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

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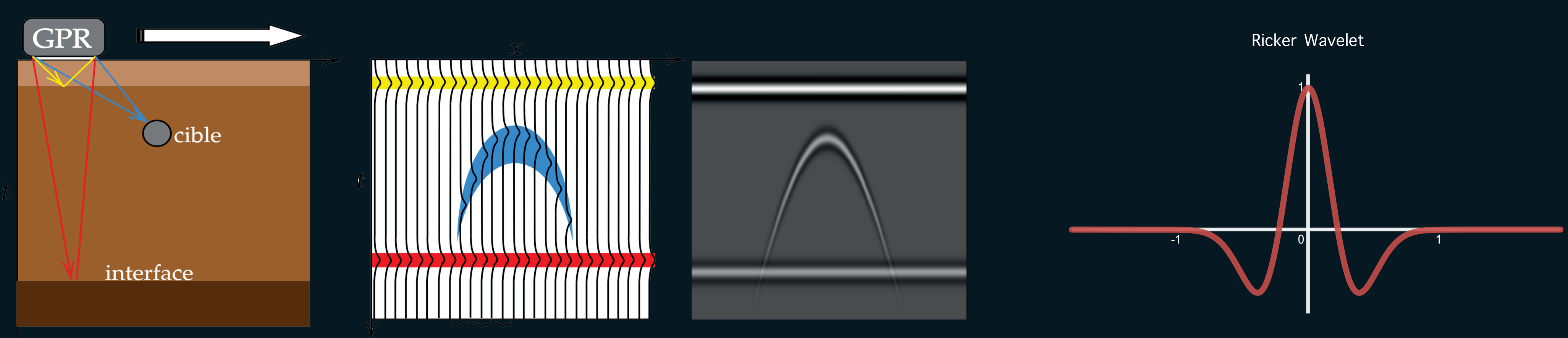
Abstract

We consider the problem of classifying Ground Penetrating Radar (GPR) signals by using covariance matrices descriptors computed on convolutional features obtained from MobileNeMtV2 Convolutional Neural Network (CNN) first layers. This apMproach allows to leverage the rich data representation obtained from CNNs and the low-dimensionality of second-order statisMtics. Then the Riemannian geometry of covariance matrices is leveraged to improve classification rate. The proposed apMproach 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

The GPR classification problem



Aim:

From the shape of hyperbola, recognise the object.

We suppose, we have ROI already in this work

State of the art:

Spectral features based classification: [Xiaang et al]

Neural Networks based approaches: [Xisto et al]

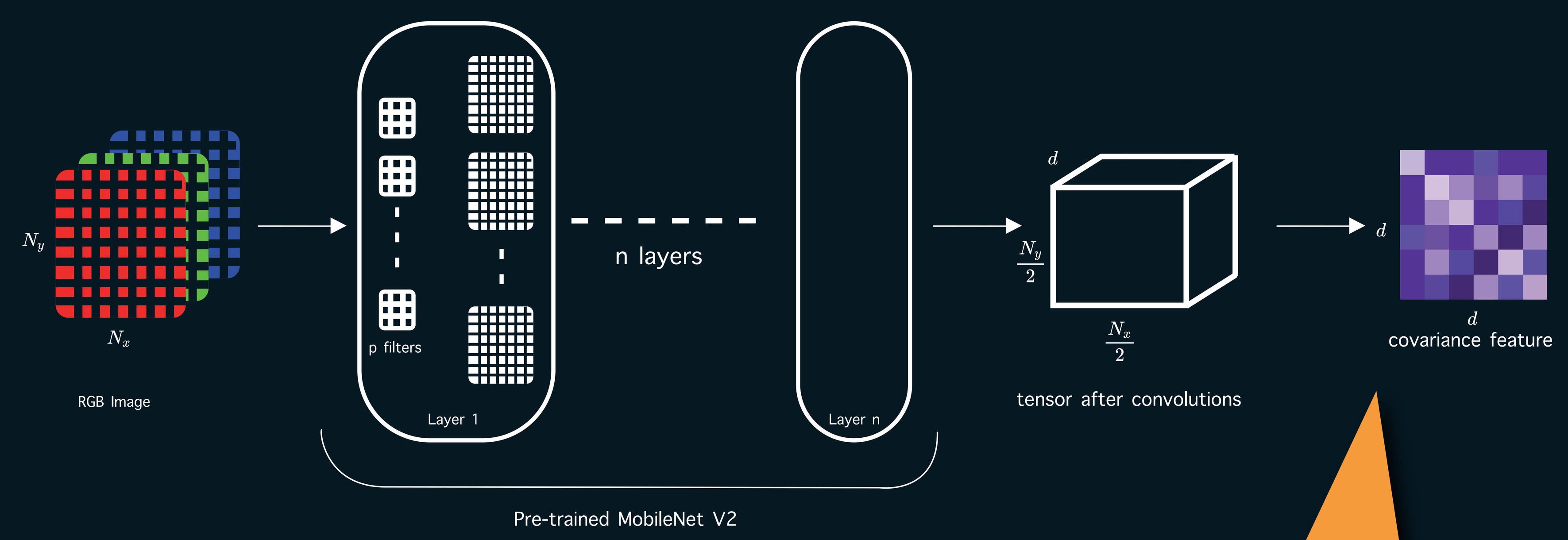
Present work's objectives:

Works with few labelled samples

Economic on number of parameters

Covariance pooling is useful in visual recognition tasks [Li et al]

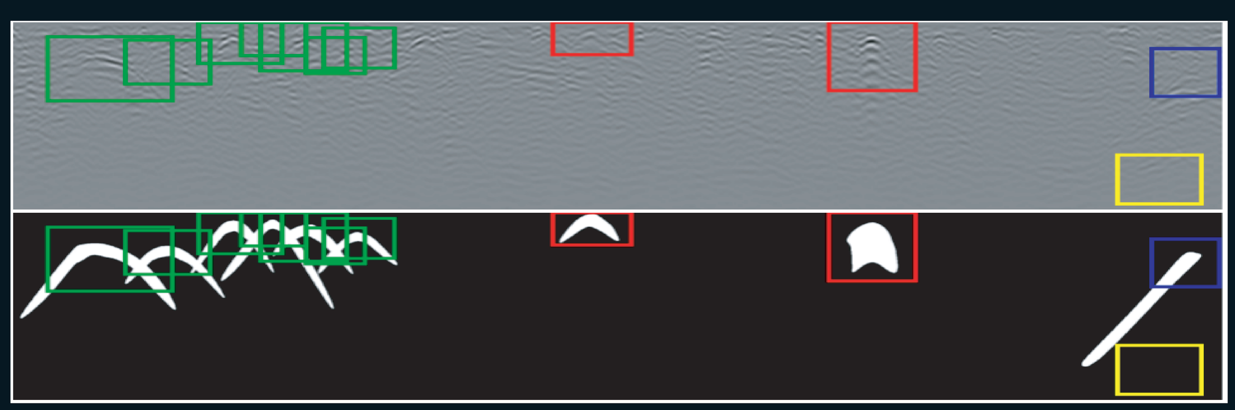
Covariance feature extraction



Feature belongs in a non-euclidean space

$\Sigma \in \mathcal{H}_d^{++} = \{\mathbf{M} \in \mathbb{R}^{d\times d}: \mathbf{M}^\dagger = \mathbf{M}, \det(\mathbf{M}) > 0\}$

Simulations setup



Dataset

- Provided by Geolithe
- 1000 radargrams of size (4000, 800) pixels
- Between 3 to 7 targets per radargram
- ROI using ground truth

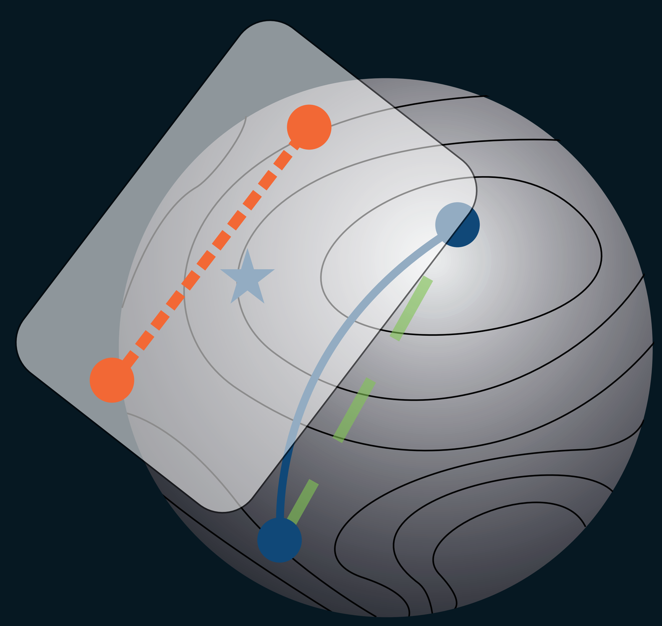
Classification

- 2 classes setup: (empty or something)
- K-fold with K=4
- d = 320
- Covariance estimation using [Ledoit et al]

Category	object, lattice, discontinuity, empty
Soil	sand, wet sand, gravel, dry gravel
Frequency	250 MHz, 300 MHz
Elevation	0 cm, 25cm, 50cm, 75cm, 100cm, 150cm

Table : Dataset physical parameters

Riemannian vs Euclidean

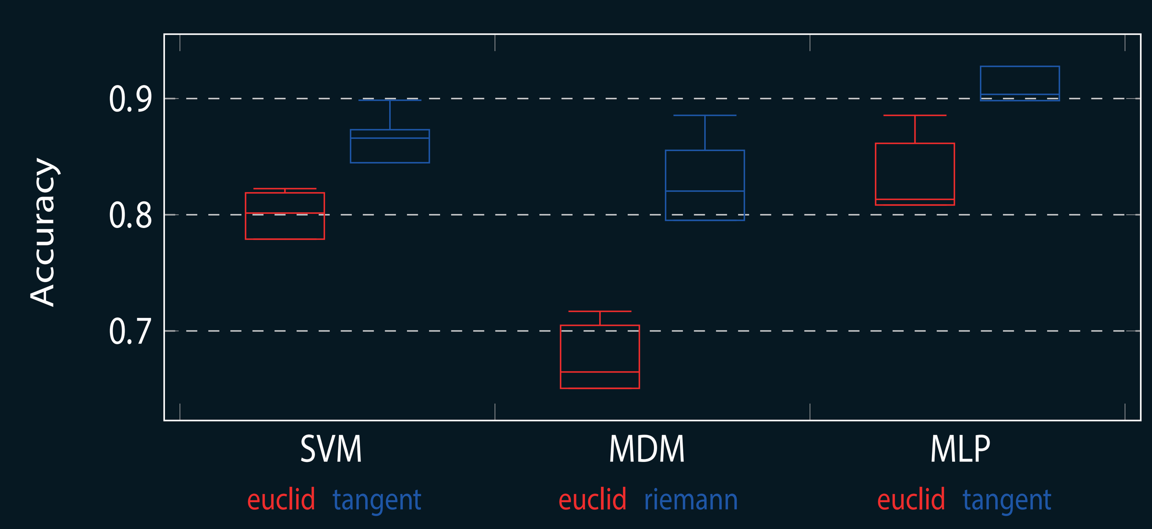


Three approaches to compute distances:

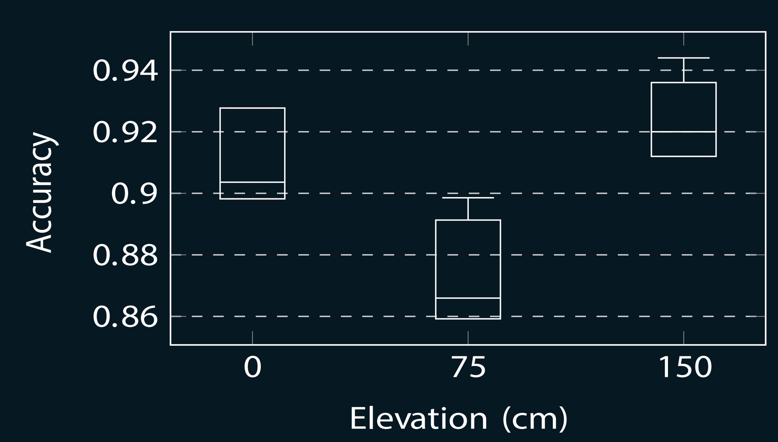
- Euclidean-based distance
- Geodesic distance
- Euclidean distance in Tangent Space

Figure: An Introduction to Optimization on Smooth Manifolds, Nicolas Boumal

Comparison between Euclidean and non Euclidean approaches:



Effect of elevation (MLP):



References

Peihua Li et al., "Is Second-Order Information Helpful for Large-Scale Visual Recognition?", in Proceedings of the IEEE International Conference on Computer Vision, 2017, 2070–78

Lei Xiang et al, "An Automatic Algorithm for Multi-Defect Classification inside Tunnel Using SVM", 2012 14th International Conference on Ground Penetrating Radar (GPR), 2012

Xisto L. Travassos et al, "Artificial Neural Networks and Machine Learning Techniques Applied to Ground Penetrating Radar: A Review", Applied Computing and Informatics 17, no. 2 (January 1, 2020)

Olivier Ledoit et al, "A Well-Conditioned Estimator for Large-Dimensional Covariance Matrices", Journal of Multivariate Analysis 88, no. 2 (février 2004)

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