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Adaptive window bandwidth selection for direction of arrival estimation of uniform velocity moving targets based relative intersection confidence interval technique

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Abstract The local polynomial approximation (LPA) beamformer is known to have outstanding statistical performance. It can be used for Direction of arrival (DOA) estimation and localizes rapidly moving targets. However, its fixed window makes it unable to track varying target scenarios, besides the high computational time associated with the LPA based intersection confidence interval (ICI). Thus, this paper proposed a DOA estimation of moving targets based on the relative intersection of the confidence interval (RICI) rule to improve the computational efficiency to track varied target scenarios. Endow with comparisons, the proposed method surpasses those based on the original ICI rule in terms of the efficiency and computational time. In addition, it demonstrates the effective performance of the LPA combined with the RICI to accurately localize the moving targets, as the divergence between the actual and the estimated angle or angular velocity values provides −4 dB and −12 dB SNR; respectively.
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1. Introduction

Localization and tracking of multiple narrowband moving sources are one of the fundamental problems in radar [1], communication [2], sonar [3], seismology [4], strategy of defense operation, etc. Besides the increased insist on the wireless technology service has spread in areas such as, sensor network, environmental monitoring, and mobile in smart antenna. With smart antenna technology, DOA estimation algorithm is usually integrated to develop systems that provide accurate

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location. The DOA algorithms can be considered as one branch of array signal processing [5]. Generally, the popular approaches for DOA estimation can be categorized into three groups: beamforming methods, time-delay based methods, and signal subspace methods. However, the bulk of the DOA estimation algorithms was expanded under convinced assumptions such as, stationary and uncorrelated source signal, adequate number of snapshots, and high signal to noise ratio (SNR). Basically, these conditions are hardly satisfied; thus, these methods attain the imperfect DOA estimation accuracy. Different algorithms are presented to solve the problem of DOA [6,7], such as Beam forming, ESPRIT [8], Maximum likelihood (ML) algorithm [9], subspace methods, Multiple SIgnal Classification (MUSIC) [10], and Eigenvector method (EV) [11], Local polynomial approximation (LPA) [12], etc.

For stationary targets, the model parameters are constant in the entire time domain. As a result, accurate parameter estimation is achieved with large observation data amount. This is not valid at the time-varying target case as the use of more observation data does not always achieve accurate parameter estimates, since the model parameters are neither constant nor varying in a predictable way. In order to augment the DOA estimation accuracy, various algorithms are developed to deal with non-stationary sources.

Commonly, for function approximation methods there are two foremost categories which are as follows:

(i) Parametric models (linear/non-linear): These presume that the primary structure of the data is known a priori, such as the parametric regression techniques [13].
(ii) Nonparametric models: These use the raw data to construct the local approximations of the function, generating a flexible data-exhaustive. The nonparametric models do not assume a precise structure of the underlying data. Examples of the nonparametric techniques are as follows:
   - A histogram: It is a simple nonparametric estimate of a probability distribution.
   - Kernel density estimation [14]: It provides better estimates of the density than histograms.
   - Data envelopment analysis [15]: It grants efficiency coefficients exclusive of any distributional assumption.
   - Nonparametric regression and semi-parametric regression [16]: These are methods based on wavelets [17], kernels, and splines [18].

Therefore, the nonparametric models produce a more accurate approximation [19] and less sensitivity to structural errors arising from a parametric model. They require continuous tracking of all the observed data values.

Since, the problem of moving source localization has been critical to several imperative applications of array processing that depends on DOA estimation. Among these approaches the local polynomial approximation method can probably be treated as one of the most theoretically justified for moving targets tracking [20]. It is a powerful nonparametric technique that provides estimates in a point-wise manner based on a mean square polynomial fitting in a sliding window called also bandwidth, width or scale. The window size of this fit is one of the LPA estimator key-parameters. The LPA window width can be realized as a scale parameter of the estimation. Since, the optimal scale is distinct by a compromise between the bias and variance of estimation, the problem of the optimal scale selection can be considered as a mathematical formulation in terms of the nonparametric approach. The estimation objective is to determine estimated values close to the true values with minimizing the estimation error. In noisy environments, the estimation quality is degraded due to the unavoidable bias and variance. However, the variance is usually inversely proportional to the bias of the biased estimators, where

- The bias is defined as the error results from erroneous assumptions in the learning algorithm.
- The variance is the error from sensitivity to small instability in the training set (sensitive to noise).

Ideally, it is required to choose a model that guarantees both:

(i) Accurately capture and rapid track sources (bias small).
(ii) Be less sensitive to noise (variance small).

Typically, achieving both requirements simultaneously is unfortunately impossible. Therefore, a bias-to-variance trade-off that guarantees minimal mean squared error (MSE) is to be calculated as a sum of the squared bias and the variance [21]. Vast researches deal with the bias/variance trade-off as in the case of the Nadaraya–Watson (local polynomial of degree zero), where the amount of smoothing is organized by selecting a suitable bandwidth. Smoothing via local polynomials was mentioned in [22]. Local polynomial regression, engages fitting the response to a polynomial via locally weighted least squares is an extension of the local mean smoothing of the Nadaraya–Watson. Local polynomials of higher order have better bias properties and do not require bias adjustment at the boundary of the regression space compared with the Nadaraya–Watson estimator.

In [23,24], the LPA is used for direction of arrival estimation for non-stationary sources. In numerous practical source tracking applications, the interval of the source stationarity may vary with time, so that array observations may contain both almost stationary data intervals and non-stationary data intervals with rapidly moving sources. Moreover, distinctive situations may occur where a number of sources move rapidly within the window exploited, whereas the motion of the other sources is weak. In such scenarios, the traditional fixed-window approach appears to be non-optimal as it leads to a very poor tracking performance [25]. Thus, the localization of the estimation is ensured by an adaptive sliding window. The Lepski's approach [26], is based on the stability of the estimates as it selects the best estimator under suitable restrictions. It searches for the largest local position of the point of estimation at which the observation model hypothesis fit well to the data for the adaptive/varying size neighborhood selection. One of the most well performed methods that belong to the class of Lepski's algorithms is the intersection confidence interval (ICI) rule [27]. This rule can be used to determine the optimal window size according to the moving source scenario.

Consequently, for DOA estimation, the LPA estimator is combined with the ICI adaptive data-driven scale procedure as presented in [28]. The estimates of the DOA as well as the target velocity and/or acceleration are estimated for a few window sizes and compared. The largest window in the set that provides an estimate which does not differ significantly from the estimates corresponding to the smaller window sizes, is considered as the optimal window size. It was proved that, the LPA-ICI algorithm gave near optimal window length for non-stationary targets, where, the minimal mean squared error (MSE) was calculated as a sum of the squared bias and the variance [22]. The estimated mean-square error (MSE) obtained by the LPA-ICI method is smaller than that obtained using the original LPA. However, the LPA-ICI has its drawbacks as follows:

(i) Requires high computational cost.
(ii) Depends on the variance and the threshold parameter to solve the bias-to-variance trade-off balance.

Consequently, this paper is concerned with the effective DOA estimation using the local polynomial approximation algorithm supported by the relative intersection confidence interval (RICI) method that deals with adaptive window size. Using LPA based RICI provides further development of the LPA-ICI beamformer, where, the RICI is originally proposed and used in [29] for de-noising and outperforms the ICI.

The paper is organized as follows. The signal model and the original LPA-ICI method for direction of arrival estimation are briefly presented in the next section. Section 3, describes the LPA-RICI method. The results and discussion are given in Section 4, while the Conclusion and future work are presented in Section 5.

2. The LPA-ICI method for direction of arrival estimation

2.1. Signal model

Consider a uniform linear array (ULA) of z sensors and receives u narrowband signals imposed from unknown time-varying source directions $\{\theta_i(t)\}_{i=1}^{u}$, where, the sources are moving with uniform velocities. The observation $z \times 1$ vector, can be modeled as

$$Y(t) = S(t)X(t) + n(t) \tag{1}$$

where
$X(t)$ is the vector of the source waveforms,
$n(t)$ is the vector of sensor noise,
$S(t)$ is the $z \times u$ time-varying steering matrix, which consists of u steering vectors.

$$L(\theta) = \left[1, \exp\left(-j\frac{2\pi}{\lambda} d \sin\theta\right), \ldots, \exp\left(-j(z-1)\frac{2\pi}{\lambda} d \sin\theta\right)\right]^T \tag{2}$$

Here, d is the inter-element spacing, and λ is the signal wavelength.

2.2. LPA beamformer estimator

Using Taylor series to model the source motion θ within the observation interval is as follows:

$$\begin{aligned}\theta(t+kT) &= \theta(t) + \theta^{(1)}(t)(kT) + \tfrac{\theta^{(2)}(t)}{2}(kT)^2 + \tfrac{\theta^{(3)}(t)}{6}(kT)^3 + \ldots \\ &= p_{0e} + p_{1e}kT + p_{2e}(kT)^2 + p_{3e}(kT)^3 + \ldots\end{aligned} \tag{3}$$

A part of the Taylor series is to be used to approximate the time-varying DOA for moving targets with uniform velocity and neglect the acceleration or decelerations term (2nd term) and the other higher terms than the 2nd one to get the instantaneous source DOA angle $\theta(t)$ and angular velocity $\theta^{(1)}(t)$ as, $\theta(t + kT) = p_{0e} + p_{1e}kT$, where, T is the sampling interval and

$$p_{0e} = \theta(t), \quad p_{1e} = \theta^{(1)}(t) \tag{4}$$

The problem is to find the estimate of the vector $P = (p_0, p_1)$.

In order to estimate the source motion parameters, the weighted local polynomial approximation (LPA) of time-varying direction-of-arrival is exploited as a beamformer for localization of the moving sources. This technique can be considered as a non-stationary extension of the Capon minimum variance beamformer [30]. It belongs to the class of high-resolution adaptive methods. Thus, the windowed LPA of the time-varying DOA is developed for nonparametric high-resolution estimation of multiple moving sources. This method gives the estimates of instantaneous values of the directions as well as their first derivatives. The asymptotic variance and bias of these estimates are derived and used for the optimal window size selection. This beamformer is able to localize and track every source individually, nulling signals from all other moving sources. Recursive implementation of the estimation algorithms is developed for estimation of DOAs with varying number of sources and multiple sources tracking in time.

By minimizing the loss function of the LPA with respect to the unknown deterministic waveform $s(t + kT)$ in order to estimate the angle and the angular velocity it is obtained that:

$$G(t,P) = \frac{1}{z\sum_k \beta_q(kT)} \sum_k \beta_q(kT) \left\{ Y^H(t+kT)Y(t+kT) - \frac{|L^H(P,kT)Y(t+kT)|^2}{z} \right\} \tag{5}$$

Since only the second term in Eq. (5) depends on P, the minimization of $G(t, P)$ is equivalent to the maximization of the LPA beamformer function based on the weighted least squares approach [31] as follows:

$$V(t,\mathbf{c}) = \frac{1}{z\sum_k \beta_q(kT)} \sum_k \beta_q(kT) \left|L^H(P,kT)Y(t+kT)\right|^2 \tag{6}$$

The maximization of this function requires 2-D search over p_0 and p_1, where, $\beta_q(kT) = \left(\frac{T}{q}\right)\beta\left(\frac{kT}{q}\right)$ is the window function, and q is the window width (scale).

The window length is considered as a critical parameter in the efficiency of the local estimators where,

- In noiseless case, the scale should be selected as small as possible since a smaller scale means a smaller bias.
- While, in the presence of noise the scale should be increased in order to suppress noise effects.
- If the target is slowly moving, this requires a large window size (scale).
- Fast target motion requires small window size.

Consequently, the original LPA using fixed window width is incapable to track changeable environment and/or target trajectories. However, the LPA-ICI algorithm combines the adaptive multiple window tracker to support the LPA algorithm. The adaptive-window selection procedure is based on the approximate minimization of the mean squared estimation error using the bias-to-variance trade-off approach. Therefore, using the ICI rule enhances the DOA tracking of any moving targets by selecting the appropriate window length to the environment.

2.3. Intersection confidence interval method

The ICI method is used to track the motion within an adaptive sliding window. The adaptive-window selection procedure is based on the approximate minimization of the mean squared estimation error in Eq. (7), using the bias-to-variance trade-off approach.

$$\Delta P = (\Delta P_0, \Delta P_1)^T = \hat{P} - P \tag{7}$$

$\hat{P}$ represents the estimate of the parameters in Eq. (5) obtained via the maximization of the LPA-beamforming function Eq. (6).

In order to characterize the accuracy of the estimates, the bias and variance are clearly defined as follows [32]:

(i) The bias, $\Pi = (\Pi_0, \Pi_1)^T$, which is defined as, $\Pi = \text{bias}\{\Delta P\} = E\{\hat{P}\} - E\{P\}$

where

$$\Pi_0 = E\{\Delta P_0\} = E\{\Delta\theta\}, \quad \Pi_1 = E\{\Delta P_1\} = E\{\Delta\theta^{(1)}\} \tag{8}$$

(ii) The variance is defined as

$$\Omega\{\Delta P\} = E\{(\Delta P - E\{\Delta P\})^2\} \tag{9}$$

Afterward, the optimal window width q^* is computed through minimizing the mean square error (MSE) between the true and estimated vectors, with respect to q:

$$\text{MSE}\{\Delta P\} = E\{(\hat{P} - P)^2\} = \Pi^2 + \Omega\{\Delta P\} \tag{10}$$

The ICI rule [33], decides the optimal bandwidth exclusively via comparing the confidence intervals of the estimates with different bandwidths. Consequently, the key idea of the ICI rule is to find the optimal window length q^* from a set of window lengths,

$$Q = \{q_l\}_{l=1}^{L} = \{q_1 \langle q_2 \langle \ldots \langle q_L\} \tag{11}$$

where the bias squared has the same order of magnitude as the variance,

$$\Xi = \frac{|\Pi|_{opt}}{\sqrt{\Omega_{opt}\{\Delta P\}}} \tag{12}$$

Here, Ξ is the threshold parameter (confidence interval length), and Π and $\Omega_{opt}\{\Delta P\}$ are the bias and the variance of the estimate; respectively. This trade-off requires that the bias squared and the variance have the same order. The threshold parameter Ξ is a natural design parameter of the algorithm, which can be used in order to refine the algorithm and to adjust it to the available observations. Therefore, the threshold parameter in Eq. (12) is used to solve the bias-to-variance trade-off where the bias is in the range of the variance squared.

The confidence interval (CI) is defined as,

$$CI_l = [Lo_l, Ub_l] \quad l = 1, 2, \ldots, L \tag{13}$$

$$Lo_l(q, l) = \hat{P}(q_l) - 2\Xi\sqrt{\Omega(q_l)} \tag{14}$$

$$Ub_l(q, l) = \hat{P}(q_l) + 2\Xi\sqrt{\Omega(q_l)} \tag{15}$$

Lo_l and Ub_l are the lower and upper bounds of the CI. The ICI rule depends on the following states:

(i) For a small value of the window width q, the bias will be small and the CI will gradually decrease with increasing value of q, while the center of the CI remains fixed.
(ii) The window width q is increased to a value where the observations cannot be adequately modeled, where, a large bias will result and the center of the CI will change significantly with respect to the intervals. Accordingly, the CI will no longer intersect those with smaller values of q.

Therefore, the ICI algorithm follows the values of the smallest upper and the largest lower confidence interval limits:

$$\overline{Lo_l}(q, l) = \max_{i=1,\ldots,l} Lo_l \tag{16}$$

$$\underline{Ub_l}(q, l) = \min_{i=1,\ldots,l} Ub_l \tag{17}$$

Then, the intersection of confidence intervals will be stated as [34],

$$I_l = \bigcap_l \text{CI}_l \tag{18}$$

According to the ICI rule, the optimal window q^*, is the largest one followed by empty CI as justified in [33], where no intersection between the intervals will exist at the optimal window width.

The parameter Ξ plays a key role in the appropriate LPA-ICI filter support selection, where:

(i) Too large Ξ, outcomes in signal over-smoothing.
(ii) Too small Ξ, results in signal under-smoothing.
(iii) A reasonable value of Ξ is used to preserve the signal and remove the noise as much as possible.

So, the ICI rule requires threshold parameter adjustment. As a result, the foremost drawback of the ICI rule is its dependence on the threshold parameter Ξ as well as its computational cost. Generally, the exact optimal bandwidth is not included in the bandwidth set Q. These problems can be solved using the relative intersection confidence interval (RICI) [35], as discussed in the next section.

3. Local polynomial approximation based relative intersection confidence interval method for DOA estimation

3.1. RICI concept

The foremost idea of the RICI method is motivated by Stanković [21] that presented the bias-variance trade-off problem and the ICI adaptive bandwidth selection algorithm. Recently, the relative intersection of confidence interval (RICI) rule combined with local polynomial approximation is applied in various applications for signal and image de-noising as demonstrated in [34,35]. As a generalization, this work uses the LPA-RICI for direction of arrival estimation to improve the ICI-LPA performance.

Therefore, from the window values set, the large window that satisfies the following equations will be chosen:

$$\overline{Lo_l}(q,l) \leqslant \underline{Ub_l}(q,l) \tag{19}$$

and

$$R_l(q,l) \geqslant R_c \tag{20}$$

where the parameter R_c is experimentally chosen, as described in [36], and also $R_l(q, l)$ is the ratio of the size of the intersection of all confidence intervals obtained so far and the size of the current confidence interval is as follows:

$$R_l(q) = \frac{(\underline{Ub_l}(q) - \overline{Lo_l(q)})}{Ub_l(q) - Lo_l(q)} = \frac{\underline{Ub_l}(q) - \overline{Lo_l(q)}}{2\Xi\sigma_l(q)} \tag{21}$$

where

$\underline{Ub_l}$ and $\overline{Lo_l}$ are the minimum upper bound and the maximum lower bound; respectively.

$\sigma_l(q)$ is the standard deviation of the estimated signal sample $\hat{P}(q_l)$.

R_l is the additional criteria in the adaptive filter support selection, which has the property that,

$$R_l(q) = \begin{cases} 0 & \bigcap_l \mathrm{CI}_i(q) = \phi \\ 1 & \bigcap_l \mathrm{CI}_i(q) = \mathrm{CI}_l(q) \\ \in \langle 0,1 \rangle & \text{otherwise} \end{cases} \tag{22}$$

So, the RICI is based on the ratio of the ICI length and the current confidence interval length meaning that it takes into consideration the amount of the confidence interval intersection with regard to the confidence interval length, while, the ICI requires only the CIs existence.

When, $q < q^*$, R_l is close to 1, and decreases toward 0 as $q \to q^*$. Therefore, the interval of selecting the optimal R_l is small, which makes it faster and easier than ICI rule. In addition, it is less sensitive to the threshold Ξ selection compared to the ICI rule.

Consequently, the RICI technique has various advantages over the ICI, which are [34–37] as follows:

(i) More sensitive to the transitions exists in the signal waveform, hence directing to a smaller estimation error and providing more accurate estimates.
(ii) Provides an accurate estimation both in terms of the bias and MSE, as it adds more parameters to select the optimal window.
(iii) Tolerates to apply wider CIs while avoiding signals over-smoothing that occurs due to large values of the threshold parameter [36].
(iv) Does not necessitate the knowledge of the optimal parameter Ξ as it depends mainly on the R_c.
(v) Solve the dependence of the ICI on the threshold parameter Ξ by introducing additional criteria, beside the ICI.
(vi) The RICI provides less computational time compared to ICI as the range of R_c is between 0 and 1, which is small range compared to the searching range in the ICI rule which extended to infinity as it depends on Ξ.

3.2. LPA-RICI algorithm for DOA tracking

The proposed algorithm for the adaptive window DOA tracking algorithm using the LPA combined with the RICI can be originated in steps as follows, and illustrated in Fig. 1:

1. Identify a set of window lengths, arranged in ascending order as in Eq. (11).
2. Estimate the target trajectory i.e., direction of arrival parameters ($\theta(t)$, $\theta^{(1)}(t)$), using the LPA beamformer (Eq. (6)) for each window length q_l in the previous set in step 1.
3. Estimate the signal to noise ratio (SNR) for each target as follows:

$$S\hat{N}R_j(t) = \frac{1}{T\hat{\sigma}^2}\sum_{t=0}^{T}\max_j \frac{\left|\left|L^H(P,kT)Y(t+kT)\right|^2\right|}{z^2} \tag{23}$$

4. Estimate the variance for each target/window length [38,39] as follows:

$$\Omega_j\{\Delta P_i\} = \frac{6\lambda^2\left(1+\frac{1}{z\mathrm{SNR}_j}\right)}{q^{2i+1}(2\pi d)^2 z(z^2-1)\mathrm{SNR}_j}\Psi \tag{24}$$

where Ψ is a function of the window parameters, and i is the LPA polynomial degree which has the values 0 and 1 in the proposed work.
5. Apply the RICI method using Eqs. (13) and (21) and the estimated variances to get the estimates of the CI intervals which also satisfy the following inequality:

$$\left|\hat{P}(q_l,t) - \hat{P}(q_{l-1},t)\right| \leqslant 2\Xi\left[\sqrt{\Omega_j(q_l,t)} + \sqrt{\Omega_j(q_{l-1},t)}\right] \tag{25}$$

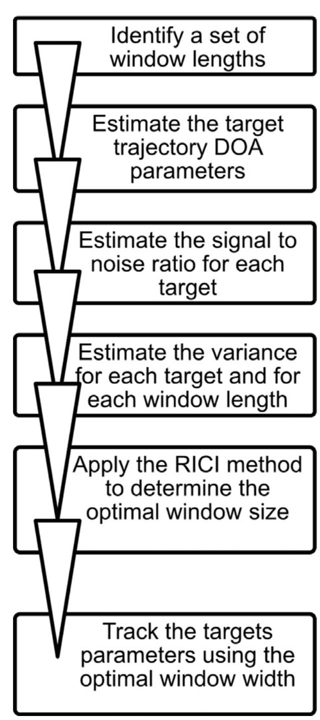

Figure 1 The proposed system steps.

Hence, the optimal window length q^* is obtained for each target location, where, the RICI determines the largest local locality of the point of estimation at which the LPA fits well to the data.
6. Finally, track the target location through applying the obtained optimal windows in the LPA beamformer function.

The experimental results and discussion are introduced in the next section, to clarify the performance of the proposed LPA-RICI algorithm for different scenarios of non-stationary target tracking. In addition, a comparison with the LPA-ICI is conducted.

4. Simulation and results

Through the following experimental process the subsequent assumptions are applied:

1. A ULA (uniform linear array) of ten omnidirectional sensors.
2. Sensors spacing equal half-wavelength.
3. SNR range from 1 till −20 dB for each source.
4. Use first-order LPA (includes the angle and the angular velocity).

The experiment is divided into two parts: first test is the performance of the LPA-RICI proposed method for different scenarios and the second test is to compare the proposed LPA-ICI algorithm and the fixed window LPA.

4.1. Test the LPA-RICI performance for different scenarios for DOA estimation

To test the performance of the proposed method with different targets that is located at the following:

5. source 1: $(\theta(t), \theta^{(1)}(t)) = (0°, 4°/\text{sample})$,
6. source 2: $(\theta(t), \theta^{(1)}(t)) = (0°, 5°/\text{sample})$,
7. source 3: $(\theta(t), \theta^{(1)}(t)) = (0.2°, 4°/\text{sample})$,
8. source 4: $(\theta(t), \theta^{(1)}(t)) = (1°, 15°/\text{sample})$.

It is clear that the first two sources have the same angle $\theta(t)$ and different angular velocities $\theta^{(1)}(t)$ that used to distinguish between them. While, the 1st and 3rd sources have the same angular velocities and can distinguish between them using the very close angle values, at the same time, the 4th source is rapidly moving with different angle and angular velocity values than all the other three sources.

Fig. 2 shows the differences between the actual sources and the estimated angles $\Delta P_0 = \theta(t) - \hat{\theta}(t)$, for different signal to noise ratios. As illustrated in the figure, the LPA-RICI is robust against the SNR changes till about −4 dB for all sources even they are closely spaced.

For the same sources, Fig. 3 indicates the differences between the actual sources and the estimated angular velocity $\Delta P_1 = \theta^{(1)}(t) - \hat{\theta}^{(1)}(t)$, for different signal to noise ratios. As illustrated in the figure, the LPA-RICI is robust against the SNR changes till about −12 dB for all sources even they are closely spaced.

4.2. Comparative study between the LPA-RICI, LPA-ICI, and fixed window LPA

The proposed RICI method is compared to the conventional LPA-ICI method and the fixed window scale LPA beamformer.

For a quantitative comparison of the algorithms, the following criterion [20] is used:

$$\mathrm{RMSE} = \sqrt{\frac{1}{uT}}\sqrt{\sum\nolimits_{t=1}^{T}\sum\nolimits_{j=1}^{u}(\Delta P_j(q))^2} \qquad (26)$$

A comparison is done for different cases as demonstrated in Table 1, where the proposed method using the Adaptive bandwidth selection LPA-RICI with threshold parameter $\Xi = 3$ and $R_c = 0.9$ is compared to the following:

(1) Fixed window LPA algorithm in [38] with window size of $q = 100$ samples.
(2) Adaptive window LPA-ICI: the traditional ICI method introduced in [28] using $\Xi = 1.5$ or 3.

The comparison is performed in terms of the RMSE of the DOA parameters estimation at SNR = −4 dB and 0 dB for different scenarios.

It is clear from the Table 1 that, the LPA beamformer accompanied with the proposed RICI rule achieves better estimation accuracy than both the LPA-ICI method and conventional fixed window LPA for all cases.

In the rapidly moving source case, it is clear that the RICI provides superior performance in terms of the RMSE, where source position, a sequence of the CIs is calculated. Then, the LPA-RICI algorithm tracks the intersection of confidence intervals and the amount of their intersection in order to find the optimal window size for the largest one. The procedure is repeated for each source in the multi-source cases resulting in effectively tracking and distinguishing between the sources, as illustrated in cases 2, 3, and 4.

A performance improvement is achieved in the case of using either the proposed algorithm (LPA-RICI) or the LPA-ICI rule as both of them involve only the knowledge of the noise variance. While, using the conventional LPA requires the estimation of both the variance and the bias, its performance is degraded.

The proposed LPA-RICI method tolerates to select larger Ξ which achieves better estimation accuracy in terms of the root mean square error (RMSE) by selecting the appropriate R_c value. While, using LPA-ICI, a larger Ξ results in wider CIs, so resulting into signal over-smoothing due to the longer window. This problem is solved using the RICI method, which allows using large values of Ξ without over-smoothing.

Generally, Table 1 establishes that, using the proposed RICI method provides optimal window size compared to the LPA-ICI method. In addition, it has outperformed performance than the conventional LPA with fixed window size.

Comparing the LPA-ICI results with different threshold parameter values ($\Xi = 1.5$ or 3) in different situations, it is noted that small Ξ value achieved less improvements than that achieved with $\Xi = 3$.

To evaluate the performances of the proposed method, Table 2 illustrates the improvement ratio achieved in the DOA parameters estimation RMSE using the proposed

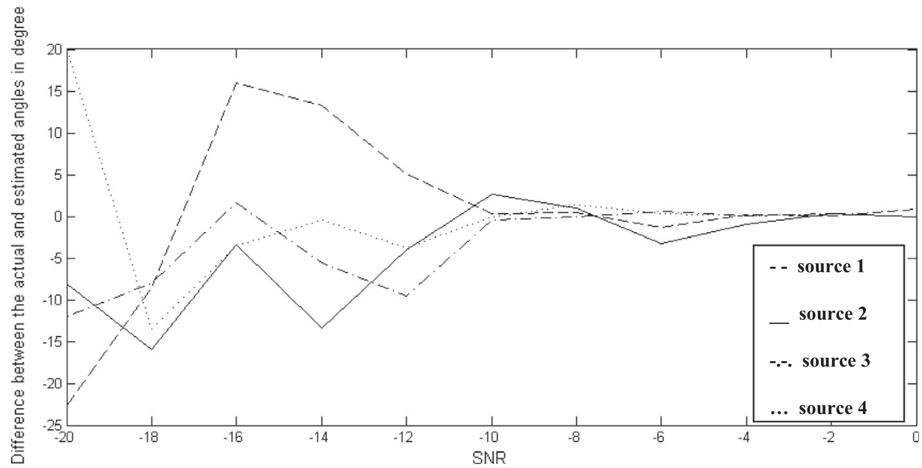

Figure 2 The difference between the actual and the estimated angle values for different targets versus different SNR.

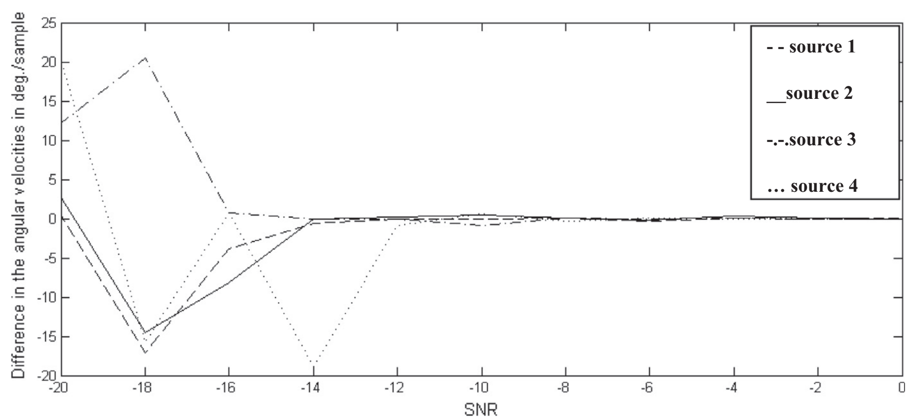

Figure 3 The difference between the actual and the estimated angular values for different targets versus different SNR.

Table 1 RMSE comparison between the LPA-RICI, LPA-ICI, and fixed window LPA at SNR = −4 dB and 0 dB.

Signal to Noise Ratio (SNR) (dB)	Proposed method LPA-RICI $\Xi = 3$ $R_c = 0.9$ (°)	LPA_ICI $\Xi = 1.5$ [28] (°)	LPA-ICI $\Xi = 3$ [28] (°)	LPAFixed window $q = 100$ [37] (°)
Case 1: One rapidly moving source tracking				
−4	0.1511	0.5822	0.6921	15.5632
0	0.1100	0.5643	0.6546	10.9972
Case 2: Two far sources tracking				
−4	0.1721	0.5735	0.6863	20.5012
0	0.1678	0.5576	0.6578	16.3651
Case 3: Two sources have the same angular velocity				
−4	0.2353	0.6931	0.7332	27.0023
0	0.2012	0.6720	0.7001	20.5000
Case 4: Two sources have the same angle				
−4	0.2098	0.7265	0.7435	26.8500
0	0.1987	0.6993	0.7023	19.0201

method (LPA-RICI) compared to LPA-ICI, and Fixed window LPA at SNR = −4 dB and 0 dB in percentage. The result obtained in Table 2 is matched with the results in Table 1 as the same scenarios and parameters values are used. Table 2 reports that:

- With improvement ratio of about 99%, the proposed method outperforms the fixed window LPA method for all scenarios independent of the SNA value.
- Generally, the proposed method outperforms the LPA-ICI regarding the improvement ratios reported in Table 2.
- In all cases, the improvement ratios with SNR of 0 dB are superior to those obtained with −4 dB.
- In case 2, the improvement ratios are less than those in case 1 of rapidly moving single source.
- In case 4, a slight difference has been achieved regarding the improvement ratios rather than those obtained in case 3. Such results are due to that the sources in case 4 have the same angles that we distinguish between them using their angular velocities. That is a result of LPA-RICI which is robust against the SNR changes with the estimated angular velocity till -12 dB as shown in Fig. 2.

Table 2 The improvements achieved in the DOA parameters estimation RMSE using the proposed method (LPA-RICI) compared to LPA-ICI, and Fixed window LPA at SNR = −4 dB and 0 dB.

Signal to Noise Ratio (SNR) (dB)	LPA-RICI improvement over the LPA_ICI $\Xi = 1.5$ [28] (%)	LPA-RICI improvement over the LPA_ICI $\Xi = 3$ [28] (%)	LPA-RICI improvement over the LPA fixed window $q = 100$ [37] (%)
Case 1: One rapidly moving source tracking			
−4	74.05	78.17	99
0	80.50	83.20	99
Case 2: Two far sources tracking			
−4	70	75	99
0	70	74.50	99
Case 3: Two sources have the same angular velocity			
−4	66.05	67.91	99
0	70	71.26	99
Case 4: Two sources have the same angle			
−4	71.12	71.78	99
0	71.59	71.84	99

Typically, both Tables 1 and 2 proved that the LPA-RICI method outperforms both the original LPA-ICI/conventional LPA methods for all SNRs.

5. Conclusion and future work

Estimating the wave angle of arrival and other parameters of a plane wave is known as DOA estimation problem. Through the last numerous decades, the high resolution DOA estimation techniques using antenna arrays have played a significant role in diverse fields, including sonar, mobile communications, radar, and seismology.

Various methods exist to address the problem of DOAs estimation of multiple sources using the signals received at the array of sensors. One of these effective algorithms for DOA estimation is the LPA, and the LPA based ICI rule, as they used to track non-stationary sources. However, they face some drawbacks that make them impractical. Therefore, in this work, a modification of the intersection of confidence interval (ICI) rule for moving targets tracking and direction of arrival estimation parameters based on the LPA-RICI method is developed.

The proposed method constructs the use of the ratio of the ICI length and the corresponding confidence interval length as an additional criterion in the proposed algorithm. It results in more accurate estimates, both in terms of bias and mean-square error, and it allows us to use wider confidence intervals while still avoiding signal over-smoothing. The proposed algorithm uses the nonparametric LPA beamformer and the RICI rule for their support selection. This algorithm is computationally effective and more efficient for tracking moving and closely spaced targets.

The results prove that RICI based method outperforms the original ICI based method in terms of the RMSE and allowing the use of larger parameter values.

The resulting system is very fast and computationally efficient without compromising accuracy in comparison with the LPA-ICI and the conventional fixed window LPA. The results reported that the proposed LPA-RICI provides improvement ratio of about 99% over the conventional LPA method.

As a future work, it is suggested to generalize the LPA-RICI algorithm for any accelerated moving targets, any type of array geometries and any source trajectories.

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