Generic Fourier Descriptors for Autonomous UAV Detection

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Abstract: With increasing number of Unmanned Aerial Vehicles (UAVs) -also known as drones- in our lives, safety and privacy concerns have arose. Especially, strategic locations such as governmental buildings, nuclear power stations etc. are under direct threat of these publicly available and easily accessible gadgets. Various methods are proposed as counter-measure, such as acoustics based detection, RF signal interception, micro-doppler RADAR etc. Computer vision based approach for detecting these threats seems as a viable solution due to various advantages. We envision an autonomous drone detection and tracking system for the protection of strategic locations. In this work, 2-dimensional scale, rotation and translation invariant Generic Fourier Descriptor (GFD) features (which are analyzed with a neural network) are used for classifying aerial targets as a drone or bird. For the training of this system, a large dataset composed of birds and drones is gathered from open sources. We have achieved up to 85.3% overall correct classification rate.

1 INTRODUCTION

Recent advances in Unmanned Aerial Vehicles (UAV) -usually preferred to refer publically as *drones*- industry made these devices highly accessible to all kinds of civilians. Licensing and regulating drone utilization has lagged behind this rapid expansion of the industry. Besides their numerous advantages, drones have a huge potential to be misconducted intentionally or non-intentionally. First of all, commercial UAVs, even the cheapest and smallest ones can be easily converted to a weapon for terrorism by attaching explosives. Moreover, irresponsible utilization of these devices may cause also panic and fatal accidents. For example, during a football game in Texas, a drone has entered the stadium's airspace, causing large panic for spectators and law enforcement units. The responsible security forces rested helplessly as they have lacked the proper surveillance and counter-measuring equipment (Humphreys, 2015). In addition to this, commercial drones being flown around airports raising concerns for civilian aviation security. Numerous incidents caused by drones were reported by aviation officers in recent years (Wild et al., 2016).Also personal privacy issue and preventing industrial or governmental espionage is another serious problem (Villasenor, 2013).

These incidents have caused a paradigm shift for the governmental defence and public security strategies, as these crafts cannot be detected efficiently with conventional methods, such as RADARs etc. due to their size and small electromagnetic signatures (Peacock and Johnstone, 2013). Industry and academy have focused on new kind of countermeasure methods, where a solid consensus still is not apparent. The mostly used methods for small to medium sized UAV detection are RF detection (detecting the RF signals for control between the operator and the drone), acoustics (detecting certain specific sounds emitted from the rotors of the drone), X-band RADAR, micro-doppler signature (RADAR for detecting small moving objects like drones) and the optical methods (detection by computer vision) (Yoon et al., 2017)(Franklin and Hearing, 2016)(Solodov et al., 2017). Each of these methods has its own advantages or drawbacks. For instance, acoustics based detection with directional microphone arrays has a relatively low range of approximately 250 meters. And they are highly sensitive to background noise, which is a complicated problem especially in urban areas. RF signal interception disregards the fact that certain drones may not be controlled via wireless connection, but may have been preprogrammed to follow a certain route. Micro-doppler and X-band radar strategy often causes high number of false alarms, caused by birds, background clutter etc. Thus, they are generally accompanied an additional detection and identification apparatus.

Among these strategies, detection by computer vision distincts itself with its efficiency and robustness. It can also be applied to infrared cameras, thus providing night time operation capability. In this paper, we present a new method for drone detection with computer vision. This method can also be applied to infrared imagery. We assume that a moving object detecting background subtraction algorithm is continuously used and detected blobs' binary silhouette is examined with the Generic Fourier Descriptor (GFD) based algorithm to detect drones. In second section, we refer to existing drone detection technologies by computer vision approach and in the third section we explain the Generic Fourier Descriptor (GFD) proposed by (Zhang and Lu, 2002) and our approach to detect drones. One of the most important challenges for drone detection is avoiding false alarms caused by the birds (Gökçe et al., 2015). Thus, we have used flying bird silhouettes also in our algorithm for better discrimination capability. Next, in the fourth section we explain our experimentation method and results. Thanks to this approach, we could have achieved 85.3% overall correct classification rate between drone and bird silhouettes.

2 COMPUTER VISION FOR UAV DETECTION

As mentioned previously, computer vision for detecting drones is a more robust, feasible and effective method compared to other existing ones. Convolutional Neural Networks (CNNs) are the state-of-the-art method for object detection and identification, which has not a long history (Ciresan et al., 2011). It is a deep learning technique, which autonomously learns the optimal features for classification by imagery, thus does not depend on human crafted features (Simard et al., 2003). Recently, for computer vision based detection various authors have oriented themselves to CNNs. Among these, we see (Schumann et al., 2017)(Saqib et al., 2017)(Aker and Kalkan, 2017), which are using very similar approach for CNNs, however with different architectures. CNNs may be the most recent and state-of-the-art solution in the literature, however they require extensive computational cost, especially for training. In addition, their accuracy may be still low for certain circumstances such as low resolution, insufficient dataset etc.

Rather than CNNs, (Unlu et al., 2017) uses SURF based keypoint features of grayscale drone, bird and background image patches. The authors propose a new kind of extended bag-of-words (BoW) approach for classification. In this paperwork, we propose a GFD based approach for classifying image patches composed of birds and drones similar to those in (Unlu et al., 2017).

3 GFD BASED DRONE DETECTION

3.1 Generic Fourier Descriptors

Fourier Descriptors have been used as an efficient shape descriptor (Persoon and Fu, 1977). The distances of each contour pixel to the center of mass of the 2D object silhouettes is represented as a vector. Fourier Transform of this vector gives a unique description of the shape as the transform itself is shift, scale and rotation invariant.

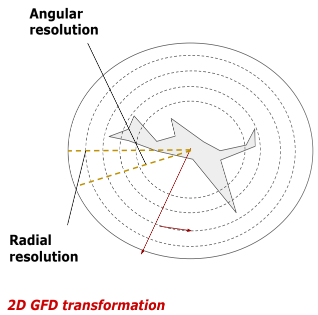
Generally, the lower frequencies of the transform contains more information on the major structural parts of the object. If we interpret the mechanism of the algorithm, we can state that higher frequencies of the transform correspond to the more intensive ripples on the contour.

However, even this approach can differentiate non-similar silhouettes with high efficiency, the classification performance degrades as the contours get similar. In addition to this, as mentioned previously, this algorithm only considers the shape of the outside contours. However, the form of the silhouettes can contain very important and distinctive information such as holes etc. An approach taking into account the complete silhouette shall be more robust to noise which can miss certain number of pixels.

Generic Fourier Descriptor (GFD) is a method proposed by (Zhang and Lu, 2002), which takes into account the 2D object silhouette in contrast the unidimensional Fourier Descriptors. The idea is to first raster and transform the pixels of the silhouette to polar coordinates with chosen angular and radial resolutions. Normalized 2D Fourier transform (Eq. 1) of this rastered function generates two dimensional matrix which we use as the representation of the shape. When this result is being used for classification with various algorithms, it is vectorized (Zhang and Lu, 2002).

$$GFD(R,T) = \sum_{r}\sum_{\theta}(f(r,\theta))e^{(-j2\pi r\frac{\theta}{R})+2\pi\frac{\theta}{T}} \qquad (1)$$

As it is normalized, this method is intrinsically scale invariant. And due to polar mapping by taking the center of mass as the origin, it is also translate



$$GFD(R,T) = \sum_r \sum_\theta (f(r,\theta)) e^{(-j2\pi r \frac{\theta}{R}) + 2\pi \frac{\theta}{T}}$$

Figure 1: The GFD transformation of a 2D object silhouette.

and rotation invariant just like the regular Fourier Descriptors. Fig. 1 illustrates the GFD calculation of a 2D object silhouette.

3.2 Aerial Surveillence by Using GFD

The binary silhouettes of objects are composed of 1s (where the pixel corresponds to object) and 0s (where pixel corresponds to background) in an arbitrary size frame. These are determined by the moving object detector (background subtraction). Then, we classify the object by using Generic Fourier Descriptor (GFD) features and a neural network. In order to train our system, we have created a dataset, composed of images of flying birds and drones, which are acquired from open sources.

To seperate the object pixels from the background, a special image segmentation algorithm is applied. We have composed the dataset from the images, where the object is darker than the background (i.e. sky). The images are chosen to be relatively low resolution in order to reflect the target case, where the autonomous tracker detect a small flying object in wide angle. All images are converted to gray scale and rescaled to 64x64 pixels. Fig. 2 shows few of the images from the dataset both for drones and birds.

Region Growing algorithm is chosen as the image segmentation algorithm to seperate the object silhouettes from the background in the images due to its efficiency (Adams and Bischof, 1994). Region Growing is a method, where pixel neighborhoods are evaluated in an iterative manner, starting from an initial seed point. Over course of the algorithm, the pixels are defined as background or foreground, by applying a clustering criterion.

After we have seperated the object silhouettes, we have applied a 2D GFD algorithm with 16 radial and 9 angular resolutions (therefore, we have feature vectors composed of 144 scalar values for each object.). In order not to lose any shape information, we have not applied any morphological operations after image segmentation phase. For most of the cases, after image segmentation there is no need for further processing to acquire the true binary silhouettes of the objects. However, in case there are more than one disconnected pixel groups, the algorithm chooses the largest pixel group as the true binary silhouette of the object. To apply GFD, the binary silhouettes of the objects have to be centered in a 2D plane, where their center of mass is the origin. Note that, as GFD is a scale and rotation invariant transform, there is no need for rescaling or rotation for the silhouettes. Fourier Transformation results are normalized and reshifted before further processing. Following this, we have created a neural network composed of approximately 6000 neurons to classify GFD features in to birds and drones.

Table 1: Confusion matrix for the classification of bird and drone silhouettes in test set.

Output Class	**Bird**	**207** **68.3%**	**29** **9.6%**	*87.7%* *12.3%*
	Drone	**14** **4.6%**	**53** **17.5%**	*79.1%* *20.9%*
		93.7% *6.3%*	*64.6%* *35.4%*	**85.8%** **14.2%**
	Target Class	**Bird**	**Drone**	

4 EXPERIMENTATION AND RESULTS

We have used 410 drone images and 930 bird images. A 5-fold approach is followed, where 4/5 of the samples are always used for training and the 1/5 of the samples is used for testing. In addition to this, to assure the validity of the experiments, the training samples are again divided in an additional 5-fold manner, where the test group is used for developing regularization parameters during the optimization of the neural network.

We have acquired an overall 85.3% accuracy on the test groups. The Table 1 shows the confusion matrix for a test group (0 : birds and 1 : drones). As it can be seen, the GFD based algorithm is especially effective at detecting bird shapes, with a true rate of 93.7%. However, we see that only 64.6% of drones are correctly identified. The overall accuracy shows

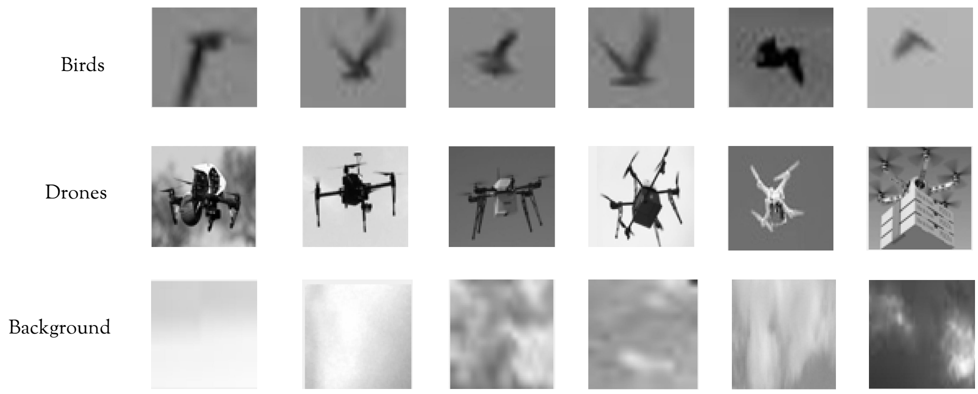


Figure 2: A few examples of the 64x64 grayscale bird, drone and background patches from the images we have collected from the internet.

that GFD is a novel 2D shape descriptor for discriminating bird and drone silhouettes for an autonomous drone surveillence system.

5 CONCLUSION

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