**Semantic-Improved Color Imaging Applications:**

**It Is All About Context**

**Abstract:**

Multimedia data with associated semantics is omnipresent in today’s social online platforms in the form of keywords, user comments, and so forth. This article presents a statistical framework designed to infer knowledge in the imaging domain from the semantic domain. Note that this is the reverse direction of common computer vision applications. The framework relates keywords to image characteristics using a statistical significance test. It scales to millions of images and hundreds of thousands of keywords. We demonstrate the usefulness of the statistical framework with three color imaging applications: 1) semantic image enhancement: re-render an image in order to adapt it to its semantic context; 2) color naming: find the color triplet for a given color name; and 3) color palettes: find a palette of colors that best represents a given arbitrary semantic context and that satisfies established harmony constraints.

**Existing System:**

Today’s social community websites often have plenty of user generated semantic information already attached to multimedia content such as tagged images on Flickr or user comments for posted content on Facebook. It is thus reasonable to explore applications that take existing semantic information as input and infer meaningful information and actions in the image domain. Many aspects of the research in this article are similar to classic computer vision. We use large databases of annotated photos and characterize the photos with image descriptors. We then learn relations between the keywords and the image descriptors. However, our work differs in two key aspects: the type of descriptors used to describe the images and the mapping function to relate the two domains.

**DisAdvantage:**

1.The Semantic dap is major challenge to solve in the multimedia community

2.The Gap is ofter understood as the difficulty to automatically infer semantic information from the multimedia domain such as face recodnition or video classification.

3.In this article we investigate the gap in the reverse direction(i.e)we are interested in applications that have the semantic domail data source and the multimedia domain as target.

**Proposed System:**

ThePropose a system where users can edit images with touch input and spoken commands such as “sharpen the midtones at the top.” Recognized commands such as sharpen midtones are mapped to the appropriate operation that is applied globally or locally in the relevant region that is determined by a keyword such as top or by the user’s touch input. The main difference between this project and our proposed semantic image enhancement framework (Section IV) is that PixelTone requires the user to explicitly verbalize the desired image processing operation. In contrast, our aim is to exploit any semantic information that comes along with images such as keywords, image titles or community comments. This semantic information is originally not meant to be used for image enhancement, but harnessing it is a promising approach due to its omnipresence in social networks and photo sharing platforms. Annotated image data can also be used to associate words with colors. An early and famous work is from Jones and Rehg where the authors propose a statistical model to find skin tones from annotated images.

**Advantage:**

1.Note that this is the reverse direction of common computers vision applications.

2.The Framework relates keywords to image characteristic using a statistical significance test.

3.It scales to millions of images and hundreds of thousands of keywords.

4.We demonstrate the usefulness of the statistical framework for three color imaging applications.

**Implementation Modules:**

1. Semantic Color Transfer
2. Semantic Depth-of-Field Adaptation
3. Color palettes
4. Quantitative Comparison

**Semantic Color Transfer:**

The method we present consists of two components that handle an image’s semantic and visual contents, respectively. The semantic component uses the keyword and its values to determine a processing that strengthens significant image characteristics. The image component then detects regions of the image where the processing has to be applied. We use significance values from 8-bin histograms of the red, green, and blue channels in order to semantically enhance an image’s colors. Fig. 5(a) shows the significance values computed from 1 million images9 for the keyword autumn. We can see that autumn images have significantly more pixels with a low blue content and a high red content (positive values).

**Semantic Depth-of-Field Adaptation:**

The framework for semantic color enhancement presented in the previous section can be used for other types of image processing. We present an application to semantically enhance the depth-of-field of an image. This is an important characteristic that professionals use to direct an observer’s focus to the image’s in-focus area and away from the intentionally blurred surrounding. For this purpose we compute significance values in the Fourier domain. Each image is transformed to the Fourier domain and the average signal per frequency band is computed. Fig. 8(a) shows a 16-dimensional vector of scores for the semantic concept of flower. The graph indicates that flower images contain significantly less signal power in the high frequency bins. This is reasonable as flower images often are close ups that have been shot with macro lenses or in macro mode.

**Color palettes:**

A color palette is a set of colors that represents a certain topic. Example palettes are reproduced in Fig. 4(c) for different topics. The automatic extraction of palettes from text can also be realized with the statistical framework and is an extension of the color naming application. An automatic approach is clearly superior to a manual palette creation, which is common on popular color palette websites such as Adobe Kuler. In order to allow users to freely describe the emotions they wish to evoke with a color palette we need an unconstrained vocabulary. Thus we use Google n-grams, a freely available database of word n-tuples from Google’s book scanning project.19 In this case we only consider unigrams, i.e. single words, from the English database. We count the frequency of all words and keep the 100,000 most frequently used words. The last three words in this list are: Bayswater,20 turbidite,21 and trabalho.22 Any word that is more common than these three is represented in our database. We download for every word 60 images using Google Image Search totalling to 6 million images.

**Quantitative Comparison:**

We want to compare the difference measures in a quantitative experiment. We thus choose the color naming application because, unlike the others, it offers a mathematical way to measure the precision of the estimations as shown in Section V-B. We focus on the English color names because this is the original data with ground truth from the psychophysical experiment . We use the same images and the same CIELAB histograms, but compute the difference distributions using all difference measures presented in the previous subsection and Table II. For each difference measure we estimate a color name’s color values.

# **Configuration:-**

# **H/W System Configuration:-**

# System - Pentium –IV 2.4 GHz

Speed - 1.1 Ghz

RAM - 256MB(min)

Hard Disk - 40 GB

Key Board - Standard Windows Keyboard

Mouse - Logitech

Monitor - 15 VGA Color.

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# **S/W System Configuration:-**

* Operating System :Windows/XP/7.
* Application Server : Tomcat5.0/6.X
* Front End : HTML, Java, Jsp
* Scripts : JavaScript.
* Server side Script : Java Server Pages.
* Database : Mysql 5.0
* Database Connectivity : JDBC.