JOURNAL OF IMAGING SCIENCE AND TECHNOLOGY® • Volume 49, Number 5, September/October 2005

Applying Median Filtering with Artificial Color

Jian Fu
Computer Science Department, Alabama A & M University, Normal, Alabama, USA

H. John Caulfield
Alabama A & M University Research Institute, Normal, Alabama, USA

Terrence Mizell
Computer Science Department, Alabama A & M University, Normal, Alabama, USA

A spectral classifier for pixels on the basis of measurements made with two or more broad, spectrally-overlapping sensitivity curves has been called Artificial Color, because animals appear to do the same thing. While Artificial Color appears very attractive in tests to date, it has the drawback of being pixel-by-pixel. We know there are neighborhood effects in the perceived color in animals. The purpose of this article is to introduce and study the effects of neighborhood operations in Artificial Color.

Journal of Imaging Science and Technology 49: 498–504 (2005)

Introduction

The overall goal of the study reported here is to explore neighborhood effects that can be introduced into Artificial Color: a simple way to segment images on the basis of their pixel-by-pixel spectral properties as detected by multiple sensors of overlapping spectral sensitivity. This is called Artificial Color, because Natural Color too is a discriminant computed using signals detected by multiple sensors of overlapping spectral sensitivity. Artificial Color is the computer formation of spectral discriminants using measurements in two or more broad spectrally overlapping bands. Natural Color is the brain formation of spectral discriminants using measurements in two or more broad spectrally overlapping bands. That is, they are identical but for what does the computation. In both cases the discriminant is attributed to the pixel and generally used for discrimination.

From the general concept of Artificial Color, we proceed to a practical means to use it called Artificial Color filtering in analogy with Natural Color filtering. The latter passes only light in some preselected spectral band to the recording region. An Artificial Color filter passes only those pixels whose spectral properties satisfy the discriminants.[1–3] Because the Artificial color filters are binary (pass or block), they can be combined by Boolean logic and refined by simple processes such as median filtering[4] or morphological processing,[5] and the like. There are many ways to segment images by color but the proposed scheme is not one of them. Rather, it is a means to segment images by conceptual class based on the spectral properties. Artificial Color has proved useful in discrimination tasks.[2,3] Showing that again is not the purpose of this article. Rather, the purpose of this article is twofold – to point out that neighborhood effects can take place in Artificial Color just as they do in Natural

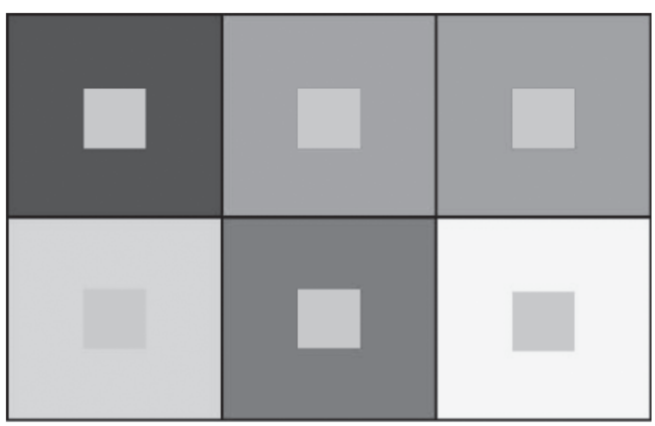


Figure 1. In Natural Color, the appearance of the neutral (gray) foreground is impacted by the color of the background, moving it slightly toward the color complementary to that background. *Supplemental Material—Figure 1 can be found in color on the IS&T website (www.imaging.org) for a period of no less than two years from the date of publication.*

Original manuscript received August 2, 2004

Corresponding Author: J. Fu, Jian.fu@email.aamu.edu

Supplemental Material—Figures 1–3, 7, 8, 10 and 11 can be found in color on the IS&T website (www.imaging.org) for a period of no less than two years from the date of publication.

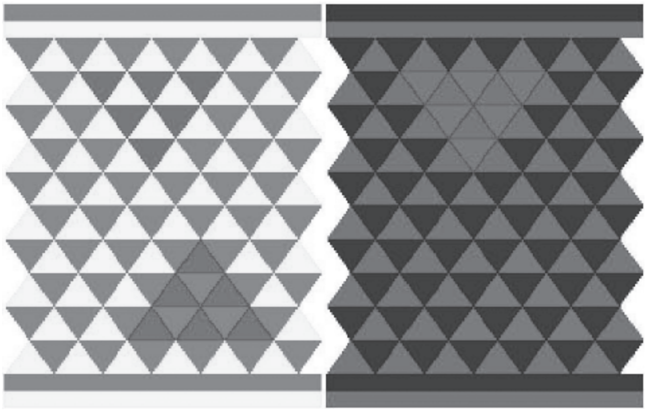


Figure 2. The red triangles on the right look brighter against the yellow than against the blue. Likewise, the green triangles on the right assimilate something from their neighbors and appear quite different even though they are the same. This is the so called Bezold–Brücke effect. *Supplemental Material—Figure 2 can be found in color on the IS&T website (www.imaging.org) for a period of no less than two years from the date of publication.*

Color and to show some of the effects neighborhood processing on the resulting images.

That Natural Color is impacted by neighborhood effects is easy to show. For example, Fig. 1 *(available in color as Supplemental Material which can be found in color on the IS&T website (www.imaging.org) for a period of no less than two years from the date of publication)* shows how subtle changes in perception of a neutral foreground are caused by changes in the background. Also, colors seem to take on aspects of their neighbors as seen in Fig. 2 *(available in color as Supplemental Material which can be found in color on the IS&T website (www.imaging.org) for a period of no less than two years from the date of publication)*.

Of course, the goal of color-based segmentation is hardly new. Cheng,[6] Schettini,[7] Littman and Ritter,[8] Borsottie et al,[9] Deng and Shin,[10,11] are among numerous references in the field of color image segmentation. Seemingly every author has his own favorite method, so adding another would seem to be without interest if Artificial Color filtering did not have special features the others do not have.

In fact, Artificial Color filtering offers a number of distinct advantages over prior color image segmentation approaches. Specifically, it alone is

- Based on algorithms aimed at super generalization,* so it should be readily applicable to other similar images without much loss in effectiveness
- Capable of allowing a tradeoff between accuracy of pixel assignments and fraction of pixels left unclassified
- Boolean or fuzzy logic combination of multiple segmenters to accomplish a specific goal.
- Image processing on the filter itself.

For this work, we consider only binary Artificial Color filters. They either multiply a colored pixel by 1 if it is recognized, or by 0 otherwise. Critical to success is good generalization, the placing of raw un-trained-on data in their proper bins. Methods such as the Support Vector Machine[12] and Boosting[13] do well in that regard. Another method that claims some superiority to those is called Margin Setting.[1–3] Margin can be thought of as a "margin for error" built into the decision process. Big margins leave room for new data to vary around the data in the training set substantially without being misclassified. The Support Vector Machine seeks to optimize the margin. But Margin Setting allows the margin to be prescribed. The penalty is that decisions become more complicated as a result.

In Margin Setting, the choice of margin has one obvious effect. Bigger margins make fewer misclassification errors but leave more data unclassifiable. That trade off may have different consequences in different circumstances. Exploring those consequences was the first step in the image segmentation process examined here.

The unique aspect of what is presented here is the use of median filtering with Artificial Color. In Natural Color, the color appearance of a pixel depends not just on the detection pattern (long wavelength band, mid wavelength band, and short wavelength band in trichromatic humans), but on spatial context, as well, Prior Artificial Color filters failed to take spatial context into account. This article illustrates one of many possible ways to take the spatial context of the pixel into account in determining the class to which the Artificial Color filter assigns it.

The Choice of Test Image

For simplicity, we limited ourselves to the study of a single image. The training data were 20 hand selected pixels in each of the sets of interest. Note that this is a very small number, but Margin Setting can overcome this to some extent. A larger sample should lead to slightly better results. Figure 3 *(available in color as Supplemental Material which can be found in color on the*

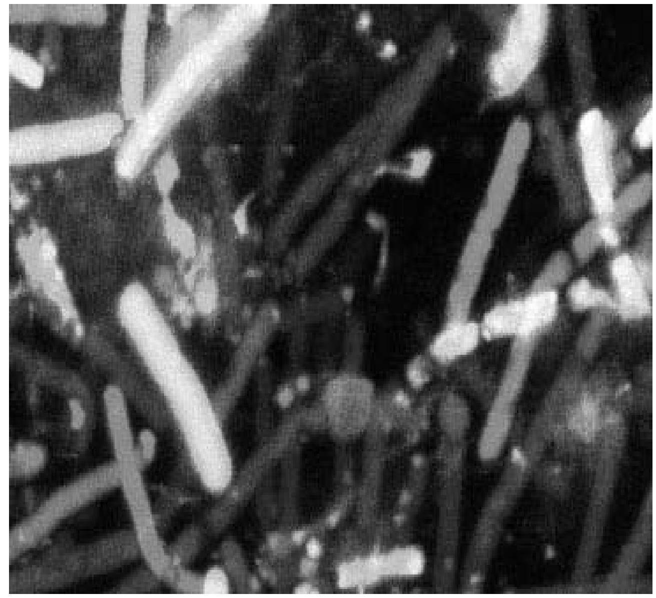


Figure 3. A mixture of live and heat-killed Bacillus cereus cells photo. Note that in some regions, there is a greenish component to the black background. This will be found automatically by our approach. *Supplemental Material—Figure 3 can be found in color on the IS&T website (www.imaging.org) for a period of no less than two years from the date of publication.*

* Generalization is the ability of a classifier to perform well on new, previously unseen data on the basis of what it learns from the training set.

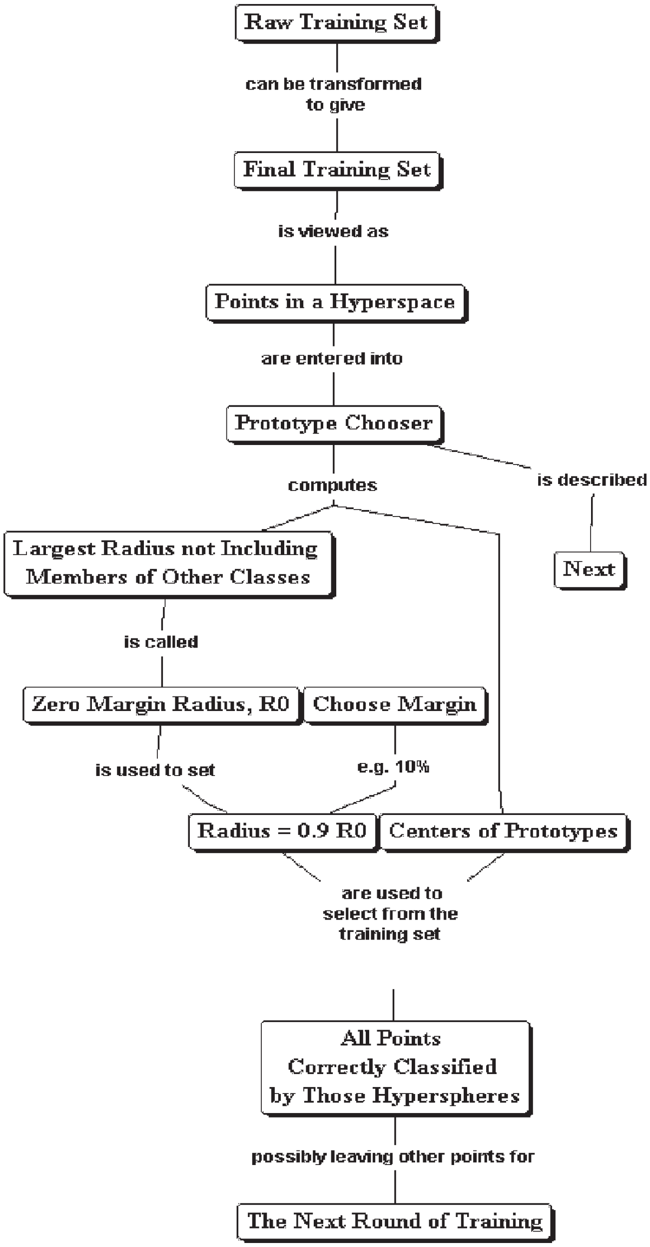


Figure 4. The training procedure

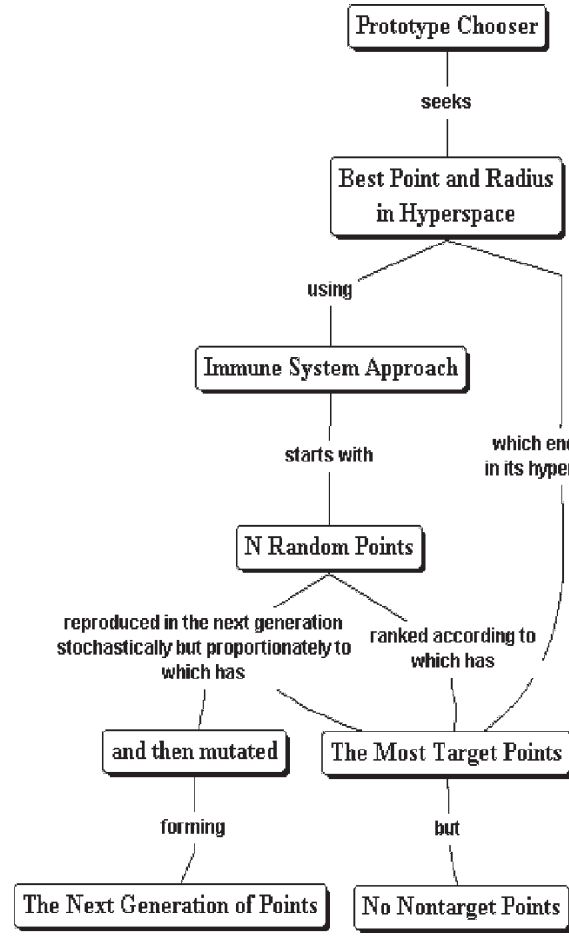


Figure 5. The prototype chooser

IS&T website (www.imaging.org) for a period of no less than two years from the date of publication) shows the chosen image. It is comprised of highly magnified stained microbes on a black background. At first glance, color segmenting such an image might seem a trivial task. It is not. We divided objects into three classes – green, red, and black (background). Of course, all three classes showed considerable within-class variability of their signatures (the so-called red, green, and blue channels). The “green” was our focus, because it seemed to show the largest within-class variability and thus to be the most difficult class. Even more troubling was the fact that there were evidently other microbes out of focus in this image or possibly leakage of stained material into the background fluid. This can be seen in the greenish tint clearly viewable in what are largely black regions. The upper left hand quadrant has large regions like that.

The Margin Setting Algorithm Employed

We used a nearest prototype classifier, evolving the prototypes by a simple immune system approach using the criterion that the best prototype for any class is the one that allows a sphere to be drawn about it in the hyperspace that includes the most members of that class without including a member of another class. The distance from such a prototype to the nearest data point not in its class is called the zero-margin radius. If classification is done by assigning everything within the zero-margin radius of a prototype to the class that prototype represents, that classifier will make no errors among members of the training set. But even the slightest variation in the wrong direction of new data from the other set represented by the data point at that distance would cause an error. Going to 90% of the zero-margin radius (a situation we call a 10% margin), we would make more room for such variations and have fewer misclassifications. After we assign a margin, we remove from the training set all members not classified so far and begin a new cycle of training. We continue in that fashion until some stopping criterion is met. Our usual criterion was four cycles. Figure 4 is a diagram that explains the overall training process: Raw training set contains training points that are viewed as points in 3D hyperspace. They are processed by a “prototype chooser” program which seeks the best hyperspheres (identified by center and radius) in the hyperspace using immune system approach. Figure 5 is a diagram for this

```
While (all T points are not classified and pre-defined number of stages has not being reached)
{
    While (when LF_{k+1} ≤ LF_k for two straight generations and pre-defined number of generations has not being reached)
    {
        For (each point in a generation of N random points)
        {
            Compute the distance to all points in T and sort them in ascending order;

            R = distance to the closet point that is non c_t;
            F = Number of c_t points that lies in the circle whose radius is R;
        }

        K = total number of points that has F and R information;

        LF = largest F;
        LR = R of the LF;
        S  = sum of F;

        f (normalized) = F/S values. Choose a random number Y between 0 and 1. Use that number to pick a c_t point. It picks object_being_trained finder n, if Y lies between f_1 + f_2 + ... + f_{n-1} and f_1 + f_2 + ... + f_n.

        Mutate this point to have N points for the next generation.
         x = x + ε_1 a_1 l;
         y = y + ε_2 a_2 l;
         z = z + ε_3 a_3 l;
    }

    For LF in each generation, calculate r = (1-χ)*R.

    Check all points in c_t, if any fall within r of any LF, mark as classified and remove from T.
}
```

Figure 6. Pseudo-code segment of Margin Setting algorithm.

program. It starts with N random points. For each random point, all training points are ranked according to their distances from this random point, and the radius of the hypersphere being sought is the distance between this random point and the closest point that is not from the object being trained. Of course, the center of the hypersphere is the random point itself.

We arrive at N hyperspheres and we rank them according to their radiuses. We select the hypersphere with the largest radius and use either a zero margin radius, or say, 10% margin radius to arrive at a hypersphere that will be used to identify all points that lie within this hypersphere. This is called a generation of hypersphere.

This process will be repeated with another set of N random points (reproduced stochastically but proportionally based on the first generation of hypersphere and is mutated) until all points that belong to the object being trained are identified or the pre-defined loop limit is hit.

With the above explanation, the Margin Setting poseudoalgorithm should be easy to understand. It is presented in Fig. 6; s_t samples are picked up from the target object and are classified as class c_t. The training set T contains all of the sample points; ε_1, ε_2, and ε_3 are random sign symbols (either + or −), and a_1, a_2, and a_3 are three random numbers ($0 \le a_i \le 1$, i = 1, 2, 3). The maximum perturbation is l. One magnitude of the perturbations is $\varepsilon_i a_i l$ (i = 1, 2, 3). In $r = (1 - \chi)^*R$, if χ = 0, it is the zero-margin.

In testing, each new entry is tested as to whether it is classified by the first set of hyperspheres. If it is, we accept that classification. If not, we continue to the next set of hyperspheres.

Experimentally, we find that the number of correct classifications is largely independent of the choice of margin. What the margin choice impacts is the classification of the other points. Large margins lead to relatively fewer misclassifications but relatively more nonclassifications than do smaller margins.

Segmentation of Green from Red and Black using Various Margins

We designed filters for the Artificial Color “green but not red and not black” using 20 widely distributed samples form each class as the training set. Figure 7 *(available in color as Supplemental Material which can be found in color on the IS&T website (www.imaging.org) for a period of no less than two years from the date of publication)* shows the original image filtered by such Artificial Color filters for margins from 0 to 0.4. For our purposes, the higher margin filters worked much better. They made fewer errors and more nonclassifications. We filter out not only red and black but also unclassified.

Improving the High-Margin Images with Median Filters

Median filters[4] tend to preserve sharp edges while smoothing out isolated anomalies. What is or is not an anomaly is defined by the data in a square array of data points about the pixel being filtered. Median filters of three different sizes (3×3, 5×5, and 13×13) were applied to the 0.4 margins Artificial Color filter for “green but not red and not black.” Figure 8 *(available in color as Supplemental Material which can be found in color on the IS&T website (www.imaging.org) for a period of no less than two years from the date of publication)* shows the effects of those smoothed filters. The hue difference histogram is plotted in Fig. 9. The smoothed result of 3×3 median filter is used as the baseline.

Improving the High-Margin Filters Themselves with Median Filters

The filters are simply binary maps: 1 where the pixel is determined to belong to the class of interest and 0 otherwise. It seems logical to try to apply median filtering to those filters themselves. Figure 10 *(available in color as Supplemental Material which can be found in color on the IS&T website (www.imaging.org) for a period of no less than two years from the date of publication)* shows the effect of median filtering the Artificial Color filters trained with various margins. Clearly, the resulting images are better smoothed than those obtained using the same size neighborhood for median filtering the images resulting from operation with the unsmoothed Artificial Color filters. In particular, it is clear that the area of the green color in the microbe images has been increased.

Joint Median Filtering – Before and After Operation

Clearly, we can do some median filtering on The Artificial Color filter before we operate with it on the original image and apply some median filtering on the resulting image. Figure 11 *(available in color as Supplemental Material which can be found in color on the IS&T website (www.imaging.org) for a period of no less than two years from the date of publication)* shows the effect of using 3×3 neighborhoods in both cases. In particular, it is clear that the area of the green color in the microbe images has been increased.

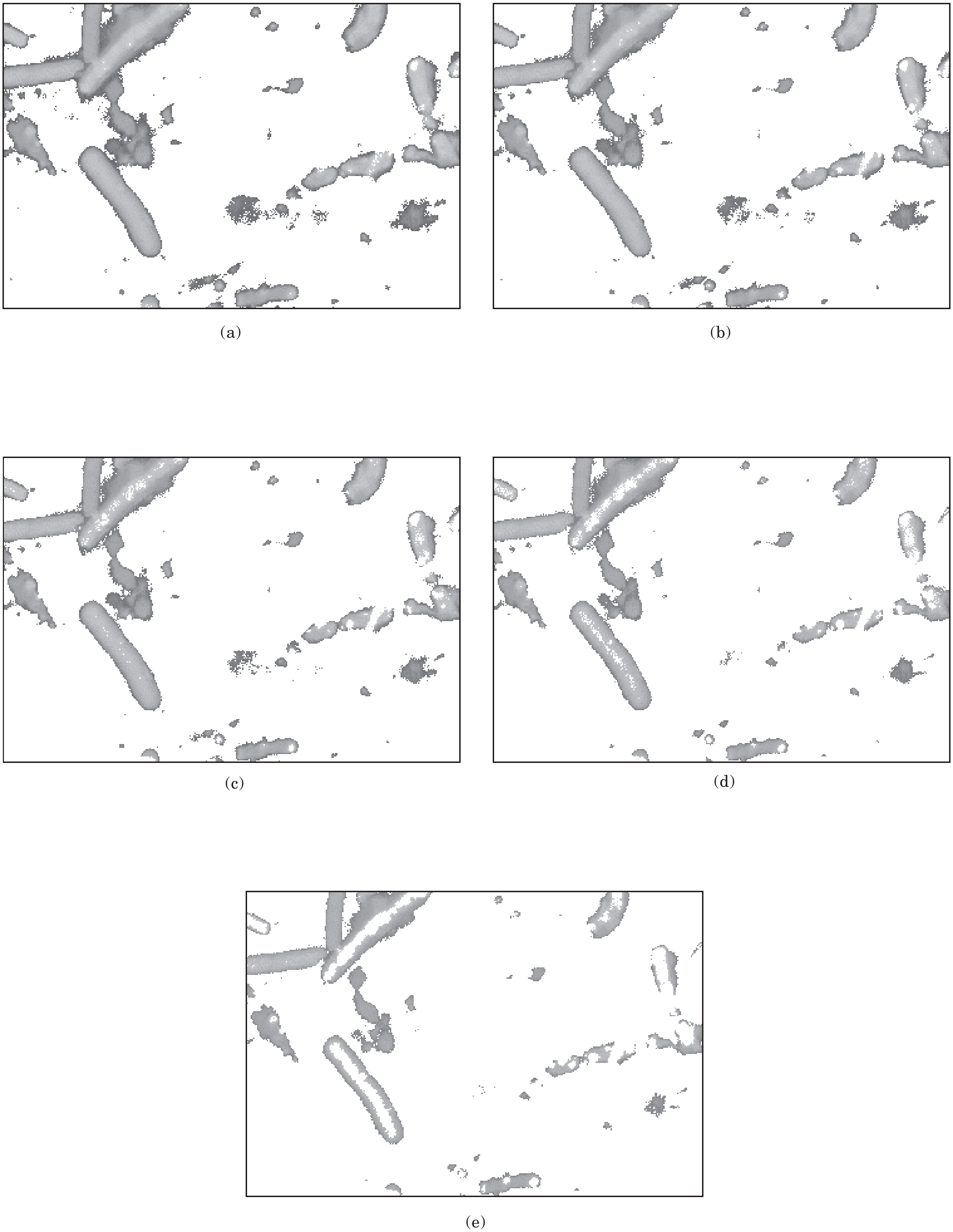
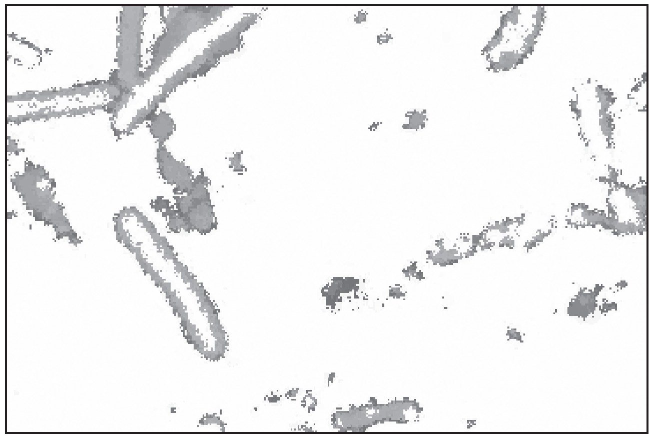
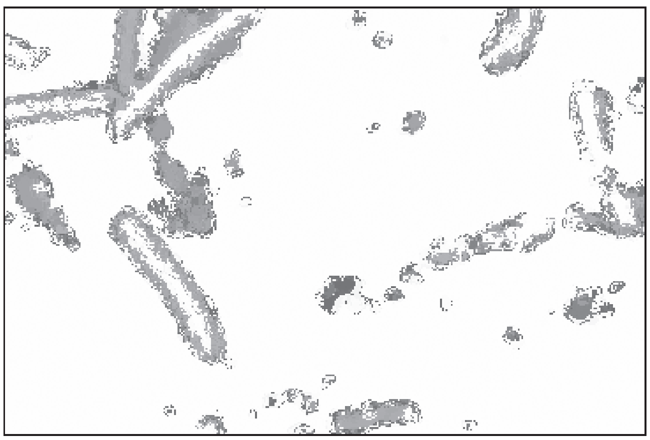


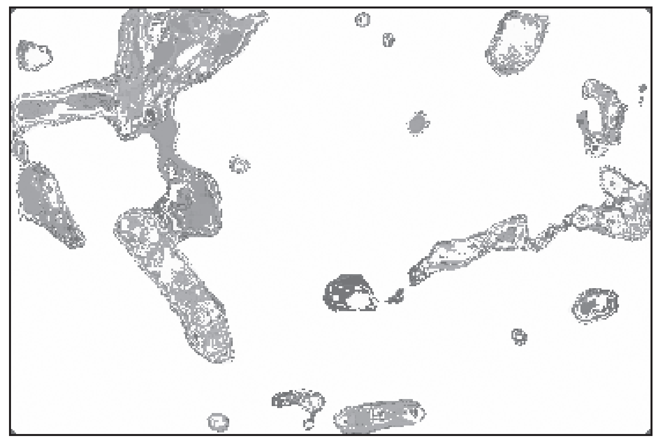
Figure 7. The original image filtered by Artificial Color filters for margins from 0 to 0.4. (a) Margin 0.0; (b) Margin 0.1; (c) Margin 0.2; (d) Margin 0.3; and (e) Margin 0.4. *Supplemental Material—Figure 7 can be found in color on the IS&T website (www.imaging.org) for a period of no less than two years from the date of publication.*



(a)



(b)



(c)

Figure 8. The effects of median filters of three different sizes (3 × 3, 5 × 5, and 13 × 13) were applied to the 0.4 margin Artificial Color filtered images. (a) 3 × 3 Median filter; (b) 5 × 5 Median filter; and (c) 13 × 13 Median filter. *Supplemental Material—Figure 8 can be found in color on the IS&T website (www.imaging.org) for a period of no less than two years from the date of publication.*

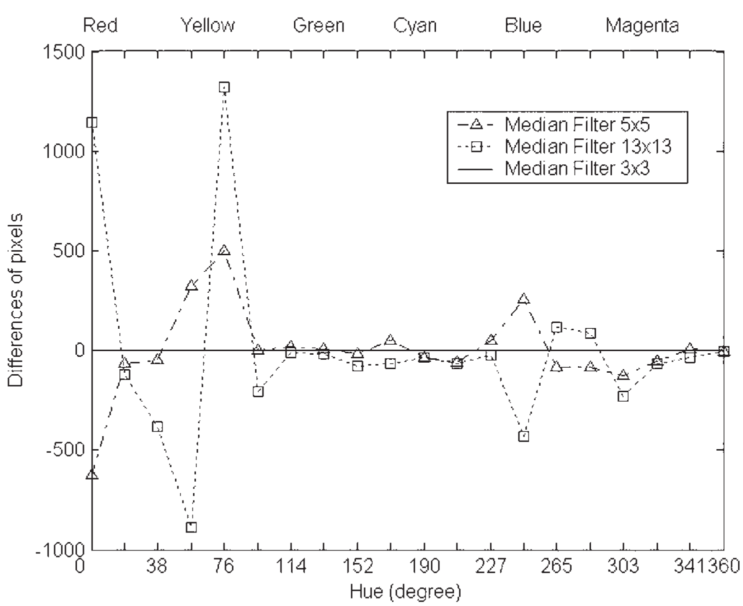
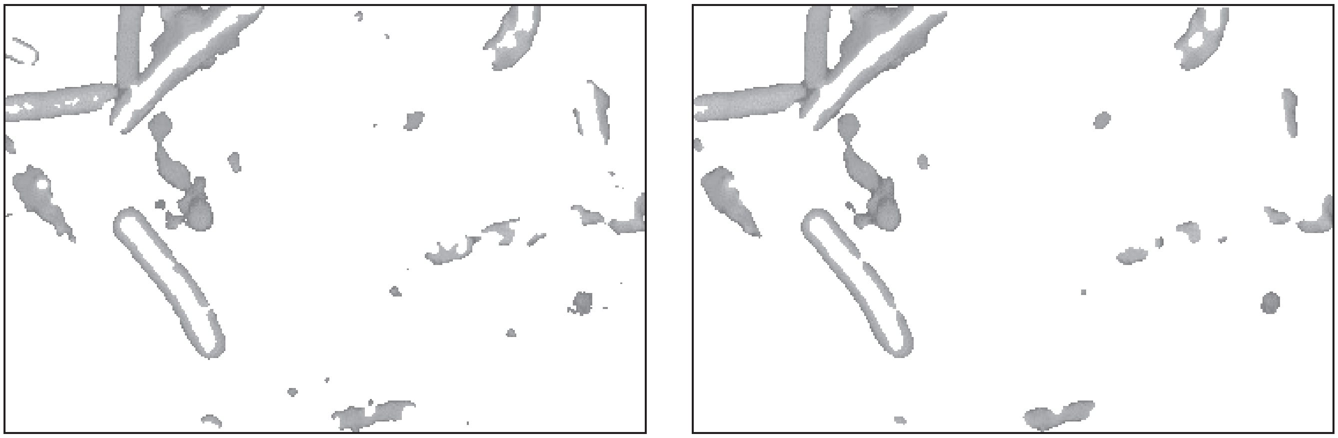
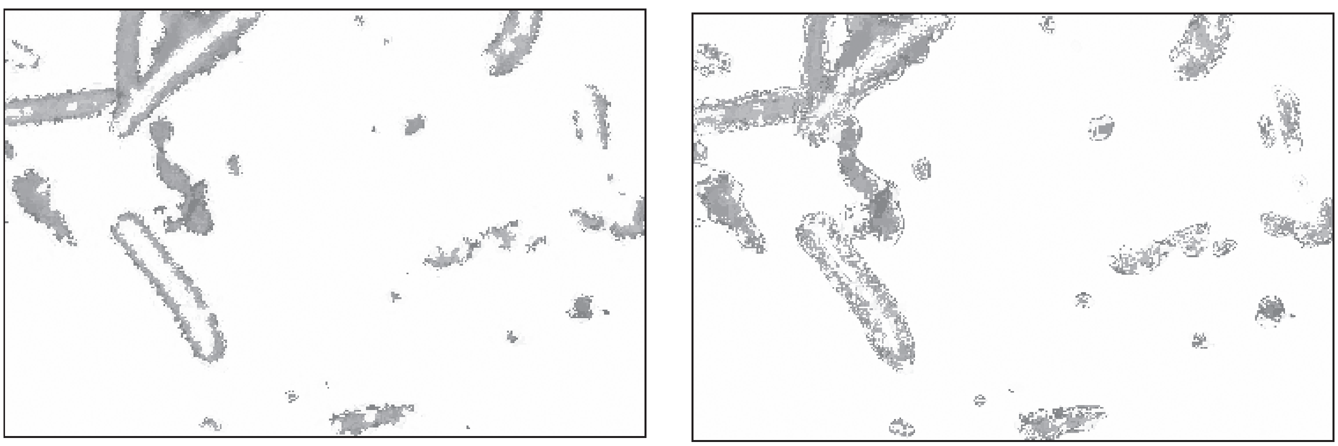


Figure 9. Hue difference histogram plot of the three median filters used in Fig. 8.



(a) (b)

Figure 10. The effect of median filtering the Artificial Color filters trained with different margins. (a) Image obtained with margin 0.5 and the Artificial Color filter 3×3 median filtered; (b) Margin 0.5, Artificial color filter 7×7. *Supplemental Material—Figure 10 can be found in color on the IS&T website (www.imaging.org) for a period of no less than two years from the date of publication.*



(a) (b)

Figure 11. The effect of using 3×3 neighborhoods in both cases. (a) Margin 0.5, Artificial Color filter 3×3, Median 3×3;l (b) Margin 0.5, Artificial Color filter 7×7, Median 3×3. *Supplemental Material—Figure 11 can be found in color on the IS&T website (www.imaging.org) for a period of no less than two years from the date of publication.*

Conclusions

The image chosen was quite specific, but the results and their explanations allow us to draw the following four conclusions. (1) Artificial Color filtering is a useful way to segment images by their spectral meaning. After the images are so segmented, they can undergo other automatic operations such as spatial pattern recognition, image enhancement, and image metrology. (2) Handling multiple classes of objects is simple and automatic. (3) Margin variation leads to pronounced differences in the segmentation. Different margin choices may be appropriate under different circumstances. (4) Image processing on the Artificial Color filters themselves may be quite helpful (as illustrated by our results with median filtering). This is the primary thing this work was designed to explore.

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