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METAL FRACTURE IMAGE ANALYSIS FOR AUTOMATED STRENGTH MEASUREMENT BY THE VISCOSITY AREA SHARE

Egor O. Volkov, Vasiliy M. Oskolkov, Olga S. Salnikova, Evgeny V. Ershov

Department of Mathematic Software of Computing Machines
Cherepovets State University, Cherepovets, 5 Lunacharsky St.
Russia, vmoskolkov@chsu.ru (V.O.); egortech@live.ru (E.V.),
ossalnikova@chsu.ru (O.S.); evershov@chsu.ru (E.E.).

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ABSTRACT

The article proposes an approach to the automated detection of the viscosity area share in a metal fracture by means of using its image, which can be used in various lighting and does not require special personnel training. The viscosity area share is determined by means of using a set of segmentation neural networks, which includes the U-NET, which finds the objects under test in the image, which are metal fractures, and the Mask R-CNN, which finds the brittle fracture areas. Neural networks were trained on a dataset provided by the customer. Experimental verification of the proposed solution confirmed the possibility of automating the process of measuring the strength properties of the metal from fracture images with an accuracy of at least 85 %.

Keywords: viscosity area, brittle area, metal fracture, image analysis, neural network, quality control.

INTRODUCTION

The quality of the metal used in the production of high-pressure pipes is subject to special strength requirements. Tests for the mechanical stability of the metal include impact bending where the nature of the surface of the resulting fracture is assessed to identify the brittle and viscosity areas, the ratio of which allows us to conclude how resistant the metal will be to mechanical overloads.

Currently, the assessment of metal fractures for the ratio of brittle and viscosity areas is carried out visually by experts at a mechanical testing laboratory, which implies a certain degree of a subjective error in the results obtained.

Brittle fracture occurs by tearing or chipping when the fracture plane is perpendicular to normal stresses. When subjected to normal stresses, an elastic deformation of the crystal lattice occurs, and after reaching the limit degree of its distortion, a successive rupture of interatomic bonds occurs with the separation of one atomic plane from another, i.e., the destruction of the metal. An example of ductile fracture of a pipeline is shown in Fig. 1.

In order to determine the viscosity and brittle fracture areas, drop-weight tests are carried out in accordance with the foreign standard API RP 5L3: Drop-Weight Tear Tests on Line Pipe and the Russian GOST 30456-2021 [1]. Metal products. Steel pipes, flat products and coiled products. Drop-Weight Impact Bending Test [2]. Such tests are done in the mechanical testing laboratory of metallurgical plants. A blank for making specimens from a pipe is cut out across the longitudinal axis; if the specimen is made from the sheet, then it is cut out across the axis of the rolled sheet in the first quarter of the sheet width. Two specimens are made for one test temperature from the selected specimens [2].

Before testing, the specimens are placed in a thermostat bath, in which a mixture of liquid nitrogen or solid carbon dioxide with ethyl alcohol or liquid nitrogen vapor is used as a coolant, where they are steadily cooled to a temperature between -20˚C and -40˚C [2].

Fig. 1. An example of ductile fracture of a pipeline.

The percentage of the viscosity area in the fracture is equal to 100 % minus the percentage of the brittle area.

The ductile fracture surface is matte and dull grey, has a fiber texture and is usually angled to the side surface of the specimen. The brittle fracture surface looks crystalline and shiny, with no visible signs of plastic deformation. Brittle fracture areas are usually adjacent to the notch base and the impact site [2].

Fig. 2 shows an image of two parts of a fracture, the viscosity area of which was measured at 70 % and 75 %, respectively, while the brittle area is circled in red. According to the standard, in determining the viscosity area, an error of ± 3 % and rounding up to 5 % are allowed [2].

The development of automated control tools would improve the efficiency of assessing the quality of the metal.

The aim of the study is to increase the reliability of the assessment of the viscosity area share in metal fractures during automated control.

The percentage of agreement of the results of automatic processing by the proposed algorithm with the initial opinion of experts at mechanical testing laboratory should be at least 85 %.

Obtaining the result of the assessment should not take more than 2 s on the recommended hardware and does not require a complex setup and calibration procedure.

The scientific novelty lies in the development of a new approach to the automated detection of the viscosity area shared in a metal fracture by its image, which can be used in various lighting and does not require special personnel training.

The hypothesis of the study is the possibility of creating an algorithm based on image processing methods and machine learning which can automatically process the results of impact bending tests with an accuracy of at least 85 %.

Fig. 2. An example of a metal fracture.

Numerous research use computer vision systems to resolve production metallurgy problem such as quality prediction [3], purpose technological process control [4], control specific parameters [5]. Surface defect detection technologies for some typical metal planar material products of steel, aluminum, copper plates and strips are used [6]. Many researchers used different machine vision methods to detect product quality defects: improved SHGA-PSO algorithm applied for the detection of gear defects obtained in powder metallurgy [7], convolutional variation auto-encoder (CVAE) for surface defect inspection system in real-time mode [8], the optical-electronic defect inspection system, using structured lighting for uneven defects recognition and detection of color change due to surface noise [9], method of neural network training for surface defect detection in real time taking into consideration neurons selectiveness and limited volume of visual information [10], algorithm of machine vision for slab notches detection using The Garbor filter [11], Support Vector Method (SVM) and Multiple Kernel Learning (MKL) for real-time steel inspection system [12], threshold segmentation algorithm for coefficient of variation to detect defects which are cracks, holes, scratches, oil spots [13]. There were no notable technical solutions identified in metal fracture inspection automation during the tests; the assessment is performed visually.

Fig.3. Image supplied to the neural network input.

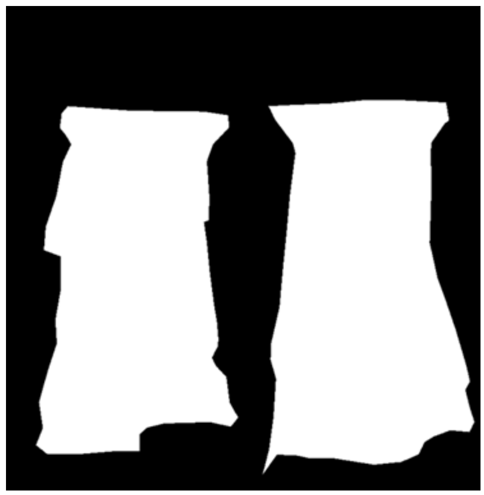

Fig. 4. Mask image acting as a feature vector.

EXPERIMENTAL

Method

To solve the task of automated inspection of the metal fractures viscosity area share, there is suggested an algorithm implementing the methods of image processing and machine learning the basis of which comprises the ensemble of U-Net и Mask R-CNN neural networks [14, 15]. The main operational stages are as follows:

1. Obtaining metal fracture digital images without the use of special lighting methods by conventional means: photo camera.

2. Initial image fracture segmentation: the convolutional U-Net neural network is used to search for the image area showing the fracture; the training set is a set of original images (Fig. 3) and a mask (Fig. 4), on which the fracture is highlighted in white [14].
The network is trained by stochastic gradient descent based on input images and their corresponding segmentation maps. Due to convolutions, the output image is smaller than the input one by a constant border width, so boundary features are lost.

The U-Net network can work with images of any size but given the proportions of the processed images and acceptable visibility of metal fractures, a fixed input image size is 512 × 256.

3. Brittle-ductile fracture areas classification. The Mask R-CNN neural network is used, with three classes assigned for its training: the first class is the fracture area to be analysed, the second is the area with absolute brittleness, which is usually an inverse fracture, and the third class is “triangles”, which are the alternating brittle-ductile areas [15].

The sequence of the Mask R-CNN neural network image processing is as follows:

1) image normalization: the value of the “average” pixel brightness is deduced; it was calculated on the basis of the pixel brightness average value of all images from the training set, from all pixels brightness of the input image;

2) image scaling: firstly, the least of the image sides is taken, which is scaled to the target size; the other side changes in proportion to the lesser side changes to keep the image proportions. However, if resulting from scaling the bigger side exceeds the established maximum size, its dimensions will change to maximum possible ones while the lesser side will change proportionally;

3) indention addition to the image: indentions are added on the right and from below the image, taking into consideration the point that the coordinate system starts from the left upper corner which allows not to convert the resultant co-ordinates any further; indention addition is necessary for each side dimensions to be a

multiple of 32 pixels;

4) decoding of limiting rectangles and the filtering of the limiting rectangles transcending the limits of the image;

5) deletion of the areas intersecting for more than the established threshold;

6) unification of the results as the previous stages are carried out separately for each feature map;

7) forming the results of the brittle fracture area detection.

An example of the image with highlighted brittle areas is shown in Fig. 5.

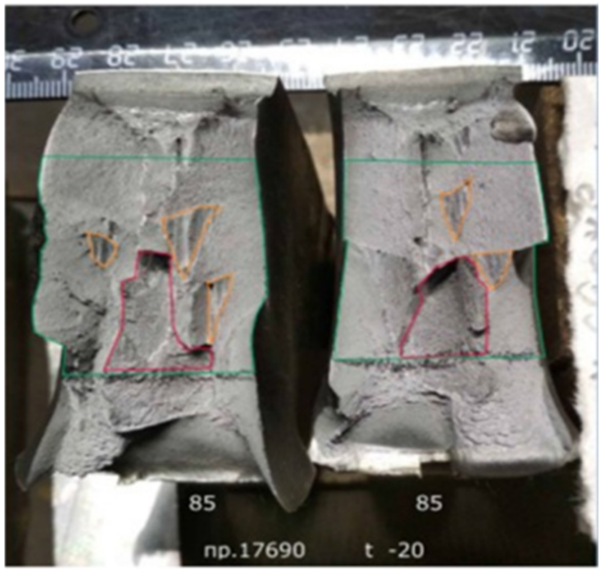

Fig. 5. Results of brittleness detection by the Mask R-CNN neural network.

RESULTS AND DISCUSSION

The peculiarities of the Mask R-CNN neural network training

Before being supplied for training, images are scaled to one size of 1024×1024, while maintaining the aspect ratio, to perform batch processing of frames.

During the training of the neural network, five components can be distinguished, which make up the resulting loss function:

- rpn_class_loss, which shows how well the network separates the background from the objects to be segmented;
- rpn_bbox_loss, which shows how well the network localizes the position of objects;
- mrcnn_bbox_loss, which shows how well the network determines the position of the detected objects;
- mrcnn_class_loss, which shows how well the network classifies the detected objects;
- mrcnn_mask_loss, which shows how well the network segments the detected objects, that is, how well the mask is formed.

The resulting loss is calculated as the sum of these components. These network learning quality metrics are

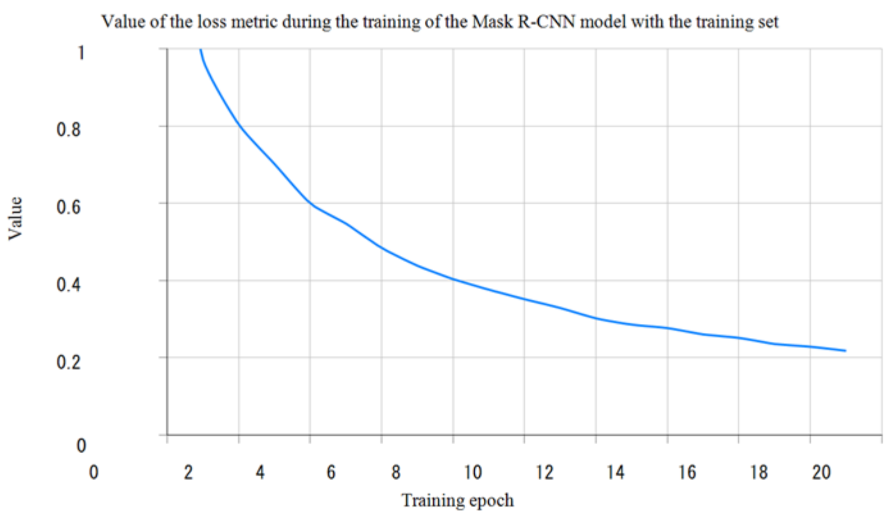

Fig. 6. Value of the loss metric during the training of the Mask R-CNN model with the training set.

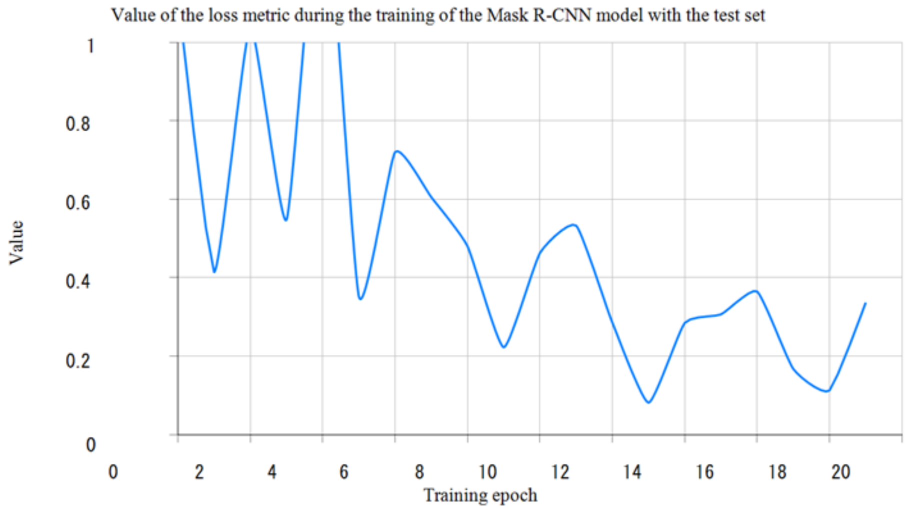

Fig. 7. Value of the loss metric during the training of the Mask R-CNN model with the test set.

calculated for both the training set and the test set. Fig. 6 shows the value of the aggregated metric of the loss function of the Mask R-CNN network with the training set, and Fig. 7 on the test set.

In Fig. 6, the loss function on the training set gradually decreases with each new training epoch, while on the test set (Fig. 7) its value does not change monotonously, with the minimum loss value (0.08) reached at epoch 15 and the value of this metric also minimal at epoch 20 (0.11). Weights from this epoch are preferable, since the value of the metric is minimal on the training set.

The WPF (Windows Presentation Foundation) library was used to develop the graphical user interface. It is a type of an interface with free navigation where the user can freely select the necessary operations, interact with it using various buttons and other controls to perform a particular task.

To determine the percentage of the viscosity area 577 photographs were obtained made by the mechanical testing laboratory personnel where impact bending tests are done, and viscosity value is analysed. The test set photographs were selected so that they could cover different situations met on the presented photographs.

To find a metal fracture in the image, the U-NET neural network was trained on the generated set.

The accuracy of the model is quite high (95 %), although there are gaps in the resulting mask and false detections occur from time to time, which can be eliminated in post-processing.

The Mask R-CNN neural network solved the problem of finding a control area where the brittle area was to be determined. The neural network tends to highlight smaller areas than those that were marked out, especially in the areas of brittleness-ductility alternation. It is quite difficult to determine visually how accurately the network worked due to the lack of clear boundaries of brittle areas on the fracture surface. The accuracy of detection and classification of brittle areas averaged 98 % for all classes.

The results with the test set in 87 % of cases agree with the expert assessment, which corresponds to the requirements stated above.

CONCLUSIONS

The proposed technical solution makes it possible to automate the determination of the viscosity area, increase the objectivity of the results obtained, and reduce the time spent by the mechanical testing laboratory personnel.

Visual assessment of metal fractures for the ratio of brittle and viscosity areas requires mechanical testing laboratory personnel to have perfect knowledge of GOST 30456-2021 and be skilful to assess fractures visually. A new approach to the automated detection of the viscosity area share in a metal fracture by its image allows working in various lighting conditions and does not require special personnel training.

Thus, the reliability of the assessment of the viscosity area share in metal fractures is gained during automated control.

As for the application prospects of the suggested approach one should mention the use at high-loaded parts production in mechanical engineering, construction and transport sphere.

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