Engineering Journal issn: 0125-8281

Article

Deep Learning Based Thermal Image Processing Approach for Detection of Buried Objects and Mines

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Abstract. Thermal imaging based mine detection technique is widely adopted due it suitability of detecting buried metallic and also non-metallic land mines in battle fields. Accurate mine detection using thermal images depends on thermal contrast between the soil and mine and it is affected by various factors such as the depth of burial; soil properties and attributes, water content in the soil, mine properties; as well as the time of day of image acquisition. With temporal temperature variations of the soil, it is difficult to distinguish and discriminate between the buried object and the background in the thermal image using the conventionally followed binary thresholding approach in gray scale. This paper presents deep learning region convolution based neural network approach to identify the buried objects in thermal images. A region interest selection using a bound box is followed for identifying the buried object in the thermal image. From the experimental results, it is found that there is temperature variation in the thermal images of the buried objects due to the change in heat carrying capacity of the surround soil. Proposed neural network method showed 90% accuracy in predicting the target locations of buried objects in the thermal images and it can be extended for land mine detection using thermal image processing approach.

Keywords: Thermal imaging, deep learning convolution neural network, region of interest, mine detection.

ENGINEERING JOURNAL Volume 25 Issue 3
Received 15 May 2020
Accepted 30 January 2021
Published 31 March 2021
Online at https://engj.org/
DOI:10.4186/ej.2021.25.3.61

DOI:10.4186/ej.2021.25.3.61

1. Introduction

In recent years, thermal infrared imaging technique is widely adopted due its advantages of detecting shallowly buried metallic landmines and also non-metallic mines [1]. The presence of a buried land mine is identified based on the difference of thermal characteristics between buried objects and the surrounding soil as the buried mine affects the heat conduction inside the soil and it leads to temperature difference between the buried object and soil. [2]. This temperature contrast is measured using a thermographic camera, which detect radiation in the infrared range of the electromagnetic spectrum and displayed as a pseudo colour in thermal images [3]. However, the mine detection in thermal images is challenging due to the temporal behaviour of the soil temperature distribution during day time and night time along with the presence of other buried objects [4]. Considering the complexity in object detection in thermal images, there is a need for developing suitable image processing based decision making tools for accurate detection of land mines.

Various researchers have proposed different methods for improving detection of buried mines in thermal infrared images. Infra-red thermal images can work with passive (natural) or active (human made) heat sources. However, it is affected by weather conditions and humidity of the soil [5]. As the thermal differences between the bare soil and the soil surface above buried mines are quite small, a circularly symmetric spatial filter is applied to amplify these differences [6]. Visibility of buried targets using Infra-red and Charge coupled camera is found to be difficult during sun rise and sun set [7]. Ederra proposed mathematical morphology tools for denoising and segmentation of individual images [8]. As the raw sensor image from thermography can hardly give satisfactory information due to sun light radiation interference, soil conditions, humidity etc, elaborate processing steps of infra-red thermography, including data acquisition, data preprocessing, anomaly detection, and estimation of thermal and geometric properties of the detected anomalies are explained with relevant techniques [9]. Image processing techniques such as Karhunen-Loève Transformation (KLT), Kittler and Young Transformation were applied to reduce the size of the data and the computation time in thermal imaging based mine detections systems [10]. KLT and watershed segmentation were proposed by Ajlouni and Sheta for landmine detection applications [11]. A spectral differencing concept and a detection algorithm based on pattern recognition principles were developed by Sendurd and Baertlein [12]. Dynamic scene behavior due to time varying and cooling of solar illumination during land mine detections and its effect on images are analysed using image processing tools [13]. A finite-difference based 3-D thermal model was introduced and validated by Thành for detecting landmines in outdoor minefield data sets [11]. It is found that infra-red thermal images can show the presence of buried objects which can be detected and isolated by suitable image processing tools. However, target detection requires further processing and reasoning for the recognition of these objects as thermal image contained buried rocks, mane mage objects, metals along with the mine [14].

Classification algorithms such as Support Vector Machine (SVM), Mahalanobis Discriminant Analysis (MDA), and Quadratic Discriminant Analysis (QDA), K-nearest neighbour algorithm are applied on processed data for detecting and classifying the most of the buried objects [6]. In order to reduce the false alarm rates, sensor fusion techniques along with the advanced signal and image processing approaches have been developed by researchers for identifying land mines. A geometrical feature-based sensor fusion framework consisting of Infra-red and Ground Penetrating Radar was proposed for the improved detection of land mines [15]. Hyper spectral imaging techniques and image processing tools at different wavelengths of light spectrum are developed for mine detection applications [16]. A surface mine detection technique with an automatic target detection algorithm exploiting spectral and spatial signatures of the mines was developed using video based multi spectral imagery [17]. Autonomous aerial drone based explosive-landmine detection system was designed and developed using software defined Ground Penetrating Radar (GPR) for improving the detection rate of land mines and reduce the false alarm rate [18]. Application of Differential Evolution with SVM and Naïve Bayes machine learning Classifiers for feature selection in image data is presented. [19].

It is found that land mine detection is an active area of research. Various image processing tools are developed by researchers for improving the detection rates and reduce the false alarms of existing thermal imaging techniques as it is affected by the changing illumination of sun light, weather conditions and humidity of the soil during the mine detection. This paper presents deep learning based thermal imaging approach for the detection of buried objects and surface mines.

This paper is organized as follows: Section.2 presents the details on thermal image acquisition for land mine detection and proposed deep learning strategy using Region Convolution Neural Network (RCNN) for buried object detection. Section.3 describes the results and inferences of the proposed methodology. Major conclusions are presented in Section.4.

2. Thermal Imaging Approach for Buried Object and Lane Mine Detection

In this work, a novel thermal imaging approach is proposed for the improved detection of buried land mines in the battlefield using a mobile robotic system carrying a thermal camera. The conceptual model of a mobile robot carrying the thermal imaging camera, electronics on a rugged platform is shown in Fig. 1.

DOI:10.4186/ej.2021.25.3.61

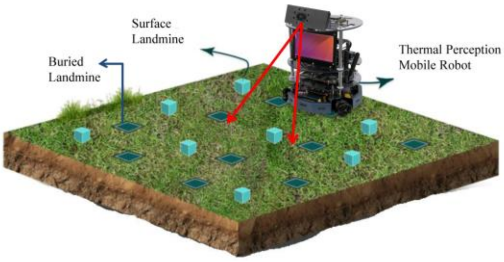

Fig. 1. A land mine detection mobile robot with a forward looking thermal imaging system.

In order to detect the buried object in the soil, temperature values of the specified region and position of the buried object is interpreted using the Histogram of the grey scale image and Co-ordinate position of bounding box (X, Y). In the present work, Region Convolution Neural Network (RCNN) based image processing approached is proposed for the detection of the buried objects, mines in the soil. The frame work for training, testing of RCNN and the steps are shown in Fig. 2.

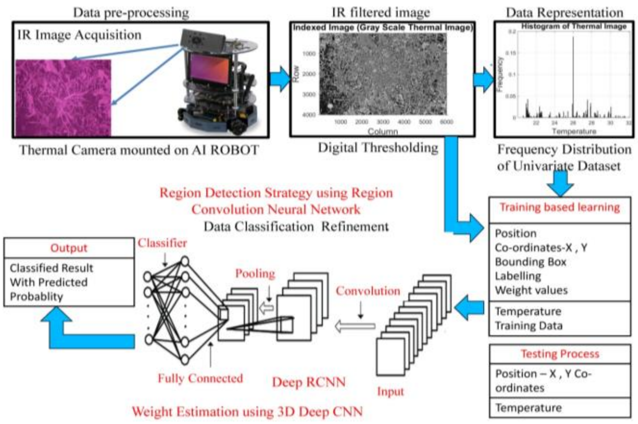

Fig. 2. Steps involved in the proposed approach.

Proposed technique requires training of neural network using an image data set of buried objects at known location. As a part of the proposed work, a test bed containing buried objects and dummy land mine is prepared as shown in Fig. 3. The steps involved in the training and testing of RCNN is given below:

Step 1: Thermal image acquisition and Augmentation of collected Images

Step 2: Gray-scale conversion of thermal image and Thresholding

Step 3: Selection of region of interest for detection of buried objects using Bounding box

Step 4: Development of RCNN using labelled data set images for region detection

Step 5: Training, Testing and validation of RCNN to predict the target location of buried object

The steps involved the proposed method is explained in the sub sequent sections.

2.1. Thermal Image Acquisition and Dataset

In the context of military applications for mine detection, there is no ground truth data available. In present work, a test bed is prepared with buried objects and dummy land mine as shown in Fig. 3(a).

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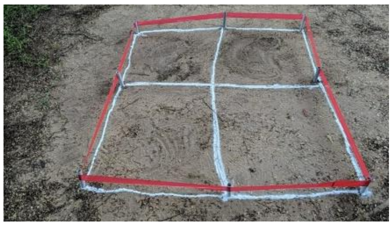
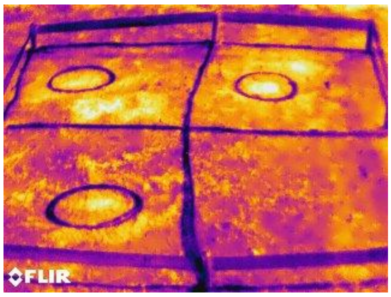


(a) Preparation of test bed

(b) Marking the location of buried object

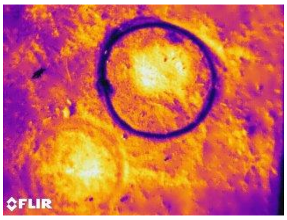


(c) Thermal image of the test bed

Fig. 3. Development of test bed for thermal image acquisition of buried objects.

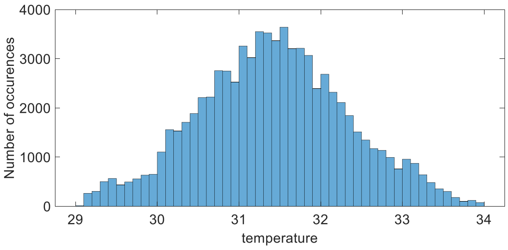
At a known location in the test bed, plastic and metal objects are buried at a shallow depth of 2 cm to simulate the surface land mines as shown in Fig. 3(b). A thermal camera (ThermaCAM-T420; FLIR, Wilsonville, OR, USA) is used for acquiring the images of the buried object. It has the spectral range of 7.5 µm to 13 µm in the long wavelength infra-red radiation and it can measure the temperature range of 20º C to 650º C with an accuracy of 2% with thermal sensitivity of 0.05 C. In the present work a large data set containing 1000 thermal images is built with the thermal images of buried object and without buried object. Fig. 3(c) shows the thermal image of the test bed, the color variations indicate the temperature variations of the soil. Here the marked regions show higher temperature in yellow color which is due to the heat carrying capacity of the buried object as compared to the surrounding soil.

DOI:10.4186/ej.2021.25.3.61

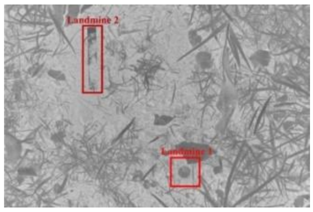


a) Cropped, marked thermal image with buried object

b) Gray scale thermal image



(c) Temperature Histogram



(d) Bounding box of buried object of different shapes

Fig. 4. Gray Scale Processing of Thermal Images for buried object detection.

2.2. Gray Scale Processing and Thresholding of Thermal Images for Buried Object Detection

For identifying the buried object from the background image, commonly followed gray scale processing based thresholding method is applied to thermal image of the buried object In the binary thresholding approach, threshold (T) is often identified based on the intensity variations in the gray scale image using the histogram. Using the temperature histogram as shown in Fig. 4(c), the maximum, minimum temperature of the region in the thermal image can be identified and the mean temperature value is fixed as the threshold. Based on the given threshold, the pixel values of the thermal image are categorized into two portions as background and foreground to distinguish the buried object.

2.3. Selection of Region of Interest Using Bounding Box for Detection of Buried Objects and Land Mines

Using the developed data set of thermal images containing the buried objects, region of interest is selected using a bounding box in the thresholded image. The target location of the buried object in the image is marked. Figure 3 (e) shows the bounding box for the buried object of different shapes as identified in the image. A labelled data set with buried objects is developed for training the neural work to identify the specified region of the thermal image.

2.4. Development and Training RCNN Using Labelled Data Set of Images

A pre-trained CNN with the standard architecture of Res Net-50 is selected to transform the selected region in the given images into the input dimensions required by the network which uses forward computation to output the features extracted from the proposed regions. The different shapes of buried objects are converted into different shapes of bounding box as required by Fully Connected (FC) layers. Based on the region of interest, pooling is carried out in the layers of the neural network. Further, this pooling is used by Region Proposal Network (RPN) for developing the feature map in single pass. Based on selective search for the given image which generates 'n' proposed regions, bounding box of regions of interests of different shapes are calculated for the CNN output. The weights are updated and stored during each epoch and updated in separate file. Further, the trained RCNN is used for predicting the regions of interest in the given image. Here the number of epochs and number of training data plays an important role in accurate detection and prediction.

3. Results and Discussion

In the present work, Python computation environment is used for developing Deep Faster Region Convolution Neural Network to search the region of interest in the given image for detecting the buried objects and landmines. The network is trained in Intel Core i5-8265U CPU @1.6GHz 1.8GHz, 8GB RAM, Windows 10 computing system using the labelled data sets of selected regions for several epochs and the pre-trained data set is used for testing, validation. In this section, the results of proposed RCNN are presented for the prediction of bounding box to detect the buried object, mines in the given thermal image.

3.1. Training, Testing and Validation of RCNN

Proposed neural network model is trained using the labelled data set of images with the region of interest bounding box. Here 70% of data set is used for training the neural network and 30 % of the data set is used for optimizing the hyper parameters of the network. The graph for loss function of the neural network for the given number of training data sets is given in Fig. 5. It can be seen that the magnitude of loss function reduces when the number of training samples increase.

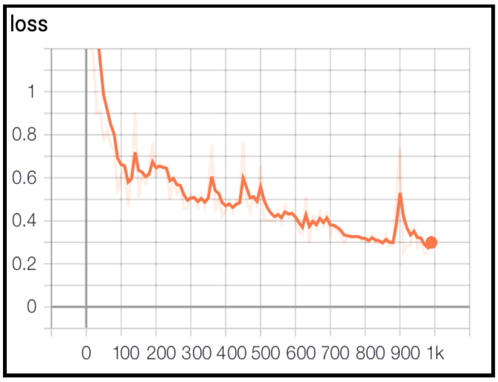
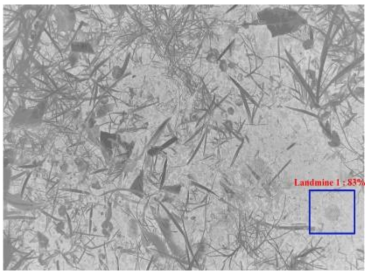
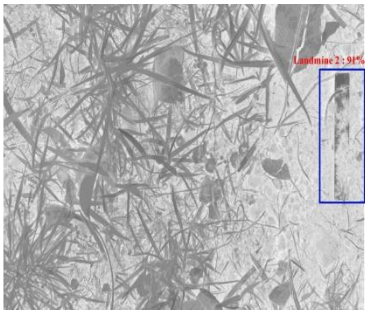


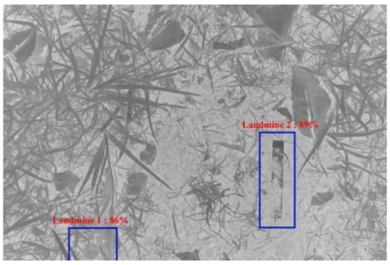
Fig. 5. Loss function.



(a) Buried object of square bounding box



(b) Buried object of rectangle bounding box



(c) Predicted bounding box for different shapes of the buried object

Fig. 6. Predicted bounding box for different shapes of the buried objects.

3.2. Prediction of Bounding Box for Buried Objects of Different Shapes in the Thermal Images

Using the trained RCNN, bounding box is predicted to detect the buried object in the given image and the results are given in Fig. 6.

As the proposed RCNN is trained for the buried objects of different shapes as shown in Fig. 4(d), it provides the bounding boxes of different shapes as identified for the given buried object as shown in Fig. 6. The accuracy of detection and classification of different buried objects are found to be 90%. During training of the neural network, the weights of the neurons are updated, by increasing the number of epochs the more accurate predictions can be made for the buried object detection in the thermal images. It is proved that RCNN is capable of distinguishing buried objects of different shapes and size in thermal images. Proposed approach can be suitably implemented for detection of surface land mines using thermal vision assisted mobile robot.

4. Conclusions

This paper presented thermal imaging based Region detection Strategy using Region Convolution Neural Network (RCNN) to identify the buried objects and landmines. A test bed containing different buried objects of different shapes is constructed to collect the thermal images at known locations. Acquired thermal image showed significant temperature variations due to the change in heat carrying capacity of the buried object and the surrounding soil. In order to distinguish the buried object in the thermal image, temperature histogram based thresholding approach is followed in the present work. A region of interest for detection of buried object in the thermal image is achieved using the bounding box. A labelled training data set of thermal images with bounding boxes of different shapes of buried object is developed and used for training the Region Convolution Neural Network (RCNN). From the training, testing and validation of RCNN, it is found that the RCNN is capable of distinguishing buried objects of different shapes in thermal images with an accuracy of 90%. Proposed thermal imaging approach can be adopted for detection of shallowly buried anti-tank mines in the soil.

Acknowledgments

Authors thank Science Engineering Research Board, New Delhi, India for funding the collaborative project under "Teaching Associateship for Research Excellence" (TAR/2018/001123) to develop the mine detection robot at Indian Institute of Information Technology Design and Manufacturing (IIITDM) Kancheepuram Chennai, Tamil Nadu, India and Vellore Institute of Technology, Vellore, Tamil Nadu, India.

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DOI:10.4186/ej.2021.25.3.61

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