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2018

Ma, X., Oh, B.-S., Sun, L., Toh, K.-A., & Lin, Z. (2018). EMD-Based Entropy Features for micro-Doppler Mini-UAV Classification. 2018 24th International Conference on Pattern Recognition (ICPR), 1295-1300. doi:10.1109/icpr.2018.8546180

<https://hdl.handle.net/10356/144627>

<https://doi.org/10.1109/ICPR.2018.8546180>

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EMD-Based Entropy Features for micro-Doppler Mini-UAV Classification

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Abstract—In this paper, we first investigate into six popular entropies extracted from a set of intrinsic mode functions (IMFs) as a feature pattern for radar-based mini-size unmanned aerial vehicles (mini-UAV) classification. The six entropies include Shannon entropy, spectral entropy, log energy entropy, approximate entropy, fuzzy entropy and permutation entropy. Via an empirical comparison among the six entropies on real measurement radar data, the first three are selected as the representative due to their high efficiency and accuracy. To enhance the classification accuracy, the three selected entropies are then extracted from eight different sets of IMFs obtained by signal downsampling, and then fused at feature level. The nonlinear support vector machine classifier is adopted to predict the class label of unseen test radar signals. Our empirical results on a set of real-world continuous wave radar data show that the proposed method outperforms the state-of-the-art method in terms of the mini-UAV classification accuracy.

I. INTRODUCTION

Recently, mini-size unmanned aerial vehicles (mini-UAVs) have become widely available in many applications such as parcel delivery, filming and agriculture. However, such useful mini-UAVs can be a threat to those security sensitive areas as they can be used for spying, reconnaissance and even for attack. Thus, during the past decade, detecting and classifying the mini-UAVs automatically at a certain level of accuracy has been among the spotlighted research topics.

The radar micro-Doppler signature (m-DS) [1] contains the unique characteristics of the micro-motion induced by rotating mini-UAV blades [2]–[8]. Because of this trait, most of the recent works for mini-UAVs classification [2]–[8] have been concentrated on deriving the m-DS from radar signals. The popular radar m-DS analysis techniques include, but not limited to, spectrogram [2]–[5], cepstrogram [3], cadence velocity diagram [5], wavelet transform [6], radar polarimetry [7] and empirical mode decomposition (EMD) [8].

Among these radar m-DS analysis techniques, it is observed that the EMD method possesses several advantageous properties over the other techniques [8]. Different from the conventional Fourier analysis based methods, EMD decomposes an input signal into a set of intrinsic mode functions (IMFs) locally and adaptively in the time domain. The EMD can thus be free from the time-frequency resolution issue [8], and be effectively applied to low-dimensional radar signals (e.g., short dwell time on the target). Among the eight features studied in [8] to capture the blade flash effects [2] appeared in IMFs for mini-UAV classification [8], an entropy measurement with

the histogram counts appears to be the most discriminative. However, there is no further investigation on the usefulness of other types of entropy for mini-UAV classification.

With these observations in mind, in this paper, we propose to compute six popular entropies from IMFs of radar signals, and then use them as a feature pattern for mini-UAV classification. The six entropies include Shannon entropy [9], [10], spectral entropy [11], log energy entropy [12], approximate entropy [13], [14], fuzzy entropy [15], [16] and permutation entropy [16], [17]. These entropies have not been explored for either radar m-DS analysis or mini-UAV classification. After the individual entropies are investigated in terms of its classification accuracy and efficiency, the first three are selected as the representative for the subsequent mini-UAV classification. To enhance the classification accuracy, the three selected entropies are then proposed to be extracted from eight sets of IMFs obtained by two signal downsamplings. After normalization, the fused features are subsequently used to train a nonlinear support vector machine (SVM) classifier [18] to predict the class label of test radar signals.

II. AN INVESTIGATION INTO THE SIX ENTROPIES ON THE RADAR M-DS OBTAINED BY THE EMD

In this section, the EMD method and the six entropies are briefly discussed. The six entropies measured on a set of IMFs are then individually investigated in terms of the classification accuracy and the computational efficiency on real measurement mini-UAV radar data (see Section IV-A for details). Via an empirical comparison, a subset of the six entropies are selected as the representative due to their high accuracy and efficiency for subsequent mini-UAVs classification.

A. A brief review of the EMD method and its application to the radar m-DS analysis

The EMD decomposes a real-valued univariate signal $\mathbf{x} \in \mathbb{R}^N$ into L number of amplitude and frequency modulated waveforms called IMFs [19] as follows: $\mathbf{x} = \sum_{l=1}^L \mathbf{m}_l + \mathbf{q}_l$, where $\mathbf{m}_l \in \mathbb{R}^N$ indicates the l -th IMF while $\mathbf{q} \in \mathbb{R}^N$ is a residue. Different from the Fourier transform which requires predefined basis functions, the EMD adaptively subtracts the highest frequency components from the input signal at each iteration. Each IMF satisfies the following two conditions: i) the number of extrema and the number of zero-crossings are equal or differ at most by one, and ii) at any point, the mean

Fig. 1. Mini-UAV blade flash responses captured using (upper panel) the spectrogram and (lower panel) the EMD method.

of two envelopes defined by local maxima and local minima is zero. We refer to [19] for more details on the process of deriving the IMFs. Since the number of obtained IMFs L varies according to the frequency contents contained in the signal, we shall use the first $K < L$ IMFs for our entropy features extraction similar to that in [8].

In our earlier work [8], we have shown that the blade flash responses [2] of mini-UAVs captured by IMFs contain certain unique patterns. Particularly, in the spectrogram shown in the upper panel of Fig. 1, the blade flash responses appear as red-colored (i.e., high value responses in dB scale) vertical bars. Within the IMFs (see the lower panel of Fig. 1 (b)), such blade flashes appear as sudden changes towards high magnitudes with fewer number of zero-crossings compared to those time segments without the blade flashes. Capturing such unique patterns from the IMFs using effective and efficient entropies is the main objective of this work.

B. A brief review of the six entropies

1) *Shannon Entropy (ShanEn)*: The ShanEn measures the average amount of information contained in a message [9]. This concept has been extended to process time-series data $\mathbf{x} = [x_1, x_2, \dots, x_N] \in \mathbb{R}^N$ in which its uncertainty and disorder is measured. The ShanEn of $\mathbf{x}$ is defined as follows:

$$ShanEn = - \sum_{i=1}^N p(x_i) \log_2 p(x_i), \quad (1)$$

where $p(x_i)$ denotes the probability mass function.

2) *Spectral Entropy (SpecEn)*: Different from the ShanEn which is computed in the time domain, the SpecEn is obtained in the frequency domain. The signal $\mathbf{x}$ is firstly transformed into the frequency domain using the Fourier transform where

the power spectral density (PSD) $P(f)$ of $\mathbf{x}$ is obtained. The normalized PSD $p(f) = P(f)/\sum P(f)$, which can be seen as a probability density function, is then used to compute the SpecEn as follows:

$$SpecEn = - \sum_f p(f) \log(p(f)). \quad (2)$$

The SpecEn is then normalized by dividing it by $\log_2 N_f$, where N_f indicates the number of frequency components contained in the PSD.

3) *Log Energy Entropy (LogEn)*: While both ShanEn and SpecEn are computed based on the signal probability analysis, the LogEn is calculated using the signal energy as follows [12]:

$$LogEn = - \sum_{i=1}^N (\log_2 p(x_i))^2, \quad (3)$$

where $p(x_i)$ denotes the probability mass function.

4) *Approximate Entropy (ApEn)*: The ApEn [13], which was proposed to measure the complexity of a system, is used to measure the regularity and predictability of a signal $\mathbf{x}$ [14]. Particularly, a series of vectors with embedded dimension m is constructed as: $\mathbf{u}_i = [x_i, x_{i+1}, \dots, x_{i+m-1}] \in \mathbb{R}^m$, where $i = 1, 2, \dots, N-m+1$. For a vector $\mathbf{u}_i$, its index $C_i^m(r)$ is $(N-m+1)^{-1}$ times the number of vectors $\mathbf{u}_j$ where the distance between $\mathbf{u}_i$ and $\mathbf{u}_j$ is less than a threshold r . By defining

$$\Phi^m(r) = \frac{1}{N-m+1} \sum_{i=1}^{N-m+1} \ln C_i^m(r), \quad (4)$$

the ApEn can be calculated as follows:

$$ApEn(m, r) = \Phi^m(r) - \Phi^{m+1}(r). \quad (5)$$

5) *Fuzzy Entropy (FuzzyEn)*: Similar to the ApEn, computing the FuzzyEn starts with generating the m -dimensional vectors $\mathbf{u}_i$ from the input signal $\mathbf{x}$. However, the local mean of each vector is removed before calculating the distance d_{ij}^m between $\mathbf{u}_i$ and $\mathbf{u}_j$. The FuzzyEn instead utilizes the concept of fuzzy sets to obtain the fuzzy measurement of the similarity degree $D_{ij}^m = \exp(-(d_{ij}^m)^n/r)$, where n denotes the weight parameter. After defining

$$\Phi^m(r, n) = \frac{1}{N-m} \sum_{i=1}^{N-m} \left(\frac{1}{N-m-1} \sum_{j=1, j \neq i}^{N-m} D_{ij}^m \right), \quad (6)$$

the FuzzyEn is then estimated as follows:

$$FuzzyEn(m, r, n) = \ln \Phi^m(r, n) - \ln \Phi^{m+1}(r, n). \quad (7)$$

In this way, evaluation is performed based on the shapes of the vector instead of the absolute coordinates [15].

6) *Permutation Entropy (PerEn)*: By quantifying the complexity using symbolic dynamics [17], the PerEn works as a complexity measure for arbitrary real-world data. The PerEn can overcome the problem of losing the temporal information of time-series data [20]. After constructing vectors $\mathbf{u}_i = [x_i, x_{i+\tau}, \dots, x_{i+(m-1)\tau}] \in \mathbb{R}^m$ with embedded dimension m and time delay τ , each vector can be mapped to a permutation pattern π_k , where $k = 1, \dots, m!$ and ‘!’ indicates the number

TABLE I

COMPARISON AMONG THE SIX ENTROPIES (EXTRACTED FROM THE FIRST $K = 5$ IMFs) IN TERMS OF THEIR CLASSIFICATION ACCURACY AND CPU PROCESSING TIME ON A SET OF CW RADAR DATA (SEE SECTION IV-A). THE NONLINEAR SVM IS USED FOR CLASSIFICATION.

Entropy	Accuracy (%)	CPU time (sec)	Parameter settings
ShanEn	69.93	0.06	N.A.
SpecEn	68.42	0.59	N.A.
LogEn	82.11	0.07	N.A.
ApEn	69.33	256.35	$m = 2, r = 0.2\sigma$ [20], [21]
FuzzyEn	75.86	451.32	$m = 2, r = 0.5\sigma, n = 2$ [22]
PerEn	69.3	10.49	$m = 2, \tau = 3$ [23]

factorial. The PerEn is then computed using the occurrence of permutation patterns as follows:

$$PerEn(m, \tau) = - \sum_{k=1}^{m!} P(\pi_k) \ln P(\pi_k), \quad (8)$$

where $P(\pi_k)$ indicates the relative frequency of pattern π_k .

C. The representative entropies selection via an empirical comparison

As discussed above, each entropy has been proposed with different motivation. Their application is then generalized to process a wide range of signals such as time-series data. Due to such differences in the motivation, the information contained in these six entropies differs from each other. Since there is no previous study in the literature along this direction, it is unclear which entropy or which combination of them is appropriate for radar based mini-UAV classification. In this subsection, individual entropies are empirically compared in terms of the classification accuracy and the computationally efficiency. A subset of them will then be selected as the representative for our mini-UAV classification (see Section III for details).

Table I shows the classification accuracy and the CPU processing time obtained using each individual entropy extracted from the first $K = 5$ IMFs. These quantities are obtained using the continuous wave (CW) radar data detailed in Section IV-A and Table II. As shown in Table I, both LogEn and FuzzyEn appear to contain more discriminative information than that of the other four entropies. However, the FuzzyEn appears to be the most computationally demanding. Such slow processing speed of the FuzzyEn (including ApEn and PerEn as well) is not desired, particularly under a real-time mini-UAV classification scenario. Besides the efficiency issue, the first three entropies (i.e., ShanEn, SpecEn and LogEn) are free from parameter settings while the last three possess two or three parameters to be tuned. With these observations in mind, the first three entropies are selected as the representative for the EMD-based mini-UAV classification.

Note that computing only the three entropies from the first K IMFs may raise a concern that the amount of the extracted features is limited to achieve a high classification accuracy. To alleviate this concern, we propose to compute the selected entropy features from several other sets of IMFs obtained by signal downsamplings as discussed in the following section.

Fig. 2. Overview of the proposed method. The EMD method is to analyze the radar m-DS.

III. EXTENDING THE AMOUNT OF EXTRACTED FEATURES VIA TWO SIGNAL DOWNSAMPLINGS

With an aim of enhancing the classification accuracy, the three representative entropies (see Section II-C for details) are then extracted from 8 sets of IMFs obtained by two signal downsamplings. These features are then fused, normalized and used to train a nonlinear SVM classifier. These processes are graphically illustrated in Fig. 2.

A. Pre-/post-downsampling and feature level fusion

Downsampling a signal has been among popular choices for reducing the computational efficiency while maintaining the signal processing performance [21], [24]. It is also shown in [22] that downsampling high-resolution images even can help to improve the face identification accuracy. Since CW radar signals are usually captured at a high sampling rate, this downsampling idea can be a promising option to derive more features (e.g., the three representative entropy features) from the given signal for mini-UAV classification.

As shown in Fig. 1, two downsamplings namely, pre- and post-downsampling are proposed in this work. The former is applied to the input signal $\mathbf{x}$ while the latter is to downsample the obtained IMFs. For example, Fig. 3 shows three sets of three IMFs obtained by the pre- and post-downsampling. The IMFs shown in Fig. 3 (a) are the EMD results on the input signal $|\mathbf{x}| \in \mathbb{R}^N$, where $|\cdot|$ denotes the magnitude. Fig. 3 (b) shows three IMFs obtained by post-downsampling the IMFs shown in Fig. 3 (a). Lastly, the three IMFs shown in Fig. 3 (c) are obtained by decomposing the pre-downsampled input signal $|\tilde{\mathbf{x}}| \in \mathbb{R}^{N/R}$ where $R (=2$ in this example) denotes the downsampling rate.

A comparison between Fig. 3 (a) and (b) shows that the post-downsampling does not deteriorate the blade flash responses (see Section II-A for details). On the contrary, as shown in Fig. 3 (a) and (c), the pre-downsampling triggers

Fig. 3. An illustrative comparison among three sets of IMFs obtained by an EMD on the (a) magnitude of the input complex-valued signal $|x| \in \mathbb{R}^N$, (b) post-downsampled magnitude $|\tilde{x}| \in \mathbb{R}^{N/R}$, and (c) magnitude of the pre-downsampled signal $|\bar{x}| \in \mathbb{R}^{N/R}$. The $R = 2$ in this running example.

an interesting effect. Particularly, the order of IMF containing the blade flash responses (e.g., IMF2 in Fig. 3 (a)) is changed to the one earlier IMF (e.g., IMF1 in Fig. 3 (c)). Considering that the IMF1 of Fig. 3 (a) is dominated by noise component as there is no blade flash phenomenon, it can be observed that the pre-downsampling brings a kind of noise reduction effect.

Fig. 1 also reveals that the EMD is respectively performed on the magnitude, the real part and the imaginary part of the complex-valued radar signal $x^i \in \mathbb{C}^N$. By extracting the

TABLE II
SPECIFICATIONS OF THE REAL MEASUREMENT DATASET

No.	Target object name	Target object type	Distance range to the target	Num. segments (50ms long)
1	Birds	non-UAV	5m–50m	1,129
2	Yak54	Fixed-wing	20m–150m	1,480
3	EasyStar			780
4	T-REX450	Helicopter	20m–70m	1,759
5	Logo 400			1,141
6	Logo 600			717
7	Parrot 2.0	Quadcopter	3m–20m	3,534
8	1 rotor	Stationary rotor (non-UAV)	5m, 10m, 15m, 20m for each	298
9	2 rotors			336
10	3 rotors			240
11	4 rotors			600

representative entropies from various data representations, we expect to have more discriminative features for fusion, and thus for mini-UAV classification performance enhancement.

B. Feature normalization and classification

The extracted features are normalized into the range [0,1] using the min-max normalization technique. The normalized features are then used to train the nonlinear SVM classifier which adopts the radial basis function (RBF) kernel. To handle the multi-category classification problem, the SVM is trained with the one-vs-one learning scheme. Due to space constraint, we refer to [18] for details on the SVM.

IV. EXPERIMENT

The main goal of this section is to evaluate the mini-UAV classification performance of the proposed method. A set of CW radar echo data from mini-UAVs and other slow moving objects is utilized in this experimental study. For performance comparison, both the classification accuracy and the efficiency of the proposed method are compared with those by the competing state-of-the-art method. The following subsections detail the experimental setup, results and our discussions.

A. Dataset and Pre-processing

Table II summarizes the radar echo data utilized in this experimental study. As shown in Table II, there are 11 types of nearby target objects including 6 types of commercial mini-UAVs. The radar data, provided by Thales Nederland, was collected at outdoors using an X-band CW radar operating at 9.7GHz radio frequency and at 192KHz sampling rate. To reduce the sampling rate, all valid signals are decimated by order 2, and then divided into non-overlapping segments of 50ms long [8]. In other words, the dwell time of the signals utilized in our experiment is 50ms. The signal segments utilized in our experiment are thus of 4,800 dimension.

B. Experiment setup

The proposed method has an adjustable parameter namely, the downsampling rate R . Since this R is closely related to the computational efficiency as well as the classification accuracy, the best value for R is empirically chosen among various $R \in \{2, 3, 4\}$ settings. Table III shows two sets of

TABLE III
ACCURACY COMPARISON BETWEEN THE PRE- AND POST-DOWNSAMPLING.

Downsampling rate, R	Accuracy (%)	
	Pre-downsampling	Post-downsampling
1 (no downsampling)	84.92 ($K=6$)	
2	83.51 ($K=5$)	85.06 ($K=6$)
3	77.15 ($K=4$)	84.50 ($K=6$)
4	75.10 ($K=4$)	84.22 ($K=6$)

accuracy values obtained by the pre-downsampling and post-downsampling, respectively. For performance comparison, the accuracy value obtained using the input signal without downsampling (i.e., $R=1$) is also tabulated in Table III. It is observed from the table that the proposed method achieves the best accuracy at $R=2$ in both cases. Interestingly, the obtained accuracy by the post-downsampling at $R=2$ is slightly higher than that with no downsampling. Based on these results, we set $R=2$ for the subsequent experiments. For the SVM, the RBF kernel width is automatically determined by setting 'auto' to a parameter 'KernelScale' of the Matlab function 'templateSVM'. According to [8], the stopping criteria for the EMD sifting process is set to 10 iteration.

The test classification accuracy is computed as follows:

$$Acc(\%) = \frac{\text{The num. of correctly classified test samples}}{\text{Total number of test samples}}. \quad (9)$$

For statistical evidence, a 10 runs of 2-fold cross-validation test is conducted where the average is recorded. In each run, the dataset is randomly divided into training and test sets. All experiments were performed on a PC (3.3GHz CPU and 16G RAM) under Matlab platform. The Matlab source code for EMD utilized in this experiment is obtained from [25].

C. Results and Discussion

1) *Experiment I. Performance comparison among the three representative entropies and their combinations:* Table IV shows the classification accuracies over the 7 possible combinations. The average CPU time for processing a sample is also provided in the table. As shown in the upper category of Table IV, the LogEn appears to be the best among the individual entropies in terms of both the accuracy and efficiency. Both ShanEn and SpecEn produce the similar classification accuracy to each other.

Among the four possible combinations, the best accuracy performance 87.81% is achieved by 'SpecEn+LogEn' where '+' indicates the vector concatenation operation. This value is about 1.7% higher than that of using the LogEn alone. Another combination 'ShanEn+LogEn' which also contains the LogEn, produces about 0.78% lower accuracy value than that of the LogEn. Interestingly, combining all the three entropy features ('ShanEn+SpecEn+LogEn' in Table IV) produces about 0.5% lower accuracy value than that of the 'SpecEn+LogEn'.

2) *Experiment II. Effects of the feature level fusion over the four EMDs:* Recall that, as shown in Fig. 1, one of our propositions is to combine the three entropy features extracted

TABLE IV
COMPARISON AMONG THE THREE SELECTED ENTROPIES AND THEIR COMBINATIONS IN TERMS OF THE FEATURE DIMENSION, CLASSIFICATION ACCURACY AND AVERAGE CPU PROCESSING TIME PER SAMPLE.

Category	Individual or combination of entropy features	Feat. dim.	Test accuracy (%)	CPU time (ms)
Using a single EMD (1 EMD, 2 sets of IMFs)	ShanEn	12	70.54	7.4
	SpecEn	12	71.83	17.6
	LogEn	12	86.04	7.8
	ShanEn+SpecEn	24	77.64	18.9
	ShanEn+LogEn	24	85.26	8.7
	SpecEn+LogEn	24	87.81	18.5
	ShanEn+SpecEn+LogEn	36	87.31	19.4
Fusion over EMDs (4 EMDs, 8 sets of IMFs)	ShanEn	34	71.04	19.0
	SpecEn	34	84.45	43.4
	LogEn	34	90.81	19.4
	ShanEn+SpecEn	68	86.51	45.9
	ShanEn+LogEn	68	89.61	21.3
	SpecEn+LogEn	68	92.61	47.6
	ShanEn+SpecEn+LogEn	102	92.06	47.5

TABLE V
COMPARISON WITH THE COMPETING STATE-OF-THE-ART.

Category	Method	A*	B*	Test accuracy (%)	CPU time (ms) elapsed for processing a 4,800-dimensional signal		
					For EMD (♦)	Feat. ext. (◇)	Total (◆+◇)
Using a single EMD	Oh et al.'s [8]	1	46	86.03	55.1	1.9	57
	Proposed (LogEn only)		12	86.04		7.8	62.9
	Proposed (SpecEn+LogEn)		24	87.81		18.5	73.6
Fusion over multi EMDs	Oh et al.'s [8]	3	138	91.89	165.6 [§]	5.8	171.4
	Proposed (LogEn only)	4	34	90.81	153.8 [§]	19.4	173.2
	Proposed (SpecEn+LogEn)		68	92.61		47.6	201.4

*A: the number of EMDs performed, *B: Dimension of the extracted features.

§Since the signal dimension is reduced by the downsampling, the CPU time elapsed for processing the 4 EMDs is lower than that of the 3 EMDs by Oh et al.'s method [8].

from the 8 sets of IMFs (by four EMDs). The lower category of Table IV, called Fusion over EMDs, shows the classification accuracies obtained by the fusion. As shown in the table, the accuracy values are increased by a gap of about 4.3-8.9% compared to using a single EMD (i.e., using two sets of IMFs). Similar to our discussions for Experiment I above, the LogEn appears to be the best entropy among the three individuals. Among the combinations, the SpecEn+LogEn produces again the highest accuracy.

3) *Experiment III. Performance comparison with the state-of-the-art:* In this last experiment, the evaluation performances of the proposed method are compared with those by Oh et al.'s method [8]. To be brief, Oh et al.'s method extracts eight statistical and geometrical features from a set of IMFs. As for feature level fusion, the eight features are extracted from three sets of IMFs obtained by three EMDs on the magnitude, real part and imaginary part of the complex-valued input signal, respectively. For more details on Oh et al.'s method, we refer to [8]. Similar to the two previous experiments, both classification accuracy and the CPU processing time are used for comparison as shown in Table V.

Similar to Table IV, Table V consists of two categories namely, using a single EMD and using multiple EMDs by feature level fusion. Firstly, as shown in Table V, ‘Single-Proposed (LogEn only)’ shows comparable accuracy performance to that of Oh et al.’s method. If the best combination of the entropies SpecEn+LogEn (see Table IV) is utilized, our proposed method yields about 1.78% higher accuracy than that of the compared method. Similarly, ‘Fusion-Proposed (SpecEn+LogEn)’ shows about 0.72% better accuracy than that of Oh et al.’s method. However, as shown in the last three columns of Table V, Oh et al.’s method appears to be slightly faster than our proposed method.

4) *Summary*: Three experiments have been conducted to evaluate the mini-UAV classification performance of the proposed method. Our empirical results have shown that the LogEn contains the most discriminative information for mini-UAV classification among the three selected entropies. By combining the LogEn with the SpecEn, as shown in Table IV, about 1.77%-1.8% higher accuracy have been achieved by sacrificing a bit of the computational efficiency. Our proposed method was then observed to be comparable or slightly better than that of the state-of-the-art in terms of the mini-UAV classification accuracy.

V. CONCLUSION

In this paper, six entropies namely, ShanEn, SpecEn, LogEn, ApEn, FuzzyEn, and PerEn were revisited and evaluated in terms of the classification accuracy and efficiency performance under a mini-UAV classification scenario. Among the six entropies, ShanEn, SpecEn and LogEn were selected as the representative due to their high efficiency and classification accuracy. To enhance the accuracy performance, the selected three entropies were then extracted from eight sets of IMFs achieved by pre- and post-downsampling the radar signals. After a fusion at feature level and normalization, the features were classified using a nonlinear SVM-RBF classifier. Our experimental results showed that the proposed method produced comparable or slightly better accuracy performance on real measurement CW radar data than that of the competing state-of-the-art.

ACKNOWLEDGMENT

We wish to acknowledge the funding support for this project from Nanyang Technological University under the Undergraduate Research Experience on Campus (URECA) program. The authors thank the Thales Nederland for providing the CW radar data.

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