Tracking of Plant Water Stress Via an Automated Optical and IR Image Registration

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ABSTRACT
Analysis of canopy temperature is significant method for monitoring the plant water status. Increase in leaf temperature detected by infrared thermography largely reflect stomatal closure as a measure of "stress". Hence this can be used as a meter for irrigation scheduling. The proposed system's key phase is where the optical image and its related infrared image are automatically registered which resolves problem of quantifying the data of the scene. From the plant canopy an optical image is captured and is registered with its corresponding IR image. The work here involves applying the Canny Edge Detection algorithm and variable resolution based on normalized cross correlation algorithm for improved image registration process while maintaining biological significance. The outcomes of the study exhibit the efficiency and reliability of the proposed system with a substantial reduction of computational complexity.

General Term
Digital Image Processing

Keywords
Optical and IR image registration, Plant water stress analysis, Thermal imagery, Variable Resolution algorithm based Normalized Cross correlation, CWSI, Canny Edge Detection

1. INTRODUCTION
About 70% of water resource is used alone for agriculture irrigation in several countries worldwide. Apparently control irrigation can curtail waste of irrigation water considerably thereby flourishing plant fertility. Automated tracking of plant water status via non-destructive, advanced techniques plays a vital role in irrigation control system expansion. Plant canopy temperature goes about as a good yardstick of the plant water status. At the point when plants encounter water stress, their temperature rises. Monitored by infrared temperature sensors, canopy temperature can provide continuous facts on water status, water use and how a plant is functioning metabolically and using these parameters regulate the potential water savings. Recent research in agriculture specifies that plant water status may be observed if canopy temperature distribution of the plant is known[1][2][3][4][5][6]

1.1 What is CWSI?
Plant water status information can be acquired through the assessment of the crop water stress index (CWSI) [1]. This index yields great potential to create a programmed irrigation control system in which plant canopy temperature distribution is attained by means of thermal imaging. Such a method aids the use of intelligent irrigation systems which are able to irrigate the exact amount of water required by a plant.

1.2 How to assess plant water stress?
Usually, reference optical image and an IR image are part of infrared (IR) thermography detection framework which assess data. By means of regular digital camera the optical image is captured at same area as the IR image to give a genuine perspective of the IR image scene, one may recognize the area of concern (e.g., plant leaves except landscape or sky) from the optical image. The plant canopy required can be perfectly recognized from the optical image. In order to assess the plant water stress, first the temperature distribution of the canopy leaf area is obtained and this estimation then leads to identifying the canopy temperature and temperatures of a dry and wet reference surface. These parameters are basis for evaluating the value of CWSI. The detection of overlap area between the pair of IR and optical images is a crucial phase in the plant canopy temperature acquisition in automatic controlled irrigation system.

Figure 1 illustrates a typical plant irrigation strategy, where the plant water status profile acquisition (inside the red dotted box) plays a paramount role in the optimization of plant productivity and water usage.

2. LITERATURE SURVEY
Preparatory outcomes from recent study [7] [8], specifies that the accuracy of canopy temperature distribution estimation, for the evaluation of the plant water stress, firmly relies on the accuracy of optical and IR image fusion registration. Nevertheless using nondestructive image registration technique to obtain the canopy temperature is challenging.

Algorithms for image registration are many and generally accessible, for instance, cross correlation [9], mutual information [10], correlation ratio [11], and SIFT based methods [12]. There are additionally some fast algorithms for example, automatic registration approach based on point features [13], automatic image registration algorithm with sub-pixel accuracy [14] and using importance sampling [15], and so forth. Image registration has been used over a series of domains.

Even though various effective image registration algorithms exist for aligning images from diverse origins and set-ups, extra algorithm enhancement is necessary. The foremost technical hitches which rise when exhaustive images are taken for image registration are as below:

- Usually with the help of various sensors and from different view angles, also at different times images are being capturedresulting in different imaging characteristics
- At the overlap area the intensities of both images can be fairly different. Hence, approaches containing image intensity are not likely to find acceptable registration.

- Apart from some similarity in overall structure, it is hard to recognize consistent feature points from both images in some popular feature spaces by means of an automatic registration method, such as the scale invariant feature transformation (SIFT) process. Figure 2 demonstrates the SIFT based methods which cannot get sufficient matching key points.The key reason is that SIFT may only apply to the registration of rigid objects using the image pairs of the same source but in this case the main stuff in the images are plant leaves which move in excess.

2.1 Problem Statement

In earlier work [16], an automated cross correlation (ACC) based image registration method was established and described. The ACC algorithm is able to effectively determine the overlapping area between the IR image and reference optical image without assistance of human and the artifacts placed in the scene to facilitate registration. The registered optical image can then be used to identify plant canopy area and extract the associated temperature distribution from measurement data.

Since the algorithm needs to compute the correlation coefficient pixel by pixel, the automated cross correlation (ACC) method is time expensive. Hence the main focus of this paper is to reduce the computational load involved in ACC and to overcome the above said technical hitches.

3. PROPOSED SYSTEM

Following the work originated in [16], the proposed system builds a 'SMART' plant water status tracking technique and information processing of canopy temperature and hence, intelligently control the related irrigation practice.

This paper describes an advanced image registration procedure where Canny Edge detector is proposed for the edge detection and a variable resolution approach to the system implementation is considered for enhancing the registration algorithm efficiency.

Image registration of optical and IR image pair plays a crucial role in the process of plant water status check as it provides the plant canopy temperature. Then by means of expected maximum value method, the wet and dry leaf temperatures can be evaluated via image fusion between the optical and IR image [7]. Color of canopy, and wet and dry leaves, are significant parts as green sunlit leave transpire most of the plants water. So, the green leaf regions are correlated with their equivalent IR image data.

The algorithm efficiency issue can be addressed by several methods such as Sequential Similarity Detection Algorithm (SSDA)[17], Bit Plane Matching Algorithm (BPMA) [18] and Variable Resolution algorithm based on normalized cross correlation (VRCA). Based on the merits of these techniques the Variable Resolution algorithm based on normalized cross correlation is used for this system and hence resolvesproblem of the slow running speed of ACC algorithm.

The key phases of the proposed system are:

a. Extraction of edges from both the optical and IR images
b. Reducing the image resolution of both the optical and IR images,
c. The lower resolution images are roughly registered,
d. Full resolution images are more accurately registered at the possible positions
e. Calculating the rotation angle

A flow chart of the variable resolution algorithm based on normalized cross correlation is depicted in Figure 3.

4. METHODOLOGY

4.1 Postulate

- Im_O (image size M×N) denotes full resolution optical image
- Im_{IR} (image size M×N) denotes full resolution IR image. These two images are considered as primary resolution layers.

4.2 Phases

Phase 1. Edge Extraction:

As there is need to register images from different sources so it requires edge detection algorithm which is considered as the initial phase of the proposed system. While performing edge detection method it is required to not affect the edge related data since the IR image is not similar to the reference optical image. This is evident from the Figure 4 as the resolution of the optical image is 2848 x 2136 pixels and that of IR image is 320 x 240 pixels i.e. lesser the resolution, lesser will be the specifications. For this reason the Edge detection is proposed as the important phase of the algorithm implementation of image registration.In our case, canny edge detection is used.

The canny edge detector is a multistage edge detection algorithm. The steps are:

i. Preprocessing

Edge detectors are prone to noise. A bit of smoothing with a Gaussian blur helps.A 5x5 Gaussian filter with standard deviation (σ)=1.4 is used for this purpose shown as below:

$$\frac{1}{159}\begin{bmatrix} 2 & 4 & 5 & 4 & 2 \\ 4 & 9 & 12 & 9 & 4 \\ 5 & 12 & 15 & 12 & 5 \\ 4 & 9 & 12 & 9 & 4 \\ 2 & 4 & 5 & 4 & 2 \end{bmatrix} \quad (1)$$

ii. Gradient Calculation

Next, gradient magnitudes and directions are calculated at every single point in the image. The magnitude of the gradient at a point determines if it possibly lies on an edge or not. A high gradient magnitude means the colors are changing rapidly - implying an edge. A low gradient implies no substantial changes. So it's not an edge.The direction of the gradient shows how the edge is oriented.To calculate these, the standard Sobel edge detector is used with the following pair of convolution masks (in x and y directions):

$$G_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \quad G_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \quad (2)$$

The magnitude of gradient ism= $\sqrt{G_x^2 + G_y^2}$(3)

The direction of gradient is$\Theta = \arctan\left(\frac{G_x}{G_y}\right)$(4)

Here, G_x andG_y are the X and Y derivatives at the point being considered.

iii. Non-maximum suppression

The aim is to alter the "blurred" edges to "sharp" edgesin the image of gradient magnitudes. Primarily this step does exactly what it means- if a pixel is not a maximum, it is suppressed. The algorithm is for each pixel in the gradient image:

- Equivalent to the use of an 8-connected vicinity, fairly accurate the gradient direction θ to nearby 45°.

- The edge strength of the current pixel is matched with the edge strength of the pixel in the positive and negative gradient direction i.e. if north is the gradient direction (theta =90°), relate with the north and south pixels.
- If the current pixel's edge strength is highest; retain the value of the edge strength. Else remove the value.

iv. Double Thresholding

Here, edge pixel's gradient value greater than the high threshold are indicated as strong; edge pixel's gradient value lesser than the lowthreshold are repressed and edge pixels in the middle of the two thresholds are indicated as weak.

As upper:lower ratio between 2:1 and 3:1 is recommended, in our case the values chosen are 150 and 50 as high and low threshold values, respectively.

v. Edge tracking by hysteresis

Edges that are strong are deduced as "certain edges", which are included in the finaledge image. While weak edges are included if and only if they are connected to strong edges.To track the edge connection, BLOB analysis is done by observing at a weak edge pixel and its 8-connected neighborhood pixels.BLOB's containing atleast one strong edge pixel are then preserved, while other BLOB's are suppressed.

The edged images which are the outcomes of the first phase are labeled as Im_{Oe} , Im_{Ire}

Phase 2. Reduce Image Resolution

Here, consider f as image zoom out factor. It is assigned the value 2, to zoom out the edged optical and IR images i.e on Im_{Oe} , Im_{Ire}. This results in the lower resolution of both the optical and IR images and are assigned the labels:

- Im_{Ole} (image size Mh×Nh) for lower resolution optical image
- Im_{IRle}. (image size Mh×Nh) for lower resolution IR image

Phase 3. Roughly register the lower resolution images

In the lower resolution layer, viz. on Im_{Ole} and Im_{IRle}, the search method is run single time for each 2×2 pixels covering the rough image registration method.

Then the normalized cross correlation for the rough registration can be expressed as:

$$\rho_l(u,v) = \frac{\sum_{i=0}^{Mh}\sum_{j=0}^{Nh}(Im_{\mathrm{Oleu,v}}(i,j) - Im_{\mathrm{IRle}}(i,j))}{\sigma_{\mathrm{Olu,v}}\sigma_{\mathrm{IRl}}} \quad (5)$$

where

- $\rho_l(u,v)$ is the coefficient of cross correlation computed from the lower resolution image pair Im_{Ole}, Im_{IRle},
- (u,v) is the coordinate index of the optical image Im_{Ole},
- $Im_{Oleu,v}$ is an image placed at $(u,v)^{th}$ of the image Im_{Ole} . Its size is the same as image Im_{IRle},
- $\sigma_{Olu,v}$ and σ_{IRl} are the standard deviation of the equivalent images respectively

Next is to select set of points$\{(u_k, v_k)\}$of the highest values of the correlation coefficient and are labeled as the registration solution candidates. This is done in order to take into account both the system and image uncertainties.

Phase 4. Accurately register the full resolution images

Similarly, for the primary resolution layer, viz. on Im_{Oe}, $Im_{Ire,}$ the search method is run pixel by pixel in the adjoining region of the rough registration location covering 4 pixels for respective direction.

Then the normalized cross correlation can be expressed as:

$$\rho(k,l) = \frac{\sum_{i=0}^{M}\sum_{j=0}^{N}(Im_{\mathrm{Oek,l}}(i,j) - Im_{\mathrm{IRe}}(i,j))}{\sigma_{\mathrm{Ok,l}}\sigma_{\mathrm{IR}}} \quad (6)$$

where,

- (k,l) is the coordinate index of the optical image Im_{Oe},
- $Im_{Oek,l}$ is an image placed at $(k,l)^{th}$ of the image Im_{Oe} and its size is the same as image Im_{IRe},
- $\sigma_{Ok,l}$ and σ_{IR} are the standard deviation of the equivalent images respectively.

In order to assure that the last point of the maximum correlation coefficient is optimum, assume a weighted coefficient

$0 < c < 1$

$$\rho_k = c\rho_l(u_k, v_k) + (1-c)\rho(u_k', v_k') \quad (7)$$

$$\rho_{k*} = max\rho_k (8)$$

where

- (u_k', v_k') is the point of image $Im_{Oe}$of primary resolution
- $\rho(u_k', v_k')$ is the coefficient of correlation for fine image registration
- $\rho_l(u_k', v_k')$ is the coefficient of correlation for image registration at lower resolution.

The output of this phase is obtaining the registration location (u_{k*}', v_{k*}').

Phase 5. Rotation angle Estimation

Here, between the optical and IR image, the rotation angle θ range is considered from -10°to 10°. The range is divided into 200 small grids. The correlation coefficient is calculated for each grid, followed by choosing a grid θ* with the maximum correlation value.

5. EXPERIMENTAL RESULTS

In this paper the refined algorithm i.e. variable resolution algorithm using normalized cross correlation for image registration was tested using grapevine image pairs. Table 1 shows the results of comparison of algorithmic run time between standard ACC algorithm and variable resolution algorithm subject to identical conditions. The zoom out value f=2 and Canny Algorithm to detect the image edges are applied to carry out the entire tests. The variable resolution method based on NCC is faster by 1/40th than normal ACC method which is comprehended from the outcomes of the study and hence the former can be selected as the optimal one. There is a need to analyze them with reference to results of manual registration as the true registration locations are unknown. The proposed algorithm built on Canny Edge Detection method is superior to Sobel Edge and Robert Edge operators which is depicted from Figure 5 and Table 2.

Table 1. Testingoutcomes of variable resolution algorithm (based on NCC) and ACC

	Number of Image pairs	**Success number**	**Running time per pair (average)**	**Registration error (max, min, average)**
ACC	20	20	610s	(6,0,2.6)
Variable resolution algorithm	20	20	15s	(6,0,2.6)

Table 2. Image registration outcomes based different edge extraction methods (10 image pairs)

Type / Edge Detection	Number of successful registration	Registration location error (minimum, maximum, average)
Sobel algorithm	10	(0,6,2.8)
Canny algorithm	10	(0,6,2.6)
Roberts algorithm	10	(0,9,3.2)

6. CONCLUSION AND FUTURE WORK

The paper explored a fast realization algorithm of automatic optical and infrared image registration. With respect to computational efficiency, though the images are merely zoomed out at 2 times, computational load is considerably reduced. Compared to standard cross correlation, the variable resolution algorithm can run about 40 times faster without degenerating registration performance.

Once an image pair is registered, the plant water status information can be determined via the method in [7], where it is proved that the accuracy of the IR and optical image registration may have substantial influence to the canopy temperature estimation.

The proposed system can moreover be used in additional applications. As stated above, the image registration is simply the first phase in the process to estimate the canopy temperature. There is scope of building methods to achieve more accurate registration and by what means to develop an algorithm suit to allow for more variation in the background images. The intention is to carry on research in this field towards a decision support system to bring real time automated irrigation control based on CWSI with the notion of creating 'Smart Plants'.

7. FIGURES

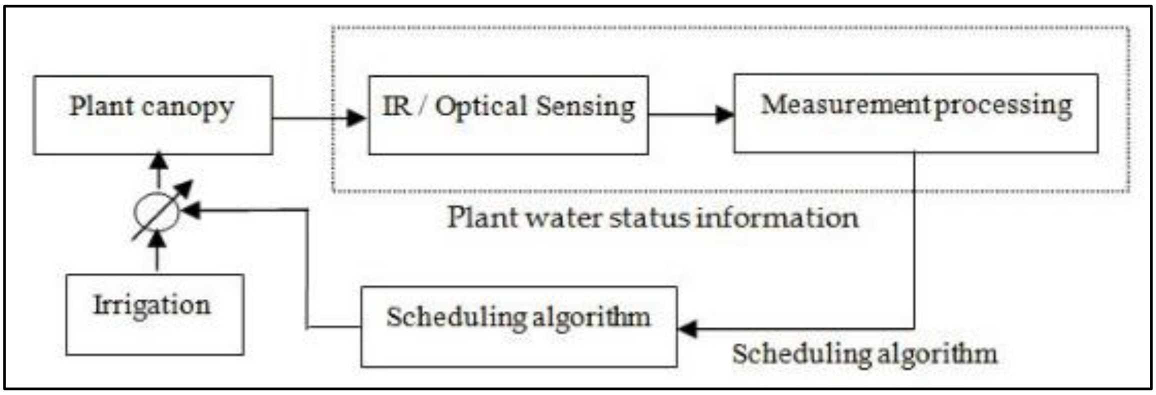

Figure 1: Illustration of irrigation actuation via a plant based sensor

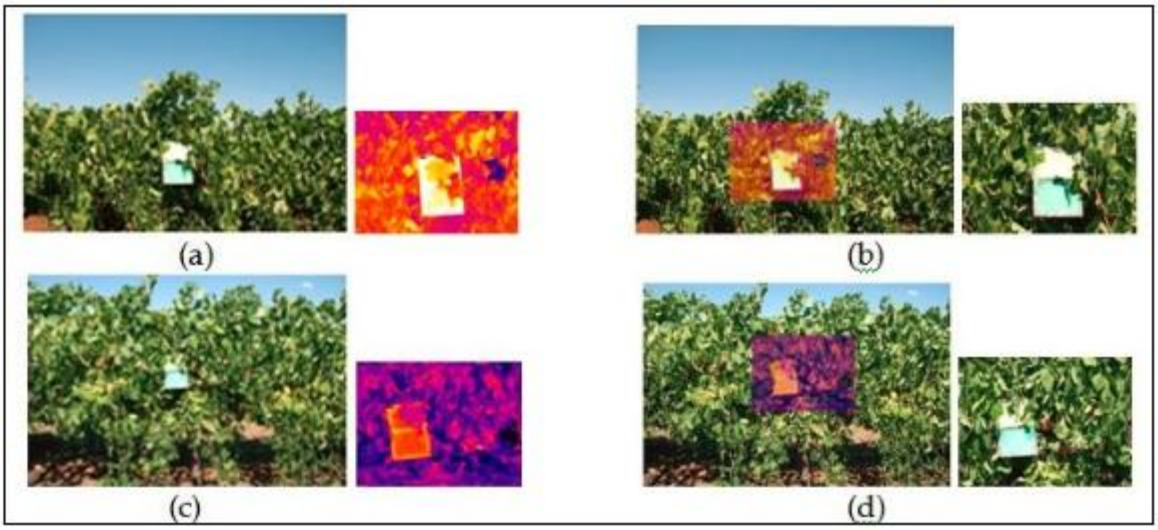

Figure 2: Outcomes of SIFT based registration algorithm (no matching key- points)

(a) 5906 key-points found in optical image, **(b)** 447 key-points found in IR image,

(c) 5666 key-points found in optical image, **(d)** 605 key-points found in IR image

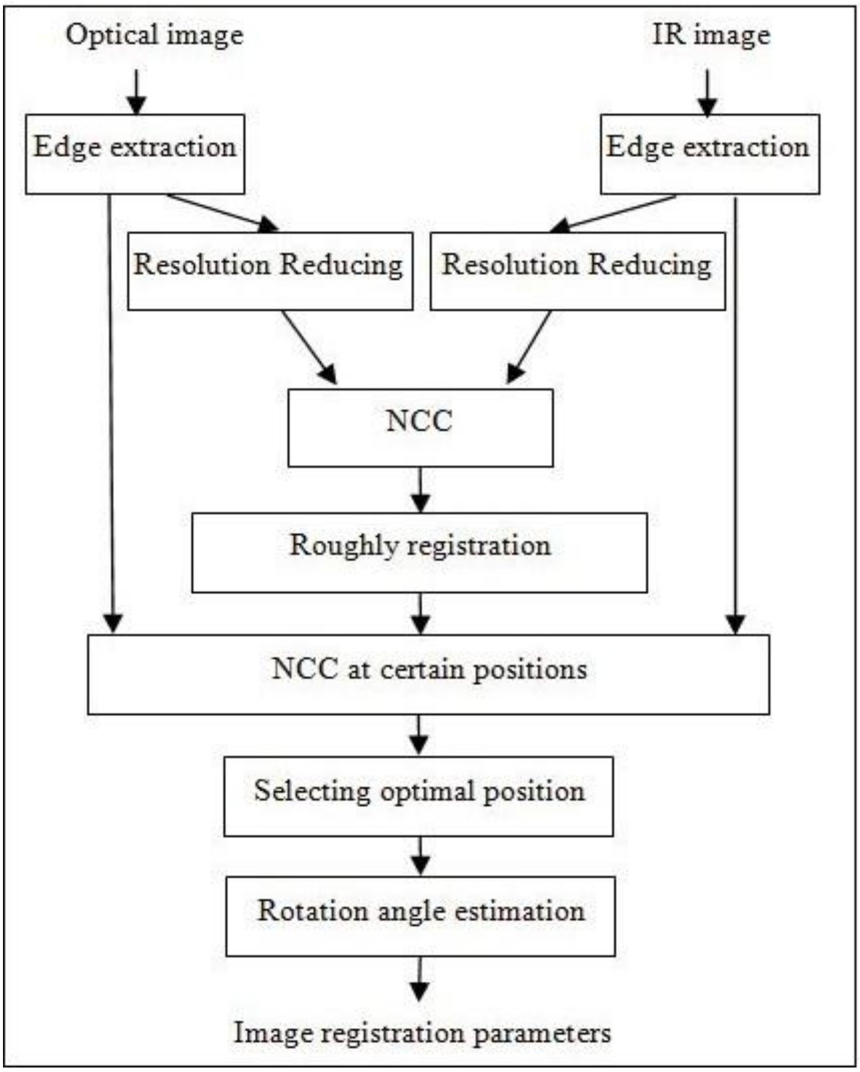

Figure 3: Flow Diagram of variable resolution algorithm based on NCC

Figure 4: One image pair

(a) An optical image**, (b)** An IR image

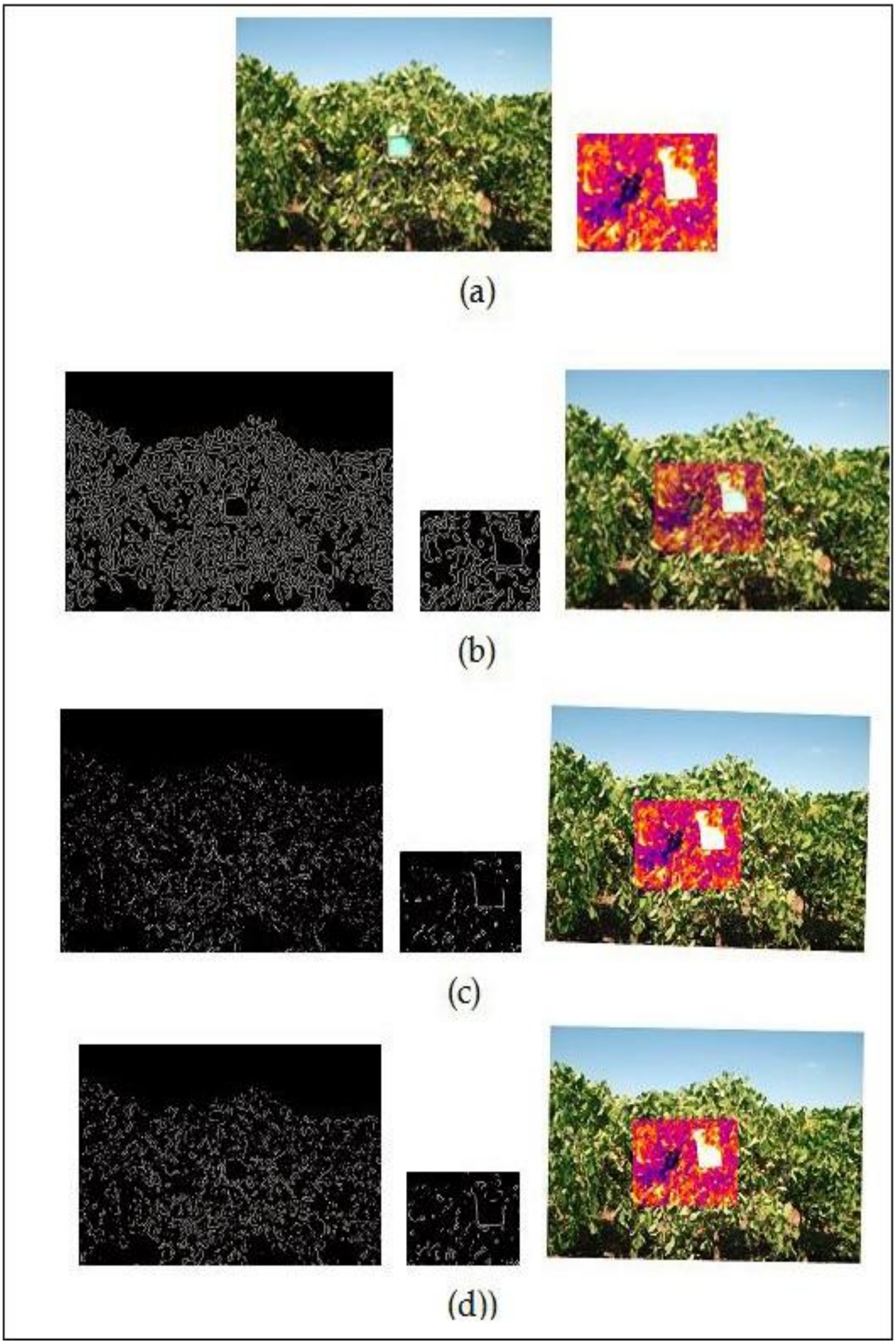

Figure 5: Tests of variable resolution algorithm based on different edge extraction methods

(a) Optical raw image (left) and infrared raw image (right),**(b)** UsingCanny algorithm (left) and its result (266, 254,-0.4),

(c) Using Roberts operators (left) and its result (265, 253, 1.8),**(d)** Using Sobel Operators (left) and its result (265, 256, 1.1)

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