IOSR Journal of Electrical and Electronics Engineering (IOSR-JEEE)
e-ISSN: 2278-1676,p-ISSN: 2320-3331, Volume 8, Issue 3 (Nov. - Dec. 2013), PP 43-53
www.iosrjournals.org

Vegetables detection from the glossary shop for the blind.

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Abstract : Automatic recognitions of vegetables from images are often termed as vegetable vision. It is a technology to facilitate the checkout process by analysing real images of vegetables and match with the picture and inform the blind. It is always related to image processing, which can control the classification, qualification and segmentation of images and recognize the image. It is a recognition system for super market and grocery stores for the blind. From the captured images multiple recognition clues such as colour, shape, size, texture and size are extracted and analysed to classify and recognize the vegetables. If the system can identify uniquely, the blind human inform the vegetable name and information and can take the vegetable that she/he wants.

Keywords: *vegetable detection, Obstacles detection, vegetable tracking*

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I. INTRODUCTION

We present automatic recognition system (vegetable vision) to facilitate the process of a supermarket or grocery stores for the blind. This system consists of an integrated measurement and imaging technology with a user friendly interface. When we bring a vegetable at camera, an image is taken, a variety of features such as colour, shape, size, density, texture etc are then extracted. These features are compared to stored data. Depending on the certainty of the classification and recognition, the final decision is made by the system. Vegetable vision is done with the image processing and image analyzing. Image processing is done by MATLAB. Before going to image process and analyze. Vegetable quality is frequently referred to size, shape, mass, firmness, color and bruises from which fruits can be classified and sorted. The classification technique is used to recognize the vegetable's shape, size, color and texture at a unique glance. Digital image classification uses the spectral information represented by the digital numbers in one or more spectral bands, and attempts to classify each individual pixel based on this spectral information. This type of classification is termed spectral pattern recognition. In either case, the objective is to assign all pixels in the image to particular classes or themes. Classification based methods for image segmentation; size, shape, color, and texture features for object measurement, statistical and neural network methods for classification.

II. Image Segmentation

Image segmentation is the process that subdivides an image into its constituent parts or objects. The level to which this subdivision is carried out depends on the problem being solved, i.e., the segmentation should stop when the objects of interest in an application have been isolated. Image thresholding techniques are used for image segmentation. In computer vision, segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as superpixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images.

This involves subdividing an image into constituent parts, or isolating certain aspects of an image:

Finding lines, circles, or particular shapes in an image, in an aerial photograph, identifying cars, trees, buildings, or roads

These classes are not disjoint; a given algorithm may be used for both image enhancement or for image restoration. However, we should be able to decide what it is that we are trying to do with our image: simply make it look better (enhancement), or removing damage (restoration).

11. Edge detection

Edge detection is a well-developed field on its own within image processing. Region boundaries and edges are closely related, since there is often a sharp adjustment in intensity at the region boundaries. Edge detection techniques have therefore been used as the base of another segmentation technique.

The edges identified by edge detection are often disconnected. To segment an object from an image however, one needs closed region boundaries. The desired edges are the boundaries between such objects.

Segmentation methods can also be applied to edges obtained from edge detectors. Lindeberg and Li developed an integrated method that segments edges into straight and curved edge segments for parts-based object

recognition, based on a minimum description length (MDL) criterion that was optimized by a split-and-merge-like method with candidate breakpoints obtained from complementary junction cues to obtain more likely points at which to consider partitions into different segments.
An edge image will be a binary image containing the edges of the input. We can go about obtaining an edge image in two ways:

1. We can take the intensity component only, and apply the edge function to it,
2. We can apply the edge function to each of the RGB components, and join the results.

To implement the first method, we start with the rgb2gray function:

```
>> fg=rgb2gray(f);
>> fe1=edge(fg);
>> imshow(fe1)
```

Recall that edge with no parameters implements Sobel edge detection. The result is shown in figure 1.9. For the second method, we can join the results with the logical "or":

```
>> f1=edge(f(:,:,1));
>> f2=edge(f(:,:,2));
>> f3=edge(f(:,:,3));
>> fe2= f1 | f2 | f3;
>> figure,imshow(fe2)
```

and this is also shown in figure 2.1. The edge image fe2 is a much more complete edge image. Notice that the rose now has most of its edges, where in image fe1 only a few were shown. Also note that there are the edges of some leaves in the bottom left of fe2 which are completely missing from fe1.

12. Color

For human beings, color provides one of the most important descriptors of the world around us. The human visual system is particularly attuned to two things: edges, and color. We have mentioned that the human visual system is not particularly good at recognizing subtle changes in grey values. In this section we shall investigate color briefly, and then some methods of processing color images.
Color study consists of

1. The physical properties of light which give rise to color,
2. The nature of the human eye and the ways in which it detects color,
3. The nature of the human vision centre in the brain, and the ways in which messages from the eye are perceived as color.

Physical aspects of color

Visible light is part of the electromagnetic spectrum: radiation in which the energy takes the form of waves of varying wavelength. These range from cosmic rays of very short wavelength, to electric power, which has very long wavelength. Figure 2.2 illustrates this. The values for the wavelengths of blue, green and red were set in 1931 by the CIE (Commission Internationale d'Eclairage), an organization responsible for color standards.

Perceptual aspects of color

The human visual system tends to perceive color as being made up of varying amounts of red, green and blue. That is, human vision is particularly sensitive to these colors; this is a function of the cone cells in the retina of the eye. These values are called the primary colors. If we add together any two primary colors we obtain the secondary colors:

magenta (purple) = red + blue,
cyan = green+ blue,
yellow = red + green.

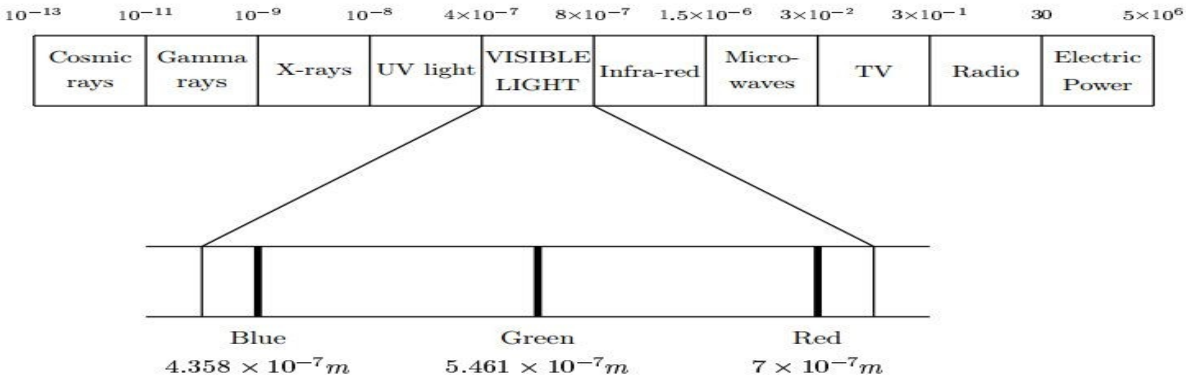

Figure: The electromagnetic spectrum and colors

The amounts of red, green, and blue which make up a given color can be determined by a color matching experiment. In such an experiment, people are asked to match a given color (a color source) with different amounts of the additive primaries red, green and blue. Such an experiment was performed in 1931 by the CIE, and the results are shown in figure 2.3. Note that for some wavelengths, several of the red, green or blue values are negative. This is a physical impossibility, but it can be interpreted by adding the primary beam to the color source, to maintain a color match. To remove negative values from color information, the CIE introduced the XYZ color model.

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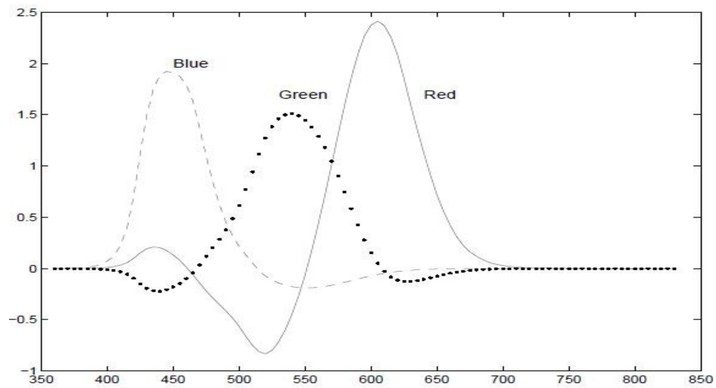


Figure 2: RGB color matching functions (CIE, 1931)

13. Color models:

A color model is a method for specifying colors in some standard way. It generally consists of a three dimensional coordinate system and a subspace of that system in which each color is represented by a single point. We shall investigate three systems.

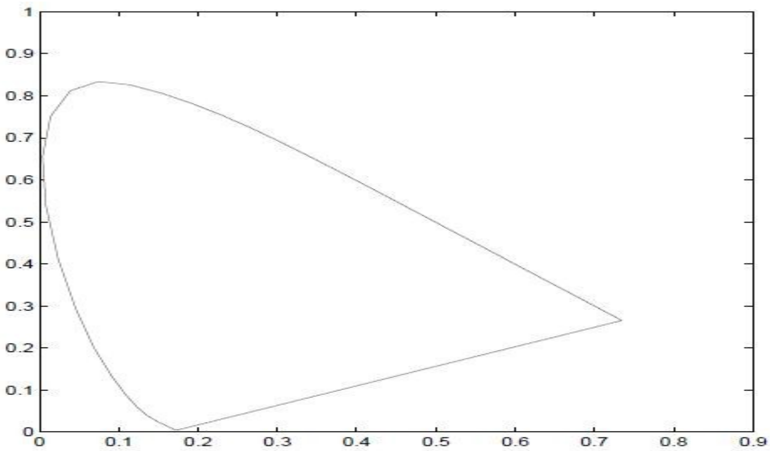
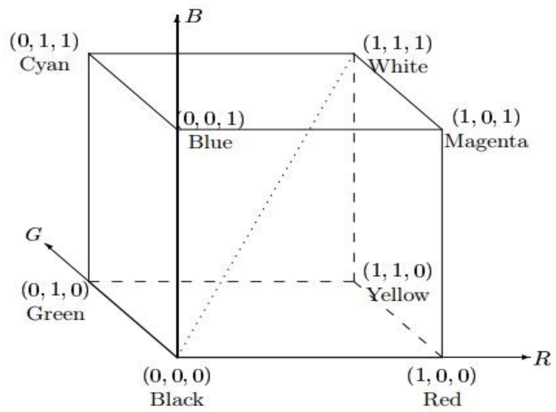


Figure 3: A chromaticity diagram

14.RGB

In this model, each color is represented as three values R, G and B, indicating the amounts of red, green and blue which make up the color. This model is used for displays on computer screens; a monitor has three independent electron "guns" for the red, green and blue component of each color. We may imagine all the colors sitting inside a "color cube" of side 1:



The colors along the black-white diagonal, shown in the diagram as a dotted line, are the points of the space where all the R, G, B values are equal. They are the different intensities of grey. RGB is the standard for the display of colors: on computer monitors; on TV sets. But it is not a very good way of describing colors. How, for example, would you define light brown using RGB?

15. Color images in Matlab

Since a color image requires three separate items of information for each pixel, a (true) color image of size m*n is represented in Matlab by an array of size m*n*3: a three dimensional array. We can think of such an array as a single entity consisting of three separate matrices aligned vertically. Figure 2.9 shows a diagram illustrating this idea. Suppose we read in an RGB image:

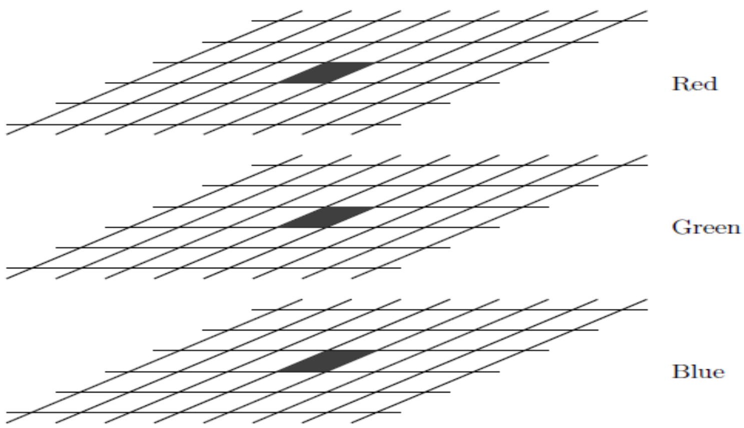


Figure 5: A three dimensional array for an RGB image

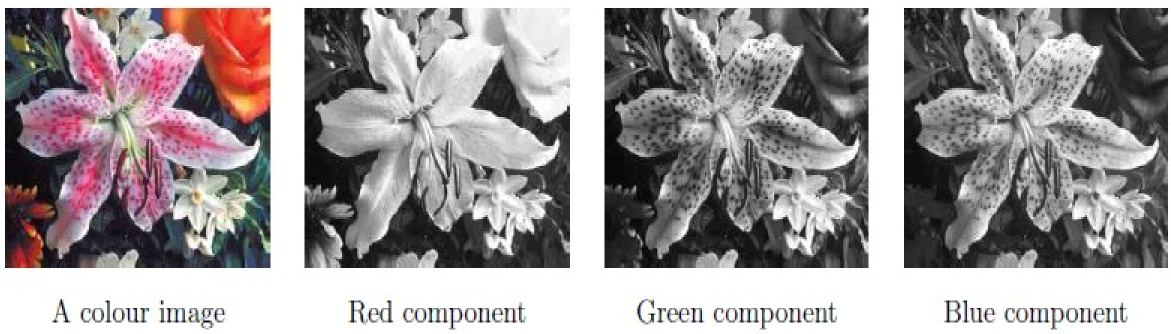


Figure 6: An RGB color image and its components

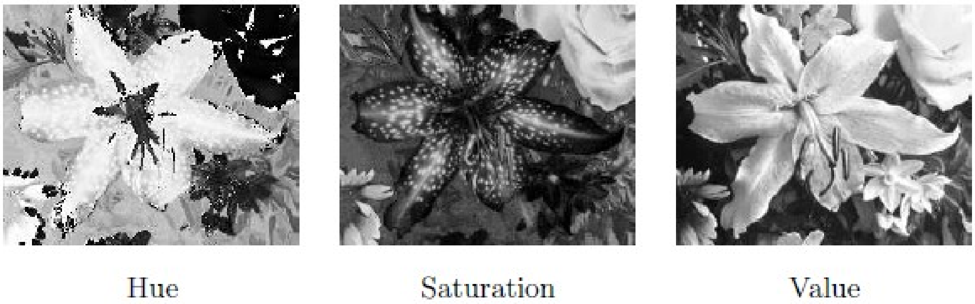


Figure 7: The HSV components

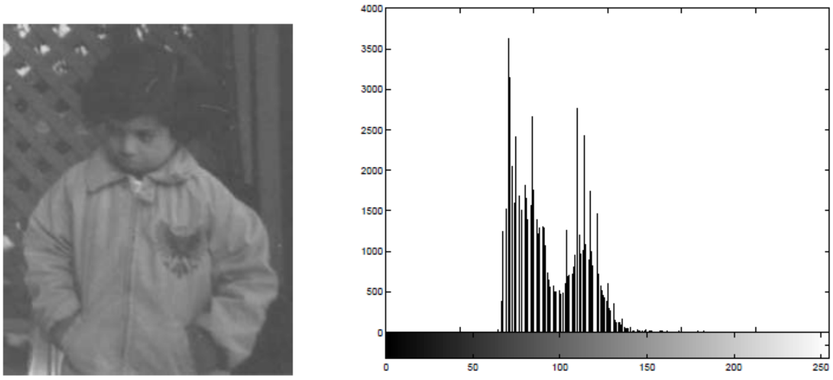


Figure 8: The image pout.tif and its histogram

16.Image texture

An image texture is a set of metrics calculated in image processing designed to quantify the perceived texture of an image. Image Texture gives us information about the spatial arrangement of color or intensities in an image or selected region of an image .

Image textures can be artificially created or found in natural scenes captured in an image. Image textures are one way that can be used to help in or classification of images. To analyze an image texture in computer graphics, there are two ways to approach the issue: Structured Approach and Statistical Approach.

17. Laws Texture Energy Measures

Another approach to generate texture features is to use local masks to detect various types of textures. Convolution masks of 5x5 are used to compute the energy of texture which is then represented by a nine element vector for each pixel. The masks are generated from the following vectors:

L5 = [+1 +4 6 +4 +1] (Level)
E5 = [-1 -2 0 +2 +1] (Edge)
S5 = [-1 0 2 0 -1] (Spot)
W5 = [-1 +2 0 -2 +1] (Wave)
R5 = [+1 -4 6 -4 +1] (Ripple)

18. Texture Segmentation

The use of image texture can be used as a description for regions into segments. There are two main types of segmentation based on image texture, region based and boundary based. Though image texture is not a perfect measure for segmentation it is used along with other measure, such as color, that helps solve segmenting in image. Attempts to group or cluster pixels based on texture properties together. Attempts to group or cluster pixels based on edges between pixels that come from different texture properties.

19.Shape

The characteristic surface configuration of a thing is as like outline or contour. The shape of an object located in some space is a geometrical description of the part of that space occupied by the object, as determined by its external boundary – abstracting from location and orientation in space, size, and other properties such as color, content, and material composition. Simple shapes can be described by basic geometry objects such as a set of two or more points, a line, a curve, a plane, a plane figure(e.g. square or circle), or a solid figure (e.g. cube or sphere). Most shapes occurring in the physical world are complex. Some, such as plant structures and coastlines, may be so arbitrary as to defy traditional mathematical description – in which case they may be analyzed by differential geometry, or as fractals. The modern definition of shape has arisen in the field of statistical shape analysis. In particular Procrustes analysis, which is a technique for analyzing the statistical distributions of shapes. These techniques have been used to examine the alignments of random points. Other methods are designed to work with non-rigid (bendable) objects, e.g. for posture independent shape retrieval [15]. Some different vegetables have the same shape. An unusually shaped vegetable is a vegetable that has grown into an unusual shape not in line with the normal body plan. While some examples are just oddly shaped, others are heralded for their amusing appearance; often representing a body part can be common in vegetables. .A giant vegetable is one that has grown to an unusually large size, usually by design. Most of these maintain the proportions of the vegetable but are just larger in size.

20.Size

Size is the dimensions, including length, width, height, diameter, perimeter, area, volume. Different vegetables have different sizes. Some also have the same sizes. Sometimes same vegetable has different sizes due to their specimen. Size is an important factor to detect different vegetables with same color and shape. Vegetables may be small or large, long or short, thin or fat, lite or heavy and sometimes complex in sizes.

21. Image Classification

Classification is the labeling of a pixel or a group of pixels based on its grey value [9, 10]. Classification is one of the most often used methods of information extraction. In Classification, usually multiple features are used for a set of pixels i.e., many images of a particular object are needed. In Remote Sensing area, this procedure assumes that the imagery of a specific geographic area is collected in multiple regions of the electromagnetic spectrum and that the images are in good registration [16]. Most of the information extraction techniques rely on analysis of the spectral reflectance properties of such imagery and employ special algorithms designed to perform various types of 'spectral analysis'. The process of multispectral classification can be performed using either of the two methods: Supervised or Unsupervised. In *Supervised classification*, the identity and location of some of the land cover types such as urban, wetland, forest etc., are known as priori through a combination of field works and toposheets. The analyst attempts to locate specific sites in the remotely sensed data that represents homogeneous examples of these land cover types. These areas are commonly referred as TRAINING SITES because the spectral characteristics of these known areas are used to 'train' the classification algorithm for eventual land cover mapping of reminder of the image. Multivariate statistical parameters are calculated for each training site. Every pixel both within and outside these training sites is then evaluated and assigned to a class of which it has the highest likelihood of being a member. In an *Unsupervised classification*, the identities of land cover types has to be specified as classes within a scene are not generally known as priori because ground truth is lacking or surface features within the scene are not well defined [17]. The computer is required to group pixel data into different spectral classes according to some statistically determined criteria.

21. Making decision

The firing rule is an important concept in neural networks and accounts for their high flexibility. A firing rule determines how one calculates whether a neuron should fire for any input pattern. It relates to all the input patterns, not only the ones on which the node was trained.

A simple firing rule can be implemented by using Hamming distance technique. The rule goes as follows:

Take a collection of training patterns for a node, some of which cause it to fire (the 1-taught set of patterns) and others which prevent it from doing so (the 0-taught set). Then the patterns not in the collection cause the node to fire if, on comparison, they have more input elements in common with the 'nearest' pattern in the 1-taught set than with the 'nearest' pattern in the 0-taught set. If there is a tie, then the pattern remains in the undefined state.

For example, a 3-input neuron is taught to output 1 when the input (X1, X2 and X3) is 111 or 101 and to output 0 when the input is 000 or 001. Then, before applying the firing rule, the truth table is;

X1:		0	0	0	0	1	1	1	1
X2:		0	0	1	1	0	0	1	1
X3:		0	1	0	1	0	1	0	1
OUT:		0	0	0/1	0/1	0/1	1	0/1	1

As an example of the way the firing rule is applied, take the pattern 010. It differs from 000 in 1 element, from 001 in 2 elements, from 101 in 3 elements and from 111 in 2 elements. Therefore, the 'nearest' pattern is 000 which belongs in the 0-taught set. Thus the firing rule requires that the neuron should not fire when the input is 001. On the other hand, 011 is equally distant from two taught patterns that have different outputs and thus the output stays undefined (0/1).

By applying the firing in every column the following truth table is obtained;

X1:		0	0	0	0	1	1	1	1
X2:		0	0	1	1	0	0	1	1
X3:		0	1	0	1	0	1	0	1
OUT:		0	0	0	0/1	0/1	1	1	1

The difference between the two truth tables is called the "*generalization of the neuron.*" Therefore the firing rule gives the neuron a sense of similarity and enables it to respond 'sensibly' to patterns not seen during training.
Every image can be represented as two-dimensional array, where every element of that array contains color information for one pixel.

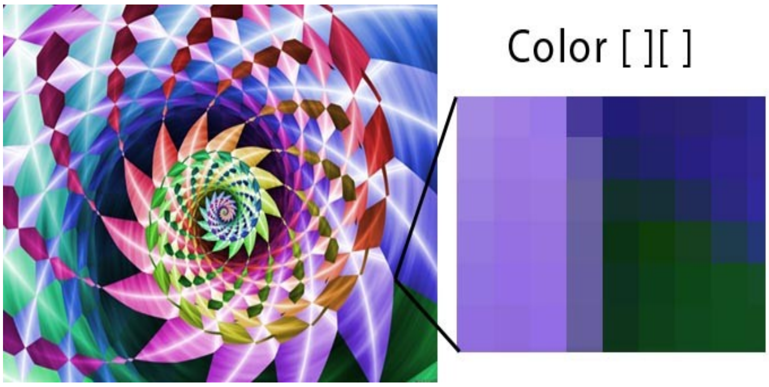


Figure 17: Image colors

Each color can be represented as a combination of three basic color components: red, green and blue.

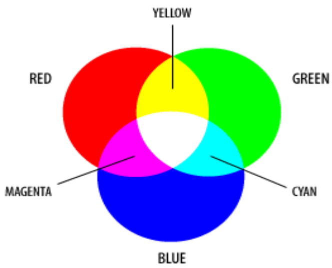


Figure 18: RGB color system

22. Methodology

Not any single method can solve any recognition problem, we have to use number of classification techniques. The Automatic recognitions of vegetables from images can recognize, analyse and process, based on color, shape, size, weight and texture. Sometimes it is used to simplify a monochrome problem by improving contrast or separation or removing noise, blur etc by using image processing technology [24]. Our Methodology can be summarized in the learning and recognition section as followings:

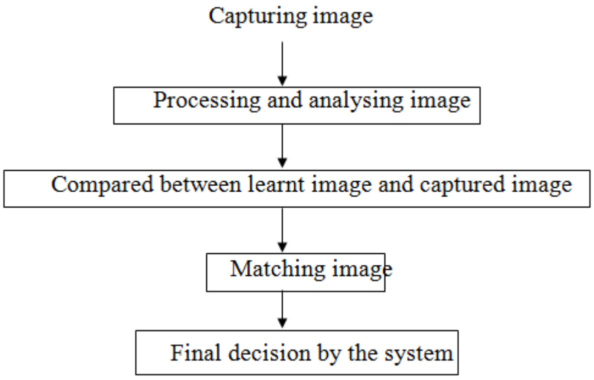
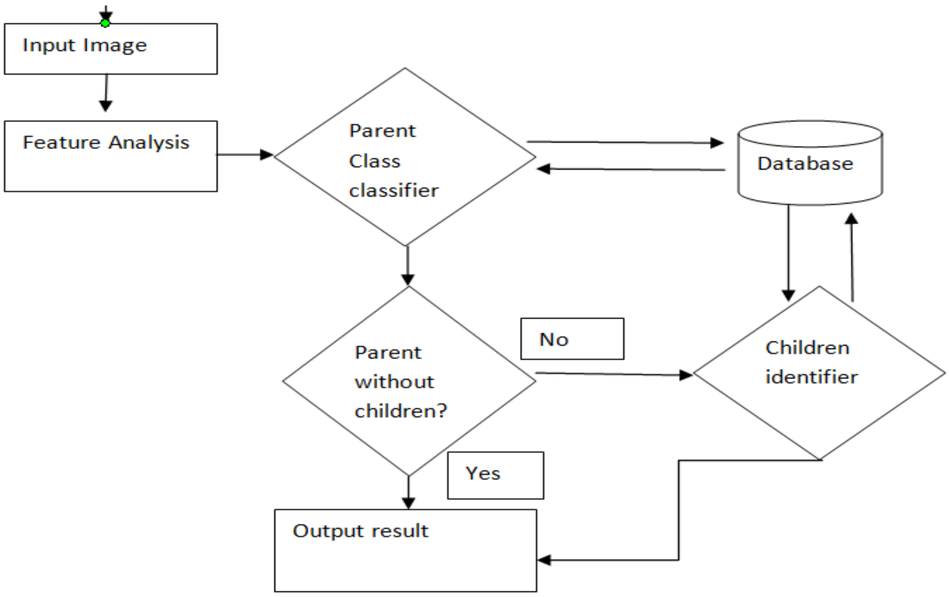


Figure 23: Flow chart of methodology

For capturing input image, take lights-off image and lights-on image and extract foreground produce from background. Make histogram of color features, texture features, shape features, and size features; concatenate them to compare with database for final output. Input images for different vegetables, in our implementation, the application had learnt cabbage, apple, zucchini, broccoli, beans.



23.Finding Children

After detecting parent class the system goes for further classification. Texture, shape and other features are used to detect the children. Assume two samples zucchini and beans which has same color response, green (Figure 4.5). So, the system detects as green class vegetables. For unique recognition of children the system needs further classifications.

For Children detection system goes for further classification. A crude solution is connected component. In this process system uses Gray level threshold. The system throws away smaller blobs and connected component labeling. Then calculate connected component size. Figure 4.6 shows the connected component.

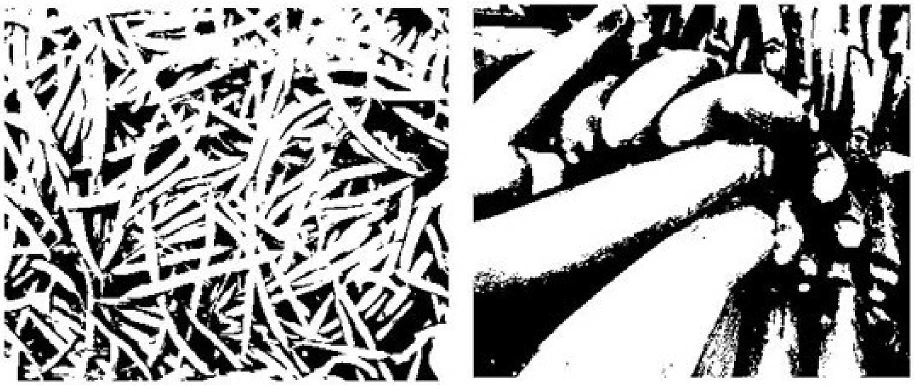


Figure24: (a) beans connected component, (b) zucchini connected component

24. Finding a single object out of collection

In vegetable vision system morphological operation does not work with test image. Hough transformation is arbitrary shape. The Hough transform is a feature extraction technique used in image analysis, computer vision, and digital image processing [25]. The purpose of the technique is to find imperfect instances of objects within a certain class of shapes by a voting procedure.

The system detects the edge and repairs the broken edge by using edge detection technology. Figure 4.12 shows the collection of green apple as sample and its edges.

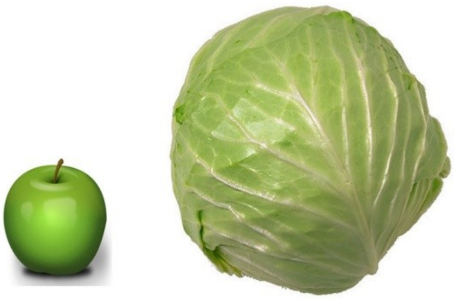


Figure 25: Size of a green apple and a green cabbage

To identify the size of vegetables from the input images the vegetable vision system measures the bounding box area. The bounding box areas of the input vegetables are shown in figure 4.14. After measuring the size of the inputs, the system compares the measurement with database information and recognizes the vegetables perfectly.

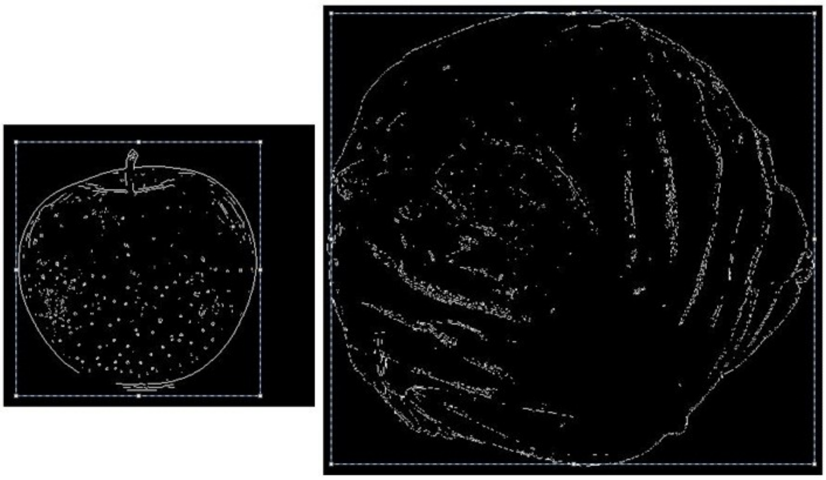


Figure 26: Measuring of bounding box green apple and cabbage

In a very few cases confusions arises in the results. But most of the time the vegetable vision is accurate in results. Figure 4.15 presents a confusion matrix which shows the results of some input samples. The system accuracy was 96.55%.

	Zucchini	Beans	Broccoli	Banana	Green Cab	Carot	Garlic	Green App	Eggplant
Zucchini	4	0	0	0	0	0	0	0	0
Beans	0	6	0	0	0	0	0	0	0
Broccoli	0	0	7	0	0	0	0	0	0
Banana	0	0	0	6	0	0	0	0	0
Green Cab	0	0	1	0	6	0	0	0	0
Carot	0	0	0	0	0	7	0	0	0
Garlic	0	0	0	0	0	0	7	0	0
Green App	0	0	0	0	1	0	0	7	0
Eggplant	0	0	0	0	0	0	0	0	4
Violet Cab	0	0	0	0	0	0	0	0	0

Figure 26: Confusion matrix of the input samples

The system described here is intended to be the base for developing new applications that use vision in vegetable vision and help to find out a blind a vegetable very easyly. It can also used in agricultural tasks such as recollection, cutting, packaging, classification, fumigation, etc. both in the country and in warehouses. That is why this paper emphasizes and solves some important practical problems, such as the EMI, and provides the core source code of the application.

25. Discussion

We have developed a vegetable vision system that uses a color camera to image the items. A special purpose imaging setup with controlled lighting allows very precise segmentation of the produce item from the background. From these segmented images, recognition clues such as color and texture are extracted. Of course, just as a human cashier, our system does not achieve 100% correct recognition. From the outset, the user interface has been designed with this in mind. Currently, color and texture are the best developed features, and the ones that contribute most to reliable recognition. Color provides valuable information in estimating the maturity and examining the freshness of vegetables. Uniformity in size and shape of fruits and vegetables are some of the other important factors in deciding overall quality performance acceptance. Using color alone, quite respectable classification results are achieved. Adding texture improves the results, in the range of 15 - 20%. Features such as shape and size can augment the feature set to improve classification results. However, incorporation of these features slows down the recognition time, which is currently less than 1 second on special purpose hardware on a PC based machine. Industrial systems benefit more and more from vegetable vision in order to provide high and equal quality products to the consumers. Accuracy of such system depends on the performance of image processing algorithms used by vegetable vision. Food and beverages industry is one of the industries where vegetable vision is very popular and widely employed.

26. Future Work

Vegetable vision has been using in different areas for years. Important areas for the vegetable vision are super market, agricultural and industrial production for the blind. The reason behind making researches about vegetable vision is, most important and effective sense is vision.

- Implement the system in neural network.
- Train the system with sufficient data with seasonal vegetables and fruits.
- Vegetable Vision can be applied for Packaging and Quality Assurance.

27. CONCLUSIONS

It is testified that Vegetable vision is an alternative to unreliable manual sorting of Vegetables. The system can be used for vegetables grading by the external qualities of size, shape, color and surface. The Vegetable vision system can be developed to quantify quality attributes of various vegetables such as mangoes, cucumbers, tomatoes, potatoes, peaches and mushrooms. The exploration and development of some fundamental theories and methods of Vegetable vision for pear quality detection and sorting operations would accelerate the application of new techniques to the estimation of agricultural products quality. The work in the project has resulted in a clear-cut and systematic sequence of operations to be performed in order to obtain the end result of some vegetables. The proposed steps are based on the assumption that the images were taken under proper illumination, due to which some regions with improper illumination are considered defects. This algorithm was tested with several images and the results were encouraging. In order to improve and enhance this application, there are some future work should be implemented, providing a user friendly interface, and expanding the range of vegetables known by the application will increase performance of the application. Future work might include a small modification in the presented algorithm in order to adapt to this irregularity. We expect that the use of vegetable vision in commercial and agricultural applications could be increased using the proposed approach, improving the automation of the production and the profits. With little modification this approach can be applied in any image recognition system which will give us computational efficiency. Our main work is to help the blind find the vegetables from the shop very easily.

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