CHAPTER 6
CONCLUSIONS AND FUTURE SCOPE OF THE WORK

In this research work, segmentation concept has been used for 3D face modeling. Features values for training the proposed BPA/ RBF/ ESNN are obtained by using CC algorithm. Prominent points corresponding to the local objects of a face are projected onto Ruth’s face.

Segmentation accuracy has been calculated by a) number of pixels correctly segmented inside a face, b) number of objects correctly segmented inside a face, and c) by overlapping the segmented image onto original.

3D facial modeling accuracy is expressed through PSNR by projecting the segmented points of the two orientations of the face of a person onto Ruth’s face.

6.1 PEAK SIGNAL TO NOISE RATIO (PSNR)

Peak signal to noise ratio (PSNR) has many definitions based on applications. It can be between the original image and noised image, or, the original image and the reconstructed image after transmission or original image and the profile of the segmented image.

<table>
<thead>
<tr>
<th>Table 6.1 Original and segmented images</th>
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</thead>
<tbody>
<tr>
<td>Original (I)</td>
</tr>
<tr>
<td>Segmented (k)</td>
</tr>
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</table>

Defining a clear-cut segmented profile is a related concept. As long as the objects are separated from the background of an image, segmentation can be accepted.

The presence of differences among the segmented profiles of the objects and the profiles of the objects in the original image can be found through comparisons of the images. When the presence of difference is equivalent to a value of zero, then the PSNR would
become infinity. This situation is ideal. Table 6.1 presents original and segmented images for person-1.

A well-defined range of PSNR value for different applications is between 30 dB (decibel) and 50 dB for lossy image and video compression and 20 dB to 25 dB for wireless transmission. Higher the PSNR better is the segmented image.

### 6.1.1 Procedure for Finding PSNR for the Segmentation

**Step 1:** If the original image is RGB, then second plane (green Plane) is chosen. Both the original and segmented images are binary operated using ‘And’ing.

**Step 2:** The number of pixels in excess or in less segmented in the segmented image when compared with the original image, is used for calculation of PSNR value.

In this research work, PSNR is evaluated between the original image and the segmented image.

Let the original image to be used for segmentation is $I_{i \times m}$. Let the segmented image is $K_{m \times n}$.

Mean squared (MSE) images = $\frac{1}{m \times n} \sum_{i=1}^{m} \sum_{j=1}^{n} [I(i, j) - k(i, j)]^2$ (6.1)

$\text{PSNR} = 10 \log_{10}\left(\max (\text{intensity of original image})^2 / (\text{MSE})_{\text{images}}\right)$ (6.2)

**PSNR for Segmentation**

The average peak signal to noise ratio (PSNR) of the segmentation algorithms are:

- CC = 27.36 db, BPA is 24.32db, RBF is 38.37db, and ESNN is 42.31db.

**PSNR for 3D Facial Modeling**

The average peak signal to noise ratio (PSNR) of the facial modeling by CC is 24.36db, BPA is 23.27db, RBF is 30.76db, and ESNN is 33.71db. The PSNR values of the proposed ANN algorithms for modelling are less when compared to the PSNR of the segmentation outputs of the ANN algorithms. The reason for the small values are due to mismatching of the chin, cheek and forehead profiles as the size of the Ruth’s face is smaller than the size of the faces of persons used in this research work. Figure 6.1 presents the PSNR values for segmentation and 3D facial modeling.

For both segmentation and 3D facial modeling, the PSNR values are small for CC when compared to that of BPA/RBF/ESNN. Even though there is less PSNR value for CC,
the performance of the ANN algorithms are better when they are trained on the features extracted by CC. ESNN has highest PSNR for segmentation and 3D facial modeling when compared to that of CC/BPA/RBF algorithms.

![Fig.6.1 PSNR for segmentation and 3D facial modeling](image)

Table 6.2 mentions the requirements of architecture and training properties for the BPA/RBF/ESNN algorithms.

<table>
<thead>
<tr>
<th>ANN algorithm</th>
<th>Input layer nodes, output layer nodes, number of patterns for</th>
<th>Number of nodes/ centers/reservoirs in the hidden layer</th>
<th>Number of iterations for convergence</th>
<th>Mean squared error</th>
</tr>
</thead>
<tbody>
<tr>
<td>CC</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BPA</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RBF</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ESNN</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Algorithm</td>
<td>Nodes 3 to 9 highest segmentation occurs</td>
<td>1366-1626</td>
<td>Optimal value= 0.01853</td>
<td></td>
</tr>
<tr>
<td>-----------</td>
<td>----------------------------------------</td>
<td>--------</td>
<td>------------------------</td>
<td></td>
</tr>
<tr>
<td>BPA</td>
<td>3 and 1, 10000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RBF</td>
<td>3 and 1, 500</td>
<td>1</td>
<td>Not applicable</td>
<td></td>
</tr>
<tr>
<td>ESNN</td>
<td>3 and 1, 100</td>
<td>1</td>
<td>Not applicable</td>
<td></td>
</tr>
</tbody>
</table>

**Calculation of computational complexity**

The time of computation keeps fluctuating in a single system. The time varies depending based on the load on the CPU. However, the computational complexity can be mentioned to give an overall computational load in segmentation.

The computational complexity of an algorithm is defined as the number of arithmetic operation required for training the proposed algorithms. Empirical formulae for computational efforts are presented for BPA/ RBF/ ESNN in Table 6.3.

**Table 6.3 Computational complexity evaluation**

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Formulae for evaluating the number of arithmetic computations</th>
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</table>
| BPA       | Forward computational effort in BPA for one pattern is given by: | \[
2 \sum_{i=1}^{L-1} n_{i+1}(n_i + 1) \] .......................... (6.3) |
|           | Reverse computational effort in BPA for one pattern is given by: |
|           | \[
a_o = 9n_L + 7 \sum_{i=1}^{L-1} n_i n_{i-1} + \sum_{i=L-1}^{2} (4n_i + 5)n_{i-1} \] ........... (6.4) |
|           | TCE for BPA= \{ (ite) a_0 \} n_p ...............................(6.5) |
| RBF       | TCE for RBF = \{ 2n_c + \text{inv}(n_c^2) \} n_c \} n_p, .....................(6.6) |
| ESNN      | TCE for ESNN =\{ 2n_c + \text{inv}(n_c^2) \} n_c \} n_p  \} n_p, (6.7) |

where:

TCE is Total Computational Effort,
6.2 SUMMARY

This thesis has proposed and implemented three ANN algorithms to improve segmentation of the facial images and projections of points of the segmented images onto a standard Ruth’s face. Facial images of ten people are considered with left and right orientations. Features are extracted from these images by using CC algorithm. These features are used as patterns for training BPA/ RBF / ESNN for segmentation of the facial images.

In the 3D modeling of the faces, the segmented points from the local objects of a face are projected onto Ruth’s face.

1. Front and side views of a person are taken for 3D modeling.
2. The contextual clustering algorithm for extracting features from a face and the features are used for training BPA / RBF / ESNN.
3. The iterations taken for the BPA to converge are 1366 when 10000 patterns are used.
4. Only one iteration is used for training RBF / ESNN as no stopping criteria are considered.
5. The average peak signal to noise ratio (PSNR) of the segmentation algorithms are CC=27.36 db, BPA is 24.32db, RBF is 38.37db, and ESNN is 42.3db.
6. The average peak signal to noise ratio (PSNR) of the facial modeling by BPA is 23.27db; RBF is 30.76db, and ESNN is 33.71db. The PSNR values of the proposed ANN algorithms for modelling are less when compared to the PSNR of the segmentation outputs of the algorithms. The reason for the low values are due to mismatching of the chin, cheek and forehead profiles as the size of the Ruth’s face is smaller than the size of the faces of persons used in this research work.
7. The ESNN and RBF algorithms helped in improving the segmentation accuracy based on the following aspects: a) a minimum number of patterns that is used for training the algorithms, and b) In the training process of the algorithms, initial weights are
converted into final weights. These final weights can be commonly used for segmenting all the faces of 10 persons.

6.3 FUTURE SCOPE OF THE WORK

The thesis work has given bright hopes for the future researchers to consider contextual clustering, BPA/ RBF/ ESNN for segmenting facial images. Many ANN algorithms can be combined to use for developing 3D facial modeling.

Different template face model should be available in the database depending on the appearance of the faces of various sections of people living in different areas. Ruth’s video may not be suitable for faces of all types of individuals.