11.1 Introduction

In the previous chapter, the potential of Simplified Fuzzy ARTMAP (SFAM) to behave as a Pattern Recognizer has been discussed. Kasuba's SFAM which is a vast simplification of Carpenter et al's [13] Fuzzy ARTMAP, inherently lacks the capability to recognize images which are subjected to perturbations or noise. Investigations on the application of SFAM to Civil Engineering problems (Rajasekaran et al [82]; Rajasekaran and Pai [84]) has resulted in the observation that the model as such, recognizes only those patterns which are an exact reproduction of the same for which it has been trained. Thus, perturbations or noise in the patterns to be inferred, results in misclassification of patterns. This characteristic has been tackled by augmenting the SFAM with a moment based RST invariant feature extractor. This feature extractor is a modification of its conventional counterpart discussed in Schalkoff [91, 92].

In this chapter, the image processing applications of the SFAM based Pattern Recognizer has been discussed. The behavior of the model during the recognition of monochrome and colour images, in the presence and absence of noise or perturbations, has been studied on two problems chosen as test-suites. The first which concerns monochrome images, is a Satellite image recognition problem discussed by Wang et al [111]. The second,
which concerns coloured images deals with the recognition of some sample, coloured test patterns.

Next, three problems chosen from Structural Engineering, viz., Prediction of Shear Stress pattern from Cross Sectional geometry and vice-versa, Prediction of load from the yield patterns of elasto-plastic analysis of clamped and simply supported plates, and Prediction of natural mode shapes of multistoried building frames have been discussed.

11.2 Experimental Study: Recognition of monochrome images

The problem of distinguishing among airplanes, tanks and helicopters from a Satellite discussed by Wang et al, is the test suite problem. The experiments conducted are categorized as under:

<table>
<thead>
<tr>
<th>IMAGE</th>
<th>TRAINING SET</th>
<th>TESTING SET</th>
</tr>
</thead>
<tbody>
<tr>
<td>Monochrome</td>
<td>Nominal (ideal) Patterns</td>
<td>Nominal Patterns</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(Noisy)</td>
</tr>
<tr>
<td></td>
<td>Rotated/ Scaled/ Translated/</td>
<td>Rotated/ Scaled/</td>
</tr>
<tr>
<td></td>
<td>Combinations (Noise free)</td>
<td>Translated/ Combinations (Noisy)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Fig. 11.1 illustrates a set of sample nominal patterns that SFAM is trained with. The results are observed for varying vigilance parameter values, $0.5 \leq \rho < 1$. The number of training epochs is kept fixed to a paltry 3. The model is tested for a set of 25 patterns absolutely noise free, but rotated or scaled or translated or combinations of one or more or all of these. Fig. 11.2
illustrates a sample set of inference patterns. Table 11.1 shows the results of the experiments.

In the next stage, for the same training set, a set of noisy patterns – nominal, rotated, scaled, displaced or a combination is presented, to test for the recognition capability. Fig. 11.3 illustrates a sample set of noisy patterns. The activation values of the top down weight nodes and the correctness of the classification is observed for varying noise levels. Since the experiment pertains to monochrome (binary) images, the noise level is determined in terms of the Hamming distance. The Recognition flag is set to 1 or 0 depending on whether the recognition is correct or incorrect respectively. Fig. 11.4 illustrates the behavior of the model for varying noise levels, when a nominal pattern is subjected to random noise. Fig. 11.5 illustrates the same for a Scaled and Translated image and Fig. 11.6 for a Rotated, Scaled and Translated noisy image.

11.3 Experimental Study: Recognition of Colour images

In this phase, a similar set of experiments is repeated with respect to coloured images. The problem pertains to the recognition of sample coloured test patterns. The experiments performed are categorized as under:

<table>
<thead>
<tr>
<th>IMAGE</th>
<th>TRAINING SET</th>
<th>TESTING SET</th>
</tr>
</thead>
<tbody>
<tr>
<td>Colour</td>
<td>Nominal (ideal) Patterns</td>
<td>Nominal Patterns (Noisy)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Rotated/ Scaled/ Translated/ Combinations (Noise free)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Rotated/ Scaled/ Translated/ Combinations (Noisy)</td>
</tr>
</tbody>
</table>
Fig. 11.7 illustrates a sample set of nominal patterns and Fig. 11.8 a set of noise free patterns but subjected to perturbations – Rotation, Scaling, Translation and combinations of the three. Table 11.2 shows the results of the experiment.

In the case of noisy patterns, a sample of which is illustrated in Fig. 11.9, the performance of the model for varying noise levels is observed. As before, the activation value of the top down weight vectors and the recognition capability of the model for varying noise levels are kept track of. Fig. 11.10 illustrates the behavior when nominal patterns are subjected to random noise. Figs. 11.11 and 11.12 illustrate the behavior for Scaled and Translated noisy image, and Rotated, Scaled and Translated noisy image respectively.

11.4 Application 1: Prediction of Shear Stress Pattern from Cross Sectional Geometry

Shear stress is a parameter of great importance from the point of view of strength, in the design of flexural members. Shear stress very much depends on the geometry of the section. The problem of prediction of shear stress pattern from cross sectional geometry (or vice versa) is a potential candidate for SFAM network, as it involves a great amount of pattern recognition. In this case both input, that is the cross section (stress diagram) as well as output category, that is the stress diagram (cross section) are geometrical patterns. Also, the association between the Shear stress diagram and the cross section is one-many. The pattern-pattern association unlike the earlier pattern-category association, has been made possible through
a simple post processor. The one-many association of shear stress with cross sectional geometry is no hurdle to SFAM, since the model exhibits the inherent characteristic to "learn" multiple inputs belonging to the same category.

Fig. 11.13 illustrates a sample set of pattern pairs that SFAM is trained with. Fig. 11.14 shows a sample pattern presented to SFAM and Fig. 11.15 the associated output inferred by it.

11.5 Application 2: Prediction of Load from Yield Patterns of Elasto-Plastic, Clamped, Simply Supported Plates

Benjamin Whang [115] has developed finite element displacement method for elasto-plastic analysis of bilinear Strain hardening orthotropic plates and shells, considering elastic unloading also. The two basic approaches adopted by Whang in the elasto-plastic analysis are, The Initial Stiffness approach and Tangent Stiffness approach, in conjunction with the Huber-Mises yield criterion and the Prandtl-Reuss flow rule in accordance with the strain hardening yield function.

Fig. 11.16 shows the uniformly loaded isotropic plates, one with clamped edges and the other with simply supported edges. The following numerical values are used:

\[ t = 1.0, \quad E = 30000.0, \quad \nu = 0.3, \quad E_p = 300.0, \quad \text{and} \quad \sigma_0 = 30.0 \]

where \( t \) is the thickness, \( E \) is the Young's modulus, \( \nu \) is the Poisson's ratio and \( \sigma_0 \) is the yield stress. The formation of plastic zone with respect to loading is also shown in the figure.

SFAM is trained with the patterns representing the plastic zones and their corresponding loading, and tested for its inference capability. Considering
the doubly symmetric nature of the patterns, only a quarter of the image is presented to SFAM for training. The behavior of SFAM while handling doubly symmetric patterns has already been discussed in the previous chapter. Fig. 11.17 illustrates sample patterns that SFAM is trained with. Observe that these are quarters of the patterns corresponding to a loading of 2.0 and 1.8 respectively. The prediction of load by SFAM is done quite correctly.

A similar exercise is carried out for uniformly loaded simply supported square plates. Fig. 11.18 shows the plastic zones, for both isotropic and orthotropic clamped square plates subjected to uniformly distributed load. The following yield stress is used:

- **Isotropic:** \( \sigma_0 = 30, \tau_0 = 17.3 \)
- **Orthotropic:** \( \sigma_{ox} = 30, \sigma_{oy} = 40, \sigma_{o45} = 35, \tau_{oxy} = 20.2 \)

Fig. 11.19 shows the patterns that are presented to SFAM. As before, the predictions by SFAM are highly accurate.

### 11.6 Application 3: Prediction of Natural Mode Shapes of Multistoried Building Frames

In this case, the patterns representing the peak values of displacements for a five-storey shear frame are presented as inputs to SFAM. Fig. 9.2 illustrates the peak values of displacements. The patterns as presented to SFAM have been shown in Fig. 11.21. The model is presented one exemplar each for every mode. The system is tested for both noisy and noise free patterns. In all cases, the predictions are quite correct.
11.7 Summary

The capability of Kasuba’s SFAM augmented with a modified moment based RST invariant feature extractor, for the classification / recognition of images both noisy and noise free, has been investigated.

The Pattern Recognizer has been initially tested over two experimental problems. The first experiment, which concerns monochrome images, pertains to recognition of satellite images, a problem discussed by Wang et al. The second experiment, which concerns colour images, deals with the recognition of some sample coloured test patterns. Also, the application of the model to real world problems has been demonstrated on three problems chosen from Structural Engineering, viz., Prediction of Shear Stress pattern from Cross Sectional geometry and vice-versa, Prediction of load from the yield patterns of elasto-plastic analysis of clamped and simply supported plates, and Prediction of natural mode shapes of multistoried building frames.
Table 11.1

Recognition of Noise free Monochrome Images

<table>
<thead>
<tr>
<th>No. of Training Epochs</th>
<th>Vigilance Parameter</th>
<th>Training Set</th>
<th>Testing Set</th>
<th>Nature of the Testing Set</th>
<th>Recognition Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>$0.5 \leq \rho &lt; 4$</td>
<td>3 Exemplars - (one in each category)</td>
<td>25 patterns</td>
<td>Rotated / Scaled / Translated / Combinations</td>
<td>100%</td>
</tr>
</tbody>
</table>

Table 11.2

Recognition of Noise free Colour Images

<table>
<thead>
<tr>
<th>No. of Training Epochs</th>
<th>Vigilance Parameter</th>
<th>Training Set</th>
<th>Testing Set</th>
<th>Nature of the Testing Set</th>
<th>Recognition Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>$0.5 \leq \rho &lt; 4$</td>
<td>4 Exemplars - (one in each category)</td>
<td>25 patterns</td>
<td>Rotated / Scaled / Translated / Combinations</td>
<td>100%</td>
</tr>
</tbody>
</table>
Fig. 11.1: Training patterns (Monochrome, Nominal) of SFAM

238
c) Helicopter

Fig. 1: (Contd.)
Fig. 11.2: Sample set of (Monochrome, Noise free) inference patterns correctly identified by SFAM.
c) Translated and Scaled

Fig. 11.2 : (Contd.)
a) Noise level 14%

Fig. 11.3: Sample set of noisy (Monochrome) patterns correctly identified by SFAM

b) Noise level 24%

Fig. 11.3: Sample set of noisy (Monochrome) patterns correctly identified by SFAM
c) Noise level 55%

Fig. 11.3: (Contd.)

Fig. 11.4: Performance of SFAM during the recognition of noisy patterns (Monochrome - Nominal)
Fig. 11.5: Performance of SFAM during the recognition of noisy
Patterns (Monochrome - Scaled and Translated)

Fig. 11.6: Performance of SFAM during the recognition of noisy
Patterns (Monochrome - Rotated, Scaled and Translated)
Fig. 11.7: Training patterns (Colour, Nominal) of SFAM
Fig. 11.8: Sample set of inference patterns (Colour) correctly identified by SFAM.
c) Translated and Scaled

Fig. 11.8 : (Contd.)
Fig. 11.9: Sample set of noisy patterns (Colour) correctly identified by SFAM
Fig. 11.9: (Contd.)
Fig. 11.10: Performance of SFAM during the recognition of noisy patterns (Colour - Nominal)

Fig. 11.11: Performance of SFAM during the recognition of noisy Patterns (Colour - Scaled and Translated)
Fig. 11.12: Performance of SFAM during the recognition of noisy patterns (Colour – Rotated, Scaled and Translated)
<table>
<thead>
<tr>
<th>S.NO</th>
<th>Cross Sectional Geometry</th>
<th>Shear Stress Diagram(category)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>![Image 1]</td>
<td>![Image 2]</td>
</tr>
<tr>
<td>2</td>
<td>![Image 3]</td>
<td>![Image 4]</td>
</tr>
<tr>
<td>3</td>
<td>![Image 5]</td>
<td>![Image 6]</td>
</tr>
<tr>
<td>4</td>
<td>![Image 7]</td>
<td>![Image 8]</td>
</tr>
<tr>
<td>5</td>
<td>![Image 9]</td>
<td>![Image 10]</td>
</tr>
<tr>
<td>6</td>
<td>![Image 11]</td>
<td>![Image 12]</td>
</tr>
<tr>
<td>7</td>
<td>![Image 13]</td>
<td>![Image 14]</td>
</tr>
<tr>
<td>8</td>
<td>![Image 15]</td>
<td>![Image 16]</td>
</tr>
</tbody>
</table>

Fig. 11.13: Patterns presented to SFAM for Training and inference
Fig. 11.14: A Cross sectional geometry pattern presented to SFAM for training

Fig. 11.15: The associated Shear stress diagram inferred by SFAM
Fig. 11.16: Isotropic plates: Clamped Vs Simply supported
Fig. 11.17: Patterns as presented to SFAM
(Prediction of load from yield patterns of Isotropic plates)
Isotropic: $\sigma_o=30, \tau_o=17.3$
Orthotropic: $\gamma_{ox}=30, \sigma_{oy}=40, \sigma_{o45}=35, \gamma_{oxy}=20.2$

Fig. 11.18: Clamped plate: Isotropic Vs Orthotropic
Fig. 11.19: Patterns as presented to SFAM
(Prediction of load from yield patterns of clamped plates)
Fig. 11.20: Patterns as presented to SFAM
(Prediction of natural mode shapes)