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Creating Color Image Features Based on Morphology Image Processing

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ABSTRACT

The stage of calculating the features of digital images is considered as one of the most important stages used in the construction of recognition and discrimination systems, and the rudder of these systems depends on the values of the features obtained at this stage. In this research, we will discuss a new method for calculating the features of a digital image, regardless of its size or type. This method will be used practically morphological hit and miss operation to detect and count the appearance of certain objects in the image, and these counts will be used to form image features. The proposed method will be efficiently used to create a unique features vector for any image. The size of the features vector will be controlled by the number of structuring elements selected for each image, and for the image features database to be created the number of structuring elements that must be fixed. The proposed method will be capable of detecting any object or shape in the image, also this object must be specified by a structuring element which will be used in the hit and miss operation needed to seek for the object. It will be shown how this method will speed up the process of features extraction by decreasing the features extraction time compared with the K-means clustering method of features extraction. The selected objects can be changed, and the proposed method can be used to find the count of any selected object.

1. INTRODUCTION

Digital images are considered as one of the most widely used types of data since they are used in many applications and vital systems such as facial recognition systems, fingerprint recognition systems, and many others [1-4]. The digital image is characterized by the ease of processing because it is represented by a three-dimensional matrix (one dimension for each of the red, green, and blue colors) and as shown in Figure 1, (Instead of using color image with huge size, we can use the image features vector, which contains a fixed small number of elements extracted from the image using a method of features extraction).

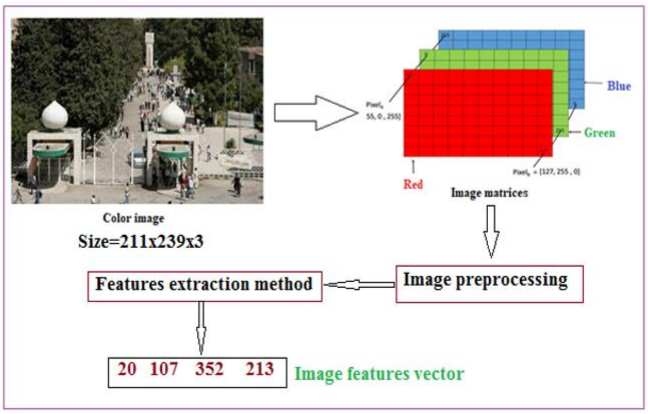

Figure 1. Color image representation

Applications that use color digital images require a high speed of implementation, but the size of the digital image is usually very large, which may lead to a negative impact on the performance of the system that uses the digital color image. This in turn requires searching for alternatives. The most important of which is the use of the features vector to represent the image and as it is shown in Figure 1.

Image features vector is an array of a fixed number of values, and this array can be used as an identifier or key to identify the image. To use the features vectors in the recognition system, the features vector must satisfy the following requirements [5-14]:

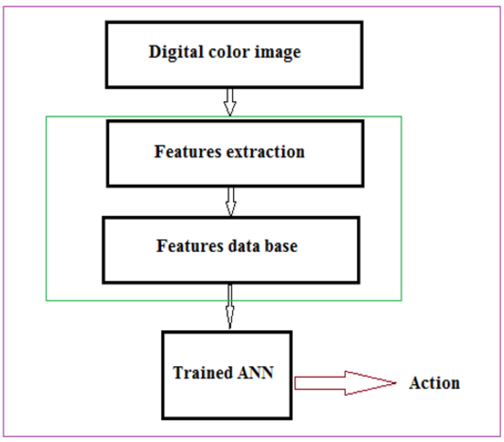

Figure 2. Features extraction phase in the color image recognition system

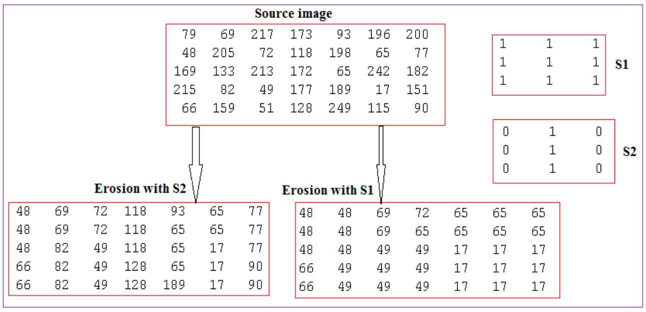

Figure 3. Erosion example

- It should be unique for each image and not be repeated for more than one image.
- It must have a fixed size and a specified number of values.
- It must be digital and processable.
- The method of calculating should be easy and effective, and it does not take much time to extract it.

The stage of extracting the features of digital images and preserving these features is one of the important stages in building the discrimination system (see Figure 2) (extracted image features must be added to images features database, which will be used in a classification system, based for example on artificial neural network (ANN)), which in the future will affect its efficiency and the accuracy of reactions to this system [6, 7].

Color digital images are processed in a variety of ways. What we need in this research is the use of some simple operations, including the erosion process. The erosion process is considered as one of the most important basic digital image morphological operations, and it is implemented using a structuring element (SE) that is composed of an array of values of one or zero, where one indicates the entry of the neighbor into the executing process, while zero indicates the exclusion of the neighbor from the processing process [14, 15].

Erosion selects the minimum neighbor value from the neighbor's values which are included by the selected SE; Figure 3 shows an example of executing erosion operation (erosion uses the input image and the structuring elements and it returns the minimum neighbor value which is cover by the structuring element) [16-23].

The organization of this paper is as follows. Section 2 presents K-means clustering. Section 3 demonstrates the proposed approach. Implementation and experimental results are conducted in Section 4, followed by result analysis in Section 5. Section 6 provides the conclusions of this research paper.

The aim of this research is to provide a simple and easy to implement method for extracting the properties of any color digital image to reduce as much as possible the extraction time and retrieve unique properties for each image. So, those properties can be used as an identifier or key to the image.

2. K-MEANS CLUSTERING

K-means clustering method is among the most important methods used to extract the features of a digital image, this method divides the pixel values into defined groups called clusters, the centroids, or the within clusters sums can be used to form the image features, Figure 4, and Figure 5 show an example input data set and the K-means clustering output, grouping the input data set to two clusters [7, 8].

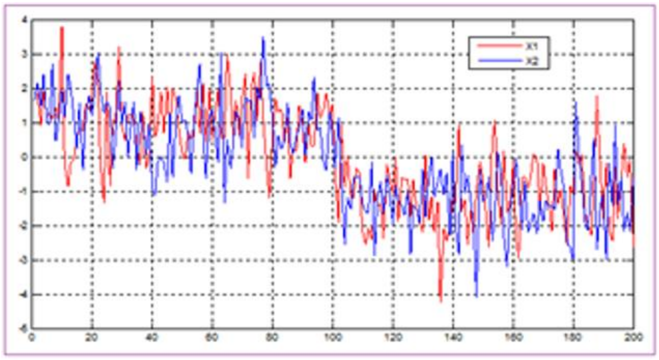

Figure 4. Input data set example

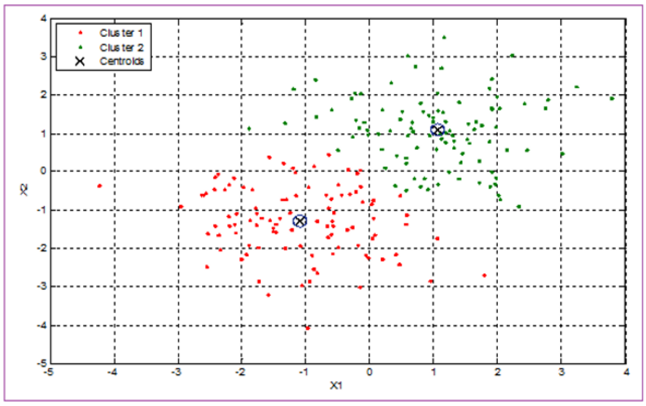

Figure 5. Grouping data set into two clusters

Table 1. Passes 1 and 2

Input dataset	Distance D1	Distance D2	Belongs to cluster	New clusters centroids	Distance D1	Distance D2	Belongs to cluster	New clusters centroids
12	8	4	2		7	3.8900	2	
5	1	3	1		0	10.8900	1	
7	3	1	2	C1=5	2	8.8900	1	C1=7.5
8	4	0	2		3	7.8900	1	
40	36	32	2		35	24.1100	2	
9	5	1	2		4	6.8900	1	
6	2	2	2		1	9.8900	1	
10	6	2	2	C2=15.89	5	5.8900	1	C2=25.75
30	26	22	2		25	14.1100	2	
21	17	13	2		16	5.1100	2	

Table 2. Passes 3 and 4

Input dataset	Distance D1	Distance D2	Belongs to cluster	New clusters centroids	Distance D1	Distance D2	Belongs to cluster	New clusters centroids
12	4.5000	13.7500	1		3.8600	18.3300	1	
5	2.5000	20.7500	1		3.1400	25.3300	1	C1=8.14
7	0.5000	18.7500	1	C1=8.14	1.1400	23.3300	1	No changes so
8	0.5000	17.7500	1		0.1400	22.3300	1	stop
40	32.5000	14.2500	2		31.8600	9.6700	2	
9	1.5000	16.7500	1		0.8600	21.3300	1	
6	1.5000	19.7500	1		2.1400	24.3300	1	C2=30.33
10	2.5000	15.7500	1	C2=30.33	1.8600	20.3300	1	No changes so
30	22.5000	4.2500	2		21.8600	0.3300	2	stop
21	13.5000	4.7500	2		12.8600	9.3300	2	

K-means clustering can be implemented by applying the following steps [9, 10]:

- *Initialization: Specify the number of clusters and specify the center of each cluster.*
- *As long as the positions' values change, perform the following steps:*
- *Calculate the absolute value between the center value and the data element value for all clusters.*
- *Determine whether the data element belongs to the cluster based on the smallest distance.*
- *Calculate the arithmetic mean of each cluster using the data elements to which it belongs and makes the calculated values the new centers of the clusters.*

Tables 1 and 2 show a worked example of clustering the input data set into 2 clusters with initial centroids equal to 4 and 8.

3. THE PROPOSED METHOD

Hit and miss operation (HAMO) is one of the powerful morphological operations for finding objects and their locations in a digital image. HAMO can be defined entirely in terms of erosion only. HAMO is very useful for detecting specific objects that are intended to extract such as isolated points, two connected points, three connected points, crosses, squares, triangles, ridges, corners, junctions, and so on [24-28].

HAMO can be implemented using erosion operation. Erosion is a pixel operation which returns the minimum value from the neighbor's values which are covered by a structuring element, and this element contains zeros and ones; one means that the associated neighbor is covered as shown in the following example (see Figure 6).

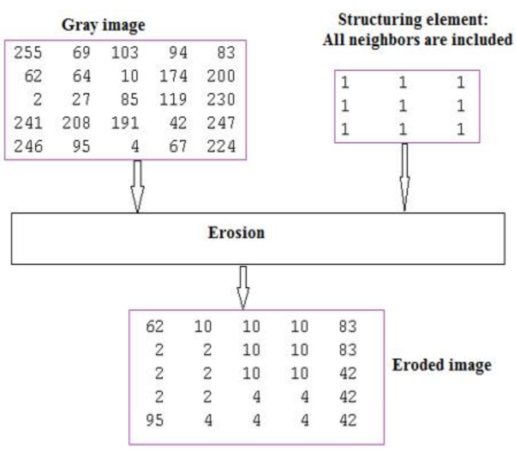

Figure 6. Erosion operation

To detect any object in the color image we must follow the following steps:

- Select a structuring (SE) element which is equal to the object to be detected (see Figure 7).

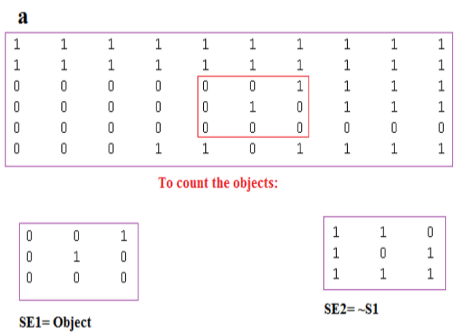

Figure 7. Detecting an object equal to SE1

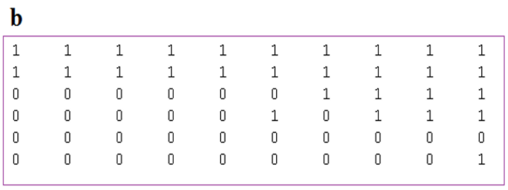

Figure 8. Eroding the image with SE1

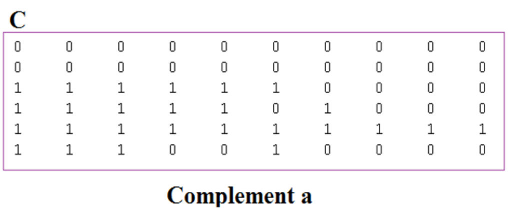

Figure 9. Finding the complement of the image

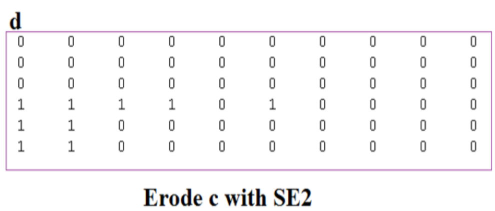

Figure 10. Eroding the complement of the image with SE2

- Erode the image with SE1 (see Figure 8).
- Find the complement of the image (see Figure 9).
- Erode the complement of the image with SE2 (see Figure 10).

- Apply ANDing b and d (see Figure 11).

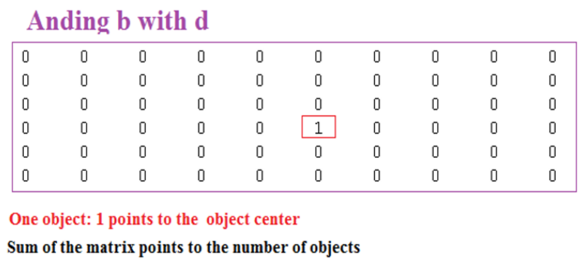

Figure 11. ANDing b and d

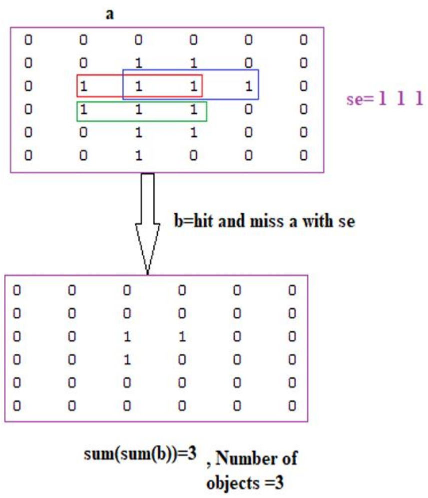

Figure 12. Counting the appearance of SE in the image

The proposed method can be implemented applying the following sequence of operations (see Figure 13).

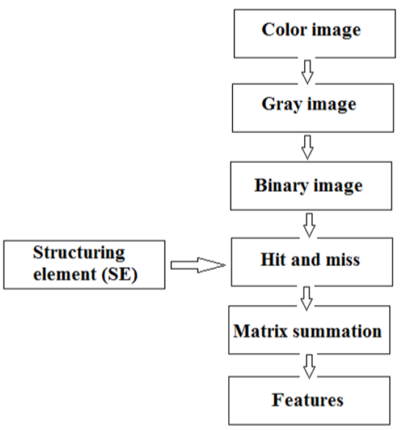

Figure 13. Proposed method algorithm

- Get the color image.
- Convert the color image to gray.
- Convert the gray image to binary image, Figure 14 shows a sample output of implementing these steps.
- Defining the required structuring elements needed to count the associated objects in the binary image, those objects are: isolated point with black color, isolated point with white color, two connected points, and three connected points, the structuring elements of the object are shown in Figures 14 to 17.
- Apply hit and miss operations using each structuring element: one time to count isolated points with black color, one time to count isolated points with white color, 4 times to count two connected points, two times to count three connected points.
- For each object apply summations of the obtained matrices to get the counts of the objects, this count can be used as a color image feature.
- Figure 18 illustrates the process of counting the object 3 connected points in an image.

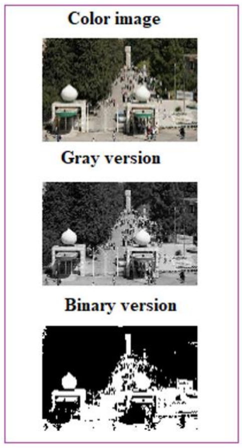

Figure 14. Counting the appearance of SE in the image

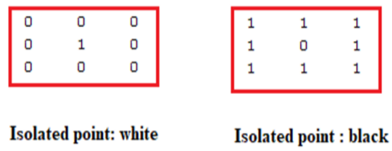

Figure 15. SE to detectisolated points

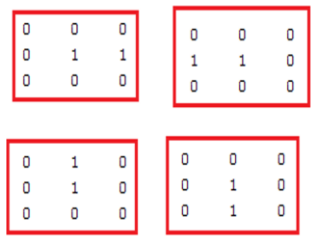

Figure 16. SEs to detect two connected points

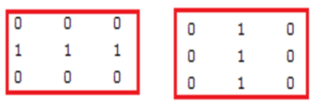

Figure 17. SEs to detect three connected points

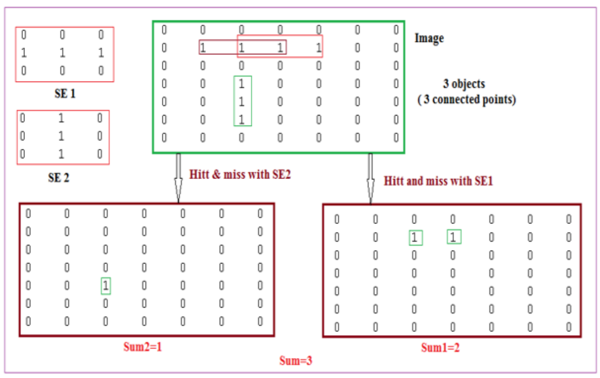

Figure 18. Counting 3 connected points

4. IMPLEMENTATION AND EXPERIMENTAL RESULTS

12 different digital color images were selected; the proposed method Mat lab code was written and executed using an I5 processor with 8 G byte RAM, and Table 3 shows the obtained results for the proposed method.

The images were resized to a fix size (256x256x3), then the resized images were treated using the proposed method, Table 4 shows the obtained experimental results (big in size image can be resized to reduce the image size, and thus the features extraction will be reduced).

The same experiments were repeated using K-means clustering (4 clusters), Tables 5 and 6 show the obtained experimental results.

Table 3. Proposed method results

Image number	Size	Number of objects: features				Extraction time
		F1	F2	F3	F4	
1	150849	108	44	184	133	0.010208
2	77976	1	104	7	5	0.008677
3	518400	138	75	241	111	0.066974
4	5140800	1778	1142	4101	2443	0.123867
5	4326210	1669	441	3595	1728	0.103873
6	122265	72	33	195	154	0.011536
7	518400	270	181	456	233	0.066975
8	150975	20	14	38	21	0.011429
9	150975	134	29	212	179	0.011977
10	151353	131	63	374	493	0.012879
11	1890000	148	173	274	94	0.067396
12	6119256	2067	2592	3988	1572	0.308409

Table 4. Resized image results using the proposed method

Image number	Number of objects: features				Extraction time
	F1	F2	F3	F4	
1	46	27	166	126	0.010880
2	3	48	7	4	0.013055
3	63	60	129	69	0.010306
4	147	48	282	157	0.010473
5	149	18	216	75	0.011198
6	40	26	170	92	0.011229
7	89	49	163	115	0.010087
8	13	11	42	14	0.016150
9	83	23	162	73	0.010260
10	83	50	287	324	0.010524
11	35	35	101	23	0.011849
12	48	23	54	4	0.013797

Table 5. K-means clustering method results

Image number	Size	Clusters centroids: features				Extraction time
		C1	C2	C3	C4	
1	150849	95.2625	172.4380	29.7922	229.3986	0.100757
2	77976	61.1192	139.1432	139.1432	237.1591	0.161162
3	518400	191.3284	65.4241	126.9648	11.2267	0.486920
4	5140800	92.6524	55.4046	201.6369	133.4006	4.399189
5	4326210	139.9841	89.8256	47.7751	195.7610	4.085609
6	122265	96.5876	43.6232	186.7237	126.7675	0.046578
7	518400	82.9890	215.4922	5.9603	135.2944	0.168570
8	150975	164.0681	46.0186	110.1487	236.9639	0.081122
9	150975	100.9316	149.0943	199.6032	51.5795	0.090160
10	151353	77.3342	188.8618	141.2851	22.7651	0.062342
11	1890000	61.7788	109.3370	174.4789	237.1791	1.534606
12	6119256	223.9887	67.6085	126.3537	147.3824	2.301860

Table 6. Resized image results using the K-means clustering method

Image number	Clusters centroids: features				Extraction time
	C1	C2	C3	C4	
1	32.6369	97.5709	172.8215	229.5397	0.102400
2	65.8860	144.1301	236.8711	202.4004	0.163203
3	11.0746	65.1815	187.7637	125.0980	0.124112
4	196.2781	89.1884	52.1862	128.6764	0.081113
5	95.6350	56.3448	147.6627	198.1477	0.177771
6	180.1088	127.0158	97.1396	44.2920	0.059601
7	5.5665	81.7954	133.6447	213.2086	0.119997
8	236.6002	109.5226	163.2401	45.7687	0.152000
9	52.9624	101.3140	149.0187	199.2455	0.091534
10	74.7323	185.7610	22.9624	138.2181	0.162757
11	177.4876	112.6088	63.4931	236.7225	0.071181
12	174.8120	233.8651	136.0829	78.2602	0.063646

5. RESULTS ANALYSIS

From the obtained experimental results, we can see the following facts:

- K-means clustering method provides a good ability to form image features vectors, each of them satisfies the requirements.
- We cannot predict the extraction time in K-means clustering, because it depends on the number of executed passes and the image size.
- Resizing the image to a smaller size reduces the extraction time in K-means clustering and in the proposed

method.

- The extraction time in the proposed method depends on the image size, and reducing the image size by resizing will reduce the extraction time.
- The proposed method provides a unique features vector for each image.

The proposed method speeds up the process of features extraction, thus enhancing the performance of the digital image features extraction process; this can be seen in Tables 7 and 8.

Table 7. Speedup of the proposed method using source images

Image number	Proposed method extraction time T1 (second)	K-means clustering method extraction time T2 (second)	Speedup of the proposed method (T2/T1)
1	0.010208	0.100757	9.8704
2	0.008677	0.161162	18.5735
3	0.066974	0.486920	7.2703
4	0.123867	4.399189	35.5154
5	0.103873	4.085609	39.3327
6	0.011536	0.046578	4.0376
7	0.066975	0.168570	2.5169
8	0.011429	0.081122	7.0979
9	0.011977	0.090160	7.5278
10	0.012879	0.062342	4.8406
11	0.067396	1.534606	22.7700
12	0.308409	2.301860	7.4637
Average			**13.9014**

Table 8. Speedup of the proposed method using resized images

Image number	Proposed method extraction time T1 (second)	K-means clustering method extraction time T2 (second)	Speedup of the proposed method (T2/T1)
1	0.010880	0.102400	9.4118
2	0.013055	0.163203	12.5012
3	0.010306	0.124112	12.0427
4	0.010473	0.081113	7.7450
5	0.011198	0.177771	15.8752
6	0.011229	0.059601	5.3078
7	0.010087	0.119997	11.8962
8	0.016150	0.152000	9.4118
9	0.010260	0.091534	8.9214
10	0.010524	0.162757	15.4653
11	0.011849	0.071181	6.0073
12	0.013797	0.063646	4.6130
Average			**9.9332**

6. CONCLUSION

Any shape or object in a digital image can be specified by a ones and zeros to form a 2D matrix. This matrix can be used as a structuring element to form an input to the morphological operation which can return the center of this object.

A new method of color image features extraction was introduced and implemented using various color images. The proposed method is simple, and it can be used for any image of any size and with any type (color, gray, binary). It is based on using morphological hit and miss operation to detect and count defined objects in the image, and those counts can be used to form a unique features vector for the image.

The proposed method is very efficient, and it minimizes the features extraction time. Compared with the K-means method, it will speed up the process of features extraction at least 10 times.

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