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Restoration of Partially Occluded Shapes: A Comparative Evaluation using Shapes of Faces

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Abstract

One of the major difficulties encountered in the development of face image processing algorithms, is the possible presence of occlusions that hide part of the face images to be processed. Typical examples of facial occlusions include sunglasses, beards, hats and scarves. In our work we address the problem of restoring the overall shape of faces given only the shape presentation of a small part of the face. In the experiments described in this paper the shape of a face is defined by a series of landmarks located on the face outline and on the outline of different facial features. We describe the use of a number of methods including a method that utilizes a Hopfield neural network, a method that uses Multi-Layer Perceptron (MLP) neural network, a novel technique which combines Hopfield and MLP together, and a method based on associative search. We analyze comparative experiments in order to assess the performance of the four methods mentioned above. According to the experimental results it is possible to recover with reasonable accuracy the overall shape of faces even in the case that a substantial part of the shape of a given face is not visible. The techniques presented could form the basis for developing face image processing systems capable of dealing with occluded faces.

1. Introduction

There has been substantial research in the areas of automatic face recognition, face detection and face reconstruction in recent years [17]. One common problem for such applications is when a face image is occluded by other objects (e.g., sunglasses). This results in decreased performance and robustness of systems dealing with face recognition, detection or reconstruction tasks.

This paper addresses the occlusion problem in the case of reconstructing the shape of an occluded facial region. The motivation of our work comes from important applications relying on robust face recognition and reconstruction, free of restrictions such as lighting, expression, pose, size and occlusion. Such applications include among others, human-robot-interaction, human-computer-interaction, information security, CCTV access control, automated surveillance, suspect tracking and investigation (see [17] for a review).

In our experiments the shape of a face is represented with the co-ordinates of a series of landmarks characterizing the shape of the overall face and the shape of individual facial features. In our work we assume that the positions of the landmarks on the visible facial region are available. More precisely each contour face is represented with 68 points given by (x,y) co-ordinates located as shown on Figure 1.

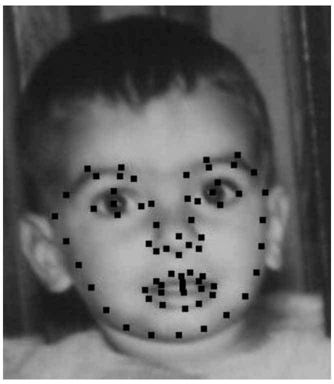

Figure 1:
Original contour face image defined by 68 landmarks

The aim of our work is to reconstruct the shape of an occluded facial region, given a shape representation of a visible region. We consider several different cases of occlusion, grouped in two settings, examples of which are given in Figures 2 and 3.

The first setting consists of six sets of occluded face shapes corresponding to occlusion of different parts of a face. For example, in Case 1 a small part of the right lower part of a face is missing, in Case 2 the right part of a face is missing and in Case 3 the entire lower part of a face is missing, as shown in Figure 2. Excluding all the points that were not excluded in Cases 1 – 3 and including all the points that were excluded in Cases 1 – 3, respectively, generates the Cases 4 – 6, as shown in Figure 2.

The second setting of occluded face shapes consists of five sets which are generated by randomly replacing the co-ordinates of 10%, 30%, 50%, 70% and 90% of the points in the original face shapes with random numbers in the range between the minimum and the maximum of the co-ordinates of the visible points. Typical examples of these occlusion cases are shown in Figure 3.

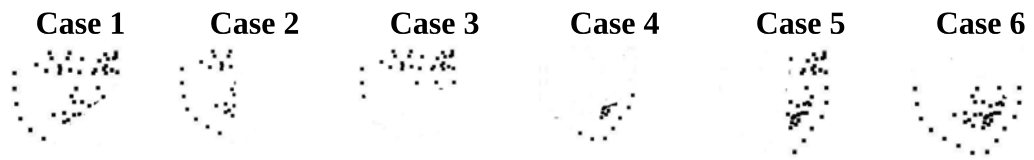

Figure 2:
Cases 1 – 6: Occlusion of different parts of the face

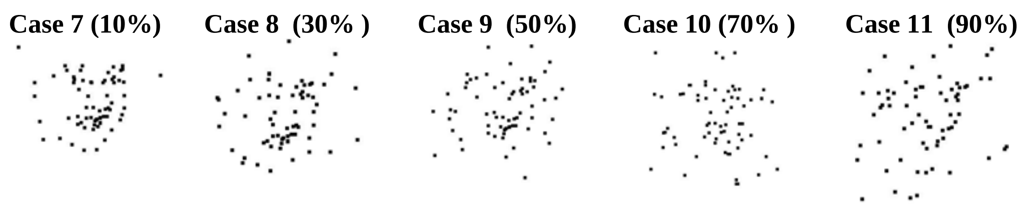

Figure 3:
Cases 7 – 11: Occluded face shapes obtained by replacing an increasing number of points in the original face shapes with random numbers

Neural network models, including Multi-Layer Perceptron (MLP), Hopfield and combination of these, are trained for each occlusion case with the co-ordinates of specific facial features to give as outputs the co-ordinates of landmarks corresponding to missing facial features. We also investigate the use of a method based on associative search for predicting the co-ordinates of the missing facial shape points using the co-ordinates of the visible points. The performance of the four methods is assessed by comparative experiments run on a publicly available face image database, the FG-NET Aging Database [18]. Typical samples from the database are shown in Figure 4.

Figure 4: Typical face images from FG-NET Aging Database

The restoration of face shapes presents an ideal test scenario for our work because face shapes display significant variation arising by differences in the shapes between different individuals. On top of that, face shapes undergo within-individual variations caused by changes in the 3D orientation and expression of faces.

The remainder of the paper is organised as follows: in section 2 we present a brief overview of the relevant literature, in section 3 we describe the methods used in our experiments, in section 4 we describe the experimental set-up, present the results obtained, and finally in section 5 we give our conclusions.

2. Literature review

A number of researchers have recently made contributions for resolving the problem of occlusion in face recognition, face detection, face identification and face reconstruction.

Kurita et al. [11], suggest recursive use of an auto-associative MLP network for reconstruction of occluded faces. Subsequently this approach is applied to face recognition and face detection. The idea of using an auto-associative neural network is based on the observation that auto-associative memory can recall a whole image from its partial image [10]. The suggested system is built with the aim of performing face recognition and the restoration of occluded face images and is limited only to the cases where the occluded face images belong to individuals whose images have been used during the learning phase.

Martinez [12], [13] used a variation of the eigenface approach [16] in order to deal effectively with the problem of recognizing occluded face images. They divide the facial region into six local regions and use a PCA (Principal Component Analysis) based local model for each local part. During recognition, the contribution of each part is weighted by the distance of the corresponding PCA coefficients from the centroid of the distribution, so that the contribution of the occluded facial regions in the recognition process is minimized.

Park et al. [14], use recursive PCA for removing spectacles from face images. Given a face image of a subject wearing spectacles, they code and subsequently reconstruct the face. The difference between the reconstructed and original image is processed in order to enhance the occluded regions. The occluded regions detected in the difference image are replaced by the corresponding pixels from the mean image among the training set. This procedure is repeated until the resulting image converges. Hwang and Lee [9] describe a method for restoring the appearance of occluded faces in images. Given an occluded face image and information about the location and size of the occlusion, they use least squares analysis for estimating the optimum weights required for decomposing the appearance of the non-occluded regions as a weighted sum of basis images. The same weights are used in conjunction with basis images of the occluded region for restoring the appearance of the occluded facial regions.

Apart from applications related to face recognition, the general topic of object appearance restoration features in other applications. Bhanu and Lin [3] use a stochastic approach based on hidden Markov modelling for the recognition of occluded objects in synthetic aperture radar images and automatic target recognition. Fukushima [4] suggests a neural network model for recognition of partly occluded letters based on the hypothesis that it is easier to recognize a letter covered with a visible object than when the letter has completely missing parts. His proposed model is an extension of the neocognitron model [5] that models the visual system with hierarchical multi-layer architecture. Fukushima [6] further develops a hierarchical multi-layered neural model that can restore missing portions of partly occluded patterns. The suggested model can restore the shape of a partly occluded pattern, if the pattern has been used in the learning phase and attempts to complete an unlearned pattern by interpolating and extrapolating visible edges. The proposed neocognitron based models for recognition and restoration of occluded patterns have been tested only on patterns of partly occluded letters and numerals.

3. Methods

3.1 Hopfield Neural Network

The Hopfield Neural Network [7], [8] is a binary artificial network which is used to store patterns in an associative or content-addressable way so that when the network is presented with noisy or partial information the full pattern can be recovered. In order to apply the Hopfield model to the problem of recovering occluded face shapes we need to first convert the facial co-ordinates into a binary form and represent each shape as a binary vector. For doing this we use the natural binary encoding which provides high resolution and it enables the conversion of the binary co-ordinate representations back to a decimal form. An alternative encoding scheme, which has been considered, is the so-called thermometer encoding [2]. This encoding has the property of preserving the proportionality of the Hamming distances and Euclidean distances between vectors, but it was not adopted as it becomes impractical if higher resolution is required. The co-ordinates (x, y) corresponding to the facial shape landmarks are scaled so that each x and y is in the interval [0, 31] and subsequently converted to 5 bit representation using the natural binary encoding. In this way each face shape is represented as a binary vector of 680 bits (2 x 68 x 5). For addressing the capacity limitation of the Hopfield network we train the model only with 102 face representations (15% of 680 neuronodes) from the data set. The natural binary encoding is applied to each of the distorted sets of face shapes. The trained Hopfield model is presented consequently with the different sets of distorted encoded face representations, which correspond to the different occlusion cases (Case 1 – Case 11) described in the Introduction (see Figures 2 and 3). The recovered patterns are decoded back to present each face shape as 68 decimal (x, y) co-ordinates. A block diagram of the method is shown in Figure 5.

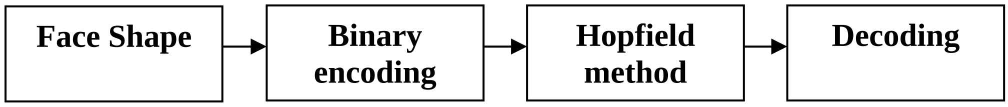

Figure 5: Block diagram of the method using Hopfield model

3.2 Multilayer Perceptron (MLP)

We have investigated the use of Multilayer Perceptrons (MLPs) with the backpropagation learning algorithm [15] for reconstructing of occluded face shapes by training eleven different models for each occlusion case corresponding to the case settings described in the introduction. Input vectors for each MLP model are the 136 dimensional vectors corresponding to the 68 (x, y) co-ordinates representing the respective occluded face shape in the specific occlusion case. The co-ordinates of the occluded points are replaced with random numbers in the range of the co-ordinates of the visible points. Output vectors contain the 136 elements corresponding to the 68 (x,y) co-ordinates representing the shapes of the original sample faces. Based on the training sets each type of network is evaluated in order to establish the optimal architecture and optimal parameters. In each case the generalisation capability of the neural network is assessed as a function of the initial parameters of the respective network.

3.3 Hopfield – MLP

Combining different neural network architectures is a common approach for improving generalization performance and efficiency of neural network models. We propose a combination of the Hopfield and MLP network models which to the best of our knowledge has not been previously employed elsewhere. The Hopfield method gives a pattern of 680 bits as a result for each recovered face shape. These patterns are decoded to present a face shape as 68 (x,y) co-ordinates, and then one of the already trained MLPs described in 3.2 is applied to these results. If we assume that we have achieved a certain percentage of correct restoration of the occluded shapes with the

Hopfield method, then using, for example, one of the trained MLPs for an occlusion case with random missing points, could result in further improvement of these results. A block diagram of this method is shown on Figure 6.

Figure 6: Block diagram of the method using Hopfield - MLP models

3.4 Associative Search

For this method we find the similarity between the visible part of a given shape and the corresponding part of the shape among all faces in the training set. Assuming that in the case that two shape segments are similar, the remaining parts of the shapes should also be similar, we propose that the hidden shape can be reconstructed as a weighted combination of all shapes in the training set. The weights used in our framework are proportional to the similarity measure between the given shape segment and the corresponding segments from faces in the training set. Equation 1 shows the formula used for calculating the weights.

$$w_i = \frac{1}{d_i \sum_{j=1}^{n} \frac{1}{d_j}} \qquad \text{Equation 1}$$

where w_i is the weight used for the i^{th} training sample and d_i is the mean Euclidean distance between the landmarks in the given shape segment and the corresponding shape segment in the i^{th} training face shape.

The co-ordinates of the occluded of a face shape are calculated as a linear combination of weights and co-ordinates of the corresponding points of the training set:

$$x = \sum_{i=1}^{n} w_i x_i \qquad \text{Equation 2}$$

where x_i is the corresponding coordinate of the point to be recovered in the i^{th} training face shape from the training set and n is the number of training samples.

In effect this method compares the similarity between the non-occluded shape given and the corresponding shapes of each of the samples in the training set. According to the similarity measure, different training samples influence in a different way the prediction of the occluded shape. This approach bears similarities to the method reported by Hwang and Lee [9], but in our case the method is applied to shape co-ordinates rather than to the parameters of the morphable model. Also, Hwang and Lee use least squares for estimating the weights required.

4 Experimental Evaluation

4.3 Experimental set up

In our experiments we use the FG-NET Aging Database [18], which is publicly available. The image database in question contains 1002 face images from 82 different individuals. On average there are 12 images available per subject. For each face image in the FG-NET Aging Database, a detailed shape annotation consisting of 68 landmarks (see figure 1) is also publicly available. In our experiments we use the shapes of 102 face images from 8 subjects in the database for training (due to the Hopfield network capacity limitation, see Section 3.1) and the remaining 900 face shapes of the remaining 74 subjects for testing. Prior to our experiments the shapes of all faces were normalized so that all face shapes had the same centre of gravity and approximately the same height. It is important to highlight that in our experiments we did not use face shapes of the same subjects both in the training and testing sets.

We use two error measures to compare the performance of the different methods. The first error measure is the mean Euclidean distance between the shape of the original faces and the corresponding recovered face shapes, which we call the *overall error*. The second error measure is the mean Euclidean distance between the original points from the occluded parts and the corresponding recovered points, which we call *restricted error*.

The training and testing time for the Hopfield model is in the order of seconds. The training time for the MLP method is in the order of minutes (1 – 2 min) and the testing time in the order of seconds. The experiments using the MLP method are performed with learning rate varying 0.1 and 0.2, momentum between 0.7 and 0.9, number of hidden units between 10 and 25, and number of iterations between 1000 to 1500. According to our experiments the optimal network architecture has one hidden layer with 15 hidden neuronodes, learning rate equal to 0.1 and momentum equal to 0.7. The combined Hopfield – MLP method additional training since the training for the Hopfield and the MLP networks is done separately as described in the previous paragraph. The testing time for the combined Hopfield-MLP method is in the order of seconds. Associative Search method does not require training and the testing time is in the order of seconds.

4.2 Results

Tables 1 and 2 display the testing set results of applying the Hopfield, Hopfield - MLP, MLP and Associative Search methods to the different occlusion cases 1 – 11 described in the Introduction. Table 1 shows the *overall error* obtained by calculating the mean Euclidean distance between the face shapes in the testing set and the face shapes recovered using each of the methods presented in section 3. The standard deviation of the *overall error* is also quoted for each case.

Table 1: Mean and standard deviation of the Euclidean distances between recovered face shapes and original face shapes for testing set in Cases 1 - 11 (*overall error*)

Method	**Case number**												**Average of means 1-6**
	1		**2**		**3**		**4**		**5**		**6**		
	mean	st dev	mean	st.dev.	mean	st. dev.	mean	st. dev.	mean	st. dev.	mean	st.dev.	
Hopfield	**0.89**	***2.33***	**3.21**	***1.68***	**4.09**	***1.77***	**6.11**	***1.9***	**2.69**	***1.72***	**2.33**	***1.93***	**3.22**
Hopfield – MLP	**0.55**	***2.14***	**2.05**	***1.67***	**2.65**	***1.97***	**3.91**	***2.22***	**1.67**	***1.74***	**1.45**	***2.01***	**2.05**
MLP	**0.41**	***1.3***	**2.6**	***1.93***	**2.97**	***1.96***	**4.42**	***2.4***	**1.88**	***1.45***	**1.25**	***1.09***	**2.26**
Associative Search	**0.85**	***0.54***	**2.55**	***1.3***	**2.86**	***1.41***	**3.90**	***1.91***	**2.27**	***1.56***	**1.99**	***1.11***	**2.40**

Method	**Case number**										**Average of means 7-11**
	7		**8**		**9**		**10**		**11**		
	mean	st. dev.	mean	st.dev.	mean	st. dev.	mean	st. dev.	mean	st. dev.	
Hopfield	**0.48**	***2.25***	**1.34**	***1.77***	**2.19**	***1.81***	**3.19**	***1.76***	**3.59**	***1.85***	**2.16**
Hopfield – MLP	**0.31**	***1.82***	**0.87**	***1.66***	**1.4**	***1.79***	**2.02**	***1.77***	**2.32**	***1.94***	**1.38**
MLP	**0.22**	***0.91***	**0.77**	***0.94***	**1.17**	***0.97***	**2.23**	***1.57***	**2.77**	***1.85***	**1.43**
Associative Search	**0.49**	***0.27***	**1.27**	***0.66***	**1.92**	***1.03***	**2.61**	***1.35***	**2.85**	***1.44***	**1.82**

Figure 7 illustrates graphical comparison of the *overall error* corresponding to the different methods.

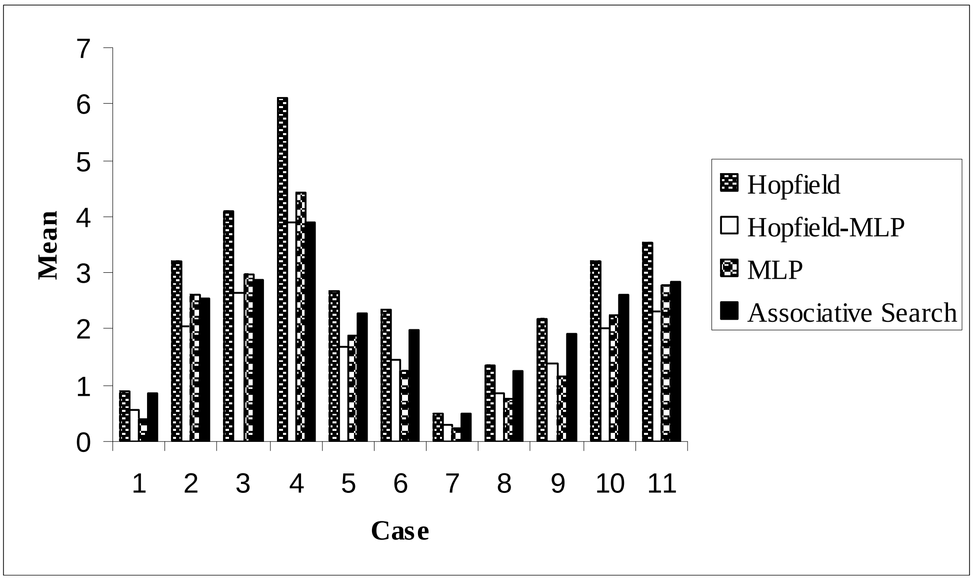

Figure 7: Comparing methods on *overall error*

Table 2 shows the *restricted error* which is the mean Euclidean distance between the real and predicted positions of landmark points by taking into account only the occluded landmarks and the standard deviation of the *restricted error*.

Table 2: Mean and standard deviation of the Euclidean distances between recovered occlusion points and original points for testing set in Cases 1 - 11 (*restricted error*)

Method	Case number 1 mean	st. dev.	2 mean	st.dev.	3 mean	st. dev.	4 mean	st. dev.	5 mean	st. dev.	6 mean	st.dev.	Average of means 1-6
Hopfield	**6.03**	***0.34***	**5.90**	***0.91***	**6.63**	***1.09***	**7.16**	***1.62***	**5.89**	***0.78***	**6.09**	***0.73***	**6.28**
Hopfield – MLP	**3.71**	***0.31***	**3.76**	***0.91***	**4.29**	***1.21***	**4.58**	***1.89***	**3.67**	***0.79***	**3.80**	***0.77***	**3.97**
MLP	**2.88**	***0.19***	**4.93**	***1.02***	**4.95**	***1.17***	**5.33**	***1.99***	**4.24**	***0.64***	**3.37**	***0.41***	**4.28**
Associative Search	**5.77**	***3.65***	**4.69**	***2.4***	**4.63**	***2.27***	**4.57**	***2.24***	**4.98**	***2.54***	**5.2**	***2.91***	**4.97**

Method	Case number 7 mean	st. dev.	8 mean	st.dev.	9 mean	st. dev.	10 mean	st. dev.	11 mean	st. dev.	Average of means 7-11
Hopfield	**5.47**	***0.19***	**5.06**	***0.47***	**5.52**	***0.72***	**5.86**	***0.95***	**6.10**	***1.09***	**5.60**
Hopfield – MLP	**3.03**	***0.16***	**3.29**	***0.44***	**3.54**	***0.69***	**3.71**	***0.96***	**3.94**	***1.14***	**3.50**
MLP	**2.52**	***0.08***	**2.99**	***0.24***	**3.04**	***0.37***	**4.22**	***0.83***	**4.84**	***1.05***	**3.52**
Associative Search	**5.5**	***3.02***	**4.79**	***2.49***	**4.85**	***2.59***	**4.81**	***2.48***	**4.85**	***2.45***	**4.96**

Figure 8 illustrates graphical comparison of the *restricted error* corresponding to the different methods.

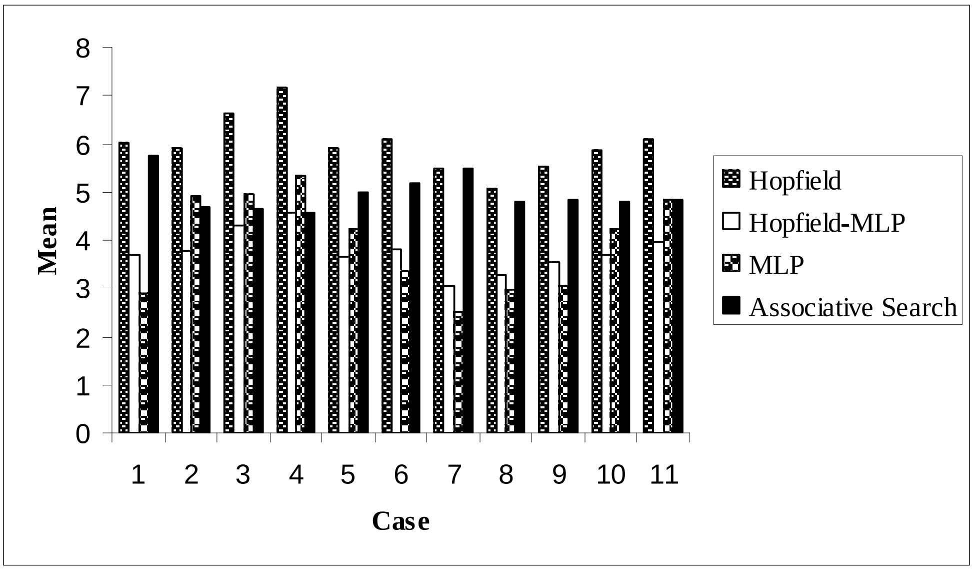

Figure 8: Comparing methods on *restricted error*

Image representations of a typical recovered face shape from the testing set for some of the occlusion cases using the Hopfield, Hopfield-MLP, Hopfield, MLP, and statistical methods are shown in Figure 9.

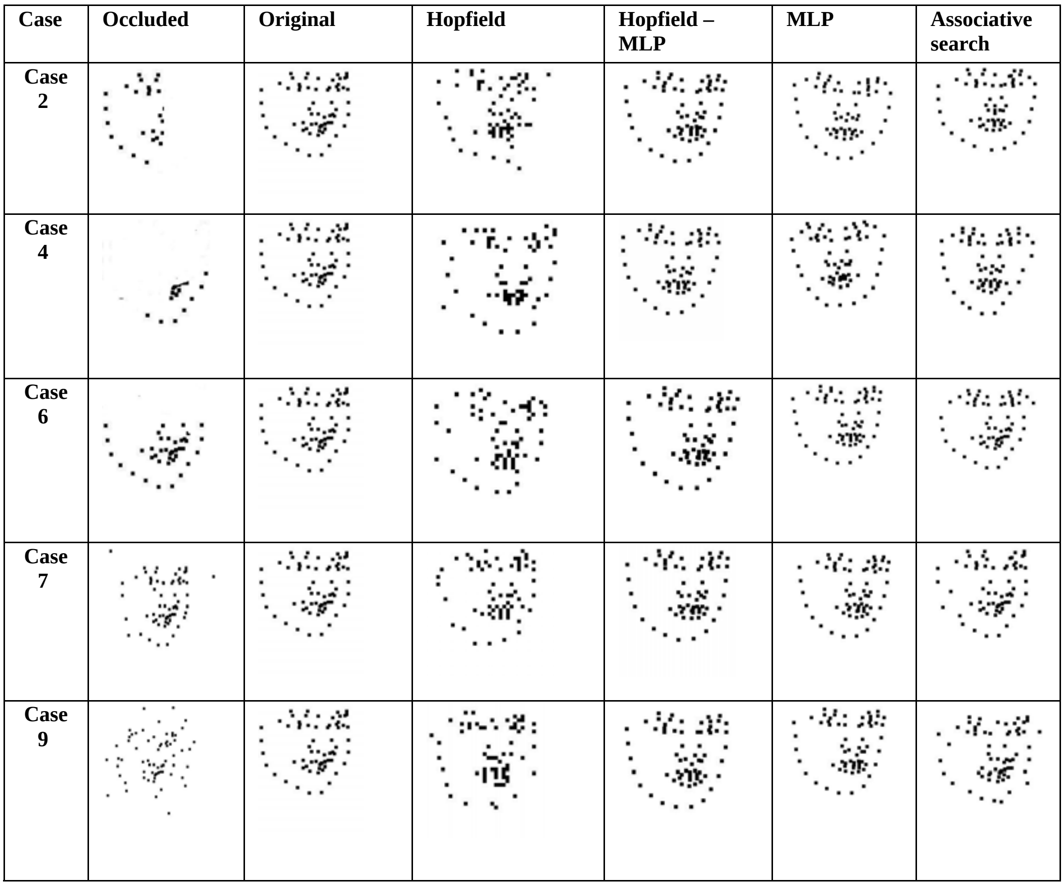

Figure 9: Face shapes as seen visually: occluded, original and reconstructed by the different methods

4.3 Discussion

The numerical results in Table 1 show, as expected, that in cases where only a small part of the face shape is missing (e.g. Cases 1 and 7) the *overall error* is small, and it gradually increases when larger parts of the face shape are missing (e.g. Cases 2, 5, 6, 9, 10 and 11). However, this increase of the *overall error* remains limited. This is also valid for the *restricted error* as we can see in Table 2 displaying the mean Euclidean distance only between the recovered occlusion points and the original points. For example, in the Cases 7 – 11 (corresponding to randomly missing percentage of points 10%, 30%, 50%, 70% and 90%) the Hopfield-MLP *overall error* increases from 0.31 to 2.32 and the *restricted error* remains less than 3.94. Similarly for the Associative Search based method the *overall error* increases form 0.49 to 2.85, and the *restricted error* is below 5.5.

The so-called *overall* and *restricted errors* for the Hopfield method are slightly higher than the other three methods in all of the cases, which are illustrated in the graphics in Figures 7 and 8. Most probably the results may improve if more than 5 bits are utilized to represent the values of the face shape co-ordinates. However, this would lead to increasing the size of the Hopfield network which would not be practical. It is well known that the Hopfield networks have two main drawbacks: limited capacity (15% of the network units) and local energy minima occurrences referred as spurious attractors. Theoretically we could overcome these limitations by using Boltzmann Machine neural network [1] (an extension of the Hopfield), which is a stochastic neural network with hidden neurons. However, in practice the learning process in the Boltzmann Machines is extremely slow making it impractical to be used in our application. In addition, since we already address one of the problems of the Hopfield network, namely the limited capacity (by training the network with patterns of the same number as 15% of the network nodes), we decided not to employ the Boltzman Machines in this study. As we suggest in section 3.3, by using one of the trained MLP networks for the occlusion cases 1-11, and feeding the results from the Hopfield network as inputs to the chosen MLP network, we obtain eventually better overall results. In our experiments we apply the already trained MLP network for case 7 (corresponding to the occlusion case of 10% randomly selected missing points) to the Hopfield results, and this results in considerable improvement of the *overall* and the *restricted errors* over the Hopfield method. In addition, the *overall* and the *restricted errors* improve over the MLP method in six cases, namely cases 2, 3, 4, 5, 10 and 11.

The last columns in Tables 1 and 2 show that the averages of all the *overall errors* and of all the *restricted errors* for the cases 1-6 and 7-11 are smallest for the combined Hopfield-MLP method. The visual results in Figure 9 demonstrate that when the Hopfield-MLP method is employed, the reconstructed shapes retain both the geometrical structure and the 3D orientation of the original face shape.

The numerical and visual results (Tables 1, 2 and Figure 9) show the feasibility of robust recovery of contour face shapes even in very general cases of occlusion such as missing large parts of the face shape (Cases 2, 4, 5 and 6) and a high percentage of random missing points (Cases 9, 10, and 11). The overall results in terms of the error measures achieved with the Hopfield, MLP, Hopfield - MLP and the Associative Search methods are similar. In the cases 1, 6, 7, 8, and 9 the overall and *restricted errors* for the MLP method are the smallest, in cases 2, 3, 5, 10 and 11 the overall and *restricted errors* for the combined Hopfield-MLP method are the smallest, and in case 4 the Associative Search method gives slightly better result than the combined Hopfield-MLP method. The standard deviations of the *restricted errors* in Associative Search (see Table 2) are significantly higher than the standard deviations in the other methods, indicating that the performance of this method is not uniform as it can be either very good in some cases but not satisfactory in other cases. In contrast, for the Hopfield, Hopfield-MLP and MLP methods, the lower standard deviations of the *restricted errors* obtained, indicate that there is more uniform performance over the testing set. One advantage of the Associative Search based method over the Hopfield and MLP methods is that it is simpler and it does not require training time.

5 Conclusions

We have presented an experimental comparative evaluation of the problem for restoration of occluded face shapes where the performance of classical neural network methods, such as Hopfield, MLP, and a combination of these, as well as Associative Search based method, were evaluated. The feasibility of such predictions is based on the strong correlation between the appearances of individual facial features.

According to the quantitative and visual results presented, the combination of Hopfield and MLP methods, the MLP method and the Associative search method give robust ways of reconstructing face shapes for very general cases of occlusion. Both the numerical results and the visual results show that the combined Hopfield-MLP, which constitutes to the best of our knowledge a novel technique, gives the best performance in most of the occlusion cases. The performance of the Hopfield, Hopfield-MLP and MLP methods is more uniform compared to the performance of the Associative Search method demonstrated with the lower standard deviations of the *restricted errors*. The Associative Search based method has the advantage over the other methods as being the simplest and fastest method.

The results show that it is feasible to develop a system based on classical methods for the automatic prediction of the shape of occluded facial features. With the suggested approaches, an occluded face shape of an unseen individual can be restored even when a large part of the face shape is missing. In practice if the type of an occluded shape does not belong to any of the occlusion cases for which we have pre-trained networks, a new network could be trained for the particular type of occlusion. Alternatively a bank of networks to cover a large number of typical occlusion cases can be trained, so that the most appropriate is chosen for a given occlusion type.

The problem of restoring occluded face shapes in such general forms of occlusion like the ones considered in our experiments has not been addressed up to now. This makes it impossible to compare directly the results from our approach to previously reported methods for restoration of occluded face shapes. Systems reported in [11], [12], [13] and [14] for restoration of partly occluded face images are developed with the aim of face recognition and in general are limited to restoration of face images of individuals whose images were used in the learning process. The performance of the neocognitron based models for recognition [5] and restoration [6] of partly occluded patterns, are only investigated so far on alphabetical and numerical symbols.

The experimental results show that it is possible to recover with reasonable accuracy the overall shape of faces even in the case that a large proportion of the shape of a given face is not visible. The feasibility of such predictions is based on the strong correlation between the appearances of individual facial features.

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