The Selection of Edge Detectors Using Local Image Structure

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Abstract

This paper summarizes a system, called SED, "Selection of Edge Detectors", which is able to automatically select edge detectors and their scales to extract a given edge. The basic organization of the SED system is a collection of edge detectors within a knowledge structure about the characteristics of the given edge, the properties of the detectors and the mutual relation between them. The combination of this information in the selection process provides a basis for avoiding a combinatorial search for appropriate edge detectors. We illustrate our approach by an example.

1 Introduction

In computer vision, we are often confronted with the problem of selecting an appropriate edge detector. Usually, the approach used consists of arbitrarily choosing of a detector and using it to find all the edges in the images being processed in the target application. The scale is often fixed by trial-and-error experiments and reused for all images. It is obvious that this approach does not lead to correct results. In fact, one detector running at one scale does not yield all edges of the image [10]. It is more suitable to focus on edges by using several detectors that differ in their scales, mathematical properties and goals. The underlying problems are multiple; various knowledge and know-how about image formation and processing techniques are required to arrive at an effective approach. Matsuyama [5] pointed out the problems frequently encountered in designing image analysis systems. Hasegawa et al. [4] implemented an intermediate solution in the IMPRESS system that is able to choose the appropriate detector to find a given edge [10]. It involves in applying all the detectors and retaining the one which generates the most similar result to the reference edge. We propose another intermediate solution implemented in a system, called SED "Selection of Edge Detectors", which is able to automatically select edge detectors and their scales to extract a given edge. The significant difference between the IMPRESS system and the SED system concerns the use of selection criteria which combine several sources of information (i.e, edge characteristics, detector properties, the mutual influence between edges and detectors, and the effective results of the run detectors) to avoid a combinatorial approach.
In the next section, we present an outline of our approach. Section 3 is devoted to the analysis of image structure. We give the selection criteria and analysis of the results in sections 4 and 5. Finally, we present a thorough study of an example.

2 System Overview

The underlying ideas of this work are drawn from research into computer vision and the knowledge-based approach. From computer vision research, we gained experience in image analysis, specifically the design and use of edge detectors. From the knowledge-based approach, we acquired suitable structures to represent knowledge. Here, we use three possible sources of knowledge for the selection of detectors and their scales. The first is the properties of the effective edges produced by the detector and the analysis of the successes and failures of this detector. The second source concerns *a priori* knowledge about the detector such as its mathematical and algorithmic properties. We consider that the edge detector is formed by smoothing and differentiation operations. The last source is edge characteristics such as position, form, profile and so on. Consideration of the first source only leads to a combinatorial solution [4]. The second and third sources are interdependent and must be used together. In this case, selection is based on a set of rules describing the mutual influence of edge characteristics and detector properties. However, usually these rules are imprecise and consequently selection errors are introduced. As explained below we use the three sources of knowledge mentioned above together to minimize possible selection errors.
The SED system has, as input, an edge represented by its location, the image that contains it (see Fig. 3), and the quality of the required results expressed as a set of constraints related to the delocalization error

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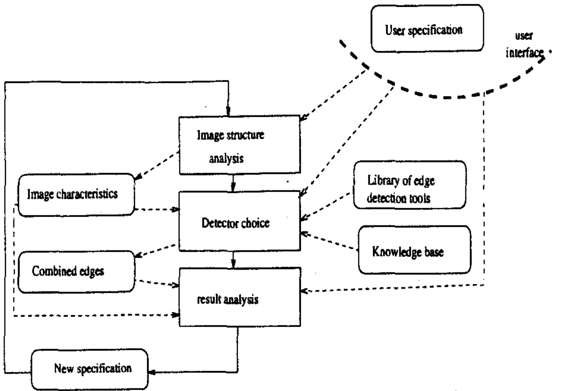

Figure 1: *Procedural control structure of the SED system*

and the computation time. The results of this system are the characteristics of the given edge, and the detectors and their scales that make it possible to find it. Fig. 1 shows the main components in the SED system and their interactions. To avoid a combinatorial approach, the SED system includes a library which contains a set of tools related to edge detection (i.e., edge detectors and cleaning algorithms) and the knowledge base required for the selection process. The first step involves computation of the pertinent characteristics of the current reference edge and its segmentation into a set of edgels. An edgel is a set of points having homogeneous characteristics. The second step involves choosing the best detector and its parameters. This is based on its performance, the effective results of previously run detectors, and a set of condition-action rules which specify the influence of the attributes of an edge and the properties of a detector on its performance. A system process matches rules against the data computed by the image structure analysis process and when a match occurs, the best rule is fired. This triggers an action that involves a run of the selected detector. Finally, the results of the selected detector are combined with the results obtained previously. If the initial reference edge is not fully found, then the missed edgels are identified and they form the new reference edge. The parameters used in the image structure analysis are updated and the feedback route is tried once. In what follows, we will give full details about the three steps of the system.

3 Image Structure Analysis

This step involves analysis of the input data and segmentation of the current reference edge into a set of edgels. It includes measurement of the geometric and photometric characteristics of the edge which influence the performance of an edge detector. The geometric characteristics are deduced from the initial reference edge and include position, orientation, and smoothness. The photometric characteristics are an accurate description of the detailed variation of image intensity in the vicinity of the edge. We consider two kinds of edge profile: the step edge (a discontinuity in the image intensity) and the double edge (two close discontinuities, i.e. pulse and staircase edges). The motivation behind this distinction is the fact that localization of the double edge requires more attention because the smoothing of each step edge is greatly influenced by its neighboring edge. Let us consider that the surfaces of the image are linear. This is a reasonable assumption if the image is smoothed before edge analysis. The attributes of the step edge are its noise, contrast (the cumulative intensity change that occurs across the edge), steepness (the surface slope within the interval, across the profile, in which the bulk of the intensity change occurs), and finally its width (the size of this interval). The attributes of the double edge are those of each step plus the distance between them.

Edge noise is estimated by using our algorithm proposed in [9]. The contrast, the steepness, the width, and the distance between the two discontinuities of the double edge are computed by using fitting technique similar to those in [3, 6]. The estimation of all of these attributes takes into account the shape of the edge profile and therefore requires identification of the edge model. For this purpose, we use a set of rules like the following two: 1) A given point is a step edge if its contrast is high and the difference of variances is smaller than twice the noise energy. 2) A given point belongs to a double edge if the maximum contrast of the two discontinuities is greater than the standard deviation of the noise, and the difference of variances is greater than twice the noise energy.

It should be recalled that the edge is segmented into homogeneous edgels and the attributes of each edgel are computed. That is, the reference edge is segmented into smoothed curves and straight-line segments. After that, these primitives are segmented according to photometric attributes (i.e., edge model, noise, width, contrast, and steepness).

4 Detector choice

Given the set of edgels determined by image structure analysis, we want to select an appropriate edge detector and its scale. In general, an edge detector includes neither the precise context in which it can be successfully used nor the scale computation rule. In practice, it is commonly viewed as a convolution operation $(f_s * I)(x, y)$ where I is the image, f_s the filter and s the scale. We propose to specify an edge detector not only by its algorithm but also by the context in which it is meaningful. The context corresponds to the characteristics of edges on which the detector can be used successfully. Since close scales produce edges having similar characteristics, we sample the scale and take into account only some values. The choice of these values depends on the properties of the detector and its implementation method (i.e, convolution masks, IIR filter, FFT). These considerations allow us to specify the knowledge base of the SED system. For this purpose, we choose a production system using *if-then* rules as a basic representation framework:

$if\ (situation_1,\ v_{11},\ \cdots,\ v_{1m}) \vee \cdots \vee (situation_n, v_{n1}, \cdots, v_{nm})$
$then\ (algorithm,\ scale)$

The condition part of the rule is a representation of the context and is formed by the disjunction of situations. Each *situation* is a conjunction of predicates formed from the edge attributes. v_{ij} is a performance vector for the pair (algorithm, scale) in the i^{th} situation where the edge has an orientation j. The orientation is sampled with period π/m. These performance include the failure probability, the delocalization error, and the computation time. The conclusion part of the production rule is formed by the couple (algorithm, scale).

The production rules represent the matching between detector properties and edge characteristics. We described the pertinent characteristics of an edge in the previous section. The properties of a given detector are those of its smoothing filter and its differentiation operator. The smoothing filter properties are the duration of its impulse response, its linearity, and its invariance to rotation. The differentiation operator properties are its linearity, its directionality, and its invariance to rotation. There are other properties of an edge detector, for instance its computational complexity and its goal; the characteristics of the edges, which can be localized by the detector (i.e., detector of straight edges, detector of closed edges). It has been pointed out [6] that directional detectors are more suitable in the case of straight-line edges. Since the edge orientation is assumed to be known, we consider two kinds of edge detectors ; directional detectors (those which are parameterized by the edge orientation), and general detectors (those which are not designed for a particular edge).

Given the set of edgels, we begin by searching for valid detectors. Since we use directional detectors, each edgel is fitted by a set of straight-line segments. For each edgel and for each segment of this edgel the detectors whose condition parts are validated by their attributes are considered. We use a forward chaining algorithm to match rules against edge attributes [7]. After the rules have been fired, we choose the detector that minimizes the linear combination of failure probability $p(d)$, delocalization error $l(d)$, and the computation time $t(d)$: $c(d) = \alpha p(d) + \beta l(d) + \gamma t(d)$, where d is a detector. User requirements for the final solution are used to compute the combination scalars α, β and γ. In practice, the number of candidate detectors and the number of edgels are low. Consequently, $c(d)$ is computed for each detector and the one having the lowest value is the best.

5 Results Analysis

The analysis of the results includes two aspects. The first one concerns measurement of the difference between the initial reference edge and the computed edge. When the current solution does not meet the requirements of the user, a new reference edge is generated and the feedback loop is run. The new reference edge is formed by edgels of the initial reference edge not yet found. The second aspect concerns the correction of selection errors resulting from the use of relatively inaccurate *a priori* knowledge. At each loop, the contribution of each run detector is updated and the falsely selected detectors are discarded.

The results analysis requires a matching process comparing the computed edge and the reference edge to identify similar edgels. To decrease the number of comparisons we propose to combine edge information obtained at the last run of the selected detector with that obtained from previous loops. The combination process consists in identically labeling, with minimum error, an edge resulting from different detectors and originating from the same physical phenomena. The similar edgels are combined to form a single image, to which are added all edgels which are not matched. This image must include all edgels, with a minimum of redundancy and a small delocalization error. These edgels must be filiform and rapidly computable. More precisely, we assume that the SED system has run several loops and that the obtained edgels have been combined. Let us consider I_c, the image obtained from the edge combination procedure and I_r the result of the last run of the detector. All edges in I_r which do not correspond to the initial reference edge are suppressed. Identification of similar edgels is done by matching I_r and I_c. The similarity between edges depends on their photometric and geometric properties. To take into account the continuity of edgels and to make the process global we updated this similarity measure using a stochastic relaxation [2]. The result of the matching process is three classes of edges: 1) Isolated edges ;

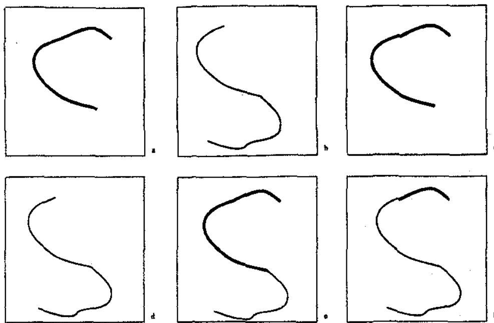

Figure 2: *a) and b) Examples of edges to be combined. c), d), e), and f) are the four possible combinations*

those belonging only to one image, 2) Similar step edges, and 3) Similar double edges. We assign to each class an appropriate combination rule. A new image I_n is created and the isolated edges are added. For similar edges, we examine each edgel and we choose the edgel belonging to I_r or the one belonging to I_c or produce an edgel that is combination of the two, as shown in Fig. 2. It should be noted that we distinguish between (Fig. 2.e) and (Fig. 2.f) because to each edge is associated the detector that produces it. We are interested in the combination procedure which reduces global ambiguity and global delocalization error. Consequently, there are 4^N different solutions to construct the image I_n, where $N = max(p, q)$, p is the number of edgels in I_c and q is the number of edgels in I_r. To avoid a combinatorial solution, we use an A^* algorithm [7] and an heuristic function $c(n)$ which represents the cost of adding the n^{th} edgel. $c(n)$ is recurrent and is defined in terms of three factors: edgel length, delocalization error and the computation time of the detector.

6 Experimental Results and Concluding Remarks

The implemented system contains twenty selection rules related to the two popular step edge detectors: 1) Deriche's gradient edge detector (DGD) [1] with a scale α taking its value in the interval $[0.75, 1.5]$ (which also we use in a particular direction to extract a linear edge that we call DGDd). 2) The Laplacian detector of Shen and Castan (DRF) [8] which has the scale $a \in [0.25, 0.35]$. It should be noted that both scales α and a are inversely proportional to the Gaussian scale. To illustrate, we give the following selection rule used in the SED system.

if *the edge is a step* ***and*** *its signal-to-noise ratio is less than 2* ***then*** *use the DGD detector with* $\alpha = 0.75$.

This rule describes a noised step edge. In this case a first order differentiation operator is more suitable, because higher order operators are more sensitive to noise. Strong (higher scale) smoothing is necessary. But to avoid detector stability problems we use $\alpha = 0.75$. Depending on the edge orientation θ, the performance of the (DGD, $\alpha = 0.75$) given in terms of the delocalization error $l(DGD)$ and the failure probability $p(DGD)$ are the following: ($l(DGD) = 0.375$, $p(DGD) = 0.251$, $\theta = 0$), ($l(DGD) = 0.453$, $p(DGD) = 0.252$, $\theta = \pi/8$), and ($l(DGD) = 0.476$, $p(DGD) = 0.254$, $\theta = \pi/4$). The performance at a particular orientation which are not given explicitly in the rule can be estimated easily using an interpolation process and the symmetry property. In fact, the performance of this detector are symmetric at $\theta = k\pi/4$, where k is an integer.

Fig. 3 presents the given edge and the image which contains it. To find this edge the SED system run three loops. In the first loop, two edgels are produced by the edge analysis step (fig. 3). The first edgel is numbered 1; its signal/noise ratio is -2.3 dB and its steepness is 41 degrees. The second is numbered 2 and its attributes are: signal/noise ratio 6.5 dB and steepness 76.7 degrees. The validated detectors are: (DRF, $a = 0.25$), (DGD, $\alpha = 1$), (DGD, $\alpha = 0.75$), (DRF, $a = 0.3$), (DGD, $\alpha = 1.2$), (DGDd, $\alpha = 1$, $\theta = 6$), and (DGDd, $\alpha = 1.2$, $\theta = 18$). The one retained is (DRF, $a = 0.3$). Fig. 4 presents the results of this detector. Note that the given edge is not completely found, so a new reference edge is generated. In the second loop the new reference edge is the one described in Fig. 4. We change the parameter values used in the image structure analysis procedure (i.e., the size of the neighborhood considered when analyzing the edge). The detector retained is (DRF, a=0.25). The edges obtained using this detector are similar to those given by the (DRF, a=0.3). Therefore, when combining edge information given by the (DRF, $a = 0.3$) and (DRF, $a = 0.25$) detectors the (DRF, $a = 0.25$) is suppressed because it has a greater delocalization error. In the last loop, the Deriche detector with $\alpha = 1$ is selected and its results are given in Fig. 4. The edges given by the DRF and Deriche detectors are combined and the results are given in Fig. 4.

The DRF detector is more efficient than the Deriche detector and its delocalization error is generally lower. Therefore, the obtained solution combines the performance of the DRF detector and Deriche detectors: the computed edge has a small delocalization error, small gaps, and can be computed efficiently. However, study of this example shows that selection errors can occur because of imprecise selection rules.

In this paper, we have presented a general approach for selecting edge detectors and automatically computing their scales. By using several sources of information and the edge combination procedure we avoid a combinatorial search in contrast with the IMPRESS system [4], and we combine some desirable qualities of edge detectors that are usually antagonistic: good accuracy, good noise reduction, low computation time. However, many improvements of the SED system are possible such as new rules and models of other edges (i.e, lines, corners, and so on). We hope to develop a learning procedure for automatic acquisition of selection rules.

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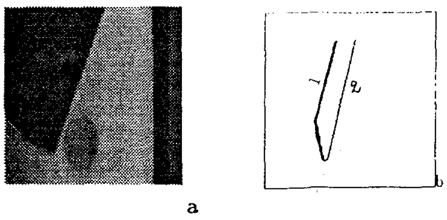

Figure 3: *a) Image, b) The reference edge*

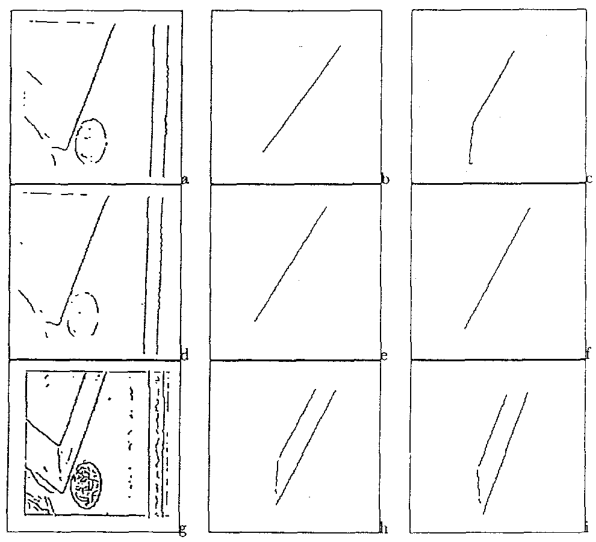

Figure 4: *a) the edges obtained by the (DRF,* $a = 0.3$*), b) the results of the elimination process (the suppression of noise edges and those which do not match the given edge), c) the new reference edge, d) the edges obtained by the (DRF,* $a = 0.25$*). e) the results of the elimination process, f) the edge obtained by the combination process of the edge information given in (b) and (e). g) the edges obtained by the (DGD,* $\alpha = 1$*), h) the results of the elimination process. i) the edge obtained by combining edge information given in f) and h).*