# Classifying Buried Objects by Combining CNN with Fourier Transform

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## ABSTRACT
Identifying buried objects needs signal processing which requires high computational power. In this paper, the frequency domain and time domain signals are used in combination with Convolutional Neural Network to classify the buried objects represented by the signals. The Fourier transform is used to change from the frequency domain to the time domain as it gives a holistic view of the environment around the antennas. The proposed method doesn't require to go into any complex signal processing steps which can save a lot of effort. A Bow Tie antenna is used to take measurements of five different setups. One setup is when the environment between the two antennas is filled with air, another is when it is filled with sand and another is when the sand contains buried rod at depth 3, 5 and 10cm. Each setup represents a class. The resulting measurements are in the frequency domain. Fourier transform is used to obtain those measurements in the time domain. The aim is to use a proposed CNN network to classify the frequency domain measurements to their corresponding classes. Another aim is to see the effect of using the frequency domain signals along with the time domain signals to classify them. The frequency domain achieved 87% accuracy in classifying the signals. While, the frequency domain and time domain signals achieved 93% accuracy.

## General Terms
Classification problem, Deep Learning.

## Keywords
Convolution Neural Network, Fourier Transform, Time Domain, Frequency Domain, Classifying Buried Objects.

## 1. INTRODUCTION
Identifying buried objects is a very active research topic that has applications in many fields. In the following lines, the efforts done in this area of research is illustrated.

Nguyen et al. states that the continuous functioning of Induction motors in some applications is crucial and highly required [1]. Sensors are attached to the motors to check its working conditions and give a clue to the users about possible faults. However, in low cost applications the monitoring of induction motors becomes relatively expensive with regards to the benefits gained. Using current transformers combined with machine learning techniques, Nguyen et al. proposed a system to expect the faults which will happen to the motors to allow ample of time for maintenance [1]. The machine learning techniques depends on obtaining the Fourier transform of the signals coming out of the current transformer to predict problems in the functioning of the motors [1]. The precision of classifying faults detections reached 99.7% by the proposed method [1].

Lafta et al. use machine learning in predicting the health conditions of patients which can play a vital role in improving the medical services to all patients [2]. The authors propose using the Fourier transform in combination with the medical measurements and scans taken from the patient during the previous days to predict whether an immediate health intervention is required or not [2]. The three algorithms of support vector machine, Naive Bayes and Neural networks are used together to make such a prediction [2]. The proposed algorithm succeeded in giving accurate recommendations for the patients and helped in reducing error in recommending immediate test or scan when it is not required [2].

Yi et al. surveys the recent immense of research papers which are done in the field of using Fourier transform with machine learning techniques to improve prediction accuracy [3]. The Fourier transform enables the user to obtain the time domain perspective for any frequency based signal. The time domain perspective helps to obtain a wider and accurate view of the meaning of the data. The survey looks to the topic of combining Fourier Transform with machine learning from four different angles of view [3]. Yi et al. researches the characteristics, used paradigms, network designs, and applications of using such combination in advancing the precision and accuracy of predications based on Fourier transforms [3].

Mehrabkhani et al. proposes using the Fourier transform method in obtaining the nonlinearities in the data used [4]. This will enable the authors to calculate the probability distribution of the signals on the classes to find out whether certain signal belong to one class or not [4]. The proposed method achieves more reasonable results than that achieved by using the supported vector machine method as it helps in explaining the probability of one signal to belong to a certain class [4]. The proposed method can be applied to huge datasets and still achieve reasonable results. It achieves good results even with overlapping classes and highly nonlinear datasets [4].

In another track, Mehrabkhani et al. proposes using a different method in applying machine learning to classification problems than the usual method which depends on separate steps of training, evaluation and testing [5]. The authors propose using the Fourier transform as a training and evaluation method which prevent users from using the least squares method to evaluate conversion to required results and accuracy [5]. This in terms avoids the appearance of the over fitting or under fitting problems. The proposed method was applied on raw data and excellent results were achieved [5].

Anaya-Isaza et al. researched the use of deep learning techniques in combination with other processing techniques to predict the severity of the Diabetes Mellitus cases from the foot thermo-imaging [6]. Diabetes Mellitus (DM) is rated among the top causes of high death rates according to the World Health Organization [6]. According to several studies, it was found that the thermo imaging of patients with DM produces unusual patterns of body temperature than normal patients which triggered the use of it to predict the severity of the disease [6]. Anaya-Isaza et al. proposed using the Fourier transform to obtain images which are mathematically manipulated to diagnose the disease early enough to take precautionary measures [6]. The proposed method used the Convolutional neural network ResNet50v2 to obtain near perfect results in classifying patients with DM [6].

Yaghoobian et al. study the use of radar signals to detect buried objects [7]. Reflected signals from the different layers of the ground is processed to obtain information about what is hidden underneath. However at penetrating the earth surface, a back scattered signal with large amplitude called clutter overshadows the whole signal preventing further processing of it. Yaghoobian et al. propose using the Chirplet transform to remove the noise caused by the clutter signal. Numerical simulations are done to study the effect of using the proposed transform on the improving the signal to noise ratio [7]. Furthermore, Yaghoobian et al. verify their results by using the Generalized Linear Chirplet Transform to reproduce real signals which has showed better results than other research papers [7].

Pham et al. propose using radar images to detect buried objects [8]. The authors propose using a modified version of Faster-RCNN on B-scan radar images to detect underground objects [8]. The proposed algorithm need to be trained and there is a shortage of finding a dataset for this aim. The gprMax toolbox is used to generate the required dataset of images [8]. The proposed CNN network is first trained on a gray scale dataset. Then, more simulations are done to select the most appropriate values for the parameters of the proposed network to give best results [8]. The detection results and accuracies are very good when compared to the already used systems which gives promises for future advancements in this direction [8].

Yurt et al. proposes the use of novel deep-learning-based modified multilayer perceptron framework on detecting the physical and geometrical properties of a cylinder buried object [9]. A dataset of images is generated using the gprMax simulation tool [9]. Then, hyperbolic signatures are extracted from the images which reduce each images to one dimensional frame that contains all data about the object under detection [9]. The framework is applied on the generated one dimensional dataset. Results are compared to the other regression techniques such as Multilayer Perceptron, Support Vector Regression Machine and Convolutional Neural Network and are found to outperform their accuracies [9]. The detection accuracy is very good with an average mean absolute error of 10mm and an average relative error of 8% [9]. The proposed framework is also applied to data that has a low signal to noise ratio and the results are equally accurate which gives confidence in applying it to physical measurements [9].

Al-Nuaimy et al. proposes using deep learning algorithms to identify the Welch Power Spectral Density Estimate representing reflections from buried objects [10]. This helps to identify parts of the images which contain important information and other parts which are of less importance. Further signal processing techniques can be applied to the important parts of the radar images thus reducing computational time and complexity [10]. Then, Al-Nuaimy et al. proposes applying the Hough Transform to the important parts of the reflections to obtain more accurate estimations of the size and depth of the buried object [10]. A high quality images are re-produced for the layers of the underground clarifying buried objects and their properties [10].

Huyen et al. proposes a method to detect buried objects in surroundings which are not physically homogeneous [11]. The authors use binary phase shift keying, time-hopping pulse position modulation, shifted time pulses with radio impulse ultra wide band systems along with the least square curve fitting method [11]. Results show that the proposed method leads to accurate detection results which outperforms other already published methods [11].

In this paper, the methodology used to obtain our results is illustrated in section two. In section three, the measurements obtained using our hardware and the creation of the needed dataset are explained. The theoretical background for our proposed neural network is explained in section four. The results achieved for the proposed classification algorithm is discussed in section five. Finally, conclusion is derived in section six.

## 2. METHODOLOGY

The hardware implementation which is used to collect our dataset is illustrated in subsection one. The layers of the proposed CNN network which is used to classify our dataset are described in subsection two.

### 2.1 Hardware Implementation

A Bow Tie Antenna is used to obtain the used measurements. The physical and electrical properties of this antenna can be found in reference [12].

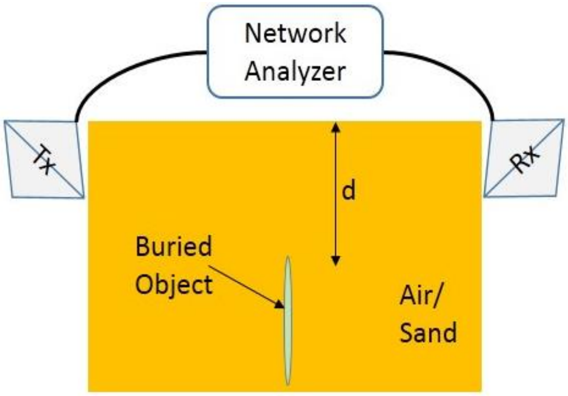


**Fig 1: An image of the experimental setup used to obtain the measurements used in this paper is shown**

Fig.1 shows the experimental setup used to make our measurements. Two Bow Tie antennas are used one as a receiver (Rx) and another as a transmitter Tx. The two antennas are connected to a network analyzer to take measurements in the frequency domain. The frequency range used is one to fifteen Giga Hertz. The measurements are repeated for five different environments between the two antennas. The first one is done while the space between the two antennas is filled with air. The second one is done while the space between the two antennas is filled with sand. The third, fourth and fifth ones are done while the space between the two antennas is filled with sand and a buried object inside it. The object is a metal rod with diameter 0.5cm and length 10cm. The object is buried at a depth under the surface of the sand at a distance of 3cm, 5cm and 10cm respectively.

### 2.2 Neural Network

In this subsection, the five layer CNN network which is used later in obtaining our results is explained. One layer is used to input the signals to the network. Another layer is used to perform 2x2 convolutions 128 times. Finally, three layers namely Fully Connected one, Softmax one and Classification one are applied. The mathematical representations for some of these layers which are mentioned earlier are explained in section five.

**Table 1: The values of the parameters implemented in obtaining our results are tabulated.**

| | |
|---|---|
| Optimizer: | Adam |
| Initial Value of Learning Rate: | 0.2 |
| Batch Minimum Size: | 5 |
| Epochs Maximum Number: | 100 |
| Drop Period of Learning Rate: | 30 |
| Drop Factor of Learning Rate: | 0.3 |

The parameters which are used in obtaining the results are given in table 1. In our results, Adam optimizer is used as it is a stable optimizer that is appropriate to use with CNN [13]. The optimizer works very well with large datasets [13]. Also, results obtained using it are not largely affected by the noise included in the datasets used [13]. Out dataset are a group of reflections from buried objects which are likely to contain noise due to the surrounding environment. In this paper, the dataset used is noisy so the Adam optimizer leads to the best results as shown later. The learning rate is set to have an initial value of 0.2. The batch size is set to have a minimum value of 5. The number of epochs is set to have a maximum value of 100. The learning rate is set to have a drop period of 30. Also, the learning rate is set to have a drop factor of 0.3. Matlab2018a is used to carry out the required calculations and Excel sheets are used to create the shown graphs. The value of the parameters shown in table 1 are obtained by trial and error until the best classification accuracy are achieved.

## 3. DATASET

In this section, the measurements obtained using the setup shown in fig. 1 and the dataset compiled using these measurements are discussed.

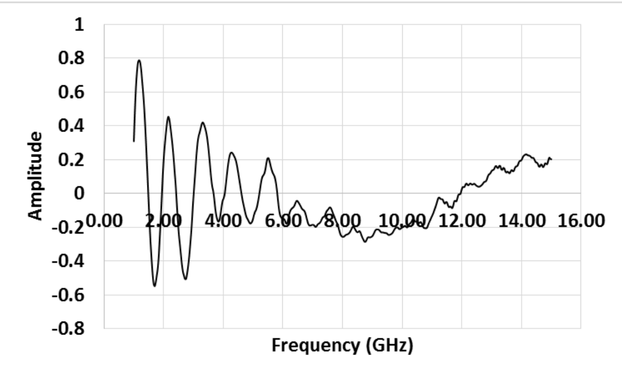


**Fig 2: The measurements taken using the Bow-Tie antenna in frequency domain while the environment between transmitter and receiver is filled with air.**

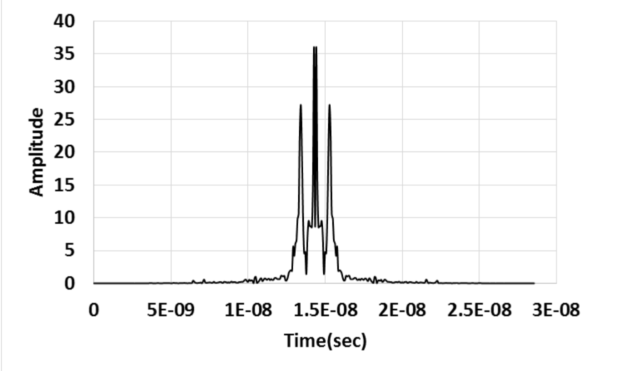


**Fig 3: Fourier transform of the measurements taken using Bow Tie antennas while the environment between transmitter and receiver is filled with air**

In fig. 2, measurements are recorded while the space between the Tx and Rx antennas is filled with air. Two Bow-Tie antennas are placed opposite to each other and connected to the network analyzer which is set to read measurements for the frequency range one to fifteen Giga Hertz. The resulting measurement is plotted in fig. 2. The amplitude of the transmitted signals is shown against the corresponding frequencies. Frequencies at which the signals are absorbed or reflected during transmission have lower amplitude than the frequencies at which signals are received by the Rx antenna at full power. Next, the Fourier transform is applied on the measurement which is shown in fig. 2 to obtain the measurement values in the time domain.

In fig. 3, the Fourier transform of fig. 2 is shown. Three peaks are seen representing reflections from the walls of the empty basin that is filled with air. The same measurement with the same setup is repeated four times with different reflections from different background environments.

The whole measurements are repeated with the five different setups which are explained in section two.

A dataset compiled from these measurements is divided into four sets. First set contains 80% of the frequency domain measurements to use them for training the proposed network. Second set contains 20% of the frequency domain measurements to use them for validation of the proposed network. Third set contains 80% of the frequency domain and time domain signals to use them for training the proposed network. Fourth set contains 20% of the frequency domain and time domain signals to use them for validation of the proposed network. Two issues are aimed at in this paper. The first aim is to classify each signal into its environment/setup in which the measurement was taken using a proposed CNN network. The second aim is to find out if the time domain signals can improve the classification accuracy of the frequency domain signals.

## 4. THEORETICAL DERIVATIONS

In this section, the mathematical equations used to obtain our results are described. The Fourier Transform equation is used to change back and forth between the frequency domain and the time domain. The equation is [14]:

$$f(\omega)=\frac{1}{\sqrt{2\pi}}\int_{-\infty}^{\infty}\exp(j\omega t)f(t)dt \qquad (1)$$

Where $f(\omega)$ is the function in the frequency domain, $f(t)$ is the function in the time domain, $\omega$ is the angular frequency domain and $t$ is the time domain [14].

Two layers of the five explained in section two are explained mathematically here. The Glorot initializer is used in the Convolution layer. It decreases the processing to increase the stability of the training process and decrease the consumed processing time of the neural network [15]. Signal $A$ can be convoluted by another signal $B$ by using the equation [15]:

$$C(j,k) = \sum_{p}\sum_{q} A(p,q)B(j-p+1, k-q+1) \quad (2)$$

Where $p$ and $q$ are indexes for the two signals $A(p,q)$ and $B(j-p+1, k-q+1)$.

Problems which contain more than two classes are solved using many equations among which the Softmax function. The Softmax layers apply the Softmax function which can be stated as follows [16]:

$$y(z)_i = \frac{\exp(z_i)}{\sum_j \exp(z_j)} \quad (3)$$

Where $\sum y = 1$ and $0 < y < 1$.

Softmax uses the exponential function to generate a probability profile for a group of values [16]. The probabilities represent the percentages by which each signal belongs to a certain class or not [16]. The higher the percentage probability the higher the probability that the signal belongs to a certain class.

The two parameters used to show the success achieved are the Accuracy and Loss parameters. The equation for the Accuracy is [17]:

$$Accuracy = 100\% - Error\_Rate \quad (4)$$

Where $Error\_Rate$ is defined as follows [17]:

$$Error\_Rate = \left| \frac{Observed - Actual}{Actual} \right| \times 100 \quad (5)$$

Where $Actual$ is the number of cases under a certain class and $Observed$ is the number of true classification for the same class.

The equation for the Loss is [17]:

$$Loss = \frac{1}{N}\sum_{1}^{N}\left(Y_i - Y_{\exp}\right)^2 \quad (6)$$

Where $N$ is the total number of classes, $i$ is an index for the classes, $Y_i$ is the number of truly classified cases, $Y_{\exp}$ is the expected number of cases for this class.

## 5. RESULTS

Two datasets are used. The first contain the frequency domain measurements to find out the accuracy of the CNN network when classifying them to their environment class. The second contains the frequency and time domain to see how much the time domain signals can improve the accuracy of classification. The measurements in the frequency domain are fed to the CNN network described in section two. The results are shown in this section. Loss and Accuracy performances are used to describe the success achieved. The aim is to classify the frequency domain measurements to their corresponding environment class. 80% of the dataset is used for the training step.

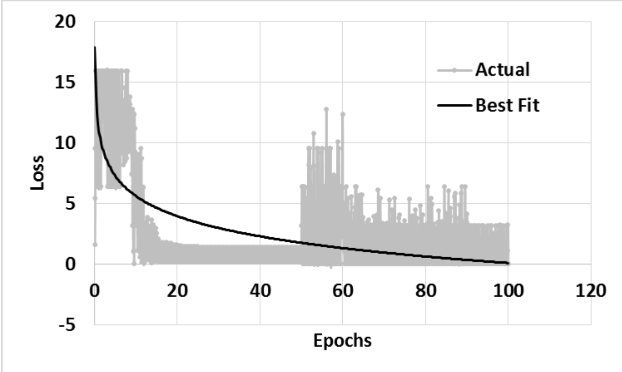


**Fig 4: Using frequency domain measurements, the Loss in the CNN network and the best fit for it are plotted.**

In fig. 4, the Loss in the CNN network is plotted against the number of epochs. The Loss drops from 15 to 2 during the first twenty epochs. It can be seen that after twenty epochs the network Loss is below 2. However, variations in the Loss increases again after 50 epochs which shows some inconsistency in the performance of the Loss parameter.

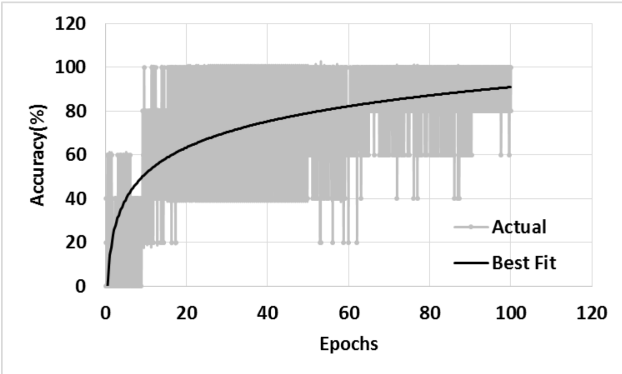


**Fig 5: Using frequency domain measurements, the Accuracy in the CNN network and the best fit for it are plotted**

In fig. 5, the percentage of Accuracy achieved in the proposed CNN network is plotted against the number of epochs. The Accuracy increases exponentially as the number of epochs increase. The Accuracy increases from 0 to above 40% during the first twenty epochs. After twenty epochs the network Accuracy continues to increase to reach almost an average of 90%. From 20 to 60 epochs, the accuracy ranges from 40 to 100%. From 60 to 90 epochs, the accuracy ranges from 60 to 100%. From 90 to 100 epochs, the accuracy ranges from 80 to 100%.

For the validation step, 20% of the dataset is used for it calculations. The dataset contains frequency domain measurements only. The accuracy was 87.5%.

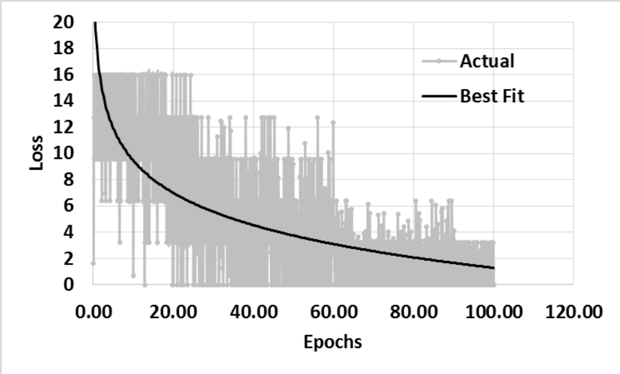


**Fig 6: Using frequency and time domain measurements, the Loss in the CNN network and the best fit for it are plotted**

Next, the measurements in the frequency domain and time domain are fed to the same CNN network. The results are shown next. Loss and Accuracy performances are used to describe the success achieved. The aim is to classify the frequency and time domain signals to their corresponding environment class. 80% of the dataset is used for the training step.

In fig. 6, the Loss in the CNN network is plotted against the number of epochs. It is shown that the Loss drops from 16 to below 4 during the first 70 epochs. It can be seen that after 70 epochs the network Loss is below 2 which is very good.

In fig. 6, the Loss in the CNN network is plotted against the number of epochs. The Loss drops from 16 to 1 during the hundred epochs. It can be seen from the best fit that the decease is consistent throughout the whole run. The ranges in the Loss values continue to diminish as the number of epochs increase.

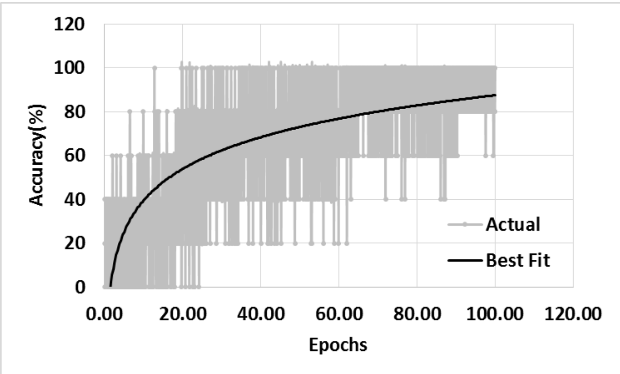


**Fig 7: Using frequency and time domain measurements, the Accuracy in the CNN network and the best fit for it are plotted**

In fig. 7, the percentage of Accuracy achieved in the proposed CNN network is plotted against the number of epochs. The Accuracy increases exponentially as the number of epochs increase. The Accuracy increases from 0 to above 40% during the first thirty epochs. After thirty epochs the network Accuracy continues to increase to reach almost an average of 90%. From 30 to 60 epochs, the accuracy ranges from 40 to 100%. From 60 to 90 epochs, the accuracy ranges from 60 to 100%. From 90 to 100 epochs, the accuracy ranges from 80 to 100%.

For the validation step, 20% of the dataset is used for it calculations. The dataset contains frequency domain and time domain signals. The accuracy was 93.75%.

# 6. CONCLUSION

Recent research papers have been done about the effect of the use of Fourier transform in combination of CNN to classify signals. In this paper, two Bow-Tie antennas are used to obtain transmitted signals in the frequency domain for five different environments/classes. One environment is when the space between the two antennas is filled with air another when it is filled with sand. Another environment is when the space between the two antennas is filled with sand and a rod is buried in the sand at distances 3, 5 and 10cm. The resulting dataset is composed of frequency domain measurements for the five setups/classes and their corresponding time domain representations. The time domain signals are obtained using the Fourier transform function. A CNN network is proposed that is composed of five layers. The dataset is divided into two datasets. The first that contains only frequency domain measurements while the second contains the frequency and time domain signals. The CNN network succeeded in classifying the frequency domain dataset with Accuracy 87%. Moreover, the network succeeded in classifying the frequency domain and time domain dataset with Accuracy 93%. Time domain signals increased the classification accuracy of the frequency domain signals by almost 6%. The time domain signals give a more overall view of the environment into which the measurements are taken. The frequency domain gives a view about the sizes of the objects reflecting the waves. The length of the object buried in the sand is directly proportional with the frequency that is reflected from the rod. However the frequency domain doesn't give information about the setup that is surrounds the antennas such as the depth at which the rod is buried. At this point, the time domain gives information about the distance between the antennas and the body reflecting the waves.

# 7. ACKNOWLEDGMENTS

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