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Robust Approach for Fruit and Vegetable Classification

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Abstract

Efficient detection of 'species and variety' of fruits and vegetables is one of the major challenges in the fruit recognition. This paper presents a texture feature based on the sum and difference of the intensity values of the neighboring pixels of the color images. The proposed improved sum and difference histogram (ISADH) texture feature is an extension of the Unser's descriptor. The result shows that proposed texture feature performs better than the other state of the art color and texture features in the fruit and vegetables classification. The classification accuracy for the proposed ISADH texture feature is achieved up to 99%.

Keywords: Multi-class SVM; Sum and Difference Histogram; Global Color Histogram; Color Coherance Vector.

1. Introduction

With the aim of being able to achieve near human levels of recognition, recognition system has emerged as a 'grand challenge' for the computer vision. The fruit and vegetable classification can be used in the super market for the automatic generation of prices for the fruits purchased by a customer. The major challenge is to correctly recognize not only the species of a particular fruit (i.e., apple, potato) but also its variety (i.e., Fuji, Agata). Formally, the system must return a list of possible candidates of the form (species, variety) of an image of fruits or vegetables of only one variety, in arbitrary position and number. Fruit and vegetable classification can be used in computer vision for the automatic sorting of fruits from a set, consisting of different kinds of fruit.

A number of challenges had to be overcome to enable the system to perform automatic recognition of the kind of fruit or vegetable using the images from the camera. Many types of fruits are subject to

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significant variation in color and texture, depending on how ripe they are. A lot of activity in the area of Image Categorization has been done. Recently, a unified approach is presented in [1] that can combine many features and classifiers. The author approaches the multi-class classification problem as a set of binary classification problem in such a way one can assemble together diverse features and classifier approaches custom-tailored to parts of the problem. In [2] the author introduces sum and difference histograms as an alternative to the usual co-occurrence matrices for image texture description.

An approach to compare images based on colour coherence vectors is presented in [3]. They define colour coherence as the degree to which pixels of that colour are members of a large region with homogeneous colour. The border/interior pixel classification (BIC), a compact approach to describe images is presented in [4] in which a pixel is classified as interior if its 4-neighbors (top, bottom, left, and right) have the same quantized colour, otherwise, it is classified as border.

In [5] the author employed Principal Component Analysis and measured the reconstruction error of projecting the image to a subspace and returning to the original image space. However, it depends heavily on illumination, pose and shape.

Color and texture are the fundamental character of natural images, and plays an important role in visual perception. Instead of considering color and texture feature separately, this paper proposes a texture feature derived from the colored images. This paper analyses the accuracy of proposed texture feature and compares with the accuracy of some other color and texture features in the multi-class fruits classification scenario.

2. Proposed Work

2.1. Proposed improved sum and difference histogram (ISADH) texture feature

Unser [2] has shown that the sum and difference of two random variables with same variances are de-correlated and define the principal axes of their associated joint probability function. In this subsection, we are describing a texture feature from the sum and difference of intensity values of neighboring pixels of an image, which is improvement in Unser approach.

ISADH Feature Algorithm

(1) Find the sum S and difference D for the 1st channel of an image I with a displacement of (1, 0) as:

$$S(x, y) = I(x, y, 1) + I(x+1, y, 1) \tag{1}$$

$$D(x, y) = I(x, y, 1) - I(x+1, y, 1) \tag{2}$$

(2) Find the sum S_1 and difference D_1 of S with a displacement of (0, 1) as:

$$S_1(x, y) = S(x, y) + S(x, y+1) \tag{3}$$

$$D_1(x, y) = S(x, y) - S(x, y+1) \tag{4}$$

(3) Find the sum S_2 and difference D_2 of D with a displacement of (0, 1) as:

$$S_2(x, y) = D(x, y) + D(x, y+1) \tag{5}$$

$$D_2(x, y) = D(x, y) - D(x, y+1) \tag{6}$$

(4) Find the histogram for the 1st channel by concatenating the histograms of S_1, D_1, S_2, and D_2.
(5) Repeat step1 to step4 for the 2nd and 3rd channel of the color image.

(6) Concatenate the histograms of all the three channels in order to find the ISADH texture feature of the input image I.

ISADH texture feature relies upon the intensity values of neighboring pixels. The histogram of two images of the same class may vary significantly. On the other hand, the ISADH feature has lesser difference for these images. If the difference in feature of two images is less, then images are more likely belongs to the same class. But if the difference is significant, then images are more likely belongs to the different class.

2.2. Fruit recognition system

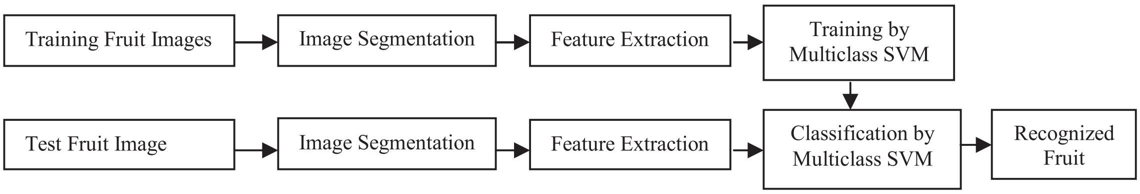


Fig 1. Fruit recognition system

The proposed Fruit recognition system, shown in Fig. 1, operates in two phases, training and second testing. Both require some preprocessing i.e. image segmentation and feature extraction.

This paper uses a background subtraction based on k-means [1]. Some examples of image segmentation are shown in figure 2.

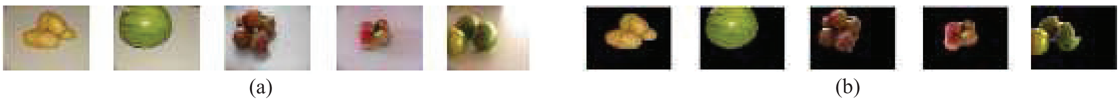


Fig 2. Extracting region of interest from the images: (a) Before segmentation, (b) After segmentation.

For the training and testing, this paper uses a multiclass Support Vector Machine (SVM) [1], which deals multiclass classification problem as a set of binary classification problems.

3. Experimental Result and Discussion

3.1. Data Set

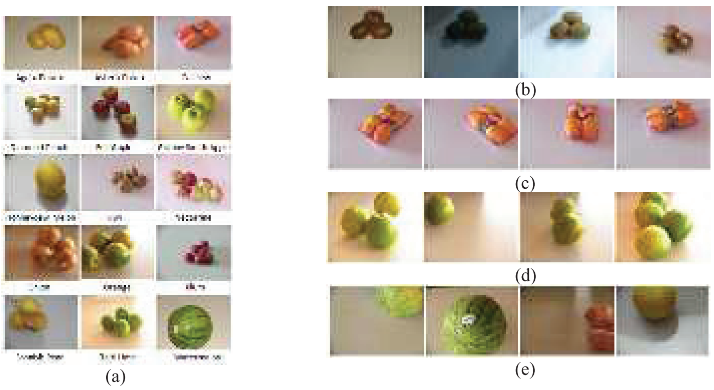


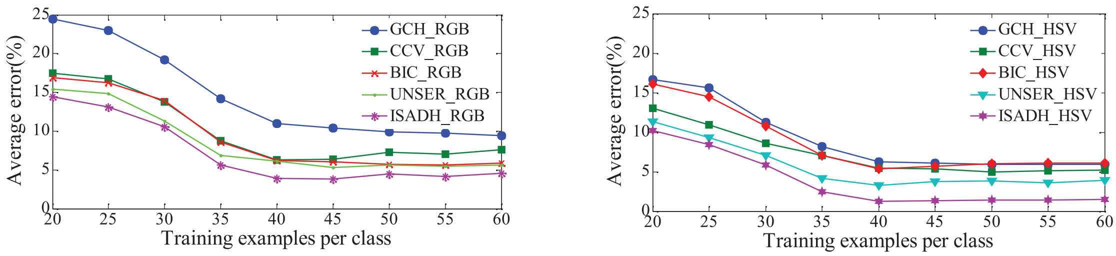
Fig 3: (a) Data Set Used, (b) Illumination differences, Kiwi category, (c) Pose differences, Cashew category, (d) Variability on the no. of elements, Orange category, and (e) Examples of cropping and partial occlusion.

To demonstrate the performance of the proposed approach, we have used a supermarket data set [6] of fruits and vegetables, which comprises 15 different categories: Plum(264), Agata Potato(201), Asterix Potato(181), Cashew(210), Onion(75), Orange(103), Taiti Lime(104), Kiwi(157), Fuji Apple(212), Granny-smith Apple(155), Watermelon(192), Honeydew Melon(145), Nectarine(247), Spanish Pear(158), and Diamond Peach(211): totalling 2615 images. Fig 3 (a) depicts some of the classes of the data set. Fig 3 (b) shows an example of Kiwi category with different lighting. Fig 3 (c) shows examples of the Cashew category with differences in pose. Fig 3 (d) shows the variability in the number of elements for the Orange category. Fig 3 (e) shows the examples of cropping and partial occlusion. These features make the data set more realistic.

3.2. Result Discussion

To evaluate the accuracy of the proposed approach quantitatively, we compare our results with the Global Colour Histograms [7], Colour Coherence Vectors [3], Border/Interior Classification [4] and Unser's descriptor [2]. In the experiments, we have used different number of images per class for training. The average error is computed by calculating the sum of average error of each class divided by total number of class.

Fig. 4 shows the average error for the Fruits and Vegetables classification for different features. The x-axis represents the number of images per class for the training and y-axis represents the average error. We have calculated the average error for each feature in RGB and HSV color space. The average error for each feature in RGB color space is shown in Fig. 4(a). The result illustrates that Global Color Histogram (GCH, 64-bin) has the highest average error because it has only the color information and it does not consider the relation among the neighboring pixels. The average error for the Color Coherence Vector (CCV, 64-bin) is less than the average error for the GCH feature because CCV feature exploits the concept of coherent and incoherent regions. Border/Interior Classification (BIC, 128-bin) feature has low average classification error than the CCV feature because BIC feature takes the values of 4-neighboring pixel into account.



(a) (b)

Fig 4. Comparison of GCH, CCV, BIC, Unser, and proposed ISADH features using SVM as a base learner in (a) RGB colour space, (b) HSV colour space.

Unser feature with 64 bins has the low average classification error than GCH, CCV, and BIC. Fig.4 illustrate that proposed improved sum and difference histogram (ISADH) outperform the other features because ISADH feature considers not only the sum and difference of neighboring pixel but also the neighboring information of sum and difference of neighboring pixel. Fig 4 (b) depicts the average classification error for the features derived from HSV color images. GCH feature achieves the highest classification error in HSV color space also. Both BIC and CCV features have high classification accuracy than GCH feature. Unser feature performs better in HSV color space also than GCH, CCV, and BIC features. ISADH feature also outperform and shows highest average accuracy among all features.

4. Conclusion

An efficient texture feature from the sum and difference of intensity values of neighboring pixel on the colored images is developed and proposed in this paper. In the proposed approach, we compute the sum and difference histogram for each channel of the colored image and combine these to make a single histogram. The fusion of neighborhood information with the color information makes this feature more discriminative than any other color and texture feature individually. The proposed feature is validated for the fruits and vegetables classification and show fairly more accurate results compared to other features.

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