Improving field management by machine vision - a review

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Abstract: Growing population of people around the world and thus increasing demand to food products as well as high tendency for declining the cost of operations and environmental preserving cares intensify inclination toward the application of variable rate systems for agricultural treatments. Machine vision as a powerful variable rate appliance has been paid vast attention by agricultural researchers and farmers as technology consumers. Various applications have introduced for machine vision in different fields of agricultural and food industry till now that confirms the high potential of this approach for inspection of different parameters affecting productivity. Computer vision has been utilized for quantification of factors affecting crop growth in field; such as, weed, irrigation, soil quality, plant nutrients and fertilizers in several cases. This paper presents some of these successful applications in addition to representing an introduction to machine vision.

Keywords: precision agriculture, field management, image processing, variable rate.

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1 Introduction

Playing a substantial role in the progression of human civilization, agriculture is taken into account as the mother of all cultures. Recently, yield per land unit has intensified many times due to great attempt to apply new techniques for agricultural practices, of which traditional forms are either cumbersome, expensive or time consuming. This attempt provides a cautious and precise management of all inputs by considering the complex interaction of soil, seed and agro chemicals (Anand and Ashwin Patil, 2012). Modern agriculture is completely different from traditional farming. The management practices have changed substantially and variable rate application (VRA) of inputs are paid attention more due to factors; such as, increasing productivity per unit area, increasing agricultural operation speed and applying precise amounts of inputs in order to prevent environmental contamination and lower the costs. Such accurate and fast operations are impossible by only human power. New techniques and among them machine vision (MV) as a powerful instrument showed great potential to realize these factors. Determining field-related factors is necessary to apply VRA. The techniques of measuring field-related factors can be broadly classified into direct and indirect methods. Figure1 summarizes some of these methods.

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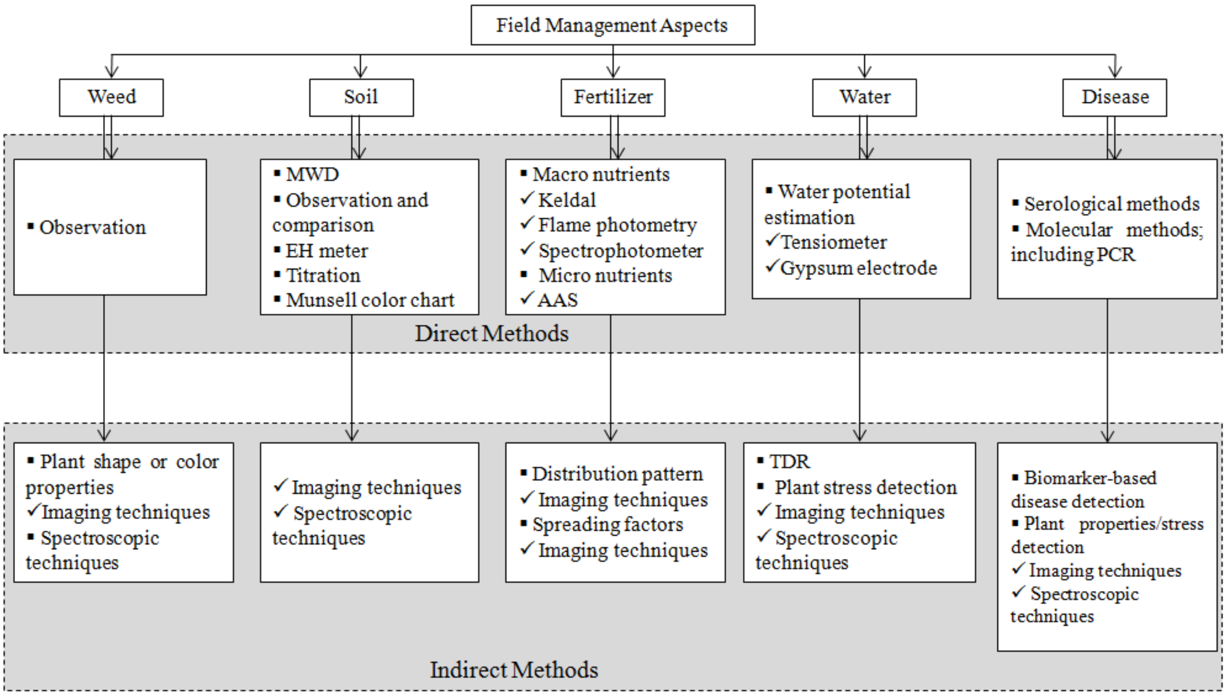

Figure 1 Methods of determining the amount of the different aspects of field management

1.1 Precision agriculture

Precision agriculture or site specific crop management (SSCM) is a farming management concept based on observing, measuring and responding to inter and intra-field variability in crops. Crop variability typically has both spatial and temporal components which make statistical/computational treatments quite involved. The aim of precision agriculture is optimizing returns on inputs while preserving resources. In fact, SSCM explains the use of environment and crop parameter variability for precision application of agricultural inputs. Based on SSCM, there exists three main approaches; including farming suspension in field or a piece of land because of its low efficiency and high cost of desirable inputs, conventional and consistent application of inputs because of a relative consistency over the farming land and trivial increasing in productivity profits due to the costs of VR methods and finally the most important approach which has been paid a great attention in the last decades is the VRA of inputs leading to lowering the cost and environmental contamination, and increasing productivity.

VRA is divided into two major parts: Map-based VRA and Sensor-based VRA. Both methods contribute to coincidence of inputs to existence conditions of farming land and plant need. Both of these methods have some advantages and disadvantages, and in order to maximize economical and environmental profits, farmers apply one of these methods or a combination of them. However the map-based VRA have some advantages, such as more process on sample d data because of time delay between sampling and input application, the errors of positioning for whether sampling or input application and temporal variability are unavoidable in this method.

1.2 The role of MV in precision agriculture

Many researchers have focused on MV around the world and this technique is improving and developing in diverse scientific and practical fields, such as safety, medicine, farming, food engineering and packaging. The theoretical and scientific improvement along with the abundance of technical apparatuses and decline in their costs justify and encourage more applications of MV especially in agriculture which is being led to automation and intelligentization to produce and supply high demand of population food. Moreover, this technique has a great perspective especially in the plant protection field, that result in crop management (Pokharkar and Thool, 2012).

However it may seem that MV in agriculture can simulate human eye to complete the measurement and the evaluation processes for replacing human's operation at first, its application in recent years demonstrated that MV-based systems can been utilized beyond the common view of eye simulation. The application of IR images for water stress detection and hyperspectral spectral indices for nitrogen content estimation are the examples of this claim and the growing use of spectral images boosts it (McCarthy et al., 2010; Li et al., 2013).

There are a number of reasons which lead to the high-extent application of MV in farming; such as, relatively low cost of apparatus, consistency, high speed and accuracy. Right now, MV is being adopted at commercial level in some cases.

2 An introduction to machine vision

MV originated in the 1960s and as mentioned previously it has been developed with its applications in various fields: remote sensing; factory automation; forensics; medical diagnostic imaging; autonomous vehicle and robot guidance. In order to take and interpret an image as non-contact optical sensing and processing devices, MV embodies several processes in sequence: image acquisition with a sensor, analysis by means of computing software and hardware for doing a predefined visual operation. Correspondingly, MV technique consists of three major steps: image acquisition, image processing-analysis, I/O control. In this paper two first steps have reviewed, i.e. image acquisition and image analysis, because agronomy researchers highlighted them more. Moreover, control components are applied without any redesigning and their producers provide some indispensable technical support (Ji et al., 2009).

2.1 Hardware

Diversity in hardware features involving power, price, computing speed and so on makes MV in agriculture more practical. Researchers choose their own acquisition and analysis methods based on case-study and their expectation from image quality. A MV system includes five fundamental constituents: illumination, a camera, an image capture board (frame grabber) for image acquisition, computer hardware and software for image analysis. It is obvious that illumination influences the quality of images and different kinds of illumination cause different characteristics in images and make the objects blurred or clarified. Insufficient precision in this stage can impose hard work in analysis step and result in low accuracy and efficiency of system.

Designing an illumination system consists of two major parts: the lighting arrangement which is grouped as front or back lighting, and the choice of light sources among incandescent, fluorescent, lasers, X-ray tubes and infrared lamps (Brosnan and Sun, 2004). Furthermore, illumination which is one of the key parts of designing MV systems is considered in two conditions i.e. outdoor and indoor. Under controlled conditions of indoor cases, analysis is easier while various conditions of outdoor cases such as the varying intensity of daylong light and different climates make analysis more complex. Shadows due to light sources, sufficient contrast, reflection, other noises and various characteristics of images especially brightness by virtue of different conditions are challenges of illumination. The mentioned challenges have motivated researchers to study different alternatives for overcoming changing parameters. For instance in a scarce work, Søgaard and Olsen (2003) replaced segmentation step by the computation of the centers of gravity in the image for detecting the position and direction of the crop rows under a wide range of natural illumination conditions. Therefore, they could reduce the computational burden of the image processing software. In this approach, gray images were divided into approximately 15 strips, vertical summations of grey values in the strip were computed and this vector then was split up into sub-vectors with corresponding lengths to the nominal inter-row spacing in the middle pixel row of the image strip, after calculation the average of strip sections to obtain a combined estimate of the positions of centers, the center of gravity was determined and the estimated row positions were projected back into the image strip.

Common sensing techniques include monocular vision with an RGB camera, stereo vision and 3D structure, multispectral and hyper spectral imaging, range sensing, and CT scanner. However outdoor applications involve difficulties which make automation challenging, such as: various natural lighting(both intensity and direction), the overlapping of neighboring plants and background material. Stereo vision, multispectral imaging and range sensing as improvement to MV reduce the effect of surrounding factors on image and lead to simpler and more reliable data processing.

Monocular sensors capture images like visual perception of humans. In other words, human vision simulation is the objective of such systems. Based on the objective of study, color or shape features can be underlined; for instance these features are considered for fruit identification and species classification. The most common sensor in this cases is CCD camera either of the array type or line scan type (Brosnan and Sun, 2004). By using color indices, vegetation discrimination from background is possible in this method(Wang et al., 2013). Moreover a particular situation for camera; for example an up-ward position under the canopy make a back-lit condition which is useful for LAI estimation(Jonckheere et al., 2004). In this class of imagery, some mechanical or optical components can be applied to make features of interest more identifiable; for example, as vegetation has higher reflectance than soil in NIR wavelengths, their dissociation is possible with NDVI (Normalized Difference Vegetation Indices). An alternative for making uniform illumination is using a cover during image acquisition which is unlikely unpractical because of the imposed inconvenience and time delay during measuring operation and its application is impossible especially for large plants. These cameras are more reliable for more controlled condition of easier indoor application. Small variation in plant configuration e.g. changes in leaf disposition which can be related to wilt and thus water stress is identifiable with RGB cameras. In addition MV assisted air blower has capability of foliage discrimination from stem and fruit because of its movement (McCarthy et al., 2010).

Stereo image has the capability of crop growth control (e.g. phyllotaxis), species discrimination (by height change identification) and reconstruction 3D models by determining structure parameters of plants. Probably the most challenging part in this domain is matching stereo images (McCarthy et al., 2010).

A multispectral image containing data at specific frequencies beyond the visible light range across the electromagnetic spectrum provides additional information that human eye fails to capture with its receptors. Differences between cellular structures, thermal and hardness attributes are recognizable by NIR, MIR and X-ray. Weed and plant classification is completely easier by means of these images awing to the significant discerning wavelength between them. Water stress detection is possible by visible, IR, NIR, UV and microwave radiation (McCarthy et al., 2010). Fruit discrimination from foliage and stem identification are possible with hyperspectral image and X-ray, respectively. However, high cost of these devices and some safety regulation limit their application. As range sensors are active, they are more reliable in various lighting conditions in comparison with passive sensors. Laser and ultrasonic sensors in this class have been used for measuring canopy characteristics (Tumbo et al., 2002).

The digitization process, in which an image is converted to numerical form containing pixels, is done by digitizer or frame grabber. Selection of the frame grabber is based on the camera output, spatial and grey level resolutions required, and the processing capability of the processor board itself (Brosnan and Sun, 2004).

2.2 Image analysis

Actually, image analysis is the core of computer vision. Image processing includes a series of image procedure in order to enhance the image quality and remove drawbacks. Image processing involves color space transforming, filtering, graying, and edge detection, etc. These procedures finally lead to object detection and feature extraction which is used in the subsequent control systems for decision making.

In this scenario, a number of preprocessing operations, such as median and Gaussian filters are applied to reduce noises and blurring, and to enhance desired features of image however some of these operations have bad effects on edges. So, one should compromise between image enhancement due to filter application and preserving the edge of image objects by controlling the size of filters.

Image enhancement is possible whether in spatial domain; for example by using spatial filtering and gray level transformation for some cases such as increasing contrast and dynamic range, or in transform domain such as frequency domain for instance by using FFT or wavelet for cases such as edge detection or smoothing. For instance in the case of sharpening image, Laplacian filter or unsharp masking, done respectively in spatial and frequency domain, are applicable.

Most of images are corrupted by sinusoidal noises specially because of camera vibration in agricultural applications. By transforming the image into frequency domain and based on noises distances, such noises can be eliminated by using notch or band reject filters. After image enhancement, the most important step of image processing is considered, "image segmentation".

The main objective of image segmentation is to divide the image into target regions which contain useful information for decision making and non-target regions of background. Depending on the difference between target and non-target regions, two segmentation methods are used: one is the segmentation of target itself, and another one is the extraction of closed border; which the first and the second ones are used for high and small differences, respectively. For this purpose, there exist three different techniques including: thresholding, edge-based segmentation and region-based segmentation (Brosnan and Sun, 2004).

Thresholding technique has applied in great number of agricultural applications owing to its intuitive properties and simplicity of implementation. In this technique, the object pixels are segmented of background pixels by using a threshold. The threshold can be simply determined by gray-level histogram and based on the existent differences between reflection features of background and object surfaces. Algorithm of Otsu is a nonparametric and unsupervised method of automatic threshold selection for image segmentation (Taghadomi-Saberi et al., 2014a). Smoothing noisy images for example by using average filter can improve the outcomes of thresholding remarkably.

Edge detection is the most common approach for detecting meaningful discontinuities in gray level. The first- and second-order digital derivatives for the detection of edges in an image are taken into consideration. In fact, whenever the first-order derivative is higher than a threshold or the second-order one has a zero transition, there exists edge possibility. Canny and SUSAN are from the methods of edge detection. SUSAN which is newer, is suitable for angular edges. Generally, edge detection methods are not advisable for closed region segmentation.

In contrast with thresolding and edge-based segmentation which are respectively based on the distribution of pixel properties (such as gray-level values) or based on discontinuities in gray-levels, regions are segmented directly in region-based segmentation. In this method, the adjacent pixels which are similar based on their features such as color or texture are detected as a single region.

Generally, a region or boundary image which is the outcome of segmentation is appropriate for size determination and texture or defect detection. In addition to image explanation, morphological operations can be applied for segmentation improvement. After image segmentation, feature extraction is done. Common features are based on region, color, texture and etc. Several researchers have introduced various color features by using statistical criteria (Taghadomi-Saberi et al., 2014a and b). Finally by using extracted features and artificial techniques, such as: ANN, fuzzy, ANFIS, GA for building database, management decisions are made and sent to control systems for VRA.

3 Applications

Now, MV has various applications in different parts of agriculture and these applications are becoming better and better in whether quality or quantity to contribute farmer for better field management. Remarkable number of articles on the inspection of variables affecting crop growth by using MV represents the high potential of this approach for farming. Recent advances in hardware and software have aided in this expansion by supplying inexpensive powerful alternatives, leading to more investigation on the development of computer vision systems in agriculture (Brosnan and Sun, 2004).

3.1 Soil

MV has applied in the quantification of soil related features in a large number, just like other parts of agriculture. Soil deformation and the effect of physicochemical stresses on it, structural changes evaluation, pore space and soil compaction characterization, surface soil organic matter estimation, soil moisture prediction, pedological features and soil redoximorphic features quantification are the examples of MV application in the quantification of soil related features which are instrumental parameters for soil management and the evaluation of plant conditions. Soil texture is determined by the size and type of particles that make up the soil (including the organic but mostly referring to inorganic material). Soil texture is really important for agriculture. It influenced some factors, such as: water infiltration into the soil. Coarse-grained sandy soils have large spaces between each grain and allow water to infiltrate quickly. Consequently, it is necessary to irrigate such soils more. However clay soils, specially weighty ones, hold water strongly. It makes water inaccessible for plant and therefore crop wilting is more probable. Generally, clay soils are known to have weak fertility and better drainage (Nasiri Tousi, 1995). Diverse in the size of soil particles, different soil textures are discernable using MV.

Soil structure is the arrangement of soil particles into groupings. These groupings are called peds or aggregates which often form distinctive shapes typically found within certain soil horizons. Developed and stable soil structures have good infiltration proportional to the climate. So working on such soil is easy and not power-demanding. From single to a few millimeters structural units are the constituents which make an appropriate soil for plant growing. Generally in regions such as Iran, adding organic material to arable soil and performing tillage operation in optimum condition (moisture content of 0.8-0.9 plastic limit) are suitable for soil structure development and preservation (Khajeh Pour, 2002).Soil structure is important for water and air infiltration and their availability to plants and microorganisms cut down perspectives which influences the soil quality. Various types of images have been used for the inspection of soil structure, such as CT scanner, back scattered electron images, and digital images.

Soil deformation is an unending process in the pedosphere that as well physicochemical stresses, primarily alternating mechanical and hydraulic stresses, permanently re-arrange the formation of solid particles. So soil structure and consequently all structure related soil functions are highly dynamic. This makes complexity that restricts the treatment of soils as static porous media (Or and Ghezzehei, 2002). Understanding the complex mechanisms involved in structure evolution and dynamics have to be overcome to better predict soil responses to changes in environmental boundary conditions resulting from natural and anthropogenic factors. Digital image processing techniques have provided useful tools for quantifying various soil attributes; for instance, Protz et al. (1992) used multi-channel images of soil thin sections to quantify soil voids, organic material, mineralogy, and SRFs. Adderley et al. (2002) refined digital image processing of soil thin sections to aid in feature interpretation. Other important cases which have been studied with MV systems are soil redoximorphic features which are useful for documenting wetland soil morphology, correlating soil water and oxygen content with soil color, studying altered drainage effects on soil morphology, correlating subsurface flow paths with soil color, and documenting restrictive and subsurface horizon effects on hill slope hydrology. O'Donnell et al. (2010) developed a new method of soil redoximorphic features identification and quantification from soil cores using a digital camera and image classification software. Digital image reconstructions were also used by Peth et al. (2010) to quantify local structural pore space characteristics and local soil deformation processes which could improve the conceptual understanding of the physical behavior of soil systems.

In the last decade of the 20th century a tendency had been existed for using back scattered electron images, providing a great contrast between pores and solid material, to characterize pore space. Sort and Alcaniz (1999) used these images and image-processing computer equipment to investigate the effect of the application of sewage sludge on soil porosity over a period of 28 months. Aydemir et al. (2004) used digital image processing and unsupervised nearest neighbor classification for the identification and quantification of pedological features in soil thin sections, such as: calcite, void, sesquioxides, and plasma with much less error than other methods. However they were not successful at identification of quartz as well, and they suggested the use of incident UV light which might overcome the difficulties with basal sections of quartz.

CT images have been applied in this field, too. In order to evaluate changes in the structure of clayey soil samples with surface compaction submitted to wetting and drying cycles, Pires et al. (2011) used a gamma-ray CT scanner for analyzing changes in soil structure of a very same sample, which cannot be obtained by using traditional techniques of MV. By the use of CT, they could specify the thickness of the compacted region and alterations in soil porosity distribution which are very important, for instance in estimating hydraulic parameters in infiltration models, water retention and movement.

Soil compaction affects the pore system, and consequently the soil mechanical parameters like pre-consolidation load or bulk density and the transport properties of the pore system. Compaction inducing the changes of water infiltrability and the availability of water and air to plants and microorganisms may hinder the functioning of the soil environment. Some researchers have focused on soil compaction by using digital image processing. Accordingly, Ewing and Horton (1999),and Forrer et al. (2000) developed methods to process images of flow patterns digitally in order to trace the infiltration pathways e.g. in compacted and non-compacted soils. Kulli et al. (2003) applied digital image analysis to study the effects of the mechanical impact applied by a sugar beet harvester on soil porosity, bulk density and on the water infiltration regime under field conditions.

Having cognizance of growing concern about the potential environmental hazards from excessive uniform fertilizer and herbicide application rates to spatially-variable landscapes and the effect of soil organic matter (SOM) content on many current herbicide and fertilizer recommendations, estimation of SOM content can be very useful for reduction of the environmental hazards associated with over-applying crop inputs such as, surface and groundwater contamination. Furthermore, OM causes positive effects. This can be useful for management decision, including the modification of soil structure, the improvement of soil ventilation and air and water infiltration into it, the supply of nutrient for plant and microorganisms and the increase of cation exchange capacity (Khajeh Pour, 2002). Aerial images can be a good and fast choice for SOM estimation as well as other features of soil (Schepers et al., 2004 and Chen et al., 2005). Accordingly, Roberts et al. (2011) focused on a variety of strategies to evaluate the capability of an active sensor and a wide-band aerial image to estimate surface SOM. Among their applied strategies, interpolation, field-specific and intercept-adjusted strategies showed more accurate predictions of OM in comparison with multiple-layer, uniform and universal prediction models. They claimed their obtained accuracy could be increased by acquiring the data when there is minimal surface residue or by accounting for soil moisture content with supplementary sensors at the time of data collection.

Soil color is a good representative for soil features in many cases. Among the possible color of soil, dark brown and black colors show high amount of humus. Good ventilation and infiltration are from features of such soil. However ventilation is less in yellow soil and yellow color represents the existence of ferric in form of ferro. Soil heat also depends on soil color. Soil heat is considerably important for agriculture. Dark color soil absorbs heat more and consequently is warmer (NasiriTousi, 1995).By using digital image analysis, van Huyssteen et al. (2006) demonstrated the quantification of soil color from 10 excavated soil pits. However this methodology could accurately reproduce only one Munsell Hue which limits the extension of this method to the continuum of soil colors. Soil color can be a characteristic of the evaluation of soil wetness. For the primary aim of the prediction of soil moisture content and SOM, Kumar Roy et al. (2006) used soil image texture statistics to extend the possibility of using RGB color space in representing composite soil color.

Now we can say that even classifying soil surface states in relation with land cover and tillage practices and detecting the agricultural operations such as harrowed fields and ploughed fields are possible with MV techniques. Hadria et al. (2009) were able to classify fields into three major classes: ploughed, harrowed, and not ploughed and not harrowed based on FORMOSAT and ASAR images with simple mapping algorithms including band thresholding and decision tree.

3.2 Weed

A harmful and unwanted plant is considered as weed. In other words, weed is a plant which grows undesirably. There are a lot of disadvantages for weed, including: entering competition for water, nutrient and light with crop, trouble causing for agricultural operations and machinery tools, weed seed and harvested crop integration which reduce the product worth, shadow shedding on crop, crop-made nutrients consumption (for example, Custasp cause remarkable damages in tobacco, alfalfa, clover and cotton) and contribution to the dispersion of pest and diseases (Rastegar, 1993). Information on weed distribution in the field is necessary to implement spatially variable herbicide application or other implements to remove weeds from the field (Kiani and Jafari, 2012). Whereas non-imaging photodiode sensors are unable to distinguish between plant species, the measurement and application should be possible on-the-go, not in two separate steps for mapping and application, since the weed management needs a fast reaction for weed control decisions during a single management operation (Andújar et al., 2012).Weed detection systems have been developed mainly to make more effective use of pesticides, either for band spraying along a crop row or detecting individual weed or crop plants for treatment (Bond et al., 2003). As mentioned in *3.1.section*, MV techniques can lead to the site-specific application of herbicides. Because of high labor, energy, and chemical demands, a method of automatic detection along with site-specific application is more efficient not only from an environmental perspective but also from an economic perspective. Using weed maps based on MV techniques, farmers can identify the weed distribution within the crop (Yang et al., 2003).The main challenge in this application of MV is to achieve appropriate discrimination between weeds, crop and soil in outdoor field images under uncontrolled conditions and varying light, soil background texture and crop damage (Burgos-Artizzu et al., 2009).There are a wide range of practical use of MV techniques for weed detection in field based on morphology, color and texture features of images.

Yang et al. (2003) developed a simple method, “greenness method”, in which the red, green, and blue intensities of each pixel were compared. Since the images were taken between corn rows, based on the percent of greenness area in the images, weed patchiness was estimated to create a weed map. Site-specific herbicide application rates were determined by use of a fuzzy logic model and resulted in saving significant amounts of herbicide.

Søgaard (2005) used young weed seedlings with up to two true leaves to establish a database containing image examples of 19 of the most important weed species in Danish agricultural fields. By using this database, an active shape model for each species was constructed and then the algorithm of image processing that could classify new unknown weed seedlings by comparing them with the weed models has been developed for the identification of weed species.

Hague et al. (2006) applied the red, green and blue channels of a conventional CCD camera to compute a vegetative index[2] which is invariant over the range of natural daylight illumination i.e. it is insensitive to the amplitude of the illuminant. The image can be segmented into soil and vegetative components using a fixed threshold. In their procedure a previously reported algorithm (Hague and Tillett, 2001) was applied to robustly locate the crop rows. In few words, they transformed the original image to gray scale and then divided it into eight horizontal bands in this algorithm. The intensity of the pixels across these bands represented a periodic variation due to the parallel crop rows. Based on information about camera position and row crop spacing, crop rows were located. So positions over and between the crop rows assessed to crop and weed growth (Hague et al., 2006).

A similar work has done on the identification of one of the most invasive and persistent weed species on European grassland, the broad-leaved dock, in complex mixtures of perennial ryegrass by Gebhardt et al. (2006).However they obtained their photographs under more controlled conditions, such as constant recording geometry and illumination. By transforming the RGB color images to grayscale intensity images and using a threshold, binary images were derived. After some morphological operation, the remaining contiguous regions were considered to be objects. At last, they calculated shape, color, and texture features for each of these objects. They also accomplished a Maximum-likelihood classification to discriminate between the weed species. Moreover, rank analysis was used to test how combinations of features affected the classification result. It was concluded that a combination of all features , including shape, color and texture attributes, is the best.

Gebhardt and Kuhbauch (2007) developed a new algorithm to improve classification accuracy. Weeds and other homogeneous regions were segmented automatically in digital color images using local homogeneity and morphological operations. Additional texture and color features were identified helpful to the differentiation between grassland weeds using a stepwise discriminant analysis in SPSS software. As well, maximum-likelihood classification, in MATLAB Classification ToolBox, was performed on the variables retained after discriminant analysis. In this way they could improve Classification accuracy. The effect of image resolution on classification results was investigated in a subsequent study. Image processing time ranged from 45 s for the full resolution images to 2.5 s for the lowest resolution ones with a trivial reduction in detection rates accuracy (Gebhardt and Kuhbauch, 2007). In most cases agricultural application of MV, the high resolution of images is not useful and it is time consuming which can lead to low accuracy especially in on-the-go systems.

[2] . index= $\frac{g}{r^a b^{(1-a)}}$, where a is a constant

Nieuwenhuizen et al. (2007) compared two color-based MV algorithms, which are faster and less complex than shape and texture-based algorithm, for in-field volunteer potato plant detection in two sugar beet fields. They used a combination of K-means clustering and a Bayes classifier as the first algorithm and training an Adaptive Resonance Theory 2 (ART2) Neural Network for Euclidean distance-based clustering as the second one. The results of both methods were closely matched within completely different fields. In another work of Nieuwenhuizen et al. (2010), an adaptive Bayesian classification method was developed for the same problem. In this way, they could improve the classification accuracy for the constant and especially changing natural light conditions (from 84.6 and 34.9% to 89.8 and 67.7%) in comparison with non-adaptive scheme.

Jones et al. (2009) developed a new method for weed detection based on modeling agronomic images of a virtual camera placed in a virtual field, and then the effectiveness of the developed algorithms was measured and compared. They evaluated the performance of two crop/inter-row weed discrimination algorithms based on Gabor filtering and based on the Hough transform for images with and without perspective effects. They concluded that the method based on the Hough transform has better results in all cases.

Burgos-Artizzu et al. (2009) processed digital images of a crop field by using a computer-based image analysis to estimate the percentages of weeds, crop and soil present in the image. They used a real time Case-Based Reasoning (CBR) system that determines which processing method, involving two non-CBR, one pseudo-CBR and one CBR methods, is the best for each image. However the images were taken indifferent fields and under different and uncontrolled conditions, such as different light, crop growth stage and size of weeds, the obtained correlation coefficients with real data were almost 80%.

In a comprehensive work, a real-time MV system for crop/weed discrimination in maize fields integrated into a treatment system was introduced by Burgos-Artizzu et al. (2011). The system which had very good results under a wide variety of conditions consisted of two independent subsystems, a real-time image processing and a slower and more precise processing to modify the first subsystem’s mistakes. This system showed acceptable results even in the presence of dramatic sowing errors or abrupt camera movements.

3.3 Disease and pest

Pathogenic agents change plant anatomy, morphology or metabolism. These microorganisms affect not only crop quality but also its quantity (Khajeh, 2002). Early disease detection and pest insect population monitor are currently key issues in agriculture. Poor control in some cases causes diseases to spread to neighboring fields. So achieving high accuracy assessment for site-specific management is completely obvious. Traditionally, pest management has been done by means of a regular spray program based on a schedule without any special attention to the presence or likelihood of presence of insects in the field. An automatic method for monitoring pest can fight bioagressors of crops and minimize pesticide usage, which is resulted in environmental and economical profits. MV has had some successful application in this part as well as other parts of precision agriculture.

3.3.1 Insects

To detect biological objects on a complex background, Boissard et al. (2008) combined knowledge-based systems for image analysis and natural object recognition, image processing programs and machine learning. They paid special attention to low infestation cases and their results finally showed that this automatic detector was reliable for detection and counting of whiteflies at a mature stage of roses. For the similar purpose of whitefly detection in a greenhouse, Qiao et al. (2008) developed a simple image processing system that estimated the density of whiteflies on sticky traps as convenient samplers based on size and color.

One of the most popular methods to monitoring pest population is distributing a set of traps strategically across an area and then collecting trap data with visual inspection done by operators every 15 to 30 days. This method is not only labor intensive and therefore costly, but also impossible to be synchronized for all monitoring traps. Inspired from this traditional method, López et al. (2012) designed and developed an autonomous monitoring system based on a low-cost image sensor, able to capture and send images of the trap contents to a remote control station. Covering large areas with very low energy consumption over several months are from positive advantages of their system.

Recently, internet is used in combination with image processing techniques to do additive works such as variable rate application map delineation, image data and other monitoring data (such as temperature) transmission and sharing data with experts (Koumpouros et al., 2004 and Fukatsu et al., 2012). This may decrease required time to perform a diagnosis and provide a more versatile way for telecommunication among experts, farmers and extensions agents. Accordingly, Fukatsu et al. (2012) used WLAN for sending acquired data to be managed and analyzed in order to provide useful information on insect count. They used the number of white pixels for estimating insect population. As another example of internet role in nowadays systems, McKinion et al. (2009) evaluated the possibility of using multispectral imaging for developing GIS maps for monitoring cotton pests for seven years in order to apply spatially variable insecticide.

Wen and Guyer (2012) used three models; including, an invariant local feature model using affine invariant local features, a global feature model using 54 global features, and a hierarchical combination model based on local feature and global feature models to develop an image-based automated insect identification and classification method. As expected, the combination model had better results in comparison with the other models because of the combine advantages of both models.

3.3.2 Pest

The fluorescence imaging has been applied in monitoring leaf diseases in some cases (Sankaran et al., 2010 and Lenk et al., 2007).The development inspection of tobacco mosaic virus infection in tobacco plants (Chaerle et al., 2007) and detecting yellow rust in winter wheat (Bravo et al., 2004) are from its examples. Multispectral and hyperspectral images provide useful information about plant diseases but researchers should focus on the selection of disease-specific spectral band and selection of statistical classification algorithm for a specific application, which depends on the data acquisition setup (Sankaran et al., 2010).Bravo et al. (2003) investigated the application of visible-NIR hyperspectral imaging for the early detection of yellow rust disease (Pucciniastriiformis) in winter wheat and they could obtain satisfying results. By using air-borne hyperspectral imaging and different vegetative indices, Shafri and Hamdan (2009) indicated the capability of these images for detection healthy from diseased oil palm plantations to ganoderma basal stem rot and management of plantations in large scale.

Han et al. (2012) studied the feasibility of on-line pest classification using MV technology. They used a digital signal processor because of its powerful data processing functions and a host control platform for further identification. They gained satisfying results and the pest images were very clear and sufficient. Pokharkar and Thool (2012) used technique of MV to detect and segment infected parts of the particular plants and then processed the segmented part to extract more features that make general idea about pests on greenhouse crops. Various technologies have been used in the past to measure temperature of plant leaves which can be related to plant health. For example, McGuire and Pearson (2006) used visual light reflectance to generate NDVI images. This patent relied on reflected light from the sun, and therefore taught that the optimum time for image acquisition using the disclosed process is within two hours of "solar noon" and on cloudless days. This makes it very impractical for a commercial application. This methodology was only able to indicate the existence of a problem after the change of plant structure and therefore its color. In many cases, this is too late to take corrective action.

Thermography is another method for monitoring the health of plants in a field. Sutton(2013) applied this method. This system acquired a thermal image indicative of thermal energy emitted by the plants and processed the thermal image to assess variations in the temperatures among the plants without any reliance on sensing reflected light or ground-based measurements. By means of a trained thermographer, Sutton could detect disease or other stress factors in vegetation before they became apparent to visual or near infrared cameras.

3.4 Water

Water is one of the major items in the development of agriculture. In fact, it plays an effective role not only in arid regions but also in moist regions. Moreover, it is the most important limiting factor for cultivation area. While water is vital for plant to live and grow, the large amount of water around root causes plant asphyxiation (lack of oxygen) (Shamsaei, 1995).

If the amount of water is sufficient in soil, plant may need less force to absorb water. Consequently, it will grow better. It is obvious insufficient irrigation causes increase in required force to absorb water and therefore decrease in the absorbed water. It results in non-optimal growing and consequently performance reduction. On the other hand, inordinate irrigation especially in warm and dry climate causes some troubles because natural drain are disable to give off the further water. Water returns to surface and evaporates. This causes solution aggregation and therefore soil salinity and infertility (Mahallati, 1995).Filling large pores with water and lacking oxygen, NO_3 converts to NO_2. NO_2 is not only unavailable for plant but also is harmful for its growing (Mahallati, 1995). In order to determine the amount and schedule of irrigation, some instruments such as tension meter and gypsum electrode are applicable for estimating water potential. Whenever a perfect irrigation is managed, a desirable performance is possible (Rastegar, 1993). It means irrigation in optimum time and content improves productivity. Determination water stress, irrigation canal leakage and discharge are from the other applications of MV in water management of field. Productivity analysis, irrigation scheduling, irrigation planning and water allocation can be handled only with timely and accurate information about water consumption by crops (González-Dugo et al., 2013).

3.4.1 Water stress

Water potential affects the amount of photosynthesis and consequently plant growing. However the response of photosynthesis and various plants growing are variable in leaves with different water potential. Generally, the rate of photosynthesis decrease is higher than the rate of water decrease in plant or soil. Moreover, retrieving photosynthesis is remarkably slow after a period of water deficit. However a complete retrieving is impossible when damages are drastic (Khajeh, 2002). As aforementioned, moisture stress as well as its effect on the vital process of photosynthesis is really instrumental. MV and IP have been frequently applied to reveal the water stress in plants (Wang et al., 2010 and Meron et al., 2010 and 2013). Recently, some researchers have focused on the feasibility of variable-rate irrigation; so mapping crop water status is unavoidable to specify site-specific crop water demands. Accordingly, Meron et al. (2010 and 2013)used remote thermal sensing for mentioned map delineation in detail by using geo-referenced high resolution thermal images and artificial reference surfaces. In this study, crop water stress was determined based on canopy temperatures. By using thresholding technique canopy-related pixels were segmented. Then the coldest 33% of the pixel histogram was considered as canopy temperatures. They found a linear relation between leaf water potentials of cotton and determined crop water stress index values. Finally stress levels were applied to divide fields into sections for spatially variable irrigation scheduling.

Typically, measurement data of the IR thermography sensing system consists of a reference optical image and an IR image. The optical image allows the underlying plant canopy of interest to be flawlessly identified. Registration of optical and IR images is crucial for variable rate irrigation system in this cases, and it is of course challenging due to the possible translation and rotation of images. Wang et al. (2010) presented an autonomous and efficient algorithm process for extracting plant water stress information which can be fed into an automated irrigation control system. In fact, they developed a completely automatic image registration algorithm for the alignment of optical and IR image pairs. The comparisons with conventional techniques confirmed the effectiveness and successes of their proposed algorithm.

In a similar study and to overcome the problem of referencing, Jiménez-Bello et al. (2011) took the thermal and visible images at the same time so that they could develop a batch processing, no operator participated method by using unsupervised classification to calculate canopy temperature and dramatically reduce the time needed for image analysis. In this way, sunlit and shady leaves could be detected and isolated.

Considering the capability of thermal imagery for water status determination, optimal time for image acquisition and other parameters, such as the angle of view should be investigated for the efficiency optimization of these systems. Generally, studies have shown that midday is the optimal time for thermal image acquisition and angle of view and spatial resolution do not have any special effect on the representation of the measured leaf water potential for canopy temperature-based expression of water status by using thermal imaging system (Alchanatis et al., 2010), moreover, crop evaluation has an important influence in the obtained results from this method (Jiménez-Bello et al., 2011). However measurement of crop temperature for estimating water stress has a wide literature, soil interference on the measured signal or directional effects involved in temperature measurements related to sun sensor angles configuration and plant structure cause some limitations into the application of this method. Luquet et al. (2003) used an energy balance model which was based on 3D description of plants to simulate the temperature variability of cotton plants in accord with water status and plant structure. Heat exchange with the plant, water balance and soil temperature were computable with this model. As this system could handle partially covering plants, analysis of the limits of water status expression based on crop temperature was possible.

Another symptom of water stress is wilting. Recently, a sensing method based on 3D images of a laser scanner was presented by Cai et al. (2013). They defined the spectrum of a 2D Fourier transform as a leaf wilting index (LWI_{2DFT}). In fact they assumed a leaf as a mathematical surface in 3D space, and therefore a wilting process refers to a series of the curved surfaces. Their acquired correlation coefficients confirmed the capability of their discussed method for sensing the stress response from trivial wilting to drastic stress levels.

Feature selection is one of challenging step in using MV for every application. Hendrawan and Murase (2011) proposed four nature-inspired feature selection techniques, including Neural-Simulated Annealing (N-SA), Neural-Intelligent Water Drops (N-IWD), Neural-Discrete Particle Swarm Optimization (N-DPSO) and Neural-Genetic Algorithms (N-GAs), to find the best set of Textural Features (TFs) which is suitable for prediction the water content of cultured Sunagoke moss. Based on their results, models using FS are remarkably better than models using individual feature-subsets or without FS. For this case Neural-Intelligent Water Drops (N-IWD) had the best prediction performance among others for selecting features from 120 features extracted from grey, HSL, HSV, RGB and L*a*b*color spaces using ten Haralick's textural equations.

The third major division of the electromagnetic spectrum (1500-3000 nm) is referred to as the middle-infrared. In this portion of the electromagnetic spectrum does moisture play a dominant role. Although other factors such as OM, iron content, and clay content have an effect, it sounds that moisture is the primary mechanism affecting reflectance. More specifically, the higher the moisture content is, the lower the reflectance is. As objects loose moisture or begin to dry, their reflectance in this portion of the electromagnetic spectrum increases. This information provide background for application of MIR for water estimation.

3.4.2 Canals

From other applications of MV in irrigation are determination of irrigation canals leakage and discharge. Excess seepage in a canal segment, point leaks from breaks or fissures in the canals or pipelines, and evaporation are from the causes of water loss which is a worldwide issue in irrigation canals. Fipps (2000) reported a 4.55×10^{8} m^{3} loss for a region in Cameron County, which is 30% of the total water supply in this region. This value must be higher in many countries with older irrigation distribution systems. As traditional methods for these leakage detections are cost- and time-consuming, exploring new methods for solving this problem are justified and even crucial. For this purpose, Huang et al. (2009) used multispectral images taken with red, near infrared and thermal sensors at low altitude. Their prediction of likely sites to have leaks was successful in 92% of cases.

The possibility of error in the traditional equipment for measurement of canal discharge is high, and some efforts have been done to use imagery to present new methods for flow measurement especially in a laboratory environment (Gallanzi, 1998; Wereley and Gui, 2003).In a research by Lee et al. (2010) in field condition, floating bubbles on the water surface and a cross-correlation analysis between two continuous images were used to determine the surface velocities in the irrigation canal. In the case of infiltration that the formation of seals on soil surfaces restricts it, seal formation is strongly affected by the drop size from spray nozzles; it means drop size is somehow effective on the amount of runoff and erosion; in addition droplet size analysis can be important for estimating spray deposition efficiency under ambient conditions (Sayınci et al., 2012). Despite the importance of this case, few studies have focused on the relationship between nozzle size, operating pressure and the drop size distribution, which is probably due to non accessibility of an accurate technique to specify the drop size. However there existed some limitations for adaptation, Sudheera and Panda (2000) revealed that image processing technique can be successfully implemented for drop size measurement accurately.

González-Dugo et al. (2013) used high spatial resolution satellite images to map evapotranspiration (ET) on large spatial scales for water management purposes at different decision levels. Such information can be useful to overcome problems due to the large scale of basin applications and the heterogeneity and small size of the irrigated fields.

3.5 Fertilizer

Fertilizing poor soil is more critical than rich soil. Generally, the amount of nutrient in sandy soil is less than clay. In addition, sandy soil capacity for suction and preservation elements is low. As such soil is flooded more, spreading a high amount of fertilizer at the same time to these kinds of soil is not advisable (Khajeh, 2002). So MV techniques are useful for discrimination of dominant soil structure. This discrimination is effective for fertilizer management.

The amount of soil nutrient depends on planting history and performed operations on it. A high amount of ferro, aluminum and calcium and active magnesium in soil make condition in which phosphorus is quickly fixed and become unavailable for plant. There exist a few conditions for consuming phosphorus fertilizer (Khajeh, 2002).

Spreading fertilizers is economic when the increase in crop performance is higher than the total cost of fertilizer and its spreading together (Khajeh, 2002). The site specific application of fertilizer can result in significant increase in the ratio of performance to fertilizing cost. Moreover, excessive application of fertilizer has got a major role in the increasing environmental imbalance observed over the past 20 years (Hijazi et al., 2010).As mentioned in soil-related sections, the existence of some elements such as ferro in soil creates some color features in soil. Such colors are detectable by MV systems. Studying the spatial distribution of broadcasting spreaders is necessary not only to limit excess fertilizer loss into the environment but also to assure of a uniform distribution and covering of fertilizer in proposed sites of the field. In a work of 1991, Pettersen et al. studied the effect of fertilizer particle size on a stationary twin-disc spreader by using image processing technique. They found that particle size affect the spatial distribution in broadcasting spreaders. Their results represented that the relative contribution of the smaller particles intensifies close to and on both sides of the spatial distribution of spreader; so larger particles contribute less in this area of the spatial distribution and more in the central and outer region of the distribution which is probably because of the overlapping effect of the two discs in the spatial distribution and large particles tendency for leaving the rotating disc earlier (Pettersen et al., 1991).Hijazi et al. (2010) developed a multi-phase cross-correlation method for motion estimation of fertilizer granules during centrifugal spreading by using a stroboscope with power-LEDs to provide consistent illumination. The application of cross-correlation in signal processing is to measure the resemblance of two waveforms. Pattern recognition, single particle analysis, and PIV (Particle Image Velocimetry) are from cross-correlation applications in image processing. Its methodology consists of the correlation between the same blocks in successive images. The difference between luminosities of the blocks is expressed as the resemblance between blocks (Fournel et al., 2003 andHijazi et al., 2010).

The distribution pattern of centrifugal spreaders relies on many parameters. In order to avoid on-spinner dynamic models and their difficulties, measurement methods, focusing on the initial conditions of the ballistic flight of the fertilizer particles, have been developed. The outlet velocity vector of the particles in three dimensions depends on the horizontal outlet angle, the disc configuration and the rotational speed; Villette et al. (2008) used a digital imaging system to measure the horizontal outlet angle and therefore determine velocity components. In a work of 2010 based on the measurement of the outlet angle of the particles, Villette et al. calibrated the same imaging system to estimate factors affecting centrifugal fertilizer spreading other than outlet velocity vector, including friction coefficient of the fertilizer against the vane and fertilizer moisture which affect the particle acceleration on the spinning disc.

Garcia-Ramos et al. (2012) analyzed the utility of 3-D laser scanner images to evaluate the quality of centrifugal fertilizer spreaders by obtaining the curve of the distribution for any forward speed, determining the surface distribution of the product, determining the maximum spreading distance, visualizing the trajectory followed by the fertilizer, and quantifying the symmetry of the fertilizer spread on both sides of the spreader.

Nitrogen is one of the main structural components of chlorophyll and thus is highly correlated with the greenness of leaves. High amount of nitrogen in plants is harmful for their consumers and nitrogen entry into underground water will contaminate it; so developing automatic methods to detect its amount according to the plants demands and therefore variable rate application of it seem perfectly reasonable nowadays. Based on the effect of nitrogen on greenness of leaves, many researchers have focused on variable rate application of nitrogen by using MV technique. There are some papers which discuss different greenness indices based on RGB channels to extract an estimation of chlorophyll content in leaves (Kawashima and Nakatani, 1998 and Pagola et al., 2009).Pagola et al. (2009) applied principal component analysis to digital color images to calculate a greenness index using RGB channels, and thus estimated the N-nutrition status of plants. This system showed the high potential of MV to detect nitrogen deficiencies affecting final yield, at least comparable to that of the expensive hand-held SPAD-502 chlorophyll meter (Pagola et al., 2009). However indirect estimation of plant N concentration may result in inconsistencies in these indices because nitrogen does not directly absorb radiation in the VIS-NIR region; therefore sufficient attention is needed for calibration system according to any existence condition (Li et al., 2013).

Wang et al. (2013) used digital images for estimating nitrogen assessment, too. They focused on canopy images segmented by setting threshold values based on the magnitude and distribution of the green channel minus red channel (GMR) value. As green vegetation had an intensive reflection peak in the green band and soil did not cause any obvious alteration in albedo in the visible band, the canopy and non-canopy areas become identifiable in GMR value. Afterward image features were successfully utilized to determine three plant indices, including above-ground biomass, N content and leaf area index before and after image segmentation. They found significant exponential relationships between the proposed indices and the image parameters.

3.6 Other applications

In addition to the mentioned cases, MV can be utilized in other aspects in order to contribute to the better management of field. Pipeline hydro-transportation has a high potential to replace truck transportation of agricultural biomass for fuel and chemical production. So the evaluation of factors affecting biomass slurry mechanical and chemical properties, such as biomass particles' shape and size, is unavoidable. Accordingly, using Image J software, Vaezi et al. (2013) developed a system to process sample images, measure particle dimensions, and analyze the particle size distributions. They proved the significance of the fibrous nature of the test material in pipeline transportation.

Working more on the application of multi and hyperspectral images is promising in agronomy. Accordingly, Köksal (2011) explored the appropriate wavelength for each agronomic indicator, for this purpose, linear regression and multivariate analysis (cluster and principal component analysis) were done between agronomic indicators and both the smoothed spectral reflectance and first-order derivative spectra of each individual wavelength between 650 and 1100 nm. In this way, he showed leaf water content, leaf relative water content, leaf area index, dry biomass and yield estimation are detectable in the various values of wavelength. The results of this research can facilitate the development of hyper spectral usage in agriculture.

4 Future directions

The results of MV application in agriculture are promising and numerous improvements in both hardware and software are achievable to reach all the requirements of an automated system which can monitor the field condition, make the best decision and treat plants accordingly. Images in different regions of electromagnetic spectrum other than visible region can provide useful information especially about nutrient level and diseases, before their critical level which results in observable consequences. This early detection can be applied to take suitable measures, so working on such systems is more probable in future. However such systems are likely to be costly, reduction in labor costs and increase in profits are expected. The probable high cost of site specific management tools is more reasonable for high value crop.

5 Summary and conclusions

The present paper reviews and summarizes MV fundamentals and some of MV applications in different aspects of agriculture, including soil feature determination, water stress detection and canal leakage location, fertilizer application, and weed and disease detection.

MV techniques can lead to the site-specific application of inputs with lower labor, energy, and chemical demands compared to traditional methods. Furthermore, MV can provide automatic detection along with site-specific application which results in environmental and economic benefits.

However image processing is the most important part of MV in any application, it sounds more challenging in agricultural applications due to uncontrolled condition, such as variable illumination and the effect of background data in the resulting data. However new advances in MV hardware such as image acquisition sensors other than visible region based sensors can eliminate some of these difficulties.

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