EDGE PERCEPTION FOR COMPUTER VISION

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ABSTRACT

The purpose of this paper is to introduce briefly the theory of edge perception for computer vision systems. This is done by transforming the 'gray-level' images from the absolute intensity domain to the preception domain by means of fuzzy set theory. Using this approach, the edges in a given gray-level image are perceived at various levels of perception in the domain [0, 1]. Two examples of such perception are included.

KEYWORDS

computer vision systems, edge detection, perception, perception of edges, fuzzy set theory.

1. INTRODUCTION

In computer vision systems, the primary objective is to recognize a given set of objects from a set of given images [2]. The objects may be partially occluded and may be lying in poor, uneven or varying lighting conditions, or shrouded by smoke, chemical fumes or steam that often exist on a factory floor. For a general robotic vision system it is imperative, therefore, to obtain a proper identification of a given class of objects for use in a feedback control system. One of the attributes, amongst many possible ones such as colour, texture, etc., that is being used extensively in robotic vision systems, is edges [1, 2, 3, 9] which determine the shapes and contours of the objects.

In a natural vision system the process of 'seeing' or 'recognizing objects' entirely depends upon the *'perception'* of certain attributes such as colour or intensity rather then the measurement of their physcial characteristics in absolute quantitative terms. The same thing is true in the perception of temperature, hearing, fragrance, etc, using natural sensors. Therefore, in natural systems 'perception' plays the same role as 'measurements' in artificial systems [6, 7, 8]. In the development of intelligent systems it is proposed, therefore, to make use of *'perceptions'* by using some sort of *perceptor* rather than absolute quantitiative measurements using conventional measuring devices.

The purpose of this paper is to introduce briefly the theory of edge perception for computer vision systems, Fig. 1. This is done by transforming the gray-level images from the absolute intensity domain to the perception domain using fuzzy set theory.

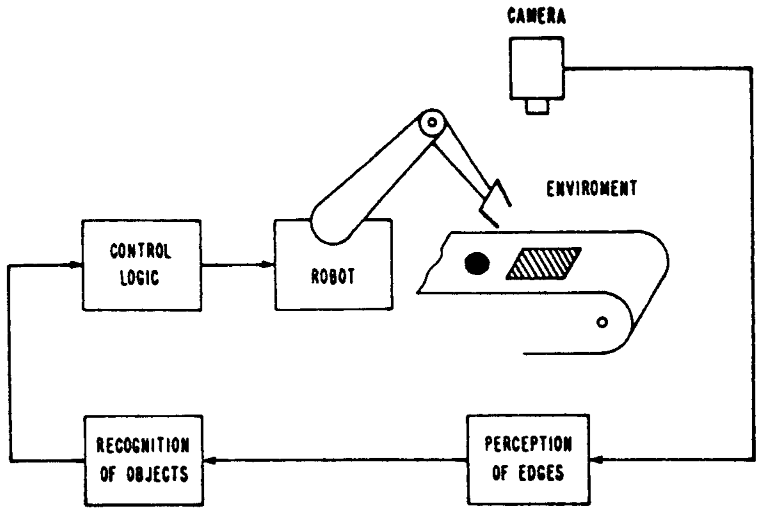


Fig. 1 Robotic Vision Control System.

2. IMAGE AMBIGUITY AND FUZZY SET THEORY

Given the gray levels of the intensity profiles of an image, the problem of edge detection by a natural vision system essentially deals with the *'perception'* of these gray intensity levels and the act of perceiving *'significant'* changes at the macroscopic level. The natural vision system, therefore, perceives the image at an aggregate or granule level rather than on an individual pixel by pixel basis. The *'granularity'* or *'aggregation'* is one of the important attributes found in human perception and thinking and, therefore, in decision making processes.

It is possible to use an artificial perceptor similarly for a machine vision system. The artificial perceptor transforms the gray intensity levels of an image found in the x-y plane into perceived intensity profiles in the x-y plane. This transformation into perceived intensity profiles in the x-y plane can be achieved using fuzzy set theory since it deals with a set of objects or phenomena which may ambiguously belong to a set. In fuzzy set theory the sets are not defined crisply as in the case of ordinary set theory *(it belongs to,* membership grade = 1; *it does not belong to,* membership grade = 0). Instead, fuzzy set theory deals with vague phenomena whose grade of membership is defined over an interval [0, 1]. Human perception deals with the fuzziness of a phenomenon that can be described like the diffusion of gas in thermodynamics. In this analogy, the higher the level of randomness, the greater is the energy or entropy associated with it. A similar concept of entropy has been used in classical (probabilistic) information theory, and a similar entropy measure can be defined for the measurement of the ambiguity associated with a fuzzy phenomenon.

2.1 Graded Membership Function, $\mu_A(x)$

A fuzzy set is a class of objects or phenomena that accepts the notion of partial membership over the interval [0,1]. Let $\mathbf{X} = \{x\}$ be a set of objects, then a fuzzy set $A \; \varepsilon \; \mathbf{X}$ is a set of ordered pairs

$$A = \{x, \mu_A(x)\}, \quad x \in X, \tag{1}$$

where $\mu_A(x)$ is called the 'characteristic function,' or 'graded membership' of x in A. The membership function $\mu_A(x)$ maps the fuzzy set A onto the interval [0,1]

$$\mu_A: A \rightarrow [0, 1].$$

In other words, the membership function $\mu_A(x)$ describes the strength of our *'perception'* or *'belief'* that $x \in A$. If $\mu_A(x) = 1$, it is *certain* that x is in A and if $\mu_A(x) = 0$, then it is *certain* that x is *not* in A. For x over $0 < \mu_A(x) < 1$, there is an uncertainty associated with x; that is, x belongs to A with the possibility $\mu_A(x)$. However, it should be noted that the assignment of a membership function to a fuzzy set is subjective and, in general, reflects the context in which the problem is viewed.

2.2 Fuzzy Mapping Functions

Let a fuzzy phenomenon X be defined over a real interval $[x_m, x_M]$, where x_m and x_M correspond respectively to the lower and upper bounds of the set X.

There are many functions described in the literature [3,4] which map a subjective and ambiguous (fuzzy) phenomenon X on a real line into a membership domain μ: $X \rightarrow [0, 1]$. Several such mapping functions, using sinusoids, will be described now.

(i) The S_1 Mapping Function

Consider again a fuzzy phenomenon X described over the interval $[x_m, x_M]$. Define a mapping function S_1 as

$$\mu_{S_1}(x) = S_1(x, x_m\, x_M)$$

$$= \sin \frac{\pi}{2}\left(\frac{x - x_m}{x_M - x_m}\right), \quad x_m \le x \le x_M. \tag{2}$$

The function S_1 in (2) thus maps x, $x_m \le x \le x_M$, into an equivalent membership function $\mu_{S_1}(x)$, $0 \le \mu_{S_1}(x) \le 1$, of a fuzzy phenomenon X.

Define now a crossover point $x = x_c$ for this mapping function as a point for which

$$\mu_{S_1}(x)\,\big|_{x=x_c} = \mu_{S_1}(x_c) = 0.5. \tag{3}$$

For the mapping function S_1 defined in (2), the crossover point x_c is given by

$$x_c = \frac{1}{3}\,(x_M + 2\,x_m). \tag{4}$$

This mapping function S_1 is not symmetrical about the crossover point x_c. For a symmetrical mapping function about x_c, we define another S function.

(ii) **The S_2 - Mapping Function**

For the fuzzy set X over the real interval $[x_m, x_M]$, define a symmetrical crossover point x_c as

$$x_c = \frac{1}{2}(x_m + x_M) \tag{5}$$

with a corresponding mapping function S_2 as

$$\mu_{S_2}(x) = S_2(x, x_c, x_M)$$
$$= \frac{1}{2}[1 + sgn(x - x_c) \left| \sin\frac{\pi}{2}(\frac{x - x_c}{x_M - x_c}) \right|^g], \quad x_m \le x \le x_M, \tag{6}$$

where the power index g is a positive real constant, $g > 0$. The mapping function S_2 assigns low membership values, between $0 \le \mu < 0.5$, to x for $x < x_c$ and higher values, between $0.5 \le \mu \le 1$, to x for $x \ge x_c$. The assignment of membership values can be enhanced by the power index $g > 1$ as shown in Fig. 2.

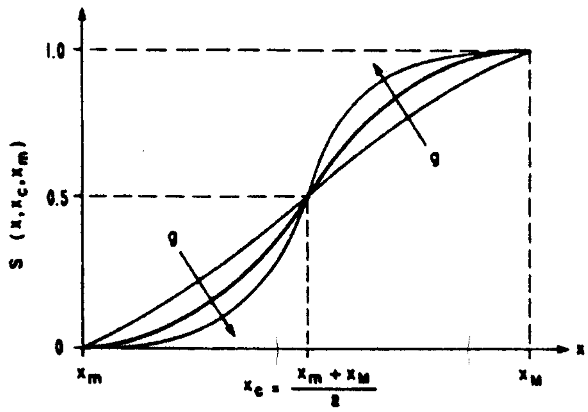


Fig. 2 Symmetrical S-Mapping Function.

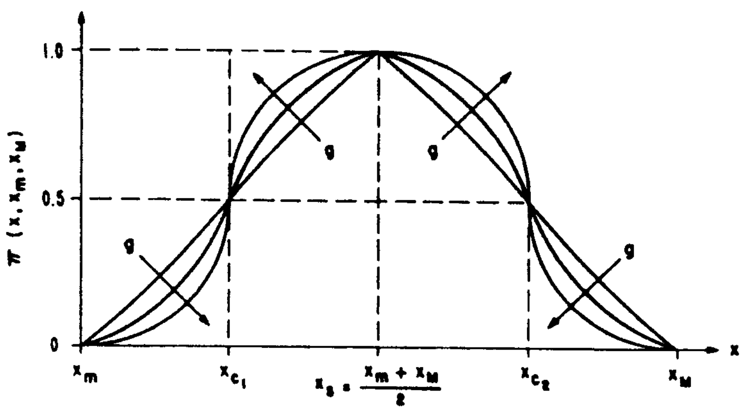


Fig. 3 Π - Mapping Function.

(iii) The π_1 Mapping Function

Let us now define a symmetrical π_1 - mapping function as illustrated in Fig. 3 for a fuzzy phenomenon **X** on a real line over the interval $[x_m, x_M]$. Using the definitions of points x_s, x_{c_1} and x_{c_2} as shown in Fig. 3, a symmetrical π_1 function can be defined as

$$\mu_{\pi_1}(x) = \pi_1(x, x_m, x_M)$$

$$= \pi_{1A}\ (x, x_{c_1}, x_s)\ U\ \pi_{1B}\ (x, x_{c_2}, x_M), \tag{7a}$$

where, as is shown in Fig. 3, $\pi_{1A}(x, x_{c_1}, x_s)$ is defined over $(x_m \le x < x_s)$ and is given by

$$\pi_{1A}(x, x_{c_1}, x_s) = S_2(x, x_{c_1}, x_s)$$

$$= \frac{1}{2}\,[1 + sgn\,(x - x_{c_1})\ \Big|\ \sin\frac{\pi}{2}\,(\frac{x - x_{c_1}}{x_s - x_{c_1}})\ \Big|^{g}]; \quad g > 1 \tag{7b}$$

and $\pi_{1B}(x, x_{c_2}, x_M)$ is defined over $(x_s \le x \le x_M)$ and is given by

$$\pi_{1B}(x, x_{c_2}, x_M) = 1 - S_2(x, x_{c_2}, x_M)$$

$$= \frac{1}{2}[1 - sgn\,(x - x_{c_2})\ \Big|\ \sin\frac{\pi}{2}\,(\frac{x - x_{c_2}}{x_M - x_{c_2}})\Big|^{g}]; \quad g > 1 \tag{7c}$$

Remarks

The mapping functions as defined above map the real values of $x \in \mathbf{X}$ over the interval $[x_m, x_M]$ into the *perception domain* over the real interval [0, 1]. Thus, for example, the S-mapping functions, map the interval $[x_m, x_M]$ onto the interval [0, 1].

The S-mapping function is a monotonically increasing function and essentially gives a perception of a phenomenon such as *'the image is bright'* for intensity profiles over the intensity levels $[x_m, x_M]$. The π – mapping function, on the other hand, monotonically increases over the interval $[x_m, x_s]$ and then decreases over $[x_s, x_M]$. This function, thus, essentially represents a perception of such a phenomenon as the *'brightness of the image is x_s'*, around the intensity profile centered at x_s over the intensity levels $[x_m, x_M]$. The S-mapping function thus covers the entire region from x_m to x_M, whereas the π – mapping function decimates this region into two sections x_m to x_s, and x_s to x_M. In image processing, situations arise where one has to decimate the entire intensity range, from x_m to x_M, into several smaller regions in order to isolate one intensity level from an adjacent one. For example, in edge detection problems one has to decimate the two adjacent regions which are characterized by a 'significant' change in intensity levels. In the following section, therefore, we define a multiple-region-mapping function which helps to decimate a range of intensity profiles into a number of distinct regions within the *'perception-domain'*.

Decimation into Multi-Region Intensity Levels

Consider a gray level digital image with varying intensities over the range $[x_m, x_M]$ and with a possible k-modal intensity profile as shown in the histogram of Fig. 4. From this histogram one can distinctly identify k intensity levels, each corresponding to a peak in the histogram.

One can perceive the histogram profile in Fig. 4 as a composition of several intensity levels, $x_1, x_2, \cdots, x_q \cdots x_k$. One can also describe this intensity profile *linguistically (fuzzily)* as follows:

'Over the intensity range $[x_m, x_M]$, the gray level digital image is composed of a set of intensity levels $(x_1, x_2 \cdots x_q \cdots x_k)$'.

In the above statement, the intensity levels x_q, $q = 1 \cdots, k$, represent a set of fuzzy numbers. These intensity levels are distinctly identified (with membership grade = 1), at their peaks x_q, $q = 1, \cdots k$. A maximum amount of uncertainty exists, however, at the valleys $x_{c_1}, x_{c_2} \cdots$, in the sense that it is not clear to which of the adjacent levels this intensity belongs. For example, the intensity level at the valley x_{c_2} may belong (equally) to the intensity x_1 or the intensity x_2 with an equal possibility of $\mu = 0.5$.

We shall now make use of the fact that a maximum amount of certainty (no ambiguity, therefore, $\mu = 1$) exists at the peaks and a maximum amount of uncertainty (therefore, $\mu = 0.5$) at the valleys of the histogram. We consider, therefore, these valleys at the crossover points with $\mu = 0.5$ and we can thus decimate the entire intensity range $[x_m, x_M]$ into several regions, $R_o, R_1 \cdots R_k$, with each region being separated by *points of maximum uncertainty*.

A histogram given over an intensity range $[x_m, x_M]$ with k valleys, x_{cq}, $q = 1, 2 \cdots k$ can be decimated, therefore, into $(k+1)$ regions. R_q, $q = 0, 1 \cdots k$, where each region is bounded by the adjacent crossover points.

The Multi-Region Mapping Function, $\Phi[x]$

The main objective in a gray digital image edge detection problem is to decimate any two adjacent intensity levels. Decimation of two adjacent intensity regions can be done by letting the intensity level of one region go to 0 (dark) and the other to 1 (maxium brightness). This process of decimating two adjacent regions into two distinct intensity levels can be achieved by, alternatively, mapping the regions $R_0, R_1 \cdots R_k$ in the histograms, Figure 5, '*low* and *high*' or '*high* and *low*' intensity profiles.

Using the alternate '*low* and *high*' intensity profiles, we may define a multi-region mapping function as

$$\Phi[x] = \bigcup_{q=0}^{k} M_q(x) \tag{8a}$$

where $M_q(x)$, $q = 0, 1 \cdots k$, are defined as follows:

(i) For the extreme left region, R_o,

$$M_o(x) = S_{LH}(x, x_m, x_{c_1})$$
$$= \sin^2 \frac{\pi}{4} \left(\frac{x - x_m}{x_{c_1} - x_m}\right), \quad x_m \le x \le x_{c_1}. \tag{8b}$$

(ii) For regions R_1 to R_{k-1} ,

$$M_q(x) = \pi_{UH}\ (x, x_{cq}, x_{cq+1})$$
$$= \frac{1}{2}\ [1 + \sin^2 \pi\ (\frac{x - x_{cq}}{x_{cq+1} - x_{cq}})] \qquad (8c)$$

for $q = 1\ 3, 5 \cdots$, odd numbered regions, over $x_{cq} \le x \le x_{cq+1}$ and

$$M_q(x) = x_{LH}(x, x_{cq}, x_{cq+1})$$
$$= \frac{1}{2}\ [1 - \sin^2 \pi\ (\frac{x - x_{cq}}{x_{cq+1} - x_{cq}})], \qquad (8d)$$

for $q = 2, 4, 6 \cdots$ even numbered regions.

(iii) For the extreme right region, R_k,

$$M_k(x) = \begin{cases} [1 - \sin^2 \frac{\pi}{4}\ (\frac{x_M + x - 2x_k}{x_M - x_k})], & \text{for } x_k \le x \le x_M \text{ and } k = even \\ \sin^2 \frac{\pi}{4}\ (\frac{x_M + x - 2x_k}{x_M - x_k}), & \text{for } x_k \le x \le x_M \text{ and } k = odd. \end{cases} \qquad (8e)$$

Figure 5 shows such a multi-region mapping function $\Phi[x]$.

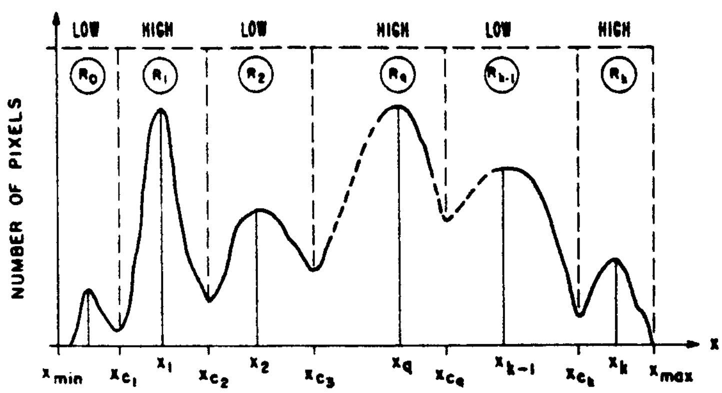


Fig. 4 K-modal Histogram For Intensity Profiles of a Grey Level Image.

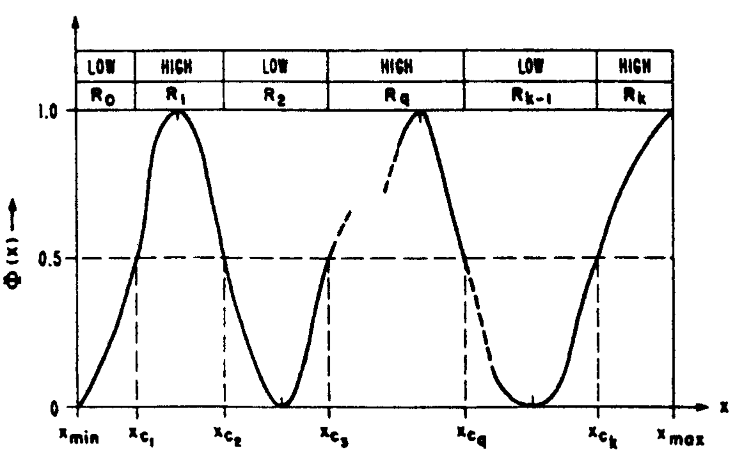


Fig. 5 Multi-Region Mapping Function, $\Phi[x]$.

2.3 Some Fuzzy Operations

The notion of graded membership that was introduced in Section 2.2 plays an important role in many fuzzy mathematical operations that are not to be found in ordinary set theory [4, 9]. We now consider a fuzzy set A as a *'representational image.'* This notion permits the advancement of the concept of image processing in the *'spatial-perception domain'*. Such an approach gives a new meaning to the membership $\mu_A(x)$ of an element $x \in \mathbf{X}$. In this approach one assigns a membership to 'gray levels' between non-membership ($\mu_A(x) = 0$) and full membership $\mu_A(x)=1$). A black and white television picture is a fuzzy subset of the white screen (or the black screen). Thus, one can think of *focusing,* of *concentrating,* of *dialating,* of *contrast intensification,* and of *blurring* a fuzzy pixel of an image.

Let A be a fuzzy set of $\mathbf{X}$ with membership $\mu_A(x)$, $x \in \mathbf{X}$, and then let us define the contrast intensification operation.

The $INT(A)$ operation has the effect of increasing the membership if it is greater than 0.5 and decreasing it if it is less than 0.5. Thus, the $INT(A)$ operation is

$$INT(A) = \begin{cases} \int_{x \in X} 2\{\mu_A^2(x) \mid x\}, & \text{for } all\ x\ such\ that\ 0 \le \mu_A(x) < 0.5 \\ \\ \int_{x \in X} \{1 - 2(1 - \mu_A(x))^2 \mid x\}, & \text{for } all\ x\ such\ that\ 0.5 \le \mu_A(x) \le 1 \end{cases} \tag{9}$$

This operation reduces the entropy and therefore is very useful in image processing problems such as image enhancement and edge perception.

3. Image Ambiguity, Perception-Domain Transformation and Contrast Intensification

Let Y be a discrete image in a two-dimensional spatial domain with L gray intensity levels. This image can be represented by a two dimensional data matrix of order $M \times N$ having an individual pixel $y_{m,n}$ in the position defined by the *mth* row and the *nth* column. Thus, we define the digital image Y as

$$Y = [y_{m,n}]_{M \times N}, \quad m = 1, 2, \cdots M; \quad n = 1, 2, \cdots N, \tag{10}$$

where the pixel $y_{m,n}$ has L possible intensity (brightness) levels, $l = 0, 1, \cdots L - 1$, for which $l = 0$ corresponds to completely dark and $l = L - l$ to completely white gray levels.

In this paper, the problem of edge perception is viewed as a phenomenon of 'perceiving' intensity levels and then tracing the locus of the vectors which correspond to *'significant changes'* in these intensity levels.

In general, a picture may have k distinct intensity levels over $(0, L - 1)$. The loci, therefore, correspond to $(k + 1)$ distinct levels of changes in intensity. The problem addressed in this paper involves, therefore, the tracing of $k - loci$ of changes in the intensity level vectors, where each locus corresponds to one edge in the image.

Figure 6 gives a functional block diagram of the edge perception system developed in this paper. A brief description of the function of each block is given below.

$I = [i_{m,n}]_{M \times N}$, the original gray level digital image (spatial - intensity domain);

$Y = [y_{m,n}]_{M \times N}$, the noise corrupted image (spatial - intensity domain);

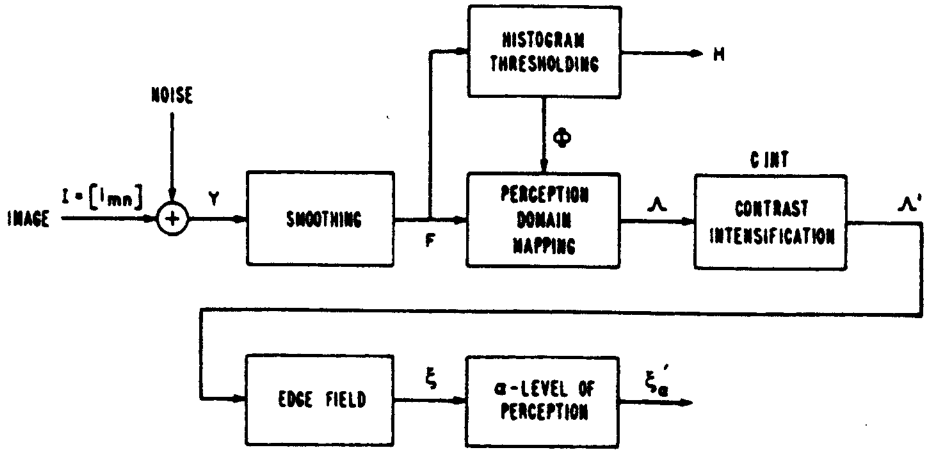


Fig. 6 Functional Block Diagram of Edge Perception System.

$F = [f_{m,n}]_{M \times N}$, the smoothed image, (spatial - intensity domain), $f_{m,n} \in [0, L-1]$ intensity levels;

$\Phi[x]$: *spatial - perception* domain mapping function with $(k+1)$ threshold intensity regions

$\Lambda = [\lambda_{m,n}]_{M \times N}$, the transformed image into *spatial - perception* domain, $\lambda \in [0, 1]$ levels of perception;

CINT $[x]$: contrast intensification operator;

$\Lambda' = [\Lambda'_{m,n}]_{M \times N}$ intensified image in *spatial - perception* domain, $\lambda_{m,n} \in [0, 1]$ levels of perception;

EDG $[x]$: Edge detection operator;

$\xi = [\xi_{m,n}]_{M \times N}$, $\xi_{m,n} \in [0, 1]$ *perceived - edges* of the image.

3.1 Smoothing Operation

Consider a noise corrupted image Y given by

$$Y = [y_{m,n}]_{M \times N} \tag{11}$$

If we take the histogram of this noisy image, the distinct regions of the various intensity levels may not be readily identifiable. This may be due to the diffusion effect of the noise on the various pixels of the image. In order to reduce the effect of the noise in image processing, we give a simple point averaging scheme taken over a window $W_{q \times q}$ of size $(q \times q)$. The size of the window can be chosen arbitrarily depending upon the noise characteristics and image intensity levels. Thus, the smoothed (m,n) pixel in the image can be defined as an average pixel intensity over the window $W_{q \times q}$

$$f_{m,n} = \sum_{W_{q \times q}} \alpha_{ij} \, y_{ij}, \quad i, j \in W_{q \times q} \tag{12}$$

where α_{ij} are the weighting coefficients such that

$$\sum_{W_{q \times q}} \alpha_{ij} = 1$$

3.2 Perception-Domain Mapping

Consider now the $M \times N$ smoothed image

$$F = [f_{mn}]_{M \times N}, \tag{13}$$

defined in the *'spatial-intensity domain'*. Let us define an operator Φ which transforms this image F into the *spatial-perception domain* Λ. Thus,

$$F = [f_{m,n}]_{M \times N} \xrightarrow{\Phi} \Lambda = [\lambda_{m,n}]_{M \times N}, \tag{14}$$

where

$$f_{m,n} \; \varepsilon \; [0, L-1]: \quad \textit{levels of intensity}, \tag{15a}$$

and

$$\lambda_{m,n} \; \varepsilon \; [0, 1]: \quad \textit{levels of perception.} \tag{15b}$$

We thus have the mapping operation

$$\Phi: \; f_{m,n} \; \varepsilon \; [0, L-1] \rightarrow \lambda_{m,n} \; \varepsilon \; [0, 1] \tag{16}$$

We map the image from the *spatial-intensity domain* into *spatial-perception domain* using the multiple region mapping function $\Phi[x]$ defined in Eqn. (8). Thus,

$$[\lambda_{m,n}]_{M \times N} = \Phi \; [f_{m,n}]_{M \times N} \tag{17}$$

where x corresponds to intensities over the range 0 to $(L - 1)$.

This mapping function decimates the entire intensity region into (k + 1) distinct regions assigning alternatively the *Low* and *High* perception values, where *Low* ε [0, 0.5) and *High* ε [0.5, 1]. As explained in the description of the $\Phi[x]$ mapping function, the crossover points correspond to the valleys in the histogram.

Thus, this mapping from $f_{m,n} \; \varepsilon \; [0, L-1]$ to $\lambda_{m,n} \; \varepsilon \; [0, 1]$ may be considered as an *aggregate phenomenon of perceiving* the intensity levels of the gray digital image: thus, the name of the mapping function *'perception domain mapping'*.

Now, as will be shown in the sequel, various operations involved in the process of edge preception, are carried out in the *spatial-perception domain* rather than in the conventional *spatial-intensity domain.*

3.3 Contrast Intensification

The assignment of alternate *Low* ε [0, 0.5) and *High* ε [0.5, 1] values to various intensity regions of an image using the Φ mapping function decimates the various intensity levels into many adjacent perception regions. These decimated perception domain regions can be enhanced further by using contrast intensification operators on the perceived pixels $\lambda_{m,n}$. Thus,

$$[\lambda'_{m,n}]_{M \times N} = \textbf{CINT} \; [\lambda_{m,n}]_{M \times N}, \quad \lambda'_{m,n} \; \varepsilon \; [0, 1]. \tag{18}$$

In this **CINT**$[\lambda_{m,n}]$ operation, the pixel values in the *Low* range ε [0, 0.5) are assigned *very low* values over the range [0, 0.5), and the pixel values in the *High* range ε [0.5, 1] are assigned *higher* values over the range [0.5, 1]. Thus, intensification operation reduces the amount of ambiguity further and, therefore, the entropy associated with each pixel. The ambiguity in the image can be reduced sufficiently by a proper choice of the power index g.

4. EDGE PERCEPTION

The edge perception operator is employed on the fuzzy image in the *spatial-perception domain* in order to define an edge between two adjacent intensity levels. This operation is performed in the *spatial-perception domain* on the enhanced perceived pixels $\lambda_{m,n}$ ε [0, 1], Eqn (18).

Let $[\lambda'_{m,n}]_{M\times N}$, $\lambda'_{m,n}$ ε [0,1], be a $M \times N$ contrast intensified image defined in the spatial-perception domain. Most of the pixels in the image $[\lambda'_{m,n}]_{M\times N}$ are either in the low perception range of [0, 0.5) or the high perception range of [0.5, 1]. However, some pixels have intensity values in the neighborhood of the perception level = 0.5; these pixels introduce an ambiguity because they are not crisply identifiable. Therefore, the decimination of two adjacent intensity levels is marked by a 'fuzzy boundary'.

In order to detect a pixel which is part of the boundary, or edge, it is necessary to perform a min-max operation over a window $W_{q\times q}$ of size $(q \times q)$. The size of the window will determine the width of the edge in the perception domain. For micro edges, a small window of size (3 × 3) is employed, while the edges in a textured region requires a larger window size.

Let $\xi_{m,n}$ be the magnitude of the perceived edge point, where the mapping $\xi_{m,n}$ ε [0, 1] of $\lambda'_{m,n}$ ε [0, 1] can be obtained by one of the following **EDG**[·] operations defined as

$$(i)\quad \xi_{m,n} = | \{\lambda'_{m,n}\} - \{\max \bigcup_{W_{q\times q}} \lambda'_{i,j}\} |, \tag{19a}$$

$$(ii)\quad \xi_{m,n} = | \{\lambda'_{m,n}\} - \{\min \bigcup_{W_{q\times q}} \lambda'_{i,j}\} |, \tag{19b}$$

$$(iii)\quad \xi_{m,n} = | \{\max \bigcup_{W_{q\times q}} \lambda'_{i,j}\} - \{\min \bigcup_{W_{q\times q}} \lambda'_{i,j}\} | \tag{19c}$$

where $(i, j) \neq (m, n)$ and (i, j) ε $W_{q\times q}$,

$\lambda'_{i,j}$ ε [0, 1] and $\xi_{m,n}$ ε [0, 1].

Finally the preceived edge locus with memberships over the real interval [0, 1] can be defined as

$$\textit{Edge locus} = \bigcup_m \bigcup_n \xi'_{m,n}. \tag{20}$$

This is the locus of all pixel points having $\alpha_1 \le \xi'_{m,n} \le \alpha_2$, where α_1 and α_2 are the values of $\xi_{m,n}$ that bound the degree of edge perception.

Remarks

With this approach it is possible to introduce several levels of edges which correspond to various *'degrees of edge perception'*. This concept introduces several advantages in the recognition process if the preceived edges are divided into various 'perception-planes', with each plane bounded by α_i and α_{i+1}, where $i = 1, 2 \cdots k$ as shown in Fig. 7.

For many recognition problems, the perceived edges can be readily divided into four equal levels of primary edges ($0.75 < \xi_{m,n} \leq 1$) secondary edges ($0.5 < \xi_{m,n} \leq 0.75$), tertiary edges ($0.25 < \xi_{m,n} \leq 0.5$), and finally no edges ($0 \leq \xi_{m,n} \leq 0.25$). This division is arbitary, however, and corresponds directly with the natural vision system which identifies the shape of an object by first detecting the primary edges which are most clearly present in the scene. These edges are visible at a glance and generally correspond to the overall outline of the object. Secondary edges are those edges that are visible but require a closer look. Finally, the tertiary edges are those that are difficult to see and, therefore, are visible only with great mental concentration. Edges detected in the no edge perception-plane are generally the result of noise introduced by the highly sensitive vision sensors, and therefore, contain almost no edge information.

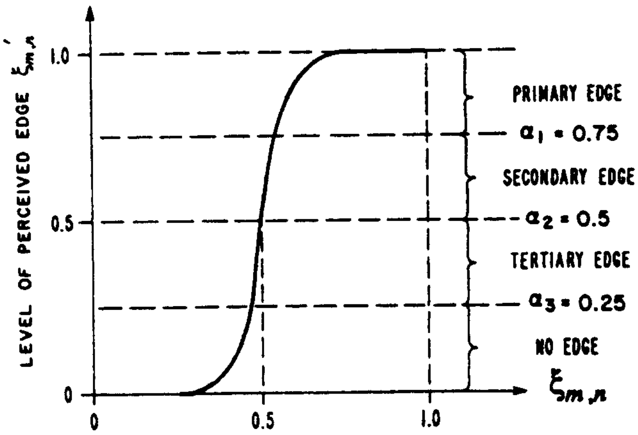


Fig. 7 The Various Degrees of Edge Perception.

5. RESULTS

The edge perception algorithm outlined in the previous sections was implemented on a VAX 11/780 computer and a COMTAL Image Processing System. Original gray-level images of 256×256 ($M \times N$) dimensions and of 256 gray levels were processed. For the edge perception operation the exponents of the various S and π mapping functions were set equal to 2. The min - **EDG** [·] operator, Eqn (19b), was used to determine the magnitude of the perceived edges.

The resultant edge perception properties of two complex images are illustrated in Figures 8 and 9. The first set of imagery show a simulated staircase scene, which has seven discrete gray intensity levels and is masked by Gaussian noise with $\sigma = 20$. The second set of imagery corresponds to a portrait of a woman.

Figures 8(a) and 9(a) show the original gray-level image while Figure 8(b) and 9(b) show the images after perception-domain mapping and contrast intensification. Figures 8(c) and 9(c) illustrate the various degrees of the perceived edge, $\xi_{m,n} \varepsilon [0, 1]$. For display purposes, as the perceived edge point, $\xi_{m,n}$, approaches a membership of 1 the corresponding pixel becomes darker.

The remaining images of both Figure 8 and 9 illustrate the edge points that exist in the various perception-planes found in the respective images. Images in 8(d) and 9(d) show the perceived edges which lie in the range $0.75 < \xi_{m,n} \leq 1$ and, therefore, correspond to primary edges. Images in 8(e) and 9(e) are the edge points over the range $0.5 < \xi_{m,n} \leq 1$, or the percieved edges that lie in both the primary and secondary edge planes. Finally, images in 8(f) and 9(f) are those perceived edge points, $0.25 < \xi_{m,n} \leq 1$, which lie in the primary, secondary and tertiary edge planes.

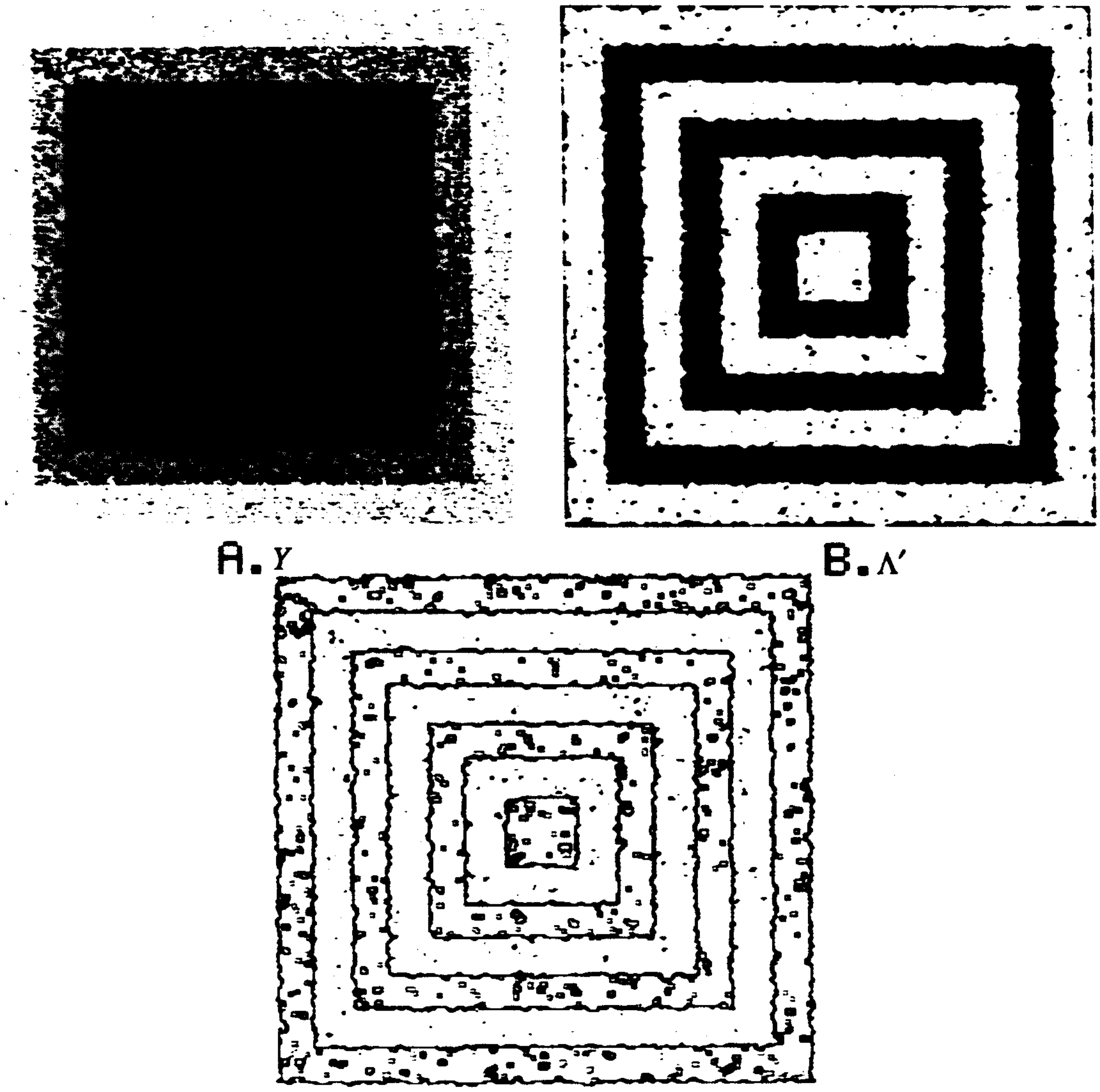
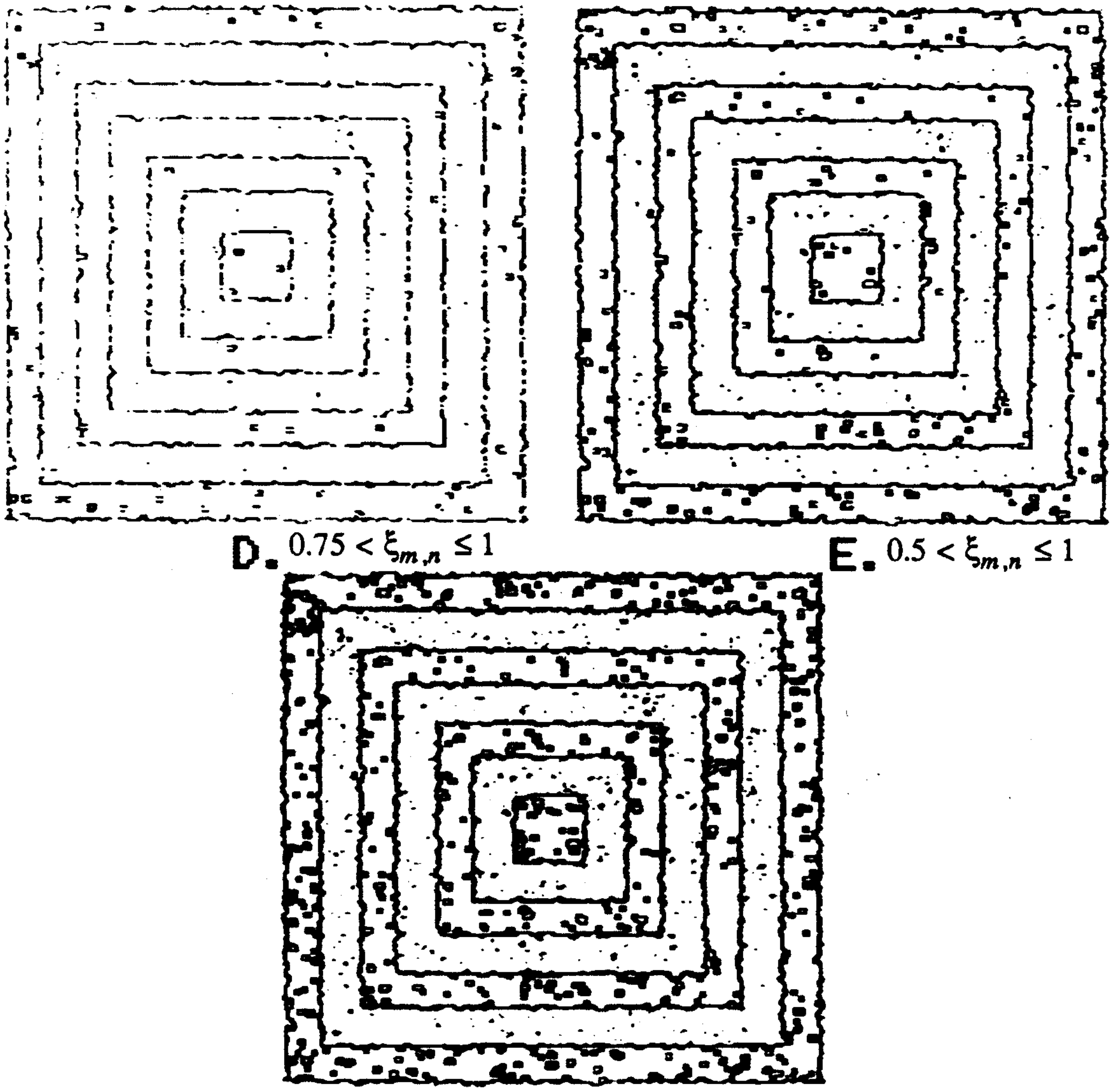


Fig. 8 Simulated Staircase Image with Noise, $\sigma = 20$, $g = 8$.



D. $0.75 < \xi_{m,n} \leq 1$

E. $0.5 < \xi_{m,n} \leq 1$

F. $0.25 < \xi_{m,n} \leq 1$

Fig. 8 (continued).

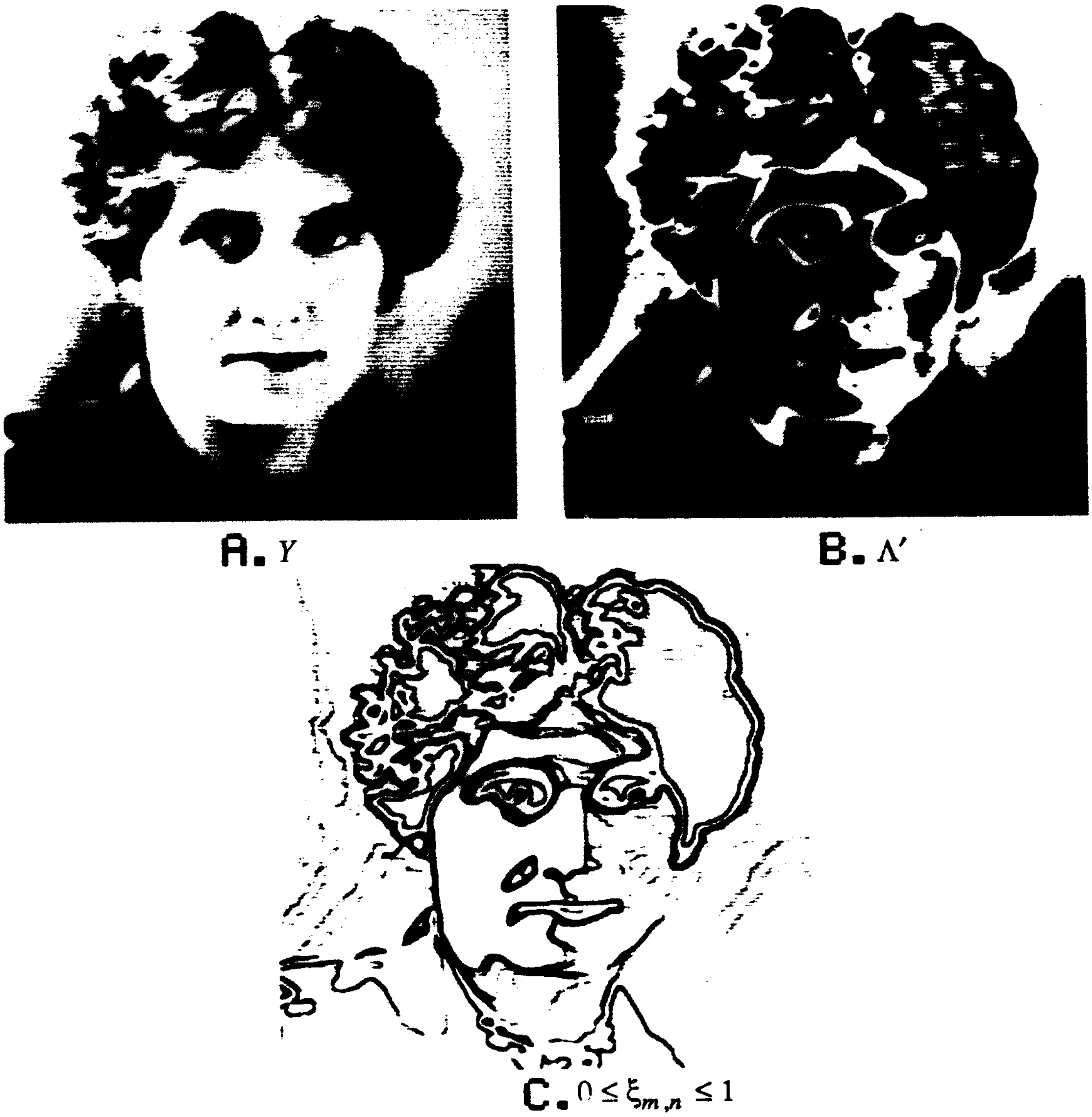
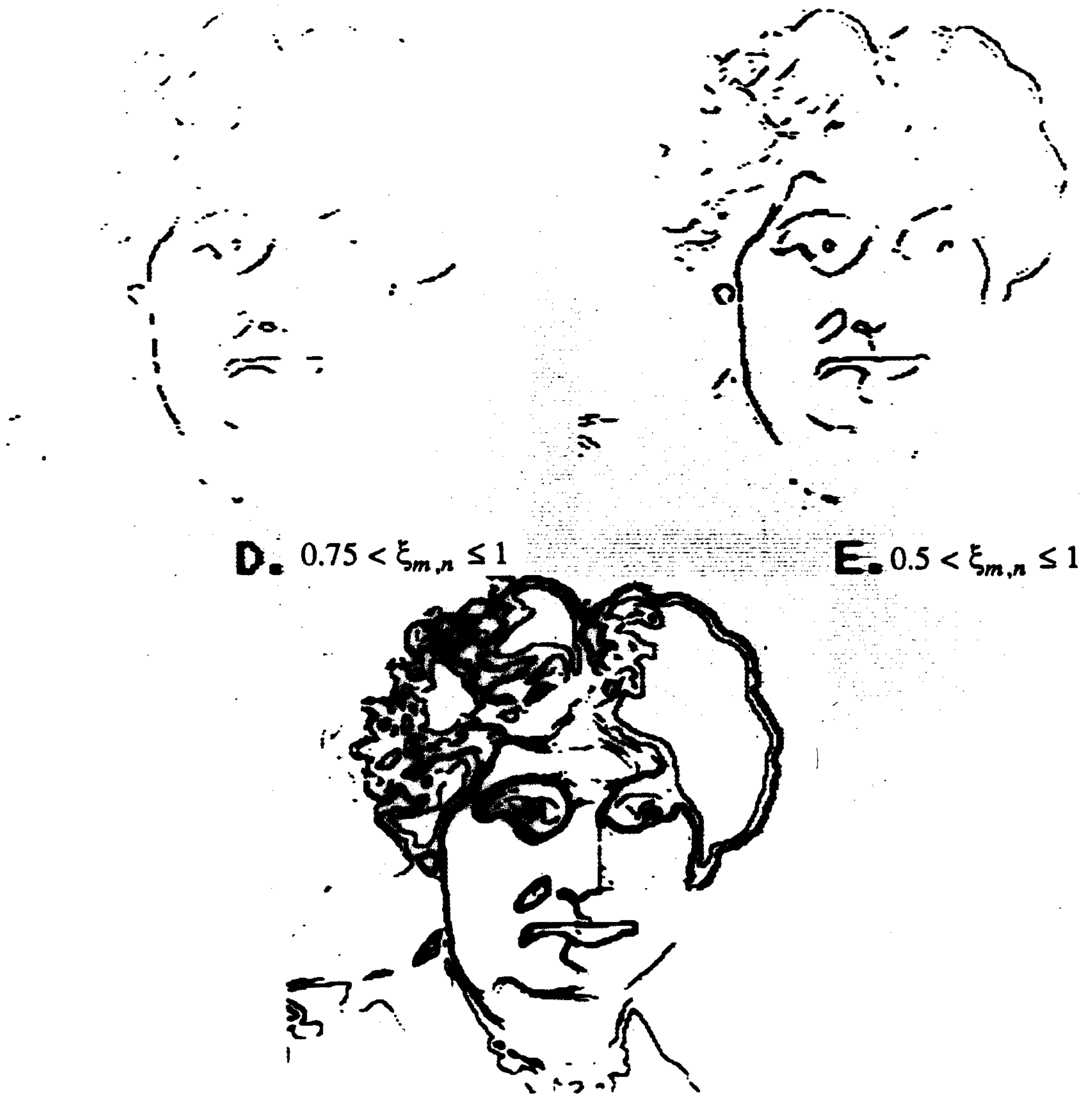


Fig. 9 Example of a Woman's Portrait, $g = 2$.



D. $0.75 < \xi_{m,n} \leq 1$

E. $0.5 < \xi_{m,n} \leq 1$

F. $0.25 < \xi_{m,n} \leq 1$

Fig. 9 (contiuned).

From these various perception planes it is demonstrated that fundamental shape description can be adequately represented by a combination of various edge planes, rather than processing all the existing edge data. Improved edge detail can be accomplished by extending the range of perceived values.

6. CONCLUSIONS

In this paper we have presented the perception of edges of gray-level images. The perception of the edges is carried out at various perception levels and is different from the conventional detection of edges in a binary sense. This method of perceiving the edge phenomenon is similar to that found in the natural vision systems, and is found to be computationally very efficient. Further work is underway for the perception of various other attributes of an image such as colour and texture.

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