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A Generalized Neuron Model (GNM) Based Human Age Estimation

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ABSTRACT

In real-world application, the identification characteristic of face images has been widely explored, ranging from National ID card, International passport, driving license amongst others. In spite of the numerous investigation of person identification from face images, there exists only a limited amount of research on detecting and estimating the demographic information contained in face images such as age, gender, and ethnicity. This research aim at detecting the age/age range of individual based on the facial image. In this research, a generalized neuron (GN), which is a modification of the simple neuron, is used, to overcome some of the problems of artificial neural network (ANN) and improve its training and testing performance. The GN is trained with discrete wavelet transform (DWT) features obtained after the application of Canny edge detection algorithm on the face Image. Validating the technique on FG-NET face images reveals that the frequency domain features obtained using the DWT captures the wrinkles on the face region, which represents a distinguishing factor on the face as humans grow older. The empirical results demonstrates that the GN outperforms the simple neuron, with detection rate of 93.5%, training time of 96.30secs, matching time of 14secs and root mean square error of 0.0523. The experimental results suggest that the GN model performs comparably and could be adopted for detecting human ages.

Keywords: Estimation, Detection, Generalized Neuron Model (GNM), Human Age & Frequency

Aims Research Journal Reference Format:
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1. Background to Study

In many practical applications, the veracity of humans to supply demographic information such as age, ethnic, gender from face images is not realistic (Babatunde et al, 2016). Automated age detection has become an interesting and challenging research problem in recent years. Some of the potential applications of automatic age estimation according to Han, Otto and Jain, 2013, includes; Security control, which could help prevent under aged from purchasing alcohol or cigarette from vending machines or accessing inappropriate web pages, Law enforcement, which could help determine potential suspects more efficiently and accurately by filtering the gallery database using the estimated age of the input mugshot, Human-computer interaction, such as a smart shopping chart which can be designed to provide recommendations according to the age of the customer.

In this twenty first century, along with fuzzy logic, Artificial Neural Network (ANN), and Evolutionary Algorithms (EA) are receiving intensive attention from Computer Vision researchers. All these techniques are kept under one umbrella called “soft computing.” Enormous research had already been done on soft computing techniques to identify a working model for various systems. The general neural network model consists of three distinct layers namely the input layer, the hidden layer and the output layer. Each of these layers consists of a number of simple neurons that are interconnected. There may be more than one hidden layer in cases involving more complex problems. Also the number of neurons in each layer depends on the type of application it is being used for (da Silva et al, 2017).
Thus it can be seen that as the complexity of the problem increases, the number of neurons and the number of weights to be found also tends to increase.

The multilayer perceptron (MLP) is not an attractive choice for complex applications due to the storage and computational expense involved in adapting weights for a large number of neurons. A reduced number of trainable weights reduces the memory and computational expense, accelerates the convergence, and reduces the number of training patterns necessary for robust generalization (Raghavendra, Ganesh and Venayagamoorthy, 2009). The training of neural network structures is time consuming and requires fast processors for practical applications. In an ANN, many of the design decisions required in developing an application are not well understood. The rules of operation in a neural network are not completely known. This makes NN to be regarded as a black-box (Charan and Argawal, 2010). The use of a sigmoidal thresholding function and an ordinary product or summation aggregation in the simple neuron model does not always give satisfactory results (Raghavendra, Ganesh and Venayagamoorthy, 2009). The combinations of summation neurons and product neurons at different layers are giving quite good results as compared to only summation neuron or product neuron in the whole network as is the case with Artificial Neural Network.

However, the Generalized Neuron (GN) model uses partly sum and partly product aggregation function. A vast amount of nonlinearity exists in real life problems, hence the GN, which has both sigmoidal and the Gaussian functions with weight sharing, can be used to overcome such problems. Due to this the GN has more flexibility and the ability to cope better with the nonlinearity involved in any application (Han, Otto and Jain, (2013). Some of the limitations of the use of Artificial Neural Network includes its inherently parallel nature, but which are by tradition simulated on sequential machines, increase in processing time as the problem size grow, and sensitivity to the quality and type of preprocessing of the input data which affects the performance of the network. Additionally, some of the advantages of the GN when compared to the conventional neural network are that there are lesser requirements in terms of memory and speed for hardware implementation. The training time for the weights can be reduced by reducing the number of unknown parameters (weights) to be determined (Kumar and Chaturvedi, 2011).

2. MOTIVATION FOR THE RESEARCH

Aging is a gradual change in appearance which is not visibly apparent over a small age gap. Also different individual has distinct rate of facial aging, coupled with the fact that aging process is determined not only by intrinsic factors such as genetic factors, but also by extrinsic factors such as lifestyle, expression, and environment (Kulkarni and Venayagamoorthy, 2009). There is need for an appropriate facial feature representation which can capture the face template in such a manner that the local primitives of the face such as edges, blurbs, contours can be extracted. The Canny edge detector offers a good candidate solution in detecting edges in an image. DWT is a powerful frequency domain feature representation technique which performs a multi-resolution analysis of a signal. Images are treated as a 2D signal which changes horizontally and vertically. It has a key advantage over Fourier Transforms because it gives localization in both time and frequency domains (Nayak and Sharma, 2012). Large training time and local minima error among others are inherent flaws of the Artificial Neural Networks (ANN's), in which a Generalized Neuron Model (GNM) overcomes by the use summation (Σ) and product (π) aggregation function. The GN has been applied in a wide range of problems like classification, prediction approximation function, etc. The GN is composed of two transfer functions (sigmoid and gaussian) connected and integrated with the output neuron, few synaptic weights, and two aggregation functions (sum and product) (Garro, Rodr´ıguez, Vazquez. 2016).

In this research, the GNM is applied for the detection of Age of individuals with the results of root mean square error, correct detection, wrong detection, accuracy of detected ages, training time and recognition time as performance metrics.

3. ALLIED RESEARCHES

Han, Otto and Jain, (2013) proposed a hierarchical approach for automatic age estimation, and analyzed the influence of aging on individual facial components using a component based representation. Human perception ability to estimate age is evaluated using crowd sourced data obtained via the Amazon Mechanical Turk service, and compared with the performance of the proposed automatic age estimation. The automated system has comparable performance with human estimates. Experimental results on the FG-NET, MORPH Album2, and PCSO databases show that eyes and nose are more informative in age estimation than the other facial components. The component based method of facial representation is robust and effective for detection and recognition task. However, they show inevitable difficulties when there exist variation in luminance, facial expressions, visual angles and other potential features such as glasses, beard, etc.

Garro, Rodr´ıguez, Vazquez (2016) carried out DNA microarray classification using Generalized Neuron model. In the work, the set of genes that best describe the disease were selected applying the artificial bee colony (ABC) algorithm. Afterwards, the genes found during the first stage are used to train a GN. The GN was trained with the differential evolution algorithm. Finally, the accuracy of the proposed methodology was tested classifying two types of cancer namely acute lymphocytic leukemia and acute myeloid leukemia using DNA microarrays. Accuracy of the results obtained showed the effectiveness of the method. Kumar and Chaturvedi (2011) present a performance comparison of an artificial neural network method, adaptive neuro fuzzy inference system and generalized neural network method of forecasting financial index. The generalized neural network outperformed the ANN and ANFIS. Charan, Srinivas and Satsangi, 2012 carried out Short Term Load Forecasting (STLF) using Generalized Neuron Model (GNM) for under sum square error gradient function. The learning rate and training epochs was varied and satisfactory results were realized.

4. METHODOLOGY

This research proposes a holistic based face representation for automatic age detection. The four stages involved in the methodology are face preprocessing, edge detection, feature extraction and GN training.

4.1 The Database

FG-NET consists of 1,002 images of 82 individuals, with an average of 12 images per individual. The entire dataset was FG-NET used for the experiment in this research. The age of subjects in FG-NET ranges from 0-69 years. More than half of the subjects in the dataset are between ages 0 and 13. 8 images per individual were used as training set for the model while the remaining 4 images were used as testing set. The sample images from the FG-NET dataset are shown in Figure 1.

Figure 1: Sample Images of FG-NET Database

4.2 Preprocessing

The face images in FG-NET dataset were captured using different methods, giving rise to inconsistent colors of faces. Therefore, since the images consists of both colored and gray-scale images, and some have color cast, there is need for color normalization by converting all color face images into grayscale. This was done in MATLAB 2015 ®. The normalized face images were cropped and resized to the same size of 100 x 100.

4.2.1 Edge detection

Edges characterize boundaries and are therefore a problem of fundamental importance in image processing and particularly in automatic feature extraction. Previous research including (Min, 2001) and (Melgar, 2008) have shown that the Canny's algorithm is very suitable for object extraction in most contexts due to the fact that it yields less number of false edges. It reduces image data and facilitates object detection. Edges identify object boundaries and are detected through abrupt changes in gray level above a particular threshold. Operators that are sensitive to the change in gray levels can be used as edge detectors. Edge detection techniques include gradient, template and morphology based (Melgar, 2008). The Canny edge detector is considered as the standard methodology of edge detection due to the quality of edges generated. It finds edges by looking for local maxima of the gradient of Image. The gradient is calculated using the derivative of a Gaussian filter and the detected edges are refined with non-maximal suppression and hysteresis. It is the most accurate as it detects edges and the computes how strong they are so you can discard small edges that may be due to noise and keep the strongest ones.

This is, mainly, due to 2 steps:

1. Non Maximum Suppression - Edges candidates which are not dominant in their neighborhood aren't considered to be edges.
2. Hysteresis Process - While moving along the candidates, given a candidate which is in the neighborhood of an edge the threshold is lower.

Those 2 steps reduce the number of "False" edges and hence create a better starting point for further process such as transformation. Other edge detection such as Robert, Prewitt, Sobel are prone to generate false edges which will in turn generate false features.

4.2.2 Feature extraction

Feature extraction is a method used to simplify the amount of features from the raw signal. It involves transformation, which eventually results in a basic and reduced feature subset, useful for further analysis. Discrete Wavelet Transform is a technique to transform image pixels into wavelets, which are then used for wavelet-based coding. The application of the Discrete Wavelet Transform (DWT) to a sample decomposes the sample to an addition of a set of signals (wavelets) made up of approximation signals and detail signals. The wavelet transform uses a discrete set of the wavelet scales and translations by processing signals (templates) using high pass and low pass filtering. The wavelet coefficients are the successive continuation of the approximation and detail coefficients

The DWT is defined as;

$$W\varphi(j0,k) = \frac{1}{\sqrt{M}}\sum_x f(x)\varphi j_0,k(x) \qquad (1)$$

$$W\psi\ (j,k) = \frac{1}{\sqrt{M}}\sum_k f(x)\psi j,k(x) \qquad (2)$$

where $f(x)$, φj_0,k(x), and $\psi j,k\ (x)$ are functions of the discrete variable x = 0,1,2,…,M−1.

The basic feature extraction procedure is as follows;

1. Decomposing the signal using DWT into N levels using filtering and decimation to obtain the approximation and detailed coefficients
2. Extracting features from the DWT coefficients.

This process generates proper and optimum set of wavelet coefficients of the face images which were considered useful features for input into the generalized neuron due to their effective time–frequency representation of the images. Once the set of features that best describes the face is selected, the next step is to train the generalized neuron (GN).

4.2.3 Training the Generalized Neuron

The conventional neural network generally consists of three layers - input, hidden and output layers. The basic problem faced during the application of neural networks to highly complex problems is large training time due to the number of neurons and the number of layers in the network. This is overcome by the GN which requires fewer neurons i.e. fewer weights, thereby reducing the training time. The GN structure also requires lesser memory and hardware requirements, making it a good option for practical application. The GN structure is shown in Figure 2. The GN model has both Σ and Π aggregation functions as earlier stated.

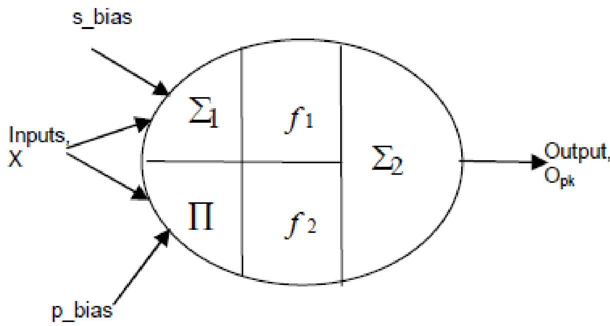


Figure 2: Generalized Neuron Model

As shown in figure 2, the sigmoidal characteristic function f1 is used with the $\Sigma 1$ summation aggregation function while the Gaussian characteristic function f2 is used with the Π product aggregation function. The output of the $\Sigma 1$ part with the sigmoidal activation function for f1 of the GN is as shown in equation (3) below

$$O_\Sigma = f_1(s\_net) = \frac{1}{1+e^{(-\lambda_s \times s\_net)}}$$

where,

$$s\_net = \sum W_{\Sigma i} X_i + X_{o\Sigma} \tag{3}$$

and λ_s and $Xo\sum$ are the gain and bias of $\sum_1$ part respectively

The output of the C part with the Gaussian activation function for f2 of the GN is as shown in equation (4) below:

$$O_\pi = f_2(pi\_net) = e^{(-\lambda_p \times pi\_net^2)}$$

where,

$$pi\_net = \prod W_{\pi i} X_i \times X_{o\pi} \tag{4}$$

and λ_p and $Xo\pi$ are the gain and bias of $\prod$ part respectively

The final output Opk of the neuron is a function of the two outputs $O\Sigma$ and $O\pi$ with the weights W and (1-W), respectively, and can be written in the mathematical form

$$O_{pk} = O_\pi \times (1 - W) + O_\Sigma \times W \tag{5}$$

The parameters of the GN (λs, λp), which determines the extent to which satisfactory results are obtained were varied over a wide range and they are determined by trial and error for the problem.

The dataset was partitioned into two: training and testing sets. The inputs to the GN model are the wavelet features extracted previously from the training set. The training set consists of six different ages (6, 12, 17, 21, 35 and 41). The GN structure was codified in terms of the synaptic weights ($W_{\sum}, W_{\prod}$, W), bias and parameter of the activation function (λ) for each of the aggregation function ($\sum$ and $\prod$). After training the GN, its generalization capability is evaluated using the testing dataset. The classification performance of the GN is measured in terms of the true positive (TP), true negative (TN), false positive (FP), false negative (FN), Accuracy. Error rates are calculated as the proportion of impostor attempts that are falsely accepted (FAR), and genuine attempts that are falsely rejected (FRR).

4.2.4 Simulation/Testing

The experiments carried out on FG-NET database used six different ages (ages 8, 13, 16, 29, 31 and 33) for testing. This was done to make the model adaptable and improve its generalization capability. Testing was done by picking each image of the testing set for all persons in the database. This yields a true positive result if the age of that individual is detected by the model in the trained set. The testing procedure compares the test age with all ages in the training set and classifies all images within that age range. Furthermore, matching is done to obtain the exact person whose image was tested. The age of such individual will be detected and the result is shown. True positives are those ages that are correctly detected from the database; false negatives are the ages that are not detected when tested (they are present, yet unclassified); false positives are the ages that were wrongly detected as the true age of the individual; true negatives are ages that were not present in the database and are not detected.

5. RESULTS AND DISCUSSION

In this section, we analyze the experimental results obtained with the proposed method. Comparison was made between different learning rate η with number of training epochs. The training epochs was simulated in MATLAB 2015. The learning rate varies with the number of training epochs. As the number of epochs increase, the learning rate also increases but the RMS error increases. The learning rate was however kept constant at η=0.150 at 801-1200 epochs so as to achieve very less error and ensure adaptability. Table 1 shows the result of the learning rate for each training epoch. The GN model learns faster than the ANN.

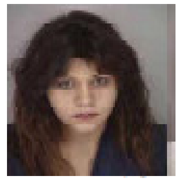
Table 1: Training epochs versus learning rate of GN model

Training epochs	Learning rate η	RMSE
100-400	0.0002	0.0191
401-800	0.040	0.0211
801-1200	0.150*	0.0523
1201-1600	0.199	0.1002
1601-2000	0.260	0.3047
2001-2400	0.300	0.6891
2401-2800	0.341	1.7542
2801-3200	0.399	3.8769

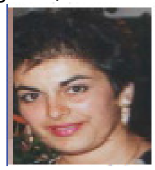
The total time recorded in seconds divided by the number of images in the training set, gives an average training time of 96.30 seconds. From the experiment, based on the total number of ages of individual tested, the total images tested were four hundred and ninety two (492). The model detected the ages of four hundred and sixty (460) individuals accurately, therefore the detection rate which is the ratio of correct detection over total tested was 93.5%. On the average, the matching time, which is the time taken to detect the age of the subject tested was 14 seconds. This result shows that the GN model can perform robust classification. Sample result of actual age and estimated age detected by the proposed model is shown on the next page.

Actual age: 22, Estimated Age: 22

Actual age 35, estimated age: 35

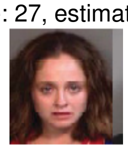


Actual age 18, estimated age: 18



Actual age: 31, estimated age: 21

Actual age: 27, estimated age: 37



Actual age: 20, estimated age: 29

The root means square error (RMSE) during testing, training time, matching time and detection rate achieved with the GN was compared against that of the feed forward neural network (FFNN) under same training condition such as learning rate, initial weights and error function. Several experiments carried out revealed that on average, the GN outperforms the feed forward neural network as shown in Table 2. The advantage of GN structures lies in the smaller number of trainable weights in comparison with that in multilayer networks. It was found that during testing GN Model gives very good performance than that of the FFNN as the errors in output generated by it is considerably less than that of the FFNN. From the table, it can be inferred that the output of the GN model for age estimation is significantly different in terms of the performance metrics used

Table 2: Performance comparison of RMSE and Detection rate

	Generalized Neuron	Feed forward Neural Network
RMSE during testing	**0.0231**	**0.8153**
Training time	**96.30secs**	**284.87sec**
Matching time	**14secs**	**38secs**
Detection Rate	**93.50%**	**87.40%**

The GN model exhibits much superior performance both in terms of convergence time during training as well as prediction error during testing. This is shown in Table 3, which reveals the result of training error and learning rate.

Table 3: Overall Performance comparison of GN model and FFNN for age estimation

Network Model	Training Error	Learning Rate
Generalized Neuron	0.7610	0.1501
Feed Forward Network	1.8920	0.9730

6. CONCLUSION AND FUTURE WORK

The empirical results obtained from this research revealed that the wavelet coefficient is an excellent technique for training a GN. The GN trained with the proposed methodology is capable of detecting true age of individuals with minimal false positives, with an acceptable accuracy and reduced training time when compared with the feed forward neural network. Experimenting the proposed technique on larger publicly available age variation database such as MORPH*, PCSO, Album2 can be looked into. In the future, we intend to carry out age detection and prediction using Deep Neural Nets. Technology evaluation was used in this research which involves using saved data i.e. previously acquired images. We intend to evaluate the model on a larger data set of wider variation, considering Scenario evaluation of an end to end system using a prototype or simulated environment. Operational evaluation in which the performance of a complete biometric system is determined in a specific application environment with a specific population is a possible research scope. Investigation of the issues involved in real-time practical implementation of age detection is also an open issue that needs to be dealt with.

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