Journal of Materials and Environmental Sciences
ISSN : 2028-2508
CODEN : JMESCN

J. Mater. Environ. Sci., 2020, Volume 11, Issue 3, Page 367-377

http://www.jmaterenvironsci.com

Copyright © 2020,
University of Mohammed Premier
Oujda Morocco

Real time Algorithm for Tree Detection, Recognition and Counting in a Video Sequence

F.Z. Bassine, A. Errami, M. Khaldoun

Department of Electrical Engineering, NEST research group ENSEM, Hassan II University Casablanca, Morocco.

Received 22 Oct 2019,
Revised 29 Jan 2019,
Accepted 01 Feb 2019

Keywords

- ✓ *Precision Agriculture,*
- ✓ *Unmanned Aerial Vehicle (UAV),*
- ✓ *digital image processing,*
- ✓ *RGB camera,*
- ✓ *Pattern Recognition.*

bassine.fatimazahra@ensem.ac.ma

Abstract

Trees planted in agricultural land offers many environmental benefits, they are an essential source of food. Therefore farmers are very interested in testing innovative solutions to improve the quality and the quantity of their products, while reducing time and energy, managing water resources and fertilizers, and reducing emissions and pollution. In this context, precision agriculture is one of many modern farming practices that make production more efficient. Unmanned aerial vehicle (UAV) remote sensing has excellent potential for vegetation mapping, In precision agriculture application, digital image processing can improve decision making to find solutions for some challenging problems one of these is the recognition of essential parameters related to agronomy with Accuracy, precision, and economic efficiency, this paper presents an automatic tree recognition and tracking, the image target is captured by RGB camera mounted on a UAV. In the case of remote sensing vegetation, there is a need to develop automatic systems for plant enumeration in tree seedling crops to save human resources and improve yield estimation. In this paper, the captured image is subjected to threshold and extract selected information. Trees tracking algorithm used to solve miss detection problems caused by motion blur and dynamic background. Kalman and Hungarian algorithms combines the recursive state estimation and optimal solution assignment. The future position estimation helps detecting and counting trees using calculated prediction. The average accuracy for each process of trees detection, tracking, and counting is 92.9%, 89.4% respectively. These techniques may be applied to recognize and count objects with different shapes and sizes in real−time.

1. Introduction

Trees offers many environmental benefits, since they provide oxygen, improving air quality, climate amelioration, conserving water, preserving soil, and supporting wildlife .also they are an essential source of food for humans and other organisms. Trees have had an essential function in our daily life; for example, it is used in building material, chemical or industrial products, cosmetics, furniture, etc. Many products are derived from trees. In order to facilitate this work and make it more efficient, this paper proposes a wide range of parallel algorithms for morphological image processing, the aim of this type of image processing is to extract or enhance features from images based on shape, they are typically used for real-time surveillance tasks in industrial systems [1], medical image processing [2], texture analysis [3]. Moreover, most sensors used in agriculture have limited resolution, and cannot acquire the full scope of available plant and soil information. Advanced sensors [4], as high-resolution RGB cameras that can characterize spatial and color information of agricultural features, plays a crucial role in the future development of precision agriculture monitoring.

Pre-processing involves some important initial processing on the original image from the camera such as enhancement and removing noise. Image enhancement has played a significant role in various applications such as medical imaging, industrial inspection, remote sensing, and plant disease detection. Image enhancement is a process used for enhancing and adjusting the contrast of the acquired image to address issues such as the variability of luminance [5]. Color conversion is used to address lighting problems in the scene of an image. For example, in [6] they applied the normalized difference index (using only green and the red channel) to reduce the illumination effect and to discriminate between plants and background. Filtering is also used in image enhancement; in agricultural application, color conversion and histogram equalization are used for plant leaf disease detection [7].

2. Overview of Segmentation Method

Segmentation is most important step in image processing, plant detection approaches aims to segment the different pixels that appear in images into two categories: plant (crop trees and weeds) and background (soil and residues). In [8], they considered image processing techniques for the detection and discrimination of plants and weeds, the plant has to be segmented from background soil, considering all field conditions [9], also most of available machine vision techniques are not sufficiently robust for real-time conditions. Thus prominent segmentation performance is required for precision application in agriculture. A large number of studies employed color index methods to segment plants(crops and weeds) from the background (soil and residues) under various image conditions [10,11] To assess the performance of the proposed algorithm, the Excess Green Index (ExG) was proposed and used as a benchmark to separate plant vegetation from the soil background. Several shape features were fed to classify between trees and weeds. These methods are most commonly based on the RGB color space [12], and they generally rely on the principle that the green channel contains more useful information than the red one. However, these methods by themselves were unable to discriminate between crop trees and weeds. Often they could not even completely separate plant pixels from the background without threshold adjustments. Furthermore, in such algorithms, the color-based methods failed to segment plant pixels from the background. To overcome this problem, several researchers proposed learning-based methods such as the Environmentally Adaptive Segmentation Algorithm (EASA) proposed by [13], the Mean-shift algorithm with Fisher Linear Discriminator (MS-FLD) [14], a Decision Tree-based Segmentation Model (DTBSM) [15], Affinity Propagation (AP) algorithm in the Hue-Saturation– Intensity (HSI) [16], and Particle Swarm Optimization clustering and Morphology Modeling (PSO-MM) [17]. Although these methods demonstrate good vegetation segmentation results, they are computationally expensive and may not suit real-time applications. In addition, they were applied only for the segmentation of all vegetation from the background, but not for distinguishing between crop tree and weeds.

Segmentation of overlapping or occluded objects is an extremely difficult task to perform because the overlapping plants appear as one object. This overlapping problem exists in various applications of computer vision, such as biomedical [18], agricultural [19], and object search [20]. Although many previous studies using image processing and computer vision have demonstrated good plant segmentation performance [21], the problem of plant overlapping has been largely overlooked. In addition, the extensive survey in [22] reported that most studies that they included in their study have not considered the overlapping and occlusion between plants. They also reported that the main source error of plant segmentation (crop/weed) was caused by overlapping between crops and weeds.

3. Material and Methods

The study area is a field located in Marrakesh, Morocco, and captured by unmanned airborne vehicle (UAV) equipped with Sony Cyber-shot DSC-H90 16.1 MP RGB digital camera. The actual ground resolution of the image is less than 1 m which truly reflects the actual vegetation distribution on the ground. This paper essentially consists to test the stability and accuracy of the extraction of vegetation information.

In a previous study a new detection algorithm for trees is described in [23]. Despite the excellent performance of the algorithm, there are still situations where the algorithm fails to detect, especially in image capture conditions (vibration, variations in speed of UAV, etc.). Hence, there is scope for further improvement. In this study, Kalman filtering and the Hungarian algorithm are used to track multiple crop plants in video sequences. The algorithm consists of two steps. First, Kalman filtering is used to predict the new position of an object (a tree plant in this case) in video sequences [24]. Second, a data association algorithm (the Hungarian algorithm) is used to assign each detected crop that appears in each frame to the correct crop tree trajectory [25]. To achieve this, the centroids of identified trees are determined and fed to the proposed tracking algorithm. While detection process, the proposed method allows locating features positions in each frame, and provides information about the movement of individual objects between frames so objects can be tracked in real time. This can help by predicting the position of tree in each frame, and object tracking can provide additional robustness.

Explicit monitoring is necessary to track object instances as they move in field of view (FoV), the spatial resolution of the sensor refers to the size of the smallest possible feature that can be detected. Spatial resolution of passive sensor depends primarily on the FoV. The FoV is the angular cone of visibility of the electro optical scanner and determines the ground resolution surface which is a given altitude at one particular time. The size of the area viewed is determined by multiplying the FoV by the distance from the ground to the sensor (Fig.1). According to a movement model given by the UAV monitor. The use of a tracking algorithm such as Kalman filtering allows refinement of the detection coordinates to have a smoother track across multiple frames.

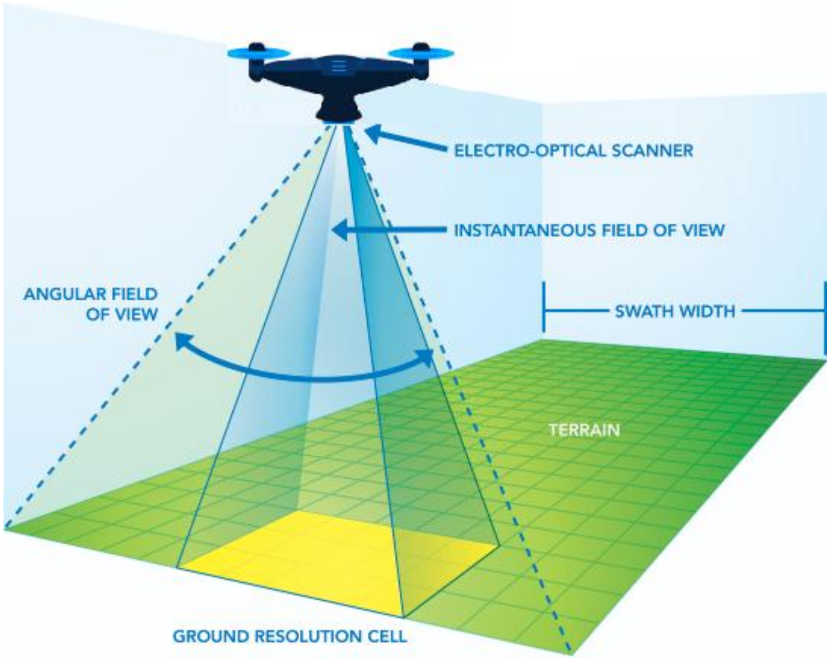


Figure 1: Spatial resolution of the sensor

Fig.2 shows a block diagram of the tracking algorithm proposed in this work. This includes: (1) preprocessing (2) detection stage and extraction of features centroid (the x and y are coordinates of the centre of each detected feature); these coordinates will be used to predict the current location of the track; (3) tracking stage, which tracks detected objects and includes association of detected objects with plant trajectories. The proposed tracking algorithm relies on a first detection algorithm in real time using calculated predictions. The method was tested against different conditions for different stages of growth. Various circumstances, such as partial occlusion between crop tree and weeds, partial crop disappearance from the scene, UAV motion caused by the wind, and various backgrounds (soil and other residues) were also included.

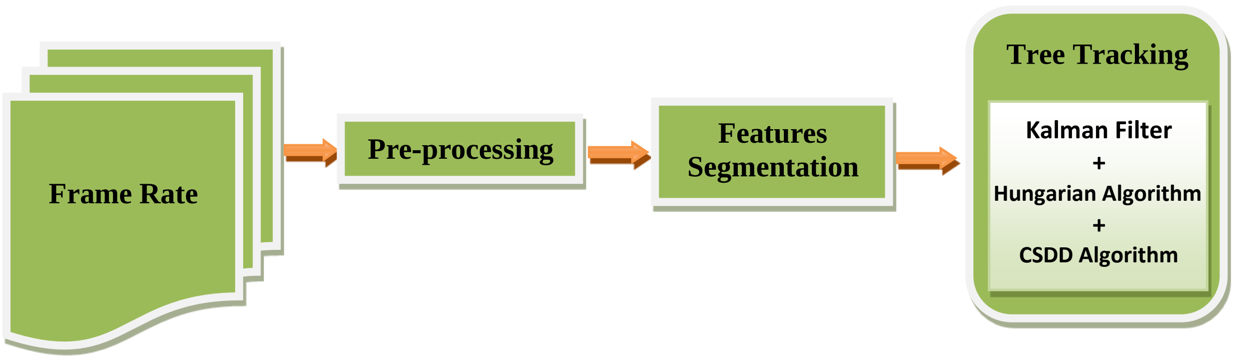


Figure 2: General scheme of the proposed tracking algorithm.

2.2. Kalman Filter for Features Tracking

The Kalman filter has been widely used and successfully implemented in many different object tracking applications. The main advantage of the Kalman filter is providing a reasonably accurate guess about the future position of any given object in a dynamic environment. To understand the Kalman filter process, assume that there is a state vector of data (x_k) of an unknown system, we wish to predict its behavior (e.g., position) at discrete time's (*k*), based on its previous behavior which stored in the vector x_k (Fig.3).

Here, the description of the algorithm comprises four stages:
Step 1- Process equation: The state of the system is determined from the following equation:

$$x_k = A.\, x_{k-1} + w_{k-1}$$

Where A represents the transition matrix, x_k denotes as the state vector at time k, and x_{k-1} denotes as the state vector at time k-1. w_{k-1} is the Gaussian process noise with zero mean and covariance Q.
Step 2- Measurement equation: Outputs of the system can be calculated as follow:

$$y_k = H.\, x_k + v_k$$

Where H is the measurement matrix, and y_k is the measurement observed at time k. v_k is the Gaussian noise with zero mean and covariance R. The state vector (x) which represents the positions and the velocity can be expressed by:

$$x = |p_x \quad p_y \quad v_x \quad v_y|^T$$

Where p_x, p_y are the center positions along the x-axis and y-axis, and v_x, v_y are the velocities in the directions of the x-axis and y-axis.
The transition matrix is given as:

$$A = \begin{bmatrix} 1 & 0 & \Delta T & 0 \\ 0 & 1 & 0 & \Delta T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

Where ΔT is time increment, which is the frame interval in a video sequence. The measurement matrix is given as:

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$$

Since Kalman filtering relies on an estimation process, errors or noise can interfere with the tracking ability. This noise can be generated from several sources, such as, e.g., plants moving in the wind. The noise in the states can be expressed as a covariance matrix (Q). Besides, whenever measuring the tracking object position, errors may occur, this will cause some variation of the real value of the actual location of a tracking object. The error in measurement can be expressed as the covariance matrix of the measurement noise(R) and should be taken into account to get high tracking performance. Choosing correct R and Q matrices is an important design factor for better performance of the Kalman filter. The optimal value of the Q matrix was determined as part of the system performance evaluation:

$$Q = \begin{bmatrix} \frac{\Delta T^4}{4} & 0 & \frac{\Delta T^3}{2} & 0 \\ 0 & \frac{\Delta T^4}{4} & 0 & \frac{\Delta T^3}{2} \\ \frac{\Delta T^3}{2} & 0 & \Delta T^2 & 0 \\ 0 & \frac{\Delta T^3}{2} & 0 & \Delta T^2 \end{bmatrix}$$

The R matrix was obtained as follows:

$$R = \begin{bmatrix} 0.01 & 0 & 0 & 0 \\ 0 & 0.01 & 0 & 0 \end{bmatrix}$$

This method is used to identify the optimal Q and R values.

Step 3- Update equations: To predict the state of x_k, the information provided by y_k is used. Thus, the predicted state estimate is $\hat{x}_k^-$ and covariance error P_k^- can be computed for the next time step k as follows:

$$\hat{x}_k^- = A.\hat{x}_{k-1} + W_K$$

$$P^-_k = A.P_{k-1}A^T + Q$$

Where Q is the process of covariance noise matrix.

Step 4- Measurement updates equations
This is also called a correction process. It involves three processes:
• Calculation of Kalman Gain it depends on the accuracy of a measurement. If the accuracy of the analysis is high, the Kalman gain has a high value. Otherwise, the Kalman gain has relatively low value.
• Update estimate with measurements y_k
• Update covariance error:

$$P_k = (1 - kH)P^-_k$$

Where P is the prediction error covariance and K is the Kalman gain.

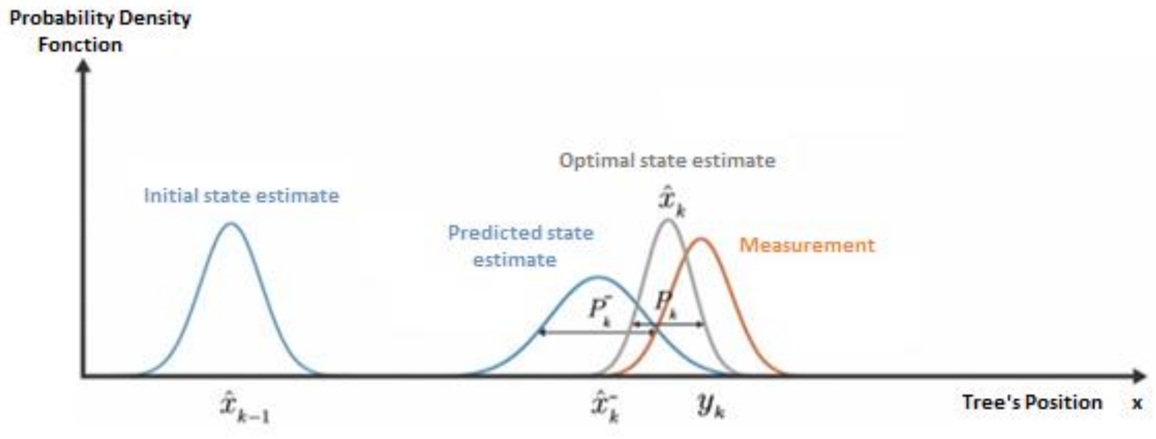


Figure 3: Optimal State Estimator Algorithm

In this study, the detected tree's centroids are tracking over successive frames in real time. To track each object, a separate Kalman filter tracker is required for each tree track. Thus, the proposed parallel system consists of a multi-object tracker to track all the existing moving trees in the video sequence rapidly. As the number of objects increases, the estimation process gets more complicated. Therefore, an association algorithm is required to correctly associate each detected object with an object track.

2.3. Hungarian Data Association Algorithm
In this study, the Hungarian algorithm is used to match the detections in each frame of tracked objects (the predicted positions with the Kalman operator), and to determine the missing identified objects in order to assign a new track. The algorithm is based on a distance matrix that contains the Euclidean distances between each combination of tracks (predictions) in the rows of the matrix, and detections in the columns; distances are calculated based on the centroids of predicted and detected plants. A smaller distance implies a higher probability of correct associated of detections to predictions. The size of the distance matrix can vary over time as crop tree density varies and plants appear and disappear in the FoV. The algorithm consists of a number of steps, as described in [26].

3.3 Additional post-processing

Features similarity between blobs is computed the current frame in correlation with all detected blobs in previous frames; the following steps have been added to increase tracking and detection reliability:

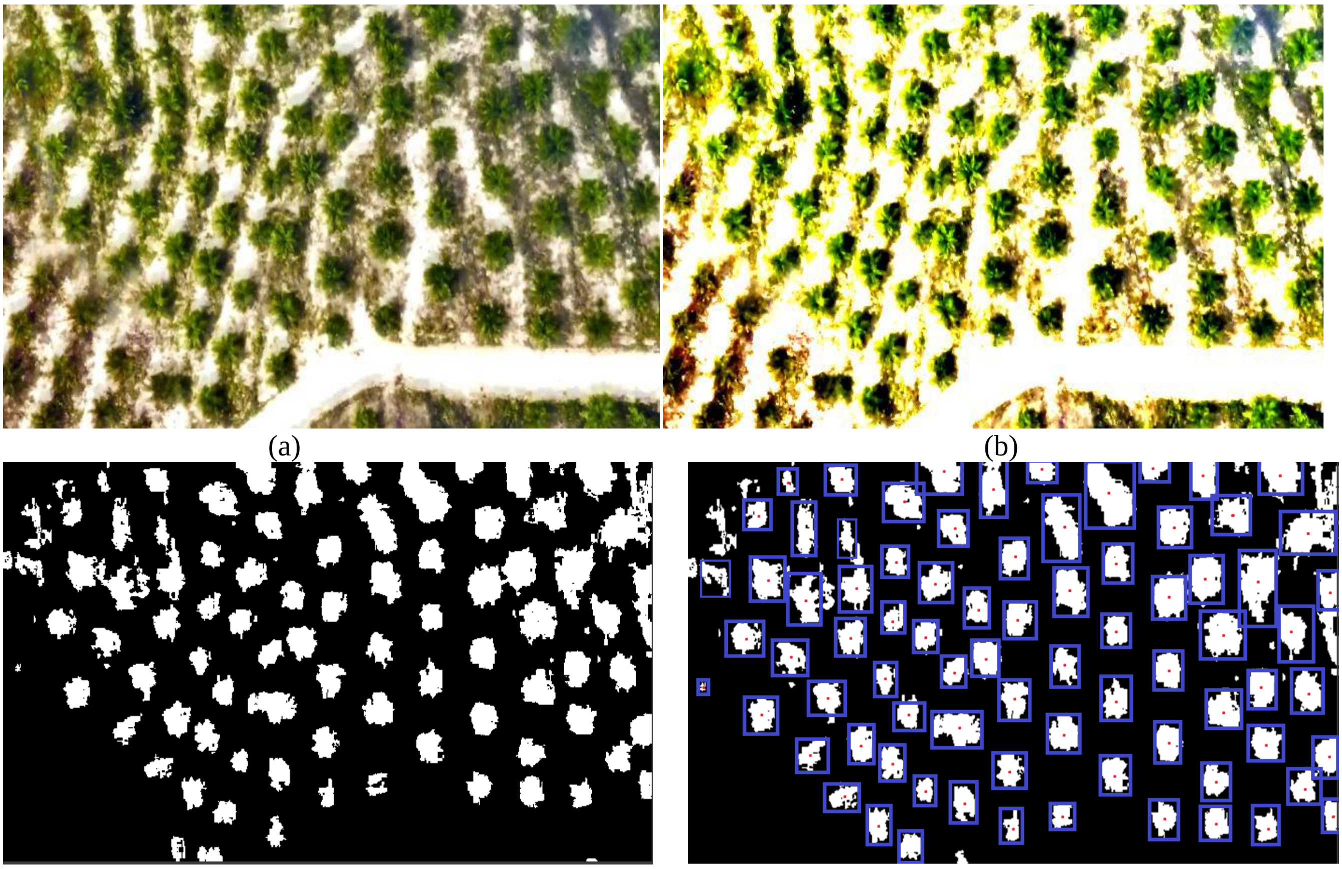
1. Finding objects in the Frame,
2. Remove matched pairs that are over a large distance,
3. If a track has no assigned detection, and then increase the skipped frame counter,
4. If a track is passed over a frame, the counter exceeds to threshold and then removes the track,
5. If the detection has been well assigned, then update tracks using the detection coordinates,
6. a feature detector which attempts to detect blobs of different tree canopy sizes (Center Surround Distribution Distance (CSDD) [27]),
7. If not, continue using Kalman predictor and back to step1.

3. Results and discussion

To illustrate the efficiency and robustness of the proposed tracking method, therefore appropriate metric and standard evaluation procedure are required. There are several conventional methods that are used in computer vision for object detection and tracking applications to determine the detected/tracked objects and ground truth annotations. As an illustration, the PASCAL Visual Object Classes (VOC) in visual object category detection and recognition [28] and the KITTI Vision dataset [29] are the commonly used approaches.

As a result, a compute intensive feature extraction algorithm CSDD, is used to detect blobs of different tree canopy sizes on an image and determine whether they standout perceptually from the background, the above discussed algorithms are implemented using MATLAB R2015.

The test-video was captured in a tree field where different tree growth stages are also accounted. Optimum tree detection performance was demonstrated with a minimum contour area threshold. Fig.4 shows an example of the detection results using the above algorithm; it includes a) test frame from the UAV video sequence, b) Enhanced image after preprocessing , c)ExG index was applied to separate plant vegetation from the soil background, d) trees are detected and identified using the proposed algorithm: This figure includes tree crops, weeds, soil.



(a) (b)

(c) (d)

Figure4: The results from the proposed algorithm of test image a) Original Image. b) Enhanced image after preprocessing. c) Segmented tress from the background. d) Detected trees.

The indicated blue rectangles represent detections produced by the algorithm, and the red points represent the centeroid of each tree. Fig 4 (c) also demonstrates how trees that are only partially visible in the frame (at boundaries) have been detected; each tree is independently detected by the algorithm and highlighted with a bleu rectangle.
Automatic tree detection is the main stage in numerous applications, once the segmentation is done (Fig.5), a simple approach is to correlate pixels count to trees number per image according to segmentation results, the system is marking tree's centers in red dots and assigns the localizations according to its geographic coordinates. In Fig.4 Red dots indicate the location of the centroid of each tree. Yellow, green and orange colors presents different sizes of trees using CSDD algorithm to detect blobs of different tree canopy sizes (Fig.6), which could help to predict : stock evaluation, general tree health, tree age , water availability, localization , Competition from other trees of the large size (overlapping trees), Presence of weeds ,insects or diseases , Nutrient availability.

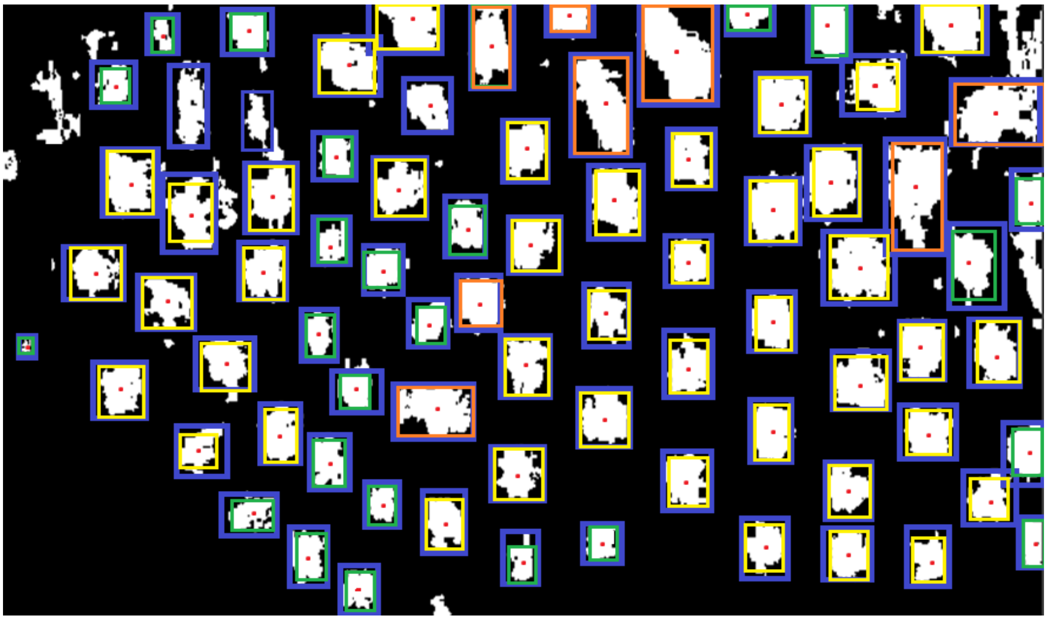
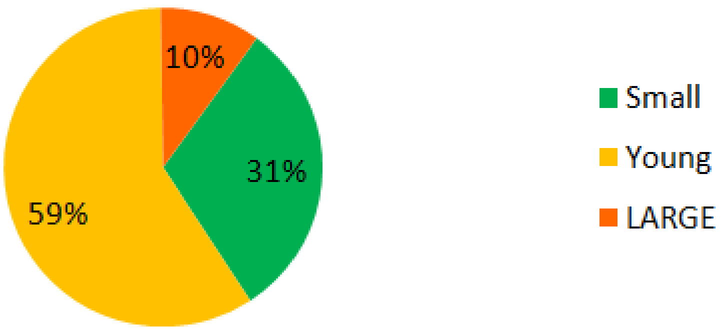


Figure 5: Tree size Small Young Large



Tree size	Number of Trees
Small	24
Young	46
Large	8

Figure 6: number of Tree according to the size in a frame test

For the training phase, more than 200 frames of video were used (Fig.7), with an input frame rate of 25 frames per second. In this study, the entire process is also tested on Central Processing Unit (CPU) and Graphics Processing Unit (GPU), Results shows that GPUs are faster than a CPUs, an optimized CPU implementation requires several seconds to perform analysis of an image [30], while the GPU based approach focuses on processing speed and improving performance by up to 29X, with no loss in accuracy (Fig.8).

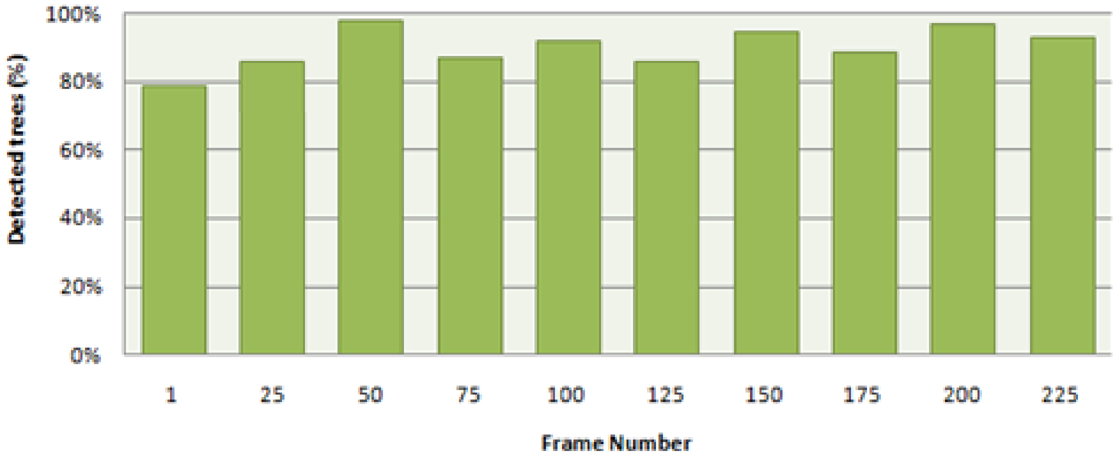


Figure 7: Detected trees in multiple test frames

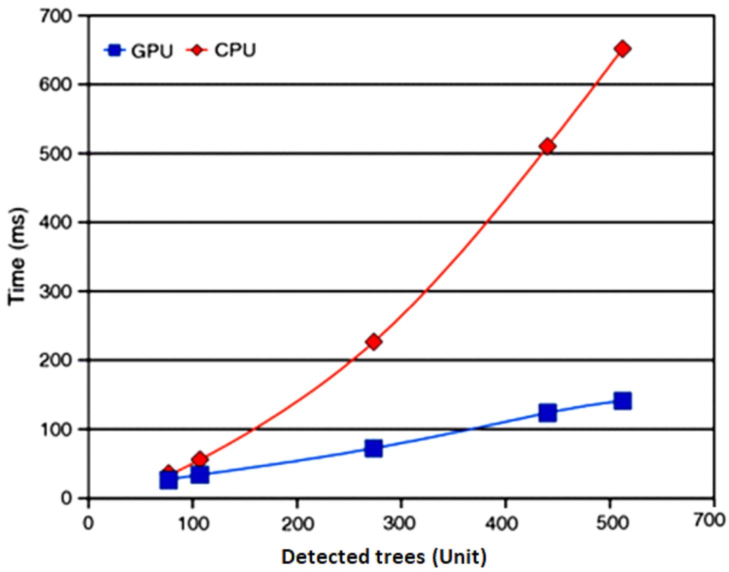


Figure 8: GPU-accelerated tree detection for UAV frames

4. Decision Making

Decision making is the final step and a key component for precision agriculture. UAV images could be applied in zonal mapping to identify anomalies in crop lands and accurate information about soil and crop spatial variation [31], the method is comparing features that are provided in previous processing levels and the content of the data base to allow a reasonable interpretation of remote sensing images in order to perform necessary decision strategies, that leads to more productive and sustainable land use by making optimal choices for problems of : erosion, soil nutrient depletion and other manifestations of land degradation ,also to solve some technological problems in processing line to extract as much information as possible from the images. Decision making systems are therefore object oriented, they always require some advanced knowledge (agriculture, computing) to be executed. Although many successful results concerning decision making have been reported [32].There are many different types of maps that could help to analyze spatial trends in agriculture, the information extracted from the this maps is more useful to make decisions including fertilizer, pesticide application, by showing precise locations in the field. These maps can also be paired with other pieces of PA technology such as VRT (variable rate technologies) like planters and sprayers [33]. These technologies connect with the GPS location of soil maps (Fig.9) in order to distribute a precise amount of product, in order to prevent over seeding, fertilizing or pesticides use and applies product at a different rate in relation to what the field actually needs.

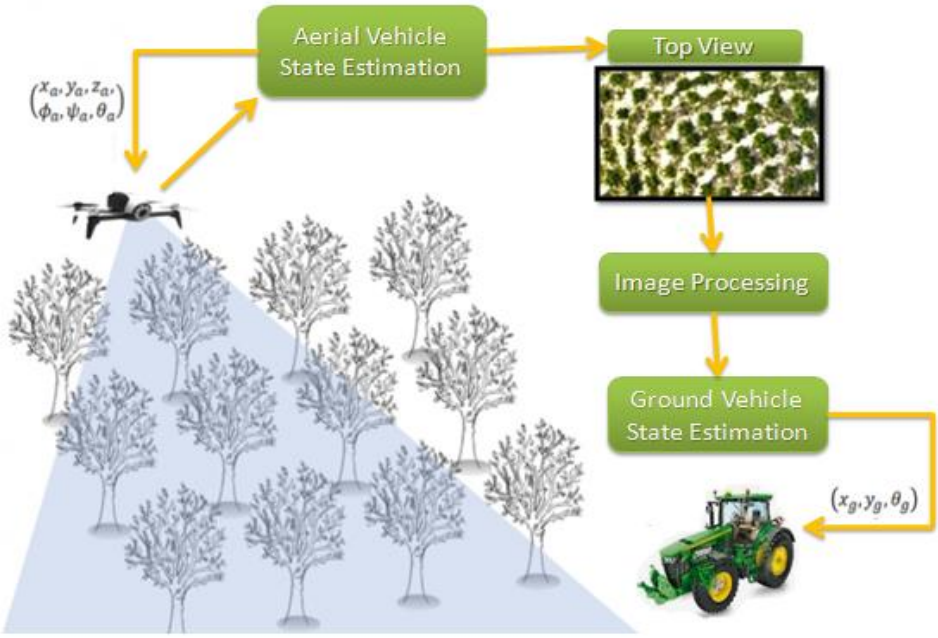


Figure 9: Decision making using Variable Rate Technologies

Conclusion

In this research, the proposed algorithm for large-scale remote sensing image processing in real time. It is a rapid high performance solution for automatic tree detection from the UAV video frames to the final detection results. The main objective of this study aims to develop a methodology that uses remote sensing and geographic information system (GIS) to map and count trees in the concerned region so as to produce tree density map that can be used as a reference document for decision making. Several image processing techniques have been used in this study; the captured UAV image is subjected to threshold and extract selected information. Trees tracking algorithm used to solve miss detection problems caused by motion blur and dynamic background. And position estimation helps detecting and counting trees using calculated prediction, the average accuracy for each process of trees detection is 92.9%, 89.4% for tree tracking and tree counting the average is 91.2%. These techniques may be applied to recognize and count objects with different shapes and sizes in real–time. High resolution RGB imagery captured by UAV, and object classification and tracking method were used to bring out the trees in density maps in order to make a decision, Maps created from the data could help farmers to have an overview on stock evaluation, general tree health, tree age , water availability, localization , Competition from other trees (overlapping trees), Presence of weeds ,insects or diseases , Nutrient availability.

References

1. E. N. Malamas, E.G.M. Petrakis, M. Zervakis. A survey on industrial vision systems, applications and tools. *Image and vision computing*, 21(2) *(*2003) 171-188. https://doi.org/10.1016/S0262-8856(02)00152-X
2. T. M. Lehmann, C. Gonner, K. Spitzer, Survey: Interpolation methods in medical image processing. *IEEE transactions on medical imaging*, 18 (1999) *1049-1075*. https://doi.org/10.1109/42.816070
3. C.E. Prema, S.S. Vinsley, S. Suresh. *Efficient flame detection based on static and dynamic texture analysis in forest fire detection. Fire technology*, 54(1) (2018) *255-288*. https://doi.org/10.1007/s10694-017-0683-x
4. F.Z. Bassine, A. Errami, M. Khaldoun. A Review of Remote Sensing Sensors and Fusion in Precision Agriculture. *International Journal of Advance Engineering and Research Development*, 5(8) (2018) 7-11. https://doi.org/10.21090/IJAERD.54654

5. X. Zou, J. Kittler, K. Messer. Illumination invariant face recognition: A survey. *IEEE international conference on biometrics: theory, applications, and systems.* (2007) 1-8. https://doi.org/10.1109/BTAS.2007.4401921
6. G.E. Meyer, J.C. Neto. Verification of color vegetation indices for automated crop imaging applications. *Computers and electronics in agriculture*, 63(2) (2008) 282-293. https://doi.org/10.1016/j.compag.2008.03.009
7. S. Sunny, M.P.I. Gandhi . An efficient citrus canker detection method based on contrast limited adaptive histogram equalization enhancement. *International Journal of Applied Engineering Research*, 13(1) (2018) 809-815.
8. K. Thangadurai, K. Padmavathi. Computer vision image enhancement for plant leaves disease detection. In: *2014 World Congress on Computing and Communication Technologies. IEEE* (2014) 173-175. https://doi.org/10.1109/WCCCT.2014.39
9. J.A. Fernandez-Gallego, S.C. Kefauver, N.A. Gutiérrez. Wheat ear counting in-field conditions: high throughput and low-cost approach using RGB images. *Plant Methods*, 14(1) (2018) 22. https://doi.org/10.1186/s13007-018-0289-4
10. J.P. Ramirez-Paredes, U.H. Hernandez-Belmonte. Visual quality assessment of malting barley using color, shape and texture descriptors. *Computers and Electronics in Agriculture*, 168 (2020) 105110. https://doi.org/10.1016/j.compag.2019.105110
11. C. Wang, W.S. Lee, X. Zou, D. Choi, H. Gan. Detection and counting of immature green citrus fruit based on the local binary patterns (lbp) feature using illumination-normalized images. *Precision agriculture*, 19(6) (2018) 1062-1083. https://doi.org/10.1007/s11119-018-9580-7
12. F.Z. Bassine, A. Errami, M. Khaldoun. Vegetation Recognition Based on UAV Image Color Index. *IEEE International Conference on Environment and Electrical Engineering and 2019 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe).* (2019) 1-4. https://doi.org/10.1109/EEEIC.2019.8783830
13. G. Ruiz-Ruiz, J. Gómez-Gil, L.M. Navas-Gracia. Testing different color spaces based on hue for the environmentally adaptive segmentation algorithm (EASA). *Computers and Electronics in Agriculture, 68(1)* (2009) 88- 96. https://doi.org/10.1016/j.compag.2009.04.009
14. L. Zheng, D. Shi, J. Zhang . Segmentation of green vegetation of crop canopy images based on mean shift and fisher linear discriminant. *Pattern Recognition Letters, 31(9)* (2010) 920-925. https://doi.org/10.1016/j.patrec.2010.01.016
15. W. Guo, U.K. Rage, S. Ninomiya. Illumination invariant segmentation of vegetation for time series wheat images based on decision tree model. *Computers and electronics in agriculture*, 96 (2013) 58-66. https://doi.org/10.1016/j.compag.2013.04.010
16. H. Xia, X. Chen, P. Guo. A shadow detection method for remote sensing images using affinity propagation algorithm. *IEEE International Conference on Systems, Man and Cybernetics. IEEE* (2009) 3116-3121. https://doi.org/10.1109/ICSMC.2009.5346147
17. X.D. Bai, Z.G. Cao, Y. Wang, Z.H. Yu, X.F. Zhang. Crop segmentation from images by morphology modeling in the CIE L* a* b* color space. *Computers and electronics in agriculture*, 99 (2013) 21-34. https://doi.org/10.1016/j.compag.2013.08.022
18. Q. Zhang, J. Wang, Z. Liu, D. Zhang. A structure-aware splitting framework for separating cell clumps in biomedical images. *Signal Processing*, 168 (2020) 107331. https://doi.org/10.1016/j.sigpro.2019.107331
19. W.H. Maes, K. Steppe. Perspectives for remote sensing with unmanned aerial vehicles in precision agriculture. *Trends in plant science*, 24(2) (2019) 152-164. https://doi.org/10.1016/j.tplants.2018.11.007
20. J.R.R. Uijlings, K.E.A. Van De Sande, T. Gevers. Selective search for object recognition. *International journal of computer vision*, 104(2) (2013) 154-171. https://doi.org/10.1007/s11263-013-0620-5

21. A. Camargo, J.S. Smith. An image-processing based algorithm to automatically identify plant disease visual symptoms. *Biosystems engineering*, 102(1) (2009) 9-21. https://doi.org/10.1016/j.biosystemseng.2008.09.030
22. C. Xia, J.M. Lee, Y. Li, Y.H. Song, B.K. Chung. Plant leaf detection using modified active shape models. *Biosystems engineering, 116(1)* (2013) 23-35. https://doi.org/10.1016/j.biosystemseng.2013.06.003
23. F.Z. Bassine, A. Errami, M. Khaldoun. Real Time Video Processing using RGB Remote Sensing by Drone. *International Conference on Electronics, Control, Optimization and Computer Science (ICECOCS)*, (2018) 1-5. https://doi.org/10.1109/ICECOCS.2018.8610584
24. C. Ridder, O. Munkelt, H. Kirchner. Adaptive background estimation and foreground detection using kalman-filtering. In: *Proceedings of International Conference on recent Advances in Mechatronics. Citeseer*, (1995) 193-199.
25. H.W. Kuhn. The Hungarian method for the assignment problem. *Naval research logistics quarterly*, 2 (1955) 83-97. https://doi.org/10.1002/nav.3800020109
26. R. Jonker, T. Volgenant. Improving the Hungarian assignment algorithm. *Operations Research Letters, 5(4)* (1986) 171-175. https://doi.org/10.1016/0167-6377(86)90073-8
27. R.T. Collins, W. Ge. CSDD features: Center-Surround Distribution Distance for feature extraction and matching. *European Conference on Computer Vision. Springer, Berlin, Heidelberg*, (2008) 140-153. https://doi.org/10.1007/978-3-540-88690-7_11
28. M. Everingham, L. Van Gool, C.K.I. Williams. The pascal visual object classes (voc) challenge. *International journal of computer vision, 88(2)* (2010) 303-338. https://doi.org/10.1007/s11263-009-0275-4
29. A. Geiger, P. Lenz, C. Stiller. Vision meets robotics: The KITTI dataset. *The International Journal of Robotics Research*, (2013) 1-6. https://doi.org/10.1177/0278364913491297
30. I. Gurcan, A. Temizel . Heterogeneous CPU–GPU tracking–learning–detection for real-time object tracking. *Journal of Real-Time Image Processing*, 16(2) (2019) 339-353. https://doi.org/10.1007/s11554-015-0538-y
31. C. Zhang, J.M. Kovacs. The application of small unmanned aerial systems for precision agriculture: a review. *Precision agriculture*, 13(6) (2012) 693- 712. https://doi.org/10.1007/s11119-012-9274-5
32. R.G.V. Bramley, J. Ouzman. Farmer attitudes to the use of sensors and automation in fertilizer decision-making: Nitrogen fertilization in the Australian grains sector. *Precision agriculture*, 20(1) (2019) 157-175. https://doi.org/10.1007/s11119-018-9589-y
33. D. Schimmelpfennig. Cost Savings From Precision Agriculture Technologies on US Corn Farms. *Amber Waves*, (2016) 1.

(2020) ; http://www.jmaterenvironsci.com