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ITERATIVE ELIMINATION ALGORITHM FOR THERMAL IMAGE PROCESSING

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Abstract

Segmentation is employed in everyday image processing, in order to remove unwanted objects present in the image. There are scenarios where segmentation alone does not do the intended job automatically. In such cases, subjective means are required to eliminate the remnants which are time consuming especially when multiple images are involved. It is also not feasible when real-time applications are involved. This is even compounded when thermal imaging is involved as both foreground and background objects can have similar thermal distribution, thus making it impossible for straight segmentation to distinguish between the two. In this study, a real-time Iterative Elimination Algorithm (IEA) was developed and it was shown that false foreground was removed in thermal images where segmentation failed to do so. The algorithm was tested on thermal images that were segmented using the inter-variance thresholding. The thermal images contained human subjects as foreground with some background objects having similar thermal distribution as the subject. Informed consent was obtained from the subject that voluntarily took part in the study. The IEA was only tested on thermal images and failed when false background object was connected to the foreground after segmentation.

Keywords: Segmentation, thermal imaging, image processing, real-time

1. Introduction

Image segmentation is a process of extracting a foreground (wanted) object from an image while discarding the background (unwanted) object. It involves the use of important features of the image such as its gray level and texture (Cretikos *et al.*, 2008) and is an important step towards image analysis. In a gray scale image, the algorithm for segmentation is based on either the discontinuity or similarity property of the image (Gonzalez *et al.*, 2010). In methods employing the discontinuity approach, the reference image is divided according to sudden changes in intensity while that employing the similarity property divides the image into parts that have similarity based on a condition.

Segmentation has been a subject of many studies and there are many proposed approaches to achieving it such as Park *et al.* (2009), Mentzelopoulos *et al.* (2013), Hillman *et al.*, (2005), Wang (2010), Pun (1981), Coleman (1979), Shi (2000), Choong *et al.* (2012) and Wang *et al.* (2012) approaches. Thresholding is one of the popular approaches to image segmentation due to its simplicity, accuracy and speed of execution with various methods developed such as those due to Otsu (1979), Kapur *et al.* (1985) and Tsai (1985) respectively. Many approaches have been used in segmenting objects in thermal images (Yuksel and Borlu, 2009, Diciotti *et al.*, 2011). A common requirement in thermal imaging of a subject is to extract the foreground (subject's body part) from the background. Foreground extraction is employed in cases such as overlaying of thermal and visual images (Schaefer *et al.*, 2006), biometric recognition using thermal imaging (Font-Aragones *et al.*, 2013) and abnormality (due to disease) detection (Snekhalatha *et al.*, 2012). A particular problem in segmenting an object or human subject in thermal images from the background is related to the similarity of the thermal distribution of the background to that of the foreground.

On their part Fernández-Caballero *et al.* (2011) in segmenting thermal images, eliminated high temperature points by considering the mean image value and then performed morphological operations to reconnect possible body regions. Any point having temperature that is above the mean value by a set percentage was eliminated. The drawback was some body parts (foreground) were eliminated in the process. In addition, some skin regions could not be re-connected by the morphological operation used due to the distance of separation resulting in split human detection. Li *et al.* (2011) achieved segmentation by using the standard deviations of the image histogram to select the threshold level. The method was not fast compared to the existing methods and cannot therefore be used in real-time processing. In the above methods, objects that belonged to the background remained as part of the foreground due to the thermal distribution similarity between the two objects. One way of eradicating these unwanted objects was the use of manual elimination by using prior knowledge of their temperatures. This would, however, be subjective and could not be employed for automated applications let alone real-time processing. This study is aimed at further enhancing the performance of such methods that fail to completely eliminate background objects for greater accuracy and use in automated applications.

The first step towards developing and testing the Iterative Elimination Algorithm (IEA) was to segment a thermal image of a human that had background objects with similar thermal distribution as that of the subject using threshold method. For this the inter-variance (Otsu method) (Otsu, 1979) was used due to its simplicity and robustness. Thresholding is generally achieved using equation 1.

$$g(x,y) = \begin{cases} 1 & if\ f(x,y) > TH \\ 0 & otherwise \end{cases} \tag{1}$$

where: TH is a segmentation (threshold) value and for a greyscale image its value is less than or equal to 255.

2. Materials and Methods

Multiple images with varying background objects were segmented using the technique reported by (Otsu, 1979). Resulting images that had background objects remaining after the segmentation were then used in evaluating the performance of the developed IEA.

An iterative elimination algorithm (IEA) whose block diagram is shown in **Error! Reference source not found.** was developed using the National Instrument's LabVIEW 2013 to automate the removal of any remaining unwanted object. To achieve this, the total number of objects (including the subject) in the image was first determined by using the algorithm reported in Burger (2008). The IEA consists of creating border of single zeros around the periphery of the image. A mask consisting of ones was also created. The mask was placed on the first pixel on the top left corner of the image and if the pixel under the centre of the mask was 0, then the mask was moved right by 1 pixel. If the centre of the mask was 1 then it was ANDed with the pixel values beneath it and if any of the eight neighbouring pixels was 1, then the associated pixels were labelled as being from the same object. The mask was then moved right by 1 pixel and the procedure was repeated until the centre of the mask reached the right hand corner of the image after which it was moved to the first column of the next row.

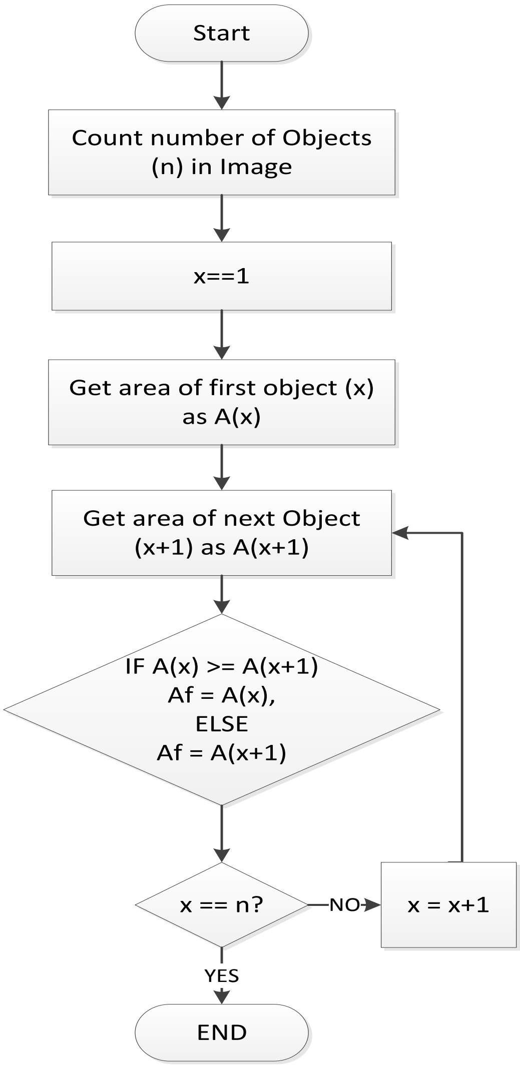

Figure 1: Block diagram of the Iterative Elimination Algorithm

A reference pixel was assigned the same label to a previously assigned pixel if it was connected to. If only the centre pixel was 1, then it was identified as an independent object and assigned a label. If there existed a direct connection between a pixel that was part of one of the 8 neighbours of a reference pixel, then the two were said to be connected as given by:

$$w' = \in N_8(w) \quad (2)$$

The image was scanned till the last pixel located at the bottom right of the image was encountered and all connected pixels with binary value of 1 considered as belonging to the same object and given the same label, *i*. The area of each object in the image was determined by summing the number of pixels in them. The area covered by a binary object was simply the number of pixels that make up the object, i.e.

$$A(F_{ci}) = |F_{ci}| \tag{3}$$

Since a foreground is only true when the pixel value at a point equals 1, then the area of a binary object is given by

$$A(F_{ci}) = \sum_{(x,y)\in F_{ci}} 1 \tag{4}$$

The total number of foreground objects N, in the binary image is simply the summation of the objects in the image, that is,

$$N = max(i) \tag{5}$$

The largest object in the image is always the subject since the Field of View (FOV) of the camera was mostly focused on them. Hence, every object except the largest was considered as an unwanted object and disposed.

In determining pixels that belonged to the same object, both 4- and 8- Neighbourhood sizes can be used. For a given a pixel (i, j); its 4-Neighbours are $(i \mp 1, j)$ and $(i, j \mp 1)$ while its 8 Neighbours are $(i, j \mp 1), (i \mp 1, j)$ and $(i \mp 1, j \mp 1)$. The 4- and 8- Neighbours are shown in **Error! Reference source not found.**.

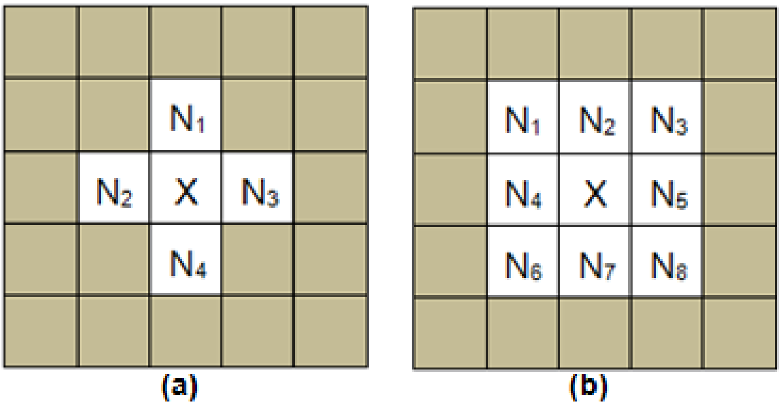

Figure 2: (a) 4-Neighbourhood (N_4) and (b) 8-Neighbourhood (N_8)

8-Neighbourhood (N_8) size was therefore used in this case as it connected pixels that were horizontally, vertically and diagonally adjacent. Thus it reduced the tendency of losing small segments of the foreground object that might have been disconnected due to sudden temperature variations.

3. Results and Discussion

Some background (unwanted) objects that had similar thermal distributions to that of the subject's body or parts of the body (such as the limbs) that did not appear connected to the body in some images remained as foreground objects in some images. **Error! Reference source not found.** (a) shows a segmented image in which tiny background objects at the top right and left hands of the image appear alongside the desired foreground object and are therefore false foreground. In **Error! Reference source not found.** (b), the false foreground was removed using the IEA.

Figure 3: Binary image (a) containing little background objects and (b) objects removed

Error! Reference source not found. (a) and (b) show the reconstructed segmented image before and after application of the IEA.

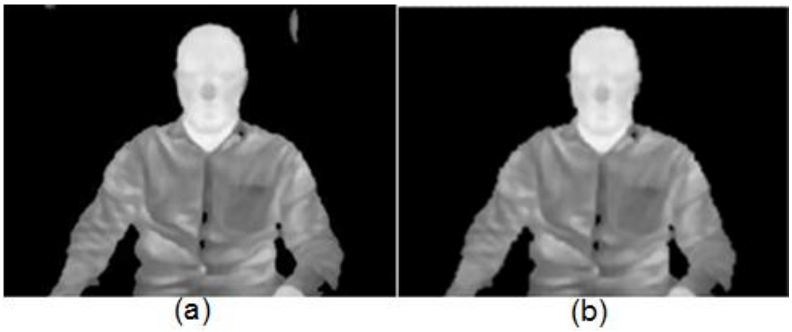

Figure 4: Reconstructed gray scale image of Figure 3 (a) with and (b) without background objects

The holes in the foreground objects were as a result of presence of colder objects (buttons in this case) that resulted in under segmentation. This however is not as a result of the IEA and does not have an effect on the performance of the algorithm. The holes can easily be filled using morphological operations and the foreground image reconstructed successfully.

The two false foregrounds in **Error! Reference source not found.**(a) are much larger than the previous case in **Error! Reference source not found.**(a), yet direct segmentation could not remove them due to the nature of thermal imaging which is based on temperature. IEA was however able to eliminate the false foregrounds as shown in **Error! Reference source not found.**(b).

Figure 5: Binary image (a) containing two large background objects and (b) objects removed.

Error! Reference source not found.(a) shows the reconstructed segmented image while **Error! Reference source not found.**(b) shows the gray image after the application of IEA. Visual inspections of both images reveal that IEA does not change the desired image with respect to size or grey level.

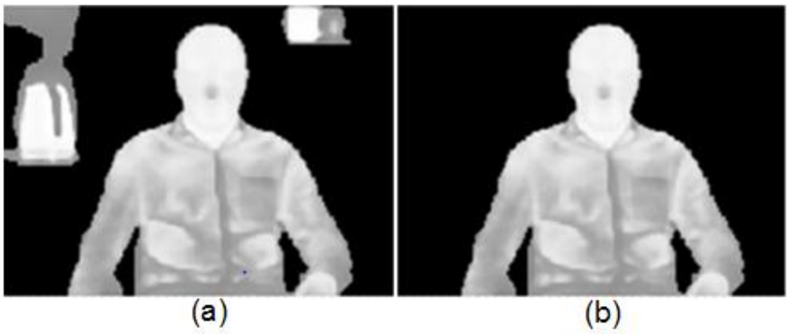

Figure 6: Reconstructed gray scale image of Figure 5 (a) before and (b) after use of IEA

Error! Reference source not found.(a) has multiple false foreground objects which were effectively removed in **Error! Reference source not found.**(b) using the IEA.

Figure 7: Binary image (a) containing multiple background objects and (b) objects removed

Error! Reference source not found.(a) shows the reconstructed thermal image of the segmented image with the false foreground while **Error! Reference source not found.**(b) shows that for the eliminated false foreground.

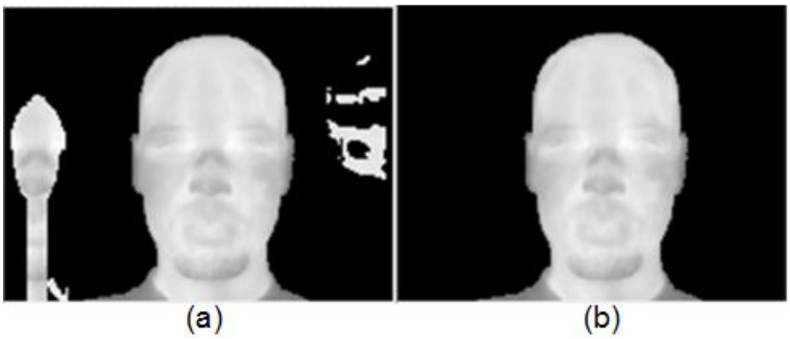

Figure 8: Reconstructed gray scale image of Figure 7 (a) before and (b) after use of IEA

Whereas Figures 3 - 6 were cases where a subject was seated and the cameras field of view (FOV) showing the upper half of the body (from abdomen up to the vertex of the head), Figures 7 and 8 were cases where the camera was close to the subject such that its FOV was mostly focused on the subject's face and neck regions.

4. Conclusion

A real-time Iterative Elimination Algorithm for Thermal Images has been developed using the National Instrument's LabVIEW 2013 and its effectiveness on removing false foreground verified on a number of thermal images in different scenarios. The Algorithm has proved to the task for which it was intended and thus can be used in removing (false) foreground that could not be automatically eliminated through direct segmentation. Under segmentation did occur due to thermal distribution of foreground object's similarity with the background. This however was not due to the developed algorithm, nor did it have any effect on its performance. However, if a false foreground were to be connected with the actual foreground, then, the IEA may not be as effective since there would be no way for it to distinguish between the two due to the connection. Perhaps the next interesting study regarding the IEA is to examine how it can be extended to remove false foreground objects in colour images.

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