensional (planar) sensor network and the wave propagation velocity are given as: (1)

$$D_{g,h} = \frac{1}{v}[(x_s - x_g)^2 + (y_s - y_g)^2]^{\frac{1}{2}} - \frac{1}{v}[(x_s - x_h)^2 + (y_s - y_h)^2]^{\frac{1}{2}} \quad (1)$$

$$g, h = 1, 2, 3, \dots, M,$$

where $D_{g,h}$ is differential time delay between spatially separated sensors $g(x_g, y_g)$ and $h(x_h, y_h)$, v is the propagation velocity through a real medium, x_s and y_s are unknown source coordinates, and M is the total number of sensors in the sensor network. Such systems in general do not need to have a unique solution. To implement network localization algorithms (1), when sensor elements are distant from each other, intersensor communication is necessary. The amount of information that has to be transmitted among sensors or network nodes determines the practical realization of the network, and hence topology of sensor networks. The fusion center has available all information necessary to formulate and solve systems of equations (1).

To preserve energy in ad hoc sensor networks, the passive sensors are predominant. Thus, passive localization of seismic sources utilizes passive vibration sensors-geophones. The source localization 2D problem can be solved by processing of signals from at least three sensors. However, it is demonstrated that simultaneous processing of signals from more than three sensors can improve the source localization [20]. In such a case, redundant parameters for source localization are obtained. To perform reliable localization with distributed sensor networks it is necessary to consider differential time delay between local sensor subarrays [14]. In fact, this means that the system (1) is expanded by equations originating from the phase difference equality conditions in sensor subarrays:

$$\cos(\varphi_h) = \frac{x_s - x_h}{[(x_s - x_h)^2 + (y_s - y_h)^2]^{\frac{1}{2}}}, \quad h = 1, 2, \dots, M \quad (2)$$

$$\sin(\varphi_h) = \frac{y_s - y_h}{[(x_s - x_h)^2 + (y_s - y_h)^2]^{\frac{1}{2}}}, \quad h = 1, 2, \dots, M. \quad (3)$$

φ_h is the angle of arrival of the signal to the h -th sensor subarray. Such condition is usually realized by transmission of complete sensor signals of the referent sensors from local sensor subarrays through existing communication channels. In the fusion center, the cross-correlation functions between referent local sensors are computed and differential delay $D_{g,h}$ between referent sensors of the local sensor subarrays is computed. Such an approach to improve the reliability of localization requires intensive utilization of communication resources and hence significantly increased energy consumption requirements of the sensor network. Using a novel FPT to determine differential delay between referent sensors, the requirements for transmission of entire signals from referent sensors are eliminated; instead only FP should be transmitted. Such parameters are used at the fusion center to perform simple computations that lead to the estimation of the differential delay between referent sensors of the local sensor network. An important condition that distributed sensor networks should satisfy is time synchronization of each particular sensor with the fusion center. Using the proposed FPT to compute differential delay of signals in sensors, the transmission of acquired signals to the fusion center is avoided. In addition to this very important property of the proposed method, some limitations related to the applications in distributed geophone networks for seismic source localization are considered.

TIME DELAY ESTIMATION (TDE)

The Basics of Cross-Correlation

Consider a signal $s(t)$ originating from remote source and picked up by two sensors in a noisy environment. Assume that $s_1(t)$ and $s_2(t)$ are spatially separated sensors outputs which can be modeled as:

$$s_1(t) = s(t) + n_1(t) \quad (4)$$

$$s_2(t) = as(t + D) + n_2(t), \quad (5)$$

where $s(t)$ is a real source signal and the noises $n_1(t)$ and $n_2(t)$ are real, uncorrelated zero-mean Gaussian random processes. The parameter a is the real attenuation factor and D is the value of differential time delay. The signal $as(t + D)$ is a shifted and scaled version of the signal $s(t)$. The basic approach to estimate the differential time delay is to shift the signal $s_1(t)$ with respect to signal $s_2(t)$, and look for similarities between them. The best match will occur at a shift equal to D . Well known method of determine the differential time delay is to compute the generalized cross-correlation (GCC) function $R_{s_1s_2}(\tau)$ [8]:

$$\hat{R}_{s_1s_2}(\tau) = \int_{-\infty}^{\infty} W(\omega) \hat{G}_{s_1s_2}(\omega) e^{j\omega\tau} d\omega, \quad (6)$$

where $W(\omega)$ is a weight function. Cross power spectra density function $G_{s_1s_2}(\omega)$ can be obtained:

$$\hat{G}_{s_1s_2}(\omega) = \hat{S}_1(\omega) \hat{S}_2^*(\omega)$$

$$\hat{G}_{s_1s_2}(\omega) = a \hat{G}_{ss}(\omega) e^{-j\omega D} + \hat{G}_{n_1n_2}(\omega), \quad (7)$$

where $\hat{G}_{ss}(\omega)$ represents estimated power spectra density of the source signal and * is complex conjugate operator. The argument τ which maximize estimated $\hat{R}_{s_1s_2}(\tau)$ is ideally equal to the time delay D :

$$\hat{D} = \arg \max_{\tau} \left| \hat{R}_{s_1s_2}(\tau) \right|. \quad (8)$$

In order to smooth the estimated cross-correlation function, various weight functions $W(\omega)$ can be used to make possible more accurate estimation of time delay between signals. *ROTH*, *SCOT*, *PHAT*, *ECKART* and *HT* weight function [9] can be used, see Table 1.

Table 1. Weight functions applied in GCC function computation.

Name of technique	Weight function $W(\omega)$
<i>CROSS-CORRELATION</i>	1
<i>ROTH</i>	$\frac{1}{G_{s_1}(\omega)}$ or $\frac{1}{G_{s_2}(\omega)}$
<i>SCOT</i>	$\frac{1}{\sqrt{G_{s_1}(\omega) G_{s_2}(\omega)}}$
<i>PHAT</i>	$\frac{1}{ G_{s_1s_2}(\omega) }$
<i>HT</i>	$\frac{ \gamma_{s_1s_2}^2(\omega) ^2}{ G_{s_1s_2}(\omega) [1 - \gamma_{s_1s_2}^2(\omega) ^2]}$

$\gamma_{s_1s_2}(\omega)$ is coherence between signals (4) and (5):

$$\gamma_{s_1s_2}(\omega) = \frac{G_{s_1s_2}(\omega)}{[G_{s_1s_1}(\omega)G_{s_2s_2}(\omega)]^{\frac{1}{2}}}. \quad (9)$$

Under ideal conditions, it is easy to exactly determine the location of the dominant peak of the cross-correlation function, i.e., to determine differential delay between the signals. The determination of the peak is ambiguity if the observation time for the cross-correlation function is unsatisfactory, especially in cases of small signal/noise ratios (SNR) [17], [22]. When cross-correlation function contains several multiple delays, the extraction of one peak becomes difficult task in practical applications. If the signals have limited length and sources of noise are correlated, the cross-correlation function will not have maximum at $\tau = D$.

The Flipped Cross-Correlation and Flipped Parameter

The classic TDE of non-coherent signal has bias. To solve this problem, we propose an analytic signal with smooth complex envelope. Such complex signals provide ambiguity free TDE [19]. Using a property of analytic signals to have one side spectrum and the fact that cross-spectrum also retains this property, a new flipped cross-correlation (FCC) and flipped parameter technique (FPT) for TDE is developed. For source localization systems where sensor signals can be modeled using Eq. (4), (5), flipped cross-correlation $R_{s_1}^F(\tau)$ can be estimated:

$$\hat{R}_{s_1}^F(\tau) = \int_{-\infty}^{\infty} \hat{G}_{s_1s_1}^F(\omega) e^{j\omega\tau} d\omega, \quad (10)$$

where $G_{s_1s_1}^F(\omega)$ represents flipped cross-spectrum and can be estimated:

$$\hat{G}_{s_1 s_1^F}^F(\omega) = \hat{S}_1(\omega) \hat{S}_1^{F*}(\omega). \quad (11)$$

$S_1(\omega)$ is Fourier transform of signal $s_1(t)$ and $\hat{S}_1^F(\omega)$ is Fourier transform of synthetic signal $s_1^F(t)$ estimated for virtual sensor associated to the real sensor:

$$s_1^F(t) = s_1^A(T-t), \quad (12)$$

where T is an observation period and $s_1^A(t)$ is an analytic signal [14]:

$$s_1^A(t) = s_1(t) + jH[s_1(t)]. \quad (13)$$

Here, $H[\bullet]$ is a Hilbert transform and $j = \sqrt{-1}$ is imaginary unit. The analytic signal $s_1^A(t)$ represents a complex signal obtained as a result of the Hilbert transform applied on the real signal $s_1(t)$. Thus, the synthetic complex analytic signal $s_1^A(t)$ has *one-side* Fourier transform, and negative frequencies of the spectrum are identical to zero [23]. The virtual signal $s_1^F(t)$ has smoothed complex envelope and flipped correlation function.

The flipped parameter of i -th sensor, DF_i (delay flipped), for observation period T , is computed according to the following expression:

$$DF_i = \arg \max_{\tau} \left| \hat{R}_{s_i}^F(\tau) \right|, \quad i = 1, 2, \dots, M. \quad (14)$$

The flipped parameter DF_i , corresponds to a differential delay between a real sensor signal $s_i(t)$ and the virtual analytic flipped sensor signal $s_i^F(t)$.

In this paper, we propose a novel method for the computation of differential delays. This is achieved based on estimated values of FP. The differential delays can be computed by directly applying the following expression:

$$D_{ij} = \frac{1}{2}(DF_i - DF_j), \quad i, j = 1, 2, \dots, M \quad (15)$$

where DF_k , $k = 1, 2, \dots, M$ are flipped parameters of k -th sensor for the observation period.

In Fig. 1, the waveforms of real and imaginary parts of an analytic synthetic signal and the flipped signal of the virtual sensor realized according to (12), (13) are shown. As can be seen from a definition of the flipped signal, (12), the complex analytic signal of the virtual sensor $s_1^F(t)$ is formed by inverting and shift signal $s_1^A(t)$ within the observation window T . A cross-correlation of such formed signal pair $s_1(t)$ and $s_1^F(t)$ is basis of the FPT.

For a signal defined by (4) and (5), flipped cross-correlations $R_{s_1}^F(\tau)$ and $R_{s_2}^F(\tau)$ can be computed. According to the definition (10), for each sensor in the sensor array, FCC in the observation period can be determined. Smooth complex envelope of the analytic signal $s_1(t)$ from Fig. 1 and the corresponding flipped correlation function $R_{s_1}^F(\tau)$ are shown in Fig 2.

We have shown that virtual sensor signals are formed based on their real counterparts, Eq. (13), which makes the FPT very suitable for source localization applications in sensor networks with limited energy resources.

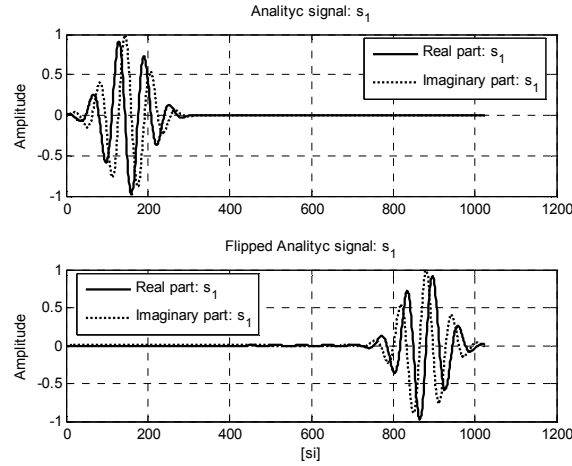


Fig. 1. Analytic and flipped signals corresponding to the same sensor.

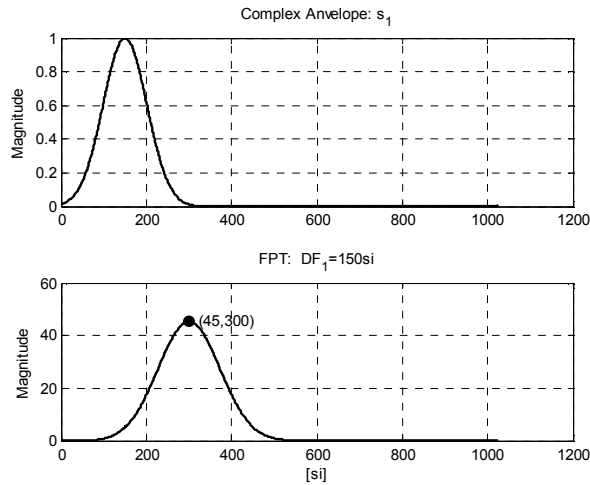


Fig. 2. The complex envelope of the analytical signal and cross-correlation function of the analytic signal and the flipped signal from Fig. 1, where the peak location corresponds to the flipped parameter value of $DF_1 = 150\text{si}$.

A main advantage of this method is the fact that computation of the differential delay requires only knowledge of the flipped parameter values DF_k $k = 1, 2, \dots, M$. From the point of sensor network source localization, it is necessary that sensor modules compute their flipped parameters during the observation period and communicate them to the local

processor or fusion center. The amount of data to be transmitted is significantly reduced than in case of *all pairs* or pairwise algorithms [14]. As a consequence, the usage of the communication modules is reduced and the power consumption of the entire distributed sensor network decreases. The fusion center determined the useful pairs of sensors and computes differential delays of signals according to Eq. (15). After the computation of the numerical expression for the differential delays D_{ij} , the algorithms at the fusion center are identical for all two-step methods of the source localization and are based on expressions from [7], [8], [10], [13] and [14].

In literature, the quality of TDE is usually assessed by the estimation of the error variance in the presence of different noise levels and computation of the CRB boundary. The graph of the TDE error variance for GCC and the proposed FPT method is given in the section 4. The conditions under which the proposed FPT method gives results comparable to the GCC are also presented in section 4.

SIMULATION EXAMPLES

The simulated signals

To study in more details characteristics of the proposed FPT estimator we modeled seismic signals. Golden [24] has studied the complex signals with amplitude and phase functions varying in time. Such modeling has found applications in various fields including seismic signal processing. The results of the simulated signals are confirmed on geophone signals from real-life acquisition. An example of the waveform of realistic geophone signals from three spatially distant sensors is given in Fig. 3. The waveform of the complex seismic signal can be approximately represented by a complex polynomial:

$$s(t) = \exp\left(a_0 + a_1 t + a_2 \frac{t^2}{2!} + \dots + a_k \frac{t^k}{k!}\right) \quad a_i \in C, \quad i = 0, 1, \dots, k. \quad (16)$$

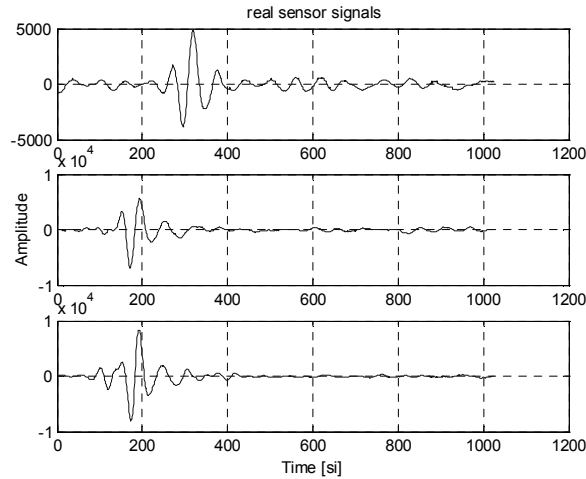


Fig. 3. Real experimental sensor signals (geophone signals) obtained from three spatially distant sensors in a distributed sensor network.

With seismic signals defined this way, the real parts of coefficients of the polynomial define the signal envelope, while the imaginary parts specify the signal phase. In our paper we apply the simplified analytic signal based on second degree polynomial in the exponent, as follows:

$$s_i(t, \tau_i) = \exp(j\omega_0 t) \cdot \exp[-\alpha(t - \tau_i)^2] \quad (17)$$

where s_i is simulated analytic signal of i -th sensor, $i = 1, 2, 3, \dots, M$ is the sensor identified, τ_i is absolute delay with respect to the origin in time ($t = 0$) and α is a real parameter defining the bandwidth. By comparison of eq. (16) and (17) the complex coefficients values as follows: $a_0 = 0$, $a_1 = 0 + j\omega_0$, $a_2 = -2\alpha + 0j$. By varying parameters α , ω_0 and τ_i it is possible to determine the bandwidth, signal center frequency and the differential delay between the simulated analytic signals. The pre-specified simulated differential delay $D_{i+1,i}$:

$$D_{i+1,i} = \tau_{i+1} - \tau_i \quad (18)$$

is to be determined using the proposed technique based on the analytic signal. In this paper, the results are compared using the classic GCC method and proposed FPT method. The estimation of pre-specified differential delay $D_{i+1,i}$ between signals $s_{i+1}(t)$ and $s_i(t)$ is performed using the GCC and FPT described in Section 2. The window function from eq. (6) is defined as: $W(\omega) = 1$. The simulated synthetic signal is sampled at $f_s = 1\text{kHz}$, the observation window with is 1024 sampling intervals, whereas the bandwidth is defined by $\alpha = 200$.

The experiment setup

In simulation examples provided in this section, the source location is determined using a non-parametric two-step CIRCLE method in a normalized sensor space [10]. The simulated sensor space is normalized with respect to measured wave propagation velocity throughout the real medium and to the distances between sensors. Sensors S1, S2 and S3, that are referent sensors of local subarrays of the distributed sensor network, are located in vertices of the equilateral triangle with a normalized parameter of intersensor distance equal to 1. Let the location of sensor S1 be at the origin of the rectangular coordinate system x - y and let the sensor S2 be located on the x axes. The coordinates of the sensors are: S1 (0, 0), S2 (1, 0) and S3 (0.5, $\sqrt{3}/2$). In such defined distributed sensor network, the simulation experiment is repeated $K=1000$ times with a normalized location of the excitation $x_s = 0.2$ and $y_s = 0.2$, M (0.2, 0.2), and pre-defined signal noise ratios $\text{SNR}=8\text{dB}$ and $\text{SNR}=5\text{dB}$. $\text{SNR}[\text{dB}]$ is defined as:

$$\text{SNR}[\text{dB}] = 10 \log_{10} \left(\frac{P_s}{P_n} \right), \quad (19)$$

where P_s is power of signal and P_n is power of Gaussian noise in the observation period.

Based on known locations of sensors and the signal source and the normalized wave propagation velocity, analytic sensor signals are modeled according to eq. (17) with pre-defined differential delays $D_{i+1,i}$ (18). Differential delay of sensor signals between particular sensors is determined on the following three ways: using classic GCC method, for methods applied on real signals - Real GCC, with complex signals - using Complex GCC and FPT.

The error variance of TDE

The signal parameters: central frequency (ω_0), signal bandwidth ($\Delta\omega$), SNR as well as the observation interval T also influence the accuracy of TDE [21], [22]. In this part of the section, we discuss the influence of SNR on the error variance when TDE is performed by a classic GCC method realized with real and analytic signals and for the FPT method. The error variance for these methods is shown in Fig. 4 as function of SNR. The simulated graphs are obtained for the following signal parameters (17): central frequency $f_0 = 16\text{Hz}$, bandwidth specified by $\alpha = 200$, $\tau_1 = \tau_2 = 150\text{si}$ and sampling frequency $f_s = 1\text{kHz}$. The observation interval has a length of $N = 1024$ sampling intervals.

From Fig. 4, one can observe that for medium SNR (from 5dB to 10dB) and low SNR (from -5dB to 5dB), GCC and FPT methods have almost identical error variance. This indicates an advantage of FPT application in distributed sensor networks, due to reduction of the data that should be transmitted. Hence, CRB and Barankin boundaries for these SNR ranges for both methods overlap. Therefore, TDE can be computed using the FPT method with the same reliability as using the GCC method. Furthermore, the error variance graph of FPT is even below the graph of the GCC method, so that the error variance of the FPT method is slightly smaller.

The error variance of the differential delay is smaller when the complex signals envelope and FPT method is used, if the noise power is high. Such conditions occur when signals are received on very distant sensors and correspond to the assumptions of our simulations.

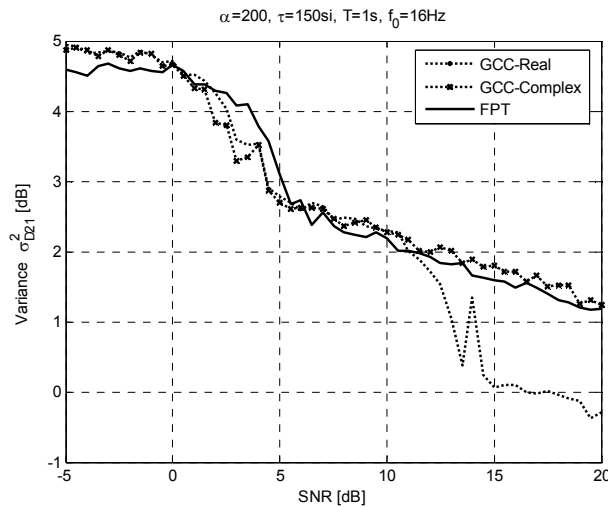


Fig. 4. Error variance of TDE for GCC and FPT methods as function of SNR .

However, when SNR is high, GCC on real signals has smaller error variance than the proposed FPT method, but on the other hand requires signal transmission to the estimator. Such a requirement implies additional energy for communication needs.

The simulation results

On the Figures 5-7, we will show the distribution of estimated source localizations for the three considered methods. Such obtained sets determine the ellipse of source localization error. The known location M of the source, $x_s = 0.2$ and $y_s = 0.2$ is denoted by square, while the estimated locations in the simulation experiments are denoted by crosses. Figures 5-7 display results of the localization obtained with Real GCC, Complex GCC and FPT used to determine differential delay.

Fig. 5 displays results of the localization obtained when Real GCC technique is used to determine differential delay. From Fig. 5, we can see that the estimated locations fit into several regions-clusters, which is drawback of the method. Moreover, each cluster is bounded by its own ellipse of error. The correct location is somewhere between the centroids of the clusters, as it can be seen from Fig. 5. The source localization for SNR=8dB is shown in Fig. 5a, while the localization for SNR=5dB is shown in Fig. 5b. Comparing Figs. 5a and 5b, once can observe the expected result that the range of obtained source locations for SNR=5dB is much larger than for SNR=8dB.

Fig. 6. shows the results obtained using the Complex GCC technique to determine differential delays. Now, the estimated locations form a single cluster, and the ellipse of the localization error are observable. The correct location is within the region defined by the ellipse. The ellipses defined by the localization errors for SNR=8dB and SNR=5dB are shown in Figs. 6a and 6b, respectively. Of course, the smaller SNR, the smaller axes of the ellipse. Comparing the error ellipses in Figs. 5, 6, one can observe that the ellipses in Fig. 6 are smaller than the ellipses in Fig. 5. Hence, it is evident that the overall variance of the error is smaller in Fig. 6. and that the x and y components of the location error are dependent.

Fig. 7. illustrates the set of estimated locations using the FPT, for the same experimental parameters as in Fig. 5 and Fig. 6. The shape of the ellipse of the source location errors is now closer to the circular, with the center corresponding to the true location. These experiments suggest that the flipped parameter technique *decorrelates* location errors in x and y directions. The radius of the circle is directly dependent to SNR. Also, from Fig. 7a (SNR=8dB) it can be observed that the radius of the error localization is smaller than the error localization radius in Fig. 7b (SNR=5dB).

We present mean square errors of the localization obtained using simulated real and complex analytic signals. Obtained values of the mean squared error of localization and its standard deviation are shown on Table 2.

Table 2. Mean square localization errors and its standard deviation for considered methods and assumed true location of the source $M(0.2, 0.2)$ and SNR=5dB.

$M(0.2, 0.2)$	GCC Real	GCC Complex	FPT
MSE	0.15661	0.05911	0.04976
σ_{MSE}	0.03652	0.03438	0.02525

Here, the mean squared error of localization, MSE, is determined as:

$$MSE = \frac{1}{L} \sum_{i=1}^L (\Delta x_i^2 + \Delta y_i^2). \quad (20)$$

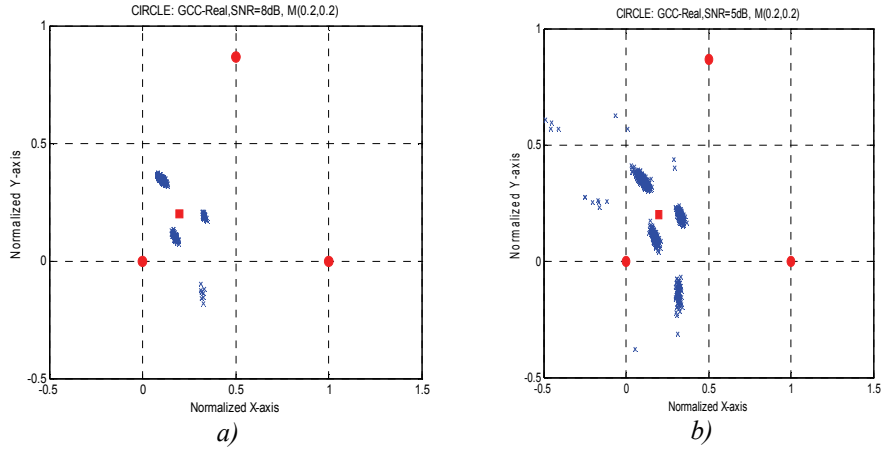


Fig. 5. Localization using the CIRCLE method based on classic GCC-Real technique to determine differential delays of real signals: a) SNR=8dB b) SNR=5dB.

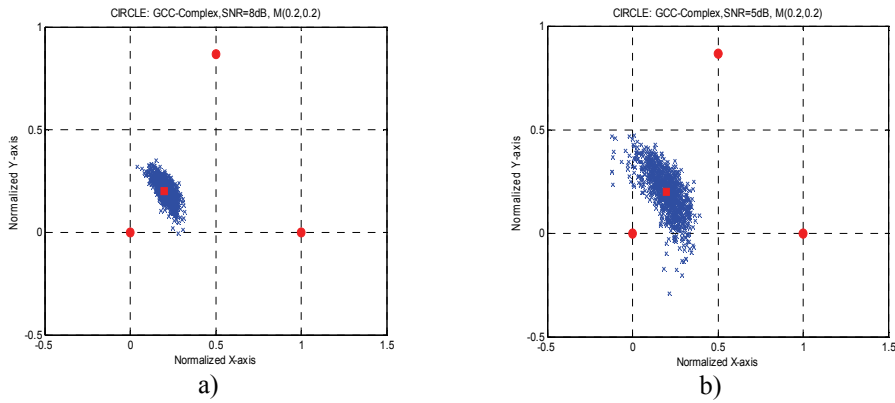


Fig. 6. Localization using the CIRCLE method based on GCC-Complex technique to determine differential delays of analytic signals: a) SNR=8dB b) SNR=5dB.

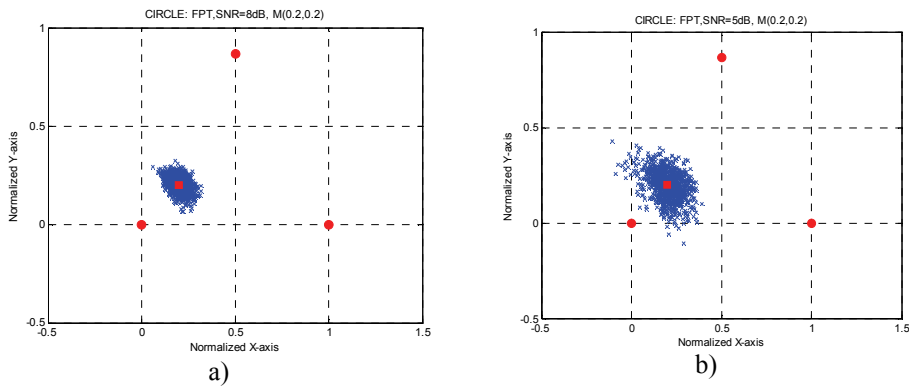


Fig. 7. Localization using the CIRCLE method based on FPT to determine differential delays of analytic complex signal: a) SNR=8dB b) SNR=5dB.

$\Delta x_l = x_s - x_l$ and $\Delta y_l = y_s - y_l$ are absolute errors of localizations along x and y directions, $l = 1, 2, \dots, L$ and L is number of simulations. As it can be seen from the Table 2, the flipped parameter method, in addition to energy savings to a distributed sensor network, also provides the smallest MSE in comparison to other considered methods, Real GCC and Complex GCC. Also, FPT has the smallest value of the standard deviation.

Fig. 8 shows dependences of average x coordinate of the estimated locations (x_s, y_s) when SNR increases, for all three considered techniques - Real GCC, Complex GCC and FPT. In these experiments, the true location of the source was $x_s = 0.35$ and $y_s = 0.35$, $M(0.35, 0.35)$, and SNR took values from the [5dB, 15dB] range. From Fig. 8 it can be observed that the average estimated coordinates converged to the true values when SNR increases, for both Complex GCC and FPT. The GCC Real technique converges with SNR, but the estimate stays biased. Bias appears as a consequence of the GCC real method sensitivity on non-coherent processing of the sensor signal.

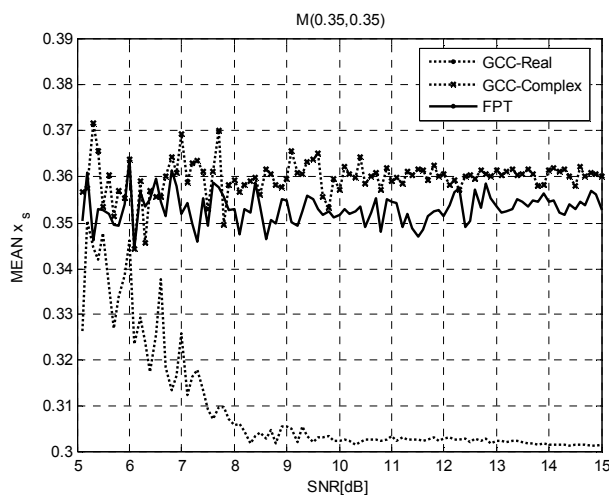


Fig. 8. Averages of the estimated x coordinate of the source location as function of SNR. For Complex GCC and FPT, these average values converge to the true coordinate of the source ($x_s = 0.35$) when SNR increases. The average x coordinate obtained by classic Real GCC procedure converges faster but remains biased with respect to the true coordinate value.

CONCLUSION

In this paper, we propose original flipped correlation and flipped parameter technique for estimation of differential delay among signals. We propose a FLIPPED parameter, computed at each sensor, solely based on the signal received from the sensor.

This way, instead of transmitting the entire sensor signal to the local processor or to the diffusion center, only the FLIPPED parameter needs to be transmitted. This parameter carries the differential delay information. Hence, using FLIPPED parameters from all the sensors, it is possible to perform source localization using two-step methods. The flipped

parameter technique could further improve efficiency of the source localization if implemented in sensor networks with local intelligence.

We compare applications of classic Real GCC, Complex GCC and FPT to perform source localization in presence of noise. The obtained results indicate that FPT has advantages in comparison to other methods and that can result with the smallest estimation errors when the noise is present. Using a set of flipped parameters D_i , $i = 1, 2, \dots, M$ for the same signal source in the sensor field, differential delay $DF_{r,k}$ between signals received at the r -th and k -th sensors can be computed directly. To compute differential delays between a given, r -th sensor, and other sensors, only $M-1$ elementary operations (differences) are necessary. Unlike classic GCC methods that require computation of $M(M-1)$ cross-correlations, the proposed FPT can determine all differential delays using only M cross-correlation functions.

For real-time systems, we envision usage of specialized digital signal processors with implemented flipped parameter technique. In distributed sensor networks, the FPT provides energy consumption savings. In practice, instead of transmitting a set of acquired sensor signals, only the transmission of the flipped parameters from an excited sensor subarray is needed. The application of the FPT may be dominant in geophysics, SONAR technology and ultrasound diagnostics.

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APLIKACIJA FLIPPED PARAMETAR TEHNIKE NA LOKALIZACIJU IZVORA U ENERGETSKI OGRANIČENIM SENZORSKIM MREŽAMA

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U ovom radu je prezentovana nova FPT tehnika za izračunavanje vremenskog kašnjenja signala primenjena u lokalizaciji izvora. Predložena tehnika za pasivnu lokalizaciju izvora je bazirana na razvoju energetski efikasnog algoritma za redukciju međusenzorske i međumrežne komunikacije. FP parametar koji je u osnovi FPT tehnike može se odrediti za svaki senzor u distribuiranoj senzorskoj mreži u opservacionom periodu. Za razliku od klasičnih TDE metoda koje se baziraju na izračunavanju kros-korelacione funkcije, FPT zahteva izračunavanje zasnovano samo na signalu iz jednog senzora. Izračunavanjem glatke kros-korelacione funkcije između signala sa senzora i njegovog analitičkog flipped para dobija se jasno izražen pik koji pouzdano određuje vremensko kašnjenje. Pomoću FP parametara mogu se odrediti sva diferencijalna kašnjenja signala u odnosu na isti izvor. FPT se može uspešno primeniti u dvokoračnim metodama pasivne mrežne lokalizacije i u poređenju sa klasičnim kros-korelacionim metodama zahteva znatno manje energije. Primena FPT metode je posebno značajna kod energetski zavisnih distribuiranih senzorskih mreža. Koristeći računarski generisane seizmičke signale ilustrovana je greška lokalizacije za klasičan i preporučeni metod u prisustvu šuma. Prikazana je prednost preporučene metode u prisustvu šuma u odnosu na klasičnu koja koristi realne signale. Prezentovana FPT metoda pokazuje bolje rezultate i u slučaju koherentnih i nekoherentnih signala.