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# Performance on Image Segmentation Resulting In Canny and MoG

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***Abstract:*** *Images are analyzed with edge and color values. Pixel information is used in the color property extraction. Texture and contrast are pixel based features. Shape or edge features are used to represent images. The images are assigned with their category values. The image features are used in the classification process. Classification techniques are used to assign labels to the images. Color constancy methods are largely dependent on the distribution of colors and color edges in an image. Natural image statistics and scene semantics are used in the color consistency methods. Color contrast and texture values are used in natural image statistics model.*

*The scene semantics model uses the edge parameter values. Classification techniques are used to learn color consistency in images. The mixture of Gaussians (MoG) classifier is enhanced with feature integration model The proposed system is designed to improve the classification accuracy. The natural image statistics and scene semantic features are combined in the classification process. Integrated feature weight is assigned for the images to perform the learning process. The MoG algorithm is enhanced with combined feature weight model. The combined feature weight is used I segmentation the class assignment process. The image similarity is estimated with the feature weight values.*

***Keywords:*** *Classification technique, Color property extraction, Mixture of Gaussian, Natural image statistic, Scene semantics.*

## I. INTRODUCTION

Color constancy can be achieved by estimating the color of the light source e, given the image values of f , followed by a transformation of the original image values using this illuminant estimate. This transformation will leave the intensity of every pixel unaltered as the proposed method will only correct for the chromaticity of the light source. Since both $I(\lambda)$ and $\rho(\lambda)$ are, in general, unknown, the estimation of e is an under constrained problem that cannot be solved without further assumptions [1]. Therefore, in practice, color constancy algorithms are based on simplifying assumptions such as restricted gamuts, the distribution of colors that are present in an image and the set of possible light sources. The system is focused on the distribution of colors that are present in an image as the major assumption. In the next section, a framework is discussed generating different color constancy methods [2], where each method is based on a specific assumption about the presence of colors and color edges in images.

Two well-established color constancy algorithms, using pixel values, are based on the Retinex Theory. The White-Patch algorithm is based on the White-Patch assumption. The color constancy methods are based on the distribution of colors that are present in an image. The incorporation of higher order image statistics, where a framework is presented that incorporates the well-known methods like [3], as well as methods based on first and second-order statistics. A wide variety of color constancy algorithms are obtained, corresponding to different instantiations of [4], where each color constancy method has its own basic assumption about the distribution of color values and edges in the image.

The focus of this system is on estimating the color of the light source. However, Inman cases, the color of the light source is of less importance than the appearance of the input image under a reference light. Therefore, the aim of most of the color constancy methods is to transform all colors of the input image, taken under an unknown light source, to colors as they appear under this canonical light source [5]. This transformation can be considered to be an instantiation of chromatic adaptation. Chromatic adaptation is often modeled using a linear transformation, which, in turn, can be simplified to a diagonal transformation when certain conditions are met [6]. Other possible chromatic adaptation methods include linearized Bradford.

The diagonal transform or von Kries Model is used, without changing the color basis or applying spectral sharpening. These latter techniques are shown to be able to improve the quality of the output image with respect to the diagonal model [8], i.e., if the color of the light source is known, then these modified algorithms result in more realistic images than the diagonal model.

**1.1. System Objectives**

The image classification system is designed to categorize the unlabeled images. The system uses the labeled images to learn about the image category patterns. The image statistic and scene semantics are used in the image classification process. The color, texture and shape features are used in the system. The feature weighting model is used for the image analysis. The image classification system is designed with the following objectives.

- To perform image classification
- To extract image features
- To estimate color consistency
- To fetch scene semantics details
- To integrate natural image statistics and scene semantics
- To estimate feature weights for similarity analysis
- To improve the MoG classifier

**1.2. Problem Definition**

The color consistency is used to manage the image collections with its features. All the image processing applications are designed with feature analysis model. The image features are extracted with image statistics and scene semantics values. The features are used in the image classification process. The system integrates the features values for the image classification process. The system uses the feature weighting model to group up the feature values.

## II. Overview Of The Project

**2.1. 1. Natural Image Statistics and Scene Semantics**

All methods that comprise the used color constancy framework are based on assumptions on the distribution of colors (edges) that are present in an image. For instance, the Gray-World algorithm assumes that the average color in a scene taken under a neutral light source is achromatic [7], while the Gray-Edge algorithm assumes that the average edge is achromatic. It has also been shown that the incorporation of spatial dependencies between colors produces more constrained gamuts improving the accuracy of color constancy in general. This means that the set of possible adjacent color values in real-world images is more restricted than the set of possible pixel values [8].

**2.1. 1.1. Spatial Image Structures**

Image structures are valuable identification cues in determining which type of scene the image is taken from. The power spectrum of an image is characteristic for the type of scene [9]. Further, it is shown that this distribution of edge responses can be modeled by a Weibull distribution. In the context of scene classification, features derived from the power spectrum and Weibull distributions have been successfully applied [10]. In this paper, we focus on modeling natural image statistics using the two parameter integrated Weibull distribution:

$$w(x) = C_{\exp}\left(-\frac{1}{\gamma}\left|\frac{x}{\beta}\right|^{\gamma}\right) \qquad (1)$$

where x is the edge responses in a single-color channel to the Gaussian derivative filter, C is a normalization constant, $\beta > 0$ is the scale parameter of the distribution, and $\gamma > 0$ is the shape parameter. The parameters of this distribution are indicative for the edge statistics of an (natural) image. In fact, the contrast of the image is indicated by $\beta$ and the grain size by $\gamma$. Hence, a higher value for $\beta$ indicates more contrast, while a higher value for $\gamma$ indicates a smaller grain size.

To fit the Weibull distribution, edge responses are computed by a Gaussian derivative filter. There exists a high correlation between the Weibull parameters that are fitted through the distribution of edges for the first derivative, second derivative, and third derivative [11]. Hence, a single filter type, although measured in different orientations, is sufficient to assess the spatial statistics of images.

In Fig. 1 which is shown in combination of illuminant estimation methods, examples are shown of images with their corresponding edge distributions which are approximated by a Weibull-fit. The intensity channel is chosen for the ease of illustration because a six-dimensional edge distribution is hard to visualize.

The relationship between the images in Fig. 1 and their corresponding color constancy algorithm becomes clear from the edge distributions that are shown together with the images in Fig. 1. Pixel-based algorithms perform better than higher order methods on images with only little texture. This reflects in an edge distribution that densely sampled around the origin, i.e., many edges with little or zero energy [12].

For instance, forest-like scenes show a similar edge distribution in Fig. 1b and are all best solved by a first-order color constancy algorithm [13]. Hence, scene semantics can steer the process of color constancy. Natural image statistics and scene semantics will therefore be used in the next sections to achieve a proper selection of color constancy algorithms.

**2.1. 2. Combinations of Illuminant Estimation Methods**

In this section, a novel strategy is proposed based on natural image statistics to select the color constancy method which performs best for a specific image. To combine and compare different fusion strategies, a basic approach is discussed based on using the output of multiple.

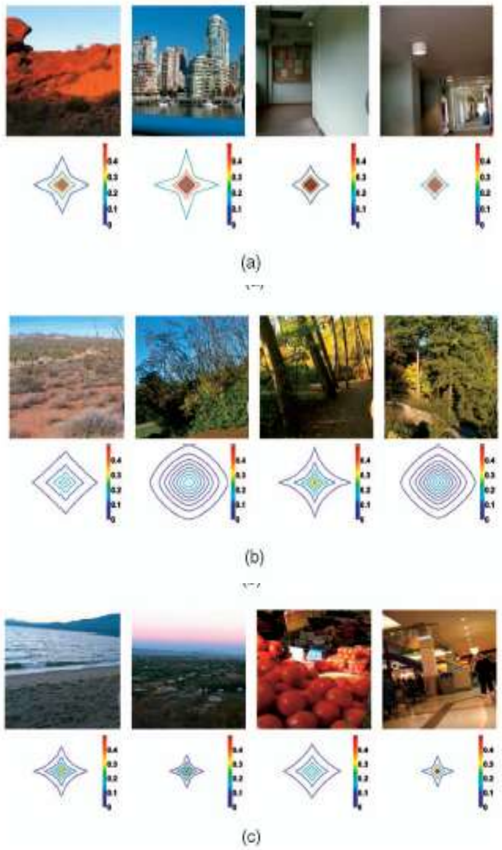


**Fig. 1. Image for color constancy process**

Examples of images that can be considered to be characteristic of the corresponding color constancy algorithms, i.e., the corresponding color constancy algorithm will perform best on these types of images. Below each image, the distribution of edges in the intensity channel is plotted. The images come from the data set published. (a) Zerothorder method. (b) First-order method. (c) Second-order method.

**Algorithms.** Then, natural image statistics are used to identify the most important characteristics of color images. Based on these image characteristics, the proper color constancy algorithm is selected for a specific image. Finally, scene semantics are used to find a category-specific combination of color constancy algorithms.

**2.1.2.1. Color Constancy Using Standard Fusion**

When using the output of multiple algorithms to generate a new estimate of the illuminant, the simplest method is to take the average of the estimates over all algorithms. A straightforward extension is to take the weighted average of the estimated illuminants. If n algorithms are combined, then the weighted average is defined as

$$\bar{e} = \sum_{i=1}^{n} w_i e_i , \qquad (2)$$

where $\sum_{i=1}^{n} w_i = 1$. The average is just a special instance of the weighted average: $w_1$ , $w_2$, $w_3$ …$w_n$}. The estimates can also be combined using a nonlinear committee.

Two algorithms were combined using a similar approach. However, the output of the two used algorithms is somewhat different than the output of a general color constancy algorithm. Both methods produce a vector of probabilities, where each element represents the probability that the corresponding illuminant is the illuminant that was used to create the current image [14]. Since this method requires the output of the color constancy algorithms to comply to a specific (irregular) form [15], this approach is not further evaluated here.

**2.1.2.2. Color Constancy Using Natural Image Statistics**

The Weibull distribution is considered as the parameterization of the edge distribution of images. Several characteristics, like the number of edges and the amount of texture and contrast, are captured by this parameterization, i.e., $\beta$ and $\gamma$. In this section, it is proposed to select different color constancy methods based on these statistics. In previous work, it is shown that applying the k-means clustering on the Weibull-features, combined with a Gaussian weighting function, provides proper color constancy [16].

In this paper, the k-means approach is generalized to a probabilistic approach, corresponding to a maximum likelihood classifier based on mixture of Gaussians (MoGs). This provides a more principled and probabilistic basis than k-means to relate natural image statistics with color constancy.

This novel algorithm aims at combining the estimates of several color constancy algorithms into a single more accurate estimate. To be precise, let M be the set of algorithms that are to be combined, where Mi denotes algorithm i. Further, the accuracy of the estimate of algorithm i on image j is denoted by $\varepsilon_i$ (j). The algorithm consists of the following steps:

First, the image statistics $\omega \varepsilon IR^{p\times q}$ for all images are computed, where p is the number of features that are computed and q is the number of images, i.e., $\omega$ ijis the ith feature of the jth image. For simplicity, the subscript i is omitted, so $\omega$ j denotes the feature vector representing the image statistics of the jth image.

Then, all images that are in the training set are labeled. The label yj of an image j is derived using the performance of the algorithms on image j:

$$y_i = \arg \underset{i}{mib} \{\in_i (j)\}, \quad (3)$$

- Apply the MoG-classifier on the training data. The likelihood of the observed image statistics $\omega_j$ for image j given color constancy algorithm $y_j$ is computed as a weighted sum of k Gaussian distributions:

$$p(w_j \mid y_j) = \sum_{m=1}^{k} \alpha_m G(\omega_j, \mu_m, \textstyle\sum_m) \quad (4)$$

- Here, $\alpha_m$ are the positive weights of the Gaussian components (with mean and variance $\mu_m$ defined as $\sum_m$ and m, respectively) such that $\sum_{m=1}^{k} \alpha_m = \alpha_m$. The parameters of the model are learned through training using the Expectation-Maximization algorithm.
- Apply the learned MoG-classifier on the test data and assign to the current image j the algorithm that maximized the posterior probability.

$$O_1 = \frac{R-G}{\sqrt{2}}, \quad - \quad - \quad - \quad (5)$$

$$O_2 = \frac{R+G-2B}{\sqrt{6}}, \quad - \quad - \quad (6)$$

$$O_3 = \frac{R+G+B}{\sqrt{3}}, \quad - \quad - \quad (7)$$

The selection of the most appropriate color constancy algorithm for the current image is done by computing the maximum posterior probability of the classifier.

**2.1. 2.3. Color Constancy Using Scene Semantics**

Natural image statistics are known to provide identification cues for the classification of different types of scenes like forest, coast, and street. Van de Weijer et al. assume that an image can be modeled as a mixture of semantic classes. The information on the different classes that are present in an image is used to estimate the color of the light source. In this section, we aim at using scene semantics to find a category specific combination of color constancy algorithms that optimize the performance of the illuminant estimation.

A data set is provided consisting of eight urban and natural scene categories. The corresponding Weibull-parameters of the images of a selection of these categories are along with the Weibull-parameters of the images that are derived from the real-world data set. It can be observed that images from the same category have similar edge distributions, resulting in similar *Weibull*-parameters.

Some categories have a larger variance in edge distribution than others. For instance, most of the images of the category Highway have a low value for $\beta$ and a low value for $\gamma$, indicating a low contrast and few edges. Images of the category Mountain, on the other hand, generally have a large variance. However, even for this category, it can be observed that most images have higher values for $\beta$ and $\gamma$, indicating higher contrast and more edges.

From these observations, a supervised selection of a color constancy algorithm for images from all scene categories can be achieved. By classifying an input image as one of these image categories, the corresponding color constancy algorithm can be applied to the image to obtain a performance that is similar to the proposed automatic selection algorithm.

## III. CANNY EDGE DETECTOR

The Canny edge detection operator was developed by John F. Canny in 1986 and uses a multi-stage algorithm to detect a wide range of edges. Most importantly, Canny also produced a computational theory of edge detection explaining why the technique works

### 3.1.1 Development of the Canny algorithm

Canny's aim was to discover the optimal edge detection algorithm. In this situation, an "optimal" edge detector means:

- good detection - the algorithm should mark as many real edges in the image as possible.
- good localization - edges marked should be as close as possible to the edge in the real image.
- minimal response - a given edge in the image should only be marked once, and where possible, image noise should not create false edges.

To satisfy these requirements Canny used the calculus of variations - a technique which finds the function which optimizes a given functional. The optimal function in Canny's detector is described by the sum of four exponential terms, but can be approximated by the first derivative of a Gaussian.

#### 3.1.1.1 Noise Reduction

Because the Canny edge detector uses a filter based on the first derivative of a Gaussian, it is susceptible to noise present on raw unprocessed image data, so to begin with the raw image is convolved with a Gaussian filter. The result is as a slightly blurred version of the original which is not a affected by a single noisy pixel to any significant degree.

#### 3.1.1.2 Finding the Intensity Gradient of The Image

An edge in an image may point in a variety of directions, so the Canny algorithm uses four filters to detect horizontal, vertical and diagonal edges in the blurred image. For each pixel in the result, the direction of the filter which gives the largest response magnitude is determined. This direction together with the filter response then gives an estimated intensity gradient at each point in the image.

#### 3.1.1.3 Non-Maximum Suppression

Given estimates of the image gradients, a search is then carried out to determine if the gradient magnitude assumes a local maximum in the gradient direction.

#### 3.1.1.4 Differential Edge Detection

A more refined approach to obtain edges with sub-pixel accuracy is by using the following differential approach of detecting zero-crossings of the second-order directional derivative in the gradient direction

$$L^2_x L_{xxx} + 2L_x L_y L_{xy} + L^2_y L_{yy} = 0,$$

that satisfy a sign-condition on the third-order directional derivative in the same direction .

$$L^3_x L_{xxx} + 3L^2_X L_y L_{xxy} + 3L_x L^2_y + L_{xyy} + L^3_y L_{yyy} < 0$$

where $L_x$, $L_y$ ... $L_{yyy}$ denote partial derivatives computed from a scale-space representation $L$ obtained by smoothing the original image with a Gaussian kernel.

**3.1.1.5. Parameters**

The Canny algorithm contains a number of adjustable parameters, which can affect the computation time and effectiveness of the algorithm.

- The size of the Gaussian filter:
  The smoothing filter used in the first stage directly affects the results of the Canny algorithm. Smaller filters cause less blurring, and allow detection of small, sharp lines.
- Thresholds:
  The use of two thresholds with hysteresis allows more flexibility than in a single-threshold approach, but general problems of thresholding approaches still apply.

**3.2 Module Description**

The proposed system is designed to improve the classification accuracy. The natural image statistics and scene semantic features are combined in the classification process. Integrated feature weight is assigned for the images to perform the learning process. The MoG algorithm is enhanced with combined feature weight model.

The scene semantics is used to extract color consistency values. The features are combined and assigned with weights under feature weighting model. The images are assigned with labels under image classification module.

**3.2.1 . Image Feature Extraction**

Low level and high level features are extracted from the images. The image pixel values are used in feature extraction process. Color and texture features identified from the pixel values. The shape features are extracted from the images.

**3.3 Natural Image Statistics**

The Weibull distribution is considered as the parameterization of the edge distribution of images. The number of edges and the amount of texture and contrast are captured by the parameterization. The k-means approach is generalized to a probabilistic approach for classification process.
The classifier is based on mixture of Gaussians (MoGs).

**3.3.1. Scene Semantics**

The classification is performed using all scene categories. The scene categories are grouped with similarity. The automatic selection scheme is used to assign image categories. The input image is compared with the category collection information.

**3.3.2. Feature Weighting Process**

The natural image statistics and scene semantics features are integrated. The images are assigned with feature weights. The feature weights are combined and image weight is produced. The weight values are used in the image category assignment process.

**3.3.3. Image Classification**

The image classification process is divided into two phases. The learning phase learns the patterns and associated labels. The testing phase assigns labels to the input images. The learned patterns are used in the testing phase. The classification model uses the features weight value.

**3.3.4 Database Design**

The image categorization system is designed with Oracle relational database. A database is a collection of inter related data stored with a minimum of redundancy to serve many applications. It minimizes the artificiality embedded in using separate files. The primary objectives are fast response time to enquiries, more information at low cost, control of redundancy, clarity and ease of use, accuracy and fast recovery.

**3.4. Input Design**

Input design is the link between the information system and the users and those steps that are necessary to put transaction data in to a usable form for processing data entry. The activity of putting data into the computer for processing can be activated by instructing the computer to read data from a written printed document or it can occur by keying data directly into the system. The designs of input focusing on controlling the amount of input required controlling the errors, avoid delay extra steps, and keeping the process simple. The input design considers the input data, input medium, user interface, messages, validation and error handling factors.

Image categorization system is designed up with user friendly and interactive forms which enable the user to operate the application with ease of use. The input forms are highly designed with data validation, data integration and consistency with databases and application logic. The users are directed with standard messages and alerts which enables them to feed the data with accuracy.

The image register form is designed to update new images to the database. The color feature selection form is designed to update color features into the database. The texture feature extraction form is designed to fetch texture features for the images. The shape features extraction form is designed to extract the edge features from the images. The image classification form is used to assign category values for the given image file.

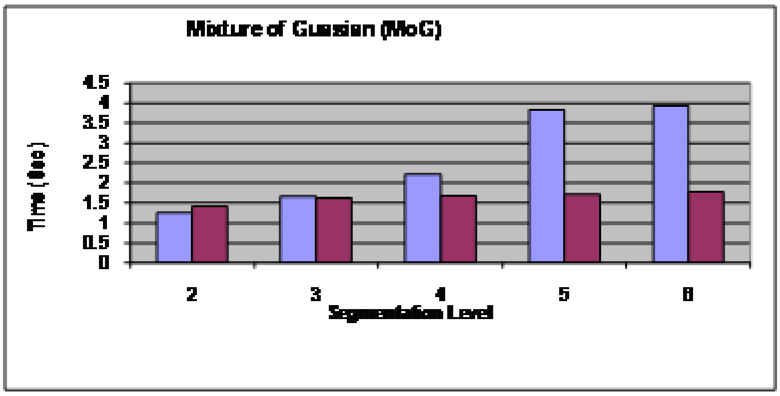
### 3.5. Output Design

The image list form is designed to list the registered images under the database. The image details are displayed with image properties. The image view form is designed to display the image contents. The color and texture features are listed separate forms. The shape features are listed for the selected image. The image patterns are

listed in image patterns form. The image weight is displayed in a separate form. The classification results form displays the image category details for the given input image.

## IV. Chart

Chart: 1 Mixture of Guasian




## V. Conclusion

Color constancy methods are largely dependent on the distribution of colors and color edges in an image. Natural image statistics and scene semantics are used in the color constancy methods. Classification techniques are used to learn color constancy in images. The mixture of Gaussians (MoG) classifier is enhanced with feature integration model. Visual and Semantic features are used for classification process. The system uses integrated features for weighting process. Feature weight based model system improves the classification accuracy levels. The system can be enhanced with content based image retrieval schemes.

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S. Ravikumar received his M.Sc., in Bharathiar University, Coimbatore and M.Phil.,and M.C.A., degree from Periyar University Salem. Currently he is working as Assistant Professor in Bannari Amman Institute of Technology, Sathyamangalam. His area of interest includes Image Processing, Texture segmentation, Clustering. He Presented a Paper in National conferences. He is a Life member of Computer Society of India and a Life member of Indian Society for Technical Education.

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