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A Multiclass Support Vector Machine Based Direction-of-Arrival Estimation Technique using Spherical Antenna Array with Undefined Mutual Coupling

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ABSTRACT

In antenna array signal processing, estimating the direction-of-arrival (DoA) remains a challenge and basic problem. In this paper, a DoA estimation technique using support vector machine (SVM) classification is developed using spherical antenna array (SAA). The source signal impinging on SAA is decomposed using spherical harmonics (SH). Both magnitude and phase features are computed from the decomposed SH signals. The magnitude and phase features are classified into DoA classes using multi-class SVM (MC-SVM) algorithm. Due to the deterministic and non-probabilistic nature of SVM algorithm, it exhibits high computational speed and less complex than the neural network-dependent learning algorithms. Numerical experiments and experimental measured data (generally accepted ground to test any method) are used to evaluate the performance of the proposed technique. The developed algorithm exhibit high level of robustness at different signal-to-noise ratios (SNR) in the estimation of DoA. Root mean square error (RMSE) performance metrics is employed in the analysis of the proposed method against the state-of-the-art. The results obtained are motivating enough for the deployment of the proposed algorithm in practical scenarios.

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1. INTRODUCTION

The Estimation of direction-of-arrival (DoA) is an important and crucial topic in different electromagnetic (EM) related research areas. It finds applications in wireless communications, radar, sonar, and telecommunication [1]-[8]. When the DoAs of a receive mode EM waves is known, the localization of the corresponding sources is effectively possible. The DoA information facilitate the positioning of the antenna array in such a way that the highest beam is channeled in the direction of desired users, and null in the direction of interference, consequently enhances the wireless and base stations performance. Hence, DoA estimation of EM signals that impinge antenna array becomes crucial.

Spherical antenna array (SAA) (Figure 1) is used in satellite communication and spacecraft. The electronic beam scanning generated by SAA is a good choice in providing a uniformly distributed gain and hemispherical [5], [6], [8]. The associated 3-D symmetrical nature of SAA enhances spatial analysis of signals [8]. The configuration and size give the degree of beam scanning and directivity in the elevation and azimuth required from the antenna array. The SAA directivity is relatively equal when the active source is dragged over the SAA surface. Therefore, estimating the DoA using SAA becomes an important topic.

There are various DoA estimation techniques for linear and planar antenna array reported in literature. Because of the associated merits of SAA, different techniques using SAA are presently under consideration [9]. For example, MUSIC (multiple signal classification) and ESPRIT (estimation of signal parameters via rotational invariance technique) have been extended to spherical harmonics (SH) [10]. These techniques are utilized for the localization of reflected signals against the DoA estimation of sources. There are learning methods reported in literature where the EM wave features obtained from measured data are used as input to neural network, which is already trained [8]. Another SH based DoA estimation

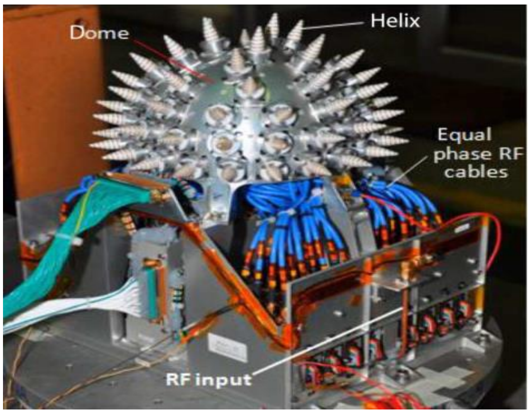


Figure 1. 64 elements SAA in an anechoic chamber [8].

techniques are GCC (generalized cross-correlation), steered response power with phase transform, and the minimum variance distortionless response [11]-[18].

This paper investigates the application of a multiclass support vector machine (MC-SVM) for the classification of SH based magnitude and phase features to various classes of DoA. The MC-SVM is applied in SH domain based on the one-versus-one method, leading to multiclass classifications to multiple binary classification challenges. Individual binary classification issue locate the hyperplane, which classifies the features into different classes. The SVM capacity to identify the hyperplane with outliers simplifies it at low SNR [19], [20]. Due to the fact that the magnitude and phase features dependent on the elevation and azimuth, two different algorithms of SVM are utilized to estimate the DoA. The SH decomposition is used as the input signal with the consideration of antenna location in the SAA [8], [21]. The features serving as input are generated from SH decomposition of the EM waves acquired at far field. Due to the fact that the directional data is embedded in the magnitude and phase components, the feature serves as input to the MC-SVM and classified into different class of DoA. The developed technique is compared with the baseline methods in terms of performance. The major contribution of this paper versus Dwivedi *et. al*. in [22] is that the SH-MC-SVM method is extended to SAA, supported with practical measurement data in EM wave vis-à-vis SAA, which is the acceptable way of testing and evaluating new methods.

2. SYSTEM MODEL

If we consider an EM wave having a source in $\Omega_s = (\theta_s, \phi_s)$ direction at far field. The source s is detected using SAA with radius r_a and M number of elements. The EM wave pressure at $\boldsymbol{r} = (r, \theta, \phi)$ on the SAA is expressed as [1], [23]

$$p(k, r, \theta, \phi) = \sum_{n=0}^{N} \sum_{m=-n}^{n} a_n^m(k) b_n(kr) Y_n^m(\theta, \phi)$$

where (1)

$$b_n(kr) = 4\pi i^n \left[j_n(kr) - \frac{j'_n(kr)}{h_n^{(2)}(kr)} h_n^{(2)}(kr) \right] Y_n^m(\theta, \phi)$$

where $a_n^m(k)$ represents the receiving EM wave made up of plane waves as $a_n^m(k) = [Y_n^m(\theta_s, \phi_s)]^* s(k)$. $b_n(kr)$ denotes the strength of the mode, $j_n(\cdot)$ and $h_n^{(2)}(\cdot)$ are the n spherical Bessel function of first kind and Hankel function of second kind. Wave number $k = 2\pi f / c$, where c is the speed of EM wave. N is the order of SAA. The SH basis function $Y_n^m(\theta, \phi)$ is described as [23]

(2)

$$Y_n^m(\theta,\phi) = \sqrt{\frac{2n+1}{4\pi}\frac{(n-m)!}{(n+m)!}}P_n^m(cos\theta)e^{im\phi}$$

where P_n^m is the Legendre parameter. The sum of the pressure received by the SAA in form of matrix is expressed as

$$\boldsymbol{P}(k) = \boldsymbol{Y}(\Omega)\boldsymbol{B}(kr)[Y(\theta_s,\phi_s)]^* s(k) + \eta(k) \quad (3)$$

where $\boldsymbol{B}(kr) = diag[b_0(kr), b_1(kr), \dots, b_N(kr)]$ denotes the mode strengths. $\eta(k)$ is the noise. $Y(\Omega) \in \mathbb{C}^{(N+1)\times M}$ denotes the SH basis function regarding the position of the elements in the SAA, and it's given as

$$\boldsymbol{Y}(\Omega) = [Y_n^m(\theta_1,\phi_1), Y_n^m(\theta_2,\phi_2) \dots Y_n^m(\theta_M,\phi_M)] \quad (4)$$

Transforming the EM wave pressure from the spatial domain to SH domain via SH decomposition, we have

$$\boldsymbol{P}_{nm}(\mathrm{k}) = \boldsymbol{Y}^H(\Omega)\boldsymbol{p}(k) = \boldsymbol{B}(kr)[Y(\theta_s,\phi_s)]^* s(k) + \eta_{nm}(k) \quad (5)$$

where $\eta_{nm}(k) = \boldsymbol{Y}^H(\Omega)\eta(k)$ denotes the SH decomposition of noise. Considering a known SAA configuration, mode strength matrix is eliminated, making the EM wave not to depend on the radial part as

$$\alpha_{nm}(\mathrm{k}) = [Y(\theta_s,\phi_s)]^* s(k) + \tilde{\eta}_{nm}(k) \quad (6)$$

where $\tilde{\eta}_{nm}(k) = B^{-1}(kr)\eta_{nm}(k)$. Analyzing the EM waves in time domain using STFT (short time Fourier transform) of Eqn. (6) gives

$$\alpha_{nm}(\zeta,\tau) = \alpha^t{}_{nm}(\zeta,\tau) + \alpha^n{}_{nm}(\zeta,\tau) \quad (7)$$

where $\alpha^t{}_{nm}$ and $\alpha^n{}_{nm}$ are the target and noise component, respectively. ζ and τ represent the frame index and frequency bin evaluated from STFT, respectively. The coefficients of SH extracted from system model here are employed for other features extraction procedure.

3. EXTRACTION OF FEATURES AND MC-SVM SCHEME

This part describes feature extraction procedure of both phase and magnitude in SH domain using SH decomposition. In addition, an SH domain MC-SVM (SH-MC-SVD) scheme for the classification of the extracted features to different DoA classes is investigated. The procedure is as depicted in Figure 2.

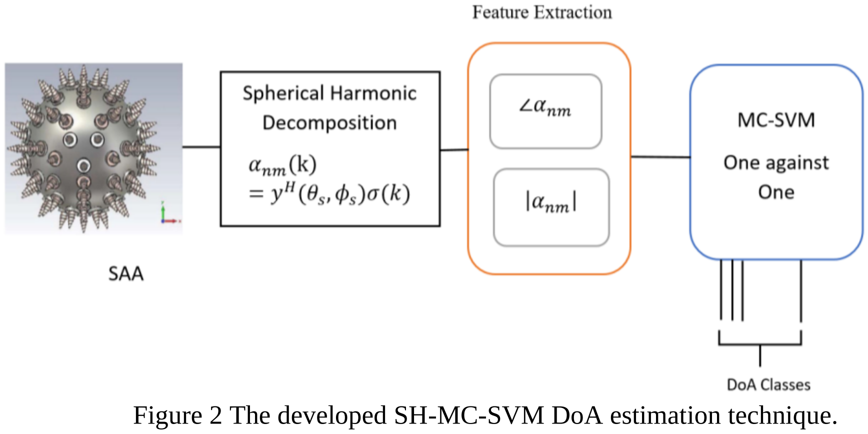


Figure 2 The developed SH-MC-SVM DoA estimation technique.

A) Feature Extraction in Spherical Harmonic Domain

The magnitude and phase features in SH domain are employed for training the MC-SVM algorithm towards the estimation of azimuth and elevation. The magnitude and phase in SH domain are extracted from EM wave SH coefficients. Zeroth degree and zeroth order (omnidirectional) coefficient of SH does not depend on DoA. Therefore, the component of the omnidirectional is removed from the remaining component features. The magnitude of SH coefficients after the consideration of directional based orders is expressed as

$$|\alpha^t{}_{nm}(\zeta,\tau)| = \sqrt{\frac{(2n+1)(n-m)!}{(n+m)!}}|P_n^m(cos\theta_s)| \quad (8)$$

The SH phase coefficients after the consideration of directional dependent orders are

$$\angle \alpha^{t}{}_{nm}(\zeta,\tau) = \begin{cases} m\phi_s & if\ P_n^m(cos\theta) \geq 0, \\ \pi + m\phi_s & if\ P_n^m(cos\theta) < 0 \end{cases} \tag{9}$$

B) Spherical Harmonic MC-SVM Scheme for DoA Estimation

The MC-SVM uses the spherical harmonic magnitude and phase features as the input and performed classification into the elevation and azimuth classes, respectively. The implemented MC-SVM is SH domain is given the acronym SH-MC-SVM. The SVM is fundamentally pictured as binary classifier that locate the hyperplane for the classification of the features into two classes.

The one-against-one (OAO) method is employed for the implementation of the MC-SVM. In OAO method, the MC classification issue is divided into multiple problem of binary classification. The entire problem of binary classification is resolved to extract the optimal hyperplanes. Using this method, $\Delta(\Delta-1)/2$ number of problems of binary classification are resolved, where Δ is the number of the estimated class of DoA. One basic merit of this model is that prior knowledge of DoA number of classes is not a prerequisite. When the SVM is optimized in terms of performance with outliers in the features, it is applicable at low SNR. Furthermore, the SVM is appreciably efficient in terms of memory, and needs smaller data for training in comparison with the neural networks algorithms. Consequently, the SH-MC-SVM exhibits faster convergence than other algorithms.

The main aim of this article is the estimation of both elevation and azimuth angles using a simple learning approach. Two different models were used to classify both the elevation and the azimuth correspondingly. Sigmoid kernel function us utilized as a support vector classifier where C equals 1. The shape of OAO decision function was used in the SVC. For a two classes of DoA *i* and *j*, the classifier is extracted resolving the quadratic optimization below

$$\begin{aligned} & min\frac{(w^{ij})^T w^{ij}}{2} + C\textstyle\sum_{i=1}^{nc} \xi_i^{ij} \text{ subject to} \\ & (\boldsymbol{\mathcal{W}}^{ij})^T x\big(\alpha^{t}{}_{nm}(\zeta,\tau)\big) + b^{ij} \geq 1 - \xi_i^{ij};\quad if\ \gamma_t = i \\ & (\boldsymbol{\mathcal{W}}^{ij})^T x\big(\alpha^{t}{}_{nm}(\zeta,\tau)\big) + b^{ij} \geq -1 + \xi_i^{ij};\quad if\ \gamma_t = j \end{aligned} \tag{10}$$

where $x(\cdot)$ represents the hyperplane feature, $\mathcal{W}$ denotes the normal weight vector that dictate the direction of hyperplane, *b* represents scalar bias that dictate the location of the hyperplane. $\xi_i^{ij} \geq 0$ is a flexible parameter sum up to arrest the situation of optimal hyperplane parameter, while $t = 1, \dots, nc$. γ is the set of class levels, and C denotes the regularization parameter. From the symbol *i* and *j* classes, if $x(\cdot)$ is observed in the i^{th} class, then the i^{th} class vote is increased by 1, else the vote for j^{th} class is increased by 1. $\boldsymbol{x_t}$ is given to the class with biggest vote. For the same vote for each class, then the one having smaller index is chosen. This method is called "MaxWins approach and thus we conduct the SVM classification. Elevation and azimuth classes are the output of the model for the DoA estimation. We conduct the angle classification for input features that corresponds to the correct labels. The developed SH-MC-SVM based DoA estimation Algorithm is given as Algorithm 1.

Algorithm 1 DoA Estimation using Spherical Harmonic SVM

Feature Extraction:
1: STFT Computation of the SH coefficients $\alpha_{nm}(k)$
2: Extract SH-magnitude and SH-phase coefficients of $\alpha_{nm}(\tau, \nu)$
3: Cancel out the omnidirectional component and extract the required SH-phase and SH-magnitude features to serve as input.
4: Train the SVM model with the SH-phase and SH-magnitude features corresponding to ϕ and θ labels.
Training:
5: Input Features : SH-phase and SH-magnitude features $\angle\hat{\alpha}_{nm}(\tau, \nu)$ & $|\hat{\alpha}_{nm}(\tau, \nu)|$.
6: Target Labels: $\phi \in [0^0, \dots, 350^0]$, $\theta \in [10^0, \dots, 170^0]$
7: Apply, sig = (SVM.SVC , kernel='sigmoid').
8: Fit the training data and training labels. DOA Estimation Phase:
9: Use SH-phase and SH-magnitude features of test data $\angle\alpha_{nm}(\tau, \nu)$ & $|\alpha_{nm}(\tau, \nu)|$, to get the predicted
DOA Estimation:
10: $\hat{\theta}$ = SVM(sig,$|\alpha_{nm}(\tau, \nu)|$) ; $\hat{\phi}$ = SVM(sig,$\angle\alpha_{nm}(\tau, \nu)$)

3. NUMERICAL SIMULATION, AND EXPERIMENT

This section compares the developed approach against the state-of-the-arts. The performance metric employed is the root mean square error (RMSE) against the SNR.

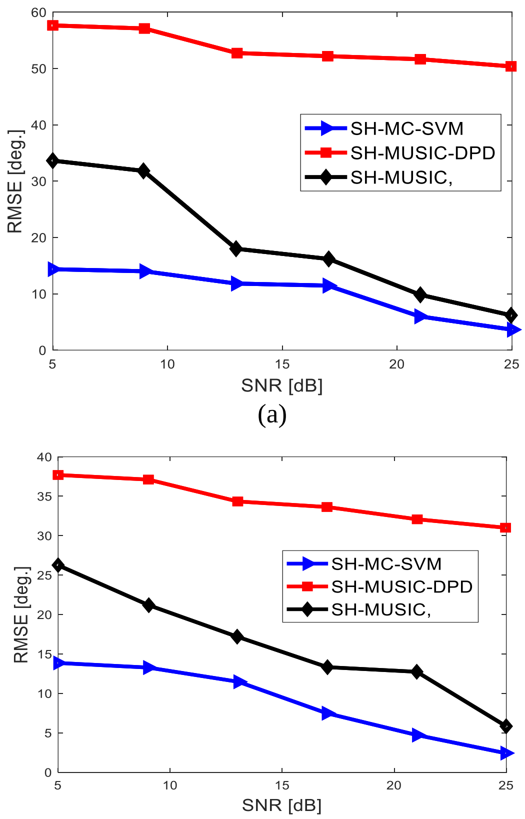
3.1 Numerical Simulations

SAA with radius, $r = 1.8\ cm$, and made up of 32 radiators that operate at 8.4 GHz, and uniformly positioned on rigid sphere, is utilized during numerical experiments or simulations [5] and [8], [11]. The spacing between 2 successive samples in the uniform sampling scheme remains the same. The uniform sampling scheme gives rise to small platonic solids. The event appears majorly for a specific number of antennas [6]. The highest order of the SAA is 4. 600 different Monte Carlo simulations were conducted using Matlab software (2019b version) operating on a laptop personal computer (PC); Intel CPU, Core i7-8565U, 8th Gen., RAM 16 GB, 1 Terabyte . We employed two iterations in the simulations. Avoiding aliasing problem, kr is maintained to be smaller than order N. In addition, narrowband amplitude modulation (AM) waves at far field was employed in each simulation case. The kind of window considered is Hanning window with length 256, and using 16 kHz sampling frequency. Avoiding the problem of aliasing, we considered frequency bins to ensure enough strength of mode [23]. The learning uses training data and validation data, as such; we divide the dataset into two. In the algorithm training, angular variations employed are $\phi \in [0^0, 350^0]$ and $\theta \in [10^0, 170^0]$. We consider azimuth and elevation with 10^0 sampling interval. The performance metric used is the RMSE, and it is expressed as

$$RMSE_{\Omega} = \sqrt{\frac{1}{\Delta}\sum_{\varpi=1}^{\Delta}\left(\Omega_{\varpi} - \widehat{\Omega}_{\varpi}\right)^2} \tag{11}$$

Δ denotes the estimated DoAs. $\Omega \in \{\theta, \phi\}$ and $\widehat{\Omega} \in \{\hat{\theta}, \hat{\phi}\}$ are the real and predicted DoAs, respectively.

The RMSE behavior of the developed technique in comparison with the SH-MUSIC [24] and SH-MUSIC-DPD [25] is presented in Figure 3. The elevation and azimuth angles employed are $[0^0, 350^0]$ & $[10^0, 170^0]$, respectively. According to Figure 3, the developed SH-MC-SVM method outperformed the SH-MUSIC and SH-MUSIC-DPD methods, even at low SNRs. The proposed method is faster and exhibits better performance with smaller training data. SH-MC-SVM computes better margin for classes separation and limits the tendency of error in the data.



(b)

Figure 3. RMSE comparison test on the SH-MC-SVM versus baseline methods. (a) azimuth versus SNR, and (b) elevation versus SNR.

3.2 Experiment

To satisfy the developing applications and needs in telecommunication, a certain number of radiators are positioned on electronic systems. The gap between the elements are smaller, causing serious mutual coupling and leading to poor performance of radiation, and impedance matching [5], [8], and [26]. Incorporating the impact of mutual coupling existing between antennas, a real measured data from experiment, which is the most trusted way to evaluate all methods is utilized. Hence, measured data are further utilized to analyse the performance and evaluate the proposed approach against the state-of-the-arts. We put the SAA in the middle of the anechoic chamber. The source is positioned at 74 DoAs, receiving from various combination of four elevations and eighteen azimuths. There was a selection of azimuths from 5^0 to 365^0 with 20 degree step size. A well detailed information about the measurement procedure is given in [8], where the publication of the experimental data were first made. The performance analysis between the SH-MC-SVM, SH-MUSIC, and SH-MUSIC-DPD is conducted using the experimental data. The gross error (GE as in Equation 12) of the DoAs for the three techniques against SNR is computed and the result is presented in Figure 4. The SH-MC-SVM shows better behavior than other methods, even in the presence of mutual coupling. Below about 12 dB SNR, the SH-MUSIC-DPD shows better performance than SH-MUSIC, while at SNR greater than 12 dB, SH-MUSIC shows better performance than the SH-MUSIC-DPD counterpart does.

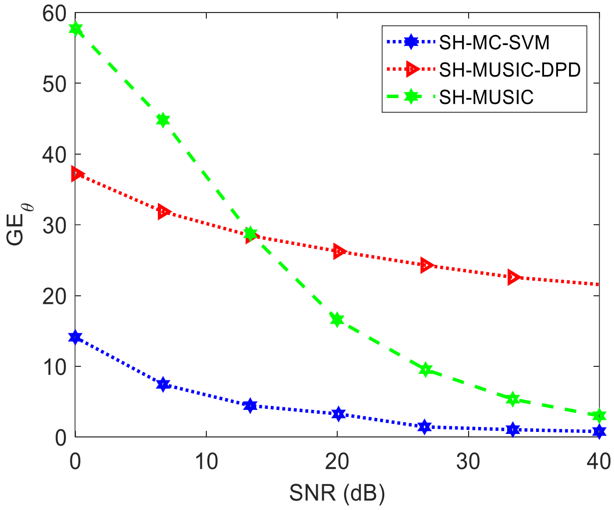


Figure 4. GE performance against SNR using experimental data for SH-MC-SVM, SH-MUSIC, and SH-MUSIC-DPD.

The measure of GE is expressed as

$$GE = \frac{1}{N_T}\sum_{j=1}^{N_T}\left[I_e\left(\Delta\left((\theta,\phi),(\hat{\theta},\hat{\phi})\right)-\lambda\right)\right] \quad (12)$$

4. CONCLUSION

Summarily, this paper presents an MC-SVM classification approach via spherical harmonic EM wave decomposition for DoA estimation. The spherical harmonic phase feature and magnitude feature are obtained and used to train the model. The magnitude feature is employed to estimate elevation, and the phase feature is utilized to estimate the azimuth. The numerical simulations and practical measured data from experiment verifies the application of the developed approach. The developed method is applicable in adequate signal processing such as sparse angular search grid. The comparison of the developed scheme with the state-of-the-arts using RMSE using numerical simulations and real measured data show the effectiveness of the proposed method. The developed method exhibit better performance than the state-of-the-arts at low SNR.

In the future, SH-MC-SVM will be applied in solving other computational problems, such as extending the method to time delay measurement and calibration in different applications, and analyse their hardiness to bewilder issues that unavoidably cause variation in practical application of antenna array.

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