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ABSTRACT

The computer vision strategies used to recognize a fruit rely on four basic features which characterize the object: intensity, color, shape and texture. This paper proposes an efficient fusion of color and texture features for fruit recognition. The recognition is done by the minimum distance classifier based upon the statistical and co-occurrence features derived from the Wavelet transformed sub- bands. Experimental results on a database of about 2635 fruits from 15 different classes confirm the effectiveness of the proposed approach.

Key words: *Fruit Recognition, Texture, Wavelet Transform, Co-occurrence Features.*

1 INTRODUCTION

The computer vision strategies used to recognize a fruit rely on four basic features which characterize the object: intensity, color, shape and texture. This paper proposes an efficient fusion of color and texture features for fruit recognition. The recognition is done by the minimum distance classifier based upon the statistical and co-occurrence features derived from the Wavelet transformed sub- bands.

Recognition system has emerged as a 'grand challenge' for computer vision, with the longer term aim of being able to achieve near human levels of recognition for tens of thousands of categories under a wide variety of conditions. The fruit recognition system can be applied for educational purpose to enhanced learning, especially for small kids and Down syndrome patients, of fruits pattern recognition based on the fruit recognition result [1]. It can be used in grocery store which makes the customers label their purchases using automatic fruit recognition based on computer vision. 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 kind of fruits are subject to significant variation in color and texture, depending on how ripe they are. For example, Bananas range from being uniformly green, to yellow, to patchy and brown.

Color and texture are the fundamental character of natural images, and plays an important role in visual perception. Color has been a great help in identifying objects for many years. It is often useful to simplify a monochrome problem by improving contrast or separation. The process of color classification involves extraction of useful information concerning the spectral properties of object surfaces and discovering the best match from a set of known descriptions or class models to implement the recognition task [2]. Texture is one of the most active topics in machine intelligence and pattern analysis since the 1950s which tries to discriminate different patterns of images by extracting the dependency of intensity between pixels and their neighboring pixels [3] or by obtaining the variance of intensity across pixels [4]. Recently, different features of color and texture are combined together for their applications in the food industry [5].

Color features have been extensively applied for apple quality evaluation mostly for defect detection. For instance, color features of each pixel in images obtained in three components of RGB spaces could be successfully used to segment defects on 'Jonagold' apples [6, 7]. Tomato is another food product in which color features are widely used, as color is an indicator of the maturity of tomatoes. The early application of color features in tomato quality evaluation was preliminarily carried out by Sarkar and Wolfe [8] who used grey intensities of images to classify green and red tomatoes. Texture features are found to contain useful information for quality evaluation of fruit and vegetables, e.g., classification of grade of apples after dehydration with the accuracy of 95% [9], and prediction of sugar content of oranges with a correlation coefficient of 0.83 [10].

Recently, different features of color, size, shape, and texture are combined together for their applications in the food industry. Normally, by increasing the features used, the performance of the methods proposed can be increased. Moreover, both surface information (color and texture) and geometry information (size and shape) of food products in images play a significant part in defect detection and class discrimination [11]. Thereby, to capture more proper information about the quality of food products from images, multiple kinds of features corresponding to the grading system of the food products should be proposed.

Color and texture features are used to locate green and red apples [12]. Here, the texture property

Journal of Emerging Trends in Computing and Information Sciences

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plays two roles in the recognition procedure. Texture based edge detection has been combined with redness measures, and area thresholding followed by circle fitting, to determine the location of apples in the image plane. It was shown that redness works for red apples as well as green apples. This increased texture contrast helped to identify apples separately from background. Three features analysis methods color-based, shape based and size-based are combined together in order to increase accuracy of recognition [1].

An unified approach that can combine many features and classifiers, where all features are simply concatenated and fed independently to each classification algorithm. The fusion approach is validated using a multi-class fruit-and-vegetable categorization task in a semi-controlled environment, such as a distribution center or the supermarket cashier. The results show that the solution is able to reduce the classification error in up to 15 percentage points with respect to the baseline [13].

The paper is structured as follows. The next section discusses the Proposed Method. The Section 3 gives the Recognition Results and Discussion. Finally, Section 4 gives the Concluding remarks of the proposed method.

2. METHODOLOGY

The two sections that involved in this work are Training and Classification. The block diagram of the proposed method is given in Figure 1.

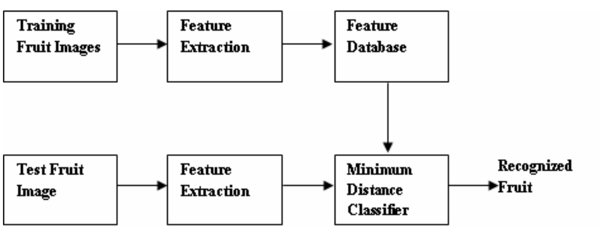

Figure 1: Fruit Recognition System

The proposed Fruit recognition system, shown in Figure 1, need a change in the color space of the images, in order to obtain one channel containing the luminance information and two other channels containing chrominance information. The HSV representation is often selected for its invariant properties. The hue is invariant under the orientation of an object with respect to the illumination and camera direction and hence more suited for object retrieval. Texture features are computed from the luminance channel '*V*', and color features are computed from the chrominance channels '*H*' and '*S*' [14]. The component which corresponds to brightness of the color (*V*) is decomposed using Discrete Wavelet Transform [15-17] and the co-occurrence matrix is constructed from the approximation sub-band by estimating the pair wise statistics of pixel intensity. The use of the co-occurrence matrix [18,19] is based on the hypotheses that the same grey-level configuration is repeated in a texture. Further, co-occurrence features such as contrast, energy, local homogeneity, cluster shade and cluster prominence are calculated from co-occurrence matrix *C(i,j)*, derived for transformed sub-bands and stored in the features library. There exist 5 co-occurrence features i.e., texture features for an image. Statistical features such as Mean, Standard Deviation, Skewness and Kurtosis are derived from *H* and *S* components. Hence there will be 8 chrominance or color statistical features for an image. Thus a total of 13 features characterize one fruit image. The feature extraction process is illustrated in Figure 2.

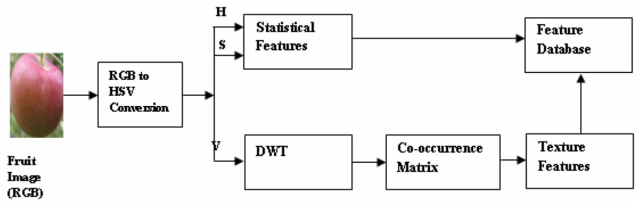

Figure 2: Feature Extraction

In the classification phase, for the test fruit image, color and texture features are derived as that of the training phase and compared with corresponding feature values, stored in the feature library. The classification is done using the Minimum Distance Criterion. The image from the training set which has the minimum distance when compared with the test image says that the test image belongs to the category of that training image.

3. RESULTS AND DISCUSSION

Data Set

The Supermarket Produce data set comprising 15 different categories: Plum, Agata Potato, Asterix Potato, Cashew, Onion , Orange , Taiti Lime , Kiwi , Fuji Apple, Granny-Smith Apple , Watermelon, Honeydew Melon, Nectarine, Williams Pear and Diamond Peach ; totalizing 2633 images are used for experimental purpose. Fig. 3 depicts some of the classes of the data set. These fruit images are divided into training and testing set, where 50% of the fruit images from each group are used to train the system and the remaining images serves as the testing set. The number of images used for training and classification for each type of fruits is shown in Table I.

Journal of Emerging Trends in Computing and Information Sciences

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Figure 3: Dataset used for Fruit Recognition

All of the images were stored in RGB color-space at 8 bits per channel. The images were gathered at various times of the day and in different days for the same category. These features increase the data set variability and represent a more realistic scenario. Fig. 4 shows an example of Kiwi and Granny-Smith Apple categories with different lighting. The differences are due to illumination, no image pre-processing was performed. The Supermarket Produce data set also comprises differences in pose and in the number of elements within an image. Fig. 5 shows examples of the Cashew category. Note that there are variations in the pose of the Cashew's plastic repository. In addition, Fig. 6 shows the variability in the number of elements within an image.

Figure 4: Illumination Differences With in Categories

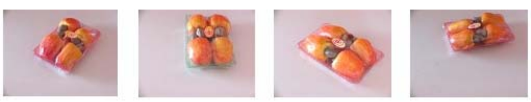

Figure 5: Pose Differences: Cashew

Figure 6: Variability on Number of elements: Plum

Table 1: List of Images in Database

S.No.	Fruits	Total No. of Fruit Images	No. of Fruit Images used for	
			Training	Testing
1	Agata Apple	201	100	101
2	Asterix Apple	182	91	91
3	Cashew	210	105	105
4	Diamond Peach	211	105	106
5	Fuji Apple	212	106	106
6	Granny-Smith Apple	155	77	78
7	Honeydew Melon	147	73	79
8	Kiwi	171	85	86
9	Nectarine	247	123	124
10	Onion	75	38	37
11	Orange	103	51	52
12	Plum	264	132	132
13	Spanish Pear	159	79	80
14	Taiti Lime	106	53	53
15	Watermelon	192	96	96
Total		**2635**	**1314**	**1326**

Preprocessing

For a real application in a supermarket, it might be necessary to cope with illumination variations, sensor capturing artifacts, specular reflections, background clutter, shading, and shadows. Therefore, in order to reduce the scene complexity, it might be interesting to perform background subtraction and focus in the object's description.

Background subtraction is a commonly used class of techniques for segmenting out objects of interest in a scene. The name "background subtraction" comes from the simple technique of subtracting the observed image from the estimated image and thresholding the result to generate the objects of interest.

The best channel to perform the background subtraction is the *S* channel of HSV-stored images. This is understandable, given that the *S* channel is much less sensitive to lighting variations than any of the RGB color channels.

Algorithm for Extracting Region of Interest

1. The input fruit image is converted to HSV colour space.

Journal of Emerging Trends in Computing and Information Sciences

http://www.cisjournal.org

2. Perform thresholding operation on the S component, since S is much less sensitive to lighting variation.
3. Close small holes using the Closing morphological operator with a disk structuring element.
4. Find the area of the Region of Interest from the binary image.
5. Crop the Region of Interest and replace the binary values with the original pixel intensity.

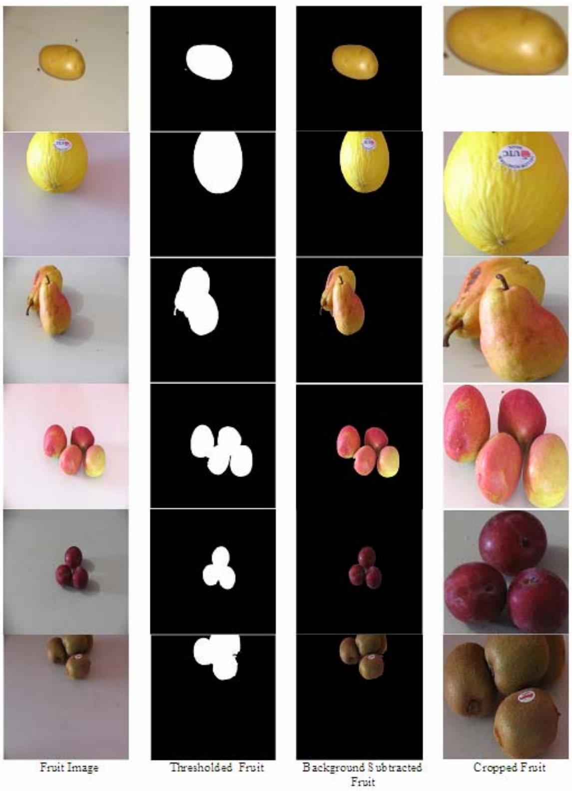

Figure 7: Extracting Region of Interest from the Image

The role of color descriptors has been demonstrated to be quite remarkable in many visual inspection tasks. In some other tasks, texture measurements are needed because of unevenly colored or achromatic surfaces. In many applications, color and texture must be combined to achieve good performance. At the same time, the computational complexity of the methods must be kept as low as possible.

The fruit images are converted to HSV color space and the Statistical features such as Mean, Standard Deviation, Skewness and Kurtosis are derived from *H* and *S* components. Hence there will be 8 color statistical features for an image. The *V* component is subjected to one level decomposition using Discrete Wavelet Transform and the co-occurrence features such as contrast, energy, local homogeneity, cluster shade and cluster prominence are derived from the Co-occurrence matrix constructed from the approximation sub-band. There exist 5 co-occurrence features for an image.
First, the fruit recognition system is evaluated with color and texture features individually. With the set of 8 statistical features the recognition rate obtained for the individual fruit images is shown in Table II.

Table 2: Results of Fruit Recognition System

S.No.	Fruits	Recognition Rate		
		Using Colour Features	Using Texture Features	Using Colour and Texture Features
1	Agata Apple	56.435	74.257	95.049
2	Asterix Apple	52.747	65.934	90.109
3	Cashew	77.1428	94.2800	99.047
4	Diamond Peach	45.283	55.660	75.471
5	Fuji Apple	34.9056	78.3018	82.073
6	Granny-Smith Apple	30.769	89.743	96.153
7	Honeydew Melon	66.216	76.056	95.945
8	Kiwi	32.558	47.6744	58.139
9	Nectarine	32.258	74.1935	79.032
10	Onion	43.24	78.378	86.486
11	Orange	30.769	40.384	69.230
12	Plum	48.484	84.090	89.393
13	Spanish Pear	32.500	60.000	86.25
14	Taiti Lime	58.490	88.679	98.1132
15	Watermelon	40.625	55.208	89.583
Total		**45.49483**	**70.85591**	**86.00488**

Hence, the color and texture information are complementary and when used together they yield good results of classification.

4. CONCLUSION

The use of computers to analyze images has many potential applications for automated agricultural tasks. But, the variability of the agricultural objects makes it very difficult to adapt the existing industrial algorithms to the agricultural domain. The proposed method can process, analyze and recognize fruits based on color and texture features. In order to improve the functionality and flexibility of the recognition system shape and size features can be combined together with color and texture features. Further, by increasing the number of images in the database the recognition rate can be increased. This algorithm can be used for smart self service scales.

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