Machine Vision Methods for the Grading of Crushed Aggregate

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ABSTRACT

We address the problems of (i) segmenting coarse from fine granularity materials, and (ii) discriminating between materials of different granularities. For the former we use wavelet features, and an enhanced version of the widely used EM algorithm. A weighted Gaussian mixture model is used, with a second order spatial neighborhood. For granularity discrimination we investigate the use of multiresolution entropy. We illustrate the good results obtained with a number of practical cases.

1. INTRODUCTION

The construction industry in the UK currently uses in excess of 218 million tons of crushed aggregate per year. Approximately 1.25 billion pounds are spent yearly in getting this material and processing it to a quality required by the end user. In terms of quality control the sector is relatively underdeveloped, with only very simple manual tests being applied to the end product. As a result produce may be produced that fails to meet the specification and must be reworked. Similarly, excessive, and wasteful, crushing and processing effort may be used to produce the desired product.

From an economic perspective it is therefore essential that maximum economic value be obtained from the quarried stone, which will require wastage to be eliminated from each stage of the processing chain. The quality of the aggregate produced in terms of the consistency of its size and shape also has a major influence on the quality (particularly in relation to workability and durability) of the concrete and blacktop mixes subsequently produced. The proposed introduction of an aggregate tax is also going to drive the need for more efficient usage of quarried rock.

Round or cubic shape aggregate particle shave traditionally has been considered the most suitable in relation to meeting the needs of industry, although it has also been suggested that bituminous mixes including non-cubic fractions can lead to better road pavement layer stability.

The development of a rapid and efficient means for classifying aggregate size and shape could therefore enable the beneficial properties of an aggregate to be more fully exploited.

Aggregate sizing is carried out in the industrial context by passing the material over sieves or screens of particular sizes. Aggregate is a 3-dimensional material and as such need not necessarily meet the screen aperture size in all directions so as to pass through that screen. The British Standard specification (as also American and European specifications) suggest that any single size aggregate may contain a percentage of larger and smaller sizes, the magnitude of this percentage depending on the use to which the aggregate is to be put. BS 63 Part 2, 1987 provides typical specifications.

To monitor the range of size of aggregate particles produced from any particular screen, regular laboratory testing is carried out. This involves sampling the aggregate from either the moving conveyor belt or alternatively from the stockpile produced. A sieve analysis test is carried out to assess the range of particle sizes present in accordance with BS 812 Part 103 1985. This test is time consuming and therefore only a relatively small fraction (2 kg per 400–500 tons) of the aggregate produced is ever tested. The quality of the result also relies heavily on good sampling technique, which means that feedback to the quarry operators can be slow and in many cases unrepresentative.

Certain shape parameters are also specified for particular uses, the most common being Flakiness and the Elongation indices (BS 812 Section 105.2 1990). These tests are also very labor intensive and time consuming, and are carried out on an even more limited number of samples.

An ability to measure the size and shape characteristics of an aggregate or mix of aggregate, ideally quickly, is therefore desirable to enable the most efficient use to be made of the aggregate and binder available.

This article presents a number of preliminary results. We want to illustrate the capabilities of image processing methods and tools. Firstly, we consider image segmentation for handling coarse aggregate, mixed with finer aggregate. Then we consider fine aggregate mixes.

2. SEGMENTATION OF STONES AND SAND

Figure 1 shows stones and sand, the segmentation of which is rendered difficult by partial obscuration. Figure 2 shows two aggregates of different granularities.

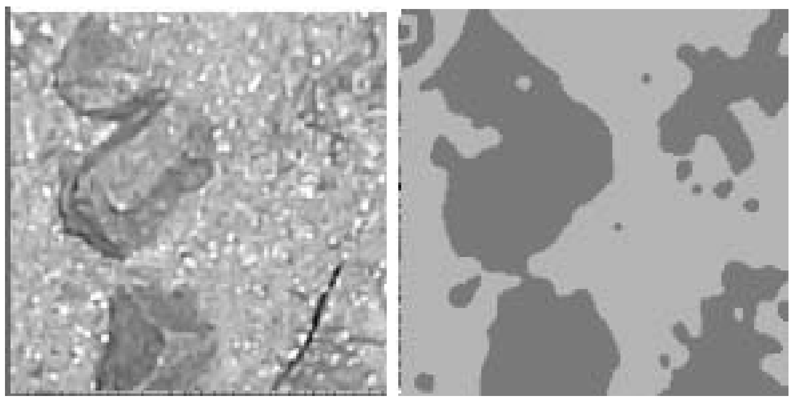

Figure 1. Left: original image. Right: segmentation.

A three-level Mallat wavelet transform was applied to each image, using biorthogonal 9/7 tap filters. An energy, defined as the cardinality-normalized sum of absolute values of wavelet coefficients, was determined in each wavelet band, at each level. (The bands at each level are usually denoted LH, HL and HH. See Murtagh et al.[3]).

Since texture is a characteristic of a local region, the wavelet transform was carried out in 65×65 sliding windows. Thus each pixel was associated with a 10-valued feature vector, where these features were provided by the set of wavelet band energies. The wavelet transform was carried out in the window centered on the given pixel.

The segmentation method applied was based on a Gaussian mixture model, fit to the 10-dimensional data, x_i, for each pixel i. The EM (expectation-maximization) algorithm was used. For K states, the probability density for this model is

$$f(x_i \mid \theta, \lambda) = \sum_{k=1}^{K} \lambda_k f_k(x_i|\theta_k), \tag{1}$$

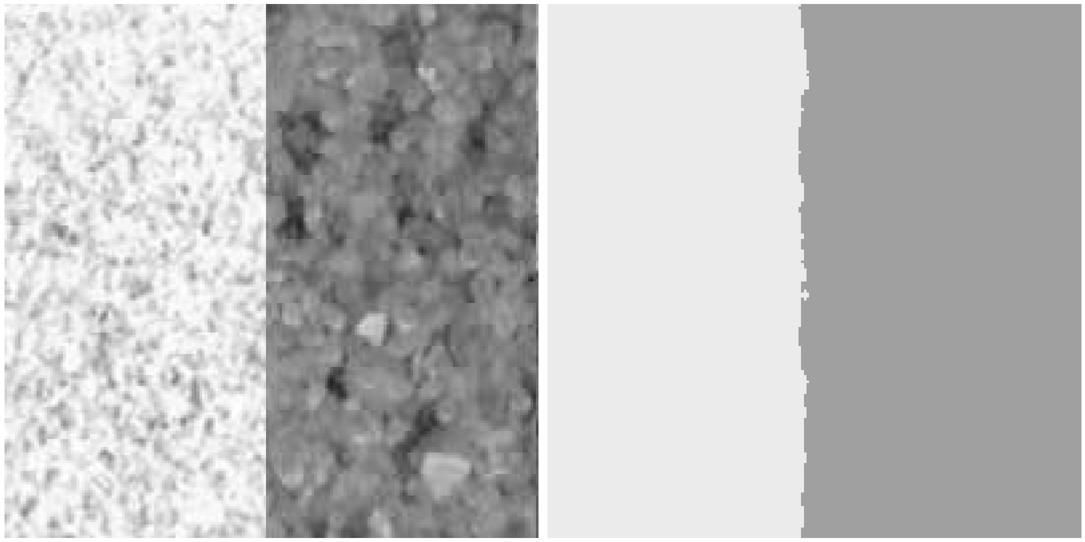

Figure 2. Left: original image, an artificial composite of the 300 and 75 micron aggregates. Right: segmentation.

where model parameters θ_k = the set of mean vectors and variance-covariance matrices, $\{\mu_k, V_k\}$; $f_k(\cdot|\theta_k)$ is a Gaussian density with mean μ_k and variance-covariance matrix V_k; $\theta = (\theta_1, \ldots, \theta_K)$; and $\lambda = (\lambda_1, \ldots, \lambda_K)$ is a vector of mixture probabilities such that $\lambda_k \geq 0$ $(k = 1, \ldots, K)$ and $\sum_{k=1}^{K} \lambda_k = 1$.

Given observations $x = (x_1, \ldots, x_{10})$, let γ be an unobserved $10 \times K$ cluster assignment matrix, where $\gamma_{ik} = 1$ if x_i comes from the k-th group, and $\gamma_{ik} = 0$ otherwise. Our goals are to determine the number of clusters K, to determine the cluster assignment of each pixel-vector, and to estimate the parameters μ_k and V_k of each cluster. In this implementation, we imposed a condition of independence, implying that the variance-covariance matrix is diagonal for each cluster.

We estimate the parameters by maximum likelihood using the EM (expectation-maximization) algorithm.[1,2] The EM algorithm iterates between the E step and the M step. In the E step, the conditional expectation, $\hat{\gamma}$, of γ given the data and the current estimates of θ and λ is computed, so that $\hat{\gamma}_{ik}$ is the conditional probability that x_i belongs to the k-th group. In the M step, conditional maximum likelihood estimators of θ and λ given the current $\hat{\gamma}$ are computed.

Spatial information is introduced by rewriting eqn. 1 as follows:

$$f(x_i \mid \theta, \lambda) = \sum_{k=1}^{K} \alpha_k \lambda_k f_k(x_i|\theta_k), \tag{2}$$

Weighting parameter α satisfies $\alpha_k > 0$ and $\sum_k \alpha_k = 1$. Let $N(x_i)$ be the neighborhood of x_i, taken here as a second order neighborhood of adjacent 5×5 pixels. Let $U(N(x_i), k)$ be the number of neighborhood pixels with state k. We define the weighting parameter for label or class k as:

$$\alpha_k = \frac{\exp(U(N(x_i)), k)}{\sum_j \exp(U(N(x_i)), j)} \tag{3}$$

Note that this is the density of pixel i being labeled k, conditional on the neighborhood, i.e. $p(x_i = k \mid N(x_i))$. This probability model for x_i is the Potts or Ising model, with spatial homogeneity parameter set to 1.

To help avoid finding local optima in the EM (with weighting) iterations, a stochastic optimization scheme motivated by simulated annealing is used. A temperature schedule is taken as proportional to the inverse of the iteration number. The temperature, T, is then used in the multivariate Gaussian: $\exp(-\frac{1}{2T}(x_i - \mu)^t V^{-1}(x_i - \mu))$. The temperature, T, is also used in the partition function, Z.

$$P(x \mid \mu_k, V_k, t) = \frac{1}{Z(t)} \exp\{-\frac{1}{2T(t)}(x - \mu_k)' V_k^{-1}(x - \mu_k)\} \tag{4}$$

for each class or label, k, where V_k is the variance-covariance matrix, μ_k the mean, t the iteration number, and Z is:

$$Z(t) = \sum_{k=1}^{K} \exp\{-\frac{1}{2T(t)}(x - \mu_k)' V_k^{-1}(x - \mu_k)\} \tag{5}$$

3. MULTISCALE ENTROPY TO QUANTIFY AGGREGATE GRANULARITY

Figures 3, 4 and 5 show three images (reduced to 1/16 of their original size) of original dimensions approximately 1544×1548, which correspond to aggregates which pass 600 microns (coarse quality), 300 microns, and 75 microns (fine). In Starck et al.[5] and in Starck and Murtagh,[4] a theory of multiscale entropy was introduced. This theory is based on the following principles.

1. The signal or image is modeled as a realization (sample) from a random field, which has an associated joint probability density function (PDF). Entropy is computed from this PDF, not directly from the signal or image pixel intensities themselves.
2. A basic "vision model" is used, which takes a signal, X, as a sum of components: $X = S + B + N$, where S is signal proper, B is background, and N is noise.
3. Extending this decomposition further, entropy is decomposed by resolution scale.

Point 3 is based on defining the entropy in wavelet transform space. The DC component (or continuum) of the wavelet transform provides a natural definition of signal background. A consequence of taking resolution scale into account is that signal correlation is thereby accounted for. Point 2 rests on a sensor (or data capture) noise model.

In Starck et al.[5,4] it was shown how entropy can be simply factored into resolution scale components, and furthermore into entropy related to signal proper, H_s, and entropy related to noise, H_n.

A B_3 spline à trous wavelet transform gives the following decomposition of the original signal: $x = \sum_{j=1}^{l} \sum_{k=1}^{m} w_{j,k}$. l is the number of scales, m is the number of samples in band (scale) m which is constant for this redundant transform. Scale l is the smooth or continuum scale. The value of l is set by the user and, given the dyadic property related to wavelet dilation, should be $\ll \log_2 m$. For the resolution scale related decomposition, we have the following. Denoting h the information relative to a single wavelet coefficient, we define

$$H(X) = \sum_{j=1}^{l} \sum_{k=1}^{N_j} h(w_{j,k}) \tag{6}$$

with $h(w_{j,k}) = -\ln p(w_{j,k})$. $p(w_{j,k})$ is the probability that the wavelet coefficient $w_{j,k}$ is due to noise. The smaller this probability, the more important will be the information relative to the wavelet coefficient. For Gaussian noise we get

$$h(w_{j,k}) = \frac{w_{j,k}^2}{2\sigma_j^2} + \text{Const.} \tag{7}$$

where σ_j is the noise at scale j (in the case of a (bi-) orthogonal wavelet transform using an L^2 normalization, we have $\sigma_j = \sigma$ for all j, where σ is the noise standard deviation in the input data).

For the signal and noise related decomposition, we have $H(X) = H_s(X) + H_n(X)$. The case of additive Gaussian noise is particularly tractable. For Gaussian noise we find:

$$
\begin{aligned}
h_n(w_{j,k}) &= \frac{1}{\sigma_j^2} \int_0^{|w_{j,k}|} u \text{ erfc} \left(\frac{| w_{j,k} | - u}{\sqrt{2}\sigma_j} \right) du \\
h_s(w_{j,k}) &= \frac{1}{\sigma_j^2} \int_0^{|w_{j,k}|} u \text{ erf} \left(\frac{| w_{j,k} | - u}{\sqrt{2}\sigma_j} \right)
\end{aligned} \tag{8}
$$

Table 1 presents results obtained with use of the redundant B_3 spline à trous wavelet transform with 5 wavelet levels (plus the sixth smooth scale which is not considered here) and a Gaussian noise model. It suffices for our purposes not to combine the sequence of entropy values here.

We note the following: the entropy values at each resolution level (band) are ranked in terms of the aggregate granularity. The signal entropies, at each resolution level, are similarly ranked. This result is not entirely unexpected, insofar as there are clear visual differences between the different granularities. This work will be pursued, in order to verify that a very comprehensive range of granularities, quantified by their passing filter sizes, will keep the same monotonic relationship with resolution scale.

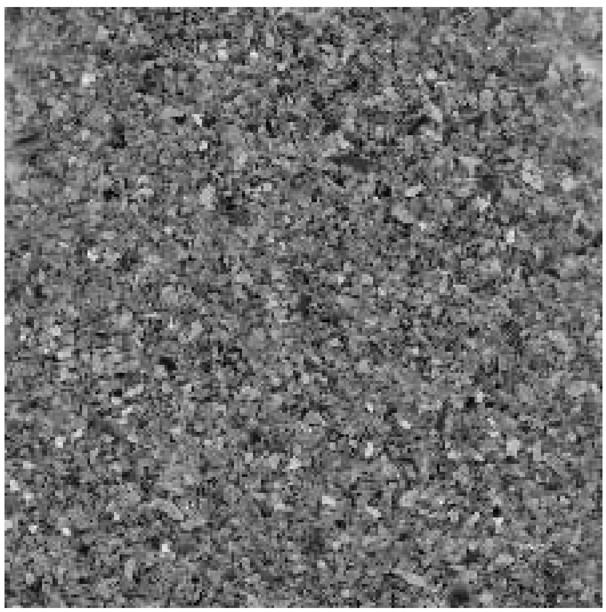

Figure 3. Grades of aggregate. 1 – pebbles passing 600 micron.

4. CONCLUSION

We have tested a new extension to the EM algorithm for image segmentation, with good results on images of aggregates containing very different object sizes, morphologies and textures.

For images of varying object granularities, we have shown that multiple scale entropy provides a good discrimination measure.

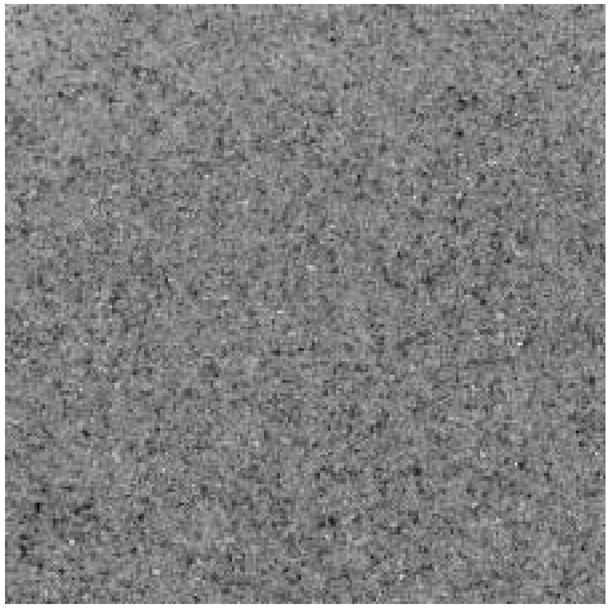

Figure 4. Grades of aggregate. 2 – gravel passing 300 micron.

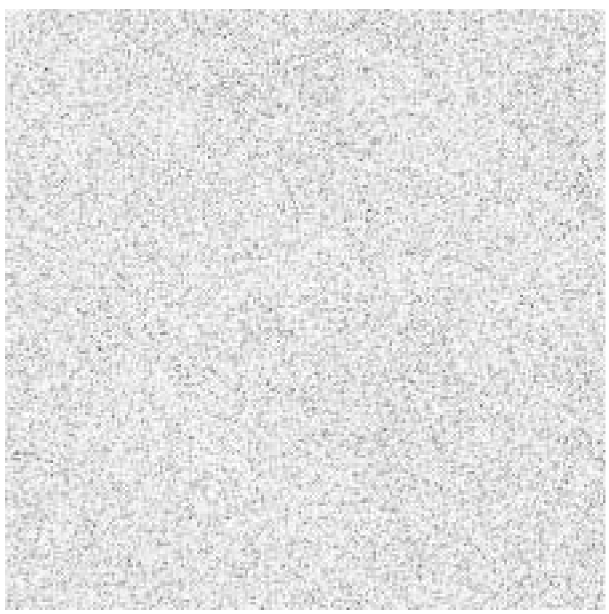

Figure 5. Grades of aggregate. 3 – sand passing 75 micron.

Aggregate	Band 1	Band 2	Band 3	Band 4	Band 5
600 micron	3.07	11.93	14.79	15.49	15.71
300 micron	2.58	11.47	14.32	15.16	15.49
75 micron	2.18	9.94	12.39	13.16	13.61
600 micron	2.65	11.84	14.76	15.47	15.71
300 micron	2.14	11.37	14.29	15.14	15.48
75 micron	1.73	9.81	12.31	13.10	13.55

Table 1. Aggregates passing coarse grade (600) to fine (75). Top half: global entropy per band. Bottom half: entropy of signal in band.

Acknowledgement

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