Optimal Scale Edge Detection Utilizing Noise within Images

Adnan KHASHMAN, Senior Member IEEE
Associate Professor, Chairman
Electrical & Electronic Engineering Department, Near East University
Lefkosa, KKTC, Mersin 10, Turkey

ABSTRACT

Edge detection techniques have common problems that include poor edge detection in low contrast images, speed of recognition and high computational cost. An efficient solution to the edge detection of objects in low to high contrast images is scale space analysis. However, this approach is time consuming and computationally expensive. These expenses can be marginally reduced if an optimal scale is found in scale space edge detection. This paper presents a new approach to detecting objects within images using noise within the images. The novel idea is based on selecting one optimal scale for the entire image at which scale space edge detection can be applied. The selection of an ideal scale is based on the hypothesis that "the optimal edge detection scale (ideal scale) depends on the noise within an image". This paper aims at providing the experimental evidence on the relationship between the optimal scale and the noise within images.

Keywords: Edge Detection, AEDS, Scale Space Analysis, Optimal Scale, Noise within Images.

1. INTRODUCTION

Image processing techniques are being rapidly developed and continually emerge to improve previous works. However, any new development into this competitive discipline must make a significant contribution to the field or offer the potential for future contributions.

Scale dependency and noise sensitivity can be problematic in image recognition [1]. Previous works suggested the use of an optimal scale in multiscale edge detection [2][3]. In our novel approach, both noise and scale dependency will be utilized to yield a single optimal scale, which will be used by the AEDS: Automatic Edge Detection Scheme [4], to provide ideal edge detection. The AEDS is based on combining three fields; namely scale space analysis, edge detection and neural networks. AEDS delivers very quick edge detection of three-dimensional objects, as well as two-dimensional objects, through the automatic selection of a single optimal scale for applying the scale space edge detection. The high computational cost can be minimized by using a fast edge detection operator. This can be combined with the parallel processing power of a successfully trained neural network that recognizes only one correct scale (referred to as the optimal scale or ideal sigma σ_{Ideal} in this paper), out of the multiscales possible in scale space.

The hypothesis presented within this paper suggests that the ideal scale is dependent upon the amount of noise present within the image and that the mapping from the image to the ideal scale is non-linear. The work presented within this paper provides experimental evidence and an in-depth understanding of the mapping hypothesis.

2. DETECTION SCALE NOISE-DEPENDENCY

A mathematical foundation is required in order to provide the experimental evidence on the methodology of using noise within images to determine an ideal detection scale. For the purpose of understanding the mapping hypothesis, let us assume the existence of two images, *image* I_A and *image* I_B. Both images represent the same three-dimensional object, but they are taken, using a frame grabber, at different times and under different conditions. The different conditions will result in the existence of different amounts of noise in both images, although they both represent the same three-dimensional object. The grey level value of a pixel P_A in image I_A at spatial co-ordinates (x_n,y_n) should be equal to the grey level value of pixel P_B in image I_B at the same spatial coordinates, as shown by Eq. (1).

$$P_A(x_n,y_n) = P_B(x_n,y_n) \tag{1}$$

where $n = 0, 1, 2, 3, \ldots, 511$ (using images of size 512x512 pixels).

The amount of noise N_A present in image I_A at spatial co-ordinates (x_n,y_n) is not equal to the amount of noise N_B in image I_B at the same spatial co-ordinates, as shown by Eq. (2).

$$N_A(x_n,y_n) \neq N_B(x_n,y_n) \tag{2}$$

Thus, the grey level value of the image at spatial co-ordinates (x_n,y_n) can be represented for both Images I_A and I_B as shown by Eq. (3) and Eq. (4).

$$I_A(x_n,y_n) = P_A(x_n,y_n) + N_A(x_n,y_n) \quad (3)$$
$$I_B(x_n,y_n) = P_B(x_n,y_n) + N_B(x_n,y_n) \quad (4)$$

where the value of Eq. (3) is not equal to the value of Eq. (4). Therefore, the total grey level value of an image at any spatial co-ordinate *I(x,y)* is dependent on the amount of noise *N(x,y)* present at that co-ordinate, as in Eq. (5).

$$I(x,y) \infty N(x,y) \quad (5)$$

The convolution between the Laplacian of a Gaussian [5] (Eq. (6)) and an image I is represented in Eq. (7).

$$\nabla^2 G(x,y,s) = A\left(2 - \frac{x^2+y^2}{s^2}\right)\exp\left(-\frac{x^2+y^2}{2s^2}\right) \quad (6)$$

$$F_s = \nabla^2 (G(s) * I) \quad (7)$$

By convoluting the image with the LoG operator, smoothing will take place before edges are located [6]. The larger the value of the standard deviation of the Gaussian function σ, the heavier the smoothing and the larger the reduction of edges due to noise *N*. This can be expressed in Eq. (8).

$$s \quad \infty \quad \frac{1}{N} \quad (8)$$

The standard deviation of the Gaussian (σ) plays a vital rule in the automatic edge detection scheme (AEDS). A compromise has to be made in order to eliminate the noise present within the image and, at the same time, preserve all the edges of the objects within the image. The determination of such a scale (σ), what we call the *Ideal Sigma* (σ_{IDEAL}), depends on the choice of the result of the convolution between the image and the LoG function. This convolution results in many images; each convoluted at a different scale depending on the value of σ [7].

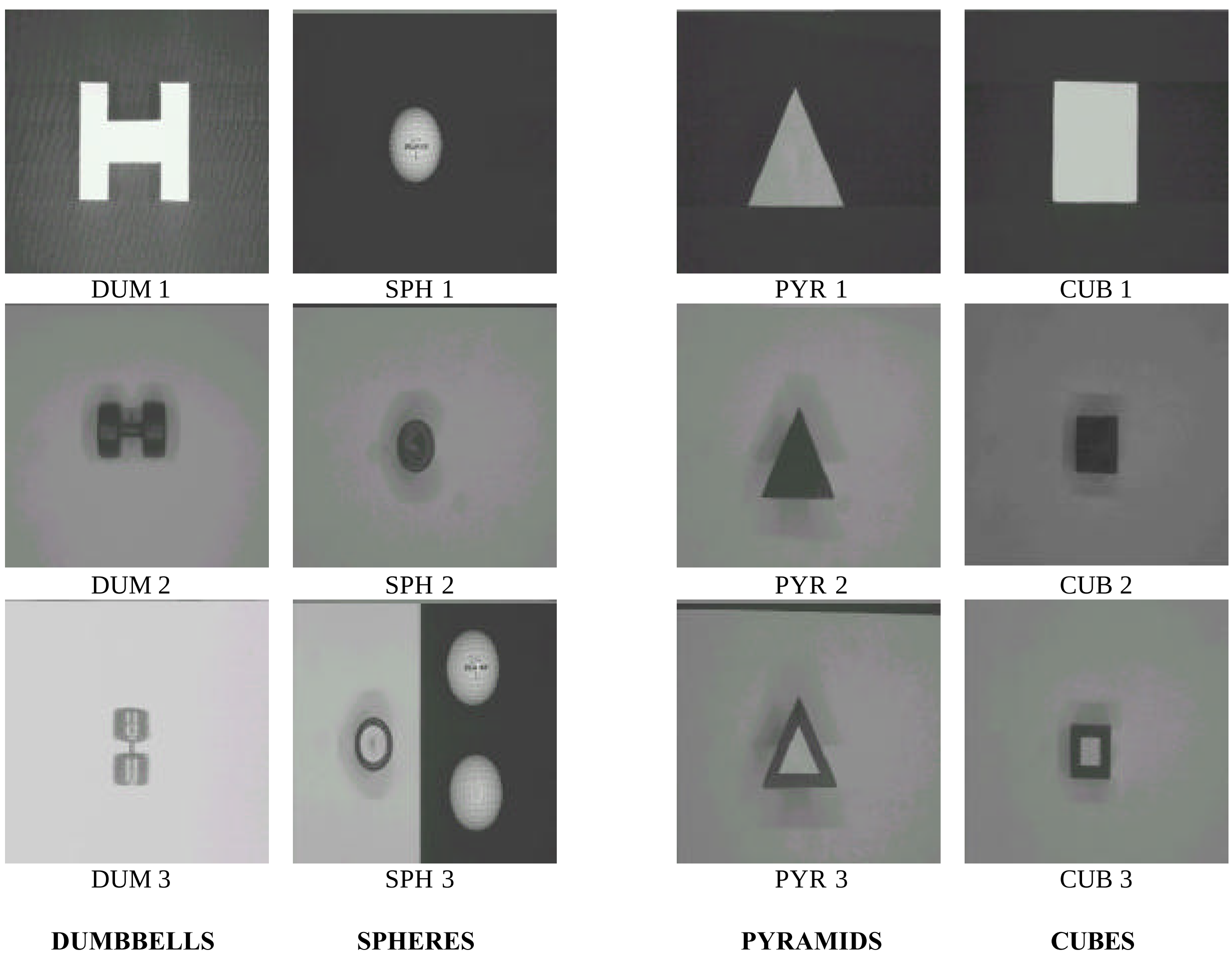

Figure 1. Twelve 2-dimensional images of the four 3-dimensional objects

Eq. (5) shows the dependence of an image on the amount of noise present within it. Whereas, Eq. (8) presents the relationship between the noise and the scale at which the image is convoluted. The choice of the ideal scale, at the *Ideal Sigma* (σ_{IDEAL}), depends on the convoluted image, which in turn depends on the amount of noise present within it. Therefore, the relationship between the *Ideal Sigma* (σ_{IDEAL}) and the amount of noise present within the image prior to convolution can be expressed as in Eq. (9).

$$\sigma_{IDEAL} = F(N) \tag{9}$$

This relationship between the *Ideal Sigma* and the noise represents a non-linear function, that is very difficult to define precisely. The amount of noise present within an image is variable and, normally, of a random nature. The scale at which the image is processed is also variable and once applied it has an impact on the amount of the noise. Thus, the AEDS utilises a neural network model to map the two vectors, throughout repeated presentations of images with different noise levels and mapping those patterns to their coherent ideal scale at their *Ideal Sigma*.

Since the mapping of the input (i.e the image) and the output (i.e the scale) represents a non-linear function, then going from one scale to another at the output is also non-linear. This non-linear relationship is what the neural network in the AEDS will be trained to recognise. The presentation of various images and their corresponding ideal scales σ_{Ideal} will teach the neural network this relationship that is impossible to solve using conventional techniques [8]. The basis of the methodology is that the alteration in the amount of noise present within the image causes a change in the choice of the ideal scale σ_{Ideal} and thus the ideal edge detection of the image. This will be shown next.

3. SIMPLE OBJECTS EDGE DETECTION

Four simple three-dimensional objects (dumbbells, spheres, pyramids and cubes [8]) providing twelve images; as in Figure 1, are used for demonstrating the change in the ideal scale in relation to the amount of noise within an image.

Distortion within the images was deliberately imposed by the addition of random noise of random values between [0 - 100]. The range of random values was chosen as it provides sufficient amounts of noise to monitor the scale space events occurring on the objects within the images, while maintaining the objects from total distortion and deformation. An example of edge deformation throughout various scale space events can be seen in Figure 2, where the analyzed object is a military plane [10]. Seven scales (σ_0 - σ_6) are used in the scale space edge detection presented within this paper. The number of scales is limited to seven since scale space events, occurring on the objects at scales higher than seven, lead to a heavy deformation of the objects [10].

Having selected the ideal scales and thus the ideal edge detection for each of the distorted twelve images according to the ideal detection criteria [9], the values of the ideal scales σ_{Ideal} are then compared to those for the same 12 images prior to the introduction of noise. All values of σ_{Ideal} are shown in Table I.

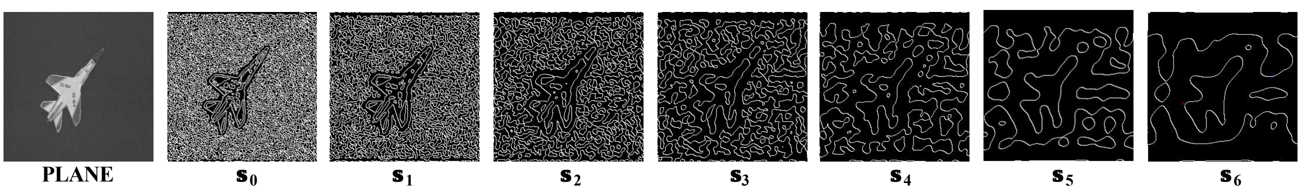

Figure 2. Example of scale space events occurring on a plane image at various scales

TABLE I

Optimal scales (σ_{Ideal}) for the 12 images before and after the additional noise

	DUM 1	DUM 2	DUM 3	SPH 1	SPH 2	SPH 3	PYR 1	PYR 2	PYR 3	CUB 1	CUB 2	CUB 3
(σ_{Ideal}) **Before** Noise	σ_4	σ_5	σ_5	σ_3	σ_5	σ_4	σ_5	σ_5	σ_2	σ_6	σ_5	σ_3
(σ_{Ideal}) **After** Noise	σ_6	σ_6	Higher than σ_6	σ_5	σ_6	σ_5	σ_6	Higher than σ_6	Higher than σ_6	Higher than σ_6	σ_6	σ_5

4. RESULTS

Four out of the twelve images are presented here to demonstrate the work carried out to provide the evidence for our methodology. These are: dumbbell (DUM 1), sphere (SPH 1), pyramid (PYR 2) and cube (CUB 3). Figure 3 shows the four images before and after the introduction of noise within a range of [0 – 100]. Figure 4 shows the scale space edge detection of dumbbell (DUM 1), sphere (SPH 1), pyramid (PYR 2) and cube (CUB 3) before and after additional noise. Three edge detection results are presented for each image:

1. The ideal edge detection and the ideal scale σ_{Ideal} for each of the four images before adding the noise.
2. The edge detection of the noisy images at the scales which are considered ideal in the case before the addition of noise.
3. The new different ideal edge detection of the noisy images as a result of additional noise.

5. CONCLUSIONS

A novel approach to image processing utilizing noise within images has been introduced within this paper. This approach addresses the setbacks of previous techniques; such as the time and computational expense due to multiscale edge detection. The hypothesis, on which, this work was based, was shown to be mathematically feasible. Here, the noise within an image can be used to determine the optimal scale (σ_{Ideal}) in scale space, at which, the outline of the object of interest within the image is at its clearest for subsequent detection. This analysis is based on the hypothesis that the ideal scale (σ_{Ideal}) is a non-linear function of noise. In this non-linear function the changes in the amount of noise within the image affect the choice of the ideal scale.

The addition of noise to the images has altered the choice of the ideal edge detection; thus altering the optimal scale σ_{Ideal}. This immediate alteration of the values of σ_{Ideal} due to the introduction of the added noise provides the experimental evidence concerning the basis of our methodology.

6. REFERENCES

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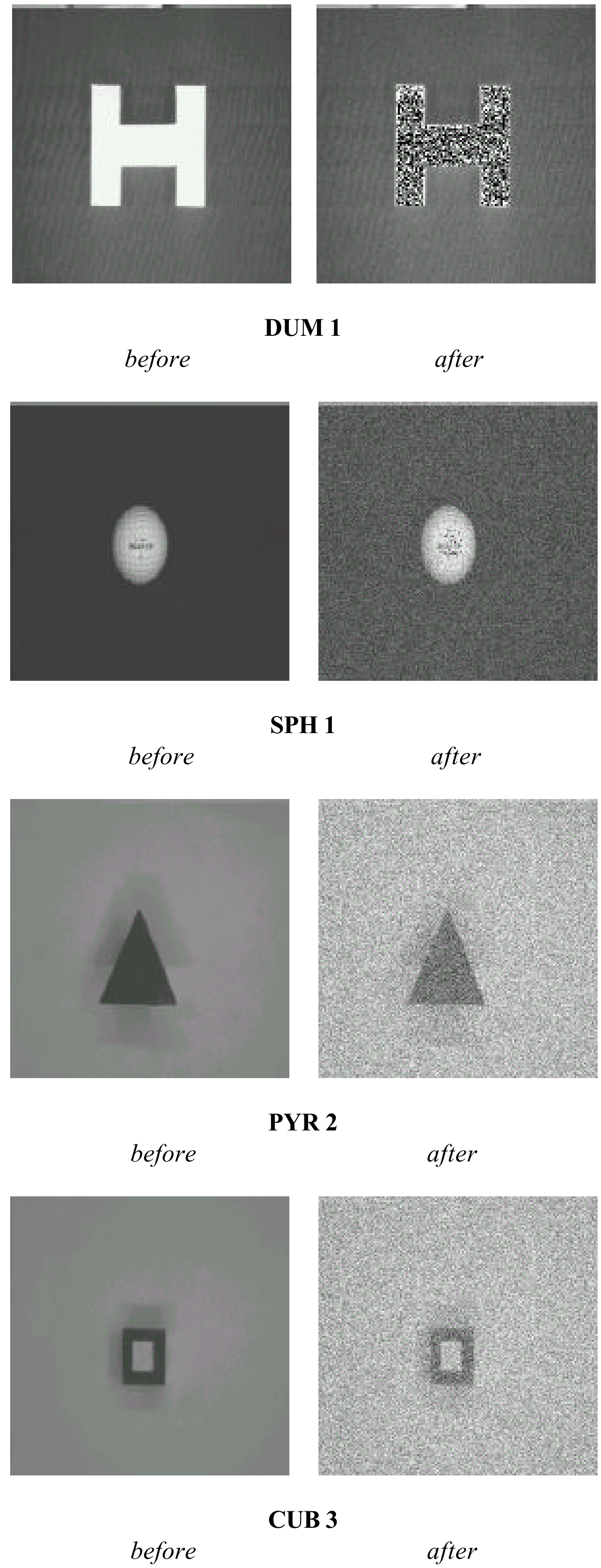

Figure 3. Images of dumbbell (DUM 1), sphere (SPH 1), pyramid (PYR 2) and cube (CUB 3) before and after adding random noise.

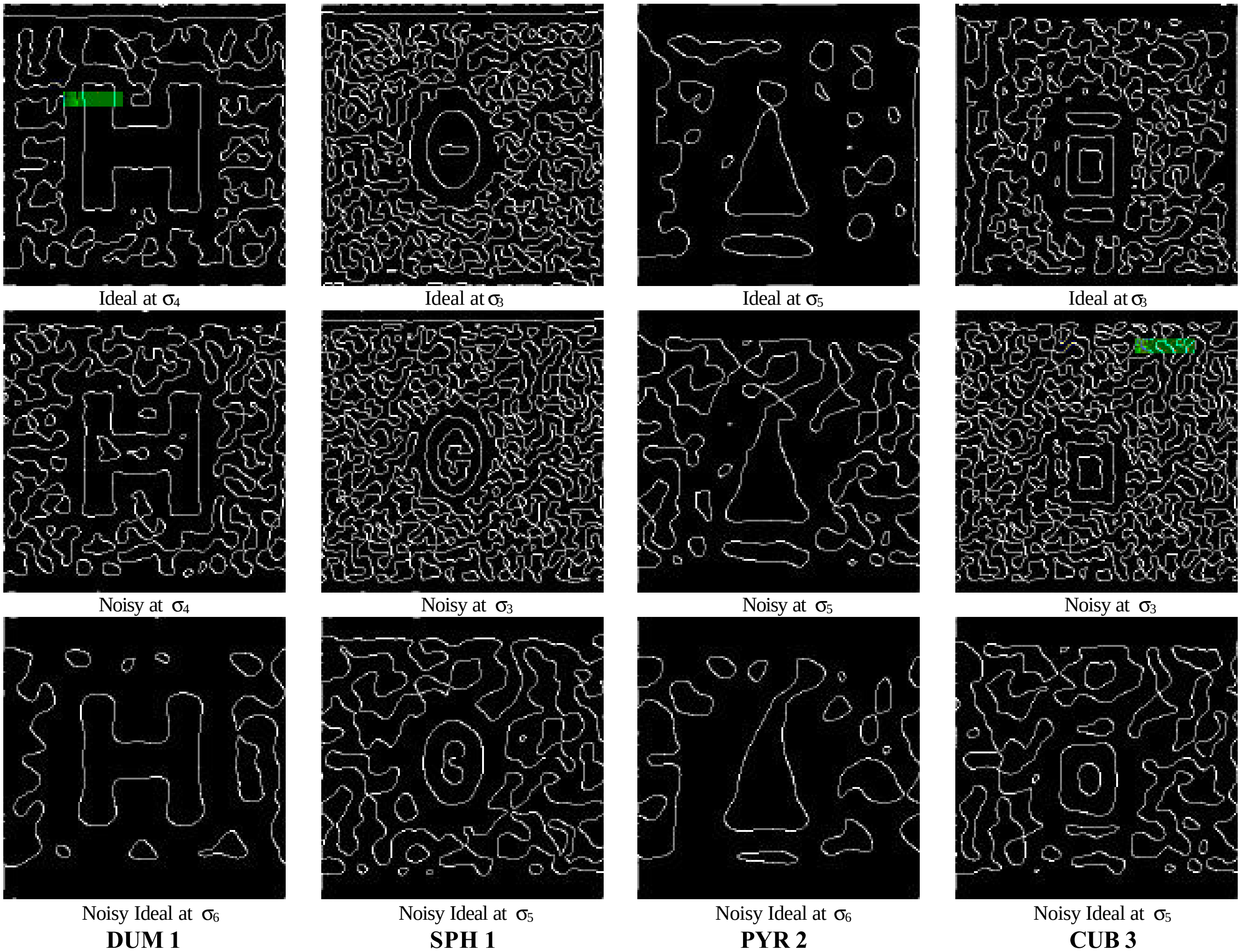

Figure 4. Edge detection of dumbbell, sphere, pyramid and cube before and after additional noise

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