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A Multi-Objective Approach Based on TOPSIS to Solve the Image Segmentation Combination Problem

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Abstract—**Recently, there has been renewed interest in the fusion of image segmentation. However, previous relevant research has been impeded by the lack of an appropriate single segmentation criterion, which yields an improved final segmentation result. This paper proposes a new framework to tackle this problem. It is based on multi-objective optimization strategy, followed by a decision making technique called: technique for order performance by similarity to ideal solution (TOPSIS). This new fusion framework aims to overcome the limits caused by using a single criterion by combining and optimizing, simultaneously, two different and complementary segmentation criteria; namely, the global consistency error (GCE) (region-based criterion) and the F-measure (edge-based criterion). This new multi-criterion fusion framework is validated on the Berkeley image dataset and compared to different segmentation algorithms (with or without fusion strategy). Experiments show that the results of our new multi-objective approach improve the state of the art in terms of popular indices.**

I. Introduction

Image segmentation is a classic problem in the image processing field. In recent years, there has been a surge of interest in the combining of several different segmentations of the same textured natural image to achieve a final consensus segmentation. In this strategy, these initial segmentations may be generated by different parameter settings applied to the same algorithm or by various segmentation algorithms.

Following this combination approach, the first relevant contribution has been introduced in [1] respecting a practical constraint, which restricts the fusion step by specifying that all input segmentations (to be fused) must be composed of the same region's number. To date, other fusion segmentation approaches have been proposed without this constraint and have been formulated in the sense of different criteria, such as: the probabilistic version of the well-known Rand index [2] (PRI [3]), the evidence accumulation [5], the variation of information (VoI) [4], the precision-recall [6], the maximum-margin hyperplane (between classes) sense [7], the within-point scatter of the cluster instances [8] or the information theory criterion [9]. Another line of research is to focus on the segmentation research space, in this context, authors in [10] proposed an algorithm which builds a binary partition tree in a collaborative fashion, from different images, thus allowing the achievement of an unified hierarchical segmentation space.

Although extensive research has been carried out on segmentation fusion, all existing studies treat it with a single criterion (objective). However, the major problem with this kind of approach (mono-criterion approach) is that it can provide a limited performance (bad and eventually weak result), firstly, because the segmentation is inherently an ill-posed problem related to the large number of possible partitioning for any image, and secondly, by the fact that the optimization process can instantiate research in a specific zone (related to the defined criterion) into the search space.

To cope with these aforementioned problems, in this paper, we propose a new fusion model called the multi-objective optimization based fusion model (MOBFM). The potential aim of this model is to take advantage of the complementarity of two different objectives, namely the global consistency error (GCE) (region-based criterion) and the F-Measure (edge-based criterion). In order to optimize these criteria we use a faster search technique called iterative conditional modes (ICM), proposed by Besag [11]. To this end, we have incorporated, in the ICM-based optimization strategy the dominance concept. This strategy, allows us to find a Pareto set of solutions, *i.e.*, an ensemble of non-dominated segmentation (related to these two criteria). To select one best solution (consensus segmentation) from the generated ensemble, we resort to a useful decision making technique called the technique for order performance by similarity to ideal solution (TOPSIS).

The rest of the paper is organized as follows. In Section II, we introduce basic concepts of the multi-objective optimization. Then, we define used segmentation criteria in Section III. We present the proposed fusion model in Section IV. Experimental results are given in Section V. The paper ends with conclusions in Section VI.

II. Approaches Based Multiple Objectives

The resolution of a multi-objective problem consists of minimizing k objective functions without degradation of the optimal values obtained compared with those obtained from a mono-objective optimization, performed one by one. Following this logic, there are three general types of methods [12]. The first is a priori preference method, which aims to assign a numerical weight to each objective and then, combines multiple objectives (by adding or multiplying all the weighted criteria) into a single composite function [13]. The second is called the progressive preference method, where the user refines his choice of the compromise during the progress of the optimization. The last type is called a posteriori preference method; instead of transforming a multi-objective problem into a mono-objective problem, we define a dominance relationship, where the overarching goal is to find the best compromise between objectives. Hence, several dominance relationships have already been proposed, but the most famous and the

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most commonly used is the Pareto dominance (or the Pareto Approach [PTA]). This domination concept will be used in our study, and it is defined as follows:

Definition 1: The solution $x^{(i)} \in S$ is said to dominate another solution $x^{(j)} \in S$, denoted $x^{(i)} \prec x^{(j)}$ (in case of minimization), if and only if: $f_l(x^{(i)}) \leq f_l(x^{(j)})$ for all $l \in \{1, 2, .., k\}$ and, $f_l(x^{(i)}) < f_l(x^{(j)})$ for some $l \in \{1, 2, .., k\}$.

where S denotes the search space and $f_l(.)$ represents the l-th objective function.

III. Segmentation Fusion Criteria

A. The F-measure (precision-recall) Criterion

In information retrieval, precision is interpreted as the fraction of retrieved instances that are relevant, while recall is represented as the fraction of relevant instances that are retrieved. Similarly, in the (edge-based) image segmentation case, these two scores represent, respectively, the fraction of detections that are true boundaries and the fraction of true boundaries detected [6].

Formally, let $S_{\text{T}} = \{R^1_{\text{T}}, R^2_{\text{T}}, \dots, R^{Nb_T}_{\text{T}}\}$ & $S_{\text{M}} = \{R^1_{\text{M}}, R^2_{\text{M}}, \dots, R^{Nb_M}_{\text{M}}\}$ be, respectively, the segmentation test result to be measured and the manually segmented image with Nb_T being the number of segments or regions (R) in S_{T} and Nb_M the number of regions in S_{M}. Let now $B(R_{\text{T}})$ be the set of pixels that belongs to the boundary of the segments R_{T} in the segmentation S_{T} and let us also assume that $B(R_{\text{M}})$ is the set of pixels belonging to the boundary of the segments R_{M} in the ground truth segmentation S_{M}. The precision (Pr) and recall (Re) are then respectively defined as:

$$Pr = \frac{|B(R_{\text{T}}) \cap B(R_{\text{M}})|}{|B(R_{\text{T}})|} \quad , \quad Re = \frac{|B(R_{\text{T}}) \cap B(R_{\text{M}})|}{|B(R_{\text{M}})|} \qquad (1)$$

where $\cap$ denotes the intersection operator and $|X|$ denotes the cardinality of the set of pixel X. Thus, precision assesses the amount of noise in the output of a detector, while recall evaluates the amount of ground-truth detected. A combined measure that estimates a compromise between the precision and recall is called the F-measure and a particular application can define a new cost (denoted as α) related to these two quantities, which controls a harmony between Pr and Re [14]. Therefore, the F-measure between the segmentations S_{T} and S_{M} can be computed as:

$$F_\alpha(S_{\text{T}}, S_{\text{M}}) = \frac{Pr \times Re}{\alpha \times Re + (1-\alpha) \times Pr} \quad \text{with } \alpha \in [0,1] \qquad (2)$$

Since the F_α is in the interval of $[0, 1]$, the value of 1 proves fully similar edges (or boundaries) between two segmentations (in the opposite case, a value of 0 identifies fully dissimilar edges).

B. The Global Consistency Error Criterion

The global consistency error (GCE) criterion is derived from the so-called local refinement error (LRE) which measures the degree of refinement between two segmentations. In this sense, segmentations are considered to be consistent, since they could represent the same natural image segmented at different scales (or level of details) [15].

Formally, let n be the number of pixels within the image and let $S_{\text{T}} = \{R^1_{\text{T}}, R^2_{\text{T}} \dots, R^{Nb_T}_{\text{T}}\}$ & $S_{\text{M}} = \{R^1_{\text{M}}, R^2_{\text{M}}, \dots, R^{Nb_M}\}$ be, respectively, the segmentation test result to be measured and the manually segmented image and Nb_T being the number of segments or regions (R) in S_{T} and Nb_M the number of regions in S_{M}. Let now p_i be a particular pixel and the couple ($R^{<p_i>}_{\text{T}}$,$R^{<p_i>}_{\text{M}}$) be the two segments including this pixel (respectively in S_{T} and S_{M}). The local refinement error (LRE) can be expressed at pixel p_i as:

$$\text{LRE}(S_{\text{T}}, S_{\text{M}}, p_i) = \frac{|R^{<p_i>}_{\text{T}} \setminus R^{<p_i>}_{\text{M}}|}{|R^{<p_i>}_{\text{T}}|} \qquad (3)$$

where $\setminus$ denotes the operator of difference and $|R|$ the cardinality of the set of pixels R. Thus, a measure of 0 expresses that the pixel is practically included in the refinement area, and an error of 1 means that the two regions overlap in an inconsistent manner [16].

However, the one major drawback of this segmentation measure is that it encodes a measure of refinement in only one direction (i.e, not symmetric) [16]. To address this issue, an interesting and straightforward way is to combine the LRE at each pixel into a measure for the whole image and for each sense. The combining result is the so-called global consistency error (GCE)[1], which forces all local refinement to be in the same direction; in this case, every pixel p_i must be computed twice, once in each sense, in the following manner:

$$\text{GCE}^\star(S_{\text{T}}, S_{\text{M}}) = \frac{1}{2n}\left\{\sum_{i=1}^{n} \text{LRE}(S_{\text{T}}, S_{\text{M}}, p_i) + \sum_{i=1}^{n} \text{LRE}(S_{\text{M}}, S_{\text{T}}, p_i)\right\} \qquad (4)$$

Since the $\text{GCE}^\star$ ranges in the interval of $[0, 1]$, the value of 0 expresses a perfect match (or good correspondence) between the two segmentations to be compared (on the contrary, a value of 1 represents a maximum difference between the two segmentations).

IV. Proposed Fusion Model

A. Multi-Objective Function Based Fusion Model

These two criteria (presented in section III), namely the F-measure (edge-based) and the GCE (region-based) can be used directly as two members of a multi-objective function in a fusion segmentation model. Formally, let us suppose that we have a set of J segmentations $\{S_j\}_{j \leq J} = \{S_1, S_2, \dots, S_J\}$ (associated with a same scene) to be combined in order to obtain a final improved segmentation result, and let also S_I be a selected segmentation map belonging to the set $\{S_j\}_{j \leq J}$. Then, this multi-objective function is simultaneously maximizing the mean F-measure and minimizing the mean GCE between S_I and the set of segmentation maps $\{S_j\}_{j \leq J}$

[1]The original version of the GCE measure is defined as follows:
$\text{GCE}(S_{\text{T}}, S_{\text{M}}) = \frac{1}{n}\left\{\sum_{i=1}^{n} \text{LRE}(S_{\text{T}}, S_{\text{M}}, p_i) + \sum_{i=1}^{n} \text{LRE}(S_{\text{M}}, S_{\text{T}}, p_i)\right\}$
with this representation we can find two degenerate segmentation cases; one pixel per region and one region per image (GCE=0). In order to avoid these two problems we propose the new measure $\text{GCE}^\star$.

Fig. 1. Examples of segmentation set and final fusion results generated by our MOBFM algorithm. From top to bottom; Three first rows: K-means clustering results for the segmentation model described in Section V-A. Forth row: Input natural image from the Berkeley image database and final segmentation map (output of our fusion model).

as follows:

$$\mathrm{MOBJ}\big(S_I, \{S_j\}_{j\leq J}\big) = \begin{cases} \arg\max \overline{\mathrm{F}}_\alpha\big(S_I, \{S_j\}_{j\leq J}\big) \\ \bigcap \\ \arg\min \overline{\mathrm{GCE}}^\star\big(S_I, \{S_j\}_{j\leq J}\big) \end{cases} \tag{5}$$

with $\overline{\mathrm{X}}\ \big(S_I, \{S_j\}_{j\leq J}\big) = \frac{1}{J}\sum_{j=1}^{J} \mathrm{X}\,(S_I, S_j)$.

In order to improve the accuracy of our segmentation result, we have proposed a modification in the multi-objective function (as proposed in [6]) allowing us to penalize outliers, by weighting the importance of each segmentation of $\{S_j\}_{j\leq J}$, for the first member (F-measure criterion), by a coefficient z_j proportional to its mean F-measure $\overline{\mathrm{F}}_\alpha\big(S_I, \{S_j\}_{j\leq J}\big)$. This coefficient is defined as:

$$z_j = \frac{1}{H}\exp\left(\frac{\overline{\mathrm{F}}_\alpha\big(S_I, \{S_j\}_{j\leq J}\big)}{d}\right) \tag{6}$$

where d is a parameter controlling the decay of the weights, and H is a normalizing constant ensuring $\sum_j z_j = J$. This modification allows us to ensure the robustness of our model when facing a possible bad segmentation map belonging to $\{S_j\}_{j\leq J}$ (far away from the fused segmentation result). In addition, for the second member (GCE criterion), we have added a regularization term, allowing the incorporation of knowledge concerning the types of resulting fused segmentation, *a priori* defined as acceptable solutions. This term is defined as:

$$T_{\mathrm{Reg}}\big(S_j\big) = \left| -\sum_{k=1}^{Nb_j}\left[\frac{|R_j^k|}{n}\,\log\frac{|R_j^k|}{n}\right] - \overline{\mathcal{Q}}\right| \tag{7}$$

with $S_j = \{R_j^k\}_{k\leq Nb_j}$ and Nb_j is the number of regions in the segmentation map S_j and where $\overline{\mathcal{Q}}$ is an internal parameter of our regularization term that represents the mean entropy of the *a priori* defined acceptable segmentation solutions. Thus, if the current segmentation solution has an entropy lower than $\overline{\mathcal{Q}}$, this T_{Reg} term favors splitting. On the contrary, if the current segmentation solution has an entropy greater than $\overline{\mathcal{Q}}$, T_{Reg} favors merging. Also, we have added a parameter $\gamma = 0.01$ to allow for weighting the relative contribution of the region splitting/merging term. Finally, with these two modifications in the multi-objective function, a penalized likelihood solution of our fusion model is thus given by the resolution of this following function: $\mathrm{MOBJ}\big(S_I, \{S_j\}_{j\leq J}\big) =$

$$\begin{cases} \arg\max\Big\{\overline{\mathrm{F}}_\alpha\,(S_I, \{z_j\}, \{S_j\}_{j\leq J})\Big\} \\ \bigcap \\ \arg\min\Big\{\overline{\mathrm{GCE}}^\star\big(S_I, \{S_j\}_{j\leq J}\big) + \gamma\, T_{\mathrm{Reg}}(S_I)\Big\} \end{cases} \tag{8}$$

B. Pareto Domination-Based Optimization

In an attempt to optimize our fusion model of multiple segmentations in the bi-criteria sense (F-measure and GCE), we used the iterative conditional modes (ICM) algorithm proposed by Besag [11]. In the single objective case, the purpose of ICM is to accept a new segmentation label (for each pixel) if this one is "better" (or decrease the energy function) than the current one. Meanwhile in our case, we are facing a multi-objective problem (resulting in a complex energy function). Therefore, we have incorporated into the ICM a domination function (defined in section II); In each iteration the modified ICM practically accepts a new solution to enter the list of non-dominated solution (L_{NDS}) only if it is not dominated by any solution in the (L_{NDS}). Finally, when the maximum number of iteration (T_{max}) is achieved and all solutions have been explored, the algorithm stops in a Pareto local optimum.

The choice of ICM is motivated by its simplicity and its good performance on various energy-based models in image processing. A detailed description of each step of our improved MOBFM fusion model is shown in Algorithm 1.

C. Decision Making with TOPSIS

After generating the Pareto frontier (*i.e.*, the output of the Algorithm 1), it is necessary to select one segmentation (see Fig. 2); therefore, it is clear that we are facing a multi-criteria decision making (MCDM) problem. To solve this problem, we resort to a useful and efficient method called the technique for order performance by similarity to ideal solution (TOPSIS) [17]. The TOPSIS technique is based on the selection of the

lgorithm 1 MO-Based Fusion Model algorithm

Mathematical notation:

$\overline{\text{GCE}}^{\star}_{\gamma}$	Penalized mean GCE
$\overline{\text{F}}_{\alpha}$	Mean F-measure
$\{S_j\}_{j\leq J}$	Set of J segmentations to be fused
$\{z_j\}_{j\leq J}$	Set of weights
$\{b_j\}$	Set of superpixels $\in \{S_j\}_{j\leq J}$ [2]
$\mathcal{E}$	Set of region labels in $\{S_j\}_{j\leq J}$
L_{NDS}	List of non-dominated segmentations (Pareto set of solutions)
T_{max}	Maximal number of iterations (=11)
γ	Regularization parameter
α	F-measure compromise parameter

Input: $\{S_j\}_{j\leq J}$
Output: L_{NDS}
. Initialization:

$$\hat{S}^{[0]}_I = \arg \min_{S\in\{S_j\}_{j\leq J}} \overline{\text{GCE}}^{\star}_{\gamma}\,(S,\{S_j\}_{j\leq J})$$

B. Steepest ocal Energy Descent:

while $p < T_{\text{max}}$ **do**
  for each b_j superpixel $\in \{S_j\}_{j\leq J}$ **do**
    Draw a new label x according to the uniform distribution in the set $\mathcal{E}$
    Let $\hat{S}^{[p],\text{new}}_I$ the new segmentation map including b_j with the region label x
    Compute $\overline{\text{GCE}}^{\star}_{\gamma}\,(S_I,\{S_j\}_{j\leq J})$ on $\hat{S}^{[p],\text{new}}_I$
    Compute $\overline{\text{F}}_{\alpha}\,(S_I,\{z_j\},\{S_j\}_{j\leq J})$ on $\hat{S}^{[p],\text{new}}_I$
    if $\hat{S}^{[p],\text{new}}_I$ **dominates** $\hat{S}^{[p]}_I$ *(see Defintion 1)* **then**
      $\overline{\text{GCE}}^{\star}_{\gamma} = \overline{\text{GCE}}^{\star,\text{new}}_{\gamma}$
      $\overline{\text{F}}_{\alpha} = \overline{\text{F}}^{\text{new}}_{\alpha}$
      $\hat{S}^{[p]}_I = \hat{S}^{[p],\text{new}}_I$
      Update L_{NDS}
    else if $\hat{S}^{[p],\text{new}}_I$ **ot dominates** $\hat{S}^{[p]}_I$ and $\hat{S}^{[p]}_I$ **ot dominates** $\hat{S}^{[p],\text{new}}_I$ **then**
      Update L_{NDS}
    end if
  end for
  $p \leftarrow p+1$
end while

alternative (solution) that is the closest to the ideal solution and the farthest from the negative ideal solution (see Fig. 3). This technique has solved many real problems in the research operation field (see [18] for more examples) and one of its advantages is the simple competition process.

V. Experiments

A. Initial Tests Setup

To generate the initial segmentation set (which will be combined by our fusion framework) we resort to the useful k-means-based segmentation technique (with the Manhattan similarity distance). We have adopted this choice for two principal reasons; firstly, to ensure a reduced computational time and cost for this important step, and secondly, to achieve more variability in this initial ensemble, since the use of three different values of the number of classes K associated with two different values of bins number $NB_1 = 4^3$ and $NB_2 = 5^3$

[2]The set of superpixels $\{b_j\}$ are the regions or segments given by each individual segmentations S_j to be combined (generated by the k-means algorithm).

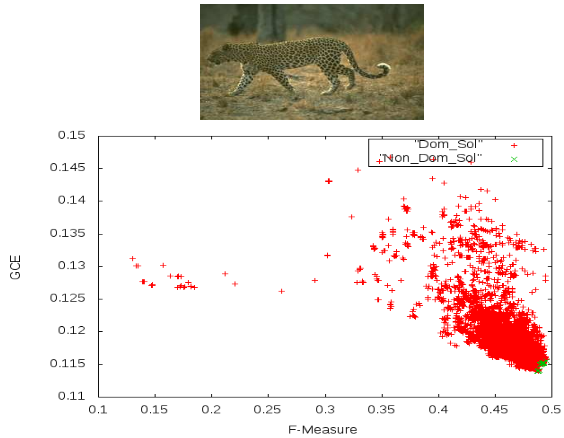

Fig. 2. First row; a natural image (n^{0}134052) from the BSDS300. Second row; the Pareto frontier generated by the MOBFM algorithm (cf, Algorithm 1).

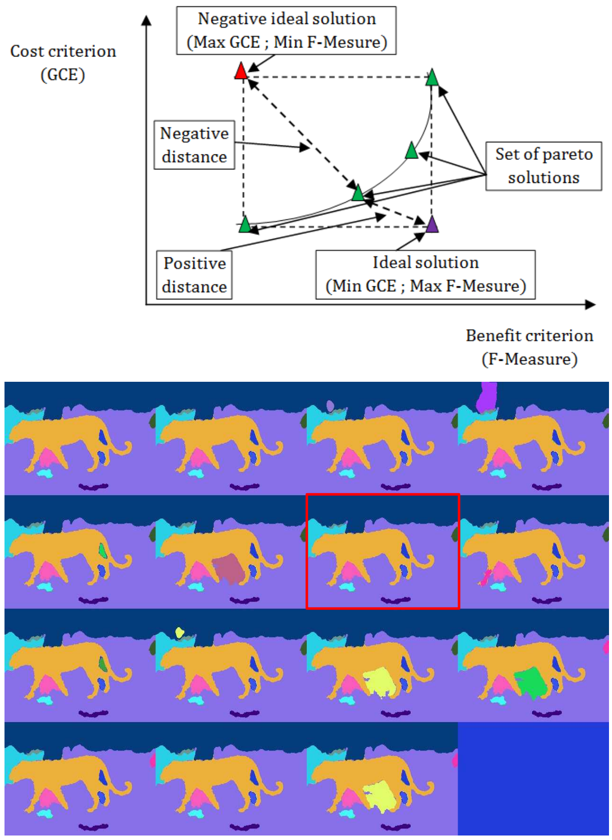

Fig. 3. From top to bottom; Graphical representation of TOPSIS method, the best solution (the segmentation marked in the red box) chosen automatically by TOPSIS among different solutions founded on the Pareto frontier (cf, Fig. 2).

for each local requantized color histogram[3], applied over 12 different color spaces, which are; YCbCr, TSL, YIQ, XYZ, h123, P1P2, HSL, LAB, RGB, HSV, i123, LUV, gives us, as a result, a total of 60 different input segmentations ($12\times[3+2]$).

TABLE I. REGION BENCHMARKS ON THE BSDS300. RESULTS FOR DIVERSE SEGMENTATION ALGORITHMS (WITH OR WITHOUT A FUSION MODEL STRATEGY). SHOWN ARE THE VoI, GCE (THE LOWER VALUE IS THE BETTER) AND THE PRI (THE HIGHER VALUE IS THE BETTER).

	BSDS300		
	VoI	GCE	PRI
-HUMANS-	1,10	0,08	0,87
-MOBFM-	**1.98**	**0,20**	**0,80**
-GCEBFM- [20]	2,10	0,19	0.80
-FMBFM- [6]	2,01	0,20	0.80
-VOIBFM- [4]	1,88	0,20	0.81
-PRIF- [3]	1,97	0,21	0.80
-FCR- [8]	2,30	0,21	0.79
-CTM- [15]	2,02	0,19	0.76
-CRKM- [21]	2,35	-	0.75
-Mean-Shift- [22] (in [15])	2,48	0,26	0.75
-FH- [23] (in [15])	2,66	0,19	0.78
-DGA-AMS- [24]	2,03	-	0.79
-LSI- [25]	-	-	0.80

Once the initial ensemble of segmentations is generated, it is necessary to study the behavior of the full algorithm with different values of its parameters. Indeed, after several (trial and error) tests where applied to the problem affecting each time new value, we have found that parameters $\overline{\mathcal{Q}}$ and α efficiently act as two regularization parameters of our model, favoring over-segmentation for α close to 0 and a high value of $\overline{\mathcal{Q}}$, and merging for value of α close to 1 and a low value of $\overline{\mathcal{Q}}$. Finally, we can note that the best result is achieved with the following values, $\overline{\mathcal{Q}} = 4,2$ and $\alpha = 0,86$.

B. BSDS300 Experiments

To provide a basis of comparison for the MOBFM model, we make use of different segmentation algorithms (with or without a fusion model strategy) evaluated on 300 color images from the Berkeley segmentation dataset (BSDS300). The BSDS serves as ground-truth for both the boundary and region quality measures, considering that human-drawn boundaries are closed and are also segmentations [19]. In terms of region performance measures, the obtained final scores are: GCE=0.20, VoI=1.98 (for which a lower value is better) and PRI=0.80 (this value means that, on average, 80 % of pairs of pixel labels are correctly labeled (on average) in the results of segmentation) on the BSDS300 (see Table I). For the boundary performance measures, our MOBFM model performs well, with an F-measure score at 0:68 (recall= 0.71, precision= 0.65) and a BDE score at 8.25 on the BSDS300 (see Table II). On average, our non-optimized code runs between 4 and 5 minutes, which is comparable to the state-of-the art existing fusion segmentation methods. Also, the algorithm can easily be parallelized, since both the generation of the different segmentation step (by K-means) and the fusion step are purely independent. These experiments confirmed the validity of our fusion procedure and illustrate also that the performance scores of the fusion model are perfectible if we combine different (and complementary) segmentation criteria in the same system. Finally, Fig 4 illustrates example results segmentation on the BSDS300.

[3]To generate the feature vector (used by k-means algorithm), we computed around each pixel to be estimated (on an overlapping squared fixed-size ($N_w = 7$) neighborhood), a local requantized color histogram.

TABLE II. BOUNDARY BENCHMARKS ON THE BSDS300. RESULTS FOR DIVERSE SEGMENTATION ALGORITHMS (WITH OR WITHOUT A FUSION MODEL STRATEGY). SHOWN ARE THE BDE MEASURE (THE LOWER VALUE IS THE BETTER) AND THE F-MEASURE (THE HIGHER VALUE IS THE BETTER).

	BSDS300	
	BDE	**F-measure**
-HUMANS-	4,99	0.79
-MOBFM-	**8,25**	**0.59**
-GCEBFM- [20]	8,73	-
-FMBFM- [6]	8,49	0,62
-VOIBFM- [4]	9,30	-
-PRIF- [3]	8,45	0.64
-FCR- [8]	8,99	0.56
-CTM- [15]	9,90	0.58
-Mean-Shift- [22] (in [15])	9,70	0.63
-FH- [23] (in [15])	9,95	0.58

VI. CONCLUSION

We have presented a new fusion model based on multi-objective optimization (MOBFM). Using two complementary (edge and region) criteria of segmentation (the F-measure and the GCE), this model aims to combine various segmentation images to provide a final improved segmentation result. To optimize our fusion model, we used a modified ICM algorithm, including a dominance function that allows us to find a set of non-dominated solutions (segmentation). Besides that, we have used an efficient technique of decision making called TOPSIS, allowing the finding of the most preferred solution from the set of non-dominated solutions. Our model was validated by different experiments on the Berkeley database, and in general, the obtained performance was improved compared to the state of the art algorithms.

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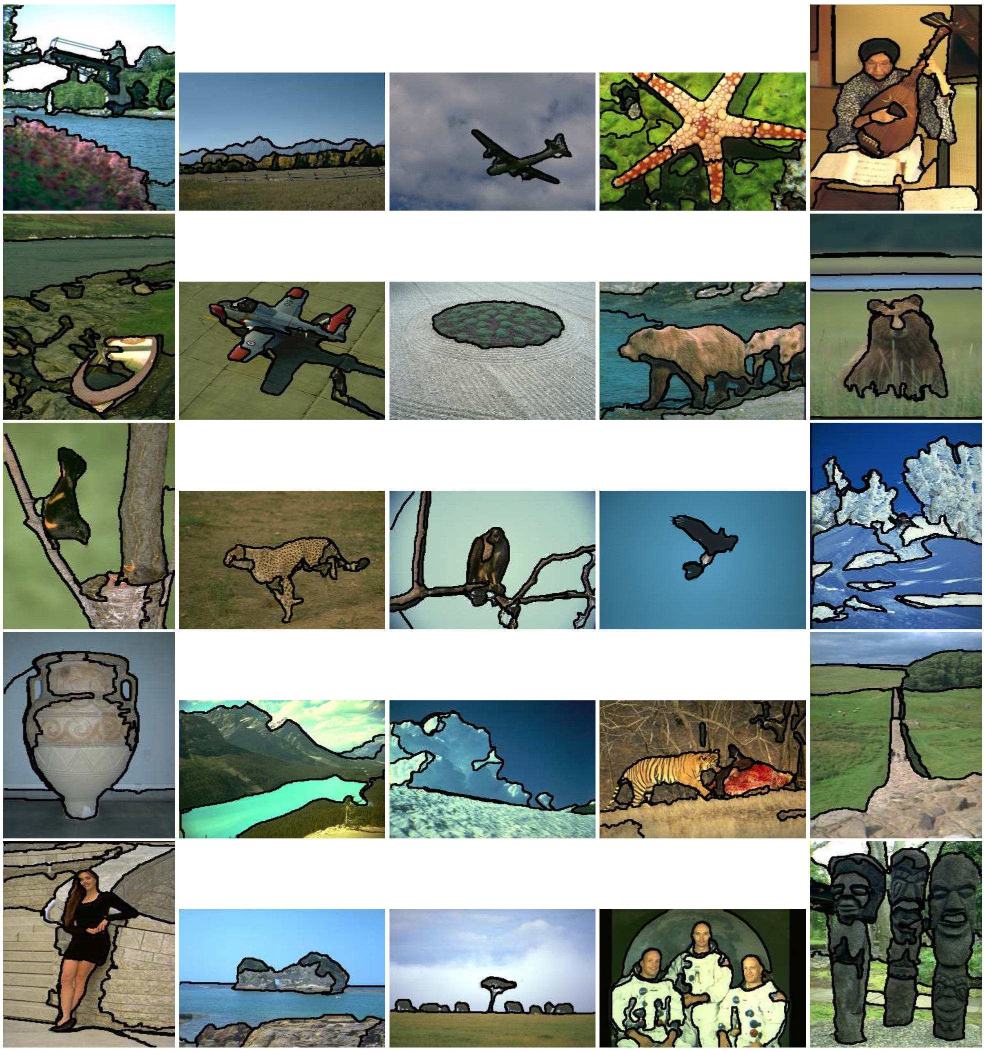

Fig. 4. Example of segmentations obtained by our algorithm MOBFM on several images of the Berkeley database.

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