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Use of finite state machines in segmentation of radiograph images

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Abstract

The problem of image segmentation is approached via finite state machines. Finite state machines are excellent tools in processing various vision tasks. In this paper, segmentation of radiograph images of welding scenes are considered. A Mealy machine has been designed to remove background nonhomogeneity and a Moore machine has been designed to isolate the welding defects from the background. Result of segmentation of several radiograph images using these finite state machines are given.

Introduction

Image segmentation is the process of partitioning an image into meaningful regions.[1] Most work in image segmentation, however, has been centered on partitioning of images into homogeneous regions. There are mainly two approaches to image segmentation, the region growing approach and the boundary detection approach.

The region growing approach involves either a top-down technique where starting from the whole image, the image is split into homogeneous regions, until a given criterion is met,[2,3,4] or a bottom-up technique, where starting at the pixel level, neighboring homogeneous regions are merged until a given criterion is met.[5,6,7,8] The boundary detection approach involves detection of boundary between regions of different property. Since boundary between regions of different property show the places where property values change sharply, and since sharp changes in an image can be detected by an edge operator, techniques in this category are assisted by different edge operators.[9,10,11,12,13,14,15,16,17,18,19,20] For images having two type of regions, one belonging to the objects and one belonging to the background, there is a simple technique of image thresholding where a global threshold value is used to segment an image.[21,22,23,24,25,26,27,28,29,30,31] Attempts have also been made to segment images into meaningful regions (rather than homogeneous regions). This class of techniques, known as the semantic techniques, interpret regions as they are being formed, and the result of interpretation is used to guide the segmentation.[32,33,34,35,36]

The region growing and the boundary detection techniques use local information in images for segmentation, while the thresholding technique uses global information in images for segmentation. Only the semantic technique uses both global and local information in images for segmentation.

In this paper, segmentation of radiograph images is considered. One of the characteristics of radiograph images is that intensity values across an image vary greatly,[37] and a technique which uses only global or only local information from images is not able to segment the images satisfactorily. The techniques that fall under the semantic category leave us some hope. However, the slow computation speed of semantic techniques does not allow real time processing of the images. A new segmentation technique was developed that can segment a class of radiograph images using finite state machines. The proposed technique has a computational complexity of order N, where N is the number of pixels in the image.

A finite state machine is defined formally by a six-tuple $(Q,\Sigma,\Delta,\delta,\lambda,q0)$, where Q is a finite set of states, Σ is a finite set of inputs, Δ is a finite set of outputs, δ is a transition funtion, λ is a mapping function, and $q0 \epsilon Q$ is the initial state. Finite state machines are of two kinds. One kind, known as the Moore machine, has its outputs associated with its states and another kind known as the Mealy machine, has its outputs associated with its state transitions. It has been shown that Moore and Mealy machines are equivalent,[38] and both can be used to accomplish the same task. In the following, examples of each machine in carrying out steps of a segmentation technique are described.

Statement of the Problem

A set of radiograph images of welding scenes are available. The problem is to detect and extract the welding defects from the images. The defects appear in the form of dark spots and can be easily detected by human observers, however, there is a need to automate the process. The process is required to be fast enough to be used for real time purposes (a 480x512 image should be processed in a few seconds).

The characteristics of the available radiographs are as follows: (see Figures,7.a, 8.a, 9.a, and 10.a)

--The defects come in different sizes, shapes, and intensities.

--In an image, the intensity distributions of the defects and their background are not disjoint. Some areas of the background may have the same intensities as the defects.

--Some images may not contain any defects at all.

--The background of an image is darker in the left and right borders and gets brighter as it nears the center of the image. In some images, this change of intensity is rather sharp while in others it is gradual.

In the following, a finite state machine is designed to preprocess the images to remove noise and the left and the right dark borders, and another finite state machine is designed to detect and extract the defects.

Preprocessing

Before making any attempt to detect the defects in an image, we have to preprocess the image for removal of noise and background nonhomogeneity. Noise removal can be achieved by a local smoothing operation. Figure 1 shows intensity values of pixels lying on a typical row of a radiograph image. After smoothing the image in a 5x5 neighborhood, the intensity values of the same row become like Figure 2. A, B, and C are the defects that should be detected in later stages of the process.

As can be seen from Figures 1 and 2, the intensities of pixels at the left and right sides of the background are considerably lower than the intensities at the central areas of the background, with some intensities similar to those of the defects and there is a need to remove the dark borders from the images. However, complete removal of the border areas is not desirable because there might be some defects present in those areas. Increase of intensity values at the border areas to the same level as those of the middle part of the image is more desirable.

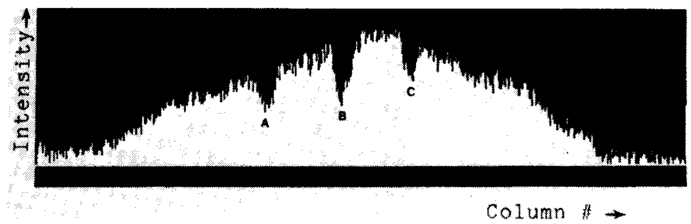


Figure 1. Intensities of pixels in a row of a radiograph image.

If we plot the row average intensities in a radiograph image, a curve similar to Figure 3 will be obtained. Starting from the leftmost column and moving to the right, the intensities constantly increase due to the left dark border until the presence of some defects makes the intensities decrease again (this is the place where peak L is observed). Starting from the rightmost column and moving to the left, again the intensities increase due to the right dark border until the existence of some defects makes the intensities decrease (This is the place where peak R is observed). The dots between L and R in Figure 3 show the presence of any number of peaks. If the leftmost and rightmost peaks are at columns c1 and c2 with values L and R, respectively, we increase the intensities of pixels to the left of c1 and to the right of c2 as below to remove the left and right dark borders. Assuming a is the average intensity of pixels in a column to the left of c1, then we increase the intensity of each pixel in that column by L-a. This will, in effect, increase the average intensity of that column by L-a. Also if b is the average intensity of pixels in a column to the right of c2, we increase the intensity of each pixel in

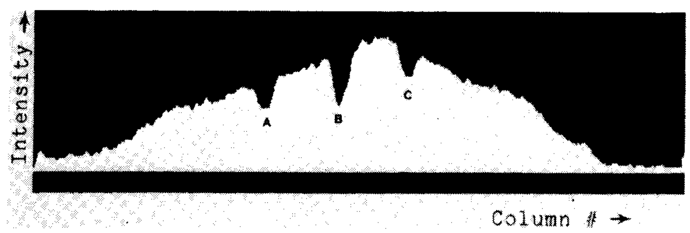


Figure 2. Intensities of pixels in the same row as Figure 1 but after being smoothed.

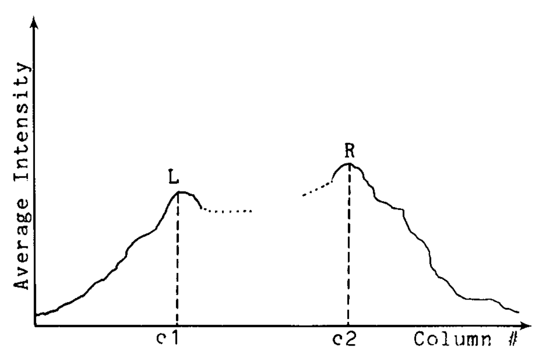


Figure 3. Average row intensity values in a radiograph image. Areas to the left of c1 and to the right of c2 are the dark borders.

that column by R-b. Now every column to the left of c1 has average intensity L and every column to the right of c2 has average intensity R. The problem that remains is to determine c1 and c2. In the following, a finite state machine will be designed which processes an image from left to right and determines c1. c2 can be determined in the same fashion by processing the image from right to left.

c1 is considered to be the column number where the intensity values start to fall to a given threshold value. The threshold value is used to detect a significant peak rather than a noisy one. We use pointer P to point to the column number where intensities start to fall. We compare the average intensity of the column pointed to by P with the average intensity of the present column and make appropriate action such as announcing the detection of a peak, updating the value of pointer P, etc. The Mealy machine of Figure 4 describes the details of this process.

Inputs

- i: Average intensity of the present column is larger than the average intensity of the column pointed to by P.
- d: Average intensity of the present column is slightly smaller than the average intensity of the column pointed to by P.
- D: Average intensity of the present column is larger than the average intensity of the column pointed to by P by a threshold value.

Outputs

- ϵ: No output.
- P: Set the pointer to the present column number.
- L: Set the peak value to the average intensity of the present column.

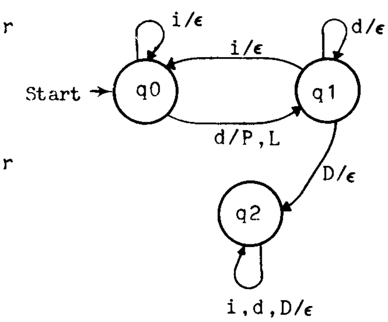


Figure 4. Mealy machine removing the dark left and right borders of images.

Initially, the value of pointer P is set to 1, showing column 1. The initial peak Value L is set to the average intensity of column 1. When the machine enters state q2, pointer P will show c1 and variable L will show the average intensity of column c1.

The machine scans the average intensities from left to right. As long as the intensities increase, the machine stays in state q0 but when a decrease in intensity values is sensed, the machine changes its state to q1 and updates pointer P to the present column number and the peak value L to the average intensity of the present column. If an increased value is sensed next, the machine goes back to state q0. If a small decreased value is sensed, the machine stays in q1. If the cumulative decreased value falls by a threshold value, the machine goes to state q2 showing the presence of a peak. To generate inputs to the machine, the average intensity of the present column is compared to the average intensity of the column pointed to by P. i is an input showing an increase in the intensity values, d is an input showing a decrease in intensity values which is below a threshold value, and D is an input showing a decrease in intensity values which is equal to or greater than the threshold value. The threshold value is used to avoid detection of noisy peaks. The larger the threshold value, the more significant the detected peak (however, if the threshold value is too large, no peak might be detected). For threshold value of 10, image of Figure 7.a was converted to image of Figure 7.b. Using this finite state machine, the intensities of the row shown in Figure 2 were replaced with intensities of the row shown in Figure 5. Note how the intensities of the left and the right borders are lifted to make the image background homogeneous. Now a simple thresholding would be able to detect the defects.

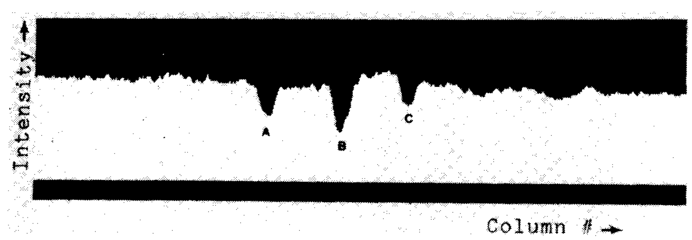


Figure 5. The same row as Figure 2 but after removal of the left and right borders.

In some radiograph images, however, intensities across an image change greatly and thresholding of the image would fail to detect the defects properly. For this reason, in the next section, another finite state machine will be designed to detect and extract the defects from the preprocessed images.

Segmentation

After removal of the noise and the left and the right dark borders from the images we would like to segment them in a way that welding defects are isolated. It should be noted that some areas of the background might still be nonhomogeneous with intensity values similar to those of the defects. However, the rate the intensities change in the background is slower than the rate intensities change between the defects and the background. The rate of change of intensities in the background was studied on different images, the sharpest change was 29 in a distance of 5 pixels. The rate of change of intensities between the background and the defects is usually more than this amount. We would not like to extract parts of the background as the defects even at the cost of losing some small and low contrast defects. It seems that a high-pass filter with an appropriate sharp cut-off frequency would be able to detect the defects. However, a high-pass filter with a sharp cut-off frequency is hard to implement and not only that, if high-pass filtering is used, many spurious edges will be obtained around the boundary of the defects, making the detetermination of boundary lines difficult. Since many types of defects are possible to exist, there is a need to determine the type of the defects from their shape boundaries. Discrimination of defects from their shape boundaries is not discussed here. However, we keep in mind that extraction of precise defect boundaries is one of the requirements in this segmentation process.

Inputs

i: $0 < f(j+2)-f(j-2) < 30$
d: $-30 < f(j+2)-f(j-2) < 0$
I: $f(j+2)-f(j-2) \geq 30$
D: $f(j+2)-f(j-2) \leq -30$
j is the column number which the output is being generated for.

Outputs

0: Background
1: Object

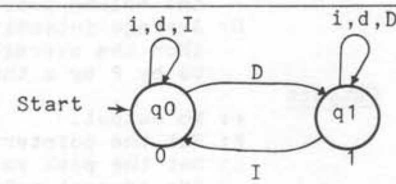


Figure 6. Moore Machine segmenting the radiograph images.

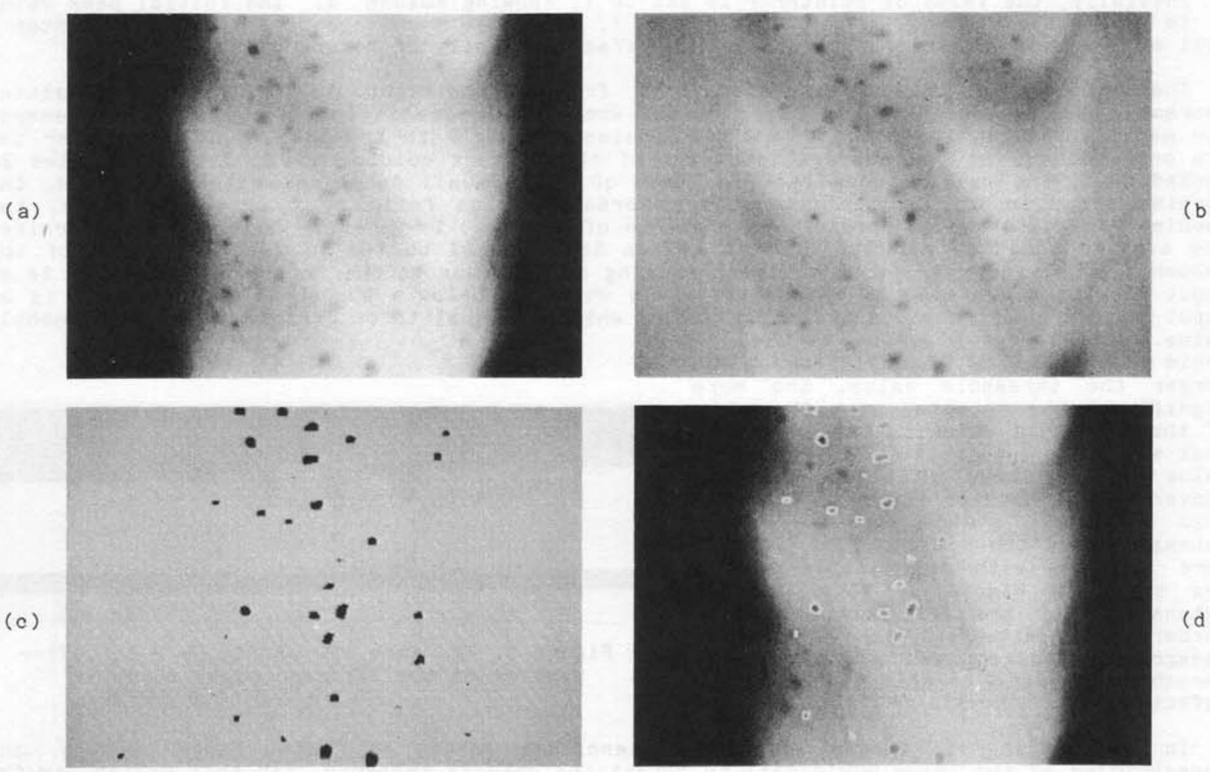
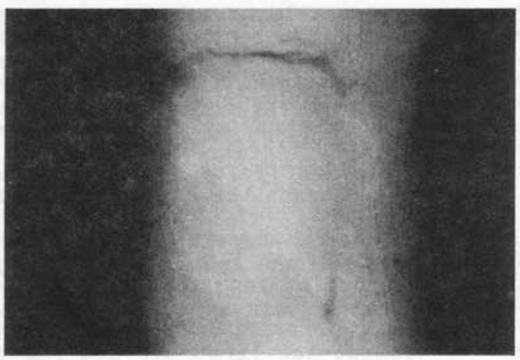


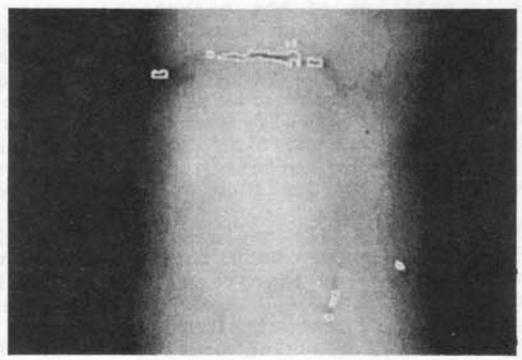
Figure 7. Segmentation steps of a radiograph image. (a) Original image. (b) Image after removal of left and right dark borders. (c) Extracted defects from the background. (d) Segmentation result.

To carry out the segmentation, a Moore machine with two states was designed. One of the states shows that the machine is scanning the background and another state shows that it is scanning a defect. Therefore, by scanning the input, we can determine the position where the transition takes place between the background and the defect. More specifically the Moore machine of Figure 6 describes the segmentation process.

This machine processes the input row-by-row. Given a row of the image, the machine starts from column number 3 and determines $\Delta f=f(j+2)-f(j-2)$, where $f(j)$ denotes the intensity at column j. If $\Delta f>-30$ then the machine stays in state q0 (showing column j belongs to the background and therefore a 0 is being generated). If $\Delta f\leq-30$ then the machine changes state to q1 showing a significant fall in the intensity values and showing it has found a defect. The machine stays in this state until a significant raise in intensity values is detected ($\Delta f\geq30$). Since processing of an image row-by-row may result in loss of some horizontal edges, the same process should be carried out column-by-column also and the result of the two processes should be combined. The result of applying this segmentation process on the image of Figure 7.b is shown in Figure 7.c. The boundaries of the detected defects is overlaid on the original radiograph in Figure 7.d to visualize the segmentation result. Figures 8, 9, and 10 show the segmentation of other radiograph images with different types of welding defects. A fixed threshold value 30 was used to generate input data for the Moore machine in segmentation of all these radiographs. As can be seen from these experiments, although some of the low contrast defects are missed, most of them are successfully detected.

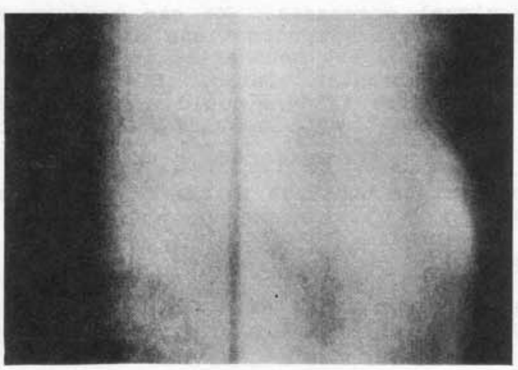


(a)

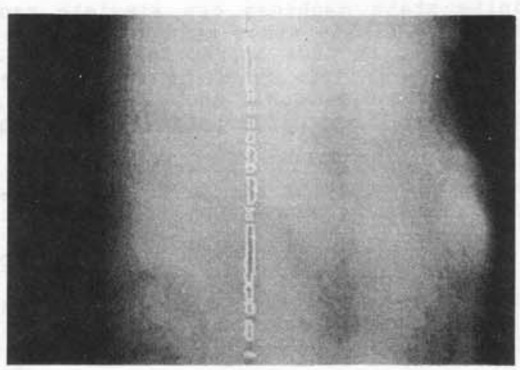


(b)

Figure 8. (a) Original image. (b) The segmentation result.

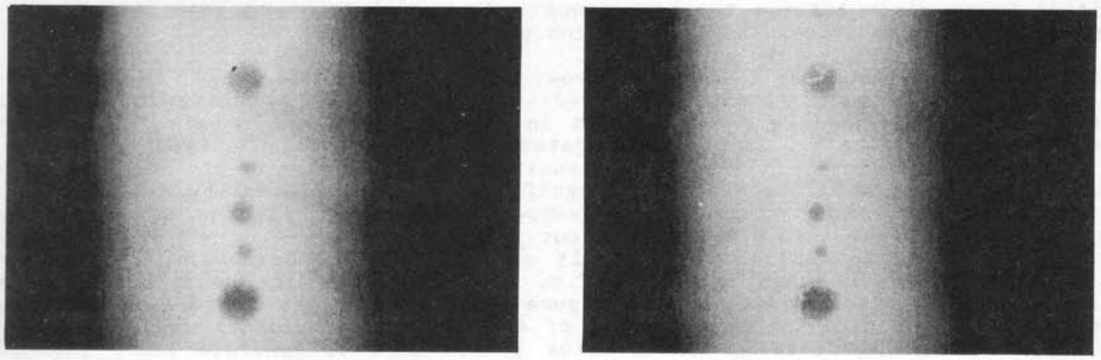


(a)



(b)

Figure 9. (a) Original image. (b) The segmentation result.



(a) (b)

Figure 10. (a) Original image. (b) The segmentation result.

Conclusion

Segmentation of radiograph images of welding scenes was discussed. The objective was to extract welding defects from the images. The defects appear as dark spots in the images and since intensities of the background across an image may vary greatly, a region growing or a thresholding technique would fail to detect the defects satisfactorily. Edge detection techniques can detect the defects, however, with the groups of edges produced around a defect boundary, determination of the boundary of the defect seems a difficult task. In this paper, a segmentation technique was introduced that uses finite state machines. A finite state machine (a Mealy machine) was designed to globally look at an image and remove backgound nonhomogeneities. If background nonhomogeneity is not removed, they could be confused with the defects in the segmentation process. A second finite state machine (a Moore machine) was designed to locally look at the images and extract the defect boundaries.

The computational complexity of the Mealy machine is N or less, where N is the number of pixels in the image. Note that detection of peaks L and R would not require processing of the whole image and therefore computation time would be an order of less than N. If L and R coincide, the machine has to look at the whole image which would require an order of N operations. The computational complexity of the Moore machine is N because the machine makes a move by scanning every pixel in the image once (except the first two and the last two columns of the image). The operations that are used by both the machines are simple operations such as additions and comparisons which are fast in computation and easy to implement in hardware. Note also that since the Moore machine segments an image one row or one column at a time, a series of these machines can be used to process a series of rows or columns in parallel for faster speed. The time required to segment a 480x512 image when the machines are implemented in software and run on a PDP 11/34 has been 55 seconds. On a CDC Cyber, the computation time would be 5 seconds.

Finite state machines can simulate many human visual processes. We can program fine details in a finite state machine and let it recognize different situations as it scans an image and let it take appropriate actions. Detection of object boundaries in an image is one of the principle problems in image processing and computer vision. Since different spatial frequencies could cause a boundary, several band-pass filters could also be used to extract edges from different spatial frequencies and then try to combine them to obtain object boundaries[11,39].

We are now studying the feasibility of using finite state machines in the general problem of object boundary extraction, template matching, and shape discrimination.

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