Journal of Imaging Science and Technology® 51(2): 148–154, 2007.

Pairing Mathematical Morphology with Artificial Color to Extract Targets from Clutter

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Abstract. *In numerous prior works, a technique called Artificial Color has been developed to extract pixels belonging to a prespecified class while rejecting pixels belonging to other prespecified sets with great reliability. The heart of the algorithm is another well described pattern recognition method called Margin Setting. Margin Setting achieves highly reliable classification by refusing to classify some borderline pixels. As a result, the image produced using Artificial Color methods is reliable in finding the target of interest but that target may contain unclassified pixels, leading to a spotty or ragged image being extracted. It is showed here that post processing that ragged image using mathematical morphology can improve the extracted image substantially, and median filtering after that produces even more improvement. © 2007 Society for Imaging Science and Technology.*
[DOI: 10.2352/J.ImagingSci.Technol.(2007)51:2(148)]

INTRODUCTION

The overall goal of this work is to extract useful images of targets from background clutter using only

(1) spectral data gathered using a few spectrally overlapping sensitivity curves (Three—the standard commercial RGB filters—in the case illustrated) and

(2) assumptions about the spatial properties of the target embodied in the morphological analysis.

In most advanced biological vision systems, the spectral information is gathered using a few spectrally overlapping sensitivity curves and processed in one part of the brain, while the spatial information is processed in a different part of the brain. The same strategy is adopted here except that it's conducted serially rather than in parallel. First, the pixels using the spectral data are classified. Then the selected pixels are consolidated into a new image by imposing the spatial assumptions embodied in the mathematical morphology.

There are four distinct technologies being combined here, brief reviews of Artificial Color, Margin Setting, mathematical morphology, and median filtering are provided as background.

Received Jun. 15, 2006; accepted for publication Nov. 28, 2006.
1062-3701/2007/51(2)/148/7/$20.00.

Then the concepts are illustrated using an example of extracting the image of the frog from its hiding place among the leaves in Fig. 1. That image was taken with a standard commercial color camera with RGB filters. The frog is very well camouflaged, so the problem is difficult. First, Artificial Color using Margin Setting will be applied to find pixels with a very high likelihood of belonging to the frog. Then there will be "clean up" of the image using mathematical morphology and median filtering.

Finally, some conclusions are drawn that are supported by the examples discussed.

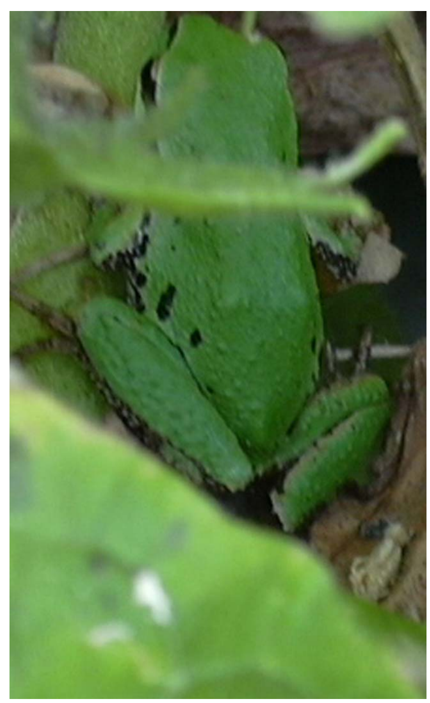


Figure 1. This frog is well hidden in its background foliage. Our illustrative example will be extracting the frog from its background using only its RGB pixels values and the assumptions implicit in the structuring element for mathematical morphology and in median filtering that the object contains mostly contiguous areas of the same colors with sharp edges and no isolated points.

It is important to note that the application of mathematical morphology to color images is neither new nor what is being discussed here. This topic has been described by several other authors.[1–5] Their goal was to improve color images. Our goal is to recover information lost by Artificial Color processing for images extracted from background clutter and camouflage by injecting physical assumptions about the object through mathematical morphology.

ARTIFICIAL COLOR

When light, produced by objects or from natural and artificial sources, falls on an object, the surface of the object absorbs specific wavelengths and reflects the rest. The reflected light contains incredibly rich spectral information—much too rich for an animal to detect or process if it did detect. In biological color, that light enters an eye and forms an image on retina. The light is detected in an eye using two or more spectrally overlapping sensitivity curves. Two or more numbers are generated with these curves for each pixel on the image. The pixels are processed in the brain and used to compute spectral discriminants which are perceived as color. The brain then attributes the spectral discriminants or colors to the percept of the object in the world that it creates. In Artificial Color, pixels are detected with special detector arrays (e.g., charge coupled devices) using two or more spectral sensitivity curves and processed in a computer to achieve the spectral discrimination goals of the user. The computer attributes the spectral discriminants to the image of the object in the world that it creates. The analogy is clear and deliberate as shown in Fig. 2. Artificial Color has proved to offer excellent discrimination under very unpromising circumstances.[6–11]

MARGIN SETTING

The concept of Artificial Color does not specify how the spectral discriminants should be classified. This study uses a supervised statistical method called Margin Setting[12,13] that provides superb generalization from only a few samples at the expense of leaving borderline pixels unclassified. The basic idea is to partition the training set into disjoint subsets each of which can be discriminated with a simple (low Vapnik–Chervonenkis dimension) classifier with high preset margin. Thus new, untrained-on members of that subset can be classified reliably. The subsets are also exhaustive, so a logical OR of the binary membership decisions made by the independent simple discriminants provides a decision for the set as a whole. Thus a new point can be classified as belonging to the set or being unclassified. Of course, multiple sets can be searched. The concept is illustrated in Fig. 3.

EDGE PRESERVING IMAGE CLEANUP

There are two conventional ways to clean up an image while preserving edge sharpness. They are mathematical morphology and median filtering.

Morphology means shape. Morphological analysis can be performed on problems, fields, and so forth. Here, however, mathematical morphology is used to describe a method

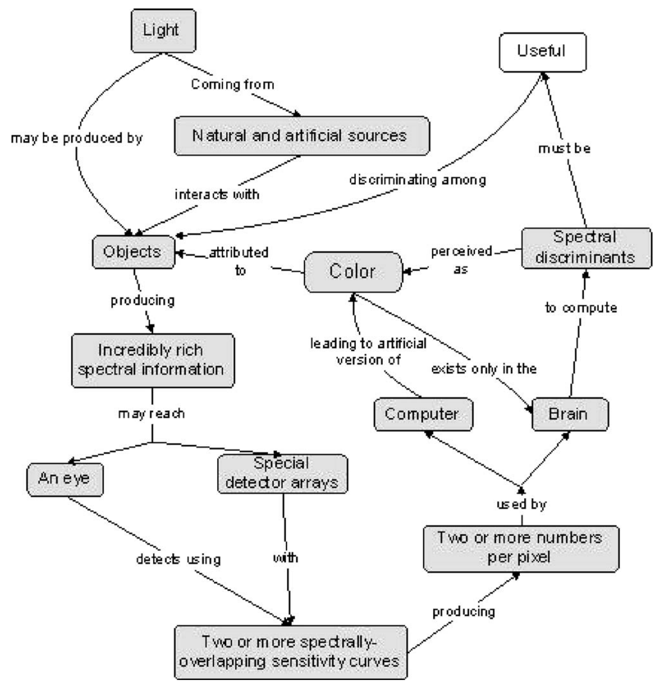


Figure 2. Biological color and Artificial Color.

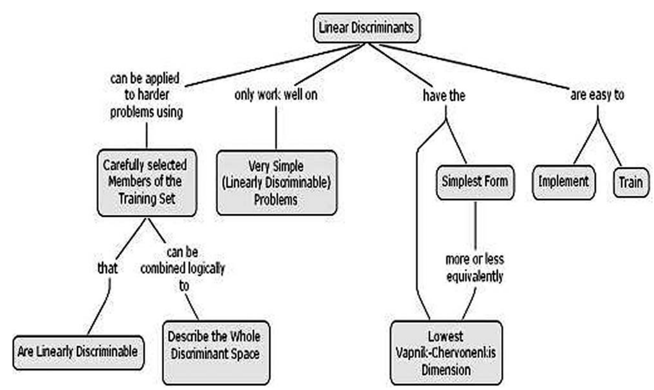


Figure 3. Margin Setting is a way of breaking the given training set into subsets that are mutually exclusive and each linearly separable with a preset margin to assure good generalization in recognizing members of that subset. A logical OR of positive identifications from each of the linear discrimination steps produces the decision for any new data.

for imposing some shape conditions on a binary image. The binary image of interest is the 2D map of pixels classified as likely to belong to a frog by the Artificial Color. This is called the Artificial Color filter, because it filters frog pixels from nonfrog pixels in a multiplicative fashion. The raw frog Artificial Color filter is likely to contain some isolated nonfrog pixels that can be recognized by their spatial isolation and some missing frog pictures that can be reconstituted on the basis of their being surrounded by frog pixels. The details are well documented.[14–17]

The details are readily available, there is a "structuring" element used to preprocess the image before applying one of the two key operations called dilation and erosion. *Dilation*, in general, causes objects to dilate or grow in size; *erosion* causes objects to shrink. In binary morphology, the dilation $\oplus$ and erosion $\otimes$ of set A by set B are defined, respectively, as

$$A \oplus B = \{s | B_s \cap A \neq \emptyset\}, \quad (1)$$

$$A \otimes B = \{s | B_s \subseteq A\}. \quad (2)$$

The amount and the way that they grow or shrink depend upon the choice of the structuring element.[18] Quite often, both operations are performed in a preset order. The morphological opening of a binary image is the erosion A by B, followed by a dilation of the result by B,

$$A \circ B = (A \otimes B) \oplus B. \quad (3)$$

Similarly, the closing of A by B is defined as

$$A \bullet B = (A \oplus B) \otimes B. \quad (4)$$

In so doing, bumps and indents can be removed from edges and isolated pixels can be removed, and so forth. This will become clearer from the illustrative example to follow.

Another way to smooth out isolated irregularities such as points or holes while preserving sharp edges is median filtering.[10] For each pixel, a neighborhood centered is constructed on it, e.g., a 3×3 array of pixels. In the processed image, center pixel value is replaced by the median of the values of all of the pixels in its neighborhood.

FROG FINDING PIXEL-BY-PIXEL USING ARTIFICIAL COLOR

The frog is well hidden among light green leaves, frog-colored leaves, and shadows. To extract likely frog pixels, the following procedure is followed:

(1) Select 20 random points each from the regions called here F, DG, LG, and DS for conveniences and standing for frog, dark green leaves, light green leaves, and dark shadows, respectively. Pattern recognition experts will recognize that 20 is a very small number to represent the large numbers of pixels in those four classes. The reason that small number is chosen is because small training sets are often a problem in more practical problems. Besides, the small number of samples is bound to lead to errors of various kinds, leaving us something to correct with mathematical morphology.

(2) Use Margin Setting to determine two independent discriminants: "F but not DG" and "F OR DG but not LG and not DS." The AND of the pixels selected in that way is formed to find F alone, hopefully. Remember that Margin Setting may not classify all of the pixels, depending on the chosen margin (and, hence, ability to generalize), it will fail to classify at all pixels that are "too close to call." The final result using a zero margin is shown in Fig. 4.

IMPROVING THE FROG IMAGE FOUND BY ARTIFICIAL COLOR THROUGH THE USE OF MATHEMATICAL MORPHOLOGY

Figure 4 shows most of the frog pixels and a few isolated nonfrog pixels. It is desirable to show more frog pixels and fewer nonfrog pixels and mathematical morphology is expected to be able to accomplish the goal. The size and shape of the structuring element used in mathematical morphology represent *a priori* assumptions about the nature of the image being injected into the processing. Two results are shown here to illustrate the effect of structuring element size. There is no reason to introduce asymmetry, as square structuring element is always used.

Figure 5 shows the effect of a 3×3 structuring element on the Fig. 4.

Figure 4. This is the result of using Artificial Color to remove the frog from its camouflage on a pixel-by-pixel basis using only the RGB values at each pixel.

Figure 5. 3×3 square structuring element filled in some of the missing frog pixels, making the frog even easier to recognize.

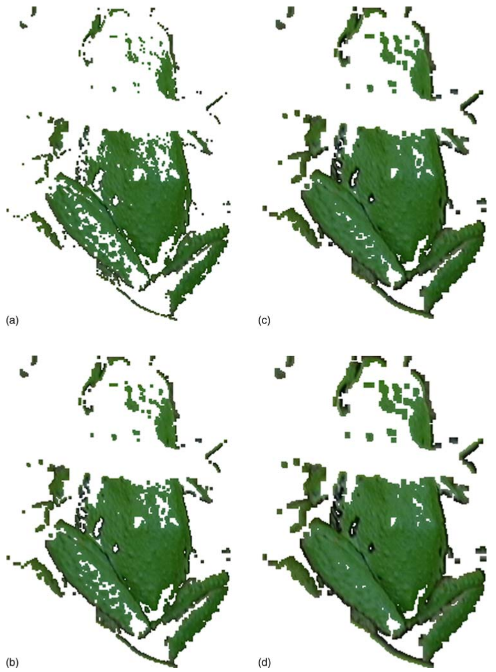


Figure 6. Shows the results of dilating an Artificial Color filter with $n \times n$ square structuring elements: (a) 2×2, (b) 3×3, (c) 4×4, and (d) 5×5.

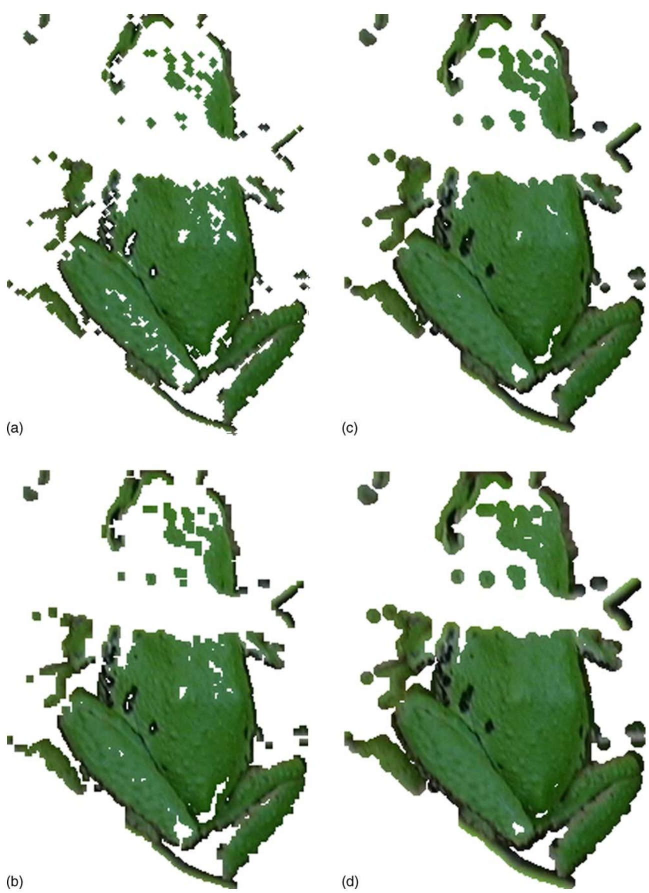


Figure 7. Shows the results of dilating an Artificial Color filter with different radius (r) disk structuring elements: (a) $r=2$, (b) $r=3$, (c) $r=4$, and (d) $r=5$.

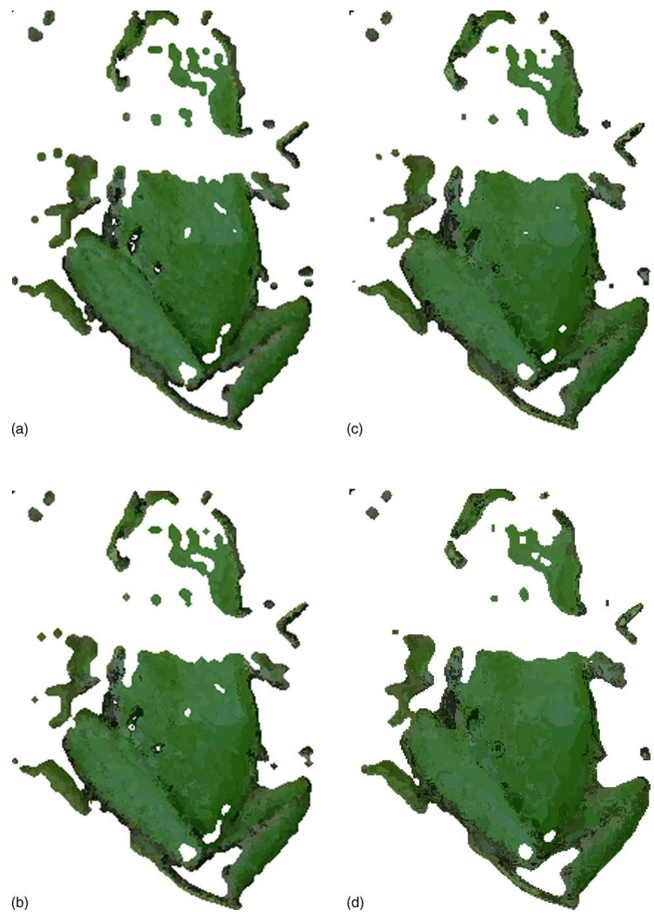


Figure 8. Joint effects of a 5×5 structuring element in morphological filtering followed by a $n\times n$ neighborhood median filter are shown here. The dimensions of filter windows are: (a) 3×3, (b) 5×5, (c) 7×7, and (d) 9×9.

Figure 6 shows the dramatic change made by making the structuring element only slightly larger.

When disk structuring elements are applied, more missing frog pixels can be extracted easily as shown in Fig. 7.

Both Figs. 6 and 7 show the size and shape of structuring element affect the clustering process. In either square or disk, even a modest increase in the size of the structuring element changed the resulting image considerably. Actually, applying dilation is an elimination of specific image detail smaller than the structuring element.[19]

SMOOTHING THE RESULTING IMAGE WITH A MEDIAN FILTER

There are many possible combinations of structuring element and median filter window. If a 5×5 square structuring element is employed, the net effects of median filters with different square filter windows are illustrated in Fig. 8.

Other ways to achieve smoothing are to perform a morphological opening and closing. The net result of these two operations is to remove or attenuate noise. Figure 9 shows smoothed versions of closing with different structuring elements. In opening operation, the erosion is applied first and a lot of frog information is lost. Then the followed dilation cannot pick up all missing information to reconstruct the

Figure 9. Shows the results of morphological closing with $n \times n$ square structuring elements: (a) 3×3, (b) 4×4, (c) 5×5, and (d) 6×6; and disk structuring elements: (e) $r=3$, (f) $r=4$, (g) $r=5$, and (h) $r=6$.

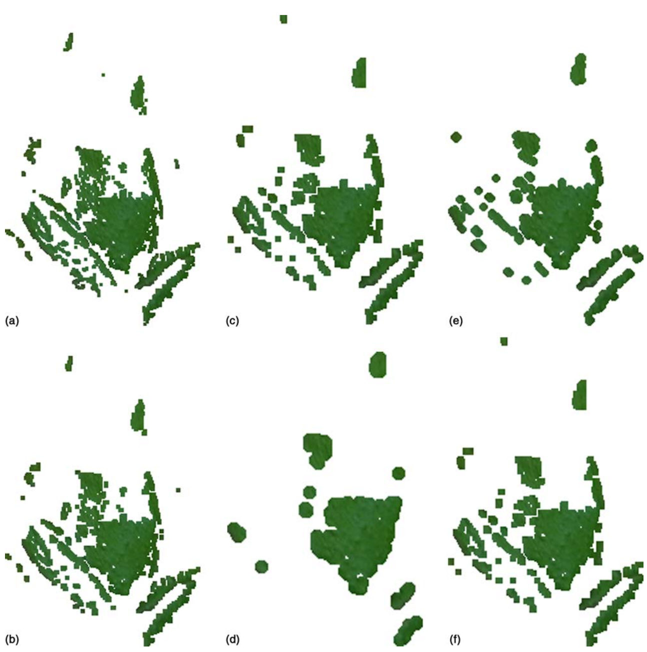


Figure 10. Shows the results of morphological opening with $n \times n$ square structuring elements: (a) 3×3, (b) 4×4, (c) 5×5 and disk structuring elements: (d) $r=3$, (e) $r=4$, (f) $r=5$.

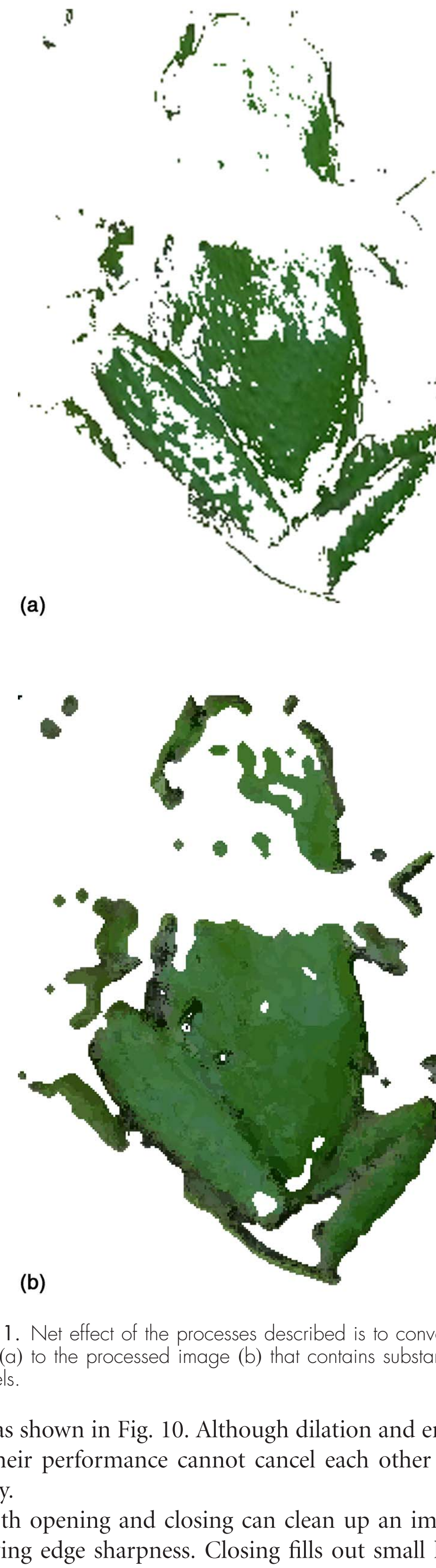


Figure 11. Net effect of the processes described is to convert from the original (a) to the processed image (b) that contains substantially more frog pixels.

image as shown in Fig. 10. Although dilation and erosion are dual, their performance cannot cancel each other morphologically.

Both opening and closing can clean up an image while preserving edge sharpness. Closing fills out small holes and gaps on the identified object. Opening eliminates small islands and results in much loss of target pixels.

Figure 12. This image features two types of green pepper and one type of red pepper.

Figure 14. Mathematical morphology filled in some of the bell pepper pixels missed in Fig. 13.

Figure 13. This figure resulted from applying a zero-margin Artificial Color filter for "bell pepper and not light green pepper and not red pepper" based on 20 samples of each.

Figure 15. No noticeable improvement was produced by using a 5×5 median filter to Fig. 14.

DISCUSSIONS AND CONCLUSIONS

Artificial Color is powerful in pixel-by-pixel extraction of targets from nontargets. But it makes some characteristic errors. It finds some isolated nontarget pixels and leaves out some target pixels. It has been shown here that mathematical morphology can at least partially repair those characteristic problems and median filtering following that produces even more improvement. The net improvement is evident in comparing Fig. 4 with Fig. 8(b). They are placed side by side in Fig. 11 to make that comparison easy.

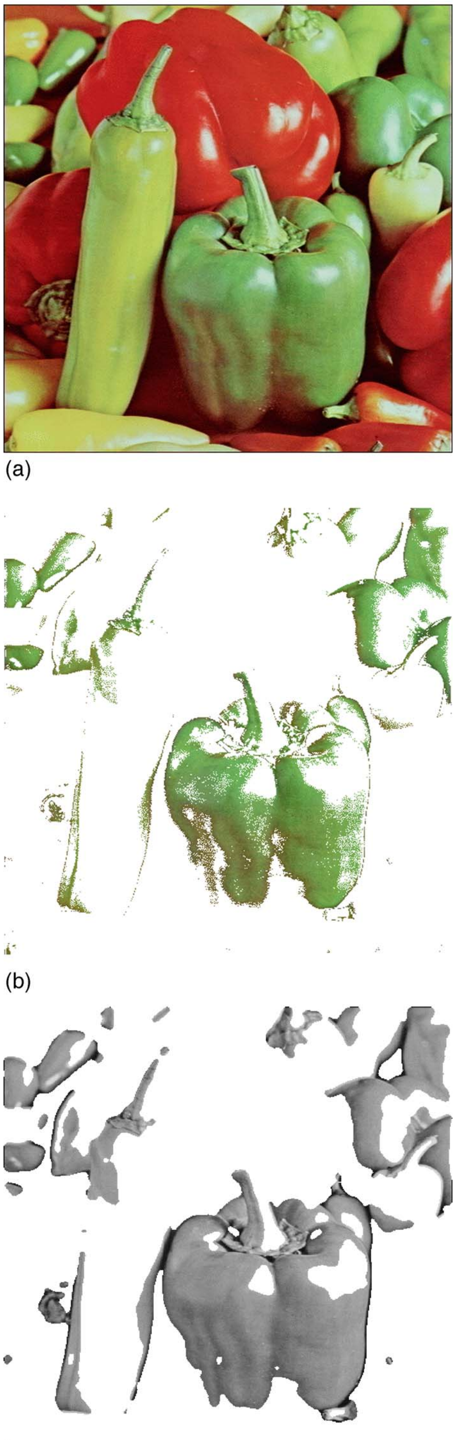
The same approach appears to work well on other images as well. For instance, we studied the image shown in Fig. 12.

It is made difficult to segment not only by the closeness of the two greens (especially in shadows) but also by the fact that the objects are shiny (more or less specular), so light from one class of object may be scattered off objects of a different class. And, of course, some regions saturated, so no meaningful data from them is to be expected. For these reasons, it would be impossible to achieve perfect segregation among images of the three types of peppers. Let us concentrate on the sweet bell pepper. Again, we used zero margin to get lots of bell pepper pixels, knowing that this would also pick up pixels from shadows on light green peppers and so forth. Figure 13 shows the image so segmented.

As expected, Fig. 13 shows most of the bell pepper pixels that did not correspond to glare but showed other pixels as well. Mathematical morphology using a 5×5 disk added even more bell pepper pixels as shown in Fig. 14.

Following that with a 5×5 median filter produced little improvement as shown in Fig. 15.

For reader convenience, Fig. 16 shows the original, the raw Artificial Color filtered, and the improved images.



(a)

(b)

(c)

Figure 16. This shows the process of segmenting the bell pepper from the other peppers using Artificial Color filtering to get the middle image from the original image on the top and improving that to get the final image on the bottom.

ACKNOWLEDGMENTS

This work is supported by AFOSR under award no. FA9550–07–1–0061.

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