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Nuclear Fuel Assembly Assessment Project and Image Categorization

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This report concerns a study which has been conducted for the Swedish Nuclear Power Inspectorate (SKI). The conclusions and viewpoints presented in the report are those of the authors and do not necessarily coincide with those of the SKI.

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ABSTRACT

A project has been underway to add digital imaging and processing to the inspection of nuclear fuel by the International Atomic Energy Agency. The ultimate goals are to provide the inspector not only with the advantages of CCD imaging, such as high sensitivity and digital image enhancements, but also with an intelligent agent that can analyze the images and provide useful information about the fuel assemblies in real time. The project is still in the early stages and several interesting sub-projects have been inspired. Here we give first a review of the work on the fuel assembly image analysis and then give a brief status report on one of these sub-projects that concerns automatic categorization of fuel assembly images. The technique could be of benefit to the general challenge of image categorization.

SAMMANFATTNING

I ett av SKI initierat projekt undersöks möjligheten att utnyttja digital bildbehandling vid IAEAs inspektioner av bestrålat bränsle. Inspektören kan då utnyttja den digitala CCD-teknikens fördelar såsom hög känslighet och möjlighet till bildbehandling. Ett intelligent system skulle kunna analysera bilderna i realtid och ge viktig information om bränslet. Inom den första fasen av projektet har flera intressanta frågeställningar dykt upp. Den här rapporten ger en sammanfattning av arbetet med bildanalysen och en statusrapport om arbetet med att automatiskt klassificera bilderna av bränsleelementen. Tekniken skulle kunna utnyttjas generellt för klassificering av bilder.

Contents

1. Assessment of spent fuel assemblies

Inspection of used nuclear power fuel assemblies in storage is an important component of the International Atomic Energy Agencies safeguards responsibilities. The Cerenkov light generated in the water surrounding the fuel is strongly in the ultraviolet and an analog image intensifier sensitive to UV has been the primary tool for IAEA inspections. The inspector uses this device to examine the distribution of light across the face of an assembly. This distribution should differ between an assembly holding real fuel and an assembly holding non-fuel fake rods. However, this effect can be very subtle and difficult to detect. A collaboration of groups headed by the Swedish Nuclear Power Inspectorate (SKI) and the Atomic Energy Control Board (AECB) in Canada is developing a CCD based Cerenkov Viewing Device, or CVD (ref.1). The CVD offers not only improved sensitivity and resolution but also provides images in digital format that can be processed with modern image analysis tools. *Real time* or near real time analysis would be especially helpful since the inspectors have only 10-20 seconds to examine each assembly. A computer attached to the CVD might run an *intelligent* assistant program that could process the data to help the inspector enhance the images (e.g. indicate that the gain should be adjusted), align the camera over the center of the (i.e. find the point where the highly collimated light is brightest), and even provide a detailed assessment of the fuel assembly properties (e.g. estimate the probability that the assembly holds fuel or non-fuel.)

Using test images made with a prototype CVD of actual fuel assemblies, we recently reported an investigation into the feasibility of automatic determination of fuel properties with digital image processing methods (ref. 2). That investigation examined: (1) image processing and recognition methods; (2) properties of the Cerenkov light distribution across the assembly face.

The sequence of image processing steps carried out by the analysis reported in ref. 2 is illustrated in Figure 1. A histogram equalization operation is first required since the brightness can vary considerably among images. The equalized image is converted to a binary image. Some of the background noise and clutter is removed with some morphological operations on the binary image. Finally, templates were scanned across the image to find the assembly in the image and determine its type. Neural network techniques, including pulse coupled neural networks, are being investigated to see if these steps, especially the assembly identification, can be improved (Ref.5).

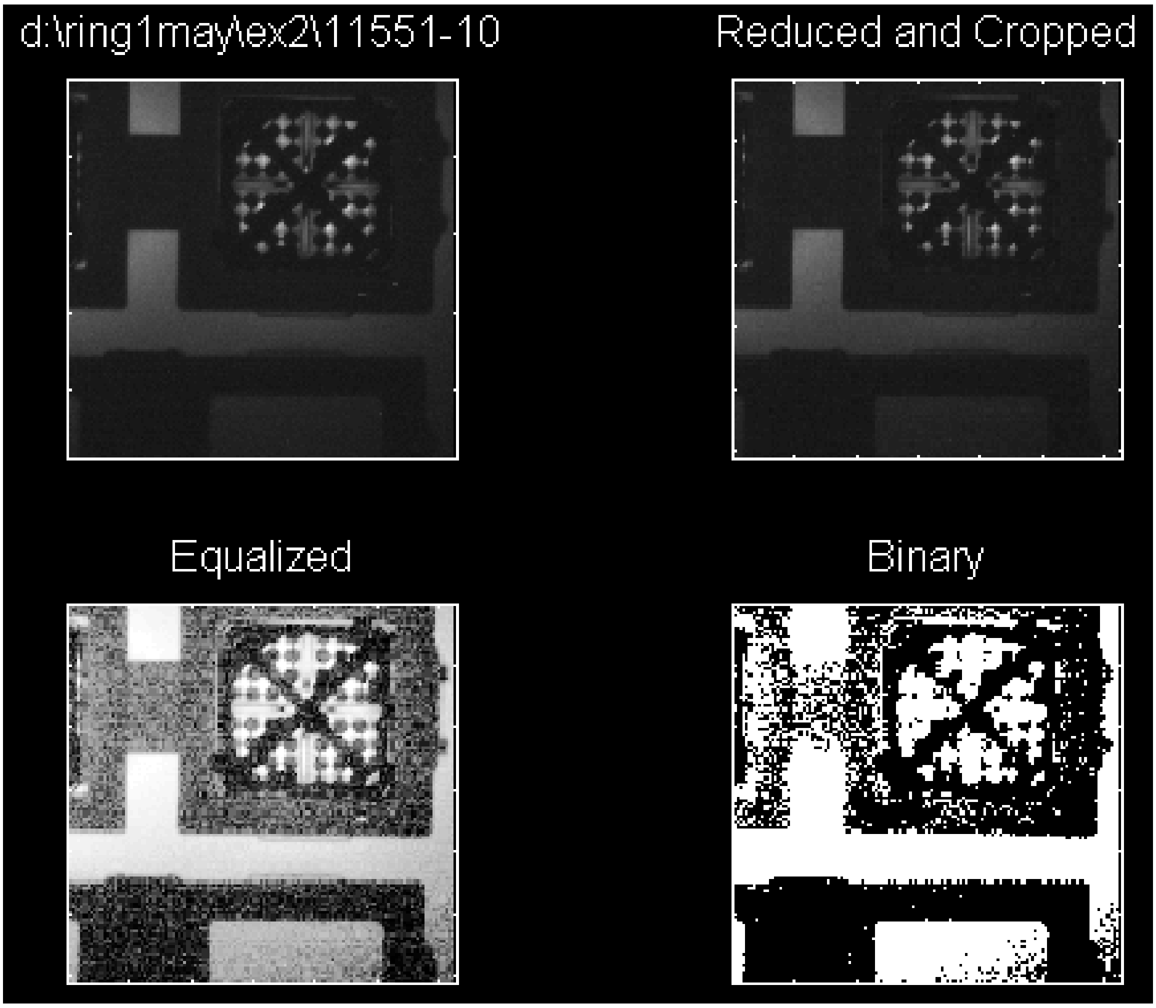

Figure 1(a) The sequence of steps required to find and identify the fuel assembly finding as reported in ref. 2. Initial image is reduced by ¼ and cropped to eliminate black bands around edges. Histogram equalization is then followed by a threshold cut at 0.5 (on 0-1 scale) to produce a binary B/W image.(Ref.2)

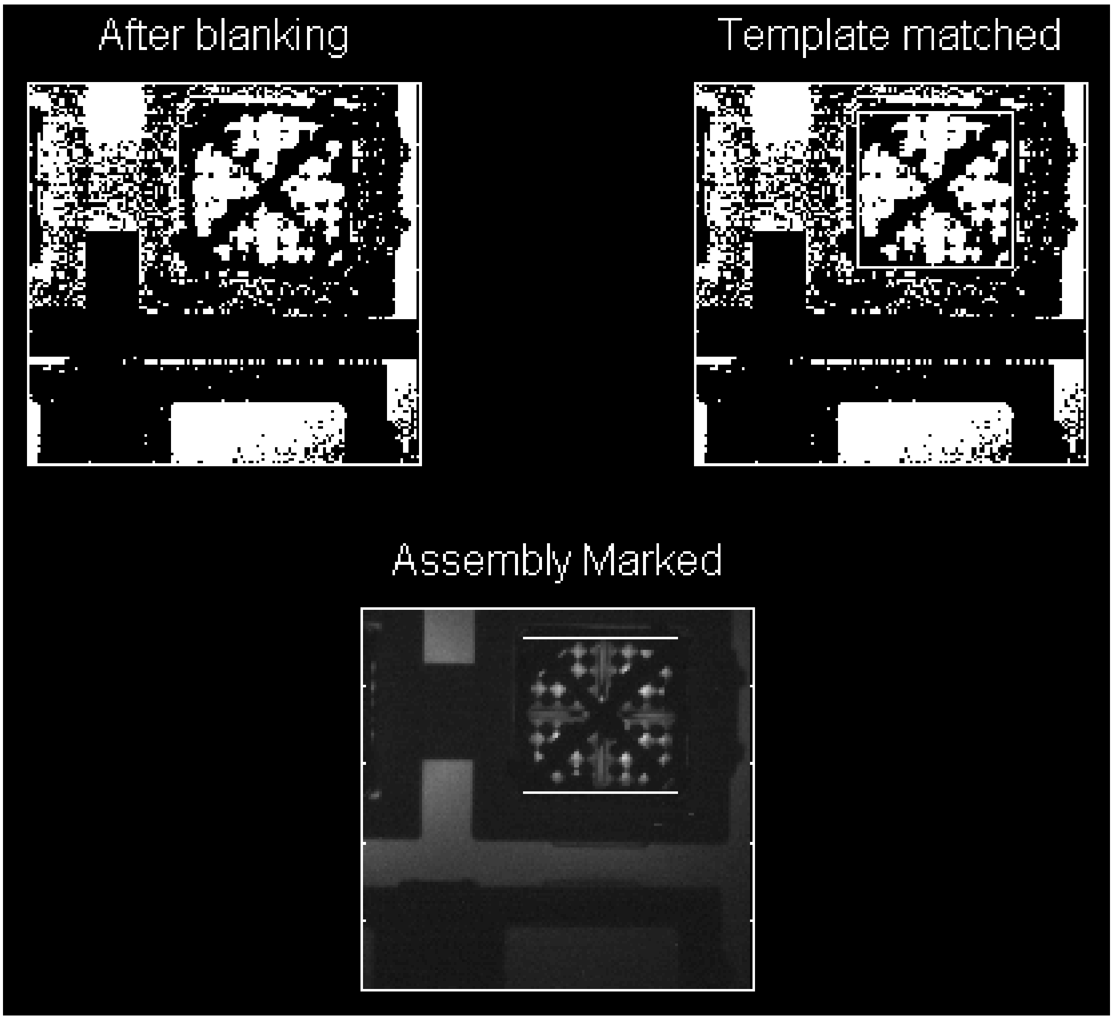

Figure 1(b) Blanking out operation on binary image is followed by template matching. Matched coordinates are determined for the original image and indicated here. (Ref.2).

2. A P-GRAM IMAGE CLASSIFICATION METHOD

There is a large variety of assembly designs around the world so a strong identification system will be required to assess the fuel since the distribution of light across the face will vary from one assembly type to another. Figure 2, for example, shows three types of assemblies - two boiling water reactor (BWR) 8x8 rod assemblies and a 15x15 pressurized water reactor (PWR) assembly.

The dark diagonal bars across the BWR assemblies are handles used to lift the assemblies. (The PWR assembly instead is grabbed by slots along the side that are not visible here.) Clearly the distribution of light across the face of the fuel assembly among just these three assembly types will vary considerably.

The challenge of identifying the assemblies inspired an image classification technique that could be of general interest for other image analysis projects besides the fuel assembly task. The inspiration for the technique comes from the success of n-grams for categorization text databases (Refs.4-5). To create an n-gram the text is scanned to determine the frequency of occurrence of particular words or letter sequences. These frequencies become the values for the elements of a vector, i.e. the n-gram. The number of elements would be the number of possible words or letter sequences. The n-gram vectors typically contain thousands or even millions of elements. Comparison of these vectors, e.g. with a scalar product, then determines the similarity of the texts. Reference 5, for example, scans texts with a window of 5 letters, and counts the number of occurrences of every possible 4 letter sequence (about 11 million such sequences for a 27 letter alphabet). Normalized vectors of documents in a large database are compared with scalar products and clustering techniques are found to correctly match texts of similar subjects nearly as well, around 70%, as more complicated algorithms. Reference 6 described the creation of n-gram vectors of UseNet texts and then categorized by a Self-organizing Map (SOM) to the same topic also with about 70% accuracy.

For images we looked for a similar approach where a vector of the frequencies of simple features would provide similar discriminating power as the n-grams do for texts. The approach chosen here involves calculating the number of times simple sub-matrices of pixels occur in binary images. Scanning the image we can count the number of times every possible pattern in a 3x3 sub-matrix occurred, resulting in a 512 dimensional vector that characterises the image. Similarly, a 4x4 sub-matrix has 65536 possible patterns, resulting in a 65536 dimensional vector to characterise the image.

These vectors will be referred to here as *p-grams*. Figure 3 illustrates the 3x3 filter used to make the p-gram vector of 512 elements. The values in the elements of the filter matrix are increasing powers of 2. An element by element multiplication and summation with a 3x3 binary matrix then yields a value between 0 and 511 corresponding to a unique 3x3 binary pattern. The p-gram element for the given value is incremented as the filter slides across the image one row and one column at a time in a convolution operation.

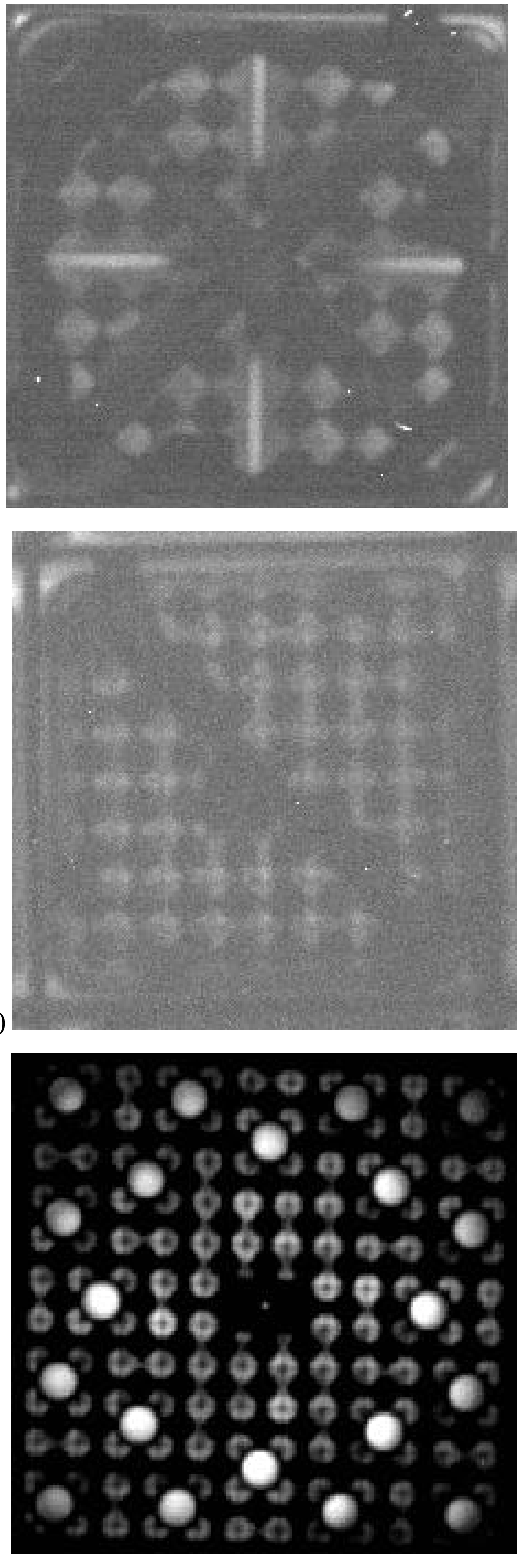
(a)
(b)
(c)

Figure 2 Three types of nuclear fuel assemblies. (a) boiling water reactor fuel assembly with 8x8 rods and cross handles; (b) boiling water reactor with single handle and 8x8 rods; (c) pressurized water reactor with 15x15 rods.

1	**2**	**4**
8	**16**	**32**
64	**128**	**256**

(a)

1	**0**	**0**	**0**	**...**
0	**0**	**1**	**1**	**...**
0	**0**	**0**	**0**	
0	**0**	**0**	**0**	

(b)

Figure 3 Illustration of p-gram construction with (a) a 3x3 filter and (b) an image matrix of binary pixels. The 3x3 filter in (a) is convoluted with the binary image matrix to count the number of times each of the 512 possible 3x3 binary patterns occur. For example, operation on the gray area in (b) would result in a value = 1*1 + 32*1 = 33, where only the non-zero multiplication is indicated. The 33rd element of the p-gram vector would thus be increment by one. The filter then slides by one column to the right and the operation

3. Results of p-gram classification tests

The first study of this technique involved real images of nuclear fuel assemblies. We sought to determine if it would correctly categorize images of the three types of assemblies in figure 2. Using a 4x4 filter, p-gram vectors of 65K elements, i.e. the number of occurrences of all possible 4x4 binary patterns, were made for each of 74 images. There were roughly equal numbers of each assembly type. Cosines were calculated between all pairs of vectors. A simple clustering algorithm found that an image of a given fuel type was correctly clustered with other images of the same fuel type in about 70% of the cases.

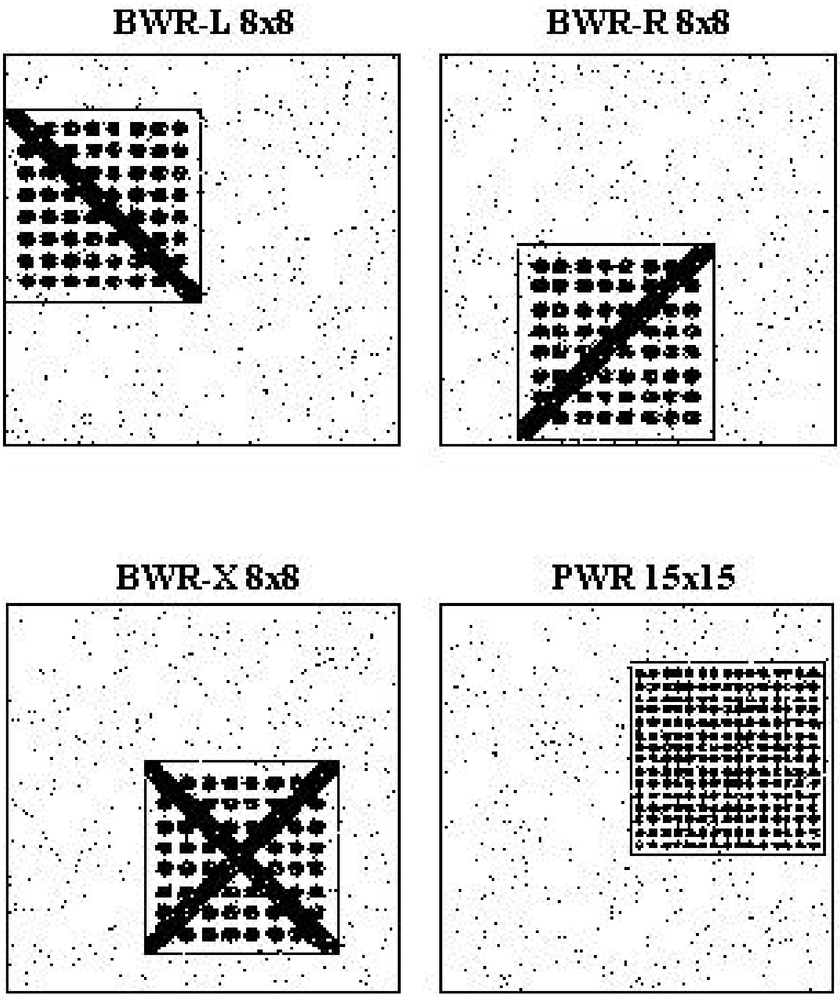

Figure 4 Here are shown the four types of artificial assembly images created to test the p-gram method with SOM categorisation. The fuel rods are not perfectly round but instead have edges with random jaggedness. Also, random noise pixels were added and the assemblies were given random translations within the image.

The second study involved categorisation of p-grams with Self-Organising Maps (SOM). In this first test we wanted a large training set so artificial binary images of fuel assemblies were created. Figure 4 shows four types of assembly images that were created with 150x150 pixels. The first three are similar to 8x8 BWR assemblies with handles in one or both of the diagonals. The fourth image is similar to a 15x15 PWR assembly. Randomly placed noise points were added and also the black rods are not perfect circles but have randomly jagged edges. Furthermore, the images were translated to random locations within the frame but were always fully contained within the frame.

Training and test sets were created by generating the images and scanning them with a 3x3 filter as described in section 2 to create 512 element p-gram vectors. These vectors were then input to a SOM in hopes that the mapping would result in separate output neurons firing for the four types of assembly types. Training sets of 1000-2000 p-grams were used.

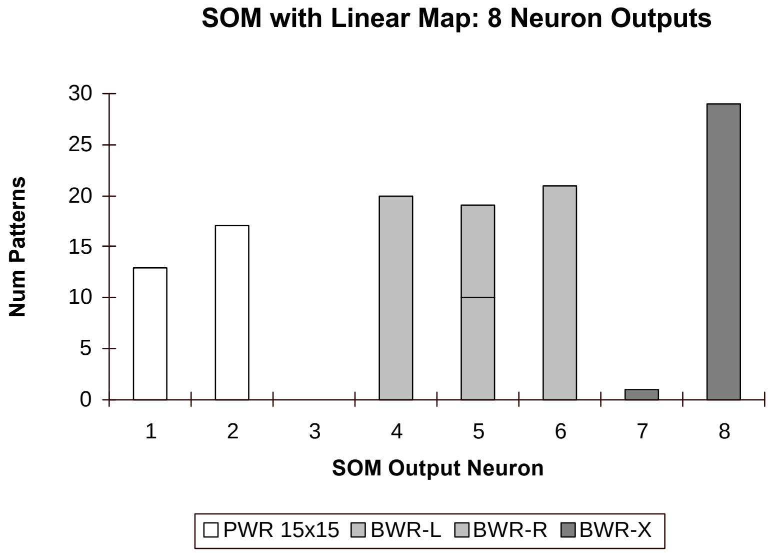

Figure 5 Outputs of the SOM neurons for 30 images for each of the four types of assembly images shown in figure 4. The BWR-L and BWR-R show overlap in the neuron 5 output. Otherwise, the 4 assembly types are well separated.

Figure 5 shows the output distribution of an 8 output linear map for a test set with 30 p-grams for each of the four assembly types. The BWR cross handle assembly and the PWR assembles are widely separated while the single handle BWR assemblies overlap somewhat. If we only trained on the two single handle assemblies, the separation was much wider with little or no overlap. Starting from such a mapping, i.e. first training on only the two single handle types and then training on all four types, leads to the these two being *pushed* together as shown in figure 5. A 4x4 SOM is shown in figure 6. Again, the single handled types overlap to some extent but are still distinctly separated.

4. DISCUSSION

The project to determine if fuel assembly assessment can be accomplished with digital image analysis has so far shown the general feasibility of the approach. A set of pre-processing steps were developed that demonstrated that a subset of assembly types could be located within the image and identified. The distribution of light across the image face was shown to vary depending on whether the fuel was real or fake or if rods were missing. However, considerable work remains to develop a useful *intelligent digital assistant* that can run in real-time, identify arbitrary fuel assembly types, assess the qualities of the fuel, keep a record of past assessments of particular assemblies, etc.

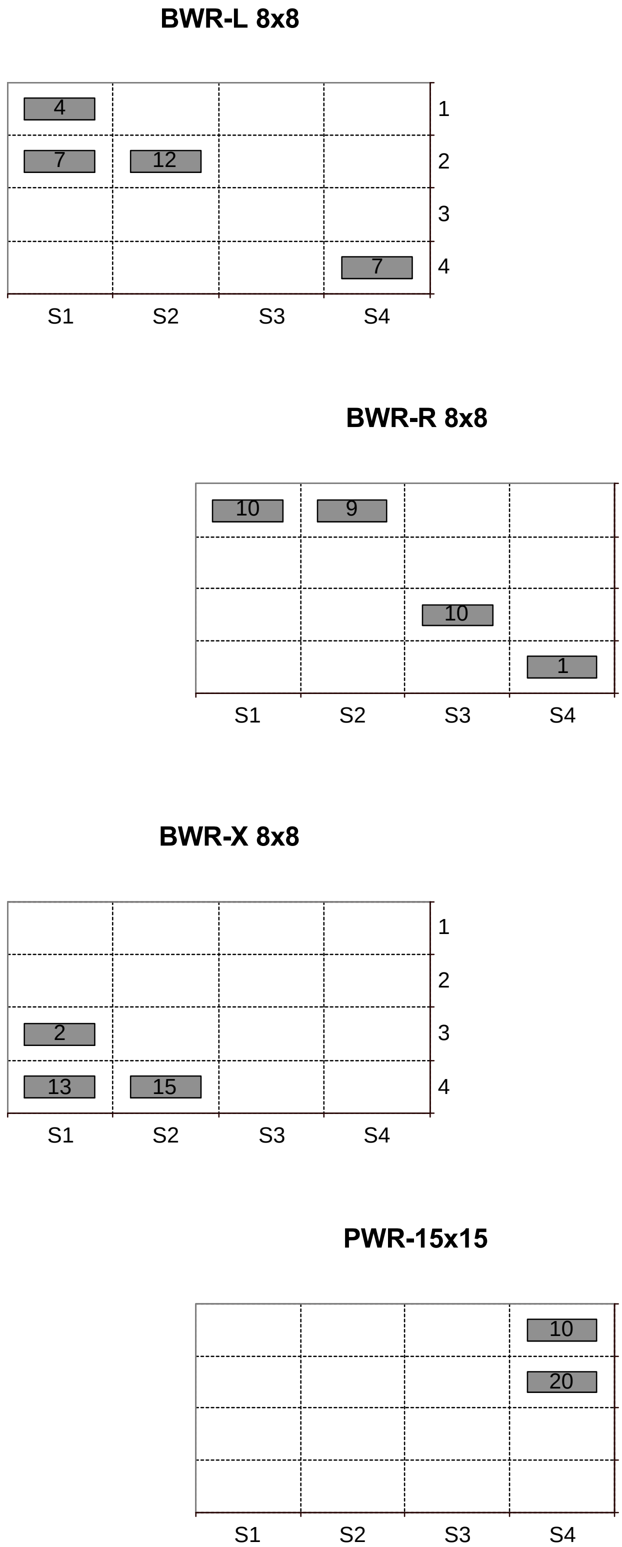

Figure 6 Outputs of a 4x4 SOM for the four types of assembly images shown in figure 4 for 30 images of each type. The BWR-L and BWR-R show overlaps in the S1-1 and S4-4 output neurons. Otherwise, the 4 assembly types are well separated.

The problem of categorising fuel assembly images inspired the development of a new technique that compares images by the frequency of occurrences of simple features. The preliminary results given here for this *p-gram* method show promise despite such a simple approach. More sophisticated image categorisations will no doubt be more accurate but they also will surely be more complicated and require greater processing. The p-gram vectors could provide an index for an image, regardless of its size or shape, that can be quickly compared to another image by a calculation of their inner product cosine or by the output of a neural network, e.g. a SOM, trained for particular types of images. (Here we assume that the images are restricted to a particular domain, e.g. fuel assemblies, rather than a set of random general images.) Further work, however, is obviously needed to investigate whether the results can be improved and extended to other kinds of images. For example, perhaps only a sub-set of the 3x3 and 4x4 patterns are needed rather than all 512 and 65K patterns, respectively.

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