

ROC Curve Analysis for Classification of Road Defects

Huong Thu Nguyen

Baikal School of BRICS

Irkutsk National Research Technical University

Ulitsa Lermontova, 83, Irkutsk, Irkutskaya oblast', Russia, 664074

Phone: +7 395 240-50-09

thuhuongyb@gmail.com

Long The Nguyen

Department of Information Technology

Irkutsk National Research Technical University

Ulitsa Lermontova, 83, Irkutsk, Irkutskaya oblast', Russia, 664074

Phone: +7 395 240-50-09

thelongit88@gmail.com

Abstract

ROC analysis is a visual and numerical method used to evaluate the performance of classification algorithms, such as those used to predict the structure and functions from string data. The main objective of the paper is to use the ROC analysis to evaluate the accuracy of the Random Forest algorithm to classify road surface defects on three different sets of data collected from Portugal, Irkutsk city - Russia Federation and Thai Nguyen city - Vietnam. This article summarizes the basics of ROC analysis and interprets the results analysis with other thresholds to build ROC curve. In addition, we present the steps to build a system to automatically classify road surface defects based on visual techniques and machine learning methods.

Keywords: Road Defect; Graph Cuts; Image Segmentation; Object Classification; Random Forest Algorithm; Machine Learning; ROC Curve Analysis.

1. Background

Automatic classification of objects plays a major role in the application of machine learning of artificial intelligence. Therefore, the reliability rating of the classification algorithm has become necessary to ensure data quality. Among the available measures and methods of performance analysis, the receiver's performance characteristics (ROC) (Zweig, & Campbell, 1993) occupy a special position. This is because, first and foremost, it provides an intuitive as well as digital summary of predictor behavior against simple performance indicators. Second, it is becoming a major method in artificial intelligence applications.

Machine learning algorithms are often used in content-based recommender systems since a recommendation task can naturally be reduced to a classification problem: A recommender needs to learn a classifier for a given user where learning examples are characteristics of items previously liked/bought/seen by the user. However, multi-valued and continuous attributes require special approaches for classifier implementation as they can significantly influence classifier accuracy (Brbic et. al., 2011).

Development of the automatic road defects classification software using classification algorithms was advocated by many researchers. Moreover, the classifier ensemble can effectively improve classification performance compared to a single classifier. The research on road defects detection and classification using classifier ensemble methods are motivated since they have not been fully exploited.

In (Nguyen et. al., 2016; Nguyen et. al., 2016) we have proposed a method to build a map of the defect based on algorithm Markov random field and graph cuts. The method was demonstrated its efficiency, but also some drawbacks. Due to the rough surface and non-uniform illumination, pavement surface images suffer with background noise. Therefore, we propose a method to improve

a quality of segmentation bases on minimum energy function of Graph cuts methods and classification by random forest. To enhance a quality of image we preprocess input images using adaptive filters and mathematical morphological operators (Nguyen et. al., 2018).

There are many different approaches for the detection of defects in the road surface. One of the most common approaches is carried out by the histogram analysis using artificial neural networks (ANN). In (Lee, 2003) authors use a neural networks combined with conventional image preprocessing and representation. A binary crack matrix was created by local statistics to tag tiles, which contains cracks. Vector features were summed along the horizontal and vertical axes, which used as input data for multi-layer perceptron classification.

The threshold based analysis approach is used to separate crack pixels from the background. Hough transformation is used to detect or classify the cracks in paper (Cheng et. al., 2001). In (Zhang et. al., 2009) a new image enhancement algorithm in ridge let domain was proposed for detection of road cracks. The method based on the principle that an image ridge let transform is equivalent to one dimensional wavelet transform in Radon transform domain. Experiment results and their comparisons with other image enhancement algorithms show that the algorithm can be effectively used in enhancement of linear character of road cracks images.

A good starting point can be found in the manuscript (Chen et. al, 2011) which reviews the techniques applied for the development of automatic pavement distress detection and classification system. They also propose a novel approach according to the following major steps: region based image enhancement (to correct non-uniform background illumination) and a skeleton analysis algorithm to classify pavement surface distress types. In (Lempert et. al., 2016) Lempert, Sidorov et. al. presented an approach to optimal pavement repair under the limited resources. The approach is based on combination of methods for identification and classification of defects using statistical analysis and machine learning (Random Forests) in combination with novel original methods for solving the infinite-dimensional optimization (optical - geometrical analogy). Automatic defects classification is important field of machine vision, e.g.

In (Sidorov et. al., 2008) Sidorov, Wang et al proposed two stages approach for automatic defects recognition and classification for vision systems development. The first offline stage of classification is based on a teaching process. On the second online stage, the inspection images are classified using features analysis. The main objectives of such systems are defect recognition and classification based on known features. The classification function is designed using cluster analysis.

2. System of road defect detection and classification

The system proposed in this paper is designed for automatic detection and classification of road defect. The system consists of three modules: (i) Image Preprocessing (ii) Segmentation of image (iii) Feature extraction (iv) Classification of road defect using Random Forest algorithm. Figure 1 shows the overall system architecture.

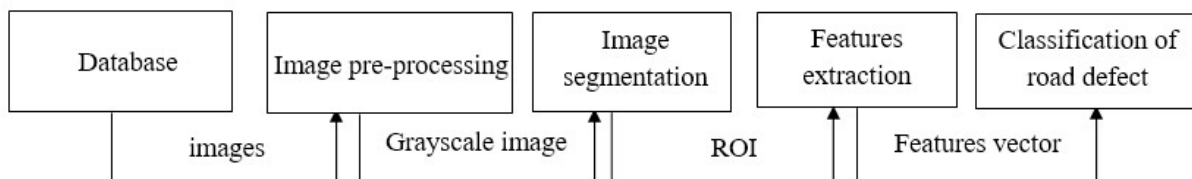


Figure 1. Block diagram of the proposed system

2.1. Image Pre-Processing and Feature Extraction Road Defects

Image acquisition is the process of obtaining a digitized image from a real-world source, passed through the pre-processing steps. Preprocessing includes noise removal and the elimination of redundant information as far as possible. Images taken from the camera are histogram equalized

for better contrast. During the process of road defects collection, the image often becomes corrupted by random noise which affects the detection of road defects. In addition, the illumination conditions may change for different image locations, resulting in a road image that is not homogenous. These problems can be solved using histogram equalization. RGB image is converted into gray scale image using NTSC gray scale conversion which is frequently used to convert RGB to gray scale conversion. The image is converted from Gray scale to binary image that is an image with pixels 0's (white) and 1's (black).

Road defects have various features that can be exploited to discriminate them from non-crack features. They ROIs have valuable photometric characteristics such as value pixels; geometric features can be recognized by elongated continuous structures and frequency features. All these features can be extracted from ROIs using computer vision algorithms and machine learning methods.

Hu-moments. The most notable are Hu-Moments which can be used to describe, characterize, and quantify the shape of an object in an image. Hu-Moments are normally extracted from the shape of an object in an image. By describing the shape of an object, we are able to extract a shape feature vector (i.e. a list of numbers) to represent the shape of the object.

Chain code histogram. The chain code histogram (CCH) is meant to group together objects that look similar to a human observer. It is not meant for exact detection and classification tasks. The CCH is calculated from the chain code presentation of a contour.

2.2. Build Graph of Road Defect Using Graph Cuts Algorithm

Graph cuts for Markov Random Fields (Delagnes et. al., 1995; Bouman et. al., 1995) - Energy minimization algorithm: the min-cut max-flow algorithm (Kolmogorov, & Zabih, 2001). To improve the quality of image segmentation the Graph-cuts algorithm (Boykov et. al., 2001) is employed (Figure 2).

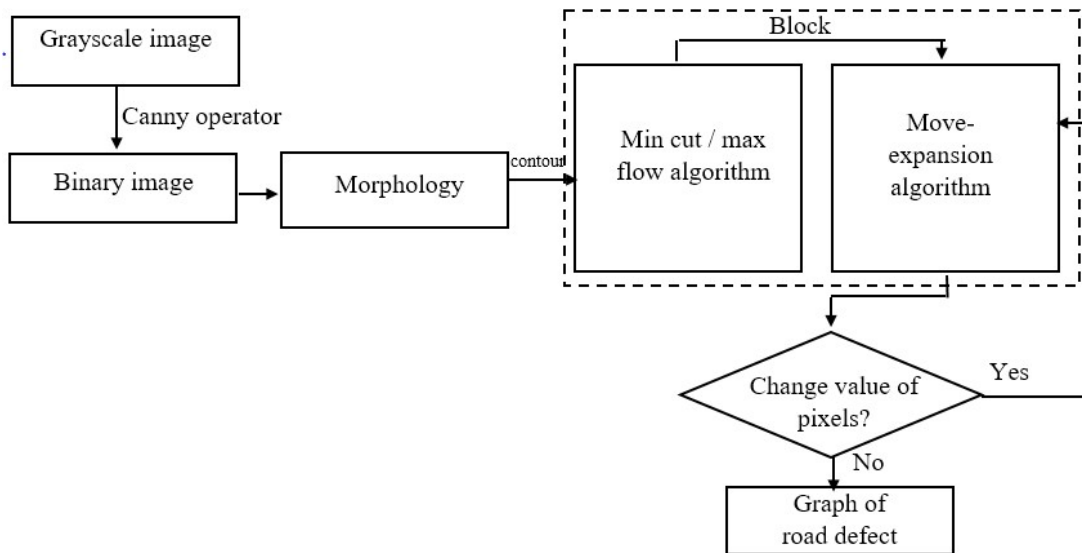


Figure 2. Block diagram of road image segmentation

A graph-based approach makes use of efficient solutions of the min-cut/max-flow problem between source and sink nodes in directed graphs. The summarization of steps used in graph cuts method can be depicted as below:

Step 1: An edge directed graph representing size and dimension of the target segmenting image has to be created.

Step 2: Object and background seeds have to be distinguished properly with formation of nodes-source s and sink t . Based on the object or the background labels, all seeds have to be connected with either source or sinks node.

Step 3: Each link of the formed graph is to be associated with suitable edge cost.

Step 4: Any minimum s - t cut method is to be used which indicates the graph nodes representing image boundaries for object and background.

Step 5: A suitable maximum flow solution for graph optimization is to be determined for graph cuts segmentation

These segments are called “sites” and have a predefined orientation of 0, 45, 90 or 135 degrees. The separation between both cases is done with parameter $k \in \{0; 1\}$. Our goal will be to segment an image by constructing a graph such that the minimal cut of this graph will cut all the edges connecting the pixels of different objects with each other.

We applied efficient graph based method to find the optimal D (Defect) – N (Not defect) as shown in figure 3 swap or D - expansion given a labeling f . Let us briefly outline the approach we used.

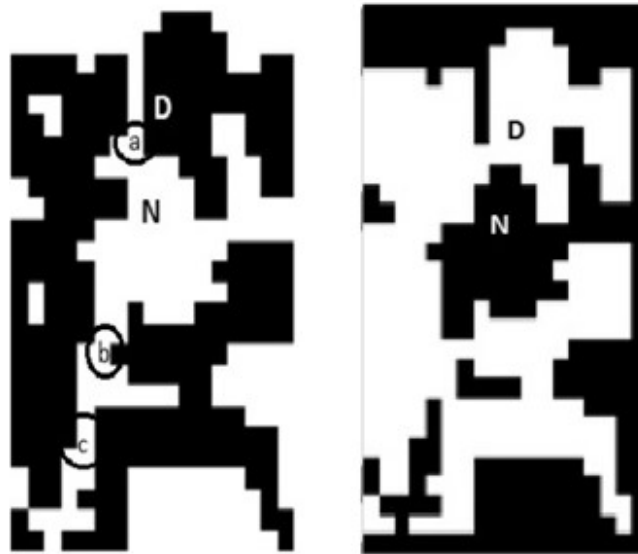


Figure 3. Example of image segmentation

Let $G = (V, E)$ be a weighted graph with two distinguished vertices called the terminals. A graph-based approach makes use of efficient solutions of the min-cut / max-flow problem between source and sink nodes in directed graphs. To take advantage of this we generate an s - t graph as follows: The set of nodes is equal to the set of pixels in the image. Every pixel is connected with its d -neighborhood $d = (4; 8)$. The minimum cut problem is to find the cheapest cut among all cuts separating the terminals. Minimum cuts can be efficiently found by standard combinatorial algorithms with different low-order polynomial complexities. Our experimental results have been obtained using a new max-flow algorithm that has the best speed on our graphs over many modern algorithms. The running time is nearly linear in practice. Some results of segmentation of classes defect road pavement are shown in figure 4.

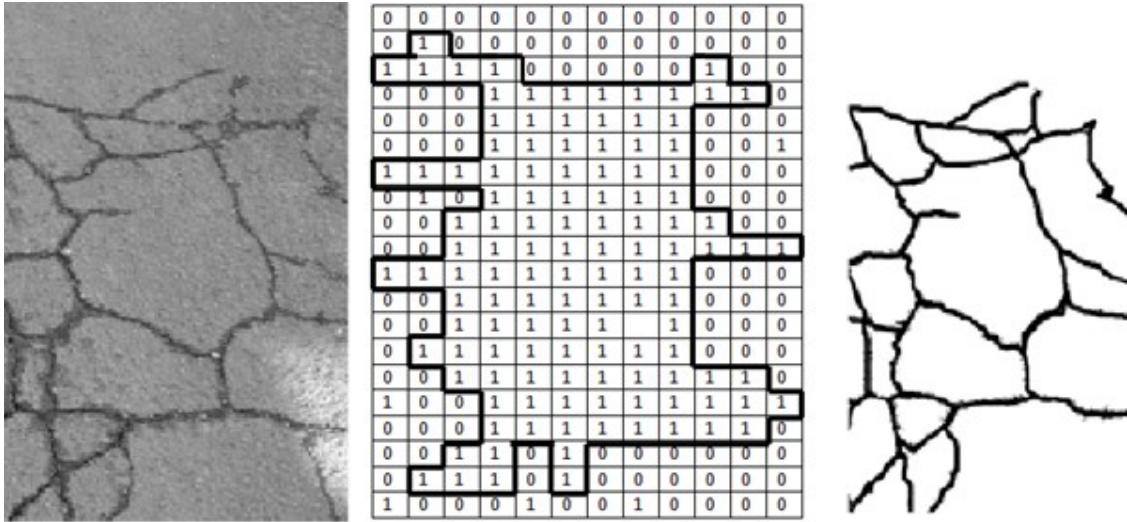


Figure 4. Result of road defect segmentation

2.3. Classification of Road Defect

The Random Forest (Breiman, 2001) classifier (Figure 5) was built using the package Random Forest 4.5-16 for the R statistical environment to classify feature vectors as defect or non-defect. The classifier was trained on pavements road dataset using Chain code histogram - CCH, Hu moments, size of defect for each variant. We also used Boosting (GBTs) to classify this dataset and to compare results from these two classification methods. The main difference between these two algorithms is the order in which each component tree is trained.

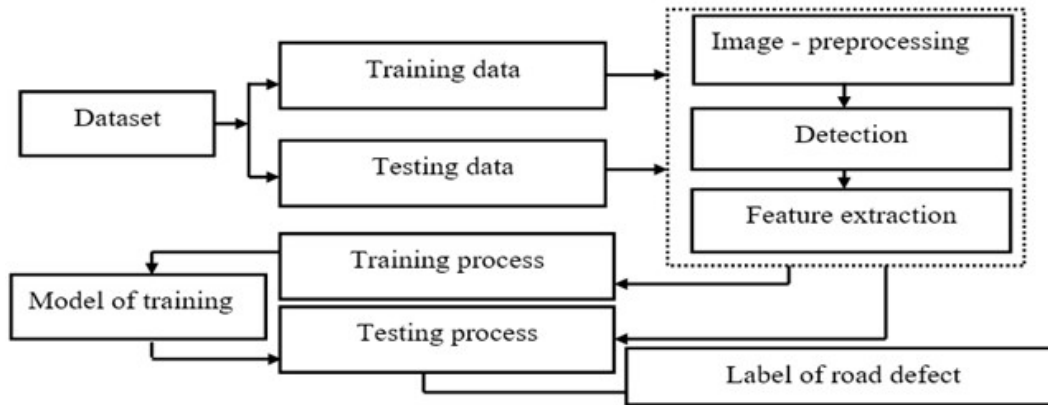


Figure 5. Block diagram of road defect classification using Random Forest algorithm

The classifier was built using the parameters $n_{tree} = (50, 100)$ and $m_{try} = 2$ and depth $= (2, 5)$. The training set consists of 500 images (200 of class 'defect' and 300 of class 'non-defect'). In 200 images of class defect included 150 images (50 Block images, 50 Longitudinal images, 50 Pothole images) for training process and 50 images for testing process. In 300 images of class non-defect included 200 for training process and 100 images for testing process. Our dataset images were built by Center for Telecommunications and Multimedia, INESC TEC, Portugal. Beside we use own our dataset, which is collected by camera (Canon D100 16 mega pixel). Images are captured in conventional daylight condition, distance from camera to surface of road is 1m-1.2m.

2.4. Using ROC Curve to Analysis of Road Defect Classification

Imbalanced data follows the idea of cost sensitive learning make random forest more suitable for learning. Class weights are an essential tuning parameter to achieve desired performance. In the tree induction procedure, class weights are used to weight the Gini criterion for

finding splits. In the terminal nodes of each tree, class weights are again taken into consideration. We introduce the concept: True Positive – TP is classified correctly as positive, True Negative – TN is classified correctly as negative, False Positive – FP is classified wrongly as positive, False Negative – FN is classified wrongly as negative. For Random Forest algorithm, there is always a tradeoff between true positive rate and true negative rate and the same applies for recall and precision.

$$\begin{aligned}\text{True negative rate} &= \frac{TN}{TN+FP} \\ \text{True Positive rate} &= \frac{TP}{TP+FN} \\ \text{Precision} &= \frac{TP}{TP+FP}\end{aligned}$$

Threshold Selection: It is immediately apparent that a ROC curve can be used to select a threshold for a classifier which maximizes the true positives while minimizing the false positives. However, different types of problems have different optimal classifier thresholds. We may be prepared to put up with a relatively high false positive rate in order to get a high true positive, it is most important to identify possible road defect. So, in this article, for defining the label of the pavement defects. We can use thresholds in the parameters of the random forest algorithm, which can be: *mtry* parameters, *tree* numbers, *Digi* indexes.

Performance Assessment Classifier Comparison: ROC curves also give us the ability to assess the performance of the classifier over its entire operating range. The most widely-used measure is the area under the curve (AUC). As you can see from figure 7, the AUC for a classifier of road defect based on algorithm Random Forest. A single threshold can be selected and the classifiers' performance at that point compared, or the overall performance can be compared by considering the AUC. In this work we selected thresh is Gini index to evaluates the accuracy of the Random Forest algorithm in classifying road surface defects. The result showed that result of classification is good and fall between 0.5 and 1 (essentially random guessing, is 0.5, because the curve follows the diagonal. The AUC for that mythical being, the perfect classifier, is 1.0). In this our case curves have status is nearer 1 value than 0.5 values.

	Road defect classification of Road defect in Thai Nguyen city			
	Random Forest		Boosting (GBTs)	
	number of tree: 50 deep: 2	number of tree: 100 deep: 5	number of tree: 50 deep: 2	number of tree:100 deep: 5
Time, (s)	150	257	140	278
Accuracy(%)	91.57	95.29	80.5	85.47

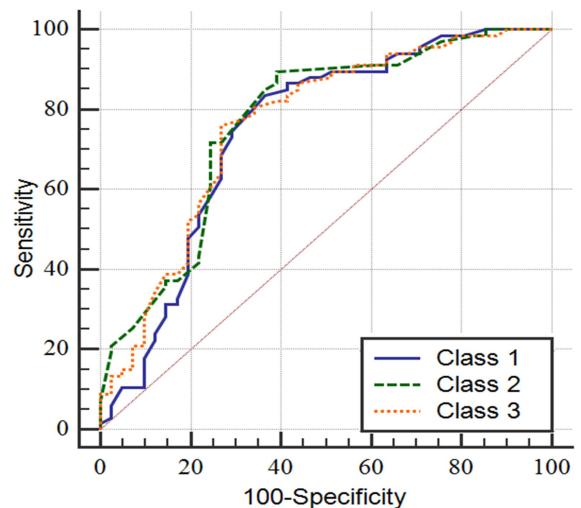


Figure 6. Result of analysis ROC for classification of road defect in Thai Nguyen city

	Road defect classification of Road defect in Irkutsk city			
	Random Forest		Boosting (GBTs)	
	number of tree: 50 deep: 2	number of tree: 100 deep: 5	number of tree: 50 deep: 2	number of tree: 100 deep: 5
Time, (s)	775	1132	830	1270
Accuracy(%)	90.50	93.75	83.0	88.50

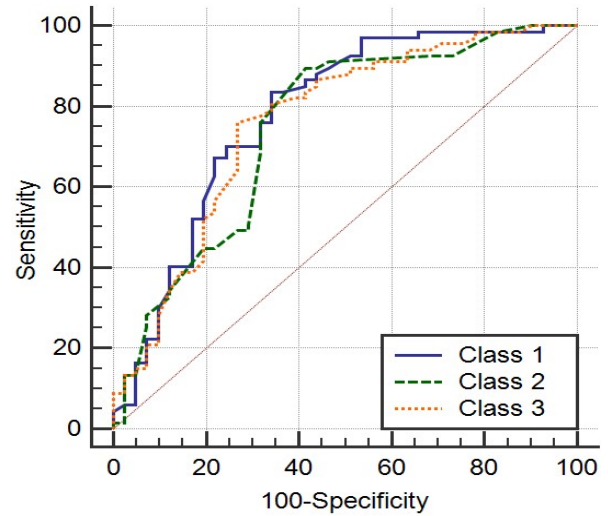


Figure 7. Result of analysis ROC for classification of road defect in Irkutsk city

	Road defect classification of Road defect in Portugal			
	Random Forest		Boosting (GBTs)	
	number of tree: 50 deep: 2	number of tree: 100 deep: 5	number of tree: 50 deep: 2	number of tree: 100 deep: 5
Time, (s)	1105	1775	1210	1808
Accuracy(%)	90.50	94.0	83.0	86.50

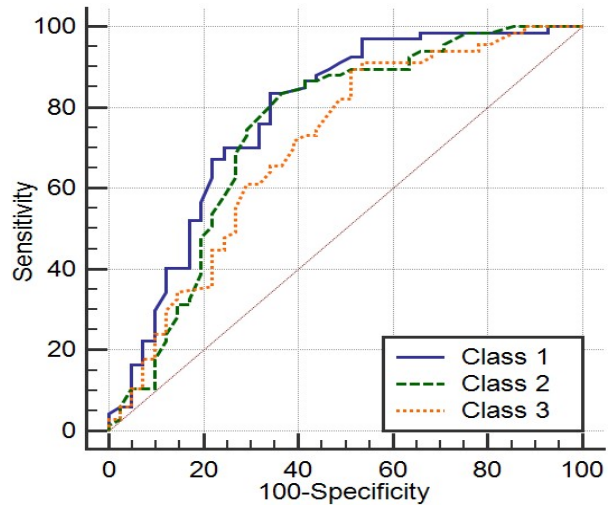


Figure 8. Result of analysis ROC for classification of road defect in Portugal

The result of ROC curve shows Random Forests algorithm in figure 6,7,8 is fast to train, but they often require deep trees. Random Forests do not over fit as easily, but algorithm's test error plateaus. Our experiments show that more trees are always better with diminishing returns. Deeper trees are almost always better subject to requiring more trees for similar performance. The above two points are directly a result of the bias-variance trade off. Deeper trees reduce the bias; more trees reduce the variance. There are several ways to control how deep our trees are (limit the maximum depth, limit the number of nodes, limit the number of objects required to split, stop splitting if the split does not sufficiently improve the fit, ...). Most of the time, it is recommended to prune (limit the depth of) the trees if we are dealing with noisy data. Finally, we can use our fully developed trees to compute performance of shorter trees as these are a 'subset' of the fully developed ones

3. Conclusion

The objective of the paper is to construct a ROC curve to evaluate the effectiveness of the method of automatically classifying road surface defects based on the Random Forest algorithm. The article details the steps of the proposed algorithm, performed experiments to prove the correctness of our approach. We run experiments using three datasets of Portugal, Russia, and Viet Nam. Experiments were performed and then evaluated the results obtained between the original Random Forest program and GBTs method. The experimental data show that the proposed method

allows the Random Forest algorithm work faster, more stable and the results are more accurate. The authors are thankful to the attention and guidance of Professor D. N. Sidorov.

References

- Bouman, A. C., Sauer, K., & Saquib, S. (1995). Markov random fields and stochastic image models, IEEE International Conference on Image Processing, 74(4), 532 - 551.
- Boykov, V., & Zabih, R. (2001). Fast approximate energy minimization via Graph Cuts, IEEE PAMI, 23(11), 1222-1239.
- Brbic, M., & Zarko, I. P. (2011). Tuning machine learning algorithms for content-based movie recommendation, Intelligent Decision Technologies, 9(3), 233-242.
- Breiman, L. (2001). Random forests, Machine learning, 45(1), 5-32
- Chen, H., & Miyojim M. (2011). Automatic pavement distress detection system, Journal of information Sciences, 108, 219-240.
- Cheng, H. D., Jiang, X. H., & Glazier, C. (2001). Novel Approach to Pavement Cracking Detection Based on Neural Network, Transportation Research Board, 1764, 119-127.
- Delagnes, P., & Barba, D. (1995). A Markov Random Field for rectilinear structure extraction in pavement distress image analysis, Volume 1, pp. 446.
- Kolmogorov, V., & Zabih, R. (2001). Computing visual correspondence with occlusions via graph cuts, In International Conference on Computer Vision, 2, 508–515.
- Lee, B. J. (2003). A Robust Position Invariant Artificial Neural Network for Digital Pavement Crack Analysis. Technical Report TRB2003-000996. <http://www.ltrc.lsu.edu>.
- Lempert, A., Sidorov, D. N., Zhukov, A. V., & Nguyen, G. L. (2016). A Combined Work Optimization Technology under Resource Constraints with an Application to Road Repair, Automation and Remote Control (Springer), 77(11), 1883-1893.
- Nguyen, H. T., Nguyen, L. T., Sidorov, D. N., Dreglea, A. I. (2018). Machine learning algorithms application to road defects classification, Intelligent Decision Technologies, 12(1), 59-66.
- Nguyen, H. T., & Nguyen, L. T., & Sidorov, D. N. (2016). A Robust Approach for Defects Road Pavement Detection and Classification, Journal of Computational and Engineering Mathematics, 3(3), 40-52.
- Nguyen, H. T., Nguyen, L. T., & Zhukov, A. (2016). On Road Defects Detection and Classification, Supplementary Proceedings of the 5th International Conference on Analysis of Images, Social Networks and Text (AIST 2016). CEUR Workshop Proceeding, 1710, 266- 278.
- Sidorov, D. N., Wong, S. W., Vasilyev, I., & Salerno, S. (2008). Automatic Defects Classification with p-median Clustering Technique, Proc. of 10th Intl Conf. on Control, Automation, Robotics and Vision (ICARCV), 775-780.
- Zhang, D. Q., Qu, S. R., Li, W. B., & He, L. (2009). Image Enhancement Algorithm on Ridgelet Domain in Detection of Road Cracks, China Journal of Highway and Transport, 22(2), 26-31.
- Zweig, M. H., Campbell, G. (1993). Receiver-operating characteristic (ROC) plots: a fundamental evaluation tool in clinical medicine, 39, 561-77.



Huong Thu Nguyen (b. March 03, 1988) received her Engineer in Informatics (2011) from Information and Communication Technology University, Thai Nguyen, Vietnam. Now she is PhD Student in Department of Information Technology, Institute of High Technology, Irkutsk National Research Technical University, Russia. She is a junior researcher at Baikal School of BRICS, Irkutsk National Research Technical University, Russia. Her current research interests in Computer Vision, Machine Learning, Image Processing. She has (co-) authored 15 papers, 6 conferences participation.



Long The Nguyen (b. March 13, 1988) received his Engineer in Informatics (2013) from Irkutsk National Research Technical University. Now he is Research fellow in Department of Information Technology, Institute of High Technology, Irkutsk National Research Technical University, Russia. His current research interests in Computer Vision, Machine Learning, Image Processing. He has (co-) authored 18 papers, 6 conferences participation.