Content-based image retrieval using OWA fuzzy linking histogram

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Abstract. Content-based image retrieval (CBIR), as a well-known retrieval method, has been widely used in various applications. The basis of this method is on features like color, texture and shape. Color image histograms are very useful tools for this purpose. As these kinds of histograms results with large variations between neighboring bins, they seem so sensitive to any kind of changes such as noise, illumination, etc. To overcome this problem, fuzzy linking histogram based on OWA aggregation operator is proposed, which is capable of projecting 3-dimensional \(L^*a^*b^*\) color histograms into single-dimension. The proposed method have been evaluated and compared with five other methods in retrieving similar images from the common database. The experimental results, reveals better performance of the proposed method in comparison with the other mentioned methods.

Keywords: Image retrieval, fuzzy color histogram, ordered weighted average (owa), fuzzy linking histogram

1. Introduction

The realm of content-based image retrieval (CBIR) has achieved great overall awareness within a wide range of scientific, commercial, art and medical domains \[30, 36\]. As the extraction of meaningful features is so critical in CBIR, it provides an open field of research to improve accuracy, flexibility and architecture of the existing approaches \[14, 15, 18\].

The very approaches to content-based image retrieval can be generally divided into those making use of the structural features \[6, 7\] of an image and those using image’s semantic specifications \[2, 31, 32, 34\].

With regard to structural content-based image retrieval, a variety of features such as color, texture, and shape can be used to retrieve the desired images \[3, 17, 23\]. In this regard, some approaches use multi-resolution color and text feature to improve the retrieval precision/recall for queries and target images of various resolutions \[5, 13\]. Meanwhile there exist some other methods which use knowledge of texture, color and binary tree structure for image retrieval purposes \[19\]. Among the methods that utilize color as a retrieval feature, color histogram can be mentioned \[12, 14, 21\] that can be widely used in image indexing for content-based image retrieval \[24\], video scene retrieval \[35\] and incremental CBIR \[22\]. The classic histogram is a global statistical feature, which describes the intensity distribution for a given image \[11\]. Its main advantage is that its manipulation to store and compare is fast. In the meantime it is insensitive to rotation and scale. A histogram-based retrieval system requires a suitable color space (such as HSV, \(L^*a^*b^*\) or \(L^*U^*V^*\)), a histogram representation (such as classic or joint histograms), and a similarity metric (like the Euclidian distance, Matusita distance \[9\] or the histogram...
2. A survey on ordered weighted averaging operator as an operator for fusion purposes

Increasing need of methods and operators for fusing information within various domains of computational applications reveals the importance of study on aggregation operators [1, 28, 29] such as: characterization, classification, scales, and selection.

They have been studied from different perspectives [28, 29] such as: characterization, classification, scales, and selection.

intersection method [27]. The classical method of color histogram creation results in very large histograms with large variations between neighboring bins. Thus, small changes in the image might result in great changes in the histogram. Here, this sensivity can be resolved by using fuzzy logic [8] that, due to its flexibility and tolerance to imprecise imagersy data, is widely used in many applications such as image understanding, hybrid querying for image retrieval [16] and automatic control. Moreover, manipulating and comparing 3D histograms is a complicated and computationally-expensive process. In this regard, the reduction of the 3 dimensions to one dimension can lead to more informative results. For this purpose, method of histogram linking [15] is used that is capable of projecting 3D histograms onto one single-dimension histogram. Besides, for separating small distances between neighboring regions in 3D color spaces, fuzzy methods seem to be very useful [15]. Extracting more details from the fuzzy linking histograms necessitates improving the existing approaches. In this respect, using aggregation operators such as OWA [33], choquet [4] and sugeno [26] can be effective.

In this paper, we propose a new fuzzy linking method of color histogram creation based on L*a*b* color space and OWA aggregation operator. The proposed method has been evaluated and compared with the results of the existing fuzzy color histogram in [15] on the datasets, which are available at URL: http://utopia.duth.gr/~konkonst/html/pics.html. As the OWA aggregation operator can reveal more detailed information of the image’s content, it is expected to be suitable in the situations where the deep details of the image are of particular significance. Examples can be mentioned for biomedical tissues images, cosmic images, materials fracture images as well as fossils and botanic images.

<table>
<thead>
<tr>
<th>Operator</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arithmetic mean (AM)</td>
<td>[ \mu_{x_1} ]</td>
</tr>
<tr>
<td>Geometric mean (GM)</td>
<td>[ \prod_{i=1}^{N} x_i ]</td>
</tr>
<tr>
<td>Harmonic mean (HM)</td>
<td>[ \frac{N}{\sum_{i=1}^{N} \frac{1}{x_i}} ]</td>
</tr>
<tr>
<td>Weighted mean (WM)</td>
<td>[ \sum_{i=1}^{N} w_i x_i ]</td>
</tr>
<tr>
<td>OWA</td>
<td>[ \sum_{i=1}^{N} w_i (\prod_{j=1}^{k} x_{\sigma_j}) ]</td>
</tr>
<tr>
<td>Choquet integral (CI)</td>
<td>[ \sum_{i=1}^{N} \left( f(x_{A_i}) - f(x_{A_i-1}) \right) \mu(A_i) ]</td>
</tr>
<tr>
<td>Sugeno integral (SI)</td>
<td>[ \max_{i=1,...,N} \left( f(x_{A_i}), \mu(A_i) \right) ]</td>
</tr>
<tr>
<td>WOWA</td>
<td>[ \sum_{i=1}^{N} w_i (\prod_{j=1}^{k} x_{\sigma_j}) - w^* \left( \sum_{i=1}^{N} p_i (x_{\sigma_i}) \right) ]</td>
</tr>
</tbody>
</table>

One of the most famous aggregation operators, which has been introduced by Yager [33], is ordered weighted average (OWA) operator. Since then, the OWA operators have been used in a wide range of applications [25] in fields including neural networks, multiple criteria decision making, database systems, fuzzy logic controllers and group decision making.

Mitchell and Schaefer have spearheaded works to remove the restrictions of crisp input arguments in the original OWA operator by applying the extension principle defined in fuzzy OWA operators that aggregate a set of ordinary fuzzy sets. Recently, the OWA aggregation with uncertain description on weights and input arguments is presented [28], too. The determination of OWA operator weights is a very important issue of applying the OWA operator for decision making. A number of approaches have been suggested for obtaining the associated weights, i.e., quantifier guided aggregation, exponential smoothing and learning. O’Hagan [20], determines a special class of OWA operators having maximal entropy of the OWA of the OWA weights for a given level of orness, it is based on the solution of a constrained optimization problem.

Here X is a reference set, \( x_i \) denote the value supplied by \( n \) with \( \mu(x_i) = \mu \in (0,1) \), \( \mu(X) = 1 \) and \( \mu(A) \subseteq \mu(B) \) then \( A \subseteq B \), \( p, w \) are weighting vectors i.e., \( p_i \geq 0 \) and \( \sum p_i = 1 \) and \( \pi \) is a permutation such that \( \pi(\sigma(A)) = \pi(A) \).
Fuller and Majlender also suggested a minimum variance method to obtain the minimal variability OWA operator weights [10].

As proposed by Yager, the ordered weighted averaging (OWA) aggregation operator is computationally simple both to determine, apply and adjust and oring behavior, to reflect the optimism of a multiple objective decision making. In the case of expert systems, the certainty factor (CF) associated with a rule is equivalent to the oring, or optimism required of the aggregation process. Formula (1) and (2) defines OWA mapping $F$ from $P$ into $I$, where $I = [0, 1]$ is called an Ordered Weighted Averaging (OWA) operator of dimension n if associated with $F( )$, is an n dimensional weighting vector $W$.

$$W_j \in I,$$

$$\sum_{j=1}^{n} W_j = 1.$$

And where $F(a_1, \ldots, a_n) = \sum_{j=1}^{n} W_j b_j = W'B$.

Where $b_j$ is the $j$th largest element in the sorted collection $a_1, \ldots, a_n$ $B$ is the vector of descending-order-sorted elements of the arguments of $F()$. Note that the constraints on permissible values for $W$ represented by formula (1) and (2) give it the flavor of a finite set of probabilities with $F$ then becoming a special form of expected value of $B$ with respect to the $W$ probability distribution. Also note that the $W_j$ are associated with a particular ordered position rather than a particular element of the argument set of $a_i$. It can easily be shown that any OWA operator $F( )$ with weighting vector $W$ is contained in $I$.

It is noted that different OWA operators are distinguished by their weighting function. Three important special cases of OWA aggregations are shown in formulas (3):

- **Max**: oring aggregation operator is given by:
  $$W' = [1, 0, \ldots, 0],$$

- **Min**: anding aggregation operator is given by:
  $$W' = [0, 0, \ldots, 1],$$

- **Average**: $W' = \{1/n, 1/n, \ldots, 1/n\}$.

Thus, by choosing the weight vector appropriately, the aggregation of antecedents in a rule/template or criteria in a multi-objective decision function can be positioned anywhere between the two extremes of pessimistic and optimistic oring.

The degree of orness associated with $F$ and the OWA aggregation operator with weighting function $W'=[W_1, \ldots, W_n]$ is according to formula (4):

$$\text{orness} (W) = \sum_{j=1}^{n} W_j h_n(j),$$

Where $h_n(j) = \binom{n}{n-j} \binom{n-1}{n-1}$.

The function $h_n(j)$ is a prototype linear stair-step function with $n-1$ steps of height $\binom{n}{n-1}$ starting with value 1 and decreasing as a function of argument $j$. With the understanding that: andness $(W) = 1 - \text{orness}$.

It is to be mentioned that the measure of dispersion is used to develop an objective function for the optimization problem whose constrained solution give an optimum $W$ for aggregation. Assume $W$ is a weighting vector with elements $W_1, \ldots, W_n$ then a measure of dispersion of $W$ is defined as formula (5):

$$\text{dispersion} (W) = -\sum_{j=1}^{n} W_j \ln (W_j).$$

Since this dispersion is a measure of entropy, if $W_j = 1$ for some $i$ then dispersion becomes minimum (dispersion $(W) = 0$). While, if $W_j = 1/n$ then dispersion becomes maximum (dispersion $(W) = \ln n$). Therefore, more disperse the $W$, more of the information about the individual criteria is being used in the aggregation of the aggregate value [33].

3. The proposed approach

3.1. Fuzzy linking histogram creation method

Although there exists various color spaces like $L^*a^*b^*$, HSV and $L^*U^*V^*$, in this paper, we have selected $L^*a^*b^*$ color space which is a perceptually uniform color space and approximates the way humans perceive color [8, 13-15]. In $L^*a^*b^*$, $L^*$ stands for luminance, $a^*$ represents relative greenness-redness and $b^*$ represents relative blueness-yellowness. All colors and grey levels can be expressed throughout a combination of the three components. However, $L^*$ does not contribute in providing any unique color but for shades of colors, white, black and grey. Thus, the $L^*$ component receives a lower weight in comparison with the other two components of the triplet.

In this experiment, $a^*$ and $b^*$ components have been subdivided into five regions representing green, greenish, the middle of the component, reddish and red for...
Fig. 1. Membership functions of L*, a*, b*.

a*, blue, bluish, the middle of the component, yellowish and yellow for b*, whereas L* should be subdivided into only three regions: dark dim and bright areas. The fuzzification of the input is accomplished by using triangular-shaped membership functions (MF) for the three input components (L*, a*, b*), which represent the regions as shown in Fig. 1.

The reason that the middle MF exists both in a* and b*, is to present black, grey and white as seen in L*, a* and b* in a way to be very close to the middle of their regions. This is a well-known fact about the L*a*b* space [26]. The Mamdani type of fuzzy inference can be used, in which the fuzzy sets from the output MFs of each rule are combined through the aggregation operator which is set to max, and the resulting fuzzy set is then defuzzified to produce the output of the system.

The implication factor, which determines the process of shaping the fuzzy set in the output MFs, based on
the results of the input MFs, is set to min and the OR and AND operators are set to max and min, respectively. The output of the system has only 10 equally divided MFs, as shown in Fig. 2. So, the final fuzzy histogram would consist of only 10 bins approximately representing (1) black, (2) dark grey, (3) red, (4) brown, (5) yellow, (6) green, (7) blue, (8) cyan, (9) magenta and (10) white. The defuzzification phase is performed using the largest of maximum method along with the 10 trapezoidal MFs, thus producing 2500 clustered bin values (for 50 × 50 image), which lead to the 10-bin final fuzzy histogram. The fuzzy linking of the three components is made according to 27 fuzzy rules, which lead to the output of the system. The rules were established through an empirical conclusion, which arose through examination of the properties of a series of colors and images in the L*a*b* color space.

To obtain the final histogram, a variety of rules have been proposed [15], which are listed in Table 2. In our approach, to evaluate the role of OWA operator on CBIR and compare the results with those obtained by applying the above mentioned operators, the experiments have been repeated using three forms of OWA (Min, Max and Average) as discussed in formulas 3. For this purpose, the \( \mu \) were ordered in a descending form, then multiplied by triple forms of weights (Max, Min and average) and being summed together. The experiments have been done with both fuzzy linking histogram and three forms of OWA linking histogram on five categories each including 100 images which are selected from 1118 available images at URL: http://utopia.duth.gr/~konkonst/html/~pics.html. The comparison results between the above mentioned methods are presented for 5 seed points of categories in this paper.

### 3.2. Experimental results

In Figs. 3–7, five query images and the respective resulting fuzzy histograms based on OWA forms and original one are presented. These images are shown as the representative prototypes of similar semantic content images in database (flower, cat, sunset, etc.), which are available at http://utopia.duth.gr/~konkonst/html/pics.html.

One can easily notice the dominant colors in each of the images. For instance, in the image (db_3192), bin 5 in Fig. 3b is highly activated, because of the green coverage of the jungle which is illustrated in the figure. By applying OWA to the same image, the resultant OWA histograms shows that min form of OWA gives better performance than the others (max and avg) as respectively bin 5, 4, 7, . . . are activated more. While in min and avg forms of OWA, some extra bins will be activated which are not the main ones.

Having the same experience on image (db_1471), reveals that because of the wide dark colors (black and brown) in the figure, bins 1 and 5 (Fig. 4b) are more activated because of the black and brown colors which exist in that. After applying OWA on the same image, the resultant OWA histograms shows that max and avg forms of OWA, both give better performance than the min one.
Table 2
Fuzzy rules for the proposed fuzzy linking histogram

<table>
<thead>
<tr>
<th>No</th>
<th>Rule</th>
<th>No</th>
<th>Rule</th>
</tr>
</thead>
<tbody>
<tr>
<td>R1</td>
<td>If (L is black) and (a is amiddle) and (b is bmiddle) then (fuzzyhist is black) (1)</td>
<td>R13</td>
<td>If (L is Lmiddle) and (a is reddish) and (b is yellowish) then (fuzzyhist is red) (1)</td>
</tr>
<tr>
<td>R2</td>
<td>If (L is white) and (a is amiddle) and (b is bmiddle) then (fuzzyhist is white) (1)</td>
<td>R14</td>
<td>If (a is reddish) and (b is bluish) then (fuzzyhist is blue) (1)</td>
</tr>
<tr>
<td>R3</td>
<td>If (L is Lmiddle) and (a is red) and (b is yellow) then (fuzzyhist is red) (1)</td>
<td>R15</td>
<td>If (L is Lmiddle) and (a is amiddle) and (b is yellowish) then (fuzzyhist is green) (1)</td>
</tr>
<tr>
<td>R4</td>
<td>If (a is reddish) and (b is yellow) then (fuzzyhist is brown) (1)</td>
<td>R16</td>
<td>If (a is reddish) and (b is bluish) then (fuzzyhist is blue) (1)</td>
</tr>
<tr>
<td>R5</td>
<td>If (L is white) and (a is green) and (b is yellowish) then (fuzzyhist is green) (1)</td>
<td>R17</td>
<td>If (a is green) and (b is bluish) then (fuzzyhist is cyan) (1)</td>
</tr>
<tr>
<td>R6</td>
<td>If (L is white) and (a is green) and (b is yellowish) then (fuzzyhist is brown) (1)</td>
<td>R18</td>
<td>If (a is green) and (b is bluish) then (fuzzyhist is blue) (1)</td>
</tr>
<tr>
<td>R7</td>
<td>If (L is black) and (b is bluish) then (fuzzyhist is red) (1)</td>
<td>R19</td>
<td>If (L is black) and (b is bluish) then (fuzzyhist is blue) (1)</td>
</tr>
<tr>
<td>R8</td>
<td>If (L is white) and (a is green) and (b is bluish) then (fuzzyhist is cyan) (1)</td>
<td>R20</td>
<td>If (L is white) and (a is green) and (b is yellowish) then (fuzzyhist is brown) (1)</td>
</tr>
<tr>
<td>R9</td>
<td>If (L is Lmiddle) and (a is amiddle) and (b is bluish) then (fuzzyhist is brown) (1)</td>
<td>R21</td>
<td>If (L is Lmiddle) and (a is reddish) and (b is yellowish) then (fuzzyhist is magenta) (1)</td>
</tr>
<tr>
<td>R10</td>
<td>If (L is white) and (a is green) and (b is bluish) then (fuzzyhist is blue) (1)</td>
<td>R22</td>
<td>If (L is Lmiddle) and (a is reddish) and (b is bluish) then (fuzzyhist is cyan) (1)</td>
</tr>
<tr>
<td>R11</td>
<td>If (a is red) and (b is bluish) then (fuzzyhist is white) (1)</td>
<td>R23</td>
<td>If (L is Lmiddle) and (a is amiddle) and (b is yellowish) then (fuzzyhist is brown) (1)</td>
</tr>
<tr>
<td>R12</td>
<td>If (L is white) and (b is bluish) then (fuzzyhist is red) (1)</td>
<td>R24</td>
<td>If (L is white) and (a is green) and (b is yellowish) then (fuzzyhist is brown) (1)</td>
</tr>
<tr>
<td>R13</td>
<td>If (a is reddish) and (b is bluish) then (fuzzyhist is blue) (1)</td>
<td>R25</td>
<td>If (L is Lmiddle) and (a is reddish) and (b is yellowish) then (fuzzyhist is yellow) (1)</td>
</tr>
<tr>
<td>R14</td>
<td>If (a is red) and (b is bluish) then (fuzzyhist is blue) (1)</td>
<td>R26</td>
<td>If (L is Lmiddle) and (a is amiddle) and (b is yellowish) then (fuzzyhist is red) (1)</td>
</tr>
</tbody>
</table>

Bin 3 (Fig. 5b) extracted from the image (db9432), is activated because of the red chair, brown because of the brown cat and magenta since the marble in the background is not actually white but a tone between blue, white and pink. After applying OWA to the same image, max form of OWA is shown to give better performance than the others (min and avg), let say, bins 3, 7 and 8 are activated more, while in min and avg forms of OWA, some extra bins will be activated which are not the main ones.

Bin 1 and 2 (Fig. 6b) extracted from the image (db9993), are activated because of the black and dark grey clouds in the sky, and bin 3 is activated because of the red light of the sun. After applying OWA to the same image, the resultant OWA histograms show that in max form of OWA, respectively bins 7, 6, 5, 4, 8 are more activated because of the green, blue, yellow and cyan lights in the image, while in the min form, bins 5, 6 are activated because of the greenish portion in the image. In avg form, bins 8, 9 are activated. It is illustrated that min form of OWA outperforms better for this image.

The histograms in the proposed scheme, though apparently rough, have proved to be efficient for accurate image retrieval. Comparing the original fuzzy linking histograms, which are shown in part (b) of Figs. 3–7 on the one side, and three forms of OWA on the other side, it becomes clear that using OWA (max, min and avg) lead to detailed information of the image, while the original fuzzy linking histogram illustrates the salient color of the image. Also, based on the major color distribution in the image, the performance of the three forms of OWA would vary.

The proposed method of OWA fuzzy linking histogram creation was compared with Lian’s et al., Swain’s and Ballard’s, Tico’s et al., and original fuzzy linking histograms [15]. Five different topics of images (cat, flower, architecture, jungle sky) were selected among those available at URL.
Fig. 3. (a) Query image (db3192), (b) its fuzzy linked histogram, (c) OWA max, (d) OWA min, (e) OWA average.

http://utopia.duth.gr/~konkonst/html/pics.html. The similarity metric used is histogram intersection [27], which acts robustly with respect to changes in image resolution, histogram size, occlusion, depth, and viewing point. The similarity ratio belonging to the interval [0, 1] can be expressed through the following equation:

\[ H(Q, C) = \frac{\sum_{i=1}^{N} \min(H_Q(i), H_C(i))}{\min(\sum_{i=1}^{N} H_Q(i), \sum_{i=1}^{N} H_C(i))} \]  

Where HQ and HC are the query and challenging histograms, respectively, and N is the number of bins.

The experiments were all run on MATLAB. All the images were scaled to a 50 50 pixel size using the nearest neighbor interpolation method in order to make the algorithms faster and to avoid later normalization of the histograms, so as to result in loss of color quantity information. For example, in Figs. 5 and 7 the
distribution of red (bin 3) is strong, but there is loss of quantity information. Different methods of color histogram creation have been evaluated and compared in [15]. Table 3 shows the performance of our proposed approach compared to the existing methods on three sets of five selected categories of the same datasets. The samples of images which are available in those sets are shown in Fig. 8.

Another aspect of retrieval performance is precision versus recall. Precision is the proportion of relevant images retrieved R (similar to query image) in respect to the total retrieved A, whereas recall is the
proportion of similar images retrieved in respect to the similar images that exist (formula 7).

\[
\text{Precision} = \frac{\text{Similar retrieved}}{\text{Total retrieved}}, \quad (7)
\]

Recall = \frac{\text{Similar retrieved}}{\text{Similar exist}}

Figure 9 shows the performance of OWA fuzzy linking histogram in terms of precision to recall, which has been discussed on three databases.

It can be figured out from Fig. 9 that, the last two fuzzy methods dominate the others, due to the fact that the very fuzziness in these methods makes it even less sensitive to changes of scene, noise or illumination. Moreover, OWA fuzzy linking histogram shows more details of an image, while the original fuzzy linking activates the salient color of the image and does not consider the others. This is mainly due to the fact that the very ordered weights being used as the
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Fig. 6. (a) Query image (db6993), (b) its fuzzy linked histogram, (c) OWA max, (d) OWA min, (e) OWA average.

4. Concluding remarks

In this paper, a new fuzzy linking method of color histogram creation based on L*a*b* color space and OWA aggregation operator was proposed. Here, L*a*b* components have been considered as fuzzy sets, ordered and multiplied by weighted average operator in three forms of max, min, avg. The proposed histogram is acquired...
Fig. 7. (a) Query image (db_7913), (b) its fuzzy linked histogram, (c) OWA max, (d) OWA min, (e) OWA average.

Table 3

<table>
<thead>
<tr>
<th>Image set</th>
<th>1 (Green)</th>
<th>2 (Brown)</th>
<th>3 (Red)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Swain and Ballard</td>
<td>80</td>
<td>70</td>
<td>90</td>
</tr>
<tr>
<td>Classic L<em>a</em>b* histogram</td>
<td>75</td>
<td>75</td>
<td>90</td>
</tr>
<tr>
<td>Tico (HIS)</td>
<td>75</td>
<td>70</td>
<td>75</td>
</tr>
<tr>
<td>Tico (L<em>a</em>b*)</td>
<td>55</td>
<td>75</td>
<td>90</td>
</tr>
<tr>
<td>Liang (RGB)</td>
<td>70</td>
<td>50</td>
<td>65</td>
</tr>
<tr>
<td>Liang (HIS)</td>
<td>90</td>
<td>67</td>
<td>80</td>
</tr>
<tr>
<td>Fuzzy Linking (L<em>a</em>b*)</td>
<td>95</td>
<td>85</td>
<td>95</td>
</tr>
<tr>
<td>OWA Fuzzy linking (L<em>a</em>b*)</td>
<td>95</td>
<td>84</td>
<td>96</td>
</tr>
</tbody>
</table>

through linking these fuzzy sets by making use of the corresponding fuzzy rules. The fuzzy-based methods discussed in the paper, have been found through several image retrieval experiments to be much more accurate and robust compared even to the classical approach based on fuzzy linking histogram. As it was discussed in the paper, the main reason for this advantage is the capability of OWA fuzzy linking histogram in revealing the details concerning the other colors in the retrieved image; an effect which is not seen in case of using the
Fig. 8. Sample sets of (a) green, (b) brown, (C) red images are applied in experiment. (Colours are visible in the online version of the article; http://dx.doi.org/10.3233/IFS-2012-0557)
OWA as an aggregation operator has the ability to attain more precise information due to its fusion effect, while the conventional approaches to linking histogram do not hold such ability to this extend. Let say, whenever more details of the image is required OWA fuzzy linking histogram reveals better performance, while in case that the salient part of an image is called for, the classical fuzzy linking histogram seems to act better. As the final conclusion, the proposed approach is expected to have a high performance in case of retrieving biomedical, organic, cosmic, materials fractures, fossils and botanic images wherein detail information in the image is called for, so as to give more accurate diagnosis results.

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