Efficient registration of optical and infrared images via modified Sobel edging for plant canopy temperature estimation

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\textbf{Abstract}

Automatic optical and infrared (IR) image registration is a crucial requirement in the estimation of plant canopy temperature. The latter is used to compute the plant water stress status which can potentially be applied to an automated control system for optimal crop irrigation management. Due to the nature of image sources and plant scene, it is difficult to find enough common features between the pair of images to register them using a simple method. In this paper an improved registration algorithm is described, where a modified Sobel edge detector is adopted and a variable resolution scheme is applied. The algorithm can improve the registration efficiency considerably compared to our previous developed registration method. Experiment results show that the modified algorithm can achieve the same registration accuracy and a better success rate compared to that from the original algorithm with a substantial reduction of computational complexity.

\section{1. Introduction}

Water is the key resource for the agriculture sector, more than 70\% freshwater is used for agriculture irrigation alone in many countries. How to use the limited freshwater efficiently and effectively is one of the most active and important research topics in the world. Advanced plant sensing techniques, which can determine plant water stress in a non-contact and non-destructive manner, enable the use of automated and smart irrigation systems which are able to irrigate the exact amount of water needed by a plant\cite{1,2}. As described in\cite{1,2}, the crop water stress index (CWSI) can be used as an effective indicator for plant water stress level.

The perennial horticulture industry is deficient in plant based sensing techniques that can aid in irrigation decisions, ‘that is when, how often and how much to water’. A ‘Smart’ plant sensing technique would be required to provide automated real-time plant water status information and thus allow dynamic water management\cite{1–5}. One such plant based sensor that can describe plant water status is based on plant temperature measurement; the crop water stress index (CWSI). It has the potential to adhere to many of the ideal ‘Smart’ sensor specifications, being an effective indicator for plant water stress with data that can be collected in real time, in ‘on farm’ robust situations. Canopy temperature may be estimated via the infrared images (IR) and an algorithm proposed\cite{6}. The precision of the computed CWSI depends extensively on the accuracy of the canopy temperature estimation (IR data) and how this data is interoperated biologically. Leaf area and colour information are obtained via the optical image. The colour information allows the detection of leaf function in a ‘farm environment’.
Therefore, the image registration process is required to align the optical image with its associated IR image; so that temperature values corresponding to functioning plant leaves can be obtained. The development of an automated plant canopy temperature estimation algorithm was developed [6]. It is observed that the quality of the image pair alignment is crucial to the canopy temperature estimation accuracy and the computational complexity of image registration dominates the overall performance of the algorithm.

The registration and matching of images have been well documented in the literature and many effective techniques are available, for example, cross correlation [7], mutual information [8], correlation ratio [9] and Scale-Invariant Feature Transform (SIFT) based methods [10]. A collection of fast algorithms have been cited, such as automatic registration approach based on point features [11], automatic image registration algorithm with sub-pixel accuracy [12], image registration using importance sampling [13] and image registration using shape matching [14]. While SIFT based methods are the best choice for many applications, they may only apply to the registration of rigid objects using the image pairs of the same source. When the pair of images are taken from different sources, possibly at different time, there are some practical challenges for the alignment of the optical and IR images, which have been discussed in our initial work in [15]. One of the major issues is the main objects in the images are time-varying plant leaves. In addition, images from different sources possess different imaging characteristics. Fig. 1 shows an example of registration failure using a SIFT based method because the number of matching key points found are insufficient.

Wavelet transform was used in [16] to extract a number of feature points as the basis for image registration, but the method is only effective for the images with rigid objects taken by the same type of sensors, and the variations of the intensity fluctuations between the two images are assumed to be small. The registration algorithm based on the linear features between the two images was proposed in [17], where the images considered are in the man-made environments and are rich with linear features. Like SIFT, it is also not suitable for the underlying application which contains non-rigid objects from quite different image sources. Therefore it may be concluded that currently cited algorithms are not pertinent for the development of an algorithm that allows for non-rigid objects while being biological relevant.

The work presented in this paper is the follow up work presented in [10] to improve the algorithm performance in terms of registration accuracy and efficiency. As analyzed in [10], apart from the overall contour structures and colours, the optical image is generally quite different from the associated IR image. Furthermore, each pair of images cannot be taken simultaneously. Therefore, an edge detector is used to extract edges from the pair of images. The image registration based on normalized cross correlation (NCC) is then performed on these edge images. In our experiment, it was observed that (1) the choice of edge detectors can heavily influence the registration accuracy; (2) the implemented NCC is time consuming. In this paper, we describe an improved registration procedure, where a modified Sobel edge detector is proposed for the edge detection and a variable resolution approach to the system implementation is considered to improve the registration algorithm efficiency. The experiment results presented in this paper show that the modified algorithm can achieve a similar registration accuracy and success rate compared to the existing approach but algorithm computational overhead has been substantially reduced. The modified Sobel edge detector and the variable resolution implementation ensure that we can obtain efficient image registration while maintaining biological significance.

The paper is organized as follows: In Section 2 the algorithm is described and the flow diagram is given. In Section 3, the modified Sobel operators and the NCC algorithm implementation in variable resolutions are discussed. The experiment results are presented in Section 4, which is followed by the discussion and conclusion.

Fig. 1. Results of SIFT based registration algorithm (no matching key-points) (optical image size is 2848 × 2136 pixels, IR image size is 320 × 240 pixels, the same below).
2. Registration procedure

The initial stage in registering an IR image to the accompanying optical image is to obtain location and rotation angle. For the problem at hand, the IR image is wholly overlapped with the reference optical image. Moreover, we assume that the space resolution of the two images is known and in our case is the same. The flowchart of the variable resolution algorithm based on normalized cross correlation is shown in Fig. 2.

Since pixel by pixel based computation is required, implementation in full the normalized cross correlation (NCC) algorithm is time consuming. The algorithm efficiency issue can be addressed by several methods such as Sequential Similarity Detection Algorithm (SSDA) [18], Bit Plane Matching Algorithm (BPMA) [19], and Variable Resolution Correlation Algorithm (VRCA). Based on the merits of these techniques, the variable resolution algorithm is adopted for this application to improve the efficiency of the algorithm. The main idea of the variable resolution approach is that we initially perform a normalized cross correlation between the images using a reduced resolution and this may roughly identify the overlapping area of the two images. A high resolution correlation is then considered near the vicinity of each possible registration point and the correct registration point can be found by such a refined cross correlation procedure.

Let \( I_{O} \) and \( I_{IR} \) (image size is \( M \times N \)) stand for the optical and IR image respectively, \( f \) be the image zoom factor; \( I_{Ole} \) and \( I_{IRle} \) (image size is \( Mh \times Nh \)) stand for the low resolution images. Let \( I_{Oe}, I_{IR_e}. I_{Ole}, I_{IRle} \) denote the edged images of the corresponding images, then the generalize cross correlation can be expressed as

\[
\rho_l(u, v) = \frac{\sum_{i=0}^{Mh} \sum_{j=0}^{Nh} (I_{Ole,i,j} - \mu_{I_{IRle}}) (I_{IRle,i,j} - \mu_{I_{IRle}})}{\sigma_{Ole} \sigma_{IRle}}
\]

\[
\rho(k, l) = \frac{\sum_{i=0}^{M} \sum_{j=0}^{N} (I_{Oe,i,j} - \mu_{I_{Re}}) (I_{IR_e,i,j} - \mu_{I_{IR_e}})}{\sigma_{Oe} \sigma_{IR}}
\]

where \( \rho_l(u, v) \) is the cross correlation coefficient calculated from the low resolution image pair \( I_{Ole} \) and \( I_{IRle} \), \( (u,v) \) is the coordinate index of the optical image \( I_{Ole} \), \( I_{Ole,u,v} \) is an image located in the \( (u,v) \)th of image \( I_{Ole} \) and its size is the same as the image \( I_{IRle} \), \( \sigma_{Ole,v} \) and \( \sigma_{IRle} \) are the standard deviations of the corresponding images respectively. \( \rho(k, l) \) is the cross correlation coefficient calculated from the low resolution image pair \( I_{Oe} \) and \( I_{Re} \), \( (k,l) \) is the coordinate index of the optical image \( I_{Oe} \), \( I_{Oe,k,l} \) is an image located in the \( (k,l) \)th pixel of the image \( I_{Oe} \) and its size is the same as image \( I_{IR_e} \), \( \sigma_{Oe,l} \) and \( \sigma_{IR} \) are the standard deviations of the corresponding images respectively.

![Flow chart of the NCC algorithm via the variable resolution approach.](image-url)
3. Modified Sobel operator

To capture the common structural features between optical and IR images, the edge detectors play a key role. There are several methods for edge detection and extraction, such as Sobel, Roberts operators and Canny algorithm, and so on. In the underlying application the optical and IR images cannot be taken at the same time. The physical nature of leaves in the natural environment must also be considered, and often leaf edges in the two images are different. In the underlying application the optical and IR images cannot be taken at the same time. The physical nature of leaves in the natural environment must also be considered, and often leaf edges in the two images are different. It is observed that the standard Sobel operators and other available edge algorithms are too "sensitive" for these small leaf edges and their edge detection results have caused weak correlation between the optical and IR images to be registered. Therefore registration failures have been observed in our experiments. To preserve more global (larger) edges and ignore those locally fluctuated (smaller) leaf edges we propose the modified Sobel operators, which include four operators rather than the standard two operators. The four operators are

\[
S_1 = \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix}, \quad S_2 = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}
\]

\[
S_3 = \begin{bmatrix} 2 & 1 & 0 \\ 1 & 0 & -1 \\ 0 & -1 & -2 \end{bmatrix}, \quad S_4 = \begin{bmatrix} 0 & 1 & 2 \\ -1 & 0 & 1 \\ -2 & -1 & 0 \end{bmatrix}
\]

(3a)

(3b)

Using these four operators to convolute with the raw images, we can get

\[
E_k(i,j) = \sum_{m=-3}^{3} \sum_{n=-3}^{3} \text{Im}(i + m - 1, j + n - 1) S_k(m,n) \quad k = 1, 2, 3, 4
\]

(4)

\[
E(i,j) = \max_k E_k(i,j)
\]

(5)

where \(E(i,j)\) is the edge of the point \((i,j)\) of image \(\text{Im}\).

The differences of edge images between the standard and modified Sobel operators are illustrated in Fig. 3. It is observed that using the proposed modified Sobel operators the smaller leaf edges, most of which contain locally time-varying disturbance, have lower gray levels (Fig. 3c) while those larger edges, most of which represent the contours of the plant and are common to both the optical and IR images, have higher gray levels compared to the result in Fig. 3b processed using the standard Sobel operators. Therefore, a higher correlation between the edge filtered optical and IR images can be obtained compared to that between the edge images produced using the standard Sobel or other edge detectors. So, in the underlying application, a robust registration is obtained via the modified Sobel operators.

Following edge detection, the registration process is initially performed via the NCC algorithm using the edged images \(\text{ImOe}, \text{ImRe}, \text{ImOle}, \text{ImIRle}\) in reduced resolution as described in the flowchart. In order to take into account both the system and image uncertainties, a set of points \(\{(u_k, v_k)\}\) of the highest values of the correlation coefficient are labeled as the registration solution candidates. As indicated in Fig. 2, a fine registration step is carried out nearby each of the candidate points \(\{(u_k, v_k)\}\) using the images of full resolution. A weighted coefficient \(0 < c < 1\) is used to ensure that the final point with the maximum correlation coefficient approaches optimal.

\[
\rho_k = c \rho(u_k, v_k) + (1 - c) \rho(u'_k, v'_k)
\]

(6)

**Fig. 3.** Edge detection results comparison for an IR image of a Grapevines. (a) Original IR image; (b) edge image using standard Sobel operators; (c) edge image using modified Sobel operators.
where \((u_k', v_k')\) is the point on the image \(Im_{Oe}\) of full resolution, \(p(u_k', v_k')\) is the correlation coefficient of the fine image registration, \(p_1(u_k, v_k)\) signifies the correlation coefficient corresponding to the image registration at reduced resolution. Following the steps (6) and (7), we can get the registration position \((u_k, v_k)\).

The final step is the estimation of the rotation angle between the optical and IR images. In the developed software, the range of rotation angle \(\theta\) is from \(-10^\circ\) to \(10^\circ\). The angle range is divided into 200 grids. The correlation coefficient is calculated at each of these grids and the rotation angle \(\theta^*\) associated with the maximum correlation value is then chosen.

### 4. Experiment results

The refined NCC algorithm for image registration discussed in this paper was tested using grapevine image pairs, where the registration error, success rate and computational load are examined statistically. All images were collected using a FLIR
Table 2
Registration performance comparison: Modified Sobel vs. Sobel and other edge method.

<table>
<thead>
<tr>
<th>Edge detector</th>
<th>Number of image pairs</th>
<th>Success rate (%)&lt;sup&gt;a&lt;/sup&gt;</th>
<th>Registration error (max, min, average)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Modified Sobel</td>
<td>68</td>
<td>100</td>
<td>(7, 0, 2.6)</td>
</tr>
<tr>
<td>Standard Sobel</td>
<td>68</td>
<td>82.4</td>
<td>(8, 0, 2.8)</td>
</tr>
<tr>
<td>Canny edge</td>
<td>68</td>
<td>88.2</td>
<td>(6, 0, 2.6)</td>
</tr>
<tr>
<td>Robert edge</td>
<td>68</td>
<td>79.4</td>
<td>(9, 0, 3.2)</td>
</tr>
</tbody>
</table>

<sup>a</sup> A registration is counted as successful if the position error is less than 10 pixels.
PM570 320X240 thermal imager and a standard Fujitsu S5600 digital camera from the Dookie College Estate vineyard, Victoria, Australia, where a research group from the University of Melbourne has conducted plant water stress monitoring experimental research using non-destructive and automated sensing technologies since 2007 [20].

The above algorithm was tested using many image pairs. All of the results are successful with errors in a tolerable range as shown in Fig. 4. The computational overhead of the proposed variable resolution method is compared to that of standard NCC under the same environment and conditions and the results are given in Table 1, which demonstrate both algorithms can achieve the same registration accuracy but the efficiency of the variable resolution algorithm is remarkably better, with only about one fortieth of the standard NCC running time.

Fig. 6 (continued)
All of the tests are run in the condition of $f = 2$ and using Modified Sobel operator to get the image edges. Two registration examples based on our presented algorithm are illustrated in Fig. 5, which demonstrate registration effectiveness. The registration performance illustration is given in Table 2 and Fig 6. From the results we can see that the performance of the algorithm using Modified Sobel edge is the best. It demonstrates the effectiveness of our proposed algorithm.

5. Discussion

From the experiment results we can see:

1. The underlying application requires an accurate registration between optical and IR images for a plant scene. This enables the plant leaf area from the IR image to be identified and thus the temperature data of the plant canopy can be obtained. The variable resolution algorithm presented is shown to be very efficient over the standard NCC method without compromising registration accuracy.

2. The use of the modified Sobel edge detector has resulted in the improvement in the processing abilities while maintaining biological significance in the following sense:
   - Smaller edges – represent the plant leaves, most of which are time-varying and should be ignored;
   - Larger edges – represent the contours of the plant, most of which are common to both the optical and IR images and should be considered as the common features.

These special requirements have caused the standard edge detectors fail to obtain desired common features from the source images.

6. Conclusion

The paper presented a fast image registration algorithm for the application of plant water stress monitoring using optical and infrared images. This is a refinement of an existing approach presented in [10]. By utilizing a variable resolution scheme and a modified Sobel edge detector, the proposed implementation has substantially improved the registration efficiency compared to a previous implementation. From our experimental results, the proposed algorithm runs about forty times faster than a standard implementation which has previously coded. In addition, as demonstrated by the statistics of field experiment results, an enhanced registration performance in terms of success rate is observed. Moreover, the improvement of this special registration algorithm makes it possible to establish a robust, real-time data sampling method for automated plant canopy temperature data collection. One would be able to determine how much, when and how often the plant should be watered by processing the data.

References


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