FAULT DETECTION USING MATHEMATICAL MORPHOLOGY
AND CLUSTERING

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Abstract. This paper describes an approach to the problem of fault detection. Fault detection is
considered here as a segmentation task. One need to segment the initial image in order to find areas of a
particular kind - faults. The approach presented combines the mathematica morphology and clustering.
The morphological treatment is based on morphological filtering by reconstruction but it includes also
some other tools like to-p hat transformation and contrast improvement. Clustering is performed by the
k-means algorithm. Three methods of fault detection are presented here. Each of them is destined to the
segmentation of the images of different kind.

Key words: fault detection, clustering, k-means, mathematical morphology, reconstruction, image
segmentation

1. Introduction

Set of images consists of three kinds of images. The images include surfaces of a met-
allurgical materials, which contain some faults. Detection of the faults is necessary to
perform later the quantitative analysis of them and to judge if analyzed material's piece
is correct or not. The presented method is divided into two steps: morphological pre-
processing and binarisation (by clustering). The first step - the main one, is performed
in order to consider spatial dependencies in the image. The main areas of the image
are transformed to more homogeneous. It means that all areas with the graytone values
considerably lighter or darker than the neighboring background, which however does not
represent the faults, are removed in order to avoid misclassifications during clustering.
The second step of proposed method is binarisation by clustering and is destined to a
classification of image's pixels. To do this the k-means algorithm is used. Binarisation is
obtained by clustering with 2 clusters. Similar methods of combination of filtering and
clustering has been previously applied to the segmentation [9, 11, 10].

1.1. Image processing tools used

1.1.1. Morphological tools

Mathematical morphology is a very efficient non-linear tool for signal and image pro-
cessing. An introduction to mathematical morphology is to find in [1]. In the current

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section all the morphological tools applied later are described.

**Morphological reconstruction**

Reconstruction by dilation (reconstruction by erosion) of a mask image $f$ from a marker image $g$ where $f \leq g$ ($g \leq f$) is defined as a sequence of successive geodesic dilations (erosions) of $f$ with respect to $g$ performed until idempotence and is denoted by: $R_g(f)$ ($R^*_g(f)$):

$$R_g(f) = \delta_g^{(i)}(f), \quad R^*_g(f) = \varepsilon_g^{(i)}(f)$$  \hspace{1cm} (1)

where $\delta_g^{(i)}(f)$ and $\varepsilon_g^{(i)}(f)$ are respectively geodesic dilation and geodesic erosion of size $i$ with mask $g$ ([7]); $i$ is such that (idempotence): $\delta_g^{(i)}(f) = \delta_g^{(i+1)}(f)$, $\varepsilon_g^{(i)}(f) = \varepsilon_g^{(i+1)}(f)$

More information about morphological filtering is in [3, 5] and about reconstruction and its algorithms in [6, 7].

**Morphological filtering by reconstruction**

Opening and closing by reconstruction are defined as follows:

$$\gamma_R^{(n)}(f) = R_R(\varepsilon_R^{(n)}(f)); \phi_R^{(n)}(f) = R^*_R(\delta_R^{(n)}(f))$$  \hspace{1cm} (2)

Unlike traditional opening and closing, opening by reconstruction and closing by reconstruction preserves shapes on the image. It is very important while using these operations as a first step of segmentation. It makes possible removal of the local peaks of gray-intensity without changing the shapes of regions (which happens in traditional opening and closing).

**Removal of the objects touching the image borders**

In one of the proposed algorithms another application of reconstruction is applied - the removal of the objects touching the image borders. The whole operation is described by using the following equation:

$$f' = f - R_I(b)$$  \hspace{1cm} (3)

where $b$ is an image containing only the 1-pixel wide image border.

**Morphological top-hat transformation**

Mathematical morphology provides also a very efficient tool for contrast improvement. It base on a top-hat transformation. Two kinds of top-hat transformation has been introduced:

$$BTH^{(n)}(f) = f - \gamma^{(n)}(f); \quad WTH^{(n)}(f) = \phi^{(n)}(f) - f$$  \hspace{1cm} (4)

First one is called black top-hat and is used to remove the background darker the objects lying on it. After that the object lighter than background are visible, the background is suppressed. Second operation is called white top-hat and is used to remove the background lighter the objects lying on it. After that the objects darker than background are visible, the background is suppressed. Both top-hats can be used to the contrast enhancement. The appropriate operator is defined as:

$$g = f + BTH^{(n)} - WTH^{(n)} = 3f - \gamma^{(n)} - \phi^{(n)}$$  \hspace{1cm} (5)
Fig 1. Original image (a), the result of closing by reconstruction followed by the opening by reconstruction - (b), after contrast improvement - (c).

Where $g$ is a image with enhanced contrast, $f$ is the initial image. The operation adds the object lighter than background to the initial image and subtracts darker ones. In such a way contrast is improved. There exists also a directional version of the top-hat transformation - it performs the opening (or closing depending on the type of the top-hat) with directional structuring element.

2.2. Clustering

Proposed clustering method bases on the $k$-means technique [4, 8]. $k$-means algorithm aims at classifying each member of given set of input data into given number of clusters. Algorithm deals with distances between samples and cluster centers. This distance is iteratively minimized in two steps performed successively. First step distributes samples into the clusters, second updates cluster centers. Each sample is classified to the cluster which center is the nearest in given metric. Updating of cluster centers is performed by computing a new cluster center by placing it in the middle (arithmetic mean value) among all of the samples belonging to the cluster. These two steps are performed iteratively while clusters centers change their position. If in the last performed iteration cluster centers did not move, it means that operation of samples classification is finished. In case of applying $k$-means algorithm for images the notions of sample and cluster center are represented by pixel's graytone. During the calculations the distance between samples and cluster centers is calculated by taking absolute value of difference between graytones of sample and cluster center. Cluster centers obtained finally represents graytones of the output image. These graytones refers to regions on the image surface. The initial cluster centers have been placed in a whole range of graytones equally distanced.

3. Solution of the problem

First case

In the first case we deal with the rather uniformly textured areas with darker spots of different size - faults; part of a such kind of the image is shown in Fig 1. At the
beginning the smallest dark spots - texture details of size 1 are removed. These spots
consists of single pixels and all of the areas 1-pixel broad. In order to do this closing
by reconstruction of size 1 is performed. In the second step one removes texture of the
surface while preserving the darker areas - faults. To do this opening by reconstruction
is performed. This operation removes lighter areas on the background. The best result
was obtained using this operation of size 6 (see Fig. 1b). In order to make the faults
more distinctive another morphological operation is applied - contrast enhancement by
top-hat operation of the size 5 (see Fig. 1c). Now the image with enhanced contrast is
binarised using the k-means algorithm. Results of fault detection using this approach
on two different images are presented in Fig. 4a,b. Those images are equal to initial
ones, with the contours of the faults added artificially. Those borders were produced as
a contour of the results of k-means clustering. One can see that all of the faults have
been found.

Second case
The second case is more difficult. The texture details are bigger, the texture is not as
uniform as in the previous case and the borders of faults are less regular (see Fig. 2a). To
treat this kind of images another algorithm is applied. At the beginning the irregularities
of the background are decreased. To do this a white top hat of size 25 is applied. It
removes the background so that only the objects darker than the background rest (see
Fig. 2b). Unfortunately, apart from the faults also some parts of the texture are still
present. In order to remove most of them (those touching the image border) one removes
the objects touching the image borders. The number of unwanted details is in such a
way reduced, but some of them still exists. To remove them one make use of their
linear property. A directional opening by reconstruction of size 10 removes them (result:
Fig. 2d). Now the image is ready for the final clustering. The result of the k-means
algorithm with k=2 is shown in Fig. 2e. The superposition with the initial image is
presented in Fig. 4c.

Third case
Third case resembles the second one - the underlying texture has linear pattern with a
size comparable of that of the faults (see Fig. 3a). The difference is that the texture is
better contrasted, while the faults are less visible. In this case the nicer property is used
already at the beginning of the treatment. Faults are detected by using the directional
Fig. 3. Fault detection using the third algorithm.

Fig. 4. Fault detection on different initial images using the proposed methods: (a),(b) - the first algorithm, (c) - the second one, (d) - the third one.

top-hat. Unfortunately the faults are not only darker but somewhere also lighter than the textured background. To deal with both lighter and darker parts of each fault one combines both black and white top-hats. Both are directional - horizontal of the size 30. Then, the supremum of two top-hats is taken (see Fig. 3b). It contains both lighter and darker areas. In order to remove less important details the opening by reconstruction of size 1 is performed (see Fig. 3c). The result of the last operation can be treated by the clustering algorithm. The result of k-means algorithm is shown on Fig. 3d. The result of clustering is then dilated with the small structuring element containing only three neighboring points (in the square grid) in order to remove some small local disturbances of the segmented image. The final result of treatment on the initial image is shown on Fig. 4d.
4. Conclusions and acknowledgements

The experiments carried out show that proposed combination of mathematical morphology and binarisation by the k-means clustering gives interesting and promising results. One of the biggest obstacles for applying k-means-like algorithms is always the spectral nature of this algorithm. It causes problems with bad-classified single points or small areas in the image. Because of that one should find a supplement that can precede the clustering step, and which can take under consideration spatial dependencies of the image. Natural answer to the question of finding such a supplement is filtering. But the most popular linear filters as well as non-linear have one important disadvantage for segmentation: they change the shape of the areas on the image. Segmentation by definition should extract shapes of the areas, so each disturbance of it cause some problems. In order to avoid this, an advanced morphological filtering is proposed: filtering by reconstruction. This solution seems to be very efficient - it allows to remove local disturbances of gray-tone without changing the shape of areas. The morphological filtering is supported by the top-hat transformation. Experiments carried out show that proposed combination of advanced morphological filtering, morphological contrast enhancement, background removal by the top-hat transformation and a binarisation by k-means considers both spectral and spatial nature of image and produces correct detection of faults on the image's surface.

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