# Crowd Region Detection in Outdoor Scenes using Color Spaces

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**Abstract:** In the last few decades, crowd detection has gained much interest from the research community to assist a variety of applications in surveillance systems. While human detection in partially crowded scenarios has achieved many reliable works, a highly dense crowd like situation still is far from being solved. Densely crowded scenes offer patterns that could be used to tackle these challenges. This problem is challenging due to the crowd volume, occlusions, clutter, and distortion. Crowd region classification is a precursor to several types of applications. In this paper, we propose a novel approach for crowd region detection in outdoor densely crowded scenarios based on color variation context and RGB channel dissimilarity. Experimental results are presented to demonstrate the effectiveness of the new color-based features for better crowd region detection.

**Keywords**: Crowd detection; Color features; Segmentation; Detection

## 1. Introduction

An ever increasing population issue is coupled with the occurrence of crowds and situations of overcrowding. Surveillance automation systems are in place to detect and monitor crowded scenarios. Since crowd detection is a fundamental step towards crowd analysis, therefore, it assumes, even more, importance. Current surveillance systems can easily detect, track and estimate pedestrians in a sparsely crowded scenarios. However, dense crowd poses more non-trivial challenges in crowd detection, classification, counting and anomaly detection applications. The challenge is further aggravated by different scenarios; such as perspective distortion, cluttered environment with buildings, roads or big objects. In such a case, current systems would face difficulty in crowd detection and therefore, a mere extension of computer vision algorithms would not yield similar results for a dense crowd [1, 2]. More precise knowledge of the crowd size in a public space can provide valuable insight for tasks such as city planning, analyzing consumer shopping patterns as well as maintaining general crowd safety for rescue or evacuation based situations. In literature, there is no fixed number of people in an image that can categorize an image to be of the dense or medium crowd. Crowd dynamics establish if a crowd is dense or not. Using a number of people present in an image patch by studying count per unit area can help to establish if it has a dense crowd or not. Dense crowd region detection in an image has several post applications; reduction in search space, quick detection of dense crowds forming up in a video surveillance and target region for search and rescue based situations, for instance.

Generally, crowd detection is divided into two categories: direct and indirect detection [3]. While direct approaches are applied in sparse crowd detection with the help of model-based approaches, the indirect approaches use texture [4-7], key point [8-11] and histogram features [12-14] for crowd detection and estimation. Texture and intensity-based features have been widely used for crowd detection and classification, [4, 6, 7, 15-21]. These approaches, however, ignore color information.

Several varying factors, such as changes in illumination, compression, shadows, and highlights, discourage many in literature to ignore color features and consider it as an unreliable information source as it may be subjected to light variations and might change from the crowd to crowd [22-24]. However, as Human Visual System (HVS) relies greatly on the information portrayed by colors of the perceived scene [25], hence in this paper, we show that extracting the information of color and finding suitable crowd color features can help detecting crowd region of interests more effectively than incorporating only intensity-based features. In this paper, the color-based features are tested and their combination with other present features is evaluated for the crowd detection in outdoor scenes. The features that we propose to extract from the colored images are representative of these variations. Testing and the evaluation of the results confirm the advantage of the proposed color based features.

## 2. Related Work

Detection of the crowd and non-crowd regions is a current computer vision issue. Crowd detection methods work on two levels, holistic and local. The commonly used holistic features use global information to detect crowd. Most commonly used holistic features are textures [5, 6, 18, 26, 27]: GLCM, GOCM,, foreground blobs [28, 29] , edge features [30], and key points [9, 27]: SURF , FAST amongst others. Arandjelovi´ [31] used SIFT features with Bag of Words approach to get crowd detection results. However, these works rely on gray level information of image such as pattern analysis and do not make use of color attributes of the image. This results in a loss of information contained in the RGB color space. A recent comprehensive survey by Francesco Bianconi [25] compared different detection methods which included both color and textures. In their work, they concatenated different feature vectors and reached to a conclusion that integrating color and texture features parallel-wise seems to be the most promising strategy.

For crowd detection, many research works utilize color features only limited to Lab or HSV [7, 32] or by processing each color channel separately [33]. While luminance based edges are influenced by shadows and shadings, color information based edges provide highly informative regions for image analysis and so do the channels of a color image [34, 35]. Some recent work that uses color information makes use of RGB-D sensors [36]. Hajer Fradi [37] suggests using skin color for human detection as used in other works [38], however, Chern-Horng, Rajmadhan [39] suggested that only depending on the skin color is not a good idea as several individuals have the different pose and a significant distance from camera [45-48]. A dense group has an extremely specific angle, made of an interwoven of hues, that is the main inspiration of this work to consider this feature to detect crowd in a scenario. While color features have been used for object detection, but the need to visualize crowd as a cluster of the high variance color textured region needs to be studied and explored [49-51]. Fig.1 exhibits a few images of the dense crowds used for training and testing stages.



Fig 1: Dense crowd images

To classify image region as crowd or non-crowd, several types of classifiers have been used; SVM [31], Discrete AdaBoost [18], Neural Networks [18, 19], K-Means Clustering [6], to name a few, Since large banks of filters are used and huge feature vectors are extracted from an image for detection purposes, the classifiers sometimes face the challenge of heavy computation and curse of dimension [7]. For solving this problem, feature reduction has to be performed [34, 40] using, for instance, partial least squares [41]. However, this challenge can be avoided if more discriminative and distinguishing features are used in the classifier [52-54]. This paper presents a method of analyzing an image using the inspiration of how a Human Visual System works. We present how color could be an important clue for crowd region detection.

## 3. The Research Framework

This section presents the methodology of crowd detection. Color content of an image can help to identify the region of interest for crowd detection. The location of the crowd can be better detected when the image is analyzed locally. Therefore, in this paper, we take an approach of local feature extraction to get better crowd segmentation results. The framework of the methodology is illustrated in Fig. 2.

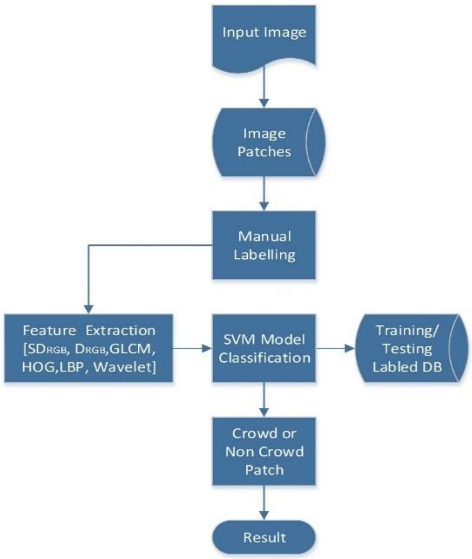




Fig 2: The flow chart of the crowd density estimation

The input images are cut into patches to extract color and texture features. Each patch is classified as crowd or non-crowd, and finally, all the local information is synthesized as crowd region estimation. Since the region of the crowd has color variations more pronounced locally, hence, the patch based architecture is adopted as in [6].

From a colored image $I_{R,G,B}$ equally sized blocks of size MxN are formed. Irrespective of geometrical or perspective distortion, color variation will be left unaffected. The color information of each Red (R), Green (G) and Blue (B) channel is saved in different matrices $M_R, M_G, M_B$. Mean of each color channel matrix is labeled $\mu_R$, $\mu_G$ and $\mu_B$ respectively. These matrices are used for further calculations.

As per the findings of Francesco Bianconi [25] which show that texture and color together get better detection results, we incorporated texture features, like GLCM, LBP and other features like HoG, and Keypoints, which have been evaluated for better suitability in outdoor dense crowd detection scenarios by David Ryan [42]. Different combination of the proposed features is made with Wavelet, GLCM, LBP and HoG features in order to get how effective are the new color-based features.

### 3.1 Color Variance for Crowd Detection

Variance of a gray image or image block can be calculated using the formula below

$$Var\,(X) = \sum_{i=1}^{N} \frac{(x_i - \mu)^2}{N-1} \tag{1}$$

The mean, μ, of a region is calculated, and the difference from each of the N pixel's intensity value is found to result in a variance. However, finding variance in a colored image can be a little complicated, since different R, G, and B values make up the information whose variance is to be found. This measure is inspired by the R,G, B channel variance calculation in [43] and R,G,B correlation calculation by Piva, Bartolinin [35], who find correlation between DCT coefficients of RGB bands as for instance, correlation among R, G channels is found by $corr_{\mathrm{Mr,Mg}} = \frac{1}{n}\sum_{i=1}^{n} E[M_{r_i}, M_{g_i}]$.

Correlation is analogous to Covariance, and variance is a special case of covariance where both the elements whose covariance is found, are equal.

$$Var(X) \Leftrightarrow Cov(X,Y)\ if\ X = Y \tag{2}$$

Covariance among R, G, B channel can be written as

$$Cov(R,G,B) = cov(R,G) + cov(R,B) + cov(B,G) \tag{3}$$

For reducing computational cost, the following estimation of covariance rule can be used as,

$$Cov(X,Y) = E(X.Y) - E(X).E(Y) \tag{4}$$

Where the covariance can be computed as the expected value of the product of the pixel minus the product of their individual's expected values. The expected value is estimated through the average value, such as $E(X) = \mu_X$, resulting in the form

$$Cov_{R,G} = E(R.G) - \mu_R\, \mu_G\ . \tag{5}$$

In Figure 3, the image blocks are shown on the left and their corresponding color values are plotted at the y-axis. Fig 3 is an illustration that the multiplicated values of the mean of two channel can be compared with the square of each channel's mean value. Hence, the analysis shows that the equation of covariance, expectation value can be replaced with the former. This step will simplify the calculation while keeping the difference among the R,G,B channels emphasized. This leads to a more conclusive but an estimated equation of finding variance of R, G, B channel in a colored image, $CVar_{R,G,B}$ as

$$CVar_{R,G,B} = \alpha(varR + varG + varB) + \beta(Cov(R, G, B))$$

Where $varR$, $varG$ and $varB$ show the overall variance of all three R, G, B channels of the image. $\alpha$ and $\beta$ are the equation correction constants. Based on our experimental findings, $\alpha = 0.3$ and $\beta = 0.67$.

Finally, the standard deviation of R, G, B band is found using standard deviation, $D$ , as $SD_{R,G,B} = \sqrt{CVar_{R,G,B}}$.

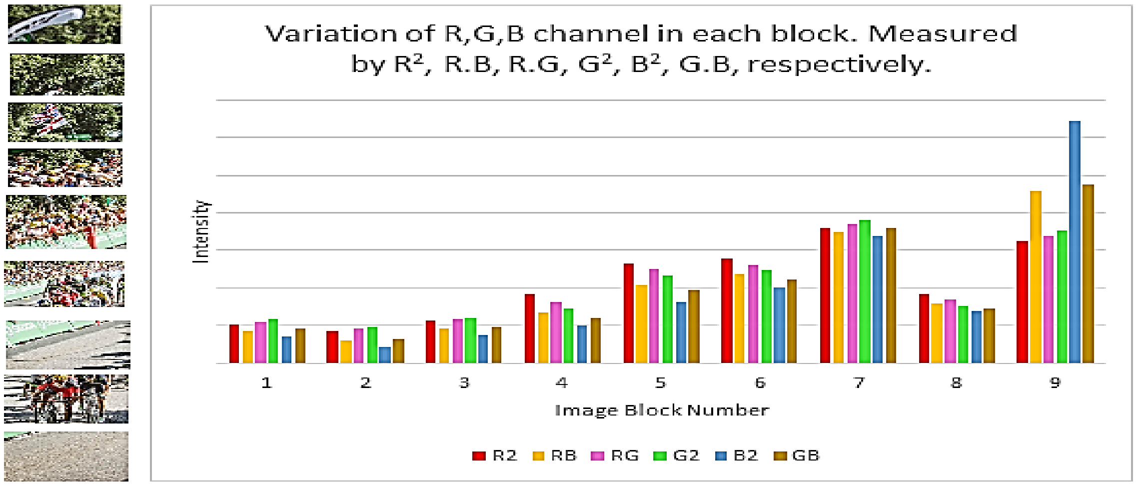



Fig 3: The image blocks are shown on the left. The result of $\mu_R.\mu_G\ \mu_B$ and other combinations $\mu_{RB}.\mu_{RG}\ \mu_{GB}$ are compared to $\mu_R{}^2.\mu_G{}^2\ \mu_B{}^2\mu_R{}^2$. The image blocks also show that perspective distortion does not limit color channel variation.

## 3.2 Dissimilarity of RGB channel

The second measure that can help in finding the difference between R, G,B values can be found using the pairwise distance between two sets of observations, for each possible combination of R,G,B channels. For this purpose, we use shape comparison statistics. For color variance of an image patch to be high, the diversity among each color channel R, G and B must be high. We modified Euclidean distance to find the dissimilarity among each patch's R,G,B distribution channel.

$$D(\boldsymbol{r}, \boldsymbol{g}, \boldsymbol{b}) = \max(\textstyle\sum_{i=i}^{n}(r_i - g_i)^2, \sum_{i=i}^{n}(r_i - b_i)^2, \sum_{i=i}^{n}(b_i - g_i)^2) \qquad (6)$$

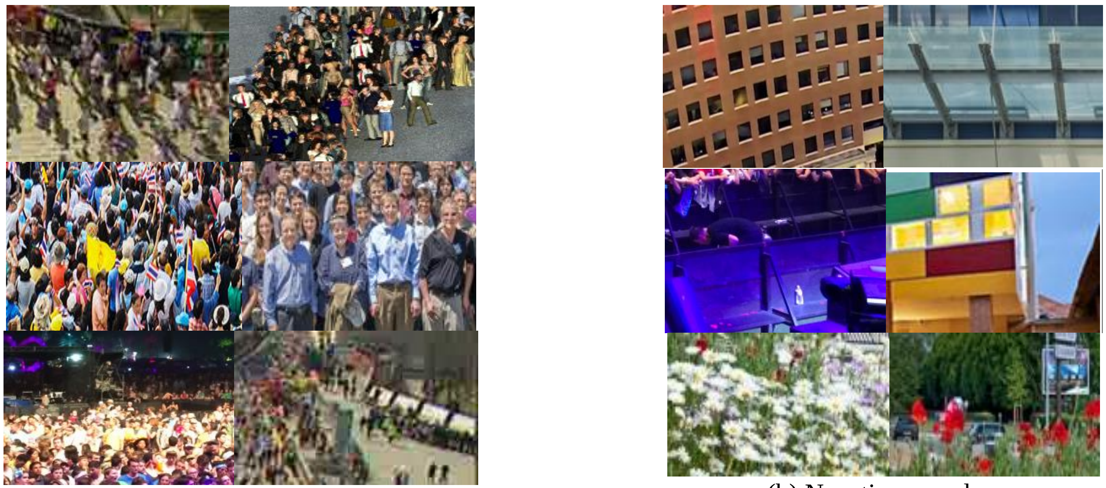
We propose that the distribution among RGB channel distributions will have a high difference in the image patch which has a crowd. This shows dissimilarity among color channels which coerces the presence of crowd in that region and is notated as $D_{RGB}$. As shown in Fig. 4, the samples of dense crowd and non-crowd images are used for detection. To make the setup more robust, we include negative samples (non-crowd images) with different colors distributions of RGB channels, such as garden of flowers, field of plants and butterflies.

## 3.3 SVM Classification

For classification, once the color based features are identified and extracted, image patches have to be labeled as the crowd or non-crowd/ background [50-55]. The ground truth for all datasets used in the evaluation was labeled manually. As we are focusing on improvement of crowd detection results at the level of image patches, we used SVM classic method which could separately classify the image patches correctly as a crowd or non-crowd, according to the value of the combined texture and color features [56-60]. For better learning classification the radial basis kernel function is used. To minimize training and test samples bias, we perform five dole cross-validation for each data while using 70% for training and 30% for testing from the dataset.

## 4. Experimental Results

This section exhibits simulation results, additionally, it compares the performance of proposed color based features when used in combinations with texture and histogram based method with the results which don't include the proposed color features.



(a) Positive samples (b) Negative samples.

Fig 4. Training image examples used for SVM training

SVM classifier is selected as the classification model based on its simplicity and performance. Figure 4 shows a sample of crowds and non-crowd images used to train the SVM classifier.

## 4.1 Test Setup

A total of 152 images is taken from google and filter to verify results on real life images. Images are divided into blocks, each block is labeled as crowd or non-crowd. From total images, 70% of the images are randomly chosen for training while 30% are kept for testing purposes. SVM classic method which could separately classify the image patches correctly as crowd or non-crowd is used for its simplicity and ease of use. The classification is done according to the value of the combined texture and color features. For better learning classification the radial basis kernel function is used. To show how these proposed color based features improve the crowd region detection results, different combinations of the features are used to analyze results. Using the five-fold cross-validation procedure, test measures are calculated such as precision, recall, accuracy, FScore and other error rates are calculated across all images. This procedure is repeated ten times each time with a different selection of images in the dataset. Finally, the quality numbers for all ten runs are averaged. Various combinations of these features are assessed, as shown in Table 1.

### 4.2 Detection Results

Before turning to classification, we discuss the crux of the proposed method and how the proposed color features contain information that is exploited for crowd detection [61-63]. Figure 5 illustrates two sample images. The top row shows a non-crowd region in an image and its corresponding R,G, B channels' standard deviation which can be calculated using the proposed formula. The plot of intensities of each channel is also shown to the image right [64,65]. The image in the second row is a positive crowd region. It can be seen that the standard deviation of R, G, B channels in a crowd region is high. The distribution of R,G,B channels is higher for a crowd region. It must also be noted that our proposed method is inspired by the correlation information of the R,G,B channels in a crowd image.

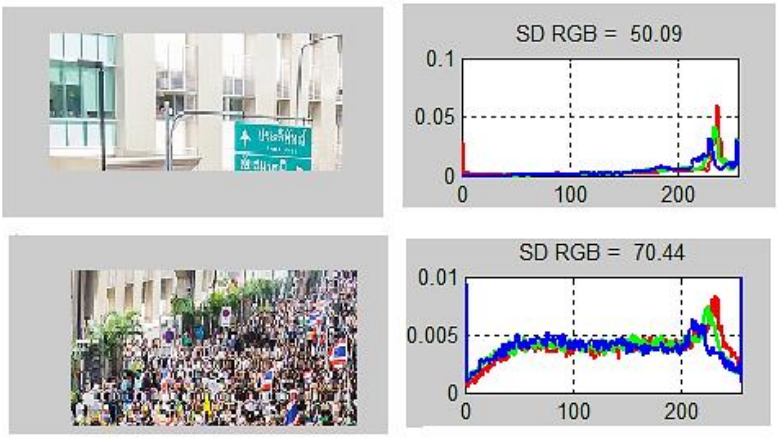



Fig 5 Sample results of standard deviation for non-crowd and crowd region. Image block with crowd has more SD (or variation) in RGB channels than building.

For quantitative analysis, the feature combinations tested for crowd detection are shown in Table 1. In Table 1, we have reported the performance and highlighted the most significant feature combinations in bold. The Accuracy is the highest with the combination of proposed features; $S_{RGB}$, $D_{RGB}$ features, with other most frequently used features in literature; Linear Binary Pattern, Wavelet, GLCM, and HoG features. This shows that the color and textural features complement each other and establishes that for crowd detection, this combination is more promising. Accuracy improves by incorporating our proposed color based features: dissimilarity distance, $D_{RGB}$, and RGB channel variation, $SD_{RGB}$,. The same combination of features also shows more than 10% improvement in the Specificity. The recall is the percentage of relevant results retrieved. So, the recall has decreased by 4% and the Precision has increased more than 6%. The performance measures are illustrated in Figure 6.

| **Features/ Measures** | | **HoG** | **GLCM, HoG** | **Wave, GLCM, HoG** | **LBP, Wave, GLCM, HoG** |
|---|---|---|---|---|---|
| Accuracy | | 63.29 | 61.30 | 59.12 | **69.78** |
| Specificity | | 53.25 | 67.28 | 60.68 | **67.22** |
| Recall | | 66.69 | 45.81 | 61.38 | 75.67 |
| Precision | | 61.61 | 67.80 | **72.16** | 70.29 |
| FScore | | 65.55 | 56.12 | 55.62 | **70.19** |
| | | | | | |
| **Features/ Measures** | **Proposed ($SD_{RGB}$, $D_{RGB}$)** | **HoG, $SD_{RGB}$, $D_{RGB}$** | **GLCM, HoG, $SD_{RGB}$, $D_{RGB}$** | **Wave, GLCM, HoG, $SD_{RGB}$, $D_{RGB}$** | **LBP, Wave, GLCM, HoG, $SD_{RGB}$, $D_{RGB}$** |
| Accuracy | 60.65 | 58.04 | 63.91 | 62.39 | **73.26** |
| Specificity | 64.90 | 68.67 | 51.20 | 64.77 | **76.58** |
| Recall | 51.99 | 54.02 | 77.25 | 62.56 | **71.04** |
| Precision | 60.80 | 64.66 | 60.20 | 70.85 | **76.96** |
| FScore | 54.76 | 55.16 | 66.86 | 57.56 | **71.77** |

***$SD_{RGB}$**= Standard Diviation among RGB channels,*** $D_{RGB}$**=Dissimilarity Measure. (Proposed color based features).

Table 1 Result of different measure of performance using different combinations of features with color based features proposed in this paper.

In Fig 6, the bar in blue is the result of crowd detection using our proposed color features only. The bar with black color represents the result of difference performance measure using our proposed method when combined with other textural features. The dissimilarity of channel R, G, B and these channels' Covariance distribution is largely sufficient to discriminate the crowd patch from the non-crowd region. The results show that crowd detection results using merely the two proposed features can result in more than 50% correct detections. This shows that the current features can distinguish crowd area much better once combined with the color based features. Table 2 illustrates the significance of using RGB color space over HSV channels as RGB has better distinguishable characteristics.

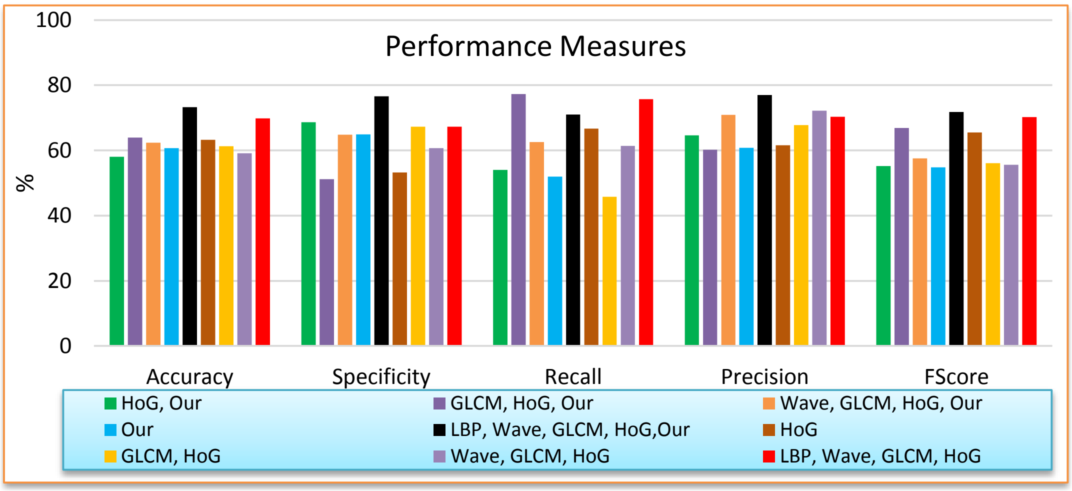



Fig 6: Performance comparison of different features with proposed features.

| Method | Accuracy | Recall | Precision | Features |
|---|---|---|---|---|
| **Proposed method implemented on HSV channel [7,32]** | 52.17 | - | - | LBP,Wave, GLCM, HoG, $SD_{HSV}$, $D_{HSV}$ |
| **Fagette *et al.* [7]** | 70.12 | 78.26 | 69.50 | LoG, Entropy, HoG |
| **Proposed approach** | **73.26** | **71.04** | **76.96** | LBP,Wave, GLCM, HoG, $SD_{RGB}$, $D_{RGB}$ |

Table 2 Comparison of different methods based on accuracy using different color spaces and methods from literature.

It must also be noted that proposed features are low dimensional. Additionally, since these color based measures do not have regional information regarding position and scale, hence they are rotation and scale invariant. It must be noted that the textural features that are present in these features when combined with color based features $SD_{RGB}, D_{RGB}$, get the highest accuracy. The Accuracy is the highest with the combination of proposed features; $S_{RGB}$, $D_{RGB}$ features, with other most frequently used features in literature; Linear Binary Pattern, Wavelet, GLCM, and HoG features. This shows that the color and textural features complement each other and establishes that for crowd detection, this combination is more promising.

## 4. Conclusion

This paper has presented a general framework for combining color information with textural information to detect region with the crowd in an image. Our ultimate goal is the improvement in crowd region detection in the images. We demonstrated that given an image of a crowd, which may be scale or view invariant, such an approach achieves much higher accuracy than those which ignore the color information during color detection. The illumination and shadows do present challenges, however, the information in variation and dissimilarity of RGB channels still holds that is taken as future work.

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