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Blurred 2D Face Restoration and Recognition Using Artificial Neural Network

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Abstract

Recognizing Human faces from images taken by digital camera is a challenging task because these faces are usually still and corrupted by various noises and blurring effects. The performance of face recognition system collapse significantly when blurred effect on faces. In this paper we present a novel method for image restoration and use the restored image as a input to the two layer feed forward artificial neural network. The performance validations, Gradients and learning rate of NN finds effective neural network solution for the recognition of the blur face by setting various parameters.

Keywords: Face Recognition, Blur, PSF, Restoration, Neural Network, Computer Vision, Soft Computing.

1. Introduction

In last decade, automatic of human faces has been developed into a highly active field of research. One of the best example of face recognition are eigenfaces [1]. Multiple commercial applications have been designed such as surveillance, security and access control system. Performance of face recognition systems drop drastically when blur effect is present on facial images. Blur can be obtainable by an incorrectly focused lens, relative motion between the camera and the scene, or atmospheric turbulence. Blurring is a form of bandwidth reduction of an ideal image owing to the imperfect image-formation process. It can be caused by relative motion between the camera and the scene or by an optical system that is out of focus. The process of image blur model could be

$$g(n_1, n_2) = (I * H)(n_1, n_2) + n(n_1, n_2) \quad 1.1$$

where (n_1, n_2) is the pixel location at which a convolution $*$ is performed between the original sharp image I and a point spread function (PSF) H , which has the same size with image I . n denotes the additive image noise coming from quantization, or other camera-induced errors. Many of algorithms for blur identification and its parameters exist now. Enlisted maximum likelihood blur estimation [3] and regularization approach [4]. Blurred images can be divided into three groups Implicit, Restoration and Direct. Implicit approach, blur is not addressed during training and blurred images are tested as other degraded images. The Restoration approach, blurred images are restored before recognition. Under the direct recognition approach, blur is addressed explicitly in the recognition model [4].

2. Types of Image blur

There are three type of image blur Gaussian blur, Out-of-focus blur and Motion blur.

2.1 Gaussian Blur Wikipedia defines, Gaussian blur also known as Gaussian smoothing is the result of blurring an image by a Gaussian function. It is a widely used effect in graphics software, typically to reduce image noise and reduce detail. Gaussian blur is defined by the following point-spread function

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad 2.1$$

Where x is the distance from the origin in the horizontal axis, y is the distance from the origin in the vertical axis, and σ is called the variance of the blur. Gaussian blur occurs due to long-time atmosphere exposure.

2.2 Out-of-focus blur this blurring is produced by a defocused optical system. It distributes a single point uniformly over a disk surrounding the point. The point-spread function of the out-of-focus blur is given by Otherwise

$$h(x, y) = c \begin{cases} 1 & \sqrt{(x - cx)^2 + (y - cy)^2} \leq r \\ 0 & \text{elsewhere} \end{cases} \quad 2.2$$

Where r is the radius and (cx, cy) is the centre of the out-of-focus point-spread function. The scaling factor c has to be chosen such that $\iint h(x, y) dx dy = 1$

2.3 Motion blur Motion blur is due to relative motion between the recording device and scene. When an object or the camera is moved during light exposure, a motion-blurred image is produced. The motion blur can be in the form of translation, a rotation, a sudden change of scale, or some combinations of these. When the scene to be recorded translates relative to the camera at a constant velocity v_{relative} under an angle of ϕ radians with the horizontal axis during the exposure interval $[0, t_{\text{exposure}}]$, the distortion is one-dimension. Defining the length of motion by

$$L = v_{\text{relative}} \times t_{\text{exposure}} \quad 2.3.1$$

The point-spread function is given by

$$d(x, y; L, \phi) = \begin{cases} \frac{1}{L} & \text{if } \sqrt{x^2 + y^2} \leq \frac{L}{2} \text{ and } \frac{x}{y} = -\tan \phi \\ 0 & \text{elsewhere} \end{cases} \quad 2.3.2$$

3. Restoration and Point Spread Function

3.1 Restoration means the removal or reduction of degradations that have occurred during the acquisition of the image. Such degradations may include noise, which are errors in the pixel values, or optical effects such as out-of-focus blurring or blurring due to camera motion.

In the spatial domain, we might have an image $f(x, y)$ and a spatial filter $h(x, y)$ for which convolution with the image results in some form of degradation. For example, if $h(x, y)$ consists of a single line of ones, the result of the convolution will be a motion blur in the direction of the line. Thus we may write

$$g(x, y) = f(x, y) * h(x, y) \quad 3.1.1$$

for the degraded image, where the symbol $*$ represents convolution. However, this is not all. We must consider noise, which can be modeled as an additive function to the convolution, Thus, if $n(x, y)$ represents random errors that may occurs, we have as our degraded image:

$$g(x, y) = f(x, y) * h(x, y) + n(x, y) \quad 3.1.2$$

We can perform the same operations in the frequency domain, where convolution is replaced by multiplication and addition remains as addition because of the linearity of the Fourier transform. Thus,

$$G(i, j) = F(i, j)H(i, j) + N(i, j) \quad 3.1.3$$

Represents as general image degradation, where, of course, F , H , and N are the Fourier transforms of f , h , and n respectively.

If we knew the values of H and N , we could recover F by writing the above equation as

$$F(i, j) = (G(i, j) - N(i, j))/H(i, j) \quad 3.1.4$$

3.2 Point Spread Function the mathematical model of point spread function of Out of focus blur, Gaussian and motion blur should be established. After setting up by the point spread function, linear convolution model of an original face is get, and the blur face image is reconstructed. The blur face image caused by point spread function, which is looked as a part of the recovery effort. The face can be recovered in the case of unknown degradation system.

$$g(x, y) = h(x, y) \otimes f(x, y) + n(x, y) \quad 3.2.1$$

$$= \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} h(x - i, y - j) f(x - y) + n(x, y) \quad 3.2.2$$

Where $f(x, y)$ is the original image, $h(x, y)$ represents the point spread function, $n(x, y)$ represents random noise, “ \otimes ” represents convolution. Degraded image is an original image and point spread function of convolution and adds the random noise superposition. The time domain convolution is equal to the product of the frequency domain, and Fourier transform linear invariance of equation 3.2.1 for spectrum domain can be expressed by equation 3.2.3

$$G(u, v) = H(u, v) \cdot F(u, v) + N(u, v) \quad 3.2.3$$

After Fourier transform, $G(u, v)$, $H(u, v)$, $F(u, v)$ and $N(u, v)$ are respectively $G(x, y)$ of degraded face, $H(x, y)$ of point spread function, $F(x, y)$ of the original image and the $N(x, y)$ of Fourier transform of noise image.

4. Wiener Filter

The Wiener filter is used to build an optimal estimate of the original image by enforcing a minimum mean-square error constraint between estimate and original image. The wiener filter is an optimum filter. The Objective of a Wiener filter is to minimise the mean square error. A Wiener filter has the capability of handling both the degradation function as well as noise shown as figure below.

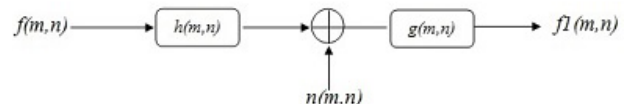


Fig 1: The Error between the Input signal $f(m, n)$ and the Estimated signal $f_1(m, n)$

$$e(m,n) = f(m,n) - f_1(m,n) \tag{4.1}$$

The square error is given by

$$[f(m,n) - f_1(m,n)]^2 \tag{4.2}$$

The Objective of the Wiener filter is to minimise the mean square error is given by

$$E\{[f(m,n) - f_1(m,n)]^2\} \tag{4.3}$$

The objective of the Wiener filter is to minimise

$$E\{[f(m,n) - f_1(m,n)]^2\} \tag{4.4}$$

According to the principal of orthogonality,

$$E\{f(m,n) - f_1(m,n) v(k',l')\} = 0 \tag{4.5}$$

$$f_1(m,n) = v(m,n) * g(m,n) \tag{4.6}$$

$$f_1(m,n) = \sum_{k=-\infty}^{\infty} \sum_{l=-\infty}^{\infty} g(m-k, n-l) v(k,l) \tag{4.7}$$

5. Related Work

In paper [2] a maximum likelihood approach to the blur identification problem, and proposes to employ the expectation-maximization algorithm to optimize the nonlinear likelihood function in an efficient way. In order to improve the performance of the identification algorithm, low-order parametric image and blur models are incorporated into the identification method. The resulting iterative technique simultaneously identifies and restores noisy blurred images. In paper [3] a space-adaptive regularization approaches to blind image restoration, which uses the piecewise smoothness of both the image and the PSF to effectively cope with the problem of insufficient information. In paper [4] a hybrid recognition/reconstruction architecture that is suitable for recognition of images degraded by various forms of blur. This architecture includes an ensemble of feed forward networks each of which is constrained to reconstruct the inputs in addition to performing classification. The strength of the constraints is controlled by a regularization parameter. Networks are trained on original as well as Gaussian-blurred images, so as to achieve higher robustness to different blur operators. The key point of this technique is blur (distorting operator) and its parameters identification using the neural network based on multi-valued neurons. The results of this identification are used as the main parameters

for the image restoration using the Wiener, Tikhnov or inverse filters [5]. A new method for removing non-uniform motion blurs from images. To achieve this goal, the problem is formulated as simultaneous estimation of multiple motions, segmentation, and spatially varying motion PSFs. The problem is solved by optimizing a regularized form of the energy function. Furthermore, the estimated PSFs are refined to achieve the restoration of images. We have evaluated the proposed method using a variety of synthetic and real-world images and validated the effectiveness of the algorithm [6]. A new blurred face identification approach which can be combined with different facial feature vector algorithms known to be invariant to different forms of acquisition problem [7].

A novel approach for recognizing blurred faces using facial deblur inference. Our algorithm inferred PSF using learned models of facial appearance variation under different amounts of blur. The inferred PSFs were used to sharpen both query and target images. Our extensive experiments on both real and artificially blurred face images demonstrated substantially more accurate PSF inference and face recognition than existing methods [8]. In paper [9] various techniques of denoising and deblurring were discussed. Wavelet and curvelet are emerging techniques that performs better deblurring in the presence of noise. The review of many different schemes of image restoration that are based on blind and non-blind de-convolution algorithm using transformation techniques [10].

6. Experiment and Result

The figure 2 shows the diagram of Two-Layer Feed Forward Neural Network. The Neural Network is created by using MATLAB (R2010a). The Neural Network is a Two Layer Feed Forward Back Propagation Network with both the layers consisting of 20 neurons each. In the figure 2, Input p1 is a restore blur face image. IW is initial weight matrix and LW is learning weight matrix. b1 and b2 is bias vector of both layers and the input to bias vector is fix to one. The first layer selected tan sigmoid transfer function that is tansig and second layer selected liner transfer function that is purelin. The a1 is output of first layer and a2 is output of neural network are given in equation (6.1) and (6.2).

$$a1 = \text{tansig}(IW * p1 + b1) \tag{6.1}$$

$$a2 = \text{purelin}(LW * a1 + b2) \tag{6.2}$$

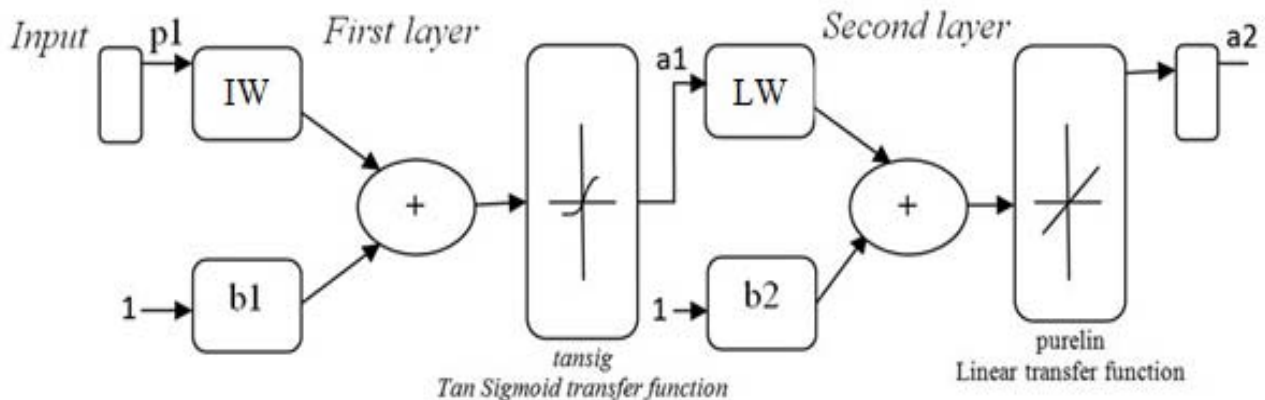


Fig 2: Two Layer Feed Forward Neural Network

The training function is a network training function that updates weight and bias values according to gradient descent momentum and an adaptive learning rate. The initial set training parameters of the Feed-Forward Neural Network is gradient descent back propagation with adaptive learning rate. The performance function is used mean squared error. The maximum number of epochs to train the neural network is 500 and momentum factor is 0.90. The goal of mean of squared error is 0.1; the network is initialized need to train the network.

The algorithm indicates the steps for the blur face image restoration by applying feed-forward neural network. The performance of two layer neural network is much better than a single layer neural network.

6.1 Algorithm for the Restoration for the Blur face image and checking the performance of Neural Network

- Step-1: Create artificial blurred Face Image
- Step-2: Face Image resized to 50 x 50 dimensions
- Step-3: Input blurs Image for the restoration
- Step-4: Apply different filter parameters (disk, Gaussian and motion) on blur face images.
- Step-5: Set and apply the PSF and remove the blur from the face images.
- Step-6: Use Wiener filter for restoration of blur face image
- Step-7: Now using neural network and obtained restored image, Recognize the face from original FEI database.
- Step-8: Calculate the performance validation of NN, Gradient, Time for forming layers, Number of epochs and Learning rate to train the NN.

7. Result

The FEI face database [12] is a Brazilian face database that contains a set of face images taken between June 2005 and March 2006 at the Artificial Intelligence Laboratory of FEI in Sao Bernardo do Campo, Sao Paulo, Brazil. There are 14 images for each of 200 individuals, a total of 2800 images. All images are colorful and taken against a white homogenous background in an upright frontal position with profile rotation of up to about 180 degrees. Scale might vary

about 10% and the original size of each image is 640x480 pixels. All faces are mainly represented by students and staff at FEI, between 19 and 40 years old with distinct appearance, hairstyle, and adorns. The number of male and female subjects is exactly the same and equal to 100. Figure 3 shows some sample of image variations from the FEI face database. Figure 4 shows the process of blur face image Restoration and Recognition. The Figure 5, Figure 6 and Figure 7 Graphs Shows Performance of NN by applying Out of focus, Gaussian and Motion blur effect. The Table 1, Table 2 and Table 3 shows the observed values of experiment.

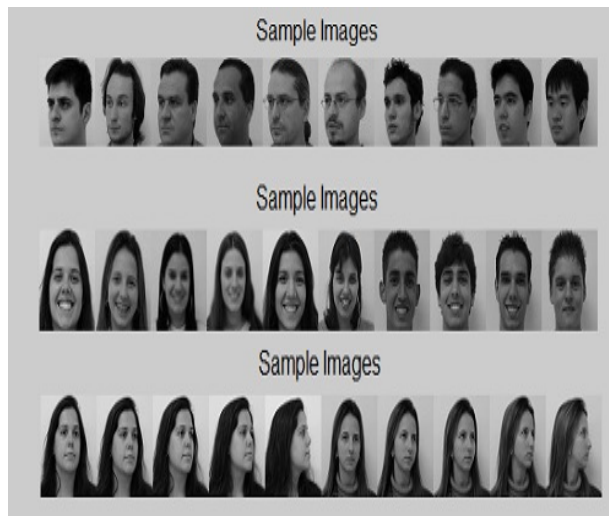


Fig 3: Sample Images from the FEI face database.

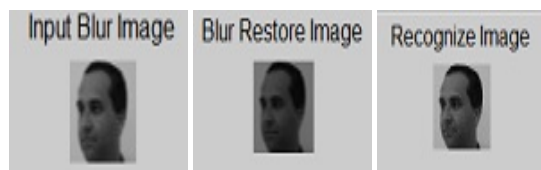


Fig 4: The process of Blur face image Restoration and Recognition

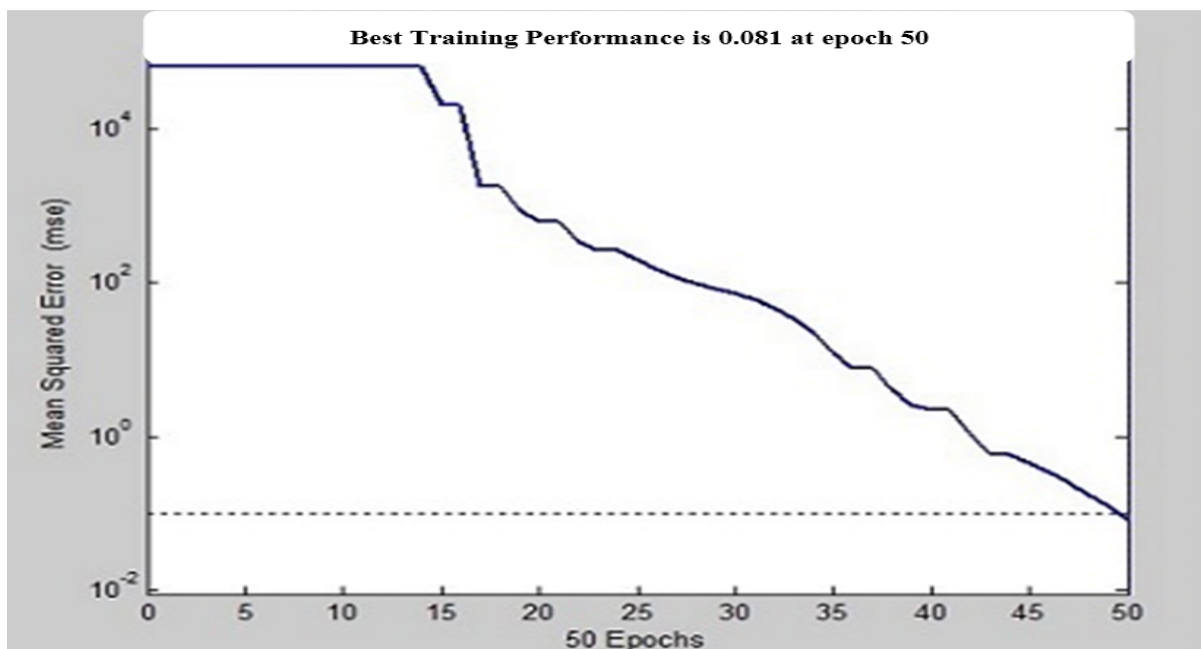


Fig 5: Graph Shows Performance of NN by applying Out of focus blur effect ~ 692 ~

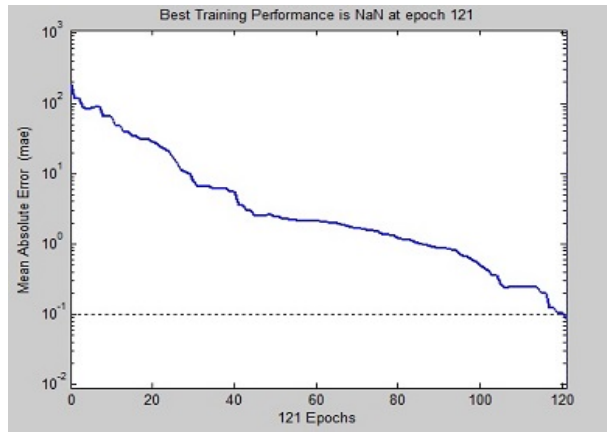


Fig 6: Graphs Shows Performance of NN by applying Gaussian blur effect

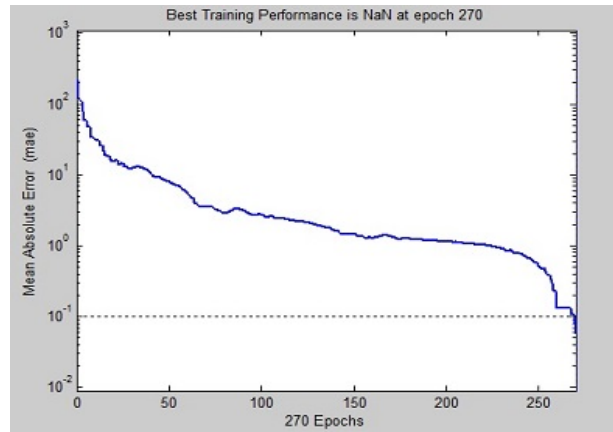


Fig 7: Graphs Shows Performance of NN by applying Motion blur effect

Table 7.1: FEI Dataset: Part 1

Filter Parameters	Epochs	Time	Performance Validation	Gradient	Learning Rate
Out-of-focus	369	00.00.03	0.099	86.4	3.1
Gaussian	371	00.00.03	0.099	80.7	1.8
Motion	147	00.00.01	0.092	72.6	8.6

Table 7.2: FEI Dataset: Part 2

Filter Parameters	Epochs	Time	Performance Validation	Gradient	Learning Rate
Out-of-focus	336	00.00.02	0.099	87.3	1.7
Gaussian	500	00.00.03	0.107	80.3	1.3
Motion	183	00.00.01	0.099	82.5	7.6

Table 7.3: FEI Dataset: Part 3

Filter Parameters	Epochs	Time	Performance Validation	Gradient	Learning Rate
Out-of-focus	50	00.00.01	0.081	37.1	2.2
Gaussian	121	00.00.01	0.088	69.0	1.2
Motion	270	00.00.02	0.056	91.0	2.0

8. Conclusion and Future Work

The result of the presented work is the effective neural network solution for the recognition of the blur face. The result of this identification can be used for the image restoration using the Wiener filter. The future work will be directed to apply blur effects on 3D-face for restoration and recognition.

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