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Multilevel Color Histogram Representation of Color Images by Peaks for Omni-Camera

Sezai Sablak Terrance E. Boult
Department of Electrical engineering & Computer Science,
Vision and Software Technology Lab
Lehigh University, PA 18015
{ses4@eecs.lehigh.edu, tboult@eecs.lehigh.edu}

Abstract— **This paper proposes the use of a vector of color histogram peaks as an efficient and effective way for many image indexing problems. It shows that histogram peaks are more stable than general histogram bins when there are variation of scale and/or scale. We also introduce the structure of a room recognition system which applies this indexing technique to omni-directional images of rooms. Experimental results shows that using only peaks leads to significantly less time and storage demands an still provides $> 92\%$ recognition rates across a database of hundreds of rooms.**

Keywords—**Color, Multilevel Color Histogram, Peak, Image Indexing, Room Recognition**

I. Introduction

This work investigates color histogram indexing, its stability and its application to the problem of room recognition. Recognition of a "room" in a complex environment with uncontrolled lighting might be used on a mobile robot, in a wheel chair assistant or on a wearable computer computer. In all of these scenarios the computational power and available storage of the system will generally be quite limited so a very efficient computation, and compact storage are critical.

In general, real-time constraint of machine vision require fast algorithms and smaller data storage[1]. Color is a very important cue in extracting information from an image, and color histogram comparison has recently become a popular technique for image and video indexing[1], [2], [3], [4], [5]. The popularity of color as an index resides in its ease of computation and effectiveness[6]. Using color in a real-time system has several relative advantages: color information is much faster to compute than most other "invariants" and it can be nearly invariant to changes in orientation and small partial occlusions of the object. Swain and Ballard suggests that color is a reasonable efficient method for identifying objects of known location, and locating objects of known appearance and practical to use color for high-speed image location and identification. We note that even though [1] claims that a color histogram is largely independent of resolution, our experimental work shows it is not independent of resolution changes that includes blurring.

Unfortunately, even though the color histogram has been shown to be an important tool in image indexing it has been used mostly with fixed image databases. Furthermore, known distance measures for the recognition process that can handle large variations in scale and illumination are computational expensive because the histogram is typically a high-dimensional distribution. Moreover, indexing on such a high-dimensional feature for large image databases, it is generally not feasible to compute the match measure against every image[7]. Thus we seek a much lower dimensional feature set while seeking to insure it maintains low levels of false detection and false rejection. We propose the use of the location of color histogram peaks, a simple to compute distance measures between the color images, and show that these are much more stable than histogram distance measures for certain fairly general cases (including for large illumination and resolution variations). As we will show, similarity retrieval based on the histogram peaks measure achieves both the goals of efficient and effective recognition system.

The next section surveys related work. Section 3 introduces the proposed algorithm as generalization of color histogram peaks indexing and describes the part of the system which we will use throughout the paper. Section 4 describes a room recognition system that uses color histograms peaks indexing of real room images and section 5 discusses its implementation. Experimental results on a database of 330 images from 205 different rooms are presented in section 6. Finally section 7 argues that histogram peaks indexing can be usefully applied to other modalities besides color and discusses topics for future work.

II. Background

While many systems have used color histograms, to our knowledge only one other has used a histogram peaks as a primary part of its representation. Das, Edward, and Bruce [8] described a new multi-phase, color-based image retrieval system, FOCUS (Fast Object Color-based qUery System). FOCUS is capable of identifying database matches for multi-colored query objects within an image in the presence of significant and interfering backgrounds. In their approach, the first phase matches the color content which is represented as the peaks in the color histogram. They split the image into a number of "cells" and used a split and merge strategy for peak detection. A combined list of peaks is produced by merging multiple copies of the same peak, and a label is assigned to each peak. The histogram peaks are detected by finding local maxima in a 3-D neighborhood window. The mismatch score is given by the sum of the city block distances between each query peak. Second phase matches use the spatial relationships between color regions in the image with the query using a spatial proximity graph (SPG) structure designed by using localized color peaks in image cells. They aimed to capture all possible adjacencies between color regions in each cell. The SPG shows all possible pixel-level adjancencies, but adds some false adjancencies as well. The running time is of the order of $O(n^m)$ where n is the size of the query adjacency matrix and m is the maximum number of instances of a color label. The second phase is a more computationally intensive matching strategy.

Finding the localized color histogram peaks by using split and merge strategy with peak detection is not a compact representation of image and too expensive a process for real time small mobile application even they observed peaks. As we shall explain, our representation is very compact representation and allows one to use it without any serious computational complexity.

For the FOCUS system, the main goal of detection of localized peaks is to create the SPG graph to handle scale/orientation changes. But this phase adds considerable computation. In contrast, we handle scaling by using multilevel color histogram representation of image peaks. Our new compact representation of image is very useful for enable the small machine to recognize their location.

III. Proposed Algorithm

A. Color Histogram Peaks Indexing

The reduction of the vast amount of information in images is one of the biggest barrier for recognition in real time. The ease of recognition in real time depends on this reduction and on the speed/accuracy of an image retrieval system which uses feature for describing images and matching strategy. For this purposes, we reduced the color information of each image to a compact representation by using the color histogram peaks and used retrieval strategy in *Fig.*[1].

In an image-processing context, the color histogram of an image normally refers to a multi-dimensional histogram of the pixel color values, i.e. the distribution of colors in the color space. Computing them is easy; a primary difficulty is the high cost computing a similarity distances between such the query histogram and all the images in a databases. The histogram feature needs to provide a discriminating capability between images which contain several objects to the query while still finding the correct object when there have been changes in illumination, scale and location of objects. Even though some examples of color feature for object recognition have been used, existing color features do not support all the requirements for an image retrieval engine, especially the size of the database and computational demands of indexing.

While the color histogram preserves considerable color information contained in an image, it is not well as compact a representation of image representation as needed for enabling small mobile machines. In contrast, the color histogram representation by peaks allows to create a very useful compact representation of color histogram for real-time applications on small machines.

For traditional color histograms, it is difficult to maintain stability for information while changing resolution, scaling, and illumination. Using this measure, two images may be considered to be very different from each other even though they have completely related semantics. We have investigated a color histogram peaks indexing scheme where computationally efficient features are used for recognition instead of more sophisticated techniques. Excellent results have been observed using a color histogram peaks representation of the color images.

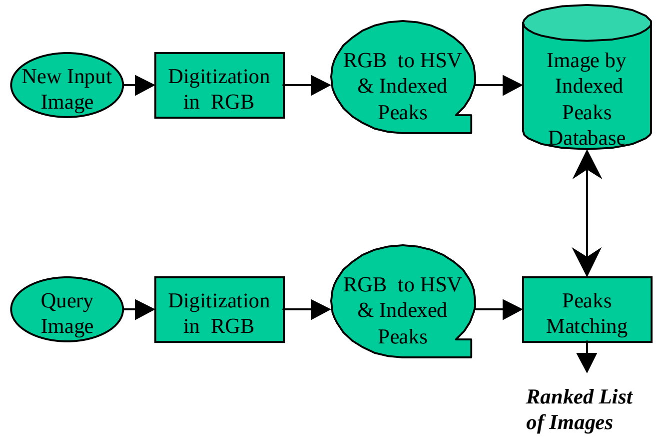

Fig. 1. A schematic histogram peak indexing system overview

The main advantages of peak-oriented representation is the reduction of computational complexity and information in real time applications which results from the smaller size of the peak detection as well as simple handling of various types of histogram shifts. Often in color histograms, the location of peaks is more stable than other histogram bins. Spatially detected peak features are necessary to effectively process such queries. In addition, these queries can be pertaining regions of different shapes, sizes or resolutions. The emphasis in the peak indexing representation is on a compact representation of an image, speed, and matching them aims to allow invariant resolution and scaling. If the discriminatory power of the peaks is not sufficient for final identification, they can still be considered a powerful “pre-filter”, reducing the potential matches to a small number were more complex histogram, or other feature-based, matching can be performed.

The aim of representation peaks indexing is to narrow the search to the images which could match the given query peaks. Simply stated, their advantages are an effective compact representation of image information, computational efficiency, simplicity, speed, lower storage requirement, and less sensitivity to small changes in camera viewpoint.

B. Detection Of Histogram Peaks

During the detection of histogram peaks, all the distinct colors in the image computed as peaks in the HSV color space histogram of images are used to create an image indexing feature. The color space representing colors along the human perceptual dimensions is crucial in grouping colors based on color perceptual similarity. The popular RGB color space is efficient for display and widely used among color processing system, but inappropriate for color feature indexing and discrimination [9]. It also does not carry direct semantic information about the color. One important criterion we use for selecting the color space is provided intuitively, where each component in this space contributes directly to visual perception. In order for color space to provide useful characterization of region color, each color in the color space must be visually distinguishable from the others and satisfactorily include all distinguishable colors.

The three axis of the HSV color space stand for hue, saturation and value the purpose of the color space is to provide users with a more intuitive mean of colors [10]. We have chosen HSV (H hue, S saturation, and V value) color space because color image processing performed independently on the color channels does not introduce false colors. Furthermore, it is easier to compensate for artifacts and color distortions. Another advantage of HSV color space is that users find navigation intuitive within this color space [11], [12]. The capability of the luminance and chromatic components of a color is extremely useful in handling images under non-uniform illumination conditions such as shade, highlight, strong contrast, and etc.[13]arranged in such a way that equal geometric distances correspond to equal perceptual differences, making it the ideal color space for our system. Using HSV one can ignore the value axis completely and concentrate processing solely on the color components of the image. However, it ignores the fact that for large values and saturation, hue differences are more perceptually relevant than saturation and value differences.

The histogram is a graph showing the number of pixels in an image at each different color value found in that image. For example, a HSV color histogram which has been quantized into k bins for H, l bins for S and m bins for V can be represented as HSV_{klm}. It is assumed that each bin will contain a range of colors characteristic of the region of the image local to the bin. In order to the get a statistically significant number of points, the bins are actually lines of each pixels in width. A color histogram is constructed from the pixel intensities within bin.

The modal method is used for histogram peaks indexing. The algorithm, in short, first attempts to find a the highest histogram peak. If successful, try to locate the position of the tallest subpeaks in histogram. Having found these peaks, look for the next sub-peaks; this is *"the peak detection"*. Depending on color distribution, the shape of the histogram peaks may contain sharp or wide peaks. However, looking at figure 3, a couple of problems present themselves:

1. There is some, often fairly obvious, spiking in the histogram. Narrow spikes near the main peak could be taken for subpeaks by naive subpeak detection algorithm.
2. There are several ranges in the histogram with zero counts, all of which could potentially contain the inter-peak minimum. Which we do select?

Our goal is to generate a subset P as peaks in histogram HSV such as $P \subset HSV$. In practice we do not want $|P| > 7$. Thus some heuristic method for selecting peaks on the histogram is required. There are several possible methods. We used a method which the first and most obvious takes the $p = |P|$ highest peaks of the histogram and call these elements $\{P_1, P_2, ..., P_7\}$. For a given color histogram peaks indexing of image, $I_n(H_p, S_p, V_p)$ is computed for n images as indexing feature in the database.

C. Histogram Peak Matching

Discrimination power of histogram peaks allows the machine vision application to perform in real time by reducing the required storage. It also has a fast matching strategy, when we compared to that using the full histogram information. When deciding the matching strategy by looking for color similarity, it is very important that it is robust to variations in illumination and scaling. As explained above, the 7 bins are selected to the range 0 to P. In our experimental work, $P = 6$ since variations of the peaks is enough to recognize the images in different illumination and scale, so that the computed histogram peaks indexing can be compared to the original.

We examined the difference of peaks measure for a matching strategy. This approach is computationally efficient because the number of peak bins in the color histogram is much less than in the all histogram. The Peak Distance measure between Q and D_n is defined $PD(Q, D_n)$ by the absolute sum of their peak differences as follows

$$PD(Q, D_n) = \sum_{i=0,j=0}^{p} \min |QHSV(i) - D_nHSV(j)|$$

where p is the number of peaks, and $QHSV$ and D_nHSV are the HSV color histograms for image Q and D_n. Even though this measure is a good criteria of the correlation of the content between two images. The most crucial advantage of this distance measure is that it is less insensitive to local feature variations instead of comparing all histogram bins.

After detection of the histogram peaks is done, the time complexity of the retrieval process is just given by $O(p \log(n))$, where p is the number of query peaks, n is the total number of images in the database. By comparing the original histogram peak indexing of the image with the query image, the resulting obtained images list is ordered by decreasing match score.

IV. Stability of Histogram Peaks Comparison Measurement

The stability of the measurements with respect to changes in the histograms is an important condition for usefulness of histogram matching for recognition. Such changes in a histogram may be caused either by changes in resolution, illumination and scaling. In our experimental work, we have considered these three effects on stability of color histogram peaks location. We note that their exact location values do not influence the analysis significantly, since we will examine the relative stability between all color histogram peak bins rather than *"absolute stability"*. It is the ability to discriminate different objects and the invariance to scale variations by histogram peak matching that are more important than absolute stability. In the following section, we show results for two different resolution, scale of color histograms.

A. Stability with Different Resolution

In order to examine the stability of histogram peak indexing measurements with respect to different resolutions for the same size images we assumed change is created by a physical process such as being farther away or via a panoramic pyramid. Histograms are only insensitive to scale reduction if it is done by subsampling; real cameras/optics blur as the resolution is reduced. Thus we change resolution by using Gaussian filtering followed by

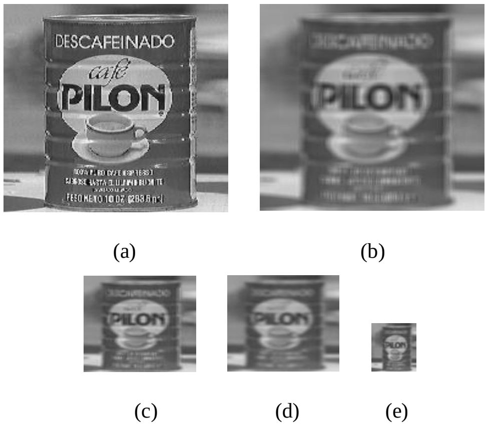

Fig. 2. (a) Original Coffee Can Image 128 by 128 (b) 128 by 128 Image Blurred (Gaussian blurring) (c) Image down-sized to 64 by 64 (d) Blurred 64 by 64 Image (e) Second Image down-sized to 32 by 32

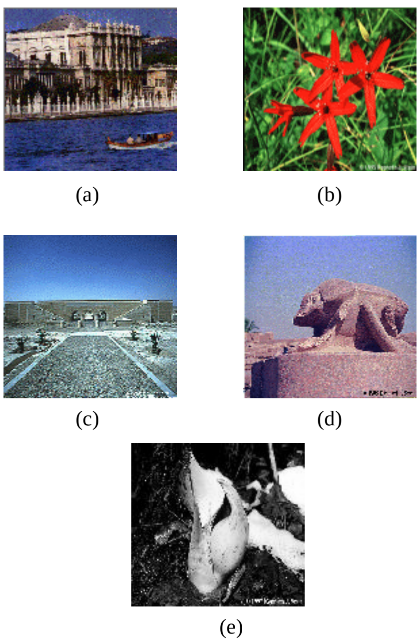

Fig. 3. (a) Palace Image (b)Redflower Image (c) Historic Scene Image (d) Art Image (e) Snowflower Image

subsampling, which can be seen as an approximation of image blur which accompanies true resolution reduction in cameras. *Fig.*[2b] and [2d] show an example image with added Gaussian blurring effect while down-sizing in *Fig.*[2c] and [2e] for the original image is in *Fig.*[2a].

For each of the examined images, we show experimental results for a color histograms of different resolution. As a first result, it indicates that the peaks of histograms give more stable results than the rest of histogram bins with independence of the comparison measurement. Tables [1], [2] and [3] show examples of how the scaling process results in a blurring effect for the blurred version of different images in *Fig.*[3] and In figures 5–7, we show one-dimensional histograms for the original and a reduced resolution PALACE image.

Note that in the first case, the Palace image, has high-frequency textures such that the largest single peak in the original image is very small after blurring and a new hue, that was rather weak in the original, has become the dominant peak. Of course, the "high-frequency" textures are were one expects such blurring to blend the colors. But when scale is also allowed to vary, almost every scene/object will eventually have such blending, though it is less likely to move a peak. The remaining examples demonstrate obvious stability results, which are obtained not only for the absolute measurements but also for the other peak-oriented measurements.

Image Name	Original	Blur	Downsize
Palace	233, 240	18, 238	18, 238
Redflower	10, 118	10, 118	10,118
Historic Scene	182, 231	182, 231	182, 231
Art	235, 345	235, 345	235,345
Snowflower	17, 180	17, 180	17, 180

TABLE I
SUMMARY OF THE LARGEST TWO HUE PEAK VALUES IN EXPERIMENTAL WORK RESULTS.

Image Name	Original	Blurring	Downsize
Palace	27, 59	15, 50	15, 59
Redflower	59, 92	59, 92	59, 92
Historic Scene	15, 69	15, 69	15, 69
Art	20, 42	20, 42	20, 42
Snowflower	15, 50	15, 50	15, 50

TABLE II
SUMMARY OF THE LARGEST TWO SATURATION PEAK VALUES IN EXPERIMENTAL WORK RESULTS.

B. *Stability with Different Scale*

The recognition of the scaled images is difficult and important in the image retrieval system because of significant nature in the vision. Most of the research handles scale process as down-sampling. On the other hand, scaling is not independent from changing the resolution in the nature of vision process. In order to calculate histograms at different scale we apply two principles: in the first step we use the Gaussian blurring to prepare the image for down-sampling and secondly we down-sample by $\frac{1}{2^n}$. Therefore, it is sufficient to reflect change on the color histogram by scaling in

Image Name	Original	Blurring	Downsize
Palace	45,60	49, 55	45, 55
Redflower	28, 62	28, 59	28, 59
Historic Scene	65, 97	67, 96	68, 95
Art	21, 70	21, 69	18, 70
Snowflower	5, 93	5, 97	7, 97

TABLE III
SUMMARY OF THE LARGEST TWO VALUE PEAK VALUES IN EXPERIMENTAL WORK RESULTS.

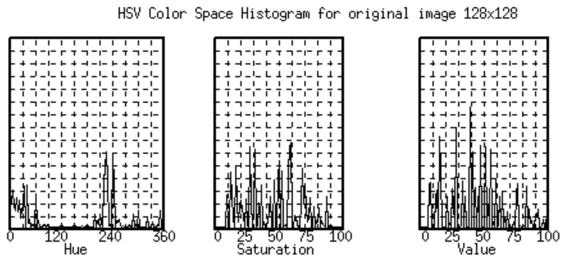

Fig. 4. H,S and V Histograms for Original 128x128 Palace Image.

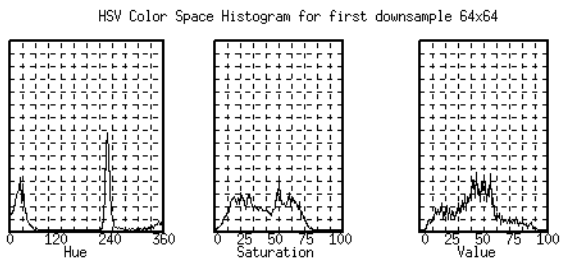

Fig. 5. H,S and V Histograms for 64x64 Palace Image.

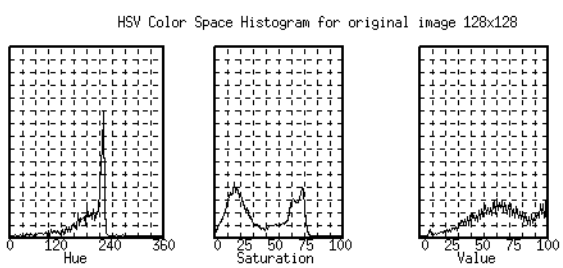

Fig. 6. H,S and V Histograms for 128x128 Historic Scene image.

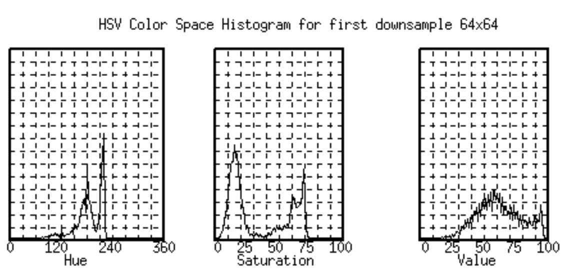

Fig. 7. H,S and V Histograms for 64x64 Historic Scene image. While there are significant changes, the peaks are in approximately the same location.

the nature of vision.

V. Histogram Peaks Indexing Technique for the Room Recognition System

In the Room Recognition system, omnidirectional video input captures the dynamic visual environment and the color histogram peaks are used to identify rooms in building by matching peaks. More specifically, we seek the ability to recognize our location, such as particular classrooms or offices, that are by a system on a mobile robot, intelligent wheelchair, or wearable computer.

A. *Omni-Directional Camera*

The system uses an omni-directional camera system to capture its environment. Conventional imaging systems are quite limited in their field of view[14]. And would required matching into a much larger set of images and also handling partial matches where the camera view matches parts of two different initial images. Using a camera that images a viewing hemisphere there is no need to have multiple views for a room, and no need for partial matches. The only occlusions/gaps are those from objects occluding each other in the room. In very large rooms, the view from different areas of the room can be significantly different as we index sub-regions of the room. We also note that since no spatial information was used, the orientation of the camera, since it captures a hemisphere, is irrelevant (but was approximately the same in our many of our datasets so we can try spatial techniques at a later date.)

In our system a parabolic mirror is imaged by an orthographic lens to produce the image. The combination of orthographic projection and the parabolic mirror provides a single viewpoint, at the focus of the parabolic surface. The image of the mirror, called the paraimage, contains the full view information, independent of the mirror size. The size of the omni-directional image depends on the image magnification and the size of the mirror. The panoramic pyramid, [15], uses a set of parabolic mirrors stacked one on top the other. Mirrors can provide any resolution reduction desired. In this case of the physical pyramids there is a small viewpoint between the different resolutions, its impact on the generated images is insignificant. While Panoramic Pyramids can have any number of levels, this paper uses a system with 2 levels, with a factor of 4 resolution reduction in each of the x and y direction.

B. *RoomID as Histogram Peaks*

The color information of each image is reduced to a color histogram peaks representation that we call the roomID of the image. A roomID contains a varying number of colors as peaks, each representing a peak of color histogram in the HSV color space. The number of peaks in the roomID varies with the color complexity of the image. Currently, we store computed feature peak values for room images in flat files.

First, the room is detected from the building using the automated omni multiresolution or pyramid structure. To compute the roomID of a color omni image, we capture a panoramic pyramid image in RGB and then transform the image into a sampled HSV color space. In our transformation, the sampled HSV color space contains 360 Hues, 100 Saturations and 100 Values. We detected and kept just top 7 peaks of omni room color image for each level.

For room recognition using color histograms peaks, we compare a histogram T from a database to a newly observed histogram H.

In order to define a similarity measure between two roomIDs, we introduce the notion of the Histogram Peak Distance(HPD). This is the minimal amount of 'match' needed to associate a roomID into with an item in the database. When comparing one roomID to another, the match is the sum of the Absolute distances done by comparing the weight of closest histogram peaks of the source roomID to those of the destination roomID. Although we do not claim that the HPD is a perceptual distance, it is an extension of distances of single colors in the HSV color space, which are perceptual distances, to distances between sets of colors. A full Hausdorff measure between the sets could be computed and will be evaluated in the future. In practice, as we show in the following sections, the HPD leads to good results. It also allows us for much less computational complexity: we compare just 7 peaks and don't care about the remaining information. This approach achieves much faster comparison by storing only 7 peaks for each channel of color space. Thus, it is possible for different location images of the same room having the same feature to recognize in different color histogram contents.

VI. Implementation

To the best of our knowledge, there are no image-based room recognition system with which to compare. However omni-based room recognition, has the same components of any image indexing recognition system. While structural information could be used, we consider only color information at this time. (Again, if it is not sufficient, we could just be using it as a good prefilter). As we shall see, this information alone is often sufficient for room identification.

While the HPD is indeed at the core of our image retrieval system, and has proven very effective, in this paper we want to emphasize a related but distinct use of this metric. Once image retrieval systems find the best matches for a given query, they usually display them in a list, sorted by their similarity to the query. While this might suffice if the desired image is in that list, this is not always the case (especially when we have only a vague idea of the desired image or approximate input). In this case, it is desirable for the system display a coherent view of the query results where the returned images should be arranged in order of their distances from the query. With such a view, the user can see the relations between the images, better understand how the query is performed, and be guided to successive queries. Our HPD approximates the perceptual difference that separates two roomIDs. The computation of the differences of these color peaks is called a matching.

Given a set of n rooms together with the HSV color histogram peaks p_{ij} for each of them, the HPD technique computes the minimum Absolute distances of peaks between the

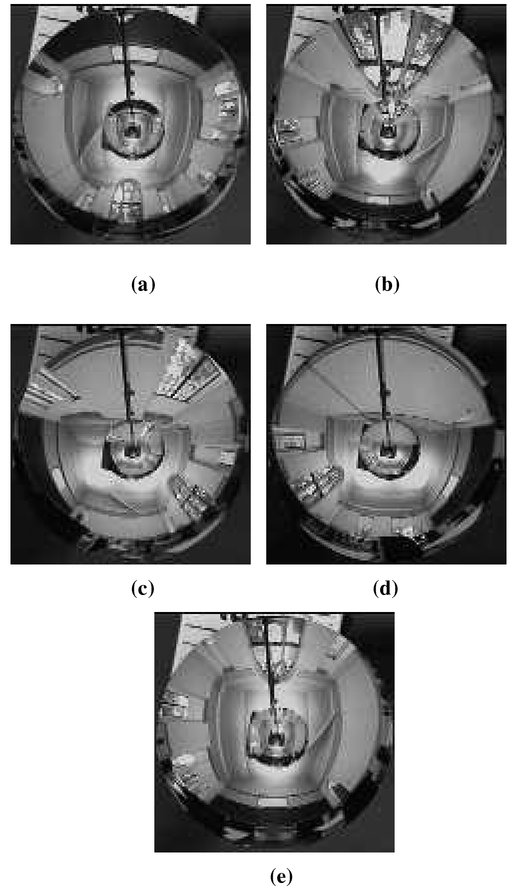

Fig. 8. a) PL508NORTH (b) PL508SOUTH (c) PL508WEST (d) PL508EAST (e) PL508CENTER

query and the rooms in M_n. Our formulation of this problem requires minimizing the following quantity:

$$MATCH = \Omega_n = \sum^{n} \sum_{i=0}^{2} \sum_{j=0}^{6} \min_{k,l} |p_{ij} - \theta_{kl}|$$

MATCH is a nonnegative number that indicates how well distances are preserved in the matching. Zero MATCH(Ω_n) indicates a perfect fit.

Fig.[5] shows 5 panoramic pyramid images taken at different locations within PL508. Suppose that we are looking for images of the PL508 room. This room will be characterized by the peaks of each hue, saturation, and value channels, so we use as our query "find images with that peaks and don't care other colors". Matching algorithm results show the ten best matches from the data bases, sorted by their absolute match difference to the query.

VII. Experimental Results

The proposed technique is implemented using X/Motif and C++ on an IBM compatible Pentium PC with MMX, operating at 200MHz. Acquisition, model building and recognition are all done in real time. To better evaluate the performance of the database, we tried to populate the database using room images with large varieties, and also included a number of similar rooms. The database is currently contains more than 300 color omni room images. Rooms to be included in the database are taken under their

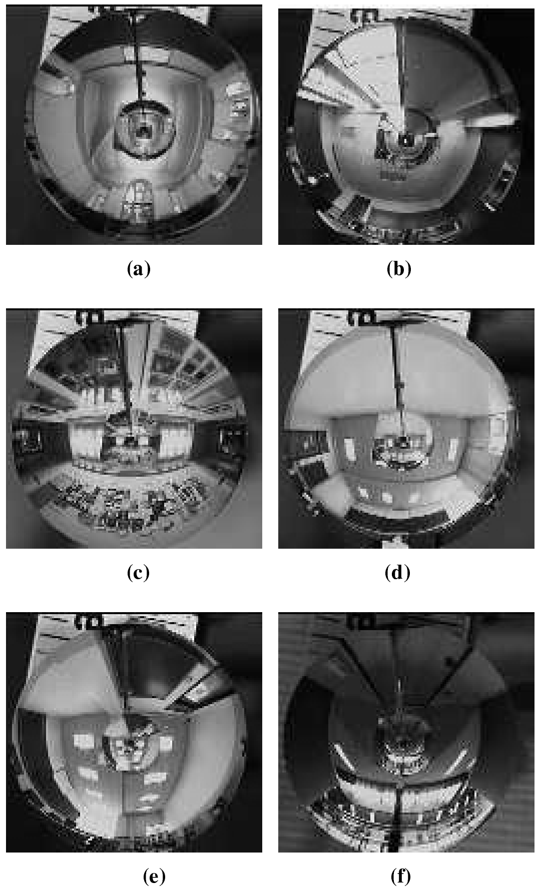

Fig. 9. a) PL508 (b) PL503 (c) PL5thFLOORWALKWAY (d) PL403 (e) PL450 (f) PL6thFLOOR

normal (nearly white) illumination. We are planning to improve our method by adding many more images in the near future. A single omni view of a room is representative of the room's chromaticity characteristics. For many rooms, its color distributions are similar regardless of changing camera location. For some rooms, different locations that result in significant occlusion or disocclusion of colors are treated as separate entries in the database, but nevertheless labelled as the same room location.

To demonstrate and examine the effectiveness of the proposed technique, we conducted a series of recognition experiments using omni room image database obtained from 205 rooms by using peaks. The histogram peaks as image content indexing is used to compute the database invariant feature. We demonstrate recognition performance on several color omni room images of different location and illumination at same height in same room. As an invariant indexing feature of omni room image, the color histogram peaks was computed from an image captured at approximately 12:00PM. To insure varying illumination was handled, and test images were taken under a range of times and lighting conditions, e.g. using images from 9AM, 11AM, 1PM, 3PM, 5PM and 7PM.

Fig.[6] illustrates some example of omni room images in our database. Illumination effects on color, while significant do not reproduce in the proceedings, and also intesnity as can be see in *Fig.*[7] image. In our experimental setup, all images were obtained using a custom panoramic pyramid system. While obtaining the room images, people and all other stuff were allowed to move freely in the room.

Overall testing with this data base of 394 images from 205 rooms produced a recognition rate of 92 percent. Many of the failures occur at extreme lightning changes, very similar rooms (as often occurs on a college campus), and moderate variations in camera placement within the room.

VIII. Conclusion and Future Work

In this paper, a computationally efficient color content based histogram peaks indexing representation technique was proposed. The experiments with real images showed that representation of color histogram peaks is a suitable feature for large variation of resolution and scaling. The proposed histogram peaks indexing technique for real time applications is very promising for its computational efficiency and its required data storage. The speed of the system and the small storage overhead make it suitable for use in large database in real time. Future investigations will be directed to developing multilevel color histogram peaks representation of multiresolution images techniques which combine the proposed approach indexing method.

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