Hardware prototype demonstration of a cognitive radar with sparse array antennas

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As a typical signal processing problem, direction-of-arrival (DOA) estimation has been adapted to a wide range of applications in radar-based systems. A high DOA resolution requires a large number of antenna elements which increases the overall cost. To minimise the cost, it is desirable to choose an optimum sub-array from a full array. To enable cognition, the subarrays are selected based on the present target scenario. By using deep learning (DL) based techniques, the authors show a cognitive sparse array selection technique. By using hardware simulations, they demonstrate the applicability of the deep learning (DL)-based sparse antenna selection network in direction-of-arrival (DOA) estimation problems. They show that the DL-based sub-arrays lead to a higher direction-of-arrival (DOA) estimation accuracy by 6 dB over random array selection.

Introduction: With the growing complexity of the dynamically changing electromagnetic environment, the concept of cognitive radar has gained ever-increasing attention in recent years, due to its flexibility of response to various environmental changes. For example, in the automotive radar application, the bandwidth available for the radars is fixed. Depending upon the number of radars needs to operate at any given instant, the bandwidth has to be adaptively shared among the radars without causing interference [1].

Another critical resource in a radar system is the number of elements in an antenna array, which determines the array resolution as well as the accuracy of the direction-of-arrival (DOA) estimation. For a given wavelength, high direction-of-arrival (DOA) resolution requires a large aperture array which leads to a large number of array elements [2]. As each array element requires its own dedicated hardware, the overall cost of the system increases. Moreover, the computational cost of processing the data stream from multiple array elements is very high. To build an economic system in terms of cost and power consumption, it is desirable to choose a subset of array elements instead of a full array at the expense of resolution. As only a few array elements are considered from the full array, we denote the sub-array as a sparse array. By assuming that the degradation of the resolution is within the acceptable limits, working with sparse arrays has two distinct advantages. First, as mentioned, the computational cost reduces as one has to work with a smaller amount of received data. Second, it facilitates cognition. For example, consider the following two cognitive systems: (i) one can choose the subset of array elements from the full array based on the current target scenario such that accuracy of DOA estimation is high; (ii) different non-overlapping subsets of array elements can be assigned adaptively to track different targets. In this Letter, we consider the first scenario and demonstrate a hardware prototype for the same.

The problem of sparse antenna array selection has been a very active research topic in recent years. In the literature, nearly most of the antenna selection algorithms adopt an optimisation-based algorithm or a greedy search algorithm, which will take a long time and obtain sub-optimum solutions [3]. Recently, Elbir *et al.* [4] proposed a deep learning (DL)-based sparse antenna array selection method by assuming a single-target scenario. The work has been extended to two target cases [5]. To select antennas in a cognitive radar, Elbir *et al.* constructed a convolution neural network (CNN) model as a multiclass classification framework where each class designates a possible sub-array. Numerical experiments have shown that the convolution neural network (CNN) classification network provides more accurate direction-of-arrival (DOA) estimates than random array selection (RAS).

In this Letter, we propose a hardware prototype demonstrating the applicability of the deep learning (DL) approach as developed in [5]. Specifically, we demonstrate a deep learning (DL)-based sparse sub-array selection technique based on the current target scenario. We show that the sub-array chosen by the trained antenna selection network can achieve almost the same estimation accuracy as the best sub-array with the lowest Cramér-Rao lower bound (CRB). Using hardware simulations, we demonstrate the applicability of cognitive antenna selection for DOA estimation and its accurate performance over random array selection (RAS). Next, we describe our cognitive radar system, followed by the details of the hardware and the simulation results.

Antenna selection in cognitive radar system: In [5], an optimal K-element sparse array is chosen to minimise the Cramér-Rao lower bound (CRB) of direction-of-arrival (DOA) estimation. Alternatively, choosing K antenna elements from a total of N elements can also be viewed as a classification problem wherein each class denotes a possible sub-array. Once the optimum sparse sub-array is obtained, we can estimate the DOAs based on the noisy observed signals from the selected antennas.

In this work, we assume the following scan mechanism. Generally, the targets move slowly compared to the high-speed switch antenna array. In the first scan, we assume that all the receive antennas are active and feed their received signals to the CNN classification network. Then the output of the network determines an optimal antenna array where only K antennas will be used and cognitive systems will continue to use this sub-array for a predetermined number of scans before switching back to the full array [4]. Our hardware prototype is designed to address this setting. We apply the following three antenna selection methods and compare their performance with that of full array.

- Best sub-array: the beam forming performance gives the lowest Cramér-Rao lower bound (CRB).
- Random sub-array: it is selected by RAS.
- convolution neural network (CNN) sub-array: it is selected by a trained convolution neural network (CNN), whose input datasets are three real-valued channels while the output is the best sub-array index among all the possible sub-arrays.

Once the antenna array is selected, the DOA is estimated from the signals from the sub-array elements by applying multiple signal classification algorithm (MUSIC).

Mathematical modelling: Consider an N-element antenna array system with the elements located at $\{\boldsymbol{p_n} d | \boldsymbol{p_n} \in \mathbb{N}^3\}$ where d is the inter-element spacing as half the carrier wavelength λ and n is the index of antennas ranging from 1 to N. The position vector $\boldsymbol{p}_n$ in the Cartesian coordinate system takes integer value.

We assume that there are K narrow-band signals impinging on the N-element array from K distinct DOAs $\{\theta_k, \phi_k\}_{k=1}^{K}$ which denote the elevation and azimuth angles in spherical coordinates, respectively. For each antenna, the received signal at snapshot time t yields a sum of K exponential components as follows:

$$y_n(t) = \sum_{k=1}^{K} x_k(t) \exp\left(-\mathrm{j}\frac{2\pi}{\lambda} d\boldsymbol{p}_n^{\mathrm{T}} \boldsymbol{\kappa}(\theta_k, \phi_k)\right), \ 1 \le n \le N. \tag{1}$$

Here $x_k(t)$ is the complex amplitude of the kth source signal and its corresponding Cartesian coordinate is $\boldsymbol{\kappa}(\theta_k, \phi_k)$ which can be calculated as $\boldsymbol{\kappa}(\theta_k, \phi_k) = [\sin(\phi_k)\cos(\theta_k),\ \cos(\phi_k)\cos(\theta_k),\ \cos(\theta_k)]^{\mathrm{T}}$.

As we discretise the angle space into M grids ($K \ll M$) with the assumption that each source direction-of-arrival (DOA) lies on the prescribed grid points, the noise-corrupted received signal vector of the whole sparse array can be modelled as

$$\boldsymbol{y}(t) = \sum_{k=1}^{M} x_k(t) \boldsymbol{a}(\theta_k, \phi_k) + \boldsymbol{w}(t) \tag{2}$$

where $\boldsymbol{a}(\theta_k, \phi_k)$ is the steering vector of the sparse array whose element is computed as $\boldsymbol{a}_n(\theta_k, \phi_k) = \exp(-\mathrm{j}(2\pi/\lambda) d\boldsymbol{p}_n^{\mathrm{T}} \boldsymbol{\kappa}(\theta_k, \phi_k))$. Here $\boldsymbol{w}(t) = [w_1(t), w_2(t), \ldots, w_N(t)]^{\mathrm{T}}$ is the additive noise vector. The target signal $\boldsymbol{x}(t) = [x_1(t), x_2(t), \ldots, x_M(t)]^{\mathrm{T}}$ is a K-sparse vector which means that only K elements of source angles are non-zero values and other $(M-K)$ elements of non-existent angles are zero. For the sake of clarity, hereafter we neglect the time index t and rewrite (2) into $\boldsymbol{y} = \boldsymbol{A}\boldsymbol{x} + \boldsymbol{w}$ where the array manifold matrix $\boldsymbol{A}$ can be written as $\boldsymbol{A} = [\boldsymbol{a}(\omega_1), \boldsymbol{a}(\omega_2), \ldots, \boldsymbol{a}(\omega_M)]$.

Based on the spatial sparsity of sources, many sparse recovery algorithms such as fast iterative shrinkage-thresholding algorithms have been widely applied to single-snapshot direction-of-arrival (DOA) estimation [6, 7]. However, as aggregated data across multiple snapshots leads to a more stable estimate, we will put more emphasis on the multiple-snapshot direction-of-arrival (DOA) estimation. We provide the DOA estimation results by using MUSIC algorithm as described in [5].

Hardware prototype: A schematic of the proposed hardware is shown in Fig. 1*a* which consists of the following main blocks: a receive (Rx) antenna array, a receiver board (Rx board) and a personal computer (PC) controller. The hardware is shown in Fig. 1*b*. The Rx antenna array operates at 2.4 GHz and it is fixedly divided into 16 sets of 4 patch antennas each. Only one antenna of each set can be selected at a time, via 4 to 1 high-speed selector. The receiver board consists of a downconverter board, two analogue-to-digital converter (ADC) cards and a field-programmable gate array (FPGA) board, where the received analogue signal is converted to the baseband digital signal. Its first step is to down-convert the amplified analogue signal to baseband by a downconverter board which will mix the received signal with a local oscillator and pass it through a baseband filter. After analogue down-conversion, an eight-channel FMC168 ADC card is adopted to sample the analogue baseband signal. Then the VC707 FPGA-based processing board transmits the digital outputs to the host PC controller in a high-speed mode where they are utilised for estimating the target DOAs.

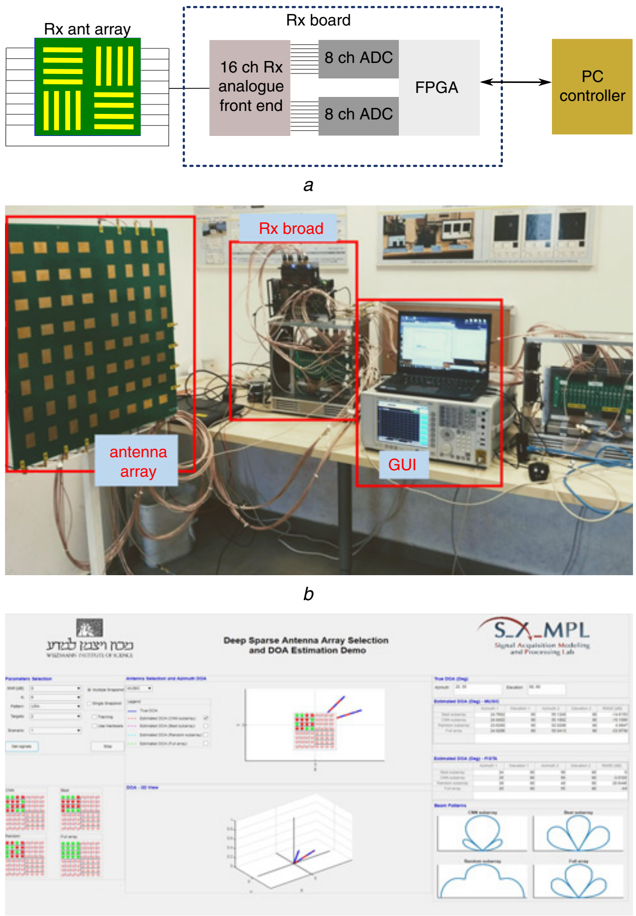

Fig. 1 *Hardware prototype of the sparse array demo*

a Flowchart of the proposed demo prototype
b Full prototype with indications corresponding to the flowchart
c Screen shot of GUI

The graphical user interface (GUI) is shown in Fig. 1*c*, wherein a single sparse array is presented in both the plane and 3D view. In the sparse array demo, the full array is formed by $N = 16$ antennas in the shape of either uniform rectangular array, diamond or a random pattern. To address adaptation in dynamic automotive environments, we implement various options in the demonstration. For example, users can choose a combination of the following configurations: six different target scenarios, three different antenna array patterns, three different numbers of antennas used in each sub-array and four decreasing noise levels. The detail view at the bottom shows the antenna patterns and beam patterns for the full array and three sub-arrays based on the configurations presented above. On the right side, we compare the performance of the full array and three selected sub-arrays in terms of the estimated DOAs as well as the root mean square error (RMSE), simultaneously for all the targets.

Next, we compare the performance of different antenna selection methods. To avoid interference due to wireless networks, specifically WiFi operating at 2.4 GHz, the data is transmitted through cables instead of over the air. In particular, we employ a 16-channel transmit board, similar to the Rx board shown in Fig. 1*a*, to transmit the signals generated in MATLAB. The signals are generated as in [5] and the DOAs from the received signals are estimated by applying MUSIC algorithm. The performance of the proposed cognitive arrayn selectio strategy under different signal-to-noise ratio (SNR) values is shown in Fig. 2. Comparing the direction-of-arrival (DOA) estimation performance of three sub-arrays, the proposed convolution neural network (CNN) approach effectively selects the best sub-array for a large range of SNRs and it provides effective performance as compared to random array selection (RAS). Especially, the convolution neural network (CNN)-based method has 6 dB lower root mean square error (RMSE) compared with random array selection (RAS) in the case of MUSIC estimation results.

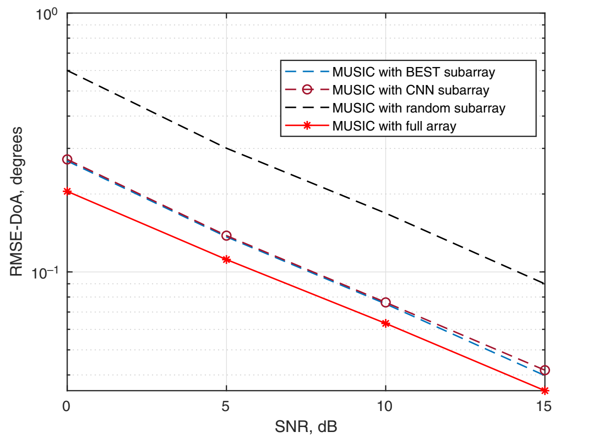

Fig. 2 *Simulation result of multiple-snapshot direction-of-arrival (DOA) estimation by applying MUSIC algorithm*

Conclusion: A high direction-of-arrival (DOA) resolution requires a large number of antennas, which usually entails dedicated hardware equipment for each radar receive antennas and results in high cost. In many radar applications, instead of the entire array, a cognitively selected sub-array offers potential advantages of balancing hardware cost and high resolution. To optimally choose the sub-arrays based on the target DOAs, we use a convolutional network which accepts the array covariance matrix as its input and selects the best sparse sub-array which minimises the root mean square error (RMSE). This approach aids in cognition where multiple antennas are simultaneously operating to track different targets in different directions based on the current target scenario.

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One or more of the Figures in this Letter are available in colour online.

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