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Segmentation by K-Means Clustering in Different Color Spaces.

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Abstract

This paper presents a new, simple, and efficient segmentation approach, based on a fusion procedure which aims at combining several segmentation maps associated to simple part ion models in order to finally get a more reliable and accurate segmentation result. The different label fields to be fused in our application are given by the same and simple (K-means based) clustering technique on an input image expressed in different color spaces. Our fusion strategy aims at combining these segmentation maps with a final clustering procedure using as input features, the local histogram of the class labels, previously estimated and associated to each site and for all these initial partitions. This fusion framework remains simple to implement, fast, general enough to be applied to various computer vision applications (e.g., motion detection and segmentation), and has been successfully applied on the Berkeley image database. The experiments herein reported in this paper illustrate the potential of this approach compared to the state-of-the-art segmentation methods recently proposed in the literature.

Keywords- **Berkeley image database, colour spaces, fusion of segmentations, K -means clustering, textured image segmentation**

I. INTRODUCTION

Image segmentation is a classic inverse problem which means consists of achieving a compact region-based description of the image scene by decomposing it into meaningful or spatially coherent regions sharing similar attributes. This low-level vision task is often the preliminary (and also crucial) step in many video and computer vision applications, such as image object localization or recognition, data compression, tracking, fasting image retrieval, or understanding.

Because of its simplicity and efficiency, clustering approaches were one of the first techniques used for Markov random field (MRF)-based statistical models mean-shift-based techniques graph-based. Finally region-based split and merge procedures, sometimes directly expressed by a global energy function to be optimized.

Some years of the research in segmentation have demonstrated that significant improvements on the final segmentation results may be achieved by using notably more sophisticated feature seon procedures, more elaborate clustering techniques (involving sometimes a mixture of different or non Gaussian distributions for the multidimensional texture features , taking into account prior distribution on the labels, region pro-cesses, or the number of classes , finally, involving (in the case of energy-based segmentation models) more costly optimization techniques.

The segmentation approach, proposed in this paper, is con-ceptually different and explores a new strategy; in fact, instead of considering an elaborate and *better designed* segmentation model of textured natural image, our technique rather explores the possible alternative of fusing (i.e., efficiently combining) several segmentation maps associated to simpler segmentation models in order to get a final reliable and accurate segmentation result. More precisely, this work proposes a fusion frame-work which aims at fusing several -means clustering results (herein using as simple cues the values of the requantized color histogram estimated around the pixel to be classified) applied on an input image expressed by different color spaces. These different label fields are fused together by a simple k-means clustering technique combining the several clusters in different color spaces.

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II INTIAL SEGMENTATIONS TO BE FUSED

The proposed segmentation approach is conceptually different and explores a new strategy. Instead of considering an elaborate and better designed segmentation model of textured natural image, this technique explores the possible alternative of most blending (i.e., efficiently combining)several segmentation maps associated to the simpler segmentation models in order to get a final reliable and accurate segmentation result. More precisely, this work proposes a fusion framework which aims at fusing several K-means clustering results (herein using as simple cues the values of the requantized color histogram estimated around the pixel to be classified) applied on an input image expressed by different color spaces. These different label fields are fused together by a simple K-means clustering techniques using as input features, the local histogram of the class labels, previously estimated and associated each initial clustering result. It demonstrates that the proposed blended method, while being simple andfast performs competitively and often better (in terms of visual evaluation and quantitative performance measures) than state-of-the-art recent segmentation methods.

Textured natural image segmentation is an important step in image analysis and pattern recognition techniques .it is the first step in the low level vision. segmentation is the process of portioning an natural image in to some non intersecting regions such that each region of an portioning image is homogenous.but the union of any two adjacent regions is not homogenous.in these different label field are fused together by asimple k-means clustering technique using as input features of an image, and local histogram of class labels and previously estimated labels of the image.and each associated intial clustering result and of the selected results of each clustering result and local histogram of class labels and here we use six color spaces provided by the same lables of the estimated given segmented result.

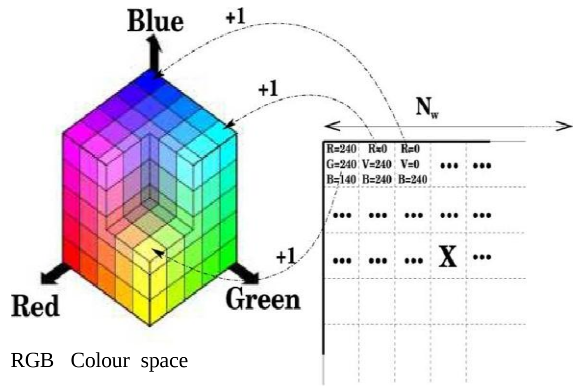

Fig. RGB Colour space

Estimation, for each pixel x, of the β = q bins descriptor in the RGB color space. The RGB color cube is first divided into β = q equal-sized smaller boxes (or *bins*). Each ζ , + , color value associated to each pixel contained in a (squared) neighborhood region (of size β 2β) entered at x, increments (←1) a particular bin. The set of bin values represents the (non-normalized) bin descriptor. We then divide all values of this β bins descriptor by (β 2β) in order to ensure that the sum of these values integrates to one.

Finally, these (125-bin) descriptors are grouped together into different clusters (corresponding to each class of the image) by the classical k-means algorithm with the classical Euclidean distance. This simple segmentation strategy of the input image into classes is repeated for different color spaces which can be viewed as different image channels provided by various sensors or captors (or as a multichannel filtering where the channels are represented by the different color spaces such as

$\mathcal{C} = \{\mathrm{RGB}, \mathrm{HSV}, \mathrm{YIQ}, \mathrm{XYZ}, \mathrm{LAB}, \mathrm{LUV}\}$

Of course, these initial segmentations to be fused can result of the same initial and simple model used on an input image filtered by another filter bank (e.g., a bank of Gabor filters or any other 2-D decomposition of the frequential space) or can also be provided by different segmentation models or different segmentation results provided by different seeds of the same stochastic segmentation model.

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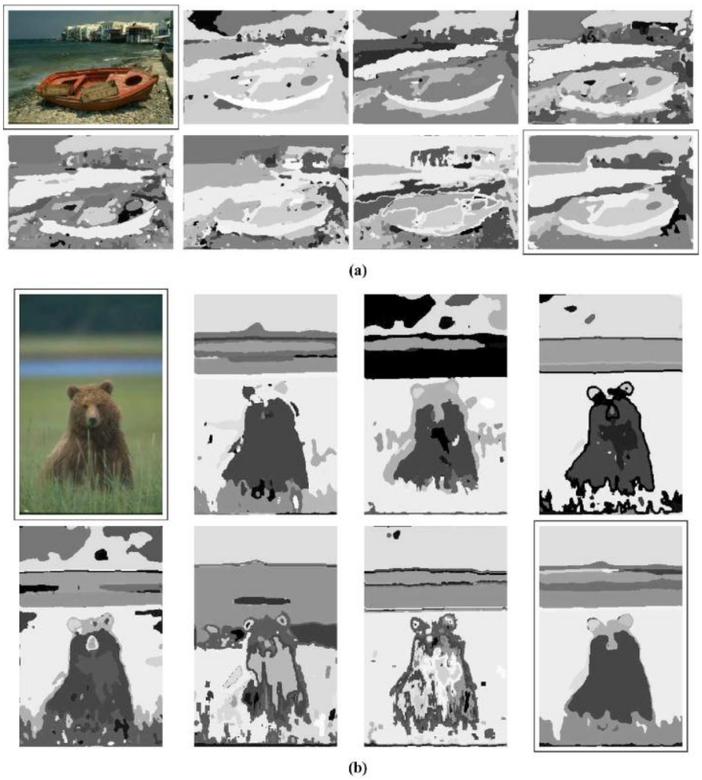

Fig 2. Examples of fusion results

From top and left to right: (top left) input bottom Natural image from the Berkeley image database. Six segmentation results (into K = 6 classes) associ ated to clustering model described on the top left in put image expressed in the RGB, HSV, YIQ, LAB, and LUV color spaces and final segmentation map (into K = 6 classes) resulting the fusion of these six clustering (bottom right) (an objective and Quantitative comparison).

III. FUSION OF SEGMENTATION MAPS

The key idea of the proposed fusion procedure simply con-sists of considering, for each site (or pixel to be classified), the local histogram of the class (or *texton*) labels of segmentation to be computed on a squared fixed-size neigh-borhood centered around the pixel, as input feature the k -bin histogram which isthen normalized to sum to one, so that it is also a probability distribution fu Sion of two pixels normally estimated by mean of k-means clustering result and we are using in the proposed k-means algorithm.

The initial segmentation maps which will be then together by k- means clustering technique by the applied on an input image expressed in different Color spaces and using image simple clues i.e Input multi dimensional feature descriptor set of values of re- quantized color histogram with equidistant binning estimated around the pixel to be classified.the local histogram is equally by re-quantized for each of three color channels in Bin descriptor computed on a square sized there Neighebourhood centered around the pixel to be Classified.

Finally, these (125-bin) descriptors are grouped together into different clusters (corresponding to each class of the image) by the classical k means algorithm with the classical Euclidean distance This simple segmentation strategy of the input image into classes is repeated for different color of course, these initial segmentations to the fused of the same and simple simple k-clustering these be provided by different segmentation models the different segmentation results is different more seeds the same stochastic segmentation by model. the intial segmentations maps which most of then together by mean of k-means clustering techniques by applied on input image by three differentcolor color spaces by square sized neighbourr hood by centered around the pixel to be classified by the means of clustering techniques and by means the Proposed k-means algorithm.

Fusion procedure is then herein simply considered as a problem of clustering local histograms of (preliminary estimated) class labels computed around and associated to each site. To this end, we use, once again, a k -means clustering procedure exploiting, for this fusion step, a histogram-based similarity measure de-rived from the Bhattacharya similarity coefficient. Given a nor-malised histogram of an image by normalised histogram the these two histograms is defined as

$$D_{\mathcal{B}}[h^{\star}, h(\mathbf{x})] = \left(1 - \sum_{n=0}^{N_b-1} \sqrt{h^{\star}(n)h(n;\mathbf{x})}\right)^{1/2}$$

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The pre estimated label fields to be fused (see Section II), along with the fusion procedure can be viewed (and qualitatively explained) as a two-step hierarchical segmentation procedure in which, first, a texton segmentation map (in each color space) is estimated and, second, a final clustering, taking into account this mixture of textons (expressed in the set of color space), is then used for a final clustering. We recall that a texton, in our framework, $\mathcal{C}$ is defined by a nonparametric mixture of colors (see Section II).

Fig.2 shows an example of k-means clustering segmentation model presented in Section II (into classes) of an input image expressed in the RGB, $K_2 = 6$ HSV, YIQ, XYZ, LAB, and LUV N_s color spaces by tice that none of them can be considered as reliable except the final segmentation result (at bottom right) which visually identify quite faithfully the different objects of the scene.

A final merging step is necessary and is used to avoid over-segmentation for some images.It must consists of fusing each region (i.e., set of connected pixels belonging to the same class) of the resulting segmentation map with one of its neighboring close region if the distance is below a given threshold (or if its size is belong image of the nearby region of $\mathcal{D}_{\text{MERGING}}$ distance sense)

$$\mathcal{D}_{\text{MERGING}} = \min_{\in\mathcal{R}} \left\{ \sum_{\mathcal{C}} D_{\mathcal{B}}[h^{\circ}(n), h^{\ddagger}(n;\mathbf{x})] \right\}.$$

IV.E XPERIMENTAL RESULTS

A. Set UP

In all the experiments, we have considered our fusion methods on initial segmentations obtained with the following parameters: the size of then $N_b =$ 7x7 squared window, used to compute the image w local histogram for the initial segmentations or the on $N_s = 6$ segmentations in the given image.

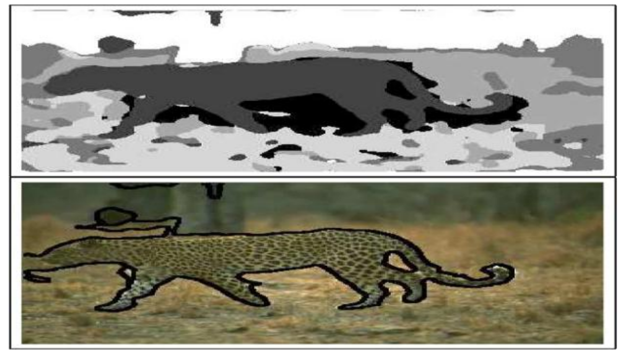

Fig 3. Example of final merging step using the Bhattacharya distance on different color spaces as merging criterion on a fused segmented image of the Berkeley database.

spaces RGB, HSV, YIQ, XYZ, LAB, and LUV. Several quan-titative performance measures will be given for several values (comprised between 6 and 13) of and , respectively, the number of classes of the segmentation to be fused and the resulting number of classes of the final fused segmentation map. The optimal value of K_1 seems to K_2 be comprised between 0.10 and 0.15.

B. Comparison With State-of-the-Art Methods

We have replicated the scenario used in the evaluation of state-of-the-art segmentation methods described .In these experiments, we have to test our segmentation algorithm on the Berkeley segmentation database consisting of 300 color images of size 481 321. For each color image, a set of benchmark segmentation results, provided by human observers (between 4 and 7), is available and will be used to quantify the reliability of the proposed segmentation algorithm. As propose we have compared our segmentation algorithm (called FCR for fusion of clustering results) against four unsupervised algorithms, available publicly. Suggested by the authors.These algorithms are namely by the segmentation algorithm by means of k= 20 segmentations in the given image results

As, all colour images are normalized to have the longest side equals to 320 pixels (in this paper, this operation was done by the Linux command *convert* which is a member of the ImageMagick suite of tools). The comparison is based on the following performance measures, namely a probabilistic measure called PRI (higher probability is better) and three metrics VoI, GCE, and BDE (lower distance is better). The qualitative meaning of these performance measures are recalled as follows.

1) The Rand index counts the fraction of pairs of pixels whose labellings are consistent between the computed segmentation and the ground truth. This quantitative measure is easily extended to the probabilistic Rand index (PRI) by averaging the result across all human segmentations of a given image.
2) Contrary to the PRI, based on pairwise relationships, the variation of information (VoI) metric is based on relationship between a point and its cluster. It uses mutual in-formation metric and entropy to approximate the distance between two clusterings across the lattice of possible clusterings. More precisely, it measures the amount of information that is lost or gained in changing from one clustering to another (and, thus, can be viewed as representing the amount of randomness in one segmentation which cannot be explained by the other).
3) The global consistency measure (GCE) measures the extent to which one segmentation map can be viewed as a refinement of another segmentation. For a perfect match (in this metric sense), every region in one of the segmentations must be identical to, or a refinement (i.e., a subset) of, a region in the other segmentation. Segmentation which are related in this manner are considered to be consistent, since they could represent the same natural image segmented at different levels of detail (as the segmented images pro-duced by several human observers for which a finer level of detail will merge in such a way that they yield the larger regions proposed by a different observer at a coarser level).
4) The boundary displacement error (BDE) measures the average displacement error.

As noticed in, PRI seems to be more highly correlated with human hand segmentations. Let us also mention that a inherent problem with the GCE measure is that it does not penalize oversegmentation at all (the highest score is given by assigning each pixel to an individual region). Some of these interesting performance measures thus have degenerate cases (i.e., unrealistic bad segmentations give abnormally high score), these complementary measures have thus to be considered.

TABLE-I
PERFORMANCE MEASURES FOR, RESPECTIVELY, THE CLUSTERING RESULT EXPRESSED IN EACH COLOR

	PERFORMANCE MEASURES			
	PRI	VoI	GCE	BDE
HUMANS	0.8754	1.1040	0.0797	4.994
Image (a)				
RGB	0.80510	2.8997	0.36994	**5.5826**
HSV	0.79946	2.8670	0.42518	5.8838
YIQ	0.87188	2.9994	**0.23586**	5.6613
XYZ	0.80458	3.3829	0.37047	5.9814
LAB	0.87949	2.9628	0.25179	6.1200
LUV	0.82565	3.2305	0.39333	5.9997
FUSION	**0.88711**	**2.3962**	0.26709	5.6369
Image (b)				
RGB	0.80910	2.1282	0.17975	**9.3065**
HSV	0.79055	2.2627	0.26257	11.1331
YIQ	0.80683	2.0082	0.25385	11.5585
XYZ	0.79904	2.4031	0.16182	9.8310
LAB	0.74751	3.0254	0.33568	10.8777
LUV	0.80549	2.4849	0.22742	9.3800
FUSION	**0.83375**	**1.6808**	**0.13678**	10.2006
			1 2	

TABLE-II
AVERAGE PERFORMANCE OF OUR ALGORITHM FOR SEVERAL VALUES OF ITS INTERNAL PARAMETERS

	PERFORMANCE MEASURES			
ALGORITHMS	PRI [19]	VoI [20]	GCE [21]	BDE [22]
Humans	0.8754	1.1040	0.0797	4.994
$\mathrm{FCR}_{[K_1=13 \mid K_2=6 \mid \kappa=0.135]}$	**0.7882**	2.3035	0.2114	8.9951
$\mathrm{FCR}_{[K_1=6 \mid K_2=6 \mid \kappa=0.130]}$	0.7842	2.3925	0.2169	9.2463
$\mathrm{FCR}_{[K_1=13 \mid K_2=13 \mid \kappa=0.145]}$	0.7849	2.5494	**0.1752**	**8.7754**
$\mathrm{FCR}_{[K_1=9 \mid K_2=6 \mid \kappa=0.140]}$	0.7835	2.2990	0.2157	9.2627
$\mathrm{FCR}_{[K_1=12 \mid K_2=4 \mid \kappa=0.125]}$	0.7789	2.2071	0.2405	9.5758
$\mathrm{CTM}_{\eta=0.1}$ [23][24]	0.7561	2.4640	0.1767	9.4211
$\mathrm{CTM}_{\eta=0.2}$ [23][24]	0.7617	**2.0236**	0.1877	9.8962
Mean-Shift [5]	0.7550	2.477	0.2598	9.7001
NCuts [6]	0.7229	2.9329	0.2182	9.6038
FH [7]	0.7841	2.6647	0.1895	9.9497

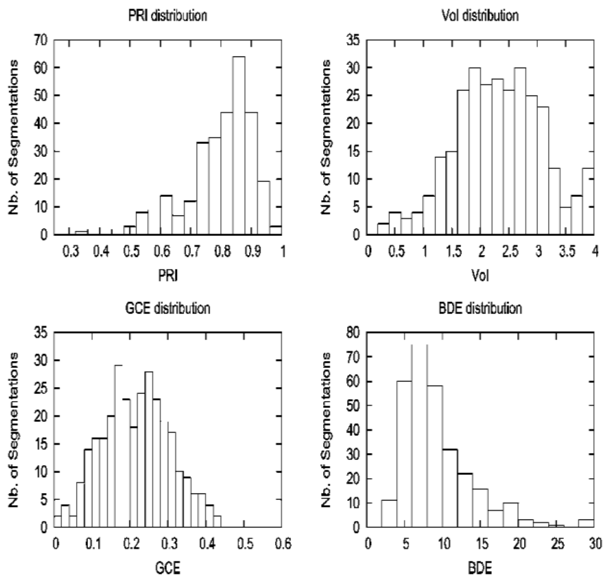

Fig.4. Distribution of the difference performance measures, respectively from top to bottom; PRI, VoI, GCE, BDE over the 300 images.

TABLE III
INFLUENCE OF THE DISTANCE CHOICE USED IN THE FINAL FUSION PROCEDURE (AVERAGE PERFORMANCE ON THE BERKELEY IMAGE DATABASE)

$FCR_{[K_1=12 \mid K_2=4 \mid \kappa=0]}$ DISTANCES	PERFORMANCE MEASURES PRI	VoI	GCE	BDE
Bhattacharya	0.7613	**2.440**	0.2424	**10.167**
Euclidean	0.7228	2.599	0.2702	11.562
Manhattan	**0.7620**	2.468	**0.2422**	10.197
Chord	0.7604	2.441	0.242	10.207
Kolmogorov	0.7388	2.665	0.2619	11.044
Histogram intersect.	0.7619	2.471	0.2423	10.225
Kullback	0.7508	2.535	0.2504	10.533
Shannon-Jensen	0.6966	3.058	0.3037	11.543

TABLE IV

INFLUENCE OF THE SIZE OF THE WINDOW β USED TO ESTIMATE THE LOCAL HISTOGRAMS.

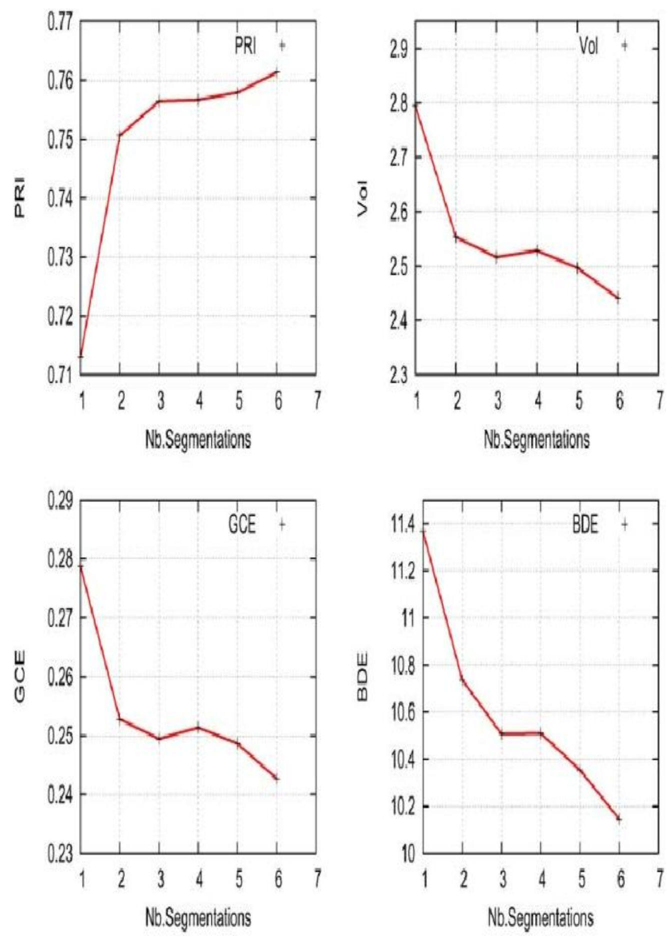

Fig. 5. Evolution of the PRI, VoI, GCE , and BDE measures as a function of the number of segmentations (β) to be fused for the 0Cζ .

algorithm. For β = 1, i.e., without fusion, the segmentation model is the one described in Section II with K = K = ♀.

We have also quantified in Table IV the influence of the size of the window (used estimate the image indices,only the CTM algorithm performs equivalently or better and for the GCE measure, our algorithm gives, on average, similar results thanothers and outperforms them all for a set of parameters (in which is high, leading to a classical over segmentation).

We can also notice (see Fig. 5) that all the performance measures are all the more better than (number of segmentation to be fused) is high. This experiment shows the validity of our fusion procedure and also the performance measures obtained by the simple segmentation model presented in Section II.

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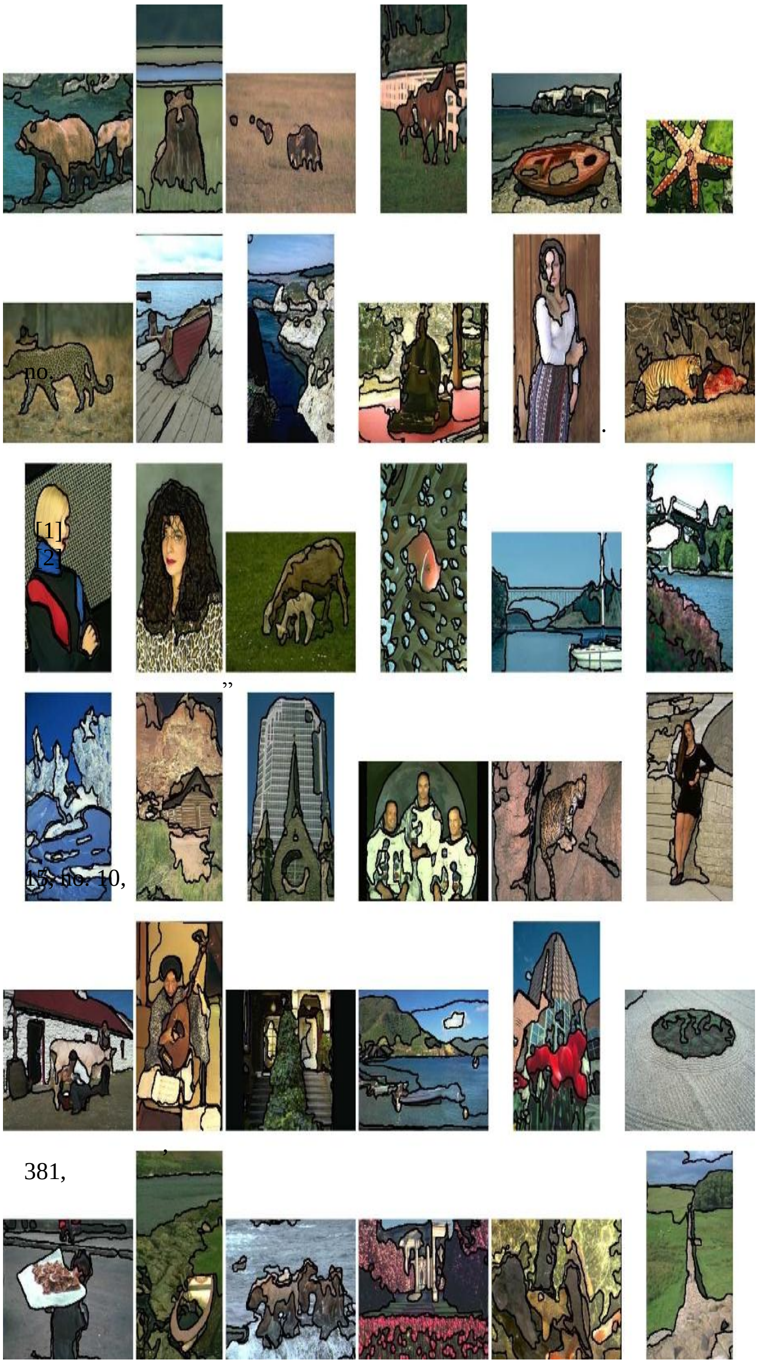

FIG 6 . Example of segmentations obtained by the algorithm on 24 images of the Berkeley image database (see Table I and Fig. 4 for quantitative performance measures.

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