



3D Object Recognition Using Grid Methods

Anwer Subhi Abdulhussein Olewi¹, Hashem B. Jehlol²

Lecturer, Avicenna Center for E-learning, Al-Mustansiriyah University, Baghdad, Iraq¹

Assistant Lecturer, Computer Center, Al-Mustansiriyah University, Baghdad, Iraq²

Abstract: This work proposed number of methods to recognize three dimensional objects from two-dimensional image with the use of 512 different poses of the object (which is represented by an airplane or a cube or a satellite). The object is rotated in the three directions (x,y,z) by an angle of $2\pi/8$ (45°). Different types of Grid Method were used to extract feature representing the desired object. Also four or five variables for each object are calculated. These variables represent fast-calculated features of the object that can speed up the recognition process. These variables are scaled and position in variant representation of the object. The mathematical model that represents the object was calculated in two methods. These were the Wavelet Transform Model and the Auto regression Model.

Keywords: Three Dimensional, Two Dimensional, Grid Method, Wavelet Transform, Auto regression Model.

I. INTRODUCTION

Recognition of an object image requires associating that image with views of the object in computer memory (Database which contains just enough different poses of the object under consideration). These views are called Object Model and it is needed because as in real world objects cannot be recognized if they have never been seen before [1]. The object is attached to the model image with the minimum distance if the distance is less than a predefined value. In real world, rendering an image is done with speed of light shining on the objects and reflecting into human eyes, but rendering of virtual worlds take much more time. This is the reason that the variable rendering quality has always been a biased balance between the computation time and the displayed effects. This setting is differed according to the application [2].

When large object is used searching will become extremely time consuming and hence not realistic. Consequently, the main concern here is to solve the combinatorial time complexity problem in an optimal manner, so that, the correct matching (recognition) is found as fast as possible [3].

II. FILTERING

Spatial filters have been used to remove various types of noise in digital images. These spatial filters typically operate on a small neighbourhood area in the range from 3×3 pixels to 11×11 pixels. If the noise added to each pixel is assumed to be additive white Gaussian, then the intensity of each pixel can be represented as follows [4]:

$$d(x,y)=I(x,y)+n(x,y) \quad \dots(1)$$

where x and y are the coordinate of the pixel under consideration in the image.

$d(x,y)$ = Degraded pixel intensity in the image.

$I(x,y)$ = Original pixel intensity in the image.

$n(x,y)$ = Additive White Gaussian function value with zero mean which represents the noise intensity added to the pixel (x,y).

Here through this work adaptive Alpha-trimmed filtering is suggested with the condition that if the filtering action is made over an edge pixel, then the filtering action will be canceled and the pixel point will have the same former value in the few filtered image. The decision for an edge point or not is made when the sum of the maximum three pixels values exceeds the sum of the three minimum pixels by a predefined threshold value which is determined experimentally. Fig. 1 illustrates the filtered object.

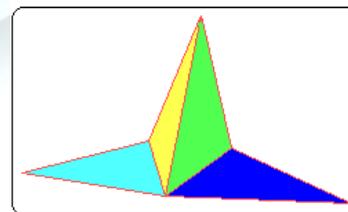


Fig. 1. Filtered objects.

III. BINARY CONVERSION

Spatial filters have been used to remove various types of noise in digital images. These spatial filters typically operate on a small neighbourhood area in the range from 3×3 pixels



to 11×11 pixels. If the noise added to each pixel is assumed to be additive white Gaussian, then the intensity of each pixel can be represented as follows [4]:

In order to distinguish the object under consideration by its boundary, the image is transferred to a binary image after filtering process. The black level represents anything other than the object in the image and the maximum shiny white level represents the object. This procedure helps in eliminating the surface details of the object and keeps only the boundary information of the object. In some application this conversion may not be used. Fig. 2 show binary image after process of filtered object.



Fig. 2. Binary object conversion.

IV. EDGE DETECTION

In this work, the main interest is in the presence of an edge not in its direction, so that Roberts operator (which is a (2×2) operator) would work well for the purpose of edge detection. This operator indicates the presence of an edge not its direction. If the magnitude of this operator exceeds some predefined value then an edge point will be detected [5]. The magnitude of this operator is defined as:

$$\text{Magnitude} = |I(x,y) - I(x-1,y-1)| + |I(x,y-1) - I(x-1,y)| \dots (2)$$

Robert operator is used here because of its computational efficiency. When the magnitude of this operator exceeds some predefined threshold, then an edge will be detected. Fig. 3 show image after Detection of edge.

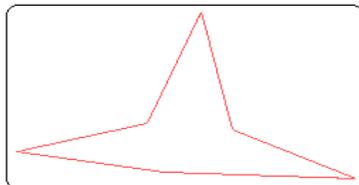


Fig. 3. Edge Detection.

V. DATA ACQUISITION

The data that represent some predefined features of the object is obtained from the object image. All the representations used are one-dimensional representations in which a single set of variables represents the object under consideration.

A. The Grid method representation

Here, in this new proposed methods for grid representation of the object are given including 3D representation. In these methods a flexible size grid of rectangular shape and contain 64 small rectangles with 8×8 distribution is used. Fig. 4 shows Proposed Grid.

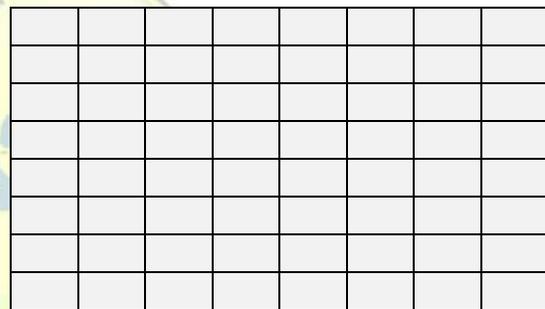


Fig. 4. Proposed Grid that contain 64 small rectangles with 8×8 distribution

The proposed grid has the following properties:

1. The grid is flexible in size, which means that the grid adapts itself to match the size of the processed object if the object may vary in size. The grid does not depend on the object direction.
2. The first horizontal line extends from the first left x coordinate to the first right x coordinate and has y coordinate of the first top pixel.
3. The last horizontal line in the grid has the same x coordinates of the first one but the y coordinates is that of the lowest bottom point.
4. The first left vertical line extends from the highest y coordinates to the lowest bottom y coordinate with the x coordinate of the first left pixel of the object.
5. The first right vertical line of the grid will have the same y coordinates of the first left line but with the x coordinate of the first right pixel of the object.
6. Seven vertical lines are drawn between the first left and the first right vertical lines starting from the left



and the distance between the consecutive lines in pixel equals:

$$\text{Distance} = \text{integer} \left(\frac{x_{\text{right}} - x_{\text{left}}}{8} \right) \dots (3)$$

The distance between the 7th vertical line and the first right vertical line may be in the range:

$$2 \times \text{integer} \left(\frac{x_{\text{right}} - x_{\text{left}}}{8} \right) > \text{distance} \geq \text{Integer} \left(\frac{x_{\text{right}} - x_{\text{left}}}{8} \right) \dots (4)$$

7. seven horizontal lines are drawn between the first top line to the first bottom line starting from the top with the distance between consecutive lines is:

$$\text{Distance} = \text{integer} \left(\frac{y_{\text{bottom}} - y_{\text{top}}}{8} \right) \dots (5)$$

The distance between 7th horizontal line and the first bottom line may be:

$$2 \times \text{integer} \left(\frac{y_{\text{bottom}} - y_{\text{top}}}{8} \right) > \text{distance} \geq \text{Integer} \left(\frac{y_{\text{bottom}} - y_{\text{top}}}{8} \right) \dots (6)$$

As it can be seen from conditions (3-6), the grid will fit itself to adapt with object size and location, giving a form of scale and location in variant representation. After the division of the grid to 8×8 distributed 64-rectangle grid, data or reference number must be assigned to each rectangle individually. Various methods for the reference assignment are suggested.

First method (method a)

- A. Before drawing the grid over the object, image after filtering must be transferred to binary image in which anything rather than the desired object (pixels) is transferred to the minimum black level ((0) level). The pixels which fall inside the object is transferred to the maximum shiny white level (16777215). Then, the grid is drawn over the binary image.
- B. After that, a reference number is assigned to each rectangle in the grid. For the first method (method (a)) if the rectangle does not contain any portion of the object then zero will be assigned to that rectangle. If the whole rectangle is filled with the white shiny pixels, (which means that it is filled with a portion of the object) then (1) will be assigned to that rectangle. If

a portion of the rectangle is filled with black pixels and the other portion filled with white shiny points forming edges in the rectangle then (0.5n) will be assigned to that rectangle where n is the number distinctive edges that appear in the rectangle. This process is repeated for the entire 64 rectangle in the grid until having a 64-element data set representing the reference numbers assigned to the 64 rectangle, which is a single dimension data set. Fig. 5 gives examples of reference assignment.

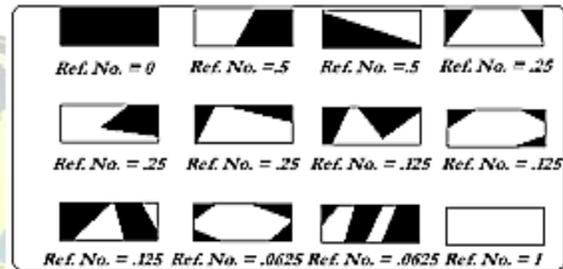


Fig. 5. Reference number for Grid Method (a).

Second method (method b)

- A. Step (A) for the second method is the same as that for the first method.
- B. The reference number of each rectangle is defined as follows:

$$\text{Ref. No.} = \frac{\text{Total No. of white pixels in rectangle}}{\text{Total No. of pixels in the rectangle}} \dots (7)$$

Since the representation is a ratio of pixels then this representation is scale and position invariant representation. Fig. 4 gives examples of reference number assignment for method (a), Fig. 6 Rectangle assignment for grid method (b) and Fig. 7 Shows the grid distribution over the object for methods a & b

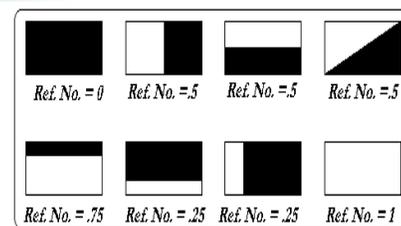


Fig. 6 Reference number for Grid method (b).

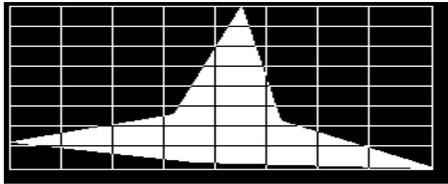


Fig. 7 Grid distribution for methods (a&b).

Third method (c)

- C. Step for the third method is the same as that for the first and second methods.
- D. After that, a reference number is assigned to each rectangle in the grid. For the first case, if the rectangle does not contain any portion of the object then zero will be assigned to that rectangle. If the whole rectangle is filled with the white shiny pixels (which means filled with a portion of the object) then (1) will be assigned to this rectangle.
- E. If the rectangle contains boundary portion then edge detection processes through that rectangle will be started. After the edge detection for all boundary rectangles is completed, searching for the following masks will be started. The number below each mask is the reference number assigned to that mask.

$$\begin{array}{cccc}
 \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} & \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} & \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} & \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix} \\
 \frac{1}{3} & \frac{2}{3} & \frac{3}{3} & \frac{7}{3} \\
 \begin{bmatrix} 0 & 1 \\ 1 & 1 \end{bmatrix} & \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} & \begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix} & \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \\
 \frac{1}{5} & \frac{2}{5} & \frac{5}{5} & \frac{7}{5} \\
 \begin{bmatrix} 0 & 0 & 0 \\ 1 & 1 & 1 \\ 0 & 0 & 0 \end{bmatrix} & \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} & \begin{bmatrix} 0 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \end{bmatrix} & \begin{bmatrix} 0 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \end{bmatrix} \\
 \frac{1}{9} & \frac{2}{9} & \frac{5}{9} & \frac{7}{9} \\
 \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} & \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix} & \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix} & \begin{bmatrix} 0 & 0 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix} \\
 \frac{1}{11} & \frac{2}{11} & \frac{5}{11} & \frac{7}{11}
 \end{array}$$

If any rectangle contains only one of these masks then the reference number of that rectangle will equal to the mask reference number. If the same mask is found distinctively in

more than one place in the rectangle then the number assigned to the rectangle is the multiplication of the mask reference number with (n) where n is the number of times the mask appear in the rectangle. If more than one mask appear in the rectangle then the reference number of that is the addition of these masks reference numbers. Fig. 8 gives grid distribution of Grid method (c). The above method suffers from long time consumption but it will give more powerful analysis of the desired object in the image.

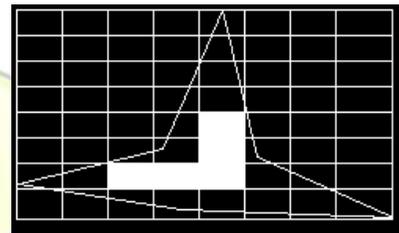


Fig. 8 Grid distribution for method (c).

The fourth method (method (d))

- A. Before drawing the grid, the three-dimension information must be extracted from the object. The patches that form the object must be specified first. These patches will depend on the color (or intensity for B&W images) distribution throughout the object. The color range of the computer is divided to six levels. The first level represents the background levels. The other five levels represent the object patches. Each level is represented by a single color and it covers a range of color distribution. So that, the new colored image will have only six colors.
- B. Each color in the new picture will be given a reference number. The reference number for the background is (0) and the other five colors will have reference number {3,5,7,9,11}.
- C. A reference number must be assigned to each rectangle in the grid. If the rectangle does not contain any portion then zero will be the reference number of that rectangle. When the whole rectangle is occupied with single patch then the reference number of that rectangle will be the same reference of the color of that patch. If the rectangle occupied with a single patch with a portion of the background then, the rectangle reference number will be equal to patch reference number divided by two. When there is more than one patch in the rectangle and it does not contain any portion of the background then the rectangle



reference number will be equal to the multiplication of patches reference numbers. If there is a portion of the background then the reference number will be the reference number divided by (2). If more than one distinctive edge appears in the rectangle then the reference number is divided by (2n). (n is the number of distinctive edges).

D. When dealing with black & white pictures (monochrome pictures) or when dealing with colored pictures with unknown color range the system is made to match automatically with the range intensities. That is, the surface of the filtered object is scanned to determine the maximum and minimum intensity pixels. The number of patches that form the object will be defined as follows:

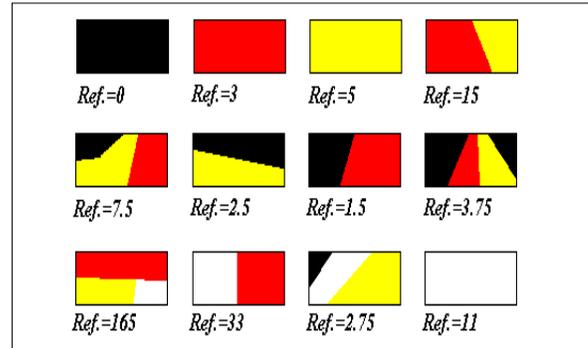


Fig.9. Reference number for Grid Method (d)

$$d = \{\text{Min object intensity} - \text{Max background intensity}\} \dots (8)$$

If the distance between the minimum and maximum object intensities is higher than the value of d then the object will be divided into patches. The range of the patch intensity levels equals to (d) provided that the total number of levels is no more than five levels. If more than five levels appear then the new distance between consecutive levels will be 2d. If the number of levels is still more than five then the distance will be 3d, 4d, and so on. If in the first place only two levels appear then the value of the distance between the intensity levels will be equal to (2/d). The number of the new levels is calculated and if it is still two then the final number of object patches will be two.

If the distance between maximum and minimum object intensities is less than the value of (d) then 2 divide the value (d). This division process is repeated until the value of the difference between the maximum and minimum intensities is higher than the result from the division process. If the object is divided into two patches then the division process is repeated only once and the algorithm is terminated.

Step (D) is applied to the unknown range of colors and also to the silhouette object images in which the condition of lighting is unknown. Fig. 9 shows the the refrence numbers assignment for grid method (d) and Fig. 10 shows the grid distribution for Grid method (d).

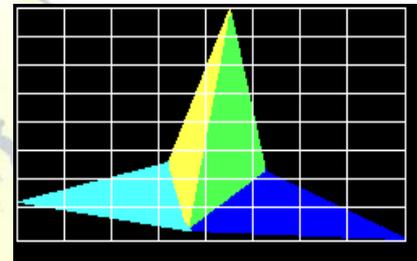


Fig. 10. Grid distribution for method (d).

B. The mathematical Models

After the data extraction from the image of the object, data manipulation must be applied in order to have a suitable Mathematical Model for the object.

Auto regression Model

The measured data can be represented or approximately represented by selected Autoregression Model [6]. The parametric spectral can be made in a three-step procedure.

1. The model set is selected (AR (all pole Autoregression)).
2. The model parameters are estimated from the data.
3. The spectral estimation is made by the estimated model parameter.

For linear systems with random input, the measurement of the output spectrum is related to the input spectrum by the factorization model[7].

$$S_{yy}(Z) = H(Z)H^*(Z)S_{xx}(Z) = |H^2(Z)|S_{xx}(Z) \dots (9)$$

Fig. 11 shows the schematic diagram of the AR model.

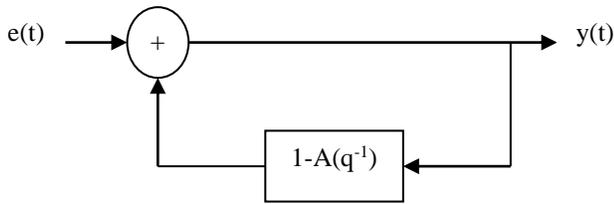


Fig.11. AR Model.

The model parametric estimation is:

- 1- Select the representative model (AR Model).
- 2- Estimation the model parameter from data, that is given $y(t)$, estimate $(A(q^{-1}))$, where AR: $H(\Omega)=1/A(\Omega)$ (all pole model).

The all pole model is defined as:

$$y(t) A(q^{-1}) = e(t) \quad \dots(10)$$

Where

- $y(t)$: is the measured data
- $e(t)$: is the zero mean, white noise sequence with variance σ^2 .
- $A(q^{-1})$: is an N_a th order polynomial in backward shift operator.

The basic parameter estimation problem for the Auto regression in the general case (infinite covariance) is given as minimum (error) variance solution to

$$\min_a J(t) = E(e^2(t)) \quad \dots(11)$$

$$e(t) = y(t) - \hat{y}(t) \quad \dots(12)$$

= {Minimum error between estimated and real value}.

$\hat{y}(t)$ is the minimum variance-estimate obtained from AR model.

$$y(t) = \sum_{i=1}^{N_a} a_i y(t-i) + e(t) \quad \dots(13)$$

$$\hat{y}(t) = \sum_{i=1}^{N_a} a_i \hat{y}(t-i) \quad \dots(14)$$

$\hat{y}(t)$ is actually the one step predictor. The one step predictor estimates $\hat{y}(t-1)$ based on the past data samples. This operation is called linear predictor. The coefficients of the predictor were calculated using Durban's recursive algorithm. The order of each predictor depends on the

number of samples (N) used in calculating the predictor coefficients and equals to the first integer $> (\ln(N))$.

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Wavelet Transform Model

Two forms of the discrete wavelet transform are used throughout this work. These are Haar and Daubechies wavelet transform.

Haar Wavelet Transform is a cold topic, their graphs are made from flat pieces {1's and 0's}. When dealing with a four elements one-dimensional signal. The Haar Wavelet Transform of this signal is a scaling function and with three Wavelet coefficients. If these scaling and wavelet coefficients are multiplied with Haar basis vectors then, the original signal vector will be retrieved [7]. The Haar four element basis vectors form a matrix of the following form:

$$H = \begin{bmatrix} 1 & 1 & 1 & 0 \\ 1 & 1 & -1 & 0 \\ 1 & -1 & 0 & 1 \\ 1 & -1 & 0 & -1 \end{bmatrix} \quad \dots (15)$$

As it can be seen the basis vectors of the Haar transform are orthogonal. This means that if any vector is multiplied by the inner product with any vector other than itself the result will be zero.

(D = the signal vector & S = Wavelet transform vector)

$$HS = D \quad \dots (16)$$

$$H^{-1}HS = H^{-1}D \quad \dots (17)$$

$$S = H^{-1}D \quad \dots (18)$$

Where



$$H^{-1} = \begin{bmatrix} 0.25 & 0.25 & 0.25 & 0.25 \\ 0.25 & 0.25 & -0.25 & -0.25 \\ 0.5 & -0.5 & 0 & 0 \\ 0 & 0 & 0.5 & -0.5 \end{bmatrix} \quad \dots (19)$$

With

$$S = \begin{bmatrix} S \\ W_1 \\ W_2 \\ W_3 \end{bmatrix} \quad \& \quad D = \begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ a_4 \end{bmatrix} \quad \dots (20)$$

Here throughout this work, Fast Haar algorithm is used which will transfer the four elements one dimensional signal vector to a scaling function with three-wavelet coefficient. This type of transform is done by the use of the Pyramid algorithm. The component of the signal vector are a_1, a_2, a_3 and a_4 . The pyramid algorithm is applied as in the Fig. 12.

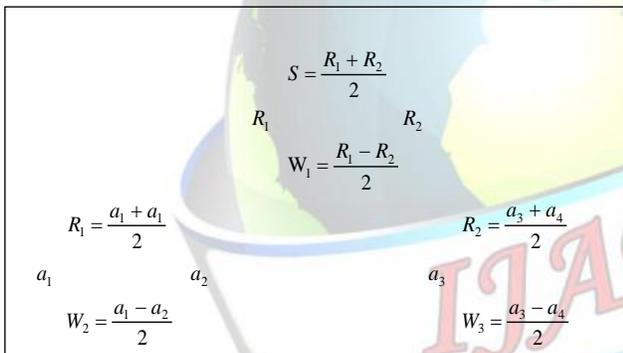


Fig.12. Pyramid Algorithm.

The ratio of the scaling function over the first wavelet coefficient with the sum of wavelet coefficient from the second wavelet coefficient to the last one divided by the first wavelet coefficient was calculated. It was found through mathematical calculation that this ratio gives a good normalized (scale invariant) mathematical representation of the data vector. This system is tested on different data sets having the same elements but with different sequences and it gives a good discrimination between these vectors.

The first ratio equals:

$$\text{Ratio1} = (S/W_1) \quad \dots (21)$$

The second ratio equals:

$$\text{Ratio2} = (W_1 + \dots + W_{n-1}/W_1) \quad \dots (22)$$

Where n is the number of elements in the data vector. This representation was extended to 32 and 64 element vector.

Some malfunction may in appear in the theoretical calculation of the fast Haar transform (such as when dealing with the two vectors of data (5,4,2,1) and (6,3,2,1). These two vectors have different elements but they have the same first ratio (S/W_1). A second ratio ($(W_2+W_3)/W_1$) must be used in order to distinguish between the two vectors. A modification over the Haar basis vectors is assigned in order to distinguish between the two vectors from the first ratio. An example of this modification is given below for four elements.

$$H = \begin{bmatrix} 1 & -2 & 1 & 0 \\ 2 & 1 & 0 & 1 \\ 2 & 1 & 0 & -1 \\ 1 & -2 & -1 & 0 \end{bmatrix} \quad \dots (23)$$

$$H^{-1} = \begin{bmatrix} 0.1 & 0.2 & 0.2 & 0.1 \\ -0.2 & 0.1 & 0.1 & -0.2 \\ 0.5 & 0 & 0 & -0.5 \\ 0 & 0.5 & -0.5 & 0 \end{bmatrix} \quad \dots (24)$$

From this for elements modified Haar transform the scaling function and the three wavelet coefficients are calculated as follows:

$$S = (a_1 + 2x(a_2 + a_3) + a_4)/10 \quad \dots (25)$$

$$W_1 = (-2x(a_1 + a_4) + a_3 + a_4)/10 \quad \dots (26)$$

$$W_2 = (a_1 - a_4)/2 \quad \dots (27)$$

$$W_3 = (a_2 - a_3)/2 \quad \dots (28)$$

The second proposed modified Haar vectors give the following form for four-element signal vector.

$$H = \begin{bmatrix} 1 & 2 & 2 & 0 \\ 2 & -1 & 0 & 1 \\ 1 & 2 & -2 & 0 \\ 2 & -1 & 0 & -1 \end{bmatrix} \quad \dots (29)$$



$$H^{-1} = \begin{bmatrix} 0.1 & 0.2 & 0.2 & 0.1 \\ 0.2 & -0.1 & 0.2 & -0.1 \\ 0.25 & 0 & -0.25 & 0 \\ 0 & 0.5 & 0 & -0.5 \end{bmatrix} \dots (30)$$

These proposed wavelet transforms were extended to 64 element wavelets.

Distance Measurement

When the Mathematical Model for the object is built, then the recognition process can be fulfilled. The decision of the object being recognized or not will depend on three types of distance measurement, these are:

- 1- When dealing with a single element set such as the variable ratio or angle1 or angle2,...etc., the direct absolute difference is used. Which is given as:

$$\text{Distance} = |R_1 - R_2| \dots (31)$$

- 2- When dealing with one dimensional vector with more than one element, such as Autoregression Model Euclidean distance is a good measure for the distance between two vectors. If the two vectors are (a_1, a_2, \dots, a_n) and (b_1, b_2, \dots, b_n) , [8] then the Euclidean distance between them is defined as:

$$\text{Distance} = \sqrt{(a_1 - b_1)^2 + (a_2 - b_2)^2 + \dots + (a_n - b_n)^2} \dots (32)$$

- 3- For the same preceding case, Non-metric measure similarity function is good distance measure also. It is defined as $S(A, B)$.

$$S(A, B) = \frac{\overline{AB}}{\|A\| \|B\|} = \text{Cos} \theta \dots (33)$$

This measurement gives high value for $\text{Cos} \theta$ when the similarity between the two vectors A & B is high.

VI. OBJECT MODEL

The first step after the filtering and edge extraction processes is the calculation of four variables. These variables represent some fast-calculation features of the designed object. These are the first four variables in the Mathematical Model of each pose in the Object Model. In the recognition process, each one of these variables for the object under

consideration is compared with corresponding variable for the pose in the Object Model. If the distance between the two corresponding variables is higher than a predefined value then the recognition process with that pose is terminated. These four variables are defined as Ratio, Angle1, Angle2 and ratio3. In some applications a fifth variable is calculated which the Average is Crossing. The variables are:

Ratio: It is the ratio of the line connecting the highest pixel to the lowest pixel in the object image to the line connecting the first left pixel to first right pixel in the object image. (When more than one pixel appear at any one of the four sides, then for the Top side it is the first left pixel. For the Bottom side it is the first right pixel. For the Right side, it is the first bottom pixel and for the Left side, it is the first top pixel).

Angle1: It is the angle between the line connecting the top pixel to the bottom pixel in the object image to the horizontal axis.

Angle2: It is the angle between the line connecting the first left pixel to the first right pixel in the object image to the horizontal axis.

Ratio3: It is the ratio of the line between the object boundaries and passing through the centre of the object horizontally to that passing through the centre vertically.

VII. RESULTS

Every proposed algorithm in this work has its own sequential database, which represent the Object Model containing the mathematical representation of all possible 512 poses of the object. Different types of desired and undesired object images were tested. When the following distances were used, the algorithms failed to recognize the correct objects and failed to reject the undesired objects.

Maximum allowable distance for variable Ratio = 0.3.

Maximum allowable distance for variable Angle1 = π .

Maximum allowable distance for variable Angle2 = 2π .

Maximum allowable distance for variable Ratio3 = 0.

For the Wavelet Transform Model and Grid Method (a) the maximum allowable distances are shown in table 1:

TABLE I

MAXIMUM ALLOWABLE DISTANCES WHEN USING WAVELET TRANSFORM MODEL AND GRID METHOD (A)

H.T	1M. H.T	2M. H.T	1M. D.T	2M. D.T	3M. D.T
-----	------------	------------	------------	------------	------------



S/W ₁	(W ₂ +.....+ W _n)/W ₁					
0.3	0.55	0.4	0.4	0.2	0.1	0.15

For the Wavelet Transform Model and Grid Method (b) the maximum allowable distances are shown in table 2:

TABLE 2
 MAXIMUM ALLOWABLE DISTANCES WHEN USING WAVELET TRANSFORM MODEL AND GRID METHOD (B)

H.T		1M. H.T	2M. H.T	1M. D.T	2M. D.T	3M. D.T
S/W ₁	(W ₂ +.....+ W _n)/W ₁					
0.3	0.55	0.4	0.4	0.25	0.15	0.15

For the Wavelet Transform Model and Grid Method (c) the maximum allowable distances are shown in table 3:

TABLE 3
 MAXIMUM ALLOWABLE DISTANCES WHEN USING WAVELET TRANSFORM MODEL AND GRID METHOD (C)

H.T		1M. H.T	2M. H.T	1M. D.T	2M. D.T	3M. D.T
S/W ₁	(W ₂ +.....+ W _n)/W ₁					
3	4	0.4	0.4	0.25	0.2	0.15

For the Wavelet Transform Model and Grid Method (d) the maximum allowable distances are shown in table 4:

TABLE 4
 MAXIMUM ALLOWABLE DISTANCES WHEN USING WAVELET TRANSFORM MODEL AND GRID METHOD (D)

H.T		1M. H.T	2M. H.T	1M. D.T	2M. D.T	3M. D.T
S/W ₁	(W ₂ +.....+ W _n)/W ₁					
5	4.5	0.45	0.35	0.3	0.25	0.25

For Autoregression Model:

Maximum Euclidean distance for grid method (a) = 0.4.

Maximum Euclidean distance for grid method (b) = 0.4.
 Maximum Euclidean distance for grid method (c) = 0.45.
 Maximum Euclidean distance for grid method (d) = 0.65.
 Maximum non-metric measure of similarity distance for grid method (a) = 0.1.
 Maximum non-metric measure of similarity distance for grid method (b) = 0.1.
 Maximum non-metric measure of similarity distance for grid method (c) = 0.15.
 Maximum non-metric measure of similarity distance for grid method (d) = 0.09.

VIII. CONCLUSION

In this work, simple, easy implemented and robust techniques for solving the 3D-object recognition are proposed. These techniques are Object Model based. The use of adaptive filter through this work saves the object edges and high frequency component from being blurred.

The four variables used in each pose mathematical model in Object Model are scale and position invariant sine they represent ratio and angles.

Grid methods provide a scale invariant representation for the objects. These methods suffer from high time consumption comparing with Centroid representation. It was found that Grid method (d) gives the more accurate representation for the objects and it deals with 3D information of the object. Grid method (a) is the fastest one but it suffers from the low boundary information about the object.

Simple Haar Wavelet transformation is the fastest method for calculating the Mathematical Model for the object. This transformation does not contain any multiplication or division processes. The malfunction of this type of transformation is that it needs to calculate two ratios for its mathematical model. The modified Haar transform proposed through this work give a good mathematical representation for the object by using only one ratio, which is S/W₁. The modified Daubechies proposed through the work gives analytical method for the calculation of the Daubechies Coefficients.

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