Histogram based method of finding representative labels in gray image classification

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Abstract- **Image classification and labeling are important problem in computer vision, but rarely considered together. Classification is usually based on some image features and the feature is based on the gray label histogram of the image. In this paper we develop a new model for classifying a gray label image based on its histogram. Each identified classes are replaced by distinct optimal representative values chosen by different strategies. Finally we use statistical tools to determine the best fitted algorithm for choosing representative value of each identified class of the image.**

Keywords - Histogram, Smoothing, Classification, Class representative values.

I. INTRODUCTION

The basic idea of image classification is to group individual pixels into regions if they are similar[5,6]. Similarity means they are probably representing a distinct entity of the image. In a single image there exist few entities like background and one or two distinguished objects. Every object has pixels of certain gray labels. Greater the objects (background, main subjects etc.) its pixels form larger peaks in the histogram[3,4]. So before applying classification techniques some major pre processing should be applied on histogram to get the better result. In our approach we have examined histogram of different images, find tall, thin, peaks and deep valleys, which will cause frequent unevenness .Smoothing[2] the histogram removes that unevenness and makes the histogram more acceptable for classification[1]. The paper is organized as follows. In section 2, we have described our model for smoothing a histogram and also identifying classes from a given histogram. Section 3 introduces the different approaches for finding representative values for each identified classes for a particular histogram. Section 4 briefly introduces the performance measurement details and describes the experimental results with analysis charts. Section 5 deals with brief comparison of replacement methods and a brief conclusion is given.

II. HISTOGRAM SMOOTHING AND IDENTIFICATION OF CLASSES

In histogram whenever we find a series of small peaks and valleys which are quite adjacent to each other, they can be termed as local maxima and local minima respectively. Whereas , when we find a drastic change in intensities of pixels which can significantly change the nature of the histogram, they are termed as global maxima and global minima respectively. In local maxima or local minima the color change is not so significant as well as the changes is not long lasting. In global maxima or global minima, the color change is significant and is also long lasting So, in order to classify image histogram into classes we can neglect local maxima-minima and highlight the global maxima-minima. To reduce the unevenness of a histogram and to suppress local maxima-minima, a technique is applied which replace local maxima- minima by a plate. At first identify a local maxima - minima pair and then calculate the average occurrence of each gray label values in that particular identified area. After that the occurrence of every gray value will be replaced by that calculated average occurrence value. If this technique is continued till the end of the histogram, we may get a relatively smooth histogram, which can be efficiently used in time of classification. The algorithm to achieve smothered histogram is discussed below is characterized by Fig.1.

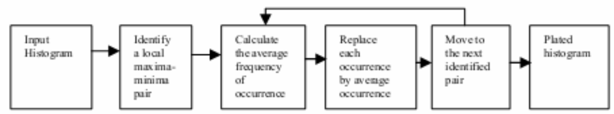

Figure 1: The framework for removing un evenness of Histogram.

To find out classes plated histogram is scanned. If we find consecutive Δ number of upward movements until a downward movement is noted, then the consecutive downward movements are also noted until there is again an upward movement. If consecutive downfall is also greater than equal to Δ, starting and ending gray values are identified as the boundary of a class. If the number of consecutive upward or downward movements are less than Δ, then it will not be treated as local maxima or minima and it will be ignored. The value of Δ is subjective and it is chosen by heuristic tic analysis. The experimental results of some sample images and their original and plated histograms along with identified classes are given in Fig.2 and Table 2.

III. VARIOUS APPROACHES FOR FINDING REPRESENTATIVE VALUES FOR EACH IDENTIFIED CLASS

After getting the plated histogram we are trying to find out a representative value for each class. Then all the gray values of a class will be replaced by corresponding representative value to distinguish different classes or components of an image clearly. Five different techniques are applied in this paper as discussed below. In first approach every occurrence (in the image matrix) of every gray values of a particular class will be replaced by maximum occurred gray value of that class. In the next approach, every occurrence of every gray value of a particular class will be replaced by the average gray value of entire occurrence of all the gray values of that class. The function, which is used here is:

$$\frac{\sum_{i=k}^{x} X_i W_i}{(x-k)} \tag{1}$$

Where k is the starting index and x is the last index of that class. X_i =particular gray value. W_i =number of occurrence of that gray value. In the next approach, weighted average is similar to an arithmetic mean, where instead of all the data points contributing equally to the final average, some data points contribute more than others. If all the weights are equal, the weighted mean is the same as the arithmetic mean. Formally, the weighted mean of non empty set of data $[X_1, X_2, X_3, ...X_n]$ with non negative weights$[W_1, W_2, W_3, ...W_n]$ is the quantity

$$\bar{x} = \frac{\sum_{i=1}^{n} W_i X_i}{\sum_{i=1}^{n} W_i} \tag{2}$$

In our approach, X_i denotes a particular gray value and W_i denotes the number of occurrence of that gray value. In next approach, one objective function has been taken for choosing the representative value. The objective is to Minimize the following function.

$$F(n) = \sum_{i=0}^{c_1} \frac{(X_i - X_0)^2}{Y_i} + \sum_{i=c_1+1}^{c_2} \frac{(X_i - X_0)^2}{Y_i} + ...$$

$$... + \sum_{i=c_{n-1}+1}^{c_n} \frac{(X_i - X_0)^2}{Y_i} \tag{3}$$

Where $c_1, c_2, c_3 .....c_n$ are crests in histogram. Minimization of the objective function using partial derivative gives the values of $X_0, X_1, ..., X_n$. These are the optimum values for respective classes. Now, the particular objective function can be minimized through either genetic algorithm or direct search approach .In genetic algorithm we can find optimum gray value to represent each class. Optimum in the sense that the gray value has a high occurrence as well as a high influence on its neighborhoods. We can modify the equation as

$$MinimizeF() = \sum (p_{ij} - x_0)^2 + \sum (p_{ij} - x_1)^2 + ... \tag{4}$$

$$... + \sum (p_{ij} - x_n)^2$$

Where x_k is the optimum value for k th class. p_{ij} is the gray values of the pixel which resides in k th class. To minimize F, each individual term also will be minimized. It depends on

i) The number of pij i.e the number occurrence of each color of k th class.

ii) Also depends on difference between pij and x_k. If the difference is small, it means the nature of the class will not be changed drastically. It means x_k has great influence on each p_{ij} .

IV. PERFORMANCE MEASUREMENT

Partially it is very hard to decide the most optimum gray values for replacement of each identified classes respectively and also to find out the methods for selecting those optimum values. So correlation coefficient is chosen here to measure the displacement between the original image pixel gray values and with replaced gray values in each identified classes. Here the correlation coefficient is an index of proximity of the replaced image to the original image. If the value of the calculated correlation coefficient is near to 1 , it indicates that the nature of the original gray image and replaced gray image does not differ considerably. It seems though the replaced image has one representative value for each identified class, it holds the basic property of the original gray image almost in- tact at least numerically. The performance of different approaches on our sample images is described below (Table1) .

Table 1: Correlation coefficient results

Sample Images	MAX	AVG	WTAVG	GA	DS
figure 3.1	0.9709	0.9710	0.9713	0.9696	0.9710
figure 3.2	0.9702	0.9666	0.9703	0.9699	0.9701
figure 3.3	0.7727	0.7727	0.7727	0.7727	0.7727
figure 3.4	0.9688	0.9746	0.9753	0.9752	0.9756
figure 3.5	0.9719	0.9709	0.9720	0.9719	0.9719
figure 3.6	0.9408	0.9411	0.9429	0.9431	0.9431
figure 3.7	0.9337	0.9353	0.9361	0.9332	0.9372
figure 3.8	0.7231	0.7231	0.7231	0.7231	0.7231
figure 3.9	0.8605	0.8602	0.8613	0.8614	0.8614
figure 3.10	0.9352	0.9431	0.9427	0.9428	0.9436
figure 3.11	0.9495	0.9569	0.9669	0.9667	0.9667


Figure 2.1


Figure 2.2

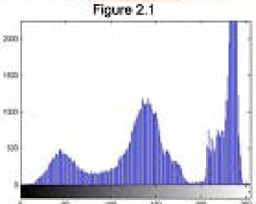
Figure 2.3

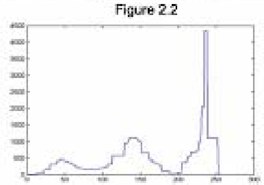
Figure 2.4


Figure 2.5


Figure 2.6

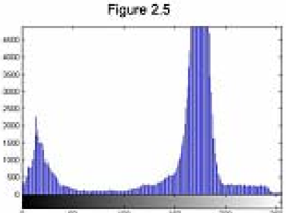
Figure 2.7

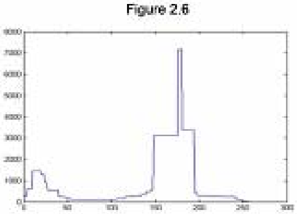
Figure 2.8

Figure 2: Figure2.1 and 2.5 are the original color images. Figure 2.2 and 2.6 are the corresponding gray images. Figure 2.3 and 2.7 are the histograms of those images. And Figure 2.4 and 2.8 are the modified plated histogram of corresponding images.

V. CONCLUSION

After analyzing a lot of gray images, it has been shown that in most of the cases correlation coefficient produced better result for direct search replacement strategy. So in future further improvement can be achieved if we use direct search replacement with any classification technique to make analysis easier. More over here each complete class is replaced by a particular representative value, so from this re- placed image different distinguished component of that particular image can be tracked easily. Future works includes improving the process of prime object detection, speeding up the processing time and making classification process more effective and accurate. These methodologies can be easily and broadly expanded to diverse types of image processing and quantitative analysis of classification for practical implementation.

Table 2: Correlation coefficient results

Sample Images	Number of detected classes	Detected classes
figure 2.1	4	0-57,58-70,71-182,183-256
figure 2.5	5	0-60,61-97,98-129,130-202,203-256

Figure 3: Sample outputs of gray image, replacement with maximum ,replacement with average, replacement with weighted average, replacement with genetic algorithm and replacement with direct search respectively. The original images are represented with names Fig(3.1),...,Fig(3.11)respectively from top.

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