APPLICATION OF ADVANCED MORPHOLOGICAL FILTERS INTO IMAGE SEGMENTATION

Marcin IWANOWSKI, Sławomir SKONECZNY, Jarosław SZOSTAKOWSKI

Warsaw University of Technology, ul.Koszykowa 75, 00-662 Warszawa, POLAND

ABSTRACT

This paper is devoted to a segmentation method using advanced morphological filtering by reconstruction followed by clustering by *k*-means algorithm. Advanced morphological filtering bases on morphological reconstruction and two filters are applied: opening by reconstruction and closing by reconstruction. This kind of operation has very important advantage from the point of view of segmentation - it preserves the borders of regions. Traditional filters (opening, closing, linear filters) remove noise, but on the other hand they cause some blur effects, which can be the serious obstacle for correct segmentaion. Morphological filtering by reconstruction has very good filtration properties without changing the shapes.
After segmentation simple *k*-means clustering is performed. Two versions of *k*-means clustering algorithm is described: classic and fuzzy one. First, 'crisp' version will be applied to cases with a knowledge regarding number of clusters given a priori. Fuzzy version should be used when it is difficult to define number of clusters. The algorithm will automatically adapt number of clusters into the structure of the image.
A combination of filtering by morphological reconstruction and clustering makes possible to consider two kind of information: spatial (filtering) and spectral (clustering).

Key words: mathematical morphology, reconstruction, filtering, clustering, *k*-means

INTRODUCTION

The presented method is divided into two steps: morphological filtering nad clustering. First step is the main one 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 of pixels with the graytone considerably lighter or darker than their background are removed in order to avoid misclassifications during the second, clustering step. Typical solution for such kind of problem is linear filtering or morphological filtering based on opening or closing. But they change shapes of regions on the image (bluring), which is the main obstacle for using this kind of filters in segmentation process. Segmentation should extract the shapes in the image, so each distortion of shape is dangerous. In order to solve this problem more advanced mathematical morphology is used: geodesic operators. Based on this operators two filters can be defined: opening by reconstruction and closing by reconstruction. They both remove lighter or darker pixels or areas on the image's surface, but they don't change the shapes. So they are very well suited for the segmentation purposes. Image filtered in such a way is an excellent input image for the segmentation algorithm. In our paper a family ok *k*-means-like algorithms is applied. This algorithm is a clustering one and is destined here to a clasification of image's pixels. It is iterative and consists of two steps: clasification and calculation of cluster centers. Each iteration gives better approximation of the cluster centers. Clusters are represented by theirs centers, and they correspond with the regions on the image. Two kinds of a *k*-means algorithms are applied. The first one is traditional and gives as the result given number of cluster centers. The second is based on fuzzy logic and gives as the result the number of clusters which can be different from those given at the beginning of the algorithm. In this case the number of clusters is adapted to the real structure of the image.
In the paper three applications are described. First deals with the segmentation of material images. They consist of some inclusions of a different materials, which should be extracted without changing theirs shape. Second application is devoted to segmentation of images with human faces on it. Advanced morphological filters are applied in the algorithm of extraction of some features of human face. Both above mentioned applications are applying traditional version of *k*-means algorithm. In that case number of clusters should be known a priori. In third application presented here some real scenes are considered and number of clusters cannot be well-defined. Some number should be given a priori, but this number is changing during the run of the algorithm.
In the next two chapters basics of advenced morphological filters and *k*-means algorithms are presented. Later the results of experiments are given.

MORPHOLOGICAL FILTERING BY RECONSTRUCTION

Mathematical morphology is a very efficient non-linear tool for signal and image processing. An introduction to mathematical morphology is to find in [6,7]. In this paper morphological filtering by reconstruction is considered. The following part describes briefly theoretical background for opening and closing by reconstruction. Both operations belong to one group called geodesic morphological transformations (Soille, 1994).

Geodesic dilation (erosion) of size 1 of the marker image f with respect to the mask image g where $f \leq g (f \geq g)$ is defined as infinimum (supremum) image of mask image and marker image after dilation (erosion) of size one - with elementary structuring element, and is denoted as: $\delta_g^{(1)}(f)$ $(\varepsilon_g^{(1)}(f))$:

$$\delta_g^{(1)}(f) = \delta^{(1)}(f) \wedge g,$$
$$\varepsilon_g^{(1)}(f) = \varepsilon^{(1)}(f) \vee g, \qquad (1)$$

Geodesic dilation (erosion) of size n consists of n succesive geodesic dilations (erosions) of size 1:

$$\delta_g^{(n)}(f) = \underbrace{\delta_g^{(1)}(\delta_g^{(1)} \ldots . \delta_g^{(1)}}_{n-times}(f)\ldots)),$$
$$\varepsilon_g^{(n)}(f) = \underbrace{\varepsilon_g^{(1)}(\varepsilon_g^{(1)} \ldots . \varepsilon_g^{(1)}}_{n-times}(f)\ldots)) \qquad (2)$$

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

$$R_g(f) = \delta_g^{(i)}(f), \quad R_g^*(f) = \varepsilon_g^{(i)}(f), \qquad (3)$$

where i such that (idempotence):

$$\delta_g^{(i)}(f) = \delta_g^{(i+1)}(f), \quad \varepsilon_g^{(i)}(f) = \varepsilon_g^{(i+1)}(f).$$

More information about reconstruction is in [9,10].

Opening and closing by reconstruction are defined as follows:

$$\gamma_R^{(n)}(f) = R_g(\varepsilon^{(n)}(f)), \quad \varphi_R^{(n)}(f) = R_g^*(\delta^{(n)}(f)). \qquad (4)$$

Unlike traditional opening and closing, opening by reconstruction and closing by reconstruction preserves shapes in 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 borders of regions (which happens in traditional opening and closing).

One of the most efficient filters are alternating sequencial filters (ASF), which consists of two families of filters. Each family contains operation of the same type but of different, increasing size. It can be defined as follows:

$$ASF_i = \alpha^{(i)}\beta^{(i)} \ldots \alpha^{(2)}\beta^{(2)}\alpha^{(1)}\beta^{(1)} \qquad (5)$$

α, β are the families of filters, i is defined as a size of filter. In most of cases α and β represent opening and closing [8]. In our case we use these operation by reconstruction where α means closing by reconstruction and β - opening by reconstruction. We will call this filter later ASF by reconstruction (ASFR):

$$ASFR_i = \varphi_R^{(i)}\gamma_R^{(i)} \ldots \varphi_R^{(2)}\gamma_R^{(2)}\varphi_R^{(1)}\gamma_R^{(1)} \qquad (6)$$

CLUSTERING

Proposed clustering method bases on the k-means technique [1,3]. 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. First one 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) of 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 notions of sample and cluster center are represented by pixel's graytone. Cluster centers obtained finally represents graytones of the output image. These graytones refers to regions on the image surface.

In version of the algorithm described above number of clusters is fixed and cannot be changed. This solution is not always sufficient. Sometimes one would have flexible algorithm which can change the number of cluster according to the real situation on the image. In this case fuzzy version of k-means algoriithm (fuzzy k-means - FKM) can be applied. Some fuzzy versions of k-means was developed. In this paper version taken from [2] is applied. The main difference between traditional and FKM algorithm is representation of the result. In traditional version each point is labelled by the cluster number. Fuzzy version produces so called 'fuzzy partition' - a vector which includes membership values. These values tell us 'how much' given point is similiar to each of the clusters. This is not only indication of the closest cluster center but also a description of similiarity with other clusters.

In order to apply the FKM algorithm to the segmentation without given number of clusters some additional steps should be made. FKM algorithm is performed until convergence. When the fuzzy-partition elements stops changing their elements, next step is executed. Cluster centers are compared in order to check if there are clusters with centers close to each other. If two or more clusters have their centers close, they represent in fact one cluster. In this case number of clusters k decreases and FKM algorithm is performed once again. When number of clusters is stable next step is performed. Now all the pixels with the

membership values high enough are classified to the clusters with the highest membership value. The thresholding operation with threshold which describes how 'high' is 'high enough' is called α-cut. All the pixels not classified (their membership values were too small to be classified properly) are classified once again using FKM.
The algorithm starts with given number of clusters and later this number can increase or decrease depending on the spectral distribution of image's pixels.

RESULTS

Proposed algorithm was used in three aplications. First one segments material images. They contain some structures with different types of inclusions inside. Segmentation is performed in order to find these inclusions.

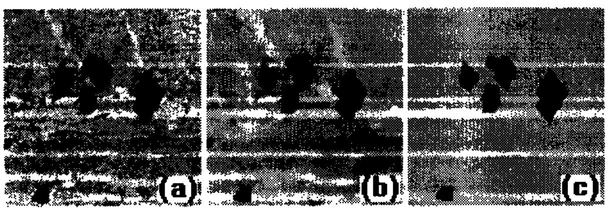

Fig. 1. (a) - input image (mangan), (b) - after ASFR of size 2, (c) - after ASFR of size 2 and *k*-means (k=2).

Fig. 1. shows the results of filtering by ASFR. It is ASFR filter of size 2 contained of closing by reconstruction and opening by reconstruction (size 1 and 2). Image is filtered without any change of shape of objects.
Image filtered by ASFR is much better input for *k*-means algorithm than image without filtering. Only the important regions exists and theirs borders are unchanged. In this case 'crisp' version of *k*-means algorithm was applied. Number of clusters is known - we have to extract darker shapes on lighter background - and is equal to 2. Result of *k*-means of size 2 is presented in Fig. 1c.

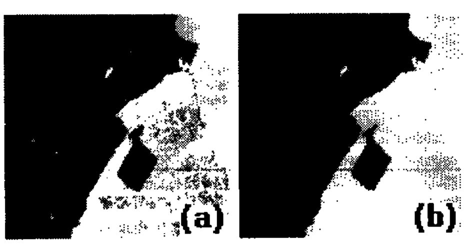

Fig. 2. Other examples: (a) granite, (b) granite after ASFR of size 2 and *k*-means (k=3).

Fig. 2. contains other aplication of proposed segmentation method also with 'crisp' *k*-means. Fig. 2a presents structure of granite. Three main areas exists on this image. This case needs ASFR of size 2 and *k*-means with *k*=3 - result is shown on Fig. 2b.

Second application, which results are presented here, were devoted to finding of specific areas on the human face as eyes, lips, etc.

Morphological filtering by reconstruction is an excellent tool for filtering without disturbing the borders of regions on the image. In case of extracting specific elements of human face this is extremely important because any unexpected disturbance of shape can cause problems with badly recognized face (in the next step of processing).

First steps of processing bases on morphological filters by reconstruction. Filters by reconstruction are extremely useful for all of the purposes where one should remove some noise or elements from the image, but without chaging the shape of remaining objects. Traditional filters remove the noise/obejects from the image, but on the other hand they cause disturbances of shape. Opening/closing by reconstruction in the first stage (erosion/dilation) removes areas of given size from the image and, in the second stage reconstructs not-removed objects.

First step is applied in order to remove the noise from the image (pre-filtering). This step consists of closing by reconstruction of size 1 preceeded by opening by reconstruction of size 1. First of these two operations removes darker than background pixels from the image, second - lighter. Result of that will be later called filtered image. Result of this step is presented on Fig. 3b - input image in on Fig.3a.

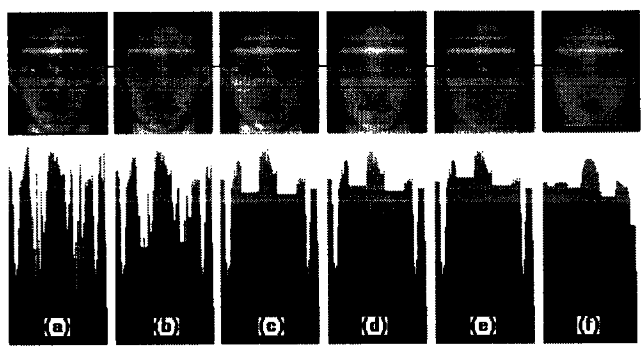

Fig.3. Filtering by ASFR of human face: input image (a), ASFR size 1 (b), size 2 (c), size 3 (d), sizc 4 (c), ASF size 4 (f).

In the second step main filtering by reconstruction is performed (ASFR). Such kind of filtering removes in each step bigger objects. The result of ASFR is shown on Fig.3c,d,e. Face on Fig.3e is not including the characteristic features like eyes, lips etc. The shape of the face is however preserved. In order to compare with traditional alternating sequential filtering (by traditional opening/closing) Fig.3f is shown. It is visible, that the shape of the face is changed. Pictures below images on Fig.3 show 1-D wievs of images made by horizontal cut of the image at y=50. On the first image some noise is visible. Second image (after ASFR of size 1) doesn't include that. Each next image doesn't contain objects of applied filter's size.

Image filtered by ASFR is now binarized in order to obtain the face area. Birnarisation is made by *k*-means algorithm with *k*=2. Result of it is the shape of the face area and is presented in Fig.4a. Now, the features of the face (eyes, lips) are going to be extracted. Image after ASFR compared with the filtered one (Fig.3b) dosn't include elements of the face. From this image initial image is now subtracted. The operation of filtering and subtracting, called top-hat by reconstruction, removes the background of the image. Only the objects of certain size (filter's size) are existing on this image. Important areas on the face are visible - eyes and lips are considerably lighter than the rest of the image.

Fig.4. Steps of proposed processing method: face area (a), top-hat (b), binarized top-hat (c), part of binarized top-hat included in face area (d), feature areas (e), feature areas + contour of face area (f).

This image can be easily binarized by *k*-means technique - see Fig. 4c. In order to remove these parts of the binarized image, which are does not belong to the face area, we just take the intersection of it and the face area. After this operation the image includes important features of our image - eyes and lips - see Fig. 4d
In order to determine not only features, but whole areas where features can be found, some additional operations are performed. After this areas are excluded from the image - see Fig. 4e.

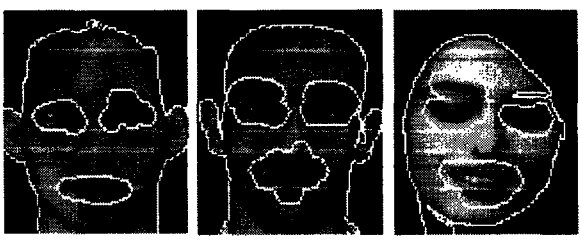

Fig.5 shows some other result of feature extraction shown on initial images. In all of them features are extracted correctly.

Using our method we can find specific elements on the human face. This specific areas on some faces are presented on Fig.5.

In applications described above number of clusters was easy to define a priori. But sometimes it is not possible. Number of clusters can be not available a priori. This can happen in scene analysis. In this case we apply fuzzy version of *k*-means (FKM). Image shown in Fig. 6a represents a scene. From the point of view of segmentation it contains a lot of noise, especially on its right-hand side. ASFR is applied in order to remove possibly lot of noise. In this case ASFR of size 5 was applied. Filtered image is presented on Fig. 6b.
Number of clusters can be defined here only roughly. In proposed FKM algorithm some parameters should be defined. Paramter *k* represents initial number of clusters. Parameter α indicates threshold for classified pixels. During the experiments $130<\alpha<190$ was chosen. Segmented images with different parameters *k* are shown of Fig. 6c and Fig. 6d. The real number of clusters is in both cases bigger than defined by parameter *k*. Result is automaticaly adapted to the image's structure. In this case 'crisp' *k*-means would give not 'natural' result - extracted regions would be not good fited to the real regions on the input image.

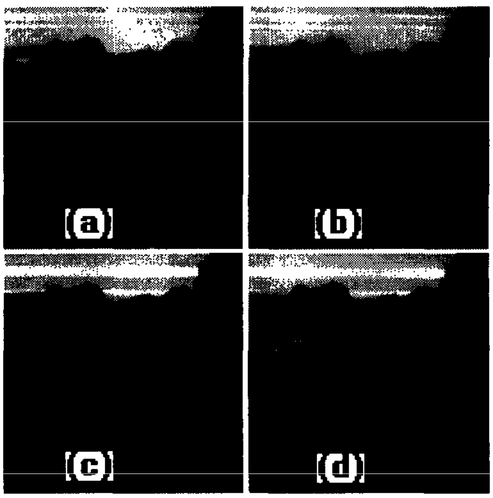

Fig. 6. (a) input image (scene), (b) ASFR of size 5, (c) FKM k=3, α=150, (d) FKM k=5, α=150.

Combination of advanced morphological filtering and FKM - applied in the last application - seems to be a good segmentation method. It can be used for e.g. some preprocessing for coding of images or sequences.

CONCLUSIONS

Advanced morphological filtering is a very good tool for segmentation purposes. It makes the regions on the image's surface more homogenious - it removes elements of given size without disturbing the shape of remaining objects. After such a filtering is no need to use a complicated segmentation algorithms. As the given examples have

shown, a simple *k*-means-like clustering is sufficient to segment well-filtered image.
Two types of *k*-means algorithm was applied: traditional version anf fuzzy one. First one can be applied to the images where number of clusters can be defined by the user. But not in all cases it can be done. For such a case fuzzy *k*-means is applied. This variant needs an initial number of clusters, but during the run of the algorithm this number can change according to real image content.
Experiments carried out show that proposed combination of advanced morphological filtering and simple clustering by *k*-means or fuzzy *k*-means considers both spectral and spatial nature of image and gives good and promising results.

ACKNOWLEDGEMENTS

This work was supported by Polish Committee of Scientifical Researches (KBN), project number: 8 T11C 027 12.

REFERENCES

1. R.O.Duda, P.E.Hart, Pattern classification and scene analysis. Willey and Sons, 1973.
2. T.L.Huntsberger, C.L.Jacobs, R.L.Cannon. Iterative fuzzy image segmentation. Pattern Recognition Vol.18., No.2., pp. 131-138, 1985.
3. M.Iwanowski. K-means algorithm for greytone reduction. Technical Report, School of Mines of Paris, N-13/96/MM, 1996.
4. M.Iwanowski, S.Skoneczny, J.Szostakowski, "Image segmentation by advanced morphological filtering and clustering", in:*Proceedings of International Conference of The Quantitive Description of Materials Microstructure*, Warsaw 16-19 April 1997 pp.307-314.
5. F.Meyer, S.Beucher. Morphological Segmentation. Journal of Visual Comm. and Image Representaion. Vol.1, No.1, September, pp. 21-46, 1990.
6. J.Serra. Image analysis and mathematical morphology. Academic Press, 1982.
7. J.Serra, ed. Image analysis and mathematical morphology. Volume 2: theoretical advances. Academic Press, 1988.
8. J.Serra, L.Vincent. An overview of morphological filtering. Circuits Systems Signal Processing Vol.11, No.1, 1992.
9. P.Soille. Geodesic Transformations in Mathematical Morphology: an Overview. Technical Report, School of Mines of Paris, N-24/94/MM, 1994.
10. L.Vincent. Morphological Grayscale Reconstruction: Definition, Efficient Algorithm and Aplications in Image Analysis, IEEE Comp.Vis. and Patt.Rec., Proceedings, 1992, pp. 622-635