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Imaging techniques are proving to be a viable alternative to mechanical sieving for determination of soil grain size distribution. While such distributions are relatively easily obtained when the soil grains are non-contacting, interpretation of in-situ images of contacting grains (assemblies) is considerably more difficult. As such, two approaches were developed for interpreting such images including: edge detection and completion by Hough transforms with active contouring; and pixel density analysis. A reasonably precise measure of grain size can be obtained using circular Hough transforms in conjunction with active contouring. However, the method is computationally very intensive and has only been tested on highly idealized assemblies of soil grains. Edge pixel densities (EPD) and their coefficients of variation with increasing sampling window size provide a rapid means for assessing grain size and uniformity and for detection of soil interfaces within an image. 14. SUBJECT TERMS Particulate media, Grain size distribution, digital image processing, Hough transforms, active contouring, pixel density 15. NUMBER OF PAGES 16. PIRCE CODE				
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TABLE OF CONTENTS

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1.0 PROJECT OBJECTIVES	4
2.0 STATUS OF THE RESEARCH EFFORT	4
3.0 CHARACTERIZATION OF PARTICLE ASSEMBLIES THROUGH DIGITAL IMAGE PROCESSING	A
3.1 Introduction	4 4
3.2 Hough Transformation and Active Contouring (Snakes) Methods	5
3.3 Edge Density Method	9
4.0 CONCLUSIONS	15
5.0 PUBLICATIONS STEMMING FROM THE RESEARCH PROGRAM	15
6.0 PERSONNEL	15
7.0 REFERENCES	16

LIST OF FIGURES

Figure 1. Location of Grain Centroids Using Circular Hough Transforms	
Figure 2. Active Contouring (Snakes) for Edge Completion	8
Figure 3. Grain Size Analysis Using Active Contour Model	10
Figure 4. Soil Grain Edge Maps.	11
Figure 5. Edge Map Griding and Sampling.	12
Figure 6. Edge Pixel Densities for Various Soils.	13
Figure 7. Coefficient of Variation versus Sampling Window Size.	14

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1.0 PROJECT OBJECTIVES

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The project objectives included investigation and development of two methods for characterizing the grain size distributions of particle assemblies, with specific reference to coarse-grained (non clay-size) soils. The two methods included:

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a) Hough Transforms and Active Contouring (Snakes)

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b) Edge Scan Methods

2.0 STATUS OF THE RESEARCH EFFORT

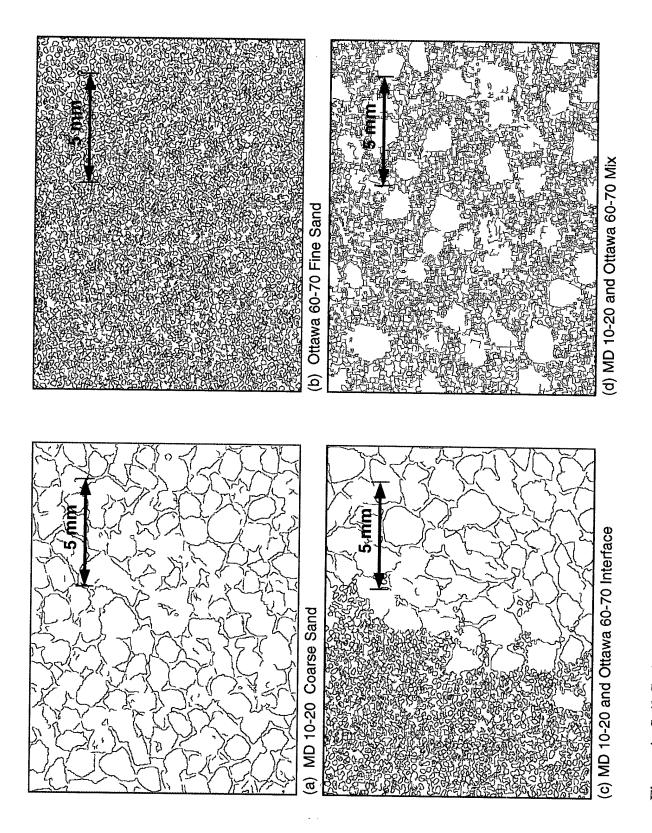
All originally proposed tasks were completed during the 1-year project period and some work was performed beyond that which had been proposed. Both the Hough Transforms/Active Contouring Method and the Edge Scan Method were shown to reliably predict grain size distributions under idealized laboratory conditions. Newer research is already underway at the University of Michigan which builds on the findings of the present study. Specifically, methods are being developed to overcome the intensive computational requirements of active contouring.

3.0 CHARACTERIZATION OF PARTICLE ASSEMBLIES THROUGH DIGITAL IMAGE PROCESSING

3.1 Introduction

Determination of grain size distribution of soils by computer vision techniques is a fairly straightforward task as long as the soil grains are non-contacting. Raschke and Hryciw (1997a) have shown that the grain size distribution of even non-uniform soil can be determined by collecting and analyzing images of a soil specimen spread out over a back-lit glass plate at a series of magnifications. Santamarina et al. (1996) have used a similar "zooming technique" to study blast fragmentation. Kuo and Frost evaluated soil uniformity while Bhatia and Soliman (1990) and Frost and Kuo (1996) studied void distributions.

When soil grains are in contact, such as in images collected in-situ by a vision cone penetrometer (VisCPT) (Raschke and Hryciw, 1997b), soil characterization becomes a much more formidable task. The major difficulties arise in edge detection and segmentation of particles. The present research effort developed two approaches for characterizing in-situ soils by computer vision techniques: 1. Edge detection and completion by Hough transforms combined with active contouring; and 2. Edge pixel density methods.





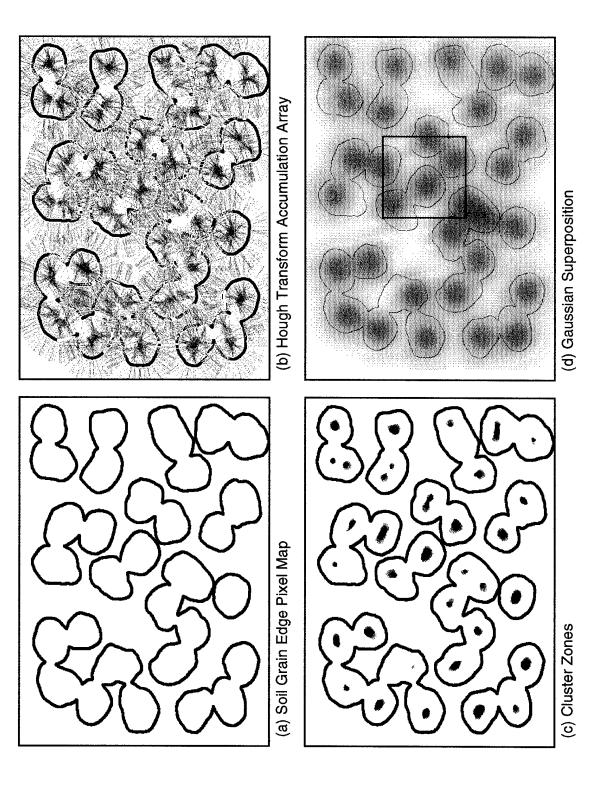
3.2 Hough Transformation and Active Contouring Methods

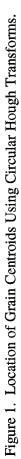
The Hough Transform (HT) is a method for the detection and segmentation of objects in an image, even when the objects' edge map is faint, partially occluded or missing. The method was initially developed by Hough (1962) to detect straight edges but was later extended to cover other objects including circular arcs by circular Hough transforms (CHT) (Duda and Hart, 1972; Nair and Saunders, 1996; Daisheng et al., 1995) and complex predefined shapes using generalized Hough transforms (GHT) (Ser and Siu, 1995).

The basic principle of the CHT method involves the construction of normals to the known edges of the soil particles at each edge pixel location. Each normal vector defines the locus of centers of all possible "voting" circles that pass tangentially through an edge pixel. An accumulator array tallies the votes by incrementing by one all cell locations through which the normal line passes. The corresponding radius of curvature of each voting circle is also saved. The process of finding voting tangential circles to the edge boundary is continued over all edge pixels in the edge map image.

Figure 1(a) is an edge map of an occluding assembly of Ottawa 20-30 sand grains. Figure 1(b) is the corresponding Hough transform accumulation array superimposed over the edge map. Pixel locations with higher accumulations are represented by darker amber color. Due to the generally convex edges of soil grains, the edge normals tend to converge towards the centers of the grains. However, because of particle non-sphericity, a region or "cluster" of pixels with high accumulations of votes develops. The clusters were delineated by passing a relatively large median filter (15 x 15) with a minimum threshold cut off of 4. This smoothing filter eliminates cells with relatively few votes. The resulting clusters are shown in Figure 1(c). The cluster position represent a potential location for the center of a particle.

The next step is to estimate the size of corresponding particle. The median radius of arcs corresponding to all of the normals passing through a pixel in the cluster is then found. The median filter was found necessary to eliminate any outlying radii belonging to that particular pixel. The average of these medians taken over all of the pixels in the cluster, R_{avg} , is an approximation of the particle size. R_{avg} was found to correlate well with the radius of rounded soil grains, but the accuracy diminished as roundness decreased. It is also observed in Figure 1(c) that more than one cluster per grain can develop, particularly for elongated particles with large aspect ratios. Thus, the information obtained from the CHT, namely cluster location and R_{avg} , must serve as input to yet a more robust segmentation technique, called "active contouring".



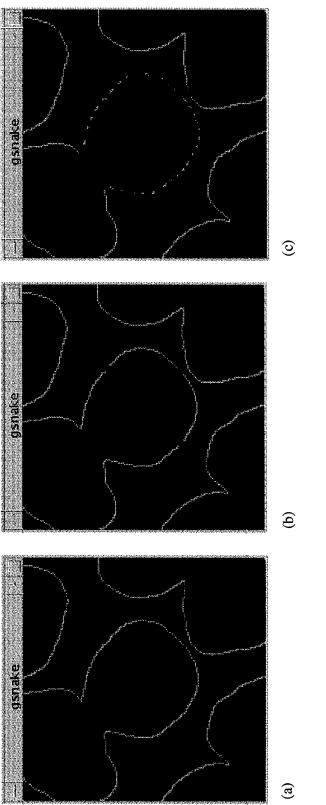


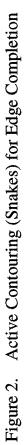
The use of active contour models, sometimes referred to as "snakes", to extract features of interest in images was introduced by Kass et al. (1987) and Terzopoulos (1987). An active contour may be described as an elastic ring of nodes connected by springs. It is placed on an image and subjected to "external" forces which move and deform it from its initial position to best fit a desired feature in the image. The elastic stiffness of the snake preserves its continuity and smoothness during deformation. The external forces may be derived from the gray scale gradients in the image, being maximum at locations of sharpest change. Sharp gray scale changes normally reflect the presence of edges in the image. Thus, the elastic snake once placed inside the image, will be subjected to attractive forces from the edges that will mobilize, deform and finally lock the snakes onto the local salient boundaries.

For the circular Hough transformed edge map described earlier, a circular active contour is placed around each cluster zone. The starting radius is set at about one-half the R_{avg} obtained from the CHT. Since all of the analysis is performed on a thresholded edge map image, no gray scale gradients are present other than at the edges. Thus, for the snake to grow and lock onto the boundary edges, a "gradient potential" must be introduced and superimposed over the image. This gradient potential will provide the required external force field that will stretch the snake radially to the extent that it can reach the edges. The combined attractive forces from the gradient potential and the edge gradient enhance the edge detection, especially when detected edges are in small disconnected segments, such as in the case of an occluding soil grain assembly.

A Gaussian gray scale distribution centered around the clusters was found to provide the needed smooth transitional gradient. The peak value is chosen such that its gray scale magnitude does not exceed that of the edge map pixels. The Gaussian distribution is adjusted so that the gradient will tend to enlarge the snake radially even beyond the grain edges. This is controlled by setting the standard deviation of the Gaussian distribution, s_G. This parameter defines the limit to which the Gaussian image has a positive normal gradient. Figure 1(d) shows the grain edge map with all Gaussian gray scale distributions over the cluster zones from Figure 1(c).

Figure 2 shows several stages of active contouring, starting with the initial snake, followed by the growth phase and finally complete edge enclosure. It is noted that the snake was able to enclose the grain even with part of its edge missing. The elastic stiffness of the snake membrane limits the snake bulging through the missing edge. Once the snake locks into position and reaches an equilibrium state with the external force field, a simple routine is run to estimate the size and possibly other shape characteristics of the enclosed grain boundary. When more than one cluster is found for a particle by the CHT, snakes are placed





around each cluster but only the snake which provides a better correlation with the edge map is retained.

Active contouring in conjunction with the circular Hough transform was performed on the grain particles shown in Figure 1, but with the grains first being detached. The "actual" grain size was obtained by pixel counting. As shown in Figure 3(a), excellent agreement (correlation coefficient, r=0.996) was found between the actual grain size and the size obtained from the active contouring. The soil particles were then pushed gently against each other to form the assembly shown in Figure 1. The same analysis was performed with three different σ_G to study the effect of this parameter on the accuracy of the method. Figure 3(b) indicates considerable underestimation of the grain sizes (r=0.139) when a small σ_G of 0.6 R_{avg} is used. This occurs because of the limited spatial distribution of the external force field resulting in an inability to push the snake to the edges. Much better agreement is achieved (r=0.899) with a larger σ_G of 2.0 Rayg as shown in Fig. 3(c). Finally, when the dispersion coefficient is drastically increased to 2.7 Ravg, many grain sizes are overestimated (r=0.667) because the high dispersion coefficients tend to bulge the snake beyond the actual particle limits through the missing edges. As a conclusion, a σ_G of 1.5 to 2.0 times Ravg is recommended.

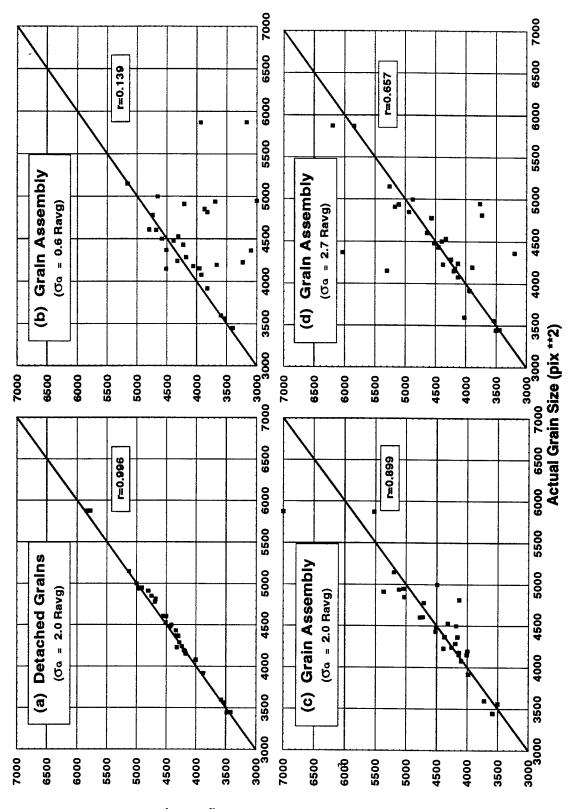
3.3 Edge Density Method

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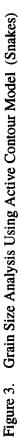
A simpler, yet similarly robust approach for soil characterization is through statistical edge data analysis. This method is based upon evaluation of the edge pixel density of an edge map using sampling windows of different sizes. Two types of soils were studied in this analysis, Muskegon Dune 10-20 sand and Ottawa 60-70 sand. Figures 4(a) and 4(b) are the edge maps of these two uniform soils after applying an edge detection filter. Figure 4(c) shows an interface between these two soils while Figure 4(d) is a mixture of the two.

The procedure is straightforward. Once an edge map is developed, sampling seeds, represented by the black dots in Figure 5, are placed on a regular grid pattern. These seed locations represent the centers of a growing sampling window as shown. The analysis commences with the smallest available sampling window, a 5 x 5 kernel size. A search routine is applied to count all edge pixels enclosed within every sampling window. The edge pixel density (EPD), defined as the ratio of all edge pixels to total pixels in the window is computed. The process of evaluating the EPD continues with successively increasing window sizes around each seed.

The EPDs of all 24 sampling windows (Figure 5) for all four soils are shown as a function of the window size in Figure 6. The window size is given by the dimensionless quantity (window size/image size). It is clear from Figures 6(a)

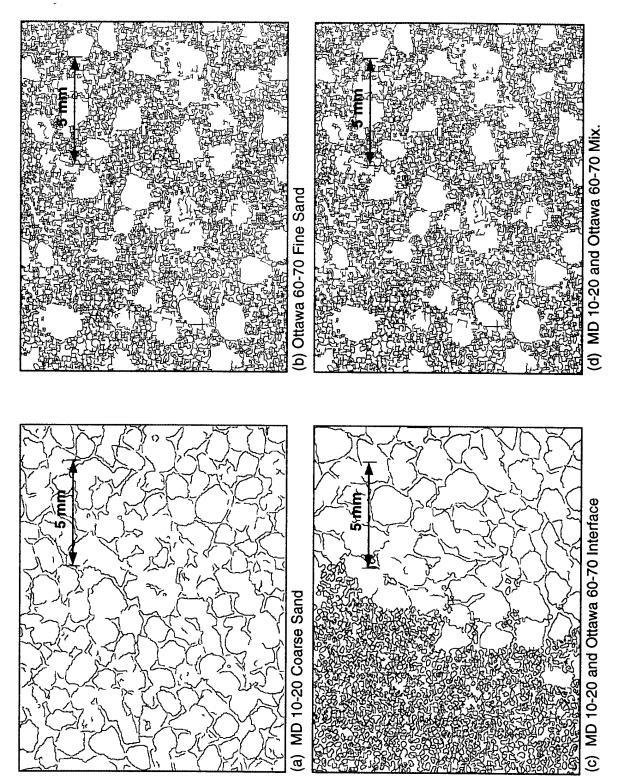


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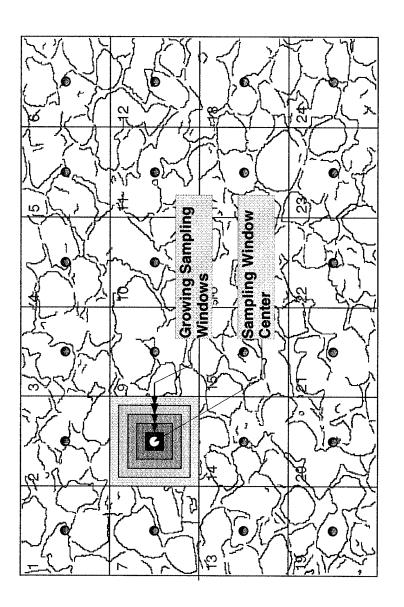
Calculated Grain Size (pix **2)

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Figure 4. Soil Grain Edge Maps.





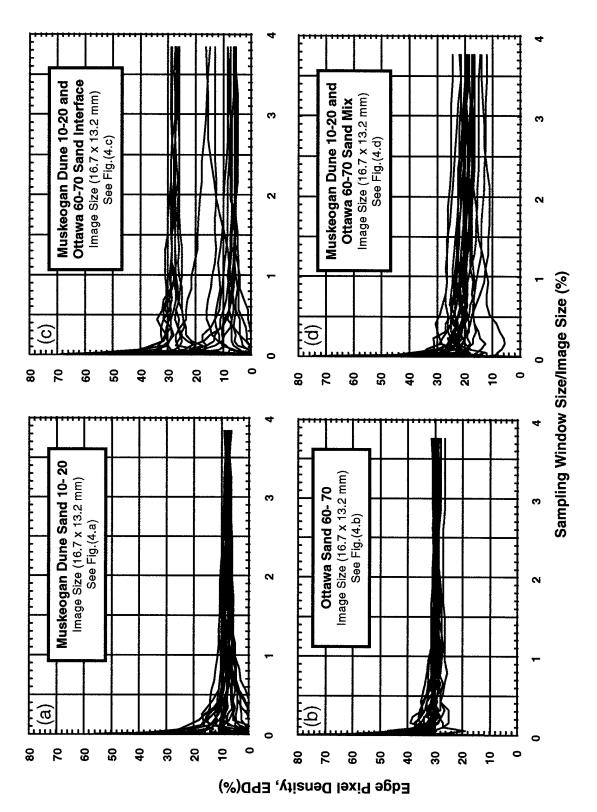


Figure 6. Edge Pixel Densities for Various Soils.

and 6(b) that for uniform soils the edge pixel density is directly related to the average soil grain size. Furthermore, the EPDs of all sampling windows tend to merge into a narrow band at an early stage in the analysis. For an interface (Figure 6(c)), the EPDs tend to converge to two narrow bands, one for each of the soils. Finally, for the case of a mixture of two soil sizes, the EPDs do not converge, even at large sampling window sizes, due to the non-uniform edge distribution across the image.

The coefficient of variation (CV) of the EPDs provides additional insight regarding soil sizes. Figure 7 shows that for uniform soils the rate of decay of the CV with image size is directly related to the average grain size with the decay for larger grain sizes being slower than for finer soils. Mixed soils tend to exhibit larger CVs than uniform soils at high sampling window sizes. Most significantly, very high CV values are a signature of an interface in the image.

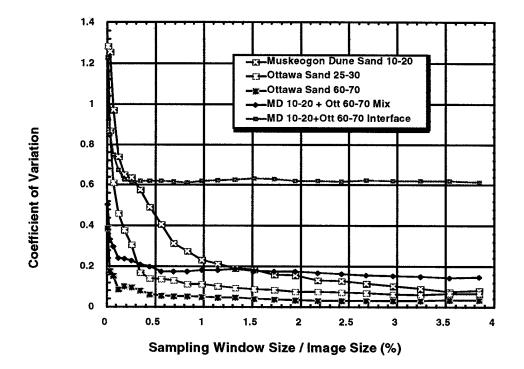


Figure 7. Coefficient of Variation versus Sampling Window Size.

4.0 CONCLUSIONS

Two methods have been developed for determination of soil grain size from images of contacting soil particles:

- 1. A reasonably precise measure of grain size can be obtained using circular Hough transforms in conjunction with active contouring. However, the method is computationally very intensive and has only been tested on highly idealized assemblies of soil grains.
- 2. Edge pixel densities (EPD) and their coefficients of variation with increasing sampling window size provide a rapid means for assessing grain size and uniformity and for detection of soil interfaces within an image.

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- Hryciw, R.D., Ghalib, A.M. and Raschke, S.A. (1997) "Methods for Soil Characterization from Images of Grain Assemblies", Proceedings of the 2nd International Conference on Imaging Technologies: Techniques and Civil Engineering Applications", ASCE, Davos, Switzerland, pp. xx-xx.
- Hryciw, R.D., Raschke, S.A. and Ghalib, A.M. (1997) "Characterization of Particulate Assemblies Through Computer Vision", in *Selected Research in Environmental Quality*, Proc. of a Joint USAF/Army Contractor/Grantee Meeting, Jan. 14-17, Panama City, FL., pp. 131-136.

6.0 PERSONNEL

The principal investigator on this research program, Roman D. Hryciw, is an Associate Professor of Civil Engineering at the University of Michigan. Dr. Hryciw's research activities are in geotechnical engineering, experimental soil micromechanics and computer vision. The research program partially supported Mr. Ali Ghalib, a Ph.D. candidate at the University of Michigan. Mr. Ghalib's Ph.D. studies focus on the use of computer vision for soil characterization.

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