EXPERIENCES OF KNOWLEDGE BASED SEGMENTATION OF DENSITY IMAGES

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ABSTRACT

The emphasis of this paper is on a particular type of images, density images. Because of the density interpretation of images, a procedure to segmentate the density images has been developed. This procedure is based on a generate-and-test idea. The hypotheses are generated by ordinary segmentation methods. The generated regions are then tested and combined by inference. The results have been promising.

INTRODUCTION

When radiation has been used in image acquisition the result image is often captured on a photographic film from which it must be digitized. The response of film to radiation is not completely linear. The photographic density obtained by a negative [2] is defined as the logarithm of the ratio of incident radiation (I) to transmitted radiation (I_t).

$$D = \log_{10} \frac{I}{I_t} \qquad (1)$$

Because the density transformation, formula 1, is unlinear the image processing operations in the following steps should be chosen carefully. This restriction concerns the segmentation, too.

All presented results have been reached by studying radiograms of paper. These images have typically heavy noise and low contrast.

Many of the obstacles in image segmentation can be removed by density transformation. It corrects for instance the shading effect. However the problem how to divide the image into homogeneous regions remains. This means the problem how to select features of the regions so that one succeeds in minimizing classification error over all classes.

$$\text{minimize} \sum_{j=1}^{K} \frac{C_{ij}\, q_j p_j(x)}{p(x)} \qquad (2)$$

where C_{ij} denotes the cost of classifying an unknown x into category i when it is actually a member of category j.

q_j is the prior probability that a point will be chosen from category j.

$p_j(x)$ is the multivariate probability density in n-space given that a x is in category j, where j =1,2,...K.

p(x) is the probability density function of all possible points.

The number of classes K is a prior not known.

Image segmentation can be done based on edges, regions, textures and models.

The edge based segmentation methods have two phases. Firstly one is detecting edge elements. This can be done by ordinary filtering methods.

Secondly the edge elements are connected together by searching [4], by Hough transformation [1], by edge following as graph searching [11], by edge following as dynamic programming [3] or by contour following [7]. These methods are very time consuming, especially the linking part. Noise and low contrast are limiting the use of these methods.

The region based segmentation can be classified by the domain in which the clustering is performed: image domain clustering , feature domain clustering or as a combination of these.

The image domain clustering methods divide the image into a set of connected regions by clustering pixels in the image plane. A typical image domain clustering method is region growing by merging [5]. The split-and-merge method of region growing splits or merges region as necessary [9]. Region growing by linking pixels assumes that a certain relation is defined on connected pixels. A graph is constructed whose vertices correspond to the pixels and edges correspond to pairs of pixels that satisfy the relation. The regions of the image are completely determined and they are grown by finding the connected components of the graph. Narenda and Goldberg [11] for instance have defined an unidirectional relation using differential images.

Feature domain clustering methods classify, identify and cluster picture elements in feature domain and after that project the results onto the image domain. The regions they produce are not in general connected and postprocessing , for instance relaxation, is therefore necessary. Some methods can be mentioned: classification of pixels by supervised learning, pixel clustering in the feature domain and recursive segmentation in feature domain.

Clustering can also be done in both image and feature domains. This technique, called spatial clustering, uses some method to partition the image into connected small regions, then cluster them in the feature domain. This method is quite unsensitive to noise.

The image segmentation based on the textures can be divided into two phases. Phase one is the measurement of textural features of a textural element. Phase two is the clustering [2]. The clustering or the segmentation can be done by similar methods as in the case of region clustering [13].

All the mentioned methods have approached the segmentation problem in bottom-up manner. It is not the only way to do it. It is also possible to use models. One tries to verify them and find the best fitting model. ACRONYM [6] for example analyzes an aerial photograph of an aeroplane using three-dimensional geometrical models. It predicts the scene and tries to verify the hypothesis. This generate-and-test idea is not a totally new one. It has been used, for instance within the artificial intelligence research[15]. The extra information needed in segmentation can be introduced by mathematical models [1], rules [12,14] or procedures [8].

SEGMENTATION BASED ON KNOWLEDGE

Knowledge can be introduced in the segmentation process by models, by rules or by procedures. It is efficient to combine all these sources. The idea of the knowledge based segmentation is that one generates some hypothesis and then tryes to verify the cooccurrence of the model and the scene. The selected model is the best fitting one, but it will not guarantee that the selected model corresponds with the reality.

Insight II has been selected as development tool, because it has the ability for forward and backward chaining. This means that the tool is suitable for hypothesis testing. It is also possible to run the development tool on a personal computer. The tool makes it possible to combine the inference part and the image processing part, which is written in Pascal.

The segmentation is carried out by six rules. Three rules are used to accept regions. Two rules combine regions . These rules build the knowledge base needed in segmentation. One rule switches between the acceptance state and the combination state. It is the control rule. Two initial hypothesis are made by traditional segmentation routines. The initial routines segmentate the image by classification of pixels by supervised learning or by edge detection with contour following. The testing part analyzes and combines the results from the initial segmentation. The testing part infers the final segmentation by calling small procedures that calculate area, contrast or orientation. As an example one rule for acceptance and combination is given.

RULE For small region
IF Accept
AND The contrast is good
AND The object is small
THEN The object is a small region CF 80.

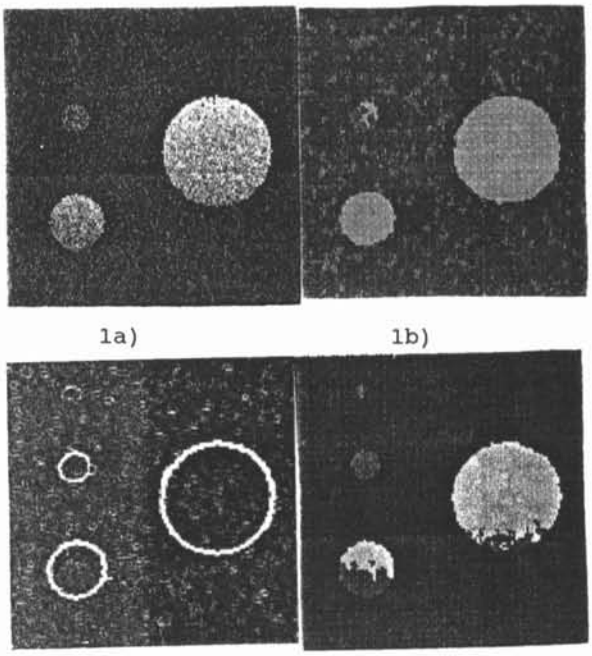
The combination has been done by rules as

RULE To combine regions
IF Combine
AND The object is small
AND The contrast is bad
AND NOT dominating orientation
THEN The merge region CF 90.

RESULTS

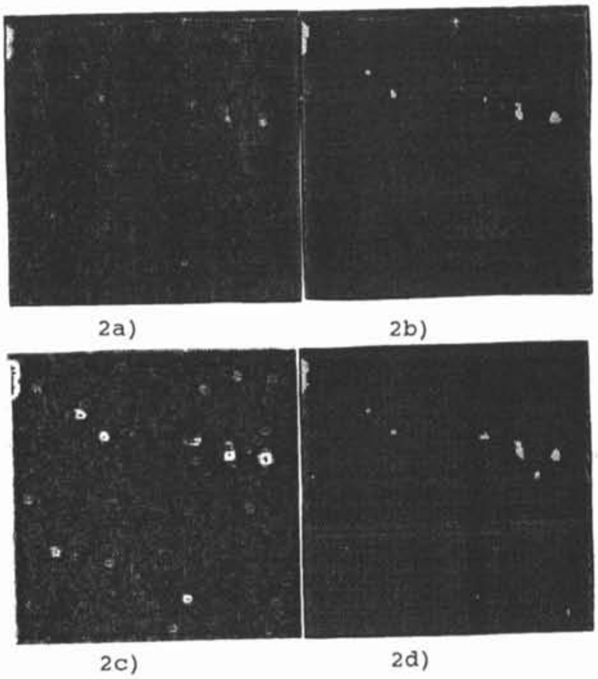
Results of the initial tests are presented to illustrate the power of the knowledge based segmentation. Figure 1a) shows the arbitary test image. The image contains four discs and noise (12dB). The discs have a specific slope. The figure 1b) shows the arbitary image segmented by the pixel based method. Supervised learning has been used. The decisions are based on the pixel values. Figure 1c) shows the image 1a) again segmented by edge detection with contour following. Median filtering has been used. The edge detection has been done by Sobel operator. Figure 1d) shows the arbitary image segmented by the knowledge based method. The result is a combination of 1b and 1c. The pixel based method is not sensitive to noise, but it has difficulties with locating edges. The edge detection based method is sensitive to noise and low contrast. The knowledge based method is not so sensitive to noise or low contrast, but it has also most knowledge in possession.

One realistic density image is presented in figure 2a. The image has been segmented by pixel values, figure 2b, and by edge detection, figure 2c and by the knowledge based method, figure 2d. The knowledge based method succeeded best in segmentating this quite difficult image.



1a) 1b) 1c) 1d)

Figure 1. An arbitary test image for segmentation. 1a) is the original, 1b) is segmented by pixel values, 1c) is segmented by edges and 1d) is segmented by knowledge.



2a) 2b) 2c) 2d)

Figure 2. One realistic density image of paper. 2a) is the original, 2b) is segmented by pixel values, 2c) is segmented by edges and 2d) is segmented by knowledge.

CONCLUSIONS

Many interesting questions have been arisen during the problem solution and verification process.

Firstly what is a suitable balance between the low level processing and the inference? It is not reasonable to process each image element by logical inference. The processing time increases linearly or more with the number of rules. On the other hand the knowledge in form of rules makes the solution flexible. There must be an optimum between the low level procedural knowledge and the rule based knowledge.

Secondly how can the reliability of the solution be descriped? Some low level methods offer a measure of the reliability, formula 2, but how are these probabilities influenced by the inference? The goal is ,of course, to increase the reliability.

The automatic goal selection is a difficult question.
How can the quality of the segmentation be measured? It is quite easy to combine all the regions to one big region or only keep the original regions.

The speed is an interesting question. The time consumption mainly depends on the complexity of the low level operations. Is it possible to find a balance between the speed of the low level operations and the complexity of the rules?

How to select the low level operations so that their preliminary results are suitable for the inference procedures? In other words what is a suitable presentation for the objects? What are the computational structures needed for the presentation?

The knowledge based segmentation is working better than the initial segmentation methods, at least in this specific area. However many questions have been arisen. They have not been answered yet, but they must be considered when one is designing knowledge based segmentation.

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