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Linear Vector Quantisation and Uniform Circular Arrays based decoupled two-dimensional angle of arrival estimation

Joseph D. Ndaw, Andre Faye, Amadou S. Maïga

Universite Gaston Berger, BP 234 Saint-Louis, Senegal

E-mail: andre.faye@ugb.edu.sn

Abstract. Artificial neural networks (ANN)-based models are efficient ways of source localisation. However very large training sets are needed to precisely estimate two-dimensional Direction of arrival (2D-DOA) with ANN models. In this paper we present a fast artificial neural network approach for 2D-DOA estimation with reduced training sets sizes. We exploit the symmetry properties of Uniform Circular Arrays (UCA) to build two different datasets for elevation and azimuth angles. Linear Vector Quantisation (LVQ) neural networks are then sequentially trained on each dataset to separately estimate elevation and azimuth angles. A multilevel training process is applied to further reduce the training sets sizes.

1. Introduction

Estimating the directions of arrival (DOAs) of narrowband signals impinging on an antenna array is an important issue in many applications such as radars and wireless communications. System performance and system capacity in noisy environment can be significantly improved with the knowledge of DOAs. An accurate characterisation of propagation environment and a precise localisation of mobile terminal are needed to optimise the link in modern wireless communications. For such purposes, DOA estimation is a mandatory technique especially in smart antenna technology[1]. The DOA is used to dynamically optimise the radiation pattern of the antenna array, making real time processing required in smart antenna technology [2].

The symmetry properties of a uniform circular array (UCA) allow 360° of coverage and uniform performance regardless of angle of arrival in the azimuth plane. Thus, a UCA array is an attractive configuration for DOAs estimation [3] and several algorithms were proposed to estimate DOAs using UCA.

Many publications on Artificial neural networks (ANN) are devoted to DOA estimations but most of them deal with 1D-DOA estimation. Radial Basis Function (RBF), Multi-Layer Perceptron (MLP) and Linear Vector Quantisation (LVQ) neural networks have been used for DOA estimation [4, 5, 6]. There are also publications reporting 2D-DOA estimations with neural networks (RBF, RBF-MLP and MLP) [7, 8, 9]. It is shown in these works that neural networks models outperform subspace based model in terms of speed of computation but computational complexity grows linearly with dimension [7].

In this work, a Linear Vector Quantisation neural network (LVQ-NN) based model is developed for real time 2D-DOA estimation through two separate 1D-DOA estimations.

2. Data model

Consider an M-element UCA with omnidirectional antennas uniformly distributed on the x-y plane. Source elevation angle, $\theta \in [0, \pi/2]$, and azimuth angle, $\phi \in [0, 2\pi]$, in a spherical coordinate system, are measured from the z and the x axis, respectively. If K narrowband incident plan waves $s_{i(i=1,2,\dots,M)}$ from directions $((\theta_1, \phi_1), (\theta_2, \phi_2), \dots, (\theta_K, \phi_K))$ impinge on the array, the complex received signal x_m at the m^{th} antenna is noise corrupted and is written as:

$$x_m(t) = \sum\nolimits_{k=1}^{K} s_k(t) e^{-j\frac{2\pi a}{\lambda}\sin\theta_k \cos(\phi_k - \phi_m)} + n_m(t) \quad (1)$$

$m = 1, 2, \dots, M$, λ denotes the wavelength. The couple of angles (θ_k, ϕ_k) is the 2D-DOA of the k^{th} incident wave, $\phi_m = 2\pi\,(m/M)$ is the element angular position and n_m denotes the receiver noise of the m^{th} element. The complex received signals are noise-corrupted and are written as:

$$[x(t)] = [A(\theta, \phi)] \cdot [s(t)] + [n(t)]\,. \quad (2)$$

$[x(t)]$, $[A(\theta, \phi)]$, $[s(t)]$ and $[n(t)]$ denote the vectors of antenna array outputs, array steering matrix, source signals and zero-mean spatially uncorrelated additive noise, respectively.

The array-processing algorithm uses the spatial covariance matrix ($\mathbf{R}$) i.e. cross-covariance information among the noise-corrupted signals. Let X be denoted as the noise corrupted data matrix composed of N snapshots of $x(n)$: $X(n) = [x_1(n)\ x_2(n) \dots x_M(n)]$.

$$\mathbf{R} = \mathbf{A}E\left\{x(t)x^H(t)\right\} \approx \frac{1}{N} X^H X \quad (3)$$

$E\{\}$ denotes the statistical expectation and X^H the conjugate transpose of X. The input vector at the input layer of the LVQ network is the $\mathbf{R}$ matrix organized as a $2M^2$-dimensional vector.

3. LVQ network

An LVQ is a feedforward network with one hidden layer of neurones fully connected with the input layer. As a supervised method, LVQ uses known target output classification for each input pattern. The accuracy of classification depends on several factors. The number of input and output neurones are given by the dimensions of the input vectors and the number of predefined classes, the number of hidden neurones as well as the learning rate are chosen to get the best classification results. This can be done through an optimisation process [6].

4. Simulations and results

LVQ networks' ability to perform accurate 1D-DOA estimation within the 3-dB bandwidth of the radiation pattern was demonstrated in reference [6]. Computer simulations are based on a 9-element UCA. A 0.73λ radius is used to avoid coupling as reported in reference [10].

The spatial covariance matrix $\mathbf{R}$ is estimated and its elements are used to represent the signal at the array output. DOA estimation is made through a multilevel procedure over predefined sectors of the array field of view illustrated on figure 1. for elevation angles. In this case a 2-level procedure is applied. The first level, the classification step, gives a coarse location of the source within predefined subsectors of width $\delta\theta_1$ spanning the field of view $\Delta\theta$. The second level, the estimation step, gives a precise estimation of the DOA of the signal by classifying it within one of the predefined classes of a subsector of width $\delta\theta_2$.

Additionally, 2D-DOA estimation is made through two 1D simulations to reduce the training set size. Up to 98% training set reduction can be obtained for a 1° angle resolution [4]. This approach is of particular interest as 2D-DOA estimation with ANN requires very large training sets. A 1° angle resolution requires a 32 760-length training set for 2D-DAO estimation training while this length falls to 451 for two 1D-DOA estimations (91 for elevation and 360 for azimuth).

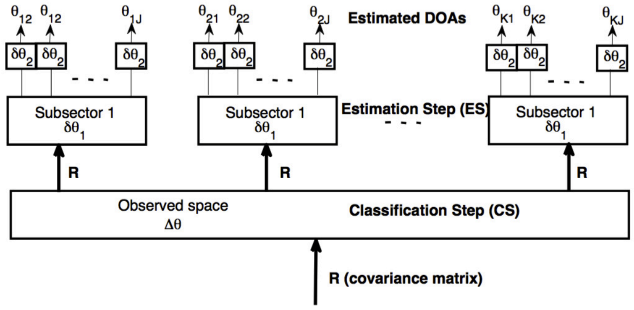

Figure 1. Sectorised field of view for multilevel LVQ model.

We first estimate the elevation angle (θ) from the array steering vector in which azimuth dependence is eliminated using UCAs circular symmetry. The array factor $A(\theta, \phi)$ of an M-element UCA is written as: $A(\theta, \phi) = \sum_i^M e^{j(2\pi/\lambda)a \sin\theta \cos(\theta_i - \phi_i)}$. The Anger-Jacobi expansion of the exponential term leads to: $A(\theta, \phi) = \sum_i^M \sum_{-\infty}^{+\infty} j^m J_m(kr \sin\theta) e^{jm(\phi-\phi_i)}$[1]. For an 9-element UCA array, the array factor can be approximated by the zero order Bessel function : $A(\theta, \phi) = M J_0(kr \sin\theta)$. This form is used to build the $\mathbf{R}_\theta$ training set, used for elevation angle estimation. A second training set with no θ dependence, $\mathbf{R}_\phi$, for azimuth angle estimation is built with the estimated elevation angle $(\widehat{\theta})$: $x_{\phi i} = x_i^{(1/\sin\widehat{\theta})}$.

Angle estimation: Training sets are built with 1024 snapshots at a 20 dB signal-to-noise ratio (SNR) and a sampling step ranging from 2° in the first level to 0.25° in the last level. Confusion matrix rates are higher than 90% in the first level and simulation time is about one second with an 8 GB RAM computer. A 2-level model with $\Delta\theta = 32°$, $\delta\theta_1 = 6°$ and $\delta\theta_2 = 1°$ is used for elevation angle estimation while a 3-level model with $\Delta\phi = 360°$, $\delta\phi_1 = 60°$, $\delta\phi_2 = 10°$, $\delta\phi_3 = 2°$, was necessary for azimuth angle estimation. Angle estimation is based on a hundred runs and DOA is selected as the most probable estimated angle [6].

Table 1. Correlation Coefficient and RMSE for Elevation and Azimuth angles estimations.

Elevation			Azimuth		
	RMSE[θ]	r[θ]	$\hat{\theta}$	RMSE[ϕ]	r[ϕ]
Case 1	0.91°	0.9959	$\theta = 5°$	1.48°	0.9999
Case 2	0.61°	0.9979	$\theta = 10°$	2.43°	0.9997
Case 3	0.84°	0.9964	$\theta = 19°$	1.50°	0.9998

Estimation results: Several simulations were performed for elevation and azimuth estimation. Estimation performance of the LVQ-NN system can be expressed in terms of Pearson product-moment correlation coefficient, r, between reference values and network responses. The correlation coefficient indicates how well the estimated angles match the actual ones. If the correlation coefficient is close to one then the neural network has an an excellent predictive ability, whereas r close to zero indicates a poor performance of the network.

The LVQ model demonstrates good generalisation and 2D-DOA angle estimation capabilities as illustrated on table 1. Correlation coefficients obtained from linear fittings and root mean-square errors (RMSE) are given for 3 elevation and 3 azimuth angles estimations. Worst correlation coefficients (0.9959 and 0.9994) for elevation and azimuth angles, respectively, are concordant with (0.9987 and 0.9997) given in reference [7] for MLP neural networks.

Estimation errors: Estimation error at a fixed elevation/azimuth angle is noise dependent as shown on figure 2. A comparison between error rates at different elevation angles is shown on figure 3. Estimation error decreases as SNR increases. Error rates are high (60% at 20 dB SNR) at the bandwidth limit ($\theta = 27°$) but negligible toward the center of the beam ($\theta = 12°$). Error is about 1° and 2° for elevation and azimuth angles, respectively.

5. Conclusion

An accurate and fast LVQ neural network-based model for 2D-DOA estimation is presented. The developed model decouples elevation and azimuth angles estimation. It takes advantage of the symmetry properties of UCA array to build elevation or azimuth dependent training sets. Decoupling elevation and azimuth angle led to smaller training sets and a faster process for two 1D-DOA searches. Angle estimate errors are 1° and 2° for elevation and azimuth angles. The advantages of this model are the execution speed and a small angle estimation error that can be reduced by increasing the number of model levels.

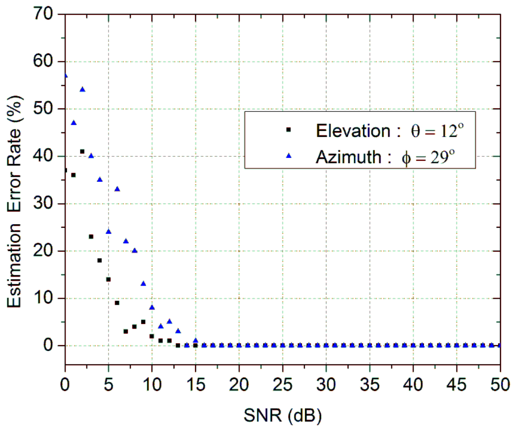

Figure 2. Estimated error rates for elevation and azimuth angles based on a 100 runs.

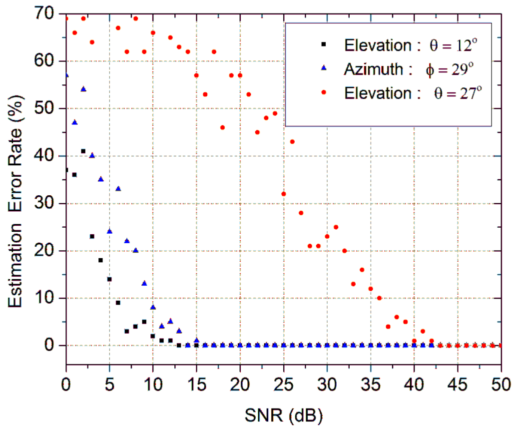

Figure 3. Estimated error rates and model limits shown at $\theta = 27°$ based on a 100 runs.

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