Research Project	UAV-based Multispectral Imaging and Semantic Computing for Global Farming Analysis
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Research outline

This research proposes the multispectral image retrieval method by using spectral feature and semantic computing which is not many studies have focused. The main contributions are to enhance the effectiveness and advantageous of global environmental analysis system and realize semantic associative search and analysis. In this work, we study multispectral image retrieval using spectral feature computed in multispectral semantic-image space. The multispectral semantic-image space is supposing to realize the interpretation of substance (materials) on earth surface which can be provided the analyzed results as human-level interpretation. Our essential approach is utilizing the semantic computing to measure the similarity between multispectral image and the meaningful keywords which according to the user's contexts. Our research results found that this method possible to acquire the spectral feature from the multispectral image and could be used in multispectral image retrieval. In this study, a multispectral image is used as the image query according to user's query contexts. Moreover, the method performance of UAV-based multispectral aerial image retrieval using spectral feature and semantic computing is measured based on the queries with three contexts of multispectral image which is indicated by previous study on agricultural monitoring system and semantic interpretation model.

Research result

The system architecture of the multispectral aerial image retrieval system consist of two phases: (1) spectral feature extraction and (2) semantic similarity using semantic computing in MMM. The first phase presents the retrieval process by extracting the spectral feature from the image data which are stored in the multispectral aerial image database. The second phase is to store the spectral feature of multispectral image into database which will be use for semantic similarity measurement and to match the image data and semantic keywords based on user's contexts. Finally, the computing retrieved results are mapped on 5D World Map System to visual the environmental computing result as the global viewpoint. Figure 1 shows the system architecture of our proposed multispectral-image retrieval method.

A. Spectral Feature Extraction of Multispectral Images

In this part, the spectral feature can be obtained from multispectral image. An image spectral pixel can be represented a spectral characteristic which is related to an object or material. The brightness of pixels of multispectral images correlate to the reflection of object. Furthermore, the brightness value in each corresponding pixel is semantically related to linguistic words [10,11]. The image spectral pixels are acquired from the multispectral image by selecting the most significant pixel, then mapped those pixels onto the projection vector and stored it into spectral feature database. Figure 5 shows the sample image (multispectral image with color filtered) and the results of spectral image pixel extraction.

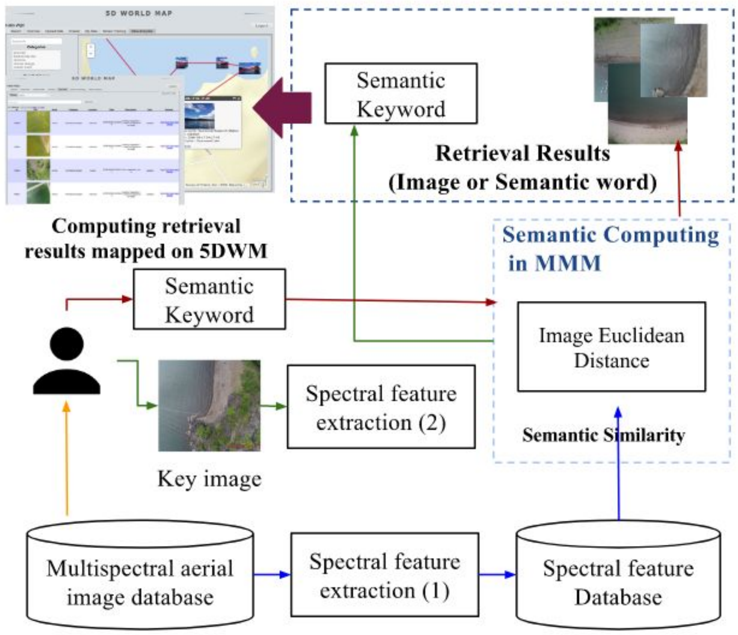

Fig 1. The system architecture of the proposed multispectral image retrieval system

B. Semantic Computing for Multispectral Images Retrieval

The important feature of our method is that multispectral are given in query to express the query context. We use the case that multispectral aerial image is given in the query to demonstrate our multispectral retrieval method. When multispectral image is given in a query, the spectral features are extracted. The most significant spectral image pixel is represented a single substance of surface feature. Then three-dimensional retrieval is created using environmental indices which are related to the agricultural monitoring and analysis. All the multispectral images in the database are projected onto the retrieval space. Multispectral images contain four spectral filter, which obtain the range of electromagnetic spectrum including wavelengths from visible spectrum to the infrared spectrum. In this paper, Euclidean distance calculation is utilizing to compute the semantic similarity of the spectral feature and user's contexts between multispectral image and keywords. Figure 2 shows the semantic similarity measurement using semantic computing in MMM.

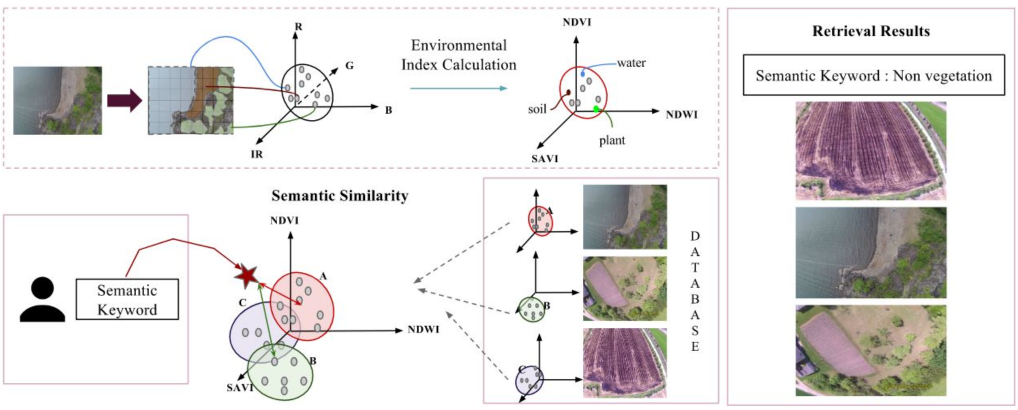

Fig 2. Multispectral image retrieval based on semantic similarity computing between user's contexts and multi spectral image data.

C. Experiment results and Analysis

In this part, a retrieval performance are measured the effectiveness of our proposed on multispectral image retrieval method by utilizing the spectral feature and semantic computing. First experiment presents the spectral feature extraction and applies the semantic similarity measurement to retrieve the multispectral image data in response to the keywords and user's context. In second experiment, we report the performance of our proposed multispectral image retrieval method using precision and recall function to evaluate the retrieval results.

- **Data Acquisition**

  The multispectral image database is contained 80 multispectral-images which are captured from UAV-multispectral sensor. The images were classified into four semantic contexts in term of agricultural health conditions based on our previous study on multispectral imagery and semantic computing for crop monitoring and analysis [2,9]. The images belonging to reliable context were computed from similarity measurement between data and represent in term of semantic meaning. An multispectral image could belong to multiple semantic contexts. Thus, this study applies the multispectral image retrieval method using spectral feature and semantic computing to improve the effectiveness of environmental analysis system. Multispectral images of three semantic contexts are used as the query images. The quantity of multispectral images per context was 20 images and stored in the multispectral image database.

  In this study, we modified the multispectral sensor from dual action cameras which consists of an array of three combined band (Red band = 700-600 nm, Green band = 500-600 nm, Blue band = 400-500 nm) and one individual channel (Infrared band= 700nm-1mm). In-house modifications made to modify multispectral sensor include UAV mountings. This sensors are utilized for capturing nature data resources as multispectral aerial images and extracted the numerical data or pixel values that extracted from multispectral image with 4 bands color spectral will be used for environmental index calculation. As we captures the aerial data from the modified UAV multispectral sensor, several factors are affected to raw data include surface conditions, atmospheric effects and sensor characteristics. In this point, we create the step for sensor correction and calibration to extract high quality multispectral data.

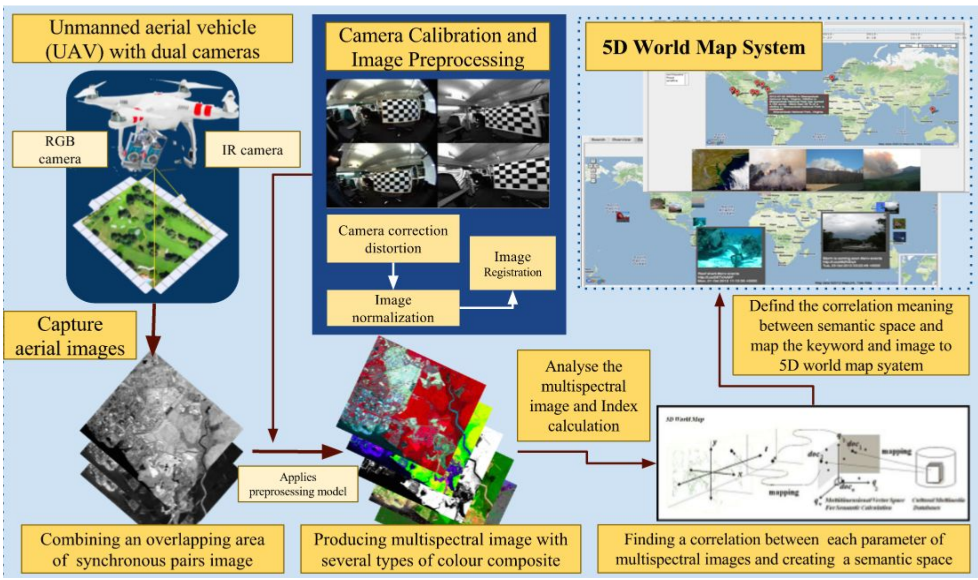

Fig 7. The overview of aerial image data acquisition including image pre-processing and multispectral image creation and analysis.

- **Experiment I**: Multispectral Image Retrieval for Agricultural Monitoring system.

  For multispectral-image retrieval, the spectral information is difficult to be classifiable by the people eyes. To enhance the capability of global environmental analysis system, multispectral image retrieval method can be utilized as a tool to understand the semantic associative search. In this section, spectral feature are extracted from multispectral key image. Spectral image pixel can be represented by brightness of pixel which related to numerical data from 0 to 255. The multispectral image used in this study consists of four spectral bands which can acquire the numerical data according to RGB and infrared (IR) values.

  This study applies the super-pixel segmentation algorithm to generate a coherent grouping of pixels [16], which is also known as image over-segmentation [17]. This method able to extract interesting objects from the background and can be used as a preliminary image processing step, followed by grouping processes that attempt to reassemble the objects into one object. Each segment derived from the image is referred to as an object, and the properties of the segments are designated as attributes or features [18]. In our study, we utilize a prior super-pixel segmentation of multispectral images as a form to describe the image similarities in each interested object. Then, applying the semantic similarity function to measure the similarity between query and image data.

  The following figure (Fig.8) shows the image processing method to extract the spectral feature from multispectral images including image segmentation using super-pixel algorithm and image spectral pixels extraction.

The following process is computing the semantic vector from spectral feature data where stored in spectral feature database using environmental indices. The environmental indices which are used in this study are described below:

- The normalized difference vegetation index (NDVI)

  NDVI is an index for detecting the "greenness" of plant or photosynthetic activity, and widely use for vegetation indices. This index can be differentiated healthy plant from other objects [12].

  $$NDVI = (IR-R)/(IR+R), \qquad (1)$$

  Where IR is the spectral value from inferred filtered image that extracted from infrared spectrum while R is the spectral value from red filtered image that extracted from red spectrum. Spectral value can be extracted from multispectral image. The calculated value of NDVI can range from -1.0 to +1.0, The highly value shows a highly photosynthetic active of plant while low value indicates non-vegetation area.

- The normalized difference water index (NDWI)

  NDWI is an index to detecting the changes of water content in leaves and delineate open water features [13].

  $$NDWI = (G-IR)/(G+IR), \qquad (2)$$

  Where IR is the spectral value from inferred filtered image that extracted from infrared spectrum while G is the spectral value from from green filtered image that extracted from green spectrum.The calculated value of NDWI can range from -1.0 to +1.0, The highly value shows a high-water content in leaves of plant while low value indicates low water content in leaves

- The soil-adjusted vegetation index (SAVI)

  SAVI is the information calculated from Infrared filter and Red filter. This index is is an index to detecting the soil moisture[14].

  $$SAVI = (1+L)(IR-R)/(L+IR+R), \qquad (3)$$

Where IR is the spectral value from inferred filtered image that extracted from infrared spectrum while R is the spectral value from red filter image that extracted from green spectrum and L is a canopy background adjustment factor (an L value of 0.5 in reflectance space was found to minimize soil brightness variations and eliminate the need for additional calibration for different soils). Spectral value can be extracted from multispectral image. The calculated value of SAVI can range from -1.0 to +1.0, The highly value shows a high soil moisture while low value indicates low soil moisture.

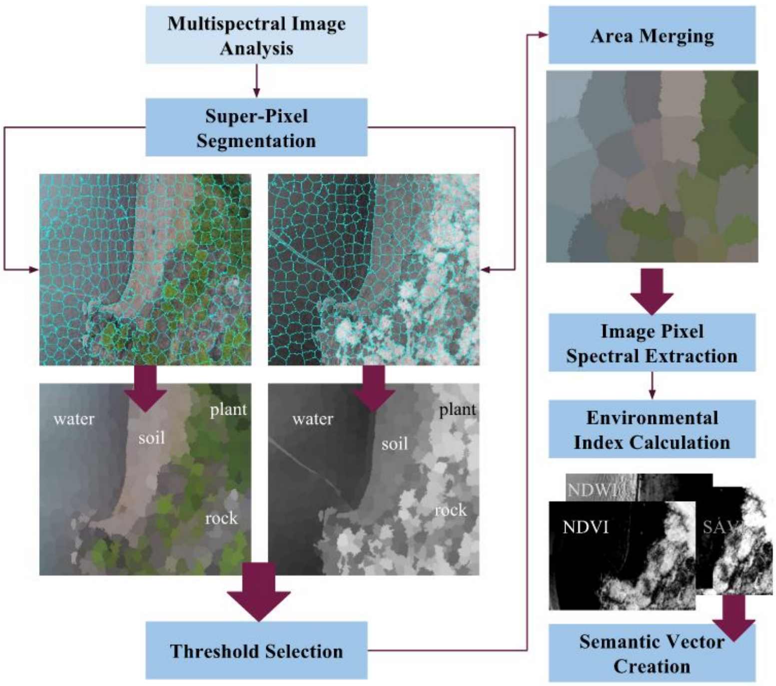

Fig 8. Overview of super-pixel segmentation process

Further, semantic retrieval space and subspace selection are performed for the dynamically semantic similarity computing between multimedia data according to user's contexts. This semantic space realizes semantic associative computing in three-dimensional orthogonal semantic space which performed by environmental indices, for searching multimedia data and computing the semantic correlations between multispectral images and keywords [1]. After computing the semantic vector, we apply the semantic similarity measurement using Euclidean distance [15] between keyword and multispectral semantic vector on semantic retrieval space. In this study, user's contexts are according to agricultural monitoring system and interpretation model [2,9]. We define the contexts as (1) Healthy vegetation in friable soil (Sometime in maximum greenness stage*), (2) Non-vegetation area with dry soil, and (3) Non-vegetation area (such as road, building) and burned land after harvest.

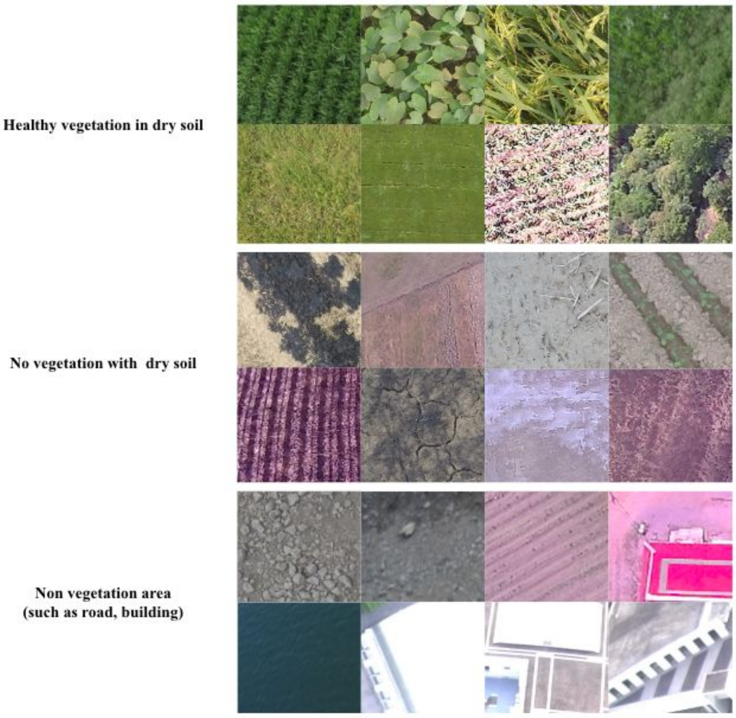

Fig 9. Example multispectral images retrieved results using spectral feature and semantic computing.

Retrieval results for semantic contexts using multidimensional semantic-image space concept

The Retrieval results according to three semantic contexts are shown in Figure 9. The actual amounts of image in each context diverge essentially. We measure a retrieval performance between various contexts which Healthy vegetation in friable soil being the easiest and non-vegetation area with dry soil the most differ context.

- **Experiment II**: Performance measure

  Each multispectral image in three semantic contexts that used in this study served as the main query image, 80 queries were executed in total. This section shows the precision of this method which is represented by the ratio of query context images of all retrieved image and a function of recall which is represented by the ratio of retrieved query context images of all image in the query context, averaged over the 80 queries.

  In this paper, we defined the number of retrieved similar multispectral image as SMI, the number of retrieved non-similar multispectral images as NSMI, and the number of non-retrieved similar multispectral image as NSMI'. The definition of precision and recall can be calculated as

$$\text{Precision} = (\text{SMI})/(\text{SMI}+\text{NSMI}) \qquad (4)$$
$$\text{Recall} = (\text{SMI})/(\text{SMI}+\text{NSMI}') \qquad (5)$$

  Precision represents the accuracy of our multispectral image retrieval method, while recall represents a comprehensiveness of method. Table 3 shows the precision-recall ration of our proposed method.

Contexts	**1**	**2**	**3**
Precision	61.5%	66.6%	100%
Recall	80%	54.5%	77.7%

Overall accuracy	68.6%

Table 3. Precision and recall ratio of multispectral image retrieval method using spectral feature and semantic computing

From Table 3, the retrieve performance as overall accuracy of our proposed method is 68.6%. The highest precision ratio is 100% corresponding to the context 3 (non-agricultural area) while precision ratio of context 1 (healthy vegetation in friable soil) and 2 (non-vegetation area with dry soil) are 61.5% and 66.6%. The recall ratio is shown 80% corresponding to context 1 and 77.7% in context 3 while the ration quite low on context 2 as 54.5%. This further shows that our proposed method is feasible to retrieve the multispectral image using spectral feature and semantic computing.

Conclusion and Future work

In this paper, a multispectral image retrieval method using spectral feature and semantic computing has been proposed. Firstly, a spectral feature extraction of multispectral aerial images is proposed using spectral image pixel. Next, Semantic retrieval space are preformed corresponding to user's context. Finally, the semantic similarity measurement of the multispectral image retrieval system is designed and computed in multispectral semantic-image space. The research results shows the possibility of our proposed method that can be used for multispectral image retrieval. In future work, similarity measurement by using the user's relevance feedback will be focused and more features of multispectral images will be utilized to the multispectral image data.

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