ISSN 2250-3153

# A Novel Algorithm for Color Image matching using Wavelet-SIFT

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***Abstract-*** This paper presents a new technique for robust Image matching based on the combination of wavelet transform and Color-SIFT (Scale Invariant Feature Transform). Low frequency and High frequency sub-bands of the image are extracted using wavelet transform and then color SIFT method is used to extract color feature descriptors. A novel matching techniques used to validate true matches by establishing relationships between candidate matching features. The proposed method is tested on many image pairs at different conditions. Performance of this method is compared with Color-SIFT and basic SIFT methods.

## I. Introduction

Image matching is to make use of image data acquired by sensor and compare, it with referenced image to obtain corresponding object position in referenced image. Finding reliable correspondence in two or more images remains a difficult and critical step in many computer vision tasks. Most conventional image matching methods based on features; use a gray channel instead of color information to reduce the complexity. Color provides valuable information in object description and matching tasks. Many objects can be misclassified if their color contents are ignored. So we have to use color information provided in the image for matching. In this paper, we present an approach to color image matching based on wavelet and SIFT techniques.

The performance of descriptors determines the matching results directly. The local extracted features should be invariant with respect to geometrical variations, such as translation, rotation, scaling, and affine transformations. SIFT [1] [2] has been proven to be the most robust among the local invariant feature descriptors with respect to different geometrical changes [3]. SIFT is designed mainly for gray images. As, color is an important factor in image matching, some researchers have already focused to make use of color information inside SIFT descriptors [4][5]. In [4], the normalized RGB model

Has been used in combination with SIFT to achieve partial illumination invariance besides its geometrical invariance. In Hue-SIFT [5], color image is converted to HSV model, from Hue component, a vector is obtained for each feature point, and is concatenated with 128 dimensional feature descriptor obtained by applying SIFT on intensity(value)

Component Accuracy of matching is less in that method since; it eliminates the features based on intensity criteria. It reduces the number of features of an image. To increase the number of features per image and increasing the number of matches, we propose a technique based on wavelet transform and color SIFT. In this, we apply wavelet transform to an image, obtain low frequency and high frequency sub bands, and then inverse wavelet transform is used to reconstruct the image. Color image features are extracted using Color-SIFT method and a novel image matching technique is applied to detect matches.

The paper is organized as follows. In section 2, SIFT method in color space is explained. In section 3, proposed method is detailed. The evaluation results showing the performance of Wavelet-color SIFT in comparison with Hue-SIFT is presented in section 4. We finally conclude in section 5.

## II. Color SIFT

Color SIFT method extracts color feature points from image. In this process, first we have to convert color input image RGB to HSV model. In HSV, hue component preserves the color information of image and saturation refers to the dominance of hue in the color. To preserve color information, these two components are not modified. Intensity (value) components below 0.1 are made equal to 0.1 and intensity components above 0.9 are made equal to 0.9. To this modified intensity component, we apply basic SIFT operation to extract keypoint.

SIFT algorithm[1] has been proposed for extracting features that are invariant to rotation, scaling and partially invariant to changes in illumination and affine transformation of images to perform matching of different views of an object or scene. Steps for extracting SIFT features are as follows.

Firstly, extreme values are detected at the different scales of the image, and are the keypoint candidates. Secondly, Taylor series and Hessian matrix are used to determine stable keypoint; thirdly, the gradient orientation is assigned to the keypoint by using its neighborhood pixels, and finally, keypoint descriptor is obtained.

### A. Detection of Scale space extrema

The first stage of keypoint detection is to identify locations and scales that can be repeatedly assigned under different views of the same object. The scale space of an image is defined as a function L(x,y,), that is obtained from the convolution of a variable scale Gaussian function G(x,y,) with an input image I(x,y)

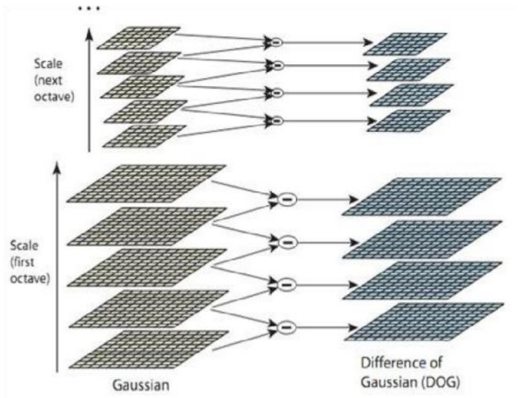



**Fig.1. the blurred images at different scales, and computation of DOG images.**

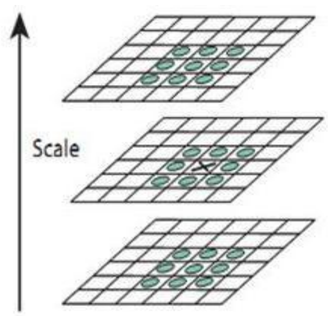



**Fig. 2. 'X' indicates sample point location**

$$L(x,y,\sigma) = G(x,y,\sigma) * I(x,y) \quad (1)$$

Where $\sigma$ is scale of blurring.

$$G(x,y,\sigma) = \frac{1}{2\pi\sigma^2} exp^{\frac{-(x^2+y^2)}{2\sigma^2}} \quad (2)$$

To efficiently detect the stable keypoint locations, we use scale space extrema in the difference of gaussian (DOG) function convolved with the image, and is computed from the difference of two nearby scales separated by a constant multiplicative factor k as shown in Fig.1,

$$D(x,y,\sigma) = (G(x,y,k\sigma) - G(x,y,\sigma)) * I(x,y)$$
$$= L(x,y,k\sigma) - L(x,y,\sigma) \quad (3)$$

The difference of Gaussian function provides a close approximation to the scale normalized Laplacian of Gaussian (LOG) $\sigma^2\nabla^2 G$ .

In order to find the local extrema (maxima or minima) of D(x,y,$\sigma$), each sample point is compared to its eight neighbours in the current image and nine neighbours in the scale above and below the image as shown in the Fig. 2.

Local extrema is selected only if the current pixel is larger or smaller than the remaining pixels and is discarded otherwise.

### B. Keypoint Localization

The location of keypoint is considered to filter the keypoints which are sensitive to noise or have no edge effect in this process. The reference [4] shows that, according to Taylor quadratic expansion, DOG(x,y,$\sigma$) can delete the extreme points which have lower contrast, and the value of Hessian vector and the ratio of determinant can reduce the edge effect.

### C. Orientation assignment

After the position and scale of the keypoint are determined, the next step is assigning keypoint's orientation, which can ensure the rotation invariance. The orientation of keypoint is obtained by its neighbourhood information. For each extreme point, L(x, y) at this scale, the gradient magnitude m(x, y) and orientation $\theta$(x, y) are computed using

$$m(x,y) = \sqrt{(L(x+1,y) - L(x-1,y))^2 + (L(x,y+1) - L(x,y-1))^2} \quad (4)$$

$$\theta(x,y) = \arctan\frac{(L(x,y+1) - L(x,y-1))}{(L(x+1,y) - L(x-1,y))} \quad (5)$$

An orientation histogram is formed from the gradient orientations of sample points within a region around the keypoint. The orientation histogram has 36 bins covering the 360 degree range of orientations. Each sample added to the histogram is weighted by its gradient magnitude and by a Gaussianweighted circular window with a $\sigma$ that is 1.5 times that of the scale of the keypoint.

Peaks in the orientation histogram correspond to dominant directions of local gradients. The highest peak in the histogram is detected and corresponding bin value is assigned as orientation. Then, if any other local peak that is within 80% of the highest peak is used to create a keypoint with that orientation. Therefore, for locations with multiple peaks of similar magnitude, there will be multiple keypoint created at the same location and scale but different orientations.

### D. Keypoint Descriptor

The descriptor for keypoint is highly distinctive and invariant to illumination and 3D view point changes. To generate a keypoint descriptor, consider a 16×16 window around the keypoint and divide it into sixteen 4×4 consecutive windows as shown in Fig. 3.

Within each 4×4 window, gradient magnitudes and orientations are calculated. These orientations are put into an 8 bin histogram. Any gradient orientation in the range 044 degrees are added to the first bin and 45-89 are added to the next bin. The amount added to the bin depends not only on the magnitude of the gradient but also on the distance from the keypoint. This is done by using Gaussian weighting function and this generates a gradient. It then multiplied with the magnitude of orientation.

Here, the purpose of Gaussian window is to avoid sudden changes in the descriptor. Doing this for each 4×4 window, with 16 pixels, we compute 16 random orientations

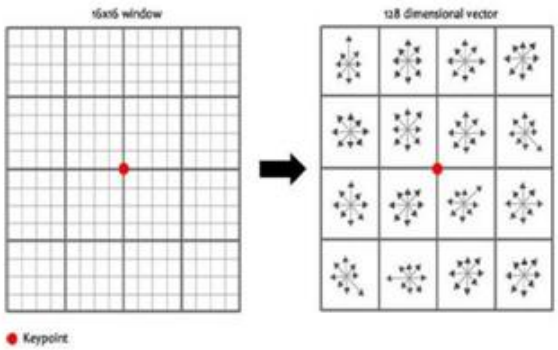



**Fig. 3.shows how 16 ×16 subdivided into 16, 4 ×4 sub windows**

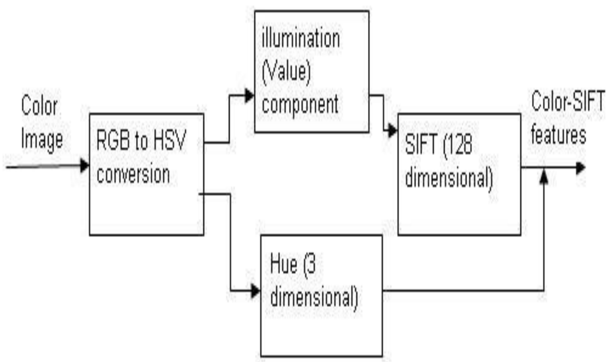



**Fig. 4.Color-SIFT block diagram**

Into 8 predetermined bins. Hence we get 4×4×8=16( 4×4 windows)×8(each window has 8 bins)=128 dimension feature descriptor corresponding to each keypoint.

To achieve Rotation independence, the keypoint rotation is subtracted from each orientation. Thus each gradient orientation is relative to the keypoint orientation.

To achieve Illumination independence, values greater than 0.2 are threshold to 0.2 and the resultant feature vector is normalized again.

For each extracted keypoint, a 16 ×16 patch is extracted from Hue component around keypoint location, and then a hue histogram with 16 equal divisions is formed. The vector of the hue histogram is normalized to unit length to reduce the scale effects. Since the dominant hue in patch plays more important role than other hues which occupy relatively smaller percentage of the image, the histograms are further refined by considering the top three hue values. Then, color-SIFT feature descriptor of 131 dimension is formed by concatenating 128 dimensional SIFT vector (obtained from value component) and top 3 hue values (obtained from hue histogram) with in 16 ×16 patch centered around keypoint location.

Figure.4 shows the block diagram of Color-SIFT method.

**E.Procedure for obtaining Color-SIFT feature descriptors**

1) Convert the input image, from RGB to HSV color space.

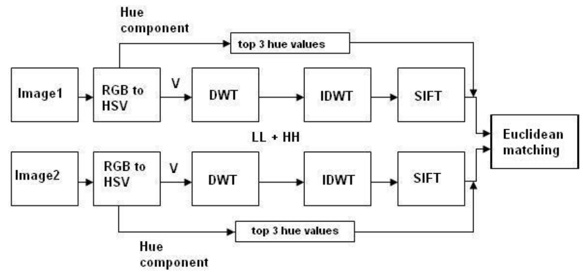



**Fig. 5.Block diagram of Wavelet SIFT method**

2) For value component (V), pixel values below 0.1 are made as 0.1 and above 0.9 are made as 0.9.

3) Apply SIFT operation on modified Value component and extract corresponding feature points & feature descriptors.

4) From Hue component, obtain top 3 dominant hue values, around extracted keypoint location.

5) Concatenate feature vector of keypoint and top 3 dominant hue components at that keypoint location, to form colour feature descriptor.

## III. PROPOSED ALGORITHM

The basic thought of wavelet transform [7] is using the same function by expanding and shifting to approach the original signal. The wavelet coefficients carry the time-frequency information in certain areas. It has good local characteristics both in time domain and frequency domain. It can maintain the fine structure of the original images in various resolutions and it is convenient to combine with human vision characteristics.

Wavelet transform decomposes an image into one low frequency sub band (LL) and three high frequency sub bands (LH, HL, HH). In the proposed algorithm, LL and HH sub bands are used to reconstruct the image, and reconstructed image is used for operation. The image information is preserved by LL component and edge information is preserved by HH component. The effect of image noise could be attenuated by eliminating other high frequency components [8].

Block diagram of the proposed method is shown in Fig. 5.

### A. Procedure for Image matching using Wavelet-Color SIFT

1) Apply Wavelet transform on input images, and extract its sub bands.

2) Reconstruct the input images using LL and HH sub bands.

3) Extract color feature descriptors for both input images using colour-SIFT method.

4) Each color feature descriptor in one image is compared with all feature descriptors of other image.

5) Calculate the number of matches between two images using matching strategy.

ISSN 2250-3153


**Fig. 6.Camellia flower Test Images**

### B. Matching strategy

To authenticate matching, the SIFT features computed in the test image should be matched with the SIFT features of the template. The matching methodology used here is distance between keypoint descriptors.

Euclidean distance between two vectors x and y is given by

$$d(\mathbf{x},\mathbf{y}) = \sqrt{\sum_i (x_i - y_i)^2} \qquad (6)$$

Image matching between the images is performed by matching each keypoint from an image to keypoints in other image. The best keypoint match is found by identifying its nearest neighbor in the other image keypoint. But, many of the features from an image will not have exact match because they may arise due to background clutter. So it is useful to discard the features that do not have good match.

An effective measure is obtained by comparing the distance of first closest neighbor to that of second closest neighbor. This method performs well because correct matches need to have the closest neighbor significantly closer than the closest incorrect match to achieve reliable matching. For false matches, there will likely be a number of other false matches within similar distances due to the high dimensionality of the feature space. Therefore, second closest match provides an estimate of the density of false matches.

## IV. EXPERIMENTAL EVALUATION AND RESULTS

In this section we present the experimental evaluation of the proposed method on various colour images with different color, illumination and view point changes. Performance of our method is compared with Hue-SIFT image matching. In Euclidean matching strategy, distance ratio is taken as 0.6.

Figure.6 shows Camellia flower with different color with same background. We can observe from Fig.7 that the proposed method (a) gives more number of matches compared to hue-SIFT method (b).

We also used the ALOI database [9], which contains 26,000 images of 1000 objects in total. The database contains six different lighting conditions which are very important for assessing color descriptors and variation in illumination color.

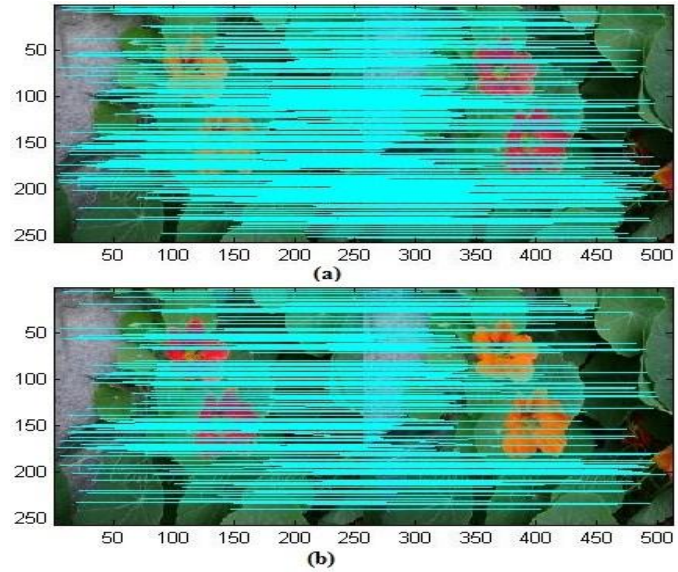



**Fig. 7. Matches between test images a) proposed method b) Hue-SIFT method**

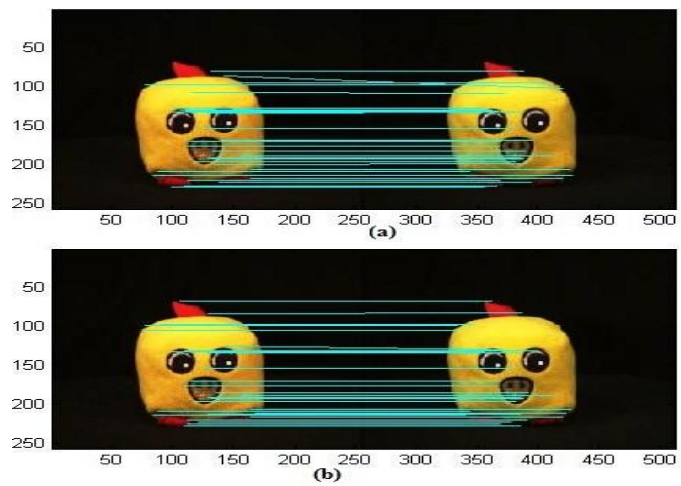



**Fig. 8. Shows matching results for change in color a) proposed method b) Hue-SIFT method**

This allows the assessment of colour constancy for colour image descriptors.

$$\%\ matches = \frac{total\ number\ of\ matches}{number\ of\ features\ in\ test\ image} \qquad (7)$$

Image matching results under colour changes are shown in Fig. 8. Fig. 9, shows the results of matching under illumination changes and Fig. 10, shows results for change in viewpoint by $10^o$. From these, we can observe that the proposed method ( a ) gives better matching performance than Hue-SIFT method ( b), because our method detect more feature points.

Figure. 11 show the evaluation results for the proposed method and Hue-SIFT method under rapid colour changes for ten ALOI images. Fig. 12 shows matching ratio results under illumination changes and Fig. 13 shows results under viewpoint changes. We can say that the proposed method gives better matching efficiency compared to Hue-SIFT method

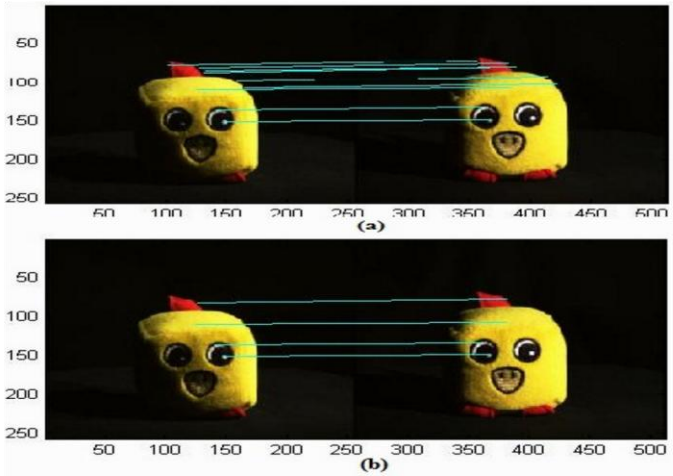
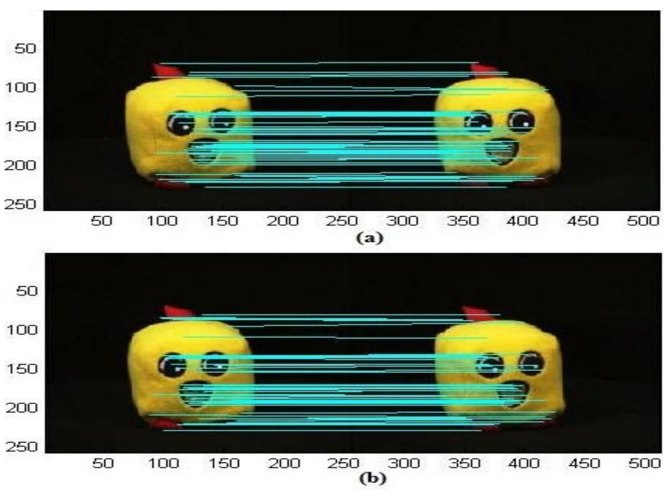



Fig. 9. Shows matching results for change in illumination a)proposed method b)Hue-SIFT method



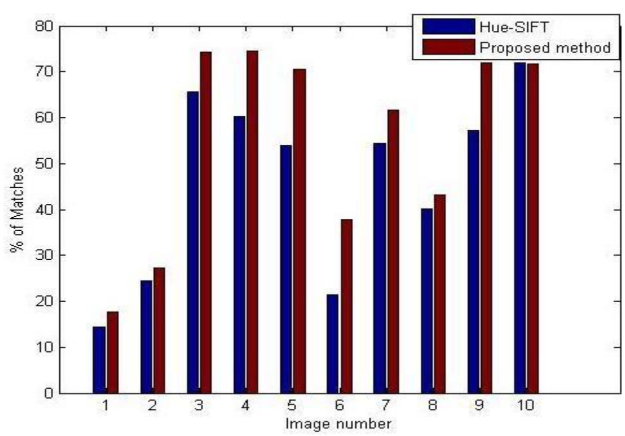




Fig. 11. Percentage increase in matches per image for Colour changes

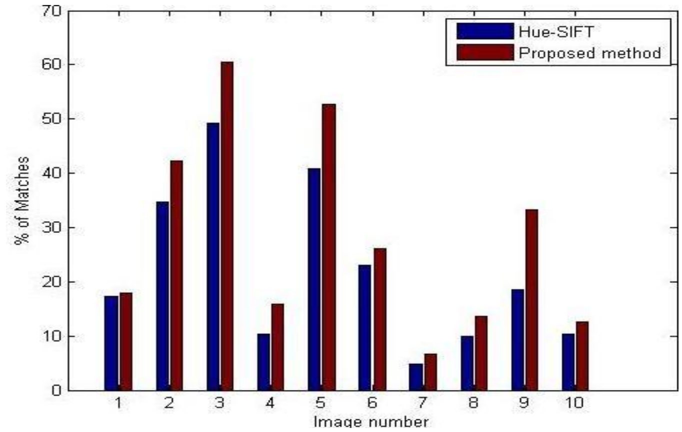



Fig. 12. Percentage increase in matches per image for illumination changes

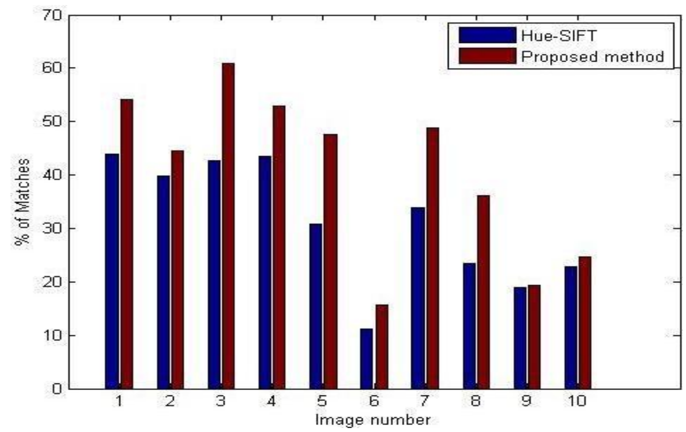



Fig. 13. Percentage increase in matches per image for viewpoint changes

## V. CONCLUSION

This paper presents a new approach for colour image matching based on Wavelet-Colour SIFT features. Experiments on various images with different color Illumination and viewpoint changes reveal that the proposed method increases accuracy of matching between images compared to hue-SIFT based image matching, with a slight increase in matching time due to more number of feature descriptors.

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