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Proposed Method for Detecting Objects

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ABSTRACT

Most of object detection and classification algorithms are only locating regions in the image, whether it is within a template-sliding mask or interested region blobs. However, such regions may be ambiguous, especially when the object of interest is very small, unclear, or anything else. This paper presents proposed algorithm for automatic object detection and matching based on its own proposed signature using morphological segmentation tools. Moreover, the algorithm tries to match the objects; neither among object's blobs nor among regions of interest; but among the constructed proposed objects' signatures. During the matching process, SURF method has presented to make a comparison of the experimental results. The performance has been tested 120 from a wide variety of unlike objects; it has been achieved 100% in the case of constructing object signatures, also it has been achieved 96% of right matching whereas SURF has achieved 85% for all test objects.

General Terms

Pattern Recognition, Object Detection, Signature Algorithm.

Keywords

Object Detection and Matching; Signature; SURF; Segmentation.

1. INTRODUCTION

The object detection plays an important role in the area of computer vision research. Nowadays, many of its applications require the locations of objects in images. In fact, there are two closely related definitions, object presence detection, and object localization. The determinations of one or more of an object class are presented (at any location or scale) in an image that means of an object's presence detection or image classification, and can be suitable for image retrieval based on an object [6]. While the object localization means finding the object location and scale an image.

Many of the object detection algorithms are following the model of detection by parts; that introduced by Fischler and Elschlager [20]. They are using the object structural modeling and reliable part detectors' methods. The basic idea behind this model is to identify that the individual parts of an object detector are easier to build than that for the full object [8], [15]. Actually, these methods of object detection are depending on sliding a window or template mask through the image, to classify each object falls in the local windows of background or target [5], [15]. In fact, this approach has successfully used to detect rigid objects such as cars and faces, and has even been applied to articulated objects such as pedestrians [4], [13], [22].

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Later, a frequency model proposed, which is dependent on a moving background containing repetitive structures. The authors considered special temporal neighborhoods of the pixels, which they have applied local Fourier transforms in the scene [3]. The feature vectors, which generated used to build a background model. However, they are applied their model for moving object and backgrounds, on both synthetic and real image sequences [14].

On the other hand, one popular approach is depending on extracting the local interest points through the image, and then classifies the regions, which contained these points, instead of looking at all possible sub windows as the previous [24]. The greatest common divisor of the above approaches is that they can fail when the regional image information is insufficient (target is very small or unclear), and this is considered as a weakness of them [7]. In this way, the image matching based on features is depending on analyzing the extracted features and find the corresponding relationship between them [24]. The image matching is not accurate enough because the images are often noisy, in different illuminations and scales. Recently, extracted features are widely applied in the field of object matching. In 1999, the Scale Invariant Feature transforms (SIFT) presented by Lowe, when a robust descriptor and Difference-of-Gaussians (DoG) detector was used [17], [18]. Fig.1.1 presents the work of SIFT [21].

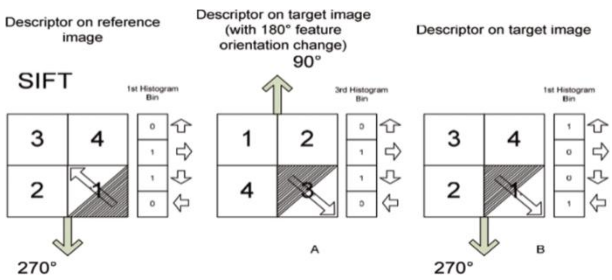


Fig.1.1. the work of SIFT

It is interesting to note that the advantages of SIFT; that it is applied on invariant rotation or image scale, is about its computation, which is very hard to calculate and take a time because it needs to extract 128 dimensional descriptors to work [26]. This problem was solved in 2008 by Bay, who proposed SURF; 64 dimensions modelled it. The experiments of SURF have assumed the integrated images to compute a rough approximation of the Hessian matrix, and this is tending to faster than SIFT [9], [10]. In 2009, Lue and Oubong compared SIFT and SURF; they have pointed out that SURF is better in performance, but it is not efficient in rotation changes [19]. Fig.1.2. presents the work of SURF [23].

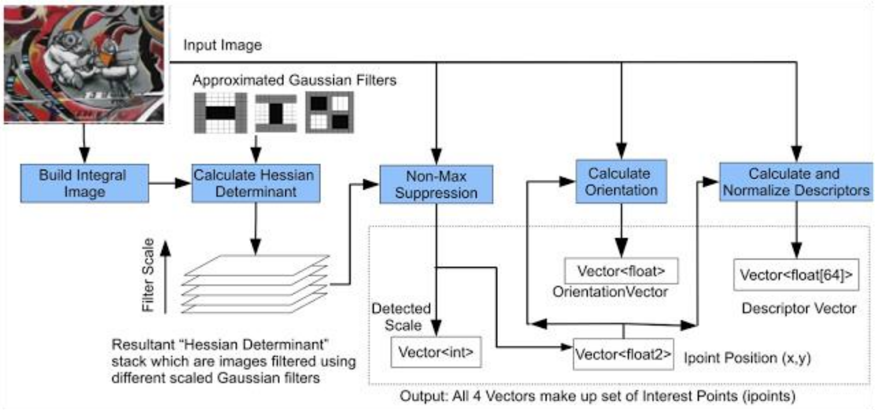


Fig.1.2. the work of SURF

In fact, the effective power of SURF has been reduced because the ignoring of features in geometric relationships [19], [25].

This paper presents proposed algorithm depending on the object geometrical shape, and relationship between outer points of the objects' contours. It is divided into two parts; one is constructing an own signature for any object in an image. Second part is matching operation among all object shapes' signatures to get exactly which they are described. In addition, four steps have to process through these parts; constructing signatures for all objects in an image and saving them as data in the system. Secondly, constructing signatures for all test input objects. The comparisons between inputs and saved signatures, which they have determined before, have operated using statistical methods in the third step. Finally, these signatures have used to detect and define the objects in the image.

In fact, the proposed approach introduces an idea to detect an object depends on its outer shape by constructing an own signature, which let the object to be free from constraints such as rotation, size, its position in the image. This proposed idea may be used in many object detection fields like identifying the kinds of plants based on their shapes, distinguishing between kinds of fruits, and so on. The next section discusses SURF method because it is the most important one in the object detection and matching ways.

The rest of this paper is organized as follows. Section 2 is introduced an overview on SURF. A brief overview on image segmentation is in section 3. In section 4, the proposed algorithm of detection and matching has illustrated. The algorithm's experimental results are shown in Section 5, and the conclusion in Section 6.

2. OVERVIEW ON SURF METHOD

The initial mention of SURF (Speeded Up to Robust Features) was by H. Bay in 2006. It has four major stages: Hessian matrix, localization of these points, orientation assignment, and descriptor, which depends on Haar wavelet response's sum [10]. In the first, Hessian matrix, which has based on detection in scale space of interested points. Additionally, the determinant of Hessian matrix has used as a preference to look for local maximum value and the detection of SURF interested point is based on theory of scale space. Equation (1) illustrates in details the components of the Hessian matrix. In this equation, there is a point *X= (x, y)* in an image *I*, the Hessian matrix *H (X, σ)* in *X* at scale *σ* has defined as follows:

$$H(X,\sigma)=\begin{pmatrix} L_{xx}(X,\sigma) & L_{xy}(X,\sigma) \\ L_{xy}(X,\sigma) & L_{yy}(X,\sigma)\end{pmatrix} \quad (1)$$

Where $L_{xx}(X,\sigma)$ represents the convolution of the Gaussian second order partial derivative. $\frac{\delta^2 g(\sigma)}{\delta x^2}$ with the image *I* in a point *X*, and similarly for $L_{xy}(X,\sigma)$ with $\frac{\delta^2 g(\sigma)}{\delta x \delta y}$ and $L_{yy}(X,\sigma)$ by $\frac{\delta^2 g(\sigma)}{\delta y^2}$.

To speed up the convolution, *9 x 9* box filter is utilized to approximate integral image and the second-order Gaussian partial derivatives with σ =1.2, [10]. The symbols D_{xx}, D_{xy}, and D_{yy}, are denoting the convolution results approximations. The determinant of the Hessian matrix is:

$$|H_{approx}| = D_{xx}D_{yy} - (wD_{xy})^2 \quad (2)$$

Where *w* is recommended at 0.9 that is the relative weight of the filter responses [9], [10]. The step after is dividing the image into many regions, each one contains different scale image templates.

The second stage is the interested point localization. First step in this stage is setting a threshold to the detected Hessian matrix of extreme points. Second step, to obtain these points a non-maximum suppression in a 3 × 3 × 3 neighborhoods have applied. The bases of selecting a feature point are that only the point with a value bigger than the neighboring 26 point value has chosen as a feature point [10].

The third stage is the orientation assignment, that is starting by calculating the Haar wavelet (Haar side: 4*s*, where *s* is the scale at which the interest point was detected) responses in *x* and *y* direction within a circular neighborhood of radius 6*s* around the interest point. The responses have centered at the interested point and weighted with a Gaussian (2*s*). At that moment, the sum has calculated for all responses within a sliding orientation, window of size π/3 to estimate the leading orientation, then determining the sum of horizontal and vertical responses within the window. A local orientation vector has produced by the two collected responses, such that the longest vector over all windows defines the orientation of the interest point. The last stage in SURF is the descriptor based on the sum of Haar wavelet responses. For the extraction of the descriptor, the first step consists of constructing a square template region (the size is 20*s*) oriented along the selected orientation and centered on the interested point. The region is split up regularly into smaller 4 × 4 square sub-regions. For each sub-region, Haar wavelet responses have computed at 5 × 5 regularly spaced sample points. Simply, the Haar wavelet response in horizontal direction is denoted by, also, the Haar wavelet response in vertical direction by. The responses and d_y are first weighted with a Gaussian (σ = 3.3*s*) centered at the interested point. Moreover, the responses and are extracted to bring in information about the polarity of changes in the intensity. Hence, the structure of each sub-region has four-dimensional descriptor vector:

$$V_{sub} = (\sum d_x, \sum d_y, \sum |d_x|, \sum |d_y|) \quad (3)$$

From the previous, by multiplying all 4 × 4 sub-regions results in a descriptor vector of length are 4 × (4 × 4) = 64 [9], [10]. Additionally, to judge whether the two feature points of images are matched or not, the distance of the characteristic vector between two feature points is calculated. Finally, it is interesting to note that SURF ignores the geometric relationship between the features, which is a very important characteristic of many objects in the image. For that reason, this paper presents proposed algorithm to detect and matching objects based on own constructed signatures.

3. IMAGE SEGMENTATION

The segmentation idea is splitting an image into many various regions containing every pixel with similar characteristics such that; texture information, motion, color, whereas the detection stage has to choose relevant regions and assign objects for further processing [1], [8]. In addition, these regions should strongly related to the detected objects or features of interest to be meaningful and useful for image analysis and interpretation. Actually, the transformation from gray scale or color image on a low-level image into one or more other images in a high-level image, which is depending on features, objects, and scenes, represents the first step in significant segmentation. Generally, the accurate partitioning of an image is the main challenging problem in image analysis, and the success of it depends on the consistency of segmentation [24]. On the other hand, segmentation techniques are divided into either contextual or non-contextual. The non-contextual techniques do not care about account of special relations between features in an image and group pixels together based on some global attribute, e.g. Gray level or color. However, contextual techniques, mainly are exploiting these relations, e.g. Pixels with similar gray levels, and close spatial locations grouped with each other [6], [8]. Actually, the proposed algorithm is trying to exploit the segmentation contextual techniques in object detection and classification. Next section illustrates in details the idea for the suggested algorithm.

4. THE PROPOSED ALGORITHM

The proposed object detection and matching framework is divided into three parts. They are consisting of segmentation, construction of objects' signatures in image and matching them to classify the object based on its signature [7]. The segmentation process represents the main stone in this algorithm, which is given initial hypotheses of object positions, scales and supporting based on matching. These hypotheses are then refined through the object signature classifier, to obtain final detection and signatures matching results. Fig.4.3. describes all steps of the proposed algorithm [11].

This Figure starts with an example of the original RGB image with all different objects, many morphological functions and filters (edge detection, erosion, dilation, determines the number of objects, watershed segmentation…) are applied to enhance the work of this image. The areas, centroids, orientations, eccentricities, convex areas for every object can easily be determined. Moreover, the boundary points (x_{ij}, y_{ij}) for each object is calculated individually, where *i* represent the number of objects, and *j* is the number of boundary points related to an object. These boundary points and the objects' previous information are saved to start construction of own proposed signature for every object based on all this information. The relation among all these information and Euclidian distance from objects' centroids is plotted and saved as an individual signature for each object that is shown in the Fig.4.3. by one object. These signatures for all objects are saved and waiting for matching with any input object's signature, as in the experimental results section. Moreover, the contour is drawn around all objects and tracing the exterior boundaries of them.

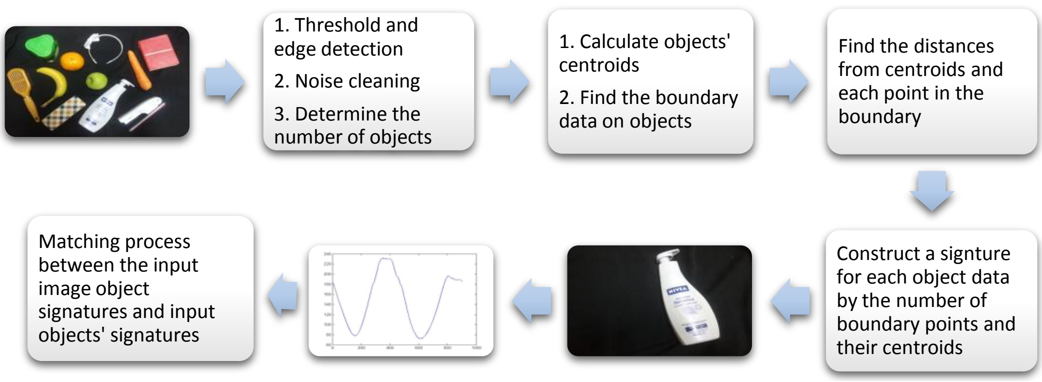


Fig.4.3. the proposed algorithm steps

The third part of this proposed algorithm after segmentation and constructing signatures is the matching process between input and saved objects' signatures as in the above. Two different ways in matching process have used to make a comparison between them in accuracy and activity; one is the using of statistical measures related to the signatures, and the second is using SURF [11].

Additionally, all shown steps in Fig.4.3 have applied to the input object to construct its signature. Actually, the matching process is depending on statistical measures on both types of objects' signatures (saved ones and input). Firstly, as shown above in Fig.4.3, not all objects in the example image are in the same size, orientation, or even shape, and afterwards, their data should not be equal in length or characteristics. For that reason and more in checking accuracy, some pre-processes of matching have carried out; one is sorting all the data of all signatures, and then computing the variance in the data set by calculating the average of the absolute deviations of data points from their mean. The equation for average deviation is:

$$AVD = \frac{1}{n_i}\sum_{j=1}^{n_i}\left|x_{ij} - \bar{x}_i\right| \quad (4)$$

For all *i*'s been the number of objects in the image and *j*'s are the number of object's signature data, represents the number of signature's data points, as they mean, and is the number of signature data rows. Secondly, the results of Equation (4) have applied to all input and saved objects to make a comparison between them to get the exact matching by least error. Equation (5) introduces a method for calculating the differences between the results of Equation (4).

$$DIF = ABS\left(ADV_{Saved} - ADV_{Input}\right) \quad (5)$$

The components of Equation (5) are the absolute value of the difference between the two results of Equation (4) related to saving and input object signatures. The decision of matching based on the least value of DIF, which is given the exact matched object.

5. EXPERIMENTAL RESULTS

The experimental results are divided into two parts; one is representing the objects and their signatures in images, and the second is showing the results of matching and comparing a proposed algorithm with SURF methods.

Fig.5.4, presents a sample of experimental clear and unclear images, which contain some standard geometrical shapes in (a), some kinds of objects varying in shapes, and luminance intensity in (b), (c), (d), (e) and (f). Sequentially, the signatures have constructed for the most distinct mentioned objects [12].

In Fig.5.5, all objects are individually be defined, detected, and matched by its signatures in the proposed algorithm. It is interesting to note that the similarity is cleared in signatures for the stand ellipse (its major axis parallel to the y-axis) and a horizontal one (its major axis parallel to the x-axis) because it is the same shape but different position.

(a) Standard shapes (b) Sample of objects (c) Sample of objects

(d) Sample of shapes (e) Sample of objects (f) Sample of objects

Fig.5.4. images of famous regular shapes in (a) and from (b) to (f) other types of different objects

Evidently, the square shape has four identical peaks in its signature because the equality of its sides; furthermore, the circle's signature is one-line parallel to the x-axis and far away its radius length. On the same way, many objects' signatures are nearest each to others, for example, the object (1, 2) (i.e. In the row 1 and column 2 in Fig.5.5) is closer in signatures with objects in cells (9, 2), (9, 4). In the same context, signatures of objects (1, 3) and (5, 4) are seemed to correspond to some. These last cases have happened because the shape's nature of the original objects not because mistakes or big errors in the proposed algorithm.

Actually, the proposed algorithm has applied on about 120 different shapes, positions, orientations, and intensity luminance of objects in RGB images. Furthermore, signature's determination of all objects has achieved 100% without any errors (in data, or wrong signature construction) for all objects.

Second part of the proposed algorithm is matching of input and saved signatures. Table.5.1 presents the matching process that is depending on Equations (4), and (5); the decision in this process is based on the least value in Equation (5). Obviously, Table.5.1 shows all input objects, images in the first row. Regularly, the first column represents all positions (1 to 11) of objects in their main image if are scanned from left to right. Sequentially, Table.5.1 consists of x rows and y columns, which contain a set of values, represent the smallest value of errors calculated by Equation (5). For example, in the cell (1, 1), the proposed algorithm is selected at least value (0.1097) in a row (1), which indicates to the first object in the image.

Fig.5.5. different objects and their signatures

Clearly, this value indicates to the exact object position selected in the main image of Fig.5.4. (b). In this case, the input object has been completely different in its position and orientation; however, the proposed matching algorithm is overcome that and succeeded. In fact, all other objects have matched by the same way and have achieved 100% of that image.

Table.5.1. The matching process of objects' signatures

											
1	0.1097	23.32694	5.452305	3.462439	27.57506	14.90506	12.47566	25.51032	1.590916	5.577318	20.90324
2	23.23969	0.022453	17.89709	19.88695	4.22567	38.25444	10.87373	2.160928	24.94031	28.92671	2.446154
3	5.145352	18.07189	0.197253	1.792613	22.32001	20.16010	7.220604	20.25527	6.845967	10.83237	15.64818
4	2.327028	20.89021	3.015577	1.025711	25.13833	17.34177	10.03893	23.07359	4.027643	8.014045	18.46651
5	27.72588	4.508644	22.38328	24.37314	0.260521	42.74063	15.35993	2.325263	29.4265	33.4129	6.932345
6	15.20056	38.4178	20.54316	18.5533	42.66592	0.185809	27.56651	40.60118	13.49994	9.513541	35.99409
7	12.41719	10.80005	7.07458	9.064446	15.04818	27.43193	0.051229	12.98343	14.1178	18.1042	8.376351

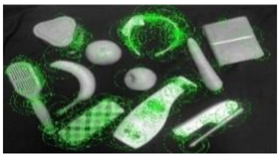
8	26.05026	2.833021	20.70765	22.69752	1.415102	41.06501	13.6843	0.64964	27.75087	31.73728	5.256722
9	1.948574	25.16581	7.291179	5.301313	29.41393	13.06617	14.31453	27.34919	0.247959	3.738443	22.74211
10	5.332486	28.54972	10.67509	8.685225	32.79785	9.682263	17.69844	30.7331	3.631871	0.354532	26.12602
11	17.84909	5.368144	12.50649	14.49635	9.616267	32.86384	5.483138	7.551525	19.54971	23.53611	2.944443

Table.5.2 presents error values for another image in the matching process based on objects' signatures, which are applied to the unclear image in Fig. 5.4. d. As in Table.5.1, all cell values represent the DIF of Equation (5), and the last value indicates to exact match of objects in an image and the input one. Clearly, as seen one mismatching is found in the second row, column two; however, this mismatching is acceptable because the objects in second and third columns are so close to each other in shape.

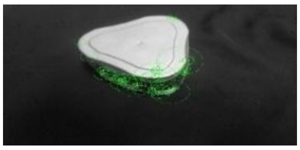
Table.5.2. The matching process of objects' signatures

							
1	0.056373	9.911202	6.924778	17.52564	4.48623	4.075137	9.227283
2	7.716881	2.250695	0.735729	9.86513	12.14674	11.73564	1.566775
3	6.836034	3.131541	0.145117	10.74598	11.26589	10.8548	2.447622
4	16.82239	6.854813	14.87723	0.759622	21.25225	20.84115	7.538732
5	4.465828	14.4334	11.44698	22.04784	0.035971	0.447064	13.74948
6	3.9633	13.93088	10.94445	21.54531	0.466557	0.055463	13.24696
7	9.283804	0.683772	2.302652	8.298207	13.71366	13.30257	0.000148

As the same way in Table.5.1, and Table.5.2, all other objects have been selected based on their signatures and have achieved 96% in the matching process. On the other hand, by applying SURF on the same image with different input objects, some mismatching is found if the input object has changed in his position or orientation, even so, this mismatching has not happened with the proposed algorithm under the same constraints. Fig.5.6 illustrates SURF Work in an example for this mismatching with the second object in the second column of Table.5.1 by 100 strongest feature points. In this Figure, the input object on the left is mismatched with its corresponding object in the original image. Additionally, this mismatch is repeated many times with the test objects using SURF. From the previous results, although SURF method and proposed algorithm have presented to detect and matching objects in an image, however, the presented algorithm is more effective and accurate in objects matching process than SURF and simply in use by some humble statistical equations without any constraints as in the other methods. The next section shows the conclusion of this work.



(a) The original image



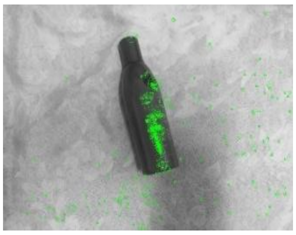
(b) The detected object

(c) The mismatch with the exact object in the image

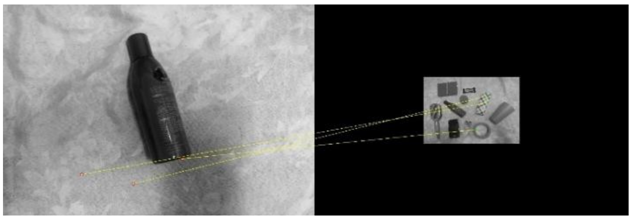
Fig.5.6. The SURF example, with the mismatch an object

In Fig.5.7, another example for mismatching of objects using the SURF method, whereas exact matching has illustrated in Fig.5.8.

(a) The original image

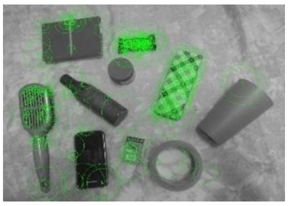


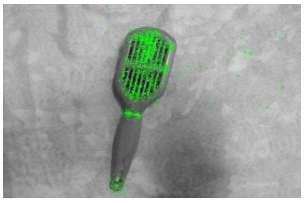
(b) The detected object



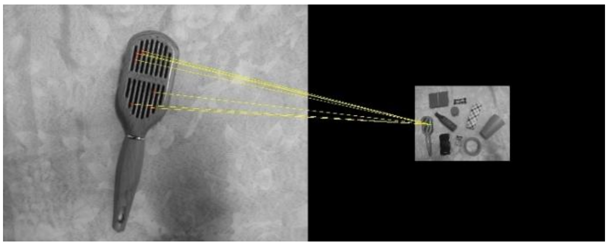
(c) The mismatch with the exact object in the image

Fig.5.7. The SURF example, with the mismatch an object





(a) The original image (b) The detected object



(c) The exact matching with the exact object in the image

Fig.5.8. the SURF example, with the exact match an object

6. CONCLUSION

This paper has presented proposed algorithm for object detection and matching based on its own signature using morphological segmentation tools. The algorithm has divided into three parts; one is segmentation process, construction of object signatures, and the last part is the matching based on them to classify and define the object. Actually, this signature has a singularity, simply to use, saving it on a small memory, and working in a variety of light levels. Moreover, the proposed algorithm is matched the objects neither among object's blobs nor regions of interest; but among the constructed signatures. On the other hand, SURF method has presented for comparison with the proposed method with the experimental results. Many difficulties are appearing in the matching process, such as object in unusual intensity luminance, shape, orientation, position, different sizes, or unclear image of objects; but the proposed algorithm has overcome on them, while SURF has not done. The performance has been tested 120 from a wide variety of different objects; it has been achieved 100% in the case of constructing object signatures, also it has achieved 96% of exact matching whereas SURF has achieved 85% for all experimental objects.

7. ACKNOWLEDGMENT

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8. REFERENCES

[1] Adel. A. Darwish., Hesham F. Ali., Hany A. M. El-Salamony. ‘’3D Human Body Motion Detection and Tracking in Video’’. The 14th IASTED International Conference on Applied Simulation and Modeling, Spain, June 15-17, 2005.

[2] C. Papageorgiou and T. Poggio. “A trainable system for object detection”. Intl. J Computer Vision, 38 (1): 15–33, 2000.

[3] C. Zahn and R. Roskies. “Fourier descriptors for plane closed curves”. IEEE Trans. Computers, 21 (3): 269–281, March 1972.

[4] D. Gavrila and V. Philemon. “Real-time object detection for smart vehicles”. In Proc. 7th Int. Conf. Computer Vision, pages 87–93, 1999.

[5] D. Huttenlocher, R. Lilien, and C. Olson. “View-based recognition using an eigenspace approximation to the Hausdorff measure.” PAMI, 21 (9): 951–955, Sept. 1999.

[6] Elsalamony, H. A., "Automatic video stream indexing and retrieving based on face detection using wavelet transformation," Signal Processing Systems (ICSPS), 2010 2nd International Conference on, volume. 1, pp: 153-157, 5-7 July 2010.

[7] Elsalamony, H. A., "Automatic object detection and matching based on proposed signature," Audio, Language and Image Processing (ICALIP), 2012 International Conference on, volume l, pp: 68-73, 16-18 July 2012.

[8] G. Bouchard and B. Triggs. “A hierarchical part-based model for visual object categorization.” In CVPR, 2005.

[9] H. Bay, A. Ess, T. Tuytelaars, and L. Van Gool, "Surf: Speeded up robust features," International Journal of Computer Vision and Image Understanding vol. 110, June 2008.

[10] H. Bay, T. Tuytelaars, and L. VanGool, "Surf: Speeded up robust features," presented at the Proceedings of European Conference on Computer Vision, Austria, 2006.

[11] Hany A. Elsalamony. “Object Detection and Matching using Proposed Signature and SURF.” 18th International Conference on Image Processing, Computer Vision, and Pattern Recognition. IPCV’14, Worldcomp’14 Proceeding, pp: 377-383, Las Vegas, Nevada, USA, July 21-24, 2014.

[12] Hany A. Elsalamony, “Detection and matching of object using proposed signature.” Emerging Trends in Image Processing, Computer Vision and Pattern Recognition. Elsevier Book Chapter: 38, 2014.

[13] Henry A. Rowley., Shumeet Baluja., and Takeo Kanade. “Human face detection in visual scenes”. Advances in Neural Info. Proc. Systems, volume 8, 1995.

[14] Imtiaz Ali, Julien Mille, Laure Tougne, “Space–time spectral model for object detection in dynamic textured background”. Pattern Recognition Letters, Volume 33, Issue 13, 1 October 2012, Pages 1710-1716, ISSN 0167-8655.

[15] Kevin Lai, Liefeng Bo, Xiaofeng Ren, and Dieter Fox. ”Detection-based Object Labeling in 3D Scenes.” International Conference on Robotics and Automation, 2012.

[16] Li He; Hui Wang; Hong Zhang. “Object detection by parts using appearance, structural and shape features”. International Conference on Mechatronics and Automation (ICMA), page(s): 489 – 494, 2011.

[17] Lowe, David G, "Distinctive Image Features from Scale-Invaria (t Key points," International Journal of Computer Vision vol. 60, January 2004.

[18] Lowe, David G, "Object recognition from local scale-invariant features," presented at the Proceedings of the International Conference on Computer Vision, Greece, 1999.

[19] Luo Juan, Oubong Gwun, "A Comparison of SIFT, PCA-SIFT and SURF," International Journal of Image Processing vol. 3, June 2009.

[20] M. Fischler and R. Elschlager. "The representation and matching of pictorial structures". IEEE Trans. Computers, C-22 (1): 67–92, 1973.

[21] Mustafa Teke; M. Firat Vural; Alptekin Temizel; Yasemin Yardımcı. "High-resolution multispectral satellite image matching using scale invariant feature transform and speeded up robust features." J. Appl. Remote Sens. 5(1), 053553 September 23, 2011.

[22] P. Viola, M. Jones, and D. Snow. "Detecting pedestrians using patterns of motion and appearance." In IEEE Conference on Computer Vision and Pattern Recognition, 2003.

[23] Perhaad Mistry, Chris Gregg, Norman Rubin, David Kaeli, and Kim Hazelwood. "Analyzing program flow within a many-kernel OpenCL application." In Proceedings of the Fourth Workshop on General Purpose Processing on Graphics Processing Units (GPGPU-4). ACM, New York, NY, USA, Article 10, 8 pages. 2011.

[24] R. C. Veltkamp and M. Hagedoorn. "State of the art in shape matching". Technical Report UU-CS-1999-27, Utrecht, 1999.

[25] Y. Amit, D. Geman, and K. Wilder. "Joint induction of shape features and tree classifiers". IEEE Trans. PAMI, 19 (11): 1300–1305, November 1997.

[26] Yan Ke, Rahul Sukthankar, "PCA-SIFT: A More Distinctive Representation for Local Image Descriptors," presented at the 2004 Proc. IEEE Conference on Computer Vision and Pattern Recognition, USA, 2004.