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Detection of Line Segments

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Abstract. *In the paper a method of line segment detection in the images is presented. It bases on existing LSD approach which was designed to be a parameterless technique dedicated to analysis of real world scenes. In consequence it encounters problems with other types of images, e.g. medical images, where the characteristic of the structures may be completely different. The method proposed in this work allows to tune its parameters for that characteristic and thus allows to achieve satisfactory results also for medical data. The effect of the approach is illustrated with mammographic images.*
Keywords: *line segment detection, image analysis, structural description.*

1. Introduction

Detection of line segments is an important task in image analysis. On the one hand those segments may directly represent some objects visible in those images (e.g. borders of the structures). On the other hand they can be treated as an alternative, structural method of image content description that can be used for its further analysis (e.g. recognition of structres basing on the shape of their border). That second aspect is utilized among others in cognitive hierarchical active partition CHAP approach where analysis of image segments may support or even replace the analysis of the individual pixels reducing significantly the considered search space ([1, 2]).

There are two classic approaches to the problem of line segment detection. First uses Hough transform ([3]). In that group of methods in a preprocessing phase some edge detection technique is applied and after that lines approximating those edges are identified. Just then those lines are splitted into line segments after the analysis of edge pixels distribution along each line. The second approach is line segment detector LSD ([4]). It does not require explicit edge detection but it analyses instead the orientation and distribution of image gradient in the image.

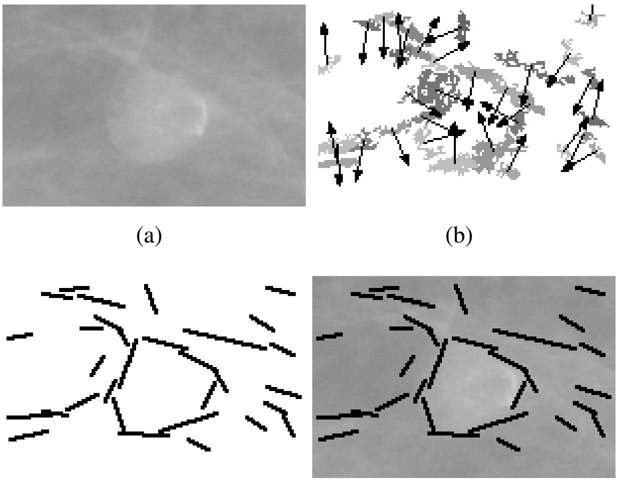
The LSD was designed to be a parameterless method and was mainly tested using images representing real world scenes. It causes that it is not always well suited for medical images. On of such specific group are mammograms where the contrast can be locally very low and structure borders are rather blurred. The proposed approach, which bases on LSD, modifies this method and introduces some parameters which tuning allows to achieve interesting results for that type of images.

The paper is organized as follows: in the second section the description of the method is presented, the third section presents the sample results and discusses the influence of the parameters, the last section summarizes the paper. The results of the proposed method are illustrated using Mammographic Image Analysis Society MIAS database available at `http://www.mammoimage.org`.

2. Method

As it was mentioned in the previous section the proposed method bases on LSD approach. There are, however, two main differences. First of all there is a different way of handling noise in pixel gradients. In the orignal approach *a contrario* model was used whereas in this work gradient averaging is applied. Secondly, the method of final segment construction from detected line support regions was also modified. In LSD it bases on principal ineratial axis while here the predominant gradient direction is taken under the consideraion.

The first step of the method requires calculation of the image gradient **g** for each image pixel. Since image domain is discrete many different approximation schemes can be of use here. To avoid noise influence it is usually convenient to apply those schemes that consider some neighbourhood of the given pixel, too. Further in this work the following procedure is used (it considers larger neigh-



(a) (b)

(c) (d)

Figure 1. Sample results for the first fragment (MIAS 142): (a) original image, (b) line support regions with avarged direction of the gradient, (c) detected segments, (d) original image with detected segments.

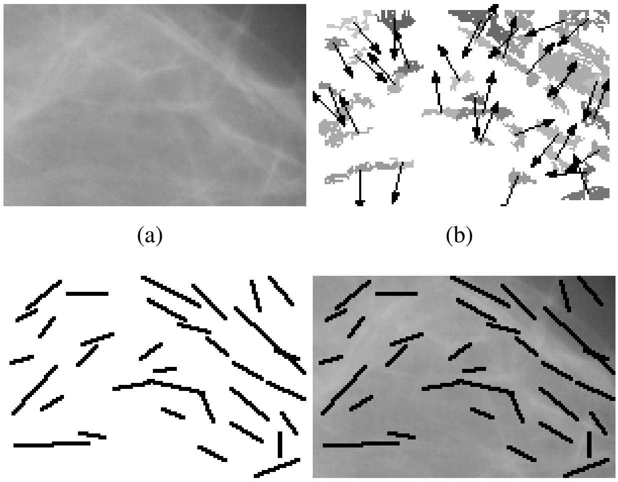
bourhood than that which was used in LSD method):

$$g_x(x,y) = \frac{\sum_{i=-1}^{1} I(x+1, y+i) - \sum_{i=-1}^{1} I(x-1, y+i)}{3} \tag{1}$$

$$g_y(x,y) = \frac{\sum_{i=-1}^{1} I(x+i, y+1) - \sum_{i=-1}^{1} I(x+i, y-1)}{3} \tag{2}$$

Image gradient is required to identify regions where potential borders of structures visible in the image are localized. In those areas its norm should have significant value since it is close to 0 only in the regions of uniform intensity. That is why only those pixels are considered where the norm of $\mathbf{g}$ is greater then assumed threshold value t. To further reduce noise influence the gradient is averaged in the neighbourhood of those pixels. The range of this nighbourhood is denoted as r.

The significant norm of the gradient, however, is not sufficient to identify regions supporting line segments as the gradient vectors can have different orientation. It may happen in this way in areas with a significant noise. Structure borders should have gradients oriented in approximately the same direction. Consequently not only norm of the gradient but also its angle needs to be considered and line



(a) (b)

(c) (d)

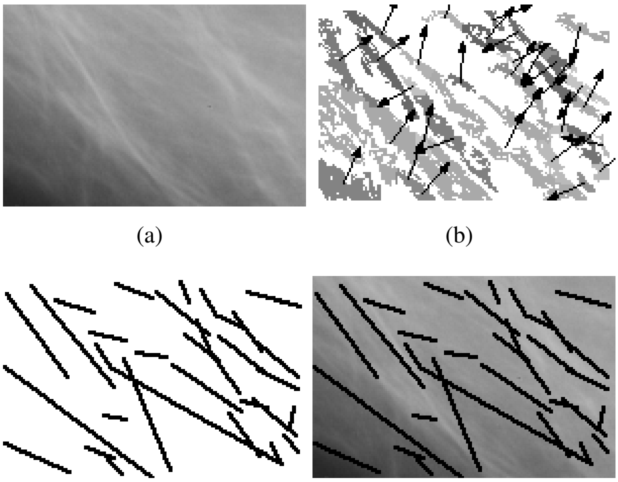
Figure 2. Sample results for the second image fragment (MIAS 142): (a) original image, (b) line support regions with avarged direction of the gradient, (c) detected segments, (d) original image with detected segments.

supporting regions can be found as connected regions with similar gradient angles (Fig. 1, Fig. 2, Fig. 3). For this purpose region growing algorithm can used where the array of image gradients is segmented. As a similarity criterion the following forumla is considered:

$$\langle \frac{\mathbf{s}}{||\mathbf{s}||}, \frac{\mathbf{g}}{||\mathbf{g}||} \rangle > s \tag{3}$$

It calculates a cosine of the angle between the gradient **s** of seed pixel and the gradient **g** of given pixel (dot product of normalized vectors) and checks if it is bigger than assumed similarity value s.

Each extracted region is used to construct a candidate line sgment. To do that an averaged direction of the gradient tn the region is sought. Those gradients arę similar but may differ depending on the assumed tolerance s. The segment should be perpendicular to this vector but its precise localization should depend on the shape of the region. This is why in the next step the smallest rectangle with one side parallel to the averaged vector and containing all region pixels is searched for. The candidate segment is the segment connecting centers of those rectangle sides that are parallel to that vector.



(a) (b)

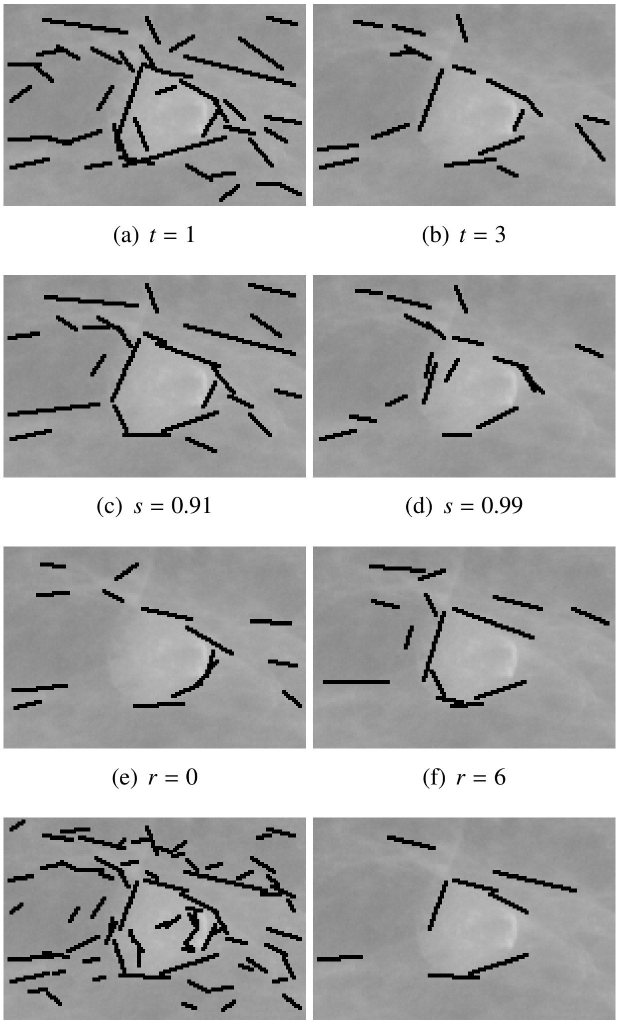
(c) (d)

Figure 3. Sample results for the third fragment (MIAS 142): (a) original image, (b) line support regions with avarged direction of the gradient, (c) detected segments, (d) original image with detected segments.

Depending on the image the presented procedure may produce very short and probably insignificant segments. Therefore additional filtering may be applied to remove those segments which length is not greater than assumed length l. Similarly to LSD method to reduce the number of such small segments also additional image scaling could be considered. This approach, however, was not used in the results presented further.

3. Results

The results are presented using images from MIAS database and consequently the parameters of the method were chosen to give satisfactory results for mammograms. The results were considered to be satisfactory if they allowed to identify borders of the structures indicated by radiologists as potentially benign or malignant lesions. This information is available in MIAS database. The best empirically identified parameters are:



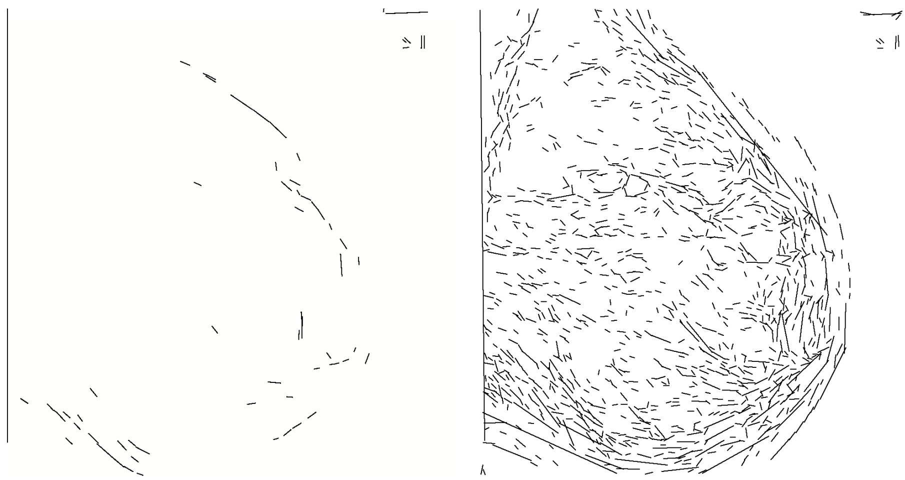
(a) $t = 1$ (b) $t = 3$

(c) $s = 0.91$ (d) $s = 0.99$

(e) $r = 0$ (f) $r = 6$

(g) $l = 5$ (h) $l = 20$

Figure 4. Influence of the considered parameters for the first image fragment (MIAS 142).



(a) (b)

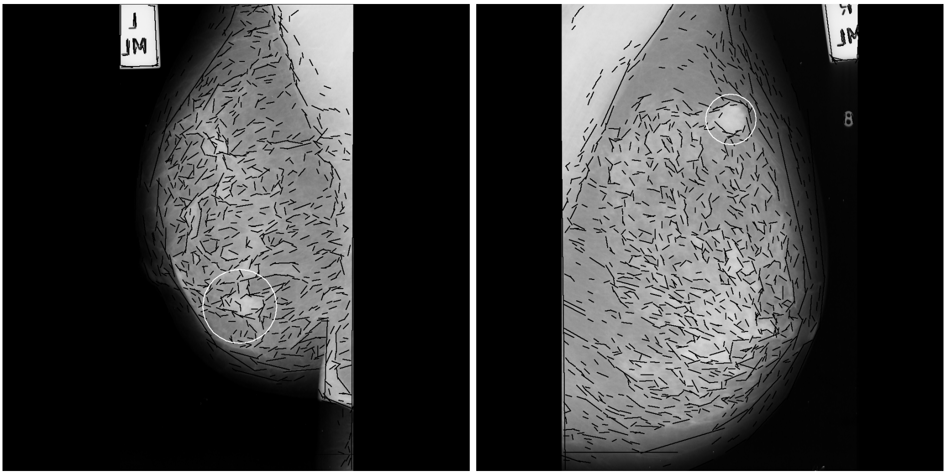
Figure 5. Comparison of the results for differend segment detection methods (MIAS 142): (a) LSD method, (b) proposed approach.

- $t = 2$ - If this value is too low very week gradients are considered leading to a larger number of insignificant segments. The large value, on the other hand, reduces the number of segments as some pixels are not considered at all (Fig. 4a, Fig. 4b).

- $s = 0.95$ - It gives approximatelly 18 degree of tolerance. The larger value of this parameter causes that only regions with precisely aligned gradients are considered which in consequence reduces the number of segments as they are shorter and are removed while segment filtering. Too small value would introduce too much tolerance leading to segments that do not precisely enough approximate borders of the structures (Fig. 4c, Fig. 4d).

- $r = 3$ - Too small value gives a noisy gradient array which leads to short segments that will be filtered out. The higher value forces stronger averaging which results with longer but less precise segments (Fig. 4e, Fig. 4f).

- $l = 10$ - Lower values will pass a lot of small segments while higher can remove significant segments which for example may not allow to describe borders of rounded structures (Fig. 4g, Fig. 4h).



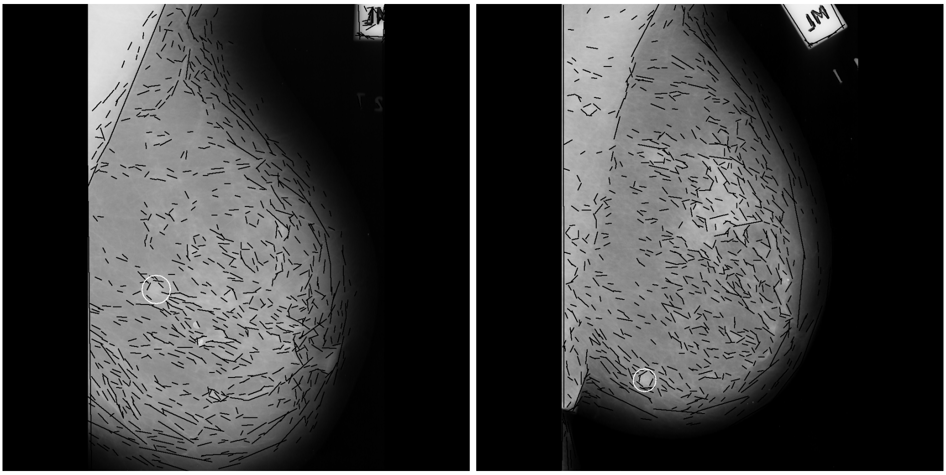
(a) MIAS 181 (b) MIAS 202

Figure 6. Sample results of the proposed method with region of interest identified by an expert.

The presented method with described above parameters allows to identify segments that using LSD method would be rejected (Fig. 5). A confirmation that the proposed method allows to obtain satisfactory results is evident when diagnostically important regions are depicted together with detected line segments (Fig. 6, Fig. 7).

4. Summary

In this work a line segment detection method basing on LSD apporach was presented. Empirically selected parameters allow to achieve satisfactory results for mammographic images and thus can be used as an input for the other algorithms analysing strucures composed by those segments. There are, however, some issues that still can be improved. For exemple while searching for line suppoting regions not only gradient orientation but also the norm of the gradient could be considered. It would allow to detect segments where there is a change in gradient strength even if the orientation of the gradient is the same. Also the seed pixels for region growing can be chosen in more systematic way. All those aspects are under further investigation.



(a) MIAS 204 (b) MIAS 206

Figure 7. Sample results of the proposed method with region of interest identified by an expert.

5. Acknowledgement

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