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Independent Vector Analysis Inspired Amateur Drone Detection Through Acoustic Signals

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ABSTRACT Detection of amateur drones (AmDrs) is mandatory requirement of various defence organizations and is also required to protect human life. In literature, various researchers contributed in this regard and developed different algorithms utilizing video, thermal, radio frequencies and acoustic signals. However, inefficiency of the existing techniques is reported in different atmospheric conditions. In this paper, acoustic signal processing is performed based on independent vector analysis (IVA) to detect AmDrs in the field. This technique is capable to detect more than one AmDrs in the sensing field at a time in the presence of strong interfering sources. The IVA is a relatively new and practically applicable technique of blind source separation and is more efficient than the independent component analysis technique. In the proposed technique, recorded mixed signals through multiple microphones are first un-mixed through using the IVA technique. Then various features of the separated signals are extracted. These features include Root Mean Square (RMS) values, Power Spectral Density (PSD) and Mel Frequency Cepstral coefficients (MFCC). Finally, signals classification is performed through Support Vector Machines (SVM)and K Nearest Neighbor (KNN) to detect AmDrs in the field. Performance evaluation of the proposed technique is carried out through simulations and observed the superior performance of the proposed technique.

INDEX TERMS IVA, KNN, MFCC, PSD, SVM.

I. INTRODUCTION

The amateur drones (AmDrs) are equipped with advanced telecommunication, electronics and control technologies, having enormous applications in various areas e.g., remote sensing [1], navigation [2]–[4], archaeology [5], journalism [6], environmental [7], [8], and agriculture sciences [9]–[11]. The ungoverned deployment of these drones can motivate unlawful activities like transfer of restricted material or violation of defence organizations boundaries [12]. These activities might cause security threats to any organization or country.

The AmDr detection is carried out in the literature and some important and relevant references are revived in as follows. In [13], the authors proposed sound based technique to detect single AmDr in the field by considering independently recorded signals of the AmDr and interfering sources. In [15], the authors developed a point to point architecture to detect a single AmDr in the field. The concept of cognitive internet of things is utilized in [16] for single AmDr detection based on sound, video, thermal, and radio frequency (RF) signals. In [17], the authors presented sound correlation based drone detection technique. The AmDr detection techniques based on RF signal, Image processing, radar technology and Video signals are presented in [16], [18]–[20] simultaneously. However, all the existing techniques are mainly focusing on single AmDr detection, which limits the applicability of these techniques in practical scenario where presence of multiple drones can occur.

Furthermore, the RF signals based AmDr detection go wrong in unfavourable atmosphere. This technique also fails to detect tiny sized drones. Likewise, the techniques utilizing video and image need costly cameras and efficient processors. Also, the fixed orientation of these techniques make it practically inefficient. Although, acoustic signal processing based AmDrs detection is cheap and practically applicable, but presence of different interfering sources makes it more difficult. In [13], the authors proposed sound based AmDr

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detection, but has considered independently recorded sounds of the AmDr and interfering sources. In practical scenario the recorded sounds will be mixtures of all the existing sounds. Thus, the technique developed in [13] is not practical feasible. In one of our previous paper, we developed an independent component analysis (ICA) [21], [22] based AmDrs detection technique [14] that is practically feasible and can detect multiple AmDrs at a time but inefficiency of ICA exist in the literature. The IVA technique [23] processes the actual recorded as well as delayed recorded signals that make it more practical as compare to ICA.

A. CONTRIBUTION

In this paper, an IVA [24], [25] based technique is developed to detect AmDrs in the presence of different interference signals. This technique processes the recorded sounds of the AmDrs and the interfering sources. The IVA algorithm is used to separate the recorded mixed signals, even in case if there exist multiple drones in the sensing area that make the proposed technique a good option for AmDrs detection in the presence of interfering sources. Furthermore, the IVA separated signals are processed for features extraction and classification to detect presence of single or multiple AmDrs. The MFCC algorithms [26] are utilized to extract Mel Frequency Cepstral Coefficients from the IVA post processed signals that are then fed to SVM and KNN [27] to classify them into drone and interference signals. In the second approach the IVA estimated signals are passed through octave band filters. In each filtered frequency band the Root Mean Square (RMS) values and the Power Spectral Density (PSD) values are calculated. These RMS and PSD values are used as feature vectors to train the SVM and KNN algorithms for detection of AmDrs.S After all, this technique is suitable for practical applications due to its ability to detect multiple AmDrs and processing of original recorded as well as delayed versions of the signals in the presence of different interfering signals.

The remaining paper is organized as: Section 2 presents the system model. The proposed IVA based AmDr detection technique is given in Section 3. Simulation results are discussed in Section 4 with the concluding remarks in Section 5. In addition, lowercase letters are used for scalars, lowercase boldface letters for vectors, and uppercase boldface letters for matrices. Transpose is denoted by uppercase superscript T.

II. SYSTEM MODEL

This section presents the AmDr and the interfering sound signals in the IVA data model. We consider K number of independent sources i.e., AmDrs and the interfering sources, and all sources contain L number of samples for D data sets. The recorded data through multiple microphones can be represented as

$$X^d = A^d S^d \quad 1 \leq d \leq D, \tag{1}$$

where matrix S^d contains source data vectors ${s^d}_1, {s^d}_2, \ldots, {s^d}_K$, length of each vector is L. All vector contain real

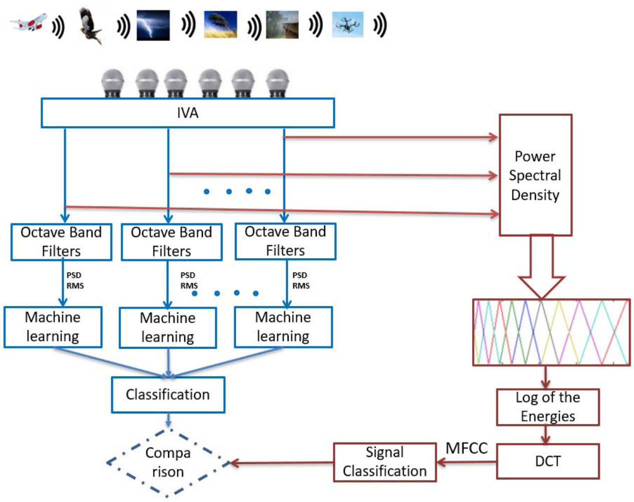

FIGURE 1. IVA based drone detection through acoustic signals.

valueed and zero mean data. A^d are random mixing matrices for D number of data sets. The IVA technique is employed to calculate the mixing matrices for all the data sets. The actual data matrices in all data sets are denoted by $(S^1)^T, (S^2)^T, \ldots, (S^D)^T$. The un-mixed data through the IVA algorithm in all data sets is given below

$$Y^d = W^d X^d \tag{2}$$

where W^d is inverse of A^d and is called the un-mixing matrix estimated for D data sets. The separated source data vectors are $y_1^d, y_2^d, \ldots, y_k^d$.

III. THE PROPOSED IVA BASED AmDr DETECTION

Multiple AmDrs detection is a difficult task in the presence of various interfering sources. The existing work detected single AmDr in the field or detected multiple drones with bad quality results and is also not acceptable for practical applications. The proposed IVA based technique is capable to detect more than one AmDrs in the presence of different interferences. The overall implementation mechanism of the proposed technique is demonstrated in Figure 1. The mixed recorded signals through microphones along with their delayed versions are first processed through the IVA algorithm [29]. The IVA algorithm separates the mixed recorded data in the form of different data sets, contain the originally recorded and their delayed recorded signals. This separation is performed through minimization of the mutual information among the estimated source component vectors (SCVs). The IVA cost function [23] is given below

$$I_{IVA} = \sum_{k=1}^{K} (\sum_{d=1}^{D} H[y_k^d] - I[y_k]) - \sum_{d=1}^{D} \log \left| W^d \right| - C \tag{3}$$

where $I[y_k]$ represent mutual information within k_{th} SCVs, H denotes entropy, W^d represents the unmixing matrices for d_{th} number of data sets, C is equivalent to $H[X^1, X^2, \ldots, X^D]$, depends on recorded data, becomes constant in the IVA processing. The IVA technique minimizes the function given in equation (3) and maximizes the mutual information in all SCV. The IVA-GGD algorithm [29] is utilized in this work. In addition, separation of the original along with the delayed signals make this technique practically applicable.

The IVA unmixed data is then passed through the octave band filtering to compute the PSD values [28]. The audio spectrum (20 Hz to 20 KHz) is divided into 11 bands according to the following equation 4.

$$\begin{aligned} f_7^c &= 1000Hz \\ f_{n-1}^c &= 0.5 f_n^c \\ f_{n+1}^c &= 2 f_n^c \end{aligned} \tag{4}$$

where f_7^c is the 7^{th} octave band central frequency, f_{n-1}^c and f_{n+1}^c are the lower and upper central frequencies. Similarly, for each central frequency the lower and upper frequencies are defined as $f_n^l = f_n/\sqrt{2}$ and $f_n^l = \sqrt{2} f_n$ respectively, keeping the bandwidth constant and equal to 70.7% per octave band.

The signal is first split into different octave bands and then the RMS and PSD of each band is calculated. Based on these feature vectors the sound signal are then classified into UAV and non-UAV sounds using SVM and KNN techniques. KNN and SVM are machine learning algorithms that classify data into different classes based on similarity index of data and finding the hyper-plane to separate data respectively. Readers are referred to [30] for detailed explanation of SVM and KNN.

The second approach is based on MFCC, which is calculated from the PSD of the sound signal by passing it through filter banks with Mel frequencies as given in equation 5. The DCT of the log of the energies obtained from filter banks is calculated. The coefficients 2 to 13 of the MFCC are used for classification.

$$H_k(n) = \begin{cases} 0, & n < f(k-1) \\ \dfrac{n - f(k-1)}{f(k) - f(k-1)}, & f(k-1) \le n \le f(k) \\ \dfrac{f(k+1) - n}{f(k+1) - f(k)}, & f(k) \le n \le f(k+1) \\ 0, & n > f(k+1) \end{cases} \tag{5}$$

where k denotes the number of filters, f represents $L+2$ mel spaced frequencies.

IV. SIMULATION RESULTS

In practical application, different interference signals exist along with the AmDr signals while performing the AmDrs detection based on acoustic signals. In this part of simulation, we considered different interfering sources e.g., birds, aeroplanes, rain, wind, and thunderstorm. The time domain version of these interferences along with the AmDr signal are demonstrated in Figure 2. All these signals are downloaded from standard databases utilized already for research and are freely available [31]. All the sound downloaded from [31] are

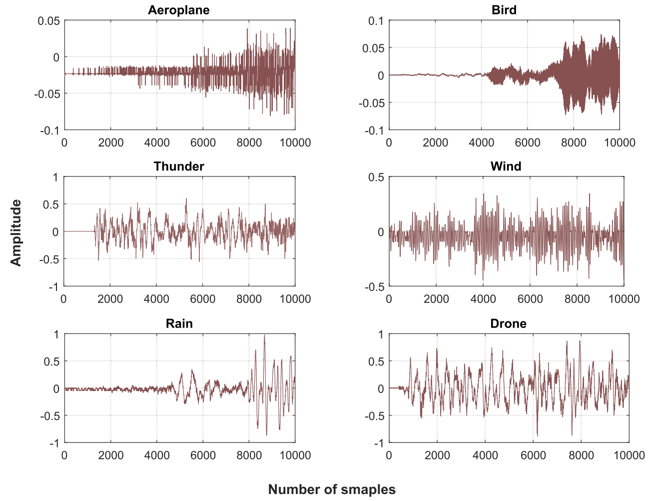

FIGURE 2. Various interference signals along with the AmDr signal.

in WAV format with sampling frequency of 96kHz and 24bit resolution.

Further, in practical applications the deployed sensors will record mixtures of the AmDrs and interferences sounds. The microphones recorded signals are given in Figure 3. We will separate these signals before processing through the classification techniques. The IVA technique is utilized for blind un-mixing of these signals.

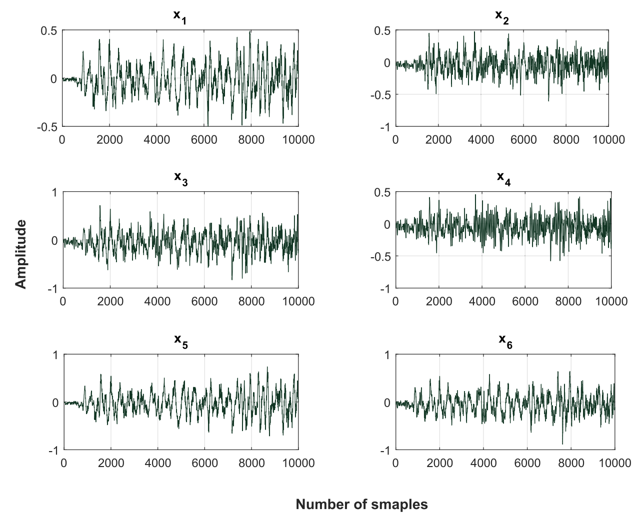

FIGURE 3. Mixed signals recorded through multiple microphones.

The IVA algorithm utilized in our simulations is IVA-GGD. Performance of this algorithms is evaluated for various SNRs ranges from 0 to 20 dB. Results are compiled using Monte Carlo simulation. We consider $K = 6$, $D = 6$, and length L ranges from 50 to 10000 samples. Moreover, to evaluate the effectiveness of the proposed technique the following performance evaluation criteria is utilized

- Common inter-symbol-interference (ISI_{com}) [23] is also utilized as a performance measure and can be

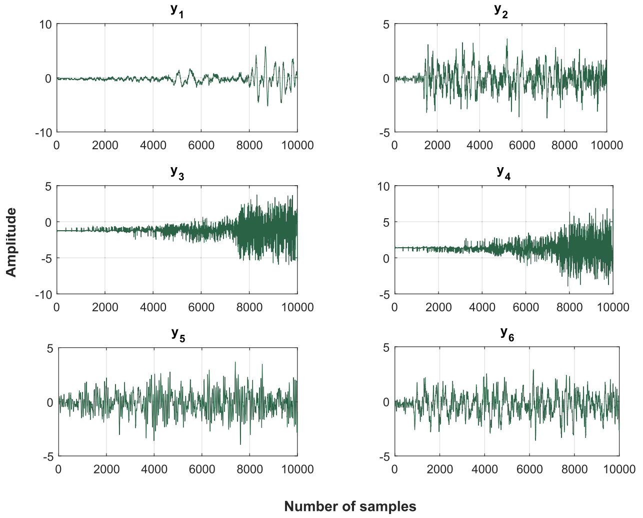

FIGURE 4. IVA estimated signals shown for a single data set.

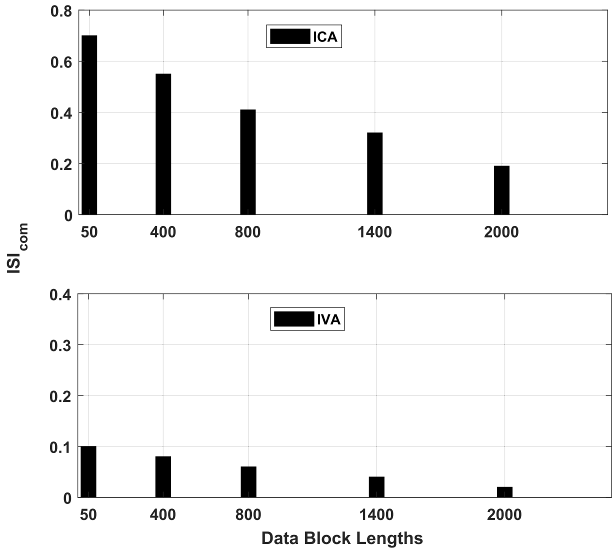

FIGURE 5. Comparison of the IVA and ICA techniques for different data block lengths.

represented as

$$ISI_{com} = \frac{1}{2K(K-1)}\left[\psi' + \psi''\right] \tag{6}$$

where

$$\psi' = \sum_{n=1}^{K}\left(\sum_{m=1}^{K}\frac{g'_{m,n}}{max_p g'_{n,p}} - 1\right)$$

$$\psi'' = \sum_{m=1}^{K}\left(\sum_{n=1}^{K}\frac{g'_{m,n}}{max_p g'_{p,m}} - 1\right)$$

and $G^d = W^d A^d$
with $g_{m,n} = \sum_{d=1}^{D} |g^d_{m,n}|$. The ISI_{com} is normalized so that its maximum value is one and minimum vale is zero, where zero value corresponds to ideal separation performance.

First, we demonstrate the effectiveness of the IVA technique in comparison with the ICA techniques. Results are compiled while utilizing the Fast-ICA algorithm [32] of ICA, and the IVA-GGD algorithm of IVA. Simulation is performed at SNR of 20dB. Performance evaluation is carried out for different values of L ranges from 50 to 2000 samples in a single data set. Results of ICA and IVA algorithms are demonstrated in Figure 5. The simulation results clearly shows that the IVA outperforms ICA technique. These results also verifies that the IVA algorithm is less sensitive to the processing data block lengths. In addition, we have also demonstrated the separation performance of the IVA technique in comparison with ICA-EBM [34] and ERBM-ICA [35] in Table 1. Where it can be been that IVA is the best choice for un-mixing in this application.

Three sets of signals, corrupted with different level of noises are classified into UAV and non-UAV sounds, after processing it using the procedure as given in Figure 1. The PSD values and the Mel energies and MFCCs of the signal without noise are given in Figure 6 and 7 respectively.

TABLE 1. Comparison of the IVA based technique with ICA-EBM and ERBM-ICA with 12 dB Noise.

Data Block Size	ICA-EBM	ICA-ERBM	IVA
L=100	0.61	0.60	0.1
L=1000	0.341	0.34	0.05
L=10000	0.26	0.24	0.01

These signals are without noise, corrupted with 5 dB and 12 dB noises are tabulated in Table 2, Table 3 and Table 4, respectively. The tables show results for both the ICA and IVA separated signals. It can be seen that the results for ICA separated signals of the RMS values of PSD gives better classification using KNN, followed by the PSD values and the Cepstral Coefficients of the Mel frequencies. Similar pattern can be seen for the signals separated by IVA, however, the IVA outperforms the classification results obtained from the signals that are unmixed using ICA. The SVM also gives similar results when the signals are unmixed using ICA and IVA, however, again the signals from IVA results in better classification as compared to that of signals from ICA. This table contains various data block sizes utilized in both ICA and IVA based techniques, shows performance improvement with larger data blocks and hence improves the classification. It is also important to note that the IVA based technique gives better results as compared to ICA based technique for the classification of noise corrupted signals.

A. DISCUSSION

After all, the proposed scheme is practically applicable for detection of multiple drones because the existing techniques normally use independently recorded sounds without interference for classification or either address single AmDr detection, which is not appropriate, as multiple drones may enter the area under surveillance. We also want to mention that

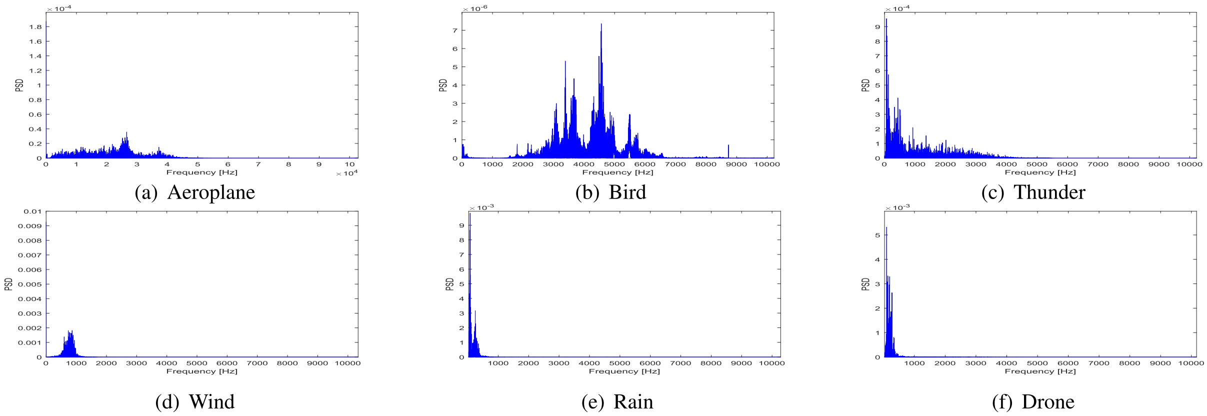

FIGURE 6. PSD values of the acoustic signals.

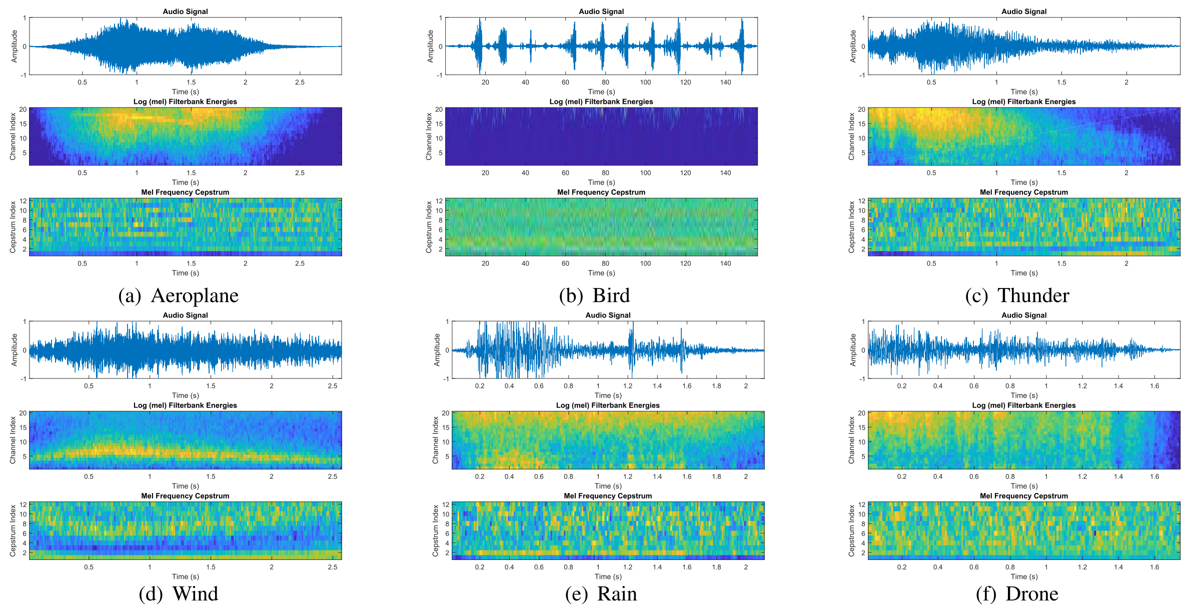

FIGURE 7. MFCC of different audio signals.

TABLE 2. Classification results of signals without noise.

Data Block Size	Method	SVM-ICA	KNN-ICA	SVM-IVA	KNN-IVA
L=10000	PSD	92.57	97.9	93.7	98.6
	RMS PSD	96.1	99.1	97.6	99.7
	MFCC	88.2	97.4	89.1	98.3
L=7000	PSD	91	97.2	92	98.8
	RMS PSD	94.9	98.3	96	99.2
	MFCC	87.6	97	89.2	98.1
L=4000	PSD	90.3	96.7	92.3	98
	RMS PSD	94.1	98	99.6	99.3
	MFCC	87.0	96.7	88.1	98.1
L=1000	PSD	89.7	96.0	91.1	97.7
	RMS PSD	93.3	97.1	94.6	98.6
	MFCC	86.8	95.3	88	97.9

the IVA technique is first time introduced for the AmDs detection in combination with the octave band filer banks. It also important to mention that it is known from the literature that performance of the ICA algorithms degrade with smaller lengths of the recorded data vectors but IVA is less sensitive to lengths of the data vectors. IVA is also less sensitive to the

TABLE 3. Classification results of signals with 5dB noise.

Data Block Size	Method	SVM-ICA	KNN-ICA	SVM-IVA	KNN-IVA
L=10000	PSD	91.34	98.4	93.0	98.4
	RMS PSD	95.0	98.0	97.3	99.5
	MFCC	87.2	98.1	87.3	99.5
L=7000	PSD	90.1	98.0	91.7	98.6
	RMS PSD	93.2	97.7	95.6	99.0
	MFCC	86.15	96.16	89.0	97.9
L=4000	PSD	89.1	95.5	92.1	97.8
	RMS PSD	93.0	97.0	99.5	99.2
	MFCC	86.1	95.4	88.0	98.0
L=1000	PSD	88.5	95.01	91.0	97.5
	RMS PSD	92.0	96.3	94.3	98.4
	MFCC	86.0	94.1	87.8	77.7

TABLE 4. Classification results of signals with 12 dB noise.

Data Block Size	Method	SVM-ICA	KNN-ICA	SVM-IVA	KNN-IVA
L=10000	PSD	85.3	92.3	91.5	93.4
	RMS PSD	89.1	92.01	95.5	98.7
	MFCC	82.3	92.71	87.7	97.6
L=7000	PSD	85.0	92.7	90.9	97.7
	RMS PSD	88.05	91.03	94.3	98.1
	MFCC	81.03	90.71	88.2	96.7
L=4000	PSD	84.0	90.0	91.0	96.9
	RMS PSD	87.1	91.01	98.6	98.5
	MFCC	81.3	90.17	87.2	97.3
L=1000	PSD	82.6	89.0	90.2	96.7
	RMS PSD	86.4	90.31	93.5	97.5
	MFCC	81.3	88.2	86.5	96.7

noise induced in the signals as compared to the ICA technique. Moreover, IVA technique is computationally heavy in comparison to ICA but produces quality results in terms of separation and classification.

V. CONCLUSION

This paper investigates the detection of AmDrs using sound signals. The audio signals from different sources in the sensing field are first recorded using multiple microphones. As every microphone received a mix of different signals therefor, these signals were first unmixed using IVA algorithm. The separated signals were then divided into octave bands. The RMS and PSD values of these signals were used with the classical machine learning algorithm for detecting the presence or absence of UAVs. The obtained results were then compared with the MFCC based AmDr detection technique exist in the literature. From the results it can be observed that the proposed technique outperformed the existing MFCC based technique and showed 99.7% accuracy. It was also recorded that the IVA based unmixed signals were better classified into AmDr and non-AmDr sounds as compared to the ICA based unmixed signals for same conditions and classification algorithms. As for as the noisy data is concerned again the IVA outperforms ICA, as the former can better unmix signals in the presence of noise. The proposed IVA based technique is more practical as compared to existing techniques due to its ability to process the originally recorded as well as delayed versions of the recorded signals.

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