Uniting the Arts & Humanities with Science & Technology

Jin Wei

Department of Electrical & Computer Engineering

06/27/2017

Deep learning cognitive radar for Micro UAS detection and classification

The University of Akron

OHIO's POLYTECHNIC UNIVERSITY

College of Engineering

Outline

- Introduction and motivation
- Doppler Radar Based Remote Sensor
- Cognitive Doppler Radar Detection and Classification System
  - SCF-based Feature Characterization Mechanism
  - Low-Complexity Deep Belief Network (DBN)
- Results and Comparison
  - Low-Complexity DBN Results
  - Comparison Results
- Conclusion

Introduction and Motivation

Micro unmanned aerial systems (UASs) are small slow-moving unmanned aerial systems, and they are less expensive and widely available for public use.

The abundance of small UAS platforms could cause security concerns because they are undetectable with military/aviation radar that are optimized for detecting conventional aircrafts and large drones [1].

We propose a low-cost Doppler radar solution that exploits a low-complexity binarized DBN based classier on Spectral Correlation Function (SCF) signatures to detect and classify UASs automatically.

Intelligent Doppler Radar Detection and Classification System

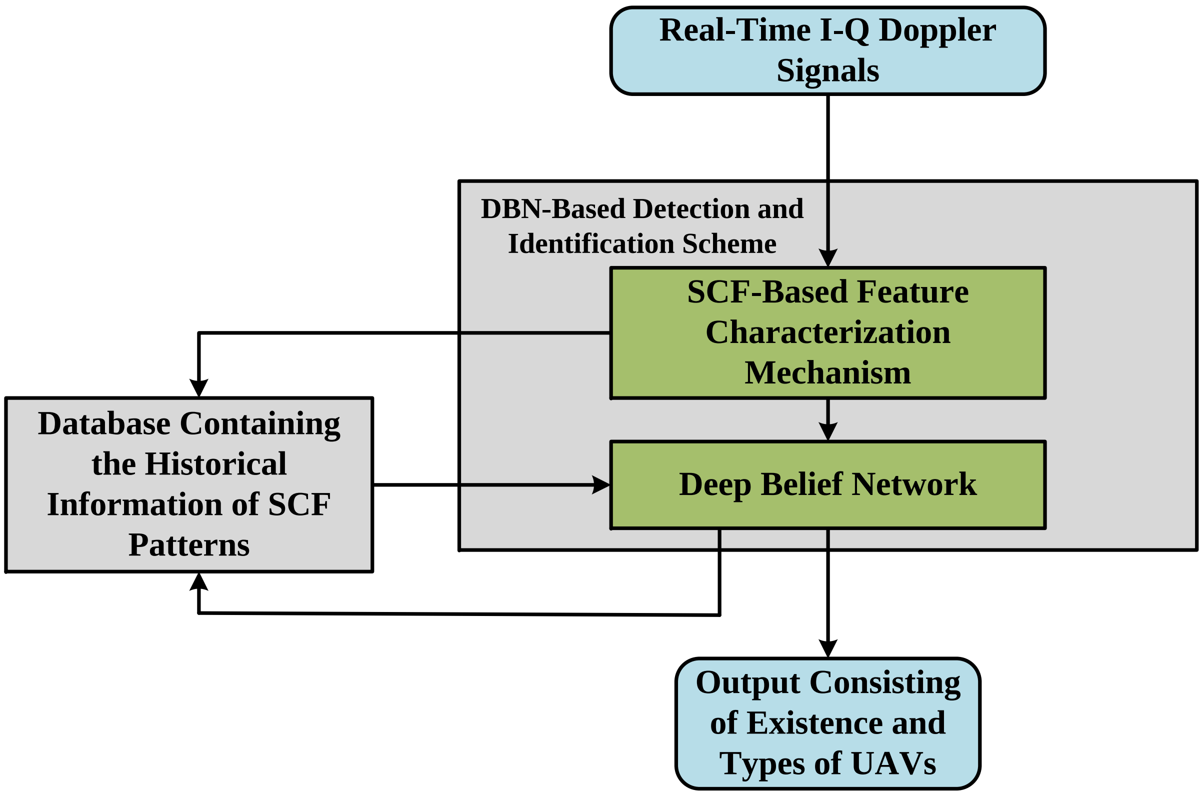


Figure: System Architecture of our proposed deep learning-based AMC method.

Doppler Radar Based Remote Sensor

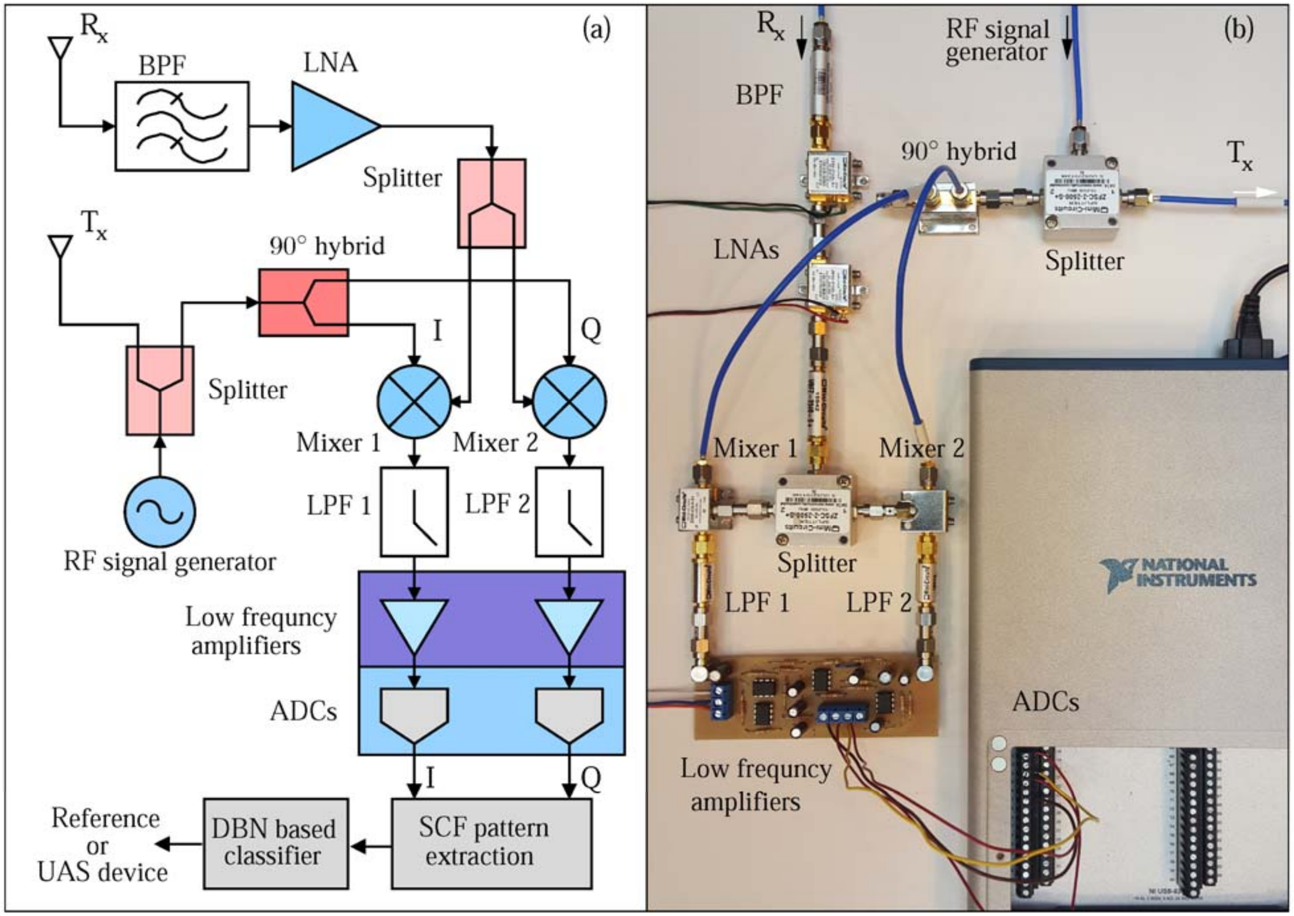


Figure: (a) Overview block diagram of the proposed UAS detection system's digital radar sensor. (b) Implemented setup of the radar sensor front end.

SCF-based Feature Characterization Mechanism

- Doppler shift on radar signals can be considered as a modulation.
  - The modulated signals are treated as cyclostationary processes that refer to the processes with periodic first-order statistics, such as mean and autocorrelation [2].
- Cyclic autocorrelation function (CAF) indicates the amount of correlation between different frequency shifted versions of a given signal and represents the fundamental parameters of their second order periodicity.
- CAF can be calculated as follows:

$$R_x^{\alpha}[l] = \left[\lim_{N\to\infty} \frac{1}{2N+1} \sum_{n=-N}^{N} x[n] x^{*}[n-l] e^{-j2\pi\alpha n} \right] e^{-j\pi\alpha l}$$

Where $x[.]$ denotes the modulated signal that is considered as cyclostationary process and α is the cyclic frequency.

SCF-based Feature Characterization Mechanism

- Spectral Correlation Function (SCF) can be obtain by calculating the Fast Fourier Transform of $R_x^\alpha[l]$.

$$S_x^\alpha[f] = \sum_{l=-\infty}^{\infty} R_x^\alpha[l] e^{-j2\pi fl}$$

Where f is the temporal frequency of the signal.

- In our proposed system, the SCF patterns are generated to represent the Doppler effect on RF that is introduced by the propellers/wings of different types of UASs.

SCF-based Feature Characterization Mechanism

- Radar architecture is implemented in a lab environment, and experiments are carried out with 3 UASs with distinguishable characteristics.

UAS	No of wings/ propellers	Rotor blade length/ Wingspan (cm)	Weight (kg)
Air Hog Firewing (UAS1)	2	41	0.039
Sky Rover Cop (UAS2)	3	25	0.052
Radioshack Surveyor (UAS3)	4	7	0.037

Figure: Images of the drone objects used for the experiment: a) Air Hog Firewing (UAS1); b) Sky Rover Cop (UAS2); c) Radioshack Surveyor (UAS3).

SCF-based Feature Characterization Mechanism

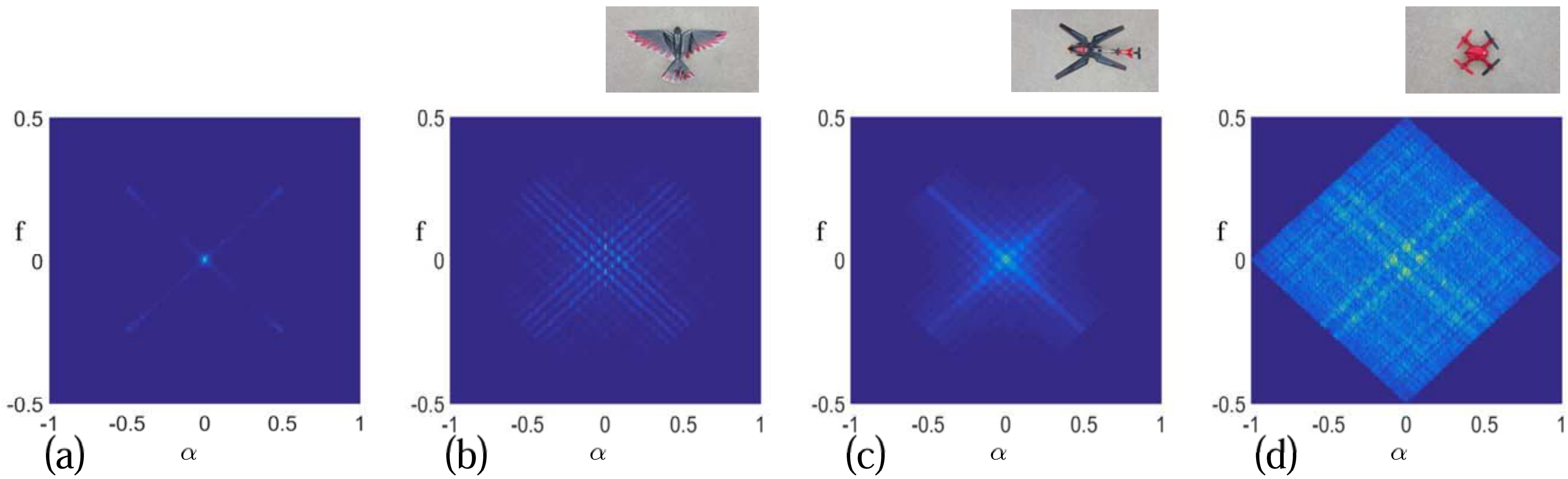


Figure : SCF patterns obtained from the experiment for (a) reference; (b) UAS1; (c) UAS2; and (d) UAS3.

Binarized-Deep Belief Network (DBN)

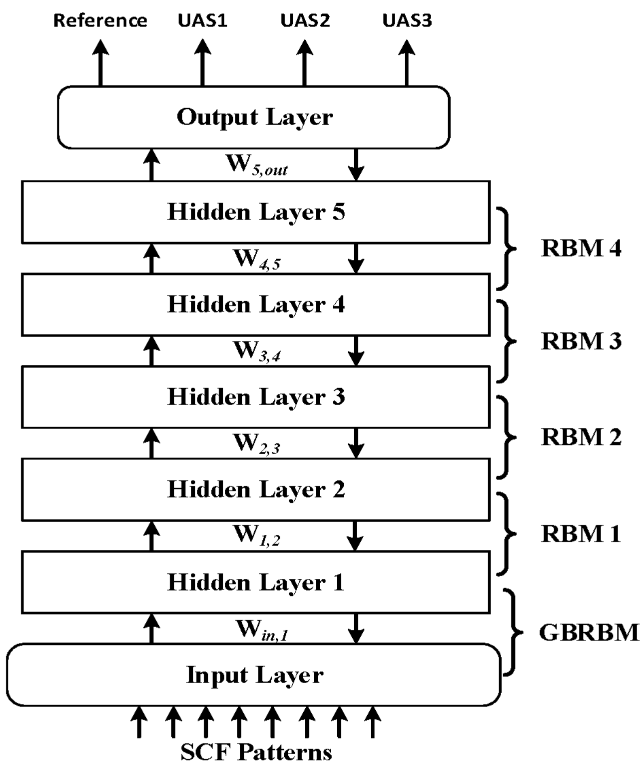


Figure: Architecture of the used binarized-DBN. Where $W_{in,1}$ contains values -2^{-3}, 0 and 2^{3} and other Weight matrices contain values -1, 0, and 1.

- We employ a Deep Belief Network (DBN) to detect and classify the UASs.
- DBN used in our identification scheme is formed by stacking three conventional Restricted Boltzmann Machines (RBMs) and a Gaussian-Bernoulli RBMs (GBRBMs) [3].
- Softmax layer is used as the output layer of DBN.
- DBN is trained through semi-supervised learning with SCF pattern data.
- Backpropagation fine-tuning algorithms is modified to achieve binariezed-DBN [4].

Deep Belief Network (DBN)

- Conventional RBMs consist of one visible layer and one hidden layer of binary units that do not have intra-layer connections [5].
- By training with unlabeled data, RBMs are able to learn the features embodied by the training data.
- Energy function of a conventional RBM is as follows:

$$E(\mathbf{v},\mathbf{h}) = -\sum_{i=1}^{n}\sum_{j=1}^{m} w_{ij}h_i v_j - \sum_{j=1}^{m} c_j v_j - \sum_{i=1}^{n} b_i h_i$$

Where v_j is the jth element of the vector consisting of input unit values, h_i is the ith element of the vector consisting of hidden unit values, w_{ij} is the ijth element of the weight matrix between the visible and hidden units, while b_i and c_j denote the ith and jth element of the bias vectors for the hidden layer and visible layer, respectively. Note that n and m are the number of hidden units, and number of visible units in theRBM, respectively.

Deep Belief Network (DBN)

- Based on Energy function, the activation conditional probability distributions of hidden and visible units of a RBM are shown in the followings:

$$p\left(h_i = 1 \mid \mathbf{v}\right) = sigm\left(b_i + \sum_{j=1}^{m} w_{ij} v_j\right),$$

$$p\left(v_j = 1 \mid \mathbf{h}\right) = sigm\left(c_j + \sum_{i=1}^{n} w_{ij} h_i\right).$$

Where $sigm\left(x\right) = 1/\left(1+e^{-x}\right)$ is the sigmoid function.

- The update rules for weights and biases of a RBM are as follows:

$$w_{ij} = w_{ij} - \rho(< v_j h_i >_m - < v_j h_i >_d),$$

$$b_i = b_i - \rho(< h_i >_m - < h_i >_d),$$

$$c_j = c_j - \rho(< v_j >_m - < v_j >_d).$$

Where ρ denotes the learning rate, and $< . >_d$ and $< . >_m$ are the expectations computed over the data and model distribution, respectively.

Deep Belief Network (DBN)

- Based on Energy function, the activation conditional probability distributions of hidden and visible units of a RBM are shown in the followings:
- GBRBM is a variation of RBM that has a visible layer comprised of real-valued input units [6], [7].
- Energy function of the Gaussian Bernoulli RBM is defined as follows:

$$E(\mathbf{v},\mathbf{h}) = -\sum_{i}^{n}\sum_{j}^{m}\frac{v_j}{\hat{\sigma}_j^2}h_i w_{ij} - \sum_{i}^{n} b_i h_i + \sum_{j}^{m}\frac{(v_j - c_j)^2}{2\hat{\sigma}_j^2}$$

Where $\hat{\sigma}_i$ is the standard deviation of the ith element of the visible units.

- GBRBM are trained by using the following update rules:

$$w_{ij} = w_{ij} - \rho(< \frac{v_j}{\hat{\sigma}_j^2} h_i >_m - < \frac{v_j}{\hat{\sigma}_j^2} h_i >_d),$$

$$b_i = b_i - \rho(< h_i >_m - < h_i >_d),$$

$$c_j = c_j - \rho(< \frac{v_j}{\hat{\sigma}_j^2} >_m - < \frac{v_j}{\hat{\sigma}_j^2} >_d).$$

Deep Belief Network (DBN)

- Based on Energy function, the activation conditional probability distributions of hidden and visible units of a RBM are shown in the followings:
- GBRBM is a variation of RBM that has a visible layer comprised of real-valued input units [6], [7].
- Energy function of the Gaussian Bernoulli RBM is defined as follows:

$$E(\mathbf{v},\mathbf{h}) = -\sum_{i}^{n}\sum_{j}^{m}\frac{v_j}{\hat{\sigma}_j^2}h_i w_{ij} - \sum_{i}^{n} b_i h_i + \sum_{j}^{m}\frac{(v_j - c_j)^2}{2\hat{\sigma}_j^2}$$

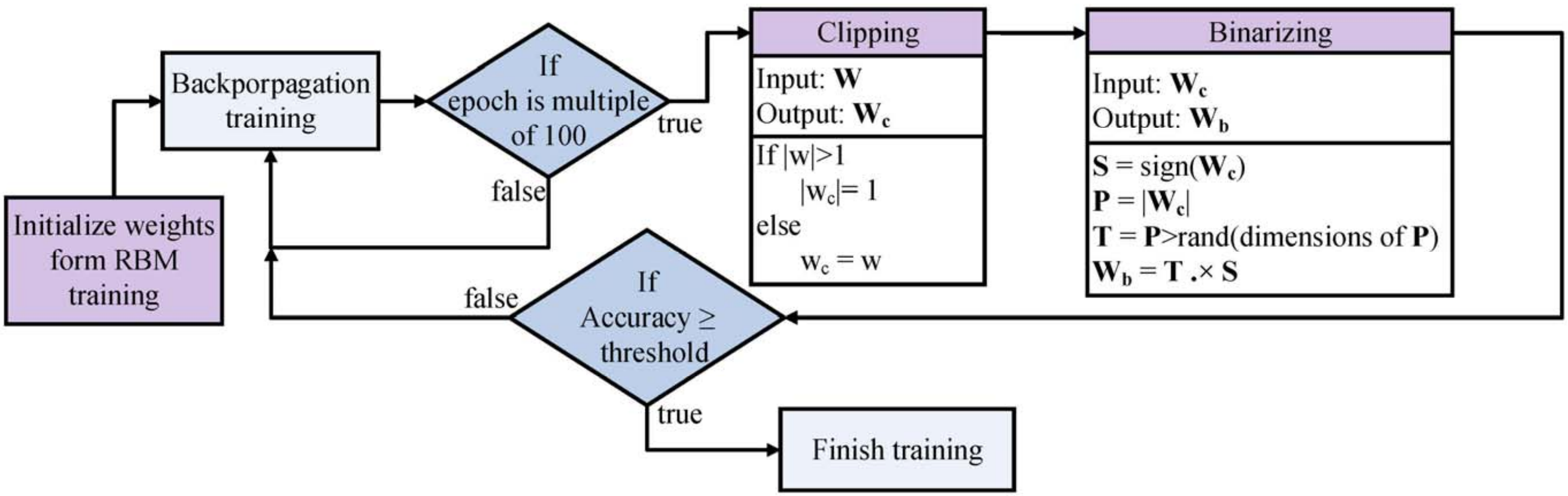
Where $\hat{\sigma}_i$ is the standard deviation of the ith element of the visible units.

- GBRBM are trained by using the following update rules:

$$\Delta z_j = e^{-z_j}\left\langle \frac{1}{2}\left(v_j - c_j\right)^2 - \sum_{i=1}^{n} w_{ij} h_i v_j \right\rangle_d - e^{-z_j}\left\langle \frac{1}{2}\left(v_j - c_j\right)^2 - \sum_{i=1}^{n} w_{ij} h_i v_j \right\rangle_m$$

Where $z_j = \log(\hat{\alpha}_j^2)$.

Modified Fine-Tuning Algorithm for Low-Complexity DBN



Distribution of weights

Weight values	No. of Weights	Percentage of Weights (%)	Mapping
0	31734	34.64	No connection
+1	12368	13.50	Connection
-1	13150	14.36	Negation
$+2^{-8}$	17170	18.75	Right shift by 8 bits
-2^{-8}	17178	18.75	Right shift by 8 bits and negation

Table: Distribution of weights and their hardware mapping .

Results and Comparison

- Low-complexity DBN is trained with 200 data from each class.
- To evaluate the noise-resilience of our proposed system, we artificially add Gaussian noise with different signal to noise ratio (SNR) levels to 150 experimental data from each UAS and reference.

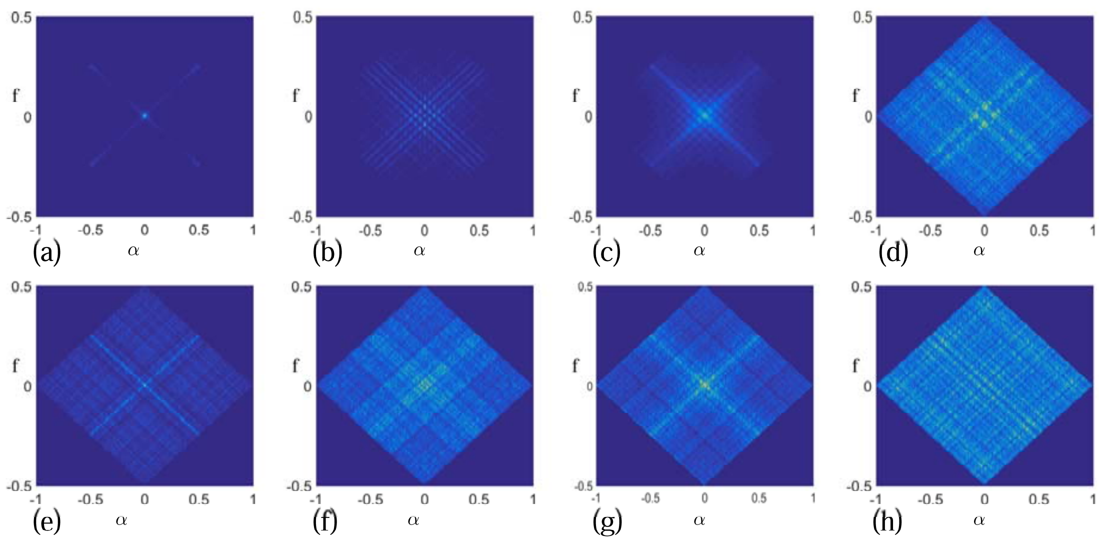
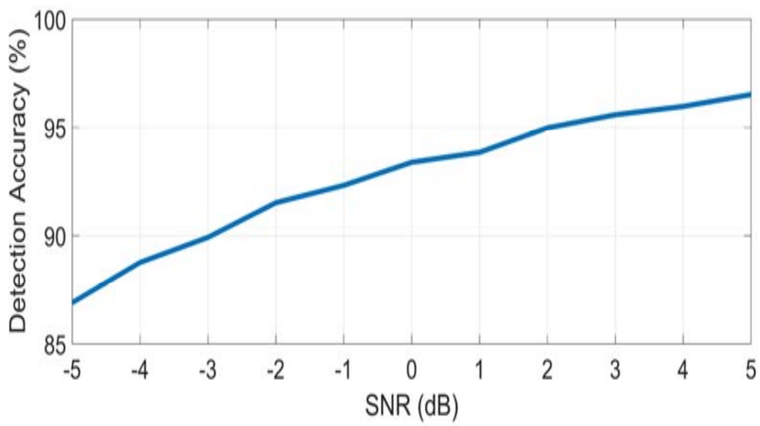


Figure: SCF patterns obtained from the experiment for (a) reference; (b) UAS1; (c) UAS2; (d) UAS3, and SCF patterns obtained in a noisy environment with SNR 0 dB are also shown for (e) reference; (f) UAS1; (g) UAS2; (h) UAS3

Low-Complexity DBN Results

- low-complexity DBN shows above 86% accuracy for detecting micro UASs even when the SNR level is as low as -5 dB. The detection accuracy remains above 90% when SNR > -3 dB.
- percentage of false alarm remains less than 10% for SNR > 0 dB.



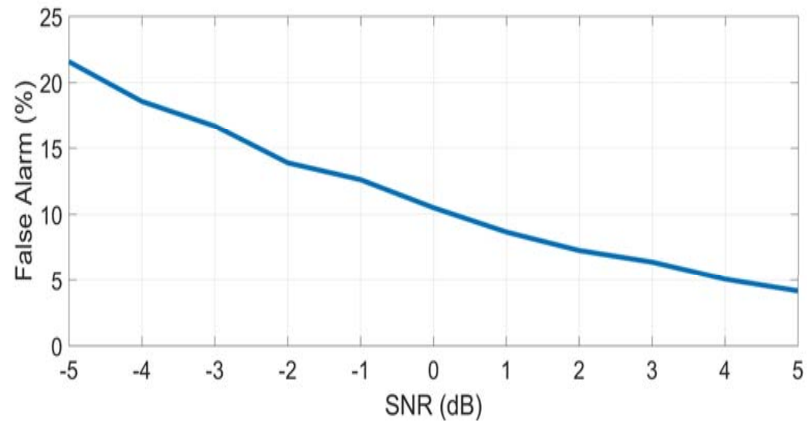


Figure: Accuracy of detection of micro UASs when the SNR of the environment noise increases from -5 to 5 dB.

Comparison Results

- The Accuracy of low-complexity DBN, regular DBN, and MAXNET neural network method, are compared for classifying UAS SCF patterns.
- low-complexity DBN and regular DBN outperform the MAXNET ANN based method.
- Low-complexity DBN performs better for classifying the UAS1 while the regular DBN performs better at classifying UAS2 and 3. Both low-complexity DBN and regular DBN show above 90% accuracy for all considered UAS SCF signature patterns when SNR > 0 dB.

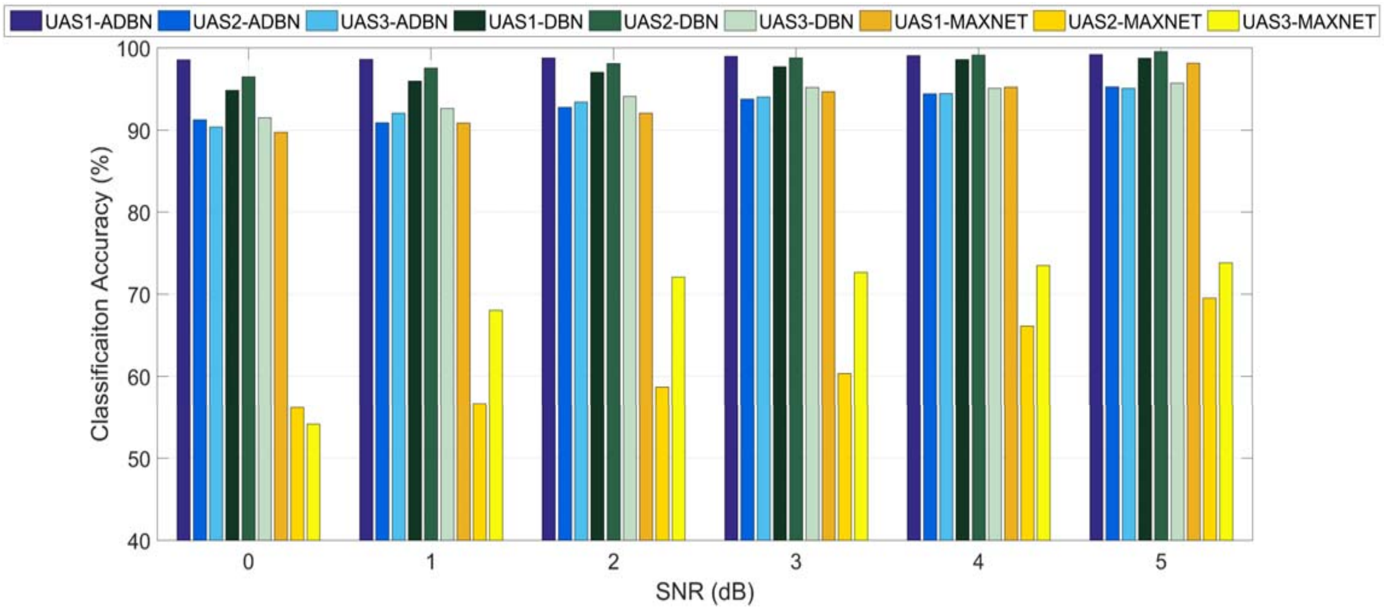


Figure: Classification accuracy of different micro UASs for low-complexity DBN (ADBN), regular DBN, and MAXNET ANN based methods [8].

Conclusion

- In this paper, we propose a deep learning-based Doppler radar sensor system to detect and classify micro UASs.
- In our proposed system, the SCF patterns are generated to represent the Doppler effect on RF that is introduced by the propellers/wings of different types of UASs.
- A low-complexity DBN technique is employed to characterize the features embodied by the generated SCF patterns and automatically detect and identify different types of UASs.
- The experiment results illustrate that our proposed system is able to effectively detect micro UASs with the accuracy above 90% when SNR > -3 dB. Percentage of false alarm remains less than 10% for SNR > 0 dB.
- In our future work, we plan to conduct the experiments to closely simulate real world scenarios by using moving micro UASs.

References

1. http://www.bbc.com/news/world-europe-31619099.
2. W. A. Gardner, A. Napolitano, and L. Paura, "Cyclostationarity: Half a century of research," *Signal Processing*, vol. 86, no. 4, pp. 639 – 697, 2006.
3. G. Hinton, S. Osindero, and Y. Teh, "A fast learning algorithm for deep belief nets," *Neural Computation*, vol. 18, pp. 1527–1554, 2006.
4. Z. Lin, M. Courbariaux, R. Memisevic, Y. Bengio, "Neural networks with few multiplications," arXiv preprint arXiv:1510.03009. October 2015.
5. A. Fischer and C. Igel, "An introduction to restricted Boltzmann machines," *L. Alvarez et al. (Eds.): CIARP 2012, LNCS*, vol. 7441, pp. 14–36, 2012.
6. K. H. Cho, T. Raiko, and A. Ilin, "Gaussian-Bernoulli deep Boltzmann machine," in *The 2013 International Joint Conference on Neural Networks (IJCNN)*, (Dallas, Texas, USA), pp. 1–7, Aug 2013.
7. K. Cho, A. Ilin, and T. Raiko, "Improved learning of Gaussian-Bernoulli restricted Boltzmann machines," in *Proceedings of the 21th International Conference on Artificial Neural Networks - Volume Part I*, (Espoo, Finland), pp. 10–17, June 2011.
8. A. Fehske, J. Gaeddert, and J. H. Reed, "A new approach to signal classification using spectral correlation and neural networks," in *First IEEE International Symposium on New Frontiers in Dynamic Spectrum Access Networks (DySPAN 2005)*, (Baltimore, Maryland USA), pp. 144–150, Nov 2005.

Questions

The University of Akron
OHIO's POLYTECHNIC UNIVERSITY
College of Engineering