

D760 (EGU - 2020 - 22503) PERFORMANCE ANALYSIS OF TWO-CLASS SVM TO DETECT THIN INTERLAYER DEBONDINGS WITHIN PAVEMENT STRUCTURES

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SESSION GI5.1

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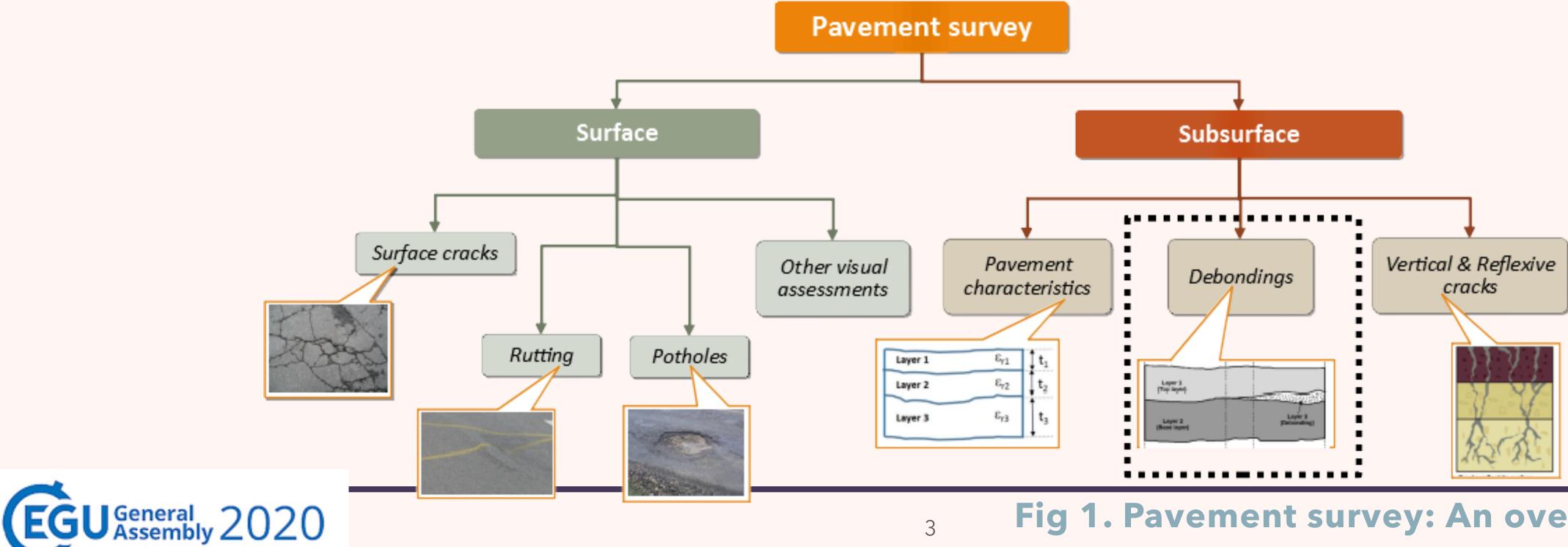


INTRODUCTION





Pavement degradation: surface (cracks) and subsurface defects (delaminations → reflexive cracks)





PROBLEM STATEMENT

Detection using Non-destructive GPR imaging and advanced processing methods

Fig 1. Pavement survey: An overview





DEBONDINGS CHARACTERISATION

- Debonding: Presence of an additional layer between the top two pavement layers
- Constructive interference of overlapping backscattered echoes (< λ_{mat} / 4)





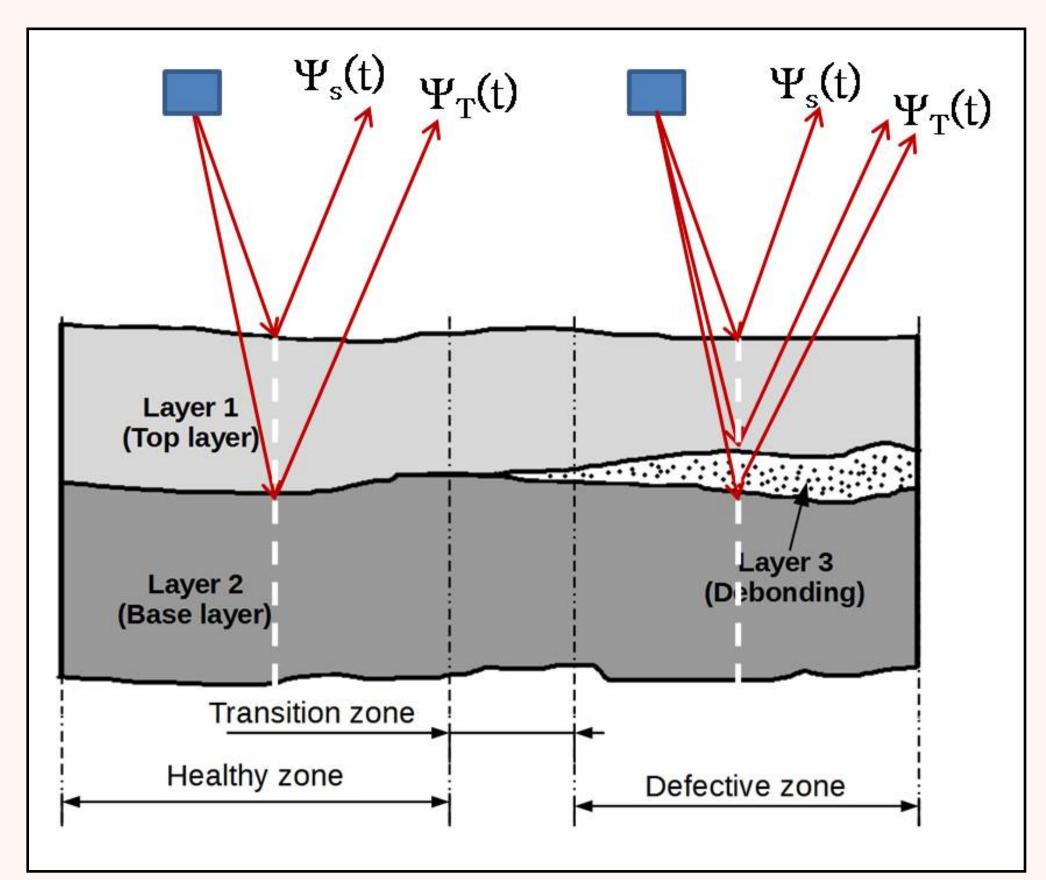


Fig 2. Debonding characterisation





OBJECTIVES

- Use of Supervised machine learning method on timedomain GPR signatures
- **Performance analysis of Two-class SVM using simulated data Result analysis of simulated and field data**





Detection of subsurface millimetre-order debondings





METHODOLOGY





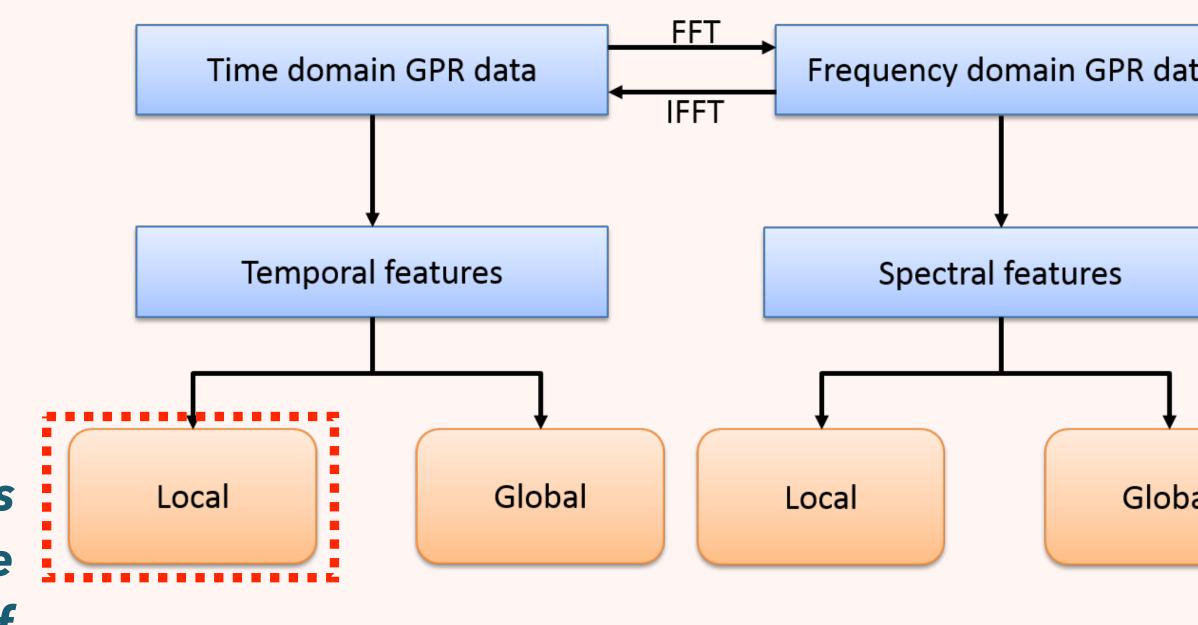
DATA PREPROCESSING



- **Local vs. Global signal features**
- Feature set consists of:
 - Standard deviation (σ), Amplitude range of second echo (A₂), Skewness (S_k), Kurtosis (K_u), Interquartile range (IQR) and Root-mean square (rms) of the signal









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DATA PREPROCESSING

- Use of automatic time-gating window
- Window length (in terms of number of samples) is a function of the sampling frequency (f_S) and the pulse width of the emitted signal (t_W)





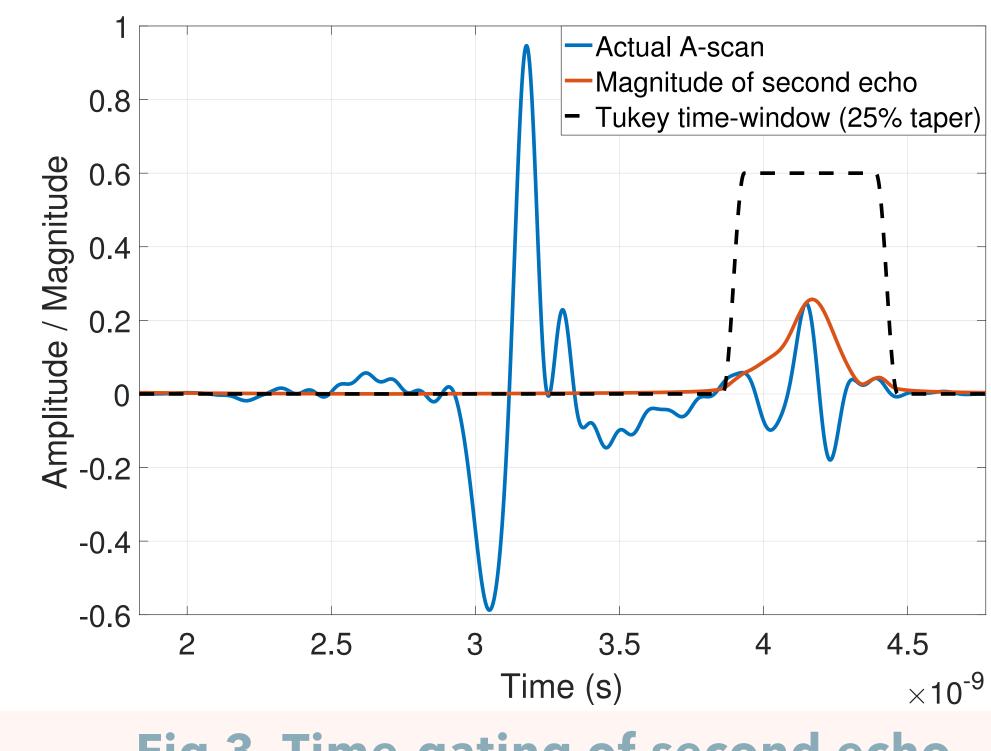


Fig 3. Time-gating of second echo





DATA PREPROCESSING

- **Use of automatic time-gating window**
- Window length (in terms of number of samples) is a function of the sampling frequency (f_S) and the pulse width of the emitted signal (t_W)





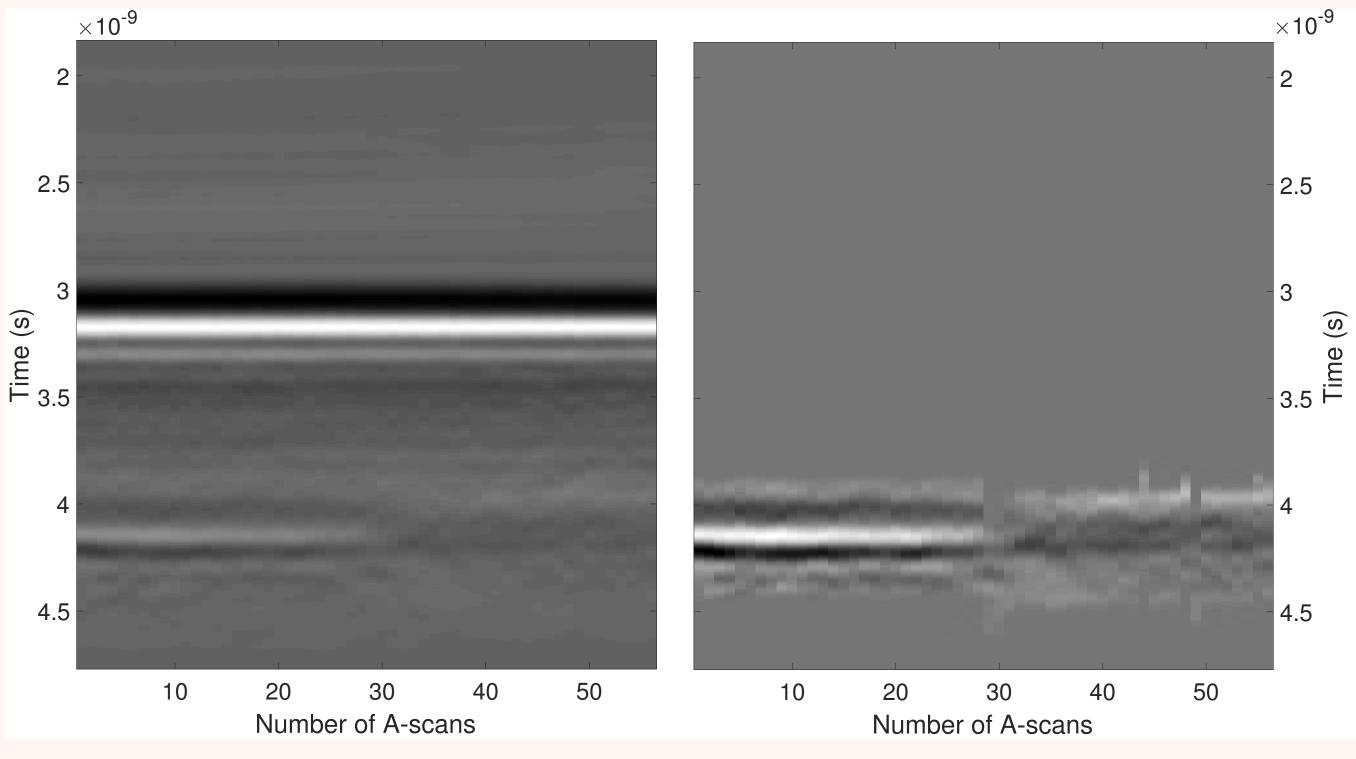


Fig 4. Ungated vs. Time-gated GPR B-scan





SUPPORT VECTOR MACHINES

- Support Vector Machines (SVM) for twoclasses
- Supervised machine learning method; relies on the use of N-1 dimensional hyperplane to separate the data mapped on a N dimensional hyperspace
- Minimisation function: Minimize $\frac{1}{2} ||\mathbf{w}||^2 + C \sum_{i=1}^N \xi_i$





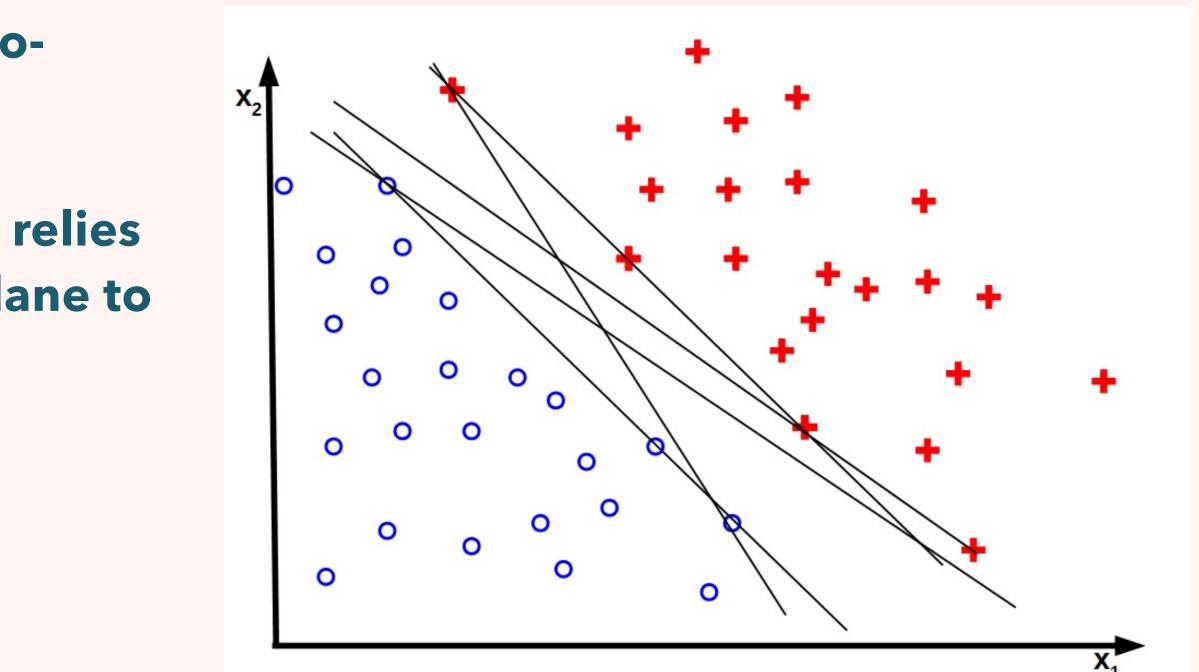


Fig 5(a). Example of possible hyperplanes for SVM classification



SUPPORT VECTOR MACHINES

- Learning data is use to create a classification model
- Test data is uses the model to classify unknown data
- Use of Linear or Non-linear kernels to find the best data separation





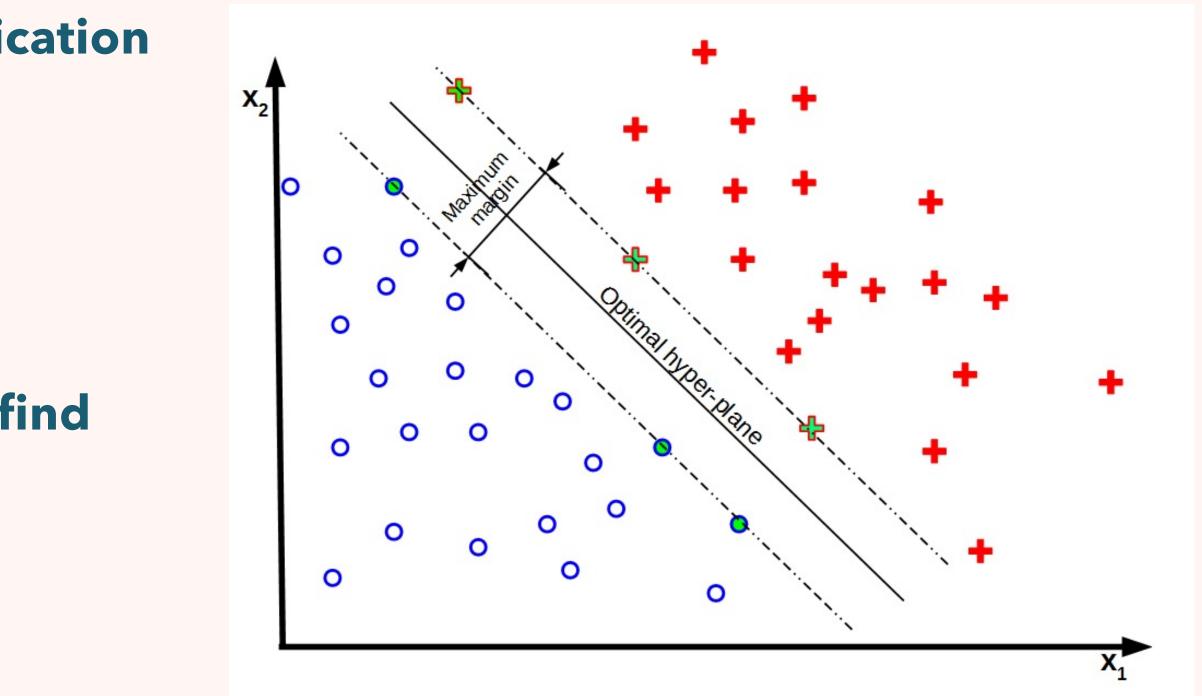
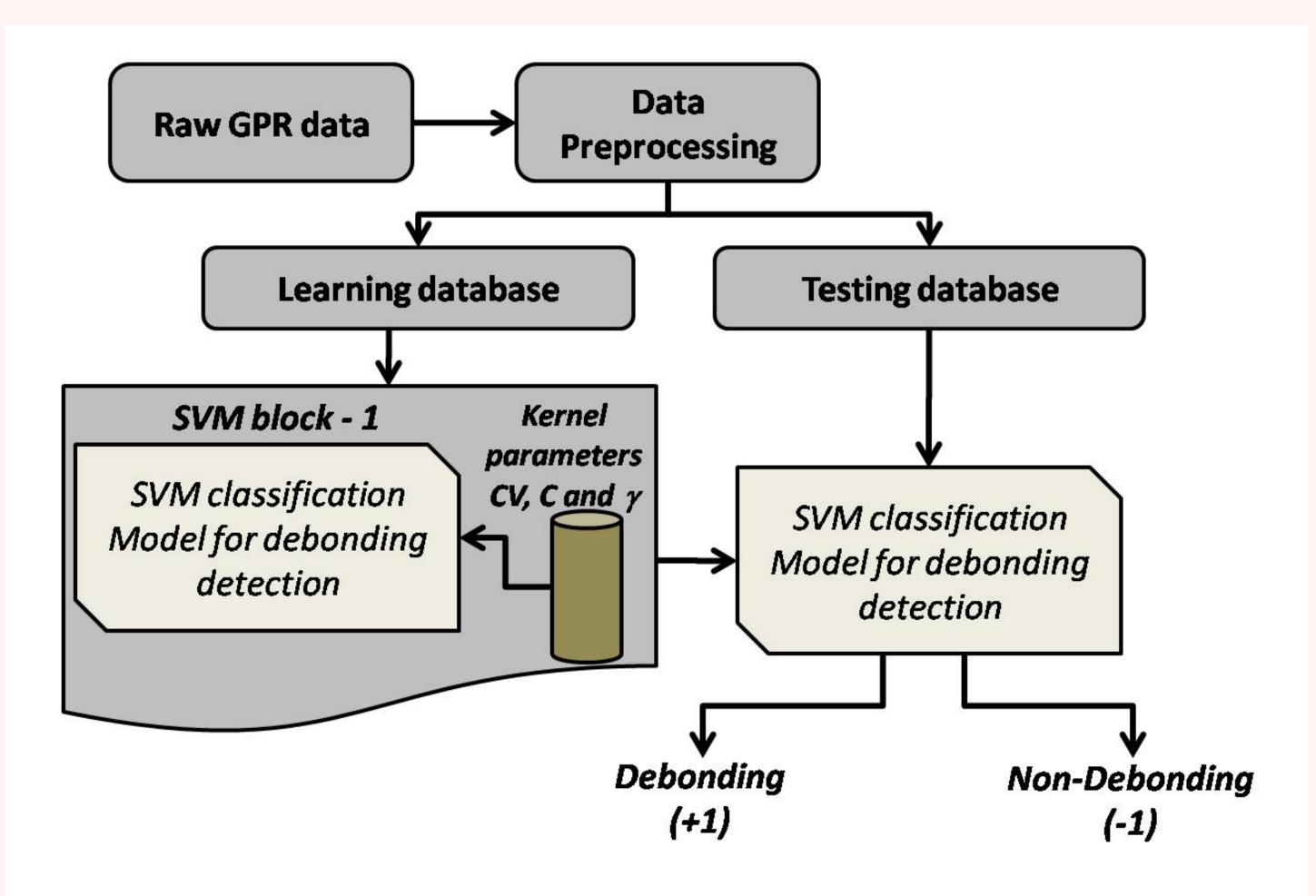


Fig 5(a). Example of the optimal hyperplane with max margin











THE SVM APPROACH







SOME RESULTS





DATABASES USED

Simulated database

- Three permittivity values: 2 (near air-void defects), 10 (near moisture/wet defects)
- Each B-scan consists of 150 A-scans with 50 debonding and 100 non-debonding Ascans
- Gaussian noise of 30 dB added to the B-scans
- **Experimental database:**
 - Collected at IFSTTAR's fatigue carousel over various loading stages using UWB SF-GPR
 - Three defect types: Geotextile, Sand and Tack-free based









SENSITIVITY ANALYSIS

- The study of relationship uncertainties between the input and its outputs
- To observe the robustness and adaptability of a method *w.r.t* various input data configurations
- **Sensitivity analysis studied:**
 - **Data-based SA: Effect of learning data size and input feature set**
 - <u>Method-based SA</u>: Effect of CV and kernel techniques
 - **Pavement-based SA: Effect of debonding thicknesses and composition**

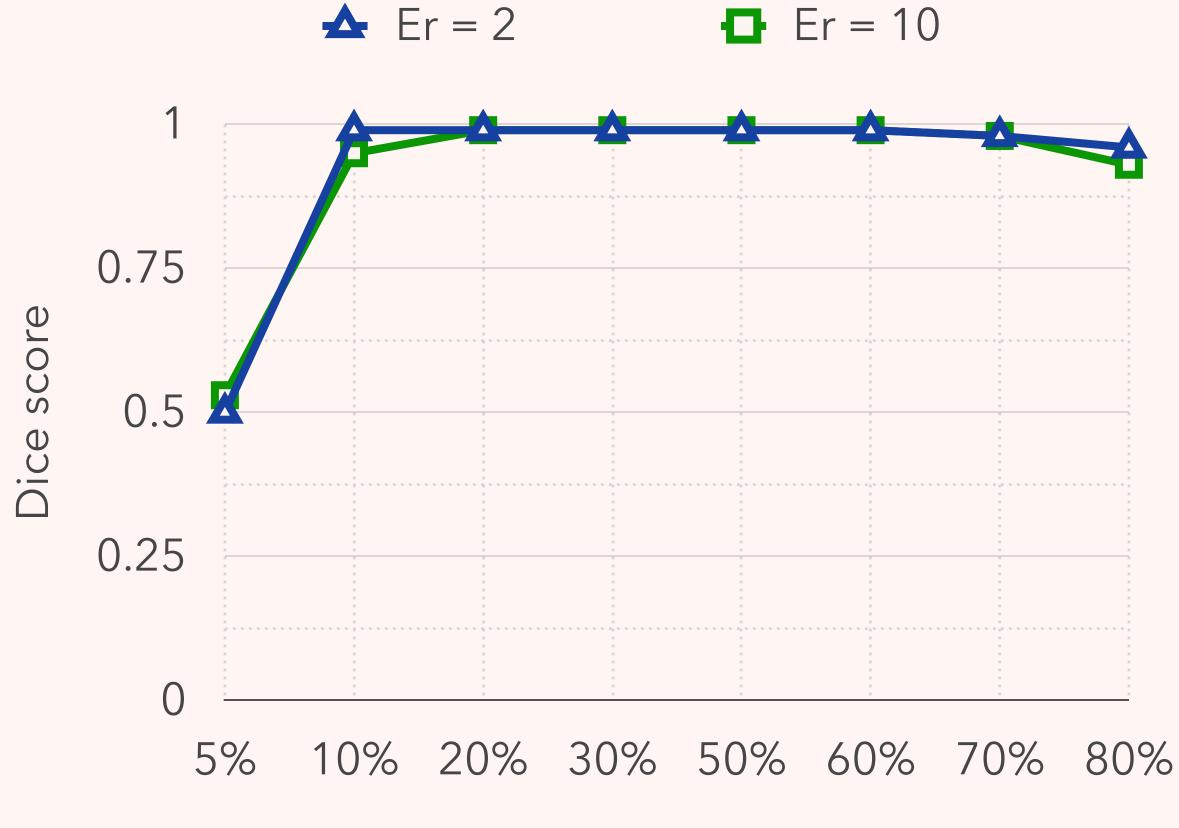
















SENSITIVITY ANALYSIS

1. SVM performance w.r.t learning data size

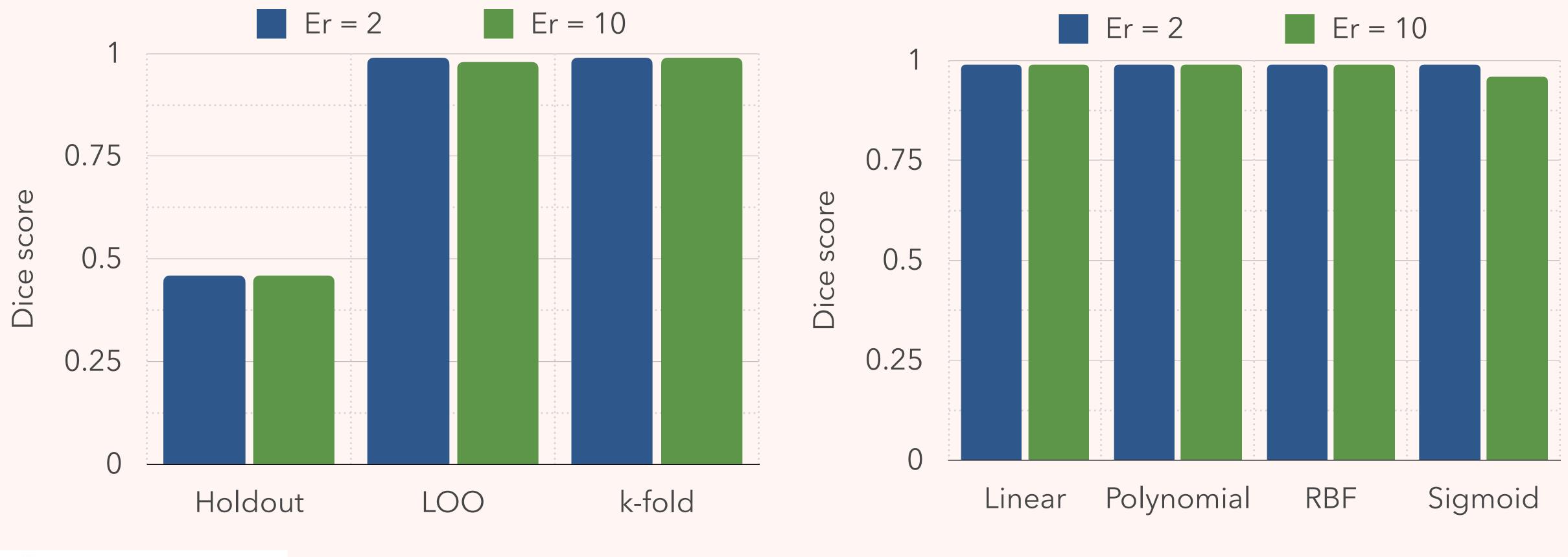
Learning data percentage





SENSITIVITY ANALYSIS

2. SVM performance w.r.t CV techniques







3. SVM performance w.r.t kernel type



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CONCLUSIONS & PERSPECTIVES





CONCLUSIONS

- Performance testing with simulated and field data **Sensitivity analysis of the SVM method w.r.t signal features**
 - - Feature sets: Performance of Local features > Global features
 - <u>CV techniques</u>: k-fold (k=5) presented the best performances
 - Learning data: Optimal learn-to-test ratio is between 1:1 to 3:1





Individual signal features do not provide conclusive results on the performance





PERSPECTIVES

Improving performance by

- Implementation of additional time domain features

Estimation of debonding layer characteristics





Adapting the conventional Amplitude Ratio test (ART) with SVM





THANK YOU FOR YOUR ATTENTION.



