Mean shift segmentation on Enhanced Color image

Poonam Chauhan, R. V. Shahabade

Information technology, Mumbai University, India Information Technology, Mumbai, India

Abstract: This paper proposed the method of mean shift segmentation on Enhanced color image. The method applies the modified histogram equalization technique for enhancement of under illuminated color image and then mean shift segmentation is applied on this enhanced image. This technique uses the lightness component in YIQ color space is transformed using sigmoid function, then the traditional histogram equalization (HE) method is applied on Y component. Once the image is enhanced mean shift segmentation is applied to the enhanced image due to which we get good segmentation results as compared to without enhanced image. Experiments on natural color images show promising results.

Keywords: YIQ, RGB, Histogram Equalization, Sigmoid function, Mean shift Segmentation

I. Introduction

A common and often serious discrepancy exists between recorded color images and the direct observation of scenes. Human perception excels at constructing a visual representation with vivid color and detail across the wide range of photometric levels due to lighting variations. In addition, human vision computes color so as to be relatively independent of spectral variations in illumination [1]. When attempting to display an image on a display device, either the low intensity areas (dim region), which are underexposed, or the high intensity areas, which are overexposed, cannot be seen. To handle this problem, various image processing techniques have been developed. Some of them are simple methods such as histogram equalization, gamma adjustment, and logarithmic method. Histogram equalization and its variations have traditionally been used to correct for uniform lighting and exposure problems. This technique is based on the idea of remapping the histogram of the scene to a histogram that has a near-uniform probability density function. This results in reassigning dark regions to brighter values and bright regions to darker values. Histogram equalization works well for scenes that have uni-modal or weakly bi-modal histograms (i.e. very dark, or very bright), but not so well for those images with strong bi-modal histograms (i.e. scenes that contain very dark and very bright regions) [2].Once the Enhancement is done segmentation technique is applied on the enhanced image. lot of image segmentation methods have been proposed: roughly speaking, these methods can be classified into [3]: (1) Histogram thresholding [19]; (2)Clustering [12, 19, 8]; (3) Region growing [7]; (4) Edge-based [17]; (5) Physical model-based [15]; (6) Fuzzy approaches [18]; and (7) Neural network methods. Mean shift segmentation technique is applied because of its efficient results. The paper is organized as follows: in section 2, ; Histogram equalization introduced in section 3 Mean shift algorithm in section 4 The proposed color image enhancement and segmentation method is given, in section 5 experiments on color image (real) segmentation with enhanced and without enhancement. The conclusion can be found in section 5.

II. Histogram Equalization

A global technique that works well for a wide variety of images is histogram equalization If lightness levels are continuous quantities normalized to the range (0, 1), and pr(r) denotes the probability density function (PDF) of the lightness levels in a given image, where the subscript is used for differentiating between the PDFs of the input and output images. Suppose that we perform the following transformation on the input levels to obtain output (processed) intensity levels [1],

$$S = T(r) = \int_0^2 P_r(w) dw$$

Where w is a dummy variable of integration. The probability density function of the output levels is uniform, such that [4]:

$$P_{s}(s) = \begin{cases} 1 & \text{for } 0 \le s \le 1 \\ 0 & \text{otherwise} \end{cases}$$
(2)

When dealing with discrete quantities, we will work with histograms, and call the preceding technique histogram equalization, such that

$$S_{K} = \sum_{j=0}^{K} P_{r}(rj) = \sum_{j=0}^{k} \frac{n_{j}}{n}$$
(3)

(1)

where j=0.....k

Where: rk is the normalized intensity level of the input image corresponding to the (non-normalized) intensity level k: $r_k = K/L(r_k = 0....1)$ and (K=0....L) and L = 255 for lightness (band with 8 bit/pixel), sk corresponds to normalized intensity level of the output image. The cumulative probability density function (CPDF) calculated by [15]

$$P_{c}(rk) = \sum_{j=0}^{k} P_{r}(rj) = \sum_{j=0}^{k} \frac{n_{j}}{n}$$
(4)

rj is normalized intensity level of the input image corresponding to the (non-normalized) intensity level j , and rj given by :

$$\mathbf{r}_{\mathbf{j}} = \frac{\mathbf{j}}{\mathbf{L}} \qquad \mathbf{j} = \mathbf{0} \dots \dots \mathbf{L} \tag{5}$$

Where nj being the number of pixel with intensity j and n is the total number of pixels of the image

III. The Mean Shift Algorithm

Mean shift algorithm has been extensively exploited and applied in low-level computer vision tasks [13, 14, 15] for its ease and efficiency. One characteristic of the mean shift vector is that it always points towards the direction of the maximum increase in the density. The converged centre (or windows) correspond to modes (or centers of the regions of high concentration) of data. The mean shift algorithm is based on kernel density estimation.

Mean shift algorithm and kernel density estimation.

Let ${Xi}i=1,...,n$ be a set of n data points in a d-dimensional Euclidean space Rd, the multivariate kernel density estimator with kernel K and window radius (band-width) h is defined as follows [1], :

$$\hat{f}(\mathbf{x}) = \frac{1}{\mathbf{n}\mathbf{h}^{d}} \sum_{n=1}^{n} \mathbf{K}(\frac{\mathbf{x}-\mathbf{x}\mathbf{i}}{\mathbf{h}})$$
(6)

The kernel function K(x) should satisfy some conditions .The Gaussian kernel is one optimum kernel, which yields minimum mean integrated square error (MISE):

In Mean Shift we are only interested in a special case of radially symmetric kernels satisfying: K(x)=ck, dk(||x||2) where ck, d, the normalization constant, makes K(x) integrate to one and k(x) is called the *profile* of the kernel. It helps us simplify the calculation in the case of multivariate data.

The *profile* of the Gaussian kernel is: $e^{-\frac{1}{2}x^2}$ and therefore, the multivariate Gaussian kernel with the standard deviation δ will be:

$$K(x) = 1 \frac{1}{2\pi\sqrt{\sigma de}} e^{\frac{1}{2} - \frac{||x||^2}{2\sigma^2}}$$
(7)

Where d is the number of dimensions. It's also worth mentioning that the standard deviation for the Gaussian kernel works as the bandwidth parameter, h.

Now having sample points {xi}i=1..n, each mean shift procedure starts from a sample point yj=xj and update yj until convergence as follows:

$$\mathbf{y}_{i}^{0} = \mathbf{x}_{i} \tag{8}$$

$$y_{i}^{t+1} = \frac{\sum_{i=1}^{n} e^{\frac{-|y_{j-x_{j}}^{t}|^{2}}{h^{2}}}}{\sum_{i=1}^{n} e^{\frac{-|y_{j-x_{j}}^{t}|^{2}}{h^{2}}}}$$
(9)

So basically all the points are considered in calculation of the mean shift but there is a weight assigned to each point that decays exponentially as the distance from the current mean increases and the value of σ determines how fast the decay is.

The mean shift is an unsupervised nonparametric estimator of density gradient and the mean shift vector is the difference between the local mean and the center of the window.

The mean shift vector M(x) is defined as:

From equation (3) and equation (4), we get:

 $Mx = \frac{h^2 \nabla f(x)}{d+2 \hat{f}(x)}$

(10)

Equation (5) firstly appeared in [17].

IV. Proposed Enhancement and Segmentation step

Modified Histogram Equalization Algorithm

1. First step in this algorithm is to transform color image from basic RGB color space to YIQ color space, the forward transform is given by

Y = I	(11)
i = 0.596r - 0.27g + 0.322b	(12)
q = 0.211r - 0.253g + 0.312b	(13)
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Where y is lightness component, i,q are chromatic components. In second step is transformed normalized lightness value by using sigmoid function that is given by

2. [18]:

 $S = \frac{1}{1 + \sqrt{\frac{1 - l_n}{l_n}}}$ (14)

3. Third step is applied HE on modify lightness component, the processing lightness component YP has been get form this step. Finally inverse transformation from YIQ to RGB color space calculated in Yp IQ that is given by [8]:

$r = Y_p + 0.956i + 0.621q$	(15)
$g = Y_p - 0.272i - 0.647q$	(16)
$r = Y_p - 1.106i + 1.073q$	(17)

The next step is applying mean shift segmentation on the enhanced image

The procedure of the mean shift on RGB and image

The Mean Shift algorithm can be described as follows:

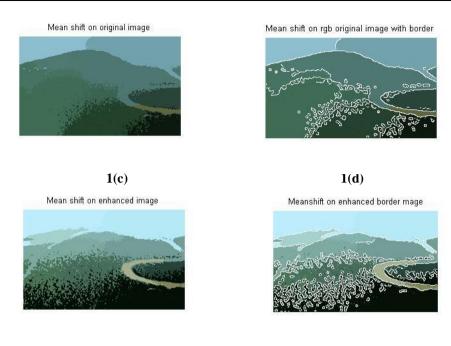
- 1. Choose the radius of the search window
- 2. Initialize the location of the window xk, k=1.
- 3. Compute the mean shift vector Mh,k(xk).
- 4. Translate the search window by computing xk+1 = Mh, k(xk)+xk, k=k+1.
- 5. Step 3 and step 4 are repeated until convergence.

The mean shift automatically finds the local maximum density. This property holds even in high dimensional feature spaces. In [4], the authors also proposed a peak-finding algorithm. Unfortunately, it is heuristically based. In contrast, the mean shift algorithm has a solid theoretical foundation. The proof of the convergence of the mean shift algorithm can be found in [14, 15].

V. Experiments on enhanced color image segmentation

We test our color image enhancement and segmentation method on natural color images. In Figure 2, part of the procedures of the HSV method is illustrated and final segmentation results are given. Figure 1 (a) includes the original image "ground". The Enhanced image of ground Figure 2 (b) Means shift on original image in fig 2(c) fig 2(d) display mean shift on Enhanced image and fig2(e) and 2(f) display output image with border, we can see that RGB obtains good segmentation results in case of t enhanced image but with original image display region which look overlap in some part of image.





1(e)

1(f)

VI. Conclusions

In this paper, we propose an enhancement of color image before segmentation we employ the concept of enhancement, and the mean shift algorithm on RGB image, in our method. Thus the proposed method considers. the modified method (MHE algorithm), this algorithm was enabled to increase both lightness and contrast in images. Figs. (10 and 14) show the histogram of enhanced images, we can note the behaviour of distribution is similar in histograms of all images. Experiments show that the proposed method achieves promising results for natural color image segmentation.

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