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Software for roof defects recognition on aerial photographs

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Abstract. The article presents information on software for roof defects recognition on aerial photographs, made with air drones. An areal image segmentation mechanism is described. It allows detecting roof defects – unsmoothness that causes water stagnation after rain. It is shown that HSV-transformation approach allows quick detection of stagnation areas, their size and perimeters, but is sensitive to shadows and changes of the roofing-types. Deep Fully Convolutional Network software solution eliminates this drawback. The tested data set consists of the roofing photos with defects and binary masks for them. FCN approach gave acceptable results of image segmentation in Dice metric average value. This software can be used in inspection automation of roof conditions in the production sector and housing and utilities infrastructure.

1. Introduction

In modern production sector and housing and utilities infrastructure, it is important to maintain and repair roofing on time, which is destroyed in the course of time by environmental effects. Running services of building and structures are successful and effective in case of periodic wide-spread monitoring of roofing maintenance factor, also based on automated defects detection using innovative methods of receiving, saving and analyzing data. Roofing condition survey, in most cases is complicated by roofing extension, inaccessibility for visual analysis, weather conditions, numerous instrumental measurements, complexity and and labour – consuming nature of data documenting, archivation, processing and dynamic analysis. The introduced method of defectoscopy has high potential if on-the-spot aerophotography followed by continuous network, data processing is used. It allows visual detecting and quantitive accentuation of major findings. Reliable technologies of aerophotodefectoscopy and roofing defects detection are absent nowadays.

Construction defects detection is manual, extremely time-consuming, season-dependent, aperiodic, occasional, cost-ineffective, not-highly professional, purposeless and does not take into account the purpose of the building usage. All these facts do not allow planing or fulfilling cost effective roofing maintenance in order to preserve technical and exploitational roofing qualities.

On–the–spot monitoring can be effective with the use of cameras-equipped air drones. Aerial images received in this way can be further manually analysed or with the help of computer vision.

Nowadays a lot of studies are devoted to areal roofing images segmentation, for example, [1] and [2], or objects fixed on roofs [3]. But their main task is to monitor building or infrasstructure development. Roofing conditions analysis is fulfilled by studying infrared images [4], done with thermal vision cameras allowing estimating heat-loss and activities on their reduction. Roofing areas segmentation at different degree of tilt are described in [5]; this work describes limitations of computer vision methods – necessity to take into account shadows, changes in objects illumination, that requires significant complexity of image recognition algorithms.

It should be noted that existing investigations has not dealt yet with different defects recognition, which appear in the course of time and can be detected on the color orthophotoplan. Detection of unsmoothness that causes water stagnation after rain is delt with in this article.

2. Task statement

The article deals with roofing defects detection algorithms in aeral images and the software is used for this.

The approach used for roofing defects detection – unsmoothness that causes water stagnation, is schematically given in Fig. 1. Color aeral images are done with an air drone – quadrocopter. Then, with the help of recognition software, defective segments are determined. The area and the perimeter of every segment are determined and saved in .xml-files, the file also contains segmentation results in the form of a half-tone image. These data can further be used for repair estimate documents.

Metric Dice is used to estimate the quality of segmentation algorithms as in papers [6] and [7]:

$$Dice = \frac{2\cdot(Y_{GT}, Y_P)+\varepsilon}{(Y_{GT}, Y_{GT})+(Y_P, Y_P)+\varepsilon}. \quad (1)$$

In formula (1), designation (Y_{GT}, Y_P) is a scalar composition of two vectors – vector Y_{GT}, containing “true” image segmentation, given as one-dimensional bulk, and vector Y_P, containing segmentation results done with the help of applied algorithm given as one-dimensional bulk. Every element of bulks in Y_{GT}, and Y_P has value in the range of [0, 1], where 0 is pixel not related with the defect, 1 is pixel related to the roofing defect image. So, the value (Y_{GT}, Y_P) is equal to the area of two areas intersection, (Y_{GT}, Y_{GT},) is equal to the true areas with (Y_P, Y_P) is equal to the defective area determined by algorithms, ε is the value equal to one pixel which is necessary in cases when neither true nor found defective roofing areas are present in the images.

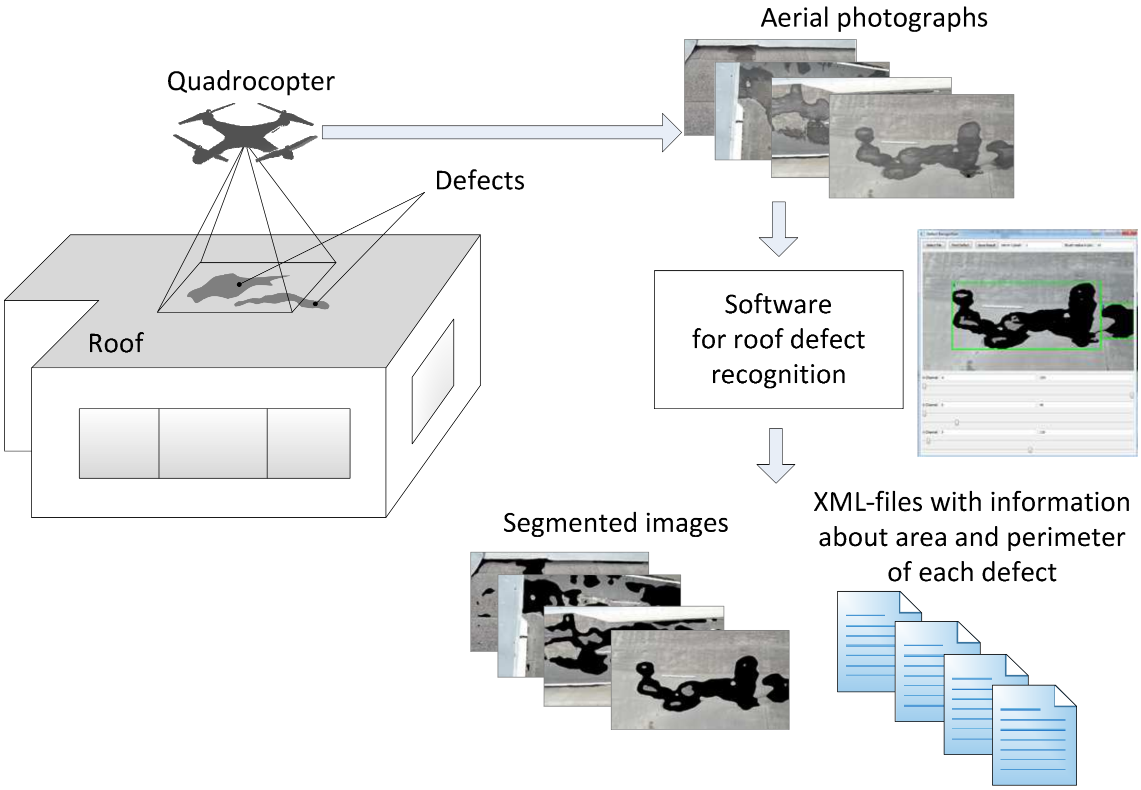

Figure 1. Structure of software for roof defect recognition

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3. Approach on segmentation of image with defects based on HSV-transform

Target defects are hollows, which cause water stagnation after rain, seen on the images as dark spots. The simplest way to determine them is to analyze a binary single-channel image, received by initial transformation of input color image into half-shade image or into HSV-transformation **Ошибка! Источник ссылки не найден.**. In this case, the transformation threshold depends on illumination, roofing surface type.

The suggested defective image segmentation algorithm based on HSV-transformation consists of the following steps.

1. Smoothing the input color image with Gaussian filter to eliminate image noises.

2. Doing HSV-transformation of smoothed input color image with receiving three components: H – hue, S – saturation, V – value.

3. Upper and lower limits choice for every component (H_{min}, H_{max}), (S_{min}, S_{max}) and (V_{min}, V_{max}); and using threshold binarization with receiving single-channel image, whose pixels are equal to 255 (turn white), if corresponding pixels of the input image are in the denoted ranges. All other pixels of the single-channeled image are equal to 0 (turn black).

4. 8-linked areas are sought for in the binarized single-channel image received with the help of two-pass algorithm, described in **Ошибка! Источник ссылки не найден.**.

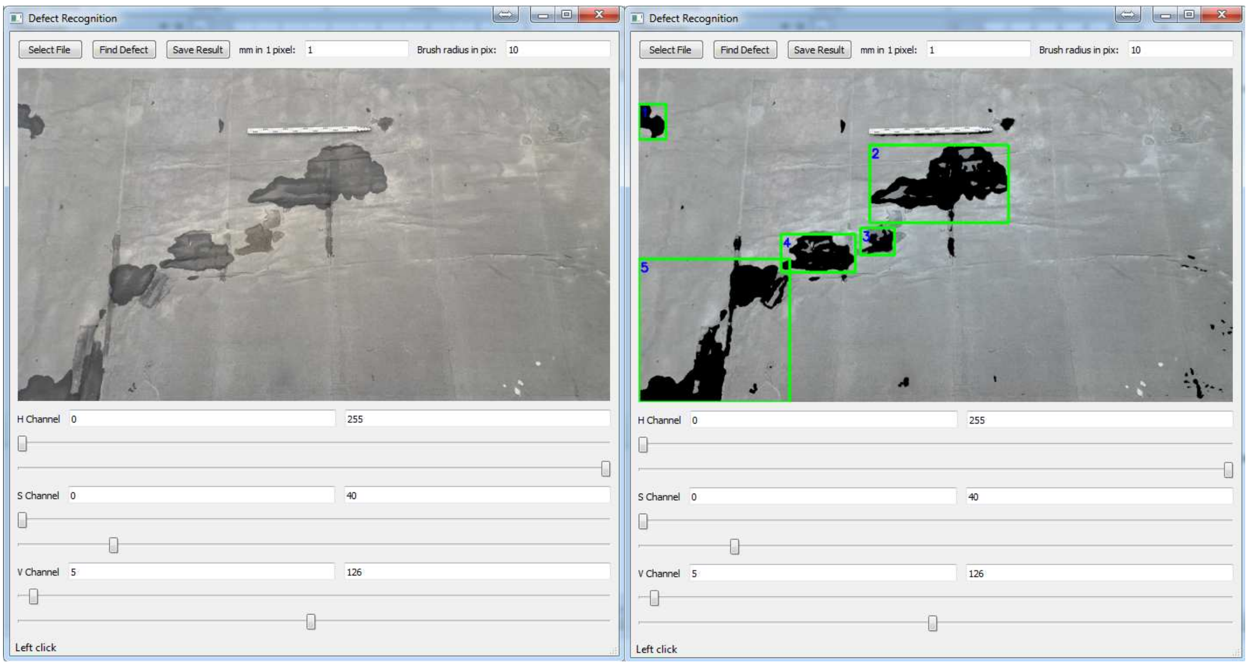
5. Among the connected areas the smallest areas are eliminated (according to the threshold value), the rest of the found areas are considered to be the roofing defects, their area and perimeter are calculated in pixels.

6. According to the scale coefficient, given for each image individually, pixels are converted into area and perimeter of the found areas in square meters and meters respectively.

7. Segmentation results of binarized image are saved in .jpg-file and information about found areas into.xml-files.

The algorithm is fulfilled via cross platform software in the programming language python 3.5; its user’s interface is shown in Fig. 2. This interface allows changing the main parameters of algorithm functioning and showing roofing defects recognition results in the downloaded images.

This algorithm has several drawbacks. Fig. 3 shows that for precise defect detection with HSV-transformation it is necessary to apply different threshold values of upper limit Vmax containing V, which can differ dramatically. Shadows and dark roofings are recognized as defects.



a b

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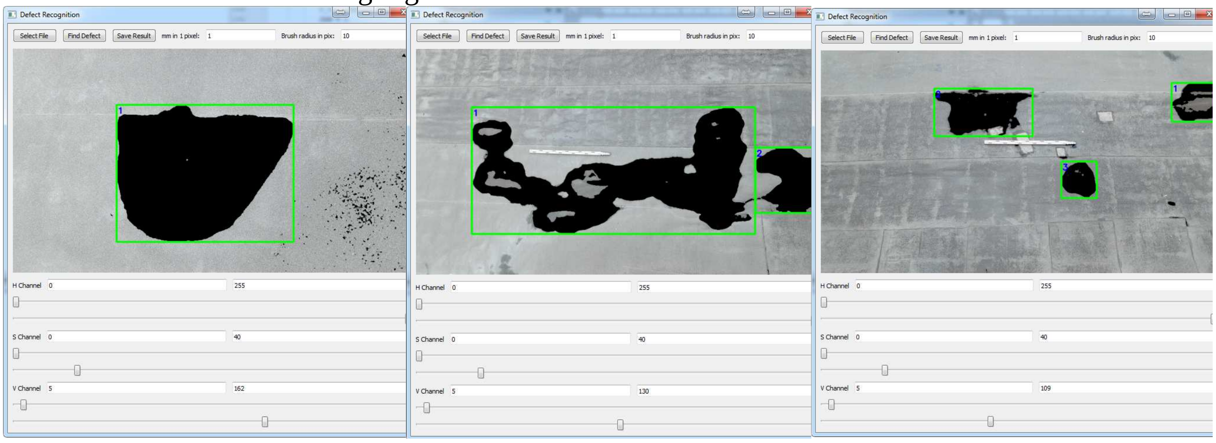
Figure 2. Software for roof defect recognition: a – loaded image, b – recognized defects

To overcome these drawbacks, possibilities of neuron network technologies, which are used in other fields, were learnt deeply [10]. The neuron network for segmentation requires precise dataset for studies, which contains a pair of images (color image, segmented binary image). To prepare such dataset manual editing of binarized image was done at the third step of algorithm, where using the tool “a brush” one can delete wrong segments and add defective areas.



V_{max} = 162 V_{max}=130 V_{max}=109

Figure 3. Usage different threshold of HSV-transform for correct image recognition

4. Segmentation of images with defects based on Deep Fully Convolutional Network

Deep fully convolutional networks allow computerized determining texture peculiarities and other characteristics of image areas that can be used to solve this problem. Choice of network architecture able to read the roofing defects areas in aerial images can be done in the approaches, which are effective in image segmentation on the dataset of marked images PASCAL VOC [11], containing 21 pixels of different types. One of such approaches is training fully convolutional networks (Fully Convolutional Networks, FCN) [12]. For biomedical images segmentation in [13] the convolutional networks are studied, as auto encoder, where additional combinations of input and output layers are added. Three types of convolutional operations base on these architectures [14]:

1) Common convolutional operation with the kernel 3 × 3 in size with strides 1 × 1, which converts the image 4 × 4 in size into feature map 2 × 2 in size.

2) Convolutional operation with the kernel 3 × 3 in size with strides 1 × 1, where the initial image has padding 1 × 1 (one additional pixel on each side of the image), which converts the image 5 × 5 in size into feature map of the same size 5 × 5.

3) Deconvolutional operation, when the image of lesser size, for example, 3 × 3 turns into the image of bigger size 5 × 5. Here, null-terminated strings and columns are added into the initial image (it is such a called unsampling operation with stride 2 × 2), and boundary pixels are added (for example, padding = 1 × 1). The kernel and convolutional string are respectively 3 × 3 and 1 × 1.

Two architectures of deep fully convolutional networks are described in this paper; they contain 13 and 17 convolutional layers, respectively FCN13, shown in figure 4, and FCN17 - shown in figure 5.

For training and checking the applicability of convolutional neuron networks 35 images with marked roofing defects were used, 33 images were selected for training, 2 images were used as valid. The size of each image is 464×825 pixels.

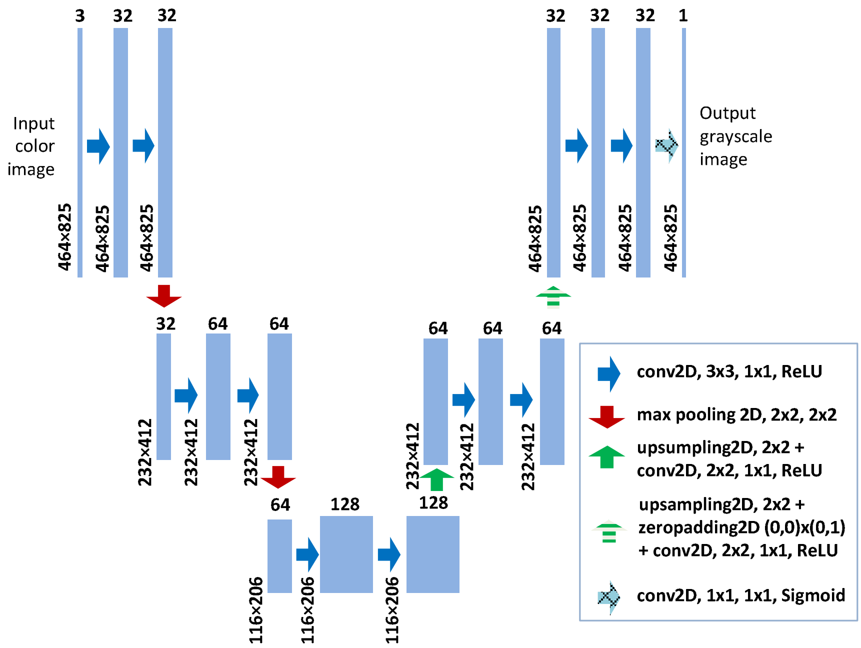


Figure 4. Architecture of deep fully convolutional network for image segmentation with 13 convolutional layers (FCN13)

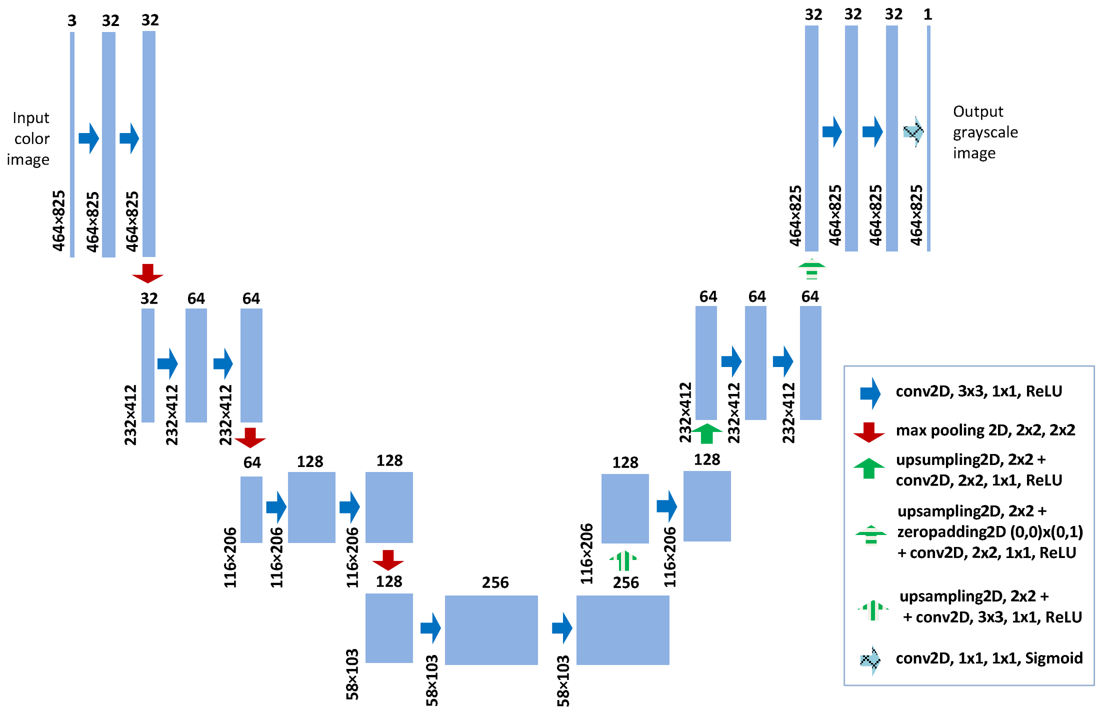


Figure 5. Architecture of deep fully convolutional network for image segmentation with 17 convolutional layers (FCN17)

For training and testing fully convolutional networks for image segmentation, Dice metric described above is used (1). Log loss, whose minimum should be provided by deep fully convolutional networks, has a view:

$$Loss = 1 - Dice. \tag{2}$$

So, during training maximum degree of intersection of found and defective roofing areas is made.

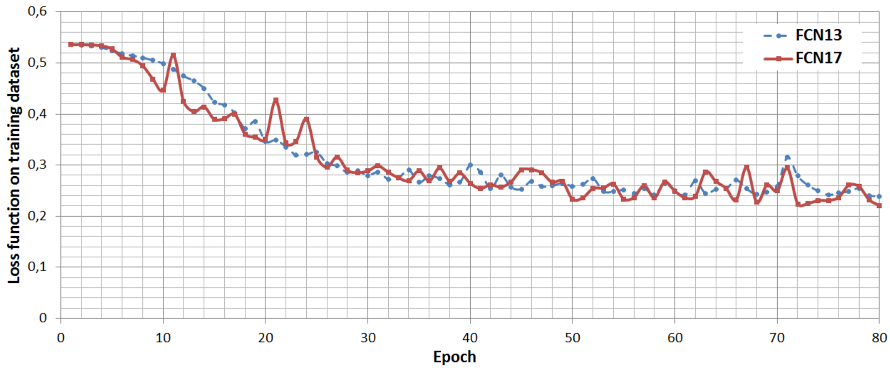
Training of deep fully convolutional networks is done with optimizer Adam [8] with training speed ratio equal to 0.00001.

Fig. 6 shows the results of training of deep fully convolutional networks on 80 epochs. They show that although the amount of training dataset is rather small neuron networks train up to the acceptable quality of segmentation $Dice = 1 - Loss$ for FCN17 reaches about 0.78, for FCN13 – 0.76. These numbers allow using deep fully convolutional networks to solve those problems; examples of segmentation in Fig. 7 prove it.

Weights received on 73 epoch of network FCN17 are chosen for testing, loss function on training dataset is 0,224, and loss function on validation dataset equals 0,021.

However, at the same time, segmentation on some images is not clear (Fig. 8) that proves necessity of further development of network architecture and widening training dataset.

a



b

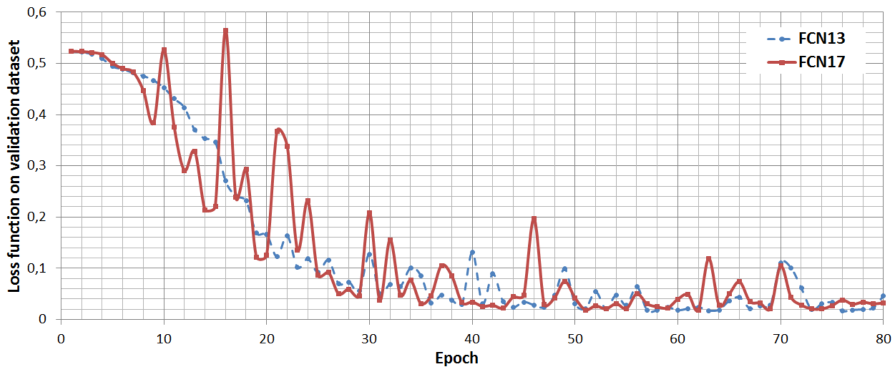
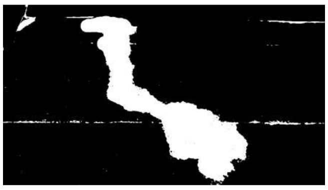


Figure 6. Training of deep fully convolutional networks on 80 epochs:
a – loss function on training dataset, b – loss function on validation dataset

Simulation experiment was conducted with NVidia CUDA technology in 64-bit operational system Windows 7, installed on the computer with the central processing unit Intel Core i-5-4570 (4 cores) 3.2 Gigahertz, RAM 8 Gigabyte and video card NVidia GeForceGTX 960, which has a graphic processor with frequency 1.253 Gigahertz and 1024 graphic cores (Shaders), also 2 Gigabites internal storage DDR5. Deep fully convolutional networks are supported with Keras library [15] for python 3.5 evaluator.

a



b

c

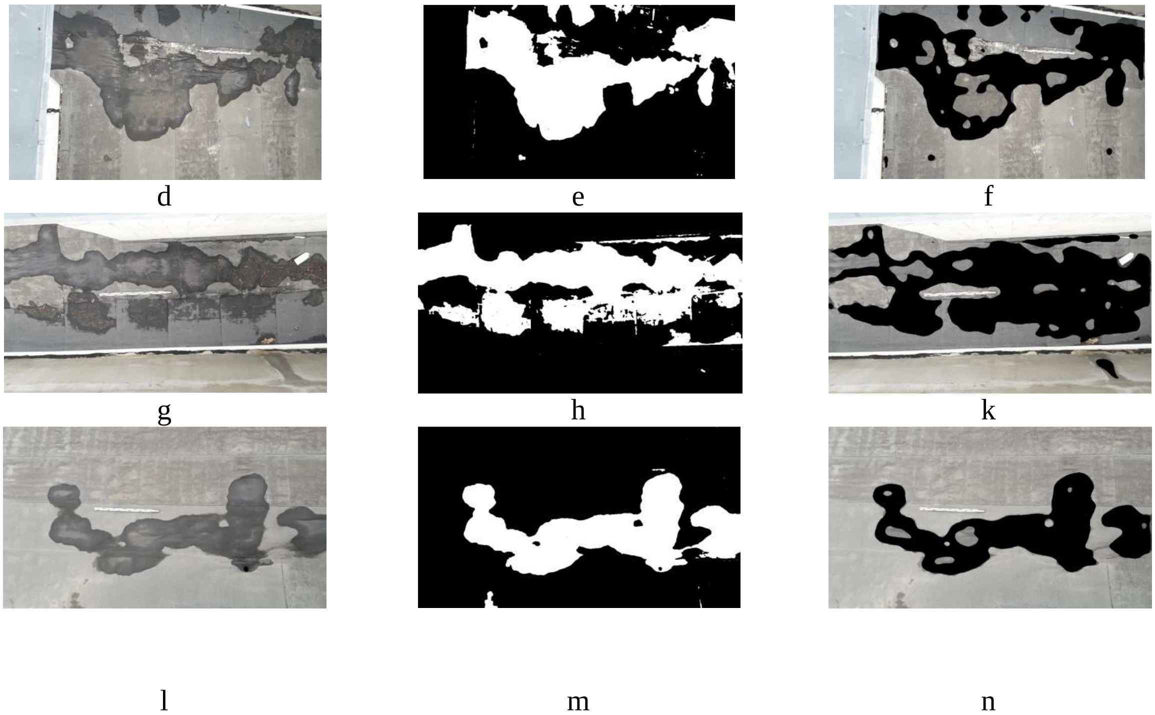


Figure 7. Examples of defect recognition using deep fully convolutional network:
a, d, g, l – source images, b, e, h, m – prepared binary masks, c, f, k, n – results of deep FCN

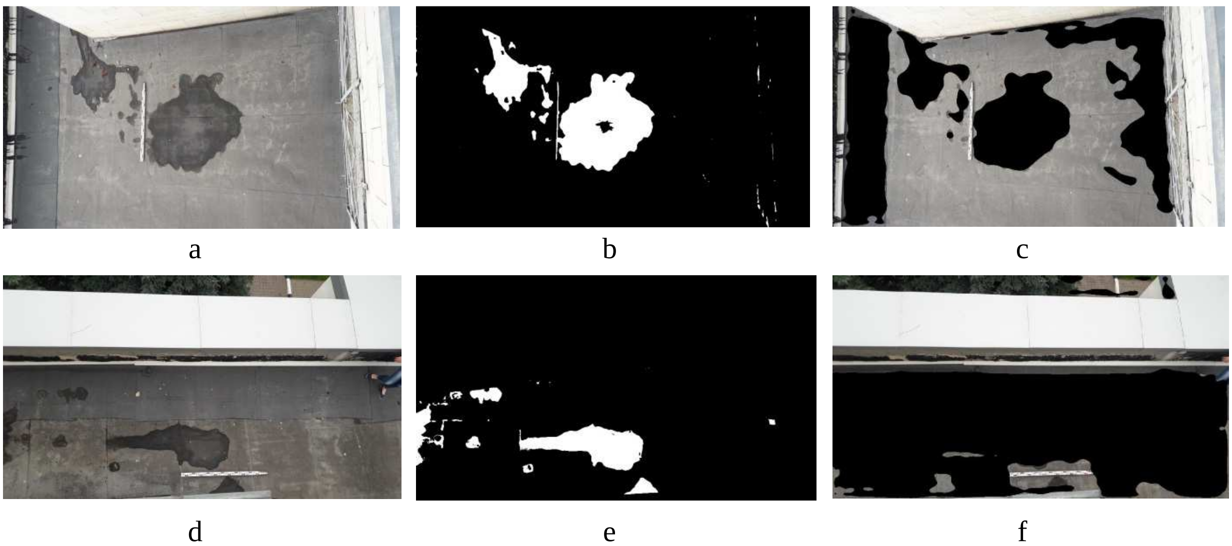


Figure 8. Examples of errors in defect recognition using deep fully convolutional network:
a, d – source images, b, e – prepared binary masks, c, f – results of deep FCN

The total training time for a fully convolutional network on 80 epochs is about 20 minutes (see Table 1), that allows quick change of the architecture and network parameters settings to achieve better segmentation results.

Table 1. Time results of deep fully convolutional network

Network architecture	Training time on 80 epochs, sec	Average time of one image segmentation in testing mode, sec
FCN17	1270.643	0,177 (5,65 fps)
FCN13	1072.485	0,151 (6,62 fps)

Trained network allows detecting roofing defects with aerial images with the speed of 6 images per second, which is acceptable for utilizing in actual applications.

5. Conclusion
Image segmentation algorithms described in this article allow determining defect areas – roof unsmoothness that causes water stagnation after rain, with acceptable quality. Deep fully convolutional networks approach was used as one of the algorithms, which enhances algorithm invariability to shadows and roofing type. This software automates the process of determining roofing defects with aerial images, as well as determining their area and perimeter. It has been tasted on the dataset of defective roofing photos and binary masks prepared for them. The approach based on FCN demonstrated acceptable results of image segmentation made from training dataset and test dataset in the sense of average amount of Dice quality metric. This software can be used in computerized inspection of roof states in the production sector and housing and utilities infrastructure; also to prepare cost estimate documents for repair and maintenance of buildings and structures of different types.

6. Acknowledgments
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