Irrigation Detection by Car: Computer Vision and Sensing for the Detection and Geolocation of Irrigated and Non-irrigated Farmland

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***Abstract*—Irrigation can greatly increase the income of smallholder farmers in sub-Saharan Africa. By providing information about current irrigation utilization, or lack thereof, we seek to encourage investment in irrigation systems and their supporting infrastructure. In this paper, we describe the design, prototyping, and testing of a novel, cost-effective, and reliable computer vision system that is capable of locating irrigated plots at scale. Our system will be mounted to a vehicle and record the depth of objects in the camera's view while the vehicle is in motion. The GPS coordinates of objects are computed based on estimated depth, vehicle coordinates, and orientation, available from included sensors. We tested our prototype on objects at various distances from the system and achieved feasible accuracy with acceptable error in the estimated depth. In the future, we hope to deploy the system in parts of sub-Saharan Africa, to detect and geolocate irrigated agricultural plots during the dry season. Then we plan to use that collected data to inform and train machine learning models that use remote sensing and satellite imagery.**

***Index Terms*—Computer Vision, Irrigation, Agriculture (SDG2), Productive Use, Clean Energy (SDG7), Economic Growth (SDG8)**

I. Introduction

The impetus for our system stems from the simple idea that irrigated farmland produces significantly higher crop yields. Irrigation is necessary for horticulture, and horticultural crops are more valuable. As of 2013, there were approximately 33 million smallholder farms in sub-Saharan Africa, comprising 80% of the total farms and contributing 90% of the food supply. Africa's population continues to grow rapidly which increases the importance of these farms and their productivity throughout the year [2]. According to a 2007 report by the USDA Foreign Agricultural Service, rain-fed agricultural work employed 75% of the workforce in Senegal with only 5% of the available land using irrigation [3]. From pilot programs done by The Quadracci Sustainable Engineering Lab at Columbia University (qSEL) in Senegal, we know anecdotally that the majority of affordable irrigation systems on the market in Senegal are inefficient gas or diesel surface pumps [4].

From visits to several different regions in Africa, members of qSEL observed that many farmers do not irrigate their crops. Pilot projects by the same lab in Senegal have shown that irrigation can add additional growing seasons, effectively doubling farmer incomes in some instances. Farmers rely on growing and selling produce to make money. To grow a steady supply of crops, farmers need steady access to water. Dry seasons last most of the year in many regions of sub-Saharan Africa, with abbreviated rainy seasons lasting only one to three months. As such rainfall collection alone cannot meet farmers' needs. Even in regions with extended rainy seasons, it is impossible to ensure constant rainfall at the correct rate, making irrigation a boon for production there as well.

Geolocating irrigated and non-irrigated farmland provides several benefits. First, pump-driven electricity demand can be mapped and overlaid on-grid power transmission lines to show off-grid consumption. This would encourage investment from utility providers to electrify rural parts of the continent. Electrification would decrease the initial capital cost of irrigation for farmers, which in turn incentivizes more farmers to irrigate. As was found in qSEL's pilot pumping systems in Senegal, when the cost to irrigate is low enough farmers water more, especially in dry seasons, and thereby experience greater yields. With the GDP of sub-Saharan Africa currently directly tied to agriculture, an increase in production to feed the increasingly large population can only grow the region's world standing. Second, a visualization of areas with high

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farming activity but little irrigation could promote investment in irrigation systems by businesses and aid organizations in those locations. Data is needed to motivate investment, we seek to provide appropriate data.

II. Background

The process of detecting irrigated farmland at scale bears several challenges. In Europe and the United States, farm plots of several hundred acres are easily detectable from space. Their African counterparts are commonly just an acre or less and are thus much harder to detect from that distance. In the United States, the USDA executes an Agriculture Census that provides a complete list of U.S. farms and ranches, small and large, across the country. It also provides a data query tool so this information can be swiftly processed and redirected to other studies or pursuits [1]. The information available for our target area is much more limited and so data collection initiatives are vital.

To date, there are several data collection technologies that can be employed. Individual farmer surveys, taken in an unbiased distribution, could provide the most accuracy but can cost between $20 to $40 per farmer from our experience. This expense, extended across the entire continent of Africa is out of reach with our resources and potentially unbalanced with the benefit of such a survey. Drones could be used to capture a high detail aerial view and GPS coordinates directly above desired features. However, drone technology is limited by very short battery life, high expense per unit, and difficulty in flight training. This makes the process of mapping large regions of land infeasible. There is some street view imagery available from mapping services, like Google and OpenStreetCam, but it is limited in rural regions of Africa. Finally, pre-existing satellite data on its own is not enough as irrigated farmland plots in Africa tend to be small and exhibit many similar features to say a cluster of trees when viewed from space.

Our solution is to gather GPS coordinates of irrigated agricultural plots from a moving field vehicle as it goes about other duties or on dedicated scouting trips. This method can be used as a middle ground between expensive hand-collected surveys and satellite imagery analysis, which is speculative without ground truth. We aim to lower the cost and increase the availability of ground truth for the training of satellite imagery machine learning models.

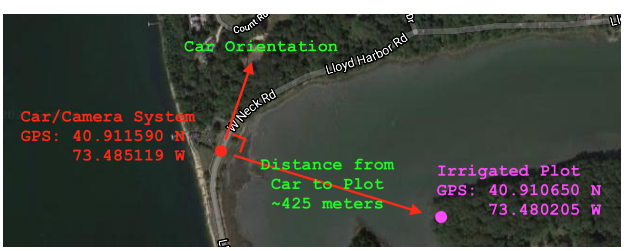

Fig. 1. Concept Sketch.

III. Concept

Our solution for cost-effective, reliable irrigation detection at scale is designed to be a portable multi-camera stereo vision system mounted to a car. As the car is moving, we want to gather the GPS coordinates of each irrigated field we pass. In order to realize this goal, the following information is required at each timestamp:

- The camera system's geolocation
- The system's orientation in relation to its GPS coordinates
- The distance between our target and the camera system
- The angle of the target from the camera's capture plane

Fig. 1 shows how the requisite information can be used to extrapolate the GPS coordinates of irrigated plots. Our system is capable of collecting all the requisite information at any given time. The system's GPS coordinates and orientation are captured by onboard sensors and are logged constantly with a corresponding timestamp. The distance between the target object and the camera unit is estimated by stereo vision, a computer vision technique to extract 3D information from multiple 2D views of a scene. By recording videos with two adjacent cameras simultaneously the depth of objects in both frames can be estimated. A timestamp is recorded with each video frame taken.

After video capture, human taggers will manually examine the video frames and identify the ones with irrigated plots in the middle of the scene, to fix the angle between the object and camera capture plane at approximately 90 degrees. By matching timestamps, the estimated depth of plots in tagged frames is paired with the camera system geolocation and orientation. Then the GPS coordinates of irrigated plots can be calculated.

Note that the area of farmland is not being detected with this method, simply the location of an irrigated piece of land within view of the roadside. However, the geolocation itself is practically valuable as this tagged GPS data can then be translated to its respective place on satellite imagery to support the training of a machine learning model being fed high-resolution satellite imagery. Our street view tagging serves as a quasi-ground truth that prevents satellite imagery from being overly speculative and allows irrigation detection to happen effectively without having to speak to each farmer. We believe our solution has the potential to be deployed in much of the developing world.

IV. Prototype

Initial prototypes were built for lab and local testing. Further units are being prepared to send in small numbers to data collection teams in Africa.

A. Hardware Architecture

The prototype units were designed to be built with all off the shelf components for around 500 USD per system. This price allows for feature detection on one side of the car and only includes materials, not shipping or assembly. The system consists of an enclosure that houses power converters and energy storage, a Raspberry Pi 3+ compute module board,

Fig. 2. Prototype Mounted to a Car.

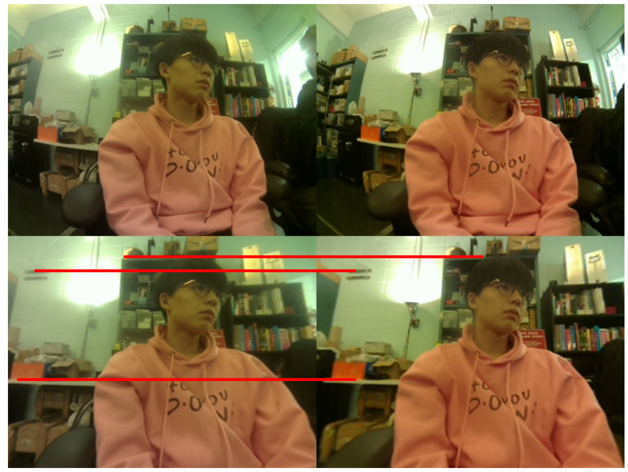

Fig. 3. Before (top pair) and after (bottom pair) rectification. Note in the bottom rectified pair, distorted edges are reprojected to be straight and at the same horizontal level (shown by red lines).

and the requisite sensors. The Raspberry Pi is a single board computer running Raspbian Linux, an offshoot of Debian for small ARM Broadcom processors. Two 5 megapixel fisheye cameras with OV5647 CMOS sensors are mounted on the exterior of the enclosure with a baseline distance between the cameras of 200mm. The other requisite sensors include a MTK3339 GPS module to capture the location of the camera system and thereby the car, a Bosch BNO055 9-DOF sensor to retrieve the Euler and Quaternion vectors of our camera system, and a DS3231 precision RTC IC to maintain system time. The units can be powered with an AC/DC wall power supply or a DC car cigarette lighter port and stores energy in a Lithium Ion battery to avoid problems presented by power fluctuations. Fig. 2 shows our prototype mounted to a car.

V. Software Pipeline

In the software pipeline, we describe how we extract the geolocation of irrigated plots from field videos.

A. Calibration

Camera calibration is the first step in the software pipeline. It is the process of estimating the parameters needed to construct a mathematical model of the camera system. We use the OpenCV implementation of the multiplane calibration technique (also known as Zhang's method) [5]. The calibration is completed by taking pictures of a chessboard pattern from multiple perspectives and solving the homogeneous linear system that is produced after matching the same points in the left and right cameras.

The estimated camera parameters are then used to reproject the left and right images (also called a stereo pair) to the same plane, making the disparity only in the horizontal direction. This step is called rectification and is a common pre-processing practice for depth analysis using stereo vision. An example of rectification using our system is shown in Fig. 3.

B. Data Capture

Data capture occurs on our car-mounted prototype units. Captured information is stored on a microSD card which can be removed after testing for easy data transfer to a central computing resource where additional processing and computations can be applied.

Before capturing data in the field, we calibrate the camera system to obtain necessary parameters for rectification. When taking stereo videos, each frame is rectified before it is written to disk. This allows our post-processing to directly work with coplanar stereo pairs that only have horizontal disparity.

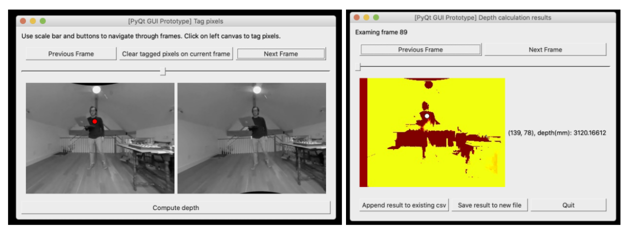

Fig. 4. Object Tagging and Result Display in GUI.

C. Object Tagging

The next step is to tag objects of interest, such as irrigated plots, from all video frames taken. We prepared a simple graphical user interface to support manual tagging and the depth estimation of tagged objects.

Upon inputting required files, the GUI allows human taggers to examine all stereo pairs in the videos selected. The human tagger then manually chooses the frame(s) where the object of interest is present in the middle of the scene and marks the object by clicking on the left stereo image. A red dot will be drawn at the selected location (Fig. 4, left).

After the user selects to proceed, the next window shows the estimated depth of all tagged objects. (Fig. 4, right)

VI. Depth Estimation

Estimating the depth of tagged objects starts with creating a disparity map. For a given rectified stereo pair, the disparity map gives us the horizontal distance between a pixel in the left frame and right frame. The intuition is that the farther an object is from the cameras, the smaller the disparity of the object between left and right images is. There are many algorithms to compute the disparity map. We experimented with Block Matching and Semi-global Block Matching (SGBM), both of which are provided with OpenCV functionality [6]. We found that the SGBM algorithm gave us better results.

Next, we perform a post-filtering technique, based on the Fast Guided Global Interpolation Algorithm for depth and motion [7], to refine the quality of the disparity map by improving consistency between the disparity map and source images. This is a common practice for improving the quality of a disparity map. We used the OpenCV functionality for this filtering algorithm.

Once we have a filtered disparity map, we can calculate the distance, Z, with the following formula. [8]

$$Z = (f * b)/d \tag{1}$$

Where f is the focal length (estimated by calibration), b is the baseline (distance between two cameras, measured from set up), and d is the disparity. We plug the disparity of the tagged object into the formula to calculate the distance. Fig. 4, right shows an example of displaying disparity map and estimated depth in the GUI, the depth results can be exported to a CSV.

The estimated depth, along with vehicle GPS coordinates and orientation (both available from sensor outputs) will be used to reconstruct the GPS coordinates of tagged objects.

VII. Interim Results

We tested the depth estimation functionality of our prototype on objects at various distances from the cameras. We used the SGBM algorithm, post-filtering, and optimized SGBM parameters for best results. Fig. 5 includes one stereo pair and corresponding disparity map for each of the three test cases we present.

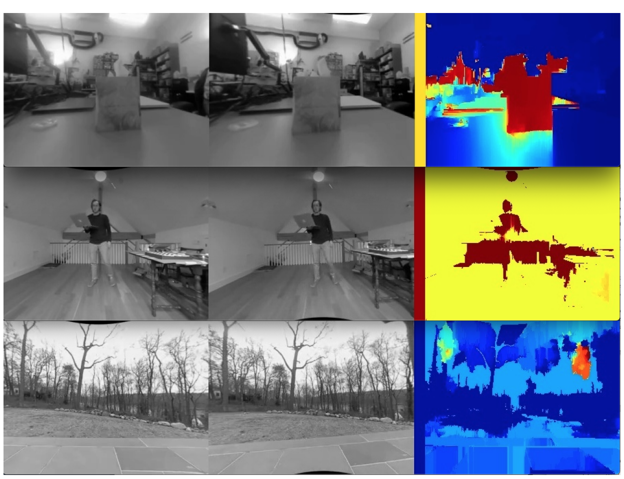

Fig. 5. Tissue Box, Loft, and Trees with SGBM.

For the first test case, we calculated a distance of 188mm for a tissue box 200mm away (6% error). For the second test case, we calculated a distance of 3120mm for a person standing 3352mm away (about 7% error). For the third test case, we calculated a distance of 10899mm for trees 9754mm away (about 11% error).

The accuracy of depth estimation is crucial, as the reconstructed GPS coordinates of objects are directly dependent on the depth. These are relatively small increases in error for very large increases in distance. We hope to retain this error pattern for distances on the order of hundreds of meters up to a kilometer.

VIII. Conclusion

In this paper, we describe the design, prototyping, and initial testing of a vehicle-mounted computer vision system that allows cheap and reliable irrigation detection and geolocation at scale. Our interim results show that the system is able to feasibly calculate the distance of objects meters away with 6% - 11% error. We hope to expand our project by refining our system to process features in moving videos one kilometer away and further reduce our error, thus improving the accuracy of geolocation.

In the future, we hope to deploy the system in parts of sub-Saharan Africa to detect and locate irrigated agricultural plots during the dry season, and use the collected data to train satellite imagery machine learning models. We argue that by showing the need for irrigation with our collected data, we can encourage investment in irrigation systems and the infrastructure that supports them. We believe this technology can be a contributing solution improve agricultural production in sub-Saharan Africa.

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