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Research Letter

On Blind MIMO System Identification Based on Second-Order Cyclic Statistics

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This letter introduces a new frequency domain approach for either MIMO System Identification or Source Separation of convolutive mixtures in cyclostationary context. We apply the joint diagonalization algorithm to a set of cyclic spectral density matrices of the measurements to identify the mixing system at each frequency up to permutation and phase ambiguity matrices. An efficient algorithm to overcome the frequency dependent permutations and to recover the phase, even for non-minimum-phase channels, based on cyclostationarity is also presented. The new approach exploits the fact that each input has a different and specific cyclic frequency. A comparison with an existing MIMO method is proposed.

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1. INTRODUCTION

In many real-world situations, man-made signals such as those encountered in rotating machines, communications, telemetry, radar, and sonar systems are nonstationary and very often cyclostationary [1, 2]. The mixtures of real-world signals are usually convolutive mixtures, so the conventional methods for the standard blind source separation (BSS) problem which assume instantaneous mixtures of stationary sources [3, 4] are no longer appropriate. In a cyclostationary context, BSS has motivated much research which we summarize, for sake of space, as follows. Liang et al. in [5] were the first, to our knowledge, to make use of the information offered by the cyclic frequencies in order to separate signals. Abed-Meraim et al. [1] introduce two second-order statistics- (SOS-) based criteria to blindly separate sources. Ferreol and Chevalier [6] show that, in a cyclostationary context, the fourth-order (FO) empirical estimators generate asymptotically biased estimates of the temporal mean of the quadricovariance. Jallon et al. in [7] introduce an FO-based contrast function whose estimation does not require the knowledge of the cyclic frequencies. Antoni et al. make use of the spectral correlation density (SCD) matrices for the blind identification [8] and signal separation [9] of sources with the same cyclic frequency.

The method offered in this letter is a frequency domain technique that exploits the cyclic spectral density matrices of the measurements to identify the mixing channel and separate convolved cyclostationary sources with different cyclic frequencies. The organization of this letter is as follows. The problem statement including the set of required assumptions is presented in Section 2. Section 3 presents the algorithm to estimate the magnitude of multiple-input multiple-output (MIMO) system as well as the methods to correct the permutation and phase. We report some encouraging results on simulated signals to demonstrate the robustness of the proposed approach in Section 4. Ultimately, conclusions are presented in Section 5.

2. PROBLEM FORMULATION

2.1. System model

We consider n-source m-sensor MIMO linear model for the received signal for the convolutive mixing problem

$$\mathbf{x}(t) = \sum_{k=0}^{L-1} \mathbf{H}(k)\, \mathbf{a}(t-k) + \mathbf{b}(t), \tag{1}$$

where $\mathbf{x}(t) = [x_1(t), \ldots, x_m(t)]^T$ is the vector of measurements, $\mathbf{a}(t) = [a_1(t), \ldots, a_n(t)]^T$ is the source vector were

the components are real-valued, cyclostationary, i.i.d., mutually statistically uncorrelated, centered (in the ensemble-average sense), and with different cyclic frequencies $\{\alpha_i,\ i = 1,\ldots,n\}$. $\mathbf{H}(t)$ is the $m \times n$ impulse response matrix whose elements are $\{h_{ji}(t)\}$, and $\mathbf{b}(t) = [b_1(t),\ldots,b_m(t)]^T$ is the additive noise vector which is assumed to be stationary, temporally, and spatially white, zero-mean, and independent of the source signals. The superscript T denotes the transpose and L is the length of the real-valued channels. By taking the discrete Fourier transforms (DFTs) (1) over N lines, we obtain that

$$\mathbf{X}(f_k) = \mathbf{H}(f_k)\,\mathbf{A}(f_k) + \mathbf{B}(f_k), \tag{2}$$

where $\mathbf{X}(f_k)$, $\mathbf{H}(f_k)$, $\mathbf{A}(f_k)$, and $\mathbf{B}(f_k)$ are the DFT of $\mathbf{x}(t)$, $\mathbf{H}(t)$, $\mathbf{a}(t)$, and $\mathbf{b}(t)$, respectively. From (2), it is obvious that at each frequency bin, the estimation of $\mathbf{A}(f_k)$ can be seen as an instantaneous complex BSS problem.

2.2. Cyclic spectral analysis

Let us introduce the SCD of the source vector [10]

$$\mathbb{E}\{\mathbf{A}(f_k)\mathbf{A}^H(f_k - q\alpha_i)\} = \mathbf{S}_a^{q\alpha_i}(f_k) = \sigma_i^2(q\alpha_i)\mathbf{I}_i, \tag{3}$$

where the superscript H denotes the complex conjugate transpose of a matrix and $\sigma_i^2(q\alpha_i)$ stands for the SCD of the signal $a_i(t)$, at the qth multiple of α_i, which is frequency-independent since $a_i(t)$ is i.i.d.. $\mathbf{I}_i$ is a matrix with only one nonzero element which is set to 1 and i is the index of the unique nonzero diagonal element of $S_a^{q\alpha_i}(f_k)$. This means that the SCD matrices of the inputs at different harmonics are diagonal, with only one nonzero element, under the independency hypothesis.

We conclude from (3) that to blindly restore the sources, we need to submit the measurements to some linear transformations so that the estimated sources will have the same algebraic structure as the primary sources.

3. MIMO IDENTIFICATION

The singular value decomposition (SVD) of $\mathbf{H}(f_k)$ is

$$\mathbf{H}(f_k) = \mathbf{U}(f_k)\mathbf{\Sigma}(f_k)\mathbf{V}(f_k), \tag{4}$$

where $\mathbf{U}(f_k)$ and $\mathbf{V}(f_k)$ are $m \times n$ and $n \times n$ unitary matrices, respectively, and $\mathbf{\Sigma}(f_k)$ is $n \times n$ diagonal matrix.

Let us introduce the SCD matrix of the measurements [10]:

$$\mathbf{S}_x^{q\alpha_i}(f_k) = \mathbf{H}(f_k)\mathbf{S}_a^{q\alpha_i}(f_k)\mathbf{H}^H(f_k - q\alpha_i) + \mathbf{S}_b^{q\alpha_i=0}(f_k), \tag{5}$$

where $\mathbf{S}_b^{q\alpha_i=0}(f_k)$ is the SCD matrix of the noise. The eigenvalue decomposition (EVD) of (5), evaluated when $\alpha_i = 0$, allows the identification of $\mathbf{U}(f_k)$ and $\mathbf{\Sigma}(f_k)$ and hence the whitening of the measurements.

The SCD matrices of the whitened processes at different cyclic frequencies $q\alpha_i$ are

$$\mathbf{S}_z^{q\alpha_i}(f_k) = \mathbf{V}(f_k)\mathbf{S}_a^{q\alpha_i}(f_k)\mathbf{V}^H(f_k - q\alpha_i). \tag{6}$$

Let us consider the norm of the last relationship in order to have a symmetric expression in the right-hand side

$$\widetilde{\mathbf{S}}_z^{q\alpha_i}(f_k) = \mathbf{V}(f_k)\widetilde{\mathbf{S}}_s^{q\alpha_i}(f_k)\mathbf{V}^H(f_k). \tag{7}$$

The aim is to find a unitary matrix that simultaneously and jointly diagonalizes the set of $\widetilde{\mathbf{S}}_z^{q\alpha_i}(f_k)$ matrices. The well-known approximate joint diagonalization (JAD) algorithm [4] will be used to this end. Once $\mathbf{V}(f_k)$ is identified, one can estimate the mixing MIMO system $\mathbf{H}(f_k)$ based on (4) as follows:

$$\widehat{\mathbf{H}}(f_k) = \mathbf{H}(f_k)\Delta\mathbf{P}(f_k)\mathbf{D}(f_k), \tag{8}$$

where $\widehat{\mathbf{H}}(f_k)$ is an estimation of $\mathbf{H}(f_k)$ with constant diagonal matrix, Δ, which introduces a scaling ambiguity, frequency-dependent permutation $\mathbf{P}(f_k)$, and phase ambiguity $\mathbf{D}(f_k)$ that introduces circular shifts to the sources (the ith diagonal element of $\mathbf{D}(f_k)$ is of the form $e^{j\Phi_D^i(f_k)}$). Certainly, the estimation offered by (8), which is inherent to SVD approaches, can no longer provide a good estimation of the actual system $\mathbf{H}(f_k)$ neither in the frequency domain nor in the time one by involving the inverse DFT (IDFT). Hereafter, we propose two techniques to cancel the permutation and the phase ambiguities, so that the mixing MIMO system will be estimated up to a general constant diagonal matrix and a uniform permutation matrix, thus giving

$$\widehat{\mathbf{H}}_{\text{opt}}(f_k) = \mathbf{H}(f_k)\Delta\mathbf{P} \tag{9}$$

which solves the blind identification issue.

3.1. Resolving the frequency-dependent permutation ambiguity

An interesting property of cyclostationary signals is their spectral redundancy. In our case, the cyclic spectra of signals will not overlap because they have distinct cyclic frequencies. This is the property that we seek to exploit in our effort to derive a new algorithm for the correction of permutations across all the frequency bins. More precisely, our approach makes use of the cyclic cepstrum of the estimated signals which are permuted.

Let us first consider the estimating sources:

$$\widehat{\mathbf{A}}(f_k) = \widehat{\mathbf{H}}^{\#}(f_k)\mathbf{X}(f_k) = \mathbf{D}^*(f_k)\mathbf{P}^T(f_k)\Delta^{-1}\,\mathbf{A}(f_k), \tag{10}$$

where the superscripts # and $*$ denote the pseudoinverse and the complex conjugate of a matrix, respectively. The SCD matrix of the estimated sources is given by

$$|\,\mathbf{S}_{\hat{a}}^{\alpha_i}(f_k)\,| \simeq \varrho_i^{-2}\,\mathbf{P}^T(f_k)\,|\,\mathbf{S}_a^{\alpha_i}(f_k)\,|\,\mathbf{P}(f_k - \alpha_i), \tag{11}$$

where ϱ_i is the ith diagonal element of Δ. The following relationship can be easily deduced from (11) for the elements in the main diagonal:

$$\gamma_{jj}^2(f_k) \simeq \varrho_i^{-2}\,|\,\sigma_i^2(\alpha_i)\,|\;p_{ij}(f_k)\;p_{ij}(f_k - \alpha_i), \tag{12}$$

where $\gamma^2_{jj}(f_k)$ is the SCD of $\hat{a}_j(t)$. Under the assumption that $\log(|S^{\alpha_i}_{\hat{a}}(f_k)|)$ is finite, the real cepstrum of (12) exists and thus leads to

$$C_{p_{ij}}(\tau) \simeq \frac{C_{\gamma^2_{jj}}(\tau) - \log\left(\varrho_i^{-2}\,|\,\sigma_i^2(\alpha_i)\,|\right)\delta(\tau)}{1+\exp\left(j2\pi\alpha_i\tau\right)}, \tag{13}$$

where $C_{\gamma^2_{jj}}(\tau) = C^{\alpha_i}_{\hat{a}}(\tau)$. Thus, the permutation $p_{ij}(f_k)$ can be computed from

$$p_{ij}(f_k) = \exp\left(\sum_{\tau=-\infty}^{\infty} C_{p_{ij}}(\tau)e^{-j2\pi f_k\tau}\right). \tag{14}$$

For a given α_i, (14) allows us to estimate the ith column of the matrix $\mathbf{P}(f_k)$. As we do not have any of these quantities $\varrho_i^{-2}|\sigma_i^2(\alpha_i)|$, it means that there is no link between the actual and the estimated sources and therefore no information is available about the actual order of the sources. A way to estimate (13) is

$$C_{p_{ij}}(\tau) \simeq \frac{C_{\gamma^2_{jj}}(\tau) - \log\left(\gamma^2_{0i}(f_1)\right)\delta(\tau)}{1+\exp\left(j2\pi\alpha_i\tau\right)}, \tag{15}$$

where $\gamma^2_{0i}(f_1)$ is the biggest value of the matrix $S^{\alpha_i}_{\hat{a}}(f_1)$. Furthermore, there is no available solution whenever $2\tau\alpha_i = 2l+1$ or $\tau = (l+1/2)(1/\alpha_i)$. In fact, (15) assumes the permutation at f_1 as the true one and try to extend it to all frequency bins. Moreover, (8) will be simplified to

$$\hat{\mathbf{H}}(f_k) = \mathbf{H}(f_k)\Delta\mathbf{P}\mathbf{D}(f_k). \tag{16}$$

3.2. Resolving the phase ambiguity

The phase retrieval of single-input single-output (SISO) systems, excited by cyclostationary inputs, has been studied in several papers [11–13]. Note that, by exploiting second-order cyclic statistics, the identification of nonminimum-phase channels becomes possible. Let us recall the phase retrieval in the case of a SISO system:

$$\psi(f_k) - \theta(\alpha_i) = \phi(f_k) - \phi(f_k - \alpha_i), \tag{17}$$

where $\psi(f_k) = \arg\{S^{\alpha_i}_x(f_k)\}$, $\theta(\alpha_i) = \arg\{S^{\alpha_i}_a(f_k)\}$, $\phi(f_k) = \arg\{H(f_k)\}$, $S^{\alpha_i}_x(f_k)$ and $S^{\alpha_i}_a(f_k)$ are the SCD of the single measurement $x(t)$ and the single source $a(t)$, with the cyclic frequency α_i, respectively, and $H(f_k)$ is the transfer function of the filter. We note that q has been set to 1 with $\theta(\alpha_i)$ being constant since the source is i.i.d.. Li and Ding's solution for the phase retrieval in the case of PAM signals is as follows:

$$\boldsymbol{\phi}(t) = \frac{\boldsymbol{\psi}(t) - \theta^{\alpha_i}(t)}{(1-\exp(j2\pi\alpha_i t))}, \quad t \neq \frac{p}{\alpha_i}, \tag{18}$$

where $\phi(t)$, $\psi(t)$, and $\theta^{\alpha_i}(t) = \theta(\alpha_i)\delta(t)$ are the IDFT of $\phi(f)$, $\psi(f)$, and $\theta(\alpha_i)$, respectively. One can interpolate the missing information whenever $t = p/\alpha_i$, assuming the continuity of $\phi(t)$. Actually, $\theta(\alpha_i)$ can be computed by summing up (17) over all discrete frequencies which yield a zero right-hand side; thus we get

$$\theta(\alpha_i) = \frac{1}{N}\sum_{k=1}^{N}\psi(f_k). \tag{19}$$

Unfortunately, the previous solution (18) is not appropriate for MIMO systems. The idea is to transform the MIMO system in $m \times n$ SISO systems, thanks to the cyclostationarity and hence, (18) will be appropriate. Let us involve $\mathbf{S}^{\alpha_i}_x(f_k)$ for a given α_i. Putting (3) into (5), the latter expression takes the following forms:

$$\mathbf{S}^{\alpha_i}_x(f_k) = \sigma_i^2(\alpha_i)\mathbf{H}(f_k)\mathbf{I}_i\mathbf{H}^H(f_k - \alpha_i) \tag{20}$$

and, moreover,

$$S^{\alpha_i}_{x\,ii}(f_k) = \sigma_i^2(\alpha_i)H_{ii}(f_k)H^*_{ii}(f_k - \alpha_i). \tag{21}$$

The relationship (21) is important because it transforms the $m\times n$ MIMO system to n, $m\times 1$, single-input multiple-output (SIMO) systems, according to each α_i in order to have the contribution of only one source. Then, we successively apply (18) over only the diagonal elements of (21) since it comprises m SISO systems. This is the key relationship that can lead to the estimation of the ith column of $\boldsymbol{\Phi}(f_k)$. Finally, by sweeping the other cyclic frequencies, the remaining columns can be estimated in the same way.

Actually, we have no knowledge on the true order of $\Phi(f_k)$ columns. The estimated columns of $\Phi(f_k)$ are affected by a permutation matrix $\mathbf{P}'$ which is different from $\mathbf{P}$:

$$\hat{\Phi}(f_k) = \Phi(f_k)\,\mathbf{P}'. \tag{22}$$

3.3. Connection between the magnitudes and the phases

As the processes of estimating the MIMO system's magnitude and phase are disconnected, the correspondence between channel magnitude and phase is missed. This can be seen by taking the absolute value of the relationship (16):

$$|\hat{\mathbf{H}}(f_k)| = |\mathbf{H}(f_k)\Delta|\mathbf{P}. \tag{23}$$

It is clear therefore that the columns of the MIMO system's magnitudes are permuted by the matrix $\mathbf{P}$, which was taken as reference of permutations over all frequencies, and the MIMO system's phases are permuted by $\mathbf{P}'$. However, to correctly identify $\mathbf{H}(f_k)$, we need to cancel the effect of $\mathbf{P}'$ as follows:

$$\hat{\mathbf{H}}(f_k) = |\mathbf{H}(f_k)\Delta|\mathbf{P} \odot \exp\left(j\hat{\Phi}(f_k)\mathbf{P}'^T\mathbf{P}\right), \tag{24}$$

where the symbol $\odot$ denotes the Hadamard product. In other words, the knowledge of $\mathbf{P}'$ is indispensable in order to make the true connection between the magnitude and the phase. Let us take the argument of (16):

$$\Phi_{\hat{H}}(f_k) = \Phi(f_k)\,\mathbf{P} + \Phi_D(f_k), \tag{25}$$

where $\Phi_{\hat{H}}(f_k)$ is the phase of $\hat{\mathbf{H}}(f_k)$ and $\Phi_D(f_k)$ is an $m \times n$ matrix whose column i, $i = 1,\ldots,n$, contains the phase of the ith diagonal element of $\mathbf{D}(f_k)$. The jth line of $\Phi_D(f_k)$ is as follows:

$$\Phi_{Dj}(f_k) = [\Phi^1_D(f_k),\ldots,\Phi^i_D(f_k),\ldots,\Phi^n_D(f_k)]. \tag{26}$$

Of course, (25) shows the existence of correlation between $\Phi_{\hat{H}}(f_k)$ and $\hat{\Phi}(f_k)$. However, the matrix $\Phi_D(f_k)$ masks this correlation and hence, it must be removed to well estimate $\mathbf{P}'$. Let us subtract the jth line of $\Phi_{\hat{H}}(f_k)$ from its ith line:

$$\Phi^i_{\hat{H}}(f_k) - \Phi^j_{\hat{H}}(f_k) = \left[\sum_{l=1}^{n}(\Phi_{il}(f_k) - \Phi_{jl}(f_k))P_{l1}, \ldots, \sum_{l=1}^{n}(\Phi_{il}(f_k) - \Phi_{jl}(f_k))P_{ln}\right]. \tag{27}$$

The way to cancel $\mathbf{P}'$ is to evaluate the correlation between the elements of (27) and the following equation:

$$\hat{\Phi}^i(f_k) - \hat{\Phi}^j(f_k) = \left[\sum_{l=1}^{n}(\Phi_{il}(f_k) - \Phi_{jl}(f_k))P'_{l1}, \ldots, \sum_{l=1}^{n}(\Phi_{il}(f_k) - \Phi_{jl}(f_k))P'_{ln}\right], \tag{28}$$

where $\hat{\Phi}^i(f_k)$ and $\hat{\Phi}^j(f_k)$ are, respectively, the ith and the jth lines of $\hat{\Phi}(f_k)$. The correlation will be made element by element and over all frequency bins. Actually, $\mathbf{P}'$ is canceled and replaced by $\mathbf{P}$, therefore, (22) becomes

$$\hat{\Phi}(f_k) = \Phi(f_k)\mathbf{P}. \tag{29}$$

The ambiguity $\Phi_D(f_k)$ can easily be deducted from (25):

$$\Phi_D(f_k) = \Phi_{\hat{H}}(f_k) - \Phi(f_k)\mathbf{P}. \tag{30}$$

Finally, the MIMO system is identified as in (9).

4. COMPARISON WITH EXISTING MIMO METHODS

We provide here a comparison between the proposed approach against the method of [14]. For each value of the signal-to-noise ratio (SNR), 20 Monte Carlo runs were implemented. For the sources, we use two independent white gaussian processes multiplied by cosine signals. The sources are filtered by a 3×2 finite-impulse response MIMO system. N is set to 128. For the algorithm of [14], the number of samples in each epoch (a short time interval) is 1000 and the number of cross-spectral density matrices is 100.

Let $\mathbf{C}(f_k)$ represent the composite mixing-unmixing system:

$$\mathbf{C}(f_k) = \hat{\mathbf{H}}^{\#}(f_k)\,\mathbf{H}(f_k), \tag{31}$$

where its (ij)th element is $c_{ij}(f_k)$. As a performance index to measure the separation performance and to make comparison as well, we here used the same index as the one used in [14], namely, the signal-to-interference ratio (SIR) given by the formula

$$\mathrm{SIR}(i) = \frac{\sum_{l=1}^{\mathrm{Mc}} \max_j(S^l_{ij})}{\sum_{l=1}^{\mathrm{Mc}}\left[\sum_{j=1}^{n} S^l_{ij}\right] - \max_j(S^l_{ij})}, \tag{32}$$

where $\mathbf{S}^l_{ij} = \sum_{k=1}^{M}|c^l_{ij}(f_k)|^2$, l is an index to the lth Monte Carlo run, and Mc is the total number of Monte Carlo runs.

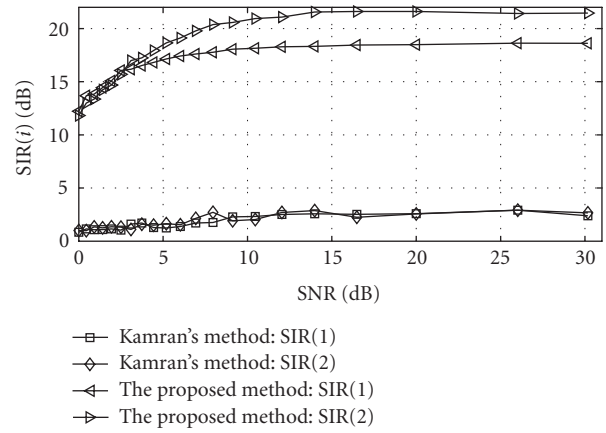

Figure 1: Comparison of the proposed method with the method of [14].

SIR(1) and SIR(2) stand for the SIR of the 1st and 2nd estimated sources.

Figure 1 shows the variation of each output's SIR, for the proposed method and the one of [14] as well, with the SNR. As can be seen from this figure, by increasing the SNR, the output SIR improves (increases). However, it shows that the proposed approach performs better than that of [14] and provides better SIRs even for low SNRs as well. Actually, Karman's method constraints the source signals to be second-order quasistationary over an epoch. This constraint is not anymore appropriate to cyclostationary signals. Based on the previous comparison results, it is clear that the exploitation of cyclostationarity makes our algorithm more robust.

5. CONCLUSION

The spectral redundancy allowed us to apply the AJD algorithm to a set of SCD matrices for every frequency. A robust algorithm to overcome the frequency-dependent permutations and to remove the phase ambiguity, based on cyclostationarity, was presented. The performance of the new algorithm was demonstrated, it is apparent, therefore, that the proposed method performs better than [14].

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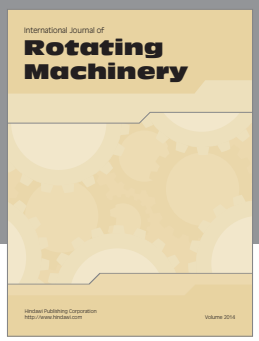

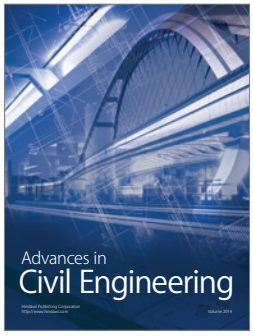

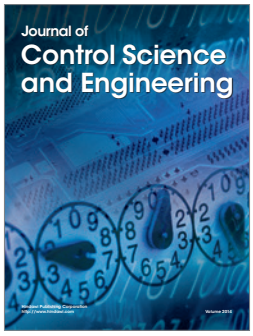

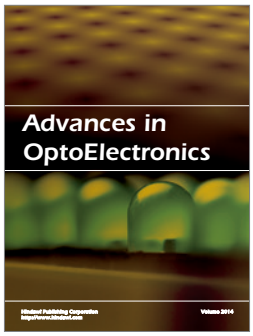

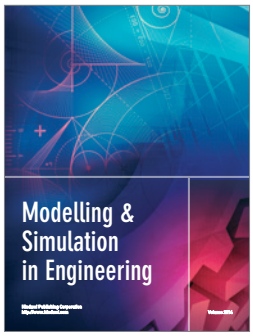

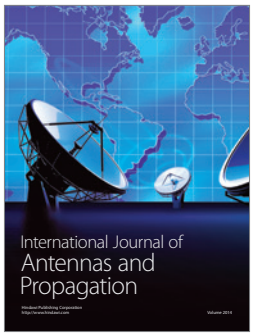

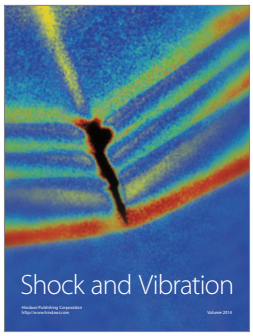

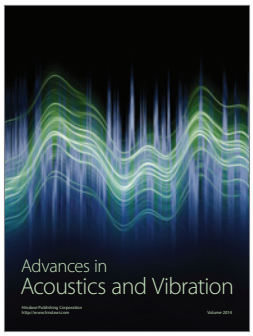

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