An Advanced Buried Threat Detection Using Convolutional Neural Networks and Recurrent Neural Networks

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Abstract

In this paper, we propose a method to further the research done on GPR and BEO's by capitalizing on recurrent neural networks and convolutional neural networks to analyze two-dimensional Ground Penetrating Radar B-scans in the x and y axis respectively. We will also analyze three dimensional volumes of Ground Penetrating Radar data.

Most prevalent mechanisms of detection are modelled using handcrafted features or pointed models, we make use of big real GPR data and data centric methodologies. Our algorithms are trained and evaluated using large experimental data covering a large surface area of 1200 square meters from varying lanes across U.S test sites. This data includes a wide set of Buried Explosive Objects consisting of different shapes below surface hidden depth and metallic content.

We also provide a quantitative analysis that compares the different results found using the algorithms and models used modelled on CNN's and conventional learning methods.

Keywords— Buried threat detection (BTD), convolutional neural networks (CNNs), ground penetrating radar (GPR), recurrent neural networks (RNNs).

INTRODUCTION

Detection as well as removal of landmines BEO's and IED's is a major issue affecting populous around the globe. The world is now polluted with an approximate 110 landmines buried at this moment. An equal amount in reserves waiting to be planted. According to the 'International Campaign to Ban Landmines Network', more than 4200 individuals, 42 percent are children who have been succumbing to landmines most in countries affected by war.

The task of finding these landmines has a track record of being extremely herculean killing two miners for every 500 removals. This is where GPR comes in, it is extensively researched and has sensors that emit electromagnetic waves covering big frequency bands into the ground through a wideband antenna and measuring reflections from the soil caused by targets based on their dissimilarities from the soil. Machine based learning then study this GPR data which is created bespoke for the intended application.

Conventionally, this is done in a process comprising of two steps.

First a detector tuned to detect anomalies is used to filter the stream of data and discover areas of interest that correspond to locations of anomalies.

The next step is an algorithm using a Machine Learning algorithm which assigns a confidence value denoting whether or not the aforementioned area of interest shows signs of a buried target or object. More recently, deep learning algorithms are being used, but a consistent limitation is that they used only a 2-Dimensional B scan, extracted from 3 D GPR volumes. This approach is lacking and inaccurate to detect narrow targets depending on their burial orientation. In this paper, we propose three unique and novel techniques that are based on 2-D CNN but explore the 3-D structure of the GPR data.

1) As discussed earlier, our method uses CNN and RNN deep learning mechanisms. The CNN algorithm is used to capture information in solitary B scans and the RNN part models the differential data in between scans.

2). The first layer of CNN uses 3-D kernels to exploit the three-dimensional shape of the GPR alarm by processing 2-D frames from the 3-D data parallelly.

3. We merge the results of the two-dimensional convolutional neural networks trained separately.

The first output is modelled and trained to remove information from the Down Track B-scans, the second network is trained to learn from the Cross-Track B-scans. The objective is to recognize when a B-scan profile in both directions can indicate finding a BEO.

For approaches one and two, we also train two networks that process the information along the x and y axis (DT and CT directions). Collating data from these two approaches can improve the accuracy of detection.

DATASET BACKGROUND

The information collected is done so by a GPR machine. This system is comprised of a combination of radar antennae attached on the front of the machine. During the collection process, each antenna gives out a wide band radar signal into the ground. As the machine goes forward, each antenna collects a set of A scans at regular intervals. This process forms a 2-dimensional image, representing a vertical slice of the ground called (depth) B scan.

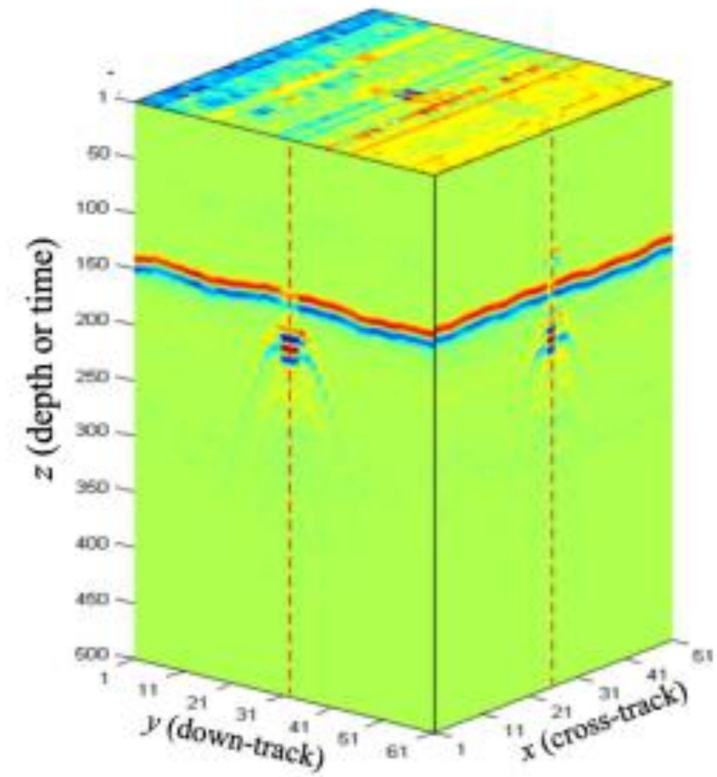

Fig 1. Three-Dimensional Rendering of data from GPR scan at a surface level

Figure 1 depicts an area where a confirmed landmine resides. The red band at 150 is regarding the response from the elemental interface. The shape visible in the middle shows us the location of the explosive object, we can easily tell as its components are notable denser than the surrounding soil.

Before we use our learning algorithms, we need to pre-process the data using techniques such as normalization, scaling, etc.

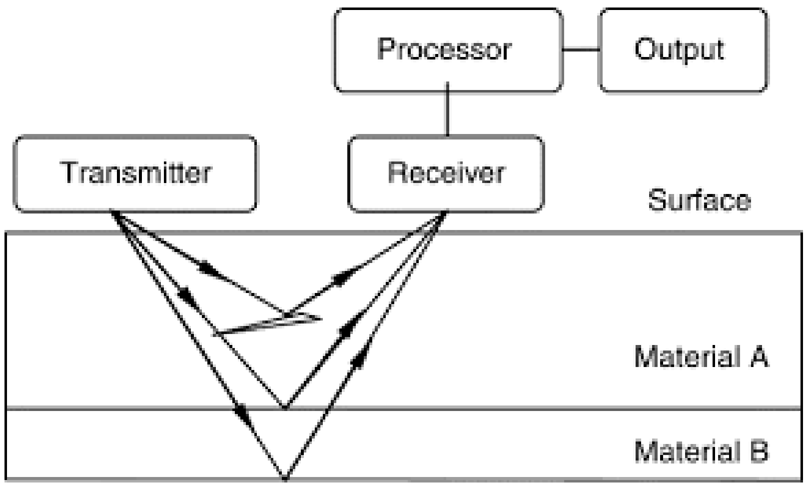

Fig. 2 Working of GPR scanner

In our experiments, for example, samples above 150 will be ignored. This is done as; all the scans are aligned and should occur at the same depth level. Next, the samples are normalized and background noise, etc. is removed. Now, the pre-processed data is analysed by a prescreener to find out the suspicious locations with unique signatures. We use pre-screening to cut down on the quantity of data, this makes it possible to perform accurately in real time. The prescreener inspects tiny areas to check for suspicious activity and returns results indicating the possibility of an explosive device. Figs. 2 and 3 show the raw and pre-processed (depth, CT) B-scan and (depth, DT) B-scan of example target alarms identified by the discrimination algorithm prescreener.

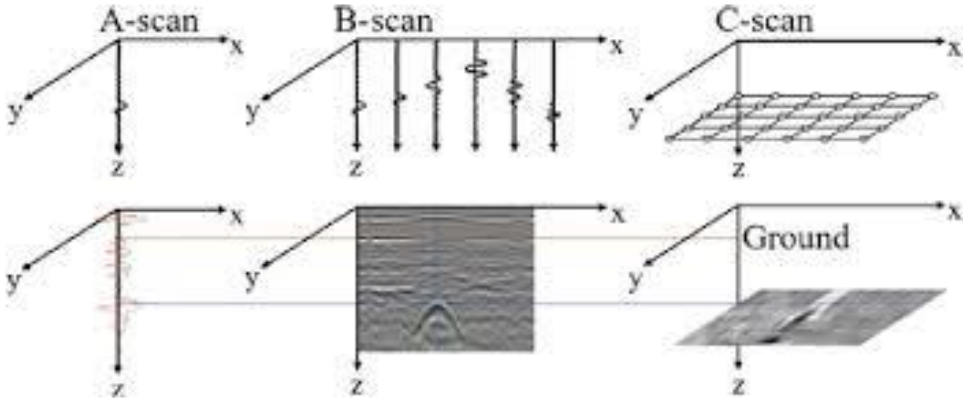

Fig.3 Different Type of Scans Used for Infrastructure Mapping

As mentioned earlier, our data set was collected using a vehicle-mounted GPR machine. It consists of data aggregated from two test sites, namely Site 'A' and 'B'. Site A has seven designated testing lanes and is located in a temperate geographic region. Site B has six lanes and is located in an arid environment. At both sites, the soil type is different, is filled with different explosive and buried objects. The objects have different degrees of metallic content buried at different depths.

Site A includes a sum of 465 different threats, and site B includes a sum of 292 unique threats. Multiple runs were made across each lane from multiple directions, across dates and with potentially varying climatic conditions.

Total No.	**Site A**	**Site B**	**Total**
Lanes	8	7	15
Runs	62	28	90
Mapped Area	57,000m2	66,000m2	123,000m2
Distinct threats	465	292	757
Threats Found	3,628	994	4622
False Positives	784	349	1133

Table.1. Ground Penetrating Radar data used for analysis

BURIED EXPLOSIVE OBJECT DETECTION USING DEEP LEARNING

In this article, we suggest using algorithms that use RNN and CNNs to analyze data in a multidimensional aspect. On comparison to existing algorithms that are based on conventional learning methods, our experimental model uses real and large data collection and legitimate proven methods that are successful in characterizing BEO's in both directions (Down Track and Cross Track). Some existing methods that use CNN, our approach takes care of all the three different dimensions of GPR information to sort the shape of the BEO. We get these results based on three different fusion levels. In the first one we train two different CNNs on orthogonal two-dimensional B scans of the three-dimensional GPR data.

Next, an RNN is added to merge the collated CNN features and learn the independent value among them to differentiate between explosive and other clutter objects. Since we use large data sets which are real, no data augmentation or transfer learning is needed.

Proposed Architecture Using Combinatory CNN-RNN

Our prosed architecture, uses a combination of CNNs and RNNs build a BEO detector. The CNN part is used to extract information in separate B-scans, and RNN is used to model the differential data amongst scans. To the best of our research, no existing methods have used such a novel combination of CNNs and RNNs for sifting through GPR data.

The proposed architecture, has a modular type design and can be trained to catch the contextual information from all 3-D aspects of the GPR data. As illustrated in Fig. 4, the first part of this network is the feature extraction component of a 2-D CNN. Any state-of-the-art architecture can be used for this module.

The second part of the model is defined by a RNN that models the captured features from consecutive B-scans as a chain of temporal data. The CNN and RNN network is continuously and rigorously trained end to end to learn visual features from B-scans and their change in growth throughout the sequence of channels. Our model uses random initialization for the weights, the Adam method for optimization, and fallout rate of 50%. The final decision of this architecture will also be obtained by aggregating the outputs of CNN-RNNs Down Track and Cross Track networks.

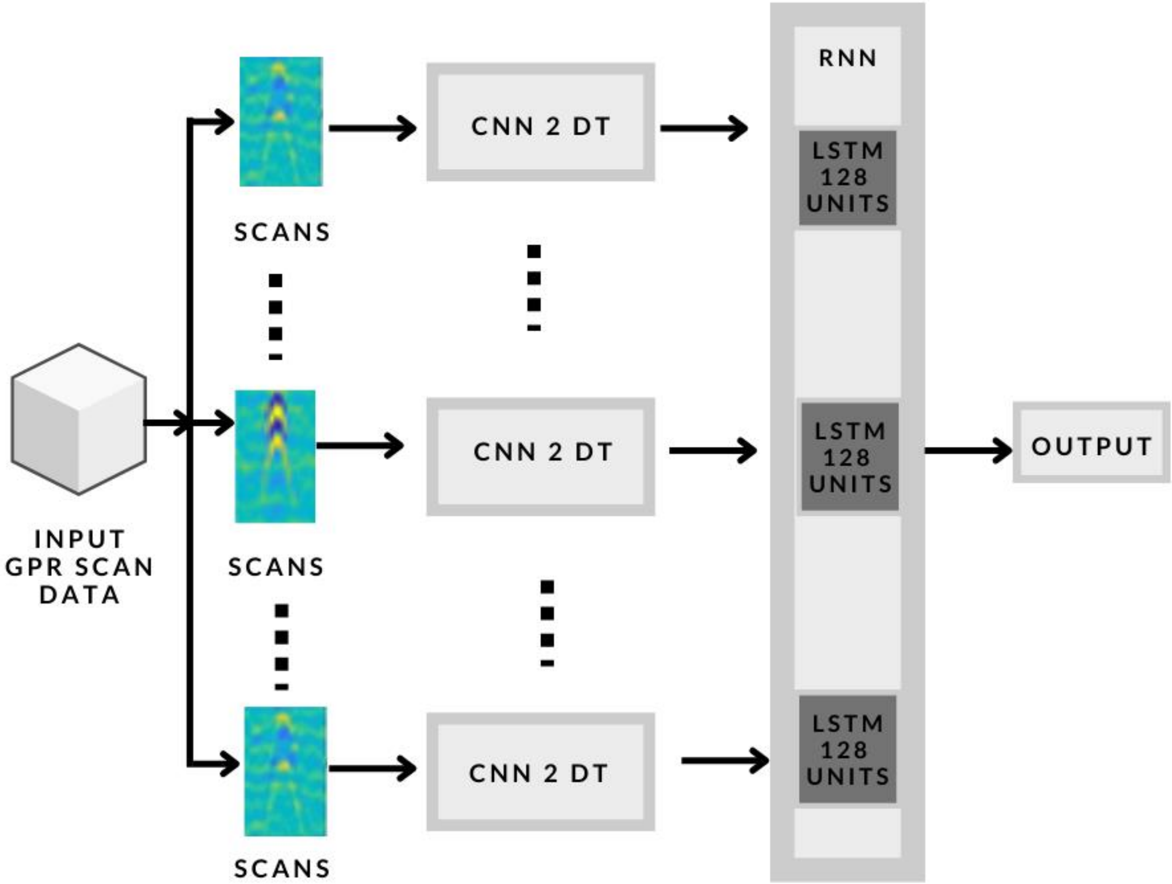

Fig. 4. Combinatory Proposed CNN-RNN Architecture

RESULTS

The results of our model as compared to multiview 2-D CNNs are shown in Fig. 5. The prescreener is also shown as a baseline reference. We can easily note that the merged result of CNN2 DT and CT outperform the prescreener and others. Thus, a fusion of the Down Track and Cross Track CNNs performs significantly better than separate networks.

To understand the results better, we outline a scatterplot of the classification of confidence of the algorithms. The red 'x' indicates targets, the blue '0' indicates objects of clutter. The top right region is associated with a strong performance of both algorithms. On the other hand, the bottom right region indicated where the CNN Down Track outperforms the Cross-Track CNN.

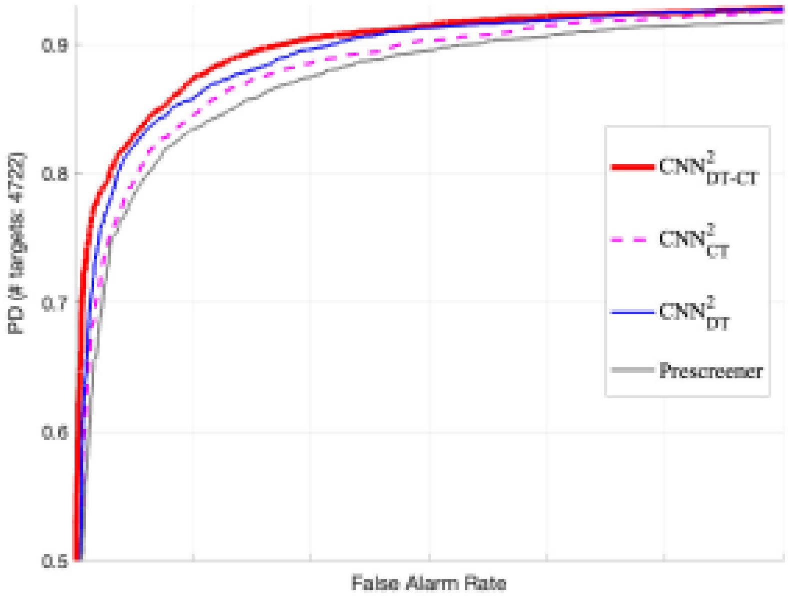

Fig. 5 ROCs obtained of the merged CNN networks

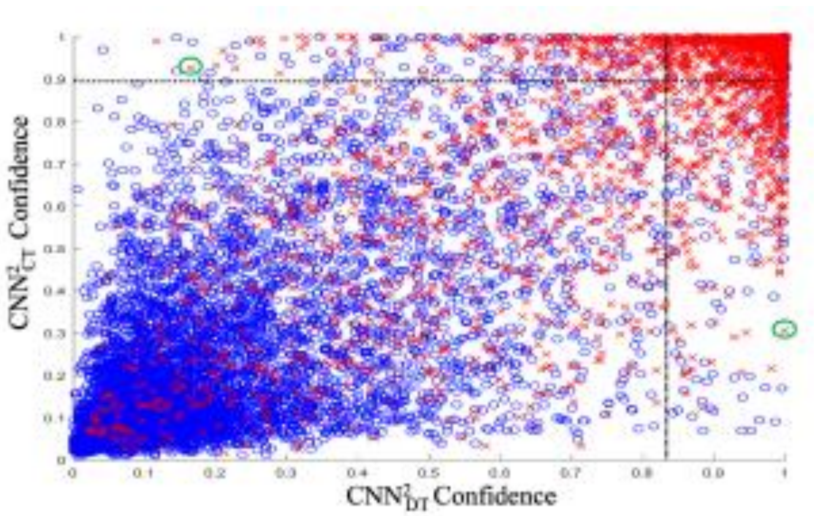

Fig. 6 Scatterplot of the confidence values assigned by the different networks

CONCLUSION

1. Our proposed BTD (buried threat detection) discrimination algorithms will use deep CNNs (convolutional neural networks) and RNNs used to assess two-dimensionalground penetrating radar scans in the cartesian x and y axis directions, as well as three-dimensional ground penetrating data radar volumes.
2. A chance to test new deep learning architects: For the classification issue, there are several structures or techniques available. We want to utilize MATLAB and Python because there is no foundation to start from in other languages. In the case of MATLAB and Python, we simply call the functions, adjust the input parameters, and run the tests.
3. Significantly decreased programming time: Integrated libraries and commands vastly reduce design and development time. We may build, create, and test various neural network designs using minimum mathematical models and deep learning approaches.

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