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Fuzzy Contrast Improvement for Low Altitude Aerial Images

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Abstract

Precision agriculture is becoming very important in improving food security. Unmanned Aerial Vehicles (UAVs) have higher possibilities in this way, improving real time data gathered with aerial sensors. Fuzzy techniques have proved to be highly effective in managing vagueness and ambiguity. The unmanned helicopters are highly valuable due to the level of maneuverability that they possess. We believe that many different degrees of autonomy and functionalities of UAVs will be useful in agriculture. We present a new process to extract data from aerial images that comes from low altitude UAVs. We combined NDVI algorithm output with the RSWHE-M method on grey scaled images. Primary results show that our method extracts images that are visually acceptable to human eye and have a natural appearance.

Introduction

Most images captured from sources such as UAVs, satellites and medical equipments may suffer from poor contrast among other weakness due to inadequate or insufficient lighting during image acquisition (Sudhavani 2014). It is therefore important to enhance the contrast of these images to provide better results for human viewers or better images for the many automated image-processing systems today. Image enhancement is an important task in image processing, it seeks to improve the visual representation of an image. Fuzzy techniques have been proposed and employed successfully in image enhancement (Kumar, Perumal, and Krishnan 2011; Kannan, Deepa, and Ramakrishnan 2012; Nedeljkovic 2004).

In the recent past the growth of UAVs in terms of flight performance and autonomous on-board processing capabilities have improved significantly. These vehicles have a number of advantages over ground vehicles. The main one is their ability to navigate rugged terrain and obstacles that are a great limitation to the ground vehicles. The unmanned helicopters are highly valuable due to the level of maneuverability that they possess.

The main motivation for this paper is the growing demand for use of UAVs in the agricultural fields and its potential use in precision agriculture (Huang, Thomson, and Hoffmann 2013). The vehicles are used for crop monitoring, fumigation and scaring of birds among other uses (Honkavaara et al. 2013). The technology has been employed by farmers mostly in expansive agricultural field (Nonami 2007). However, for government officials and small scale farm holdings this information is very important to enable planning and avoid food shortage. A wide acceptance of precision agriculture exists today, this type of agricultural practice involves provision of actionable data on time (Binder, Feola, and Steinberger 2010) to enable indicator-based sustainable assessment in agriculture. In this paper the potential use of UAVs in small scale land holdings for precision farming is presented. The image captured by the low cost camera is then enhanced using *Recursive Separate and Weighted Histogram Equalization (Mean based)* (RSWHE-M) for brightness preservation and image contrast enhancement (Chen and Ramli 2003).

Small Scale Land Holdings

Half of the world's population still lives by subsistence agriculture. It follows that in the debate on world food issues, the traditional paradigm of production i.e. how to promote further growth in production and the associated focus on agricultural research and technology, will continue to reign supreme in significant parts of the world. It is very important to understand how to improve the productivity through the potential use of information technologies (Reddy and Ankaiah 2005).

Population growth has resulted in small land holdings in some areas, where productive areas are highly populated leading to a lot of land subdivision. Fig.1(a) and (b) below show examples of small scale land holdings in Kenya and mature maize crops respectively.

(a) Small Scale Fields (b) Mature Maize Crops

Figure 1: Small Scale Fields and Maize Plants

To make use of UAVs in these kind of environments (shown in Fig.1(a), a number of factors need to be considered:

1. UAVs in such small land holding areas should target the crop consultants and not farmers.
2. Provision of regular crop surveys, which is highly possible with the aerial vehicles due to their policy of *anywhere anytime access to the sky*, means timely data for the stakeholders.
3. Multicopters which can take off and land anywhere are the most attractive for such areas.
4. The most important aspect for the users (crop consultants and farmers) is the images obtained and a decision about the crop performance.
5. Even within a crop like maize a lot of differences exist both on the physical properties and the images captured. Generation of actionable data is not easy. The standard currently in use for crop surveying is the *Normalized Differential Vegetation Index* (NDVI) which shows the difference between regular red light reflected from plants and near-infrared light. A further discussion of this measure is presented below.

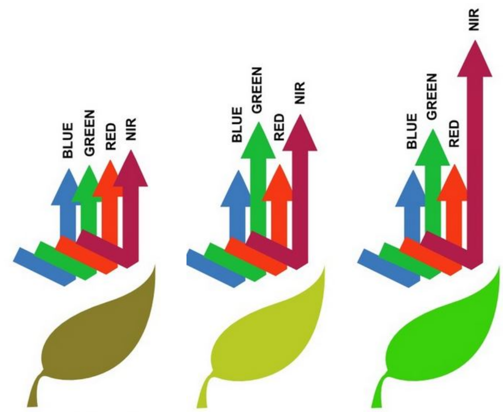
Normalized Differential Vegetation Index (NDVI)

The main aim of aerial images is to provide users with actionable data for crop classification and mapping, crop forecasting, yield predictions, crop status and condition, weed detection, disease detection, nutrient deficiency and photosynthetic pigment content (Berni and Zarco-Tejada 2009; Laliberte et al. 2011; Perumal and Bhaskaran 2010; Yuan and Bauer 2007). A lot of work has been done on the use of chlorophyll estimation with the Compact Airborne Spectrographic Imager (Yuan and Bauer 2007), leaf water content measure from the Airborne Visible Infrared Imagining Spectrometer which have the upper hand in the minimizing of background effects on traditional indices such as NDVI index. NDVI was developed by Compton Tucker in 1977 (Govaerts and Verhulst 2010), it is a ratio of near infrared (NIR) reflectivity minus red reflectivity (VIS) over NIR plus VIS. Values of NDVI can range from -1.0 to +1.0. Higher values signify larger differences between the red and near infrared radiation recorded by the sensor (Berni and Zarco-Tejada 2009) a condition associated with highly photo synthetically active vegetation.

$$NDVI = (R_{NIR} - R_{Red})/(R_{NIR} + R_{Red}) \tag{1}$$

Fig. 2 illustrates the differences between dead, stressed and healthy leaves.

The technique uses only red and near infrared data, two aligned *Charge Coupled Device* (CCD) chips of the red and NIR channel are generally used. However, they are expensive because of the precise optical alignment required (Dworak et al. 2013). Research activities in precision agriculture has taken interest in the design and development of a smart, low-cost cameras (Dworak et al. 2013; Yuan and Bauer 2007). Researchers have also considered others ways of measuring crop health and photosynthetic activity including improvement of NDVI, due to some weakness of the measure (Matsushita et al. 2007; Xu 2006).



(a) Dead (b) Stressed (c) Healthy

Figure 2: NDVI Values for Dead, Stressed and Healthy Leaves

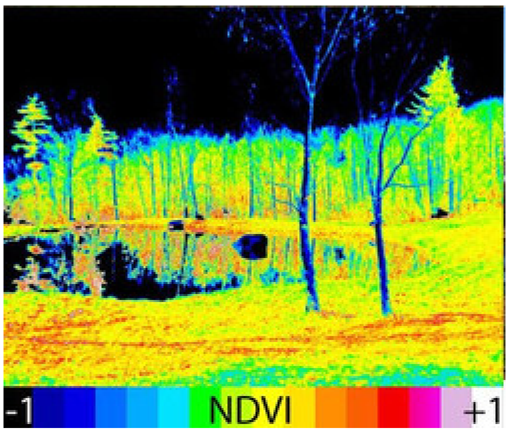
Image Acquisition and Data Processing

Different camera models have been discussed that have the ability to provide output images that have pure NIR, red and green channels thus true NDVI and NDWI indices can be calculated (Dworak et al. 2013; Xu 2006). Among a number of considerations for such cameras is the cost, big enterprises such as large farms can use near-infrared photography by mounting expensive sensors on airplanes and satellites. After a review of existing literature on existing solutions, a modified digital camera (*infragram*) to capture near-infrared and blue light in the same image, but in different color channels was selected. The single camera technique involves removing the infrared-blocking filter from any digital camera and adding a specific blue filter i.e. NGB filter. Fig. 3 shows the results of modified digital camera and the NDVI imaging. The tree trunks, brown grass and rocks in Fig. 3 have very low NDVI values since they are not photosynthetic. Healthy plants NDVI values is between 0.1 and 0.9. Once images are processed an integrative knowledge-based approach is used. This approach combines imagery (NDVI output), expert knowledge and geographical data within the framework of an intelligent recognition system.

Contrast Enhancement

Contrast enhancement is important in the field of digital image processing for human visual perception and computer vision (Sharma 2013). A number of methods have been developed for contrast enhancement. The choice of an enhancement method largely depends on the objectives of the resultant image(s). Histogram equalization is one of the most popular method, it distributes the pixels intensity over the full intensity range (Sharma 2013). Several variations of histogram equalization methods have been proposed (Sharma

(a) Normal Color Photo (RGB)



(b) NDVI Image

Figure 3: Normal Color Photo and NDVI Images

2013), and after a comparative study of images captured by UAVs and enhanced using histogram equalization methods it was found that RSWHE-M offers better brightness preservation, better contrast enhancement and better structure similarity index as compared to other methods.

Recursive Separate and Weighted Histogram Equalization (Mean based)-(RSWHE-M)

To enhance and preserve the image brightness RSWHE-M is used. The technique consists of three modules (Jayaram, Narayana, and Vetrivel 2011).

1. Histogram segmentation
2. Histogram weighting
3. Histogram equalization module

After the histogram segmentation module that generates 2^r sub-histograms, i.e. $H_i^r, 1 \leq i \leq 2^r$ the recursion level r is known. The histogram weighting module specially modifies the probability density function of each sub histogram using the normalized power law function (Sharma 2013). For each sub-histogramH_i^r, corresponding original PDF $p(X_k$, the weighted PDF $P_W(x_k$, the probability density is described in (2).

$$p_w(X_k = p_{max}(\frac{p(X_k - p_{min}}{p_{max} - p_{min}})^{\alpha_i} + \beta, (L_i \leq k \leq U_i) \quad (2)$$

Where, p_{max} and p_{min} are maximum and minimum probability value from original histogram respectively. α_i is an accumulative probability value for i^{th} sub-histogram $H_i^r(X)$. α_i is calculated for each sub-histogram.

$$\alpha_i = \sum_{k=L_i}^{U_i} p(X_k) \quad (3)$$

β is a value which is ≤ 0. The degree of mean brightness and contrast enhancement of output image can be controlled by adjusting β. The eventual use of this image is to show the crop consultants and also compare it with the standard dataset created with expert's input. When this comparison is made a decision on how well the plants are doing can be made. Fig. 4 shows the resultant gray scale image and the resultant histogram.

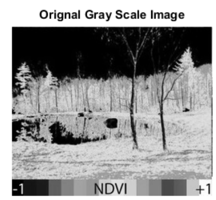


Figure 4: Original Gray Scale Image (Normal Color Photo and NDVI Images)

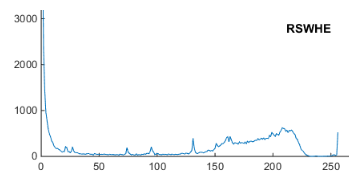


Figure 5: Resultant Histogram (Normal Color Photo and NDVI Images)

The image captured by the modified digital camera and enhanced using RSWHE-M, uses expert knowledge in order to overcome the difficulties in crop state recognition. During this process we have to be especially careful that the processed image is not distinctly different from the original image, which could make the identification process worthless. We have processed some initial NDVI images using the above approach, Table 1 below shows the initial results. The performance is then evaluated on the basis of the following widely-used metrics absolute mean brightness error (AMBE), structure similarity index measure (SSIM) and peak signal to noise ratio(PSNR). The richness of the details in the output image is measured using the entropy.

A UAVs solution for precision agriculture must collect usable data to improve yields and overall profitability. The most important factors for sustainable UAVs in agriculture noted are: the platform, communication system, sensors, data processing and integration, legal and ethical issues and operation. These components must work together for the successful implementation of UAVs solution in small scale

Table 1: Initial Results

NDVI IMAGE	AMBE	SSIM	PSNR	ENTROPY
IMAGE 1	2.57	0.99	35.18	3.98
IMAGE 2	1.70	0.98	30.05	6.55
IMAGE 3	5.45	0.88	23.99	5.88
IMAGE 4	1.89	0.97	32.29	5.60

land holdings. The most challenging part is the collection of data. As shown in Table 1. a good balance is needed to be able to put this images together and generate one homogeneous data set. A number of factors affect the output image captured by the drones and a number of properties for the images needs to be established before and after enhancement.

Conclusion

In this paper we have proposed the use of RSWHE-M on images captured by a low cost camera. The aim is to enhance contrast for human visual perception and computer vision. The normalized differential vegetation index is used to measure the health status of plants. The fuzzy methods offer a powerful framework for use of expert knowledge in the processing of data and presentation of the same to the crop consultants and farmers. Future work includes creating an application with the capability to compare this images and give feedback to farmers on the crop status.

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