A Deep Learning-Based Approach for Defect Detection and Removing on Archival Photos

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Abstract

Many archival photos are unique, existed only in a single copy. Some of them are damaged due to improper archiving (e.g. affected by direct sunlight, humidity, insects, etc.) or have physical damage resulting in the appearance of cracks, scratches on photographs, non-necessary signs, spots, dust, and so on. This paper proposed a system for detection and removing image defects based on machine learning. The method for detecting damage to an image consists of two main steps: the first step is to use morphological filtering as a pre-processing, the second step is to use the machine learning method, which is necessary to classify pixels that have received a massive response in the preprocessing phase. The second part of the proposed method is based on the use of the adversarial convolutional neural network for the reconstruction of damages detected at the previous stage. The effectiveness of the proposed method in comparison with traditional methods of defects detection and removal was confirmed experimentally.

Introduction

The solution to the problem of automatic detection of defects is widely used in practice in the search for defects in the road surface, the textile industry, as well as in the virtual restoration of archival photo images. Solving the problem that arises when detecting defects allows us to speed up work in this field.

Some reasons for defects (spots, scratches, cracks, etc.) in the images are aging, physical exposure, improper storage or operation. Traditionally, such defects are removed by manual processing which makes difficulties to restore archived photographs.

In work [1] a method based on machine learning for the detection of defects in the image is described. Morphological operations are used for a mask with estimated localization defects, "top and bottom hat" − to detect light and dark cracks. The machine learning method helps to reduce false labeled areas on the preliminary mask with defects. Hue, saturation, and value (HSV) are used as the descriptor. The neural network (MRBF) with a median radial basis function is used for classification pixels on mask obtained after morphological filtering.

In work [2] is used the same method as in [1]. The importance of this work is that it is used the method of filling in damaged areas. To restore damaged areas, use the search for blocks similar to the damaged ones. The sum of squares of differences (SSD) is used as a similarity indicator. If a similar unit was not found, the bad block is filled with average values.

In work [3] morphological operation "top hat" is used for detecting the defects followed by binarization with the automatic selection of the threshold value [4]. The selection of the threshold value depends on the separability of the original image histogram. The idea of the method is to separate the histogram iteratively. Threshold values minimizing the variance are selected within the class which is defined as a weighted sum of the variances of the two

classes. In this work, the author showed that the minimizing of the variance within a class is equivalent to maximizing the variance between the classes.

In [5] it is shown the algorithm consisted of three steps. The first one is the improvement of the contract in a pre-input image. Then it calculates the convolution of the modified image from different directions Gaussian kernels. The second step is to obtain mask defects by applying morphological operations top hats with various sizes of the structure-forming elements. The last step is a pre-defect mask method using K-SVD. The point of this step is to train the algorithm on pre-prepared templates, followed by the classification of areas on the original image. The method to-medium is used for reducing the number of false positives. The handle is a color component, the length, orientation and eccentricity ratio. After all described steps three masks are combined into one by voting

Most image reconstruction methods can be divided into the following groups:
- methods based on the solution of differential equations
- methods based on texture synthesis
- methods based on machine learning

Methods based on the solution of partial differential equations use the information around the damaged region, extending it into the damaged region. In work [6] propose a method for reconstructing the pixel values of images using the classical field dynamics – Navier-Stokes equation. The boundary conditions for image restoration are to match the intensity of the image brightness values at the boundary of the restoration area, as well as the direction of the contour lines.

The most popular methods based on texture synthesis include exemplar-based methods (EBM) [7]. The main idea of the method is to fill the damaged area with blocks from neighboring undamaged areas. Priority in the restoration has areas with sharp differences in brightness, corresponding to various kinds of boundaries and texture elements. Priority reduction occurs when moving away from the boundary between the damaged and undamaged areas.

Machine learning-based methods are currently the most effective in recovering large damaged areas, provided the semantic information is preserved. In work [8], a method for reconstructing damaged areas in an image based on adversary neural networks is proposed. Three convolutional neural networks are used for this: a restoring neural network, a local and a global critical neural network. The main advantage of using such architecture is that it allows restoring areas that are not found in intact areas.

In this paper, we propose a new approach to detection and removing defects on archival photographs. The defect detection method includes two main stages: preliminary localization of defects and subsequent accurate classification of detected defects. The second part of the proposed method is based on the use of the adversarial convolutional neural network for the reconstruction of damages detected at the previous stage.

Proposed method

Damages encountered in the photo image include various kinds of spots, scratches, cracks and other foreign objects. Their appearance can be caused by aging, physical stress, improper storage or use. In this paper, we focus on crack detection.

Defect detection

The detecting damage to an imaging method consists of two main steps: the use of morphological filtering as a pre-processing and the use of the machine learning method which is necessary to classify pixels that have received a large response in the preprocessing phase (see Fig.1). Morphological filtering reduces the computational complexity of the algorithm so only those pixels that received the higher response are needed to process. The use of morphological filtering operation gives the opportunity to reduce the number of false alarms [9].
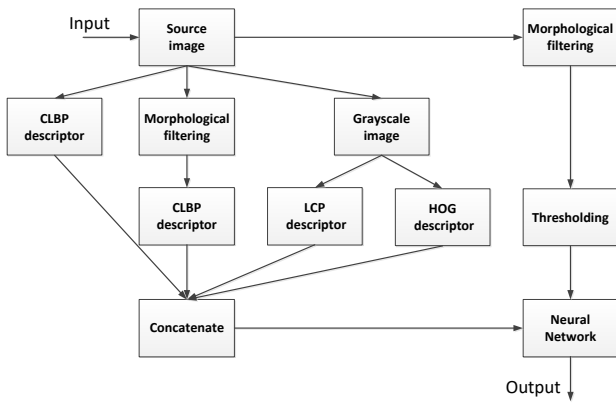

Figure 1. General scheme of the proposed method of defect detection

We use the morphological operation "bottom hat". The point of this operation is to subtract from the original image $I_{r,c}$ the result of its "opening" with the structural element B. "Bottom hat" helps to locate the expected defects in the image.

$$Mask_{r,c} = Y_{r,c} - (Open_{r,c})^B$$

$$(Open_{r,c})^B = (Y_{r,c} \ominus B) \oplus B)$$

$$(Dilate_{r,c})^B = MAX_{(u,\upsilon) \in B}(Y_{r,c}(r+u, c+\upsilon) - B(u,\upsilon))$$

$$(Erode_{r,c})^B = MIN_{(u,\upsilon) \in B}(Y_{r,c}(r+u, c+\upsilon) - B(u,\upsilon)),$$

where B is structural element with size pixel size $u \times \upsilon$, $\ominus$ - erode, $\oplus$ - dilate.

After the procedure of morphological filtering, the preliminary mask with defects contains both correctly detected defects and a number of false positives. To reduce the number of false alarms, we use a neural network as a classifier.

Neural network allows reducing false alarms on the preliminary mask obtained by morphological filtering. The network consists of 3 hidden layers. Each layer includes 250 neurons. The logistic sigmoid is used as the activation function:

$$f(x) = \frac{2}{1 + e^{-x}} - 1,$$

where x - feature vector.

To determine the losses, we use the binary cross-entropy function. This is defined according to the expression:

$$H(y, y') = -\frac{1}{m} \sum_{l=1}^{m} [y \cdot \log(y') + (1-y) \cdot \log(1-y')]$$

,

where y - prediction Conv.Net, y'_j - true value.

Additionally, we use the method of optimization Adam, proposed in work [10], with the learning rate is equal to 0.0005. Its training took approximately 45 epochs.

We united the following descriptors as input for the neural network: CLBP [11], HOG [12], and LCP [13] to one.

Texture CLBP operator is an extension of work [14]. The main difference is in the preservation of the sign and the magnitude of the component:

$$d_p = s_p * m_p, \begin{cases} s_p = sign(d_p) \\ m_p = |d_p| \end{cases}, \qquad s_p = \begin{cases} 1 & d_p \geq 0 \\ -1 & d_p < 0 \end{cases}$$

where d_p is the vector of difference between the Central pixel and its neighbors, s_p is the vector of the sign component, m_p is the vector of the magnetic component.

To get the accuracy of the texture description higher than the original LBP method which uses only the sign component it is necessary to use two components.

Texture operator LCP is a combination of feature vectors of the LBP method and weighted coefficients (MiC). Coefficients are calculated for adjacent pixels to the center, in the LBP pattern. The formula for calculating the coefficients is written as follows:

$$E(a_0, ..., a_{P-1}) = \left| g_c - \sum_{r=0}^{P-1} a_r g_r \right|,$$

where g_c is the center pixel, g_r is the adjacent pixel, a_r is the weight coefficient calculated for each. g_r

To calculate the weights a_r, the least squares method is used:

$$C_L = V_L A_L,$$
$$A_L = (V_L^T V_L)^{-1} L_L^T C_L,$$

where C_L is the vector of the types of patterns of interest, V_L is the intensity (brightness) of adjacent pixels, A_L is the vector with unknown values of the weight coefficients a_r, L is the type of pattern.

To get Image rotation stability we apply the Fourier transform to a vector A_L:

$$H_L(k) = \sum_{i=0}^{P-1} A_L(i) \cdot e^{-j2\pi ki/P},$$

where $A_L(i)$ is i the vector element A_L.

We get an additional vector (MiC) for the original LBP method by leaving the amplitude component of the vector. Normalization of local contrast is used to increase the accuracy of the description of the texture features of the image.

The algorithm for constructing the feature vector consists of several stages. Firstly, the values of the gradients are calculated. To calculate the gradients, a one-dimensional differentiating mask is used in the horizontal and vertical directions. Then, the calculated

gradients are used to form a histogram for each of the cells, passing the weighted voting procedure.

To normalize the gradient cells are grouped into larger connected blocks. Normalization of blocks occurs in accordance with the expression:

$$f = \frac{v}{\sqrt{\|v\|_2^2 + e^2}}$$

where f is the normalization factor, v is the non-normalized vector, $\|v\|_2$ is its norm, e is a certain small constant.

The resulting descriptor has a length of 469 values, of which 108 values correspond to CLBP operator, which is calculated for each color component of the color image, 36 and 289 values, correspond to the texture operators HOG and LCP, respectively, calculated for the grayscale image, and also 36 values correspond to the CLBP operator calculated for the image after morphological filtering. This composite descriptor is calculated for a local window with 20×20 the pixel size.

Defect removing

An adversarial neural network is an extended version of the convolutional autoencoder. The main difference from standard autoencoders is the addition to the main error (for Example, L1 or L2 loss), additional losses obtained from two convolutional neural networks called a local and global critic. The evaluation of the global critic is aimed at the General semantic composition of the reconstructed image, while the evaluation of the local critic is aimed only at the quality of the restored area. Adding losses from critics allows making the result of reconstruction sharper. However, the use of critics can complicate the task of training a restoring autoencoder. The main difficulty lies in the different learning rates of critics and autoencoder. A disproportionate error from critics (when they are better trained than the autoencoder) can cause the autoencoder to collapse, which in turn will stop correctly reconstructing the damaged areas. In order to reduce this probability, we use the rapid preliminary restoration of the damaged area by the method proposed in [6], based on the experience of the authors in [15]. Additionally, we use different learning rates: the reconstructing network has a learning rate of 0.0001, the global critic 0.00001, the local critic has a learning rate of 0.00001. The general scheme of the reconstructing adversarial network is shown in figure 2.
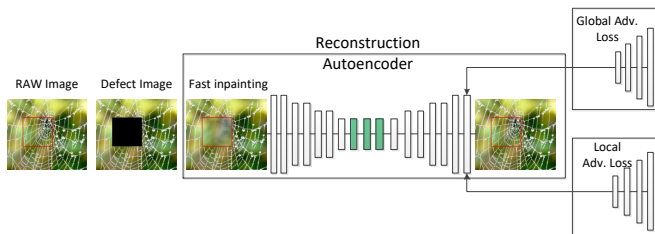

Figure 2. The proposed adversarial neural network for reconstruction damaged arias.

In our work we construct a model of reconstructing neural network having the following parameters: model has 18 convolution layers with kernel size 3 for all layers: C64-C64-MP-C64-C128-MP- C128- C128-MP-C256-C256D2-C256D4-C256D8-C256-US-C128-C128-US-C128-C64-US-C64-C64-C3 (C-feature map, MP-max pooling, D-dilation rate, US-up sampling). The global discriminator has 4 convolution layers and 1 fullyconnected layer:

C64K5S2-MP-C128K5S2-MP-C256K5S2-MP-C256K3-FC1 (K-kernel size, S-strides, FC-fullyconnected). The local discriminator also has 4 convolution layers and 1 fullyconnected layer: C64K5S2-MP-C128K5S2-MP-C256K3-MP-C256K3-FC1. The local and global critic does not have a combined last layer, so they produce two independent estimates of the reconstructed area.

All networks (reconstruction autoencoder, local and global critic) have the following same parameters. The activation function is ELU [16], which is a more efficient modification of the activation function ReLU [17]. Using ELU, there is no need to apply the normalization batch. Here, as well as in the defect detection method, the ADAM method is used as an optimizer. As activation function in the last layers for all neural networks, a logistic sigmoid is used.

To train the reconstruction autoencoder, we use three types of losses: global absolute difference, adversarial loss from the global critic, adversarial loss from the local critic. Totally reconstruction autoencoder losses are calculated according to the expression:

$$Loss_G = \lambda_1 L_{l1\_glob} + \lambda_2 L_{adv\_loc} + \lambda_3 L_{adv\_glob},$$

$$L_{l1\_glob} = \left| x_{glob} - G(x_{def}) \right|,$$

$$L_{adv\_loc} = \arg\max_G E \log\!\big(D_{loc}\big(G\big(x_{def}\big)\big)\big),$$

$$L_{adv\_glob} = \arg\max_G E \log\!\big(D_{glob}\big(G\big(x_{def}\big)\big)\big)$$

where x_{glob} - undamaged source image, x_{loc} - local undamaged area on the source image, x_{def} - image with defect, $\lambda_1, \lambda_2, \lambda_3$ - coefficients of proportionality (in our work $\lambda_1 = 30$, $\lambda_2 = \lambda_3 = 0.01$).

For both discriminators (local and global) losses are calculated according to the expression:

$$L_D = \arg\max_D E \log\!\big(D(x)\big) + E \log\!\big(1 - D\big(G\big(x_{def}\big)\big)\big),$$

where x – source image, the size of which depends on what discriminator is used.

The size of the damaged area has a fixed size of 32×32 pixels, but the position of the lost area at each iteration is random, which allows further reconstructing arbitrary damaged areas.

Experiments

To compare the effectiveness of detecting damage in the image, the proposed method is compared with methods based on machine learning: convolutional neural networks (CNN) and support vector machine method (SVM). Three color components of the image are used as input to the convolutional neural network. The first convolutional layer has 10 feature maps, the second layer has 20 feature maps, the third layer has 30 feature maps. The size of the convolution filters is 5×5 pixels. ReLU is used as an activation function in hidden layers. The following parameters were also used: the learning rate is 0.001, the size of the training data batch is 20 samples, for the training, was using the "Adam" method. The support vector machine used a linear separating hyperplane, with an acceptable error of 5%. The previously described texture descriptors are used as a descriptor.

Figure 3 illustrates the result of the proposed method for detecting defects, a method based on support vector machine and the method based on the use of convolutional neural networks.
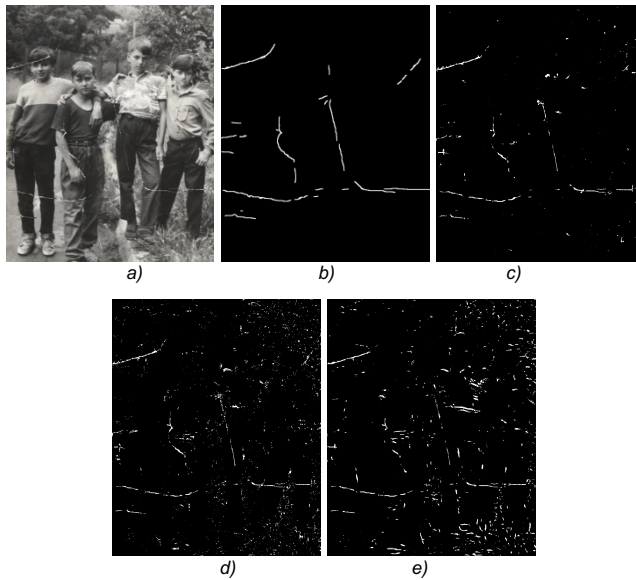
Figure 3. Crack detection results: a) image with defects (Correspond 9 image in Table 1); b) ground truth; c) proposed method; d) SVM; e) CNN.

For training all methods it was used 2,500 samples containing cracks as well as 2,500 undamaged samples. Table 1 shows the results for 13 test images. Test images obtained from free access.

Table 1. Crack detection comparison

	Probability false alarm			Prob. correct detection
	Proposed method	CNN	SVM	
Img. 1	**0.035**	0.056	0.053	0.92
Img. 2	**0.027**	0.073	0.063	0.83
Img. 3	**0.051**	0.053	0.115	0.79
Img. 4	**0.00215**	0.00247	0.00237	0.6
Img. 5	**0.0074**	0.0110	0.0138	0.5
Img. 6	0.0250	**0.0190**	0.0347	0.7
Img. 7	**0.0108**	0.0267	0.0158	0.6
Img. 8	**0.0235**	0.0307	0.0395	0.6
Img. 9	**0.0175**	0.0603	0.0550	0.6
Img. 10	**0.0745**	0.0794	0.0823	0.4
Img. 11	0.00911	**0.00885**	0.01047	0.8
Img. 12	**0.0128**	0.0266	0.0168	0.55
Img. 13	**0.0305**	0.0705	0.0595	0.56
Aver.	**0.0251**	**0.0398**	**0.0432**	**0.65**

The results providing by the proposed method from the table 1 show the reduced number of false positives by an average of 1.6 times. The main drawback of the classifier is a low generalizing ability with not enough training data. The support vector machine classifier is not efficient to classify a multi-part descriptor with multiple texture operators.

To train and evaluate the effectiveness of the proposed method on the basis of the adversarial reconstructing convolutional neural networks, we used the dataset (CelebA) presented in the work [18], which contains the faces of celebrities. The training was conducted on pre-cropped images measuring 200 by 160 pixels. As a well-known reconstruction method, we used the EBM method described

in [7]. Figure 5 shows an example of reconstructing test images (the test image was not used in the learning process) using the proposed method and the EBM method.
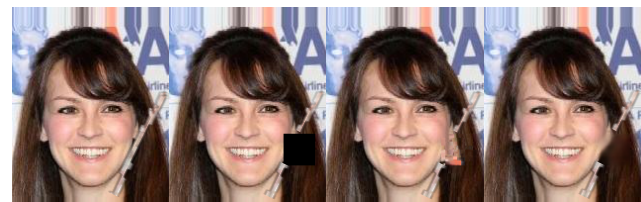

Figure 4. The first column corresponds to source images (Corresponds 1, 2, 10, 9 images in Table 2); the second column – image with defect; the third column – EBM method; the fourth column – proposed Adv.Net.

Table 2 shows the estimates of the reconstruction efficiency of the test images shown in image 5 for the proposed method (images taken from validation set and not used in training) and the EBM method [7].

An analysis of the results confirms the high efficiency of the proposed methods for the detection and reconstruction of damaged areas in the image.

Conclusions

In our work we proposed a deep learning-based approach for defect detection and removing on archival photos. The method for detecting damage to an image consists of two main steps: the first step is to use morphological filtering as a pre-processing, the second step is to use the machine learning method, which is necessary to classify pixels that have received a massive response in the preprocessing phase. The using of neural networks for detection of defects in the image and adversarial network for reconstruction damaged areas allowed preserving semantic information. The obtained result probably can be improved according to specific tasks.

Table 2. Comparison quality of reconstruction of damaged images

	Img. 1	Img. 2	Img. 3	Img. 4	Img. 5
Peak Signal-to-Noise Ratio (PSNR)					
Criminisi et al. [7]	24.448	37.188	32.149	32.374	34.3299
Proposed Adv.Net.	33.857	42.076	35.8376	36.4364	38.1666
Mean-squared error (MSE)					
Criminisi et al. [7]	0.0036	0.0002	0.0006	0.0006	0.0004
Proposed Adv.Net.	0.0004	0.0001	0.0003	0.0002	0.0002
Structural Similarity Index (SSIM)					
Criminisi et al. [7]	0.9782	0.9947	0.9825	0.9869	0.9949
Proposed Adv.Net.	0.9888	0.9981	0.9909	0.9934	0.9978
	Img. 6	Img. 7	Img. 8	Img. 9	Img. 10
Peak Signal-to-Noise Ratio (PSNR)					
Criminisi et al. [7]	33.074	35.146	35.505	25.250	38.2432
Proposed Adv.Net.	38.004	38.976	37.603	33.820	41.0256
Mean-squared error (MSE)					
Criminisi et al. [7]	0.0005	0.0003	0.0003	0.0030	0.0001
Proposed Adv.Net.	0.0002	0.0001	0.0002	0.0004	0.0001
Structural Similarity Index (SSIM)					
Criminisi et al. [7]	0.9907	0.9863	0.9896	0.9813	0.9987
Proposed Adv.Net.	0.9959	0.9941	0.9930	0.9929	0.9994

Acknowledgment

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