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Role of Artificial Neural Networks (ANN) in Image Processing

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ABSTRACT: This paper presents Artificial Neural Networks (ANNs) as a means of image processing. ANN is a powerful technology used to solve many real-world problems in the world of image processing. The primary purpose of this paper is to put light into some studies in this area which will hopefully motivate other researchers in this area to utilize this technology in resolving the problems in image processing. This paper will also help in increasing the awareness of image processing researchers in the area of Neural-network based algorithms. The paper will give light to neural network based image processing techniques used in the past, which will help in further research activities in facial expression recognition using ANNs. The most modern man-machine interfaces require computers to closely understand the biometrics of human system. Some of the biometrics is face, iris, fingerprint and Gait. Among these face plays an important role and in biometrics through face, eyes are a vital part. A technique of detection of expressions from face helps in the development of various applications.

KEYWORDS: Image Processing, Facial Emotion Recognition, FER, Artificial Neural Networks, ANN

I. INTRODUCTION

Artificial neural networks (ANNs) are a form of computing inspired by the functioning of human brain and nervous system. ANNs have been used to carry out cognitive tasks performed naturally by the brain, including face recognition, learning to speak and understand a language, identifying handwritten characters, and determining that a target seen from different angles is in fact the same object. However, the number of uses for ANNs is increasing rapidly, and in recent years they have been successfully used for the prediction of emotions from facial expressions. In this paper a brief review of ANNs is given (section 2). The conclusions of the study are given in last section.

II. A REVIEW OF ARTIFICIAL NEURAL NETWORKS

ANNs are a type of parallel computer, which differ from conventional computers in the way they process information. The operation of conventional computers is controlled by a single central processing unit (CPU), which holds the computer's memory and processes information in a sequential manner. Parallel computers, on the other hand, consist of a number of smaller processing elements (PEs), that are linked together. As a result, the computer's memory is distributed and information is processed in a parallel manner. This is similar to the Copyright 1996 by the American Geophysical Union. Paper number: 95WR03529. 0043-1397/96/95WR-03529505.00. The cerebral cortex of the human brain is an example.

A. *NATURAL NEURAL NETWORKS*

The structure and operation of NNNs is discussed by a number of authors [Vemuri; Hecht-Nielsen]. NNNs consist of tens of billions of densely interconnected nerve cells (neurons). Neurons essentially behave as microprocessors. Each neuron receives the combined output of many other neurons through input paths called dendrites (Figure 1). If this signal is strong enough, the neuron is activated and produces an output, which is transmitted through output structures

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called axons. The axon splits up and connects to the dendrites of many other neurons via junctions called synapses. The strength of the synapses is modified as the brain learns.

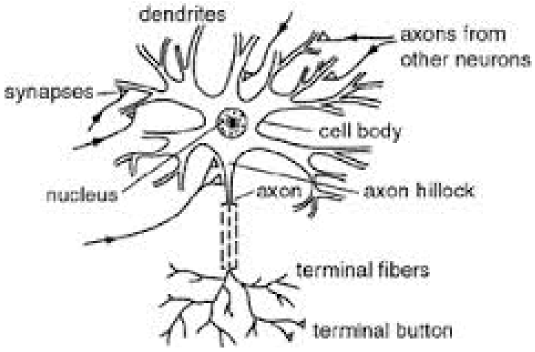

Figure 1

B. *ARTIFICIAL NEURAL NETWORKS*

The structure and operation of ANNs is discussed by a number of authors [Ranjithan et al; Rogers and Dowl; Lippmann; Hecht-Nielsen; Marenet al; Burke and Ignizio; Vemuri]. ANNs are loosely based on the structure of NNNs but exhibit only a small portion of their capabilities. ANNs are similar to NNNs in that they consist of interconnected PEs and are only allowed to receive information supplied locally.

C. *STRUCTURE*

The PEs are usually arranged in layers: an input layer, an output layer, and one or more layers in between called hidden layers (Figure 2). The PEs in the various layers are either fully or partially interconnected. The connections between the PEs are weighted. The strength of each connection weight can be adjusted; a zero weight represents the absence of a connection, and a negative weight represents an inhibitory relationship between two PEs.

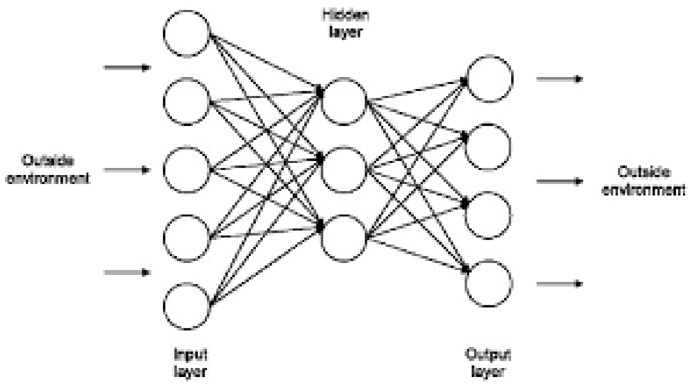

Figure 2

D. *OPERATION*

The propagation of data through the network starts with the presentation of an input stimulus at the input layer. The data then flow through, and are operated on by, the network until an output stimulus is produced at the output layer (Figure 2). Eac h PE receives the weighted outputs (wiixi) from the PEs in the previous layer, which are summed and added to a threshold value (0•) to produce the node input (I•) (Figure 3). The purpose of the threshold is to scale

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the input to a useful range. The node input (Ii) is then passed through a nonlinear transfer function (f(I•)), such as the hyperbolic tangent function (Figure 3), to produce the node output (y•), which is passed to the weighted input paths of many other PEs.

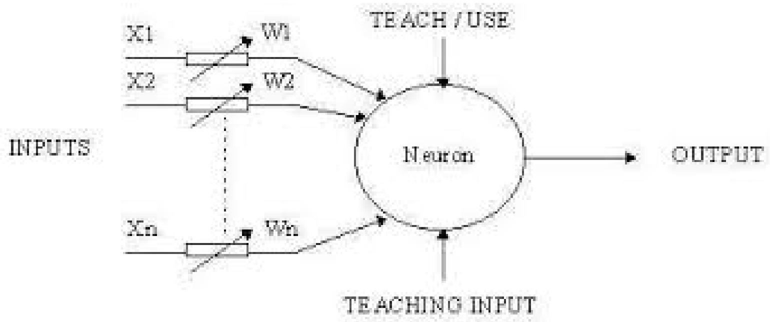

Figure 3

III. ARTIFICIAL NEURAL NETWORKS IN IMAGE PROCESSING

In this section, we will review neural networks trained to perform one of the six tasks in the image processing chain (3.1–3.6).

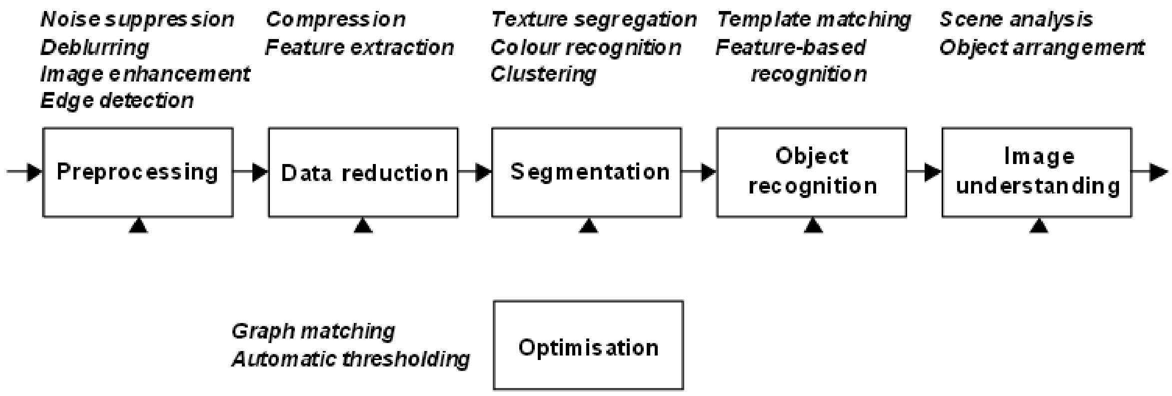

Figure 4

A. *PREPROCESSING*

Preprocessing is the first step in image processing chain. Preprocessing can be defined as an operation in which the input consists of sensor data and output is a full image. The operations in preprocessing can be categorized as:

1) Image reconstruction
2) Image restoration and
3) Image enhancement

Role of Artificial Neural Networks in these three preprocessing categories are discussed below. ANNs can be applied directly to pixel data as well as features.

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1. Image reconstruction

Image reconstruction is the process of reconstructing an image from a number of parameters acquired from sensors. Reconstruction problems often require complex computations. Unique approach is needed for each application. A Hopfield Network can be used to perform the inverse Radon transform for reconstruction of computerized tomography images. The Hop1eld network contained “summation” layers to avoid having to interconnect all units. Meyer and Heindl [1] used regression feed-forward networks to reconstruct images from electron holograms. Wang and Wahl trained a Hopfield ANN for reconstruction of 2D images from pixel data obtained from projections [2].

2. Image restoration

Image restoration is the process of removing aberrations, if any, introduced by the sensor, including noise. A number of applications of ANNs in preprocessing are found in image restoration. In general, image restoration is to restore an image that is distorted by the measurement system. The distortion includes noise, motion blur, out-of-focus blur, other distortions caused by low resolution, etc. There are various ANN designs ranging from relatively straightforward to highly complex, modular approaches. In the most basic approach, noise is removed from an image by simple filtering. Greenhil and Davies [3] used a regression feed-forward network in a convolution-like way to suppress noise (with a 5× 5 pixel window as input and one output node). Guan et al. [4] developed a network-of-networks for image restoration. This system consists of loosely coupled modules, where each module is a separate ANN.

3. Image enhancement

This is the amplification of certain desired features, which may facilitate later processing steps such as segmentation or object recognition. The most well-known enhancement problem is edge detection. A straightforward application of regression feed-forward ANNs, trained to behave like edge detectors, was reported by Pugmire et al. [5]. A number of more complex, modular systems were also proposed. Formulating edge detection as an optimization problem was also proposed. Some enhancement approaches utilise other types of ANNs. Shih et al. [6] applied an ART network for binary image enhancement.

B. *DATA REDUCTION AND FEATURE EXTRACTION*

Image compression and feature extraction are two of the most important applications of data reduction. An image compression algorithm, used for storing and transmitting images, generally contains two steps: encoding and decoding. ANNs were used to implement both these steps. Feature extraction is used for segmentation or object recognition, which is subsequent to compression. The features of interest often correspond to particular geometric or perceptual characteristics in an image such as edges, corners and junctions, or application dependent ones, e.g., facial features or expressions.

1. Image compression applications

The following are the two major types of image compression approaches:

1. direct pixel-based encoding
   This method uses one ANN to perform the encoding operation [7]
2. pixel-based encoding
   This approach uses a modular technique to perform the encoding [8]

Several different types of ANNs were trained in the past to perform image compression: feed-forward networks, Self-organizing Maps (SOMs), adaptive fuzzy leader clustering, a fuzzy ART-like approach and a learning vector quantifier. The feed-forward networks contain at least one hidden layer, with fewer units than the input and output layers, are then trained to recreate the input data. The bottle-neck architecture forces the network to project the original data onto a lower dimensional, possibly non-linear, manifold from which the original data should be predicted. Other

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approaches rely on a SOM, which after training acts as a code book. The advanced approaches are based on specialized compression modules, which either combines different ANNs to obtain the best possible compression rate or more traditional statistical methods with one or more ANNs.
ANN approaches have to compete with well-established compression techniques such as JPEG, which should serve as a reference. The major advantage of ANNs is that their parameters are adaptable, which may give better compression rates when trained on specific image material when compared with traditional compression techniques.

2. Feature extraction applications
Feature extraction is a special kind of data reduction technique which will help in finding a subset of features of interest from the image data. This is one of the necessary steps in object recognition which is a vital step in facial expression recognition.
Some feature extraction approaches are designed to cope explicitly with orientation of objects. It is important to make a distinction between application of supervised and unsupervised ANNs for feature extraction. For a supervised ANN, the information loss implied by the data reduction can be measured directly on the predicted output variables, which is not the case for unsupervised feature extraction by the SOM. Both supervised and unsupervised ANN feature extraction methods have advantages compared to traditional techniques such as PCA. Feed-forward ANNs with several hidden layers can be trained to perform non-linear feature extraction.

C. *IMAGE SEGMENTATION*

Segmentation is the partitioning of an image into smaller parts that are coherent according to some criterion. In a classification task, the purpose of segmentation is to assign labels to individual pixels. Neural-based approaches perform segmentation directly on the pixel data, obtained either from a convolution window or the information is provided to a neural classifier in the form of local features.

1. Pixel data based

Many ANN approaches have been presented in the past by researchers that segment images directly from pixel data. Several different types of ANNs were trained to perform pixel-based segmentation: feed-forward ANNs, SOMs, Hopfield networks, probabilistic ANNs, radial basis function networks, CNNs and constraint satisfaction ANNs. A self-organizing architecture with fuzziness measures was used [9]. Biologically inspired neural-network approaches also were proposed which were able to segment images from surfaces and their shading. Hierarchical segmentation approaches were designed to combine ANNs on different abstraction levels. The guiding principles behind hierarchical approaches are specialization and bottom–up processing: one or more ANNs are dedicated to low level feature extraction and their results are combined at a higher abstraction level where another neural classifier performs the final image segmentation.

In general, pixel-based supervised ANNs were trained to classify the image content based on

- texture [10] or a combination of texture and local shape
- connecting edge pixels;
- identification of surfaces;
- clustering of pixels [11];

In most applications, ANNs were trained as supervised classifiers to perform the desired segmentation.

2. Features based

Several feature-based approaches apply ANNs for segmentation of images. Different types of ANNs were trained to perform feature-based image segmentation: feed-forward ANNs, recursive networks, SOMs, variants of radial basis function networks and CNNs. Hierarchical network architectures were developed for optical character recognition. Feature-based ANNs were trained to segment images based on the differences in

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- texture [12] or a combination of texture and local shape
- estimation of ranges [13]
- connecting edges and lines;
- region growing.

Texture segregation is one of the most frequently performed segmentation by feature-based ANNs.

D. *OBJECT RECOGNITION*

Object recognition consists of locating the positions and possibly orientations and scales of instances of objects in an image. The purpose may also be to assign a class label to a detected object. Our survey of the literature on object recognition using ANNs indicates that in most applications, ANNs have been trained to locate individual objects based directly on pixel data. Another less frequently used approach is to map the contents of a window onto a feature space that is provided as input to a neural classi1er.

1. Pixel data based

Among the ANN approaches developed in the past for pixel-based object recognition, several types of ANNs can be distinguished: feed-forward-like ANNs [14], variants using weight sharing, recurrent networks, the ART networks [15] etc. Besides, interesting hardware ANNs have been built for object recognition: the RAM network [16] and optical implementations [17]. SOMs are also occasionally used for feature extraction from pixel data where output of the map is propagated to a neural classi1er.
Recurrent ANNs (with feed-back loops [18]) can be used to develop special approaches for object recognition [19]. The added value of recurrent network architecture lies in its memory: the current state contains information about the past, which may constitute valuable context information. The recurrence principle introduces averaging, which can give a more robust performance.

2. Features based

Several neural-network approaches have been developed in the past for feature-based object recognition including: feed-forward ANNs [20], Hopfield ANNs [21], a fuzzy ANN [22] and RAM ANNs [23]. SOMs are occasionally used to perform feature extraction prior to object recognition, although SOMs have also been trained to perform object classification.
The smaller variety of neural architectures developed for feature-based object recognition compared to the pixel-based approaches discussed in the previous section, rejects the fact that most effort is focused on developing and choosing the best features for the recognition task. Common for many feature-based approaches is that variations in rotation and scale are coped with by the features, e.g., statistical moments. A certain amount of noise will influence the computed features and deteriorate the recognition performance. So the major task of the subsequent classifier is to filter out noise and distortions propagated by the features. Moreover, when the object to be detected is large and needs to be sampled densely, feature extraction is inevitable. Otherwise, a neural classifier will contain so many parameters that a good generalization will be impeded.

E. *IMAGE UNDERSTANDING*

Image understanding is the process of actually interpreting those regions/objects to figure out what's actually happening in the image. This may include figuring out what the objects are their spatial relationships to each other, etc. It may also include ultimately making some decision for further action. It is a complicated area in image processing. It couples techniques from segmentation with knowledge of the expected image content. A major problem when applying ANNs for image understanding is their black-box character. It is virtually impossible to explain why a particular image interpretation is the most likely one. As a remedy, Stassopoulou et al. mapped the trained ANN onto a Bayesian belief network after training had been performed. An alternative approach to coping with the black-box problem is to use the generic explanation facility developed for ANNs [24] or to use rule extraction [25]. Another

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problem in image understanding relates to the level of the input data. Image understanding is the most dubious application of ANNs in the image processing chain.

F. *OPTIMIZATION*

Some image processing tasks such as graph and stereo matching can best be formulated as optimization problems, which may be solved by Hopfield ANNs [26]. In some applications, the Hopfield network is obtained pixel-based input [27], in other applications the input consisted of local features [28] or detected structures.

IV. CONCLUSION

Here throughout this paper we briefly discussed the basics of Neural Networks, Natural Neural Network, Artificial Neural Networks, its functioning, application of neural network in image processing domain etc. This paper will encourage the further initiatives to be taken for implementation of work in such domain.

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