

Measurements and analysis of multistatic and multimodal micro-Doppler signatures for automatic target classification

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Abstract—The purpose of this paper is to present an experimental trial carried out at the Defence Academy of the United Kingdom to measure simultaneous multistatic and multimodal micro-Doppler signatures of various targets, including humans and flying UAVs.

Signatures were gathered using a network of sensors consisting of a CW monostatic radar operating at 10 GHz (X-band) and an ultrasound radar with a monostatic and a bistatic channel operating at 45 kHz and 35 kHz, respectively. A preliminary analysis of automatic target classification performance and a comparison with the radar monostatic case is also presented.

I. INTRODUCTION

Echoes from moving targets present a shift in frequency which is proportional to their radial velocity. By measuring the Doppler shift (i.e. the difference between the received frequency f_r and the transmitted frequency f_0) a radar system can estimate the radial velocity v_r of a target by inverting the expression $f_D = -2v_r f_0/c$. Common targets are complex and often composed of components that move, vibrate or rotate with velocity vectors which are different from that inducing the main Doppler shift. These generate a frequency modulation around the main Doppler shift which is commonly called a target micro-Doppler signature. Micro-Doppler signatures contain unique target features and can be used to perform target classification and target recognition.

The use of micro-Doppler signatures for target classification has some advantages with respect to other techniques. Firstly, processing time can be much lower than that required for high range resolution imaging techniques and secondly because range resolution is not a strict requirement it can be employed by low cost sensors with a low bandwidth. This offers the attractive option to upgrade legacy low range resolution systems through a suitable retro-fitting.

The micro-Doppler effect was originally introduced in a coherent laser system to measure the kinematic properties of an object, such as the vibration rate and the displacement of the vibration [1]. Since then, radar micro-Doppler signatures have been widely studied and the micro-Doppler signatures of various targets including humans, helicopters and jet engines

can be found in the literature [1][2][3][4]. Micro-Doppler signatures have also been used in combination with Inverse Synthetic Aperture Radars (ISAR) to aid classification performance [5]. A recent review of the use of micro-Doppler signatures in radar emerging techniques is presented in [6]. In recent years, target classification by micro-Doppler signatures has been also applied to the acoustic regime and ultrasound signatures of a range of targets and particularly of humans and animals have been collected and studied for short range surveillance applications [7][8][9].

Although a few researchers and institutions have studied target classification by monostatic micro-Doppler signatures there has been very little work to investigate whether multistatic and multimodal micro-Doppler signatures can be used to improve detection and classification performance. In [10] the authors analysed the radar multistatic signatures of personnel targets and carried out an experimental trial to collect real multistatic micro-Doppler signatures at 2.4 GHz (S-band). In [11] and [12] the authors derived the multistatic micro-Doppler signature of personnel targets for a simulated network of radar systems and proposed a set of features for target classification. In these papers, target micro-Doppler signatures were simulated using a library of existing video motion capture data. An experimental trial to collect multimodal data from walking humans is presented in [13]. Here, the authors used a network of acoustic sensors, including transmitters deployed on co-operative human targets, combined with seismic sensors capable to record vibrations due to the target footsteps. However, no RF sensors were deployed in the trial.

Gathering simultaneous target micro-Doppler signatures from different aspect angles and various sensors may provide additional information which can potentially result in improved detection and classification performance. For these reasons the exploitation of multimodal and multistatic signatures is an imperative under the current economic climate. Most countries are striving to exploit new low-cost solutions to improve performance and this can be potentially achieved by employing co-operative existing systems of different types in a single system network. The challenge is to investigate what kind of

TABLE I
SENSOR PARAMETERS

	Transmitted Frequency	sampling Rate
Radar	10 GHz	10 MHz
Acoustic Monostatic	45 kHz	10 MHz
Acoustic Bistatic	35 kHz	10 MHz

transmitter-receiver arrangements are best to achieve multi-static target recognition and investigate if better performance can be obtained with respect to the monostatic case.

In this paper we present the results of an experimental trial carried out at the Defence Academy of the United Kingdom to measure simultaneous multistatic and multimodal micro-Doppler signatures of various targets, including humans and flying UAVs. A preliminary analysis of automatic target classification by multi-static and multimodal micro-Doppler signature is also presented.

II. DATA COLLECTION AND PRE-PROCESSING

A. Experimental Setup

The experimental setup is shown in Fig. 1 and Fig. 2. Data was collected with a CW monostatic radar operating at 10 GHz (X-band) and with an ultrasound radar system consisting of a monostatic and a bistatic channel. The target under test was placed 1.86 m from the monostatic ultrasound radar and 1.32 m from the monostatic CW radar. The monostatic and bistatic ultrasound channels were generated by transmitting two pure tones, at 45 kHz and 35 kHz, respectively. These were transmitted with two Ultrasound Advice S55 loudspeakers and echoes were recorded with one Ultrasound Advice microphones as shown in Fig. 2. Both monostatic radars were looking at the target from the same direction although the RF radar was deployed at floor level with its antenna beams pointing at the target with an angle of about 40 degrees. The bistatic angle was set to 90 degrees. Both the acoustic and RF radar systems were transmitting pure tones hence no range information was available. The operational parameters of the sensors are summarised in Table 1.

Data was collected for various targets including humans, a fan and flying UAVs. The rotating fan was positioned so to form an aspect angle of about 45 degrees with respect to both the monostatic and the bistatic channels (Fig. 2) while the personnel target was facing the monostatic acoustic radar whilst swinging both arms on the spot. A photo of the fan and a sketch of the personnel target with its physical characteristics is given in Fig. 3.

B. Signal pre-processing

The two output of the radar module consist of the in-phase $I(t)$ and in-quadrature $Q(t)$ components of the radar echoes. These were digitised at 100 kHz to form the sequence $S_{rx}(k) = I(k) + jQ(k)$ representing the complex envelope of the RF received signal. The acoustic echoes were instead digitized at "radio frequency" and then down-converted with Matlab to generate a complex envelope $S_{rx}(k)$ for each one

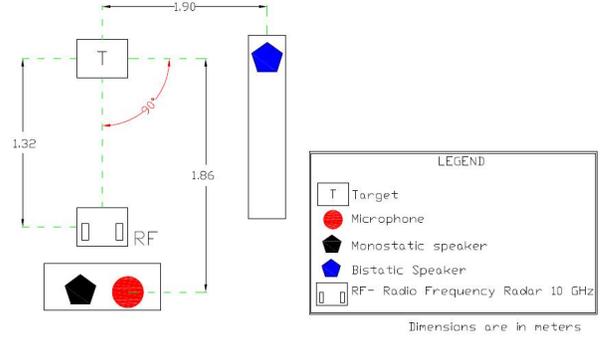


Fig. 1. Top view of the experimental setup.

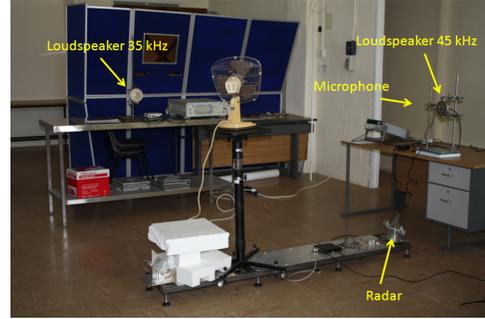


Fig. 2. Photo of the experimental setup. The rotating fan was positioned so to form an aspect angle of about 45 degrees with respect to both the monostatic and the bistatic channels.

channel. The mean values were subtracted from the input signal ($S_{rx}(k)$) to remove the direct signal components and all stationary clutter as:

$$S_{meanRx}(k) = S_{rx}(k) - \frac{1}{N_s} \sum_{i=0}^{N_s-1} S_{rx}(i), \quad (1)$$

where N_s is the number of samples of $S_{rx}(k)$.

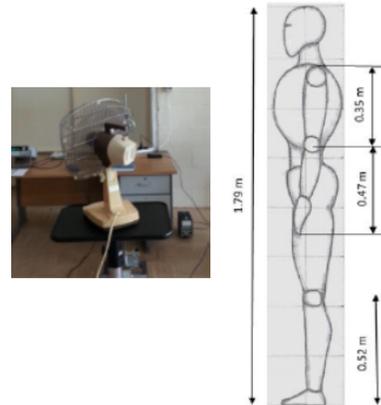


Fig. 3. Photo of the fan and a sketch of the personnel target measured in the experiments.

III. RESULTS

A. Spectrograms

The spectrograms of the fan and the personnel target are shown in Fig. 4 and Fig. 5, respectively. These show the spectrum of the non-stationary target echoes as a function of time in a dB scale and were obtained with a sliding Hanning window of duration $T_w = 10.24$ ms. The radar micro-Doppler signature of the fan presents a strong component around zero-Doppler and periodical spikes between about -1 kHz to +1 kHz. The low Doppler contribution is due to both the vibrating main body and the rotating fan nacelle whilst the higher periodical Doppler contribution is due to the rotating blades. The signature obtained from the monostatic ultrasound channel shows the same periodicities as a function of time although it presents significant differences. As expected the maximum Doppler shift due to the rotating blades is about four times higher than that obtained in the radar case due to the much lower operating wavelength at 45 kHz (7.6 mm against 3 cm at X-band leading to a ratio of about 4). It is also evident that the acoustic micro-Doppler signature is not symmetrical and this is due to the fact that the blade of the fan are twisted as well as to the geometrical arrangement between the fan and the sensor. This characteristic has been observed in the past as typical of the blades of wind turbines as well [14]. The bistatic acoustic signature shows the same periodical behaviour as the monostatic signatures but presents a lower Doppler shift due to the 90 degrees bistatic angle and the target aspect angle with respect to the transducers forming the bistatic channel. Fig. 5 shows the RF and acoustic signatures of the personnel target. This is characterised by a strong oscillating component around zero-Doppler due to the target torso and a weaker periodical component characterised by a higher maximum Doppler shift induced by the target lower and upper limbs moving towards or away from the sensor. The monostatic RF and acoustic signature present almost the same characteristic, with a strong power component around 0 Hz Doppler. As in the case of the fan, the acoustic signature is more detailed due to the better frequency resolution for a given dwell time. We found that the acoustic micro-Doppler signatures of all the measured UAVs were swamped in wide-bandwidth ultrasound noise. This may be generated by the electric engines and is currently under investigation.

B. Classification Performance

The extracted micro-Doppler signatures were used to assess the performance of a Naïve Bayesian classifier and a K-NN classifier in combination with two feature extraction algorithms; the Cepstrum and the Principal Component Analysis (PCA). Classification performance was assessed on a total of $N_w = 400$ 5ms-long windows. Data from different sensors was first normalised and then fused before feature extraction by appending simultaneous windows from different sensors together in a single data vector. The classifier was trained by using the features extracted from 100 windows whilst the remaining 300 were used to form the test set. The number

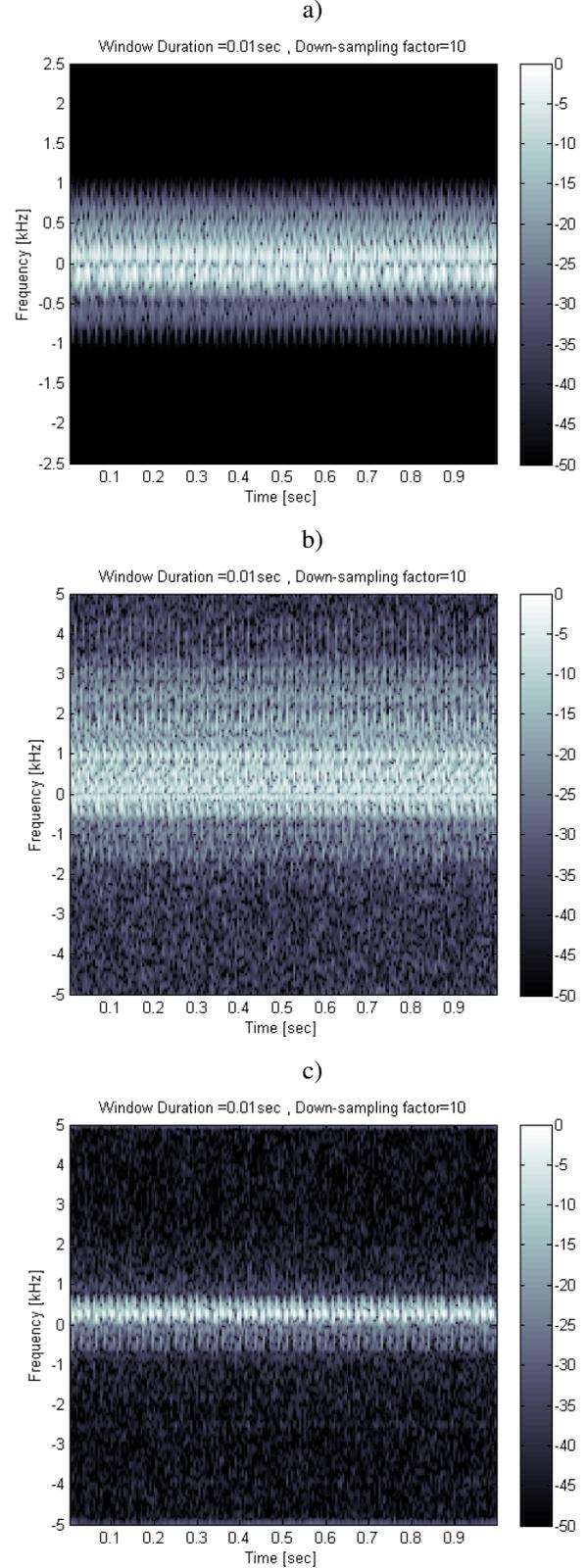


Fig. 4. Micro-Doppler signature of the fan; a) Monostatic Radar, b) Monostatic ultrasound and c) bistatic ultrasound.

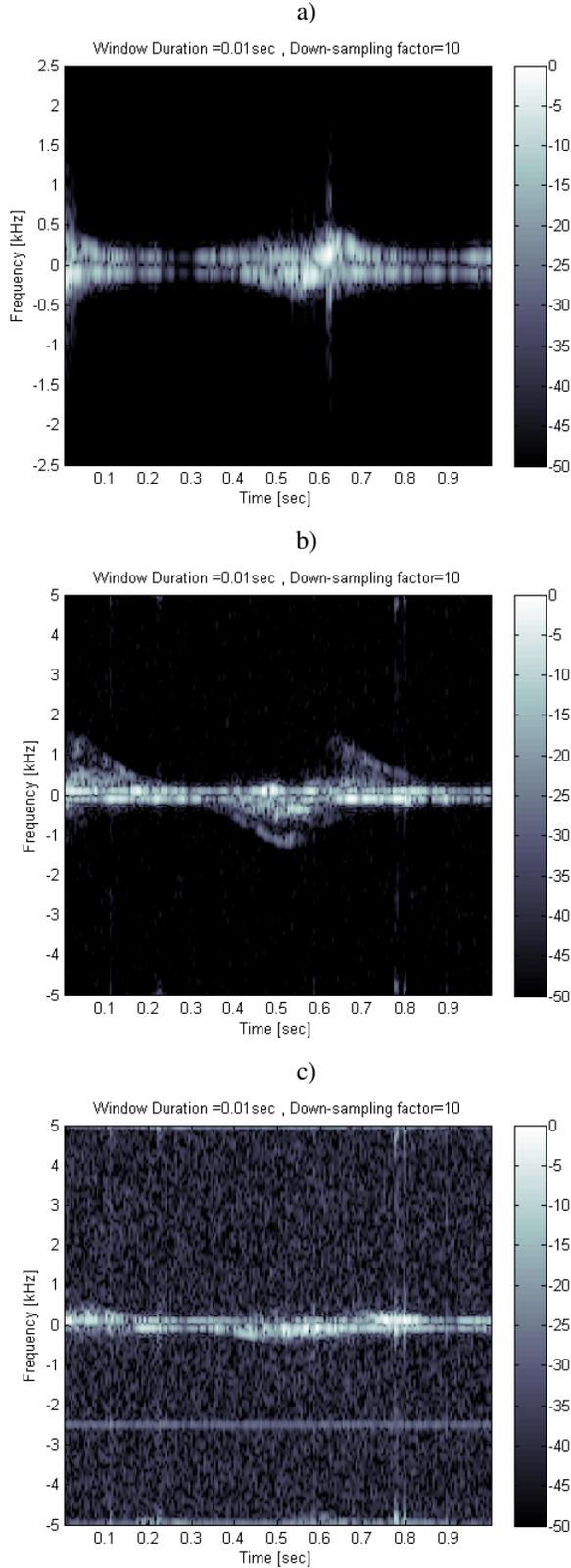


Fig. 5. Micro-Doppler signature of the personnel target; a) Monostatic Radar, b) Monostatic ultrasound and c) bistatic ultrasound.

TABLE II
CORRECT CLASSIFICATION PERFORMANCE (P_{cc}) OF THE K-NN CLASSIFIER (OBTAINED WITH 5MS-LONG WINDOWS AND USING 15 MAIN TARGET FEATURES).

Sensor	Cepstrum	PCA
Radar	83%	83%
Radar & Acoustic Monostatic	91%	88%
Radar & Acoustic Monostatic+Bistatic	99%	96%

TABLE III
CORRECT CLASSIFICATION PERFORMANCE (P_{cc}) OF THE NAÏVE BAYSIAN CLASSIFIER (OBTAINED WITH 5MS-LONG WINDOWS AND USING 15 MAIN TARGET FEATURES)

Sensor	Cepstrum	PCA
Radar	71%	59%
Radar & Acoustic Monostatic	85%	91%
Radar & Acoustic Monostatic+Bistatic	96%	87%

of training windows was selected by taking into account that the higher the number of the training set, the longer the computational training phase and that the larger the amount of the training windows, the better the estimates of the signature parameters. It was experimentally observed 100 to be a good compromise in order to achieve good parameter estimates without burdening the computational load. The PCA was applied to the micro-Doppler signatures to extract the main 15 target features and similarly the first 15 Cepstrum coefficients were extracted from the signatures by taking the inverse FFT of the signature Cepstrum.

The probability of correct classification of the K-NN classifier and the Naïve Bayesian classifier are shown in Table II and Table III, respectively. These are relative to the binary case of the fan vs the personnel target. Each table present the results of one classifier for both feature extraction algorithms as a function of the type of data used for the analysis. The first row of each table shows the performance obtained with the radar signature only, whilst the second row shows that obtained by using both the monostatic radar and acoustic signatures and the third row that obtained by using the data from the entire network. Results show that correct classification performance can significantly increase when the monostatic radar signature is fused with the acoustic monostatic signatures for both classifier and both feature extraction algorithms. Results also show that a further increase in performance can be achieved when the bistatic signature is fused with the monostatic data.

IV. CONCLUSION AND FUTURE WORK

We measured simultaneous multistatic and multimodal micro-Doppler signatures with a network of sensors consisting of a monostatic CW radar operating at 10 GHz and an acoustic radar with a monostatic and a bistatic channel operating at 45 kHz and 35 kHz, respectively. Signatures were gathered from various targets including a personnel target and a rotating fan. The main features of the micro-Doppler signature were extracted using the Cepstrum and the PCA algorithms and these were used to assess classification performance with a

k-NN classifier and a Naïve Bayesian classifier. A preliminary analysis of classification performance shows that an increase in performance can be achieved by fusing multistatic and multimodal data.

Future work will look at collecting data for a larger set of targets under various multistatic geometries. The analysis of classification performance will be significantly extended in order to corroborate our initial results. Classifiers will be tested on more similar targets for which class separation is commonly difficult to obtain.

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