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Pattern Recognition Letters 27 (2006) 578–586

Pattern Recognition Letters

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Mean shift based clustering of Hough domain for fast line segment detection ☆

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Received 29 April 2005; received in revised form 29 August 2005
Available online 2 November 2005

Communicated by R. Davies

Abstract

This paper proposes a new algorithm for extracting line segments from edge images. Basically, the method performs two consecutive stages. In the first stage, the algorithm follows a line segment random window randomized Hough transform (RWRHT) based approach. This approach provides a mechanism for finding more favorable line segments from a global point of view. In our case, the RWRHT based approach is used to actualise an accurate Hough parameter space. In the second stage, items of this parameter space are unsupervisedly clustered in a set of classes using a variable bandwidth mean shift algorithm. Cluster modes provided by this algorithm constitute a set of base lines. Thus, clustering process allows using accurate Hough parameters and, however, detecting only one line when pixels along it are not exactly collinear. Edge pixels lying on the lines grouped to generate each base line are projected onto this base line. A fast and purely local grouping algorithm is employed to merge points along each base line into line segments. We have performed several experiments to compare the performance of our method with that of other methods. Experimental results show that the performance of the proposed method is very high in terms of line segment detection ability and execution time.

Keywords: Line segment detection; Random window randomized Hough transform; Mean shift based clustering; Line segment grouping

1. Introduction

The detection of linear structures in images is an important task in computer vision because they are frequently used as an input to higher-level processes such as stereo matching or object recognition. Over decades, many models have been reported in literature to detect line segments. These models can be broadly classified into three main categories: Hough transform (HT) based approaches (Ji and Xie, 2003), gradient based approaches (Nelson, 1994) and line segment grouping approaches (Boldt et al., 1989; Nacken, 1993).

The HT and its extensions constitute a robust method for extracting line segments. Basically, the principal concept of the standard HT is to define a mapping between an image space and a parameter space. Each feature point in an image is mapped to the parameter space to vote for the parameters whose associated lines pass through the data points. The votes for each line are accumulated, and after all the points have been considered, local maxima in the accumulator correspond to the parameters of the detected lines (Ji and Xie, 2003). Despite the fact that the HT endures noise and discontinuities in an image, it has some inherent limitations such as high computing time and unwieldy memory requirement. Besides, HT based approaches can fail when pixels constituting a long segment are not exactly collinear. To solve these problems, a coarse quantization of parameter space is normally performed (Jang and Hong, 2002), but it causes inaccurate

☆ This work has been partially granted by Spanish Ministerio de Educación y Ciencia (MEC) project no. TIN2004-05961.
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0167-8655/$ - see front matter
doi:10.1016/j.patrec.2005.09.023

detection of lines. Section 2.1 describes several extensions to the standard HT which have been proposed to alleviate these problems. In the gradient based approaches, gradient magnitude and orientation of each image pixel are explored for the purpose of detecting line segments. The principle of these approaches is to use the gradient direction to split the image into a set of support regions. However, these approaches fail to identify even linear edges sometimes, if they happen to be parts of curve segments (Guru et al., 2004). Instead of looking at edge images, the line segment grouping approaches looks at images containing a number of short line segments, such as the output of an edge detection and line segment fitting algorithm. Adjacent line segments are grouped according to some grouping criteria and replaced by a new line segment. This process is repeated until no new line segment occurs. The main disadvantage of these approaches is that its process is generally purely local and, therefore, the globally optimal grouping is not guaranteed. To overcome this problem, Jang and Hong (2002) proposed a grouping approach that incorporate the concept of line detection by voting from HT based models. Finally, there are other models that cannot be easily classify into these three groups. Thus, Mansouri et al. (1987) proposed a hypothesize-and-test algorithm to extract line segments of specified lengths by hypothesizing their existence by the use of local information. This method could be classified as a statistical based approach.

In this paper, we propose a new algorithm for extracting line segments from edge images. The proposed method performs two consecutive stages. In the first stage, the algorithm follows a line segment randomized HT (RHT) based approach. The RHT method is based on the fact that a single parameter item can be determined uniquely with a pair of edge points. Such point pairs are selected randomly, the parameter point is solved from the line equation and the corresponding cell is accumulated in the accumulator space. This random selecting is called random sampling. The RHT is iteratively run to detect global maxima by thresholding the accumulator space. When a line is detected, it is removed from the edge image and the algorithm starts again with the remaining edge pixels. Despite the merits of the RHT, it suffers from some problems mainly due to random variations (Kälviäinen et al., 1995). In our case, a variant of the RHT (the random window RHT, RWRHT (Kälviäinen et al., 1995) is employed to select an initial set of items of the parameter space. In the second stage, these items are clustered by using a mean shift based clustering algorithm (Comaniciu and Meer, 2002). The efficacy of mean shift analysis has been demonstrated in computer vision problems such as tracking and segmentation (Comaniciu and Meer, 2002). To avoid the specification of a scale parameter (the global bandwidth of the mean shift procedure), we employ the variable bandwidth mean shift algorithm (VBMS) proposed by Comaniciu et al. (2001). This clustering stage permits the algorithm to avoid the global maxima detection. Therefore, our implementation of the RWRHT algorithm run faster than the current one because it will be used without accumulator actualisation and thresholding. Cluster modes are used to extract a set of base lines from the edge image. Finally, edge pixels belonging to lines that have been clustered together are projected onto the base line that they generate. The projections of these points onto each base line are grouped into line segments by using a fast and purely local merging procedure.

This work is related to a previous work of Walsh and Raftery (2002). In that paper, a simple clustering procedure is employed to avoid the peak detection by thresholding. Basically, they threshold the sampled parameters. Then, they place each parameter in a cell of an accumulator space and run a connected component algorithm on the nonempty cells in the array. The parameters contained in the cells associated with a particular connected component are assumed to be associated with one curve in the image. The main disadvantage of this method is that it conserves a thresholding procedure, whose importance is great because it determines the set of occupied cells in the parameter space. If the threshold value is too low, this clustering algorithm can merge two different lines into a single one. If it is too high, the algorithm can lose short lines. Besides, the cell size must be appropriately chosen for the curves to be detected accurately (Walsh and Raftery, 2002). As it is commented in (Jang and Hong, 2002), a coarse quantization of the parameter space usually causes inaccurate detection of lines.

This paper is organized as follows. Section 2 describes previous work related to the two stages of the proposed method. Section 3 presents the proposed method. The experimental results revealing the efficacy of the proposed method are presented in Section 4. The results of the comparative study of the proposed method with other methods are given in Section 5. The paper concludes along with discussions and future works in Section 6.

2. Related work

2.1. HT based approach to line segment detection

Works in line segment detection using the HT focuses on improving its two main drawbacks: its high consuming of time and memory and the selection of an optimal and efficient resolution of the parameter space. The extensions of the standard HT can be categorized as nonprobabilistic and probabilistic approaches. For the nonprobabilistic HT, every image pixel is employed to obtain the line parameters. To reduce computational time, Gerig and Klein (1986) proposed a backmapping which links the image space and the parameter space. After the accumulation, each image pixel can be linked to the most evident location in the parameter space to obtain the parameters of the line it is part of. Since every image pixel is mapped to one parameter location, computational time is significantly reduced. In the hierarchical HT proposed by Princen et al. (1990), the image is divided into small subimages and the HT is performed on these subimages. Because of the small subimages, the size of the needed parameter space can be kept small which will lead to an efficient process. The combinatorial HT (Ben-Tzvi and Sandler, 1990) uses two image pixels to calculate the line parameters. Each pair of two image pixels determine one point in the parameter space. In order to limit the number of pixel pair combinations, the image is segmented and the voting process is performed segment by segment. An improved version of this method has been proposed by Costa et al. (1990). Finally, Stephens (1991) proposed a probabilistic approach to the HT, that it is defined as a likelihood function in the output parameters. Although this method is more accurate than the standard HT, it is computationally expensive. On the other hand, the probabilistic HT uses random sampling for selecting only a small subset of the image pixels. For a curve expressed by a n parameter equation, the randomized HT (RHT) (Xu et al., 1990) selects n pixels by random and mapped them into one point of the parameter space. Thus, in line detection, the parameter space can be built as a small 2D linked list, instead of a 2D accumulator array. Several extensions of the RHT have been posteriorly suggested (Kultanen et al., 1990; Kälviäinen, 1993). Roth and Levine (1992) have presented a probabilistic Hough method of random sampling of minimal subsets. This algorithm is a generalization of the RANSAC (Fischler and Firschein, 1987). The probabilistic HT proposed by Kiryati et al. (1991) only used a small set of randomly selected image pixels. Although the execution time can be considerably reduced, the algorithm's performance depends on the fraction of the image pixels used. Ylä-Jääski and Kiryati (1993) have proposed several improvements to the probabilistic HT. The Monte Carlo HT (Shvaytser and Bergen, 1991) uses random sampling partially similar to the RHT. However, this method has a fixed size parameter space. Walsh and Raftery (2002) suggest to improve probabilistic HT by specifying a target distribution and weighting the sampled parameters accordingly to make identification of curves easier. The importance sampling HT (ISHT) also includes a clustering algorithm to simultaneous identify multiple curves in an image.

2.2. Parameter space unsupervised clustering

The goal of clustering is to identify distinct groups in a dataset. In our case, these groups correspond to line segments in the edge image. Although there are a lot of published clustering methods, most of them are not adequate to solve our problem. Methods which rely upon a priori knowledge of the number of groups are not valid because this number is initially unknown. Besides, methods which implicitly assume the same shape (most often elliptical) for all the groups are not able to handle the complexity of this feature space. Fig. 1(b) shows that there is a continuous transition between groups and a decomposition of the space into elliptical clusters could introduce severe artifacts. It can be also noted that the clustering algorithm proposed by Walsh and Raftery (2002) to group cells of the parameter space is excessively simple. Fig. 2(b) shows the parameter space associated to Fig. 2(a). Fig. 2(c) represents a thresholding of the parameter space with a low threshold. In this case, two lines are merged and only three lines are detected. If the threshold value is increased (Fig. 2(d)), the method loses one line and it detects only three lines. It is very difficult to correctly threshold the parameter space by using a fixed value.

To cast clustering as a statistical problem we regard the data $\boldsymbol{x}_1, \ldots, \boldsymbol{x}_n$, in the d-dimensional space $\mathscr{R}^d$, as a sample from some unknown probability density $f(x)$. There are two statistical approaches to clustering. Model-based clustering assumes that each group is represented by a density function that is member of some parametric family. Although these methods can estimate the number of groups, G, it always requires optimizing the likelihood for many different values of G (Tantrum et al., 2002). Nonparametric clustering is based on the premise that groups correspond to modes of the density $f(x)$. The goal then is to estimate the modes and assign each observation to the domain of attraction of a mode. Since nonparametric clustering does not have embedded assumptions about the structure of the feature space, they can analyze arbitrarily structured feature spaces (Comaniciu and Meer, 2002). There are a lot of nonparametric clustering methods in

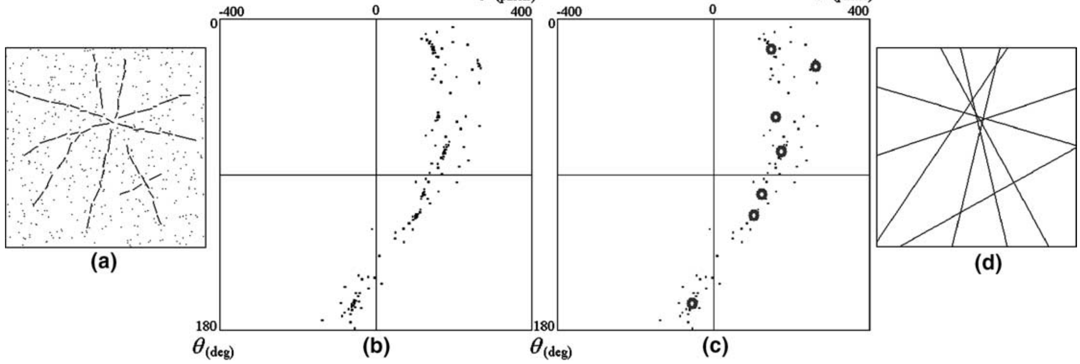

Fig. 1. Base lines detection: (a) simulated 256 × 256 binary edge image; (b) ρ–θ parameter space; (c) detected modes (marked circles) in (b) and (d) detected base lines.

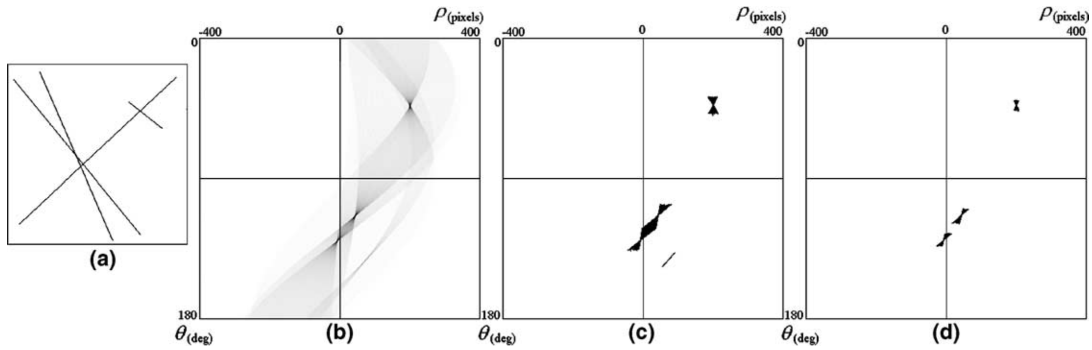

Fig. 2. Clustering procedure in the importance sampling HT: (a) simulated 256×256 binary edge image; (b) ρ–θ parameter space (cell size in $\{\rho, \theta\}$ notation of $1.8 \times 2\pi/100$); (c) connected regions after thresholding with a low importance weight threshold and (d) connected regions after thresholding with a high importance weight threshold.

the literature that can be classified into two large classes: hierarchical clustering and density estimation. Hierarchical methods either aggregate or divide the data based on some measure (Jain and Dubes, 1988). Agglomerative clustering takes each entity as a single cluster to start off with and then builds bigger clusters by grouping similar entities together until the entire dataset is encapsulated into the final set of clusters. Divisive hierarchical clustering works the opposite way around—the entire dataset is first considered to be one cluster and is then broken down into smaller subsets. These methods tend to be computationally expensive and the stopping criterion for fusion or division is not easy to define. Density estimation-based clustering regards the feature space as the empirical probability density function (p.d.f.) of the represented parameter. Then, dense regions in the feature space correspond to the local maxima of the p.d.f. and to the modes of the unknown density. The cluster associated with each mode is delineated based on the local structure of the feature space (Herbin et al., 1996).

3. Proposed method

The proposed method of line segments detection has two stages. Firstly, an edge image is obtained by employing a suitable edge detector on a gray-scale image. This edge image is used as input of a RWRHT based approach, the output image of which is a set of Hough parameters. Then, these items are clustered by a variable bandwidth mean shift algorithm. Cluster modes are selected as the set of base lines. Projections of the edge points onto the corresponding base line are grouped to obtain the line segments. Next subsections deal with the two stages of the proposed method.

3.1. First stage: HT based approach

The proposed approach employs the RWRHT algorithm (Kälviäinen et al., 1995) to obtain an initial set of parameter items. The RWRHT is a version of the RHT that selects one edge point randomly and apply the RHT procedure in a square window of random size. Random sampling is repeated R times. Lines are detected one by one until a desired number of lines have been found. The original algorithm of Kälviäinen et al. (1995) has been slightly modified because the next clustering stage permits the algorithm to avoid the global maxima detection. Therefore, the RWRHT will be used without accumulator actualisation and thresholding. The RWRHT algorithm consists of the following steps:

1. Create the dataset D of edge pixels.
2. Select one point d_i randomly from the set D. If the number of edge pixels in D is minor than the minimum line segment length, $l_{\min}$, then stop.
3. Select the window size m randomly between $m_{\min}$ and $m_{\max}$. Generate a window centered in d_i with size $m \times m$.
4. Create the dataset W of edge pixels into the selected window. If the number of edge pixels in W is minor than $l_{\min}$, go to Step 2.
5. Set a number of random selections R as $m \cdot m$. Set $k := 0$.
6. Select one pair (w_i, w_j) randomly from W.
7. If the Euclidean distance between w_i and w_j is minor than a threshold $d_{\min}$, or greater than threshold $d_{\max}$, go to Step 6; otherwise continue to Step 8.
8. Solve the parameter space points (ρ, θ) from the line equation with the points (w_i, w_j). Accumulate the item (ρ, θ) in the Hough parameter space. Set $k := k + 1$.
9. Take out of D all pixels lying on the line defined by (ρ, θ). Pixels removed from the image are classified into line segments. This set of elementary line segments (ELSs) will be posteriorly employed by the algorithm. Each line has an associated list which contains the ELSs lying on it. If $k < R$ go to Step 6; otherwise go to Step 2.

Fig. 1(b) shows the Hough parameter space associated to Fig. 1(a). The obtained set of lines is very similar to that obtained by applying a standard HT algorithm and thresholding the parameter space by $l_{\min}$. However, the computation time is more than 20 times lower. The obtained results are very similar to the ones reported by Kälviäinen et al. (1995).

3.2. Second stage: HT parameter space clustering

Kernel density estimation or Parzen window technique is one of the most popular density estimation method. If it is assumed that each data point $\boldsymbol{x}_1, \ldots, \boldsymbol{x}_n$ is associated with a bandwidth value $h_i > 0$, the multivariate adaptive bandwidth kernel density estimate is defined by Comaniciu et al. (2001)

$$\hat{f}_K(\boldsymbol{x}) = \frac{1}{n} \sum_{i=1}^{n} \frac{1}{h_i^d} k\left(\left\| \frac{\boldsymbol{x} - \boldsymbol{x}_i}{h_i} \right\|^2 \right), \tag{1}$$

where the d-dimensional vectors $\boldsymbol{x}_1, \ldots, \boldsymbol{x}_n$ represent a random sample from some unknown density $f(x)$. This nonparametric estimator of the density at location $\boldsymbol{x}$ in the feature space is based on a spherically symmetric kernel K with bounded support satisfying

$$K(\boldsymbol{x}) = c_{k,d} k(\|\boldsymbol{x}\|^2) > 0 \quad \|\boldsymbol{x}\| \leqslant 1, \tag{2}$$

where the function $k(x)$, $0 \leqslant x \leqslant 1$, is called the profile of the kernel and $c_{k,d}$ is a normalization constant that assures that $K(\boldsymbol{x})$ integrates to one. The terminology adaptive bandwidth is due to the fact that h_i is not held constant across $\boldsymbol{x}_i \in \mathscr{R}^d$. This estimator is called the sample point density estimator (Comaniciu et al., 2001). To define h_i, most methods use a pilot density estimate, that can be easily obtained by nearest neighbors (Georgescu et al., 2003). If $\boldsymbol{x}_{i,k}$ is the k-nearest neighbor of point $\boldsymbol{x}_i$, the bandwidth value h_i is defined by

$$h_i = \|\boldsymbol{x}_i - \boldsymbol{x}_{i,k}\|_2, \tag{3}$$

where L_2 norm is used because it is the most suitable for our data structure. The number of neighbors k must be chosen large enough to assure that there is an increase in density within the support of most kernels having bandwidths h_i.

An estimator of the gradient of $f(x)$ is the gradient of (1):

$$\nabla \hat{f}_K(\boldsymbol{x}) = \frac{2}{n} \left[\sum_{i=1}^{n} \frac{1}{h_i^{d+2}} g\left(\left\| \frac{\boldsymbol{x} - \boldsymbol{x}_i}{h_i} \right\|^2 \right) \right] \times \left[\frac{\sum_{i=1}^{n} \frac{\boldsymbol{x}_i}{h_i^{d+2}} g\left(\left\| \frac{\boldsymbol{x} - \boldsymbol{x}_i}{h_i} \right\|^2 \right)}{\sum_{i=1}^{n} \frac{1}{h_i^{d+2}} g\left(\left\| \frac{\boldsymbol{x} - \boldsymbol{x}_i}{h_i} \right\|^2 \right)} - \boldsymbol{x} \right], \tag{4}$$

where $g(x) = -k'(x)$. This relation implies that it is assumed that the derivative of the kernel profile $k(x)$ exists. Using $g(x)$ as the profile, the kernel $G(\boldsymbol{x})$ is defined as

$$G(\boldsymbol{x}) = c_{g,d} g(\|\boldsymbol{x}\|^2), \tag{5}$$

where $c_{g,d}$ is a normalization constant that forces G to integrate to one.

The last bracket in (4) represents the variable bandwidth mean shift vector (Comaniciu et al., 2001)

$$M_v(\boldsymbol{x}) = \frac{\sum_{i=1}^{n} \frac{\boldsymbol{x}_i}{h_i^{d+2}} g\left(\left\| \frac{\boldsymbol{x} - \boldsymbol{x}_i}{h_i} \right\|^2 \right)}{\sum_{i=1}^{n} \frac{1}{h_i^{d+2}} g\left(\left\| \frac{\boldsymbol{x} - \boldsymbol{x}_i}{h_i} \right\|^2 \right)} - \boldsymbol{x}. \tag{6}$$

Comaniciu and Meer (2002) have demonstrated that the mean shift vector points toward the direction of maximum increase in the density. That is, if the mean shift procedure is defined recursively as the evaluation of the mean shift vector, $M_v(\boldsymbol{x})$, followed by the translation of the kernel G by $M_v(\boldsymbol{x})$, this procedure leads to a stationary point (zero gradient) of the underlying density. Most often these stationary points are the local maxima (modes) of the density. If the sequence of successive locations of the kernel G is denoted by $\{\boldsymbol{y}_j\}_{j=1,2,\ldots}$, the weighted mean at $\boldsymbol{y}_j$ computed with kernel G and weights $1/h_i^{d+2}$ is defined by

$$\boldsymbol{y}_{j+1} = \frac{\sum_{i=1}^{n} \frac{\boldsymbol{x}_i}{h_i^{d+2}} g\left(\left\| \frac{\boldsymbol{y}_j - \boldsymbol{x}_i}{h_i} \right\|^2 \right)}{\sum_{i=1}^{n} \frac{1}{h_i^{d+2}} g\left(\left\| \frac{\boldsymbol{y}_j - \boldsymbol{x}_i}{h_i} \right\|^2 \right)}, \quad j = 1, 2, \ldots \tag{7}$$

This iterative procedure is a hill climbing technique to the nearest stationary point of the density. The initial point of the procedure $\boldsymbol{y}_1$ can be chosen as one of the data points $\boldsymbol{x}_i$. Points of convergence of the iterative procedure are the modes or local maxima of the density. If the mean shift procedure is applied to a representative number of data points, a robust nonparametric clustering of the data is achieved. After convergence, detected modes are clusters centers, and the shape of the clusters is determined by the basins of attraction. Fig. 1(c) shows the modes obtained from the Hough parameter space clustering of sample points in Fig. 1(b). Each mode represents a base line in the original image. Fig. 1(d) shows these base lines.

Once base lines have been extracted, the algorithm detects the actual line segments by using a simple grouping approach. In grouping approaches, linear structures are detected by replacing a number—often two—of short line segments by a single longer one and repeating this until the large linear structures in the image are formed. In our approach, the algorithm groups the set of ELSs obtained by the RWRHT algorithm into actual line segments along each base line. Since each base line has been defined by a cluster of Hough parameters, the algorithm that groups ELSs along a base line takes into account only ELSs registered in the lists of the lines that participate in the construction of that base line. The algorithm for grouping ELSs along a base line is schematized in Fig. 3. Basically, if $\text{ELS}_i^{(\rho,\theta)_k}$ and $\text{ELS}_j^{(\rho,\theta)_k}$ are two ELSs lying on the base line $(\rho, \theta)_k$, they are grouped into the same line segment if their projections onto the base line has a gap minor than a threshold T_g. Although more complex schemes can be applied (Jang and Hong, 2002), this simple merging is very fast and experimental results show that it provides good results.

4. Experimental results

This section shows the results of several tests conducted to reveal the performance of the proposed algorithm. The method has been implemented in C++ Language on a

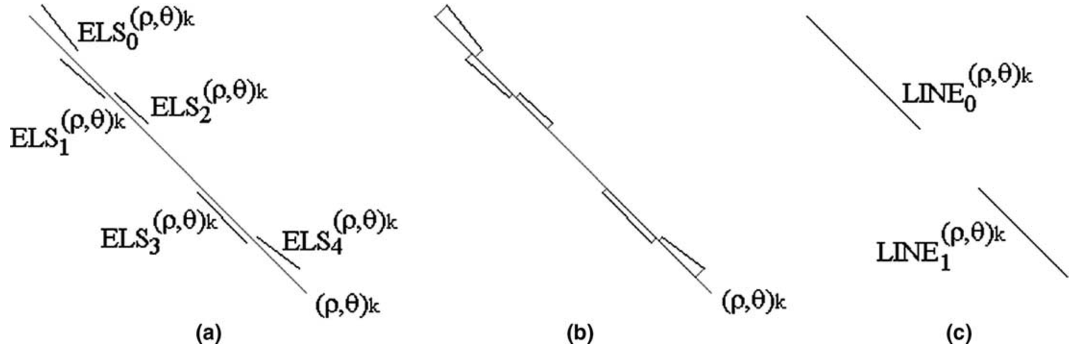

Fig. 3. Grouping ELSs along a base line: (a) base line and its associated ELSs; (b) ELSs projections and (c) grouped ELSs.

Pentium II 266 MHz PC. Experiments on real images have been conducted. The presented benchmark images have been chosen from various research papers. Fig. 4(a)–(c) show three benchmark real images (Galambos et al., 1999; Jang and Hong, 2002). The Canny edge detector (Canny, 1986) has been used to obtain an edge image, since most of the researchers have used this edge detector in their works. Fig. 4(d)–(f) show the obtained edge image associated to Fig. 4(a)–(c). The proposed line segment detector is then employed to obtain the desired line images

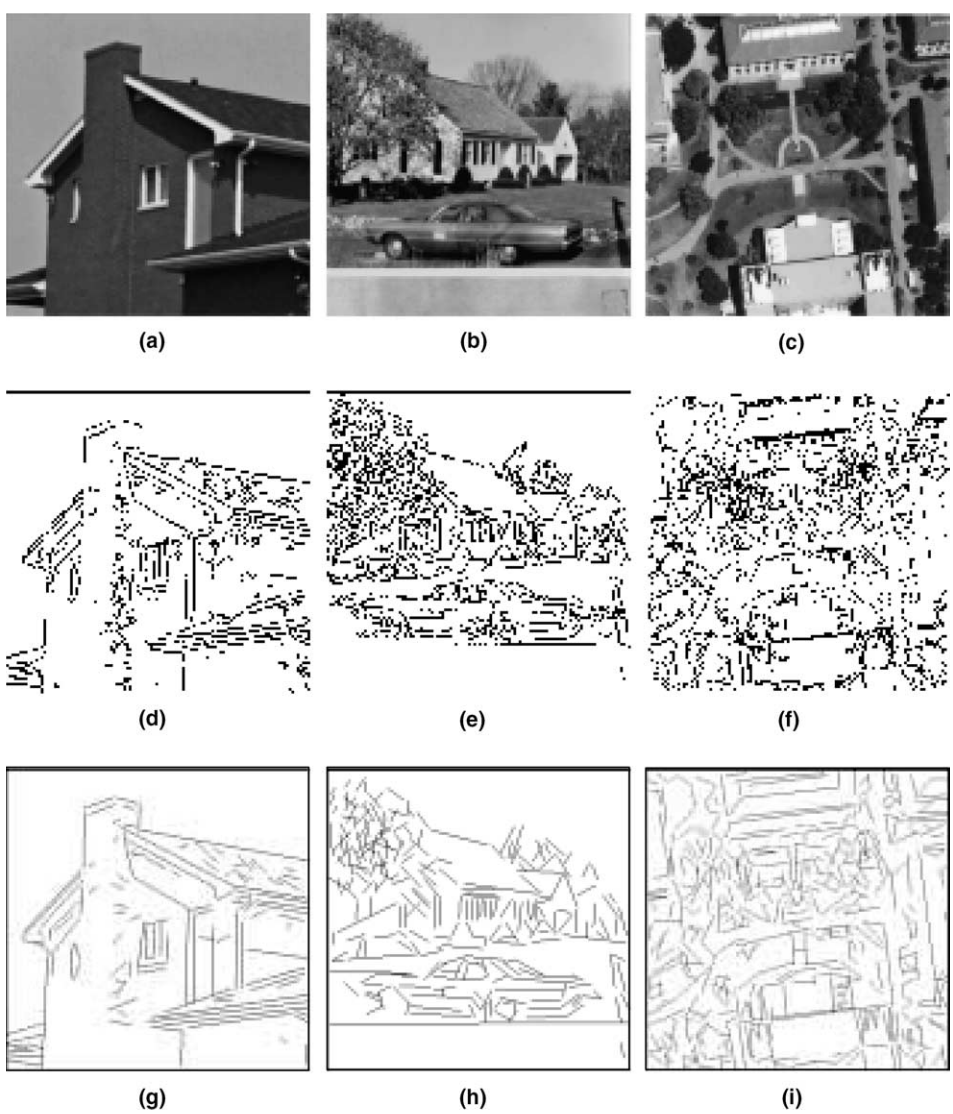

Fig. 4. (a)–(c) Input 256 × 256 gray-scale images; (d)–(f) edge images associated to (a)–(c) and (g)–(i) detected line segments associated to (d)–(f).

(Fig. 4(g)–(i)). Since we do not know the ground truth line segments of these real images, a quantitative performance comparison of the method with other published methods is not possible. However, by looking at each line segment detection result and comparing it with the edge images, it is possible to determine if the detection result is reasonable or not. From Fig. 4(g)–(i), we can assert that the proposed method works well on real images.

4.1. Estimation of parameters

One of the main disadvantages of the proposed method is the existence of a set of parameters to adjust. These parameters are

- The minimum line segment length, $l_{\min}$.
- The minimum and maximum window sizes, $m_{\min}$ and $m_{\max}$, respectively.
- The minimum and maximum Euclidean distance limits between two points in the same window, $d_{\min}$ and $d_{\max}$, respectively.
- The number of neighbors to obtain h_i, k.
- The minimum gap between two line segments, T_g.

Two of these parameters, $l_{\min}$ and T_g, are user-specified parameters that must be chosen depending on the final application. In our tests with real images, $l_{\min}$ and T_g are set to 10.0 and 5.0, respectively. The point distance criterion determines that, at each iteration, the two points chosen to calculate the line parameter are within a certain distance ($>d_{\min}$ and $<d_{\max}$). Sensible choices of these parameters lead to an increase in the probability of sampling points on a curve present in the image (Walsh and Raftery, 2002). Thus, Kälviäinen et al. (1995) proposes to limit the maximum distance of points in a tuple to 25 pixels in real images. Similar influence has the window size limits, $m_{\min}$ and $m_{\max}$. In order to decide values for these parameters, images containing randomly generated synthetic lines with different orientations and lengths were experimentally studied. Several combinations of the parameters were selected and the best combination was chosen. In our tests, the best choices for the window sizes were 10×10 and 50×50, respectively. The selected Euclidean distance limits were $d_{\min} = 1$ and $d_{\max} = 30$.

A fast algorithm to perform neighborhood queries when computing (7) can be implemented by sorting the data according to each of the d coordinates. To illustrate the influence of the parameter k, the number of neighbors used for the pilot estimation, a dataset containing 15,000 points in a two-dimensional plane was generated. From these 20×250 points belonged to twenty spherical normal distributions. The remaining 10,000 points were uniformly dis-

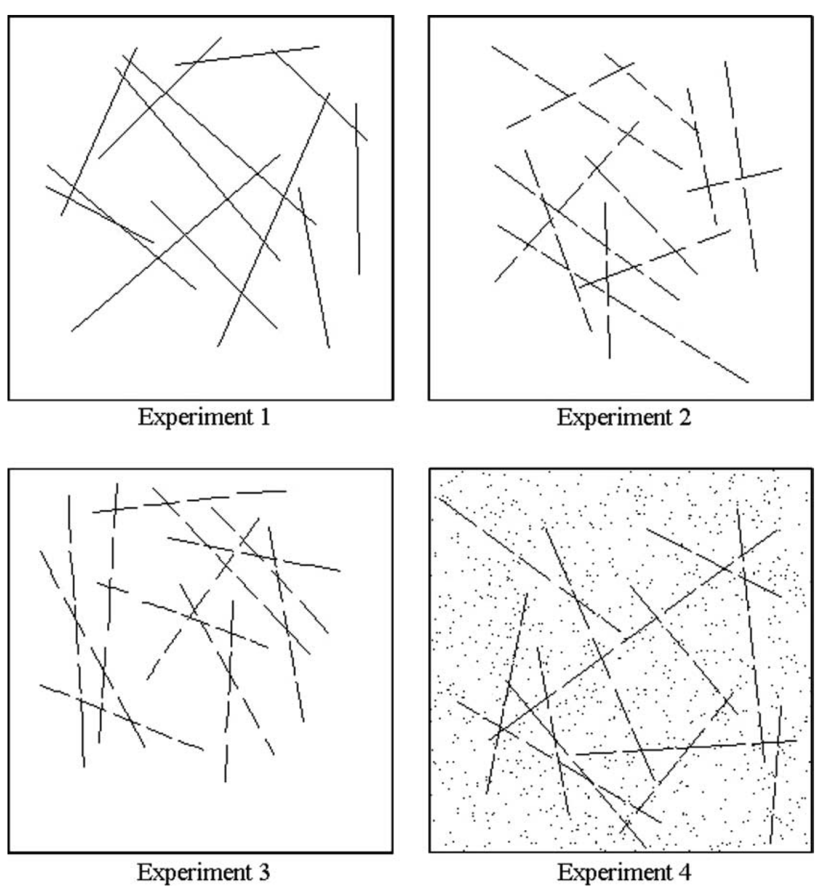

Fig. 5. Test images.

Table 1
Results of different line segment detection approaches

	Nacken (1993)	Yuen et al. (1993)	Jang and Hong (2002)	Proposed
Number of line segments detected				
Experiment 1	13.6	14.4	14.4	13.4
Experiment 2	15.6	17.0	15.0	12.8
Experiment 3	15.2	13.8	15.8	13.6
Experiment 4	16.0	14.4	18.5	14.0
Match score 0.0–0.9				
Experiment 1	4.6	0.6	1.2	1.6
Experiment 2	4.4	11.2	1.2	1.2
Experiment 3	4.4	9.6	1.0	1.2
Experiment 4	5.6	9.0	3.0	3.4
Match score 0.9–1.0				
Experiment 1	7.6	12.4	11.4	11.8
Experiment 2	8.2	0.6	11.8	11.6
Experiment 3	8.0	0.6	12.0	12.4
Experiment 4	7.2	1.0	9.5	10.6
Execution time (ms)				
Experiment 1	1347	620	164	97
Experiment 2	6024	673	192	174
Experiment 3	6210	840	212	207
Experiment 4	35,712	2140	850	351

tributed in the two-dimensional plane. Obtained results show that the data is processed correctly for $k = 10$–40, except for a few points. Thus, we can conclude that the parameter k does not have a strong influence. A similar experiment has been previously conducted by Georgescu et al. (2003) in high dimensional spaces to obtain the same conclusion.

5. A comparative study

The proposed method has been compared to several line segment detection methods to test its performance. Particularly, we chose for the purpose of comparison the methods proposed by Nacken (1993), Jang and Hong (2002) and Yuen et al. (1993). In order to compare the performance of the different methods, four sets of edge images have been created (Jang and Hong, 2002). The size of test images is 256×256 pixels and each image contains 13 true line segments with a random length of 40–200 pixels (Fig. 5). A total of 50 images are generated and tested in each experiment. In Experiment 1, images only contain the 13 true line segments. In Experiment 2, the line segments are broken into fragments, but the orientation of these fragments is preserved. In Experiment 3, the line segments are also broken into short fragments, but now the fragments orientation is randomly changed by adding a small perturbation. Finally, in Experiment 4, small noisy line segments are added to each test image. The experiments were performed on a Pentium II 266 MHz PC and they were repeated several times to choose good parameter values for each method. The experimental results are shown in Table 1. In this table, it can be noted that all methods usually detect a number of line segments greater than the real one (13). Only some of these segments can be matched to real ones. Two line segments are matched if the difference between their associated line parameters are lower than ± 5 pixels in ρ and $\pm 1.43°$ in θ (Kälviäinen et al., 1995). Then, a "match score" value is associated to every match. This value represents the length similarity between a detected line segment and the corresponding real line segment (Jang and Hong, 2002). Thus, a "match score" equal to 1.0 means a perfect length match between the detected line segment and the corresponding real line segment. A "match score" equal to 0.9 means that the detected line segment is 0.9 or 1.1 times longer that the corresponding real one. The table shows that the performance of the proposed method is almost highest among all the methods tested in terms of line segment detection ability and execution time.

6. Conclusions

This paper proposes a new method for finding line segments in edge images. The method overcomes the drawbacks of the global nature of a conventional HT based approach while retaining most of its advantages. The clustering process of the HT parameter items permits to obtain high accuracy line detection with a reduced computational time. Experimental results show that the proposed method is fast and possesses a good line segment detection ability compared to other approaches.

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