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Progressive Image Segmentation by Wavelet Transform for Content-Based Image Retrieval

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Abstract

Recently, image segmentation is widely used in the multimedia applications. For a content-based image retrieval system, appropriate image segmentation techniques lead the image retrieval to be performed effectively and vitally. In this paper, we propose a novel segmentation algorithm based on progressive wavelet transform to segment out the notable objects in an image. The proposed algorithm, which is fitting for the use of the simplest wavelet transform, i.e., Haar wavelet transform, has high efficiency and feasibility. To further handle the stress of color differences, we invoke the whitening transform for the composition of processed color signals to meet the visual perception. The progressive processing will recursively remove the insignificant color differences by the suppression thresholds resulting from the proposed assignment algorithm. Thus, the colors within image objects will be unified level-by-level. Consequently, our algorithm can not only effectively extract significant objects, but also make the decomposition of the Haar transform be automatically stopped according to picture characteristics. Further, our method is very efficient for the segment that its speed is almost four times as fast as the previous Lin's method in average.

Keywords: image segmentation, wavelet transform, content-based, retrieval the whitening transform

I. Introduction

Image segmentation is significant in many applications, such as computer vision, pattern recognition and image database creation. Recent researches on content-based image retrieval integrate different features of images like color, shape and texture to measure the image similarity. It continues to be a challenge work to extract meaningful objects from a large amount of images to provide useful features for efficient image retrieval [1]. To automatically extract

various features for object recognition is necessary while an image is inserted to the image database. However, the automated object recognition is difficult, computationally expensive, and domain specific. Many known image segmentation algorithms [2,3,4,5] involving pattern recognition processing generally require high computational complexity and result in superfluous representations. In multimedia database systems, nowadays, the vast and diverse multimedia data collections are quickly growing but the response speed of users' queries will be requested faster and faster. The image features obtained by above algorithms very possibly appear too verbose to just in time measure the similarity of images in large collections of images and such features. In order to develop efficient and effective methods for retrieving multimedia data, a high-speed object extracting algorithm yielding a concise feature notation or signature is much more useful than ones obtaining objects' precise outlines or meanings.

Recently, since extracting objects' features becomes critical preprocessing in modern multimedia database systems, many researches on feature extraction for image retrieval had been proposed. In 1997, Lin *et al.* [6] proposed a color segmentation method for image retrieval and Belongie *et al.* [1] address another for image color and texture in 1998. However, these approaches are still time-consuming. In this paper, we propose an efficient wavelet-based segmentation algorithm to extract objects from images. The proposed segmentation algorithm exploits the idea that the neighboring pixels in an image belong to the same object if the chrominance and luminance of pixels are close enough. Therefore, it depends on color merging techniques. Thus, object isolation effectiveness is based on the full fulfillment of enhancing the homogeneity inside each object and heterogeneity between adjacent objects.

The wavelet transform can decompose the specified coefficients of various frequency resolutions

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by various basic waveforms for different applications [2]. In our proposed scheme, we first adopt Haar wavelet transform as an analytic key [7] since the transformed high-frequency coefficients can directly represent the differences of the around pixels. Thus, by passing the YUV pixel sequences through Haar wavelet transform, we exploit the whitening idea to the composition of processed color signals. The colors in distinct objects are classified by analyzing the distributions of composed color signals resulting from high-frequency coefficients. By the histogram analysis and the efficiency requirement, we use the technique of sub-variance equalization [8] to determine the appropriate thresholds of pixel clustering and merge near colors. The high-frequency color signals lower than these thresholds will be viewed as the color changing caused by the light inside the identical object. Thus, these signal removing can facilitate the grouping about clusters. Applying the above processing to LH, HL and HH subbands in each level of the wavelet transform domain, recursively, the criteria will be increasing level by level. By testing various images thoroughly in our experiments, it can be found that a good visual segmentation can be generated when a process termination criterion is met while a level ratio is smaller than a critical threshold. The wavelet processing will stop at that time. While an appropriate critical threshold is given, the proposed method will stop at lower transform levels automatically if images contain few simple objects. On the contrary, complicated images will fail the halting condition until higher processing levels. At the end of the decomposition, color reference vectors [9] are extracted from color coefficients of the LL-subband in the last level. Then all the pixels are grouped into their corresponding regions to sketch significant objects.

Since the decomposed objects by our method are near the visual perception of human beings, we can select the significant objects for further analysis to catch more features like objects' shapes and spatial relationships. Such features should be simple and meaningful for images representing and retrieving. This paper is organized as follows. We will review some important related researches in Section II. Then, the proposed progressive wavelet-based and the color signal composition methods are presented in Section III. The experiments and results are demonstrated in Section VI. At last, we make a conclusion in Section V.

II. Related works

QBIC system [10] is one of the most famous image retrieval systems. The QBIC system was developed by IBM Almaden Research Center, which integrates color, texture, shape, and sketch into the descriptor of each image inside the database. The other well-known systems include Virage [11], Photobook [12], VisualSEEK [13] and so on. Virage and

Photobook further permit users to specify more flexible queries owing to the use of more sophisticated representation relating image properties. In VisualSEEK, color and texture features of several regions are used to index an image. All above systems involve the issue of image segmentation, the problem of image segmentation is getting important for content-based image retrieval in the modern image databases. The Blobworld system [14] used a well feature extraction algorithm to precisely isolate natural objects on the proposed joint color-texture-position feature space. Although the segmented results are precise, the computational cost is still too high for query by image examples. However, the segmenting issue will be simpler and more efficient if we focus only on entire objects of an image regardless of the texture inside each image's object.

To specify regions of objects by uniform or smooth colors for image retrieval, the color segmentation algorithm proposed in [2] exploited a simple color classifier to perform adaptive color classification on fine art images. It addresses a region-based approach to promote the image annotation technique. It needs pre-specify or pre-define the desired classes such that we can apply the knowledge of human beings to obtain good segmentation results for special objects. For further outstanding objects, Lin *et al.* [6] proposed an effective block-based color segmentation method. In this method, each basic 8×8 pixels block is assigned a representative color initially, which is the mean color of the pixels inside the block of itself. From basic blocks, the algorithm merges smaller adjacent blocks with the closest colors into larger regions recursively. During all the merging procedure, the suitable number of separated classes can be automatically determined by checking the occurrence of the maximal change between the merged pictures and their previous merged ones. In this algorithm, the basic contour for the separated objects can be clearly displayed, but finer and more detailed features will not be exhibited obviously.

Jacobs *et al.* [15] used the Haar wavelet transform to generate a feature vector for each image that the feature vectors including color, texture and shape can be captured very fast. However, for lack of segmenting techniques to extract the individual objects, the user cannot perform partial queries through the corresponding image databases. To overcome such drawbacks, the WALRUS [16] system employed a novel similarity model, which uses some sliding windows of varying regions for decomposing an image into many rectangular regions, based on the proximity of their signatures. Although this algorithm is effective and regular, the information about shapes of objects is not actually expressed and the significant objects cannot be identified due to segmented superfine

regions. Moreover, the representative information of such algorithm is too verbose to provide image retrieval efficiently and even effectively under a large image database. Therefore, we propose a wavelet-based technique to improve the efficiency and effectiveness of image segmentation. After the effective segmenting, the significant objects in an image can be extracted to provide image retrieval by indexing the features of the objects.

III. The proposed segmentation algorithm

For achieving image segmentation effectively and efficiently, a wavelet-based image segmentation algorithm is proposed in this paper for isolating the significant objects with complete contours. Our method can decompose an image into separate objects that satisfy the visual perception automatically. Moreover, the proposed technique applies the fastest wavelet transform to perform the progressive processes. The progressive coding technique is very popularly used in scaleable transmission systems [7], and the concept of progressive processing is used to construct the framework of segmentation in this paper.

The detailed processing will be shown in the following four subsections.

A. Progressive Procedure of Wavelet Transform

The discrete wavelet transform (DWT) can achieve entropy concentration, de-correlation and feature detection to provide excellent signal analysis. It decomposes a discrete time sequence into coefficients of different frequency resolutions that, theoretically, different wavelet subbands can be analyzed and processed individually. At the same time as the target image is progressively decomposed, the influence and the effect can be traced from the updating of each individual subband at various levels. In this paper, by examining all the experimental results, without loss of generality, it can provide adequate solutions that all subbands are only classified into two parts after each Haar wavelet transform. One part includes the LL-subband coefficients in the current level of wavelet transform, i.e., the coefficients of the present lowest band. And, another contains all the high-frequency coefficients in LH, HL and HH subbands of all levels. Except the final decomposition, only the latter part is remained to analyze chromatic and luminous differences as well as perform color smoothing for all objects behind each decomposing.

Our proposed algorithm can segment objects very rapidly in the image retrieval applications. We adopt

YUV images to pass their Y , U and V components through the 2D Haar DWT. In our method, the so-called high-frequency coefficients are referred as the coefficients of transforming outcomes in the generated HH-subband, HL-subband and LH-subband of all levels, and the so-called low-frequency coefficients are located in the LL-subband of the current transform domain. For characteristics of Haar wavelet transform, the differences of pixels' colors between two adjacent areas can be directly or indirectly represented by high-frequency coefficients. Hereafter, we denote the high-frequency coefficients of the i th level HL, LH and HH subbands as Y_{Hi} , U_{Hi} and V_{Hi} , respectively, and the low-frequency ones in the lowest LL subband of the i th level as Y_{Li} , U_{Li} and V_{Li} , respectively. For simplicity, generality and the consideration of perceptual effect, we will use the transformed Y , U and V coefficients to compose the appropriate color signals as the analyzed medium for our proposed algorithm.

B. Color Signal Composition

Motivated by the whitening transform idea in [17], each transformed YUV coefficients in the i th level are weighted and unified to form the proposal color signal shown as:

$$c_{Hi} = \frac{Y_{Hi}}{\sqrt{\lambda_{Hy}}} + \frac{U_{Hi}}{\sqrt{\lambda_{Hu}}} + \frac{V_{Hi}}{\sqrt{\lambda_{Hv}}}$$

$$\text{and, } c_{Li} = \frac{Y_{Li}}{\sqrt{\lambda_{Ly}}} + \frac{U_{Li}}{\sqrt{\lambda_{Lu}}} + \frac{V_{Li}}{\sqrt{\lambda_{Lv}}}, \quad (1)$$

where λ_{Hy} , λ_{Hu} and λ_{Hv} as well as λ_{Ly} , λ_{Lu} and λ_{Lv} are the eigenvalues of all high-frequency subband coefficients and the lowest LL-band coefficients of Y , U and V up to the present decomposition status, respectively. For fitting the dynamic region for different bands, above inverse process by the whitening transform lead the Y , U and V signals to even significant influences for effectively fitting the human perceptual vision of interests. In order to consider the processing speed under remaining the functionality of whitening for a large image collection, the computation load of (1) should be reduced. For simplifying (1), with simulation verification, we approach (1) by replacing the eigenvalues by the means of the high-frequency subbands and the lowest LL-band;

$$c_{Hi} = \frac{Y_{Hi}}{M_{Hy}} + \frac{U_{Hi}}{M_{Hu}} + \frac{V_{Hi}}{M_{Hv}}$$

$$\text{and, } c_{Li} = \frac{Y_{Li}}{M_{Ly}} + \frac{U_{Li}}{M_{Lu}} + \frac{V_{Li}}{M_{Lv}}, \quad (2)$$

where M_{Hy} , M_{Hu} , M_{Hv} , M_{Ly} , M_{Lu} and M_{Lv} are the Y , U and V means of all high-frequency subband coefficients and the lowest LL-band ones, respectively. After use (2) to achieve the composed color signals, the proposed

segmentation procedure will analyze the histograms related to these signal for colors mergence and modification.

C. Suppression Threshold Determination

The proposed procedure performs the wavelet transforming once, the composed color signals in high frequency subbands are partitioned into two regions according to their strengths. The region with relatively smaller signals is considered to be the precise change of colors in individual objects. Such values may blur the judgement of boundaries between neighboring objects, they should be neglected for clarifying the contours and smoothing the colors of objects. Fig. 1 shows one of the experimental examples that the high-frequency signals in the region R_0 will be truncated to zeros. The parameter τ_i at cutting line is a decided suppression threshold after the i th decomposition that it partitions the signals into two regions, R_0 and R_1 . In the following, we will illustrate the method of the progressive wavelet transform and the determination of the suppression threshold in detail.

For generalizing the truncation procedure, to eliminate the high-frequency signals lower than the suppression threshold can be formulated as a recursive form along the progressive decomposing. As the wavelet transform of the i th level LL-subband is performed, the corresponding histogram is generated and denoted as $h_i(c_{Hi})$. A local suppression threshold τ_i is determined for dropping the high-frequency signals and the corresponding Y , U and V coefficients in the i th level. Meanwhile, the i th global suppression threshold T_i is proceeded to partition the high-frequency signals of all levels, in which signals are less than T_i and need be set as zero signals. The histogram processing function $f_i(C_{Hi})$ is formulated in the following recursive functions:

$$\begin{cases} f_1(C_{Hi}) = h_1(c_{Hi}) \cdot U(c_{Hi} - \tau_1); \\ f_i(C_{Hi}) = [f_{i-1}(C_{Hi-1}) + h_i(c_{Hi}) \cdot U(c_{Hi} - \tau_i)] \cdot U(C_{Hi} - T_i), \text{ for } i > 1, \end{cases} \quad (3)$$

where c_{Hi} denotes the high-frequency color signals of the i th level and C_{Hi} is the global high-frequency signals including the first level up to the i th one. The unit-step function $U(x)$ is used for truncating color signals denoted as

$$U(x) = \begin{cases} 1, & x \geq 0; \\ 0, & x < 0. \end{cases} \quad (4)$$

It is used to mask signals less than the thresholds τ_i or T_i to be zeros. By the recursive formulas in (3), the unimportant signals will be dropped out and color smoothing can be quickly obtained.

For the achievement of above appropriate histogram, it is necessary to decide the suppression thresholds τ_i and T_i , in advance. Observing Fig.1, we find the histogram is too non-regular and sprawling to model them with celebrated distributions such as the multi-Gaussian function especially after the recursive

process by (3). In addition, the process speed is one of the focuses in the proposed algorithm. Therefore, we addressed a variance equalization technique to derive the suppression thresholds by dividing the histograms of signals into two regions with equal variances. In Fig. 1, as soon as the $(i-1)$ th level LL-band is decomposed by Haar wavelet transform, the histogram $h_i(c_{Hi})$ is separated into two regions R_i^0 and R_i^1 . Then their individual variances V_i^0 and V_i^1 are computed as

$$\begin{cases} V_i^0 = \sum_{c_{Hi} \in R_i^0} \left[\frac{p_i(c_{Hi}) \cdot (c_{Hi} - E_i^0)^2}{\sum_{c_{Hi} \in R_i^0} p_i(c_{Hi})} \right], \text{ where } E_i^0 = \sum_{c_{Hi} \in R_i^0} \left[\frac{p_i(c_{Hi}) \cdot c_{Hi}}{\sum_{c_{Hi} \in R_i^0} p_i(c_{Hi})} \right] \\ V_i^1 = \sum_{c_{Hi} \in R_i^1} \left[\frac{p_i(c_{Hi}) \cdot (c_{Hi} - E_i^1)^2}{\sum_{c_{Hi} \in R_i^1} p_i(c_{Hi})} \right], \text{ where } E_i^1 = \sum_{c_{Hi} \in R_i^1} \left[\frac{p_i(c_{Hi}) \cdot c_{Hi}}{\sum_{c_{Hi} \in R_i^1} p_i(c_{Hi})} \right] \end{cases} \quad (5)$$

where E_i^0 and E_i^1 are the means of regions R_i^0 and R_i^1 , respectively. By continuously moving the intermediate boundary τ toward the region of the larger variance, the most proper boundary just noted as τ_i can be obtained by terminating the moving while the difference between V_i^0 and V_i^1 is minimal or small enough. Therefore, this suppression threshold determination can be formulated as

$$\tau_i = \underset{\tau}{\text{Arg}} \{ \text{Min}(|V_i^1 - V_i^0|) \}. \quad (6)$$

where $\text{Arg}\{.\}$ is invoked to obtain the argument parameter, which meets the criterion inside the brace. The similar processing can be performed on the global high-frequency subbands, then the global suppression threshold T_i can be yielded. With the recursive procedure mentioned above, the unimportant color differences are progressively truncated to zeros level by level such that the population of the zero high-frequency signals grows up. Thus, the colors of merged neighboring pixels are getting closer and closer along each Haar wavelet transform. Finally, every object uses a homogeneous color for identifying itself for isolation facilitation.

D. Significant Object Indication

The proposed progressive procedure will decompose images more detailed while the process level of wavelet transform is higher. Now we face the problem how many levels of decomposition is the best result. A critical threshold should be decided to achieve the goal that major individual objects can be successfully separated out according to human visual perception.

There is an important property for the eliminating criteria in different levels. This property is that the values of criteria will tend to increase along the decomposition level of wavelet transform. The reason is that the values of high-frequency signals below the

criteria are removed by forcing them as zeros. Simultaneously, dropping insignificant signals will lead the lower region under the current decomposition to have a lower variance than under the previous one. It will make the eliminating criteria increasing in next level of transformation. However, such processing does not influence the larger frequency signals, i.e., significant differential colors. For above phenomenon, a level ratio for the progressive processing is defined as

$$\gamma_i = \frac{\text{Max}\{c_{Hi}\} - \tau_i}{\text{Max}\{c_{Hi}\}} \quad (7)$$

where level ratio γ_i is obtained after the i th decomposition by Harr wavelet transform. Thus, we select a proper critical threshold ξ , and then set a process termination criterion defined by follows. As soon as the ratio γ_i is less than ξ , the progressive procedure halts immediately. Certainly, the design of the critical threshold should be based on image natures, individual query requirements and human visual perceptions of various interests for letting the segmentation automatically stop according to the image characteristics.

At the end of proposed segmentation, the remained larger high-frequency coefficients can effectively strengthen the discrimination between the significant objects. The Y , U and V coefficients in the lowest LL-band are re-quantized by an experimental quantizer such that the number of color vectors can be effectively constrained. Then, these YUV vectors play the key color references that each pixel is mapped into the most possible object by searching the nearest key color reference. The key color references will become the color features of image objects and be inserted into the index of image database for subsequent applications of content-based image retrieval.

IV. Simulation Results

For demonstrating the execution speed and effectiveness, the proposed segmentation method was implemented in C++ language on a personal computer with Intel Pentium 233 CPU and 64M RAM. The total number of test images is about 1000. Each tested image is in size of 256×256 . Types of the images include trademark, natural scene and texture. The contents of images have various characteristics more or less in each type. Some of the pictures are simple but some of them are of different complex extents. To segment all images appropriately and automatically, the decision of critical threshold ξ is significant in our approach. Since the number of wavelet processing levels in our method determines the result of segmentation, various number of wavelet processing levels should be found for different types of images after some off-line analysis processes. Here, the value of ξ is used to handle the termination of progressive process. The segmentation

algorithm will be halted when the level ratio is either less than or equal to ξ . For simple pictures, such as trademarks or pictures with simple and few objects, the level ratios have been already quite small in lower levels, i.e., first level or second level, because most of the large variation of colors occurs only on the edges of objects. These simple images can be decomposed well at lower levels. Complicated images, contrary to simple images, have larger level ratios and the decomposed results of lower levels cannot fit the visual perception. It always needs segmentation of higher levels. Thus, the value of ξ is the key parameter for deciding the quality of segmentation. According to our experiments, the segmented results are close to human observation when the value of ξ is 0.01 for most images. Consequentially, we are also able to analyze all the various kinds of images precisely to derive the suitable ξ values that may lead the recursion of segmentation algorithm to converge more naturally.

All experimental results are exhibited in Fig. 2. The series of pictures shown in this paper are randomly selected from the 1000 test images. The original images are shown in the first column. The names of original images are given below the original images. The pictures in middle columns are the results of segmentation of our proposed method with $\xi = 0.01$. The second and third columns respectively represent the results from the algorithm without the whitening process and one with using the whitening. Under the segmented images, the terminal levels of progressive process and execution times are listed. The pictures in the right column show the segmented results of Lin's method proposed in Lin [6] and their execution times.

In Fig. 2, both RGB001 and RGB002 pictures are trademarks and RGB001 is simpler. They are decomposed only at level 1 and level 2. For simple natural pictures having clear boundaries and few objects, like RGB003 and RGB004, the algorithm will be stopped at level 3 and level 4, respectively. The segmented results are obviously better than that by the Lin's method. For complicated pictures, such as RGB005, RGB006 and RGB007, they usually have more objects with distinct color features in them or possibly vague boundaries caused by shadows or out of focus. These pictures will not be decomposed well until level 5. Basically, the more complicated pictures with active background or texture require the decomposition process to continue up to higher levels. But, the decomposition depth will not be unlimited even for the consecutive increase of image complexity. In our simulation testing, no matter how active the pictures are, the decomposition of seven levels is enough as the last two rows in Fig.2 as shown.

However, we suggest that developers had better use other models to capture the features of such pictures, because it is difficult to recognize objects from these pictures correctly even for the human.

However, the segmented results of our method are more effective and meaningful than that of Lin's method. For computation time, our method is far less than Lin's method. It takes half of computation time of Lin's method even in the worst case. Most of the pictures can be decomposed in one second successfully. Significantly, in comparison with the method without using whitening factors, after invoking the whitening factors in the color signal composition, we can find in Fig. 2 that more complete contours of significant objects are exhibited just like that of the black cat and the purple ball in the third row in this series of test pictures. In addition, as Fig. 2 shown, the segmented objects have more desired signatures and less redundant details, thus the segmentation results can fairly match human visual perception of interest.

V. Conclusions

Image segmentation is an important task in many applications. In this paper, we develop an effective and efficient method based on the progressive Haar wavelet transform to segment the significant objects out of an image. By exploiting the natural characteristics of each image, the proper number of decomposition levels can be determined automatically. After our experiments, the result of segmentation is close to the visual perception of human. The proposed segmentation mechanism can be applied to image retrieval as Lin [6] directly. The results show that the proposed mechanism indeed improves the efficiency and effectiveness. Further, with the whitening factors used to color signal composition, the segmented objects have quite complete outlines and, be remained more desired features and eliminated more color redundancies than without the use of whitening factors. Nevertheless, more significant features and signatures can be extracted from our results of segmentation, e.g., shapes and representative colors. Consequently, after performing the proposed segmentation algorithm, the shape and significant features belonging to an object can be tracked and captured precisely for the application of content-based image retrieval.

VI. References

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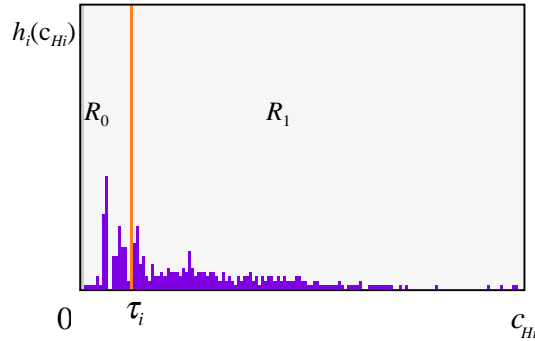


Figure 1. The decision of suppression threshold τ_i .

Original Image	Proposed Method Without Whitening factors		Proposed Method With Whitening factors		Lin's Result
RGB001	Level 1	0.206 sec	Level 1	0.206 sec	4.212 sec
RGB002	Level 2	0.606 sec	Level 2	0.608 sec	4.415 sec

Figure 2. The test pictures and segmentation results





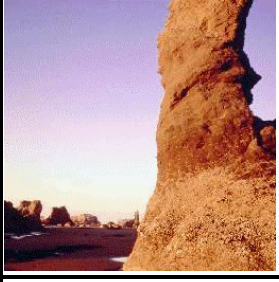





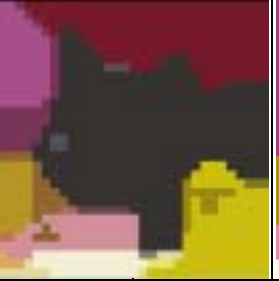
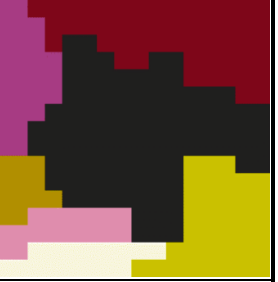
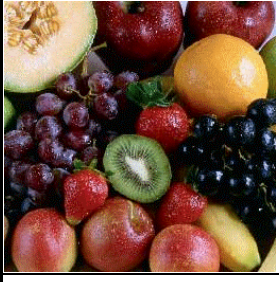


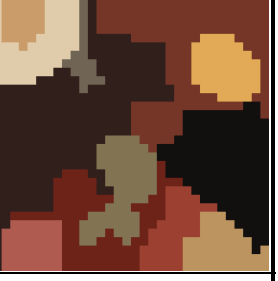




					
RGB003	Level 3	0.861 sec	Level 3	0.861 sec	3.975 sec
					
RGB004	Level 4	1.081 sec	Level 4	1.082 sec	4.4 sec
					
RGB005	Level 5	1.375 sec	Level 5	1.377 sec	4.221 sec
					
RGB006	Level 6	1.777 sec	Level 6	1.78 sec	4.413 sec
					
RGB007	Level 7	2.021 sec	Level 7	2.02 sec	4.434 sec

Figure 2. (Continued) The test pictures and segmentation results