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Improved RSS-Based DoA Estimation Accuracy in Low-Profile ESPAR Antenna Using SVM Approach

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***Abstract*—In this paper, we have shown how the overall performance of direction-of-arrival (DoA) estimation using low-profile electronically steerable parasitic array radiator (ESPAR) antenna, which has been proposed for Internet of Things (IoT) applications, can significantly be improved when support vector machine (SVM) approach is applied. Because the SVM-based DoA estimation method used herein relies solely on received signal strength (RSS) values recorded at the antenna output port for different directional radiation patterns produced by the antenna steering circuit, the algorithm is well-suited for IoT nodes based on inexpensive radio transceivers. Measurement results indicate that, although the antenna can provide 8 unique main beam directions, SVM-based DoA of unknown incoming signals can successfully be estimated with good accuracy in a fast way using limited number of radiation patterns. Consequently, such an approach can be used in efficient location-based security methods in Industrial Internet of Things (IIoT) applications.**

Keywords—Switched-beam antenna, electronically steerable parasitic array radiator (ESPAR) antenna, direction-of-arrival (DoA), received signal strength (RSS), support vector machine (SVM), Internet of Things (IoT), Industrial Internet of Things (IIoT)

I. INTRODUCTION

Physical layer security is one of key factors in secure and reliable Internet of Things (IoT) applications that utilize wireless communication [1], [2]. Unprotected physical layer of a wireless system can be prone to eavesdropping, spoofing or jamming attacks, which would have a huge impact in terms of safety and financial losses when IoT network is deployed in an industrial site. Therefore, in order to mitigate risks with such attacks, location-based security mechanisms for WSN [1] and IoT node improvements using directional antennas on the legitimate nodes [2] has been proposed.

To improve physical layer security in wirelessly operating IoT nodes and also whole networks in an affordable way, one can apply cost- and energy-efficient reconfigurable antennas [3], [4] which usually have a single radiating element in the middle and a number of passive elements connected to variable reactances that can be controlled digitally [5]. In consequence, using such antennas, one can, by connecting radio frequency (RF) IoT node output to a single radiating element and IoT node's digital input-output (DIO) ports to the variable reactances' control ports, form a directional radiation pattern and also change its direction electronically in more efficient way than using classical beamforming methods that rely on multiple digital signal processing (DSP) units or a number of active RF devices [5], [6].

In the above context, electronically steerable parasitic array radiator (ESPAR) antenna is one of the most promising reconfigurable antenna concepts. Besides beamforming and localization capabilities, it can also be used to estimate direction-of-arrival (DoA) of incoming signals in wireless sensor network (WSN) applications with single degree precision [5], which can be used to improve connectivity, coverage and energy efficiency of the whole network [3]. In most of practical implementations, power-pattern cross-correlation (PPCC) algorithm is used for DoA estimation as it relies on recorded received signal strength (RSS) values at the antenna output port, which in low-profile ESPAR antennas designed for IoT applications with 8 possible directional radiation patterns allows one to estimate DoA of an unknown target with 2° precision in an anechoic chamber [8]. Therefore, because similar precision can be obtained in high-profile ESPAR antennas having 12 passive elements, DoA estimation performed by a WSN node equipped with recently proposed low-profile ESPAR antenna can be performed 33 % faster. The time required for DoA estimation can further be shortened by using less than 8 directional radiation patterns but, unfortunately, this has a negative impact on the overall DoA estimation accuracy [8].

In this paper, we investigate how the DoA estimation capabilities of low-profile ESPAR antenna can further be improved by using recently proposed RSS-based DoA estimation algorithm utilizing machine learning approach based on support vector machine (SVM) method [9], [10]. Thus far, SVM-based DoA estimation algorithm has been successfully applied only in high-profile ESPAR antennas having 12 passive elements , which has resulted in higher overall estimation accuracy than the deterministic PPCC method. Measurement results presented in this paper indicate that when SVM-based DoA estimation algorithm is applied to low-profile ESPAR antennas the overall results, both in terms of accuracy and time required for the estimation process, are even more pronounced and such an approach could successfully be used in order to implement efficient location-based security or jamming mitigation mechanisms in Industrial Internet of Things (IIoT) applications.

II. Low-Profile ESPAR Antenna for IoT Applications

The considered antenna, originally proposed in [8] and shown in Fig. 1, consists of two $0.95\ mm$ height FR4 substrate layers with $\varepsilon_r = 4.4$, separated by $5\ mm$ height air gap. On the top layer, nine loaded-disk microstrip radiators were located while, on the bottom layer, groundplane and switching circuits have been placed. The central radiator is fed by a coaxial connector via the central pin and is surrounded by eight passive radiators that can modify the antenna radiation pattern when proper loads are connected. To achieve conical radiation pattern, increase available bandwidth and reduce the patch size, each disk radiator is loaded with two shorting pins. The antenna steering is realized by connecting central pin of each passive element to the ground via a dedicated switching circuit realized using SMP1320-040LF PIN diode (Fig. 1). It influences the microstrip radiator resonance via centrally located load (close to open or short circuit). In result, the proposed antenna provides 360° beam steering with 45° discrete step using $N = 8$ directional radiation patterns. Consequently, nth radiation pattern will have its main beam direction equal to φ_{max}^n, for which the radiation pattern will have its maximum in the horizontal plane. Thus, antenna configuration can be denoted by the corresponding steering vector $V_{max}^n = [v_1\ v_2 \cdots v_s \cdots v_8]$, where v_s denotes the state of each passive disk's switching circuit: $v_s = 1$ for s th passive radiator connected via corresponding switched pin to the ground and $v_s = 0$ for opened. In table I, all steering vectors with associated main beam directions are gathered. The proposed antenna has been designed and optimized in Altair FEKO simulator at the center frequency 2.45 GHz to provide the narrowest directional beam with low sidelobe level (SLL) in the horizontal plane, which was achieved for three passive radiators connected to the ground. Antenna measurements (fig. 2) show that radiation pattern with half power beamwidth $HPBW = 69°$ and $SLL = 7\ dBi$ has been achieved for $\theta = 90°$, while measured gain for $\theta = 90°$ and the maximal gain are equal $4.7\ dBi$ and $7.5\ dBi$ respectively. The differences between simulation and measurement are due to imperfections in fabrication of the antenna. Additionally, measured input impedance matching for all configurations is below $-10\ dB$ in the considered operation frequency band.

TABLE I
Low-Profile ESPAR Antenna's Main Beam Directions for Different Steering Vectors (See Text for Explanations)

n	V_{max}^n	φ_{max}^n
1	11000001	0°
2	11100000	45°
3	01110000	90°
4	00111000	135°
5	00011100	180°
6	00001110	225°
7	00000111	270°
8	10000011	315°

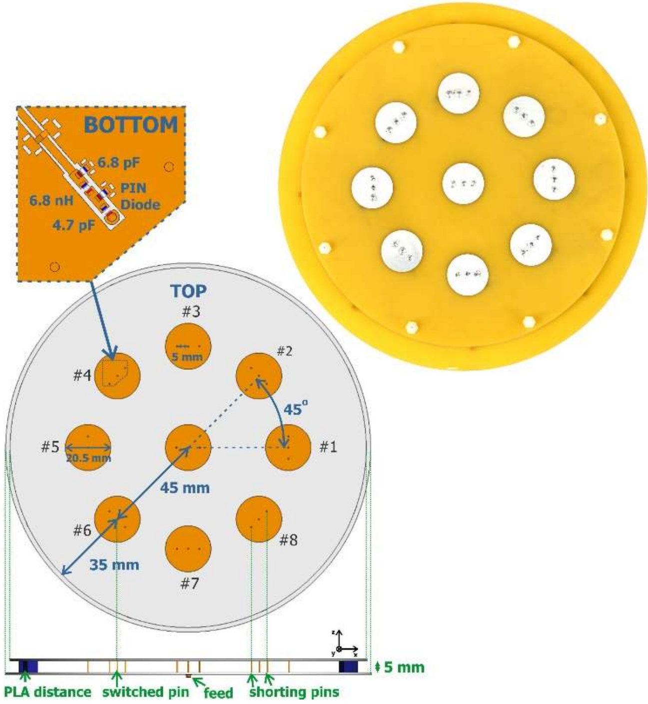

Fig. 1. Low-profile ESPAR antenna together with its dimensions (in millimeters) and numbering of its passive elements (see text for explanations).

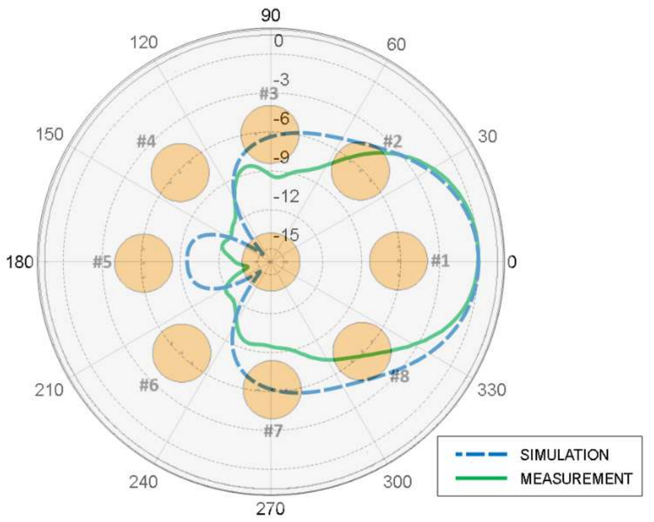

Fig. 2. Simulated and measured normalized radiation patterns of E_θ field component in the horizontal plane with respect to the central active element of the considered antenna for the steering vector $V_{max}^1 = [11000001]$.

III. RSS-Based DoA Estimation Using SVM-Based Classification for ESPAR Antennas

Taking signal strength values from 8 radiation patterns as an observation (features) set $\{Y(V_{max}^1), Y(V_{max}^2), \ldots, Y(V_{max}^8)\}$ and associated direction of arrival angle φ as a discrete outcome, DoA estimation problem can be approached as a categorization task, which relies on 8 ESPAR antenna's radiation patterns $\{P(V_{max}^1,\varphi), P(V_{max}^2,\varphi), \ldots, P(V_{max}^8,\varphi)\}$ measured in an anechoic chamber in the horizontal plane for all considered steering vectors $\{V_{max}^1, V_{max}^2, \ldots, V_{max}^8\}$ during so called calibration procedure [9], [10]. Because the radiation pattern $P(V_{max}^n,\varphi)$ is measured with an angular step resolution $\Delta\varphi$, it can be represented as a vector $\boldsymbol{p}^n = [p_1^n, p_2^n, \cdots, p_I^n]^T$, in which all I values correspond to discretized angles φ that can be written as $\boldsymbol{\varphi} = [\varphi_1, \varphi_2, \cdots, \varphi_i, \cdots, \varphi_I]^T$. Consequently, one can match a particular angle φ_i with a vector $\boldsymbol{p}_i = [P(V_{max}^1,\varphi_i), P(V_{max}^2,\varphi_i), \ldots, P(V_{max}^8,\varphi_i)]$ containing corresponding antenna patterns values and form a training set $D = \{(\boldsymbol{p}_0,\varphi_0), (\boldsymbol{p}_1,\varphi_1), \ldots, (\boldsymbol{p}_I,\varphi_I)\}$ which can be applied in a supervised learning approach to get a trained classifier able to provide estimated direction-of-arrival angle $\hat{\varphi}$ based on measured observation set during the test phase.

Among many classifiers Support Vector Machine (SVM) is one of the most investigated and robust [11]. It proved its accuracy in a demanding task of optical character recognition while keeping fast performance despite a large number of features. This type of classifier is based on finding the most optimal boundary between classes in terms of separation of a training set. In N-dimensional space, where N is the number of features, the algorithm computes decision boundary according to inequality [12]:

$$\hat{y} = \begin{cases} 0, when\ \boldsymbol{w}^T \cdot \boldsymbol{x} + b < 0 \\ 1, when\ \boldsymbol{w}^T \cdot \boldsymbol{x} + b \geq 0 \end{cases} \tag{1}$$

where $\boldsymbol{w}$ and b are defining the hyperplane boundary and $\boldsymbol{x}$ represents input observation (features) to be used in classification which results in binary values of $\hat{y}$. The goal is to find hyperplane which represents the widest margin from each observation with features lying on its border, called support vectors. It has been shown, that this forms a constrained optimization problem of minimization of $\|\boldsymbol{w}\|$ in subject to (1):

$$\underset{\boldsymbol{w},b}{\text{minimize}}\ \frac{1}{2}\boldsymbol{w}^T \cdot \boldsymbol{w}$$
$$\text{subject to: } t^{(k)}\left(\boldsymbol{w}^T \cdot \boldsymbol{x}^{(k)} + b\right) \geq 1, \tag{2}$$

where $t = \pm 1$ represents one of the binary class and $k = 1,2,\ldots,K$ is a training sample number. After optimization, which forms a training phase of the classifier, new feature vectors $\hat{\boldsymbol{x}}$ can be used to derive the prediction $\hat{\boldsymbol{y}}$. This allows for binary classification only, so multiple binary classifiers have to be used in order to cover more output values. An approach called "one-versus-rest" can be applied [9], [10] which, in this particular case, uses I binary classifiers – one for each considered angle of arrival. It is rarely the case that training samples comprises linearly separable set in N-dimensional space. To overcome this problem the technique called *kernel trick* can be introduced [9]. This approach transforms feature set by using nonlinear *kernel* function $\boldsymbol{\phi}(\boldsymbol{x})$ in order to expand the dimensions of features and do not affect the linearity of decision boundary in resulting space at the same time. A more detailed description can be found in [9].

IV. Measurements

To verify the overall RSS-based DoA estimation accuracy using low-profile ESPAR antenna, anechoic chamber measurements using recently introduced SDR-based setup was configured [13], [8]. To this end, the ESPAR antenna was mounted on a turntable at $H = 4.1\ m$ in our $11.9\ m \times 5.6\ m \times 6.0\ m$ anechoic chamber, shown in Fig. 3, situated 8 meters from the transmitting antenna, that was placed on a pole stand at the same height, and both antennas has been connected to an SDR-based device (NI PXIe-5840) acting as a signal generator and a signal analyzer as it is presented in Fig. 3. Then, in the calibration phase, all the antenna radiation patterns associated with the eight main beam directions have been measured at 2.484 GHz in the horizontal plane with the angular step resolution $\Delta\varphi = 1°$, which has provided $I = 360$ calibration points. For each point, 100 sinusoidal snapshots were sent via the transmitting antenna and then received and averaged at the ESPAR antenna output port. This continuous wave (CW) approximation is suitable for narrowband IoT systems.

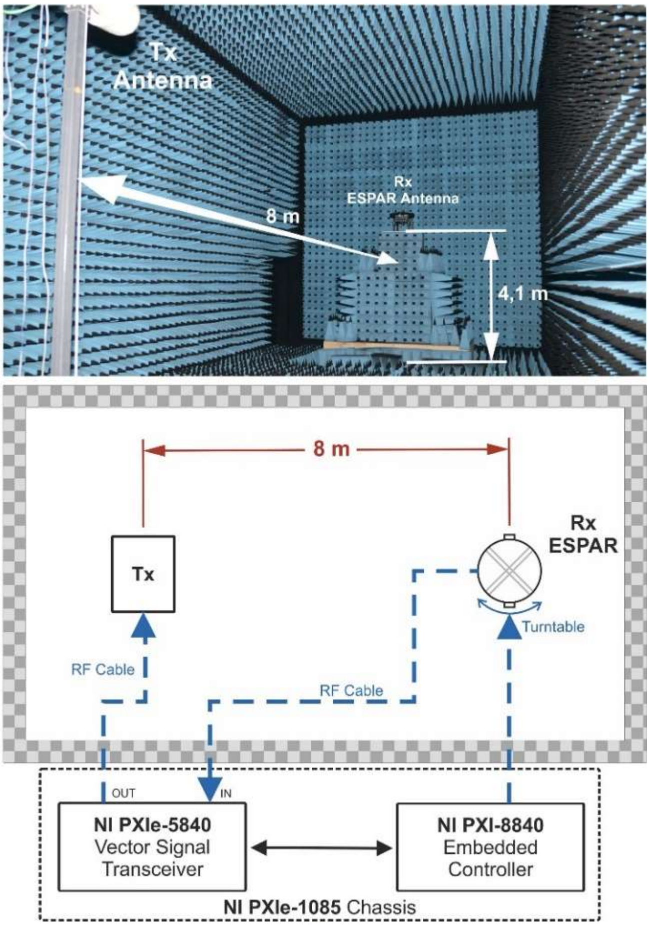

Fig. 3. An SDR-based setup installed in the anechoic chamber to conduct the measurements. NI PXIe-5840 is sending signals to the transmitting antenna and these signals are then received by the same device connected to the output of the investigated ESPAR antenna (see text for explanations).

After the initial calibration phase, SVM implementation from LIBSVM [14] was used for DoA estimation. The "one-versus-rest" approach with I classifiers was applied to achieve multi-classification ability. Gaussian Radial Based kernel function was used for better separation between classes. Then, to determine DoA estimation accuracy, 10 snapshots of 10 dBm 2.484 GHz binary phase shift keying (BPSK) test signal has been generated in our SDR-based setup and sent via the transmitting antenna in the same anechoic chamber. Then these snapshots has been received at the antenna's output, additive white Gaussian noise has been added to obtain a required signal-to-noise ratio (SNR) and then the obtained signal has been averaged to get an associated RSS value. This procedure is applied to approximate real world operating conditions of the system in terms of noise in channel. To compare our results with those already available in the literature, test signal's directions were set by rotating the receiving low-profile ESPAR antenna with discrete angular steps equal to $\Delta\varphi_t = 10°$ in horizontal and elevation directions respectively and, for every test direction in DoA estimation process, eight RSS measurements for the eight main beam directions have been measured. In consequence, 36 test directions $\varphi_t \in \{0°, 10°, \dots, 350°\}$ for signals impinging the ESPAR antenna, were generated.

To compare DoA estimation results obtained using SVM-based classification algorithm for ESPAR antennas proposed originally in [9] with the results already available for deterministic power pattern cross-correlation (PPCC) algorithm in [8], the estimated DoA angle has been calculated using the SVM algorithm described in the previous section for the BPSK test signal coming from all 36 test directions and SNR equal to 20 dB. This has resulted in 36 DoA error values shown in Fig. 4, with total root-mean-square (RMS) error equal to 0.41° and 1° precision being the maximum error value. Additionally, the cumulative error values have been calculated for different number of radiation patterns used and gathered, together with corresponding SNR values, in table II.

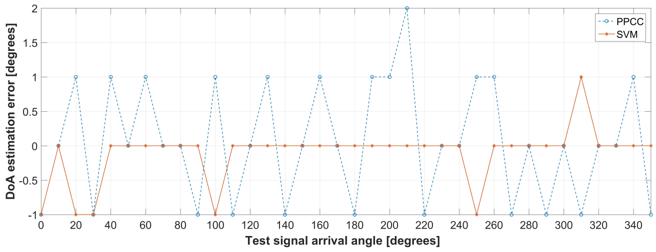

Fig. 4. Comparison of DoA estimation error results for the considered low-profile ESPAR antenna obtained from the measurements at SNR=20 dB using SVM and PPCC methods (see text for explanations).

TABLE II
DoA Estimation Errors Obtained for the Considered Low-Profile ESPAR Antenna When Only Specific Radiation Patterns Are Used for SVM and PPCC Algorithms (see text for explanations).

	Radiation patterns used	SNR = 20 dB		SNR = 10 dB		SNR = 0 dB	
		RMS	prec.	RMS	prec.	RMS	prec.
PPCC	[1 2 3 4 5 6 7 8]	0.85°	2°	1.32°	4°	2.52°	8°
	[2 4 6 8]	1.29°	4°	2.92°	11°	4.19°	11°
	[1 3 5 7]	2.37°	11°	4.59°	25°	9.89°	40°
	[1 4 7]	1.55°	5°	3.70°	16°	4.12°	12°
	[2 5 8]	1.37°	4°	1.76°	5°	3.93°	12°
SVM	[1 2 3 4 5 6 7 8]	0.41°	1°	0.71°	2°	1.47°	4°
	[2 4 6 8]	0.47°	1°	1.07°	3°	3.59°	11°
	[1 3 5 7]	0.75°	2°	1.29°	4°	2.05°	6°
	[1 4 7]	1.03°	4°	1.31°	4°	2.35°	6°
	[2 5 8]	0.83°	2°	1.05°	3°	2.41°	7°

Comparing the obtained DoA estimation results with those already available for PPCC algorithm in [8] for the same measurement setup one can easily notice that, in case of low-profile ESPAR antenna, SVM-based DoA estimation outperforms PPCC method as it was the case in high-profile ones [9], [10]. However, when low-profile antennas are used with radiation patterns better suited for practical IoT implementations [8], it is possible to obtain better results for SVM approach based on 3 radiation patterns only (see table II for radiation patterns [2 5 8]), than for all 8 radiation patterns with PPCC method. What is even more promising, these results provide the same precision level for SNR equal to 20 dB as previously available for high profile ESPAR antenna with 12 passive elements. It means that, for $SNR = 20$ dB, the proposed SVM-based approach provides 2° precision at 75% and 62.5% shorter time than in case of PPCC method used together with high- and low-profile ESPAR antennas respectively.

V. Conclusions

In this paper, it has been shown, how the overall accuracy of RSS-based DoA estimation using low-profile ESPAR antenna can be improved when support vector classification is applied. To this end, a training set for the learning process to obtain SVM algorithm for RSS-based DoA classification has been created based on antenna radiation patterns measured in an anechoic chamber. Measurements indicate that the proposed method provide as accurate DoA estimation results as previously achievable for the PPCC algorithm but using low number of radiation patterns, which makes it well-suited for implementations of efficient location-based security or jamming mitigation mechanisms in Industrial Internet of Things (IIoT) applications.

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