IoT Middleware for Precision Agriculture: Workforce Monitoring in Olive Fields

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***Abstract*—Precision Agriculture systems allow farmers to have a deeper, more detailed knowledge about the agricultural field, and helps them make better management decisions. However, the existing solutions rely upon significant investment in new equipment and changes in field layouts making it impractical to farms with less mechanized methods.**

In this paper we propose an *Agricultural Workforce Monitoring* system to enrich data on production models. Our approach uses a conventional smartphone embedded with sensors to monitor workers' locations and movements that allow for activity inference. The solution uses GPS and Dead Reckoning to capture worker's locations in the agricultural field, and Machine Learning to classify the agricultural worker activities throughout their working day. The developed system was implemented and evaluated in actual olive fields.

***Index Terms*—Precision Agriculture, Sensor Integration, Location, GPS, Dead Reckoning, Internet of Things**

I. Introduction

According to the latest United Nations projections, by 2050 there will be 9.7×10^9 people on the planet [1]. With traditional agricultural production methods it will not be possible to match the need for greater amounts of food. New agricultural production methods will be necessary to increase productivity and to rationalize environmental resources.

Precision Agriculture envisions agricultural data capturing, gathering data in each step from planning to final product, in the agricultural production process. Furthermore, Precision Agriculture systems can help farmers with decision making and resource management while integrating different information sources such as sensors, satellites and meteorologic forecasts.

The existing solutions are adapted to mechanized production methods and they are not suitable to smaller scale farms or are unable to capture data in each step of the process. There are also farms with speciality crops (fruits, vegetables and flowers) where there are no big machines involved on the activities and farmers need to use manual labor in the production process. No solutions were found that can simultaneously monitor the human labor and machines working in the field.

To overcome the agricultural worker monitoring problem, there is a need to create solutions capable of tracking the behavior of each individual and tools to integrate data from different workers, using distinct location systems with other sources of information given by several sensors present in the field.

The fragile nature of specialty crops usually requires farmers to choose to harvest their crops with a human workforce rather than mechanized systems. In this type of crops it is important to farmers to know where an agricultural event occurs with an accuracy that leaves no doubt where it took place, so we consider specialty crops to have low error tolerance.

Rural environments have communication and energy infrastructure limitations which leads the system to have the necessity to minimize energy consumption and external communications. This is in contrast with a Urban Environment, where Internet of Things (IoT) [1] systems are usually targeted, and it is assumed that we have the necessary *energy* and *communication* infrastructures in place. A solution that is meant to be used in the rural world should not depend on the connection with external systems. Since this solution is to be used either on large or small farms, it must be accessible to those who can not afford expensive machinery, and since smartphones are getting cheaper and equipped with better location detection technologies, so the solution will start by using smartphones, but we will leave open the possibility of using other devices. Therefore, the system must function as long as the smartphone has battery in normal climacteric conditions.

The solution should be able to track workers in the agricultural field with an adequate margin of error to the crop, being able to distinguish, in the case of a fruit orchard for example, in which side of the fruit tree the agent is present at any given moment.

In a human monitoring application that has the goal to capture productivity metrics it is important that worker's performance is not affected with the solution, nor the production process is changed. In this way, the system must be adapted to different human bodies (i.e. height, weight, gender) in order to monitor each of those who work in a farm without their performance and comfort being affected.

A. *Case Study*

Agricultural activities can vary according to the crop that is installed in the field. The case study for this work was the *olive* crop. It that was chosen due to the ease of access to olive orchards and heterogeneity of tree sizes and field displacement

[1] https://www.un.org/development/desa/en/news/population/un-report-world-population-projected-to-reach-9-6-billion-by-2050.html

between different orchards, which helps when evaluating the system for real use cases.

Olive Orchards can be classified as Traditional, Intensive and Super-Intensive according to density of trees per hectare and their dimensions. In our case study we will compare the system in a Traditional Olive Orchard with a plant density of 80 to 120 trees/Ha and in an Intensive Olive Orchard with a plant density of 200 to 600 trees/Ha.

II. Solution

The goal of our system is to monitor agricultural workers in specialty crops using off-the-shelf hardware. The solution uses a set of sensors available in recent smartphones: GPS, accelerometer, magnetometer and gyroscope. With this system it is captured data about agricultural human labor using inertial sensors rather than field sensors or agricultural machine sensors.

Our approach is to split the problem in two worker monitoring tasks: *Location Detection* and *Activity Monitoring*. The architecture of the system is represented in Figure 1.

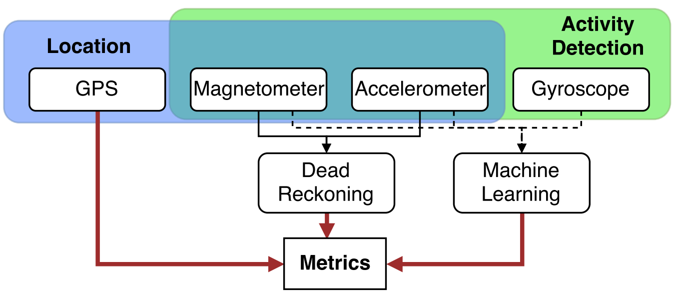

Fig. 1. Architecture of the system.

The *Location Monitoring* process corresponds to tracking the path that workers take throughout the field making it possible to farmers to know where a worker is at any given moment. To capture this type of geographical data are used the smartphone GPS receiver and the inertial sensors. However worker's positions are not representative of the activities they perform throughout the working day, therefore, we need a human *Activity Detection* mechanism to take place.

A. Worker Location Monitoring

Initial experiments in our solution showed that GPS technology is not accurate enough to be used as the main Location Tracking provider. In this solution we will capture worker locations with the help of the inertial sensors in the smartphone using a Dead Reckoning technology. In order to determine the new relative coordinates, the Location Monitoring module will have to detect user steps and give them a direction.

The first phase requires the user to walk a previously known distance and count the number of steps it takes in that path in order to calibrate the worker's average step length required by the algorithm. Knowing this value the application uses accelerometer data to detect new user steps.

The Android operative system [2] provides a `getOrientation()` function that takes accelerometer and magnetometer data as input and calculates a vector with the angles around each of the device axes in radians, anticlockwise.

By averaging Dead Reckoning and coordinates captured by GPS, our solution will be able closely match the worker's path on the field. A GPS accuracy of 8 meters will allow deviation to be corrected.

B. Worker Activity Detection

Human Activity detection systems use Inertial Sensors that are close to the human body and are able to detect which activity is being made at any given time.

The activities that need to be detected depend on the agricultural production methods, on the monitored crop and on the field's layout.

To lower implementation costs of such system we have considered to use off-the-shelf devices such as smartphones or smartbands that workers wear on his body.

We propose an agricultural activity detection that makes it possible to farmers to analyze the productivity of each worker, a common practice that is usual in agriculture, but it is typically based on less objective information. The solution we propose is to capture annotated data from agricultural activities and use Machine Learning algorithms [3] to classify the activities.

Machine Learning algorithms have three distinct phases: Learning, Validation and Classification. The first phase is when the algorithm learns to classify data-points by creating a knowledge model with the most relevant data features. Machine Learning algorithms take annotated data as input and create a model, that serves as input for the next phase. In this system the data features vary from the set of statistical operations applied to each of the smartphone's inertial sensors' data. After creating the model from example inputs with a certain classifier, the model needs to be validated with a different set of annotated data. This process tells us the ratio of correctly and incorrectly classified data-points in a confusion matrix. The last phase is to feed non annotated data to Machine Learning algorithm in order to be classified. The algorithm will compare the non annotated data-points with the model built in the Learning phase and decide on the activity represented by this new data-points.

An Android application [2] that captures accelerometer, gyroscope, and magnetometer data from the smartphone sensors was developed. Each sensor has 3 axes adding for a total of 9 data-points captured at a period of 0.02 milliseconds. Those data-points are introduced in a sliding window that applies to them a set of statistical operations: average, minimum, maximum, kurtosis and standard deviation, for a total of 45 features (3 sensors, 3 axes, 5 statistics). The size of the sliding window is set as 3 seconds (150 data-points) with an intersection of 1.5 seconds.

III. Evaluation

The evaluation of this solution is focused on three main aspects of agricultural worker monitoring. In the first place it is necessary to evaluate the capacity the system has to correctly detect the path taken by agricultural workers. Following that it must be evaluated the performance of the activity detection mechanism to detect human held agricultural activities. Finally the battery consumption in both system modules will be analyzed.

We have chosen two olive orchards with different characteristics in order to evaluate the performance and behavior of smartphone sensors in a rural environment. The first olive orchard uses a Traditional production method with no irrigation where the distance between trees is 10 by 12 meters and the crown width is 6 meters in average with a 2 meters deviation. The second olive orchard is installed in an area with hundreds of hectares with olive trees, it uses an Intensive production method with irrigation and it was planted less than a decade ago. In this orchard the distance between trees is 5 by 7 meters and the average crown width is 2,5 meters with a 50 centimeters deviation.

A. *Worker Location Monitoring*

Our solution uses data captured with a smartphone using the GPS receiver, accelerometer and gyroscope sensors to track workers in an agricultural field. A set of tests were made to analyze the performance of this system to detect the correct path of agricultural workers in a non-mechanized olive orchard.

The system will be tested applying different weights to captured signals with different accuracies while using the Dead Reckoning technology. We need to compare the combinations of both location technologies in order to be as close as possible from the real path. We will compare the real path taken by the smartphone operator with the one captured using the application. The real path will be manually drawn trying to match as close as possible what the worker does in the field.

The user has a Samsung Galaxy S7 in a belt near the left lumbar area of his body.

In this test we compared the performance of our solution when tracking an Agricultural Worker in a Traditional Olive Orchard. In Figure 2 is represented the path captured by a solution that only uses GPS, and in Figure 3 it is represented the path captured with our solution.

When comparing our solution with a solution that only uses the GPS receiver to track the worker throughout the field we can observe that in Figure 3 that it is more precise, being possible to observe path that is almost identical with the real path.

Solutions that only use GPS will struggle to be correct when the weather is not favorable or when the tree density is too high. With a Dead Reckoning solution we are capable to match very closely the real path of the worker, correcting the error with GPS coordinates when the accuracy of GPS signal is better than 8 meters, doing an average with the Dead Reckoning coordinates.

Fig. 2. Navigation using GPS in a Traditional Olive Orchard.

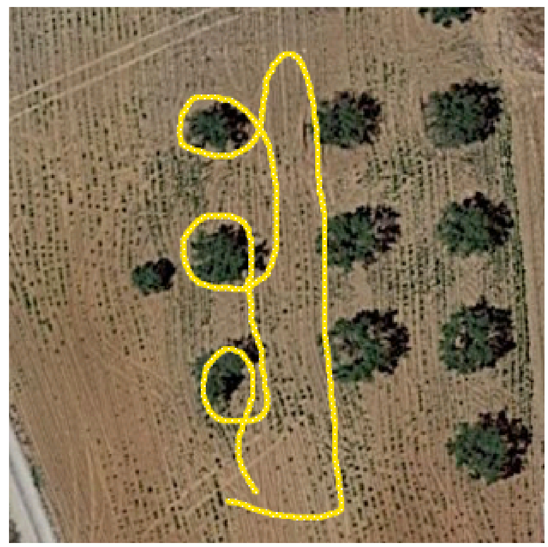

Fig. 3. Navigation using our solution in a Traditional Olive Orchard.

In our tests we evaluated the GPS energy consumption while navigating throughout the olive orchard. Device energy is a scarce resource in the rural world In the tests we have got a battery drain of 2% of the 3000mAh battery in a 10 minute period, with the GPS capturing a location point at every 60 seconds. When that period was decreased to 10 seconds the smartphone had the same 2% battery drain. This is due to the fact that the GPS needs to be continually receiving GPS signals to serve the Android Location Service in such a short period of time as 60 seconds. We can conclude that the sampling does not affect the battery drain. However this energy consumption might lead to complete battery drain in the period that workers stay in the field, which is a problem to our solution.

The Dead Reckoning technology is less energy-demanding than GPS and with this smartphone it could operate for a day of work without being charged.

B. Worker Activity Detection

Our solution implements a module that detects human activities in a rural context making use of a smartphone and Machine Learning algorithms to detect worker activities in the field.

In an olive orchard we will have workers that are different from each other. Since body movements vary from person to person, it is necessary to evaluate the algorithm's learning phase and its efficiency when classifying activities form various workers. With this experiment we evaluated the performance of various Machine Learning algorithms in both classifying data based on the models learned from the same person data models and with data from other people.

This experiment analyzed the learning capabilities in classifying a data-set from one worker with data learned from a different worker. Beyond that we measure the efficiency in activity detection with a simulation with different workers, where we will access the productivity metrics when compared to what is observed by the experiments leader.

The list of activities to be monitored is: *Walking Forward*, *Walking Backwards*, *Running*, *Picking Fruit* and *Digging*.

In the first test we evaluated the performance of this solution when classifying data from a single person with a model with data from the same individual. For each activity we captured about 2 minutes worth of data, for a total of 10 minutes of data that was individually classified.

All data was taken as input for the Machine Learning algorithms to build the Classification Models with the number of data instances reaching 255.

With a CFS Subset Evaluator, using a Best First Algorithm, it was possible to determine that the most meaningful features were the following:

- accMeanX
- accMinX
- accKurtosisX
- accSTDX
- accMeanY
- accMinY
- accKurtosisY
- accSTDY
- gyroMaxY
- compMeanY
- compMinY

It is possible to notice that the most important sensor to the Classification Models is the *Accelerometer*, as it is able to capture the forces created by body movements when the worker is performing the activities.

In this first test, after the validation phase the BayesNet algorithm had 95.29% of correctly classified datapoints and the MultilayerPerceptron improved that number to 98.04%.

After the validation process we proceeded with classification of new annotated datapoints for each of the activities.

In the results, presented in Table I we can observe that the system is able to distinguish between agricultural and non-agricultural activities with success rates being over 90% in both algorithms.

However, when comparing between *Walking Forward* and *Walking Backwards* the system struggles to correctly classify the activities since they are very similar and the amount of data-points only correspond to 10 minutes.

TABLE I
ACTIVITY EVALUATION RESULTS - PERCENTAGE OF CORRECTLY CLASSIFIED DATA-POINTS

Activity	BayesNet	MultilayerPerceptron
Forwards	75%	87.5%
Running	100%	100%
Backwards	80.70%	82.46%
Digging	91.67%	91.67%
Picking Fruit	98.04%	98.04%

In the second test we evaluated the performance of the solution when classifying data from a single person with a model with data captured from other person. In this test we only focused on activities that usually happen in the agricultural field: walking forwards, picking fruit and digging. For this test we have used the same model as the previous test, while we classify data from 2 new workers.

With a Classification Model that was built with data from a different worker both tests with these two workers presented a high percentage of correctly classified agricultural activity data-points using any of the algorithms. It is also possible to observe that both algorithms presented a large volume of incorrectly classified data-points when classifying the *Walking Forwards* activity. In comparison to what was visualized in the first test, most of the those data-points were classified as a *Walking Backwards* activity.

TABLE II
FIRST WORKER ACTIVITY EVALUATION RESULTS - PERCENTAGE OF CORRECTLY CLASSIFIED DATAPOINTS

Activity	BayesNet	MultilayerPerceptron
Forwards	38.60%	8.77%
Digging	91.23%	92.98%
Picking Fruit	87.5%	87.5%

TABLE III
SECOND WORKER ACTIVITY EVALUATION RESULTS - PERCENTAGE OF CORRECTLY CLASSIFIED DATAPOINTS

Activity	BayesNet	MultilayerPerceptron
Forwards	38.98%	42.37%
Digging	81.35%	81.35%
Picking Fruit	89.83%	91.52%

C. Results

In less than half an hour it is possible to manually classify a number of data-points that is sufficient to classify agricultural activities automatically in over 90% of the time, either when the model uses data from that same worker or data from another one.

It is difficult to distinguish between *Walking Forward* and *Walking Backward*, which can be seen in Table II and Table III. This is even more pronounced when the classification model uses data from other people as they have different walking paces. However this is not a problem to our solution since the two activities can be classified just as *Walking* without affecting the goal to distinguish between agricultural activities held by agricultural workers.

When the Classification Model uses data from a different worker there is a small decline in the percentage of correctly classified activities, with values averaging between 80% and 90%.

We consider that this is a promising starting point for the use of this technology in human activity detection and, with further work, these values can be improved. The amount of effort for a farmer to install such a system is low, even if a new model needs to be created for each agricultural worker.

D. Discussion

The Agricultural Worker Monitoring system that we present in this work is capable to monitor the positions and the activities that workers perform in the field with success.

The Location Monitoring module is capable to track workers with an accuracy that is very close to the real paths they take in the field. However the decision to use GPS to correct the accumulated error of Dead Reckoning causes the battery to drain very fast, which is a problem for such a system.

The Activity Detection module is able to detect agricultural activities when data is intermixed with a set of other human activities with success classification rates that are over 90%. The MultilayerPerceptron algorithm revealed a better sucess rate than the BayesNet, however the time it takes to classify data is much bigger. In this case the best choice is to use the BayesNet algorithm that does not compromises the ability to correctly classify activities and it is faster.

IV. Related Work

Modern agriculture introduced *Agricultural Production Models* that are the bridge that connects the entities that make part of the Agriculture industry. In order to feed those models, it is needed to perform production process analysis with the entities involved. Figure 4 shows the main activities.

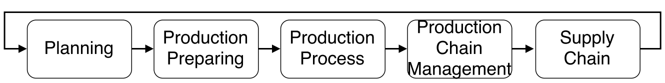

Fig. 4. Agricultural Production Model

Ferreira et. al [4] introduced an integrated model applied to the Brazilian orange production system. The authors present a model that aims to integrate the whole Brazilian orange producing business, in order to reduce costs and to improve the end-product income. When describing the model, the authors address a set of agricultural variables needed to analyze the business, and those variables include production costs, administrative costs and variables tied with the production process.

Vellidis et. al [5] developed a Wireless smart sensor array for irrigation scheduling that uses RFID tags to transmit data. However, with the decision to use tags operating at the 2.4GHz frequency, some wireless transmission problems occurred. The surrounding plants make a significant impact on the wireless transmitters and they needed to be positioned above the top of the plants in order to avoid signal attenuation.

Focusing specifically on *workforce monitoring*, it is a new area in Precision Agriculture and there is little research on the topic. A notable exception is the work by Ampatzidis et. al [6] [7] [8], which developed a wearable module to record worker positions, applied to orchards or protected cultivation environments, where GPS signal is typically unavailable. The goal of their project is to track the paths taken by agricultural workers in the field making use of both relative and absolute position location systems. As an alternative to GPS, that suffers from signal attenuation when close to trees their solution was to use a Dead Reckoning Module, a miniature electronic device that can be worn by people and provides the user's position relative to a initial point.

Global Positioning System (GPS) is a Global Navigation Satellite System (GNSS) that provides end-devices with location or position determination as well as time information on planet Earth, in despite of the weather conditions. Standalone GPS receivers are only dependent on their satellite constellation signals. The problem occurs when satellite signal is poor, such as in urban areas, tunnels. Or, in the case of agriculture that is relevant to us, when the receiver is close to tree canopy.

Dead Reckoning [9] is a navigation technology capable to deduct relative displacements to a previously known initial position by capturing the body movements of users. Inertial sensors, such as *accelerometers* and *magnetometers*, are used to measure the displacement relative to the initial position.

In large scale agricultural systems there are solutions that track machine behavior, but when we move to specialty crops, such as fruits, vegetables and flowers, there is no way to automate data collection, due to the need to use workers to perform the agricultural activities, instead of machines. Several approaches to solve the traceability problem have been tested, making use of RFID, GPS, barcodes and other mobile solutions. Cunha et. al [10], Kuflik et. al [11], Morais et. al [12] and Luvisi et. al [13], have been using mobile solutions related with data collection, on the field.

V. Conclusion

Precision Agriculture is an area in development and there is still room for improvement. Internet of Things technologies enable the interconnection between agricultural agents to create shared knowledge, that is then at the farmers' entire disposal.

In this work we developed and evaluated an Agricultural Worker monitoring system that is adapted to farms with specialty crops.

Our solution enables any farmer with a specialty crop farm of any size to monitor his crop using a smartphone that is installed next to the worker's lumbar area with a belt. To test this solution we had to chose a crop that was widely available and with heterogeneous characteristics to access if it was possible to use this system in other crops. We have chosen the Olive Orchard and its different production methods: traditional and intensive.

The decision to use a regular smartphone to capture worker data created the challenge to deal with low precision technology. By using a regular smartphone we are able to lower installation costs but smartphone sensors are imprecise and have limited energy available. Unlike urban environments, farms have communication and energy limitations which leads the system to have the necessity to minimize energy consumption and external communications.

When comparing GPS and Dead Reckoning navigation technologies we have found that Dead Reckoning is more accurate and has no problem with trees when comparing to a GPS based solution. To overcome those problems we have presented a solution that uses Dead Reckoning as the main location tracking provider and the accumulated error is corrected by determining an average with the GPS absolute coordinates.

To monitor worker activities we use Machine Learning algorithms that will classify what the worker is doing at any given moment using smartphone's inertial sensors. Machine Learning techniques have shown to be appropriate and with potential to be used in this system, presenting good success ratios in human agricultural activities classification.

A. Future Work

The navigation solutions that were used in this solution are inaccurate leaving behind a margin of associated error when capturing worker paths in the farm. A solution to this problem would be to create a solution based on Bluetooth Beacons that would create a wireless mesh in the agricultural field. By measuring the power of the Bluetooth signals coming from each beacon it would be possible to do a triangulation and find the position of the worker in the field. This solution would increase the costs of the system but depending on its success it would provide another source of location data.

There are privacy concerns regarding the data collected by our solution. In future work, personal data privacy requirements will be analyzed and adequate protections will be put in place. For example, the system may compute the useful metrics for the collective work force, but discard results for individual workers.

In the future farmers will be able to manage their entire farms accessing real-time information and alerts about what is happening in the field while keeping their goals of high *efficiency* and high *productivity* with lower costs.

ACKNOWLEDGEMENTS

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