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New Fast Fuzzy Method for Query Region Extraction in Color Images

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Abstract— **Finding the region similar to a given query region has many applications in computer vision and computer graphics. The first step towards an efficient query region extraction is to have a proper likelihood measure. This issue has been neglected in the computer vision community and the researchers commonly use the Euclidean distance for query region extraction in some standard color spaces. In this paper, we analyze the performance of the Euclidean distance in 12 standard color spaces, each one examined in 7 distinct possible representations. Also, we investigate the Mahalanobis distance and the linear partial reconstruction error (LPRE). Here, a new query region extraction method is proposed and its repeatability, robustness, and time efficiency are investigated. Also, the effects of the used parameters are comprehensively analyzed.**

I. Introduction

Query region extraction is the process of finding the region similar to a given query region in an image [1]. The similarity is defined in terms of color, texture, and the forth. Query region extraction is used in many computer vision applications like image and video segmentation [2], face detection [3], [4], [5], [6], [7], region–based coding [8], and so on. Also, it is used in computer graphics applications such as alpha–estimation [9], [10], [11], [12], colorizing gray–scale images [13], [14], [15], and recoloring color images [16], [17].

There exists many *crisp* approaches to color region extraction with more or less satisfactory results (*e.g.*, see [18], [19], [20], [21], [22]). But it is proved that, the fuzzy approach is more capable of facing the tolerances and characteristics of image segmentation [23]. Thus, here we focus on the fuzzy approach to the query region extraction problem. There are a few available works about fuzzy region extraction [24], [25], [26], [1], which they all use histogram dissimilarity measures in a very expensive window sliding framework.

Color is one of the most important properties; which humans use for object discrimination. In other words, it is a component which adds a new dimension to machine vision, and has been overlooked in the past [27]. Although, the performance of the color features is generally accepted in the computer vision community, little attention has been spent on the proper choice of the likelihood measures in this field. In fact, researchers commonly use the simple Euclidean distance–based likelihood measures, combined with some further processes to compensate the ill results [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37]. Also, no agreement exists for the proper choice of the standard color spaces. For example, in [33] the authors use Euclidean–based fuzzy rules in HCI, in [32] the authors use the Euclidean distance in $CIE-La^*b^*$, and in [27] the authors use a *Kohonen self–organized feature map* (SOFM) based on the Euclidean distance between color components in RGB. Also, there exists many methods that neglect the correlation among color components and work on them independently. The results are then fused to produce the final extraction(*e.g.*, see [38]). Note that, the above mentioned works are only few examples of the vast available literature.

A recent work [39] considers the effects of color space selection on the skin detection performance, reporting that none of the eight color spaces of: *normalized RGB* ($NRGB$), $CIE-XYZ$, $CIE-La^*b^*$, HSI, *spherical coordinate transform* (SCT), YC_bC_r, YIQ, and YUV perform significantly better than others. In [40], the authors compared the twelve standard color spaces of RGB, $CMYK$, HSI, $I_1I_2I_3$, $CIE-La^*b^*$, $CIE-L^*H^oC^*$, $CIE-Lu^*v^*$, $CIE-XYZ$, YC_bC_r, YIQ, and YUV, according to the results of spotting colors, (in an image containing eight different objects with different colors). Also, taking advantages of the *principle component analysis*(PCA), a new adaptive color descriptor is proposed, which performs more accurately and more stable, when compared to the standard color spaces under investigation [40]. It is proved that, the *linear partial reconstruction error* (LPRE) results in a proper likelihood measure for processing natural color images [40]. The comparison of the LPRE with the conventional Euclidean and Mahalanobis distances [41], has proved its superiority, (both in terms of likelihood measurement and homogeneity decision) [42]. In fact, The Euclidean and the Mahalanobis distances are leading to spurious likelihood and homogeneity decisions in color fields [42]. In this paper, we use the Euclidean distance in the 12 standard color spaces of RGB, $HMMD$ [43], HSI [44], HSV [45], $I_1I_2I_3$ [46], $CIE-XYZ$ [47], $CIE-Lu^*v^*$ [47], $CIE-La^*b^*$ [47], $CIE-L^*H^oC^*$ [47], YC_bC_r [48], YIQ [49], and YUV [50].

In this paper, we use the LPRE distance to propose a new fast region extraction method using fuzzy concepts. The method is designed for applications like the content–based image retrieval which need ultra–fast tools. Also, in this paper we examine the standard color spaces and their applicability for the same purpose.

The rest of this paper is organized as follows: Section III-A introduces the proposed single region extraction method which uses the information extracted from a given region to find the similar regions in the image. Section IV states the experimental results and discussions, and finally, Section V concludes the paper.

II. LIKELIHOOD MEASURES

The Euclidean distance is the most generally used likelihood measure, defined as:

$$\tau_r^E(\vec{c}) = \sqrt{(\vec{c}-\vec{\eta}_r)^T(\vec{c}-\vec{\eta}_r)}, \tag{1}$$

where $\vec{c}$ is the vector that we intend to measure its distance to the cluster r, $\vec{x}^T$ denotes the transpose operations, and $\vec{\eta}_r$ is the expectation values of the color vectors of r defined as $E_{\vec{c}\in r}\{\vec{c}\}$.

The Mahalanobis distance is another well–known likelihood measure, defining the membership of $\vec{c}$ to the cluster r as:

$$\tau_r^M(\vec{c}) = \sqrt{(\vec{c}-\vec{\eta}_r)^T\Sigma_r^{-1}(\vec{c}-\vec{\eta}_r)}, \tag{2}$$

where, Σ_r denotes the covariance matrix of the color vectors of cluster r defined as:

$$\Sigma_r = E_{\vec{c}\in r}\{(\vec{c}-\vec{\eta}_r)(\vec{c}-\vec{\eta}_r)^T\}. \tag{3}$$

In [40], the authors proposed to use the error made by neglecting the two least important principal components, (the second and the third), as a likelihood measure. such that, the distance of the vector $\vec{c}$ to the cluster r is defined as:

$$\tau_r^R(\vec{c}) = \|\vec{v}_r^T(\vec{c}-\vec{\eta}_r)\vec{v}_r - (\vec{c}-\vec{\eta}_r)\|, \tag{4}$$

where $\vec{v}_r$ shows the direction of the first principal component and $\|\vec{x}\|$ denotes the normalized L_1 norm.

$$\|\vec{x}\| = \frac{1}{d}\sum_{i=1}^{d}|x_i|. \tag{5}$$

Investigating (1), (2), and (4) shows that, to make $e_r^\star(\vec{c})$ comparable over different regions, a normalization scheme is crucial. In [40] the authors proposed to use the following stochastic margin as the normalization factor:

$$\|f\|_{r,p} = arg_e\Big\{P_{\vec{x}\in r}\{f(\vec{x}) \le e\} \ge p\Big\}, \tag{6}$$

where, p is the inclusion percentage and $P_{\vec{x}\in r}\{f(\vec{x}) \le e\}$ denotes the probability of x being less than or equal to e. Equation (6) leads to the definition of the normalized likelihood measures:

$$\bar{\tau}_{r,p}^\star(\vec{c}) = \frac{\tau_r^\star(\vec{c})}{\|\tau_r^\star\|_{r,p}}, \tag{7}$$

where $\tau_{r,p}^\star(\vec{c})$ is one of the above mentioned measures of $\tau_{r,p}^E(\vec{c})$, $\tau_{r,p}^M(\vec{c})$, and $\tau_{r,p}^R(\vec{c})$. Also, $\|\tau_r^\star\|_{r,p}$ is used as the homogeneity criteria. Note that, the Euclidean likelihood measure is applicable in any of the standard color spaces discussed in Section I.

III. PROPOSED ALGORITHM

A. *Query Region extraction*

Assume the image I and query region r (within I). The goal is to find the binary image M containing one connected component with smooth edges and few holes. The mask image is desired to highlight a *maximal* homogenous region in I, containing large portion of the query region.

Assume that, we have deliberately selected one of the normalized likelihood measures discussed in Section II. As shown in Figure 1, using the query region and the likelihood function, $\bar{\tau}_{r,p}^\star$, the given image is first converted to a likelihood map showing the likelihood of each pixel to the query region r. Here, the parameter p rules the margins of the resulting segment. In fact, p controls the inclusion of the outliers in the color scheme, yielding a limit on the margins of the selected color mood. To incorporate the spatial information into the likelihood map, it is then fed into a conventional low–pass filter to result in a smooth segment. To avoid the time consuming *Fourier* domain operations, we propose to use spatial domain averaging using a disk with radius ρ. Holding the points with values of the filtered likelihood lower than unity and rejecting others, a binary map is obtained. This map has smooth edges, because of the used spatial filtering process. Also, it contains no holes with radius lower than ρ, because such holes are filled by the filtering process. As described above, the mask should contain only one connected component, thus, the produced map is decomposed into its connected components and the one correlating more with the query region, is selected.

Assume that, for the given query region, r, we have manually computed the desired mask, call it $M_\circ$. Also, assume that a query region extraction process has resulted in M. We propose two measures to investigate the performance of such methods. These two measures compare M and $M_\circ$ in terms of *recall* and *precision*, denoted by μ_r and μ_p, respectively.

$$\mu_r = \frac{\|M\cap M_\circ\|}{\|M_\circ\|}, \tag{8}$$

$$\mu_p = \frac{\|M\cap M_\circ\|}{\|M\|}, \tag{9}$$

where, $\|A\|$ is the cardinality of the set A defined as the number of its members, (here interpreted as its area). While, μ_r computes the intersection between M and $M_\circ$, evaluating the desired area highlighted by the method, μ_p focuses on the amount of outlier points. Thus, a query region extraction method is desirable if it results in $\mu_r \simeq 1$ and $\mu_p \simeq 1$. Note that, the above defined measures are both in the range of $[0,1]$.

IV. EXPERIMENTAL RESULTS

The proposed algorithms were developed in *MATLAB* 6.5 using the Image Processing Toolbox 3.2 on a PIV 2800MHz personal computer with 256MB of RAM. The data set used for the tests is a set of 25 color images with spatial resolution of 512×512 pixels, in *jpeg* format. Three of the samples are the standard images of *Peppers*, *Lena*, and *Mandrill*, and

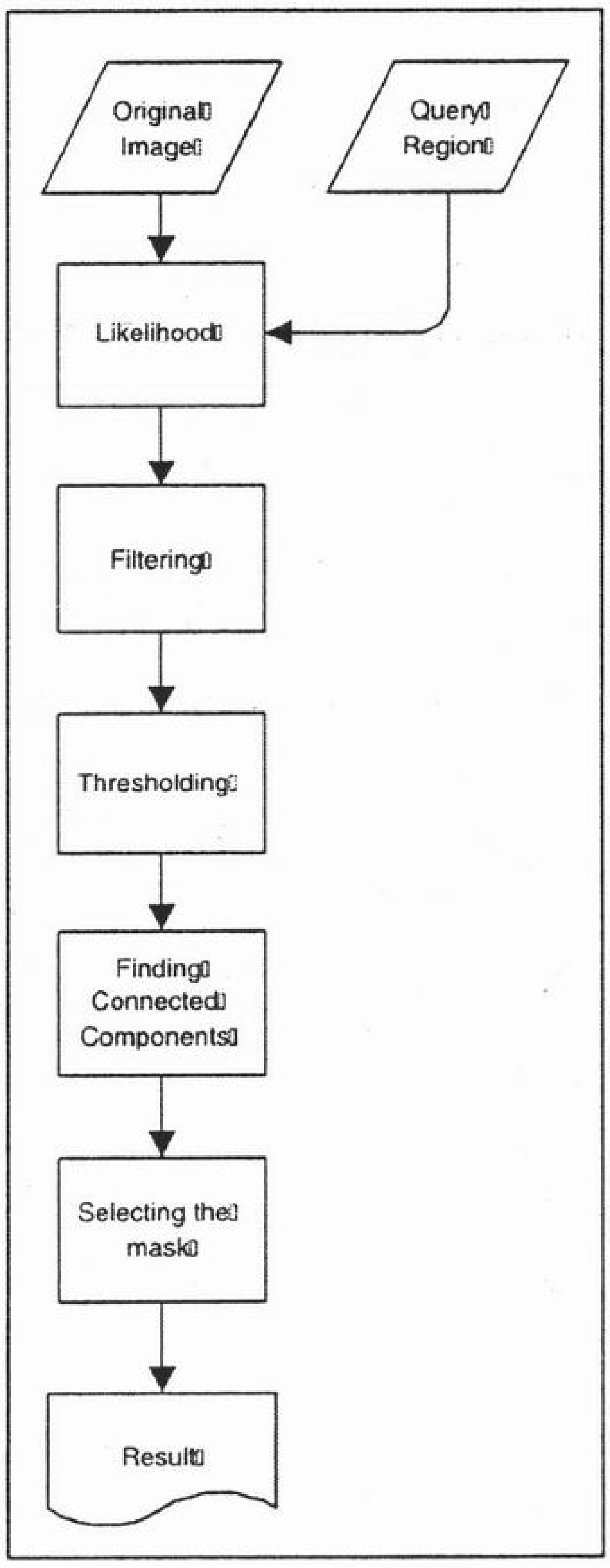

Fig. 1. Flowchart of the proposed query region extraction.

the others are taken by an *A60 Canon* digital camera.Figure 2 shows the sample images collocated with the corresponding query regions.

The desired result of query segmenting each sample image using the corresponding query regions, is simulated manually (see Figure 3). These results are used as the ground truths. Note that to give a better printing result, the backgrounds are shown in white, while for the points in the mask, the corresponding pixels in the original image are used.

For each sample image, the proposed query region extraction is performed $12 \times 7 + 2 = 86$ times. This number comes from 7 Euclidean distances corresponding to the 7 representations of each of the 12 standard color spaces plus the Mahalanobis and the LPRE distances. The 7 representations of a color space, when used in RGB, result in spaces made by R, G, B, RG, GB, BR, and RGB, as an example. In each representation, only the selected components are used in measuring the Euclidean distance. This is in contrast with the LPRE and Mahalanobis distances, which are only computed in 3–D spaces.

Note that, the only parameters of the proposed query region extraction, are the radius ρ and the inclusion percentage p.

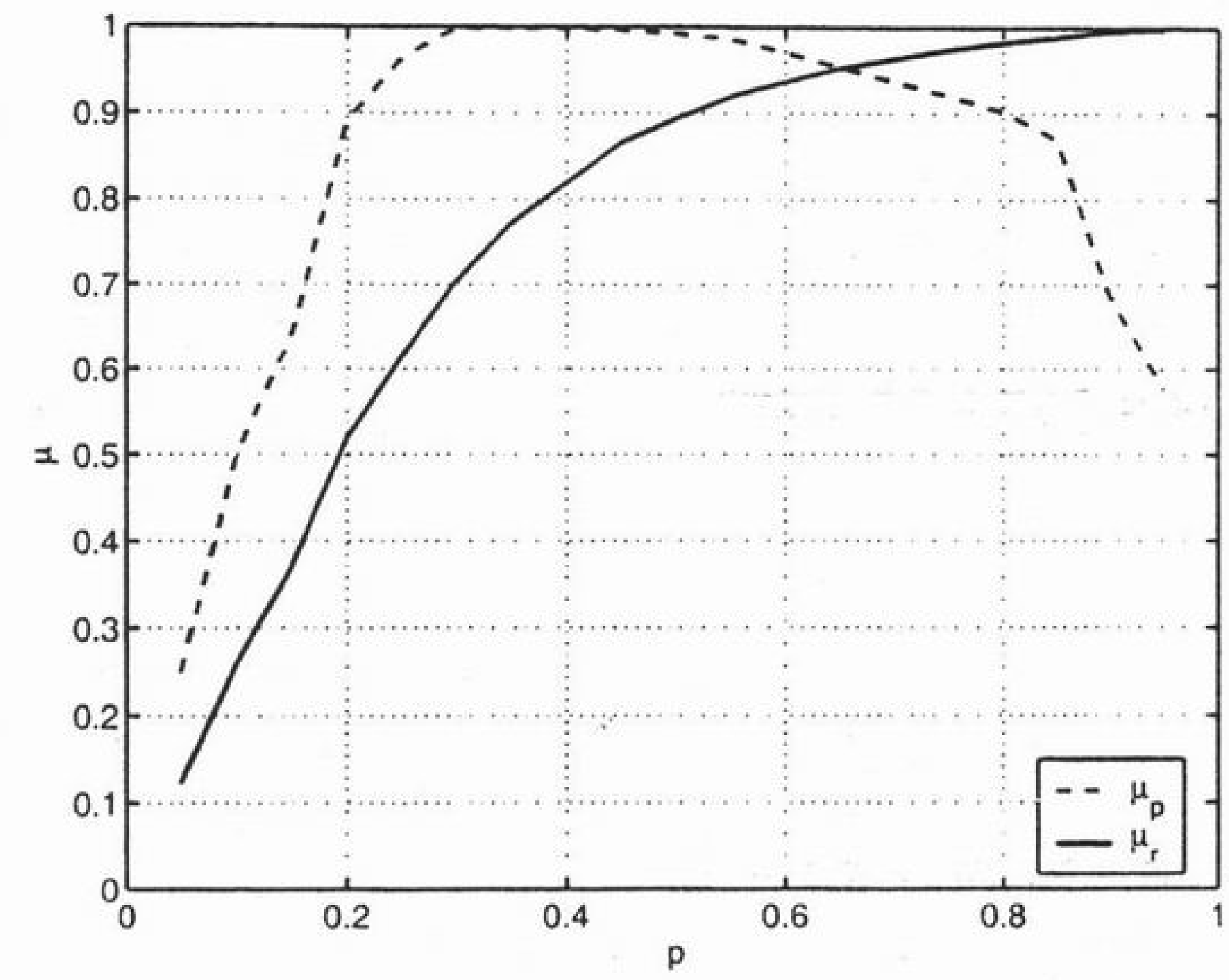

Fig. 4. Average precision and recall rates of the proposed query region extraction method using LPRE, with varying p.

While ρ controls the spatial smoothness of the resulting mask, p serves as a margin influencing the result massively. Thus, in this stage, ρ is set constantly equal to 5. Also, p is set to 0.75 and the $86 \times 25 = 2150$ query region extraction tasks are performed and the corresponding values of μ_r and μ_p are computed. Table I shows the results on different images. Selecting those likelihood measures with both recall and precision rates of more than 0.7, the only choice is LPRE. Note the promising results of the LPRE, compared to all others, even to the Mahalanobis distance. The same results are observed for different values of p. Thus, it is clear that LPRE is the best available solution for query region extraction. In the rest of this paper, the LPRE is used.

Another test was performed to check the effects of p on μ_r and μ_p. All samples images were analyzed by the proposed query region extraction, while setting $\rho = 5$ with varying values of p in the interval $[0.05, 0.95]$. Figure 4 shows the average recall and precision rates. As expected, the recall rate grows as p converges to the unity. Also, the precision grows and then declines by increasing p, because in the first phase we are adding relevant points and in the second phase we are adding irrelevant ones to the color mood. Note that, the midway, $p = 0.5$, is a good compromise between μ_r and μ_p, resulting in μ_r of about 0.9 and μ_p of more than 0.98.

It worths to mention that, the average elapsed time is 530ms with the standard deviation of 49ms with no explicit dependency to p. Figure 5 shows the same measures while setting $p = 0.5$ constantly and varying ρ. Figure 6 shows the corresponding elapsed times. As Figure 5 shows, the precision is not changing with ρ significantly. One decade increase in ρ, produces a 0.1 declines in the recall rate. The effect of ρ on recall rate, relates to the over–smoothed edges. Figure 6 shows that the elapsed time relates quadratically to ρ, because of the increased computing demands of the averaging convolution kernel. In all cases the average elapsed time is less than 800ms.

Figures 7 illustrate the visual results of changing p and ρ.

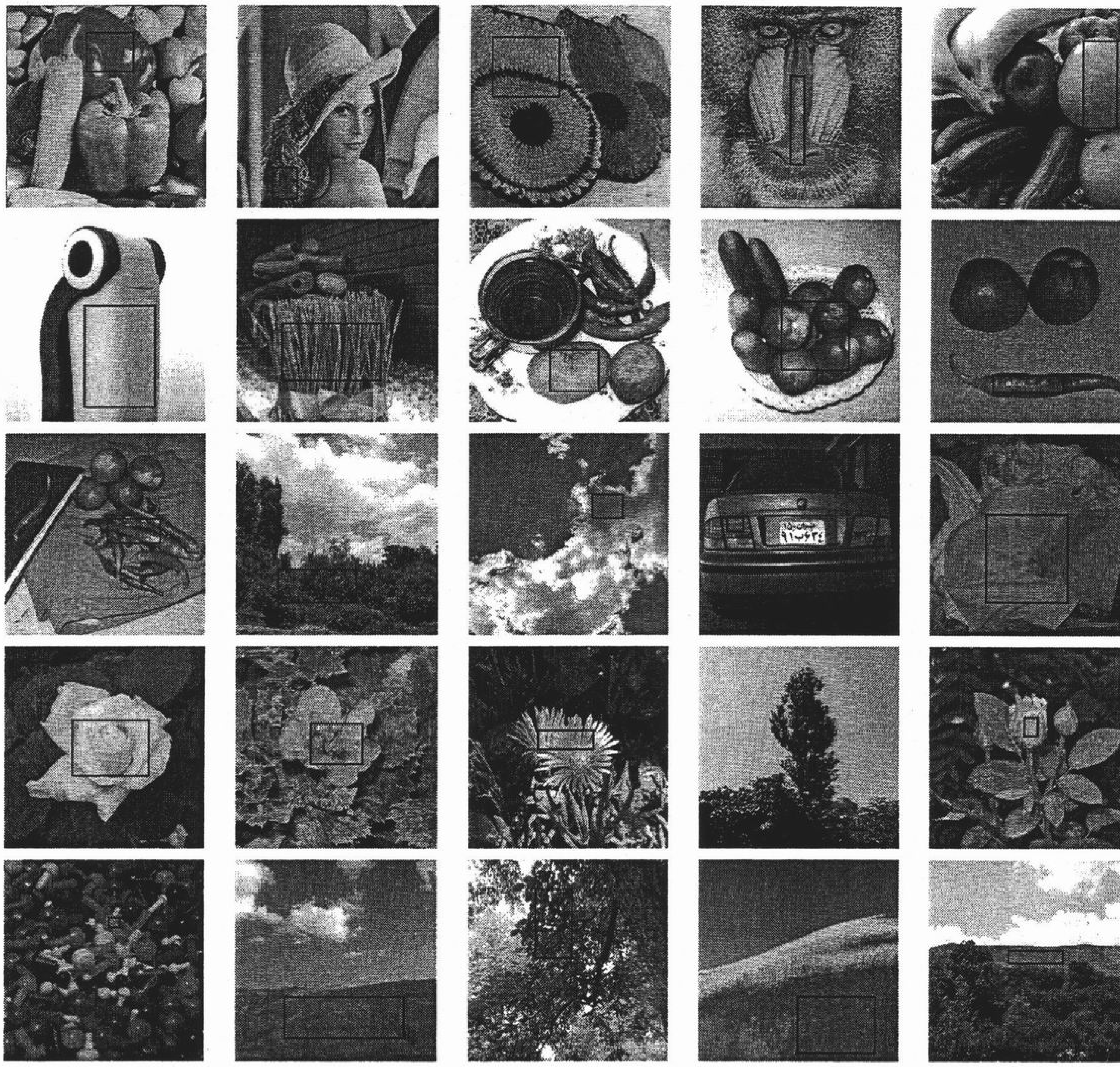

Fig. 2. Sample images and query regions used in this paper.

As expected, increasing p too much, vanishes the performance of the resulted segment by widening the color mood interval excessively, while large ρ over–smoothes the segment, forcing to ignore the details. These results are complying with the curves shown in Figure 5.

Figure 8 shows a sample results of the repeatability test. Here, 10 distinct query regions containing the same material, are manually selected and the proposed query region extraction is performed on them. Analysis of the 90 values of correlation between the resulting masks, shows the mathematical expectation of more than 0.98 with standard deviation of less than 0.02. Along with other observations, this proves the repeatability of the proposed method.

Figure 9 shows a typical result of the robustness test of the proposed method to the existence of the outliers. Note that, while using partially non–homogenous regions as the query region, the proposed method shows good levels of robustness towards rejecting the irrelevant vectors. In this test, using 5 different regions containing averagely 5% irrelevant points, the average correlation of the results is 0.97% with standard deviation of 5%.

V. Conclusion

A new query region extraction method is proposed that uses a custom likelihood measure. The efficiency of the Euclidean distance in 12 standard color spaces is investigated. Each of the color spaces is analyzed in all its 1–, 2–, and 3–D representations. Also, the Mahalanobis and the linear partial reconstruction error(LPRE) distances are investigated. The tests include comparison of the result of query region extraction using each distance with the ground–truth. Results

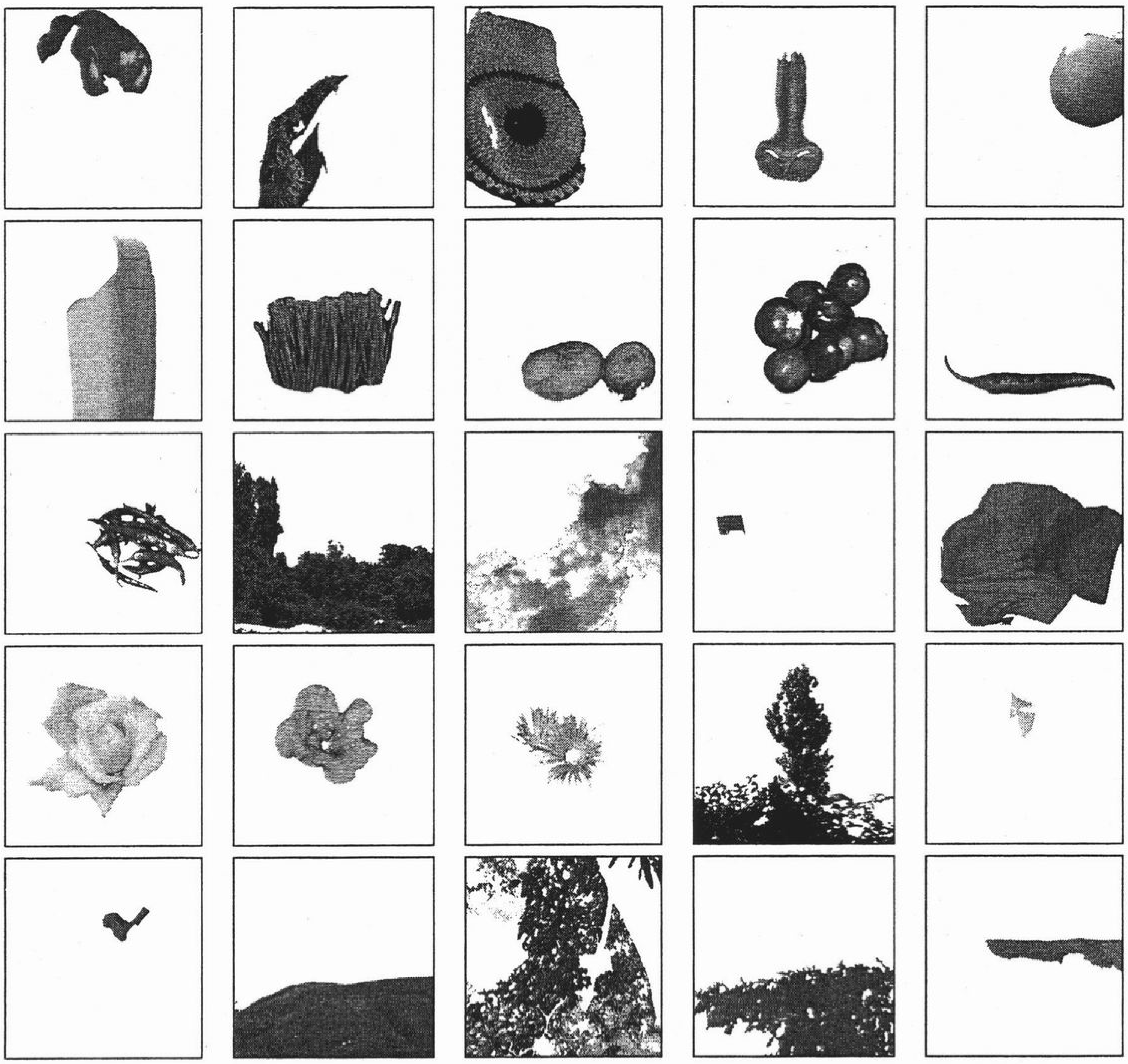

Fig. 3. The ground–truth results of query region extraction for the images shown in Figure 2 with corresponding query regions.

show that, the Euclidean distance in none of the standard color spaces and in none of the 7 possible representations gives a proper likelihood measure (in fact, the Euclidean distance is giving desperate results). While the Mahalanobis distance results more precisely than the Euclidean distances, it fails to give acceptable recall rate. The proposed LPRE distance shows perfect correlation with the ground–truth both in terms of recall and precision rates (both more than 90%).

The proposed query region extraction method using the LPRE distance is investigated carefully. The proposed method includes only two intuitive parameters. The effects of the parameters are investigated and proper default values are proposed. While, when working on a 512×512 color images, the proposed method takes less than ones second, its repeatability and robustness are proved.

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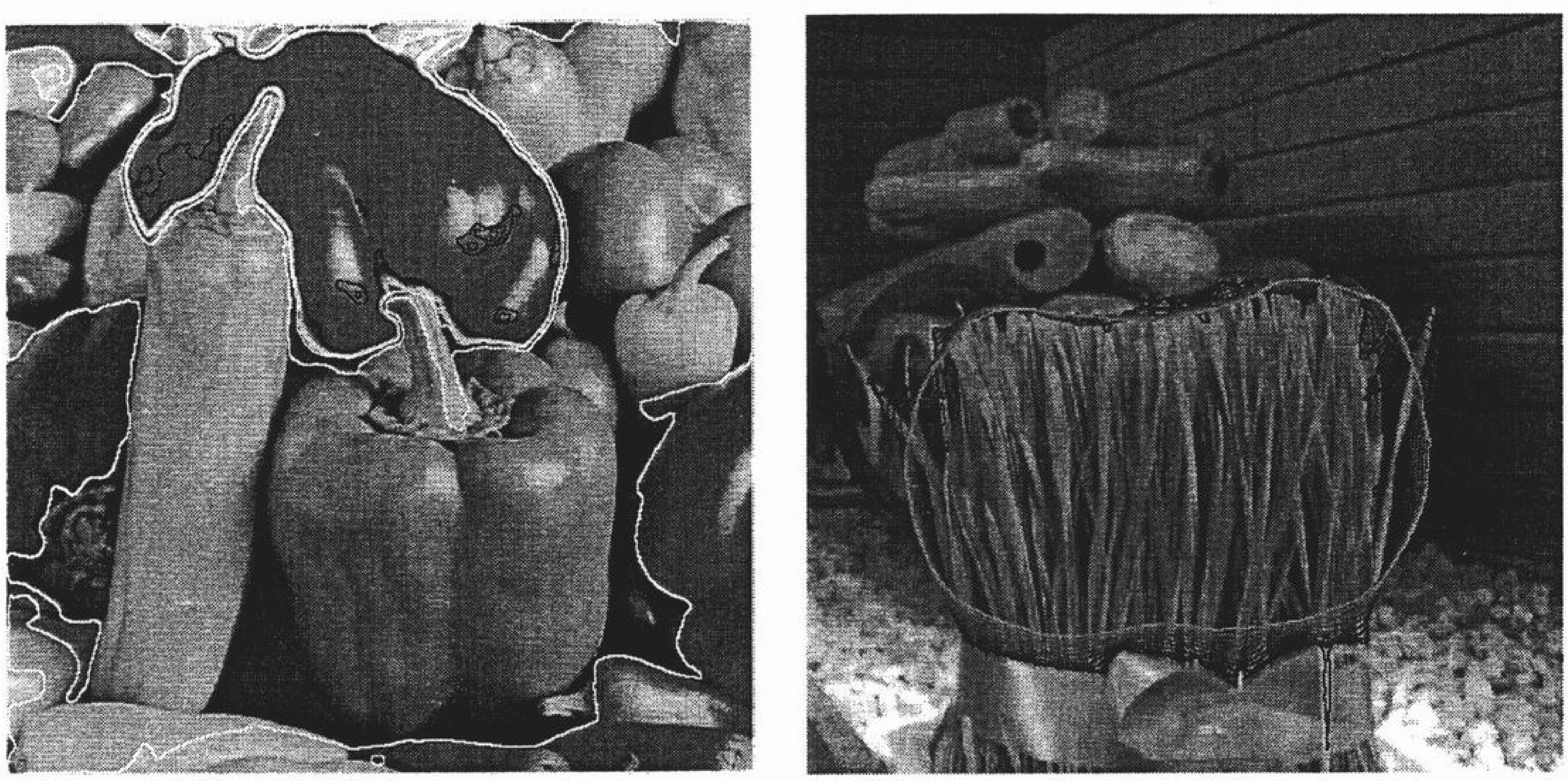
TABLE I

QUERY REGION EXTRACTION RESULTS USING THE EUCLIDEAN DISTANCE IN TWELVE STANDARD COLOR SPACES, MAHALANOBIS, AND *LPRE*. [μ_r: RECAL, μ_p: PRECISION]

Color Space	1–D						2–D						3–D	
	c_1		c_2		c_3		c_1,c_2		c_2,c_3		c_3,c_1			
	μ_r	μ_p	μ_r	μ_p	μ_r	μ_p	μ_r	μ_p	μ_r	μ_p	μ_r	μ_p	μ_r	μ_p
RGB	0.57	0.82	0.61	0.72	0.62	0.79	0.57	0.96	0.59	0.84	0.55	0.93	0.56	0.99
$HMMD$	0.61	0.87	0.64	0.77	0.58	0.80	0.60	0.95	0.57	0.96	0.56	0.94	0.55	0.99
$I_1I_2I_3$	0.59	0.87	0.60	0.84	0.63	0.87	0.57	0.92	0.57	0.96	0.57	0.97	0.56	0.99
HSI	0.61	0.87	0.64	0.65	0.59	0.87	0.63	0.91	0.59	0.90	0.57	0.99	0.57	0.99
$CIE-XYZ$	0.58	0.87	0.60	0.80	0.63	0.78	0.59	0.88	0.59	0.90	0.56	0.92	0.57	0.94
HSV	0.54	0.76	0.63	0.70	0.58	0.80	0.55	0.82	0.57	0.97	0.52	0.83	0.53	0.92
YC_bC_r	0.60	0.80	0.62	0.86	0.61	0.94	0.59	0.90	0.57	0.97	0.58	0.96	0.57	0.99
$CIE-La^*b^*$	0.61	0.80	0.68	0.84	0.66	0.78	0.60	0.85	0.62	0.91	0.59	0.90	0.58	0.92
YIQ	0.60	0.80	0.60	0.92	0.64	0.87	0.58	0.94	0.58	0.97	0.59	0.94	0.57	0.99
$CIE-L^*H^oC^*$	0.61	0.80	0.60	0.81	0.68	0.72	0.54	0.89	0.58	0.87	0.58	0.89	0.53	0.88
YUV	0.60	0.80	0.62	0.86	0.60	0.94	0.59	0.90	0.57	0.96	0.58	0.96	0.57	0.99
$CIE-Lu^*v^*$	0.61	0.80	0.63	0.90	0.67	0.81	0.57	0.97	0.60	0.98	0.58	0.93	0.56	1.00
Mahalanobis													0.52	0.99
LPRE													0.92	0.97



(a) (b)

Fig. 7. (a) Effects of changing p in query region extraction. (a) Effects of changing ρ in query region extraction.

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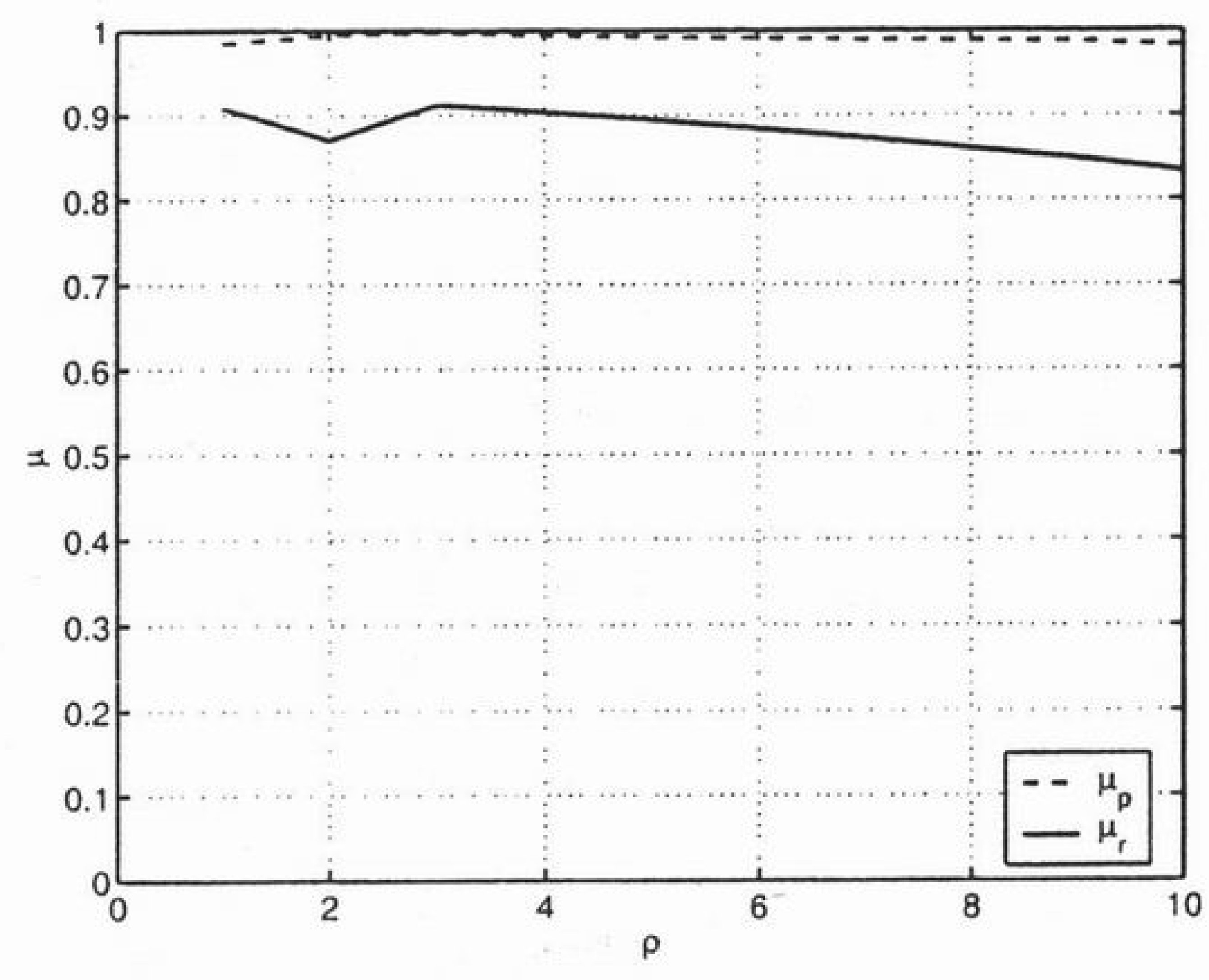

Fig. 5. Average precision and recall rates of the proposed query region extraction method using LPRE, with varying ρ.

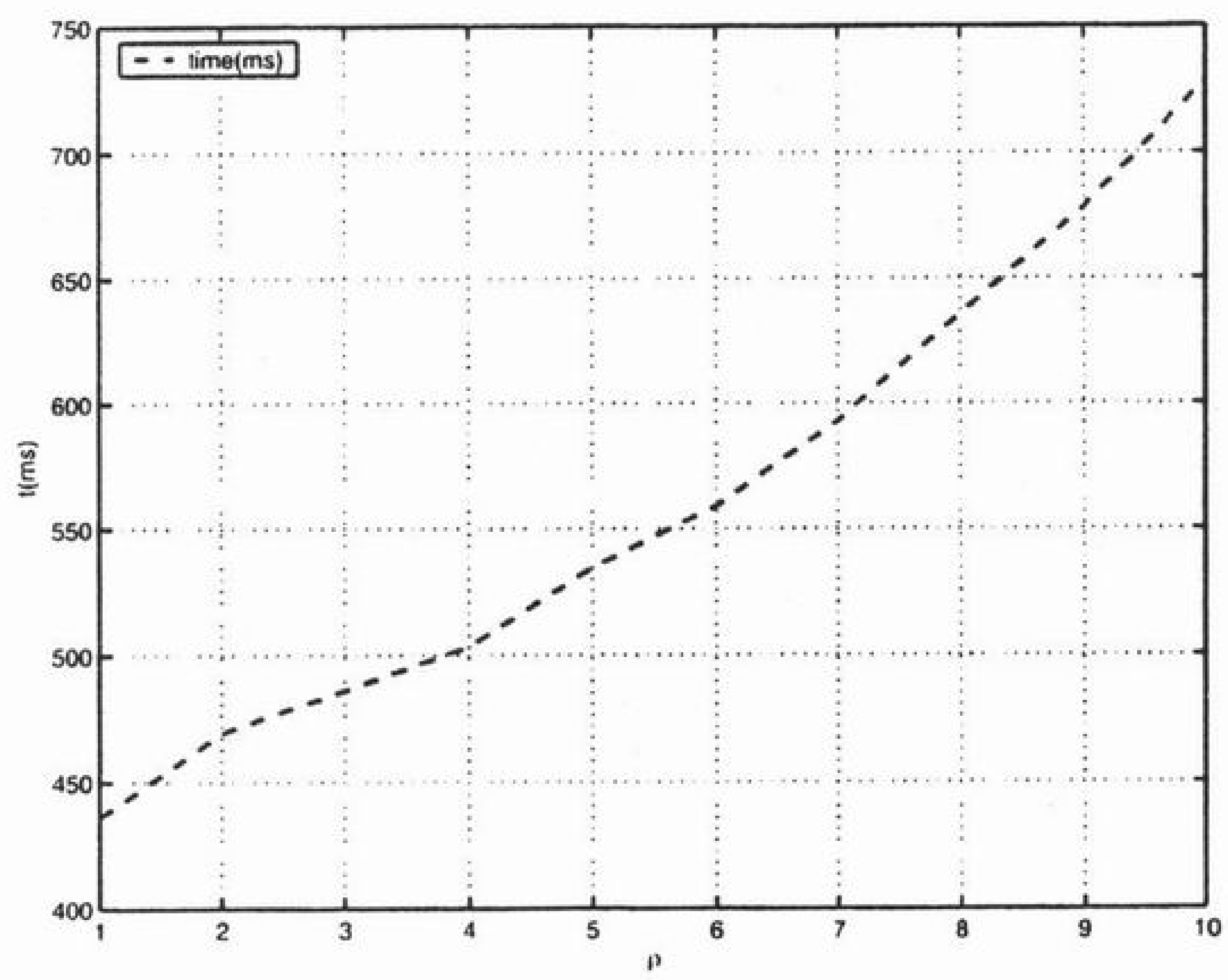

Fig. 6. Elapsed time of the proposed query region extraction using LPRE, with varying ρ.

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