A Fast HSV Image Color and Texture Detection and Image Conversion Algorithm

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Abstract: In order to identify the perceived qualities of texture and color in an building mathematical models for object, a optimized and efficient algorithm 'A Fast HSV Image Color and Texture Detection Algorithm' based on color intensity using Artificial Intelligence is presented in this paper. we used color intensity method over conventional method. The 'Fast HSV Image Color and Texture Detection Algorithm' focuses to integrate the detection of image color with detection of texture using AI and Color detection has been among the widest research area in the field of computer science. In computer vision, there are several pre-existing color models for describing the specification of the colors such as RGB, CMY and HSV. This paper presents detection of color using HSV-based (hue, saturation, value) color model since it greatly decreases the size of color and grey-scale information of an image .This paper can be treated as a reference for getting in depth knowledge of the Color detection and texture detection.

Keywords: Red Green Blue (RGB), Cyan Magenta Yellow (CMY), Hue Saturation Value (HSV), Comission internationable del' Eclairage (CIE), Content Based Image Retrieval (CBIR)

1. Introduction

This paper focuses on two things color and texture of modeled object.

Color: We have to focus to detect objects in different colors and shapes in an active vision circumstance, many commonly used computer vision algorithms are included and some of them are developed in several previous thesis and projects. In computer vision, there are several pre-existing color models for describing the specification of the colors such as RGB, CMY and HSV. This thesis uses HSV-based (hue, saturation, value) color model since it greatly decreases the size of color and grey-scale information of an image. A set of isolated points are clustered into objects by color extraction. Hue filtering is used to segment the specified color.

Texture: In many machine vision and image processing algorithms, simplifying assumptions are Made about the uniformity of intensities in local image regions. However, images of real objects often do not exhibit regions of uniform intensities. For example, the image of a wooden surface is not uniform but contains variations of intensities which form certain repeated patterns called visual texture.

Texture-based objects are those objects for which, unlike shape-based objects, there is no obvious visible inter-object part-wise correspondence. These objects are better described by their texture than the geometric structure of reliably detectable parts. These tasks are performed on a large set of images which were collected as a benchmark for the problem of scene understanding. The final system is able to reliably identify cars, pedestrians, bikes, sky, road, buildings and trees in a diverse set of images. [2]

Textures provide important characteristics for surface and object identification from aerial or satellite photographs, biomedical images and many other types of images.[6] In computer vision, there are several pre-existing color models for describing the specification of the colors such as RGB, CMY and HSV. This thesis uses HSV-based (hue, saturation, value) color model since it greatly decreases the size of color and grey-scale information of an image. A set of isolated points are clustered into objects by color extraction. Hue filtering is used to segment the specified color. When the value of hue is set, a mask is applied to the image. In a binary image, when the value of pixels satisfy a specified criterion, such as hue, the value transformed by masking. Function is set to zero which shows in white color; otherwise. All the pixels in the appointed hue range are marked as foreground which are shown in white and other pixels are marked as background are shown in black.





Figure 1: shows only blue objects in detection

1.1 The Color Models and its Functionalities

Main Color Spaces

- CIE XYZ, xyY
- · RGB, CMYK
- · HSV (Munsell, HSL, IHS)
- · Lab, UVW, YUV, YCrCb, Luv,

CIE Standard

- CIE: International Commission on Illumination (Comission Internationale de l'Eclairage).
- Human perception based standard (1931), established with color matching experiment
- Standard observer: a composite of a group of 15 to 20 people



Figure 1: CIE Experiments

CIE Color Space

- 3 hypothetical light sources, X, Y, and Z, which yield positive matching curves
- Y: roughly corresponds to luminous efficiency characteristic of human eye

The RGB Cube

RGB color space is perceptually non-linear

RGB space is a subset of the colors human can perceive Con: what is 'bloody red' in RGB?



600

λ (nm)

Figure 2: RGB monitor And RGB cube

RGB and CMY

· Converting between RGB and CMY





Figure 3: HSV Presentation

1.2 Color model conversions

Conversion between RGB and HSV

The HSV color model can be considered as a different view of the RGB cube. Hence the values of HSV can be considered as a transformation from RGB using geometric methods. The diagonal of the RGB cube from black (the origin) to white corresponds to the V axis of the hex cone in the HSV model. For any set of RGB values, V is equal to the maximum value in this set. The HSV point corresponding to the set of RGB values lies on the hexagonal cross section at value V. The parameter S is then determined as the relative distance of this point from the V axis. The parameter H is determined by calculating the relative position of the point within each sextant of the hexagon. The values of RGB are defined in the range [0, 1], the same value range as HSV. The value H is the ratio converted from 0 to 360 degree.

1.2 Color Model Pros and Cons

• RGB

- + Cartesian coordinate system
- + Linear
- + Hardware-based (easy to transform to video)
- + Tristimulus-based
- Hard to use to pick and name colors
- Doesn't cover gamut of perceivable colors

- Non-uniform: equal geometric distance ---unequal perceptual distance

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• CIE

- + covers gamut of perceived colors
- + based on human perception (matching experiments)
- + linear
- + contains all other spaces

- non-uniform (but variations such as CIE Lab are closer to Munsell, which is uniform)

- xy-plot of chromaticity horseshoe diagram doesn't show luminance Color Model.

• HSV

- + easy to convert to RGB
- + easy to specify colors
- nonlinear
- doesn't cover gamut of perceivable col ors
- nonuniform

2. Methodology

Colour statistics histograms

- Histograms are a useful tool for greyscale image analysis.
- We suggest a similar tool for use with colour images.
- Calculated as follows:
- The luminance is quantised into N+1 levels
- For each level $\ell = \{0, 1, \dots, N\}$, we calculate
- The saturation-weighted hue mean.
- The associated mean length.
- We have two histograms as a function of luminance.
- For visualisation, we create one histogram by:
- Setting the heights of the bars equal to the mean length.
- Setting the colour of the bars based on the hue mean.

RGB to HSV conversion formula

The R,G,B values are divided by 255 to change the range from 0..255 to 0..1:

R' = R/255 G' = G/255 B' = B/255

$$\begin{array}{l} {}^{Cmax\,=\,\max(R',\ G',\ B')}_{\Delta\,=\,Cmax\,-\,Cmin} \quad H = \begin{cases} 60^{\circ} \times \left(\frac{G'-B'}{\Delta}mod6\right) &, Cmax = R'\\ 60^{\circ} \times \left(\frac{B'-R'}{\Delta}+2\right) &, Cmax = G'\\ 60^{\circ} \times \left(\frac{R'-G'}{\Delta}+4\right) &, Cmax = B' \end{cases}$$

Hue calculation:

$$S = \begin{cases} 0 &, \Delta = 0 \\ \frac{\Delta}{Cmax} &, \Delta <> 0 \end{cases}$$
 Saturation calculation:

Value calculation: V = C max

Hue Statistics

- For the brightness and the saturation, one can use standard statistical methods for calculating the mean, standard deviation, etc.
- For data a_i (i = 1, 2... n) distributed on the unit circle, the mean direction is that of the resultant vector obtained by adding unit vectors with directions a_i .
- A measure of the variation in the directions of the data is given by the length of this vector divided by *n* (the mean length), which has the following characteristics:
- range [0:1]
- Values close to $1 \Rightarrow$ the data is less spread out.



Mean

- Given *n* values of the hue *H*,
- The mean direction *H* is calculated as follows:

$$A = \sum_{i=1}^{n} \cos H_i, \quad B = \sum_{i=1}^{n} \sin H_i, \quad R^2 = A^2 + B^2 \{1\}$$
$$= \begin{cases} \arctan(\frac{B}{A}) & \text{if } B > 0, A > 0\\ \arctan(\frac{B}{A}) + \pi & \text{if } A < 0 \end{cases}$$
(2)

$$\left| \arctan\left(\frac{B}{d}\right) + 2\pi \text{ if } B < 0, A \right|$$

The mean length R is:

>0

(3)

Hue Mean which Takes the Saturation into Account

- The previous formulation is standard in the texts on circular statistics, but it ignores the fact that not all hues have the same importance.
- We take this into account by weighting the length of each hue vector by the associated saturation value.

Example (1)



(Original Image)



(HUE)



(Saturation)



(Luminance)

3. Algorithm Detail

(a)Color Level Histogram

The conventional color histogram (CCH) of an image indicates the frequency of occurrence of every color in the image. From a probabilistic perspective, it refers to the probability mass function of the image intensities. It captures the joint probabilities of the intensities of the color channels.

The CCH can be represented as;

h A,B,C(a,b,c) = N. Prob(A=a, B=b, C=c)

Where A, B and C are the three color channels and N is the number of pixels in the image [3].

Computationally, it is constructed by counting the number of pixels of each color (in the quantized color space).

(b) Color histogram based on Fuzzy Logic

In the fuzzy color histogram (FCH) approach, a pixel belongs to all histogram bins with different degrees of membership to each bin. More formally, given a color space with K color bins, the FCH of an image I is defined

as F(I)=[f1,f2,...fk] where

$$f_i = \frac{1}{N} \sum_{j=1}^{N} \mu_{ij}$$

Where N is the number of pixels in the image and μij is the membership value of the jth pixel to the ith color bin, and it is given by $\mu ij = 1/(1 + dij/\varsigma)$, where dij is the Euclidean distance between the color of pixel j(a 3- dimensional vector of the H, S and V components), and the ith color bin, and ς is the average distance between the colors in the quantized color space.

(c) The Color Correlogram

The color correlogram (CC) expresses how the spatial correlation of pairs of colors changes with distance. A CC for an image is defined as a table indexed by color pairs, where the *dth* entry at location (i,j) is computed by counting number of pixels of color j at a distance d from a piel of color i in the image, divided by the total number of pixels in the image.

(d) Color Indexing

In color indexing, given a query image, the goal is to retrieve all the images whose color compositions are similar to the color composition of the query image. Typically, the color content is characterized by color histograms, which are compared using the histogram intersection distance measure.

4. System Model

Color feature of HSV

We evaluate the content based image retrieval HSV color space of the images in the database. The HSV stands for the Hue, Saturation and Value, provides the perception representation according with human visual feature. The HSV model, defines a color space in terms of three constituent components: Hue, the color type Range from 0 to 360. Saturation, the "vibrancy" of the color: Ranges from 0 to 100%, and occasionally is called the "purity". Value, the brightness of the color: Ranges from 0 to 100%. HSV is cylindrical geometries, with hue, their angular dimension, starting at the red primary at 0° , passing through the green primary at 120° and the blue primary at 240° , and then back to red at 360° [8, 9].

The quantization of the number of colors into several bins is done in order to decrease the number of colors used in image retrieval, J.R. Smith designs the scheme to quantize the color space into 166 colors. Li design the non-uniform scheme to quantize into 72 colors. We propose the scheme to produce 15 non-uniform colors.

$$H = \cos^{-1} \frac{\frac{1}{2} [(R - G) + (R - B)]}{\sqrt{(R - G)^2 + (R - B)(G - B)}}$$

$$S = 1 - \frac{3}{R + G + B} (\min(R, G, B))$$

$$V = \frac{1}{3} (R + G + B)$$

The formula that transfers from RGB to HSV is defined as below:

The R, G, B represent red, green and blue components respectively with value between 0-255. In order to obtain the value of H from 0o to 360 o, the value of S and V from 0 to 1, we do execute the following formula:

H= ((H/255*360) mod 360 V= V/255 S= S/255

RGB to HSV conversion formula

The R,G,B values are divided by 255 to change the range from 0..255 to 0..1: R' = R/255 G' = G/255 B' = B/255

Cmax = max(R', G', B')

 $Cmin=\min\{R',\,G',\,B'\}$

 $\Delta = Cmax - Cmin$

 $H = \begin{cases} 60^{\circ} \times \left(\frac{G'-B'}{\Delta}mod6\right) &, Cmax = R'\\ 60^{\circ} \times \left(\frac{B'-R'}{\Delta} + 2\right) &, Cmax = G'\\ 60^{\circ} \times \left(\frac{R'-G'}{\Delta} + 4\right) &, Cmax = B' \end{cases}$

Hue calculation:

$$S = \begin{cases} 0 &, \Delta = 0 \\ \frac{\Delta}{Cmax} &, \Delta <> 0 \end{cases}$$

Saturation calculation: Value calculation: V = C max

5. Proposed Approach

The flow of algorithm is explained in the flow chart, it also explain the how the one test process or retrieval of images from large database is done. The below flow chart showing the steps in implementation:



Method for Texture Detection

Light Reflectance Value (LRV), is a measure of the percentage of visible and usable light LRV.

- A measurement that tells how much light a color reflects & absorbs.
- Runs on a scale from 0% to 100%.
- Zero assumed to be an absolute black and 100% reflective white.
- The average blackest black has a LRV of 5% and the whitest white 85%.

• On finding the value of LVR Scale we can get the idea of texture of

6. Results



Cograf 500 tops PDV Tops Na bard standard and



(Separation of HUE, Saturation, Value Bands)





(Texture Detection of Image)

7. Conclusion

In this the basic concepts and various methods and techniques for processing textured and color of object of models

Volume 3 Issue 6, June 2014 <u>www.ijsr.net</u>

are presented. We separated HUE, Saturation and Value Bands, Texture of an HSV image. Color is a prevalent property of most physical surfaces in the natural world. It also arises in many applications such as satellite imagery and printed documents. Many common low level vision algorithms such as edge detection break down when applied to images that contain textured surfaces. It is therefore crucial that we have robust and efficient methods for processing textured images. It is therefore crucial that we have robust and efficient methods for processing textured images to be implemented. Texture and color processing will be applied to practical application domains such as automated inspection and camera imagery. It is also going to play an important role in the future as we can see from the promising application of texture to a variety of different application domains. We will also convert an HSV image into RGB.

Table 1: Statistical results obtained from experiments on

Image				
Image	Hue,	Saturation,	Value,	Texture
	Hue	Saturation	Value	Detection
	Mask	Mask	Mask	
%Accuracy of Testing	76.1	73.8	77.3	72.5
% Success Rate	89.9	91.7	93.7	87.9
Accuracy Validation	65.2	64.3	65.3	67.3
% Error	10.1	8.3	6.3	12.1
Overall	77.06	76.6	78.76	75.9

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