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An Overview on Outdoor Image Segmentation: Indian Agriculture

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Abstract – The use of computer to analyze images has many potential applications for automated agricultural tasks. The development of precision farming technology has lead to new efforts to transfer machine vision technology into the agricultural sector. Robotic harvesting is a essential for Indian Agriculture as labors moving towards the urban area in the search of new view. We aim to focus on key factors discovered for effective utilization of image segmentation for agriculture boost up, at least on the surface. We have suggested EASA for outdoor image segmentation. An environmentally adaptive segmentation algorithm (EASA) was developed for outdoor field plant detection. Based on a partially supervised learning process, the algorithm can learn from environmental conditions in outdoor agricultural fields and build an image segmentation look-up table on-the-fly. The algorithm can adapt to most daytime conditions in outdoor fields, such as changes in light source temperature and soil type. When compared to a static segmentation technique which was trained under sunny conditions, the EASA improved the image segmentation by correctly classifying 26.9 and 54.3% more object pixels under partially cloudy and overcast conditions, respectively.

Keywords: Image Processing, Computer vision, Outdoor lighting, Segmentation, Agriculture.

I. INTRODUCTION

The development of precision farming technology has led to new efforts to transfer machine vision technology into the agricultural sector. Researchers have studied the possibilities of using machine vision as a local sensor to control farm machinery in the fields. To use machine vision systems in outdoor fields the special difficulties of an unstructured work environment must be addressed. Light source temperature is one of the key issues that must be carefully studied. Variability in light source temperature causes the colors of objects in the image to change, making image segmentation very difficult. These changes may result in poor quality images, causing incomplete object segmentation or noise in the background area, which eventually degrades the subsequent pattern recognition processes.

Another important issue is the non-even illumination (e.g. shadows) of the object being identified by the imaging system. The level of illumination of an object is closely related to the lighting conditions. Generally speaking, the absolute illumination level of an object in an outdoor scene would be sufficient for a vision system during the daytime. The problem is the variation of the illumination level within the same view (shadows). The auto iris system of a video camera uses the average intensity value of the scene to determine how to set the lens aperture. Non-uniform illumination often causes some objects in the image to be too dark or too bright because of the limited dynamic range of CCD cameras. In contrast, humans can always see non-uniformly illuminated objects clearly except in extremely bright or dark conditions. This is due to an ability to assign a local threshold to each individual viewing area.

To develop a robust machine vision system for outdoor field conditions, algorithms must be developed to extract useful information in the presence of noise associated with unstructured lighting conditions. Image segmentation is a task of pixel aggregation. After segmentation, each image pixel is assigned into one of several specific classes. One of the widely used methods for image segmentation is thresholding. The ideal situation for thresholding is an object of uniform brightness on a background of uniform brightness, where the intensities of the two regions are different. Many machine vision systems operating in a controlled environment use thresholding as the method of segmentation (Ballard and Brown, 1982; Shiraishi and Sumiya, 1996). In practice, a thresholding method may be applied even when the objects or the background are not uniformly bright, as long as the two parts (object and the background) belong to two different brightness regions. For outdoor images, however, the brightness of objects and that of the background frequently overlap. In this case multi-spectral information often proves superior to a simple monochrome thresholding method.

Studies about outdoor field applications of machine vision were mainly in fruit harvesting. This may have been because fruit generally has a regular shape and distinguishable color compared to background. Optical segmentation (color filters) were often used in this early research (Parrish and Goksel, 1977). Two to three optical filters were thought to be necessary for a machine vision system to locate fruit in a tree canopy under sunlight. Using information about color and multi dimensional data classification theory to improve the performance of segmentation proved effective in processing outdoor images of fruit in an orange grove (Slaughter and Harrell, 1989). Chrominance plus intensity in the RGB color space provides much more information than one-dimensional intensity data from object and background regions.

While most of the work in outdoor machine vision detection of fruit has been based on color, there have been special cases where a specific type of object can be distinguished by its brightness making identification via thresholding possible in outdoor fields. Jia . (1990) investigated the use of machine vision to locate corn plants in outdoor fields. In

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this case they were able to use intensity thresholding to successfully identify the main veins of corn leaves from a top view in outdoor images.

The above studies mainly used segmentation to identify the objects and their locations in images. A unique object color or intensity was essential in these applications. If the use of color (or intensity) alone cannot completely separate an object from background, additional features have to be added for object identification. For example, to identify some crop species from weeds in the field, it may be necessary to use pattern recognition based upon plant morphological features because the spectral reflectance of both crop and weed leaves is similar (Tian, 1995). Using morphological features to recognize objects requires a high level of detail, and the segmented images must be of high quality (Pao, 1989). The noise (errors in the boundary and holes in an object) caused by imperfect lighting conditions may result in errors in feature calculation, eventually affecting crop plant identification. In an unstructured outdoor environment, an environmentally adaptive segmentation algorithm is needed.

II. ROBOTIC HARVESTING

The automatic harvesting of citrus has been done entirely by hand and the cost of this labor fluctuates around 25% [2], 30% [3] and 33% [4] of the total production costs. So, an efficient robotic system could reduce the production costs significantly and this is one of the reasons why the use of an automated robotic system for harvesting is so attractive. The other reason is to improve the quality of the fruit that would make the product more competitive.

There are several techniques used for the harvesting of fruits which are not appropriate for the fresh fruit market due to the damage caused to the fruit during its collection. These techniques include the shaking of tree limbs or tree trunks, oscillating forced-air removers and the complementary chemical treatment. Fruits are usually bruised when striking limbs during the landing. So, there is a need for a non aggressive method to perform the harvesting of fruits as delicately as possible. The manual picking is the most delicate way to perform the harvesting, but it is expensive and time consuming.

The use of robots to pick tree fruits was first proposed by Schertz and Brown [5] in a review of mechanical citrus harvesting systems. The basic concepts of robotic harvesting were established in this paper. One of these concepts was the line-of-sight approach to fruit picking. This consists of the following three steps: 1) to visually locate the fruit with an optical sensor, 2) to guide the fruit detachment device along the line of sight to the fruit, and 3) to actuate the device when the fruit is contacted. A robotic system based on the Schertz approach consisting of a simple robotic arm, a B/W TV camera and a control computer was built for the harvesting of apples [6]. The TV camera was used to locate the fruit attached to an artificial canopy. The control computer directed the robot arm along the line-of-sight to the targeted fruit until a contact was made by a mechanical whisker. No detachment device was implemented.

D'Esnon and Rabatel [7] presented the first version of the apple pi king robot, known as MAGALI. The robot consisted of a hollow tube mounted in a vertical support frame. Attached to the end of the tube was a rotating cup end-effector used to detach a fruit from a simulated apple tree canopy. The hollow tube could slide in and out, rotate left and right, and move up and down the support frame. A B/W camera was attached to the support frame to detect the fruit. When the fruit was detected, the tube was aligned with the fruit. The tube would extend out until a contact with the fruit was detected by a reflectance sensor in the endeffector. The cup would rotate behind, cutting the stem and allowing the detached fruit to roll down the hollow tube into a collection bin.

Other extensive research has been directed at using robots for a variety of agricultural harvesting tasks: grapes[8], [9], asparagus [10], cucumbers [11], mushrooms [12] and apples [13]. Kawamura investigated the harvesting of tomatoes and used a stereoscopic vision system to obtain the 3-dimensional location [14]. An Italian company, AID Catania, designed and built a prototype of a citrus harvesting autonomous robot with a single arm, driven by a vision system which was operated both in the laboratory and in the orange grove [3] [15] Harrell presents the design of a citrus picking robot CPR [16].

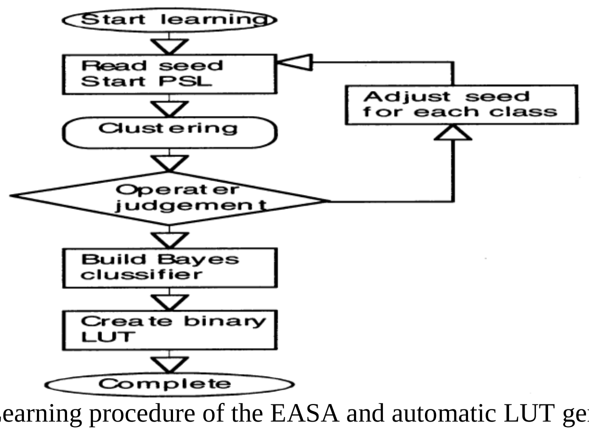

Fig. 1. Learning procedure of the EASA and automatic LUT generation

The Japanese company, Kubota [17] developed a fruit-picking robot which uses a mobile platform to approximate a small four degrees-of-freedom manipulator to the detachment area. The Spanish-French CITRUS project to harvest oranges. For the harvesting of apples, the AUFO robot was developed at the Central Enterprise for the Organization of

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Agriculture and Food Industry [13]. The harvesting of melons was studied and a prototype harvester was constructed to selectively harvest these fruits [18] [19] [20].

Stepanov presents a review of different robotic systems developed in Russia under different projects (21). The MAVR-1 is an autonomous grape robot, the MOP-1 is a vegetable harvesting robot to harvest melons, pumpkins and cabbage and the MIIP-1 is a fruit picking robot to collect oranges and apples.

The AGRIBOT is a Spanish project [22] to harvest fruits with the help of a human operator who has the main responsibility of the fruit detection task. The operator using a joystick moves a laser pointer until the laser spot is in the middle of the fruit. The 3- dimensional coordinates are recorded and the parallelogram manipulator is controlled toward the fruit. A gripper system based on a pneumatic attaching device and an optical proximity sensor is used to detach the fruit.

III. ADAPTIVE IMAGE SEGMENTATION ALGORITHM

An environmentally adaptive learning process includes an environmentally adaptive segmentation algorithm (EASA) [1] and an algorithm for automatic generation of a look-up table (LUT) for real-time color image segmentation (Fig. 1). The EASA was designed to learn from local viewing conditions in different fields or at different times of day, including the specific lighting and color conditions of different crop plant varieties, weeds, and soil types. Results from the EASA were used to create a Bayesian classifier (decision surface) which was implemented in real-time using a LUT. The kernel of an EASA is the adaptive or self-learning process where an attempt is made to find structure in a set of observations about which very little is known. Clustering has been implemented as a self-learning process using both top-down and bottom-up methods. That is, the process can either start with the undifferentiated data set and split it successively until satisfactory clusters are obtained, or it can select certain seeds for the clusters and organize data points around them. Clustering was used in this research to form the basis of the EASA.

The clustering portion of the EASA was designed to find the 'natural' clusters of pixels in color space corresponding to object classes. Some general data structure properties of the images in this study were known. For example, the crop plants should always be green, while the background color should be anything but green. A modified clustering method called partial-supervised learning (PSL) was introduced. PSL is not a totally unsupervised learning process. Instead, the procedure starts from a set of manually selected seeds which are stored in a data file. Pixels in sample images are then clustered until a required number of classes are found. An operator then assesses the accuracy of the classification and determines if the performance is acceptable and can proceed to construction of the LUT or must be revised.

The clustering algorithm was designed to find the 'natural' clusters of pixels in sample images under a transformed feature space. Here assumed that there were four natural pixel clusters in the sample images because preliminary results showed that more accurate classification could be achieved with four clusters rather than with only two (a background and an object class). In this experiments, green (0, 1, 0), red (1, 0, 0) blue (0, 0, 1) and gray (1:3, 1:3, 1:3) were generally used as the seeds (starting centers). Clustering was the only learning procedure in this

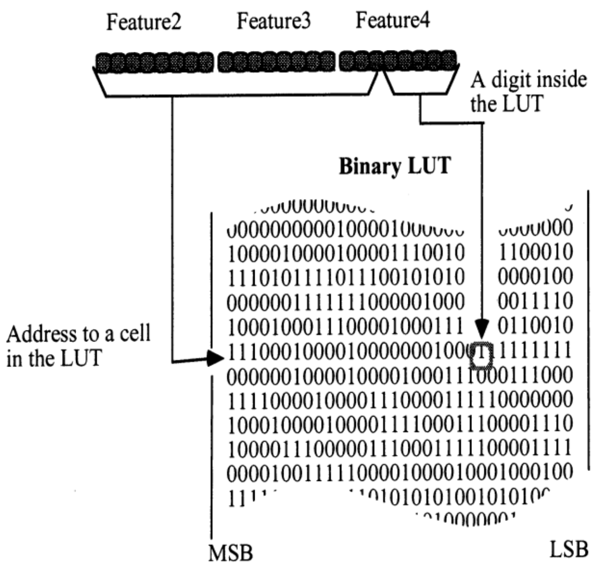

Fig. 2. Illustration using the feature sum value to locate the desired cell in the LUT. If the resulting read from the LUT is 1, then the feature combination represents an object pixel; otherwise , it represents a background pixel.

system. The final single decision boundary was generated by means of Bayes' decision theory based on the clustering results, and normally it was a hyperquadratic decision surface. The steps used by the algorithm were:

Step 1. Assign predicted seed points as the initial center for each cluster.
Step 2. Assign points in the training data set to their closest seed point (in Euclidean distance).
Step 3. Re-compute cluster centers as a function of all the points assigned to them.
Step 4. If the difference between any old seed point and the calculated center of the cluster that contains it is greater than an established a priori amount, return to Step 2.

Step 5. Output clustering results for human assessment and object class assignments.
Step 6. If results are not acceptable, then generate new seed points and return to Step 1.
Step 7. Calculate statistical data for each class and build a Bayesian classifier based look-up table.

The program shows the classes to the operator by displaying each class of objects in the image using a different pseudo color. The operator decides which pseudo colored region(s) should be considered as 'object' (plant) and which background choosing more than one of the four clusters to form an object (or background) class as necessary. The computer then builds the segmentation look-up table automatically. The computer could also assign classes to the clusters automatically if the a posteriori probability of class membership was provided. The Bayesian classifier LUT was used for real-time image segmentation.

IV. BAYESIAN CLASSIFER AND REAL-TIME CONSIDERATION

The Bayesian classifier is based upon Bayes' rule for estimating the a posteriori probability that a pixel belongs to one of two possible classes (plant or background). The a posteriori probability of class v*j*, given the random vector in feature space **x**: $P(\omega j|\mathrm{X})$ is found by using Bayes' rule (Duda and Hart, 1973):

$$P(\omega j|\mathrm{X}) = \frac{P(\omega j|\mathrm{X})\mathrm{P}(\omega j)}{\mathrm{p(X)}} \quad \text{Where } p(X) = \sum_{i=1}^{\mathrm{N}} P(\omega j|\mathrm{X})\mathrm{P}(\omega j)$$

A pixel is assigned to a class with the largest a posteriori probability. If the data are multivariate normal, the Bayesian classifier is the optimum method to minimize the overall error in classifying objects (Tou and Gonzalez, 1974). With EASA, a classifier could be sharpened for each particular viewing condition and helped to avoid using one classifier under viewing conditions which were substantially different from the training conditions.

To achieve the real-time sensing goal, image-processing algorithms should not be computationally intensive. One method for real-time classification is the use of a look-up table (LUT). This procedure trades memory for time. A LUT is an exhaustive list of all the possible feature combinations covering the entire range of the sensing (imaging) system. The feature combination is used as the address in the table, and the class label of this feature combination is stored at that address. Because each feature may have hundreds of possible values (this is dependent on the nature of individual problems), a LUT generally uses a lot of memory. A LUT is created by listing all possible combinations for the three-feature (*R*, *G*, and *B*) vector. A LUT used in this study was a three-dimensional table because we used three 8-bit features (*r*, *g*, and *b*) in our Bayesian classifier. In the memory of a computer, all data arrays are stored as one dimensional lists, so the *rgb* feature combination was defined in the form of a shifted sum of all three features. The LUT list could be easily retrieved by using the sum value as the address (Fig. 2):

Sum = Feature1 × 2^{16} + Feature2 × 2^{8} + Feature3

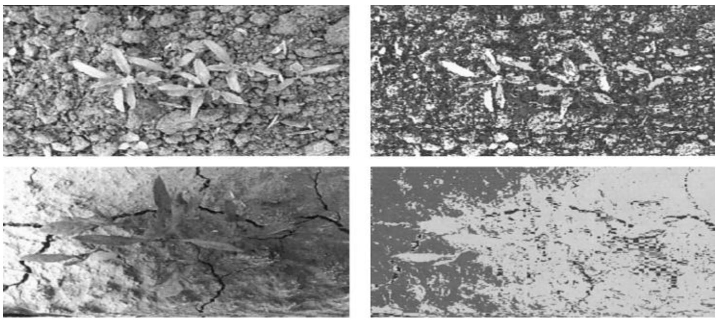

Fig.3. The clustering test in RGB color space. The four resulting clusters depended mainly on the pixel intensity level. Images on the left are raw color images, and clustered images appear on the right.

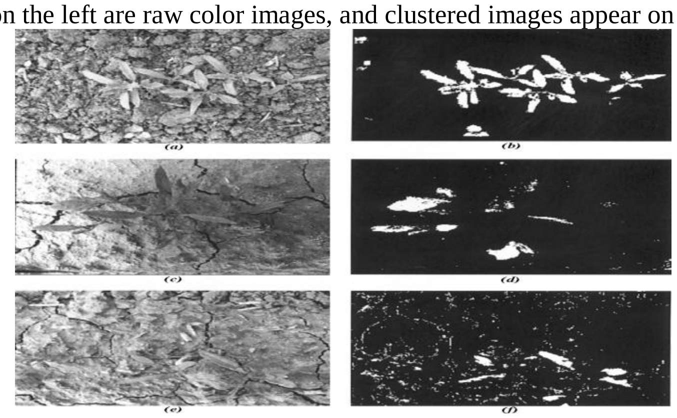

Fig. 4. Examples of static image segmentation (the images are not included in the training set, with an RGB classifier trained with high quality image samples). The raw images in left column (a), (c), and (e) were from three different fields. Image (a) was captured with diffused sunlight (high quality image), images (c) and (e) were captured when lighting conditions were not very good (cloudy).

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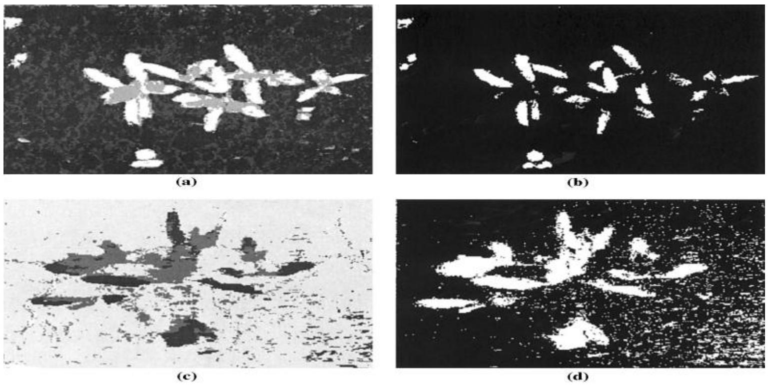

Fig. 5. Unsupervised learning in normalized color space. The images on the left are cluster groups, and the images on the right show the segmentation results. For ideal lighting conditions (top row) , the color difference between tomato cotyledons and its true leaves was detectable(b). For poor lighting condition s (bottom) , almost all the pixels belonging to plants are clustered into black and gray clusters.

TABLE I
Performance of EASA under different lighting conditions

Lighting Conditions (10:00- 15:00 h)	**Average leaf area (pixel count)**			**Variance analysis (ANOVA)**	
	Static	**EASA**	**Improve (%)**	**F- value**	**Pr>F**
Sunny	2542.37	2530.48	-0.47	2.063	0.3265
Partially cloudy	1478.54	1876.23	26.9	3.968	0.0562
Overcast	2130.74	3287.43	54.3	4.522	0.0320

TABLE II
Pattern recognition results affected by different segmentation algorithms

Lighting Conditions (10:00 – 15:00 h)	**Number of images**	**Cotyledons in images**	**Cotyledon detected**		**Improvement with EASA (%)**
			Static	EASA	
Sunny	50	174	114	116	2
Partially cloudy	50	148	25	94	276
Overcast	81	218	3	99	3200

V. COMPARISON

EASA [1] is compared with two conventional static segmentation techniques. The first method was based on the accuracy of image segmentation in terms of the plant leaf area. The second method was based upon the accuracy of plant recognition using sequential application of image segmentation and morphology-based pattern recognition. The static classifier was trained with sample images taken under ideal (sunny) lighting conditions. The EASA classifier, on the other hand, was adjusted automatically for each of three lighting conditions (sunny, partially cloudy, and overcast). Altogether 45 image frames (15 frames for each of three lighting conditions) were tested in the leaf area test. For each lighting condition (sunny, partially cloudy, and overcast), the same set of images was used to evaluate each classifier. Because we were processing the same image set with two algorithms, the average leaf size (pixel count) was correlated with the segmentation accuracy (relative). The leaf structure used in the leaf shape pattern recognition test was restricted to the cotyledon of tomato plants because their shape and size are relatively uniform. Using four cotyledon shape features, an algorithm was developed to identify cotyledons and determine their size automatically.

A Bayesian classifier was trained with sample images from one lighting condition. When this classifier was used to segment images under a range of lighting conditions, only the images from the same lighting conditions were correctly segmented. More than 50% of plant leaves were classified as background in images from different lighting conditions using the static technique. The result of the first clustering test using *R*, *G*, *B* color space is shown in Fig. 3. The clusters were mainly correlated to pixel intensity. The four clusters obtained using this method corresponds to different intensity levels as is especially apparent in the bottom image of Fig. 3. The upper-left corner of this image was clustered into one cluster regardless of pixel color. Fig. 5 shows the result of clustering images in normalized color space. These images are the same ones shown in Fig. 4, but the results are quite different.

Table 1 shows the performance of EASA under different lighting conditions and Table 2 shows the pattern recognition results affected by different segmentation algorithms.

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VI. CONCLUSION

India is developing at faster rate but due to the urbanization crop fields are getting converted to new forms of the urban world. Also farming community is becoming narrower day by day due to better opportunities. Currently, mKrishi has been installed in few villages in the western state of Maharashtra to help Cotton, Grape, Potato and Soybean farmers. By using WSN and Robotic harvesting we can decrease the cost of production and increase the efficiency of production. Robotic harvesting with a aid of adaptive segmentation technology attracts more and more attentions of countries and enterprises with its powerful advantages and market potential. This technology will bring greater opportunities to the agricultural development. The EASA-based algorithm had much higher segmentation accuracy in poor lighting conditions than the static algorithm. In ideal lighting conditions, EASA is similar to the static algorithm. When the lighting conditions were ideal, the EASA could even distinguish the subtle color differences between the tomato true leaves and cotyledons in (Fig. 5). If the true leaves and cotyledons of a plant are separable, the so-called occlusion problem is reduced, and the process of plant identification can be efficient and able to meet the requirements of a real-time system. The results of this system showed that an adaptive machine vision system could be developed for real-time field operations using current technology.

A well-designed outdoor image acquisition and segmentation system could increase the segmentation quality so that computationally expensive procedures could be avoided in the plant pattern recognition process which is really essential for developing countries.

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