

# Regressive Convolutional Neural Network for ARTVA detection

1<sup>st</sup> Bruno Strano

*Dept. of Electrical, Electronic,  
 and Information Engineering "Guglielmo Marconi" DEI  
 University of Bologna  
 Bologna, Italy  
 bruno.strano2@unibo.it*

2<sup>nd</sup> Lorenzo Marconi

*Dept. of Electrical, Electronic,  
 and Information Engineering "Guglielmo Marconi" DEI  
 University of Bologna  
 Bologna, Italy  
 lorenzo.marconi@unibo.it*

**Abstract**—In Search and Rescue operations signal detection is an essential feature, especially when drones are involved and technologies like ARTVA are used. This study introduces a new method of ARTVA signal detection via regressive convolutional neural network. The network takes the signal of the 3 axis of the antenna and the altitude of the quadrotor and outputs the estimate of the distances between transmitter and receiver. The results encourage an online implementation, extending the detection to multiple ARTVA.

**Index Terms**—CNN, UAV, ARTVA, Signal Detection.

## I. INTRODUCTION

Over the past decade the request for UAVs (Unmanned Aerial Vehicles) is grown in many different applications likes SaR (Search and Rescue) operations. Usually, the UAV has to identify the position of the victim and communicate it to the rescue teams. In alpine environments, the ARTVA technology is often used. The ARTVA system is composed of two elements which are: a transmitter, worn by the missing people, and a receiver, held by the rescuer. The transmitter emits a pulsating (electro-) magnetic field which is sensed by the rescuer device. The signal identification plays a crucial role in the success of the whole operation but the ARTVA receiver is usually incompatible with UAVs due to the high EMI (electro-magnetic interference) produced by the electrical AC motors and avionics. To overcome this problem, in [5], an EMI shielded UAV, with an ad-hoc version of the ARTVA receiver, has been produced. Using this special setup, the challenge is to give a reliable estimation of the position of the missing people based on the reading of the ARTVA sensor, that can still be affected by EMI. In this work we propose a Multi Output Multivariate Regressive CNN to overcome the challenge.

## II. METHODS

We developed a RCNN to detect the ARTVA signal and estimate the distance between receiver and transmitter. Our setup is composed by:

- 100Hz 3D ARTVA receiver;
- Airborne's shielded UAV;
- ARTVA transmitter;



Fig. 1: EMI shielded UAV with 3D ARTVA sensor

The quadrotor telemetry has been synchronized with the data coming from the receiver using a ground-truth signal coming from the RC (Radio command). The signals coming from the three axis of the ARTVA receiver  $x, y, z \in \mathbb{R}^3$  are amplified through an analogical filter and used as input in the network. The altitude of the UAV  $h \in \mathbb{R}$  is used as a fourth input, obtaining the following input vector:

$$U = \begin{bmatrix} x \\ y \\ z \\ h \end{bmatrix} \in \mathbb{R}^4 \quad (1)$$

The network outputs the x-distance and y-distance respect to the UAV local reference frame.

$$Y = \begin{bmatrix} x_{bf} \\ y_{bf} \end{bmatrix} \in \mathbb{R}^2 \quad (2)$$

### A. Training Data generation

The dataset for training and testing has been collected by performing some well known search pattern (Greek, triangular grid) with different yaw angles. The relative altitude has been kept fixed during the search pattern, as in a real SaR operation. Additionally, some data have been generated performing free flights. The flights have been taken in two different days for a total of almost 40 minutes of flight time. The dataset has been augmented to avoid overfitting. The augmentation has been performed by shifting the timeseries as in [3]. The inputs are timeseries of 200 samples, this traduces is ARTVA signal of 2 seconds. The data with a sample time  $t_c \leq 100Hz$  have been interpolated using splines to be consistent with the

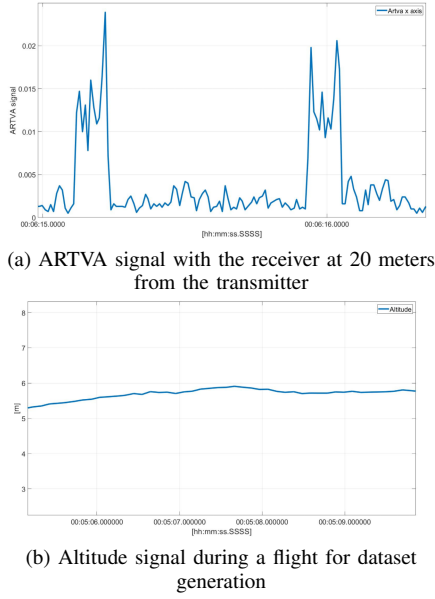


Fig. 2: Timeseries used as input in the network

ARTVA data. Finally, the outputs of the network  $x_{bf}, y_{bf}$  have been normalized. Since the *Home* position of the quadrotor is coincident with the position of the transmitter, through the telemetry data is possible to check the real distance from transmitter and receiver and express in body frame using the attitude data. Therefore, the datasets have been labeled and divided into training (75%), validation (20%) and test (5%) sets.

### III. NETWORK USED

We decided to use a Multi Output Multivariate Regressive CNN because of the good performance of the convolution in feature extraction from timeseries [2]. The network is composed of the first layer of 80 fully connected nodes and two convolution layers. The fourth input  $h$  is used in the first convolution layer. The fully connected layer handles just the ARTVA data. We selected *Adam* as optimizer and used to following loss function:

$$Loss_{RMSE} = \sqrt{\frac{1}{N} \sum (Y_{true} - Y_{pred})^2} \quad (3)$$

Where,  $Y_{true} \in \mathbb{R}^2$  is the vector of the measured outputs,  $Y_{pred} \in \mathbb{R}^2$  is the vector of the predicted outputs.  $N$  is the total number of samples of the timeseries.

### IV. RESULTS

In this work, we intend the accuracy of our network as the cross correlation between the predicted outputs and the measured outputs. Using a batch size  $b_s = 16$ , the predicted signal is 91.4% similar to the real signal. The loss function during training and validation can be seen in Fig. 3. Since the datasets have been created in two different experiments, transfer learning has been used to improve the results of the

first dataset. In Fig. 4 the performances during the testing procedure are shown. The signals represent the distances between ARTVA receiver and ARTVA transmitter, normalized.

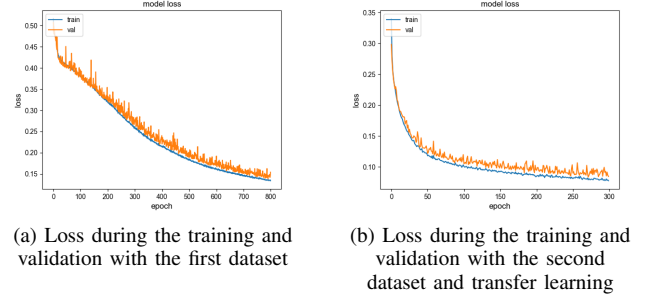


Fig. 3: Loss functions

### V. CONCLUSIONS

In this work, we presented the application of a multi Output Multivariate Regressive CNN for ARTVA signal identification and distance estimation. We used the Airborne's EMI shielded quadrotor to reduce the noise acting on the antenna and the synchronized telemetry of the quadrotor for labeling. The results are encouraging in the development of an online algorithm. The performances can be further improved by extending the dataset. We aim to fully develop the algorithm in a real time scenario and extend it by adding multi ARTVA recognition since is the typical case in real SaR operations. The repository with the dataset can be found in [7].

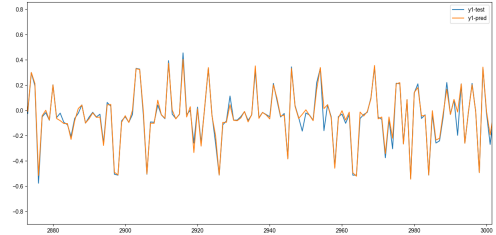


Fig. 4: Predicted distances versus measured distances during testing procedure

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