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DOA ESTIMATION USING TIME-FREQUENCY CONVERSION PRE-PROCESSING METHOD

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Abstract—In many cases, the study of DOA estimation techniques is developed based on ideal condition of signal sources and array sensor antennas. But, there are much more errors as a result of signal shadow effects from noise contribution and interference of installation environment in real system. In this paper, the DOA estimation algorithm using the de-noising pre-processing based on time-frequency conversion analysis was proposed, and the performance was analyzed. This is focused on the improvement of DOA estimation at a lower SNR and interference environment.

1. INTRODUCTION

The direction of arrival (DOA) estimation is an important technology for the identification of a measured target signal. This is a core technology to resolve illegal interference signals for spectrum monitoring.

A study of DOA estimation techniques is generally based on ideal conditions of a signal source and sensor array. But there are many errors as a result of signal shadow effects and physical limits of antenna construction. The performance of a DOA estimation system is also affected by noise contribution and interferences from installation environments. Most of the algorithms are using the amplitude and phase responses of an array antenna. Various super resolution algorithms are proposed by the analysis of a spatial covariance matrix of an array antenna such as a MUSIC [1]. The performance of super-resolution algorithms is generally limited by the ever-present sensor noise, restricted observation time period, array geometry and

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modelling errors. It can be assumed that the accuracy of DOA estimation can be remarkably improved by modelling the accurate array response. This is accomplished by measuring the steering vectors for the signal-subspace algorithms such as MUSIC [1, 2], ESPRIT [3] and ML [4]. But there are many limitations to collect the calibrated steering vectors. And, there are much more errors as a result of signal shadow effects from noise and interference of installation environment in real system [5].

The wavelet denoising is a useful tool for various applications of image processing and acoustic signal processing for noise reduction. There are some trials for DOA estimation by applying the wavelet transform method into several subbands MUSIC scenarios [6–8]. But they do not consider larger noise bandwidth with interference signal included in processing samples. In this paper, the DOA estimation algorithm using a time-frequency conversion pre-processing method with a signal OBW (Occupied Bandwidth) analysis was proposed and the effectiveness was verified through the simulation. This is focused on the improvement of DOA estimation performance at lower SNR and interference environment. This is in compliance with the radio usage trends of lower power and widening signal bandwidth especially.

2. SUBSPACE BASED DOA ESTIMATION

A DOA estimation algorithm can estimate the direction by the correlation of amplitude and phase information from the array antenna. This is realized by the synchronized processing of multi channel signals from an array antenna [9].

The complex received signal $x_m(t)$ $(1 < m < M)$ of the m-th sensor z_m $(1 < m < M)$ by the incident signal of k_n $(1 < n < N)$ at time t can be expressed as Equation (1). It is assumed that N narrow band signals of a directional vector $k = [k_1, k_2, \ldots, k_N]$ are projected on the M omni-directional sensors with the sensor location vector of $z = [z_1, z_2, \ldots, z_M]$. The narrow band signal is defined as $s_n(t - \tau_n(m)) \approx s_n(t)$. There is nearly no change of the signal envelope $s_n(t)$ for the time delay $\tau_n(m)$ of passing the array antenna [2, 10].

$$x_m(t) = \sum_{n=1}^{N} s_n(t) e^{j\{\omega_0(t-\tau_n(m))+\varphi_n\}} + \eta_m(t) \tag{1}$$

$$\tau_n(m) = \frac{z_m \cdot k_n}{c} \; (1 \leq m \leq M) \tag{2}$$

Here φ_n is a random phase of the n-th signal, $\eta_m(t)$ is random variable noise with a mean zero and a variance of σ^2, and c is the velocity of a radio wave. The generalized received signal vector model can be expressed as Equation (3).

$$x(t) = A(\theta)s(t) + \eta(t) \tag{3}$$

Here, $x(t)$ is a $[M \times 1]$ received signal vector of an array antenna, The $A(\theta)$ is a $[M \times N]$ steering vector matrix for an incidence angle θ_i, $s(t)$ is a $[N \times 1]$ signal source vector, and $\eta(t)$ is a $[M \times 1]$ noise vector.

The correlation between the outputs of each element of the array antenna includes the information about the direction of incident signals. This spatial covariance matrix can be a useful parameter for the DOA estimation [11, 12]. The $M \times M$ spatial covariance matrix of an M array antenna is defined as following,

$$R_x = E\left[x(t)\ x^H(t)\right] \tag{4}$$

Here, E means the expectancy of an ensemble average and H is the hermitian complex conjugate transpose.

This spatial covariance matrix is represented by the signal and noise covariance matrix with the assumption of a spatially white noise uncorrelated with a signal. Let R_s be the covariance matrix of emitter signals and σ^2 be the noise variance at a sensor.

$$R_x = A(\theta)R_sA(\theta)^H + \sigma^2 R_\eta \tag{5}$$

$$R_s = E\left\{s(t)\, s^H(t)\right\} \tag{6}$$

$$R_n = \sigma^2 R_\eta = E\left\{\eta(t)\, \eta^H(t)\right\} \tag{7}$$

R_η would be the unitary matrix $\mathbf{I}$ if the random processing noise vector $\eta(t)$ is spatially white noise with an average zero. And, the covariance matrix shown in Equation (5) separates into the signal eigenvector (6) and noise eigenvector (7).

The estimation process of a covariance matrix from finite data is performed by the time average with the assumption of an ergodic process. The vector space technique separates the vector space as a signal subspace and a noise subspace through the eigen de-composition of a covariance matrix. The vector space technique estimates the DOA from this subspace. It is a method using the orthogonal property of a signal subspace and a noise subspace. The representative MUSIC estimation function is described as Equation (8).

$$P_{MUSIC}(\theta) = \frac{A^H(\theta)A(\theta)}{A^H(\theta)R_nR_n^HA(\theta)} \tag{8}$$

This MUSIC algorithm method searches for the directions that the noise subspace is orthogonal to the steering vectors correlated with a signal subspace. The resolution and statistical stability of this algorithm is generally superior to the classical DOA estimation methods [13, 14].

3. NEW APPROACH OF DOA ESTIMATION

A signal subspace based DOA estimation performance is affected by the two factors of an accurate array manifold modeling and a spatial covariance matrix of a received array signal. A higher SNR signal for a target source is required for an accurate estimation from finite received signal samples. But the DOA estimation performance is limited by the lower SNR from interference signals and environmental noise.

For the performance improvement of DOA estimation, this paper proposed a pre-processing technique of time-frequency conversion methodology for signal filtering. This method includes a time-frequency conversion technique with a signal OBW (Occupied Bandwidth) measurement based on wavelet de-noising method as shown in Fig. 1. This is a DOA method for SNR improvement based on time-frequency conversion approach. The improvement of a DOA estimation performance was verified by the simulation.

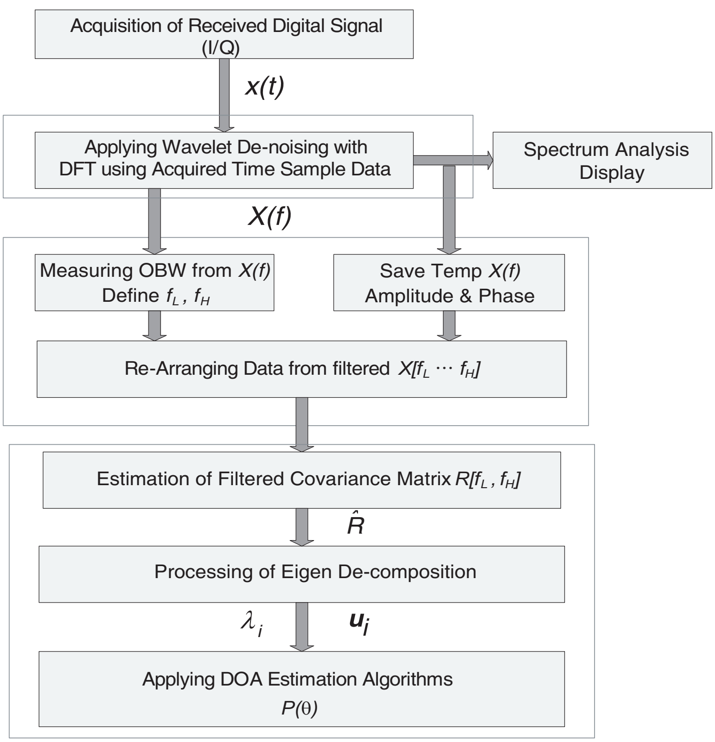


Figure 1. Proposed DOA estimation method.

This is proposed to overcome the limitation of existing DOA estimation techniques based on only time domain analysis. The more effective estimation is expected by the improvement of SNR from the proposed pre-processing techniques of frequency domain analysis. The proposed method collects a time sampled signal $x(t)$ from an array antenna as shown in Fig. 1. The upper and lower 99% — OBW limits f_L and f_H of a signal are determined from $X(f)$, which is the DFT result of a received signal $x(t)$. The filtered covariance matrix $R[f_L, f_H]$ can be obtained from the estimated signal energy, $X[f_L, f_{L+1}, \ldots, f_H]$ with an improved SNR. And the more exact OBW measurement is expected through the proposed wavelet de-noising method based on time-frequency analysis. The proposed OBW limits are defined as following measurement concepts of Equations (9) $\sim$ (12). This process can effectively eliminate small interference noises from the target signal streams by the frequency domain analysis [15, 16]. Where P_X is a power of each spectrum frequency elements $\{f_1, \ldots, f_N\}$. The 99% OBW is calculated from the upper limit f_H and the lower limit f_L of 0.5% OBW point from each spectrum boundary.

$$P_{rel} = \sum_{i=f_1}^{f_N} P_X(i) \tag{9}$$

$$\Delta P_{\beta/2} = P_{rel} \times \beta/2[\%\ ]\ (\beta = 1 \text{ for } 99\% \text{ OBW analysis}) \tag{10}$$

$$f_L = \arg\min_{f_L} \left[\left| \sum_{f_L=f_1}^{f_N} P_X(f_L) - \Delta P_{\beta/2} \right| \right] \tag{11}$$

$$f_H = \arg\min_{f_H} \left[\left| \sum_{f_H=f_N}^{f_1} P_X(f_H) - \Delta P_{\beta/2} \right| \right] \tag{12}$$

An improved DOA estimation is expected from the filtered covariance matrix and eigen-decomposition processing at particularly low SNR signal conditions. By the proposed pre-processing, it can effectively reject adjacent interferences at low SNR conditions. Moreover, it can acquire the signal spectrum with an improved DOA estimation spectrum simultaneously without additional computation. This improved signal spectrum is important results for radio surveillance procedure.

The signal de-noising is achieved by the discrete wavelet transform-based thresholding to the resulting coefficients, and suppressing those coefficients smaller than certain amplitude. An appropriate transform can project a signal to the domain where the signal energy is concentrated in a small number of coefficients.

The proposed Wavelet de-noising process get a de-noised version of input signal obtained by thresholding the wavelet coefficients. In this paper, the wavelet procedure applied the heuristic soft thresholding of symlet wavelet decomposition at level one. This de-noising processing model is depicted as following simple model.

$$s(n) = f(n) + \sigma e(n), \quad n = 0, \ldots, N-1 \tag{13}$$

In this simplest model, $e(n)$ is a Gaussian white noise of independent normal random variable $N(0, 1)$ and the noise level is supposed to be equal to 1. Using this model, it follows the objectives of noise removal by reconstruct the original signal f. It can be assumed that the higher coefficients are result from the signal and the lower coefficients are result from the noise. The noise eliminated signal is obtained by transforming back into the original time domain using these wavelet coefficients [17–19].

4. THE SIMULATION RESULTS

The effectiveness of the proposed method is verified by the simulation for low SNR signals which is a measurement limit under on-air condition. DOA estimation according to various SNR signals was performed based on the Monte Carlo methodology for performance analysis of the proposed method.

The simulation is conducted for 5-elements UCA model with $R_n = 0.5\lambda$. The incident signal was supposed as only azimuth model with 90 degree elevation for convenience. The proposed simulation is performed for the low SNR signals at 100 deg incident angle from -20 dB to 0 dB with an -30 dB SNR interference signal. The normalized frequency of each signal was assumed as 0.15 rad/sec and 0.35 rad/sec with the incident angles of 100 deg and 50 degree, respectively.

Figures 2–4 show the simulation results for -12 dB SNR condition as examples. Fig. 2 compare the signal spectrums between the received noisy signal and the wavelet de-noised signal using soft heuristic thresholding at the level 1 by the 8-tap symlet wavelet [20, 21]. The wavelet de-noised signal is eliminating the noise spectrum outside of the desired signal well, and the improved SNR is expected from the simulation. The Mark-A indicates a desired -12 dB SNR signal and the mark-B is a simulated interference signal after de-noising stage.

And, the eigenvalues for the simulation signal are compared through the eigen decomposition of a covariance matrix for the 1024 time sampled data in Fig. 3. Figs. 3(a) and 3(b) are the eigen values from the conventional method and the proposed method, respectively. Fig. 3(b) shows that the rank of a covariance matrix can be more

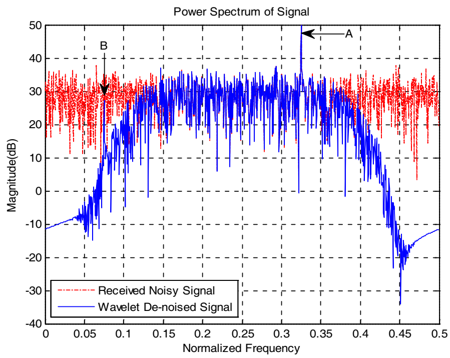
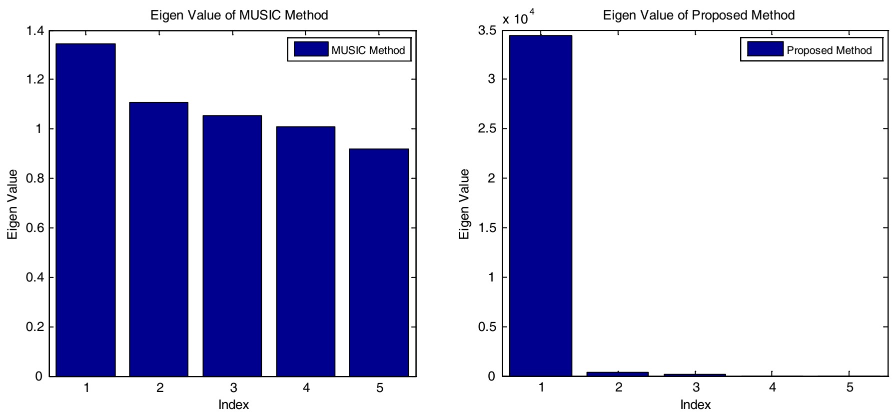


Figure 2. Comparison of signal spectrum.



(a) Classical MUSIC method
(b) Proposed method

Figure 3. Comparison of eigen values for the simulation.

accurately decided from the proposed method compared to Fig. 3(a). The signal contribution is concentrated on the first eigen value. It can be assumed that the signal and the noise subspace are separated effectively by the improvement of SNR using the proposed method.

Figure 4 shows a DOA estimation spectrum for the conventional DOA estimation and the proposed method using this pre-processing stage. From the simulation, the DOA performance was improved to more than 10 dB by the proposed pre-processing of OBW analysis with a wavelet de-noising method. The broken line shows the result of a conventional method and the unbroken line shows the improved spatial spectrum spurious for the proposed method.

Figure 5 summarises the successful probability for the proposed trials for each DOA estimation method. The successful condition is

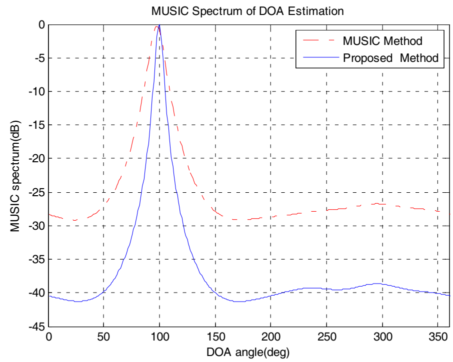
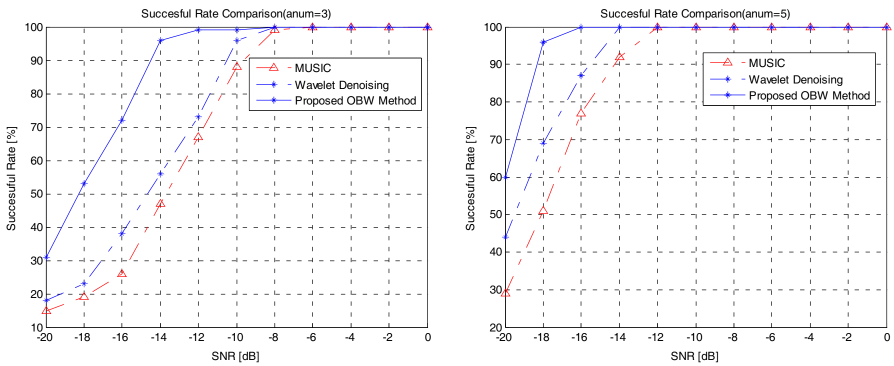


Figure 4. Comparison of DOA estimation spectrum.

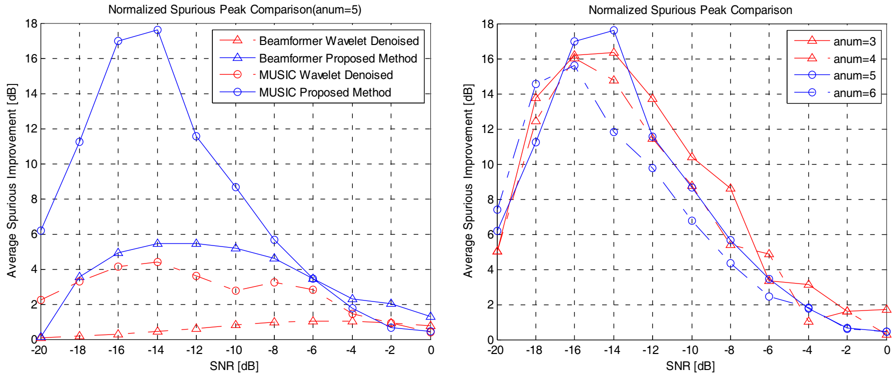


(a) For 3-antenna elements (b) For 5-antenna elements

Figure 5. Probability of successful DOA estimation.

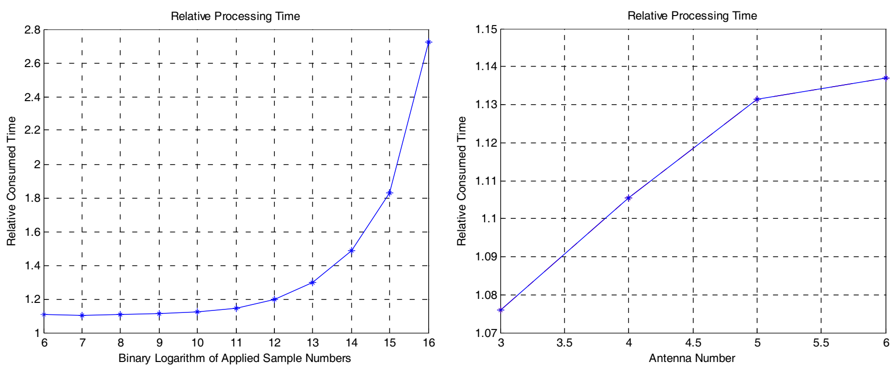
defined as 5-degree rms of DOA estimation accuracy for each SNR simulation. Fig. 5(a) and Fig. 5(b) compare the each successful probability result at 3-elements UCA and 5-elements UCA condition. From the simulation, the reliable DOA estimation process can be expected for -18 dB SNR signal using the proposed method, but for -12 dB SNR signal using the conventional method at 5-elements UCA condition.

Figure 6 shows the comparison results of DOA estimation performance for low SNR signals with interference and noise. The DOA estimation performance was compared by the spurious peak of DOA estimation spectrums which increase a measurement ambiguity and probability of successful DOA estimation. The performance improvement is normalized by the spurious peak for each DOA estimation simulation of conventional method. The simulation was



(a) Comparison for various estimation method (b) Comparison for various antenna elements

Figure 6. Comparison of spurious peak (normalized to conventional method).



(a) Results for the applied samples (b) Results for the antenna numbers

Figure 7. Comparison of relative processing time of proposed method.

performed for arbitrary random signals using the MUSIC DOA estimation algorithm. It shows the relative improvement of an averaged spurious peak of a spatial spectrum normalized for a conventional DOA estimation method. Fig. 6(a) compares the performance improvement for Eigen-based Beam-form method and MUSIC method by applying the proposed pre-processing. Fig. 6(b) is MUSIC simulation results for various UCA antenna elements.

Form the simulation results, the proposed method improves the DOA estimation performance of accuracy and spurious peak of spatial spectrum especially for lower SNR signals. The proposed method improves the spurious peak characteristic more than 10 dB at less than -10 dB SNR signal condition by applying MUSIC estimation. Fig. 7 shows the computing complexity for several condition of applied samples (Fig. 7(a)) and antenna numbers (Fig. 7(b)). The relative processing time increases about 13% by applying the proposed method for 5-elements with 1024 samples and increases corresponding to sample numbers for DOA estimation processing.

5. CONCLUSION

The spectrum components coming from other signal sources will bring quality degradation by distorting the original spectrum distribution. In this paper, the improvement of DOA estimation capability was considered at on-air condition of noise and interferences.

The proposed DOA estimation method includes the wavelet denoising technique with OBW Analysis pre-processing for low SNR conditions by applying the time-frequency conversion. This method is applied to an UCA DOA estimation model for the performance analysis. The effectiveness is verified by the simulation for a low SNR signal model. The proposed method shows an improved ability of DOA resolution and estimation error at the noise and interference conditions. These are the measurement limits at on-air environment.

For the effective spectrum analysis, it needs a time domain analysis for DOA estimation and a frequency domain analysis for an interference spurious and OBW measurement. The proposed DOA estimation method gets a more than 10 dB ambiguity improvement of DOA estimation spectrum from the simulation.

It is expected to have more effective and reliable radio spectrum monitoring through the proposed spectrum monitoring techniques. But, it needs more researches to improve the proposed performance for various radio conditions such as co-channel multi-path and impulsive noise environment. The co-channel interference and the adjacent channel interference would be common conditions of spectrum monitoring due to wideband, high frequency and low power communications.

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