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AUTOMATED AGGREGATE SHAPE ANALYSIS AND RUTTING/STRIPPING PERFORMANCE

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16. Abstract

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Automated Aggregate Shape Analysis and Rutting/Stripping Performance

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Abstract

Fine aggregate shape has been identified as a factor in determining asphalt pavement rutting susceptibility. In an effort improve test methods for measuring aggregate shape characteristics, a video-based, computer-controlled imaging system was developed. Individual aggregate particles were characterized by shape attributes. A neural network classifier used these attributes to calculate a single number classification index that relates to expected performance. Expert judges were used to train the neural net classifier by scoring a set of particle outlines. Discrepancies in the expert's scores indicate that considerable differences still exist in the concept of "angularity". The neural network performed better than the experts and was compared to the NAA Method A test for measuring shape. Above 43% voids, the NAA test appeared to lose accuracy, suggesting Superpave fine aggregate angularity criteria may need reconsideration.

Project Goal

Develop a means of measuring aggregate angularity using off-the-shelf video and computer technology.

Introduction

In 1880 Sorby *(1)* developed a method for classifying sand into five groups based on shape and surface characteristics. Today, it is desirable to use video and computer technology to rapidly accomplish direct classification and quantification of aggregate shape to aid in hot mix asphalt (HMA) designs. In 1991, Barksdale *et al. (2)* described a method for quantifying aggregate using a digitizing table and computer. At the same time, Landis *(3)* began the first studies at our institution for aggregate analysis using particle outlines obtained by video imaging. More recently, Li *et al. (4)* used the concept of fractal dimension; and, Wilson and Klotz *(5, 6)* used the Hough transform for aggregate quantification using outlines.

Hawkins *(7)* and Beddow *(8)* each published an excellent text reviewing the history and methods of particle shape analysis. Hawkins summarizes the views of Meloy and Clark (p 4,5), two researchers that spent fifteen years developing mathematical descriptions of particle outlines, as follows: "one must use intelligence and experience to work out a relevant shape characteristic and then find a method to measure it". Drescher *et al. (9)* and Winkelmolen *(10)* suggested that single particles should be characterized free of presupposition and that relevant parameters be selected by cluster and discriminance algorithms. Our research approach follows this paradigm. First, it was assumed that experienced pavement engineers could differentiate between the outlines of "rounded" and "angular" aggregate in a monotonic fashion. Then an algorithm was developed to match the expert judgement on a particle-by-particle basis. In this way, the judgement of the panel defined angularity which, in this context, translates into anticipated performance in an asphalt mix. Parameters thought to be important in assessing aggregate performance were computed for each outline; and, using these parameters as input data, a neural network was used to estimate the score provided by the experts.

We demonstrate that with a neural network, performance comparable to human judgment can be obtained. Further, the NAA Method A test and a limited set of rutting data are compared with the results of the analysis by the neural network.

Materials and Methods

A. Previous Work

Prior to this effort, we had reported the development of several parameter extraction algorithms and an automated video imaging system suitable for collecting images of particles as small as +100 seive. *(5, 6)* Two useful algorithms are based on the Hough transform, a mathematical formulation for identifying straight edges in digital images. The S_i index was developed to identify an outline with one or more long straight edge(s). By definition, the S_i index was scaled to vary between 0.0 and 1.0 with a value greater than 0.6 indicating a high probability of angularity. Values below 0.6 indicate a lack of angularity, but not necessarily roundness. A second index, the R index, was developed to provide a test for roundness and was also defined to lie between 0.0 and 1.0. An R index value greater than 0.75 indicates a well-rounded outline, while a value below 0.75 is undefined. Both the S_i index and the R index were designed to be used in a pass/fail fashion to count the number of angular particles and the number of rounded particles in a sample. Neither the S_i index nor the R index was designed to give a smooth measure of angularity all the way from well-rounded to angular.

In addition to S_i index and the R index, algorithms to compute various geometric parameters had also been developed. These include perimeter, area, minimum and maximum caliper dimension, and elongation (i.e., defined as 1/aspect ratio and called the E index).

B. Data Collection

Thirty-three different samples of aggregate were obtained for study. These samples represent poor to excellent quality material for asphalt pavement construction as determined by experience and other tests for angularity. Trained personnel tested all samples by NAA Method A. Each sample was seperated by size using standard sieving procedures. For shape testing, two size ranges were used. Size Range #1 was all material that passed sieve size #4 and was retained on sieve size #16 (4.75 mm to 1.18 mm). Size Range #2 was all material that passed sieve size #16 and was retained on sieve size #50 (1.18 mm to 0.30 mm). Multiple specimens of most samples were measured. Both size range specimens were not available for some samples and some samples had multiple specimens, taken from different sites.

The video system was calibrated for scale and aspect ratio. Then several hundred particles were manually spread on a glass plate mounted to an XY table. The particles were illuminated from below to provide high contrast between background and sample, simplifying the process of extracting the outline of each particle. The XY table was pre-programmed to move in small increments between each captured video image until the entire sample plate was examined. The XY table coordinates and the extents and position of every outline in every image provided the means of rejecting multiple copies of the same particle. Every outline from every sample was stored on hard disk for later analysis. Several hundred outlines were stored for each sample.

C. Expert Ranking

Keeping to the project paradigm, an expert panel defined angularity (or perfomance). To accomplish this, a panel of six experts judged the same 135 outlines placed 45 to a page in random order. The outlines were selected from rounded, subrounded, subangular, and angular material and printed by laser printer. Each expert was instructed to mark each outline from 0 (rounded) to 10 (angular) and return the sheets for compilation. The scores assigned to each outline were averaged on an outline-by-outline basis and then divided by ten so that the scores ranged form 0.0 to 1.0. This set of 135 scored images became the standard used to develop algorithms. In addition to the experts, three non-experts were given the same task. Finally, all data sets were standardized (scaled to have the same mean and standard deviation). The expert scores range from 0.0 to 1.0 and can be divided into four ranges for classification purposes:

Rounded	0.0	to	0.25
Sub-Rounded	0.25	to	0.50
Sub-Angular	0.50	to	0.75
Angular	0.75	to	1.00

D. T Index

An algorithm was developed to provide some measure of coarse texture. See Figure 1. The T index is a straightforward calculation. Consider the outline to be a solid shape with area (A_p) and the area defined by a rubber band stretched around the solid outline. The area defined by the rubber band is (A_h) and is refered to as the convex hull. Then the T index is given by:

$$T = 1 - \left(\frac{A_p}{A_h} \right) \tag{1}$$

The T index approaches zero for a smooth, rounded object and increases as the surface becomes irregular and is, in a sense, a measure of texture on a macroscopic level.

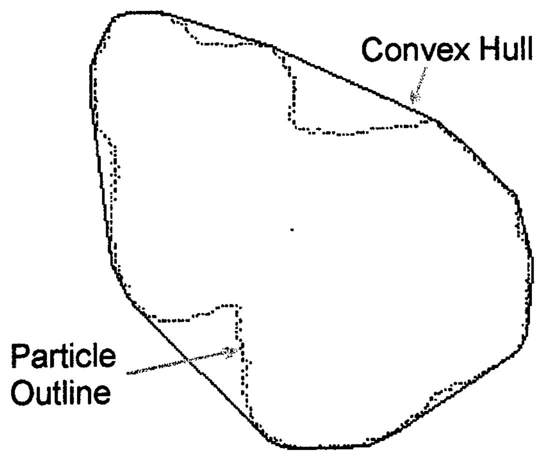

Figure 1. Illustration of convex hull

E. Harmonic Components of S(θ) Function

Refer to Figure 2 in which the Hough transform of a triangular outline is displayed. The projection of the intensity of the Hough transform, shown directly over the Hough transform, is the S(θ) function. Figure 3 shows an expanded view. Note that for each long straight edge on the outline of the triangle there is a peak in the S(θ) function of proportional height. The S(θ) function is very descriptive of the original outline and is almost identical to the slope density function used by Li *et al (4)*. In that work the fractal dimension of the slope density function was used to discriminate different shapes. The Fast Fourier transform (FFT) of the S(θ) function (Figure 4) was used to provide improved shape discrimination. Harmonic components 2 through 16 are normalized and used as inputs to the neural network because they provide information not contained in the other measured parameters or indices.

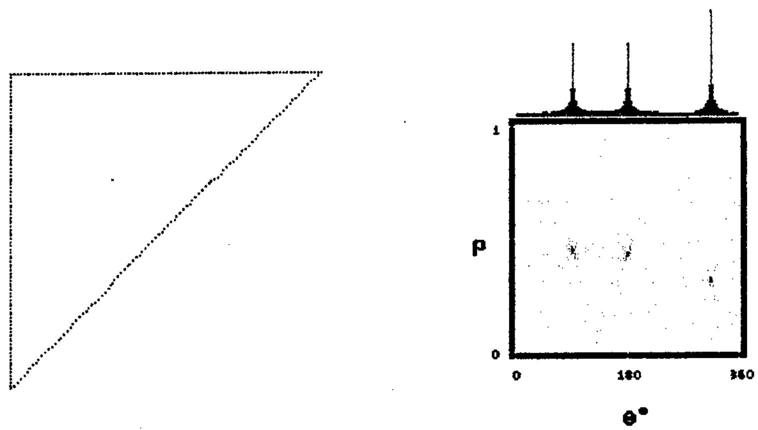

Figure 2. Triangle test shape (left) and its Hough Transform (right).

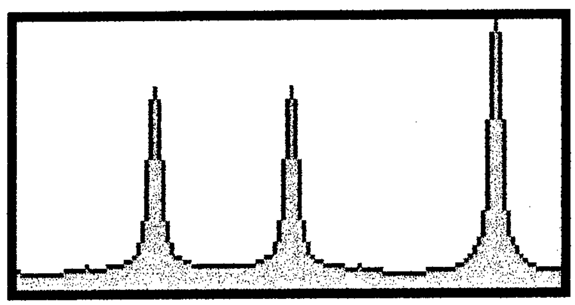

Figure 3. The S(θ) function.

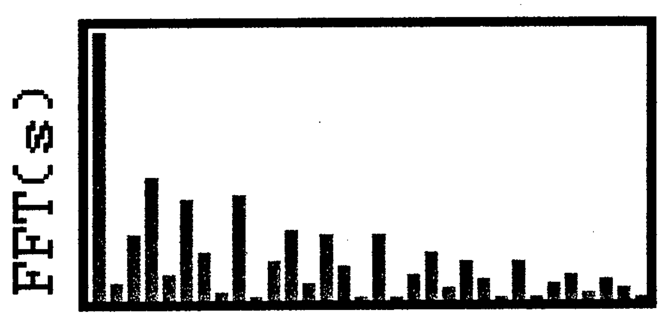

Figure 4. Harmonic components of S(θ) function.

F. Neural Network and K Index

A neural network was developed to combine the various indices and geometric parameters into a single, monotonic, estimate of angularity (or anticipated performance) of each particle as defined by the expert panel's scored examples. In this application, the neural network is a non-linear transformation of all the available information (indices and harmonic components) into a single linear estimate. Neural networks are not programmed, they are trained by example. Training is accompished by applying data from an outline to the inputs of the neural network and comparing the computed output with the desired results. When there is difference between the network output and the desired output, weighting factors within the network are adjusted to move the output toward the desired value. This process is repeated thousands of times using several hundred examples. Normally, the available examples are divided into a training set and a test set, and the network is trained with the training set and tested for accuracy using the test set. All 135 expert-scored examples were saved for the test set and a new set of data for training was developed. First, all 135 expert examples were sorted by score and reprinted in sequence as a reference template. Then several hundred new outlines were assigned a score by finding the closest match among the 135 scored examples and giving the new outline the same score. The new data set became the training set for the neural network. Although this process seems highly subjective, it worked quite well.

For a given sample, several hundred outlines are recorded and analyzed. The K number is defined as the output of the neural network. When plotted as a cumulative distribution, the K number at the 50th percentile is the K_{50} index.

Results and Discussion

A. Test Set Data

Linear regression was computed for each expert, each non-expert, the T index and the K index to determine the correlation with the averaged expert values assigned to the test set outlines. Further, to remove the bias of having their own estimates contributing to the standard, the linear regression was computed for each expert compared to the average assigned by the other five experts. The r^2 correlations are shown in Table 1. There was little or no correlation between the S_i, R, and E indicesand the expert scores. It is important to note that the S_i and R indicesare meaningful only within certain ranges and are not necessarily linear, therefore correlation over the whole test set was not expected.

Table 1. Linear Correlations

	r^2, All Six	r^2, Other Five (unbiased)
Expert #1	0.7468	0.6290
Expert #2	0.6593	0.5217
Expert #3	0.7709	0.6671
Expert #4	0.6237	0.4804
Expert #5	0.5789	0.4244
Expert #6	0.7145	0.5917
Non-Expert #1	0.5983	-
Non-Expert #2	0.6476	-
Non-Expert #3	0.4037	-
T Index (coarse texture)	0.5169	-
K Index (neural network)	0.7238	-

It is clear from the regression coefficients that the experts do not completely agree in their judgement concerning angularity. Further, the unbiased judgement of the experts was only slightly better than the non-experts. This should not be taken to mean that each expert does not recognize angular shapes, but that each expert had a different concept of angularity. The neural network correlated reasonably well with the experts and outperformed the expert's unbiased judgments. However, the neural network was trained against a predefined standard, which was visually derived from a researcher's subjective decisions while looking at the outlines and scores in the test set. This demonstrates that there can be consistancy in visual judgements if a well-established standard is used. Further, the process of parameter extraction combined with interpretation by a neural network performed better than the human judges in absence of a standard. Non-expert #2 working alone produced the data set used to train the neural network, yet the neural network outperformed that individual.

The experts agreed on certain classes of shape. Figure 5 is a scatter diagram of the standard deviation plotted against the mean for each outline in the test set. For rounded outlines (0.0 to 0.25) the standard deviations are smaller, indicating better agreement in that range. This is reported in the literature - a circle is easy to recognize. Experts tend to agree on highly angular outlines as well. The greatest disagreement occurs at the boundry between sub-round and sub-angular. A difference of 0.25 would indicate a complete class difference, for example a sub-round object classified as sub-angular.

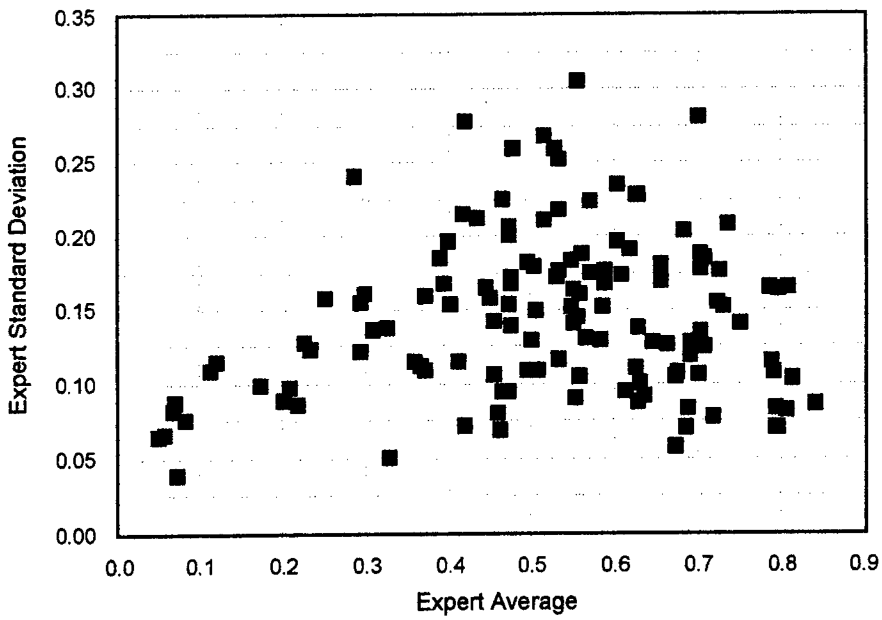

Figure 5. Standard deviation vs average for each outline scored by the experts.

Of all of the extracted parameters and indices, the T index had the highest correlation ($r^2 = 0.5169$) with the expert judgement (Figure 6). This was an unexpected result since most of the previous research had discribed angularity in terms of straight edges or shape classes such as "cubical" or "triangular". In our view, this explains the expert disagreements; some hold coarse texture in higher regard than others.

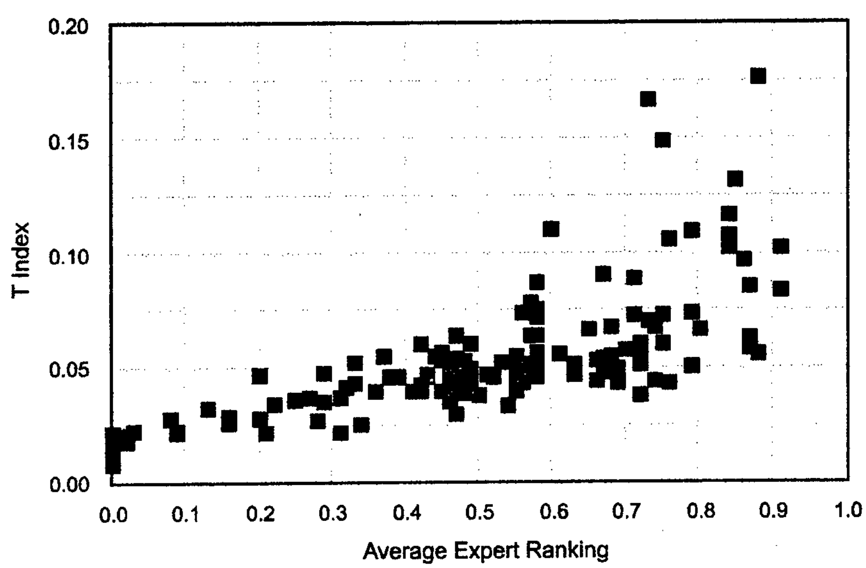

Figure 6. T index compared to the Experts

The response of the neural network to the test set is shown in Figure 7. The correlation was $r^2 = 0.7238$ for the data shown. Some of the computed K numbers exceeded 1.0. If limited to a maximum of 1.0, the correlation improves slightly to $r^2 = 0.7322$. Also, 68.7% of the K values was within 0.125 of the expert ranking or one half of a class size as defined above. Since the neural network performed better than the T index, one must conclude that significant information is carried in the other indices and harmonic components.

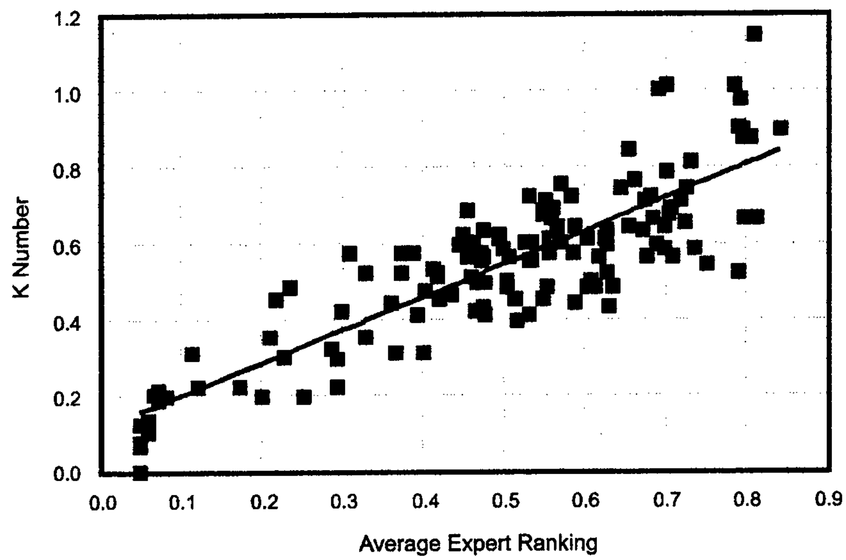

Figure 7. Neural network output compared to the Experts

B. Aggregate Distributions

The K number is a shape descriptor produced by the neural network for individual particles. The distributions of three samples are shown in Figure 8. Samples designated as 09A and 32A represent examples from the extremes well rounded to angular. In all of the samples tested, the material described as "angular" had significant subangular and subround content but very little rounded content.

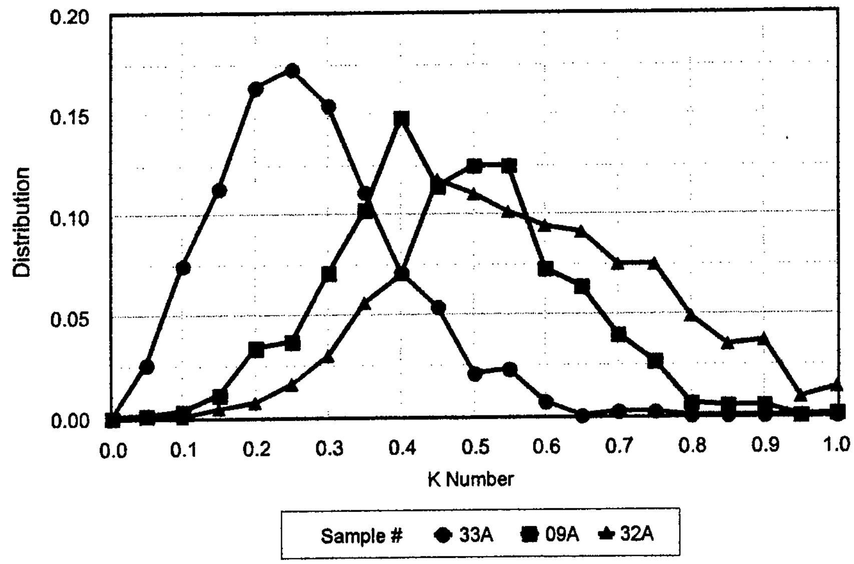

Figure 8. K number distributions of three aggregate samples: Rounded(33A) Subangular Natural (09A), and Angular Manufactured (32A)

The 50th percentiles of the cumulative distributions (K_{50} index) were convenient for comparing samples. Figure 9 shows four different sands with multiple measurements on each. In each case several hundred outlines were taken, then the sample plate was swept clean and fresh material from the same source was placed on the sample plate and imaged again. The data in Figure 9 demonstrate how well the measurements can be repeated. The K_{50} values of the distributions in Figure 9 are shown in Table 2.

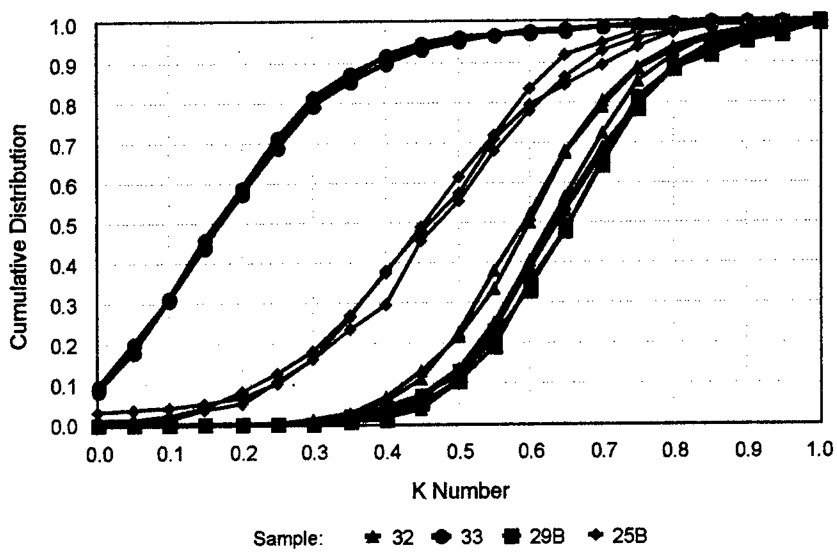

Figure 9. Multiple cumulative K number distributions of four samples.

Table 2. K_{50} Values for Multiple Measurements

	Sample	K_{50}
1	32	.64
2	32	.64
3	32	.61
4	32	.60
5	32	.63
1	33	.18
2	33	.17
3	33	.17
4	33	.17
1	29B	.66
2	29B	.66
3	29B	.66
1	25B	.47
2	25B	.48
3	25B	.46

C. NAA Percent Voids

The NAA percent voids values were available for thirty one samples. The comparison is presented in Figure 10. Although there are two outliers, a general correlation can be seen between the two methods below NAA percent voids of 46%. Sample #26 was problematic in that the sample had small particles that attached to larger material giving the appearance of texture. That data point should be ignored, but others should not. Sample #31 is river sand and is clearly rounded. Further, the NAA percent voids measurement was repeated several times. In this case, the K_{50} value is much more believable than the NAA percent voids measurement. Some of the most angular material measured by our method had NAA percent voids of about 45%, the minimum criteria for Superpave heavy traffic HMA designs. What correlation there may be above 47% NAA percent voids is unclear.

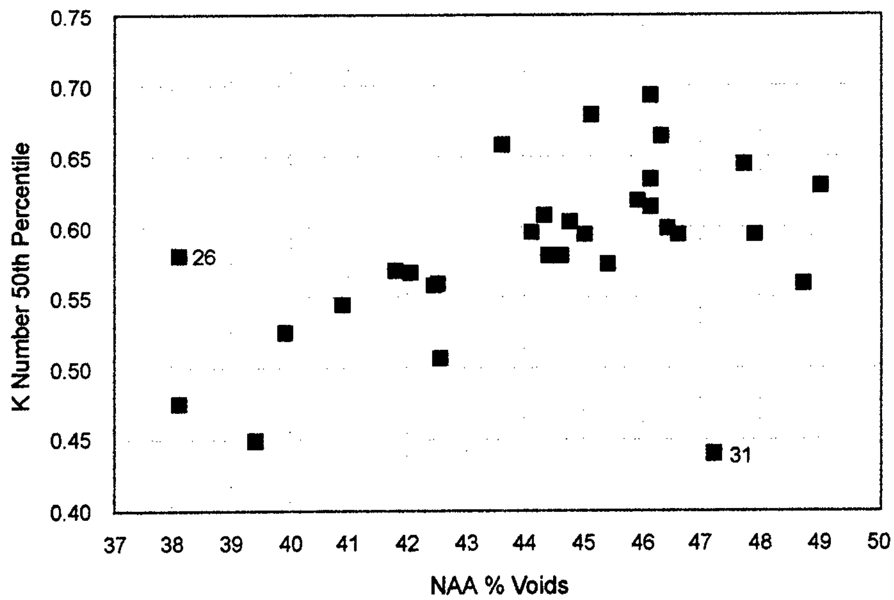

Figure 10. K_{50} Value vs NAA Percent Voids.

D. Rutting Data

Six samples that had been used in an earlier study also had rutting data available. The data is presented in Figure 11. Although there were not enough data points to draw a conclusion, the general trend appears to be correct.

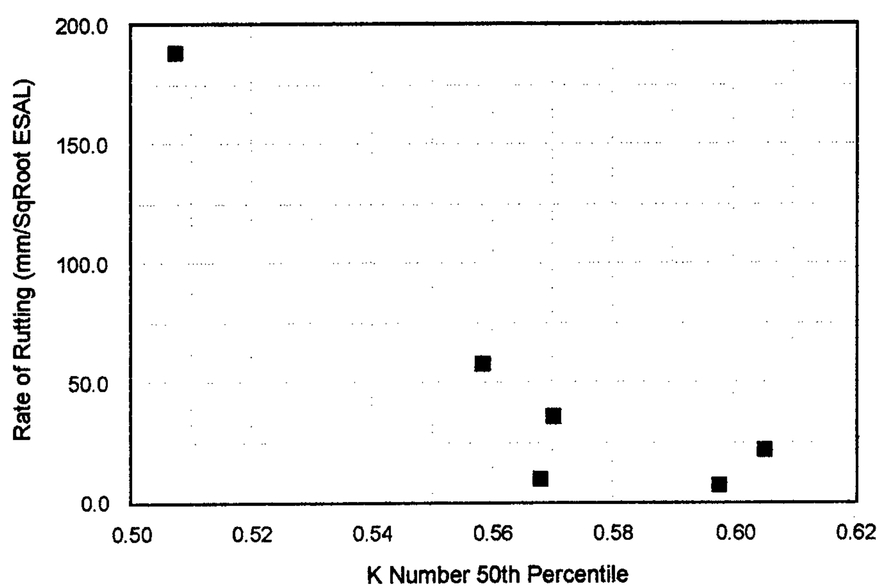

Figure 11. Rate of Rutting vs K_{50}.

Conclusions

Using a panel of experts to define angularity on a particle-by-particle basis provided insight into the meaning of angularity. The term angular implies high performance, but apparently coarse texture is an important issue for many experts and must be considered in future work. It is also seen that angularity can be defined by example rather than by explicit mathematical formulation and that angularity so defined can be implemented by means of a neural network. One can convienently change the definition of angularity in arbitrary ways and observe which definition best predicts outcome thereby discovering what shapes or combinations actually control field results.

The neural network K values correlated well with the expert values ($r^2 = 0.7238$). It should be possible to improve correlation by eliminating the intermediate step of creating a training set. Only 135 outlines scored by expert were available in this study. Therefore, we were forced to create our own training set, an imperfect example of the original. The process of creating the second data set likely introduced error. A larger data set provided by experts should eliminate the intermediate step and improve performance.

Recommendations

Characterizing aggregate shape by imaging is feasible and flexible. Since tests for aggregate angularity should indicate expected performance in HMA, further development of the technique should focus on predicting rate of rutting from direct field measurements. These studies could also help evaluate other common tests (ie. loaded wheel tests, shear tests, etc) for their accuracy.

Above 43%, the NAA Method A test appears to lose accuracy. Superpave's specification of 45% voids for high-traffic HMA designs may be too high, and should be reconsidered. Below 43%, the NAA test appears to identify rounded aggregates. The single outlier may indicate that other tests should confirm NAA test results when warranted.

While the algorithms presented appear to work well, comparison with other techniques, such as fractal dimension and Fourier descriptors, is recommended to determine the most rapid and accurate technique for quantifying shape. Using neural network classifiers to characterize aggregate shape with a single number appears to be a good approach. In the absence of rigorous mathematical models that relate particle shape to HMA performance, the empirical nature of using neural networks is appropriate.

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