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Object recognition by Feature Weighted Matrix – A novel approach Sivaraman K.S, Gautam S, Sarvesh S, Archit Khullar, A. Baskar and Shriram K.Vasudevan Amrita School of Engineering, Amrita Vishwa Vidyapeetham University. Email:a_baskar@cb.amrita.edu,kv_shiram@cb.amrita.edu ABSTRACT Object detection and identification is essentially challenging, and plays an important role in the area of computer vision. Commonly the object detection is carried out through two stages, namely learning stage, and testing stage.

6**In the learning** stage, **the machine uses a set of images which contains objects belonging to** a **pre-**

defined path of studies. Based on the study, the objects are recognized. In testing stage,

6**the algorithm uses its knowledge to identify the**

input image to a specified class. In this research, we propose a novel approach called object recognition by feature Weighted Matrix (WM). Our algorithm works in two phases, in the first phase the feature Weighted Matrix Model will be constructed using geometrical modelling and histogram bin. In the second phase Diagonal Rank Matrix (DRM) is used to recognize the target object. It improves the results through various illumination and scaling conditions and this has been discussed in results and analysis section. KEYWORDS Object recognition, geometrical modelling, histogram bins, Weighted Matrix, Diagonal Matrix, Object identification, Object detection. 1. INTRODUCTION Identifying meaningful region of interest in an image and video is a last two decade research problem in computer vision. Object recognition [1-4] is the ability to perceive an object's physical attributes such as regions of disparate spatial description; shape, color, and salient texture pattern. There have been several methods and approaches to formulate object recognition. Some of the available approaches to model objects are geometric shape modeling, appearance based modeling and local or global feature modeling. One such technique, mentioned under appearance based method, is finding the histogram [9, 10] of intensities of a given image, or a region. Geometric shape modeling [5-8] refers to the technique of realizing the shape of the object, or its outline, and representing it in a generalized form, more specifically, a mathematical function. Many methods are established to realize the shape of an object, using dominant point detection and polygonal approximation, or assuming the outline of an object to be a collection of vertices, representing the object as a graph, and finding the most important vertices which lead in the shape of the outline. In our approach boundary of the target is divided using 32 equally spaced horizontal lines along with their height. For example, an upright triangle has its wide increasing along its height proportionally. Or a circle has its wide increasing till it reaches the center, and then, decreases, with the same rate it increased. Any random object, given its outline, can be identified in this manner. This method will be delineated in the proposed work. In this paper, a novel approach called object recognition by feature weighted Matrix is proposed. Our algorithm recognizes the object in two phases, the feature Weighted Matrix Model will be constructed using feature vector and is estimated by Geometrical modelling and Histogram bin in the first phase and in the second phase target, the objects are identified using Diagonal Rank Matrix. 2. PROPOSED WORK The proposed method recognizes the target object in two phases; in the first phase, the front and top position of the training image is acquired at a distance 50 cm and 100 cm respectively, and a weighted matrix for training dataset is modelled from the corresponding feature vector (Geometric modelling and Histogram bin) and feature matrix for test image is estimated. In the second phase Diagonal Rank Matrix (DRM) is made to discern the target object. The detailed overview of the proposed method illustrates in Figure1. Fig. 1 Block diagram for proposed work 2.1 Training data set In this work commonly used home based rigid objects are considered as an input and the process of collecting the training data set is as follows: The front and top view of training image is acquired at the distance 50cm and 100 cm respectively, and for each view and distance, there are five different shots of the same object being generated. A similar procedure can be extended to n objects to obtain a considerable input data set. It is summarized in table1. Table 1 Training Dataset Representation Distance of 50 cm Distance of 100 cm Object Front View Top View Front View Top View Object 1 5 5 5 5 . . . . Object n 5 5 5 5 2.2 Feature Extraction Feature extraction is the first phase of the proposed work; the acquired training dataset is fed into two feature extraction algorithm, Geometrical modelling and Histogram bin. Geometric modelling uses Classical edge detection algorithms in pre-processing, and the detecting boundary of the target. The detected boundary is divided using 32 equally spaced horizontal lines ((ymax-ymin) /33) along with their height. It is illustrated in figure 2a-2c. The length of each line <l(i, 1), l(i, 2)... l(i, 32) > used as a feature vector. Egi is the corresponding feature vector of Geometric modelling, and it is derived from the equation below. Egi = [□(i, 1)□(i, 2)□(i, 3) . . . □(i, 32)] Where, n= Number of Objects i∈ [1,5] Fig. 2a Sample Input Image Fig.2b Boundary of the Object Fig.2c 32 equally spaced Horizontal Line Histogram bin is a type of histogram that represents the tonal distribution of object by plotting a relation to the number of pixel values and its corresponding intensity by grouping them into the bin (In proposed are used 32 bins), and Feature vector is estimated. The below equation derives the feature vector for the Histogram bin (Ehi). The figure 3.a shows sample Input image and the corresponding Histogram bin shows in figure 3.b. Ehi = [I(i, 1) I(i, 2) I(i, 3) . . . I(i, 32)] Where, i∈ [1,5] Fig. 3a Sample Input Fig.3b Histogram Bin 2.3 Weighted Matrix The feature vectors (Egi, Ehi) are fed into the newly introduced novel model called Weighted Matrix (S)KxK. The weighted matrix estimates the likelihood of the input image belonging to the correct category, further the DRM is generated, which gives the likelihood according to the rank. The weighted matrix is obtained by processing the Feature vector through six phases, namely: ? Minimum matrix (m) ? Maximum Matrix (M) ? Input Augmentation (Calculating matrix T from vector t) ? Finding Max deviation matrix (R) ? Finding Min Deviation matrix (r) ? Weighted matrix Estimation (S) 2.3.1 The minimum matrix: The minimum matrix is formed, by combining the minimum vectors along the row and m(1,j) m(2,j)m(3,j)m(4,j) are the corresponding minimum vectors, where j varies from 1 to 32. This can be obtained by finding the minimum of all the components, along the columns from the input dataset, which consists of feature vector obtained for five images of an object in the front view at a distance of 50 cm, five images at a distance of 100 cm, five images taken from the top view at a distance of 50 cm, and another five at a distance of 100cm. The steps are illustrated below using an intermediate matrix m (I, j). Minimum matrix for Geometrical modelling: Minimum vector m (1, j) is described below for the front view of an object is placed at a distance 50 cm □

4**(1, j) □(2, j)**□(1, **j)** = Min **□(3, j) □(4, j) [□(5, j)]**

Minimum vector m (2, j) is described below for the top View of the object is placed at a distance 50 cm

1**□(6, j) □(7, j)**□(2, **j)** = Min **□(** 8, **j) □(** 9, **j) [□(** 10, **j)]**

Minimum vector m(3, j) is described below for the front View of the object is placed at a distance 100 cm

1□(11, j) □(12, j)□(3, j) = Min □(13, j) □(14, j) [□(15, j)]

Minimum vector m(4, j) is described below for the top View of the object is placed at a distance 100 cm

1□(16, j) □(17, j)□(4, j) = Min □(18, j) □(19, j) [□(20, j)] Where, □(1, j) . . . □(20, j)

Feature vector of input data set j∈ [1, 32] Minimum matrix for histogram bin: Minimum vector m(1, j) is described below for the front view of an object is placed at a distance 50 cm

5□(1, j) □(2, j)□(1, j) = Min □(3, j) □(4, j) [□(5, j)] Minimum vector m (2, j)

is described below for the top View of the object is placed at a distance 50 cm

2□(6, j) □(7, j)□(2, j) = Min □(8, j) □(9, j) [□(10, j)]

Minimum vector m(3, j) is described below for the front View of the object is placed at a distance 100 cm

2□(11, j) □(12, j)□(3, j) = Min □(13, j) □(14, j) [□(15, j)]

Minimum vector m(4, j) is described below for the top View of the object is placed at a distance 100 cm □(16,

3j) □(17, j)□(4, j) = Min □(18, j) □(19, j) [□(20, j)] Where, □(1, j) . . . □(20, j)

Feature vector of input data set j∈ [1, 32] The minimum vectors described above are combined along the row and a minimum matrix for geometrical modelling(mg) and histogram bin (mh) is obtained as follows. □(1, 1) ⋯ □(1, 32) □□ = [⋮ ⋱ ⋮] □(4, 2) ⋯ □(4,32) □(1, 1) □ℎ = [⋮ □(4, 2) ⋯ ⋱ ⋯ □(1, 32) ⋮] □(4,32) Where, Size of mg and mh is (4n x32),n is the number of objects considered. 2.3.2 The Maximum Matrix (M) The procedure estimating the maximum matrix is similar to that of finding the minimum matrix; in this case we find the maximum of all the components along the column present in the input data set is considered. The steps are illustrated below using an intermediate matrix M(i,j) . Maximum matrix for Geometrical modelling: Maximum vector M (1, j) is described below for a front view of an object is placed at a distance 50 cm □

4**(1, j) □(2, j)**□(1, **j)** = Max **□(3, j) □(4, j) [□(5, j)]**

Maximum vector M(2, j) is described below for top View of the object is placed at a distance 50 cm

1**□(6, j) □(7, j)**□(2, **j)** = Max **□(** 8, **j) □(** 9, **j) [□(** 10, **j)]**

Maximum vector M(3, j) is described below for front View of the object is placed at a distance 100 cm

1**□(11, j) □(12, j)**□(3, **j)** = Max **□(** 13, **j) □(** 14, **j) [□(** 15, **j)]**

Maximum vector M(4, j) is described below for top View of the object is placed at a distance 100 cm

1**□(16, j) □(17, j)**□(4, **j)** = Max **□(** 18, **j) □(** 19, **j) [□(** 20, **j)]** Where, **□(** 1, **j) . . . □(** 20, **j)**

Feature vector of input data set j∈ [1, 32] Maximum matrix for histogram bin: Maximum vector M(1, j) is described below for the front view of an object is placed at a distance 50 cm

5□(1, j) □(2, j)□(1, j) = Max □(3, j) □(4, j) [□(5, j)] Maximum vector M (2, j)

is described below for top View of the object is placed at a distance 50 cm

2□(6, j) □(7, j)□(2, j) = Max □(8, j) □(9, j) [□(10, j)]

Maximum vector M(3, j) is described below for front View of the object is placed at a distance 100 cm

2□(11, j) □(12, j)□(3, j) = Max □(13, j) □(14, j) [□(15, j)]

Maximum vector M(4, j) is described below for top View of the object is placed at a distance 100 cm □(16,

3j) □(17, j)□(4, j) = Max □(18, j) □(19, j) [□(20, j)] Where, □(1, j) . . . □(20, j)

Feature vector of input data set j∈ [1, 32] As done previously for the minimum matrix, the maximum matrix is formed, by combining the maximum vectors along the row. The following matrix Mg and Mh describes the maximum matrix for geometrical modelling and histogram bin respectively. □(1, 1) □□ = [⋮ □(4, 2) ⋯ ⋱ ⋯ □(1, 32) ⋮] □(4,32) □(1, 1) □h = [⋮ □(4, 2) ⋯ ⋱ ⋯ □(1, 32) ⋮] □(4,32) Where, Size of mh and mg is (4n x32) n is the number of objects considered 2.3.3 Calculating Matrix T from vector t Given an input test image, feature vector (tg and th are the feature vector for Geometric model and Histogram bin respectively) is extracted from the feature extraction module. Matrix Tg and Th obtained from the feature vectors (tg and th) separately by replicating 4n times in a row order, where 'n' refers to the number of objects and 4 refers to two state of top and front view of the object. Initially the feature vectors present in the matrix Tg / Th are assumed to be a true positive object and in the subsequent process objects are recognized using matrix R, r and DRM. The below equation describes the feature vector for test image and followed by matrix Tg and Th respectively. □□ = [□1 □2 . . . □32] □h = [□1 □2 . . . □32] □1 □□ = [⋮ □1 ⋯ ⋱ ⋯ □32 ⋮] □32 □1 □h = [⋮ □1 ⋯ ⋱ ⋯ □32 ⋮] □32 2.3.4 Deviation from Maximum(R): The training data set maximum matrix Matrix (Mi) is subtracted with the test image feature matrix (Ti) is obtained from the previous step, and the corresponding deviation from the maximum Ri matrix is obtained and it has been described below equation. □□ = □□ − □□ Where, Mi stands for Max Matrix Ti stands for Input matrix replicated k times □ ∈ □ (□□)h 2.3.5 Deviation from Minimum(r): The test image feature matrix (Ti) obtained from the previous step is subtracted with training data set minimum matrix Matrix (mi) and the corresponding deviation from the minimum ri matrix is obtained and it has been described below equation. □□ = □□ − □□ Where, mi stands for Max Matrix Ti stands for Input matrix replicated k times □ ∈ □ (□□)h 2.3.6 Formulating the weighted matrix (S kxk): The weighted matrix (S) estimates the likelihood of recognizes the target object and it is obtained by multiplying The deviation from the maximum Ri matrix and transpose of deviation from the minimum ri matrix. □ = □□. □□□□□(□□) Each element in S is a sum of products of the corresponding values in Riandri, respectively. The resultant product of the respective element has remained positive where x' lies between 'a' and 'b'. The product would become negative, If one of the elements does not satisfy the condition of 'x' being between 'a' and 'b', elements in Riorri, where 'x' is an element of the, and 'a' belonging to mi, and 'b' belonging to Mi. The function given below summarizes: if a <□ <□ then (b − x)and (x − a) both positive { if x <□, □h□□ (□ − □)□□ positive and (x − a) is negative if x >□, □h□□ (□ − □)□□ □□□□□□□□ □□□ (□ − □) □□ □□□□□□□□ 2.3.7 Diagonal rank matrix (DRM) Diagonal rank matrix is the final step of our proposed model; it is used to recognize the object based on ranking, which is estimated by weighted matrix S and then it is scalar multiplied by the Identity matrix I4n.The below equation describes the diagonal rank matrix DRM = S. I4n The diagonal elements in DRM are a result of the sum of products of Ri and the transpose of ri. The largest positive value of the diagonal element contributes recognizes the likeliness of the target object. From the above function as noted before, the resultant product of the respective element has remained positive where x' lies between 'a' and 'b'. The positive product contributes to the weight and thereby, increasing the likelihood. The diagonal elements in DRM are a result of the sum of products of Ri and the transpose of ri. As mentioned earlier, whenever either of the components (let a or b) is negative their multiplication will result in a negative value. This negative value would lead to a reduction in the sum and thus a reduced weight and if both the components are positive (let a or b), the positive product contributes to the weight and thereby, increasing the likelihood. The largest positive value of the diagonal element contributes to recognize the likeliness of the target object. 3. IMPLEMENTATION DETAILS We have identified commonly used home based objects namely coffee bottle, Ketchup bottle and coffee cup. The first two objects used as training data set in this work and their different view and distance is summarized in the table2. In this section we graphically visualize, how the minimum vector and maximum vectors to represents for Geometrical model and Histogram bin to the training data set. The algorithm has been implemented Python-OpenCV and tested on a Pentium i5 processor with 4 GB RAM and the training and testing images were taken using a normal 2 mega pixel web camera. The figure 4 shows different views and distance of the training data set. Distance of 50cm Distance of 100 cm Object Front View Top View Front View Top View Coffee bottle 5 5 5 5 Ketchup bottle 5 5 5 5 Table.2 Training Data set Fig. 4 Training data set. 3. 1 Geometric modelling The figure 5 and 6 illustrates Minimum and Maximum Feature Vector Visualization for Geometrical model of coffee bottle and ketchup bottle, the red line in this figure describes the minimum widths, representing the minimum matrix values of the corresponding categories and the blue line describes the maximum widths for the same. Duly note that this is done for graphical representation for ease of visualising, and by no means is used for any calculation. Fig. 5 Minimum and Maximum Feature Vector Visualization for geometrical model to coffee bottle Fig. 6 Minimum and Maximum Feature Vector Visualization for geometrical model to ketchup bottle 3.2 Histogram bins The Minimum and Maximum Feature Vector Visualization for Histogram bin of coffee bottle and ketchup bottle is exemplifies in figure 7 and 8, the red line represents the minimum value of the corresponding bin of each category. The blue line represents the maximum values for the same. For a given test image to qualify in one of the categories, the input's histogram bin feature vector has to preferably, lie between the blue and the red line and test image does not belong to a category, the histogram will not fall between the red and the blue lines. Fig. 7 Minimum and Maximum Feature Vector Visualization for Histogram bin to coffee bottle Fig. 8 Minimum and Maximum Feature Vector Visualization for Histogram bin to ketchup bottle IV. RESULTS AND ANALYSIS To appraise the performance of the proposed method, we experiments the algorithm in three different cases namely Identification of Coffee bottle, Identification of Ketchup bottle and Object not containing training data set. The first two cases test image taken from training data set and the third case we used coffee cup, which in not contained in training data set and their results are conferred in this section. Case 1: Identification of coffee bottle. The front view of the coffee bottle at the distance of 50 cm is fed as input and is shown in figure 9 and their graphical representation of the minimum and maximum feature vector of Geometric model for the training data set front view at distance 50 cm and coffee bottle front view at distance 50 cm is shown in figure 10.a, top view of training data set at distance 100 cm and coffee bottle front view at distance 50 cm is illustrates in figure 10.b, front view of training data set at distance 100 cm and coffee bottle front view at distance 50 cm is shown in figure 10.c and top view of training data set at distance 50 cm and coffee bottle front view at distance 50 cm is illustrates in figure 10.d. The largest positive values presents in CF50 in the below described diagonal rank matrix noticeably identified the target object is coffee bottle front view at the distance 50 cm same has been visualize in figure10.a. Fig. 9 Input Image for coffee bottle. Fig. 10 (a-d) Minimum and Maximum Feature Vector Visualization for geometrical model to coffee bottle vs training data set. Where, CF50 - represents coffee bottle front view at distance 50 cm. CF100- represents coffee bottle front view at distance 100 cm. CT50 -represents coffee bottle top view at distance 50 cm. CT100- represents coffee bottle top view at distance 100 cm. KF50 -represents ketchup bottle front view at distance 50 cm. KF100- represents ketchup bottle front view at distance 100 cm. KT50 - represents ketchup bottle top view at distance 50 cm. KT100- represents ketchup bottle top view at distance 100 cm. The graphical representation of the minimum and maximum feature vector of Histogram for the training data set front view at distance 50 cm and coffee bottle front view at distance 50 cm is shown in figure 11.a, top view of training data set at distance 100 cm and coffee bottle front view at distance 50 cm is illustrates in figure 11.b, front view of training data set at distance 100 cm and coffee bottle front view at distance 50 cm is shown in figure 11.c and top view of training data set at distance 50 cm and coffee bottle front view at distance 50 cm is illustrates in figure 11.d. The largest positive values presents in CF50 in the below described diagonal rank matrix noticeably identified the target object is coffee bottle front view at the distance 50 cm same has been visualize in figure11.a. Fig. 11 Histogram bin for coffee bottle Vs Training data set. Case 2: Identification of ketchup bottle The front view of the ketchup bottle at the distance of 100 cm is taken from training data set and figure 12 illustrates the same. The graphical representation of the minimum and maximum Feature vector of Geometric model versus training data set is shown in figure 13 (a-d). The largest positive values presents in KF100 in the below described diagonal rank matrix evidently identified the target object is ketchup bottle front view at the distance 100 cm same has been visualize in figure12.c, which is ketchup bottle front view at distance 100 cm and training data set front view at distance 100 cm. Fig. 12 input image for ketchup bottle. Fig. 13 (a-d) Minimum and Maximum Feature Vector Visualization for geometrical model to ketchup bottle Vs Training data set. The graphical representation of the minimum and maximum Feature vector of Histogram bin versus training data set is shown in figure 14 (a-d). The largest positive values presents in KF100 in the below described diagonal rank matrix evidently identified the target object is ketchup bottle front view at the distance 100 cm same has been visualize in figure14.d, which is ketchup bottle front view at distance 100 cm and training data set front view at distance 100 cm. Fig. 14 Histogram bin for ketchup bottle Vs training data set. Diagonal Rank Matrix Case 3:Object not containing training data set. The front view of the coffee cup at the distance of 100 cm is given as a test input image, which is not present in the training data set and figure 15 illustrates the same. The diagonal rank matrix of the geometrical model and Histogram bin is presented below reveals that there is no match found, since the diagonal matrix has got all non-positive numbers. Fig. 15 Input image for coffee cup. Diagonal Rank Matrix 4. CONCLUSION In this research we have implemented a novel approach called object recognition by feature Weighted Matrix (WM). The proposed method identifies the object in different views namely front and top view. It improves the results in diverse illumination variation conditions for geometrical based feature vector and different scaling variations for both Geometrical based feature vector and Histogram bin feature vector. This feature weighted matrix can be extended to solve multiple objects present in the image and different invariant conditions. REFERENCES [1] Prasad, Dilip K. "Survey of the problem of object detection in real images." International Journal of Image Processing (IJIP) 6.6 (2012): 441. [2] Mundy, Joseph L. "Object recognition in the geometric era: A retrospective." Toward category- level object recognition. Springer Berlin Heidelberg, 2006.3-28. [3] Andreopoulos, Alexander, and John K. Tsotsos. "50 Years of object recognition: Directions forward." 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