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APPLICATIONS OF MACHINE VISION IN AGRICULTURE

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ABSTRACT

Machine vision is an emerging field of technology that is expected to create a pervasive impact in the future. A simple definition of machine vision is "the ability of a machine to see". As a sensory input, machine vision can be made a feedback to closed-loop control system such as robotic applications. Sorting for quality and feature recognition are some of the most common applications of machine vision. In this paper, the development of machine vision systems was reviewed and highlighted. Several machine vision configurations are proposed that can be subjects of future research work.

I. Introduction

Various machine vision applications are now in use either as components of robots or as stand-alone systems. Using machine vision robots have been made to sort cucumber, monitor animal behaviour, and harvest apples. As stand-alone system it has been made to characterize corn growth and development, detect plant wilting, simulate and measure potato leaf area. Other uses includes plant feature identification, plant identification based on color texture characterization of canopy sections. A rice crack detector have been developed using machine vision system.

Machine vision. Machine vision is a machine eye-brain (camera-computer) system which provides some of the capabilities of human visual perception. A machine vision system (MVS) maybe composed of a camera, computer, and a monitor. In fruit and vegetable grading, defect detection using machine vision system was accomplished in a series of steps; [a] image generation, [b] product location, [c] scrutiny, [d] measurement, and [e] classification (Yang, 1992).

The image generation step includes presentation of the produce, the use of camera, and the lighting design. Presentation of products means it may be singulated, oriented or positioned so that the image can be taken by the camera. This may require a special mechanism, a flat belt conveyor is selected for higher throughputs. For products that translate through the field of view, line scan cameras maybe used. When the product is rotated in the field of view, matrix CCD (charge-coupled device) cameras are used to cover evenly the surface and varying sizes of produce. The number of images or cameras are determined by the given method of presentation. Depending on the application, front lighting is required as in defect detection. Diffuse lighting provides uniform illumination, eliminate shadows and minimize specular reflection.

Product location and scrutiny are accomplished by image processing in two segmentation steps. First the product is separated from the background and from the other objects in the image, then the surfaces are differentiated as in defect detection. Hardware or software pre-processing may be needed to enhance contrast and correct for non-uniformity of illumination. A broad range of techniques are available for image segmentation such as region splitting and growing technique; thresholding using histogram analysis, and global or local statistics, color transform for color images by using hue instead of the original tristimulus values. Segmentation results in pixel (picture elements) or areas that would indicate natural features or defects which could be a basis for recognition or identification.

After a feature is identified, the product is measured and classified based on a grading standard. Size of the product may be measured by counting pixels and compared to threshold of a classifier, which then makes the identification of grading decision.

Visual perception. Visual perception involves the active pick-up of information specific to the environment and the changing ambient light surrounding the observer (J.J. Gebron, as cited by Hatsopoulus). Mackworth (1977) cited Roberts (1965) for his working model of perception as a alternation of image segmentation and its interpretation, composed of a cycle of four processes: discovering cues, activating a hypothesis, testing the hypothesis, and inferring the consequences of a established hypothesis (Figure 1). Everyday human perception is an on-going equilibrium of similar processes.

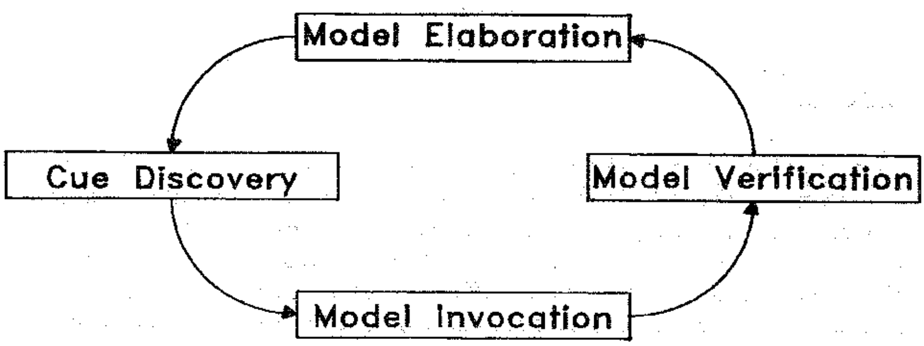


Figure 1. The cycle of perception (Mackworth 1977)

Visual perception or the ability to detect simple stimuli such as spots, edges, and bars of light depends not only on such properties as the brightness, size, and duration of the spot, but also on the brightness of the background against which the background appears. The ability of the visual system (VS) to detect fine spatial detail is known as acuity. Acuity not only depends on background luminance, but also varies greatly with the position of the stimulus. For edges or contours which are abrupt changes in luminance, VS displays "overshoots" known as Mach bands which enhance or deblur the edges.

The wavelength of the light, which produces the visual stimulus, determines the perceived color. As wavelength varies different colors are perceived from red, corresponding to the longest visible wavelength, through orange, yellow, green, and blue, to violet. The appearance of a colored spot of light can be described in terms of its brightness, its hue, and its saturation.

An understanding of human visual system is important to the designer of MVS. However, the subject of visual perception is very broad and complex. Some topics that should be understood are as follows: brightness and contrast, acuity and contour, color, pattern and texture, shape and space, duration and motion, detection and recognition. These topics can be found in listed references, but is beyond the scope of the paper.

II. Developments in Machine Vision

2.1 Cucumber sorting machine

A vision based cucumber sorting facility was reported by McClure (1983) after a visit in Japan in 1980 at Miyazaki University. The facility was part of a farmer-owned cooperative. The system (Figure 2) built by Mitsubishi Electric Corp. was purchased by the farmer cooperative for sorting cucumbers into nine categories. The cucumbers were placed in buckets or pans by hand on a conveyor, one cucumber per pan. A single line scan camera positioned above the sorting line inspects 3 lines of pans as the pans under it, and sends shape pattern information to the microcomputer based sort control unit.

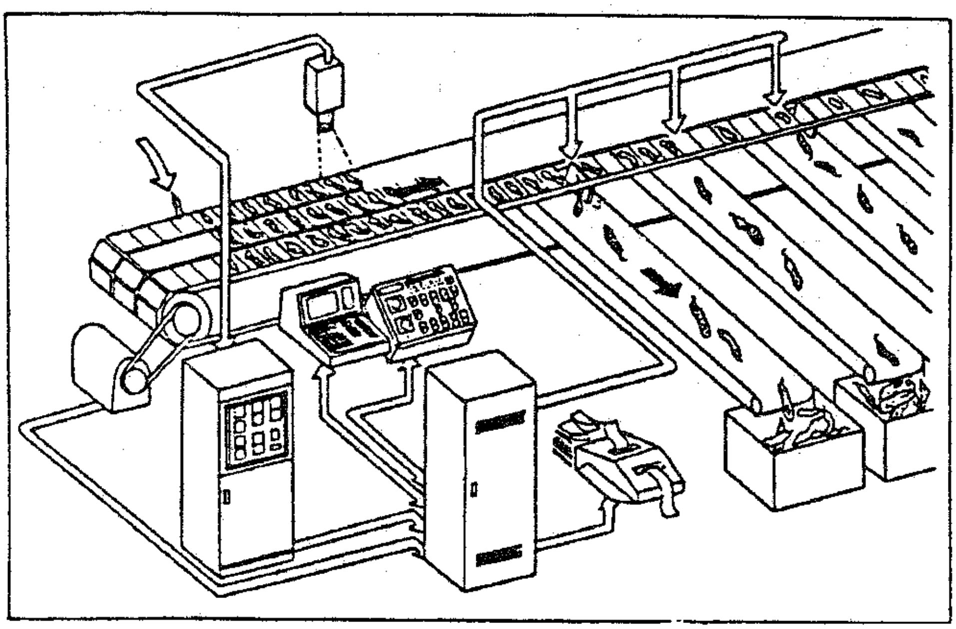


Figure 2. Cucumber sorting machine in Japan (as reported by McClure, 1983)

The sort control unit grade and classifies the cucumbers and relays the result to a separate microprocessor based drop-out (sorting control unit). The function of the sorting control unit is to drop the pans downward at the required cross-conveyor. At the same time, the drop-out unit signals the display counter and the line printer to register the result of the sorting for each cucumber. Table 1 shows specifications of the sorting system.

Table 1. Specifications of the Mitsubishi Automatic Sorting System for Sorting Cucumbers

Feature	Specification
1. Maximum processing capacity	36,000 pcs/hr
2. Conveyor Speed	23 m/sec
3. Field of view (one pixel)	1.2 x 1.6 mm
4. Sorting standards	Length, oddness
5. Maximum measurement range	Length:260 mm, Thickness: 40 mm Curvature: 60 mm, Max. Thickness: 30 mm

2.2 Tomato grading

Quality separation of fresh market tomatoes using computer vision was developed (Sarkar and Wolfe, 1985). The computer development system consisted of a Dage-666 vidicon camera together with a pair of Datacube video graphics boards, which formed the sensor-digitizer combination.

The digitizer boards were installed in a Plessey Micro-II computer which uses the DEC LSI II/23 16 bit CPU and RT-11 operating system. Memory consisted of 64K bytes of MOS directly addressable memory and 192K bytes of virtual memory. Data storage consisted of two 8-in floppy disk drives, 32 Mb hard disk storage, and 16Mb tape carriage storage. Tomatoes were illuminated by a 33-W fluorescent tube mounted on a cylindrical set-up. A device was designed to orient the tomatoes into the proper presentation. A schematic of the computer vision development system is shown in Figure 3.

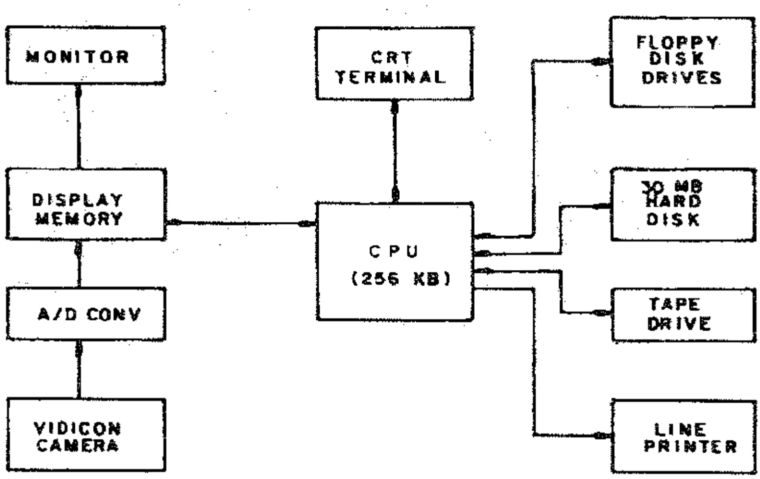


Figure 3. Computer vision development system (Sarkar and Wolfe, 1985)

An image processing technique was associated for each tomato attribute such as size, shape, color, orientation, stem end defects, and blossom end defects. These image processing techniques or algorithms were combined in a sequential manner to form a complete tomato sorting package. After grabbing one view of the tomato, a shape analysis was done to ascertain if the tomato is of an acceptable shape. Abnormally shaped tomatoes are rejected, while orientation is determined for the remainder. Color evaluation follows, with red tomatoes separated for fresh market or for processing. Then mature green tomatoes are checked for surface defects using the appropriate defect detection algorithm corresponding to the tomato orientation. Again defective tomatoes are rejected, with the remainder inverted to evaluate the opposite end. Another check is made for orientation, with tomatoes showing the same orientation for both views, rejected. A second check for color and defects is made then the mature green tomatoes are classified according to size.

Performance testing using sample of 1014 PIK RED tomatoes showed a low error rate of 3.5%, which dropped to only 0.4% when slight defects were used as tolerance and their misclassification were not considered.

2.3 Row crop guidance information

Vision systems can act as a sensor to estimate steering corrections to guide the tractor through a field relative to some guidance course, or directrix, observed by the vision sensor (Reid, 1998). Row-crops facilitate vision-based guidance system because of the directrix is defined by the geometric arrangement of the crop canopy against the soil background (Figure 4).

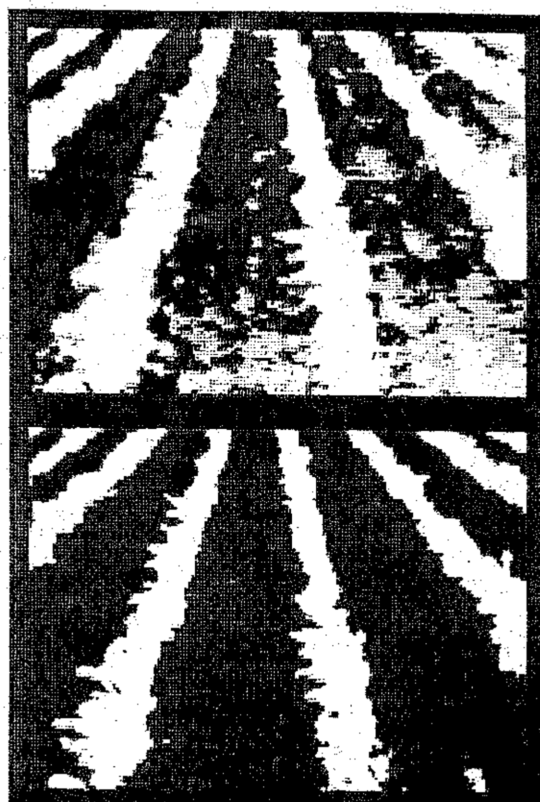


Figure 4. A gray level and thresholded image of a small crop canopy which was successfully segmented (lower part of Figure) by Bayes classifier (Reid & Searcy, 1988)

2.4 *Crack detection in rice*

To detect cracks in milled rice Fast Fourier Transform (FFT) was used to transform the intensity image in the spatial frequency domain (Talsma, et al., 1989). The spatial frequency of a fissured kernel was higher than that of the whole kernel. The FFT method for crack detection had a classification accuracy of 77%. They also employed the image enhancement method which involves identification of each kernel and measurement of its dimensions, intensification of the cracks, and classification of each kernel as whole of fissured based on a predefined image criterion. This crack detection algorithm was designed to classify each kernel based solely upon its gray levels. The overall accuracy with this method was 92.4%.

2.5 *Tree trunk growth/damage prognostic technique*

Widespread use of mechanical trunk shakers for harvesting tree crops cause bark damage and may have long term effect on fruit tree growth and yield. A tree trunk growth and damage prognostic technique was developed (Affeldt et.al., 1989) without destroying the tree. Using a contour tracking instrument tree trunk contours were replicated (Figure 5). Algorithms from using invariant moments, normalized Fourier expansions, profile mapping, band width, and thinness ratios, were applied to cherry trunk images and compared. All methods detected trunk shape change which indicated tree trunk damage.

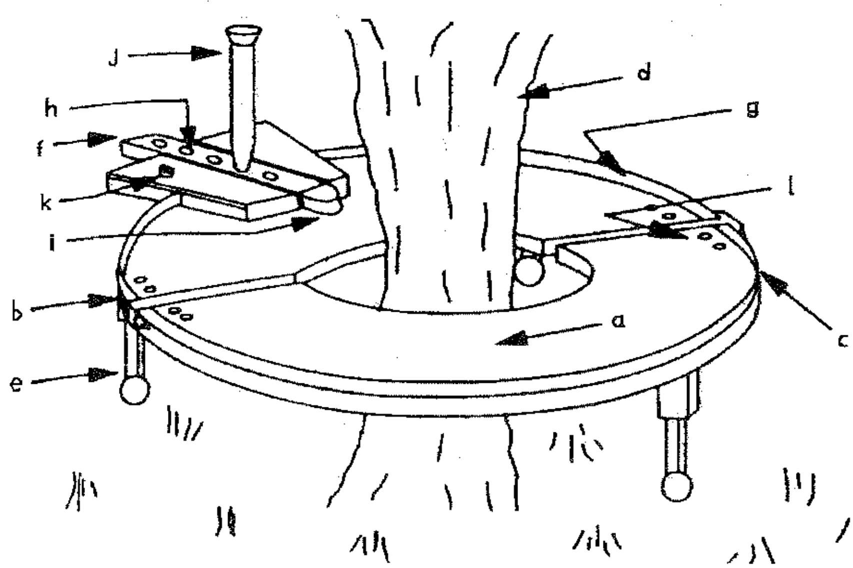


Figure 5. Contour tracking instrument. This instrument consisted of [a] toroidal aluminum table, hinged on one side [b], with a spring loaded clasp opposite [c]. The instrument encircled the tree [d]. Three adjustable legs [e] allowed positioning and leveling. A leveling bubble [k] ensured consistent alignment. A sliding pointer [f] mounted on the table's rail border [g] consisted of a teflon pen carrier [h] with pen [j] precisely fitted with an aluminum cam follower [i] at its head. Alignment pins [l] were used to accurately position pre-cut paper on the table (Affeldt et.al. 1989).

2.6 Vision-guided propagation of microplants

Micropropagation is a process used in the horticultural industry to produce large numbers of genetically identical plants, involving repeated dissection and replanting of microplants grown in closed containers on an agar jelly. The manipulation of microplants, which are 2-3 cm high, is labor intensive and must be carried out under aseptic conditions to prevent contamination by bacteria. An algorithm (Tillett, 1990) was developed using a corner finding technique to classify objects in the image and then calculate the location and orientation of the desired plant pieces. Implementation of the algorithm was made on a robotic planter. The robot is cartesian type allowing movement in x, y, z directions with vertical axis rotation on the wrist. The camera is mounted above the robot looking vertically down on the working area. The planting tool available for the linked system was a simple crossbar used to push the lower stem of the node down into the agar jelly so that the node stood up vertically. Three varieties of chrysanthemum was used in the test. Overall performance resulted in only 62% of the sample located correctly, while only 52% was planted correctly.

2.7 Oyster orientation positioning system

Shucking, the removal of the oyster meat from the shell, consumes the majority of labor required in processing oysters (Wheaton, 1972). Mechanical shuckers require proper orientation of oysters before entering the machine. Using computer vision, Tojeiro and Wheaton (1991) developed an automated orientation positioning system for oyster. The system used one black and white video camera and a plane mirror to simultaneously collect both a top and side projected view of an oyster. A processing software was developed which determines the principal oyster axis and calculates two width to thickness ratios, one taken 1.5 cm from each end of the principal axis. A stepping motor attached to a rotary plate rotates the oyster to the desired position. The system (Figure 6) was capable of correctly orienting 98.3% of a given sample to within ± 0.13 rad.

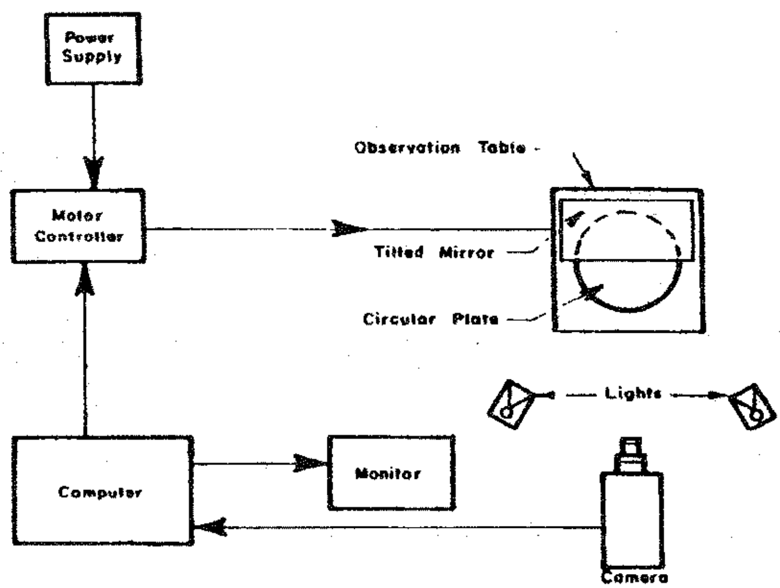


Figure 6. Oyster orientation positioning system (Tojeiro & Wheaton, 1991)

2.8 *Peach defect detection*

The postharvest handling and packaging of fresh market peaches has been extensively automated, with the exception of the sorting and grading operation which continue to be a manual effort (Miller & Delwiche, 1991). Some $384 million worth are produced annually making peaches the fourth largest tree fruit tree crop in the United States. USDA grade standards for peaches specify the extent of defects and damage such as bruises, cuts, scar, scale, wormholes, brown not of peaches.

A laboratory machine vision system was developed to detect and identify surface defects of fresh markets peaches. Peach images were taken in both the near-infrared (NIR) and visible regions of the electromagnetic spectrum. For color image acquisition on solid-state color TV camera (Model 1815-2200, Cohu Inc. San Diego, California), NIR images were taken with a solid-state monochrome TV camera. Video signals from the cameras were digitized by a color frame grabber board (Model DT2871, Data Translation, Marlboro Massachusetts) mounted in a micro computer. An illumination chamber was constructed from a 584 mm section of 300 mm diameter plastic pipe, painted white on the inside and smoked with magnesium oxide. Four 50 W tungsten halogen bulbs were used for lighting. System accuracy from experimental tests to estimate defect area and estimate defect type was 31% error rate for NIR system and 40% for the color system. Correlation coefficients between predicted and manually measured defect areas ranged from 0.56 for scale to 0.92 for brown rot.

2.9 *Hatching egg fertility detection*

It is estimated that U.S. hatcheries spent about $14 million to incubate eggs that were infertile. Sorting infertile eggs will allow its marketing for table consumption thus become a source of added income. A method (Figure 7) using machine vision for detecting well developing eggs

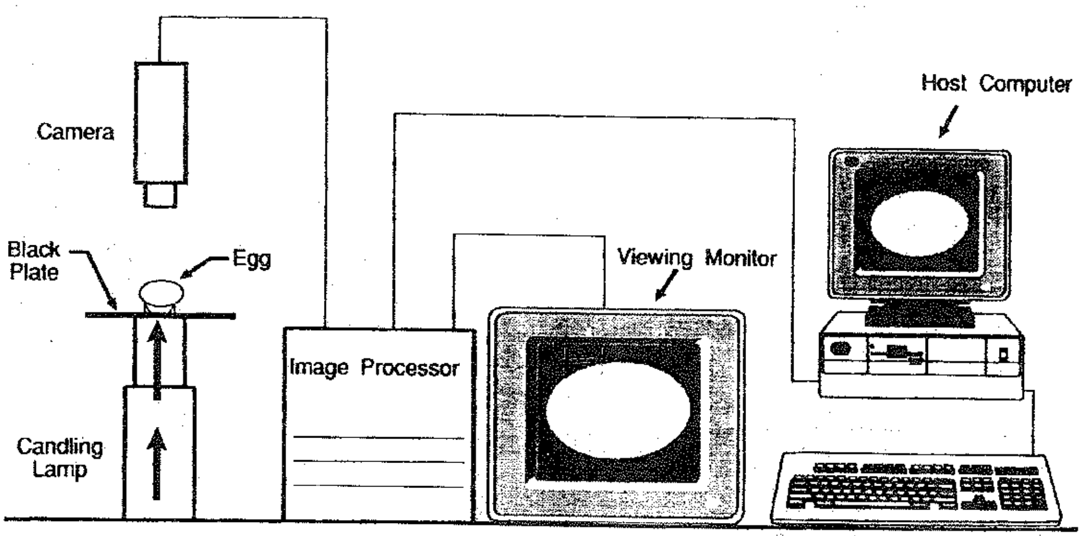


Figure 7. Hatching egg fertility detection system (Das & Evans, 1992).

during the third and fourth day of incubation was developed by Das and Evans (1992). Images of eggs were acquired using backlighting with a high intensity candling lamp. A histogram stretch enhanced the image and the shape of the histogram provided a description of the resulting image. The computed histogram shape parameters was used to develop an algorithm to distinguish fertile from infertile eggs. The algorithm performed with accuracies of 96 to 100% at day 4 of incubation and 88 to 90% at day 3 of incubation.

2.10 Solid wood content assessment of stacked logs

Major discrepancies and inadequacies occur in applying measurement techniques used in trading raw and processed timber. In South Africa, this situation results in less than equitable trading, with possible loss to both seller and buyer. Error using current methods may range from 10-20%. A robust technique using machine vision was developed to determine the diameter distribution within a stack of logs and to measure the overall solid wood volume.

Images of stack faces were captured using a tripod-mounted CCD Panasonic WVBL200/G video camera which was equipped with a 12.5-75 mm zoom lens. Lighting was provided by a 1500 W flood light positioned to eliminate effects of shadows, caused by other light sources on the stack face. The machine vision system utilized a Cortex-I Video Frame Grabber installed in a 80486 CPU computer.

Three different types of images were tested during the development of this system: images containing simulated data, images captured of the test stack under laboratory conditions, and images captured in the field. The algorithmic technique based on Hough transform was successfully tested on simulated and real images of log stacks. The machine vision system achieved direct volume and size assessment of stacked roundwood timber with an error level of 9.64%.

III. Proposed Machine Vision Systems

3.1 Rice variety recognition/identification system

Rice variety recognition or identification is a visual assessment of the appearance of the rice grain or the rice plant. The identification or recognition process may be based on a set of criteria for objectivity, but subjective assessment cannot be completely eliminated. As a visual function, the accuracy of identification is dependent upon the assessor's skill, visual acuity and previous experience. The task therefore, is an integrative process taking into consideration all the relevant factors that will rationalize the identification decision. We can call this ability to rationalize our identification decision as visual perception.

Given a grain lot, a person tasked identify the rice variety will take a sample and a visual assessment starts following the cycle of said processes to identify the rice grain. Identifying whether a variety is Japonica or Indica variety is fairly easy since the shape of both grains have evident difference.

Among Indica varieties however, it is not simple task using the naked eye to identify which variety is. The shape and color appear the same and there is no apparent difference even if compared by close visual inspection. Under normal procedure a grain sample is tagged and care is needed not to lose the tag. An accepted method of recognition or identification is using a reference variety, an unknown variety is compared, for example to IR8, and the identification is indicated as "IR8" or "not IR8".

Machine vision is useful for extracting profile shape features of the grain kernel for variety classification and quality inspection (Liao et. al. 1993). Zayas et. al. (as cited by Liao) used a machine vision system to extract morphological profile shape features from wheat images and used these features to discriminate wheat varieties and nonwheat components.

Standard descriptors for rice (O. Sativa L.) were developed in 1978. The minimum list was published jointly by IRRI-IBPGR in 1980, containing some 50 descriptor and descriptor-states for the rice plant, of the 50 items about 29 items involve visual classification in terms of dimensions, angle color, and absence-presence of a character. To describe grain characteristics 16 descriptor items were outlined, of which 7 items must be determined visually. Also included is a decimal scale for recording varietal reactions to diseases and insect pests.

The main components of the rice grain are the hull, caryopsis, endosperm, and embryo. The rice caryopsis is surrounded by a hull (husk) composed of two modified leaves, the palea and a larger lemma. The palea and lemma are held together by hooklike structures (Bechtel and Pomeranz 1978 as cited by De Datta, 1981). The cells of the mature hull are highly lignified and brittle with high concentrations of silica in the hull cells, presumably in the outer epidermal cells (Figure 8). The profile of the lemma and palea, as well as the shape of the awn base and length, offer opportunities for identification of rice varieties. The hypothesis is that at the pixel-level, differences in patterns of the registered image will provide significant deviations from which to

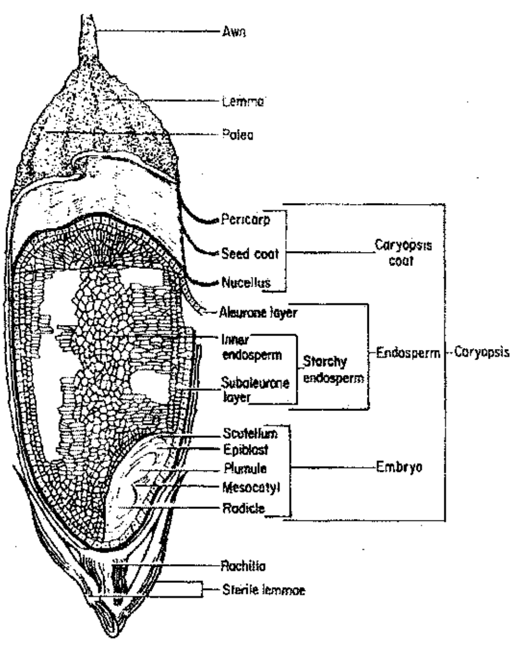


Figure 8. Structure of the rice grain (De Datta, 1981).

base varietal identity. At the plant level, we might be able to use the panicle (Figure 9), to provide a basis for establishing varietal identification specifically, differences in branching and spikelet distribution.

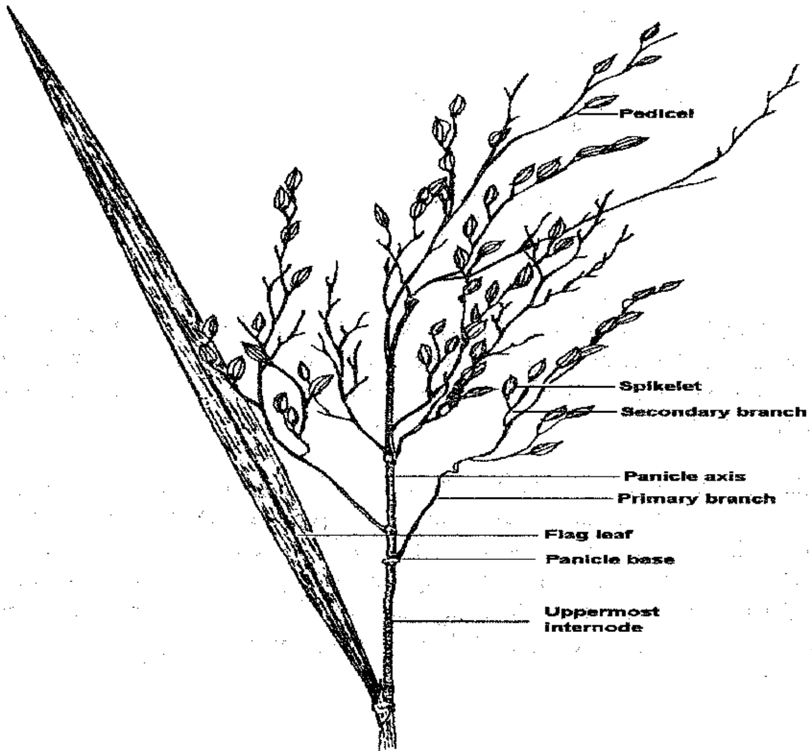


Figure 9. Components of rice plant panicle (De Datta, 1981).

Blade pubescence is a leaf characteristic which refers to the characteristic surface of the leaves. Blade surfaces are classified as glabrous (smooth) including ciliated margins, intermediate, and pubescent. These characteristic surface may exhibit a certain pattern or texture that can be used to differentiate one leaf blade from another. For blade color, seven broad classes are recognized: pale green, green, dark green, purple tips, purple margins, purple blotch, and purple, observed at the late vegetative stage. More of these potential visual parameters are listed on the said IBPGR-IRRI bulletin.

Grain kernel identification by profile analysis was investigated by Segerlind Weinberg (1973). Using Fourier series expansion of the periphery radius about the grain's two dimensional center of gravity, they were able to estimate the grain kernel shape.

The radius is a function of angle, therefore the Fourier series representation is

$$R(\theta) = R_0 + \sum_{n=1}^{\infty} A_n \cos n\theta + \sum_{n=1}^{\infty} B_n \cos n\theta$$

where

$$R_0 = \frac{1}{2}\int_0^{2\pi} R(\theta)d\theta$$

$$A_n = \frac{1}{\pi}\int_0^{2\pi} R(\theta)\cos n\theta d\theta$$

$$B_n = \frac{1}{\pi}\int_0^{2\pi} R(\theta)\sin n\theta d\theta$$

and θ is the polar angle measured from an arbitrary reference line. The method of analysis commences by calculating the center of gravity from the rectangular periphery coordinates. Once the center of gravity is known, the peripheral points are converted to polar coordinates and the values of A_n and B_n at each harmonic level are calculated.

After estimating grain shape, a two-step procedure for discriminating shape was used. First, training classes are formed using known data, as second step, an unknown kernel is classified according to which class it is closet to. A training class is the collection of data for a particular kernel which is used as the standard. In this study the training class was a column vector whose coefficient were the average values of the first ten Fourier coefficients. If a particular training class, i, is denoted by $\mathbf{M}^{(i)}$, then the coefficient of $\mathbf{M}^{(i)}$, $\mathbf{m}_n{}^{(i)}$, are given by

$$m_n{}^{(i)} = \frac{1}{N}\sum_{k=1}^{n(i)} R_{nk}$$

where N is the number of samples and
$\mathbf{R}_{nk}$ is the Fourier coefficient R_n from the kth sample

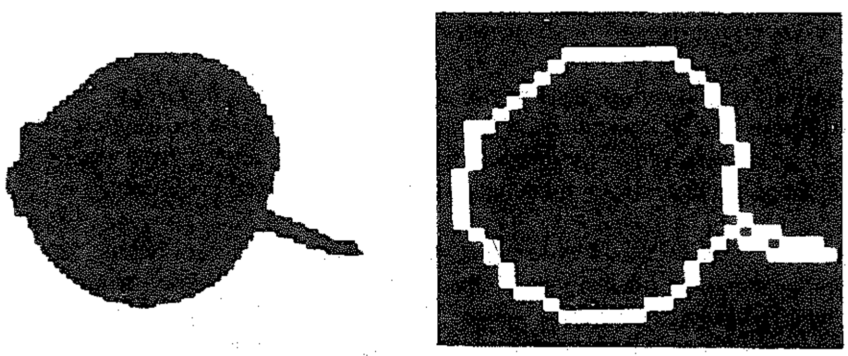
The classification process was carried out by calculating the distance from a kernel to the center of each training class. They recommended implementation of the technique using combined photoelectric detector for obtaining information about the kernel periphery and a minicomputer for performing calculations.

Wolfe and Sandler (1985) developed a fruit stem detection algorithm based on the assumption that binary profile images can be obtained which show the stem or protrusion from a fruit boundary. The algorithm was based on syntactic analysis of angle patterns in the boundary chain code of profile images. Syntactic pattern recognition involves describing an object of interest in terms of elementary primitives (Fu, 1982 as cited by Wolfe and Sandler, 1985). A human observer may visualize a stem as a protrusion interfaced to the fruit by two concave corners, thus the basic boundary structure for representing a stem should be a concave-convex-concave (CVC) angle sequence.

This syntactic analysis routine of angle patterns in the boundary chain code of profile images (Figure 10), was trained for blueberries and cherry peppers by determining various parameters values (Wolfe & Sandler, 1985). Overall stem detection error rate was 1.5% for blueberries. Good results were obtained for cherry peppers.

Simonton and Pease (1990) developed a plant image analysis technique to anatomically characterize the branching geometry of a geranium cutting. A data structure was created containing information required to identify various plant parts. This dynamic data structure from two-dimensional binary image data, grouped pixels of the cutting into logical segment records. A segment record may represent such plant parts as stem internodes; petioles; or sections of one or more leaf blades, the non-stalk portion of the leaf. Pointers showed which segments were adjacent, and were directed so that one segment would be the parent of two child segments. A simple geranium cutting could be completely represented by the segment records and the pointers within the segment record.

This data structure is called a directed graph (Aho et.al., as cited by Simonton & Pease, 1990). Using information in the directed graph, the basic plant parts and each part's associated area, length, width, and orientation were located and identified.



(a) Profile image at 0.28 mm/pixel.

(b) Boundary chain code representation at 0.56 mm/pixel.

Figure 10. Digitized images of blueberries (Wolfe & Sandler, 1985).

The above mentioned methods, individually or in combination, can comprise a viable rice variety recognition and/or identification technique using machine vision. Implementation of the proposed technique requires component hardware. A miniature breadboard type CCD camera is now commercially available for machine vision, instrumentation, and OEM applications. The unit features a 3.7 mm pinhole lens built into the breadboard assembly. It is wired for 9 Volt DC power input and video output.

3.2 Plant disease prognosis

Viral fungal, and bacterial diseases of rice reduce grain yield. Characteristic symptoms needs to be identified so that proper control measures can be employed. Five common viral diseases in Asia are tungro, yellow dwarf, grassy stunt, ragged stunt, and orange leaf.

Identification and description of the symptoms are determined visually. Most diseases are characterized by colored manifestations that can be used as basis for rice disease recognition using machine vision.

Humans are able to distinguish between colors using three independent attributes such as intensity, hue, and saturation (Nevatia, 1982 as cited by Shearer & Holmes, 1990). Shearer and Holmes investigated the feasibility of using visual texture sensation to identify objects within agricultural scenes. They pointed out that the visual sensation of color have been ignored in texture analysis. Furthermore, they argued that if attributes describing color were included in texture analysis, a more accurate classification might result. They developed a method of identifying plants based on color texture characterization of canopy sections.

This method was carried out by deriving co-occurrence matrices from image matrices, one for each color attribute: intensity, saturation, and hue. Eleven texture features were calculated from each of the co-occurrence matrices. These features were used in a discriminant analysis model to identify parts. Overall classification accuracy of 91% was achieved when this method was used to identify seven common cultivars of nursery stock. This method exhibited a significant improvement over previous methods which used intensity data only.

3.3 Machine-vision-based pest monitoring and control

Organisms considered as pests of rice are weeds, insects, fungi, rat, mice, and rodents. Before these pests can be controlled, they must be recognized. Weeds are classified as grasses, sedges, and broadleaf weeds. There are sufficient differences among these weed classes to enable the application of machine vision for recognition and or identification purposes.

Similar differences also exist in insect pests of rice such as stem borers, rice bug, rice leaf folder, leafhoppers, and planthoppers. Characteristic outline and color of insects can become a basis for the application of machine vision. Insects also infest drying and storage areas, and therefore pest monitoring using machine vision should be trainable or adaptable to functional requirements.

3.4 Grain quality assessment of rough rice and milled rice

Next to yield, grain quality is the most important factor considered by plant breeders. If consumers do not accept the taste, texture, aroma, or appearance of a newly developed variety, its usefulness is greatly impaired. In the developed countries, and in the rice-exporting countries, physical appearance of the grain is often more important than grain yield.

Grain appearance is largely determined by endosperm opacity, the amount of chalkiness, either on the dorsal side of the grain (white belly) or in the center (white center), and the condition of the "eye" or pit left in the embryo when the grain is milled. Rice samples with damaged eyes have poor appearance and low market acceptability. Similarly, the greater the chalkiness, the lower the market value. The ultimate test of a rice variety is in the market place where consumers generally decide on the basis of physical appearance.

Made Oka et.al. (1989) pointed out that in Indonesia, the use of a single characteristic, such as grain moisture level may not be adequate for use in grain procurement. Millers use in quality assessment of rough rice, in addition to moisture level, characteristics such as empty grains, grains appearance, levels of green and damaged grain. For milled rice, millers use head rice, and milling degree as the main quality determinant.

The same study showed that in buying rough rice, about 28.97% of millers used moisture content to determine the procurement price of paddy, 27.59% used empty and mixed grain as a second quality criteria, 16.55% used grain appearance, while 10.34% used green and broken grain.

The physical characteristics observed on the grain appearance include filled grain, shape and surface of the rough rice grain. Other rough rice price determinant used by millers are size of the grain, smell, and the duration of the grain in the storage.

They also recommended the standardization of quality assessment in rice, arguing that standardization can be an attractive incentive to promote improved postharvest handling, particularly at farmers level. When this happens, a rapid assessment technique will be required that can be implemented by a machine vision system. Specifically, capabilities of present hand-held moisture meter may be expanded to include assessment of grain appearance.

IV. Conclusion

The development of applications using machine vision in agriculture is accelerating. This is an opportunity that agricultural engineers can exploit. More applications are definitely forthcoming, made possible by advances in microelectronics and computer technology. New developments in computer architectures, such as the use of neural networks, have increased the capabilities of machine vision systems, making it trainable and used in real-time or on-line applications (Liao, et.al. 1993). In horticulture, in forestry, in aquaculture, machine vision systems are now in the use to grade the quality, measure the quantity, and process agricultural produce.

Cost effective configurations are needed to encourage development of more MVS applications. It may not be long before we shall have hand-held plant disease diagnostic MVS, grain quality MVS, and machine-vision-based pest monitoring and control system.

References

1. Affeldt, H.A. Jr., G.K. Brown, N.L. Pason, C.L. Burton and E.J. Timm (1989). Tree trunk growth and damage prognoses by digital image analysis. Trans ASAE, Vol. 32, No.5, pp. 1812-1820.

2. Batchelor, M.M. and S.W. Searcy (1989). Computer vision determination of the stem/root joint on processing carrots. Journal of Agricultural Engineering Research, No.43, pp.259-269.

3. Beerwinkle, K.R. and R.A. Stermer (1972). A device to facilitate optical sorting of milled rice bases on translucence differences. Trans ASAE, Vol.15, pp. 476-481.

4. Berlage, A.G., T.M. Cooper and J.F. Aristazabal (1988). Machine vision identification of diploid and tetraploid ryegrass seed. Trans ASAE, Vol.31, No.1, pp. 24-27.

5. Buckley, D.J. and W.E. McAdam (1972). A television-scanned, digital planimeter and dimension gage for measuring size of agricultural produce. Trans ASAE, Vol.15, pp.1168 - 1170.

6. Buckley, D.J., W.S. Reid and H.D. Voldeng (1973). A digital leaf-area measuring system using a television-scanned conveyor. Canadian Agricultural Engineering, Vol. 15, No.2, pp. 107 -109.

7. Casady, W.A. and M.R. Paulsen (1989). An automated kernel positioning device for computer vision analysis of grain. Trans ASAE, Vol. 32, No.5, pp. 1821 -1826.

8. Casady, W.W., M.R. Paulsen, J.F. Reid and J.B. Sinclair (1992). A trainable algorithm for inspection of soybean seed quality. Trans ASAE, Vol. 35, No.6, pp. 2027 -2034.

9. Churchill, D.B., D.M. Bisland and T.M. Cooper (1992). Comparison of machine vision with human measurement of seed dimensions. Trans ASAE, Vol. 35, No.1, pp. 61-64.

10. Churchill, D.B., D.M. Cooper and D.M. Bisland (1991). Rotating table for measuring seed physical properties. Trans ASAE, Vol. 34, No.4, pp. 1842 -1845.

11. Das, K and M.D. Evans (1992). Detecting fertility of hatching eggs using machine vision I: Histogram characterization method. Trans ASAE, Vol.35, No.4, pp.1335 -1341.

12. Das, K. and M.D. Evans (1992). Detecting fertility of hatching eggs using machine vision II: Neural networks classifiers. Trans ASAE, Vol. 35, No.6, pp. 2035 -2041.

13. De Datta, S.K. (1981). Principles and practices of rice production. Wiley Interscience Publications. pp.146 -161.

14. Dowell, F.E. (1992). Identifying undamaged and damaged peanut kernels using tristimulus values and spectral reflectance. Trans ASAE, Vol.35, No. 3, pp. 931-937.

15. Edan, Y.T. Flash,I. Shmulevich, Y.Sarig and U.M. Peiper (1990). An algorithm defining the motions of a citrus picking robot. Journal of Agricultural Engineering Research, No.46, pp. 259 -273.

16. Franz, E., M.R. Gebhardt and K.B. Unklesbay (1991). Shape description of completely visible and partially occluded leaves for identifying plants in digital images. Trans ASAE, Vol. 34, No. 2, pp. 673 -681.

17. Franz, E., M.R. Gebhardt and K.B. Unklesbay (1991). The use of local spectral properties of leaves as an aid for identifying weed seedlings in digital images. Trans ASAE, Vol. 34, No.2, pp. 682-687.

18. Goodrum, J.W. and R.T. Elster (1992). Machine vision for crack detection in rotating eggs. Trans ASAE, Vol. 35, No. 4, pp. 1323-1328.

19. Gunasekaran, S., T.M. Cooper, A.G. Berlage (1988). Evaluating quality factors of corn and soybeans using a computer vision system. Trans ASAE, Vol. 31, No.4, pp. 1264-1271.

20. Gunasekaran, S., T.M. Cooper, A.G. Berlage and P. Krishnan (1967). Image processing for stress cracks in corn kernels. Trans ASAE, Vol. 30, No.1, pp. 266-271.

21. Hatsopoulus, N.G. and W.H. Warren Jr. (1991). Visual navigation with a neural network. Neural Networks, Vol.4, No.3, pp. 303-317.

22. IBPGR-IRRI Rice Advisory Committee (1960). Descriptors for Rice Oryza sativa L. An IRRI bulletin.

23. Jones, P.T., S.A. Shearer and R.S. Gates (1991). Edge extraction algorithm for feather sexing poultry chicks. Trans ASAE, Vol. 34, No.2, pp. 635-640.

24. Klinger A., K.S.Fu, T.L. Kunii (1977). Data Structure, Computer Graphics, and Pattern Recognition. Academic Press, New York, USA.

25. Liao, K.M., M.R. Paulsen, J.F. Reid, B.C.Ni, and E.P. Bonifacio-Maghirang (1993). Corn kernel breakage classification by machine vision using a neural network classifier. Trans ASAE, Vol. 36, No.6, pp.1949-1953.

26. Liao, K.R.P. Cavaliere and M.J. Pitts (1990). Hausdorff dimensional analysis and digital imaging based quality inspection. Trans ASAE, Vol. 33, No.1, pp.298-303.

27. Ling, P.P. and S.W. Searcy (1991). Feature extraction for machine-vision based shrimp deheader. Trans ASAE, Vol. 34, No.6, pp. 2631-2636.

28. Mackworth, A.K. (1977). Vision research strategy: black magic, methaphor, mechanisms, miniworlds and maps. Workshops on computer vision systems. University of Massachusetts, Amherst. Computer vision systems, pp.53-59.

29. McClure, W.F. (1983). Agricultural robotics in Japan: A challenge for U.S. agricultural engineers, in Robotics and intelligent machines in agriculture. Proceedings of the First International Conference on Robotics and Intelligent Machines in Agriculture. October 2-4, 1983, Curtis Hixon Convention Center, Tampa, Florida ASAE Publication 4-84, pp. 76-83.

30. McDonald, T. and Y.R. Chen (1990). Application of morphological image processing in agriculture. Trans ASAE, Vol. 33, No.4, pp.1345-1361.

31. Miller, B.K. and M.J. Delwiche (1989). A color vision system for peach grading. Trans ASAE, Vol. 32, No.4, pp.1484-1490.

32. Miller, B.K. and M.J. Delwiche (1991). Peach defect detection with machine vision. Trans ASAE, Vol. 34, No.6, pp. 2588-2597.

33. Made Oka A., D.S. Damardjati, S.S. Tabor (1989). Socio-economic evaluation of rough and milled rice quality assessment at commercial mills level in West Java, in Grain Postharvest Research and Development: Priorities for the nineties . Proceedings of the Twelfth ASEAN Seminar on Grain Postharvest Technology. ed. by J.O. Naewbanij.ASEAN Grain Postharvest Programme.Bangkok, Thailand, pp. 177-189.

34. Naugle, J.A., G.E. Rehkugler and J.A. Throop (1989). Grapevine cordon following using digital image processing. Trans ASAE, Vol. 32, No.1, pp.309-315.

35. Paulsen, M.R., W.D. Wigger. J.B. Litchfield and J.B. Sinclair (1989). Computer image analyses for detection of maize and soybean kernel quality factors, Journal of Agricultural Engineering Research, pp.4393-101.

36. Pitts, M.J. and G.M. Hyde (1992). Algorithms for determining shape of tuber and seed piece. Trans ASAE, Vol. 30, No.2, pp. 566-570.

37. Qui, W.and S.A. Shearer (1992). Maturity assessment of broccoli using the discrete fourier transform. Trans ASAE, Vol. 35, No.6, pp. 2057-2062.

38. Rehkugler, G.E. and J.A. Throop (1989). Image processing algorithm for apple defect detection. Trans ASAE, Vol. 32, No.1, pp. 267-272.

39. Reid, J.F. and S.W. Searcy (1988). An algorithm for separating guidance information from row crop images. Trans ASAE, Vol.31, No.6, pp.1624-1632.

40. Reid, J.F., A.C. Hansen and C.E. Goering (1989). Quantifying diesel injector coking with computer vision. Trans ASAE, Vol.32, No.5, pp.1503-1506.

41. Rigney, M.P. and G.A. Kranzler (1988). Machine vision for grading southern pine seedlings. Trans (ASAE), Vol.31, No.2, pp. 642

42. Rigney, M.P. and G.H. Brusewitz (1992). Asparagus shape features for quality assessment. Trans ASAE, Vol.35, No.5, pp. 1607-1613.

43. Rigney, M.P., G.H. Brusewitz and G.A. Krnazler (1992). Asparagus defect inspection with machine vision. Trans ASAE, Vol.35, No.6, pp.1873-1878.

44. Rosenfeld, A..A.C. Kalk (1976). Digital Picture Processing. Academic Press, New York, USA 457 p.

45. Sarkar, N. and R.R. Wolfe (1985). Feature extraction techniques for sorting tomatoes by computer vision. Trans ASAE, Vol. 28, No.3, pp. 970-974.

46. Sarkar, N. and R.R. Wolfe (1985). Computer vision based system for quality separation of fresh market tomatoes. Trans ASAE, Vol. 28, No.5, pp.1714-1718.

47. Segerlind, L.J. and B. Weinberg (1973). Grain kernel identification by profile analysis. Trans ASAE, Vol.16, pp. 324-327.

48. Seginer, I., R.T. Elster, J.W. Goodrum, and M.W. Rieger (1992). Plant wilt detection by computer-vision tracking of leaf tips. Trans ASAE, Vol.35, No.5, pp. 1563-1567.

49. Shearer, S.A. and F.A. Payne (1990). Color and defect sorting of bell peppers using machine vision. Trans ASAE, Vol.33, No.6, pp. 2045-2050.

50. Shearer, S.A. and R.G. Holmes (1990). Plant identification using color co-occurrence matrices. Trans ASAE, Vol.33, No.6, pp. 2037-2044.

51. Simonton, W. and J. Pease (1990). Automatic plant feature identification on geranium cuttings using machine vision. Trans ASAE, Vol.33, No.6, pp. 2067-2073.

52. Sites, P.W. and M.J. Delwiche. 1988. Computer vision to locate fruit on a tree. Trans ASAE. Vol. 31, No.1, pp. 257-263.

53. Slaugther, D.C. and R.C. Harrell (1987). Color vision in robotic fruit harvesting. Trans ASAE, Vol.30, No.4, pp.1144-1148.

54. Smith, L.A., R.A. Schafer and R.E. Young (1985). Control algorithms for tractor-implement guidance. Trans ASAE, Vol. 28, pp. 415-419.

55. Srivastava, A.K., G.H. Nieswand, D.R. Mears and M.J. Moore (1972). Development of a computer simulation model of a theoretical asparagus processing plant. Trans ASAE, Vol.15, pp. 556-562.

56. Talsma, S., P. DeVisser, E. Dekker, V. Ransibrahmanakul and F.E. Sistler (1989). A crack detector for milled rice. Paper presented at the 1989 joint ASAE/CSEA International Summer Meeting. Quebec Municipal Convention Center, Quebec, PQ, Canada, 25-28 June 1989.

57. Tarbell K.A. and J.F. Reid (1991). A computer vision system for characterizing corn growth development. Trans ASAE Vol. 34, No.5, pp. 2245-2254.

58. Trabell, K.A. and J.F. Reid (1991). Spatial and spectral characteristics of corn leaves collected using computer vision. Trans ASAE, Vol. 34, No.5, pp. 256-2263.

59. Thai, C.N. and R.L. Shewfelt (1991). Modeling sensory color quality of tomato and peach: Neural networks and statistical regression. Trans ASAE, Vol. 34, No.3, pp. 950-955.

60. Thomas, D.L., F.J.K. daSilva and W.A. Cromer (1988). Image processing technique for plant canopy cover evaluation. Trans ASAE, Vol.31, No.2, pp. 428-434.

61. Throop, J.A., G.E. Rehkugler and B.L. Upchurch (1989). Application of computer vision for detecting watercore in apples. Trans ASAE, Vol. 32, No.6, pp. 2087-2092.

62. Tillett, R.D. (1989). A calibration system for vision-guided agricultural robots. Journal of Agricultural Engineering Research, No. 42, pp. 267-273.

63. Tillett, R.D. (1990). Vision-guided planting of dissected microplants. Journal of Agricultural Engineering Research, No.46, pp. 197-205.

64. Tojeiro, P. and F. Wheaton (1991). Oyster orientation using computer vision. Trans ASAE, Vol. 34, No.2, pp. 689-693.

65. Trooien, T.P. and D.F. Heerman (1992). Measurement and simulation of potato leaf areas using image processing. III. Measurement. Trans ASAE, Vol.35, No.5, pp. 1719-1721.

66. Trooien, T.P. and D.F. Heerman (1992). Measurement and simulation of potato leaf area using image processing. II. Model results. Trans ASAE, Vol.35, No.5, pp. 1713-1718.

67. Trooien, T.P. and D.F. Heerman (1992). Measurement and simulation of potato leaf area using image processing. I. Model Development. Trans ASAE, Vol.35, No.5, pp. 1709-1712.

68. Wolfe, R.R. and M. Swaminathan (1987). Determining orientation and shape of bell peppers by machine vision. Trans ASAE, Vol.30, No.6, pp. 1853-1856.

69. Wolfe, R.R. and W.E. Sandler (1985). An algorithm for stem detection using digital image analysis. Trans ASAE, Vol. 28, pp. 641-644.

70. Yang, Q. (1992). The potential of applying machine vision to defect detection in fruit and vegetable grading. Agricultural Engineer incorporating soil and water. Autum 1992, pp. 74-79.