ROCK DETECTION USING NEURAL NETWORKS

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Abstract

The analysis of rock scenes can provide important information for many processes in the mining industry. Rock scenes are difficult to segment using machine vision because they contain many possible complicated configurations of rocks, and each rock is different. The problem with image segmentation techniques is a lack of general image content information. This paper presents a pattern recognition scheme based on neural networks for analysing a rock scene to determine all the rock sizes and positions in the image. This information will greatly simplify the task of segmenting the image as starting points will be known.

1 INTRODUCTION

The measurement of fragmentation or distribution of rock sizes has application in the mining industry, especially in gold mining, where sophisticated control systems are used to monitor and control the milling of ore. Computer vision is an ideal tool for non-invasively measuring rock sizes at the feeds to such mills. A paper by Hunter, *et al* [2] discusses computer vision based methods for characterising size distributions of blasted rock.

Computer vision provides several advantages over more conventional rock size measurement techniques:

- The measurement can be performed on-line without disturbing the feed.
- It can operate for 24 hours per day.
- Increasing computer power will increase the sampling frequency.
- Systems at different locations will produce comparable results.

Some systems [1], [3] and [6] have been developed for measuring rock size distributions using machine vision. Most currently available systems, however, tend to suffer from some common problems:

- Slow calculation times.
- Easily confused by complex rock situations caused by overlap and shadows.
- Attempt to calculate to pixel accuracy along edges while making gross mistakes by splitting or merging rocks.

The difficulties encountered by the available systems are largely caused by their dependence on microscopic or pixel based image segmentation techniques. Rock scenes are very complex at a microscopic level and all the irrelevant information acts to confuse any analysis scheme which does not take the overall picture into account.

A Neural Network Rock Recognition scheme is proposed as a solution to the problems encountered by the microscopic segmentation techniques. The rock recognition scheme would involve scanning an image to determine the macro features, in this case the general location and size of rocks. This information could then provide the vital contextual information required by segmentation techniques to analyse each rock individually on a microscopic level.

Neural networks are ideal for application in this problem for several reasons:

1. General suitability to pattern recognition problems.
2. Ability to generalise solutions and thus cope with unseen problems.
3. Possibility of high speed parallel implementations.
4. Ability to identify their own features for classification.

[5] is a very good introductory text on neural networks and their use for pattern recognition in biological and artificial systems.

The basis of this Neural Network Rock Recognition scheme is the subject of this paper which describes how images are fed to the neural network, how the network is trained to recognise rocks, and some results which have been achieved so far.

2 NETWORK INPUT

The objective of the input to the neural network is to provide sufficient information to the network to allow classification into one of two possible categories:

1. The input describes a rock meeting the predefined parameters — described in section 3.
2. The parameters are not met and the input is not seen as a rock.

Rock images are presented directly to the input as a picture array. Each input node is fed the pixel intensity of a particular element of the array. The array size was determined as the smallest from which a human viewer could reliably perform the classification.

Another important consideration is the use of preprocessing of the image and picture array. In this application, preprocessing was used to directly modify the pixel intensities of the image and hence input picture array. The main goal of preprocessing the image is to increase the distinction between the two sets of solution. Lighting, size and shade of rocks make them appear different to one another and more difficult to classify. By reducing spurious information and highlighting useful features which are applicable to the problem, the task of the neural network can be greatly simplyfied.

Two forms of preprocessing have been investigated:

1. Contrast enhancement to reduce the differences at different parts of the image caused by lighting and rock shading to make all rocks appear more uniform.
2. Edge enhancement to detect edges at a scale proportional to the size of rock being detected to reduce the effects of different rock sizes.

3 NETWORK TRAINING

The input picture array is conceptually divided into two regions to facilitate the training of the neural network. They are a core region surrounded by a peripheral region. The peripheral region was discovered to be necessary to ensure that what may appear as a rock in the core region is not actually just part of a larger rock. A valid rock is then defined as being centred in the picture array and being just large enough to touch the perimeter of the core region. Some examples are given in figure 1 to illustrate these restrictions.

A systematic method was developed to facilitate the generation of a suitable training set. The method involves:

- selecting several rocks in an image by positioning a square representing the core region around them. This provides the positive learning cases.
- several random position and size displacements are generated which are greater than a certain error tolerance. For each of these displacements, the operator must accept or reject the resulting square position and size as suitable for use as a negative learning case.

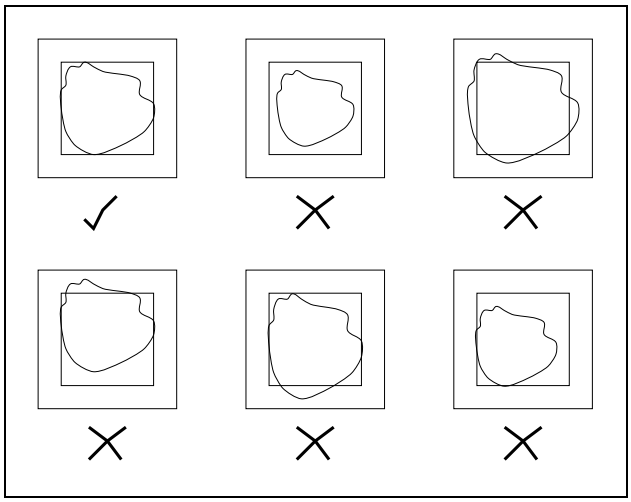

Figure 1: The valid rock size marked with a tick is centred in the array and is just large enough to touch the sides of the core region. The remaining rocks should be rejected because they don't meet the requirements.

If a sufficient number of rocks are selected, and for each positive case, enough negative samples are accepted, all possible rock configurations will be covered well enough to allow reasonably accurate network generalisation.

A standard feedforward back-propagation network was used for all experiments performed. The network was trained using the standard back-propagation algorithm which uses an iterative gradient method designed to minimise the mean square error between the actual output of the network and the desired output.

The training set contained typically 2000 sample inputs and network convergence occurred after approximately 4–5 epochs of the training set. Network training progress was measured using a separate test data set which was extracted in the same way as the training set but using different rocks.

4 RESULTS

Results were generated for this paper by scanning two rock pictures with two different neural networks.

The first network was trained to recognise rocks with image intensity as the input picture. The only preprocessing used was histogram equalisation of the whole image and convolution with the Gaussian function

$$G(x,y) = \frac{1}{2\sigma} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

where σ is proportional to the size of window being detected. This normalises the window scale and allows the input picture to be extracted from the complete image by subsampling it without any aliasing problems.

Figures 2 and 4 show the results of scanning the two rock images using the first neural network. The top picture is the actual rock image and the bottom three are the results of scanning the top picture at three different scales. Assuming that the actual rock size is 1 then the network was used to detect rocks of the relative scales 1/1.3, 1 and 1.3 as shown at the bottom of each picture in the image.

The second network was trained to recognise rocks with an edge enhanced input picture. As with the first example, histogram equalisation was used for contrast enhancement. The edge enhancement was performed by convolution with the Laplacian of the Gaussian function

$$\nabla^2 G(x,y) = \left(\frac{x^2+y^2}{\sigma^2} - 2 \right) e^{-\frac{x^2+y^2}{2\sigma^2}}$$

where σ is proportional to the size of the rock being detected. In this case the σ value was ten times greater than for the first network since this network was detecting relatively large rock edges as opposed to a focussed rock image with finer surface and lighting details. This function also allows the input picture to be extracted from the complete image by subsampling it without any aliasing problems.

The use of the $\nabla^2 G(x,y)$ operator is supported by strong evidence [4, pg 54] that the receptors in the human eye perform immediate filtering of that form. In addition, [5, pg 30] state that implementing a similar system for edge enhancement substantially improved the performance of their neural network pattern recognition system.

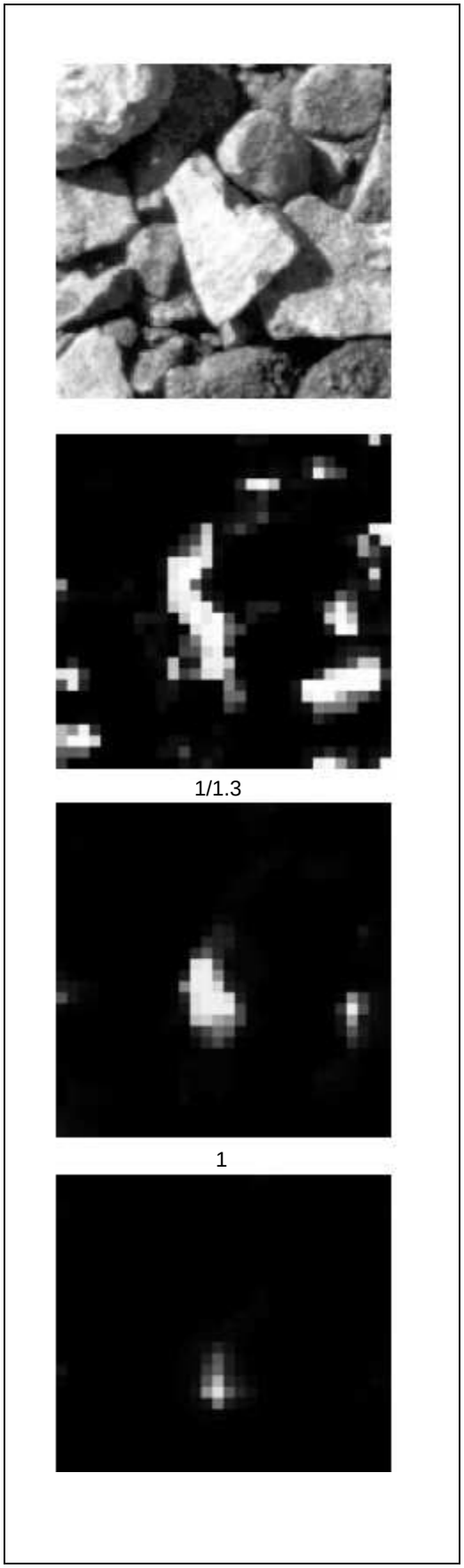

Figure 2: Rock 1 scanned with the network 1.

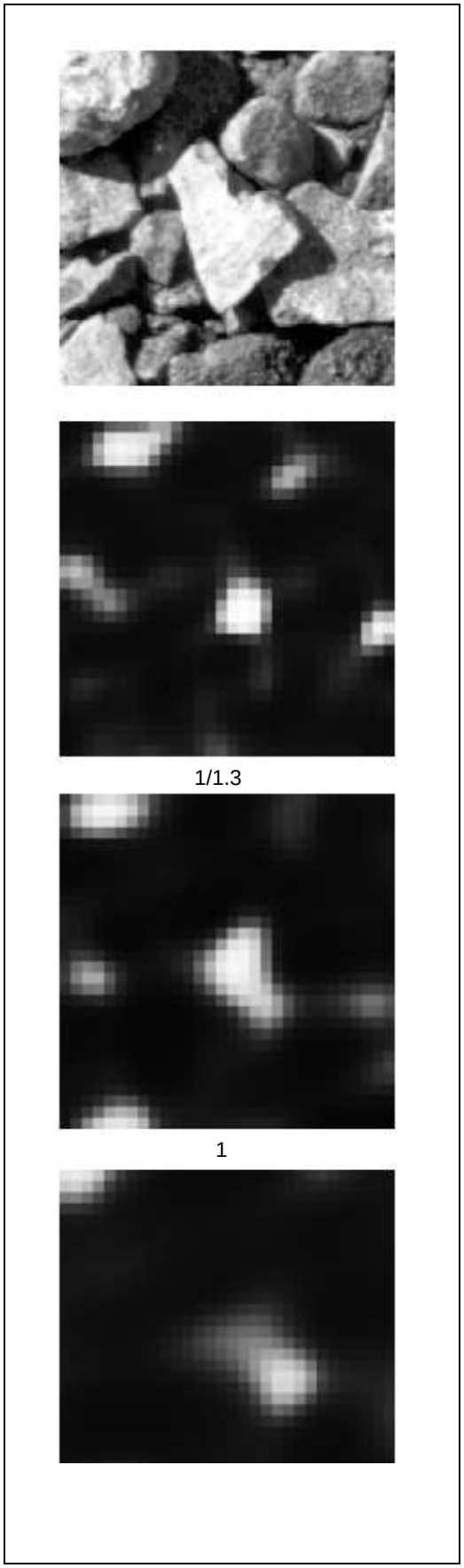

Figure 3: Rock 1 scanned with the network 2.

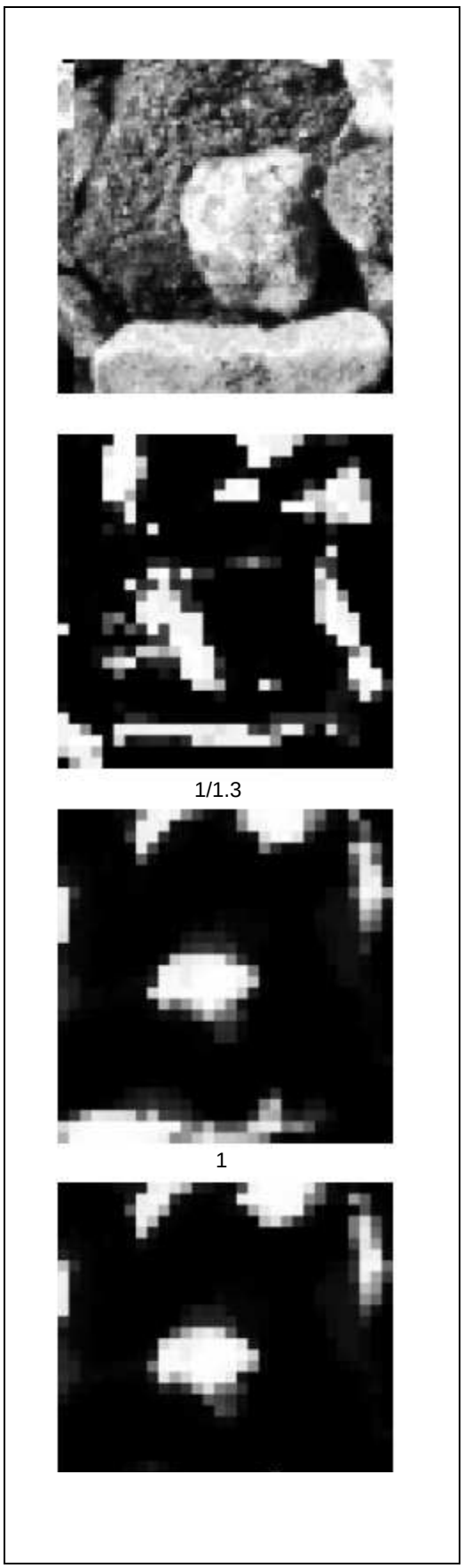

Figure 4: Rock 2 scanned with the network 1.

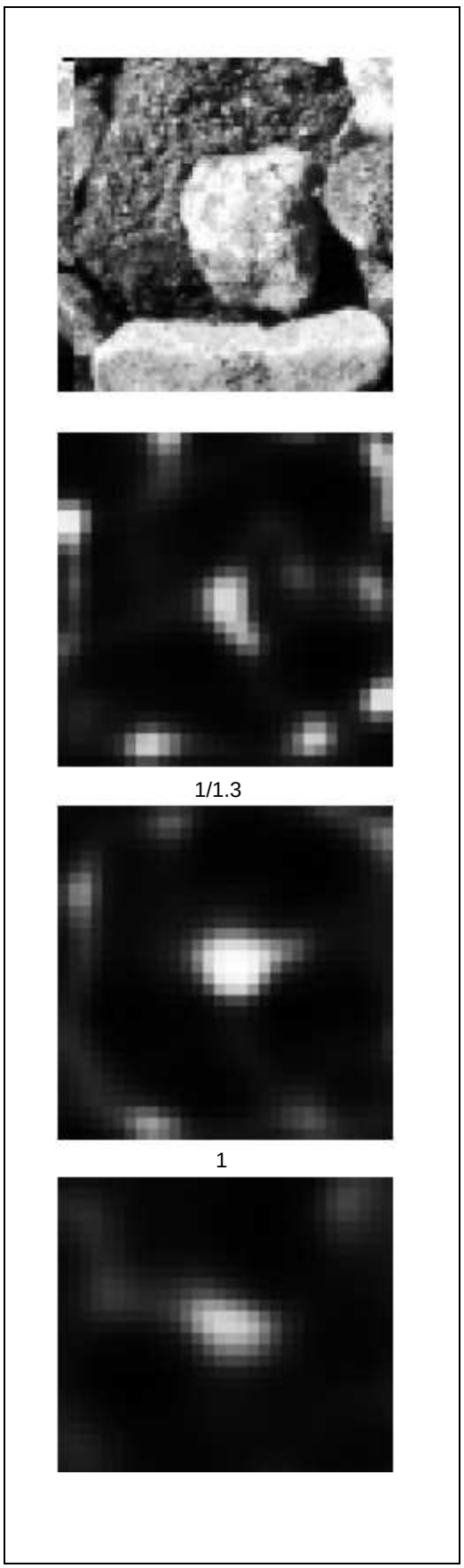

Figure 5: Rock 2 scanned with the network 2.

Figures 3 and 5 show the results of scanning the two rock images using the second neural network. A comparison between the sets of results from each neural network show that:

1. both networks respond to the central rock in all three scans.
2. the first network acts as an edge detector on relatively large rocks.
3. the second network acts as a corner detector on much larger rocks.
4. the first network is generally insensitive to rock size and position.
5. the second network has a more apparent peak of response to rocks at the correct size.
6. the second network has a more localised response to individual rocks.

5 CONCLUSIONS

In addition to the results presented here, previous experimentation have shown that the networks seldom completely miss a rock. They do however misfire when certain other features appear and often appear rather insensitive to the actual rock position.

While the performance of the system is not yet adequate for reasonably certain rock size and position measurement, several steps can still be taken to improve the general performance of the system:

- The training sets can be made more comprehensive to correct network response to incorrect features which may be detected as rocks.
- Contrast enhancement schemes can be investigated to improve on the very simplistic histogram enhancement method used so far.
- Further experimentation must be performed to determine the best σ value to use relative to rock size for optimum neural network performance.

References

[1] Gűnther Franz-Martin Berger. Software for a particle-size analyser based on image analysis techniques. Master's thesis, University of the Witwatersrand, 1985.

[2] G. C. Hunter, C. McDermott, N. J. Miles, A. Singh, and M. J. Scoble. A review of image analysis techniques for measuring blast fragmentation. *Mining Science and Technology*, 11(1):19–36, July 1990.

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[6] David Wigeson. Fragmentation analysis using computer vision techniques. Master's thesis, University of the Witwatersrand, 1987.