International Journal of Computer and Communication Technology

Volume 3 | Issue 4 Article 3

October 2012

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Recommended Citation

JAYARAMAN, NITHYASHRI and KULANTHAIVEL, G. (2012) "NEURAL NETWORK BASED AGE CLASSIFICATION USING LINEAR WAVELET TRANSFORMS," *International Journal of Computer and Communication Technology*: Vol. 3 : Iss. 4 , Article 3.
DOI: 10.47893/IJCCT.2012.1148
Available at: https://www.interscience.in/ijcct/vol3/iss4/3

NEURAL NETWORK BASED AGE CLASSIFICATION USING LINEAR WAVELET TRANSFORMS

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Abstract - The facial image analysis for classifying human age has a vital role in Image processing, Pattern recognition, Computer vision, Cognitive science and Forensic science. The various computational and mathematical models, for classifying facial age includes Principal Component Analysis (PCA) and Wavelet Transforms and Local Binary Pattern (LBP). A more sophisticated method is introduced to improve the performance of the system by decomposing the face image using 2-level linear wavelet transforms and classifying the human age group using Artificial Neural Network. This approach needs normalizing the facial image at first and then extracting the face features using linear wavelet transforms. The distance of the features is measured using Euclidean distance and given as input to Adaptive Resonance Theory (ART). The network is trained with an own dataset consisting of 70 facial images of various age group. The goal of the proposed work is to classify the human age group into four categories as Child, Adolescence, Adult and Senior Adult.

Keywords *- Linear Wavelet Transform, Euclidean Distance, Age group, Feature Extraction, Neural Network.*

I.INTRODUCTION

Face recognition based on Illumination , Pose, Expression and Age variations has been an active area of research and more challenging in various fields like Pattern recognition, Image processing and Computer vision. The age–separated faces has unique characteristics which makes age classification as a complex task. The classification of age has its application in finding missing individuals, identifying criminals in forensic sciences etc., This paper focuses on age classification in which the facial images are classified into four age groups: Child , Adolescence, Adult and Senior Adult. This proposed method proves that human age can be classified based on the facial features using Artificial Neural Network.

The craniofacial growth, plastic surgery, environmental changes, chronic diseases, changes the face with an increasing age. This is the first work done in age classification and was developed by Kwon and Lobo[6] . They used four categories of age group for classification : Babies, Young, Adults and Senior Adults. They used Snakelets to find wrinkles to distinguish the young and the old.

The proposed work includes normalizing the face image and this pre-processed image is said to undergo linear wavelet transform to extract the face features. The distance of different face features are measured using Euclidean distance and these features are given as inputs to the ART network to classify the various age groups. The datasets are trained using ART Network which yields better results. The ultimate goal of the proposed work is to classify the age group of the given facial image and not to recognize the faces.

II. RELATED WORK

There are various age classification methodologies that has been developed so far and they are summarized as below. The various approaches in this area includes Age prototypes[10] , Statistical models [8] and distance based techniques [9]. Moreover, age estimation techniques can be used as a basis for developing - age progression algorithms[11].

A.J.O'Toole, H. Abdi, K.A. Deffenbacher and J.CBarlett [7] used an auto associative memory technique to classify faces by gender and race. This approach consists of a set of associative memory of completely interconnected units. The Eigen vectors were extracted and the difference in co-efficients helps in classifying male/female and Japanese and Caucasian classification.

Horng, Lee and Chen [5] developed classification of age groups based on facial features. They used four categories of age group for classification : Babies, Young adults, Middle- aged adults and Senior Adults. They used two Back Propagation Networks for age classification phase, in which, one is used to check whether the image is a baby and the other is to classify whether young adult, middle- aged adult or senior adult.

Asuman & Varif [3] developed an automatic age classification using Local Binary Pattern . In this work, the faces are divided into small regions from which LBP histograms are extracted. Later they are concatenated into a feature vector. In the classification phase, minimum distance, k- nearest neighbor classifiers are used.

Feng Gao and Haizhou [4] introduced a face age classification on consumer images using Gabour Feature and Fuzzy LDA method. To solve intrinsic age ambiguity problem, Fuzzy LDA method was used. Gabour Feature is extracted for face representation and later used in LDA classifiers.

Age Estimation based on Neural Networks using Face features was developed by Nabil Hewachi et.al [1]. They used four categories for classification : Child, Young, Youth and Old. A supervised back propagation network was used for classification. Later they tested the face images using two databases : FGNET and MORPH.

Laura , Bradley and Ken [2] developed a new set of young adult Caucasian male faces and was created with FaceGen software with which an internet based version of testing was done. They conducted a series of experiments and found that the ability to learn and recognize unfamiliar faces improves until the early 30's.

The craniofacial growth, plastic surgery, environmental changes and chronic diseases changes the face with an increasing age . It was first developed by Kwon and Lobo [6]. They used three categories of age group for classification namely Young, Adults and Senior Adults. The snakelets are used for finding wrinkles so as to distinguish young and old.

Ye Sun et al, [12] developed an Embedded Hidden Markov Model(EHMM) to recognize face and age. The nonlinear relationship between the feature points in the face are estimated and different ages of the same face are used to train EHMM , so as to estimate ageing face.

Allison C Lamont et al, [13] presented a study on recognition accuracy based on ageing effects. The face recognition accuracy decreases with young faces when compared to old aged faces.

III. PROPOSED WORK

A. Overview of Proposed Work

The face features were extracted by decomposing the input image using 2- level linear wavelet transformation. In this work linear wavelets like Haar, Symlet, and Daubechies wavelet transformations were used for decomposition.

The results of 2- level linear wavelet yields the face features which includes the eyes, nose, lips and chin etc., The distance between the face features were estimated using Euclidean distance and they are referred as Feature Point Distance(FPD). These FPD's were given as input to a Neural Network for classifying the age group. Adaptive Resonance Theory (ART) algorithm is used for classifying the human age. A own dataset including 70 face images of various age groups are trained using ART. In this work the age groups are classified into Child(0 to 12 years), Adolescence(13 to 18), Adult(19 to 55) and Senior Adult(56 & above). The entire representation of this work, can be seen in the fig 3.1.

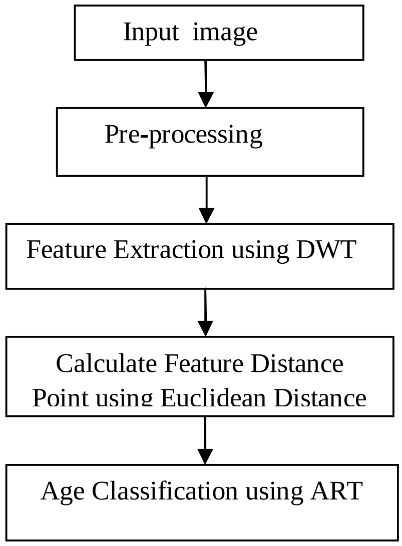


Fig. 1. Block Diagram of the Proposed Work.

B. Normalizing the image

The face images are normalized or pre-processed , which includes converting a RGB image into Gray Scale image. A RGB (Red, Blue, Green) image is an array of pixels and the number of bits used to represent a pixel value determines the bit depth of RGB image. The RGB images are converted into Gray Scale images for easier processing of facial images.

C. Feature Extraction using Linear Wavelet Transforms

The Wavelet Transform (WT) provides a time-frequency representation of the signal. Wavelet transforms are used to reduce the number of bits required to represent an image. Image Compression is done in order to get useful information from the image. A 2-D transform is done by applying 1-D transform twice. The decomposition of can be achieved with various Linear Wavelet Transformation. It includes Haar, Symlet, and Daubechies transformations.

The gray scaled image or the normalized image, undergo 2-level Wavelet decomposition and the face image is decomposed using linear wavelets. The face features of different age groups namely Child, Adolescence, Adult and Senior Adult were obtained. The features including Eyes, Nose, Lips, Chin are extracted after two-level wavelet decomposition.

D. Finding Feature Point Distance

In this work, 4 different types of Feature Point Distance are measured namely, **FPD1, FPD2, FPD3**, **FPD4.** The mid-point of line joining the two eyes be measured as **FPD1.** The distance between the mid-point of eyes and the nose be measured as **FPD2**.The distance between the mid-point of eyes and the lips be measured as **FPD3**. The distance between the midpoint of eyes and the chin be measured as **FPD4.** These feature points are given as input to a Neural Network for classifying the age group. The distance between feature points were measured using Euclidean distance . The distance between the pixel **(i,j)** and the pixel **(k, l)** were calculated by the formula

$$D_E \; [(i, \; j), \; (k, \; l)]=[\; (i-k)^2 \; + \; (j-l)^2]^{1/2} \quad (1)$$

E. Age Classification using Adative Resonance Theory

Artificial Neural Network has been developed as a generalization of Mathematical models of Human Cognition or Neural Biology. Artificial Neural Network consists of many nodes and these processing units were analogous to neurons in the human brain. Adaptive Resonance Theory Network (ART) is used for classification of age and is explained in detail as below.

The basic architecture of adaptive resonance neural network consists of three types of neurons as shown in the figure 2.

1. Input Unit – F1 layer
2. Cluster Units – F2 layer
3. Reset mechanism to control the similarity of patterns placed on same cluster.

Input Processing (F1 layer) is divided into two regions namely the input region and the interface region.
(i) Input region (denoted as F1(a)).
(ii) Interface region (denoted as F1(b)).

1. Input Unit

The input region represents the input vector whereas the interface region combines the signal from the input region with the F2 layer. The interface region F1(b) layer is connected to F2 layer through bottom up weights and F2 layer is connected to F1(b) layer through top down weights.

2. Cluster Unit

The cluster unit with largest net input is selected to learn the input pattern. The activation of all other F2 units are set to zero. The intermediate units now combine the information from the input and the cluster units.

3. Reset mechanism

Based on the similarity of the input vector and the top – down weight, the cluster unit may or may not be allowed to learn the pattern. If a cluster unit is not allowed to learn , then a new cluster unit is selected.

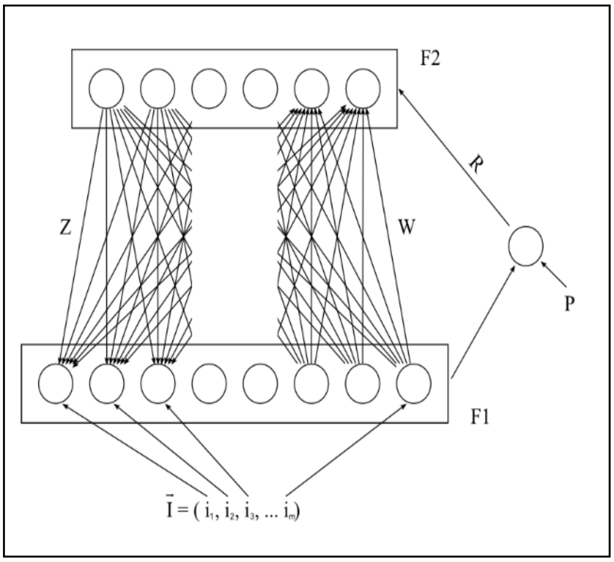


Fig. 2 : Adaptive Resonance Theory Network

The following are the steps involved in classifying the age groups.

1. The Feature point distances namely **FPD1, FPD2, FPD3**,and **FPD4** were given as input to input vector of a Adaptive Resonance Theory Network.
2. Let the threshold value be fixed as 0.6.
3. The input vector is compared with the threshold value

```
for i=1:r
   for j=1:(c-1)
      if(x(i,j)<0.6)
         ip1(i,j)=0;
      else
         ip1(i,j)=1;
      end
   end
end
```

4. The ART network is said to be trained

   and the time taken and the efficiency in training the patterns are tabulated.
5. The feature point distance FPD3 (the distance between eyes and lips) consists of wrinkles near the eyes and nasal lines.
6. Therefore, pixels in this region will be greater, when compared to other regions.

7. Greater the number of pixels, more will be the age.

IV RESULTS AND DISCUSSIONS

The experimental work is done using own dataset consisting of various face age groups and totally 70 images were used. The implementation of this work is done using MATLAB. The input facial images were converted into Gray-scale images. The sample input face images and the gray scaled images are shown in Fig.3 and Fig.4 respectively.

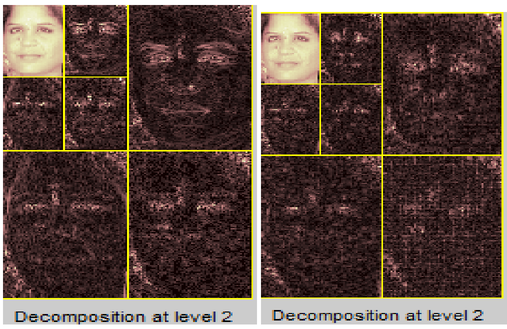
Child Adolescence Adult

Fig.3. Sample input face images

Child Adolescence Adult

Fig.4. Gray-scaled Images

The gray scaled images were decomposed using various Linear Wavelet Transformations like Haar, Symlet (sym8), and Daubechies wavelets (db6). The figure 5, shows the decomposition of a face image using linear wavelets.



a) Haar b) sym8.

c) db6

Fig. 5 : a) Haar b) symlet c) Daubechies wavelet transformation

The face features were extracted as a result of decomposing the gray scaled image. The features like eyes, nose, lips and chin were extracted from the facial images. The Euclidean distance for these feature points were measured and tabulated as below. The Feature Point Distance measured from 2-level Haar, sym8 and db6 are listed in the table 1, 2 and 3 respectively.

Table 1 Feature Point Distance measured from 2-level Haar wavelet transformation

FACE IMAGES	FPD1	FPD2	FPD3	FPD4
IM1	0.6756	0.8518	0.9457	1.6103
IM2	1.3841	0.9816	1.7501	2.2289
IM3	1.0279	0.9157	1.4993	2.0339
IM4	1.2828	0.9485	1.5895	2.1297
IM5	1.4159	0.9677	1.8459	2.3798
IM6	0.7443	0.8968	0.9541	1.7380
IM7	1.4763	0.9738	1.8307	2.4899
IM8	1.8086	0.9982	1.9849	2.7015
IM9	1.8960	0.9826	1.9982	2.8459
IM10	1.1774	0.9023	1.5609	2.0597

Table 2 Feature Point Distance measured from 2-level Sym 8

FACE IMAGES	FPD1	FPD2	FPD3	FPD4
IM1	0.6851	0.8520	0.9459	1.6211
IM2	1.3839	0.9811	1.7522	2.2332
IM3	1.0276	0.9160	1.4997	2.0433
IM4	1.2825	0.9488	1.5892	2.1311
IM5	1.4251	0.9679	1.8460	2.3810
IM6	0.7450	0.8965	0.9547	1.7379
IM7	1.4771	0.9733	1.8310	2.4888
IM8	1.8092	0.9984	1.9851	2.7022
IM9	1.8965	0.9816	1.9988	2.8433
IM10	1.1771	0.9027	1.5611	2.0599

Table 3 Feature Point Distance measured from 2-level db6

These feature point distances were given as input to ART neural network to classify the age group and is trained using threshold value and is listed in the table4

Table 4 Threshold $\rho = 0.6$

S.no	Training in %	Testing in %	Time in (ms)	Efficiency in %
1	10	90	0.0439	77.7778
2	20	80	0.0571	87.5
3	30	70	0.0718	85.7143
4	40	60	0.0666	83.3333
5	50	50	0.0911	80

The ART network is trained as shown in the table – V. The total number of pixels for the feature point FPD3 is calculated for all the images. If pixel count is lesser than 120 pixels , the classified age group is Child. If the pixel count is in between 120 and 160, then the age group is classified as Adolescence. The classified age group is Adult, if the pixel count is greater than 160 and less than 400. If the number of pixels exceeds 400, then the classified age group is Senior Adult. The results of Age classification with Haar, Sym8 and db6 are listed in the tables 5,6 and 7 respectively. The classification rate of these wavelets is compared and is shown in the figure 6.

Table 5 Results of Age classification with Haar

Face images	FPD3	pixel count	Classification
IM1	0.9457	109	Child
IM2	1.7501	344	Adult
IM3	1.4993	148	Adolescence
IM4	1.5895	155	Adolescence
IM5	1.8459	361	Adult
IM6	0.9541	115	Child
IM7	1.8307	355	Adult
IM8	1.9849	464	Senior Adult
IM9	1.9982	497	Senior Adult
IM10	1.5609	151	Adolescence

Table 6 Results of Age classification with Sym 8

Face images	FPD3	pixel count	Classification
IM1	0.9459	112	Child
IM2	1.7522	348	Adult
IM3	1.4997	149	Adolescence
IM4	1.5892	154	Adolescence
IM5	1.8460	360	Adult
IM6	0.9547	118	Child
IM7	1.8310	359	Adult
IM8	1.9851	469	Senior Adult
IM9	1.9988	499	Senior Adult
IM10	1.5611	155	Adolescence

Table 7 : Results of Age classification with db6

Face images	FPD3	pixel count	Classification
IM1	0.9455	110	Child
IM2	1.7525	349	Adult
IM3	1.4991	146	Adolescence
IM4	1.5895	157	Adolescence
IM5	1.8466	364	Adult
IM6	0.9549	118	Child
IM7	1.8315	356	Adult
IM8	1.9855	466	Senior Adult
IM9	1.9991	499	Senior Adult
IM10	1.5620	154	Adolescence

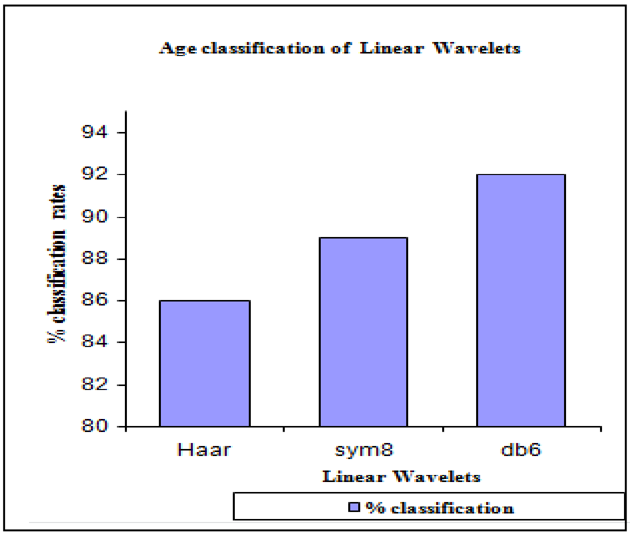


Fig. 6 : Comparison of Age classification with three Linear Wavelets

V CONCLUSION

This work proposes a Linear Wavelet Transform for extracting the face features and an Adaptive Resonance Theory for classifying age groups. The network is trained with images of different age groups and out of the three waveforms, it is observed that db6 classifies 92% of images correctly. It is proposed to improve the performance by training with more images and working with other wavelet transforms.

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