LEDCOM: A Novel and Efficient LED Based Communication for Precision Agriculture

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***Abstract*—Wireless Sensor Networks and Satellite Remote Sensing are some of the existing techniques that are used to collect, analyze and interpret data from the agricultural crop sites. However, there are certain limitations common to both of these techniques that are concerned with the latency and the resolution of the data collected. UAVs (Unmanned Aerial Vehicles) are becoming another alternative that has become integral nowadays due to its affordable and scalable nature while offering user friendly requirements and customizations. This proposes a novel and cost-effective technique (LEDCOM) that harnesses the capabilities of ground sensors and unmanned UAV while using computer vision methods to produce a qualitative data analysis system that describes the crop site under supervision. An UAV is assumed to collect the ground based sensor node data in the form of binary patterns on LED Arrays that is encoded in the image taken by a camera of a drone. Image processing techniques are used to identify and decode the LED sequences from the arrays. The performance of the proposed system is evaluated under different features and image resolutions within the same lighting conditions. A promising performance is observed for LED pattern identification from the challenging images taken from a height.**

***Index Terms*—Wireless Sensor Networks, Remote Sensing, Precision Agriculture, UAVs, Computer Vision, LED Pattern Identification**

I. INTRODUCTION

Satellite based remote sensing is one of the most widely used technique for the analysis of the crop data from images in precision agriculture [1], [2], [3], [4]. The images acquired by satellite face a lot of challenges like cloud cover, frequency of acquisition, low-resolution due to capturing from high altitude and other orientation and vignetting effects [5].

Nowadays, the advancement of Unmanned Aerial Vehicle (UAV)/Drone industry paved a technique to acquire high resolution images with user defined requirements [6], [7], [8], [9]. Moreover, the UAVs have become an accepted solution worldwide to overcome the limitations of existing methods of satellite based image acquisition. Employing UAVs for precision agriculture applications has opened up a wide range of possibilities like monitoring, mapping, surveying crop lands and analyzing the crop health [10]. Drones can be customized as per the required applications and provide a diverse range of solutions to active consumers and researchers worldwide [11]. Numerous studies have addressed problems like crop area classification, weed determination, crop species identification, smart city applications, [12], [13], [14] and many more. Louaragant et al. assess the spectral information of images captured with an unmanned aerial vehicle, in the context of crop & weed discrimination [5]. Drones are also used in regulating intra-field variations arose due to manual application of fertilizers and pesticides, through variable rate technology, but their operational success is determined by accurate mapping, weed detection, pest management, and other soil conditions thus requiring rigorous analysis. Duggal et al. have developed a novel and scalable solution of utilizing the monocular camera of a Quadcopter to monitor the plantation and estimate the yield by surveying a pomegranate site [15]. Although their work was specifically for a pomegranate site, the authors presented it as a solution for diverse crop plantations. The UAV equipped with multi-spectral cameras is a low cost and efficient solution for many aspects of precision agriculture. Moreover, the low altitude flight of UAVs results in better resolution of the images captured. Sometimes, the indices used to parameterize the crops may not be as reliable as they are in other cases and also their application varies from crop to crop [16]. Thus, the ground truth based validation schemes are a definite requirement in such scenarios to judge the performance of data capturing using UAVs. The accuracy of the system can be improved with additional information of sparsely placed ground sensor nodes. Ground sensor nodes are distributed in the field and data should be sent to UAV/drone and thereby to remote servers through a long distance communication link.

Wireless sensor network (WSN) of end ground sensor nodes and UAV gateway system is an alternative approach for the domain of precision agriculture with UAV systems. It is a scalable solution and also offers varied customizations [17]. Above techniques proposed using WSN are always affected by one or more of these factors: reliability, end-to-end delay, congestion among the nodes, high transmission energy for battery based ground nodes.

The system proposed in this paper introduces a novel data communication methodology between ground sensor nodes and a UAV with image-based data acquisition rather than traditional wireless communication. In the proposed system, a drone hovers over the sensor nodes and collects the image data from the LED arrays connected to the sensor nodes. These sensor nodes encode the data collected from the crop-site into the locally attached LED array units. The UAV during its flight collects the image and video samples from the field at regular intervals of time. The data collected by the UAV are processed using a template based feature matching procedure. Thus, the proposed model overcomes the congestion of the traditional

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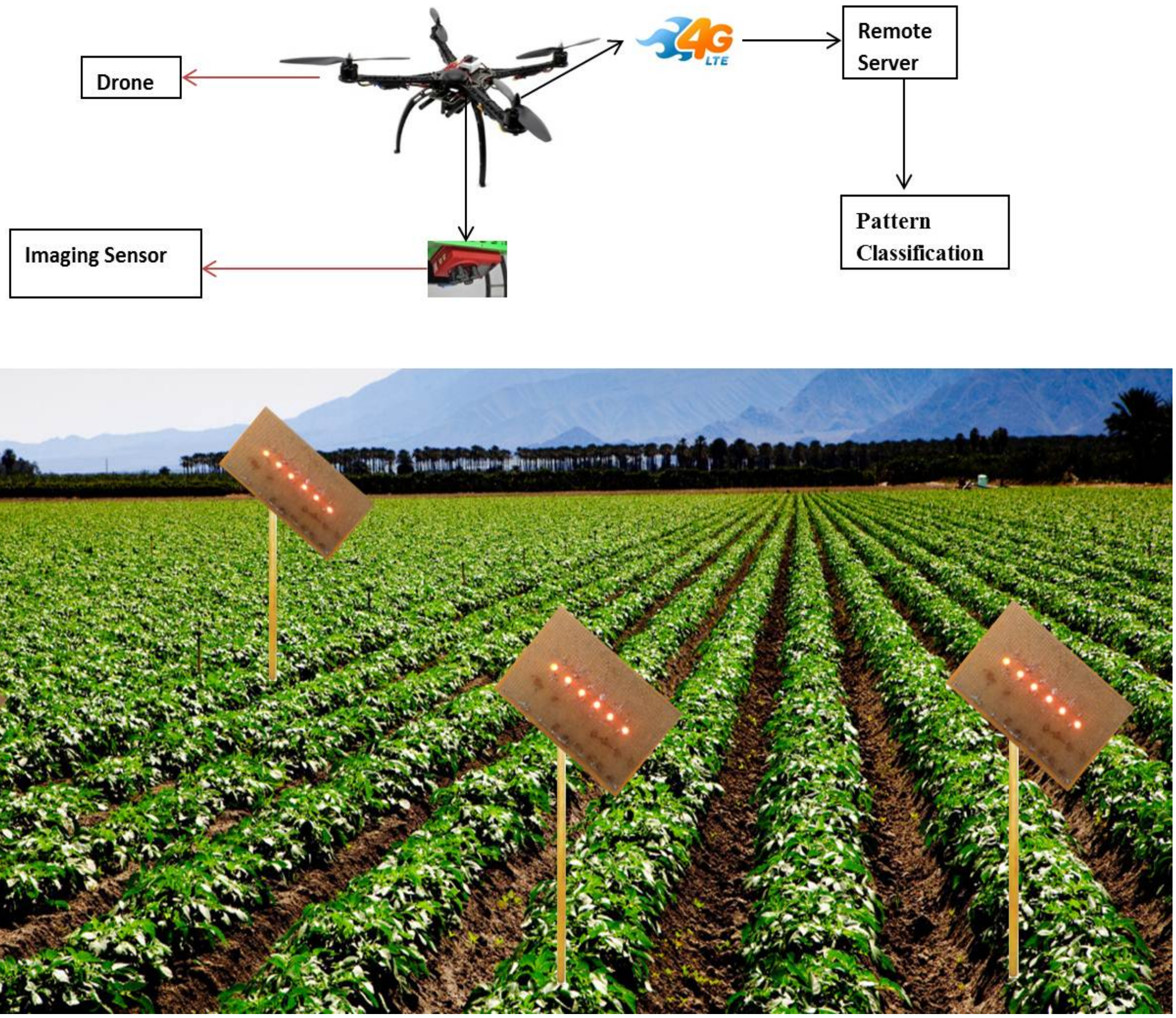

Fig. 1: The work flow of the proposed LEDCOM method to sense the ground data using LED and computer vision based encoding, communication and decoding. The ground sensor data is encoded in the binary form using '1' and '0' which is reflected as the 'ON' and 'OFF' states of the LEDs, respectively. The LED pattern is captured in the form of images using the imaging sensors deployed with an UAV which hovers over the LED arrays. The original binary pattern is extracted from the LED array image using the template image matching approach. Finally, the ground sensor node data is computed using the extracted binary pattern from LED array images.

wireless ground nodes by capturing a single image of all ground sensor nodes. It also reduces the power required for the transmission of the ground sensor nodes and saves the battery power. For the experimental purpose, the close range dataset is collected using a smart-phone camera under ideal conditions in a uniform background. The promising preliminary results are obtained using the state-of-the-art image feature matching technique in a uniform background and lighting conditions.

This paper is organized as follows: Section 2 proposes the novel LEDCOM methodology for sensing the ground data; Section 3 presents the experiments and analysis; and Section 4 concludes the paper with the future scope of research.

II. Methodology

The entire methodology is divided into three key phases: A) Ground sensor data encoding using LED pattern, B) LED pattern capturing using imaging sensor, and C) LED pattern extraction from image.

A. Ground Sensor Data Encoding using LED Pattern

In this paper, a novel data communication is proposed by combining sensor networks and computer vision together. The methodology proposed in this paper is explained with an example of agriculture application shown in Fig.1. Different sensors like soil moisture, temperature, humidity etc. are interfaced to embedded boards which are termed as ground sensor nodes. Each node in the field is assumed to be connected to an embedded board like Arduino UNO with an onboard ADC (Analog to Digital Converter) channel of N bits shown in Fig.1 where N is the number of LEDS in the PCB boar. Sensor data digitized by ADC of each node should be communicated to the

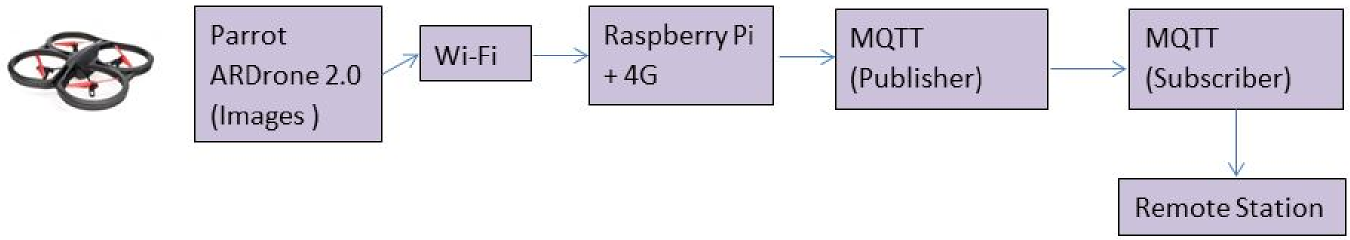

Fig. 2: Image acquisition pipeline of proposed LEDCOM method.

remote server for further analysis and decision/acuation process. It is proposed that an UAV/drone will collect data from all the ground nodes periodically according to the application requirements as shown in Fig.1. An array of LEDs equal to or less than the number of bits in ADC of the ground sensor node is connected to the same embedded board which is interfaced to the sensor node in the field. The LED's connected to the embedded board represents either exact ADC pattern or scaled versions of sensor ADC value. A new data communication model is proposed in this paper between ground sensor node and a hovering drone by transferring the ADC values of ground sensor nodes as an image/video of LED sequences and decoding them again in either drone or remote server. Above computer vision based approach for data communication using images of LED patterns is designed and experimented as proof of concept. The communication methodology between the ground sensor nodes and drones is explained with an example in the next paragraph.

Let us assume a soil moisture ground sensor data should be communicated to the drone. Soil moisture sensor is interfaced to an embedded board of 8 bit ADC. In traditional communication models, first the values of the soil moisture sensor are mapped to a value between 0 and 255 by ADC and then these values are converted in proper units using a characteristic equation of the sensor. Soil moisture values are transported to user/remote server either through wired or wireless communication protocols like Wi-Fi/Bluetooth/ZigBee. In this paper the ADC value of the sensor is reflected as LED patterns on a PCB board. This LED pattern is captured by a drone camera as an image. The ADC value of the particular board is converted into 8 bits using image template matching. Conversion of 8 bits in soil moisture units can be carried out in the drone and can be redirected to a user/remote server through a long range 3G/4G communication. The values of 'N' sensors in the UAV camera range can be sent to drone by capturing a single image of the area. This methodology will eliminate high congestion of traditional wireless ground sensor nodes when each sensor is trying to get access to drone radio for its data transfer. Proposed model also eliminates the necessity of wireless radio cost and radio transmission energy, thereby extending the ground sensor nodes battery lifetime by many folds. Translation of LED pattern into digital bits is explained in next sub subsection.

B. LED Pattern Capturing using Imaging Sensor

The UAV used in the initial experimentation is a Parrot ARDrone 2.0 which is equipped with a Raspberry Pi (RPi) 3 board with a 4G network interface. Images are captured by an UAV camera and are sent to a remote station over a 4G connection as shown in Fig.2. Images taken by the drone camera are sent to the remote station through the MQTT (Message Queuing Telemetry Transport) protocol. MQTT is a light weight protocol that provides a simple way for resource constrained clients to communicate with remote servers. In MQTT protocol, publisher(s) and subscriber(s) and mediated by a broker. In the proposed model, provision is made to sent the picture from drone's camera to the remote station over a 4G connection using the above publisher and a subscriber model of standard MQTT protocol. Though the system is developed as a proof of concept, due to payload limitation in the existing Parrot drone, we have used mobile phone based imaging sensor with 12MP camera to collect the images which are used in our experiments.

C. LED Pattern Extraction From Image

The images of the LED arrays are taken with varying number of LEDs ranging from 4 to 6. The proposed idea intends to be a real-time system where the sensor node information (in voltage levels) is mapped/encoded into binary sequences on the LED array of template size N (N can be 4, 5, and 6, etc). The LED pattern captured images are processed using a template based feature matching procedure using several 'ON' templates for the LEDs. The KAZE features [18] of both the original image and the template image are extracted and matched. If a significant number of matches are found, then the LED is classified under 'ON' state, otherwise it is classified under 'OFF' state.

1) KAZE Features: Alcantarilla et al. proposed the KAZE features as a novel 2D feature detection and description algorithm in non-linear scale spaces [18]. Authors used an efficient Additive Operator Splitting (AOS) technique with variable conductance diffusion for building the non-linear scale space. There are several other feature detectors like SIFT [19] and SURF [20] that describe features at different scales by approximating a Gaussian scale space of an image. The KAZE method uses a locally adaptive blurring technique that reduces noise while maintaining the details hence producing superior localization and accuracy [18].

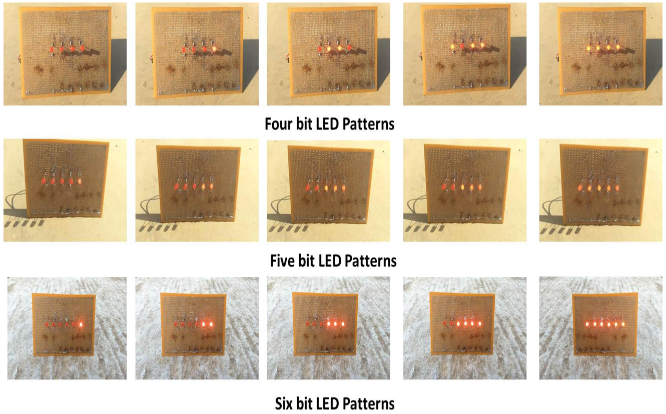

Fig. 3: Different LED arrays considered. The sample images of LED arrays with 4, 5 and 6 LEDs are shown in 1^{st}, 2^{nd}, and 3^{rd} row, respectively. In a row, the LED array images with different 'ON' status are depicted.

Fig. 4: The LED templates used for the classification by matching the KAZE features. The purpose of this matching is to find out which LED is 'ON' in order to decode the LED array pattern from the image.

TABLE I: The performance of LED pattern decoding from images using KAZE features. The LED pattern images of resolution 1920×1080 are taken from a mobile phone with 12MP imaging sensor.

Array Size	Total Levels	Correct Matches	Accuracy	Time (sec)
4	16	15	93.75%	172
5	32	32	100%	296
6	64	62	96.975%	475

III. Experiments and Observations

In this section, first the LED array dataset preparation is described and then the experimental results of the LED array pattern identification are reported and analyzed.

A. Dataset Preparation

In this experiment, we have considered three different arrangements of LED arrays with 4, 5, and 6 number of LEDs. This paper focuses only on binary states of LED (i.e., 'ON' and 'OFF'). An LED array with a N number of LEDs represents 2^N different patterns. Thus, the LED arrays with 4, 5, and 6 number of LEDs can encode 16, 32, and 64 binary patterns or levels, respectively. The binary sequences of each LED array (i.e., the 'ON' and 'OFF' sequences) are generated through an *Arduino UNO Micro-controller Board* set-up. We have used the mobile phone based imaging sensor with 12MP camera to capture the images of LED arrays for the template matching purpose. The images are taken in a sunny day with frontal views. A total of 16, 32, and 64 images are taken off the board having 4, 5, and 6 LEDs respectively, with one image per binary pattern. The sample images of binary LED state sequences with 4, 5, and 6 LEDs are shown in the 1^{st}, 2^{nd}, and 3^{rd} rows of Fig. 3, respectively. We have created two datasets by varying the distance between board and imaging sensor. The dataset created from less distance has the images with resolution 1920×1080, whereas second dataset has the images with resolution 960×540.

In order to perform the template matching with the 'ON' LED state, we have generated the LED templates in 'ON' state. The four LED templates used in this work for matching are displayed in Fig. 4.

B. Experimental Results and Analysis

We have performed the template matching experiments to encode the binary LED pattern in terms of the sequence of the 'ON' and 'OFF' states of the LEDs. We have used the KAZE features [18] to perform the template matching. The KAZE features of 'ON' LED templates (see Fig. 4) are compared with the LED features of the input images. We have computed the number of binary patterns successfully identified along with the time taken to perform the template matching. The lighting conditions in the images used were sunny and very bright. The LED state is classified in 'ON' state, if the significant match is recorded between the template image and the input LED image, Otherwise, it is classified as 'OFF' state.

The results in terms of the number of correct matches, accuracy of template matching and time taken are summarized in Table I and Table II for the high resolution (i.e., 1920×1080) and low resolution (i.e., 960×540) LED array images, respectively. The 2^{nd}, 3^{rd}, and 4^{th} row of Table I and Table II represent the performance for LED arrays with 4, 5, and 6 number of LEDs, respectively. Note that the accuracy is computed as $100 \times CorrectMatches/TotalLevels$. Promising performance is observed using KAZE features for template matching when the image resolution is high. The performance for low resolution images with less number of LEDs in the LED array is also very appealing. Based on the experimental results, it is observed that the ground sensor data can be converted in the binary form which will reflect as the LED pattern and can be recorded by the imaging sensors deployed with UAVs. Recorded images can be decoded with the help of computer vision techniques to send to the server.

To the best of our knowledge, the proposed work is first of its kind to read the sensor data through images of LED patterns. Thus, comparison with existing WSN methods is not feasible. However, in terms of the power consumption, the proposed method is 2-4 times more efficient than existing WSN based methods.

IV. Conclusion

This paper presents a novel approach for data communication in precision agriculture. The sensor data is represented with low power LEDs using Arduino Board, which is captured

TABLE II: The performance of LED pattern decoding from images using KAZE features. The LED pattern images of resolution 960×540 are taken from a mobile phone with 12MP imaging sensor.

Array Size	Total Levels	Correct Matches	Accuracy	Time (sec)
4	16	16	100%	34
5	32	28	87.5%	62
6	64	55	85.94%	109

as an image using UAVs and decoded using computer vision techniques without any need of wireless communication. The ground sensor data is first encoded into the binary patterns. Binary bit '1' or '0' are realized by the LEDs 'ON' and 'OFF' states, respectively. The images of the LED arrays are captured using the imaging sensors deployed with the UAVs and transferred to the server. The image matching techniques are used over the captured images of the LED array to decode the binary pattern of data. The experiments are performed using the images captured through the imaging sensor with varying number of LEDs. The presented idea is tested only under sunny and bright conditions. The KAZE features are used for the temple matching. A very satisfactory performance is observed to recognize the LED array binary patterns. It is also noticed that the high resolution images are best suited for this problem. The proposed methodology can address congestion of traditional wireless sensor networks, power consumption of battery operated tiny ground nodes. The proposed approach is also very cost effective by removing the dependency on wireless communication between ground sensors and UAV. Further, the high resolution images will be considered in the future taken from the low altitude flight of the UAVs/Drone.

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