Evaluation of Various Aggregation Operators Applied to a Content Based Image Retrieval System

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***Abstract*— Fuzzy Hamming Distance is successfully used in a Content-Based Image Retrieval (CBIR) system as a similarity measure. The system performs a $m \times n$ partitioning of the compared images and for each partitions pairs evaluates FHD. In the last step the FHD are defuzzified and the results are combined in a final score. In order to take full advantage of the use of fuzzy sets, the current study investigates the possibility of reversing the order of the defuzzification and aggregation steps: aggregate fuzzy set and defuzzify final result for ranking. Several t-norm and associated t-conorm aggregation operators are experimented with. The results are illustrated on retrieval operations from an image database.**

Keywords: fuzzy sets aggregation, image retrieval systems, CBIR, fuzzy hamming distance.

I. Introduction

The goal of content based image retrieval systems(CBIR) is to allow querying images databases in a natural way, by the image content. To achieve this goal, various features such as sketches, layout or structural description, texture, colors, are extracted from each image. A query might be: *Find all images with a pattern similar to this one* (the query pattern), and then the system finds a subset of images similar to the query image. QBIC, Query By Image Content, from IBM [1], is one of the earliest such a system, using a weighted Euclidean distance on colors, texture, shape and sketch to assess similarity between two images.

In previous studies, [2], [3], [4], the Fuzzy Hamming Distance (FHD) has been used to assess content similarity between two images based on color information. In such an approach aggregation is expected to play an important role towards obtaining a final score of similarity.

II. The Fuzzy Hamming Distance

The Fuzzy Hamming Distance [5] is a generalization of Hamming distance over the set of real-valued vectors defined as the (fuzzy) number of different components of the input vectors, captured by the *difference fuzzy set*. The fuzzy set shows the degree to which the input vectors are different by 0, 1,...,n, where n is the size of the vectors. In short, the Fuzzy Hamming Distance is the *fuzzy cardinality* of the difference fuzzy set. A crisp version of it, $nFHD$, can be also defined, which, when the input vectors are binary, reduces to the classical Hamming distance. Moreover, FHD can be parameterized to control the extent, context dependent, of the difference, in order for this to be considered meaningful. Previous studies [5], [2], show that FHD can be viewed as an adaptive decomposition of the Euclidean (and other distances, such as Minkowski distance).

III. Overview of the Content Based Image Retrieval System

The CBIR system proposed in [2], [4] and further studied in [3], consists of the three modules as shown in Fig. 1:

1) The **Preprocessing Module** splits each image (query image and every image in database) into partitions of granularity $m \times n$, to include position information; from each partition it extracts the information of interest (in this study the color histograms). The output is a collection of color histograms, one for each partition, stored as real-valued vectors.
2) The **Similarity Assessment Module** takes as input the information from the preprocessing module and computes the similarity (actually the FHD), between the query image and each image in the database. The output of this module is a collection of fuzzy sets (FHD).
3) The **Ranking Module** defuzzifies the input (FHD of each partition), aggregates the results into a score (e.g. using a weighted sum), ranks the scores in decreasing order.

The current study investigates the possibility of reversing the order of the defuzzification and ranking steps. The motivation behind this is as follows: since defuzzification of a fuzzy set consists of extracting a (*representative*) point from it, its result is necessarily an approximation (of the original set). Additionally, in the context of the current CBIR system, where defuzzification is followed by aggregation of scores, the number of defuzzification operations is equal to $m \times n$ (partition granularity) and therefore such approximations may, ultimately, impact the outcome of the system. Reversing the order of aggregation and defuzzification steps would result then in one aggregation step - this time of fuzzy sets, rather than crisp numeric scores - and *one defuzzification operation* - to obtain the final score.

Only t-norms and t-conorms operators are used to aggregate the fuzzy sets; other aggregation operators are omitted for rea-

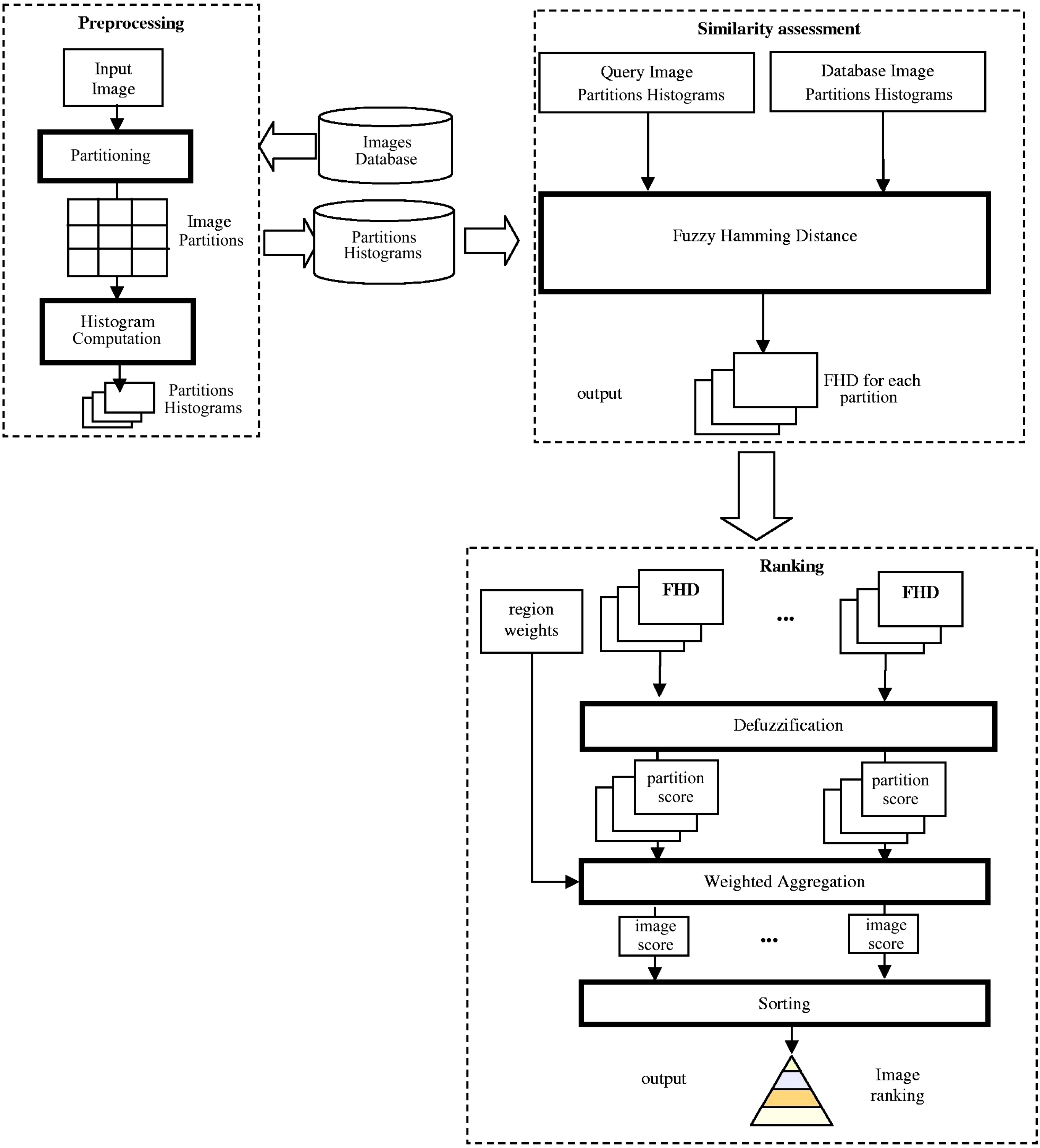

Fig. 1. The CBR system architecture.

TABLE I

t-NORMS AND ASSOCIATED t-CONORMS USED IN EXPERIMENTS ($\wedge$ AND $\vee$ DENOTE THE OPERATIONS OF min/max RESPECTIVELY).

Name	t-norm	t-conorm
min/max	$t_{min}(a,b) = a \wedge b$	$s_{max}(a,b) = a \vee b$
Lukasiewicz	$t_L(a,b) = 0 \vee (a+b-1)$	$s_L(a,b) = 1 \wedge (a+b)$
algebraic	$t_{alg}(a,b) = ab$	$s_{alg}(a,b) = a+b-ab$

sons to be clarified later. It is expected that system sensitivity to the similarity between images is enhanced.

IV. Preliminary Evaluation of Aggregation Operators

Triangular t-norms, $t : [0,1] \times [0,1] \rightarrow [0,1]$, constitute a class of aggregations of fuzzy sets for implementing intersection of two fuzzy sets. The t-conorm corresponding to a t-norm, $s : [0,1] \times [0,1] \rightarrow [0,1], s(a,b) = 1 - t(1-a, 1-b))$ implements a union operator. Table IV shows the operators used for the experiments carried out in the current study. The subject of t-norms is well understood and extensively covered in the literature (see, for example [6]).

All t-norms and t-conorms satisfy the properties:

$$t(a,b) \leq a \wedge b; \quad s(a,b) \geq a \vee b \tag{1}$$

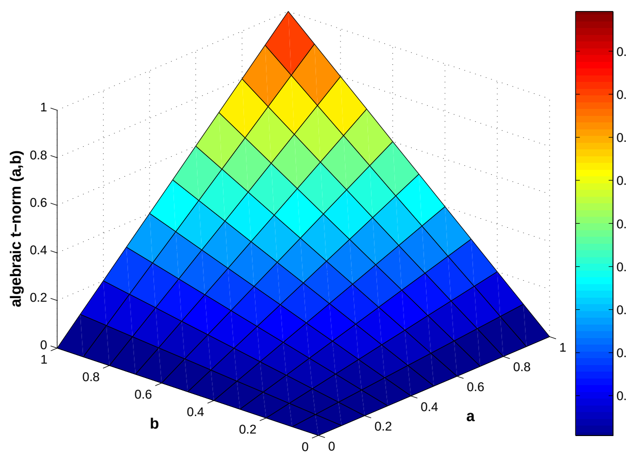

Fig. 2. Agebraic t-norm $t_{alg}(a,b)$

As indicated in the previous section, in the current experiments, the results of the **Similarity Module** are first aggregated to produce one fuzzy set, and then, for ranking purposes this fuzzy set is defuzzified.

Thus the **Ranking Module** has now the following two steps:

1) Aggregate the input fuzzy sets.
2) Defuzzify the resulting fuzzy set: For this study, for the preliminary results, the center of gravity (COG) is considered. Recall that for a discrete fuzzy set $A \equiv \sum_{i=1}^{n} x_i/\mu_i$ COG is given by $COG = \sum_{i=1}^{n} x_i\mu_i \;/\; \sum_{i=1}^{n} \mu_i$.

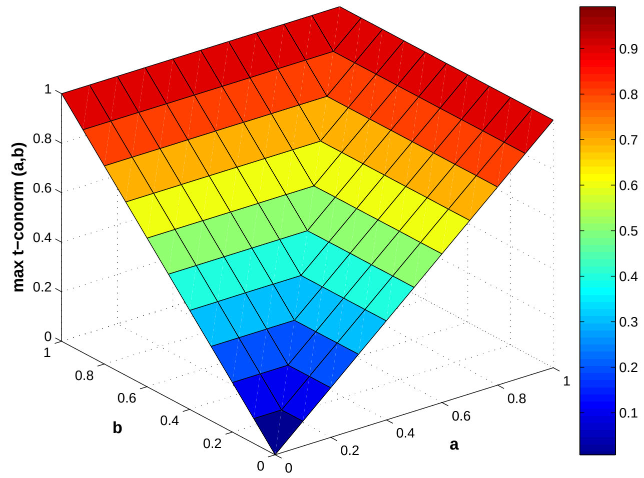

Fig. 3. Max t-conorm $s_{max}(a,b)$

Two options present themselves for aggregation, leading to the following scenarios:

- **Scenario 1 (S_1):** Aggregate the difference fuzzy sets and then compute fuzzy cardinality of the result to obtain the overall FHD (Fig. 4);
- **Scenario 2 (S_2):** Compute $m \times n$ FHDs (fuzzy cardinality of the difference fuzzy sets) and aggregate them into the overall FHD (Fig. 5).

A. Selection of t-norms and t-conorms

As already noted, a t-norm is a generalization of an AND operator. To understand the effect of this aggregation in the context of the CBIR system, consider the two scenarios, S_1, S_2 described above:

- In S_1, let $D = \{\mu_{ij}, |\ i = 1,\ldots,m; j = 1,\ldots,n\}$ be the difference fuzzy sets for two images, each partitioned with granularity $m \times n$, $P = (P_{ij})_{i=1,\ldots,m;j=1,\ldots,n}$. Then, the overall difference, obtained using a t-norm, $t(\mu_{11},\ldots,\mu_{mn})$ is the fuzzy set of difference *"along P_{11} and P_{12} and ... and P_{mn}"*. Equation (1) implies that in order for $t(\mu_{11},\ldots,\mu_{mn})$ to contribute to the overall FHD, that is, to be large enough, μ_{ij}, for all i,j must be large enough.
- Likewise, in S_2, where the problem is to aggregate FHDs, again, from (1) it follows that the overall degrees of the resulting fuzzy set will be at most equal to those being aggregated, and this will be reflected in the subsequent defuzzification step.

To summarize, when a t-norm is used for aggregation, the result is that for a color to be considered as changed from one image to another, the change must be in *all partition cells*. This is a strict aggregation which will determine a lower degree of change, which subsequently translates in a lower discrimination ability.

A similar discussion holds in connection with the use of a t-conorm operator, except that in this case, for a color to be considered as changed from one image to another, it is sufficient for the change to occur in *at least one cell* of the partition.

Aggregation operators different from t-norms/conorms fall between these and therefore in this context they do not seem useful.

V. Results

The dataset used for this study comes from University of Washington [7]. It consists of 855 jpeg images grouped into 19 categories based on what their content (e.g. *Arborgreens, Barcelona, Italy* ...). For test purpose six images are randomly chosen from different categories. The CBIR system uses a 2×2 partitioning of each image. Testing is executed in the following steps:

1) For each image the query result set is evaluated using the two scenarios, S_1 and S_2, to compute the final score (as shown in Figures 4, and 5.
2) For each scenario, evaluate the *category agreement* for the first 20 images in the result set. Category agreement shows how many images, out of 20, are in the same category with the query image. In general, for any CBIR system, the relevance of the result set varies according to the individual user. However, a measure like *category agreement* allows an objective evaluation of the result set.

The results are compared with those obtained without aggregation, with FHD_{COG} and with Euclidean distance, and are shown in Table II, which should be read as follows:

- Columns 2 and 3 display the results without aggregation, using 1×1 and 2×2 partitioning. For each image two rows are listed: first sub-row is the COG defuzzification result; the second sub-row is the result obtained with the Euclidean distance;
- The remaining columns show the results obtained using different operators. For each test image two rows are listed: first sub-row corresponds to the first scenario(S_1) described in Fig. 4; the second sub-row corresponds to scenario 2 (S_2) described in Fig. 5.

For each image the best result is highlighted in bold type. Based on these limited experiments, the following conclusions can be drawn from the Table II:

- With respect to aggregation versus no aggregation, although the results obtained with and without aggregation are different, there seem to be consistency between their magnitudes. The output images are similar in both cases.
- It can be seen that for three out of the six images tested, the best results were obtained using FHD_{COG} *and no aggregation*. For each of these images, the next best results, using aggregation were close to the best results: For image 757, best result without aggregation is 0.95, with aggregation it is 0.8, for image 626, best result without aggregation is 0.8, with aggregation 0.6, and for image 664, best with aggregation is 1, and without aggregation is 0.9.
- For the remaining three images, best results were obtained using aggregation. Although it seems that the algebraic t-norm and maximum t-conorm yield the best results, the values are too close to be concluded as significant.

It can be concluded that use of aggregation operators before deufzzification while speeding up the step of calculating similarity index does not seriously affect the output of the system. Future studies will evaluate other aggregation operators and ranking directly on fuzzy sets, avoiding defuzzification.

Acknowledgments

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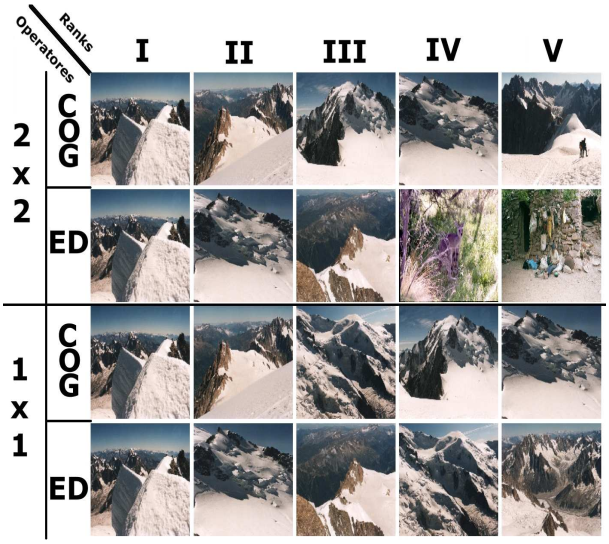

Fig. 6. Results without aggregation, using FHD and Euclidean distance (ED) for 2×2 and 1×1 partitioning.

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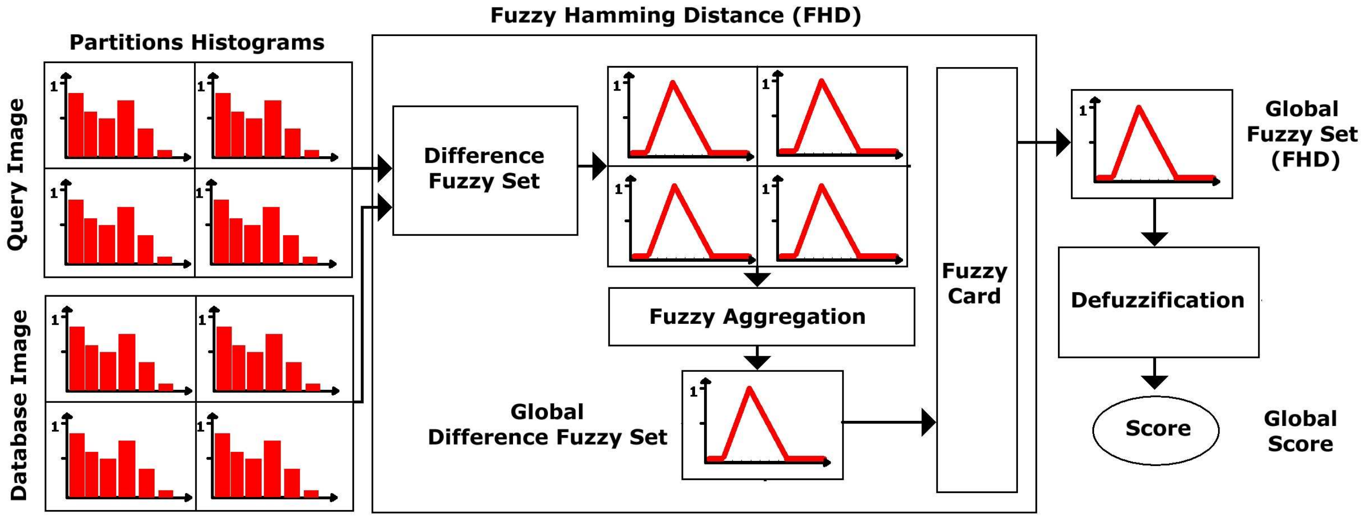

Fig. 4. Scenario 1. The aggregation is applied to the difference fuzzy sets and then FHD is computed.

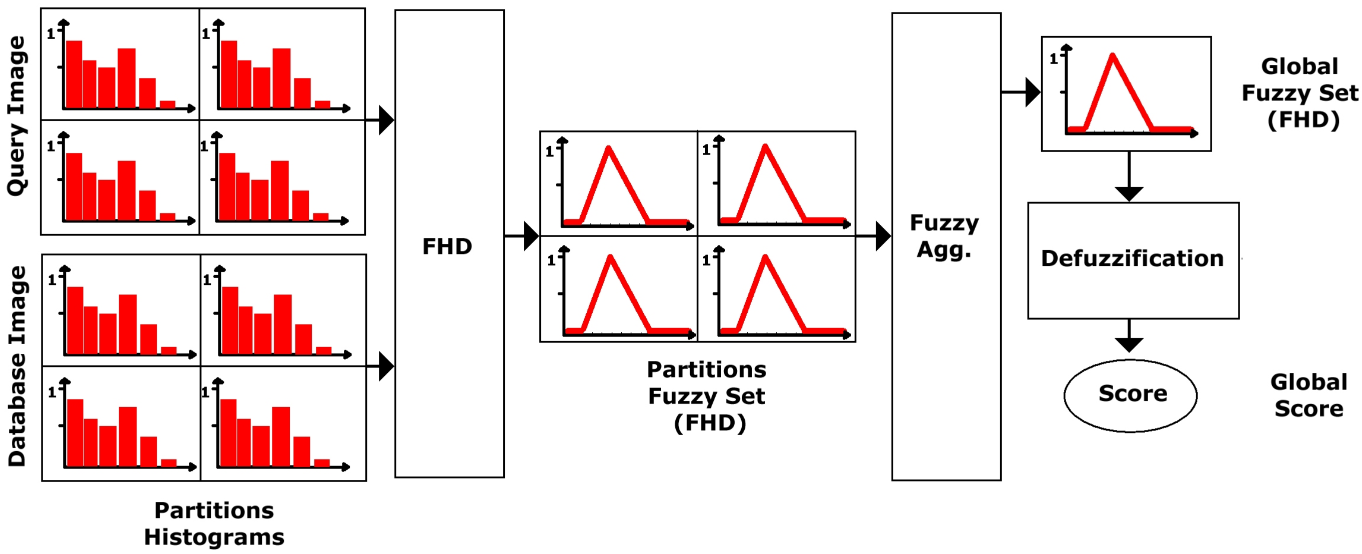

Fig. 5. Scenario 2. First evaluate FHD for each partition and then apply aggregation.

TABLE II

CATEGORY AGREEMENT OF THE RESULT SET FOR DIFFERENT AGGREGATION OPERATORS IN TWO SCENARIOS.

Img	COG/ED		Sce-narios	Aggregation operators					
	1×1	2×2		s_{max}	t_{min}	t_L	t_{alg}	s_L	s_{alg}
788	0.85	0.8	S1	**0.85**	0.25	0.8	**0.85**	0.8	**0.85**
	0.35	0.25	S2	0.55	0.6	0.2	0.15	**0.9**	0.5
757	1	**0.95**	S1	0.75	0.4	0.8	0.75	0.8	0.75
	0.7	0.7	S2	0.55	0.8	0.2	0.25	0.1	0.75
626	0.7	**0.8**	S1	0.55	0.55	0.5	0.6	0.5	0.6
	0.4	0.25	S2	0.5	0.35	0.15	0.2	0.2	0.35
816	0.15	0.25	S1	0.15	0.2	0.15	0.15	0.15	0.15
	0.45	0.2	S2	0.15	0.2	**0.35**	0.25	0.25	0.15
664	0.95	**1**	S1	0.9	0.95	0.9	0.85	0.9	0.85
	0.65	0.65	S2	0.7	0.8	0.2	0.25	0.05	0.9
627	0.3	0.3	S1	0.25	0.2	0.3	0.4	0.3	**0.4**
	0.15	0.15	S2	0.2	0.15	0.15	0.15	0.1	0.15

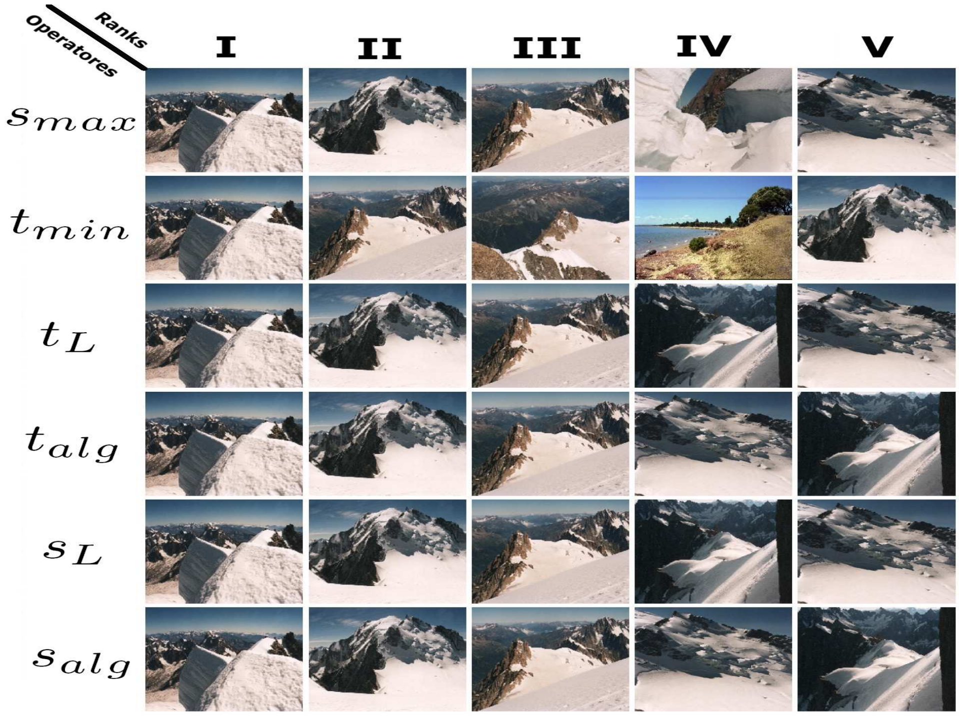

Fig. 7. Results using the aggregation operators on the difference fuzzy sets as shown in Fig. 4, for 2×2 partitioning.

Fig. 8. Results using the aggregation operators on FHD fuzzy sets as shown in Fig. 5, for 2×2 partitioning.