THE MOST SIGNIFICANT EDGES:
AN EFFICIENT IMAGE DESCRIPTION FOR MACHINE VISION APPLICATIONS

A. Schrift, Y.Y. Zeevi and M. Porat

Department of Electrical Engineering
Computer Vision Laboratory
Technion-Israel Institute of Technology
Haifa 32000, Israel

ABSTRACT

Efficient edge detection is accomplished by means of a hierarchical processing scheme which implements spatial frequency channels similarly to processing in biological visual systems. We use such a pyramidal data structure to efficiently create the channels and thereby extract a set of edges from the various scales of the image. The set of selected edges serves as a compact and simple representation of the image, and as such appears to be most useful in image description for machine vision applications. To assess the importance of the information represented by the most significant edges thus extracted vis-a-vis image structure, images are reconstructed from these edges and compared with the originals based on human subjective (perceptual) criteria.

I. INTRODUCTION

Most schemes of image analysis and machine vision extract edges at the early stages of the processing, to efficiently represent the most relevant information regarding image structure [1]. A preferred approach which is motivated by biological processing of visual information, and as such lends itself to pyramidal data structures, and to parallel processing algorithms and architectures, extracts the edges from several scales of an image and inter relates them [2-5]. To implement this approach, one has to devise a method for selection of the most significant edges extracted from the various scales of the processing. Although the problem of how to combine the edges was addressed previously, no algorithm was presented [2,3,6].

In this paper, we first present an algorithm which, based on the coincidence of edges extracted from different scales, directs the processor to "areas-of-interest". We then assess the information represented by the selected set of most significant edges, by reconstructing the image and comparing the reconstructed image with the original one.

II. EDGE DETECTION IN DIFFERENT SPATIAL FREQUENCY BANDS

The effect of the bandwidth of a (low-pass) filter on the image operated thereupon was investigated in several studies [2,7]. Hildreth (1983), and Berzins (1984) utilized the popular edge detector wherein the zero crossings are extracted from the image after application of the Laplacian of a Gaussian operator. Alternatively, we applied the gradient operator after filtering with Gaussian low-pass filters of various bandwidths, ω_k, where k denotes the level of the pyramid [5].

These are our main conclusions based on our analysis of the gradient operator:

1. Long straight edges are detected in all frequency bands, at the same location, though the threshold should be reduced as the cutoff frequency becomes lower, yielding wider and less accurate edge-lines. The lowered threshold enables the detection of smoother edges which could not be detected in higher frequency bands.

2. Edges of strip like objects, with width d, are better detected when $\omega_k > 1/d$. The accuracy of the definition in the edge-location is good and almost independent of ω_k. If, however, $\omega_k < 1/d$, a higher contrast is required. This implies that less edges of this kind would be detected as ω_k would get lower, and, further that the localization of these edges would be less accurate. This fundamental fact, which is a consequence of uncertainty regarding positional and frequency information (see Porat and Zeevi [8]), may cause mismatch between edges detected in separate frequency bands.

3. Edges positioned near points of extremum behave in a similar way to what has been described above, i.e., they appear to be in different position in each of the channels. Below a certain contrast value, they may even disappear in the low frequency bands.

4. The lower frequency bands are better immuned against disturbance by noise. Application of the Gaussian LPF and gradient operator to white Gaussian noise, generates a noise vector with the expected value of the magnitude being proportional to ω_k^2.

III. HIERARCHICAL EDGE DETECTION IN PYRAMIDS

Pyramids are data structures created by sequential low-pass filtering and decimation of an image [9,10]. The pyramidal structure enables efficient processing of the image in several scales.

Examples of edge detection in several low-pass filters are depicted in Fig. 1, for processing of a nonpyramidal data structure (Fig. 1b), and processing with a pyramidal realization (Fig. 1c). ω_k is equal to $[3\omega_0/(4^k-1)]^{1/2}$ as a result of using a single Gaussian filter in the pyramid creation. The effective threshold in each channel is $T_k=T_0/2^k$ where T_0 is the basic threshold. This is a consequence of using T_0 in all the pyramid's levels, and approximating derivatives by differences, in images with various decimation factors [5].

This pyramidal structure, combined with the behavior characteristic of the gradient and threshold edge detector, led us to introduce the following hierarchical edge detection scheme. Processing according to this scheme, starts at the top of the pyramid, and progresses towards the bottom. Edge detection at a given level of processing is controlled by the results of edge detection at the previous level. This restricts the application of the edge detector to interesting regions only. The scheme was further elaborated to incorporate feedback mechanism in order to overcome problems in cases where edges in adjacent levels do not coincide. Edge detection, implemented in this scheme required only 20-50% of the computations necessitated by a non-hierarchical detection. Results are shown in Fig. 2, where they are depicted along with the resultant image representation by the integration map of the most significant edges. such an image representation is used in the following section for reconstruction of the image.

(a)

(b)

(c)

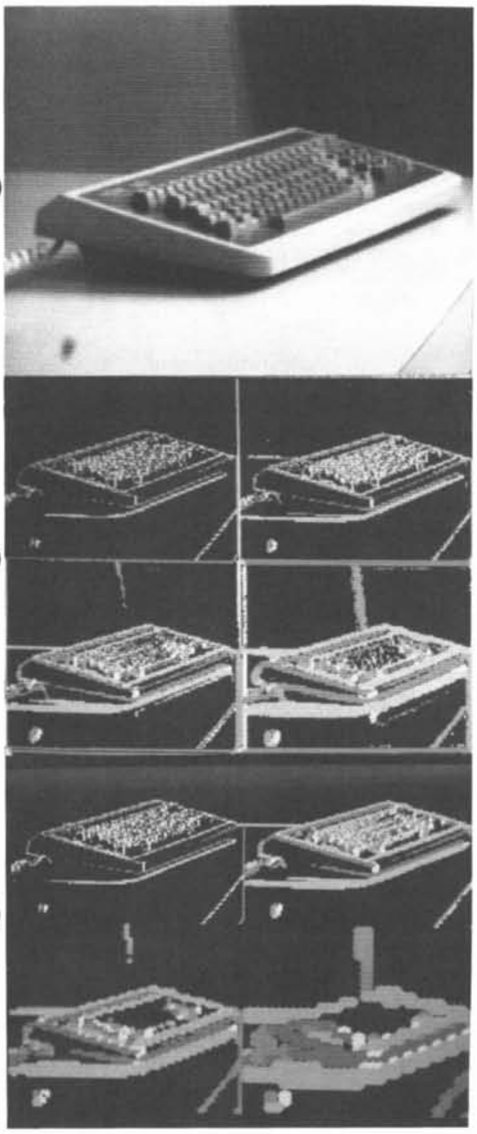

Fig. 1 - (a) Original Image. (b) Edges extracted from image components of various frequency bands. Processing was carried out without decimation. Directional information is encoded in this edge-map by the gray level. (c) Edges extracted from the various frequency bands implemented by the pyramidal scheme.

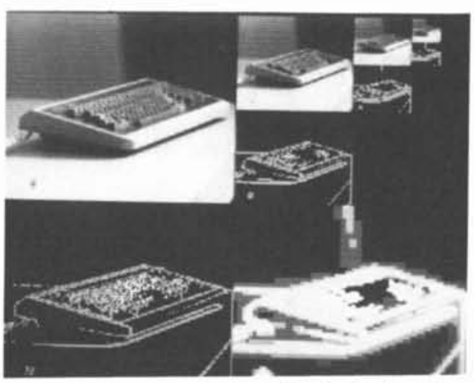

Fig. 2 - Edges extracted by the hierarchical edge detection scheme, and the image reconstructed from this edge-map (bottom right).

IV. IMAGE RECONSTRUCTION FROM EDGES

The purpose of extracting the edge-map by the above-described scheme, is to facilitate image understanding and the development of efficient machine vision. In such applications it is not necessary to reconstruct the image, and further processing can be pursued in the edge space. However, to asses the information represented by the extracted set of edges, we introduce a reconstruction algorithm. Further, instead of using the conventional and rather ineffective criterion of mean squared error, we assess the results of the reconstruction algorithm with reference to the criteria adopted by human observers.

The algorithm is an integration process. The input edge map contains a gradient (directional) information, quantized to two bits per edge pixel. This is sufficient for guiding the integration process. The integration is executed as follows:

1. The image is scanned along a raster trajectory.

2. For each edge pixel the threshold value is added or subtracted to the values of the neighboring pixel according to the directional information specified at the point of operation.

3. The value of a pixel which does not belong to an edge is determined by averaging the value of its neighbors.

The result shown in Fig. 3 represents a combination of integration in four directions [11]. Such a multidirectional integration (along four or more directions) eliminates low-frequency stripe pattern artifacts, generated by broken edges which are co-directional with the integration process. This effect of the artifact is also diminished by using edges from several bands, since the edges from lower bands fill-in the missing portions along the broken edges. A comparison of results obtained by implementing the multi-channel scheme, with those obtained by using a single frequency channel, are shown in Figures 3 and 4 respectively.

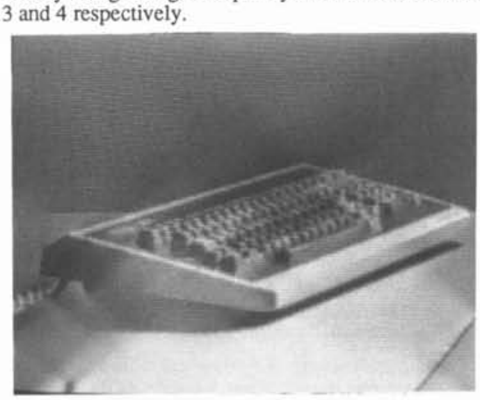

Fig. 3 - Image reconstruction from edges of a single channel (four integration directions).

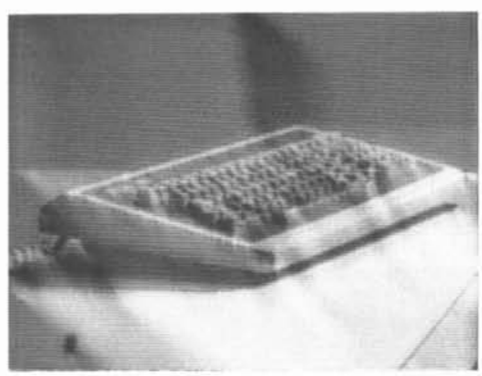

Fig. 4 - Image reconstruction from edges of several channels (one integration direction).

V. ITERATIVE RECONSTRUCTION WITH FREQUENCY CONSTRAINT

The above integration algorithm creates images endowed with frequencies higher then those which exist in the original. We therefore introduce an iterative algorithm in which the bandwidth of the original image (considered to be known) is imposed on the result of each iteration. For the sake of simplicity, we present the one-dimensional version. Each iteration contains three stages:

1. Apply low-pass filter, with cutoff frequency equal to the frequency constraint to the edge signal, $e_0(x)$. The filtered signal is $\tilde{e}_0(x)$.

2. For any point of discrepancy between $e_i(x)$ and $\tilde{e}_i(x)$, create an updated edge function $e_{i+1}(x)$, where the following conditions constitute a discrepancy:
$e_i(x)=1$ and $\tilde{e}_i(x)<1$ or
$e_i(x)=-1$ and $\tilde{e}_i(x)>-1$ or
$e_i(x)=0$ and $|\tilde{e}_i(x)|>1$.
Updating is accomplished by an increment or decrement of $e_i(x)$ in a direction that would minimize or diminish the discrepancy.

3. Repeat until number of points of discrepancy is zero (or small enough).

Integrate the last $\tilde{e}_i(x)$ to get the reconstructed signal.

Results obtained with this iterative algorithm are shown in Fig. 5.

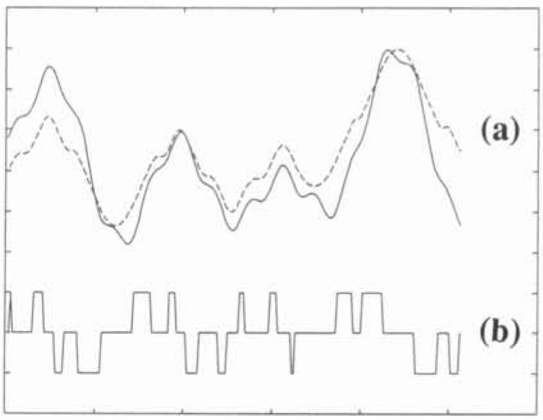

Fig. 5 - One-dimensional signal reconstruction from "edge information" using an iterative algorithm which constrains the results of each iteration by the proper bandwidth of the signal. (a) Superimposed are the original signal (continuous line) and the signal reconstructed after 17 iterations (dashed line). (b) Edge information.

VI. CONCLUSIONS

The hierarchical scheme presented in this paper extracts edge information which does not lack any of the features exhibited by the edge-map extracted in a conventional (i.e. nonhierarchical) way. The advantage is in terms of computational effort which is typically, according to our experience, only 20-50% of that required by a conventional scheme. Image reconstruction from the most significant edges extracted by the hierarchical scheme, demonstrates the relation of the edge-map to image structure, and the potential of this compact, and relatively simple, image representation in the areas of image understanding and machine vision. In both of these areas of potential application the subsequent operation can be performed in the edge space, including comparison to templates, segmentation and higher level operations.

Although for the purpose of machine vision it isn't necessary to reconstruct the image, this seems to be a fruitful direction of research which we are currently pursuing. The iterative algorithm appears to be in particular attractive in view of recent developments which permit parallel processing by hybrid digital-optical systems.

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