

1-1-2014

A survey of image processing techniques for agriculture

Lalit Saxena

Leisa Armstrong
Edith Cowan University

Follow this and additional works at: <https://ro.ecu.edu.au/ecuworkspost2013>



Part of the [Agricultural Science Commons](#), and the [Computer Sciences Commons](#)

Saxena, L., & Armstrong, L. (2014). A survey of image processing techniques for agriculture. Proceedings of Asian Federation for Information Technology in Agriculture. (pp. 401-413). Perth, W.A. Australian Society of Information and Communication Technologies in Agriculture. Available [here](#)

This Conference Proceeding is posted at Research Online.

<https://ro.ecu.edu.au/ecuworkspost2013/854>

A survey of image processing techniques for agriculture

Lalit P. Saxena¹ and **Leisa J. Armstrong**²

¹Department of Computer Science, University of Mumbai, Mumbai, India
lasaxmail@aol.com

²School of Computer and Security Science, Edith Cowan University, Perth, Australia,
l.armstrong@ecu.edu.au

Abstract

Computer technologies have been shown to improve agricultural productivity in a number of ways. One technique which is emerging as a useful tool is image processing. This paper presents a short survey on using image processing techniques to assist researchers and farmers to improve agricultural practices. Image processing has been used to assist with precision agriculture practices, weed and herbicide technologies, monitoring plant growth and plant nutrition management. This paper highlights the future potential for image processing for different agricultural industry contexts.

Keywords: Precision agriculture, image processing, farming practices, computer-vision applications

Introduction

With the continued demand for food with an increasing population, reductions in arable land, climate change and political instability, the agriculture industry continues to search for new ways to improve productivity and sustainability. This has resulted in researchers from multiple disciplines searching for ways to incorporate new technologies and precision into the agronomic systems. There is a need for efficient and precise techniques of farming, enabling farmers to put minimal inputs for high production. Precision agriculture is one of such techniques that is helping farmers in meeting both the above needs, Mulla (2013). It can assist in improving the farming practices by using information technology tools, which enables farmers to observe, assess and control farming practices, such as adequate fertilizers, pesticides and water usage, Aubert et al. (2012). It also provides region specific information to the farmers about the resources in controlling soil and environment parameters. In addition, using satellite imagery and geospatial tools in farming practices adds as a segment to precision agriculture.

Precision agriculture can assist farmers in decision making about seed selection, crop production, disease monitoring, weed control, pesticides and fertilizers usage. It analyzes and controls farmers' requirements using location specific information data and imagery techniques, Schellberg et al. (2008). In many parts of the world, mainly in the rural areas this kind of data is inaccessible, and the cost of procurement of these techniques is also not affordable by the farmers, Mondal and Basu (2009). The trends towards precision farming techniques are reliant on location specific data including the taking of multiple image databases. The use of image

processing techniques is one way that these data sets can be used to assist by providing high-resolution pictures to be used for decision-making.

Image Processing in Agricultural Context

Image processing techniques can be used to enhance agricultural practices, by improving accuracy and consistency of processes while reducing farmers' manual monitoring. Often, it offers flexibility and effectively substitutes the farmers' visual decision making. Table 1 summarises some of the image processing terminologies applicable in agricultural practices.

Table 1 some of the image processing terminology applicable in agriculture [Sankaran et al. (2010), Du and Sun (2004), Chen et al. (2002), Gonzalez and Woods (2002)].

Image processing term	Meaning
Image acquisition	Process of retrieving of a digital image from a physical source capture an image using sensors
Gray scale conversion	Process of converting a color or multi-channel digital image to a single channel where image pixel possess a single intensity value
Image background extraction	Separation of image background, retrieving foreground objects
Image enhancement	Improvement in perception of image details for human and machine analysis
Image histogram analysis	Pixel plot analysis in terms of peaks and valleys formed by pixel frequency vs pixel intensities
Binary image segmentation	Foreground objects separation from background in a binary (black-and-white) image
Color image segmentation	Image objects separation in a color image, regions of interests
Image filtering	Process of distorting an image in a desired way using a filter
Feature extraction	Process of defining a set of features, or image characteristics that efficiently or meaningfully represent the information important for analysis and classification
Image registration	Process of transforming different sets of data into one coordinate system
Image transition	Process of changing state or defining a condition between two or more images
Image object detection	Process of finding instances of real-world objects such as weeds, plants, and insects in images or video sequences
Image object analysis	Process extracting reliable and meaningful information from images

This paper presents recent advancements of using computer-vision based applications in the field of agriculture. A computer-vision application using image processing techniques involves five basic processes such as image acquisition, preprocessing, segmentation, object detection and classification. This survey highlights these approaches in context of agricultural practices and summarises their relevancy to precision farming. Table 2 summarises research that has been reported on applications developed using image processing techniques and provides an assessment of techniques used and the applicability and practical usability in an agricultural context.

Table 2 Applications/ models/ systems developed using image processing techniques and remarks over its accuracy and usability.

References	Application/ Model/ System	Developed for/ Applied over	Accuracy and Remarks
Chikushi et al. (1990)	SPIDER software	Cucumber root length measurement	98% correctness, analysis and study of plant root system
Yang et al. (2000)	Fuzzy logic decision making system for precision farming	Weeds coverage detection and recognition	15–64% reduction in herbicides usage, IT tools usage in future
Chen et al. (2002)	Machine vision technology and applications	Detecting diseases, defects on poultry carcasses and apples	Focus on Hyperspectral imaging systems
Du and Sun (2004)	Five steps image processing chain	Food quality evaluation	Stress on using cost-effective, multipurpose image processing systems
Erives and Fitzgerald (2005)	Portable Hyperspectral Tunable Imaging System (PHyTIS)	Recover scaling, rotation, and translation hyperspectral images	Induces image registration, enhances precision farming applications
Puchalski et al. (2008)	Combination of image processing techniques	Apple defects detection	96% classification correctness in detecting bruises, frost damage, and scab
Schellberg et al. (2008)	Review on precision agriculture applications	Grassland	Image processing, remote sensing, yield and site-specific management
Tellaeché et al. (2008)	Image segmentation and decision-making	Eliminating <i>Avena sterilis</i> , a weed growing in cereal crops	Strategy for selective spraying of herbicides
Artizzu et al. (2009)	Case-Based Reasoning (CBR) system	Differentiating weeds, crop and soil in outdoor field images	80% using correlation coefficients, for different fields and its conditions
Jin et al. (2009)	Adaptive and fixed intensity interception and Otsu segmentation	Yellow-skin potatoes defects detection	92.1% classification, 91.4% recognition and 100% inspection
Mondal and Basu (2009)	Adoption of precision agriculture technologies	India and other developing nations	Using medium and low-tech PA tools, chlorophyll meter and leaf color chart
Terasawa et al. (2009)	Graphical software for image correction and analysis	Observing plant growth status	Using remote sensing technology, enhanced color difference measurements
Weis and Gerhards (2009)	Image processing describing shape features	Detecting weed densities and species variations	Bi-spectral images got good separation between plants and background
Yaju and Zhenjiang (2009)	Computer-vision system	Monitoring plant growth	0.665< Nitrogen content (chlorophyll) of leaves using red, green standard deviation
Artizzu et al. (2010)	Computer-vision-based methods	Vegetation segmentation, crop row elimination and weed extraction	Correlation 84% bio-mass, 96% cereal and 84% maize images, low complexity
Beers et al. (2010)	Image visualisation techniques	Agricultural image transition towards sustainable development	Focus on transition management and strategic niche management
Ehsanirad and Kumar (2010)	Gray-Level Co-occurrence matrix and Principal Component Analysis	390 leaves, 13 kinds of plants, 65 new or deformed leaves images	78.46% GLCM, less computation time and fast recognition, 98.46% PCA
Guijarro et al. (2011)	Autonomous robot navigation imaging, supervised fuzzy clustering, thresholding	Identification of green plants, barley, corn, cereal, weed textures	Verifying viability for crops like wheat or rye, less computation time in future
Li et al. (2011)	Fisher linear discriminate analysis, cold	Citrus fruit images	Non-removal of white noise, time and

	mirror acquisition system, segmentation		segmentation accuracy issues remaining
Aubert et al. (2012)	IT based tools for Precision agriculture	Monitoring soil and crop conditions and analyze treatment options	Emphasize farmers' expertise, provides theoretical and empirical basis for PA
Cope et al. (2012)	Review on computational, morphometric and image processing methods	Analyzing shapes of leaves, petals and whole plants images	Consider small number of classes, less features, web-based herbal encyclopedia
Reis et al. (2012)	Grape recognition system	Detection of bunches of white and red grapes in color images	97% red, 91% white grapes classification, focus on finding cheaper alternatives
Sansao et al. (2012)	Excess green index images using Gabor filters	Determining weed coverage percentage	Monitoring weed growth, control over herbicides usage
Silva et al. (2012)	Image processing using LabView software	Determination of weed coverage percentage	Color camera suitably calculate weed coverage in tillage and no-tillage systems
Guerrero et al. (2013)	An automatic expert system	Crop row detection in maize fields	Considering high weed pressure and a great number of weed patches in future
Mizushima and Lu (2013)	Image segmentation using Otsu's method and support vector machine	Apple sorting and grading	Segmentation error 3% to 25% for fixed SVM, 2% for adjustable SVM
Montalvo et al. (2013)	An automatic expert system based on image segmentation procedures	Weeds/crops identification in maize fields	Loss of greenness analysis, adding automatic thresholding methods in future
Mulla (2013)	Review of 25 years remote sensing in precision agriculture	Near real time soil, crop and pest management	Emphasis on hyperspectral sensing systems, spectral indices, data archives
Pastrana and Rath (2013)	Image processing algorithms for leaf detection	Identification of individual plantlets under overlapping situations	Rely on shape constraints, reported error of faulty plant detections
Romeo et al. (2013)	An automatic and robust expert system	Greenness identification in agricultural images	Tested in maize and barley fields, extension to soil materials analysis
Wu et al. (2013)	Image processing and segmentation using Otsu's method	Automatic foreign fiber inspection in cotton products	Results in accurate and speedy segmentation, faster methods in future
Kelman and Linker (2014)	Apple detection algorithm	Detecting mature apples in tree Images	40% non-convex apple profiles, 85% apple edges had 15% non-convex profiles

Gray scale conversion

After image acquisition, pre-processing of the images involves gray scale conversion, Eerens et al. (2014) and Jayas et al. (2000). Du and Sun (2004) highlights gray scale conversion as an intermediate step in food quality evaluation models. They reported various applications evaluating food items like fruits, fishery, grains, meat, vegetables and others the use of image processing techniques applicable to different areas of food quality assessments. Other work by Wu et al. (2013) reported on the use of gray level determination of foreign fibers in cotton product images that enhanced background separation and segmentation. Jayas et al. (2000) also demonstrated the image analysis techniques using neural networks for classification of the agricultural products. This study reported that the multi-layer neural network classifiers are the best in performing categorization of agricultural products.

Image background extraction

In applications, where the background is of minimal use, it is preferable to extract it from the images. Such images having regions of interests—solid objects—in dissimilar background are easily extractable. This results in non-uniform gray levels distribution between objects of interests and the image background, Eerens et al. (2014) and Jayas et al. (2000). Following this understanding, Du and Sun (2004) report various applications where background is not taken into consideration while evaluating the food products quality including pizza, corn germplasm and cob, etc. Similarly, Wu et al. (2013) extracted background of the foreign fiber images detected in cotton products. This aids in the clear detection of foreign fibers which were difficult to trace out. A survey on advanced techniques by Sankaran et al. (2010) highlight the use of fluorescence spectroscopy and imaging, visible and infrared spectroscopy, hyperspectral imaging in detecting plant diseases and on future enhancements, which could focus on the metabolic activities of the plants and trees releasing volatile organic compounds.

Image enhancement

Image enhancement is an image processing technique applied to images to reduce problems of poor contrast or noise (Chen et al. 2002). There are several operations that comprise image enhancement procedures like morphological operations, filters, and pixel-to-pixel operations, used to minimize irregularities in the images caused by inadequate and/or non-uniform illumination. This is the basis of several machine vision applications which have been used for agricultural domain are discussed in studies by Chen et al. (2002), Eerens et al. (2014) and Jayas et al. (2000). The algorithm developed by Wu et al. (2013) uses a three-piece linear transform model for the images enhancement. The model enhances image features that made improvement in the contrast ratio of the enhanced image. Thus, enhances the foreign fiber images making it easy for further image processing implementations.

Image histogram analysis

The use of image histogram can reflect the direct effect caused by the illumination where the contrast is a feature for greenness identification as reported by Romeo et al. (2013). They designed a system based on histogram analysis of images with decision-making module determining sufficient greenness. Other work on yellow-skin potato defect detection was presented by Jin et al. (2009) which observed that the majority of defects lies through dark or black spots with low proportion and no significant peak in gray level histogram, see Figure 1. In continuing image enhancement procedure, Wu et al. (2013) analyzed image histogram and noticed the gray rate in the enhanced image. This helped in deriving appropriate enhancement algorithm for foreign fiber detection in cotton products.

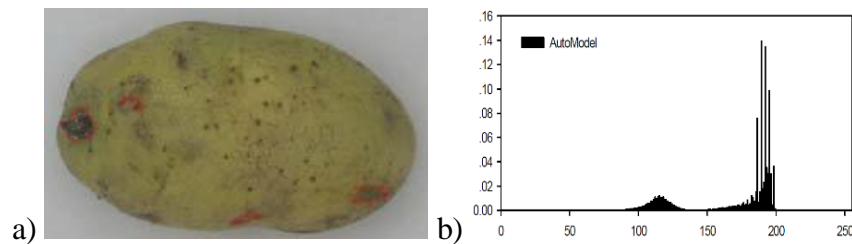


Fig.1 The results Jin et al. (2009) with labeled defects and the corresponding histogram.

Binary image segmentation

Du and Sun (2004) evaluated several food quality assessment methods separating defects and infirmities in the food products using image segmentation. They reported the effectiveness of various segmentation algorithms applied for apple defects detection, pizza sauce separation and detecting touching pistachio nuts. An image processing system developed by Puchalski et al. (2008) detected defects on the apple surfaces, see Figure 2. This system reported an accuracy of 96% in detecting bruises, frost damages, and scabs from the combination of the images. In addition other work by Mizushima and Lu (2013) proposed an image segmentation method using Otsu's method for apples defects detection and support vector machine for apples grading and sorting.

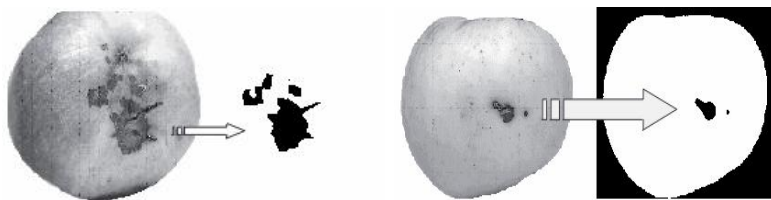


Fig.2 Examples of processed image on apples by Puchalski et al. (2008).

Using binary image segmentation separating weeds from crops proposed by Tellaecche et al. (2008) was used for farmer decision-making for herbicide management in weed affected areas. An automatic expert system proposed by Montalvo et al. (2013) identified weeds and crops, and Guerrero et al. (2013) study was able to identify crop rows, in images from maize fields using

image segmentation. Rainfall effects and dead weeds are the reported issues that may have caused inefficient segmentation in weeds and crops.

Color image segmentation

A study by Li et al. (2011) used image data for citrus fruit separation based on color image segmentation. The methods were found to be effective but were unable to suppress white noise in the image data. Observations performed by Terasawa et al. (2009) consider the proficiency of the imaging systems in monitoring plants growth. Such a monitoring would have following advantages, knowing crop state and growth rate, predicting harvesting time and quantity, diseases discovery, and overall quality evaluation. Other work by Yaju and Zhenjiang (2009) developed an application monitoring plant growth based on computer-vision technique use the young plants' growing leaves images. While Artizzu et al. (2009) developed a system based on computer-based image analysis determining proportions of crops, weeds and soil in the image (see Figure 3). This system considered varying light, soil background texture and crop damage conditions including crop growth stage and size of weeds as hindrances in processing of the images.

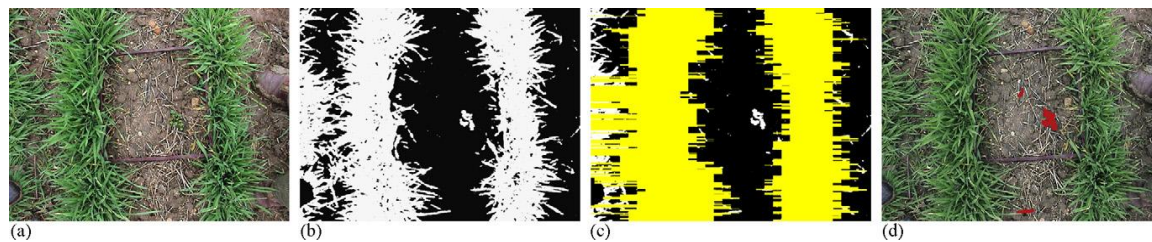


Fig.3 Image processing by Artizzu et al. (2009): (a) input image, (b) segmented image, (c) image after crop row elimination, and (d) final image after the filtering step and weed identification.

Image filtering

Using Gabor filter is a unique approach proposed by Sansao et al. (2012) to assess weed coverage percentage in images. This approach used excess green index images for filtering crops regions to assess patches of weeds. An automatic image segmentation algorithm developed by Guijarro et al. (2011) used to separate barley, cereal and corn crops including weeds from the soil, provided in Figure 4. They suggested possible future improvements in the effectiveness of the method by using homomorphism filtering.

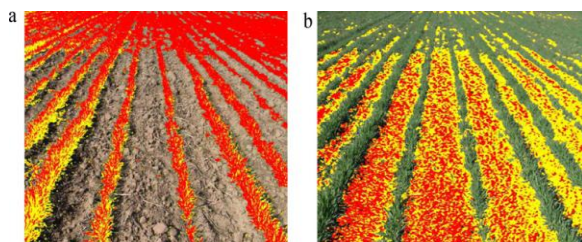


Fig.4 Classification results by Guijarro et al. (2011): (a) two different classes of green plants; (b) two different classes in the soil.

Feature extraction

An attempt to detect weeds using image segmentation from images has been reported by Weis and Gerhards (2009). The weeds classification was based on shape features and perfectly classified weeds into weeds classes. It was reported that results obtained were better than manual weed sampling. The textural features, namely, gray level co-occurrence matrix needs gray levels in an image, were reported by Ehsanirad and Kumar (2010) who extracted these features for leaf recognition for plant classification. Other work by Jayas et al. (2000) studied morphological, Fourier descriptors, wavelet transforms, boundary chain codes, spatial moments, color and textural features in the images and extraction techniques. This study further discussed features classification techniques, including nearest neighbor classifier, neural networks, and multi-layer neural network.

Image registration

Erives and Fitzgerald (2005) developed a portable hyperspectral tunable imaging system (PHyTIS) to recover scaling, rotation, and translation in airborne hyperspectral images. The system collects images for image-to-image co-registration to match the band-to-band pixel locations using phase correlation method. The method is computationally efficient in registering images with large or small displacements. The proposed future enhancements include sub-pixel registration accuracy and ground controlled georegistration. Other research by Zhang et al. (2003) used hyperspectral remote sensing in detecting late blight disease in tomatoes. This work employed an airborne visible infrared imaging spectrometer system to capture images of the diseased tomatoes for the experimentation. The system precisely detected the diseases and assisted in the diseases classification and identification.

Image transition

A case study done by Beers et al. (2010) explored TransForum, a large-scale innovation programme transitioning Dutch agriculture. Image visualization techniques are used to monitor and manage images reducing transition complexities and raising future potentials. The objective of the study considered agricultural image transition towards sustainable development focusing on transition management and strategic niche management.

Image object detection

Artizzu et al. (2010) developed a system detecting and extracting soil, crops and weeds regions as image objects using computer-vision-based methods. The system obtained 84%, 96% and 84% correlation for bio-mass, winter cereal images and maize images respectively, and proposed to reduce computational complexity in future developments. Other research by Silva et al. (2012) proposed an algorithm differentiating plants and weeds coverage in color images based on digital image processing. The study evaluated the performance of the algorithm considering both color and near infrared images of the common bean crop.

A grapes recognition system proposed by Reis et al. (2012) detects bunches of red and white grapes in color images taken in natural environment with an accuracy of 97% and 91% correct

classifications, respectively. The system uses color mapping, morphological dilation, stem and black areas detection, as inbuilt image processing techniques.

Another study by Cope et al. (2012) reviewed various computational, morphometric and image processing methods analyzing images of plants measuring leaf outlines, flower shape, vein structures and leaf textures. They proposed a robust automated species identification system which could enable people in botanical training and working expertise. The study suggested that by having a small number of classes and restricted set of features improvements could be made in the efficiency of the system.

Image object analysis

The shape and color analysis of the mature apples detection in tree images proposed by Kelman and Linker (2014) was based on 3D convexity analysis. This procedure deals with the analysis of three-dimensional convex objects, the Golden Delicious apple variety orchard under natural light conditions. The procedure obtained 94% correctness in apples detection when the edges were identified using Canny filter. Pastrana and Rath (2013) presented a novel approach in segmenting plantlets suffering with the problem of occlusion, testing with plants having 2, 3 and 4 leaves. The method solved leaf complexities by ellipse approximation and found leaves clusters using active shape models.

Other studies by Yang et al. (2000) integrated a system using digital camera and a personal computer in precising decision-making in using herbicides in agricultural fields. The system process the color images of the agricultural fields affected by weeds and suggest the amount of herbicides to be sprayed. The efficiency of the system is the prediction in the reduction of herbicide use (for a case it obtained 15–64% reduction, see Figure 5).

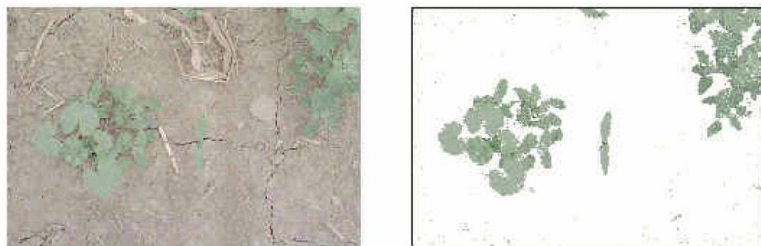


Fig.5 15.61% of the greenness ratio determined by Yang et al. (2000)

Other methods have been proposed measure cucumber root systems by Chikushi et al. (1990). This system obtained 98% accuracy in root length measurement, with advantages like, there is no effect of randomness and direction of root images, and the system does not need any additional tool.

Discussion

The review of research papers on the use of image processing techniques, in particular, segmentation showed that these techniques can be useful to assist agricultural scientists. A number of examples were provided of the uses for both research and delivery of information to

farmers and other stakeholders. The deep approach which is a subcategory of machine learning, dealing with the use of neural networks to improve applications in computer vision, automatic speech recognition and natural language processing, Bengio (2009) is emerging as the preferred approach. The review found that crop identification, disease detection, image segmentation/ clustering, cloud detection, practice classification, remote sensing, nutrient deficiency detection, environment classification were the common uses for the technique.

Conclusions

This paper presented a survey on using image processing techniques used in an agricultural context. Employing the processes like segmentation, feature extraction and clustering can be used to interrogate images of the crops. There is a need to select the most appropriate techniques to assist decision-making. Several examples of vision-based applications also have been reported and developed to assist the agricultural production.

The image processing techniques have been used across a vast range of agricultural production contexts. It can be effective in food quality assessment, fruit defects detection, weed/ crop classification. There are a number of applications and methods to choose from for implementation to real time needs. While the existing applications sustaining the needs of today, there are more and more new methods are evolving to assist and ease the farming practices. It is evident that these approaches will all contribute to the wider goal of optimizing global food production.

One factor, which could increase the development of image processing techniques for agriculture is the availability of online data sets. No online images databases are available on food quality assessment, fruit defects detection or weed/ crop classification. Similar to databases like handwritten or printed documents and characters, faces, there is a need of agricultural databases that will ease in the testing and verification of newly developed image processing methods.

References

- A. Ehsanirad and Y. H. S. Kumar (2010), Leaf recognition for plant classification using GLCM and PCA methods, *Oriental Journal of Computer Science & Technology*, 3 (1), pp. 31–36, 2010.
- A. Mizushima and R. Lu (2013), An image segmentation method for apple sorting and grading using support vector machine and Otsu's method, *Computers and Electronics in Agriculture*, 94, pp. 29–37, 2013.
- A. Tellaache, X. P. B. Artizzu, G. Pajares, A. Ribeiro and C. F. Quintanilla (2008), A new vision-based approach to differential spraying in precision agriculture, *Computers and Electronics in Agriculture*, 60, pp. 144–155, 2008.
- B. A. Aubert, A. Schroeder and J. Grimaudo (2012), IT as enabler of sustainable farming: An empirical analysis of farmers' adoption decision of precision agriculture technology, *Decision Support Systems*, 54, pp. 510–520, 2012.

- C. C. Yang, S. O. Prasher, J. A. Landry, J. Perret and H. S. Ramaswamy (2000), Recognition of weeds with image processing and their use with fuzzy logic for precision farming, *Canadian Agricultural Engineering*, 42 (4), pp. 195-200, 2000.
- C. J. Du and D. W. Sun (2004), Recent developments in the applications of image processing techniques for food quality evaluation, *Trends in Food Science & Technology*, 15, pp. 230–249, 2004.
- C. Puchalski, J. Gorzelany, G. Zagula and G. Brusewitz (2008), Image analysis for apple defect detection, *Biosystems and Agricultura Engineering*, 8, pp. 197–205, 2008.
- D. S. Jayas, J. Paliwal and N. S. Visen (2000), Multi-layer neural networks for image analysis of agricultural products, *J. Agric. Engng Res.*, 77 (2), pp. 119–128, 2000.
- D. J. Mulla (2013), Twenty five years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps, *Biosystems Engineering*, 114, pp. 358–371, 2013.
- E. E. Kelman and R. Linker (2014), Vision-based localisation of mature apples in tree images using convexity, *Biosystems Engineering*, 114, pp. 174–185, 2014.
- H. Eerens, D. Haesen, F. Rembold, F. Urbano, C. Tote and L. Bydekerke (2014), Image time series processing for agriculture monitoring, *Environmental Modelling & Software*, 53, pp. 154–162, 2014.
- H. Erives and G. J. Fitzgerald (2005), Automated registration of hyperspectral images for precision agriculture, *Computers and Electronics in Agriculture*, 47, pp. 103–119, 2005.
- J. C. Pastrana and T. Rath (2013), Novel image processing approach for solving the overlapping problem in agriculture, *Biosystems Engineering*, 115, pp. 106–115, 2013.
- J. Chikushi, S. Yoshida and H. Eguchi (1990), A new method for measurement of root length by image processing, *Biotronics*, 19, pp. 129–135, 1990.
- J. Jin, J. Li, G. Liao, X. Yu and L. C. C. Viray (2009), Methodology for Potatoes Defects Detection with Computer Vision. *Proceedings of the 2009 International Symposium on Information Processing (ISIP'09)*, pp. 346-351, August 2009.
- J. M. Guerrero, M. Guijarro, M. Montalvo, J. Romeo, L. Emmi, A. Ribeiro and G. Pajares (2013), Automatic expert system based on images for accuracy crop row detection in maize fields, *Expert Systems with Applications*, 40, pp. 656–664, 2013.
- J. P. H. Sansao, M. C. Silva, L. A. Mozelli, F. A. C. Pinto and D. M. Queiroz (2012), Weed Mapping Using Digital Images, *International Conference of Agricultural Engineering CIGR-AgEng2012*, July 2012.

- J. Romeo, G. Pajares, M. Montalvo, J. M. Guerrero, M. Guijarro and J. M. Cruz (2013), A new Expert System for greenness identification in agricultural images, *Expert Systems with Applications*, 40, pp. 2275–2286, 2013.
- J. S. Cope, D. Corney, J. Y. Clark, P. Remagnino and P. Wilkin (2012), Plant species identification using digital morphometrics: A review, *Expert Systems with Applications*, 39, pp. 7562–7573, 2012.
- J. Schellberg, M. J. Hill, R. Gerhards, M. Rothmund and M. Braun (2008), Precision agriculture on grassland: Applications, perspectives and constraints, *Europ. J. Agronomy*, 29, pp. 59–71, 2008.
- L. Yaju and C. A. I. Zhenjiang (2009), A Research in the Application of Computer-Vision to Plant Growth Monitoring, *University Journal, Hebei, China*, pp. 522–526, 2009.
- M. C. Silva, F. A. C. Pinto, D. M. Queiroz, G. R. Ruiz, J. G. Gil and L. M. N. Gracia (2012), Determination of weed coverage percentage using digital images, *International Conference of Agricultural Engineering CIGR-AgEng2012*, July 2012.
- M. Guijarro, G. Pajares, I. Riomoros, P. J. Herrera, X. P. B. Artizzu and A. Ribeiro (2011), Automatic segmentation of relevant textures in agricultural images, *Computers and Electronics in Agriculture*, 75, pp. 75–83, 2011.
- M. J. C. S. Reis, R. Morais, E. Peres, C. Pereira, O. Contente, S. Soares, A. Valente, J. Baptista, P. J. S. G. Ferreira and J. B. Cruz (2012), Automatic detection of bunches of grapes in natural environment from color images, *Journal of Applied Logic*, 10, pp. 285–290, 2012.
- M. Montalvo, J. M. Guerrero, J. Romeo, L. Emmi, M. Guijarro, G. Pajares (2013), Automatic expert system for weeds/crops identification in images from maize fields, *Expert Systems with Applications*, 40, pp. 75–82, 2013.
- M. Weis and R. Gerhards (2009), Detection of weeds using image processing and clustering, *Bornimer Agrartechnische Berichte*, 69, pp. 138–144, 2009.
- M. Zhang, Z. Qin, X. Liu and S. L. Ustin (2003), Detection of stress in tomatoes induced by late blight disease in California, USA, using hyperspectral remote sensing, *International Journal of Applied Earth Observation and Geoinformation*, 4, pp. 295–310, 2003.
- P. J. Beers, A. Veldkamp, F. Hermans, D. V. Apeldoorn, J. M. Vervoort and K. Kok (2010), Future sustainability and images, *Futures*, 42, pp. 723–732, 2010.
- P. Li, S. H. Lee and H. Y. Hsu (2011), Study on citrus fruit image data separability by segmentation Methods, *Procedia Engineering*, 23, pp. 408–416, 2011.

P. Mondal and M. Basu (2009), Adoption of precision agriculture technologies in India and in some developing countries: Scope, present status and strategies, *Progress in Natural Science*, 19, pp. 659–666, 2009.

R. C. Gonzalez and R. E. Woods (2002), *Digital image processing*, 2nd edition, Prentice Hall, Upper Saddle River, New Jersey, USA, 2002.

S. Sankaran, A. Mishra, R. Ehsani and Cristina Davis (2010), A review of advanced techniques for detecting plant diseases, *Computers and Electronics in Agriculture*, 72, pp. 1–13, 2010.

X. P. B. Artizzu, A. Ribeiro, A. Tellaeche, G. Pajares, C. F. Quintanilla (2009), Improving weed pressure assessment using digital images from an experience-based reasoning approach, *Computers and Electronics in Agriculture*, 65, pp. 176–185, 2009.

X. P. B. Artizzu, A. Ribeiro, A. Tellaeche, G. Pajares and C. F. Quintanilla (2010), Analysis of natural images processing for the extraction of agricultural elements, *Image and Vision Computing*, 28, pp. 138–149, 2010.

Y. R. Chen, K. Chao and M. S. Kim (2002), Machine vision technology for agricultural applications, *Computers and Electronics in Agriculture*, 36, pp. 173–191, 2002.

Y. Bengio, (2009), Learning deep architectures for AI, *Foundations and Trends in Machine Learning*, 2, pp. 1–71, 2009.

Y. Terasawa, M. Terasawa, Y. Terasawa, Y. Minamizawa and Y. Saito (2009), Observation of condition of plant growth by image processing system, *Agricultural and Forest metrology*, 75, pp. 85–102, 2009.

Y. Wu, D. Li, Z. Li and W. Yang (2013), Fast processing of foreign fiber images by image blocking, *Information Processing in Agriculture*, 2013, (In press) doi: 10.1016/j.inpa.2013.05.001.