CLASSIFICATION OF GPR SIGNALS VIA COVARIANCE POOLING ON CNN FEATURES WITHIN A RIEMANNIAN FRAMEWORK

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ABSTRACT

We consider the problem of classifying Ground Penetrating Radar (GPR) signals by using covariance matrices descriptors computed on convolutional features obtained from MobileNetV2 Convolutional Neural Network (CNN) first layers. This approach allows to leverage the rich data representation obtained from CNNs and the low-dimensionality of second-order statistics. Then the Riemannian geometry of covariance matrices is leveraged to improve classification rate. The proposed approach allows then to perform automatic classification of buried objects with few labeled data available. We also consider the scenario of an airbone radar and provide results at different elevations.

***Index Terms*—** GPR, classification, Convolutional Neural Networks, Covariance matrix

1. INTRODUCTION

Ground Penetrating Radars (GPR) are imaging systems allowing to view the underground of a field in order to study the layer composition of the soil or the presence of buried objects. Such images are usually characterized by a very low Signal to Noise Ratio (SNR) due to the electromagnetic properties of the ground. Moreover, by design, buried objects are observed as hyperbolas for which the shape may be linked to the object type (cavity or pipe for example). In this context, classification of buried objects is of importance in civil applications such as recovering the position of buried gas pipes [1] or military applications such as land mine detection [2]. To perform this recognition, some works have considered the improvement of SNR by using signal inversion techniques [3] for manual interpretation by geophysicists. When confronted with many images to handle, this solution can be impractical since it requires dedicated human resources. Thus automatic recognition methodologies have become needed and are considered by the community.

Automatic classification of GPR signals are performed in two steps. Firstly, Regions Of Interest (ROI) corresponding to isolated hyperbolas are obtained. This can be done thanks to inversion approaches [3]. Then the image of a single hyperbola is assigned to a class thanks to a learning algorithm. We consider presently the second step of classification. This task has been investigated in previous works where it is performed by using Support Vector Machine (SVM) algorithm in [4, 5], dictionary learning techniques in [2] and convolutional neural networks (CNN) in [6]. The SVM based approaches rely on either the use of the polarimetry information or Fourier coefficients estimation as features for the classification. On one hand, polarimetry is not always available since it requires specific GPR systems which makes this approach impractical. On the other hand, spectral information can provide less rich information than convolutional filters of CNN which have been the norm in computer vision for a decade. Dictionary learning is an interesting approach but suffers from a heavy computational cost and requires extensive dataset since it has to learn all dictionary elements with regards to very different objects. Finally neural networks have been increasingly attractive to profit from the rich representation of convolutional features and provide a computationally lightweight (once the network is trained) methodology. In that regard, the use of deep learning in GPR data is still a very emergent issue with very few works due to the lack of large datasets for training which are needed to obtain good performances.

In order to handle the lack of labeled data while still benefiting from convolutional filters features representation we propose in this work to consider the approach of covariance pooling of CNN features which has been shown to be very effective in this situation for computer vision [7] and earth observations classification tasks [8]. After estimating the second order statistics we propose then to consider a Riemannian framework to handle the classification task on those features in order to take into account the natural geometry of covariance matrices. This approach has been shown to provide improvement in accuracy in applications where covariance matrices are used [9]. The combination of both aspects is expected to provide a lightweight approach that can provide good accuracy of classification with few labeled samples. Moreover, we propose to use pre-trained convolutional

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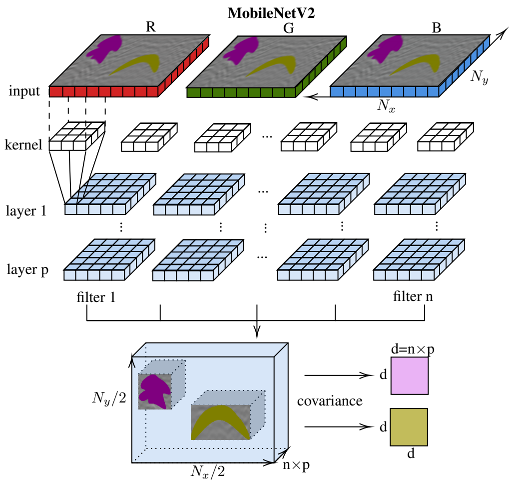

Fig. 1. Diagram of the proposed approach. p is the number of convolutional layers, n is the number of filters per layer.

layers which allows to reduce the number of parameters to be learned. We test this approach on a labeled dataset obtained from experimental measurement campaign done by Geolithe. The dataset provided has been obtained with different elevations of the GPR sensor from the ground that we take into account in the experiments.

2. COVARIANCE FEATURES EXTRACTION

The process of obtaining the covariance matrices is schematized in Figure 1.

Convolutional filters: From images of dimension $N_x \times N_y$ we extract new features thanks to a trained CNN with ImageNet learning weights. This solution allows to have a large variety of filters adapted to the classification of images, thanks to a training on a large database, which are richer than a simple extraction by spectral content.

In the present work, we selected the MobileNetV2 network which had the advantage of keeping the same filter size on its first 9 layers. We first adapt the input size and the number of channels of the CNN to match our GPR data as shown in the input layer on Figure 1. Once this input adaptation is done, we select the outputs of the first 9 layers as shown in blue in Figure 1. All these filters are stacked to form a single tensor of size $(N_x/2 \times N_y/2 \times d)$ with $d = n \times p = 320$. Then ROI is performed thanks to the labeled data in order to obtain a single tensor for each hyperbola. Finally the covariance matrix is calculated along the convolutional features dimension d.

Second order statistics: In order to obtain a low-dimensional feature to classify we perform the so-called covariance pooling. Covariance matrices are low dimensional features which capture the correlation between all the CNN features. As demonstrated in [7], this approach is effective for visual recognition tasks. To obtain the covariance matrices of the convolutional features, a simple approach is to use the Sample Covariance Matrix (SCM) given by $\mathbf{\Sigma} = N^{-1}\sum_{k=1}^{N}(\mathbf{x}_k - \overline{\mathbf{x}})(\mathbf{x}_k - \overline{\mathbf{x}})^T$, where $\mathbf{x}_k \in \mathbb{R}^d$ are the pixels data of single hyperbola after ROI estimation, N is the number of pixels in the region and $\overline{\mathbf{x}}$ is the mean of the pixels on the region. This gives us a matrix of dimension $d \times d$. In our case, we prefer to use a Ledoit-Wolf shrinkage covariance estimator [10] which has the advantage of outputting full-rank matrices. We indeed observed that CNN features tend to be linearly dependent, i.e the yielded covariance can be low-rank which is impractical from a numerical stability standpoint. At this point, we have a single covariance matrix for each hyperbola to be used in classification.

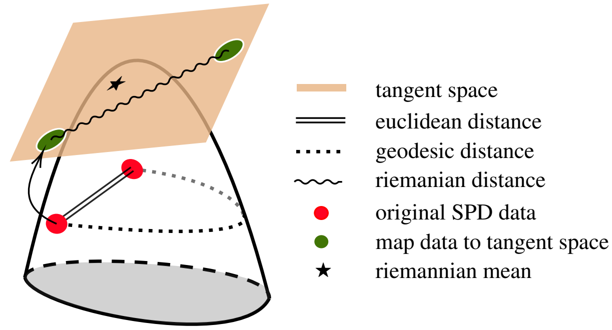

Fig. 2. Illustration of the three approaches

3. RIEMANNIAN CLASSIFICATION FRAMEWORK

As explained earlier, covariance matrices are interesting features as they allow to retain precious information of the convolutional layers while being low-dimensional. In order to fully exploit these features, it has been shown that it is of importance to consider the fact that those matrices belong not to a euclidean feature space but a curved Riemannian manifold: the manifold of Symmetric Positive Definite Matrices (SPD) [8, 9]. Indeed, introducing Riemannian geometry in problems dealing with classification of second-order statistics has brought improvement in terms of accuracy especially in applications where the number of labeled samples is low.

The main idea behind classification on Riemannian manifolds is to consider distances which are able to take into account the curvature of the feature space. Once a distance is obtained, Euclidean based classification algorithms can be adapted to depend on this distance. To handle classification of covariance matrices, three approaches illustrated in Figure 2, can be leveraged:

- Vectorize the matrices and consider solely a Euclidean framework. In this case, the distances do not respect the properties of the feature space.
- Map the matrices to the tangent space located at the mean value of data in order to approximate the dis-

tances between data points to a Euclidean space where a Euclidean distance used. This approach has the merit of allowing a variety of algorithms to be adapted into a Riemannian framework.

- Consider a geodesic distance which follows the curvature of the SPD feature space. While being the optimal one in terms of keeping the natural distances between data points, it has a higher computational cost and not all classification algorithms can be adapted to handle it.

In the present work, we consider the use of three algorithms to showcase the usefulness of the Riemannian framework: the SVM classifier used in previous works related to GPR classification, the Minimum Distance to Mean (MDM) classification which is often used associated with a Riemannian distance [9] and a Multilayer Perceptron (MLP) which is usually used as a classifier in the last layers of a deep learning approach. For both SVM and MLP, the adaptation to Riemannian framework is obtained from mapping data to tangent space while MDM which relies solely on distances can be used associated with a Riemannian distance.

4. RESULTS

category	object, lattice, discontinuity, empty
soil	sand, wet sand, gravel, dry gravel
frequency	250MHz, 300MHz
elevation	0cm, 25cm, 50cm, 75cm, 100cm, 150cm

Table 1. Characteristics of the dataset

Dataset description: The full dataset provided is composed of 1000 radargrams of a medium size of $(N_x, N_y) = (4000, 800)$ pixels associated with a mask labels for labels. An example is given in Figure 3. Each of these radargrams are obtained thanks to a GSSI GPR, used on a test area of about 46 m long and 7 m deep. For each radargram, between 3 and 7 targets of interest on average are labelled. Many other characteristics are given for each image as shown in Table 1. We first adapt the input of the CNN network for each individuals radargrams and extract the first 9 layers. So by concatenating all these outputs we get $d = 320$ filters. Then we extract windows centered on the mask of each labelled hyperbola by using DBSCAN (Density-Based Spatial Clustering of Applications with Noise) algorithm for clustering and erosion technique to separate overlapping masks. The windows have variable size to cover the area detected by erosion. Once these thumbnails extracted we gathered the 3 categories object, lattice, discontinuity into one: hyperbola. We added an empty class by selecting randomly areas of the average size of the hyperbola windows in order to realize a binary classification. We have thus created 3 sets of data: one with with the antenna on the ground (elevation = 0 cm) and the two others with an elevation of 100 cm and 150 cm respectively. All the other parameters given by table Tab.1

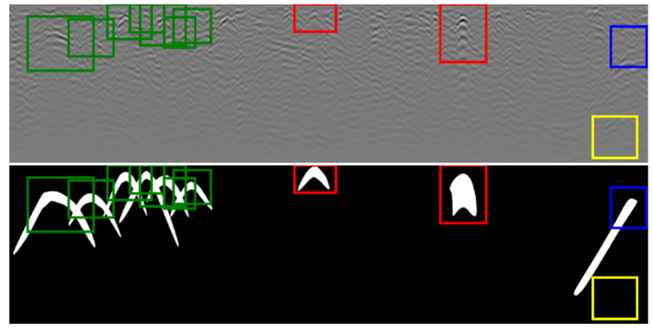

Fig. 3. Extract of a full radargram and its mask. The bounding boxes represent the ROI used.

are selected and the final numbers of covariances matrix of dimension $d \times d$ for the datasets are precised in Table 2.

elevation	empty	hyperbola
0cm	550	555
75cm	330	335
150cm	250	250

Table 2. Number of images per class for the 3 sub-datasets

Experiment setup: The development was done under Python 3.6.13 with the package pyRiemann[1] to handle tangent space mappings and Riemannian distance computation. In order to select the best performances for each classifier, we first performed a search for the optimal parameters on a training set by K-folds cross-validation with $K = 4$. Then evaluation is performed on a separate set using those optimal parameters and with a 4-Fold cross validation.

Results obtained: The results are presented in Figures 4 and 5 as a box-plot with the four values of the K-fold validation. In the framework of the MDM we have displayed only the results obtained with the rieammnian metric because they were strictly equivalent to those obtained on the tangent plane.

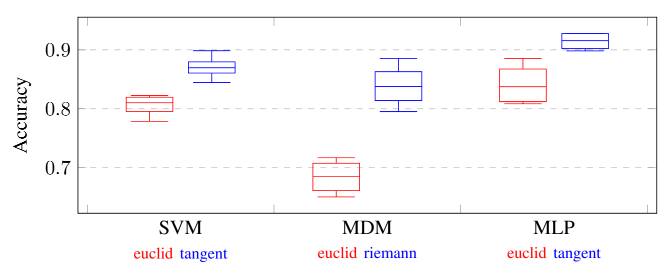

Fig. 4. Classication results at elevation 0 cm

Use of Riemannian geometry : In Figure 4 we reported the results of the 3 algorithms at elevation 0 cm. This first showcases the usefulness of the Riemannian framework for classification. Indeed in all the reported results a gain, of average 6%, is observed compared to the Euclidean approach.

[1]https://github.com/pyRiemann/pyRiemann

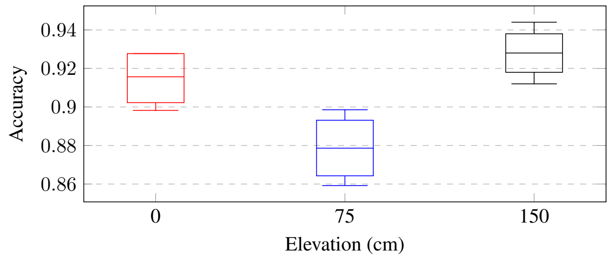

Fig. 5. Classification results for MLP classifier in tangent space at different elevations

Elevation effect : In Figure 5, we have reported the results of classification for the MLP algorithm in tangent space, which has the overall best performance, for different elevations of the radar. We notice that naturally the performance drops when the elevation increases, which can be understood by the increase of the signal attenuation. However the clear improvement of the performances observed when the elevation is of 150 cm, is to be relativized. Indeed the number of images is divided by 2 compared to the 0 cm dataset. Moreover one can imagine that the labeling is made only on objects which have a significant radar response, which comes out better on this very strongly attenuated radargram than on a radargram with the antenna clamped where the attenuation gives way to more noise. Thus we cannot conclude about the effects of elevation in this experiment.

5. CONCLUSIONS

In this paper we showed that CNN feature pooling and Riemannian geometry can be leveraged to classify GPR data when few samples are available. The proposed solution is lightweight since very few parameters are to be learned compared to CNN architectures. The reported results have shown that the Riemannian framework is more suitable than the Euclidean one when classifying covariance matrices in this GPR data context as expected from previous results in other applications. This study will be extended in future studies to other convolutional layers than MobileNetV2. Comparison to other neural networks approaches will also be done.

6. REFERENCES

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