A Comparison of various Edge Detection Techniques used in Image Processing

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Abstract

In this paper the important problem is to understand the fundamental concepts of various filters and apply these filters in identifying a shark fish type which is taken as a case study. In this paper the edge detection techniques are taken for consideration. The software is implemented using MATLAB. The main two operators in image processing are Gradient and Laplacian operators. The case study deals with observation of Shark Fish Classification through Image Processing using the various filters which are mainly gradient based Roberts, Sobel and Prewitt edge detection operators, Laplacian based edge detector and Canny edge detector. The advantages and disadvantages of these filters are comprehensively dealt in this study.

Keywords: *Canny, Laplacian, Prewitt, Robert, Sobel.*

1. Introduction

The filters are used in the process of identifying the image by locating the sharp edges which are discontinuous. These discontinuities bring changes in pixels intensities which define the boundaries of the object. The object is shark fish and a new methodology is applied to identify the shark type using its morphological features.

Here, it is applied for different 2D filters, comparative studies and displays the result. In this edge detection method the assumption edges are the pixels with a high gradient. A fast rate of change of intensity at some direction is given by the angle of the gradient vector is observed at edge pixels.

In Fig. 1, an ideal edge pixel and the corresponding gradient vector are shown. At the pixel, the intensity changes from 0 to 255 at the direction of the gradient. The magnitude of the gradient indicates the strength of the edge. If we calculate the gradient at uniform regions we end up with a 0 vector which means there is no edge pixel. In natural images we usually do not have the ideal discontinuity or the uniform regions as in the Fig. 1 and we process the magnitude of the gradient to make a decision to detect the edge pixels. The elementary processing is applied for a threshold. If the gradient magnitude is larger than the threshold, we decide the method in corresponds to the edge pixel.

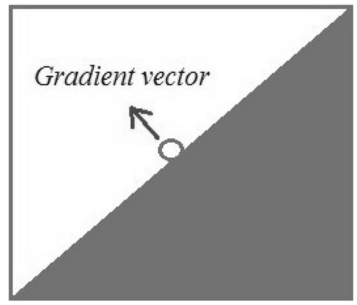


Fig. 1 The gradient and an edge pixel. The circle indicates the location of the pixel.

An edge pixel is described by using two important features, primarily the edge strength, which is equal to the magnitude of the gradient and secondarily edge direction, which is equal to the angle of the gradient. Actually, A gradient is not defined at all for a discrete function, instead the gradient, which can be defined for the ideal continuous image is estimated using some operators. Among these operators "Roberts, Sobel and Prewitt" can be shown. In the sub-sections these kinds of operators are studied. We apply the Laplacian based edge detection in the sample of shark fishes and identify its type. The Laplacian based edge detection points of an image can be detected by finding the zero crossings of the second derivative of the image intensity [5]. The idea is illustrated for a 1D signal in Fig.4. However, in calculating 2^{nd} derivative is very sensitive to noise. This noise should be filtered out before edge detection [8]. To achieve this, "Laplacian of Gaussian" is used. This method combines Gaussian filtering with the Laplacian for edge detection. In Laplacian of Gaussian edge detection uses three steps in its process. The First one is filter which is the image object. Secondly, it enhances the image object and finally detects. That can be identified through the shark type case study. Here, Gaussian filter is used for smoothing and the second derivative is used for the enhancement step. In this detection criteria, the presence of a zero crossing, In the second derivative with the corresponding large peak in the first derivative, that is referred in Fig.*5***.** In this approach, at first the noise is reduced by convoluting the image with a Gaussian filter [4]. The isolated noise points and small structures are filtered out. However the edges are spread with smoothing. Those pixels are locally maximum gradient which are considered as edges by the edge detector in which the zero crossings of the second derivative are used. The zero crossings are only insignificant edges to avoid the detection that corresponds as the first derivative is above some thresholds, which are selected as edge points. The edge direction is obtained using the direction in which zero crossing occurs. The convolution operation of the Laplacian of Gaussian operator is, h(x,y) in which the output obtained in equation 1.

$$h(x,y) = \Delta^2[g(x,y) * f(x,y)]$$
$$= [\Delta^2 g(x,y)] * f(x,y)$$

Where

$$\Delta^2 g(x,y) = \left(\frac{x^2 + y^2 - 2\sigma^2}{\sigma^4} \right)^{-(x^2+y^2)/2\sigma^2} \qquad (1)$$

is generally known as the mexican hat operator.

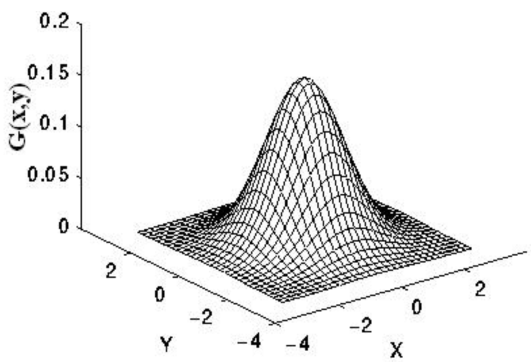


Fig.2 The two dimension Laplacian of Gaussian(LoG)

In this the LoG mainly uses two methods which are mathematically similar. At first, let us convolve the image object with Gaussian smoothing filter and then compute with the Laplacian result. Secondly, we shall convolve the image object with the linear filter which is the Laplacian of the Gaussian filter. This is also the case in the LoG. Smoothing (filtering) is performed with a Gaussian filter. The enhancement is done through transforming edges into zero crossings and the detection is done by detecting the zero crossings for the various samples of shark images primarily to identify its type.

2. Methodology

There are many ways to perform the edge detection. However, it may be grouped into two categories, that are gradient and Laplacian. The gradient method detects the edges by looking for the maximum and minimum in the first derivative of the image. The Laplacian method searches for the zero crossings in the second derivative of the image to find edges. This first Fig. 3(c) shows the edges of an image detected using the gradient method (Roberts, Prewitt, Sobel) and the Laplacian method (Marrs-Hildreth). It can compare the feature extraction using the Sobel edge detection with the feature extraction using the Laplacian [3]. It seems that although it is better for some features (i.e. the fins), it still suffers from mismapping some of the lines. A morph is constructed using individual selected points which will work better. It also should be noted that this method suffers the same drawbacks as the previous method, due to large contrast between images and the inability to handle the large translations of features [10].

2.1 Laplacian Edge Detection

It wishes to build a morphing algorithm which operates on features extracted from target images automatically. It can be a good beginning to find the edges in the target images. Here, we have accomplished this by implementing a Laplacian Edge Detector.

Algorithm:

Step 1: Start with an image of a Shark as a sample Fig. 3(a) that is compared with the various types of other Sharks images.

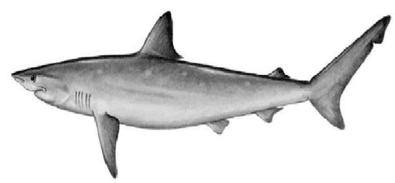


Fig. 3(a) Shark image

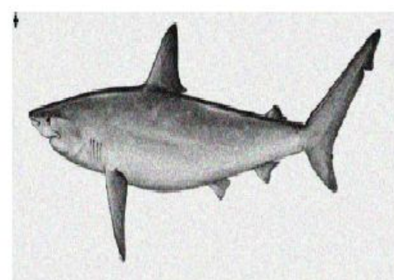


Fig. 3(b) Image with noise

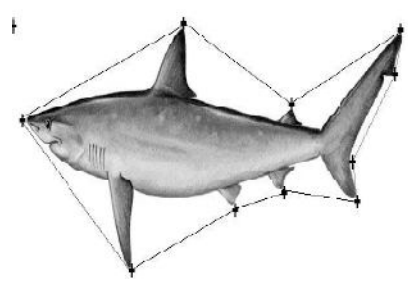


Fig 3(c) Image with Edge Detected

Step 2: Blur the image Fig. 3(b). On identifying the Shark type, the edges are selected to perform a morph, it is not really needed to detect the "every" edge in the image, but only in the main features Fig. 3(c). Thus, the image has been blurred prior to edge detection. This blurring is accomplished by convolving image with a Gaussian.

Step 3: Perform the laplacian on this blurred image. It is necessary to perform the laplacian transformation. For example the laplacian operation is as follows:

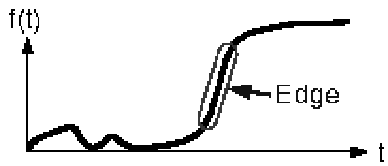


Fig.4 First derivative

Fig. 4 shows the gradient of this signal that has been marked which is in one dimension, which is the first derivative with respect to‘t’.

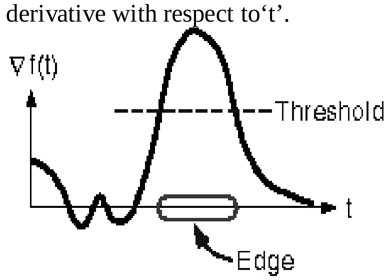


Fig.5 Second derivative

In Fig.5 distinctly it shows the gradient which has a large peak centered on the edge. By comparing the gradient to a threshold, through the edge. Whenever the threshold is exceeded (as shown above). In this case, an edge is found, but the edge has become "concentrated" due to the thresholding. As the edge occurs at the peak, the laplacian operation can be applied in one dimension, it is the second derivative with respect to t and finding the zero crossings.

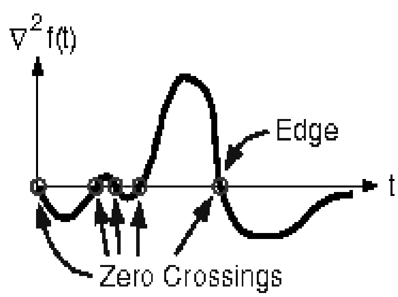


Fig.6 Identification of Zero Crossing

In Fig.6 it depicts the laplacian operation of one-dimensional signal. As expected, the edge corresponds to a zero crossing, but other zero crossings are corresponding to small ripples in the original signal which is also marked. In this method the laplacian operation is applied to test the image. In this study, the image of the Shark has been taken for testing the laplacian operations.

2.1.1 Roberts

The Roberts cross operator provide a simple approximation to the gradient magnitude:

$$G[f[i,j]] = |f[i,j] - f[i+1,j+1]| + |f[i+1,j] - f[i,j+1]|$$

Using convolution masks, this becomes:

$$G[f[i,j]] = |G_x| + |G_y| \qquad (2)$$

Where G_x and G_y are calculated using the following masks:

Table 1- Masks used by Roberts Operator

G_x=

1	0
0	-1

G_y=

0	-1
1	0

As with the previous 2 x 2 gradient operator, the differences are computed at the interpolated point [i + 1/2, j + 1/2]. The Roberts operator is an approximation to the continuous gradient at the interpolated point and not at the point [i, j] as it might be expected. As per the Roberts Edge Detection Filters, the image of the Shark is shown in the Fig. 7

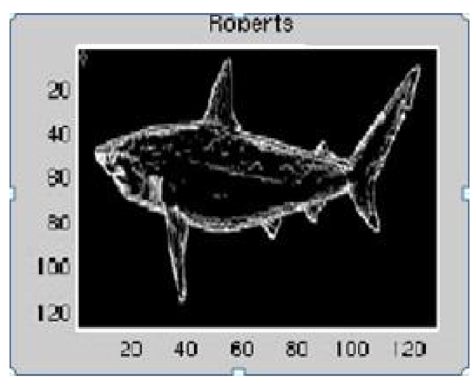


Fig. 7 Roberts Edge Detection Filter (sample)

2.1.2 Sobel

A way to avoid having the gradient calculated about an interpolated point between the pixels which is used 3 x 3 neighborhoods for the gradient calculations [6]. On The arrangement of pixels are about the pixel [i, j] shown in the Table 2**.** The Sobel operator is the magnitude of the gradient computed by:

$$M \sqrt{s_x^2 + s_y^2}$$

Where the partial derivatives are computed by:

$$s_x = (a_2 + ca_3 + a_4) - (a_0 + ca_1 + a_6)$$
$$s_y = (a_0 + ca_1 + a_2) - (a_6 + ca_5 + a_4) \quad (3)$$

With the constant c = 2.

Like the other gradient operators, S_x and S_y can be implemented using convolution masks:

Table 2: Masks used by Sobel Operator

S_x=

-1	0	1
-2	0	2
1	0	1

S_y=

1	2	1
0	0	0
-1	-2	-1

Note that this operator is placed on an emphasing pixels that are closer to the center of the mask. The Sobel operator is one of the most commonly used edge detectors.

Table 3: The labeling of neighborhood pixels

a_0	a_1	a_2
a_7	[i , j]	a_3
a_6	a_5	a_4

As per the Sobel Edge Detection Filters, the image of the Shark is shown in the Fig. 8.

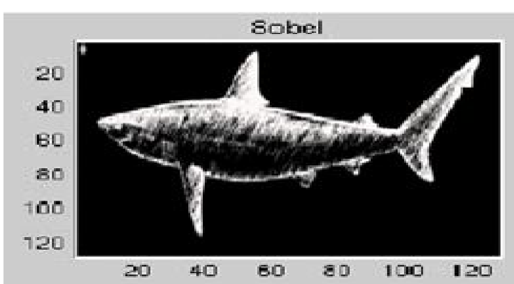


Fig. 8 Sobel Edge Detection Filters

The next pair of images are shown in the horizontal and vertical edges selected out of the group shark images with the Sobel method of edge detection. Now you will notice the difficulty it had with certain shark features, such as the gills, mouth, fins and tails of different sharks as shown in the following Fig. 9 to 13.

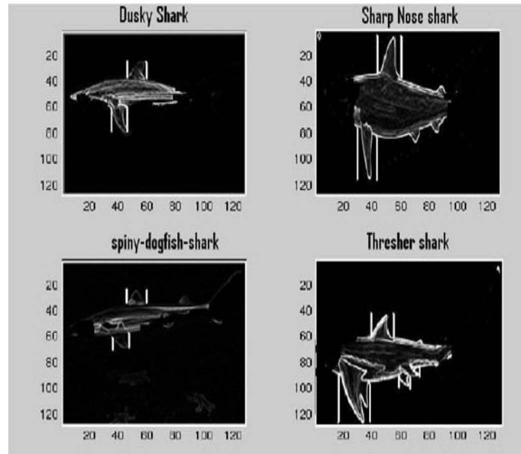


Fig. 9 Vertical Sobel Filter

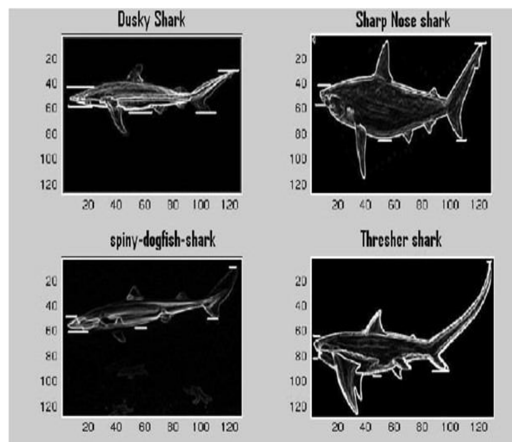


Fig. 10 Horizontal Sobel Filter

2.1.3 Prewitt

The Prewitt operator uses the same equations as the Sobel operator, where constant c = 1.

Table 4 Masks used by Prewitt gradient Operator

S_x=

-1	0	1
-1	0	1
-1	0	1

S_y=

1	1	1
0	0	0
-1	-1	-1

Therefore, note that, unlike the Sobel operator, this operator does not place any emphasis on pixels that are closer to the center of the masks [7]. As per the Prewitt Edge Detection Filters, the image of the Shark is shown in the Fig. 11.

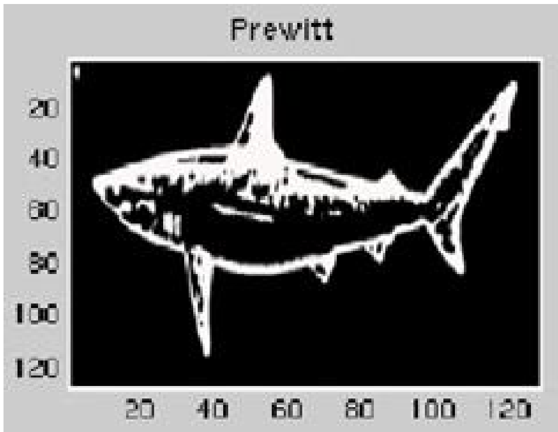


Fig. 11 Prewitt Edge Detection Filter

2.2 Other Methods of Edge Detection

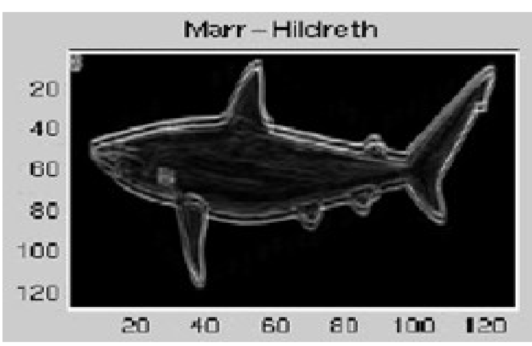
There are many ways to perform edge detection. However, the familiarized method can be grouped into two categories, gradient and Laplacian. The gradient method detects the edges by looking for the maximum and minimum in the first derivative of the image [1]. The Laplacian method searches for zero crossings in the second derivative of the image to find edges [2].

2.2.1 Marr-Hildreth

Marr-Hildreth uses the Gaussian smoothing operator to improve the response to noise, which is differentiated by the Laplacian of Gaussian is called the LoG operator [9].

$$\nabla^2 g(x,y) = \frac{1}{\sigma^2}\left(\frac{(x^2+y^2)}{\sigma^2} - 2\right) e^{\frac{-(x^2+y^2)}{2\sigma^2}} \tag{4}$$

Edges are at the 'zero crossings' of the LoG, where there



is a change in gradient.

Fig. 12 Marr-Hildreth Edge Detection Filte

2.2.2 Canny's Edge Detection

The Canny Edge Detection Algorithm has the following Steps:
Step 1: Smooth the image with a Gaussian filter.
Step 2: Compute the gradient magnitude and orientation using finite-difference approximations for the partial derivatives.
Step 3: Apply nonmaxima suppression to the gradient magnitude, Use the double thresholding algorithm to detect and link edges.
Canny edge detector approximates the operator that optimizes the product of signal-to-noise ratio and localization. It is generally the first derivative of a Gaussian. For example, in our case study shown the shark type is identified in Fig 13 (a) and (b).

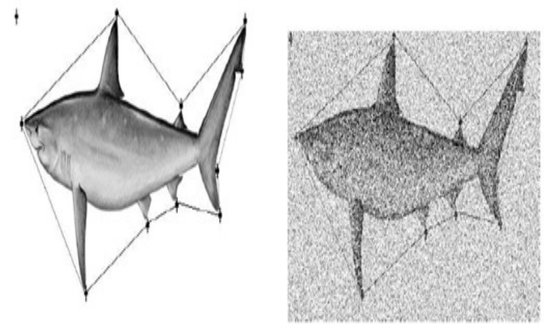


Fig.13 *(a)*-Shark image

Fig. 13*(b)*-Edges using a Canny Detector

The Smoothing is computed as *I[i,j]* to denote the image. *G[i,j,σ]* has to be a Gaussian smoothing filter where σ is the spread of the Gaussian and controls the degree of smoothing. The result of convolution of *I[i,j]* with *G[i,j,σ]* gives an array of smoothed data as:

$$S[i,j] = G[i,j,\sigma] * I[i,j] \tag{5}$$

Firstly, the Gradient is calibrated for the smoothed array *S[i,j]* is used to produce the x and y partial derivatives *P[i,j]* and *Q[i,j]* respectively as:

$$P[i,j] \approx (S[i,j+1] - S[i,j] + S[i+1,j+1] - S[i+1,j])/2$$
$$Q[i,j] \approx (S[i,j] - S[i+1,j] + S[i,j+1] - S[i+1,j+1])/2 \tag{6}$$

The x and y partial derivatives are computed with averaging the finite differences over the 2x2 square. From the standard formulas for rectangular-to-polar conversion, the magnitude and orientation of the gradient can be computed as:

$$M[i,j] = \sqrt{P[i,j]^2 + Q[i,j]^2}$$
$$\theta[i,j] = \arctan(Q[i,j], P[i,j]) \tag{7}$$

Here the arctan(x, y) function takes two arguments and generates an angle. The Nonmaxima Suppression is evaluated using the magnitude image array. One can be applied for the thresholding operation in the gradient-based method and end up with ridges of edge pixel. But canny has a more sophisticated approach to the problem. In this approach an edge point is defined as a point whose strength is locally maximum in the direction of the gradient. This is a stronger constraint to satisfy and is used to thin the ridges found by thresholding. This process, which results in one pixel wide ridges which is called Nonmaxima suppression. After Nonmaxima suppression one ends up with an image. N[i,j] = nms(M[i,j], ζ[i,j] which is zero everywhere except the local maxima points. The local maxima points at the value are preserved. The Thresholding is required in spite of the smoothing performed as the first step in edge detection, the Non-maxima suppressed magnitude image N[i,j] may contain many false edge fragments which are caused by noise and fine texture. The contrast of the false edge fragments is small. These false edge fragments in the Nonmaxima suppressed gradient magnitude should be reduced. One typical procedure is to apply a threshold to N[i,j]. All values below the thresholds are set as zero. After the application of threshold to the Nonmaxima suppressed magnitude, an array E(i,j) containing the edges detected in the image I[i,j] is obtained. However; in this method applying the proper threshold value is difficult but involves in trial and error. Because of this difficulty, in the array E(i,j) there may be some false edges if the threshold is too low or some edges may be missing if the threshold is too high. A more effective thresholding scheme is used for two thresholds.To overcome the problem, two threshold values, T_1 and T_2 are applied to N[i,j]. Here $T_2 \approx 2T_1$. With these threshold values, two thresholded edge images T_1[i,j]T_1[i,j] and T_2[i,j] are produced. The image T_2 has gaps in the contours but contains fewer false edges. With the double thresholding algorithm the edges in T_2 are linked into contours. When it reaches the end of a contour, algorithm looks in T_1 at the locations of the 8-neighbours for edges that can be linked to the contour. This algorithm continues until the gap has been bridged to an edge in T_2. The algorithm performs edge linking as a by-product of thresholding and resolves some of the problems choosing a threshold. The Shark is identified by using of the edge detection methodology. The target image and the original image with the crossing lines are mapped through the Shark type as shown in the following Fig. 14 and 15.

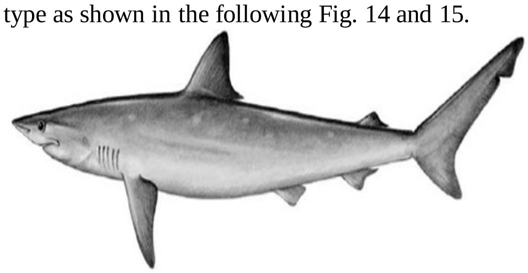


Fig. 14 Target Image

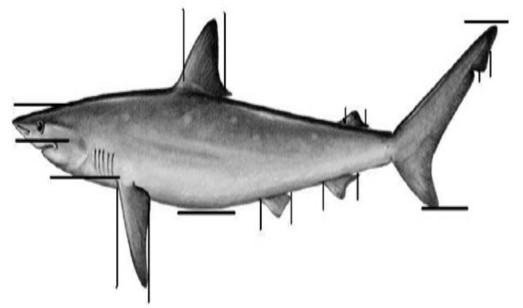


Fig.15 Original Image with crossing lines

Fig.16 The Final Horizontal and vertical pair of edges which helps to identify the Shark fish

2.3 Comparison of the Various Edge Detectors

As edge detection is a fundamental step in computer vision, it is necessary to point out the true edges to get the best results from the matching process. That is why it is important to choose edge detectors. In this respect, we first present some advantages and disadvantages of Edge Detection Techniques, They are as follows:

2.3.1 Classical (Sobel, Prewitt)

The primary advantages of the classical operator are simplicity. The Roberts cross operator provides a simple approximation to the gradient magnitude. The second advantages of the classical operator are detecting edges and their orientations. In this cross operator, the detection of edges and their orientations is said to be simple due to the approximation of the gradient magnitude.

The disadvantages of these cross operator are sensitivity to the noise, in the detection of the edges and their orientations. The increase in the noise to the image will eventually degrade the magnitude of the edges. The major disadvantage is the inaccuracy, as the gradient magnitude of the edges decreases. Most probably the accuracy also decreases.

2.3.2 Zero Crossing (Laplacian)

The advantages of the zero crossing operators are detecting edges and their orientations. In this cross operator detection of edges and their orientations is said to be simple due to the approximation of the gradient magnitude is simple. The second advantage is the fixed characteristics in all directions. The disadvantage is sensitivity to the noise. In detecting the edges and their orientations are increased in the noise to the image this will eventually degrade the magnitude of the edges. The second disadvantage is that, the operation gets diffracted by some of the existing edges in the noisy image.

2.3.3 Gaussian (Gobar Filter)

Gabor filter for edge detection is based on frequency and orientation representations. Gabor filters are similar to those of the human perception system that is related to particularly appropriate for texture representation and discrimination. 2D Gabor filter is a Gaussian kernel function modulated by a sinusoidal plane wave. Gabor filters are linked to Gabor wavelets. They can be designed for a number of dilations and rotations. In general, the expansion is not applied for Gabor wavelets. These needs are the computation of bi-orthogonal wavelets, which is very time-consuming. To overcome this problem a filter bank consisting of Gabor filters with various scales and rotations are created. The Gobar filters are convolved with the signal, resulting in so it is called Gabor space, its advantages is Gabor function which is a good fit to the receptive field weight functions. The Gabor Filter is very useful in image processing applications using edge detection. In our case study we use it for identification of shark fish image. It is well suited for a specific spatial location in distinctive between the objects of an image. The main important activations can be extracted from the Gabor space in order to create a sparse object representation.

2.3.4 Gaussian (Canny)

The Smoothing concept has been applied in this Gaussian operation, so the finding of errors is effective by using the probability. The next advantage is improving the signal with respect to the noise ratio and this is established by Nonmaxima suppression method as it results in one pixel wide ridges as the output. The third advantage is Better detection of edges especially in noise state with the help of thresholding method. The major disadvantage is the computation of Gradient calculation for generating the angle of suppression. The main disadvantage is Time consumption because of complex computation.

2.3.5 Marr-Hildreth

The main advantage of Marr-Hildreth is tested and established among the wider area around the pixels. Thus finding the correct places of edges seem to be very easy, which also the outermost advantage in Marr-Hildreth Edge Detection.The Laplacian of Gaussian (LoG) operator uses the Laplacian filter for Marr's edge detection. The disadvantage is that it reduces the accuracy in finding out the orientation of edges and malfunctioning at the corners, curves, where the gray level intensity function variations.

3. Conclusions

The edge detection is the primary step in identifying an image object, it is very essential to know the advantages and disadvantages of each edge detection filters. In this paper we dealt with study of edge detection techniques of Gradient-based and Laplacian based. Edge Detection Techniques are compared with case study of identifying a shark fish type. The software was implemented using MATLAB. Gradient-based algorithms have major drawbacks in sensitive to noise. The dimension of the kernel filter and its coefficients are static and it cannot be adapted to a given image. A novel edge-detection algorithm is necessary to provide an errorless solution that is adaptable to the different noise levels of these images to help in identifying the valid image contents produced by noise. The performance of the Canny algorithm relies mainly on the changing parameters which are standard deviation for the Gaussian filter, and its threshold values. The size of the Gaussian filter is controlled by the greater value and the larger size. The larger size produces more noise, which is necessary for noisy images, as well as detecting larger edges. We have lesser accuracy of the localization of the edge then the larger scale of the Gaussian. For the smaller values we need a new algorithm to adjust these parameters. The user can modify the algorithm by changing these parameters to suit the different environments. Canny's edge detection algorithm is more costly in comparing to Sobel, Prewitt and Robert's operator. Even though, the Canny's edge detection algorithm has a better performance. The evaluation of the images showed that under the noisy conditions, Canny, LoG, Sobel, Prewitt, Roberts's are exhibited better performance, respectively. The various methodologies of using edge detection techniques namely the Gradient and Laplacian transformation. It seems that although Laplacian does the better for some features (i.e. the fins), it still suffers from mismapping some of the lines.

4. References

[1] Canny, J., "A Computational Approach to Edge Detection", *IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 8:679-714,* November 1986.
[2] Chen, L., "Laplacian Embedded Regression for Scalable Manifold Regularization", *Neural Networks and Learning Systems, IEEE Transactions*, Volume: 23, pp. 902 – 915, June 2012.
[3] Chunxi Ma, et.al.; "An improved *Sobel* algorithm based on median *filter*", Institute of Electrical and Electronics Engineers, 2nd

International IEEE conference, China, Volume: 1, pp. 88-93, Aug 1, 2010.

[4] Huertas, A. and Medioni, G., "Detection of intensity changes with sub pixel accuracy using Laplacian-Gaussian masks," *IEEE Trans. On Pattern Analysis and Machine Intelligence, PAMI, vol. 8,* pp. 651–664, 1986.

[5] D. Mintz, "Robust Consensus Based EdgeDetection", *CVGIP: Image Understanding, Volume 59, Issue 2, March 1994*, pp. 137–153, 26 April 2002.

[6] Nick Kanopoulos, et.al. ; "Design of an Image Edge Detection Filter using the Sobel Operator", *Journal of Solid State Circuits, IEEE, vol. 23*, Issue: 2, pp. 358-367, April 1988.

[7] Seif, A.,et.al. ;"A hardware architecture of Prewitt edge detection", *Sustainable Utilization and Development in Engineering and Technology (STUDENT), 2010 IEEE Conference, Malaysia*, pp. 99 – 101, 20-21 Nov. 2010.

[8] N. Senthilkumaran, R. Rajesh, "Edge Detection Techniques for Image Segmentation and A Survey of Soft Computing Appro*aches", International Journal of Recent Trends in Engineering, Vol. 1, No. 2,* PP.250-254, May 2009.

[9] T.G. Smith Jr., et.al. ; "Edge detection in images using Marr-Hildreth filtering techniques", *Journal of Neuroscience Methods, Volume 26, Issue 1*, pp. 75–81, November 1988.

[10] WenshuoGao, et.al. ; "An improved Sobel edge detection", Computer Science and Information Technology (ICCSIT), *2010 3rd IEEE International Conference, China*, Volume: *5*, pp. 67 – 71, 9-11 July 2010.