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FEATURES EXTRACTION IN AGRICULTURAL PRODUCTS USING COMPUTER IMAGE PROCESSING

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ABSTRACT

The study was based on the application of image processing and machine vision technology in the extraction of some features of interest in agricultural products. It involved the development of an algorithm that used some computer programs written in the FORmular TRANslation (FORTRAN 95) programming language to carry out tests on some input data images. The input data images were obtained by digitizing the original images of some Amaranthus vegetables, cowpea seedlings and some food samples on which some fungi were found to be growing as captured by a digital camera. The results of this study carried out on the images showed that the algorithm was able to extract both the boundary of the leaves and the crop position by discriminating between the crop and the uncovered soil surface as well as the growth of the fungi on the food samples. The extracted images as produced by the programs compared favourably well with the original images as captured by the digital camera. This visual comparison showed that the approach is very promising in developing automated sorting and quality inspection techniques which can be applied to some agricultural and food products.

Keywords:*mage Processing, Machine Vision Technology, Formular Translation, Automated Sorting, Quality Inspection Techniques.*

INTRODUCTION

In the developing countries, leafy vegetables are part of the daily diets used as the soup to accompany the common and popular solid staple food. The production of these vegetables is one of the new initiatives embarked upon in empowering the youth who are encouraged to be self employed. The increased production has been found to make the markets for food products very competitive. This has made the customers' choices to be based on the quality of the products. The harvesting of these products by pruning, inspection and quality evaluation still depends largely on manual labour which has been found to be tedious, laborious, costly and highly subjective in approach (Pujari *et al.*, 2014). There is therefore, a need to explore other methods of carrying out these processes which are suitable and cost effective in these regions to ensure the success of the youth economic empowerment programme.

The potential of applying computer vision to the food industry has been recognized (Tillett, 1990). Recently, it has been gaining much research and development attention in the food industry (Sun, 2004) and it is increasingly being applied to quality inspection of a wide range of food products. A review of some of the researches and studies carried out to investigate the prospects of computer vision automation sorting systems in agricultural process operations in Nigeria was reported by Raji and Alamutu (2005). One of the useful areas identified is the automatic quality inspection of produce which helps in grading and sorting of produce according to their internal characteristics, size, texture, colour, shape and defects on agricultural products such as bruises, dark spots, dirt, cracks and so on.

The primary aim of the computer vision system is to ultimately replace the human visual decision-making process with automatic procedures. Therefore, it tries to imitate human behaviour of performance in colour, content, shape, and texture inspection (Domenico and Gary, 1994). It involves the application of image processing programs, combined with an illumination system, in connection with electrical and mechanical devices to substitute the human manipulative effort in the performance of a specific task. This also involves the provision of a mechanism in which human thinking process is simulated artificially and can help in making complicated judgments accurately, quickly and very consistently over a long period of time (Abdullah *et al.*, 2004).

Many studies have been carried out by some researchers and scientists with varying degrees of success. Some of these include classification of apples based on bruises using image processing and neural networks (Shahin *et al.,* 2002), features measurement system for grafted tomato seedlings (Yi-Chich *et al*., 2006), and prediction of mango ripeness (Federico, 2002) with a relatively high degree of accuracy. Other studied aimed at obtaining some quality parameters of tomato such as colour, colour homogeneity, defects, shape and stem detection for proper classification (Laykin *et al.,* 2002); weed discrimination from crop (Tsheko, 1998; Kavdir, 2004; Burgos-Artizzu *et al.*, 2010) estimation of crop position using template matching in rice production (Kentaro *et al.,* 2003); measuring the three dimensional locations of fruits on trees for apple harvesting in an orchard (Teruo *et al.,* 2002); judging the presence of stems of Huanghua pears using templates with different sizes (Ying *et al.,* 2003); measuring hog weights without physical contact (Wang *et al.,* 2006); detection of skin tumours on chicken carcasses (Kim *et al.,* 2004); prediction of the tenderness of cooked beef using its textural features (Jeyamkondan *et al.,* 2001); identifying pests from images captured from a paddy field using the digital values of colour, shapes and texture features (Abdul-Rashid *et al.,* 2006); detecting and quantifying tetrazolium staining in sectioned corn kernels (Xie and Paulsen, 2001); grading egg plants by inspecting the fruit colour, size, shape, bruise, disease and dark spots as well as checking the fruits position and orientation (Kondo *et al.,* 2004).

Raji (1999) also developed an algorithm for determining the area of two-dimensional objects by image analysis. This can be adapted in the detection of the leaf-type as a form of sorting to select the desired ones during harvesting and for selective weed destruction. With these advantages and benefits, this study aimed at investigating the potential of image processing and machine vision in feature extraction of objects with special reference to agricultural and food products.

MATERIALS AND METHODS

Amaranthus (green) vegetables and cowpea were raised on blocks of soil on the experimental farm of the Department of Agricultural and Environmental Engineering, University of Ibadan, Nigeria. Coloured images of the plants were taken and captured using a 5 Megapixel TEKXON digital camera (TX 410) with optical zoom lens (5x).

These images were obtained on a daily basis as the crops grew within a space of two weeks. A wooden framework to hold the camera was constructed over the plot such that the digital camera was always at a constant height (of about 1.2 m above the surface of the soil on which the vegetables were planted) and at the same position, such that the camera was kept on the same spot throughout the experiment. Snapshots of the vegetables were taken on a daily basis from this specified spot as they continued growing. The framework on which the camera was mounted during the period of image acquisition and the camera slot are as shown in Plates 1 and 2. Images of growing cowpea seedlings and fungi growth on some food samples were also obtained for analysis.

Plate 1: The framework for holding the camera

Plate 2: The camera slot.

The relatively high resolution of the camera helped to prevent loss in the image quality that could have been experienced if scanned photographic images were used. This also helped to minimize the effect of noise, which refers to the unwanted features existing in form of data that appear in an image to mask the features of interest.
The acquired images were transferred to a personal computer (PC) system and converted to digitised-picture format portable pixel map (*.ppm) format using Paintshop Pro 7.02. The ppm files were opened and read as digits with the gray scale values of each pixels in a text readable application and used as input into the programs or opened and read as images in graphic applications. Digitization involved the conversion of images to the digital form, that is, the numerals that could be used for carrying out further processing on the images.
The Eight-Connectivity or Star Method of Edge Detection was used for the boundary detection for the images. It involved the consideration of all the eight neighbouring pixels of the particular pixel tested for an edge pixel. Assuming that P(i, j) is the pixel being tested, we have the pixels of the neighbouring pixels as arranged in Figure 1.

i-j, j-1	i-j, j	i-1, j+1
i, j-1	**i, j**	i, j+1
i+1, j-1	i+1, j	i+1, j+1

Figure 1: Arrangement of the eight neighbouring pixels for star method

It follows that the pixel at (i, j) i.e. P(i, j) is an edge pixel on the object to be detected if at least one of the neighbouring pixels is not a background or is not a portion within the object whose edges are to be detected. This condition was capable of picking all the objects within an image no matter how small the object was. This condition was represented as:

$$P(i, j) = \text{edge pixel if} \quad \left[\begin{array}{l} \{ (P(i-1, j-1) \text{ or } P(i-1, j) \text{ or } P(i-1, j+1) \text{ or } P(i, j-1) \text{ or} \\ P(i, j+1) \text{ or } P(i+1, j-1) \text{ or } P(i+1, j) \text{ or } P(i+1, j+1) \} \\ \neq \text{background pixel} \end{array} \right.$$

This method produced good edges since it considered all the eight neighbouring pixels that are closest to the pixel being tested with a subsequent reduction in the effect of noise.
Some programs were written in the FORmula TRANslation (FORTRAN 95) programming language using the principle of eight-connectivity or star method of edge detection as described. The equations or relationships developed between the particular pixel being tested and all the eight surrounding or neighbouring pixels were utilized by the computer programs developed. The two programs were used to extract the images of the leaves (of the Amaranthus vegetables and the cowpea seedlings) as solid objects, thereby differentiating them from the surrounding or the background (which in this case was the uncovered area of the soil) as well as the extraction of the boundary or the edges of the leaves. Meanwhile, the overlapping of the leaves was not put into consideration. These programs were also used to detect and extract fungi as they grew on some food samples.
Microsoft Excel was firstly employed in importing data from the output files of the programs and then plotting the pixel coordinates. This method is usually referred to as post-processing since it involved saving the output from the programs in output files and then plotting the pixel coordinates after the programs have been executed and run completely. This worked well for images of small sizes but it was found to be unsuitable for plotting the coordinates of images that were larger in size. This was due to the limitation of Microsoft Excel package in terms of the capacity of data that can be plotted at a time. This limitation led to the use of Fortran Online graphics package in plotting the pixel points. This helped to plot the pixel coordinates directly as they resulted from the

program tests, one by one, without necessarily saving unto a file. This reduced the quantity of data that were to be handled per time and thereby, helped in saving computer memory space.

RESULTS AND DISCUSSION

The results of the tests carried out to determine the adequacy of the developed algorithm to extract the boundaries and solid forms of the objects were obtained from the study. The original images as captured by the digital camera were presented with the respective figures showing the extracted solid form of the images and that of the extracted boundary or edges for the basis of comparison. The changes in the area covered by the leaves with respect to the total area of the soil surface were also determined.

Cowpea seedlings

The original captured images of the cowpea seedlings are presented in Plate 3 while the images extracted by the program tests as solid objects and the extracted boundary of the leaves are as shown in Figures 2 and 3. The images of the cowpea seedlings produced by image processing compared favourably well with the original images as captured by the camera.

The green portions represent the position of the crops while the background was represented with the grey colour in the figures showing the solid form of the leaves. Since the seedlings do not have too many flaps that are lying over another, it was very easy to differentiate between the area of soil covered by the crops and the portions left uncovered. The figures showing the extracted boundary of the leaves also compared well with the original images. The only limitation was that the program did not take the overlapping of the leaves into consideration.

With the possibility of obtaining the area covered by the leaves from the pixel analysis, the variations in the leaf area index (LAI) were plotted against the number of days as shown in Figure 4. The leaf area index was calculated as the ratio of the area covered by the leaf to the total area of the plot. This is an indication of the vegetative cover which is useful in determining soil-water evaporative factor, risk of weed survival and planning of weedicide and fertilizer application. This showed that the LAI of the cowpea seedlings increased with time as the crops continued to grow since the area covered by the crops continued to increase with an equivalent decrease in the area of soil left uncovered. The rate of increase of the leaf area index as the crops continued to grow was high initially but as the number of days increased, the growth rate decreased. This clearly indicated that the growth rate of cowpea decreased as the plant approached maturity. This reduction in the growth rate with the number of days can therefore, be used to predict the growth stage of the crops under similar soil and environmental conditions.

Plate 3: Original images of the cowpea seedlings on days 10 and 14 of image acquisition

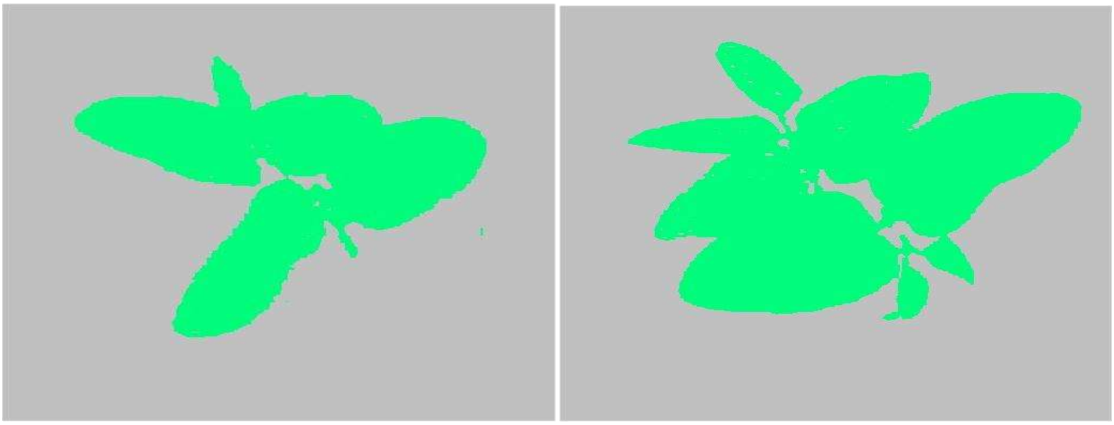


Figure 2: Solid forms extracted by image processing

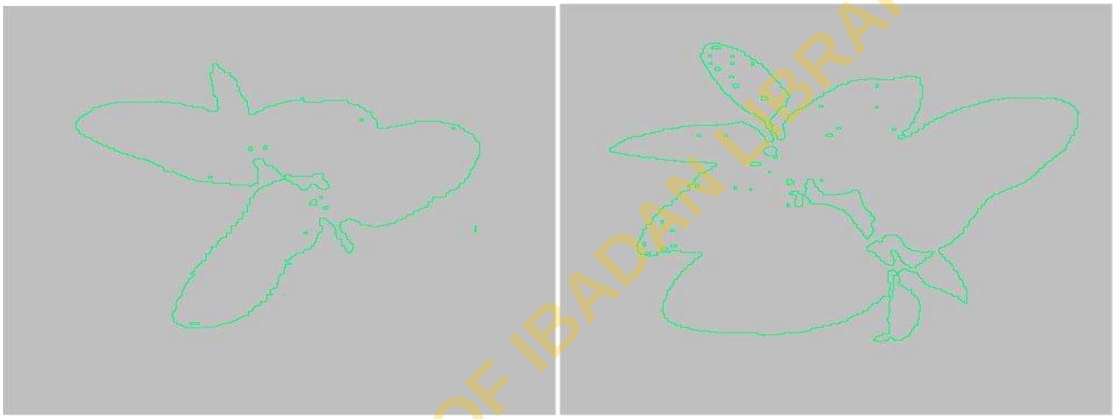


Figure 3: The extracted boundary of the cowpea leaves

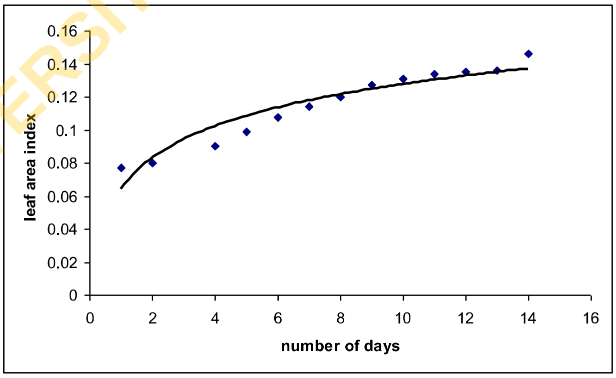


Figure 4: Leaf area index of cowpea

Amaranthus vegetables

Original images of the Amaranthus vegetables as captured by the digital image are presented in Plate 4 while the images as extracted by the programs are presented in Figures 5 and 6. The images of the vegetables extracted by the programs as solid objects (Figure 5) and the extracted boundary of the leaves (Figure 6) compared well with the original images but the major limitation is that there was excessive overlapping of the leaves which could not be detected by the program. Further studies to consider the overlapping boundaries are thereby recommended.

Plate 4: Original images of the vegetables for day 14 and 16 of image acquisition

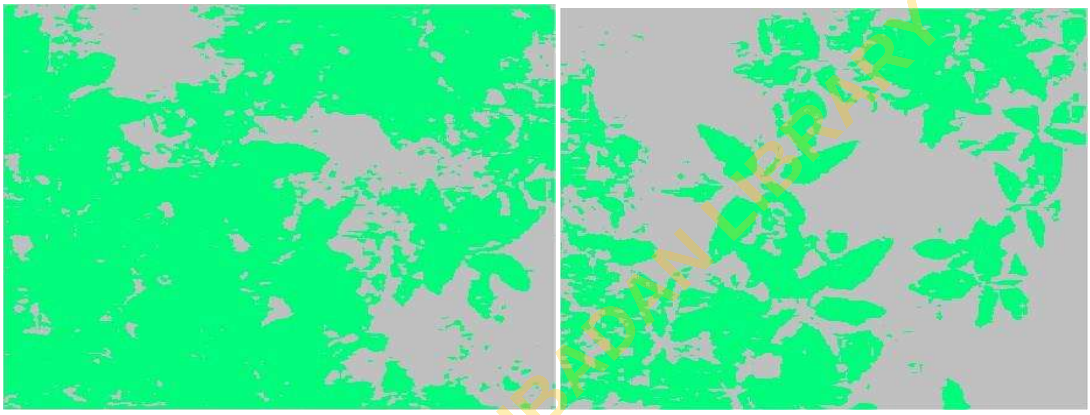


Figure 5: Extracted solid form

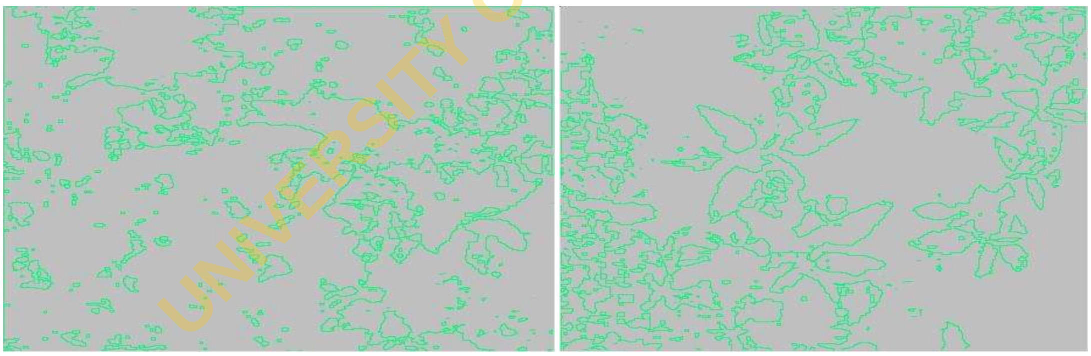
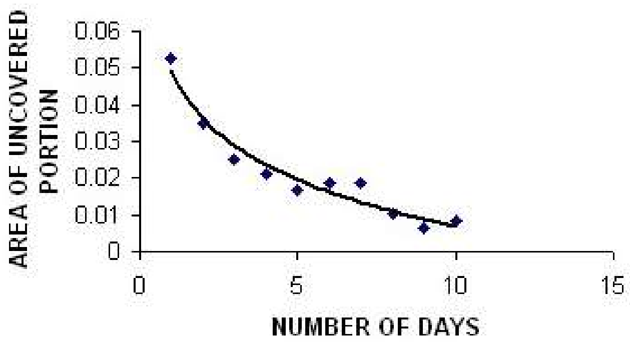


Figure 6: Extracted boundary of Amaranthus leaves

Variations in the area of uncovered soil surface and LAI as the crops continued growing are presented in Figures 7 and 8 respectively. The ratio of the uncovered portion to the total area of land continued to reduce while the LAI continued to increase. The rate of decrease of the uncovered portion of the land as the crops continued to grow was high initially but as the number of days increased, the rate was found to be reducing. This was also due to the reduction in the rate of crop growth which was very high at the early stage of the crop growth resulting in greater coverage of the soil surface.

The extraction of the crop positions and the discrimination between the leaves of the seedlings and the background or the uncovered portions of the soil can be used to predict the growth stage of the crops.



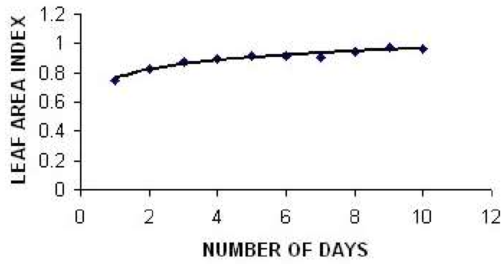


Figure 7: Area of uncovered soil

Figure 8: Leaf area index

Fungi Growth

The programs were also used to detect and extract some fungi as they were found growing on some food samples. The original images of the fungi on the food samples are as shown in Plate 5 while the extracted images of the fungi growth are presented in Figures 9. The program was able to detect and extract the location of the fungi practically well and the results from such extraction could be of use in determining the growth rate of the fungi species and the level of deterioration of the food samples under specified conditions can be known. This was only used to confirm the flexibility of the program for other products other than leaves.

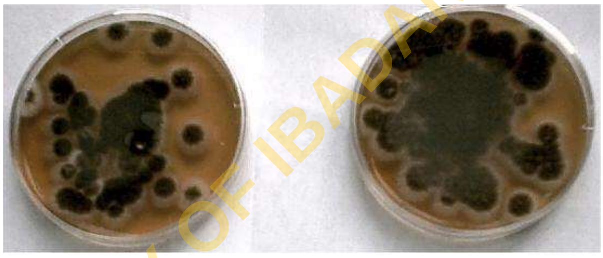


Plate 5: Original images of fungi growing on some food samples

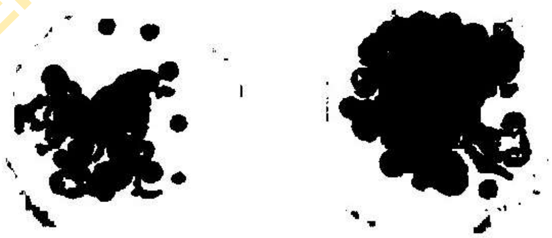


Figure 9: Image of the fungi as extracted by image processing

It is very obvious that the programs worked well in extracting the boundary of the leaves as well as their location as demonstrated by the results produced through image processing. There was virtually no noise level contained or noticed in the analyzed images due to the high resolution of the camera used. The approach employed in this study is very promising in developing a technique that can detect and extract features of interest from agricultural and food products. It could also be used to automate sorting by detecting spread of deterioration in the products being tested.

CONCLUSION

This study presents an algorithm for extracting the features that are of particular interest on agricultural and food products using the principle of computer image processing.

From the results obtained, it can be deduced that:

- The eight-connectivity or star method, which involves the consideration of all the eight surrounding or neighbouring pixels of the particular pixel being tested, is a promising approach;
- The image capturing device, the digital camera with high resolution, helped to maintain the quality of the images generated as compared to the original images of the crops and the fungi on the food samples, and this enhanced better extraction of the features;
- The algorithm is applicable in determining the area index in agricultural production and processes such as LAI, the tree density in a forest using aerial photographs, spread of deterioration in processed products and automatic detection of plant leaf diseases.
- The approach is very promising in developing automated sorting and quality inspection techniques which can be applied to some agricultural and food products.

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