Multiscale Relaxation Labeling of Fractal Images

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Abstract

This paper describes multi-scale relaxation labeling for segmentation of fractal images. The images used are of pavement distress, on which simple edge detection schemes perform poorly. We use relaxation labeling to improve upon initial edge-based segmentation. Earlier work has shown that pavement distress can be well-modeled by fractals; the scale-invariance property of fractals suggests that information at different scales of resolution may be combined to improve segmentation. Thus, we have developed a multi-scale relaxation technique for use in a pavement distress detection system. To better model pixel interactions, we have included non-linear terms in the relaxation process. Symmetry arguments and careful engineering allow a 93% reduction in the complexity of this approach. To demonstrate the necessity of the multi-scale approach, examples with and without multi-scale relaxation are shown. We found that performance was greatly improved by multi-scale relaxation.

1 Introduction

This paper describes the application of multi-scale relaxation to segment fractal images. Pavement distress (cracking) has been shown to be well-modeled by fractals [2]. This is a useful property which can be exploited to differentiate distress from the rest of the image. A fractal object or curve will appear to have the same fractal dimension, regardless of the scale that is used or the distance from the object [3]. The scale-invariance property of fractals suggests that information at different scales of resolution may be combined to improve segmentation. Thus, we have developed a multi-scale relaxation technique for use in a pavement distress detection system.

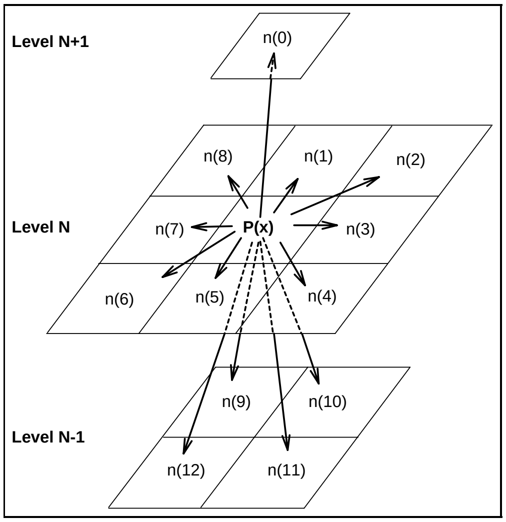

Figure 1: Neighbor Label Sets for Data Point X

2 System Overview

We are interested in segmenting pavement images into three classes of pixels: Aggregate, which corresponds to sound pavement, Crack, which represents distressed pavement, and Boundary, which separates the other two classes. Associated with each pixel is a 3-vector $[A, B, C]$ representing the probability that the pixel is in each class. We require that $A + B + C = 1$. The relaxation algorithm [5] adjusts these probabilities to make a pixel more consistent with is neighbors.

Initially, zero crossings of a second directional derivative edge detector [4] are used to detect the boundaries in the image. After these boundaries have been detected, initial crack and aggregate regions are set up in the image using simple intensity value comparisons.

The self-similarity across scales property of fractal curves can be exploited to aid in the labeling process by using multiple resolutions. Standard relaxation algorithms work by considering the influences of four- or eight-connected neighboring points upon a given data point; points which do not "touch" the given point are not considered. In this work, a neighborhood does not just consist of points which lie around a data point, but also neighbors which lie on the image at scales both above, and below the current scale at higher and lower resolutions, respectively. The neighborhood of a given pixel is extended to include neighbors at the same, high, and lower resolutions or scales so that, in total, a data point has thirteen neighbors (Figure 1). Because pavement distress retains the same properties at all scales, relaxation can be performed at each scale using the same update rule, i.e., coefficients.

In order to perform relaxation labeling, a set of relaxation coefficients must be found. Therefore, a two phase process is defined. The first (training) phase produces a coefficient vector which is used by the relaxation algorithm in the second phase. The system is trained on images whose labels are known; relaxation coefficients are estimated using a least-suqares optimization. The second (relaxation) phase uses the coefficient vector and input data to generate new labelings of the image. These updated labelings are then re-input to the system and relaxation is repeated until the system converges.

It might appear that 3 classes to be estimated × 13 neighbors × 3 neighbor classes = 108 coefficients are needed. In practice, many fewer coefficients are needed for two reasons: 1) $C = 1 - A - B$, and 2) the influence of neighbors 10-13 should be identical. Similar arguments effect additional savings, so that only $2 \times 7 \times 2 = 28$ coefficients are needed. A more complicated non-linear model of pixel interactions was ultimately used, with attendant symmetry savings. The reader is referred to [1] for details.

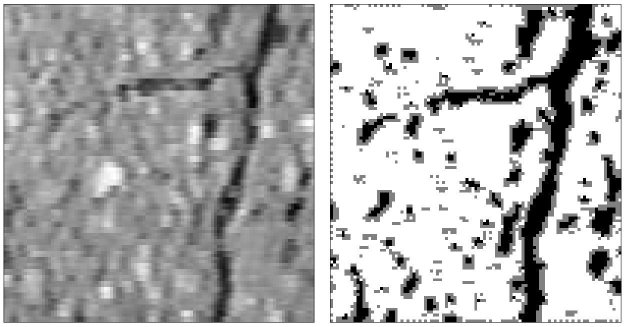

Figure 2: Pavement distress image (left) and initial edge-based segmentation (right).

3 Results

A single-scale system was implemented to demonstrate the need to incorporate information from multiple scales. Figures 2(L,R) are the input image and the initial labeling to the system, respectively. Note the many incorrectly labeled pixels. After four iterations, the system is hopelessly lost, as shown in figure 3(L). Since the two dimensional relaxation system was unable to correctly label the images correctly, the multiple scale relaxation system was used instead. The same image and initial guess are used as in the single-scale experiment. Figure 3(R) depicts the progress of the relaxation after 25 iterations.

In conclusion, the process of accurately segmenting fractal images has been demonstrated to be a non-trivial task, yet excellent results were obtained.

References

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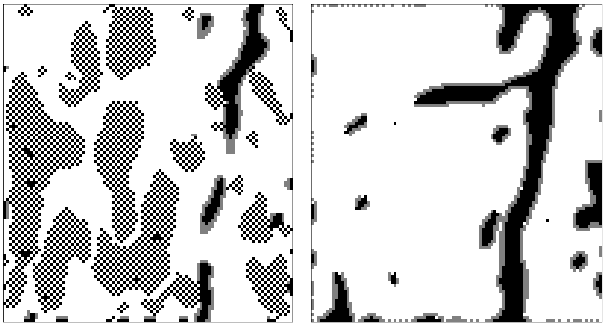

Figure 3: Four iterations of single-scale (left) and 25 iterations of multi-scale (right) relaxation.