Computer Vision for Automated Bridge Deck Evaluation from Ground Penetrating Radar Scans

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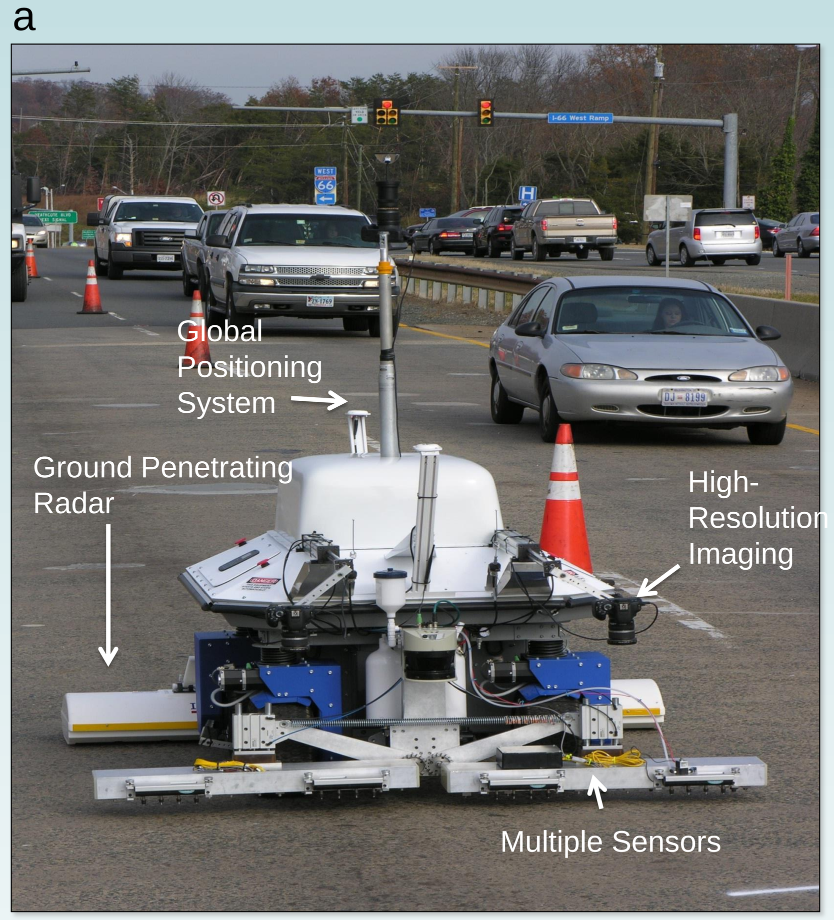
Introduction

Ground Penetrating Radar (GPR) is used to obtain a deterioration map of reinforced concrete (RC) bridge decks based on measuring signal attenuation at the upper rebar mat. The existing methods for obtaining rebar deterioration map using GPR data are semi-automated and usually require manual interaction with the tools for offsite processing. We propose a robust automated algorithm for obtaining rebar location and condition by fitting the GPR data with a hyperbola model using statistical inference. To generate an accurate deterioration map of the bridge deck, automated depth-correction is applied so that the signal attenuation caused by variation in rebar depth does not skew the results. We show that the deterioration maps obtained for the bridges using automated algorithms are similar to those obtained using semi-automated methods.

Robot for automated bridge deck evaluation

a



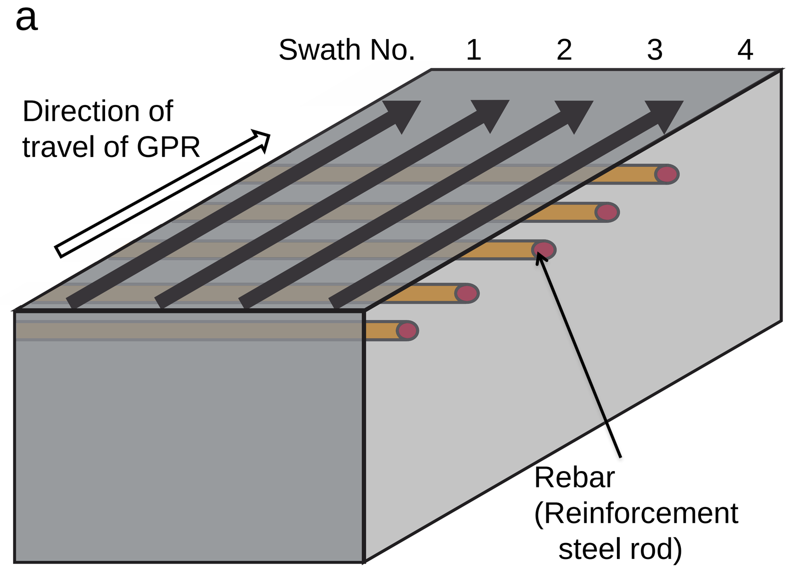
b

Figure 1: Automated bridge deck evaluation. (a) Autonomous system for data collection and bridge deck evaluation developed by integrating multiple sensors with Seekur robot[1]. (b) Rebars are embedded in concrete to form a stronger structure. They deteriorate over time due to ingress of moisture and chloride ions. A GPR is used to obtain the rebar deterioration map.

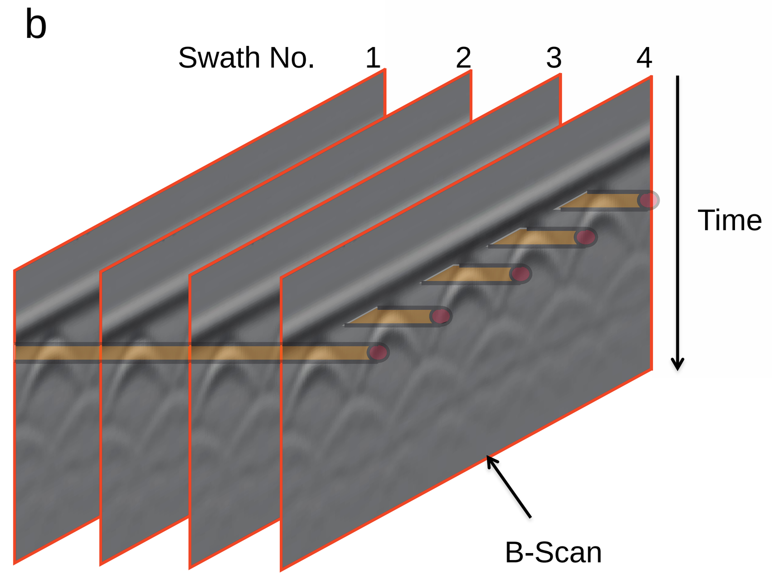
[1]The entire team for robot: Ali Maher, Nenad Gucunski, Hung La, Ronny Lim, Basily Basily, Kristin Dana, Parneet Kaur, Prateek Prasanna, Francisco Romero, Hooman Parvardeh, Seong-Hoon Kee

Formation of B-scans

a



b



c

Figure 2: Data collection using GPR. (a) Data is collected along parallel lines, in direction perpendicular to rebars. (b) Data collected in each swath is represented as a B-scan. (c) Rebar forms a hyperbolic signature in a B-scan.

Rebar region detection using classification

	Positive Samples	Negative Samples
Training Set	1200	1200
Test Set A	1000	1000
Test Set B	1000	1000

Table 1: Datasets for classification. Datasets are constructed by manually labeling samples of size 52x32 pixels from B-scans. All three sets are from three different bridges.

a b

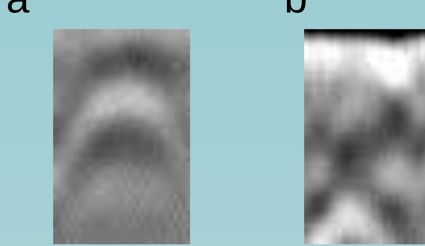
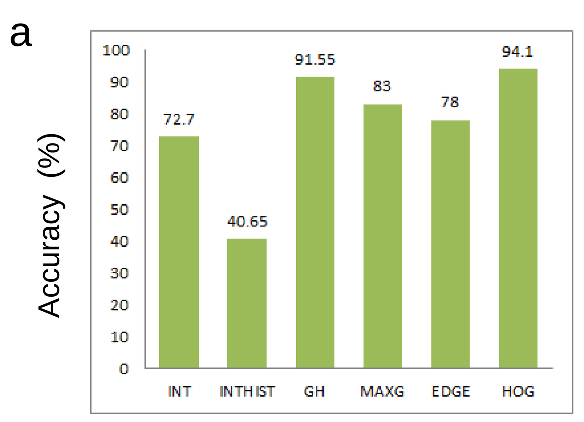
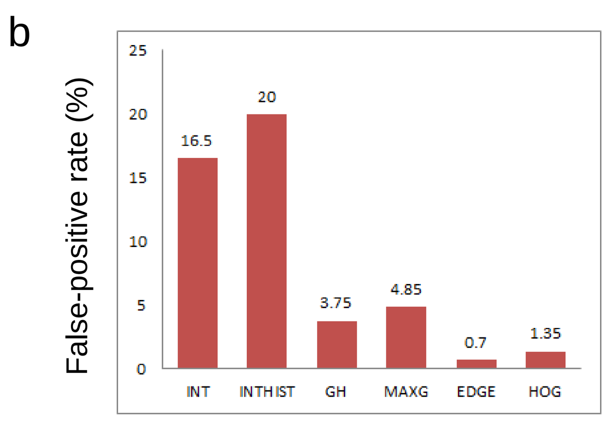


Figure 3: Examples of (a) Positive sample, (b) Negative sample.

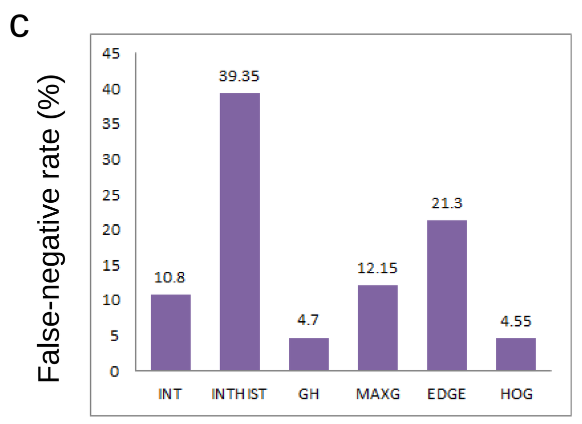
a



b



c



Feature vectors:
INT: Intensity values
INTHIST: Intensity histogram
GH: Gradient orientation histogram
MAXG: Maximum gradient bin
EDGE: Edge pixels
HOG: Histogram of Oriented Gradients

Figure 4: SVM classification results using six different feature vectors for Test Set A. (a) Accuracy (b) False-negative rate, (c) False-positive rate. HOG feature vectors give the best accuracy and least false-negative and false-positive rate. Similar results are observed for Test Set B.

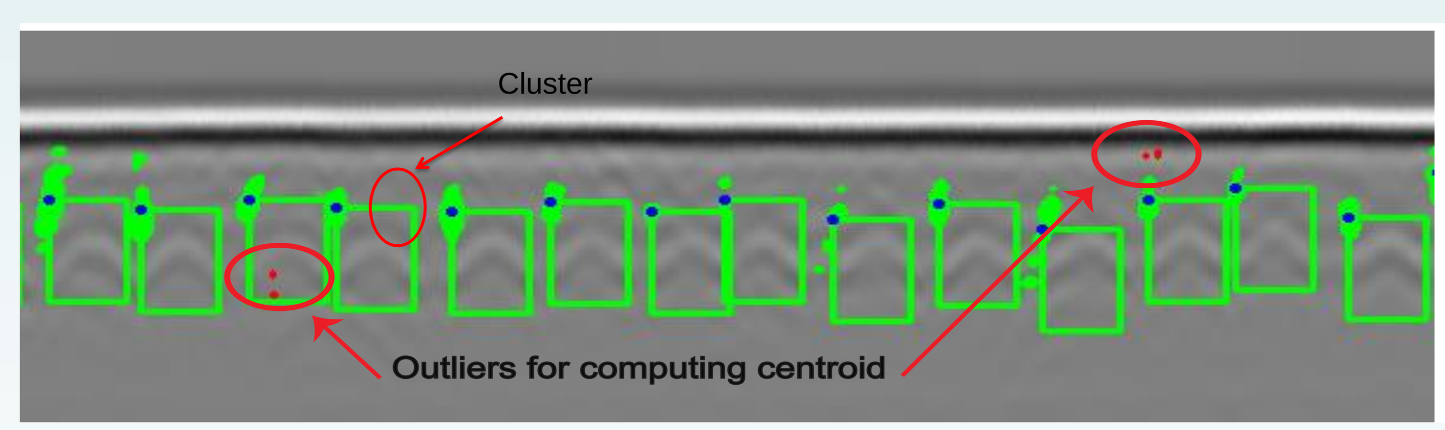


Figure 5: Rebar region detection in a B-scan using HOG feature vectors. There are multiple detections (multiple green dots) around each rebar region, which form a cluster. Cluster centroid (blue dot) is found by ignoring the points with distance greater than 3σ and marked as a rebar region (green rectangle).

Rebar location using hyperbola-fitting

a b c

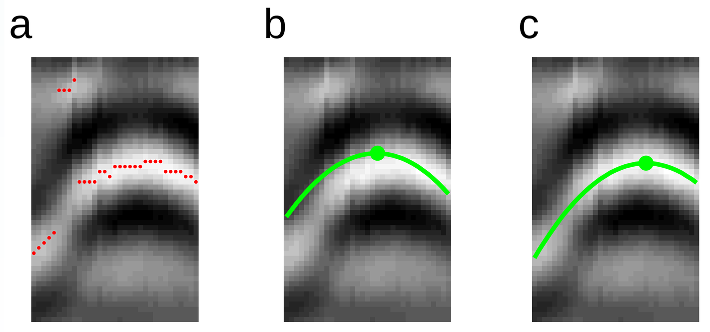


Figure 6: Hyperbola fitting in each rebar region to find hyperbola peak. (a) Input points for hyperbola fitting (red dots). Hyperbola fitting using (b) non-linear curve fitting and (c) RANSAC. Hyperbola peak is identified correctly (green dot) in (c).
Signal amplitude at each peak determines its relative condition (deterioration).

Performance evaluation

Bridge	Length (ft)	No. of B-scans	Actual no. of rebars	Average detection rate (%)	Total Time (min)
A	335.5	11	7212	92.45 ± 2.38	~44
B	124	18	4122	91.5 ± 1.23	~27

Table 2: Performance evaluation using HOG feature vectors for classification and hyperbola fitting. Time for manually detecting rebars in these bridges using existing tools with manual interaction is estimated to be 3 days or more depending on engineer's expertise.

Deterioration maps

Depth-correction is applied prior to obtaining deterioration maps to accommodate for signal attenuation caused due to variation in rebar depth. We use RANSAC, instead of traditionally used linear regression, to fit a line and shift the amplitude values such that rebars at variable depths have same amplitude

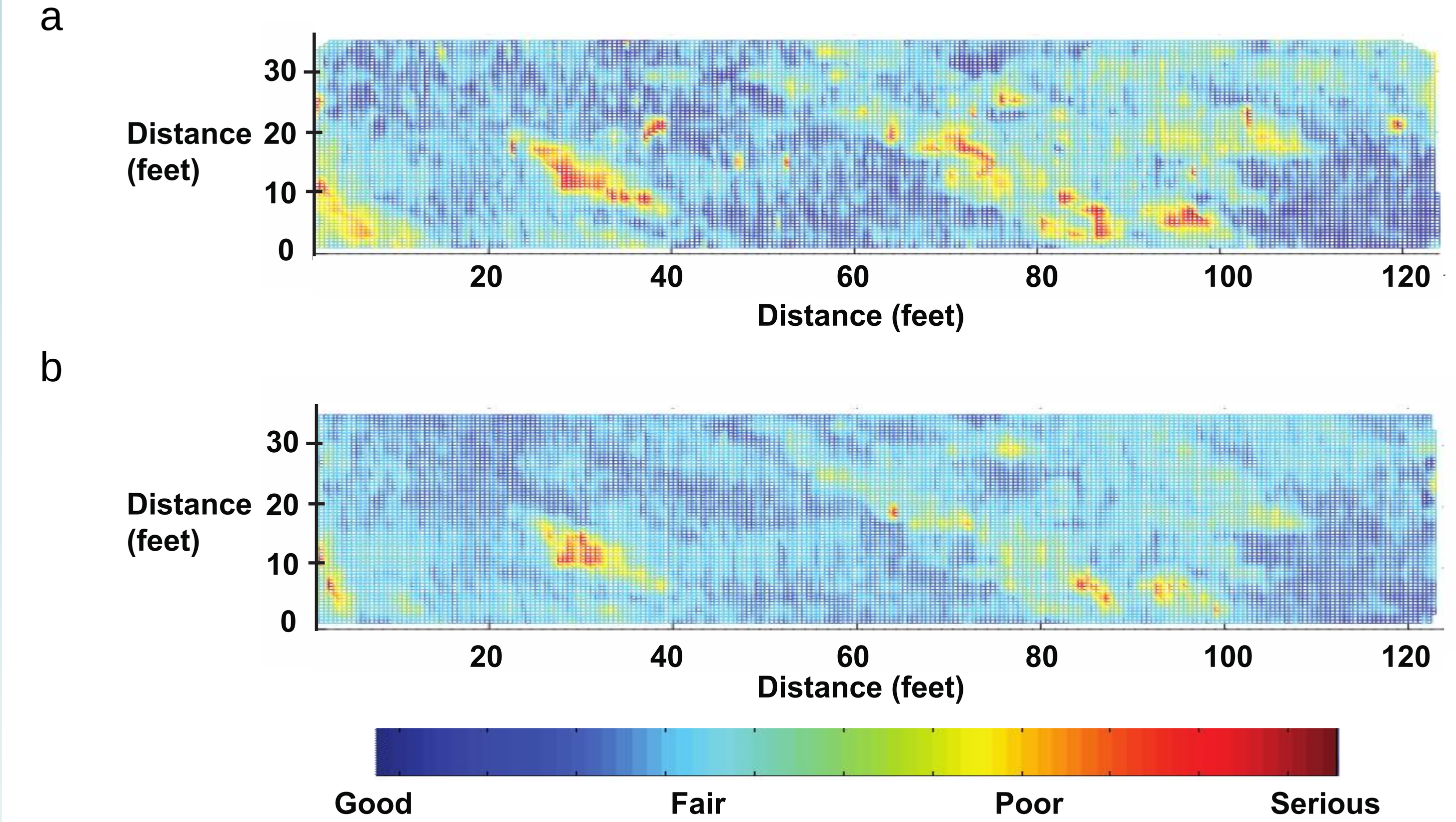


Figure 7: Deterioration maps after depth-correction. Deterioration maps are obtained using depth-corrected signal amplitudes at each rebar location. Maps obtained using (a) our algorithms, (b) semi-automated method (GSSI RADAN software). For semi-automated method, false-positive rebar detections are manually removed and missing rebar detections are manually added.

Conclusions

- HOG feature vector is the best for detecting rebar regions in a B-scan.
- Hyperbola fitting using RANSAC identifies the exact rebar location.
- For depth-correction, RANSAC is used instead of linear regression for a robust line-fit in presence of outliers.
- Deterioration maps obtained are comparable with semi-automated methods.

Acknowledgments

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