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ConvNet Fine-Tuning Investigation for GPR Images Classification

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Abstract

Deep learning has been widely implemented as a new classification platform during the past few years. One of the main problems facing deep learning is the problem of data dependency as it requires a very large amount of data for training. Therefore, transfer learning (TL) has been introduced as a solution to this problem. This study focuses on the fine-tuning strategy of the transfer learning and how it can be implemented to classify the ground-penetrating radar (GPR) images. The GPR data has been collected and processed using the matched filter algorithm and further clutter reduction techniques. The resultant GPR images compromises of a limited number of samples, therefore, the deployed convolutional neural network (ConvNet) has been trained first using another larger dataset, then fine-tuned using the GPR dataset. The obtained results are promising and show a high degree of precision and accuracy compared to previously conducted researches.

1 Introduction

Transfer learning can be used with the problems which suffer from insufficient data [1]. It relaxes the hypotheses that the training data must be independent and identically distributed with the test data. While traditional learning is isolated and based on specific tasks and datasets, the knowledge in TL can be leveraged from previously trained models to newer ones without being affected by the data in the new models [1]. Due to the proper solutions offered by the TL, this research investigates the GPR images classification using this concept. The GPR is being widely used in a wide range of applications including archaeology [2] and geophysics [3]. It also provides an efficient and safe tool for the explosive mines detection operations [4]. The GPR mainly depends on sending microwave signals toward the area of interest and based on the reflected scattered energy, it can detect the presence of the buried objects within this area due to the change of the material properties between the objects and the surroundings. One of the main interests regarding the GPR processing is the ability to classify the processed images, therefore, a ConvNet is developed in this research for this purpose. The ConvNets are simply data analysis methods and algorithms, indirectly based on the nervous systems of humans and animals [5]. This technology is the most effective artificial intelligence technology for pattern recognition and many other areas of computer vision [5][6]. Different researches have been conducted to provide accurate solutions for GPR images classification [7][8]. In this paper, the authors introduce a ConvNet to facilitate classifying the GPR images with a high degree of accuracy. To achieve this purpose, the ConvNet has been first trained using a larger dataset which is the Fashion-MNIST dataset [9]. The authors have selected this dataset as it contains a very large number of grey-scale samples which represent various types of fashion products. The ConvNet parameters have been optimized using this benchmark dataset and then the learned features have been transferred to the limited GPR dataset by different TL strategies. These strategies include implementing the ConvNet as a feature extractor or by fine-tuning the ConvNet parameters [1]. Both methods have been implemented and the results have been monitored to emphasize the better solution for our classification problem. The paper is organised as follows. An introduction to the TL techniques is explained in section 2, while the GPR data collection is presented in section 3. The ConvNet architecture and the classification results are illustrated in section 4 and finally, a conclusion is given in section 5.

2 Transfer Learning Techniques

Transfer learning focuses on leveraging gained knowledge from a dataset and apply this knowledge to different data samples [10]. While traditional learning is isolated and occurs purely based on specific datasets, TL provides suitable solutions for different applications which don't have sufficient samples. The implementation of TL can be accomplished by two main techniques. The first technique is to use the pre-trained ConvNet as a feature extractor. In this method, the final connected layers of the pre-trained ConvNet are replaced with a new classifier and utilize the knowledge gained from the source dataset to extract features from a new domain task [1]. The other technique focuses on fine-tuning the pre-trained ConvNet. This technique is more involved where the final layers are not just replaced, but also some previous layers are selectively retrained using a very small learning rate. This is motivated by the observation that the earlier features of a ConvNet contain more generic features that should be useful to many tasks, but later layers of the ConvNet become progressively

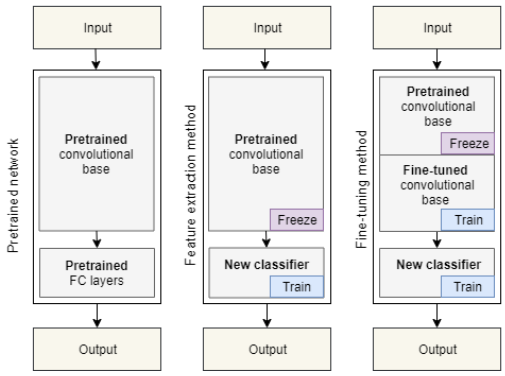

Figure 1. Feature extraction vs fine-tuning

more specific to the details of the classes contained in the original dataset [10]. For more detailed realization, both techniques are presented in Fig. 1. This study is mainly interested in the latter technique as it offers more possibility to adjust the network parameters and achieve even higher results in many problems and applications, including the GPR images classification problem. However, both techniques have been implemented to compare the obtained results.

3 GPR Images Formation

The GPR measurements have been carried out on a sandbox scenario. The utilized sandbox measures a total size of 2.5x1.2x1.2m^3 and it is filled with dry sand providing a permittivity of approximately 2. Furthermore, the test stand provides a precise linear positioning system, which carries a dual-polarized, ultra-wideband Vivaldi antenna. This antenna covers the requested frequency range and the main design parameters for the GPR antenna such as polarimetric setup for recording trans-polarizing effects, low antenna ringing to distinguish between multiple antenna reflections and low reflective targets in close antenna proximity, sidelobe suppression for avoiding cross-talk in multistatic radar setups and reasonable gain for increasing the signal-to-noise ratio. More details about the used antenna can be found in [11]. The free space distance between antenna and soil was approximately 20 cm and the test measurements setup is shown in Fig. 2. The measurements were performed with a calibrated Rohde & Schwarz ZNB 8 VNA within a frequency range of 0.8-5GHz. The GPR data has been gathered for multiple targets placed at different positions and depths in a total area of $1m^2$ and the collected scattered data has been stored for further processing. Afterwards, the stored data has been processed by the matched filter algorithm [12]. Moreover, further processing to reduce the clutter level has been accomplished by implementing the moving average background subtraction (MA-BS) method[13]. An example of the image formation process output is shown in Fig. 3. This result indicates precisely the position of three buried objects. These objects include two stones with different shape and simple construction of triggered improvised explosive device (IED). Different measurements have been carried out and the resultant images have then been divided into sections, each of size 28×28 pixels. These sections include the resultant targets responses and unwanted clutter reflections. These sections formulate a total number of 1384 labelled samples divided into 1000 samples for training and the remaining have been assigned for validation.

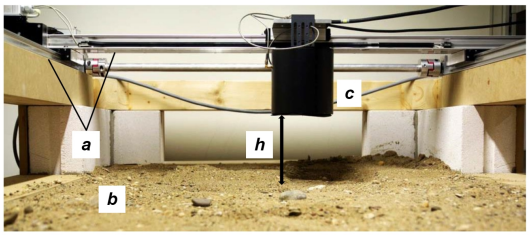

Figure 2. Photograph of the measurement setup showing: a) X-Y positioning system, b) sandbox, c) ultra-wideband antenna

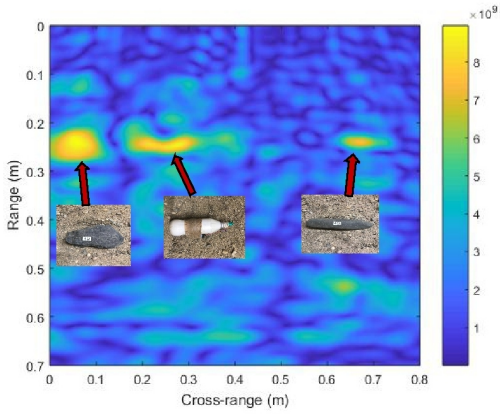

Figure 3. GPR image formation result

4 The ConvNet Architecture and Classification Results

In this section, the structure of the implemented ConvNet and the classification results are presented. The network is composed of 2 major convolutional layers. The convolutional layer is considered as the most important layers of ConvNet. It performs convolution which is a linear operation that involves the multiplication between the input and a set of weights, called a filter. This filter is used to scan the whole image matrix and the multiplication process results in a 2D matrix called the activation map [6]. The activation maps are then passed to a leaky-ReLU layer, which is responsible for adding non-linearity to the activation maps [14]. The resultant activation maps are then passed to a max-pooling layer to produce a lower version of the feature map [15]. The fully connected layers (FLC) consists of a flatten layer followed by 2 dense layers separated by a leaky-ReLU layer. The main purpose of the flatten layer is to convert the data into a 1-dimensional array

Table 1. The ConvNet architecture

Layer Type	Output shape	Parameters
Convolutional1	(None, 28, 28, 32)	320
ReLU	(None, 28, 28, 32)	0
Pooling1	(None, 14, 14, 32)	0
Dropout1	(None, 14, 14, 32)	0
Convolutional2	(None, 14, 14, 64)	18496
ReLU2	(None, 14, 14, 64)	0
Pooling2	(None, 7, 7, 64)	0
Dropout2	(None, 7, 7, 64)	0
Flatten1	(None, 3136)	0
Dense1	(None, 64)	200768
LeakyReLU3	(None, 64)	0
Dropout3	(None, 64)	0
Dense2	(None, 10)	650

for inputting it to the next layer, while the dense is a normal layer used to change the dimensions of the vector till we obtain the final output. To prevent over-fitting, dropout layers have been included in the ConvNet design to randomly ignore some selected neurons during each iteration of the training process. This operation has been performed with a dropout rate of 0.3. The structure and the number of training parameters of the network are shown in table 1. Due to the limited available GPR images, the ConvNet parameters have been optimized by using the Fashion-MNIST dataset [9]. This dataset has been selected as it compromises of 28×28 grayscale images of 70000 fashion products. These images are divided into 10 categories, each of 7000 images. The training set contains 60000 images and the remaining have been assigned to the test set. After finishing the training, the learned features have then transferred to the GPR dataset by applying the feature extraction and fine-tuning methods. Recalling the ConvNet architecture mentioned in table 1, the feature extraction has been accomplished by replacing the fully connected layer with a new classifier. The new added layers include 2 dense layers and a dropout layer with a dropout rate of 0.3 after the first dense layer. The trained parameters of the first 8 layers have been preserved and the new classifier parameters have been optimized for the GPR dataset by using Adam optimizer with default parameters [16]. This implementation has led to a very high accuracy in classifying the GPR results as shown in Fig. 4. According to the obtained results, the ConvNet has achieved a promising validation accuracy of 93.5% in GPR images classification, however, these results have been acquired after using the ConvNet only as a feature extractor. For emphasizing the performance improvement of the feature extraction method, the ConvNet has been trained directly using the GPR dataset without any TL methodology. The ConvNet validation performance has been monitored and as shown in Fig. 5, the ConvNet has achieved an accuracy of 91.5%, which is lower than the feature extraction result.

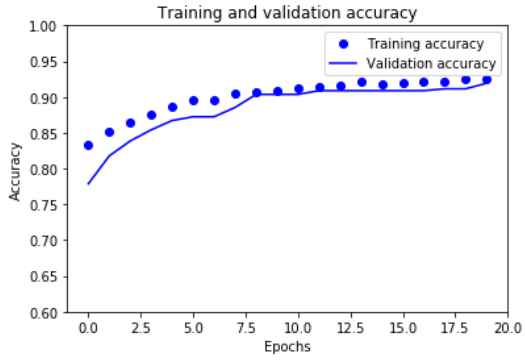

Figure 4. Training and validation accuracy after feature extraction

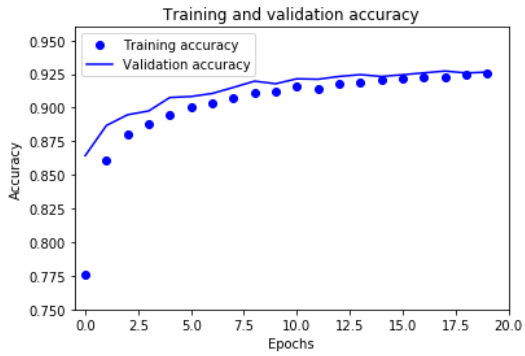

Figure 5. Training and validation accuracy without TL

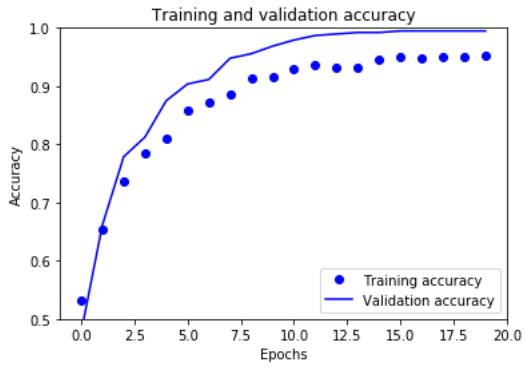

Figure 6. Training and validation accuracy after fine-tuning

Further processing has been accomplished by applying the second TL technique and notice any possible improvement compared to the feature extraction results. The second technique involves fine-tuning the final layers of the network starting from the second convolutional layer to the last layer, using a low learning rate of η = 1e-4. According to the results given in Fig. 6, the ConvNet has achieved a higher performance with a validation accuracy of 98.5% which indicates a significant improvement compared to the previous results. According to the obtained performance, it can be concluded that the implementation of the proposed ConvNet with the fine-tuning strategy has proven to be a better choice regarding classifying the GPR responses.

5 Conclusion

This research is focused on investigating the fine-tuning TL and its impact on GPR images classification. The authors have presented a ConvNet for this purpose to overcome the data dependency problem. The ConvNet has been trained at the beginning using the benchmark Fashion-MNIST dataset. This large grayscale dataset has been used for optimizing the network parameters. Afterwards, the trained ConvNet has been fine-tuned to classify the GPR images. The fine-tuning process compromises of 2 steps. The first includes implementing the ConvNet as a feature extractor by replacing the final layers with a new classifier. The second step tends to apply fine-tuning to some of the previous layers and the newly added layers with a very low learning rate. The results obtained has reached a high degree of accuracy in classifying the GPR images with the lowest possible error.

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