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

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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. Classification of buried objects is of importance in civil applications such as recovering the position of buried gas pipes [3] or military applications such as land mine detection [2].
Automatic recognition methodologies have become needed and are considered by the community to handle the large amount of images.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. 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 [5] and earth observations classification tasks [1]. After estimating the second order statistics we propose then to consider a Riemannian framework 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 [6]. We propose to use pre-trained convolutional layers to extract features and test this approach on a labeled dataset obtained from experimental measurement campaign done by Geolithe.

2. COVARIANCE FEATURES EXTRACTION

The obtaining of the covariances is shown 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. 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. All

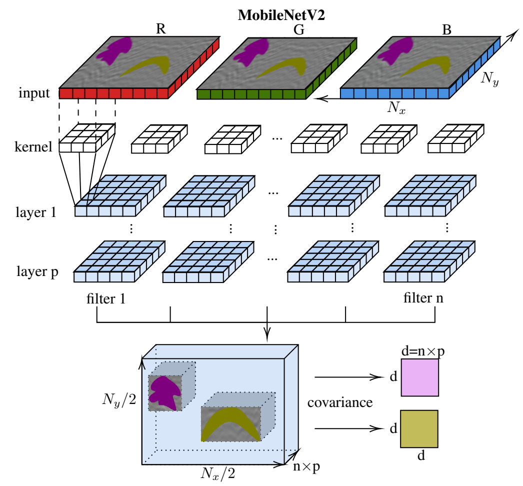

Fig. 1. Diagram of the proposed approach. p is the number of convolutional layers, n is the number of filters per layer.

the outputs of the first 9 layers are stacked to form a single tensor (as shown in Figure 1). Then ROI is performed thanks to the labeled data and by using DBSCAN[1], 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 [5], 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 the tensor after ROI selection, N is the number of pixels in the region and $\overline{\mathbf{x}}$ the mean of the pixels. This gives us a matrix of dimension $d \times d$. We observed that the resulting covariance can be low-rank which is impractical from a numerical stability standpoint. For this reason, we prefer to use a Ledoit-Wolf shrinkage covariance estimator [4].

3. RIEMANNIAN CLASSIFICATION FRAMEWORK

It has been shown that to fully exploit covariance matrices and improve accuracy, we must take into account the fact that

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[1] Density-Based Spatial Clustering of Applications with Noise

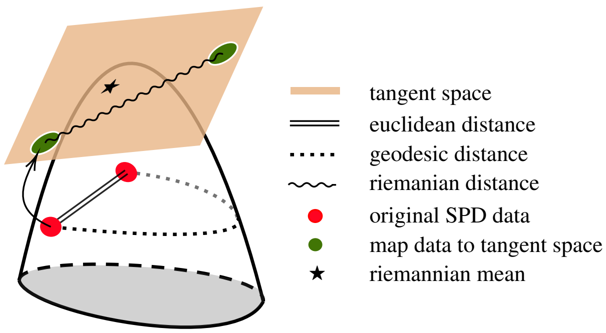

Fig. 2. Illustration of the three approaches

they belong not to a euclidean feature space but a Riemannian manifold of Symmetric Positive Definite Matrices (SPD) [1, 6]. The classification on Riemannian manifolds consider distances which are able to take into account the curvature of the feature space, and three approaches illustrated in Figure 2, can be leveraged:

– Vectorize the matrices and consider a Euclidean framework, but it does not respect the properties of the manifold.

– Map the matrices to the tangent space located at the mean value of data where a Euclidean distance can be used. It 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.

We consider the use of the three following algorithms to show the usefulness of the Riemannian framework: the linear SVM and Multilayer Perceptron (MLP), where the adaptation to Riemannian framework is obtained from mapping data to tangent space and Minimum Distance to Mean (MDM) which relies on geodesic distances [6].

4. RESULTS

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 into two classes: *empty* and *hyperbola*. We have calculated the covariance using the first 9 layers of MobileNetV2. Finaly the number of covariances matrix of dimension $d = 320$ are 550 and 555, respectively for the category *empty* and *hyperbola*.

Results obtained: The results are presented in Figures 4 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.

In Figure 4 we reported the results of the three algorithms, and this showcases the usefulness of the Riemannian framework

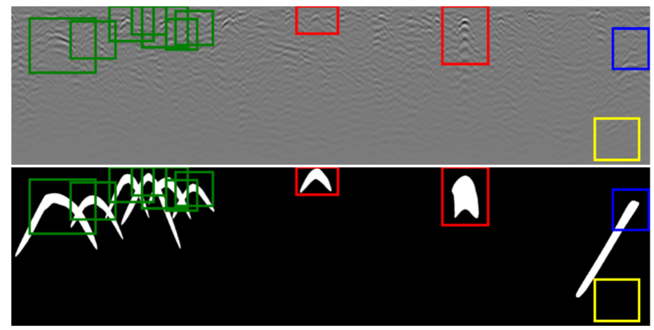

Fig. 3. Radargram and its mask, the empty classes in yellow box and the rest of the boxes for the hyperbola classes

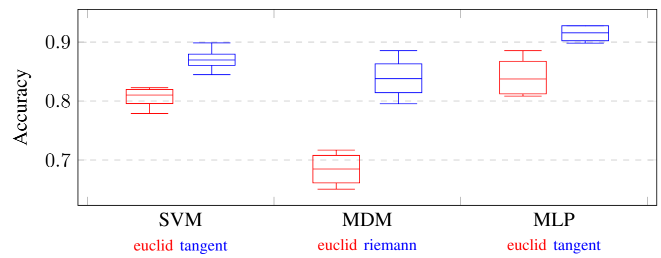

Fig. 4. Classification results

for classification. Indeed in all the reported results a gain, of average 6%, is observed compared to the Euclidean approach.

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 lighter than a end to end CNN solution and have few hyperparameters. Finally, the results show that the Riemannian framework is more suitable than the Euclidean one when classifying covariance matrices in this GPR data context.

6. REFERENCES

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