Abstract – In this paper, we evaluate the efficiency and accuracy of a method of detecting fabric defects that have been classified into different categories by a neural network. Four kinds of fabric defects most likely to be found during weaving were learned by the network. Based on the principle of the back-propagation algorithm of learning rule, fabric defects could be detected and classified exactly. The method used for processing image feature extraction is a co-occurrence-based method, by which six feature parameters are obtained. All of them consist of contrast measurements, which involve three spatial is placements (i.e., 1, 12, 16) and four directions (0, 45, 90, 135 degrees) of fabric defects’ images used for classification. The results show that fabric defects inspected by means of image recognition in accordance with the artificial neural network agree approximately with initial expectations.

It has become more and more important for textile engineers to use automatic techniques in production processes and management procedures. At present, fabric inspection still depends on human sight, and inspection on-line monitoring of fabric defects in weaving.

In this study, we use a neural network topology known as “multi-layer perception,” which has not been used in the past because of the lack of effective training algorithms for it. Recently this has changed due to the development of an iterative gradient procedure known as the back-propagation algorithm [7]. Through this supervised learning algorithm, the neural network can become a classifier of fabric defect. Because of the highly parallel operation and quick response nature of a neural network, it is easy to apply this method to on-line monitoring of fabric defects in weaving.

Keywords – Neural Networks, Knitted Fabrics, Sigmoid Transfer Function, Textile, Pattern Recognition.

I. EXTRACTING FEATURE PARAMETERS OF A FABRIC DEFECTS' TEXTURE

Texture may be defined with respect to the global properties of an image or to the repeating units that compose it. In this paper, we use a gray level co-occurrence matrix [1, 4, 9] to extract various feature parameters of a fabric defect’s texture image to evaluate defects in various categories.

Texture Image, regarded as a two-dimensional function of light intensity, can be illustrated as a function \( f(x, y) \). For each coordinate \((x, y)\) (or pixel-x, y) in a two-dimensional image, there is a corresponding function value of light intensity. Because the image exists in an energy form [2], the magnitude of function \( f(x, y) \) for the image can be any value except zero and can be shown as \( 0 < f(x, y) < \infty \).

Generally speaking, the reason the image of an object can be observed by human vision is the light intensity reflected from it, which consists of two parts, the light intensity illuminating the object itself and the light intensity reflected from the surface of the object. The former is illumination, represented by \( i(x, y) \), and the latter is reflectance, represented by \( r(x, y) \). The image of an object can thus be shown using Equation 1:

\[
F(x, y) = i(x, y)r(x, y)
\]  
Where \( 0 < i(x, y) < \infty \) and \( 0 < r(x, y) < 1 \)

The magnitude of \( r(x, y) \) is between 0 (indicating no reflection from the surface of an object) and 1 (indicating full reflection from the surface). The magnitude of reflectance \( r(x, y) \) depends on the light intensity reflected from the surface of the object.

In order to permit a continuous spatial image, function \( f(x, y) \) for the image through digitized processing becomes a discrete spatial function. This process is called “image sampling”. Every pixel of an image can then be represented as \( f(x, y) \), and the \( N \times N \) size of image in its digital form can be stored as a two-dimensional array using Equation 2:

\[
\begin{align*}
F(x, y) &= f(0,0) \quad f(0,1) \quad \ldots \quad f(0, N-1) \\
f(1,0) &= F(1,1) \quad \ldots \quad f(1, N-1) \\
&\quad \quad \ldots \quad \quad \quad \ldots \\
F(N-1,0) &= \quad f(N-1,1) \quad \ldots \quad f(N-1, N-1)
\end{align*}
\]  
(2)

This digital image \( f(j, k) \) is \( N \times N \), and its gray level resolution is \( G \). We used two parameters-d, the distance between two pixels, and \( \theta \), the position angle between two pixels \((j, k)\) and \((m, n)\). Thus, there were four directions of position angle-the horizontal direction \( \theta = 0^\circ \), the right diagonal direction \( \theta = 45^\circ \), the vertical direction \( \theta = 90^\circ \), and the left diagonal direction \( \theta = 135^\circ \). The four kinds of relative positions between two pixels can be denoted using Equation 3:

\[
\begin{align*}
\theta &= 0^\circ \quad R(d) : |j - m| = d, |k - n| = 0 \\
\theta &= 45^\circ \quad R(d) : (j - m = -d, k - n = -d) \\
\theta &= 90^\circ \quad R(d) : (j - m = d, k - n = d) \\
\theta &= 135^\circ \quad R(d) : (j - m = -d, k - n = d)
\end{align*}
\]  
(3)

Based on this definition, the relationship between the pixel pairs and the co-occurrence probability of gray levels \( p \) and \( q \) can be illustrated using Equation 4:

\[
P(p, q \mid d, 0) = \# \{ R_{II}(d), f(j, k) = p, f(m, n) = q \}
\]
P(p,q,d, 45°) = \# \{ R_{RD}(d), f(j,k) = p, f(m,n) = q \}

P(p,q,d, 90°) = \# \{ R_{\gamma}(d), f(j,k) = p, f(m,n) = q \}

P(p,q,d, 135°) = \# \{ R_{LD}(d), f(j,k) = p, f(m,n) = q \}

The symbol \# \{ \} denotes the probability sum of occurrence of all events in the parentheses. P is a function of four parameters p, q, d, θ. As for an image of gray level 0-3, its co-occurrence matrix is illustrated in Figure 1 a. An image size of 4 X 4 is illustrated in Figure 1 b, and each co-occurrence matrix of direction 0°, 45°, 90°, 135° is shown in Figures 2a, b, c, and d.

Fig. 1. (a) General form of co-occurrence matrix for image with gray level 0-3 (b) 4 x 4 image with four gray level 0-3 and the arrows show four direction angles of position between two pixels

\[
P_{N}(d=1, \theta = 0°) = \begin{bmatrix}
4 & 0 & 0 & 0 \\
2 & 4 & 0 & 1 \\
0 & 0 & 6 & 0 \\
0 & 0 & 0 & 4
\end{bmatrix}
\]

\[
P_{RD}(d=1, \theta = 45°) = \begin{bmatrix}
2 & 1 & 0 & 2 \\
1 & 4 & 0 & 0 \\
0 & 0 & 0 & 3 \\
2 & 0 & 3 & 0
\end{bmatrix}
\]

\[
P_{V}(d=1, \theta = 90°) = \begin{bmatrix}
4 & 0 & 0 & 2 \\
0 & 6 & 1 & 1 \\
0 & 1 & 0 & 3 \\
2 & 1 & 3 & 0
\end{bmatrix}
\]

\[
P_{LD}(d=1, \theta = 135°) = \begin{bmatrix}
2 & 1 & 0 & 1 \\
1 & 2 & 1 & 2 \\
0 & 1 & 0 & 2 \\
1 & 2 & 2 & 0
\end{bmatrix}
\]

Fig. 2. (a-d) illustrate calculations of four direction angles of position in co-occurrence matrix.

A co-occurrence matrix is processed using the normalization method \[6, 9\] to make the sum of all the entries in the matrix equal to 1. Then the ASM (angular second moment), the parameter for the evenness distribution degree of the image, and CON (contrast), the parameter for the gray level contrast of the image, are obtained using Equations 5 and 6:

\[
ASM = \sum_{p} \sum_{q} \left( \frac{P(p,q)^2}{R} \right)
\]

and

\[
CON = \sum_{n=0}^{m-1} S^2 \sum_{p=1}^{n} \left( \frac{P(p,q)}{R} \right)
\]

where R denotes the sum of all the entries of the co-occurrence matrix.

II. CONSTRUCTION AND TRAINING OF THE NEURAL NETWORK

A network consisting of one input layer, one output layer, and one hidden layer is used in the pattern recognition system of fabric defect texture in this study. Its construction is illustrated in Figure 3.

Fig. 3. A multi-layer perceptron with one hidden layer

"Training" is equivalent to finding proper weights for all the connections of nodes between layers such that a desired output is generated for a corresponding input. The major training steps of the back propagation algorithm are as follows \[3, 7, 8, 11\]: (a) Initialize all the values of connection weight (Ws) between node j in the upper layer and node i in the layer below. (b) Present an input for each node in the input layer and specify the desired output for each node in the output layer. (c) Calculate actual outputs of all the nodes using the present value of Ws. The output of node j, denoted by Yj, is an on linear function (called a Sigmoid function and shown in Figure 4) of its total input:

\[
Y_j = \frac{1}{1 + e^{-nelt_j}}
\]

where netj = \( \sum_i Y_i W_{ij} \). (d) Find an error term for each output node and hidden node. If d_{ij} and Y_{ij} stand for desired and actual values of a node, respectively, for an output node,

\[
\delta_j = (d_{ij} - Y_{ij}) Y_j(1 - Y_j)
\]

and for a hidden layer node,

\[
\delta_j = Y_j(1 - Y_j) \sum_k \delta_k W_{kj} \Sigma_k
\]
addition to these normal fabrics, there were various kinds of warp and T/W weft, which are both folded yarns. In defective fabrics with computer with CPU 486 DX-50. Calculated by an IBM personal equipment and randomly divided into two groups. One half was used for training and the other half for testing.

The fabrics used in this study were twills woven by T/W warp and T/W weft, which are both folded yarns. In addition to these normal fabrics, there were various kinds of defective fabrics with nep, broken ends, broken picks, and oil stains, all of which appear fairly often during weaving. The characteristics of the normal fabrics are shown in Table I. From each of the four kinds of defective fabrics, ten samples were taken by image capture equipment and randomly divided into two groups. One half was used for training and the other half for testing.

<table>
<thead>
<tr>
<th>Tex Density, yarn/in.</th>
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<td>Warp 30</td>
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The image capture system is shown in Figure 5. Images were captured using a panasonic CCD camera (Solid Color WV-CD 110) equipped with a 20X lens. Each image was digitized by Ip-8/AT card into 100 X 100 pixels with a gray level of 0-255 and stored as a Two-dimensional array. Samples were illuminated by two halogen lights positioned approximately 20 cm above and to the right and left of the sample to supply illumination in diagonal directions of 45°. Captured images could be reproduced on the graphic display, whose resolution power was 320 X 200 with a gray level range of 0-255. The feature parameters of each fabric defect’s texture were calculated by an IBM personal computer with CPU 486 DX-50.

\[
\text{Where } k \text{ is over all nodes in the layer above node } j. \text{ (e) Update weights by:}
\]

\[
W_{ij}(t+1) = W_{ij}(t) + \alpha \delta_j Y_t
\]

\[+
\gamma(W_{ij}(t) - W_{ij}(t-1))
\]

where \(W_{ij}(t)\) stands for connection weight value between node \(j\) in the upper layer and node \(i\) in the layer below, \(\alpha\) is a learning rate, and the momentum factor \(\gamma\) is a constant between 0 and 1. (f) Return to step b to present another new input for each node until all the training sets have been learned and the weights have stabilized.

\[
\text{Fig. 4. Sigmoid transfer function}
\]

**III. EXPERIMENTAL**

**Samples And Image Capture**

The fabrics used in this study were twills woven by T/W warp and T/W weft, which are both folded yarns. In addition to these normal fabrics, there were various kinds of defective fabrics with nep, broken ends, broken picks, and oil stains, all of which appear fairly often during weaving. The characteristics of the normal fabrics are shown in Table I. From each of the four kinds of defective fabrics, ten samples were taken by image capture equipment and randomly divided into two groups. One half was used for training and the other half for testing.

**Table I. Characteristics of normal fabrics.**

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**Fig. 5. Schematic illustration of the inspection system**

**IV. PROCEDURES**

Gray Scale Histogram Equalization Preprocessing

There are two reasons to use the histogram equalization processing method [5, 6] to reduce a 256 gray level resolution of the image to a 16 gray level. The first reason is to conserve computation time and the second is the recognition that human vision is commonly below the 16 gray level.

Through histogram equalized processing, we obtained a more uniform gray level distribution of the images, thus avoiding varied results from image capture conditions.

Acquiring the Repetition Units of Normal Fabrics Using reduced image data, the co-occurrence matrix for a normal fabric’s texture image can help determine the repetition distance \(d\) along a direction angle of \(\theta\). If the intensity distribution of all the pixels in an image is a normal distribution, the angular second moment (ASM) and contrast (CON) \([1, 4, 9]\) can be calculated using Equations 5 and 6.

Regardless of the kinds of direction, if there is any periodicity in the direction of \(\theta\), the diagonal elements in a co-occurrence matrix become large values \([4, 9]\). Thus, the value of ASM in Equation 5 becomes the maximum and the value of CON in Equation 6 becomes the minimum. Figure 6 illustrates ASM and CON statistics plotted against \(d\) for \(\theta = 0\) and \(90^\circ\). The figure reveals that the periodic signals in normal fabrics are strongest in the horizontal and vertical directions (weft and warp). The maximum ASM and the minimum CON at the distance of 12 pixels (\(d = 12\)) along the horizontal direction \((\theta = 0^\circ)\) are shown in Figures 6A and B, respectively, and those at a distance of 16 pixels (\(d = 16\)) along vertical direction \((\theta = 90^\circ)\) are illustrated in Figures 6C and D, respectively. Thus, of the normal fabrics, the repetition unit along the weft direction is 12 pixels and that along warp direction is 16 pixels.

Acquiring Feature Parameters Through the gray-level co-occurrence matrix method, we obtained a feature vector \((f_1, f_2, f_3, f_4, f_5, f_6)\) for each fabric defect texture. Among the feature vectors, \(f_1, f_3, f_5\) and \(f_6\) are the contrast measurements of texture images along \(0^\circ, 45^\circ, 90^\circ, 135^\circ\) when spatial Displacement \(d\) is equal to 1, while \(f_2\) and \(f_4\) are the contrast values at \(d = 12, \theta = 0^\circ\), and \(d = 16, \theta = 90^\circ\), respectively. The feature parameters can be illustrated...
by \( f_1 = \text{CON}(d = 1, \theta = 0^0) \), \( f_2 = \text{CON}(d = 1, \theta = 45^0) \), \( f_3 = \text{CON}(d = 1, \theta = 90^0) \), \( f_4 = \text{CON}(d = 1, \theta = 135^0) \), \( f_5 = \text{CON}(d = 12, \theta = 0^0) \), and \( f_6 = \text{CON}(d = 16, \theta = 90^0) \).

Training and Testing Sets Having obtained the feature parameters for fabric defects, the next step is to generate training and testing sets. From each of the four kinds of parameters for fabric defects, the network to develop a classifier of fabric defects. Using a software package called Professional II / PLUS [10], we tried different network topologies: a 6-12-5 network gave the best results. The input consisted of six input nodes corresponding to the number of feature parameters. A hidden layer of twelve nodes fed into the output layer of five nodes, representing the five kinds of fabric defects (including the normal fabrics). Learning rate and momentum factor were 0.5 and 0.4, respectively. For this study, we used a Sigmoid transfer function.

VI. RESULTS AND DISCUSSION

Selecting Feature Parameters

Each kind of defect found on a certain area of a fabric will result in a different texture from that of the normal fabrics. The textures of different kinds of fabric defects should be different from each other as well.

Based on the point of view mentioned above, a good feature should satisfy two requirements. The first is that those that are slightly different textures with similar general characteristics should have numerically close feature values, and the second is that the features from different classes should be quite different numerically from each other. Furthermore, in order to conserve computation time, it is necessary to find a set of numerical features (a feature vector) whose dimensions are much lower than the original data of texture imaging.

The degree of success of an inspection system heavily depends on how adequate, general, and compact the representation of each kind of fabric defect is. For instance, each texture of the normal fabrics and the four kinds of defective fabrics are illustrated in Figure 7A.

Through human vision, the textures of both normal and defective fabrics can easily be classified, but when applying the pattern recognition technique to classification of fabric defects, it is essential to extract some good feature parameters mentioned above.

<table>
<thead>
<tr>
<th>Fabric defects</th>
<th>Input vector, ( f_1, f_2, f_3, f_4, f_5, f_6 )</th>
<th>Output vector</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal</td>
<td>((0,0,0,0,0,1))</td>
<td>(1,0,0,0)</td>
</tr>
<tr>
<td>Nep</td>
<td>((0,0,0,1,0,0))</td>
<td>(0,1,0,0)</td>
</tr>
<tr>
<td>Broken end</td>
<td>((0,1,0,0,0))</td>
<td>(0,1,0,0)</td>
</tr>
<tr>
<td>Broken pick</td>
<td>((0,1,0,0,0))</td>
<td>(0,1,0,0)</td>
</tr>
<tr>
<td>Oil stain</td>
<td>((0,1,0,0,0))</td>
<td>(0,1,0,0)</td>
</tr>
</tbody>
</table>

Fig. 6. Results of ASM and CON with the change of distance at being equal to \(0^0\) and \(90^0\) (A) ASM (\(\theta = 0^0\)) (B) CON (\(\theta = 0^0\)) (C) ASM (\(\theta = 90^0\)) (D) CON (\(\theta = 90^0\))

Randomly partitioned into two sets. One was used for training, shown in Table II, and the other for testing, shown in Table III.

V. NEURAL NETWORK ARCHITECTURE

In this paper, we used a back-propagation neural network to develop a classifier of fabric defects. Using a software package called Professional II / PLUS [10] , we tried different network topologies: a 6-12-5 network gave the best results. The input consisted of six input nodes corresponding to the number of feature parameters. A hidden layer of twelve nodes fed into the output layer of five nodes, representing the five kinds of fabric defects (including the normal fabrics). Learning rate and momentum factor were 0.5 and 0.4, respectively. For this study, we used a Sigmoid transfer function.
occurrence matrix. Among them, contrast (CON), which is can be applied to extract useful information from a co-

First, we extracted CON measures along four directions of parameters (CON measures along 0°, 45°, 90°, 135°, respectively), we extracted two more feature parameters for fabric defect to represent the original image data and conserve computation time.

Artificial neural networks (ANNs) are capable of many functions, among them, clustering, mapping, optimization, and classification [3, 7, 11]. In this study, we used the network as a supervised classifier, which is a decision-making process that requires the network to identify the category best representing an input fabric defect texture pattern. The identifying method is outlined in a block diagram shown in Figure 8.

Accuracy and Efficiency of Recognition

In the past, the traditional technique of pattern recognition has been pattern matching, which was easily affected by noise, thus ruining its accuracy. In addition to a highly parallel operation and quick response, artificial neural networks also have the advantage of fault tolerance.

Some samples of broken end defective fabric texture used for the ANN classifier in the testing process are shown in Figure 7B. These samples, whose textures differ somewhat from each other, can still be accurately classified by an ANN. The results in Table IV show that the accuracy rate of classification is as high as 96.96.

VI. CONCLUSIONS

Feature extraction for each 100 X 100 digitized fabric defect texture takes around 30 seconds to obtain the six feature parameters, f1-f6, using the gray level co-

Table 3. Training set for various kinds of fabric defects.

<table>
<thead>
<tr>
<th>Fabric defects</th>
<th>Input vector, f1, f2, f3, f4, f5, f6</th>
<th>Output vector</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal</td>
<td></td>
<td>(1,0,0,0)</td>
</tr>
<tr>
<td>Nep</td>
<td></td>
<td>(0,1,0,0)</td>
</tr>
<tr>
<td>Broken end</td>
<td></td>
<td>(0,0,1,0)</td>
</tr>
<tr>
<td>Broken pick</td>
<td></td>
<td>(0,0,0,1)</td>
</tr>
<tr>
<td>Oil stain</td>
<td></td>
<td>(0,0,0,0,1)</td>
</tr>
</tbody>
</table>

Fig. 7. (A) A 100 x 100 digitized sample of each texture of normal fabrics and various kinds of defective fabrics, from top and from left to right Normal, Nep, Broken End, Broken Pick, Oil Stain (B) Samples of various textures of Broken End fabric defect determining the repetition units of normal fabrics along the horizontal (d = 12) and vertical directions (d = 16)

In Tables II and III, broken ends have a large f6 value and a small f4 value while broken picks have a small f6 value and a large f4 value. From these two feature parameters, we obtained a more specific feature vector for classifying different fabric defects.

Using the gray level co-occurrence matrix [9], we obtained six feature parameters for each kind of fabric defect to represent the original image data and conserve computation time.

Haralick et al. [4] proposed a variety of measures that can be applied to extract useful information from a co-occurrence matrix. Among them, contrast (CON), which is a measure of the amount of local variation present in an image, is able to characterize each kind of fabric defect. First, we extracted CON measures along four directions of each sample defect (f1, f2, f3, f4) from the co-occurrence matrix to characterize each defect. To promote the correct classification rate in fabric defects, apart from f1-f6 feature parameters (CON measures along 0°, 45°, 90°, 135°, respectively), we extracted two more feature parameters f5 and f6 by

\[(f_{11}, f_{12}, f_{13}, f_{14}, f_{15}, f_{16}) = \text{CON}(0°, 0°, 0°, 0°, 0°, 0°)\]

\[(f_{21}, f_{22}, f_{23}, f_{24}, f_{25}, f_{26}) = \text{CON}(135°, 135°, 135°, 135°, 135°, 135°)\]

\[(f_{31}, f_{32}, f_{33}, f_{34}, f_{35}, f_{36}) = \text{CON}(45°, 45°, 45°, 45°, 45°, 45°)\]

\[(f_{41}, f_{42}, f_{43}, f_{44}, f_{45}, f_{46}) = \text{CON}(90°, 90°, 90°, 90°, 90°, 90°)\]

\[(f_{51}, f_{52}, f_{53}, f_{54}, f_{55}, f_{56}) = \text{CON}(0°, 135°, 135°, 45°, 45°, 90°)\]

\[(f_{61}, f_{62}, f_{63}, f_{64}, f_{65}, f_{66}) = \text{CON}(0°, 45°, 90°, 135°, 0°, 0°)\]

Accuracy and Efficiency of Recognition

In the past, the traditional technique of pattern recognition has been pattern matching, which was easily affected by noise, thus ruining its accuracy. In addition to a highly parallel operation and quick response, artificial neural networks also have the advantage of fault tolerance.

Some samples of broken end defective fabric texture used for the ANN classifier in the testing process are shown in Figure 7B. These samples, whose textures differ somewhat from each other, can still be accurately classified by an ANN. The results in Table IV show that the accuracy rate of classification is as high as 96.96.
occurrence matrix method with an IBM PC and CPU 486 DX-50. Classification of texture takes only a fraction of a second, and the main computational requirements of an ANN occur during its training process, which can be performed off line. Thus a pattern recognition system in accordance with ANN is a pretty good classifier for online monitoring of fabric defects in weaving. Through the feature vector consisting of \( f_1 \), \( f_2 \), \( f_3 \) of each kind of fabric defect. The detection process uses the learning capacity and fault tolerant nature of the artificial neural network. Through the supervised learning algorithm of back-propagation, the neural network can become a good classifier for fabric defects. Experiments on various kinds of fabric defects have yielded satisfactory results.

Table 4. results of discrimination Output vector

<table>
<thead>
<tr>
<th>Fabric defects</th>
<th>Desired</th>
<th>Actual</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>a Normal</td>
<td>1.0000</td>
<td>0.0000</td>
<td>.8702</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>.0009</td>
</tr>
<tr>
<td></td>
<td>0.0000</td>
<td>0.0000</td>
<td>.1220</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>.1920</td>
</tr>
<tr>
<td></td>
<td>0.0000</td>
<td>0.0000</td>
<td>.8695</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>.0872</td>
</tr>
<tr>
<td></td>
<td>0.0000</td>
<td>0.0000</td>
<td>.0310</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>.1364</td>
</tr>
<tr>
<td></td>
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<td>0.0000</td>
<td>.0144</td>
</tr>
<tr>
<td></td>
<td>1.0000</td>
<td>0.0000</td>
<td>.6864</td>
</tr>
<tr>
<td></td>
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<td>.0482</td>
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<td>0.0000</td>
<td>0.0000</td>
<td>.0305</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>.3440</td>
</tr>
<tr>
<td></td>
<td>0.0000</td>
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</tr>
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<td>.0382</td>
</tr>
<tr>
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<td>0.0000</td>
<td>.0240</td>
</tr>
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<td></td>
<td>.0276</td>
</tr>
<tr>
<td></td>
<td>0.0000</td>
<td>0.0000</td>
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</tr>
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<td>0.0000</td>
<td>.8926</td>
</tr>
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<td></td>
<td></td>
<td>.0119</td>
</tr>
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<td>0.0000</td>
<td>0.0000</td>
<td>.1027</td>
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REFERENCE


AUTHOR'S PROFILE

Dr. P. Satyanarayana presently working as a java and integration Lead developer to the ministry of interior affairs at kingdom of Saudi Arabia. Awarded Ph.D. by Osmania University in the year 2014 in Neural networks applications to textile industry.

Prof. M. V. Ramana Murthy, Professor in department of mathematics and computer science, Osmania University, since 1985. Obtained Ph.D. degree from Osmania University in 1985 and visited many a countries across the globe in various capacities and participated in many academic programs. Research fields includes plasma, Artificial Neural Networks, and Network computational securities.