Demonstration of Spider-Eyes-Like Intelligent Antennas for Dynamically Perceiving Incoming Waves

Zhedong Wang, Chao Qian,* Tong Cai, Longwei Tian, Zhixiang Fan, Jian Liu, Yichen Shen, Li Jing, Jianming Jin, Er-Ping Li, Bin Zheng,* and Hongsheng Chen*

1. Introduction

Whether for humans or other animals, obtaining a full view and complete information of the surrounding dynamics has been a longstanding topic as it provides the most basic inputs for sensing, imaging, navigation, orientation, and so on. For example, the jumping spider (Figure 1a) can perceive a nearly omnidirectional field of view in a static state due to its unique compound eye structure, capable of preying and protecting itself from predators in a fast and agile manner. Compared with the jumping spider, human vision behaves slightly worse, typically limited to 210° in the horizontal direction. When things of interest are out of view, humans always need to twist the neck or rotate the eyeball to adjust the visual focus. Generally speaking, all the aforementioned ubiquitous examples are in essence to perceive the information of the scattered waves generated by the targeted object or termed as incoming waves. Such a mechanism has been widely used in a variety of applications, such as source...
location, wireless communication, and self-adaptive systems,[3,4] ranging from the microwave to visible.

To perceive incoming waves, a high-performance electromagnetic (EM) detector plays a pivotal role.[5,6] Beyond the basic attainments of EM strength and frequency, high-performance EM detector should also be able to simultaneously sense other fundamental information, such as direction of arrival (DOA) and polarization, with the properties of compactness, broadband, full-view, low-cost, and real-time. Toward this, conventional methods utilize either the phase or the amplitude, or the complex form of the signal, to obtain DOA-only information, solved by spatial spectrum estimation.[7] As these methods heavily rely on a priori knowledge of array structure and a trial-and-error solution fashion, it is challenging and costly to design a system to estimate multiple parameters simultaneously in the presence of random noise, mutual coupling among antennas, especially in consideration of practical volatile scenarios.[8] In addition, to access a wider view, conventional amplitude-based methods typically rely on a beamforming network to step-by-step scan the whole space, rendering the detection system bulky and expensive.[9] Although subspace methods can bypass such disadvantages, sophisticated phase-sampling devices and tedious iterative calculations are still unavoidable. Other methods such as deep learning are also applied in this field and make great achievements.[10,11] These methods feed the neural networks with signal from MIMO antenna system and train them directly. The trained neural networks are typically more robust to the noise and other imperfections in experiments than conventional methods. However, most of the deep learning methods for DOA estimation in MIMO arrays are still based on phase information, where sophisticated phase-sampling devices are necessary. In addition, they are also vulnerable to polarization variation of incident waves that should not be ignored for a multifunctional EM detector.

Here, the visual mechanism of the jumping spider inspires us somehow to address these challenges. We note that the jumping spider has two familiar but extraordinary components, that is, information acquisition and information processing. For information acquisition, eight eyes distributed around the top of the head provide the jumping spider with a panoramic view. To mimic this, we consider a set of polarization- and orientation-sensitive subwavelength elements distributed along one antenna array.[12] As such, for different incoming waves, the elements can induce different responses such as surface voltages. The advantages of the proposal include its low cost, ease of integration, quiescent operation, and flexible design. For information processing, the machine learning method,[13] as an emerging method that has already improved state-of-the-art image classification, optical computing, material designing, and so on,[14–17] can be considered as a superior candidate. Such a type of data-driven learning architecture has a high similarity to the biological nervous system of a jumping spider, which directly maps the relation between inputs and outputs. According to the universal approximation theorem,[18] machine learning methods can represent an arbitrary complicated function and do not require prior knowledge of the detector itself, such as antenna geometries,

![Figure 1. Schematic of jumping spider’s visual system and machine-learning-driven incoming wave detector. a) Left is a front view of the jumping spider. Eight eyes are located on the top of the head in a ring shape, each of which covers a specific spatial region, enabling omnidirectional vision in total. The nervous system processes the signal received by each eye and offers the correct understanding of surrounding objects, such as a fruit fly. b) Schematic of a machine-learning-driven incoming wave detector. The intelligent detector consists of an antenna array, an RF processor, and a GRNN for simultaneous attainments of frequency $f$, DOA (elevation $\theta$ and azimuth $\psi$), and polarization $p$. The antenna array behaves as a jumping spider’s compound eyes to receive incoming waves from arbitrary orientations. The frequency component can be readily retrieved by a frequency sweep and Fourier transform, and the amplitude-only vector will be fed to the machine learning model to predict the DOA and the polarization state of the incoming wave.](image-url)
or of the surrounding environment with stray ambient waves. Moreover, due to the inherent properties of one single feed-forward computation, these data-driven methods no longer involve tedious calculations, saving a significant amount of time.  

Taking the microwave as verification, we design a hexagonal eight-port antenna array, where the collected amplitude-only information is fed to our machine learning model for simultaneous output of frequency, DOA, and polarization in the microwave band. Here, the specific type of machine learning is not limited, and we deploy a Generalized Regression Neural Network (GRNN) based on its performance; see the comparison with the deep neural network (DNN) in the Discussion. The whole procedure, including the detection time, GRNN’s computing, and instruction time, takes about 60 ms in practice. Over the entire X band from 8.2 to 12 GHz, both simulated and experimental measurements demonstrate that the average accuracies of the detection of the azimuth angle, elevation angle, and polarization reach 89%, 94%, and 98%, respectively. This work not only opens a new avenue for efficient and intelligent detection but also inspires other intelligent devices for various functionalities.

2. Results

2.1. Architecture of the Intelligent Incoming Wave Detector

A schematic view of the proposed intelligent incoming wave detector and its operation principle is displayed in Figure 1b, consisting of an eight-port hexagonal antenna array, an RF processor, and a GRNN. The antenna array plays a similar role to that of the eyes of the jumping spider to obtain the incoming wave in the whole space. According to antenna signal processing theory, when a signal with polarization $p$ impinges onto the antenna array with elevation angle $\theta$ and azimuth angle $\varphi$, it can be written as

$$S_i(t) = a_i(t)e^{-j(\omega_t+\varphi_i(t))}$$

(1)

wherein $a_i(t)$ is the amplitude of the signal, $\omega_t$ is the central frequency, and $\varphi_i(t)$ is the initial phase. Thereby, for the $j$th antenna element, the received signal from the $i$th input wave can be written as

$$R_j(t-\tau_j) = g_{ij}a_i(t-\tau_j)e^{-j(\omega_t(t-\tau_j)+\varphi_i(t-\tau_j))}$$

(2)

wherein $\tau_j$ represents the time delay and $g_{ij}$ represents the coupling coefficient to the incoming wave. For a narrow-band input wave, we obtain a simplified expression after the approximation of $a_i(t) \approx a_i(t-\tau_j)$ and $\varphi_i(t) \approx \varphi_i(t-\tau_j)$

$$R_j(t-\tau_j) \approx g_{ij}a_i(t)e^{j\omega_t\tau_j}$$

(3)

Therefore, the total signal received by the $j$th antenna becomes

$$x_j(t) = \sum_{i=1}^{C} R_j(t-\tau_j) + n_j(t)$$

(4)

wherein $G$ is the number of input waves and $n$ represents the noise. In these equations, $g_{ij}$ is mainly affected by the properties of the antenna itself, such as polarization and radiation pattern, and the surrounding environment. Basically, for a well-designed antenna array having a distinct characteristic polarization and radiation pattern, each type of incoming wave will induce a specific and unique amplitude sequence on the antenna array. Therefore, it is possible to build up an inverse mapping $F: A^K \rightarrow S^M$ from the amplitude space $\{a = [a_1, a_2, \ldots, a_K]\}$ to the source space $\{s = [s_1, s_2, \ldots, s_M]\}$ to predict the source information, wherein $K$ is the number of array elements and $M$ is the number of parameters. Here, the source information includes the frequency ($f$), DOA($\theta, \varphi$), and polarization state ($p$).

For the frequency component, it can be readily retrieved via the Fourier transform of the time-varying signal. For other components, we resort to the machine learning method to address this inverse mapping, with a set of labeled data $\{a(i), s(i)\mid i = 1, \ldots, N\}$ ($N$ is the number of labeled data). To be specific, we utilize the GRNN, a class of radial basis function neural networks, to inversely deduce the information of one source. As shown in Figure 1b, the GRNN contains an input layer, pattern layer, summation layer, and output layer. Consider an input vector $a(u)$ is fed to the pattern layer, each summation layer node $L_k$ (except for the red node $L_r$ shown in Figure 1b; the red node in the summation layer is the sum of pattern layer outputs) calculates the weighted sum of the pattern layer outputs using labeled data $y_j$. Therefore, the output of the pattern layer is

$$L_r = \sum_{j=1}^{N} e^{-\frac{|a(u)-y_j|^2}{2\delta^2}}$$

(5)

This equation in essence is a Gaussian function, and $\delta$ is a hyperparameter of the GRNN controlling the influence of basis functions. $L_r$ is the red node in the summation layer, and other green nodes read

$$L_k = \sum_{j=1}^{N} y_j e^{-\frac{|a(u)-y_j|^2}{2\delta^2}}$$

(6)

wherein $i = 1, \ldots, M$. Therefore, the prediction result is

$$s(\text{out}) = \frac{L_k}{L_r}$$

(7)

When a suitable number of labeled data are collected, the amplitude sequence captured by the antenna can be processed by the GRNN to predict the incoming wave ($\theta, \varphi, p$) with high fidelity.

2.2. Detector Design and Simulation Results

For a single dipole antenna, the angle- and polarization-sensitive radiation pattern lays a theoretical foundation for perceiving multiple parameters of incoming waves, indicating the possibility of perceiving the incident angle and polarization by a dipole antenna array. In the simulation, we consider an eight-port antenna array, with the relative permittivity and the thickness of 3.5 and 0.8 mm, respectively. For each dipole antenna in Figure 2a, two parasitic patches are mounted
unbalance (BALUN) is used to render impedance φ (consistent with the experimental setup) with a step of 5°, " with 0° while sweeping from 0° to 90°. In this case, the induced voltage waveforms increase with a step of 6°. As φ increases, not only does the voltage amplitude decrease (from 0.4 to 0.2 mV), but also the phase shifts. d) Induced voltage from one antenna element as a function of φ for a TM wave at 10 GHz and θ = 20°. As φ increases, the voltage amplitude increases (from 0.15 to 0.4 mV) due to the increased horizontal electric field component. e) The voltage of all eight ports of the antenna array under a random TM wave at 10 GHz. f) The predicted accuracy by the machine learning method in the entire X band (8.2–12 GHz).

Figure 2. Detector design and simulation results. a) 3D illustration of the antenna element. The transparent substrate has a relative permittivity of 3.5, with the detailed geometrical parameters a = 18.4 mm, w = 5 mm, t = 0.8 mm, b = 1.7 mm, and c = 7.8 mm. b) Radiation pattern of the antenna at 10 GHz. It features a disc-shaped main lobe along the z-direction and a side lobe in the inverse direction. c) Induced voltage from one antenna element as a function of φ for a TM wave at 10 GHz and θ = 20°. As φ increases, not only does the voltage amplitude decrease (from 0.4 to 0.2 mV), but also the phase shifts. d) Induced voltage from one antenna element as a function of φ for a TM wave at 10 GHz and θ = 0°. As φ increases, the voltage amplitude increases (from 0.15 to 0.4 mV) due to the increased horizontal electric field component. e) The voltage of all eight ports of the antenna array under a random TM wave at 10 GHz. f) The predicted accuracy by the machine learning method in the entire X band (8.2–12 GHz).

on both sides to expand the bandwidth, and one trapezoid balance–unbalance (BALUN) is used to render impedance match. At the center frequency of 10 GHz, the radiation pattern exhibits a disc-shaped main lobe along the z-direction and a back lobe along the inverse direction (Figure 2b). Specifically, the gain is 6 dB, the beam width is 65.1° (135.8°) in the horizontal (vertical) plane, and the back-lobe level is −6.1 dB. Together with the radiation patterns at other frequencies (Figure S3, Supporting Information), we can conclude that it is possible to deduce the incoming wave from the amplitude-only sequence based on this antenna. To validate this point, we make some simulations as follows. Taking 10 GHz and TM-polarized (transverse magnetic, whose magnetic field is parallel to the horizontal plane.) as an example, we fix θ = 20° while sweeping φ from 0° to 90° with a step of 10°. The induced voltages from one individual antenna are plotted in Figure 2c. Due to the variation of φ, not only does the amplitude decrease, but also the phase (signal’s peak) shifts. In contrast, we fix φ = 0° while sweeping θ from 20° to 90° with a step of 10°. In this case, the induced voltage waveforms increase from ≈1.5 to 4.5 mV (Figure 2d). Furthermore, for a random incoming wave, the induced voltages from all eight elements are also considered, distinct from each other (Figure 2e and Figure S4, Supporting Information). These simulations lay a foundation for inversely reasoning the incoming wave information from an amplitude-only sequence.

We then progress to the simulation data collection (with the consideration of multiple couplings among antenna array) for our machine learning model. In this process, θ ranges from 24° to 90° (consistent with the experimental setup) with a step of 5°. φ ranges from 0° to 360° with a step of 6°. f ranges from 8 to 12 GHz with a step of 0.2 GHz, and p includes two states, TM and TE (for the TE-polarized, the electric field is parallel to the horizontal plane). At each frequency, we gather around 1300 training data and 200 test data, respectively. The input layer has 8 nodes for the input 1 × 8 vectors, the pattern layer has 1320 nodes, and the hyperparameter δ is optimized to 0.02. To quantize the GRNN performance, we judiciously deploy some criteria. For θ and φ, the correct prediction appears only when |θ_GRNN − θ_true| ≤ 3° and |φ_GRNN − φ_true| ≤ 5°, wherein the subscripts “GRNN” and “true” represent the prediction result and the ground truth, respectively. For the polarization state, we binarize the output value to “1” or “2,” corresponding to TE and TM, respectively. The simulation result turns out that the average accuracies over the X band reach 98%, 99.6%, and 100% for θ, φ, and p, respectively (Figure 2f). Notably, the slight downward trend of the accuracy over frequency may originate from the deformation of the radiation pattern and the decrease of the antenna gain, which deteriorates the mapping relation.

As a comparison, we also consider a multiple signal classification algorithm (MUSIC) one of the most common
algorithms for DOA) to deduce the incoming direction. We design a uniform circular array (UCA) with eight elements, and its radiation pattern is the same as the antenna shown before. The number of snapshots is 200 and the searching step is 1°. Table S2, Supporting Information, indicates that although the MUSIC algorithm can offer a satisfactory accuracy over the entire X band, it unfavorably entails a lengthy searching process (about 1.4 s on a quad-core CPU), in contrast to the machine learning model used here.

2.3. Experimental Setup and Results

In the experiment, we utilize an analog signal generator as the signal source for the transmitting antenna; see Figure 3 and the Experimental Section. In tandem with an electric turntable (tuning the azimuth angle $\phi$) and an arch for tuning the elevation angle $\theta$, we can imitate an arbitrary incoming direction. To mitigate the complexity and the cost of the receiving system, two RF switches are used to serially read eight channels’ output from the antenna array. The entire detection takes about 60 ms, among which 35 ms is for frequency sweeping, 10 ms is for the machine learning calculation, and $\approx 15$ ms is consumed by other data-processing algorithms, such as fast Fourier transform and median filter. Since we only consider amplitude information here, phase disturbances introduced by the switches and other miscellaneous components will not greatly affect the experimental accuracy.

In terms of the experimental data collection, similar to the simulation setup, $\theta$ is set to range from 24° to 90° (for experimental convenience) with a step of 3°, $\phi$ ranges from 0° to 360° with a step of 3°, and $f$ ranges from 8.2 to 12 GHz with a step of 0.2 GHz. So, for both TM and TE, around 5500 training data and 400 test data (8%) at each frequency are collected, respectively. We integrate the GRNN on the ARM (Acorn RISC Machine) part of ZYNQ (a high-end embedded system produced by Xilinx) and optimize the hyperparameter $\delta$ to be 0.01. In Figure 4a,b, the pink (blue) and purple (dark blue) dots represent the prediction and ground truth in the TE (TM) mode, respectively. Two different colored dots connected by a white line represent a group of data (prediction and ground truth). Obviously, the two pairs of dots are very close to each other, and their absolute errors are mostly within 3°, in accord with the theoretical expectation (the resolution is 3°). Applying the same criterion in the simulation, we obtain the accuracy over the X band in Figure 4c. It shows that the average accuracy of polarization is 98%, and the elevation angle $\theta$ (azimuth angle $\phi$) has an average accuracy of about 94% (89%). In general, the accuracy decreases over the frequency. This might be caused by the deformation and the shrinking of the antenna radiation pattern, making the received voltages sensitive to random noises in some directions. Due to the limitation of the analog-to-digital converter (ADC), we can not keep increasing the receiving gain to compensate for such shrinking. To tackle this, we can further design an antenna geometry or increase the sampling upper limit of the ADC.

2.4. Real-Time Detection under Dynamic Incoming Waves

In a real-world scenario, the detector often works in a nonstationary situation. To mimic this, we continuously rotate the transmitting antenna or the receiving antenna array to examine the
real-time performance and robustness of our intelligent detector; see Movie S1, Supporting Information. First, we set $f = 8.4$ GHz, $p = \text{TM}$, and $\phi = 45^\circ$ and allow the transmitting antenna to move from $\theta = 30^\circ$ to 80°. In Figure 5a, the second row denotes the normalized voltage amplitude, and the third row denotes the output of the GRNN displayed on a customized interface. As one can see, the GRNN’s outputs $\theta_{\text{GRNN}} = 39^\circ$ and $\phi_{\text{GRNN}} = 47.9^\circ$ are very similar to the ground truth $\theta_{\text{true}} = 40^\circ$ and $\phi_{\text{true}} = 45^\circ$. Second, we fix $f = 8.4$ GHz, $p = \text{TM}$, and $\theta = 60^\circ$, and allow the electric turntable to rotate from $\phi = 0^\circ$ to 360° (Figure 5b). Finally, we randomly set the incoming waves, including some cases outside of the collected data set (Figure 5c and Figure S2, Supporting Information). All these experimental results are in good agreement with the ground truth, exhibiting a holistic generality.

3. Discussion

3.1. Comparison of the DNN and GRNN for Our Detector

As a comparison, we also consider a deep neural network (DNN) to handle this issue based on the same experimental data. However, the DNN’s average accuracies only reach 73.5%, 50.2%, and 98.5% for $\theta$, $\phi$, and $p$, respectively (Table S3, Supporting Information). This indicates that, for a relatively small amount of data, the GRNN performs better than the DNN. Moreover, the constructed DNN contains over 12 000 neurons (needs 60 ms for one single feed-forward computation), whereas the GRNN only involves about 5500 neurons (needs 10 ms on ZYNQ), except from the heavy requirement on the computational resource; see Supporting Information. Finally, as the function space is continuous in our work, the GRNN used here can take full advantage of its function-approximation property and the speed, albeit paying less attention to the generality.

4. Conclusion

In conclusion, we have introduced a new strategy to perceive dynamic multiple parameters of incoming waves and experimentally demonstrated an X-band intelligent antenna detector with an average accuracy of up to 89%, on a platform of an eight-port planar antenna array driven by a GRNN. This facile yet viable approach for detecting frequency, DOA, and polarization only...
real-time intelligent detection. a) Detection results when $f = 8.4$ GHz, $p = TM$, $\varphi = 45^\circ$, and the transmitting antenna moves from $\theta = 30^\circ$ to $80^\circ$ continuously. The second row is the normalized amplitude from the eight ports, and the third row is the GRNN’s output displayed on a computer interface in real-time. b) Detection results when $f = 8.4$ GHz, $p = TM$, $\theta = 60^\circ$, and the transmitting antenna moves from $\varphi = 0^\circ$ to $360^\circ$ continuously. The time-evolution of (a) and (b) can be found in Movie S1, Supporting Information. c) Detection results for several random incoming waves, including random angles, frequencies, and polarizations.

Figure 5. Real-time intelligent detection. a) Detection results when $f = 8.4$ GHz, $p = TM$, $\varphi = 45^\circ$, and the transmitting antenna moves from $\theta = 30^\circ$ to $80^\circ$ continuously. The second row is the normalized amplitude from the eight ports, and the third row is the GRNN’s output displayed on a computer interface in real-time. b) Detection results when $f = 8.4$ GHz, $p = TM$, $\theta = 60^\circ$, and the transmitting antenna moves from $\varphi = 0^\circ$ to $360^\circ$ continuously. The time-evolution of (a) and (b) can be found in Movie S1, Supporting Information. c) Detection results for several random incoming waves, including random angles, frequencies, and polarizations.

5. Experimental Section

Experimental Setup: The experiment was performed in a microwave anechoic chamber. Due to the limitation of the RF processor and experimental condition, the frequency band from 8.2 to 12 GHz and $\theta$ from $24^\circ$ to $90^\circ$ were selected. A rectangular horn antenna (works from 8.2 to 12.4 GHz) was fixed on a circular arch, allowing the antenna to rotate with the arch motor digitally. Here, an analog signal generator (Agilent N5183A) was used as the signal source and connected to the transmitting antenna. The output amplitude was set to 20 dBm, and the output wave was a continuous sinusoidal wave. The hexadecagonal antenna was connected to an electric turntable through a metal rod. The rotation of the electric turntable was precisely controlled by a circuit composed of an microcontroller unit (MCU) and the motor driver and the solution of the turntable was set to $1^\circ$. An eight-port antenna array was connected to two RF switches (HMC641ALC4). The RF switches were controlled by a circuit composed of a negative voltage generator and optocoupler, which enabled the switches to switch from P1 to P8 in microseconds. Furthermore, the signal was amplified by a broadband amplifier (gain was 25 db) and downconverted to 0.2-4 GHz. In this work, the AD9361 was used as the RF processor and a low-noise amplifier, mixer, and other components inside the chip were used to process the signal. After sampling by ADC, a discrete periodic voltage sequence was obtained. In this experiment, the Xilinx ZYNQ was used for data processing with an accelerator in calculation assisted by field programmable gate array (FPGA).

Detection Process: For the data processing, the step size of the local oscillator (LO) tuning was set as 28 MHz, and the incoming frequency was detected by continuously adjusting the LO frequency and Fourier transform. After the correct frequency was obtained, the LO was tuned to $f_0 - f_0'$ ($f_0'$ is the frequency of the input wave, and $f_0$ is a user-defined frequency of amplitude sequences). Here, $f_0 = 0.5$ MHz was set. The receive gain was tuned following the previously collected gain table (the selected gain can maximize the voltage amplitude within the limits of the ADC). To guarantee the accuracy of the collected amplitude values, only analog filters were used, instead of the digital filters in AD9361. The sequence from the ADC of each port contained 128 voltage values (to cover more than one complete cycle). After sorting, the voltage sequences from the eight ports formed a $1 \times 8$ matrix that contained each port’s amplitude. Then multiple median filtering was used to reduce the effect of random noises and measurement errors and the final voltage amplitude sequence was obtained. The normalized amplitude sequence served as the input of the GRNN, and subsequently, the predicted results were obtained from the intelligent system’s output.

Supporting Information

Supporting Information is available from the Wiley Online Library or from the author.

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Conflict of Interest
The authors declare no conflict of interest.

Author Contributions
C.Q. and Z.W. conceived the idea of this research. Z.W. performed the simulation and experiment. Z.W. and C.Q. wrote the article. Z.F. performed the deep neural network prediction. L.T., B.Z., J.L., T.C., J.J., and E.L. shared their insights and contributed to discussions on the results. C.Q., B.Z., and H.C. supervised the project.

Data Availability Statement
Research data are not shared.

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