Noise Removal of Facial Expression Images using Wiener Filter

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ABSTRACT

This paper presents a novel approach for the detection of emotions in highly corrupted noisy environment. The approach involves removal of noise from the image by the Wiener Filter. An automatic system for the recognition of facial expressions is based on a representation of the expression, learned from a training set of pre-selected meaningful features. However, in reality the noises that may embed into an image document will affect the performance of face recognition algorithms.Images will be tested from database in noisy environment of speckle noise. The proposed method uses Wiener Filter for the removal of noise.

1. INTRODUCTION

Effective Human Computer Intelligent Interaction (HCII) requires the information about the user's identity, state and intent which can be extracted from images, so that computers can then react accordingly. The most expressive way humans display emotions is through facial expressions. With the ubiquity of new information technology and media, more effective methods for HCII are being developed which rely on higher level image analysis techniques whose recent applications in HCII include automatic interactive tutoring, multimedia, process control and user authentication. For these tasks, the required information about the identity, state and intent of the user can be extracted from images and make the computers to react accordingly, e.g. by observing a person's facial expressions. Noise is added as unwanted variations in the image when image is transmitted over the network [22]. It causes a wrong conclusion in the identification of images in authentication and also in pattern recognition process. Firstly there should be the removal of noise from the image then features are detected. Noise in imaging systems is usually either additive or multiplicative. In practice these basic types can be further classified into various forms such as amplifier noise or Gaussian noise, Impulsive noise or salt and pepper noise, quantization noise, shot noise, film grain noise and nonisotropic noise. However, in our experiments, we have considered only speckle noise.

2. RELATED WORK

Automatic recognition of facial expressions may act as a component of natural human machine interfaces Such interfaces would enable the automated provision of services that require a good appreciation of the emotional state of the service user, as would be the case in transactions that involve negotiation[1], for example Some robots can also benefit from the ability to recognize expressions. Automated analysis of facial expressions for behavioral science or medicine is another possible application domain. From the viewpoint of automatic recognition, a facial expression can be considered to consist of deformations of facial components and their spatial relations, or changes in the pigmentation of the face[1]. There is a vast body of literature on emotions. Recent discoveries suggest that emotions are intricately linked to other functions such as attention, perception, memory, decision making, and learning. This suggests that it may be beneficial for computers to recognize the human user's emotions and other related cognitive states and expressions. Ekman and Friesen [1] developed the Facial Action Coding System (FACS) to code facial expressions where movements on the face are described by a set of action units (AUs).Ekman's work inspired many researchers to analyze facial expressions by means of image and video processing. The AAM approach is used in facial feature tracking due to its ability in detecting the desired features as the warped texture in each iteration of an AAM search approaches to the fitted image. Ahlberg [7] use AAM in their work. In addition, ASMs - which are the former version of the AAMs that only use shape information and the intensity values along the profiles perpendicular to the shape surface are also used to extract features such as the work done by Votsis et al. [9].Many algorithms have been developed to remove speckle noise in document images with different performance in removing noise and retaining fine details of the image, like: Simard and Malvar [10] shows image noise can originate in film grain, or in electronic noise in the input device such as scanner digital camera, sensor and circuitry, or in the unavoidable shot noise of an ideal photon detector.

Beaurepaire et al. [2] tells the identification of the nature of the noise is an important part in determining the type of filtering that is needed for rectifying the noisy image. Noise Models from Wikipedia [11] shows the noise in imaging systems is usually either additive or multiplicative. Image Noise [12] shows in practice these basic types can be further classified into various forms such as amplifier noise or Gaussian noise, Impulsive noise or salt and pepper noise, quantization noise, shot noise, film grain noise and nonisotropic noise. Al-Khaffaf [13] proposes several noise removal filtering algorithms. Most of them assume certain statistical parameters and know the noise type a priori, which is not true in practical cases.

Prof. K. M. Passino [8] proposed an optimization technique known as Bacterial Foraging Optimization Algorithm (BFOA) based on the foraging strategies of the E. Coli bacterium cells. Until date there have been a few successful applications of the said algorithm in optimal control engineering, harmonic estimation in Ref [15], transmission loss reduction in Ref [16], machine learning in Ref [14] and so on. Its performance is also heavily affected with the growth of search space dimensionality Kim et al [17] proposed a hybrid approach involving GA and BFOA for function optimization. Biswas et al [18] proposed a hybrid optimization technique, which synergistically couples the BFOA with the PSO.

3. PROPOSED ALGORITHM FOR EMOTION RECOGNITION

Proposed work will be divided into three major modules:

- The first module is Image Pre-processing.
- Second module is a Recognition technique, which includes Training of the images.
- Third module is testing and classification of emotions.

3.1 Image Preprocessing

The image processing phase includes several image-processing techniques like Filtering, Feature Extraction, Region of Interest clipping, and Quality enhancement of image. First noisy face image is taken then wiener filter is used to remove the noise then remaining noise has to be removed by the Mutation Bacteria Foraging Optimization Technique. After removing the noise features has to be extracted. The facial features that correspond to a facial expression, namely the eye block, lips, mouth has to be extracted from the face image .Then recognize the emotion from the extracted facial features. Statistical analysis has to be done by that mean, median and standard deviation of the noisy frame, restored frame, cropped frame and enhanced frame. Though various methods exist for emotion recognition, neural networks hold its position due to its robustness. So, we will apply a Back-Propagation and Radial Basis neural network for training and recognizing emotions.

4. PROPOSED METHODOLOGY OF FACIAL EXPRESSION RECOGNITION SYSTEM

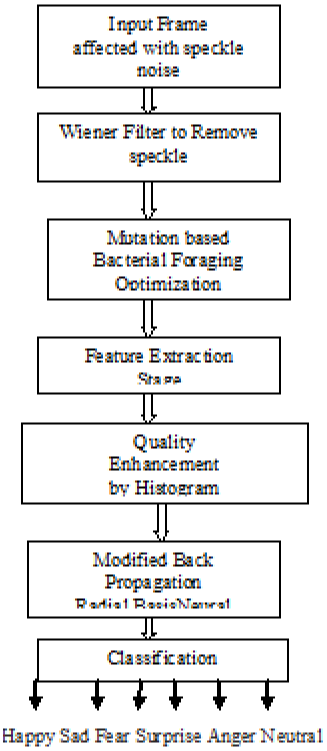

Fig 1: Implementation overview

4.1 Input Noisy Image

The first module shows the input phase. To this module a noisy face image of speckle noise is passed as an input for the system. The input image samples are considered from JAFFE database. The input image is picked up from the database used for training and evaluated for the recognition accuracy.

4.2 Wiener Filter

wiener2 lowpass-filters an intensity image that has been degraded by constant power additive noise. wiener2 uses a pixelwise adaptive Wiener method based on statistics estimated from a local neighborhood of each pixel. It estimates the local mean and variance around each pixel.

$$\mu = \frac{1}{NM} \sum_{n_1, n_2 \in \eta} a(n_1, n_2)$$

$$\sigma^2 = \frac{1}{NM} \sum_{n_1, n_2 \in \eta} a^2(n_1, n_2) - \mu^2$$

where is the N-by-M local neighborhood of each pixel in the image A. wiener2 then creates a pixelwise Wiener filter using these estimates,

$$b(n_1, n_2) = \mu + \frac{\sigma^2 - v^2}{\sigma^2}(a(n_1, n_2) - \mu)$$

4.3 Mutation Bacteria Foraging Optimization

In the first stage Wiener filter is used to remove the speckle noise. In the second stage, both the noisy and Wiener filter output images will be passed as search space variables in the BFO technique [20] to minimize errors due to differences in filtered image and noisy image.

- Bacterial Foraging Optimization with fixed step size suffers from two main problems

I. If step size is very small then it requires many generations to reach optimum solution. It may not achieve global optima with less number of iterations.

II. If the step size is very high then the bacterium reach to optimum value quickly but accuracy of optimum value gets low. Similarly, in BFO, chemotaxis step provides a basis for local search, reproduction process speeds up the convergence, elimination and dispersal helps to avoid premature convergence. To get adaptive step size, increase speed and to avoid premature convergence, the mutation by PSO is used in BFO instead of elimination and dispersal event by equation 1.

$$\theta^i(j+1,k) = \theta^i(j+1,k) + {}^*r_1 * C_1(\theta^i(j+1,k) - \theta_{global}$$

$\theta^i(j,k)$ = Position vector of *i*-th bacterium in *j*-th chemotaxis step and *k*-th reproduction steps

θ_{global}= Best position in the entire search space .The BFpfPSO follows chemotaxis, swarming, mutation and reproduction steps to obtain global optima.

4.4 The step by step algorithm of BF-pfPSO is presented below.

Initialize Parameters *p, S, Nc, Ns, Nre, Ned, Ped* and *C (i), i*= 1, 2... *S*. Where,
p = Dimension of search space
S = Number of bacteria in the population
Nc = Number of chemotaxis steps
Ns = Number of swimming steps
Nre = Number of reproduction Steps
Pm = Mutation probability
C (i) = Step size taken in the random direction specified by the tumble

i (j, k)= Position vector of the *i*-th bacterium, in *j*-th chemotaxis step, in *k*-th reproduction step and in l-th elimination and dispersal step

***Step 1:* Reproduction** loop: *k = k+1*
***Step 2:* Chemotaxis** loop: *j = j+1*

a) For *i*= 1,2…*S*, take a chemotaxis step for bacterium i as follows

b) Compute fitness function *J (i, j, k, l)*

c) Let *Jlast =J (i, j, k,)* to save this value since we may find a better cost via a run.

d) Tumble: Generate a random vector $\Delta(i) \in \Re^p$, with each element $\Delta_m(i)$, m = 1, 2…p, a random number on [-1 1]

e) Move: Let

$$\theta^i(j+1,k) = \theta^i(j,k) + C(i)\frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}}$$

f) Compute J (i, j+1, k, l)
g) Swim
i) Let m =0 (counter for swim length)
ii) While m < Ns (if have not climbed down too long)

- Let *m = m+1*
  If *J (i, j+1, k, l) < Jlast* (if doing better),
- Let *Jlast = J (i, j+1, k, l)* and let

$$\theta^i(j+1,k) = \theta^i(j+1,k) + C(i)\frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}}$$

And use this $\theta^i(j+1,k)$ to compute the new $J(j+1, k)$.

- Else, let *m = Ns*. This is the end of the while statement

h) Go to next bacteria *(i+1)* if *i ≠S*

Step 3:* Update** $\theta_{pbest}(j,k)$ ***and θ_{global} If j <Nc, go to step 3.
In this case, continue chemotaxis, since the life of bacteria is not over.

***Step 4:* Reproductions:**
a) For the given k and l, and for each i = 1, 2…S, let

$$J^i_{health} = \sum_{j=1}^{Nc+1} J(i,j,k)$$

be the health of bacterium i . Sort bacteria and chemotaxis parameter C (i) in order of ascending cost Jhealth (higher cost means lower health).
b) The Sr =S/2 bacteria with the highest Jhealth values die and other Sr=S/2 bacteria with the best values split.

Step 5: (New step): Mutation
For i = 1, 2…S, with probability Pm, change the bacteria position by pfPSO.

Step 6*:*
If k < Nre, go to step 2. We have not reached the specified number of reproduction steps. Therefore, we have to start the next generation in the chemotaxis loop.

4.5 Pre-Processing and Feature Extraction

In image processing step, the region of interest (ROI) of a lip and an eye or only lips region or only eyes region has to be selected independently in the acquired images through the mouse. The ROI image will be converted into grayscale image.

4.6 Histogram Equalization

A histogram equalization method has to be applied before obtaining the filtered grayscale image. Histogram equalization improves the contrast in the grayscale and its goal is to obtain a uniform histogram. The histogram equalization method also helps the image to reorganize the intensity distributions. New intensities are not introduced into the image. Existing intensity values will be mapped to new values but the actual number of intensity pixels in the resulting image will be equal or less than the original number.

4.7 Modified Back Propagation and Radial Basis Neural Network

The neurons are trained by hit and trail method, a total of 625 input neurons has to be taken, hidden neurons are 75 and output neurons are 4. Total of 13 pair are trained with the different emotions of happiness, sad, surprise, anger, fear and neutral. In this phase epochs and errors are calculated of particular face region. Two parameters are used; total numbers of epochs and errors are calculated in neural network. For more accuracy more computation time is needed. The main accuracy or goal is 0.01 then it takes more computation time. The Classification of Neural Network includes two types of neural networks that has to be trained based on the input parameters extracted. Two types of neural networks will be trained based on the

(i) Back Propagation Neural Network
(ii) Radial Basis Neural Network

(i)Back Propagation Neural Network

The most widely used neural network is the Back Propagation algorithm. This is applied at input to hidden layer, due to its relative simplicity, together with its universal approximation capacity. The learning algorithm is performed in two stages: feed-forward and feed- backward. In the first phase the inputs are propagated through the layers of processing elements, generating an output pattern in response to the input pattern presented. In the second phase, the errors calculated in the output layer are then back propagated to the hidden layers where the synaptic weights are updated to reduce the error. This learning process is repeated until the output error value, for all patterns in the training set, are below a specified value. The Back Propagation, however, has two major limitations: a very long training process, with problems such as local minima and network paralysis; and the restriction of learning only static input -output mappings. To overcome these restrictions, RBF Neural Network is used.

(ii) Radial Basis Functions

Radial Basis Functions (RBF) has attracted a great deal of interest due to their rapid training, generality and simplicity. When compared with traditional multilayer perceptrons, RBF networks present a much faster training, without having to cope with traditional Back Propagation problems, such as network paralysis and the local minima. These improvements have been achieved without compromising the generality of applications. It has been proved that RBF networks, with enough hidden neurons, are also universal approximates. The RBF is basically composed of three different layers: the input layer, which basically distributes the input data, one hidden

5. EXPERIMENTAL RESULTS

Wiener filter is used to remove the noise and Mutation based bacteria Foraging optimization techniques has to be used to remove the remaining speckle noise. In this paper multiple feature options such as face, eyes and lips will be used for emotion detection. The global, local features of facial expression recognition images has to be independently selected through the mouse for identification for feature extraction. The Radial Basis Neural Network requires has to be used.

Radial Basis Neural Network requires has to be used face images get more affected and sometimes are not visible. Applying the Speckle noise with mean and variance equal to 0.05 on all the images of the JAFFE face database forms the probing image set. Subjects have rated each image on 6 emotion adjectives. Noises are introduced in the JAFFE database face images. Figure 1 shows the sample of image database. Figure 2 shows the noisy image with variance 0.9. Figure 3 shows the restored image using Wiener filter.

layer, with a radially symmetric activation function, hence the network's name and one output layer, with linear activation function.

The classification system of Neural Network has to be performed in three stages.

1. Training of Neural Network
2. Testing of Neural Network
3. Performance Evolution of Neural Network

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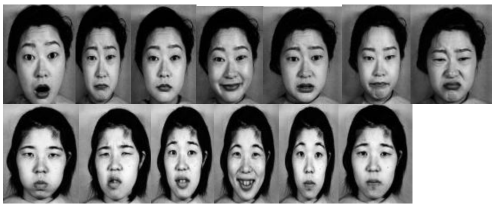

Fig -1 Sample images from JAFFE Database

Fig- 2 Noisy image

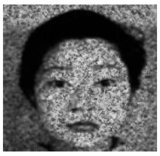

Fig-3 Restored image after applying wiener filter

6. CONCLUSION

In this paper we present human facial emotion detection in noisy environment. Wiener filter is used to remove the noise. Results shows that the noises are not removed properly so for removing the remaining noise Mutation based bacteria Foraging optimization techniques has to be used.

7. REFERENCES

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