COLOR EDGE DETECTION IN RGB USING JOINTLY EUCLIDEAN DISTANCE AND VECTOR ANGLE

Slawo Wesolkowski
Systems Design Engineering
University of Waterloo
Waterloo (Ont.), Canada, N2L 3G1
s.wesolkowski@ieee.org

Ed Jernigan
Systems Design Department
University of Waterloo
Waterloo (Ont.), Canada, N2L 3G1
jernigan@uwaterloo.ca

Abstract

Typically, the edge detection problem in color images has been addressed using the Euclidean Distance or similar metrics. Recently, the Vector Angle metric was introduced to use the hue and saturation components in a color image in order to capture more accurate edge data. However, both the Euclidean Distance and Vector Angle metrics have some limitations. Two methods which combine both metrics are introduced. They try to leverage the advantages of each metric to better detect edges in complex color images. The edge detection operators used are based on the Vector Gradient and the Difference Vector operators. Preliminary results are presented and discussed.

1. Introduction

The purpose of a general image understanding system is to recognize objects in a complex scene or document. Typically, one of the first steps in such a system is edge detection. Edge detection algorithms usually detect sharp transitions within an image. These transitions are characteristic of object edges. Once edges of an object are detected other processing such as region segmentation, text finding, and object recognition can take place. Researchers have concentrated in the past few decades on devising algorithms for grayscale image understanding. With the advent of powerful personal computers, it is now possible to move to the more computationally intensive realm of color image understanding. There are many benefits in doing so including the increased amount of information for object location and processing.

In color image understanding, similar tasks are performed as in the previously described grayscale image world. The fundamental difference is the availability of chromaticity information. The perception of color is fundamental to the human visual system. Humans rely on hue, saturation and intensity to make sense of the world. It would make sense, therefore, to try to use this information to improve the accuracy of current grayscale algorithms.

Several researchers have already used color images for complex applications: text finding [10], enhancing binary check documents [9], automatic granite inspection [8], and color image map segmentation [6].

A typical color image capturing system relies on a trichromatic input based on the additive primary colors Red, Green and Blue. This is commonly know as the RGB color space. There exist a number of other equivalent color spaces such as CMY [2] (complementary primary colors of Cyan, Magenta and Yellow), YIQ (opponent color representation), HSI [2] (Hue, Saturation and Intensity) or its generalized form HSV [3] (Hue, Saturation and Value), LUV (Luminance, Chrominances U and V) [3], etc.

The RGB model corresponds most closely with the physical sensors for colored light such as the cones in the human eye or red, green and blue filters in most color CCD sensors. However, the human perception of color qualities is reflected more accurately by the HSI model [12]. The hue component is associated with the fundamental or dominant color. It is measured as an angle on a color circle where primary colors are separated by 120^{O} angles (red at 0^{O}, green at 120^{O} and blue at 240^{O}). The saturation component represents the purity of a color where mixed shades have low saturation values and pure spectral colors are fully saturated. The hue and saturation components specify the chromaticity information of a color. The third component is the intensity representing the overall brightness of a point. It is independent of color. On the other hand, the LUV space was designed to be perceptually correct which means that the Euclidean distance quantifies perceptual differences in this space [3].

The use of color in edge detection increases the amount of information needed for processing which complicates the definition of the problem. For grayscale images, edges are typically modeled as brightness discontinuities. Most edge detectors use local gradient information or a difference operator in some fashion.

For color images, a number of approaches have been proposed from processing individual planes [6,7] to true vector-based approaches [1,4,5,8]. The Sobel operator has been applied successfully to all three planes in the RGB space and the gradients were summed to obtain the resultant edges in [6]. The Sobel operator was also applied to each component of the HSI space and the individual results were combined using a trade-off parameter between hue and intensity [7]. An interesting feature of this trade-off parameter was its dependence of the level saturation. Several researchers have applied vector order statistics methods such as vector mean and vector median filters [5] or the minimum vector dispersion (MVD) edge detector [4] in the RGB space. Another approach for edge detection is the calculation of the vector gradient using the Euclidean distance [8]. This algorithm was found to work best in the CIE LUV space. Finally, the Vector Angle and Euclidean Distance metrics were compared based on a modified Roberts operator in [1].

Ultimately, the performance of edge detectors depends on the application at hand. In general, any algorithm using a different space than RGB needs to compensate for the computational complexity of the transformation. Certain transformations such as YUV and YC_BC_R can be performed very quickly while others such as HSI and CIE LUV are very complex. On the other hand, RGB suffers from the high correlation among the three planes. However, a reliable and relatively simple method for obtaining hue and saturation difference information directly from RGB is the vector angle measure [1].

In this paper, we propose a method for combining chromaticity difference information in the form of the vector angle and intensity difference information in the form of Euclidean Distance. One of the advantages of such a combination is the ability to perform intensity-invariant segmentation directly from the RGB image in highly colored image regions and intensity-dependent segmentation in areas of low color. The paper is organized as follows. In the second section, the Euclidean distance and vector angle metrics will be described and their differences shown. In the next section, the adaptation of the vector gradient and difference vector operators for edge detection to the metrics is discussed. In the fourth section, the combination methods are illustrated. In the following section, results are described. Finally, the paper ends with discussion and conclusion sections.

2. Distance Metrics

Two color distance metrics will be described in this paper. The first metric is the Euclidean Distance, the second is the vector angle [1]. These metrics could be applied to other color spaces; however, in this paper we will discuss only implementations in the RGB and LUV color spaces.

2.1. Euclidean Distance

Euclidean Distance (ED) is the metric usually used in N-dimensional vector space. It is defined as

$$D(\vec{v}_1,\vec{v}_2) = \|\vec{v}_1 - \vec{v}_2\|$$

where $\|\bullet\|$ is the L_2 vector norm. For a color coordinate system with three planes, the distance calculated is

$$D(\vec{v}_1,\vec{v}_2) = \sqrt{(v_{1,1}-v_{2,1})^2 + (v_{1,2}-v_{2,2})^2 + (v_{1,3}-v_{2,3})^2}$$

where $\vec{v}_1 = [v_{1,1}\, v_{1,2}\, v_{1,3}]^T$ is a color triplet.

In the RGB space, the Euclidean distance measure does not quantify color similarity as well as it does in the perceptually correct LUV space [8]. However, in general it can be said ED is sensitive to variations in intensity, but not very sensitive to variations in hue and saturation [1].

2.2. Vector Angle

An alternate metric could be the Vector Angle (VA) measure [1] that is defined as

$$\cos\theta = \frac{\vec{v}_1^T \vec{v}_2}{\|\vec{v}_1\| \cdot \|\vec{v}_2\|}$$

As opposed to Euclidean distance, vector angle is insensitive to intensity differences, but quantifies well hue and saturation differences. Furthermore, two drawbacks to using the angle θ as an edge value are the complex calculation of the inverse cosine and the problematic computation of statistics on values in angular coordinates [11]. A problem with using $\cos\theta$ or $1-\cos\theta$ is that the dynamic range of values for small angles is small compared to the dynamic range for small angles when using $\sin\theta$. This is important since we are interested in emphasizing hue differences however small they may be. Therefore, the $\sin\theta$ was proposed in [1] as the actual measure and is defined as

$$\sin\theta = \left(1 - \left(\frac{\vec{v}_1^T \vec{v}_2}{\|\vec{v}_1\| \cdot \|\vec{v}_2\|}\right)^2\right)^{1/2}$$

2.3. Euclidean Distance vs. Vector Angle

To illustrate the difference between Euclidean distance and vector angle several artificial images were constructed. The definition of how good a metric is largely depends on the application it is going to be used for. Therefore, both of these metrics have advantages and disadvantages in different situations which could be easily exploited. In [1], the authors show how vector angle can be used to detect strong edges in areas of differing hues and very weak edges in areas of high hue similarity. However, hue difference becomes irrelevant at low RGB values since small variations in one of the three values can produce large differences in the angle between two colors. On the other hand, low intensity areas are not a problem for Euclidean distance, which is unable to assess the similarity of two pixels given their nearly identical hue [1,8].

It seems that a combination of the vector angle and the Euclidean distance metrics using a trade-off parameter could overcome these limitations. Two combination schemes will be discussed in Section 4.

3. Edge Detection Methods

In this paper, we will concentrate on vector-based approaches for edge detection. For this purpose, we have adapted the Difference Vector and Vector Gradient edge detectors to both the Euclidean distance and vector angle metrics.

3.1. Difference Vector Edge Detectors

A well-known edge detector in image processing is the Difference Vector Edge Detector [4,5] which is a 3x3 operator calculating the maximum gradient across the central pixel. The Euclidean distance version of this edge detector can be written as

$$E_{DV} = \max_{i=1\ldots4}\{\|\vec{v}_i(x,y) - \vec{v}_{4+i}(x,y)\|\}$$

where i represents one of the first four (out of a possible eight) positions around the central pixel. This is done in order to obtain measurements for the four directional gradients (i.e., horizontal, vertical, left and right diagonals) across that central pixel. $\vec{v}_i(x,y)$ is the i^{th} color vector around the central pixel (x,y).

The vector angle version of the Difference Vector Edge Detector, on the other hand, can be characterized by

$$S_{VG} = \max_{i=1\ldots8}\left[\sqrt{1-\left(\frac{\vec{v}_i^T(x,y)\cdot\vec{v}_0(x,y)}{\|\vec{v}_i(x,y)\|\|\vec{v}_0(x,y)\|}\right)^2}\right]$$

3.2. Vector Gradient Edge Detectors

The Vector Gradient Edge Detector is local operator which computed the maximum distance in the desired metric between the center pixel and the 8-connected pixels adjacent to it. It has already been used successfully with the Euclidean distance metric in the LUV space [8].

The Euclidean distance version of this operator can be simply defined as

$$E_{VG} = \max_{i=1\ldots8}\{\|\vec{v}_i(x,y) - \vec{v}_0(x,y)\|\}$$

where i is a counter representing each of the eight neighboring pixels.

The vector angle version of this operator is written as

$$S_{VG} = \max_{i=1\ldots8}\left[\sqrt{1-\left(\frac{\vec{v}_i^T(x,y)\cdot\vec{v}_0(x,y)}{\|\vec{v}_i(x,y)\|\|\vec{v}_0(x,y)\|}\right)^2}\right]$$

4. Combination Methods

The Euclidean distance and the vector angle metrics together take into account the intensity and the chromaticity information from a color image. Therefore, it is desirable to combine both of them to exploit their particular characteristics. There are several possible ways of combining these two metrics. Two will be explored in this paper.

4.1. Intensity-Based Combination

A simple method of combining both metrics would involve using the intensity plane of the image. One way of calculating intensity involves taking a simple average of the RGB components. The use of intensity as a trade-off variable is a logical choice given that the vector angle metric breaks down for low values of intensity (see Section 2.3). Therefore, vector angle could be used when both pixels being compared have high intensity and Euclidean distance would be used when one of the two pixels would have low intensity.

4.2. Saturation-Based Combination

A saturation-based combination of hue and intensity planes for edge detection was first attempted in [7]. Carron and Lambert converted the RGB color image into an HSI representation using the YC_1C_2 transformation as an intermediary step. They argued that this form of saturation is less sensitive to nonlinear effects than the classical saturation formula as defined for HSI [7].

Carron and Lambert show that the noise variance within the hue component is higher than within the intensity component when saturation is low (i.e. intensity is more relevant than hue). They also show the converse is true when saturation is high (i.e. hue is more relevant than intensity). We use the same saturation calculation.

The vector angle provides a good measure of hue difference and Euclidean distance a good measure of intensity difference directly within the RGB space. This is potentially an improvement over using the hue and intensity planes from a complex transformation as shown in [7]. Therefore, when both pixels are highly saturated, Vector Angle would be used, and when one of the pixels is low in saturation Euclidean distance would be used.

4.3. Hue Relevance vs. Intensity Relevance

The relevance or trade-off parameter between an intensity difference measure and a hue difference measure can be calculated in the following manner. Given that for each of the above methods, two parameters have to be calculated (one for each pair of points being evaluated), a transition function between the intensity and hue relevance is necessary for each point in the pair.

For example, consider the case of saturation-based combination. The sigmoid is a smooth transfer function and is defined by

$$\alpha(S) = \frac{1}{1+e^{-slope(S-offset)}}$$

where *offset* defines the transition midpoint and *slope* describes the slope at that point. Both the *slope* and the *offset* are application dependent and are set experimentally in this paper. In this case, as saturation increases the function's output slowly changes from 0 (i.e. Euclidean distance bias) towards 1 (i.e. vector angle bias).

However, since every time two points are considered, the vector angle metric should be used only if both points are highly saturated, otherwise the Euclidean distance metric or a combination of both should be used. This combined function [7] is defined as

$$\rho(S_1, S_2) = \sqrt{\alpha(S_1) \cdot \alpha(S_2)}$$

4.4. Combined Edge Detection Operators

The saturation-based combination of the Difference Vector operator would be represented by

$$C_{DV} = \max_{i=1\ldots4} \left(\begin{array}{l} \rho(S_1,S_2)\sqrt{1-\left(\dfrac{\vec{v}_i^T(x,y)\cdot\vec{v}_{4+i}(x,y)}{\|\vec{v}_i(x,y)\|\,\|\vec{v}_{4+i}(x,y)\|}\right)^2} + \\ (1-\rho(S_1,S_2))\cdot\|\vec{v}_i(x,y)-\vec{v}_{4+i}(x,y)\| \end{array} \right)$$

Notice that the maximum is being computed on the whole gradient calculation. This is done in order to conserve the relative meaning of the pixels. That is, we want to combine the Euclidean distance Difference Vector operator with its vector angle counterpart.

The saturation-based combination of the Vector Gradient operator would be

$$C_{GV} = \max_{i=1\ldots8} \left(\begin{array}{l} \rho(S_1,S_2)\sqrt{1-\left(\dfrac{\vec{v}_i^T(x,y)\cdot\vec{v}_0(x,y)}{\|\vec{v}_i(x,y)\|\,\|\vec{v}_0(x,y)\|}\right)^2} + \\ (1-\rho(S_1,S_2))\cdot\|\vec{v}_i(x,y)-\vec{v}_0(x,y)\| \end{array} \right)$$

The question of normalizing the Euclidean distance and vector angle components arises. For the purposes of this paper, both metrics were normalized with respect to the maximum obtainable value with the metric. In the case of Euclidean distance this is $255\sqrt{3}$, whereas the values for vector angle are already scaled within the 0-1 range.

The same methodology was applied to the intensity-based combinations.

5. Results

As a preliminary evaluation of the effectiveness of the combination methods, one image was tested. The image shown in Figure 3 has several important features that make it suitable for showing the effectiveness of the algorithms presented above. It has several important features: shadows, areas with the same hue, but varying saturation or intensity, areas of differing hue, but similar intensity. As computer vision moves to an unconstrained environment effectively dealing with such constraints is very important. The edge detection is done on a smoothed image; i.e., a 3x3 averaging kernel on each of the three RGB planes has been used.

The edges have been computed using the various methods presented earlier in the paper and were scaled to the 0-255 range. The edges displayed constitute the top 2% (in relative strength) of the edges found for the vector gradient approaches and the top 5% for the difference vector approaches. We have found this to give more reliable results than absolute thresholds. A relative threshold also enables us to compare edge images more easily. Results are shown in Figures 3-12.

In general, it can be noticed that the edges obtained using the Euclidean distance-based edge detectors (Figures 3-6) were much more cluttered than either the vector angle-based (Figures 7 and 8) or combined distance measure-based (Figures 9-12) methods. In this example, the use of the LUV space (Figures 3 and 4) does not seem to enhance the edge detection over the RGB-based results (Figures 5 and 6) as was claimed in [8]. Many edges are missing as in the LUV case and many shadow edges can still be discerned.

The vector angle-based techniques produce weaker intensity-based edges than Euclidean distance-based methods. Of course this is an expected result. The edges caused by the shadows have now almost entirely disappeared since the hue of the shadow is practically identical to the hue of the object it falls on (i.e., the presence of a shadow changes the intensity of the color of the object the shadow falls on). Both of these statements illustrate the shortcomings of ED- and VA-based approaches discussed above.

The edge images obtained using the combined Euclidean distance and vector angle (Figures 9-12) successfully show the elimination of false object edges due to shadows and the restoration of edges that have disappeared due to similar hues on both sides of the edge (although the saturation and intensity were not the same); e.g., the edge between the blue container and the purple paper. This can be noticed especially for the intensity-based combinations (Figures 11 and 12). The vector gradient edge detector used with the intensity-based combined metric shows the most promise although there is some noise in the image and (Figure 12).

Other still color images were also tested (e.g. "Lena", etc.); however, they showed neither improvement nor degradation over the Euclidean distance-based edge detectors. From this it can be hypothesized that most probably only specific applications (e.g. robot vision) where chromaticity information such as hue and saturation are important would benefit from this new methodology. As computer vision algorithms try to understand scenes from increasingly unconstrained environments, the accurate processing of color images will become more important.

5.4. Discussion

The combination of Euclidean distance and vector angle metrics helps to bridge the gap between intensity-based and hue-based differences. The results obtained using the combination methods enhance both metrics. This is especially visible in areas of the image with a high intensity or saturation.

However, there are still numerous problems to be resolved. First, the problem of proper metric normalization arises. In this paper, we assume that the distances are equivalent in both metrics. This is a preliminary step to discovering whether there is some kind of correspondence between the two. Does a 0.1 measurement within the normalized Euclidean distance metric mean the same as 0.1 within normalized vector angle metric? Certainly not. This is a fundamental question which needs to be resolved before the full benefit of such a combination can be seen.

Second, in this paper, one combination method with two variants was used (intensity- and saturation-based combinations). This is a classical way of combining two disparate metrics that try to achieve similar results. A mix of saturation and intensity might achieve better combination results since intensity is needed to make sure hue is not used for low RGB pixel values and saturation is needed to decide whether two pixels are highly saturated and, therefore, more likely to have stable hue values.

Third, as mentioned before, the application is very important when assessing the results of an algorithm. In this case, edge detection constitutes only a preliminary step in an image understanding process. The edge detectors shown here should be evaluated in a broader context to verify that their functioning is consistent with our preliminary results. To this effect, more tests will be carried out on artificial and real images to fully assess the usefulness of the methods.

6. Conclusions

Two combination methods for combining Euclidean distance and vector angle metrics in an edge detection context were shown in this paper. Preliminary results show that there is merit to trying to find a good way to combine these intensity- and hue-based metrics. However, before a good combination is found several questions need to be answered. Research is currently underway to find these answers.

References

[1] R.D. Dony and S. Wesolkowski, "Edge Detection on Color Images Using RGB Vector Angle," *Proc. IEEE CCECE'99*, Edmonton, Canada.

[2] R.C. Gonzalez and R.E. Woods, *Digital Image Processing*, Addison-Wesley, 1993.

[3] H. Levkowitz, *Color Theory and Modeling for Computer Graphics, Visualization, and Multimedia Applications*, Kluwer Academic Publishers, 1997.

[4] P. Trahanias and A.N. Venetsanopoulos, ``Color edge detection using vector statistics," *IEEE Trans. on Image Processing*, vol. 2, pp. 259-264, April 1993.

[5] Y. Yang, *Colour edge detection and segmentation using vector analysis*, Master's thesis, Electrical and Computer Engineering, University of Toronto, Toronto, ON, Canada, 1995.

[6] M. Hedley and H. Yan, ``Segmentation of color images using spatial and color space information," *Journal of Electronic Imaging*, vol. 1, pp. 374-380, October 1992.

[7] T. Carron and P. Lambert, ``Color edge detector using jointly hue, saturation and intensity," in *Proc. IEEE*

International Conference on Image Processing, pp. 977-981, October 1994.

[8] L. Shafarenko, M. Petrou, and J. Kittler, ``Automatic watershed segmentation of randomly textured color images," *IEEE Trans. on Image Processing*, vol. 6, pp. 1530-1544, November 1997.

[9] S. Wesolkowski, P. Bowman, and D. Tunnah, ``A high speed colour cheque image capture and processing system," in *Proc. IEEE Canadian Conference on Electrical and Computer Engineering*, (Waterloo, ON), pp. 457-460, May 1998.

[10] Y. Zhong, K. Karu and A.K. Jain, "Locating Text in Complex Color Images," *Pattern Recognition*, vol. 28, no. 10, pp. 1523-1535, October 1995.

[11] G. S. Watson, *Statistics on Spheres*, Wiley-Interscience, 1983.

[12] Q.-T. Luong, "Color in computer vision," in *Handbook of Pattern Recognition and Computer Vision*, C.H. Chen, L.F. Pau and P.S.P. Wang, editors, pp. 311-368, World Scientific Publishing Company, 1993.

Figure 1: Original image

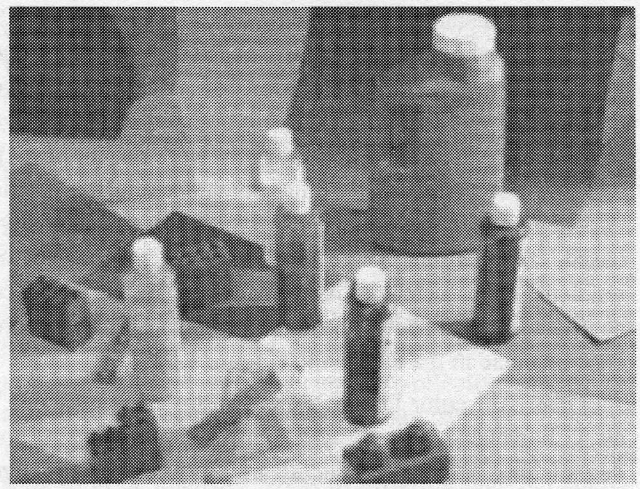

Figure 2: Smoothed version of Figure 1

Figure 3: Euclidean Distance Difference Vector operator applied to the LUV space.

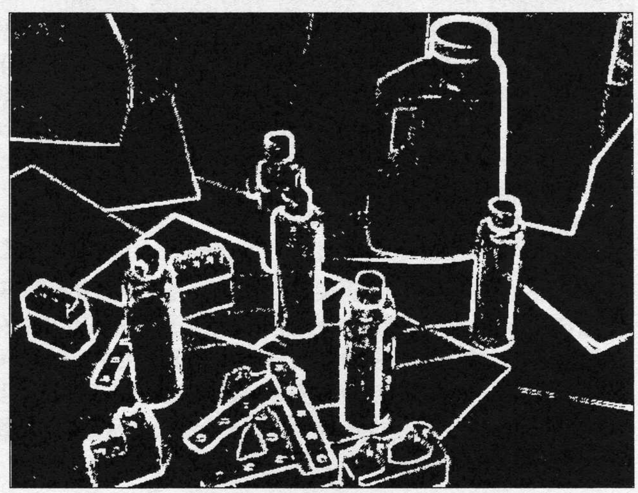

Figure 4: Euclidean Distance Vector Gradient operator applied to the LUV space.

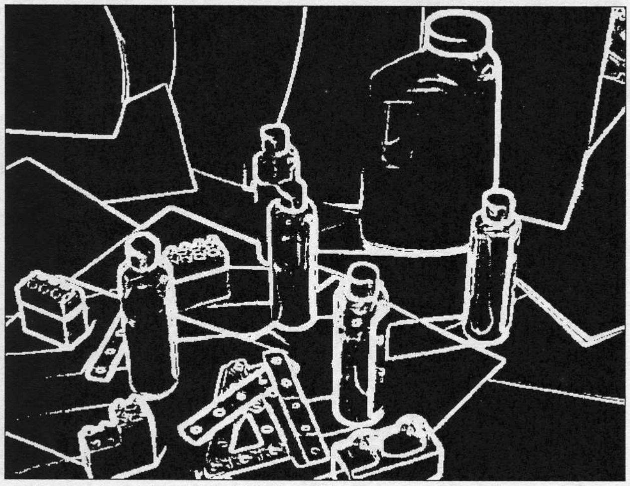

Figure 5: RGB Euclidean Distance Difference Vector.

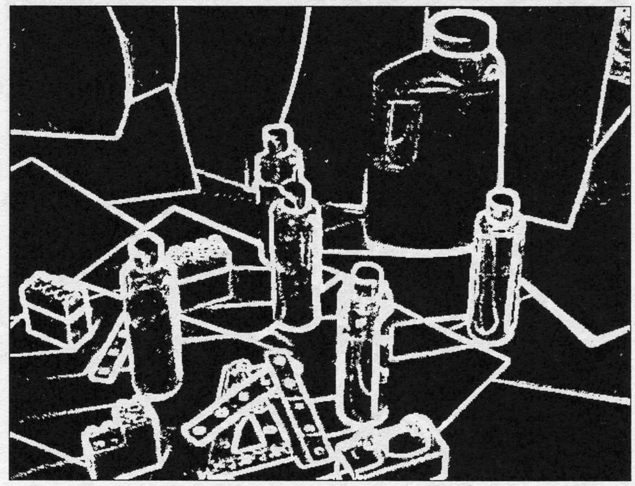

Figure 6: RGB Euclidean Distance Vector Gradient.

Figure 7: RGB Vector Angle Difference Vector.

Figure 8: RGB Vector Angle Vector Gradient.

Figure 9: Difference Vector with saturation-based combined measure applied to the RGB space (offset=0.10 and slope = 75).

Figure 10: Vector Gradient with saturation-based combined measure applied to the RGB space (offset=0.25 and slope = 75).

Figure 11: Difference Vector with intensity-based combined measure applied to the RGB space (offset=0.10 and slope = 75).

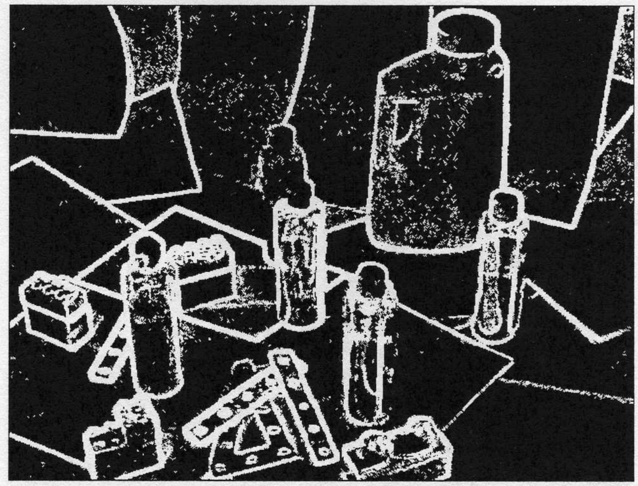

Figure 12: Vector Gradient with intensity-based combined measure applied to the RGB space (offset=0.40 and slope = 75).