Biologically-inspired approach to automatic processing of fly eye radar antenna array patterns with convolutional neural networks

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ABSTRACT

Autonomous Air Vehicles (AUV) are used for survey, patrol and exploration purposes. Command and control of such vehicles is usually done by a human operator through use of joystick and visual camera. Most of the perception, target detection, and maneuvering is also done by a human. This approach does not allow for autonomy to evolve much further. Additionally, path planning algorithms are limited in scope and do not account for real-time events.

A proposed fly eye antenna array system, gives an opportunity to scan its surroundings and detect multiple targets. It consists of angularly – spaced directional and overlapping antennas with wide – area coverage. Each directional antenna is coupled with front end circuit, and a digital processor. Signals coming from such an antenna array records information about position, direction, target proximity with good penetration through scattered media [1].

Object detection using radio frequency signals from such sensors is challenging. The object reflects electromagnetic signals, coming from multitude of the fly-eye antennas. Based on the correlative values obtained from the sensors, a determination is made of the location, shape, and size of the object. Such patterns are recorded and used for convolutional neural network training purposes. The reflected and positional information of the radar sensors provides valuable information to the pattern system: 9 sensor covering 360 C view, with a correlative signal strength matrix. The objective of using signals from antenna array of signals with together with artificially labeled data makes a system intelligent. This approach is much simpler and we think it will have better generalization and performance then other RF signal processing approaches.

Keywords: AUV, RF imaging, signal processing, holograms, AI learning, antennas, navigation.

1. INTRODUCTION

In this research project, a novel approach will be presented in order to realize a new biologically-inspired approach to radar imaging and its processing system. The design is modeled after fly-eye vision that uses an ultra-wideband monopulse antenna array, with the purpose to detect and classify different types of UAVs carrying IR/EO sensor threats, to survey grounds and collect intelligence. Hence, the proposed design of the multi-beam antenna array will cover the entire sky and can provide a low power monopulse microwave imaging system with enhanced penetration capability. The project is based on the knowledge gained through earlier work on a handheld microwave through-wall imaging system [1]. It is important to note that existing RF and microwave through wall detection systems do not contain imaging information at all. In addition, command and control of such vehicles is usually done using RF signals by a human operator through use of joystick and visual camera. Most of the perception, target detection, and maneuvering is also done by a human. This approach does not allow autonomy to evolve much further. Additionally, path planning algorithms are limited in scope and do not account for real-time events. This paper will focus on the proposed approach of processing RF signals based on the correlative values obtained from the fly eye radar antenna. Ultimately, this activity is aimed at a novel, biologically-inspired, sensing, and (determination is made of the location, shape and size of the object) development of autonomous controls.

1.1 Background

To realize a bio-inspired sensor, it must be capable of autonomously scanning surroundings, detecting targets and using this information to make autonomous decisions. Detailed analysis of the current state of art, with a focus on the RF

Unmanned Systems Technology XIX, edited by Robert E. Karlsen, Douglas W. Gage, Charles M. Shoemaker,
Hoa G. Nguyen, Proceedings of SPIE Vol. 10195, 101950C · © 2017 SPIE
CCC code: 0277-786X/17/$18 · doi: 10.1117/12.2261432

imaging sensors that have to keep specific characteristics in terms of range or operation, wavelength and width of the mono-pulse finder is important, but will not be discussed in this paper. The paper is focused on presenting new approaches in both design and data processing that are aimed to mimic decision-making approaches for autonomous controls.

With regard to the first item, we point to the large body of our previous work previous work on fly-eye radar or micro-radar sensor technology, and in particular, the recent development of a prototype [1]. Secondly, some recent advances in deep learning have gained fame due to the ability to learn data representation in an unsupervised manner and generalize previously unseen data samples into classes. Among them, deep-learning based on a Deep Belief Network, which does not require domain knowledge or user manipulation [2] and a Sparse Autoencoder used to detect objects in the ImageNet dataset [3] produces state-of-the-art results. However, most of this work was done with regular camera images, not holographic RF images of radio frequency signals. But these aren't unique solutions for radar imagery. In fact, most of the images processed by deep belief networks and convolutional neural networks train the models view image in the 2D domain, which describes shape, size, and identity of the object, but does not estimate temporal or spatial data. Another impressive example is represented by the novel technique of determining the 3D shape of the object from 2D images using a Deep Belief Network for scene understanding in a 3D context [4].

Bio-inspired sensor design will use multibeam monopulse radar with an array of directional antennas that are positioned on a UAV. Radar signals simultaneously transmitted and received by multiple angle-shifted directional antennas with overlap patterns will provide the 360 degree sky coverage, successively, during each scan it provides RF/microwave, all weather high resolution imaging with a high sampling frequency [1]. When testing the fly eye radar, is necessary to identify the learning space and test various visual targets. This type of information is then used to create a database of labeled images and spatial pattern flowcharts that will be used to train a network to make intelligent decisions for autonomous controls. It is worth mentioning that knowledge accumulation (rule database and flexible associations) are necessary to develop intelligent control mechanisms.

1.2 Fly-Eye Technical Approach

In order to realize the proposed sensor, the design has to follow two principal components: the sensing and the processing stages. A proposed microwave imaging system presented in Figure 1, is the next step in developing the passive monopulse direction finder proposed by Stephen E. Lipsky in the 1980's [5]. Monopulse is the concept of receiving a signal simultaneously in a pair of antennas covering the same field of view and then comparing the signal ratios (Fig 1). Monopulse angle information always appears in the form of a ratio.

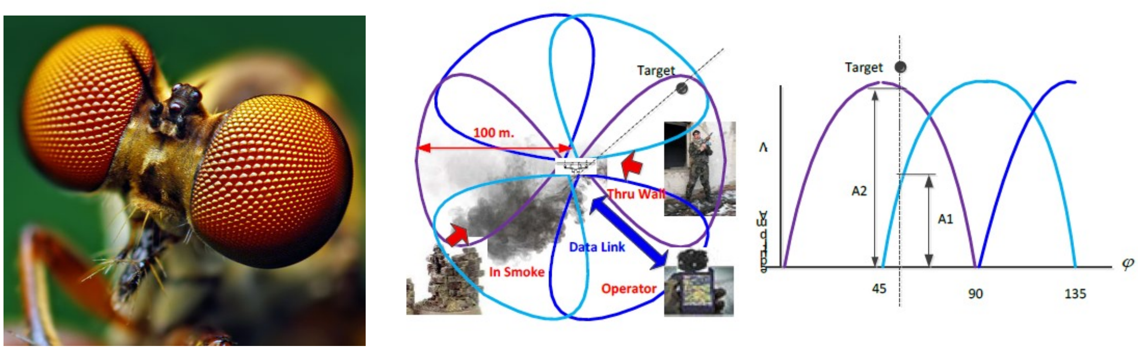


Fig.1. Imaging system installed on UAV for remote imaging [1].

The ratio value is independent of the signal and any common noise or modulation present [5]. The proposed monopulse microwave imaging system can work in passive, monostatic or bi-static regimes. Using the PMI proposed system [1] images are created and recorded using a real time digital hologram sampled through an ultra-wideband monopulse antenna array with a wide field of view capability. The approach uses digital holograms to process and reconstruct obtained data from the recorded measurements, delivering a 3D surface model. The imaging occurs due to the difference in phase shifts between the reference and the reflected signals returned by multiple objects located at different depths, it is possible to achieve higher contrast for one object or another by switching through frequencies in the selected bandwidth. Through Fourier transforms of received signals, similar results are obtained by phase shifted measurements of primary signal harmonics.

2. IMAGE PROCESSING AND LEARNING FROM THE PHASE RADAR

2.1. Through-wall imagery example

An example of the potential view of the radio frequency (RF) image, is shown below. The example of the compressive processing was thoroughly describe in previous publications [6]. Here, imaging results from through wall imaging research is shown after background subtraction.

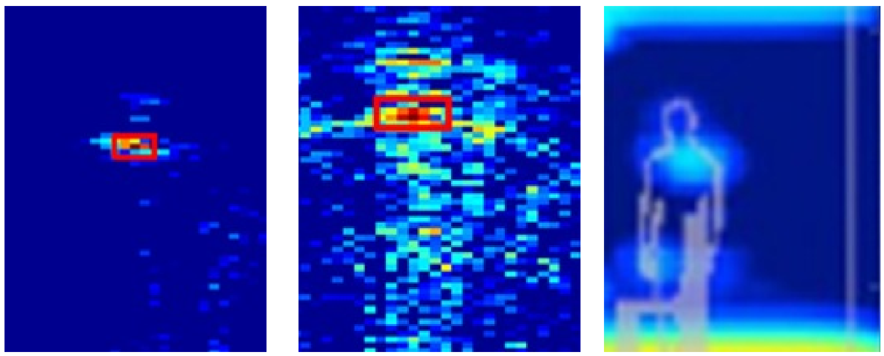


Fig 2. Examples of the holographic image of the human at different distance resolution [6].

An example of the dataset that yet has to be collected during the demonstration exercise will have similar characteristics. The processing imaging data will come from processing signal of digital hologram. By imaging reflection from reference and object antennas and calculating phase differences. The data collection process and quality of the data obtain will define the future steps of image pre-processing steps, such as noise reduction or image contrast. It is important to point out, that current data available through wall imaging devices differs from the fly-eye concept because they obtain signal from a single phase antenna. Overlapping multiple phased antennas will provide a hologram its high resolution, therefore less image preprocessing will be required.

3. PROPOSED FLY- EYE RADAR CNN MODEL

3.1. Object Recognition

The collection of imagery obtained from fly eye radar model will be recorded in the form of the hologram and displayed in raw data format. Once the data is converted into the compressed format, it will be possible to label it with the objects that it observes. The proposed training algorithm will mostly likely use human figures and or man-name objects at different detection angles and different poses. The labeling stage is not yet completely defined, as the model should be able to correlate object information under different wall distance metrics. As the distance changes with motion the object detection and classification of human figure will present a challenge. Currently the approach is to define the body (chest) and deduce information from it. It may be relatively straightforward task for the human, however it possesses a pattern recognition challenge for the researcher working with holographic imagery. In addition, when there are multiple objects and or a crowd of people the refraction from the monopulse radar will create a reflection with mixed signals.

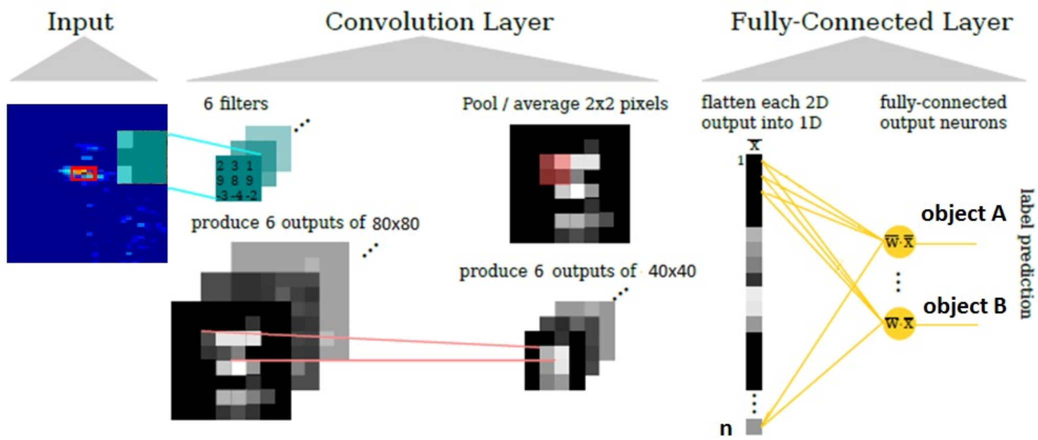


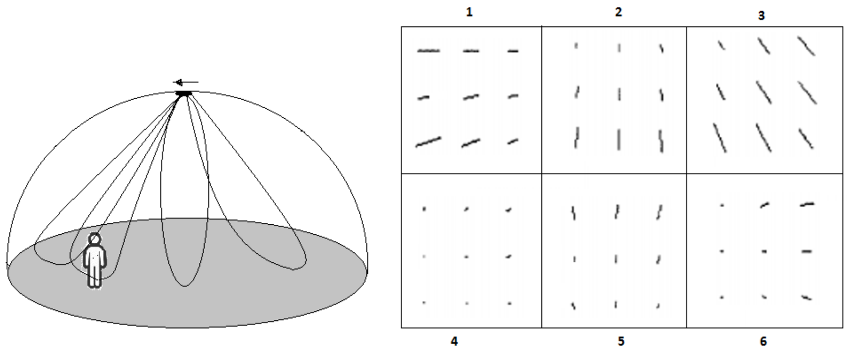
Fig 3. Proposed architecture of the CNN for fly-eye processing of holographic imagery. CNN network consists of the input set of holograms different of object under varying conditions.

The proposed architecture starts out with a simple, one layer network and a sufficient labelled data sample available for training and testing of the network. The size of the imagery and number of images used for training and validation is yet to be defined, however, images have to be taken from holographic equipment and distance to and from the wall must be also recorded to verify accuracy of object detection. Stochastic gradient descent (SGD) will be the optimal choice to optimize the network parameters such that the back-propagation error on the training dataset was minimized. SGD is the most commonly used optimization approach for neural network training, configured with a batch size of 10-20 images and varying iterations through the training set. We will experiment with altering batch size and training epochs using other image sets [7], evaluating the accuracy for each configuration. Smaller batch sizes reduce training time, potentially at the cost of accuracy and generalization to unseen data.

3.2. Learning Navigation

Another approach to achieving flight autonomy comes from the ability to recognize objects of interest under different view angles. Complex eyes of many insects, rely only on visual information to forage and establish flight path. For example, insects that are able to find path, use reasoning to select the single object from different flight directions. A similar approach can be also achieved with command and control of flight paths. This aspect is particularly of high importance in the GPS - challenged environment. It can use both prior knowledge, obtained from training, and the on-board reasoning system to make decisions about the nature of the object.

With a fly-eye radar system, there is a benefit of using multiphase directional radar that significantly reduces the amount of directional angles because of the encompassing view it gives of the single object. For navigation purposes, the response of the monopulse radar will not depend on the angle of the view, because object variation for each phase is defined. Fusing views from all angles together creates a complete picture of the object under varying conditions. Below, is a simplified abstract example, the sample object collected under differed viewpoints, is obtained by each loop of a radar response. For example, a reflection from a human is picked up by one of the arrays, other arrays do not see the same object, but provide a sense of direction in relation to the object, Figure 4. Each state in the table above represents the response: shorter lines represent proximity to x-plane (ground), then all four lines indicate the observation angle, and the shape of the one of the four lines (not shown) represents a reflected signal from one of the monopulse radars and illustrates the object type.



Figire.4. Illustration of the working principle of monopoles radar response from fly-eye detector.

Because each response obtained from monopulse radar system is already defined in the 3D space, it contains both information about the object and spatial information from other directions. Fused together, the spatial information obtained from the multiple radars gives encompassing information of the object.

The reason why, in our opinion, data represented in this way creates valuable feature space that takes into account both positional and object information in one flight. Use of machine learning, and in particular convolutional neural networks (CNN), can be used to train a flight controller about the object as composition of positional maps, associated with this object. Similar efforts were employed during the development of cognitive radar systems, where one of the aspects is preservation of the information content of radar returns [8]. Baig and Rashid have also presented an algorithm based on the swarming of honey bees called Honey Bee Foraging (HBF), which they proposed as useful for multimodal and dynamic natural optimization problems [9]. Similarly, multiple sensor radars used by one UAV, can collectively create spatial maps and use them for autonomous navigation and learning. Automation of processing such data allows the use of a biologically applied concept in both radar design and insect-like reasoning.

4. CONCLUSIONS

This paper introduced a novel approach to a biologically inspired radar antenna and two types of application of information processing. One approach can be used for classification of holographic images and objects by use of convolutional neural networks. A CNN learns a set of labeled pairs of different objects and or distances, while non-linear filters learn to produce feature maps and the associative label of the input. Further investigation of imagery will provide insight into specific processing of holographic imagery and describe the learning stage in depth. Another use of the neural networks, is used for navigation and autonomous perception of input signals. When object data is sensed in the 3D domain, insects' associative memory learns to navigate and learn map-like spatial memory the environment. The use of multiple sensors that collectively capture positions of the object allow the autonomous vehicles to navigate and learn from the environment. The exploratory memory will the study area at altitude, adjusting its position randomly until visual snapshot of landscape objects of interest are found. The autonomy will use this information to guide itself toward the object until the signal becomes stronger. Such behavior is often used by flying insects during foraging and learning flights.

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