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A Survey On Image Processing Using Artificial Neural Network (ANN)

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ABSTRACT
Image processing is a method to perform some operations on an image, in order to get an enhanced image or to extract some useful information from it. It is a type of signal processing in which input is an image and output may be image or characteristics/features associated with that image. Nowadays, image processing is among rapidly growing technologies. It forms core research area within engineering and computer science disciplines too. One dimension specifies the type of task performed by the algorithm: pre-processing, data reduction/feature extraction, segmentation, object recognition, image understanding and optimization. The other dimension captures the abstraction level of the input data processed by the algorithm: pixel-level, local feature-level, structure-level, object-level, object-set-level and scene characterization. Each of the six types of tasks poses speci1c constraints to a neural-based approach.

Keywords :- Digital Image Processing, Artificial Neural Network, Pre-processing, Image reconstruction, Image restoration, Image enhancement, Image segmentation, Feature extraction applications, Object recognition, Image understanding and Optimization**.**

I. INTRODUCTION

Image Processing

There are several types of images, namely, light intensity (visual) image, range image (depth image), nuclear magnetic resonance image (commonly known as magnetic resonance image (MRI)), thermal image and so on. Light intensity (LI) images, the most common type of images we encounter in our daily experience, represent the variation of light intensity on the scene. Range image (RI), on the other hand, is a map of depth information at different points on the scene. In a digital LI image, the intensity is quantized, while in the case of RI the depth value is digitized. Nuclear magnetic resonance images represent the intensity variation of radio waves generated by biological systems when exposed to radio frequency pulses. Biological bodies (humans/animals) are built up of atoms and molecules. Some of the nuclei behave like tiny magnets, m commonly known as spins. Therefore, if a patient (or any living being) is placed in a strong magnetic field, the magnetic nuclei tend to align with the applied magnetic field. For MRI the patient is subjected to a radio frequency pulse. As a result of this, the magnetic nuclei pass into a high-energy state, and then immediately relieve themselves of this stress by emitting radio waves through a process called relaxation. This radio wave is recorded to form the MRI. There are two different types of relaxation: longitudinal relaxation and transverse relaxation resulting in two types of MRIs, namely, T1 and T2, respectively [9]. In digital MRI, the intensity of the radio wave is digitized with respect to both intensity and spatial coordinates. Thus in general, any image can be described by a two-dimensional function if(x, y), where (x, y) denotes the spatial coordinate and f'(x, y) the feature value at (x, y). Depending on the type of image, the feature value could be light intensity, depth, the intensity of radio wave or temperature. A digital image, on the other hand, is a two-dimensional discrete function f(x, y) which has been digitized in both spatial coordinates and magnitude of feature value. We shall view a digital image as a two-dimensional matrix whose row, column indices identify a point, called a pixel, in the image, and the corresponding matrix element value identifies the feature intensity level.

Fig. 1 Image Processing

Segmentation is the first essential and important step of low-level vision [10], [11], [12], and [13]. There are many applications of segmentation. For example, in a vision-guided car assembly system, the robot needs to pick up the appropriate components from the bin. For this, segmentation followed by recognition is required. Its application area varies from the detection of cancerous cells to the identification of an airport from remote sensing data, etc. In all these areas, the quality of the final output depends largely on the quality of the segmented output. Segmentation is a process of partitioning the image into some non-intersecting regions such that each region is homogeneous and the union of no two adjacent regions is homogeneous. Formally, it can be defined [14] as follows: if F is the set of all pixels and P( ) is a uniformity (homogeneity) predicate defined on groups of connected pixels, then segmentation is a partitioning of the set F into a set of connected subsets or regions (S_1, S_2,..., S_n).

Image Processing Algorithms

Traditional techniques from statistical pattern recognition like the Bayesian discriminant and the Parzen windows were popular until the beginning of the 1990s. Since then, neural networks (ANNs) have increasingly been used as an alternative to classic pattern classi1ers and clustering techniques. Non-parametric feed-forward ANNs quickly turned out to be attractive trainable machines for feature-based segmentation and object recognition. When no gold standard is available, the self-organizing feature map (SOM) is an interesting alternative to supervised techniques. It may learn to discriminate, e.g., different textures when provided with powerful features.

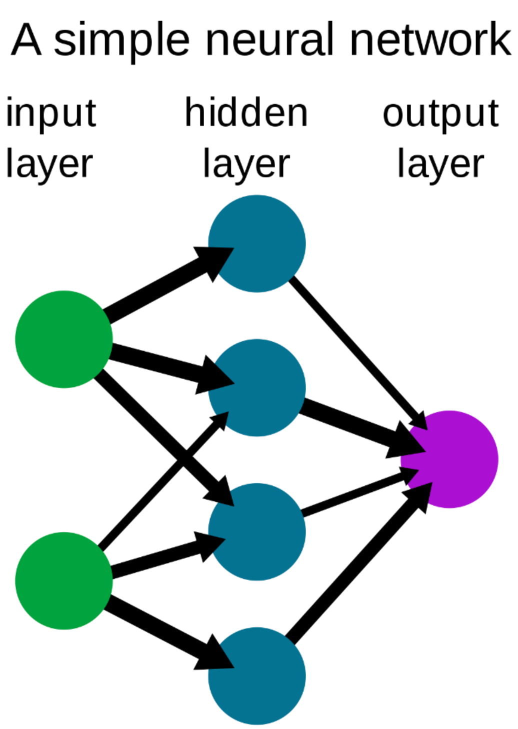

Fig. 2 Most Simplest Example of Artificial Neural Network

The current use of ANNs in image processing exceeds the aforementioned traditional applications. The role of feed-forward ANNs and SOMs has been extended to encompass also low-level image processing tasks such as noise suppression and image enhancement. Hop1eld ANNs were introduced as a tool for 1nding satisfactory solutions to complex (NP-complete) optimization problems. This makes them an interesting alternative to traditional optimization algorithms for image processing tasks that can be formulated as optimization problems.

The different problems addressed in the 1eld of digital image processing can be organized into what we have chosen to call the image processing chain. We make the following distinction between steps in the image processing chain (see Fig. 1):

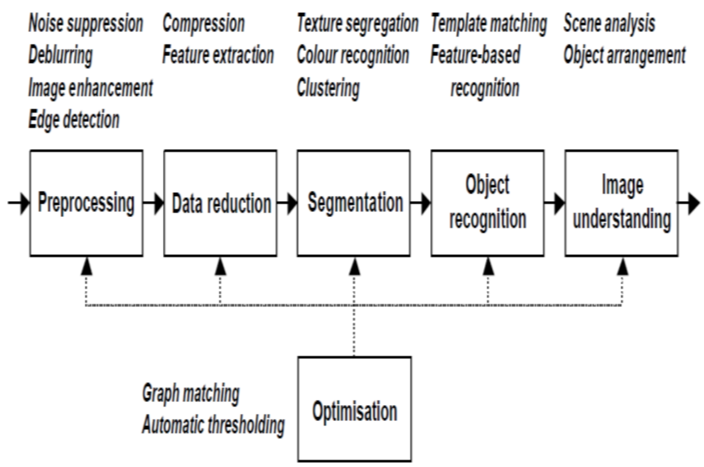

Fig. 3 The image processing chain containing the five different tasks: preprocessing, data reduction, segmentation, object recognition and image understanding. Optimization techniques are used as a set of auxiliary tools that are available in all steps of the image processing chain.

1. Preprocessing/Filtering. Operations that give as a result a modi1ed image with the same dimensions as the original image (e.g., contrast enhancement and noise reduction).
2. Data reduction/Feature Extraction. Any operation that extracts signi1cant components from an image (window). The number of extracted features is generally smaller than the number of pixels in the input window.
3. Segmentation. Any operation that partitions an image into regions that are coherent with respect to some criterion. One example is the segregation of different textures.
4. Object detection and recognition. Determining the position and, possibly the orientation and scale of speci1c objects in an image, and classifying these objects.
5. Image understanding. Obtaining high-level (semantic) knowledge of what an image shows.
6. Optimization. Minimization of a criterion function, which may be used for, e.g., graph matching or object delineation.

Optimization techniques are not seen as a separate step in the image processing chain but as a set of auxiliary techniques, which support the other steps.

Besides the actual task performed by an algorithm, its processing capabilities are partly determined by the abstraction level of the input data. We distinguish between the following abstraction levels:

A. Pixel level. The intensities of individual pixels are provided as input to the algorithm.
B. Local feature level. A set of derived, pixel-based features constitutes the input.
C. Structure (edge) level. The relative location of one or more perceptual features (e.g., edges, corners, junctions, surfaces, etc.).
D. Object level. Properties of individual objects.
E. Object set level. The mutual order and relative location of detected objects.
F. Scene characterization. A complete description of the scene possibly including lighting conditions, context, etc.

Table 1 contains the image processing algorithms that results from combining the steps of the image processing chain with the abstraction level of the input data.

Table 1 The image processing tasks categorized into a two-dimensional taxonomy[a]

	Preprocessing	Compression/feature extract	Segmentation	Recognition	Image understanding	Optimization
Pixel	26	25	39	51	3	5
Feature	4	2	19	38	2	3
Structure			2	6		5
Object						1
Object set				2	2	
Scene						

[a]Each cell contains the number of applications in our survey where neural networks accomplish a specific task in the image processing chain.

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.

Preprocessing

The first step in the image processing chain consists of preprocessing. Loosely de1ned, by preprocessing we mean any operation of which the input consists of sensor data, and of which the output is a full image. Preprocessing operations generally fall into one of three categories: image reconstruction (to reconstruct an image from a number of sensor measurements), image restoration (to remove any aberrations introduced by the sensor, including noise) and image enhancement (accentuation of certain desired features, which may facilitate later processing steps such as segmentation or object recognition).

Applications of ANNs in these three preprocessing categories will be discussed separately below. The majority of the ANNs were applied directly to pixel data (level A); only four networks were applied to more high-level data (features, level B).

Image reconstruction

Image reconstruction problems often require quite complex computations and a unique approach is needed for each application. In Ref. [15], an ADALINE network is trained to perform an electrical impedance tomography (EIT) reconstruction, i.e., a reconstruction of a 2D image based on 1D measurements on the circumference of the image. Srinivasan et al. [16] trained a modified Hop field network to perform the inverse Radon transform (e.g., for reconstruction of computerized tomography images). The Hop field network contained "summation" layers to avoid having to interconnect all units. Meyer and Heindl [17] used regression feed-forward networks (that learn the mapping E(y|x), with x the vector of input variables and y the desired output vector) to reconstruct images from electron holograms. Wang and Wahl trained a Hop1eld ANN for reconstruction of 2D images from pixel data obtained from projections [18].

Image restoration

The majority of applications of ANNs in preprocessing can be found in image restoration [19–38]. In general, one wants to restore an image that is distorted by the (physical) measurement system. The system might introduce noise, motion blur, out-of-focus blur, distortion caused by low resolution, etc. Restoration can employ all information about the nature of the distortions introduced by the system, e.g., the point spread function. The restoration problem is ill-posed because conflicting criteria need to be ful1lled: resolution versus smoothness.

Image enhancement

The goal of image enhancement is to amplify speci1c (perceptual) features. Among the applications where ANNs have been developed for image enhancement [39–49], one would expect most applications to be based on regression ANNs [44, 45, 47, and 49]. However, several enhancement approaches rely on a classi1er, typically resulting in a binary output image [39, 42, 43, 46].

Image segmentation

Segmentation is the partitioning of an image into parts that are coherent according to some criterion. When considered as a classi1cation task, the purpose of segmentation is to assign labels to individual pixels or voxels.

Some neural-based approaches perform segmentation directly on the pixel data, obtained either from a convolution window (occasionally from more bands as present in, e.g., remote sensing and MR images), or the information is provided to a neural classi1er in the form of local features.

Feature extraction applications

Feature extraction can be seen as a special kind of data reduction of which the goal is to find a subset of informative variables based on image data. Since image, data are by nature very high dimensional, feature extraction is often a necessary step for segmentation or object recognition to be successful. Besides lowering the computational cost, feature extraction is also a means for controlling the so-called curse of dimensionality [50]. When used as input for a subsequent segmentation algorithm, one wants to extract those features that preserve the class separability well [51, 52].

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 classifier.

Image understanding

Image understanding is a complicated area of image processing. It couples techniques from segmentation or object recognition with knowledge of the expected image content. In two applications, ANNs were used in combination with background knowledge to classify objects such as chromosomes from extracted structures (input level C) [53] and to classify ships, which were recognized from pixel data (input level A) by an advanced modular approach [54]. In another application, ANNs were used to analyze camera images for robot control from local features (input level B) [55]. Neural (decision) trees [56], semantic models based on extracted structures (input level C) [57] or neural belief networks [58] can be used to represent knowledge about the expected image content. This knowledge is then used to restrict the number of possible interpretations of single objects as well as to recognize different con1gurations of image objects. Especially, the approaches by Reinus et al. [57] and Stassopoulou et al. [58] perform genuine image interpretation. Reinus trains an ANN to diagnose bone tumors. The recognition approach of Stassopoulou et al. predicts the degree of deserti1cation of an area from a set of detected objects=segments, such as rocks, eroded areas, etc., in remote sensing images (input level E).

Optimization

Some image processing (sub) tasks such as graph and stereo matching can best be formulated as optimization problems, which may be solved by Hop1eld ANNs [18, 59, and 60, 61–70]. In some applications, the Hop1eld network obtained pixel-based input (input level A) [18, 59, 60, 66, 70], in other applications the input consisted of local features (input level B) [64, 68] or detected structures (typically edges, input level C) [62, 63, 65, 67, 69].

II. RELATED WORK

H.A. Rowley et.al in [1] present a neural network-based upright frontal face detection system. A retinally connected neural network examines small windows of an image and decides whether each window contains a face. The system arbitrates between multiple networks to improve performance over a single network. We present a straightforward procedure for aligning positive face examples for training. To collect negative examples, we use a bootstrap algorithm, which adds false detections into the training set as training progresses. This eliminates the difficult task of manually selecting nonface-training examples, which must be chosen to span the entire space of nonface images. Simple heuristics, such as using the fact that faces rarely overlap in images, can further improve the accuracy. Comparisons with several other state-of-the-art face detection systems are presented, showing that our system has comparable performance in terms of detection and false-positive rates.

K. Suzuki et.al in [2] developed an image-processing technique for suppressing the contrast of ribs and clavicles in chest radiographs by means of a multiresolution massive training artificial neural network (MTANN). An MTANN is a highly nonlinear filter that can be trained by use of input chest radiographs and the corresponding "teaching" images. We employed "bone" images obtained by use of a dual-energy subtraction technique as the teaching images. For effective suppression of ribs having various spatial frequencies, we developed a multiresolution MTANN consisting of multiresolution decomposition/composition techniques and three MTANNs for three different-resolution images. After training with input chest radiographs and the corresponding dual-energy bone images, the multiresolution MTANN was able to provide "bone-image-like" images, which were similar to the teaching of bone images. By subtracting the bone-image-like images from the corresponding chest radiographs, we were able to produce "soft-tissue-image-like" images where ribs and clavicles were substantially suppressed. We used a validation test database consisting of 118 chest radiographs with pulmonary nodules and an independent test database consisting of 136 digitized screen-film chest radiographs with 136 solitary pulmonary nodules collected from 14 medical institutions in this study. When our technique was applied to non-training chest radiographs, ribs and clavicles in the chest radiographs were suppressed substantially, while the visibility of nodules and lung vessels was maintained. Thus, our image-processing technique for rib suppression by means of a multiresolution MTANN would be potentially useful for radiologists as well as for CAD schemes in the detection of lung nodules on chest radiographs.

R. Parisi et.al in [3] describe an experimental system for the recognition of Italian-style car license plates. Images are usually taken from a camera at a toll gate and preprocessed by a fast and robust 1-D DFT scheme to find the plate and character positions. Characters are classified by a multilayer neural network trained by the recently developed BRLS learning algorithm. The same neural network replaces both the traditional feature extractor and the classifier. The percentage of correctly recognized characters reaches the best scores obtained in literature, being highly insensitive to the environment variability, while the architecture appears best suited for parallel implementation on programmable DSP processors.

J.G. Daugman et.al in [4] present neural network approach, based on interlaminar interactions involving two layers with fixed weights and one layer with adjustable weights, the network finds coefficients for complete conjoint 2-D Gabor transforms without restrictive conditions. In wavelet expansions based on a biologically inspired log-polar ensemble of dilations, rotations, and translations of a single underlying 2-D Gabor wavelet template, image compression is illustrated with ratios up to 20:1. Also demonstrated is image segmentation based on the clustering of coefficients in the complete 2-D Gabor transform.

V. Koval et.al in [5] describe the smart vehicle screening system, which can be installed into a tollbooth for automated recognition of vehicle license plate information using a photograph of a vehicle. An automated system could then be implemented to control the payment of fees, parking areas, highways, bridges or tunnels, etc. There are considered an approach to identify vehicle through recognizing of it license plate using image fusion, neural networks, and threshold techniques as well as some experimental results to recognize the license plate successfully

S. Lawrence et.al in [6] present a hybrid neural-network for human face recognition, which compares favorably with other methods. The system combines local image sampling, a self-organizing map (SOM) neural network, and a convolution neural network. The SOM provides a quantization of the image samples into a topological space where inputs that are nearby in the original space are also nearby in the output space, thereby providing dimensionality reduction and invariance to minor changes in the image sample, and the convolutional neural network provides partial invariance to translation, rotation, scale, and deformation. The convolutional network extracts successively larger features in a hierarchical set of layers. We present results using the Karhunen-Loeve transform in place of the SOM, and a multilayer perceptron (MLP) in place of the convolutional network for comparison. We use a database of 400 images of 40 individuals, which contains quite a high degree of variability in expression, pose, and facial details. We analyze the computational complexity and discuss how new classes could be added to the trained recognizer.

A. Khotanzad et.al in [7] presented a neural network (NN) based approach for classification of images represented by translation-, scale-, and rotation-invariant features. The utilized network is a multilayer perceptron (MLP) classifier with one hidden layer. Back-propagation learning is used for its training. Two types of features are used: moment invariants derived from geometrical moments of the image, and features based on Zernlike moments, which are the mapping of the image onto a set of complex orthogonal polynomials. The performance of the MLP is compared to the Bayes, nearest-neighbor, and minimum-mean-distance statistical classifiers. Through extensive experimentation with noiseless as well as noisy binary images of all English characters (26 classes), the following conclusions are reached: (1) the MLP outperforms the other three classifiers, especially when noise is present; (2) the nearest-neighbor classifier performs about the same as the NN for the noiseless case; (3) the NN can do well even with a very small number of training samples; (4) the NN has a good degree of fault tolerance; and (5) the Zernlike-moment-based features possess strong class separability power and are more powerful than moment invariants.

G. Peter Zhang et.al in [8] proposed a hybrid methodology that combines both ARIMA and ANN models to take advantage of the unique strength of ARIMA and ANN models in linear and nonlinear modeling. Experimental results with real data sets indicate that the combined model can be an effective way to improve forecasting accuracy achieved by either of the models used separately.

III. CONCLUSION

In this review paper, we presented our study related to various factors on which the image processing is to be done using the artificial neural network. We have studied and presented the various aspects of image processing such as Preprocessing, Image reconstruction, Image restoration, Image enhancement, Image segmentation, Feature extraction applications, Object recognition, Image understanding and Optimization etc. All these techniques or methodologies are one of the various techniques who play the vital role in the overall image-processing schedule.

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