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A multispectral machine vision system for invertebrate detection on green leaves

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ABSTRACT

Detection and identification of invertebrate pests in farming fields is a prerequisite necessity for integrated pest management (IPM), however, current sensing technologies do not meet the requirements for IPM. Currently, farmers have to first sample pests and then manually count and identify them, in a way that is time-consuming, labour-intensive and error-prone. Machine vision technology has taken over part of the work in a more efficient and accurate manner. However, current machine vision systems (MVSs) have limitations in detecting pests on crops and the counting and identification are constrained in laboratories or pest traps, resulting in the exact time and locations of pests being unknown, hindering more proper decisions and efficient actions. In this study, we developed a multispectral MVS to detect common invertebrate pests on green leaves in natural environment. First, it was found that, besides visible light and near-infrared, the ultraviolet is a good indicator to distinguish green leaves from other materials. Then for multispectral or hyperspectral data processing, we proposed two models, one named normalised hypercube and another named hyper-hue, which are less affected by uneven illumination and can reflect data distribution, resulting in more accurate classification than the normal method of spectral angle mapper (SAM). Further, the relationship between spectral angle and the relative angle of hyper-hue was studied and it was found that usually, data of hyper-hue has larger inter-class distances which could contribute to better classification. At last, to solve the practical problems of image registration and real-time infield applications, instead of registering 2D images, the MVS created and registered 3D point clouds. In an experiment of detecting twelve types of common invertebrate pests on crops, the proposed MVS showed acceptable accuracy.

1. Introduction

1.1. Research background and aim

Using broad-spectrum pesticide to control invertebrate pests has caused serious problems, including the increase of pesticide resistance, compromise of food safety and the elimination of beneficial species (Clarry, 2013; GRDC, 2012; Umina et al., 2012; Schellhorn et al., 2013). These increasing challenges have driven the implementation of integrated pest management (IPM) which uses the combination of different pest control methods to control pests more efficiently and effectively (Kogan and Hilton, 2009; Boissarda et al., 2008). Detection and identification of invertebrates in farming fields is a prerequisite necessity of IPM because (1) the technique could provide an accurate time when pests occur; (2) it could provide the exact location where crops are infested; (3) based on the time, location and species, a robotic system could take actions in real-time, such as selective spraying, (4) the information could be forwarded to an IPM system to make more optimised decisions (Liu et al., 2016).

However, current sensing technologies do not meet these requirements. Currently, farmers have to use sweep nets, traps or beat sheets to sample pests in fields, and then manually count and identify the pests (GRDC, 2014). These manual approaches are time-consuming; labour-intensive, error-prone and cannot provide the exact time and location that pests occur. There two research branches for automatic pest detection: acoustic methods and machine vision systems (MVSs). Acoustic methods are suitable for detecting pests in plant tissue, soil or stored grain. While MVSs have provided more efficient and accurate solutions for some counting or identification tasks (Liu et al., 2016). Nevertheless, because of the challenges in natural farming environments, such as unstable sunlight or complex background, most of the studies of MVSs have not focused on detecting pests on plants in natural environment and the current approaches are limited to counting and identifying specimens in sample containers or pest traps. Usually, moths

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are trapped or manually caught and then put in an ideal artificial environment for counting and identification (Liu et al., 2016). However, using the approach of "sample and then count", decisions will tend to be late with reduced effect. Due to their short life cycle, pests might have finished reproduction and the population could have exceeded the threshold for minimal intervention management before adults are detected (Miles, 2015; Baker and Jennings, 2015). Regarding invertebrate pest detection or plant recognition, the visible light and near-infrared (NIR) between 400 and 1500 nm (Singh et al., 2010; Saranwong et al., 2011; Haff et al., 2013; Liu et al., 2014; Liu et al., 2013) and the soft X-ray between 0.1 nm and 10 nm (Chelladurai et al., 2014; Neethirajan et al., 2007; karunakaran, 2005) have been studied. However; there is very limited literature regarding the ultraviolet (UV) between 300 nm and 400 nm.

Our aim is to develop a robotic system that can detect common pests on crops as early as possible. Pest sensing is a prerequisite, however, it is a research gap. Thus, at the current stage, the specific objective is to develop a vision system that can detect common invertebrate pests on crops in natural farming environments. The system should be more robust to handle the complex conditions in cropping fields and be more accurate for detecting camouflaged pests. Considering the balance between the robustness of detection and feasibility for infield applications, a multispectral imaging system is more effective than a colour camera and more flexible than a hyperspectral imaging system (Liu et al., 2016). As the variety of crops are huge, at the initial stage, to simplify the problems, this study is focusing on to detect pests on green leaves only. First, the spectral features of green leaves in the UV band was studied. Then, two algorithms were designed based on the study of different models, the data distributions of green leaves and the intrinsic relationship between spectral angle and relative angle of hyper-hue. In addition, the conflict between synchronising the time of image acquisition and registering multispectral images was solved using multispectral 3D point cloud registration. Finally, the system was evaluated using twelve types of common invertebrate pests in South Australia.

1.2. Preliminaries

This section introduces the preliminaries of hypercube and hyper-hue which are needed in the materials and methods in Section 2.

A set of original hyperspectral or multispectral data is represented in a multi-dimensional space in the form of hypercube. In a hypercube, the direction of a vector represents a certain material while its norm stands for intensity. In the hypercube, the same materials could have different values under different illumination. Hence, the data in a hypercube cannot be directly used for material classification under unstable illumination, such as natural sunlight. One often used method to measure material similarity in a hypercube is the spectral angle, or usually called spectral angle mapper (SAM). SAM can determine the spectral similarity between two spectra by treating them as vectors in a space with dimensionality equal to the number of bands and calculating the angle between the spectra. Smaller angles represent closer matches of the two spectra. As SAM is irrelative to the norms of the vectors, it is less affected by illumination (Kruse et al., 1993; Petropoulos et al., 2010). Although this method is relatively insensitive to illumination, it does not consider the distribution of data, which, from the point of view of probability, should be taken into account for material classification. For example, if the distribution of the data of a certain material is uneven, that is the values of standard deviation are different in different components, then although the points have the same spectral angle to the sample mean, they could have a different probability of being the same material.

Hyper-hue is a high-dimensional analogy to the norm hue transformed from RGB colour space. For material classification in multispectral or hyperspectral data, Liu, et al. (Liu et al., 2017) proposed a high-dimensional colour space named hyper-hue-saturation-intensity (HHSI), which is a high-dimensional analogy to the trichromatic colour space hue-saturation-intensity (HSI) transformed from the RGB colour cube (Gonzalez and Woods, 1992; Perez and Koch, 1994). In an n-dimensional hypercube, along with the hyperachromatic axis, which is the segment connecting the points $(0, 0, \dots, 0)$ and $(1, 1, \dots, 1)$, all the points are projected to a space called hyperchromatic space that is perpendicular to the hyperachromatic axis. In this space, the norms of all of the vectors are normalised so that all the points are in the space of a hypersphere with the radius 1. The values of the normalised points in the hypersphere are the values of hyper-hue which is $(n-1)$ dimensions. It has been proven that hyper-hue is more robust to uneven illumination when doing material classification (Liu et al., 2017).

2. Materials and methods

2.1. The spectral features of green leaves at UV band

Considering the balance between the system complexity and the power of detection, the five spectral bands of UV, blue, green, red and NIR were used to detect invertebrates. While for generalisation, the spectral features of green leaves were studied in both multispectral and hyperspectral data. As the spectral features of green leaves from the visible light to near-infrared in the range of 400–1100 nm have been well studied (Shafri et al., 2006; Liu et al., 2013; Liu and Lee, 2015), this section only discusses the spectral features of green leaves in the UV range of 300–400 nm. Liu, et al. (Liu et al., 2016) evaluated the contribution of UV for pest detection through an experiment, however, their study of the spectral features of the UV light is not adequate and need a further investigation. The hyperspectral reflectance data was provided by the floral reflectance database (FReD) (Arnold et al., 2010). A total of 50 sample points of green leaves were randomly selected from over 2000 sample points in the database. The reflectance data is from 300 nm to 699 nm at 1 nm bandwidth, resulting in 400 dimensions for each sample point. The values of the sample points are plotted in Fig. 1, in which each point is plotted with a random colour and the mean and standard deviation of the points are marked with the red and blue bold curve respectively. From the observation, the reflectance of green leaves between the UV bands from 300 nm to 400 nm is below 0.15 which is relatively lower than that at higher spectral bands. In further observation, in the UV bands, the standard deviation is below 0.03, showing that the reflectance of the green leaves is more stable in the UV bands than that at higher spectral bands.

A similar experiment was conducted in a set of multispectral images of UV, blue, green, red and NIR which were collected by a multispectral imaging system developed by Liu, et al. (Liu et al., 2016). The peak transmittance of the filters in the system is 330 nm (UV), 465 nm (blue), 528 nm (green), 630 nm (red) and 748 nm (NIR) respectively. Total 2,960,000 sample points of green leaves were collected from a variety of plants under different illumination and the result is plotted in Fig. 2. It shows that both the mean and standard deviation of the intensity of the UV light is about 0.1 which is lower than those at other bands. In summary, green leaves have relatively lower and more stable reflectance at the UV spectra between 350 and 400 nm. This property of green leaves indicates that UV light would be a good indicator to distinguish green leaves from other materials.

2.2. Normalised hypercube

We recommended two models that are less affected by illumination and at the same time can describe the distribution of data: the normalised hypercube (NH) and hyper-hue (Liu et al., 2017). Hyper-hue has been introduced in Section 1.2 and this section explain the concept of NH.

An NH can be simply obtained by normalising the norms of all the vectors in a hypercube to 1. After this transformation, all the points are in a space of hypersphere and each point represents the direction of the corresponding vector in the hypercube and therefore, can represent a