ARTIFICIAL INTELLIGENCE BASED QUALITY CONTROL OF AGGREGATE PRODUCTION

by

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ABSTRACT: This paper discusses a quality control method, based on artificial neural networks, that enables a plant operator to quickly detect property variations during the production of stone aggregates. The group texture concept in digital image analyses, two-dimensional wavelet transforms, and artificial neural networks are reviewed first. An artificial intelligence based aggregate classification system is then described. This system relies on three-dimensional aggregate particle surface data, acquired with a laser profiler, and conversion of this data into digital images. Two-dimensional wavelet transforms are applied to the images and used to extract important features that can help to differentiate between in-spec and out-of-spec aggregates. These wavelet-based features are used as inputs to an artificial neural network, which is used to assign a predefined class to the aggregate sample. Verification tests show that this approach can potentially help a plant operator determine, in a fast and accurate manner, if the aggregates currently being produced are in-spec or out-of-spec.

KEYWORDS: aggregate, artificial neural networks, group texture, laser profiling, wavelet transforms

1. INTRODUCTION

The importance of using high quality stone aggregates is gaining increased recognition within the construction industry. To rapidly acquire the data needed to ensure that aggregate products have the desired properties, automated methods for characterizing construction aggregates have been developed. By implementing automated methods of measuring basic material properties in testing laboratories, at large construction sites, and so forth, construction material quality can be improved.

Digital image analysis (DIA) has been widely studied as a means of automating aggregate tests [1]. In DIA, an aggregate sample from the production stream is photographed with a camera; this image is then digitized for computer analysis. To extract size information on each particle in the digital image, algorithms for image segmentation and size measurement are used. That is, after the particles in the image are separated by the segmentation algorithm, all of the particles are measured, one by one, in a computationally intensive manner.

However, if the application is primarily concerned with variations in the product rather than complete sample characterization, a much faster approach is possible. For example, in aggregate production plants, product gradation can be monitored by tracking variations in the percent passing a selected sieve size [2]. By monitoring variances in this one measure, plant operators can know when the production process needs to be adjusted. The method of extracting simple variance information

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facilitates faster analysis because it does not require the complete characterization of each particle following segmentation. In addition, this approach can potentially enable the plant operator to assess the properties of aggregates on a conveyor belt without acquiring discrete samples from the belt.

This paper proposes a neural network based quality control method for aggregate production. The Laser-based Aggregate Scanning System (LASS) [3], developed at the University of Texas at Austin, is used to acquire accurate three-dimensional (3D) data on stone particles. To generate meaningful features for input to the neural network, two-dimensional (2D) wavelet transforms are suggested for processing the 3D data. Aided by the multi-resolution feature of the wavelet transform, the neural network is expected to provide the necessary information for real-time quality control during aggregate production.

This paper begins with a literature review covering group texture, 2D wavelet transforms, and artificial neural networks. Then, an aggregate classification system is proposed for monitoring variations in an aggregate product stream. This system is focused on detecting variations in particle size distribution (gradation). Finally, experimental results and conclusions are presented.

2. LITERATURE REVIEW

2.1 Group Texture and Wavelet Transforms

In the machine vision field, texture is defined as "something consisting of mutually related elements" [4]. Namely, texture can mean a combination of texture elements and the relation between each element. In an attempt to identify the most suitable method for objectively quantifying the properties of an aggregate sample, machine-vision-based texture quantification (or classification) methods were investigated. These methods included the use of statistical moments, co-occurrence matrix, edge based method, Law's energy, surface based method, fractal geometry, mathematical morphology, and Fourier transform.

Wavelet analysis, where edges on various scales are detected and processed, is a method that belongs to the edge based texture quantification methods. A wavelet analysis decomposes a signal into a group of linear combinations, with each combination having different resolutions. This transform is conducted using the finite length of a basis function called a "mother wavelet". The mother wavelet is compared with the signal to be analyzed by changing its length (dilation) and location (translation) in order to find where and how much each dilated and translated version of the mother wavelet coincides with the signal. The dilation and translation mechanism of the mother wavelet enables not only production of localized information in the space and frequency domains, but also effective representation of the data signal.

A comprehensive explanation of 2D wavelet transforms can be found in [5,6,7]. With a 2D wavelet transform, a digital grayscale image can be represented as:

$$
\begin{aligned}
f(x,y) = &\sum_{j=-\infty}^{\infty}\sum_{k=-\infty}^{\infty} c_0(j,k)\varphi(x-j)\varphi(y-k) \\
&+ \sum_{i=0}^{\infty}\sum_{j=-\infty}^{\infty}\sum_{k=-\infty}^{\infty} d_{i,0}(j,k)\varphi(2^{-i}x-j)\psi(2^{-i}y-k) \\
&+ \sum_{i=0}^{\infty}\sum_{j=-\infty}^{\infty}\sum_{k=-\infty}^{\infty} d_{i,1}(j,k)\psi(2^{-i}x-j)\varphi(2^{-i}y-k) \\
&+ \sum_{i=0}^{\infty}\sum_{j=-\infty}^{\infty}\sum_{k=-\infty}^{\infty} d_{i,2}(j,k)\psi(2^{-i}x-j)\psi(2^{-i}y-k)
\end{aligned}
\tag{1}
$$

where $f(x,y)$ is the grayscale image, φ is the scaling function of the 1D wavelet transform, ψ is the wavelet of the 1D wavelet transform, j and k represent a location in the wavelet domain, i represents a decomposition level, and c_0 and $d_{i,l}$ ($l = 0, 1, 2$) are coefficients for a scaling function and wavelets, respectively.

2.2 Artificial Neural Networks

Artificial Neural Networks (ANNs) are pattern recognition systems that imitate biological nervous systems. ANNs can be used either as classifiers, to allocate a predefined category to the data representing a given case, or as estimators for predicting a certain value based on the given environment. A typical ANN consists of three different layers: the input

layer, hidden layer, and output layer. While there is only one input layer and one output layer, the number of hidden layers used usually depends on the degree of complexity in the pattern recognition problem. Each layer has one or more processing elements called neurons (or nodes), which are typically connected with those of the next layer. These neurons take input signals, process them, and produce output signals. These signals are weighted and transferred using the connections between neurons.

To operate properly, ANNs must be trained with many examples. This study uses a backpropagation training algorithm, one of the simplest and most general methods for training multilayer neural networks [8]. In the backpropagation method, the network propagates the errors, determined by the differences between the actual and desired output values, backward (from the output layer to the input layer) while adjusting the connection weights between neurons. A more comprehensive treatment of ANNs can be found in [8].

3. PROPOSED METHOD

3.1 Laser-based Aggregate Scanning System

The "Laser-based Aggregate Scanning System" (LASS) was developed to acquire 3D aggregate particle surface data. The LASS consists of a laser line scanner, a horizontal gantry system, and a personal computer (Fig. 1). The laser scanner, which is mounted on the gantry system, passes over an aggregate sample, scanning it with a vertical laser plane. The laser line scanner can move approximately 1.5 m along the Y axis while performing 25 scans per second, with a scan width (X axis) of 120 mm and a scan height (Z axis) of 220 mm. The resolution of the LASS data is as good as
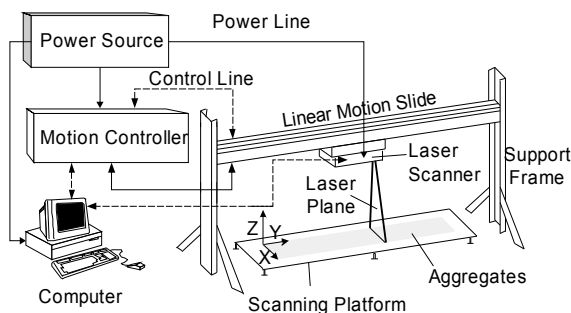

Figure 1. The Laser-based Aggregate Scanning System (LASS).

0.3 mm, 0.1 mm, and 0.5 mm in X, Y, and Z directions, respectively. A comprehensive description of the LASS can be found in [3].

3.2 Artificial Intelligence Based Aggregate Classification System

Texture can be defined as a combination of texture elements and the relations between each element. Aggregate particles can correspond to texture elements with certain special relationships with each other. If a group of construction aggregates is scanned into an image, this image can be considered as a texture. One method to quantify texture uses edge information in the image. For example, the number of edge pixels in a certain area can be used for texture description.

Texture descriptions are highly scale dependent [4]. For instance, edges detected with high resolution would be ignored if low resolution was used. However, wavelet analyses can be used to advantage in overcoming this problem. 2D wavelet analysis provides vertical, horizontal, and diagonal edge information on various scales. With this information, it is possible to quantify the texture of an aggregate image effectively and objectively. Then, by comparing this quantified information between in-spec and out-of-spec aggregate images, an aggregate group with an out-of-spec gradation can be detected as unacceptable.

A flow chart for the proposed aggregate classification system is shown in Fig. 2. Aggregate samples are first scanned by the LASS to obtain 3D laser images. The height value of each data point is represented by a grayscale value ranging from 0 to 255. Then, 2D wavelet transforms are applied to the images so that the following features can be obtained:

$$\sum_{j=-\infty}^{\infty} \sum_{k=-\infty}^{\infty} \sum_{l=0}^{2} \left| d_{i,l}(j,k) \right| \qquad (2)$$

Basically, the features are energies (summation of absolute values of all the elements) of the decomposition level i. Since particles are randomly spread and scanned, no distinction is necessary between horizontal, vertical, and diagonal edges in the wavelet transformed

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image. This is why d_0, d_1, and d_2 can be added together. In other words, all the edge information on a resolution level is summed to obtain one feature value, which is then put into a classifier to determine the appropriate categories for the aggregate sample. In this approach, the number of decomposition levels in the 2D wavelet transforms applied to the image is naturally the maximum number of features that can be used in the proposed classification system.
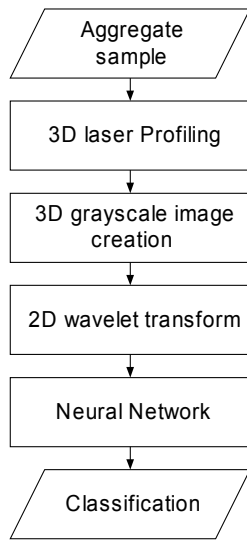

Figure 2. Artificial intelligence based aggregate classification system.

In this study, an artificial neural network (ANN) is used as a classifier to determine whether or not an aggregate sample is out-of-spec. Since this research is focused on detecting only variations in particle size distribution, the following three groups (categories) are defined: Norm, Large, and Small. Group Norm is composed of 100 % of the same size of aggregates (which would pass a certain mesh size and be retained on a certain smaller mesh size). Group Large has a certain percentage of larger particles and Group Small has a certain percentage of smaller particles. Thus, this system can classify an aggregate sample into three categories: in-spec, out-of-spec with larger particles, and out-of-spec with smaller particles.

In a field application, these classifications could be used to adjust the aggregate production process. If the plant operator finds that the aggregates currently being produced

are classified as out-of-spec with larger particles, the crusher settings could be tightened to produce fewer oversized particles. If the categorization indicates out-of-spec with smaller particles, the crusher's settings could be opened to produce fewer small particles. Depending on the specific needs of the aggregate producing plant, more than three categories could also be defined.

Fig. 3 shows the neural network model for the aggregate classification system. It is composed of an input layer with two neurons, a hidden layer with five neurons, and an output layer with three neurons. The number of input features naturally determines the number of input neurons, while the number of output neurons is determined by the number of categories used to classify the aggregate samples. A sigmoid nonlinear function and backpropagation with a momentum learning method were adopted for training the neural network model.
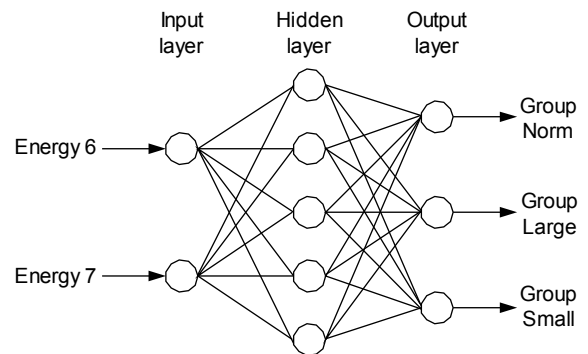

Figure 3. Neural network model for the aggregate classification system.

Sixth and seventh energy levels, which correspond to relatively low frequencies in the wavelet domain, are fed into the neural network model. These two features were selected because preliminary experiments indicated that those energy levels are most apt to differentiate between aggregate groups with different gradations. This preliminary examination of the energy features saves a significant amount of computing effort by reducing the complexity of the neural network. It is also worth noting that the network has three output neurons matching the three categories defined as Norm, Large, and Small, whereas the number of neurons for the hidden layer was determined from trial and error.

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The aggregate classification system was implemented using the C++ programming language, LabView (a graphical programming language), the IMAQ Vision image processing tool, the Wavelet and Filter Bank Design Toolkit, and the DataEngine (an off-the-shelf Neural Network subroutine). LabView, IMAQ Vision, and the Wavelet and Filter Bank Design Toolkit are all products of National Instruments (Austin, Texas), while the DataEngine is a product of MIT GmbH (Germany).

4. EXPERIMENTS

To check the validity of the group texture and artificial intelligence based aggregate classification method, the proposed system was used to classify three aggregate samples described in Table 1. Norm particles, Large particles, and Small particles are defined as particles that fall within the size ranges of 1/2" to 3/4" (12.7 mm ~ 19.0 mm), 1" to 1-1/4" (25.0 mm ~ 31.5 mm), and No. 4 to 3/8" (4.75 mm ~ 9.5 mm), respectively. Then, Group Norm consists of 100 % of Norm particles, Group Large has 50 % of Large particles and 50 % of Norm particles, and Group Small has 50 % of Small particles and 50 % of Norm particles. These aggregate samples were randomly spread on the scanning platform of the LASS such that there are no overlapping particles. They were then scanned and converted into digital images. Fifty-six images were created for each group, resulting in a total of 168 images. Each image is 566 by 180 pixels and covers a rectangular area of 120 mm by 50 mm. Eighty-four images (half the total number of images) were used to train the neural network model described in Fig. 3, while the other 84 images were used to test the classification system.

To obtain the energy values that are representative of each aggregate sample, a running (moving) average value of every five images was used instead of separate energy values for each image, as follows:

$$RA_i = \frac{1}{5} \sum_{j=i}^{i+4} I_j \qquad (3)$$

where RA is a running average and I is an energy feature of one image. In other words, for every five images in the same aggregate group, the energy values were averaged to produce more stable and representative features. Note that this running average approach reduced the total number of training sets (or test sets) from 84 to 72.

Table 1. Description of aggregate test samples.

Group	Size fraction	%	kg
Group Norm	No. 4 ~ 3/8" (4.75 mm ~ 9.5 mm)	0	0
	1/2" ~ ¾" (12.7 mm ~ 19.0 mm)	100	5
	1" ~ 1-1/4" (25.0 mm ~ 31.5 mm)	0	0
Group Large	No. 4 ~ 3/8" (4.75 mm ~ 9.5 mm)	0	0
	1/2" ~ ¾" (12.7 mm ~ 19.0 mm)	50	2.5
	1" ~ 1-1/4" (25.0 mm ~ 31.5 mm)	50	2.5
Group Small	No. 4 ~ 3/8" (4.75 mm ~ 9.5 mm)	50	2.5
	1/2" ~ ¾" (12.7 mm ~ 19.0 mm)	50	2.5
	1" ~ 1-1/4" (25.0 mm ~ 31.5 mm)	0	0

Table 2 shows the classification results. With only one incorrect classification in identifying Group Large, the 99 % classification accuracy demonstrates that the group texture approach, in conjunction with artificial intelligence classifiers, is a promising method to detect variations in an aggregate production stream.

Table 2. Classification results.

Group	Accuracy (Number)	Accuracy (%)
Group Norm	24 / 24	100
Group Large	23 / 24	96
Group Small	24 / 24	100
Total	71 / 72	99

5. CONCLUSION

This paper explored the possibility of using group texture of aggregate images in conjunction with an artificial neural network to quantify gradation properties. First, an aggregate sample was scanned by the Laser-based Aggregate Scanning System, and

converted into 3D images. Then, 2D wavelet transforms were applied to those images to extract wavelet coefficients and calculate energies at different scales. Finally, these energies were used as inputs to an artificial neural network that assigns a predefined class to the aggregate sample. Verification tests show that this approach can potentially classify aggregates in a fast and accurate manner.

Further work is needed to develop and verify the proposed artificial intelligence based approach. First, while reducing gradation variations in the training samples, different network architectures can be constructed and evaluated to optimize the neural network model. This requires testing with different numbers of neurons, different numbers of hidden layers, different transfer functions, and different learning methods. Second, efforts are needed to develop good features that can represent the aggregate properties well. A system using the standard deviation or other statistics of the wavelet coefficients at a certain decomposition level might be successful in grouping similar aggregate samples. Third, different classifiers, such as the K-Nearest-Neighbor method, Linear discriminant function, Fuzzy logics, etc. [8], could be investigated. These relatively simple methods are sometimes more effective than complicated neural networks.

6. ACKNOWLEDGMENT

7. REFERENCES

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