UDC 004.932

SEGMENTATION OF CORROSION DAMAGE IMAGES WITH UNKNOWN BACKGROUND BY ENERGY MINIMIZATION

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The problem of rusted areas segmentation on painted constructions is considered. The rust percentage on the coatings can be computed using digital image processing methods. Segmentation method by energy minimization using graph cut is applied. The results demonstrate that the proposed approach can be effectively used for rust segmentation.

Keywords: *image processing, segmentation, rust, graph cuts*.

СЕГМЕНТАЦІЯ ЗОБРАЖЕНЬ КОРОЗІЙНИХ ПОШКОДЖЕНЬ НА НЕВІДОМОМУ ФОНІ МЕТОДОМ МІНІМІЗАЦІЇ ЕНЕРГІЇ

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Розглянуто задачу сегментації кородованих ділянок поверхонь на фарбованих конструкціях. Відсоток іржавіння на покриттях обчислено методами обробки цифрових зображень. Застосовано метод сегментації за допомогою мінімізації енергії на основі розрізу графа. Виявлено, що пропонований підхід ефективний для сегментації іржі.

Ключові слова: *обробка зображень, сегментація, розріз графів.*

A wide range of image processing techniques has been recently used for the segmentation of rusted areas on protective coatings.

Use of a digital camera allows to obtain images of damaged protective coatings of hard-to-reach objects, such as metal surfaces of tanks, pipelines of refineries, bridges. Computerized systems for localization and evaluation of damage coatings are widely used to determine deterioration and roadworthiness of the object of increased danger. It is a fast and cost effective way in comparison with engineer inspection.

Methods for automated evaluation of corrosion on digital image of metal surfaces are based on color, wavelet and texture feature extraction for processing of damaged surfaces [1]. At the same time neural networks, fuzzy logic, classification using support vector machine [2] were used to solve such problems.

Color and texture features are used for rust segmentation on different background colors [3]. Fourier transform was used to minimize of the impact of non-uniform illumination and increase the recognition accuracy. The texture mathematical models are analyzed in [4]. The statistical descriptors are used to estimate the sensitivity of results. Gray-scale co-occurrence matrix is used in the method for NDT inspection of metal surfaces [5]. Wavelet transform and color relevant features are used for automatic detection of damaged coatings and analysis of quantitative assessment methods [6].

Authors of [7] affirm that two- or three-group clustering might not properly reflect the rust intensity or rusting severity on a rust image. They propose to apply the artificial-neural-network-based rust intensity recognition approach. It integrates the root-mean-square standard deviation and artificial neural network to cluster a rust image based on its rust intensity or rusting severity. Together with a pre-defined rust color spectrum, it is able to perform human-visual-perception – like rust intensity recognition and screen out background noises.

In paper [8] authors compare standard computer vision techniques with Deep Learning models and show that that the Deep Learning model performs better in a real case scenario.

Researcher in [9] aimed to develop an application on smartphone, which could enhance the efficiency and reduce the equipment costs for bridge engineers to do regular test and maintenance. They used Canny edge detection operator and mathematical morphology.

To improve the detection accuracy of the rusted areas on steel bridges, Liao and Lee [10] proposed a digital image recognition algorithm that consisted of three different detection techniques: K-means method in the H layer in the HSI color space, the double-center-double-radius (DCDR) algorithm in the RGB color space and DCDR in the HSI color space.

Authors in [11] also used HSI color space. Then J48 decision tree algorithm was applied for classification of the rust area. They achieved a success rate of 97.48% in the determination of the areas to be blasted.

An evaluation of fractal dimensions of corrosive images that represented two-dimensional and three-dimensional morphology of the corrosion properties of the damaged surface was proposed in [12].

The development of the methods and intelligent systems for protective coatings damage inspection that will reduce the risks to human life and minimize economic losses during facilities service is an important task.

This paper is organized as follows. Markov random field modelling and energy minimization are briefly described in Section II. Then statistical model for pixel color based on Gaussian mixture is described in Section III. The proposed approach is presented in Section IV. Experimental results are summarized in Section V.

Our goal is to segment all pixels of the input image of rusted material in two sets. All pixels that are considered to depict rusted areas belong to one set and all the non-rusted areas belong to another set.

One of the well-known approaches to image segmentation is energy minimization technique. This paper deals with probabilistic approach to image segmentation. In particular Markov random field (MRF) is chosen as powerful and flexible probabilistic model for such purposes.

X is said to be MRF with respect to neighborhood system $N = \{N_s, s \in S\}$ if the following conditions are satisfied:

1) $P(X = x) \geq 0 \quad \forall x \in \Omega_X$,

where Ω_X is the set of all possible labelings x on S;

2) $P(x_s \mid x_{\Omega_X - s}) = P(x_s \mid x_{N_s})$,

where $S = \{s = (i, j) \mid 1 \leq i \leq H, 1 \leq j \leq W\}$ is the set of image lattice sites and H, W are image height and width respectively.

More formally, let y be a set of image pixel observations, x – a set of labels corresponding to each image pixel. The image segmentation consists in finding such x that maximizes $P(x \mid y)$, where P measures the probability on the set of all possible labelings, given the observation x.

$$x^* = \arg\max_x P(x \mid y) = \arg\max_x \frac{P(y \mid x)P(x)}{P(y)}. \tag{1}$$

Assume that $P(y)$ is a constant, maximization of (1) is equivalent to minimizing the following

$$x^* = \arg\min_x \left(-\log(P(y \mid x) - \log(P(x))\right), \tag{2}$$

Rewrite (2) in terms of energy minimization as follows

$$E = E_{\text{data}}(x) + E_{\text{smoothness}}(x) = -\log\left(P(y \mid x)\right) - \log\left(P(x)\right), \tag{3}$$

where $-\log\left(P(y \mid x)\right)$ is a data term that measures correspondence of image data with the given model and $-\log\left(P(x)\right)$ is a smoothness term and it corresponds to homogeneity in final segmentation map.

Hammersley–Clifford theorem states that random field X is Gibbs random field

$$P(X = x) = \frac{1}{Z}\exp\left[-\frac{1}{T}E(x)\right], \tag{4}$$

with respect to its neighborhood system N if X is a MRF with respect to its neighborhood N, where Z is normalization constant; T is a temperature parameter; $E(x)$ is an energy function.

Minimization of energy (3) has a number of widely used solutions like ICM [13], simulated annealing [14], and much more efficient graph cuts [15] and Loopy Belief Propagation [16] etc.

Modeling pixel features probability distribution. Computation of data term in (3) requires conditional probability $P(y \mid x)$ estimation. The shape of $P(y \mid x)$ depends on the ground truth data and its accuracy is very important for segmentation process. In this paper the Gaussian mixture model (GMM) was used for $P(y \mid x)$ estimation.

The GMM is a probabilistic model developed to model complex probability distributions of random variable Y by mixtures of Gaussians. Probability density of Y given model parameters θ can be written in terms of GMM as follows:

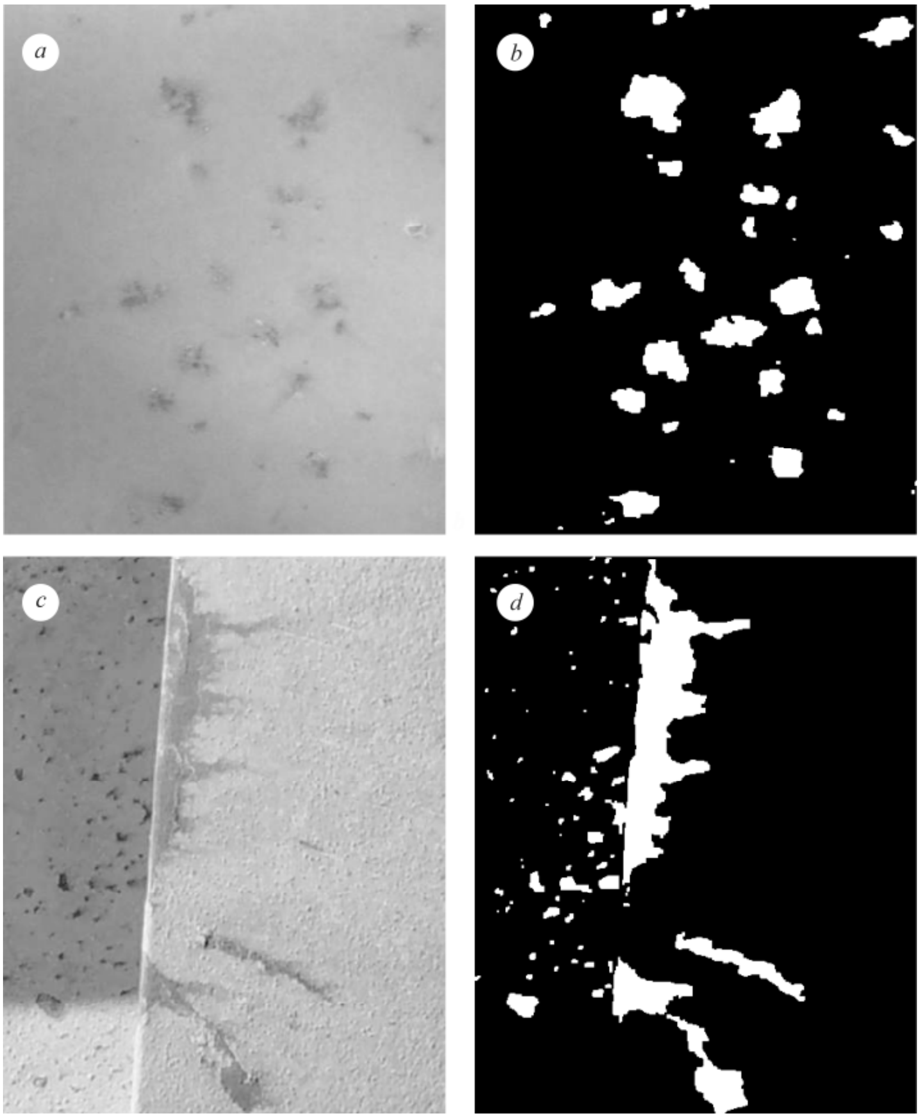
$$p(y_i \mid \theta) = \sum_{k=1}^{K} r_k\, p(y_i \mid \mu_k, c_k), \tag{5}$$

where $\theta = \left(\{r_k\}_{k=1}^{K}, \{\mu_k\}_{k=1}^{K}, \{c_k\}_{k=1}^{K}\right)$, μ_k, c_k and r_k are the mean, covariance matrix and probability that pixel belongs to subclass k respectively; K is the number of mixture components and $p(y_i \mid \mu_k, c_k) = \frac{1}{\sqrt{2\pi c_k{}^2}}\exp\left(-\frac{(y_i - \mu_k)^2}{2c_k{}^2}\right)$ for $i \in S$. Parameters of the model are estimated by maximum likelihood (ML):

$$\hat{\theta}_{ML} = \arg\max_{\theta} \log P(y \mid \theta), \tag{6}$$

where $P(y \mid \theta) = \prod_{i} p(y_i \mid \theta)$.

The problem of computer aided rust images processing is a particularly important task in inspection of large engineering constructions and elements of infrastructures like bridges, oil tanks, electric power transmission lines etc. Rust is an iron oxide formed by reaction of iron and oxygen in the presence of water or air moisture. To construct statistical model of rusted areas and uncorrupted areas of the inspected objects the ground truth data should be provided. For a particular object of inspection we can easily construct such a model giving the images priory labeled by the expert. But in case of development of computer system for inspection the task becomes more difficult. The problem is that color domain for rust is more or less constant because of the nature of its material (iron oxide). But background highly depends on the inspected object and its protective coating, so the color model for it is much more complex and in general priory unknown.



Segmentation results of rusted construction elements: *a*, *c* – images of painted surface with rust; *b*, *d* – results of Graph Cut segmentation with unknown background estimation.

So, for practical applications a method for background statistical model estimation without any prior knowledge is required. For this purpose in this work we used the following approach for background estimation. Based on model (3) for rust region, to each pixel x_i of an input image a probability p_i that belongs to damaged area is assigned. Then the threshold T is applied to each p_i to determine whether it belongs to background. Pixel x_i is assigned to the background area if it satisfies the condition $p_i < T$. Based on the set of background pixels $X_{bg}(x_i \mid p_i < T)$ the model (3) for background is estimated.

Finally, both foreground and background models minimization of (3) is performed by graph cuts algorithm [15].

All described algorithms and methods were implemented in Python 2.7 as a part of automatized system for rust damage inspection on the surface of engineering constructions. The presented results are obtained for RGB as a color model for pixel features. Both GMM for background and foreground contain five components.

The proposed model was tested on real images of rusted elements of engineering constructions (see Figure *a*, *c*). Results of rust segmentation are shown in Figure *b*, *d*.

As it can be seen that even with missing prior information on the background, the model for it can be estimated with the proposed approach based on the information about foreground. Constructed in the proposed way segmentation algorithm lacks some segmentation accuracy around the edges of the rusted area. It is explained by not precise enough background model compared to the one built with ground truth data. Nevertheless the proposed approach provided acceptable results of rusted areas segmentation.

Development of computer aided systems for rust inspection of engineering constructions demands the construction of accurate statistical models for rust and background. Statistical model for rust suitable for a wide range of construction materials can be easily built based upon priory available data. In contrast to the rust model, the background model is much more complicated because of much less predictable background appearance and its dependence on the inspected object and protective coating. That is why the development of the unknown background model estimation approach is required. The proposed in this paper approach has shown its effectiveness. Based on available foreground model it allows us to estimate the model for priory unknown background for a given input image. Obtained results proved the validity of the proposed approach and its possible use in a wide range of image segmentation applications.

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Received 17.10.2018