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An efficient ultra sound kidney image retrieval using neural network approach

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ABSTRACT

The content of a kidney image can be expressed in terms of different features such as auto correlation, contrast, promenance, shade, dissimilarity, energy, entropy, homogeneity, maximum probability, variance, co-variance, correlation, inverse difference moment and inertia. Retrieval methods based on these features can be varied depending on how the feature values are combined. Many of the existing approaches assume linear relationships between different features, and also require users to assign weights to features for themselves. In this paper, we study the neural network-based image retrieval system. This approach allows the user to select an initial query image and incrementally search target images through training the images which are stored in the image database. The experimental results show that this approach provides better image retrieval performance than the existing linearly combining approach methods.

Introduction

Most systems do not give many details on the distance measurements or comparison methods used which most likely implies an Euclidian vector space model using either a simple Euclidean distance (L2) or something close such as city block distance or L1. To efficiently work with these distances even in large databases, the dimensionality is often reduced. This can be done with methods such as Principal Component Analysis (PCA) [1, 2] or Minimum Description Length (MDL) [3] that try to reduce the dimensionality while staying as discriminative as possible. In principle, redundant information is removed but this can also remove small but important changes from the feature space. Techniques such as KD-trees [4] and R-trees [5] are also used in medicine for efficient access to such a large feature spaces.

On the other hand, statistical methods are used for the comparison of features that can be trained with existing data and that can then be used on new, incoming cases. These can be neural networks for the classification of mammography images [6, 7] or on images extremely reduced in size (18x12 pixels) in [8]. Other statistical approaches use Bayesian networks [9] or Hidden Markov Models (HMMs) [10]. In [11], an associative computing approach is proposed for retrieval assuming that a query is performed with a local part of the images. A ROC (Receiver Operating Characteristic) curve for the comparison of methods is used. This is well known in the medical domain and easily interpretable.

A fundamental difference between a computer vision pattern recognition system and an image retrieval system is that the human is indispensable part of the latter system. Early literature emphasizes 'fully automated systems' and tried to find 'single best features'. In such approaches, the best features and representations and their corresponding weights are fixed, which can not effectively model high level concepts and user's perception subjectively. Motivated by the limitations of such approaches, the resent research focus in image retrieval has moved to 'interactive systems' and 'human in the loop' that involve human as a part of the retrieval process[12].

In this paper we propose a neural network based image retrieval which is the human computer interaction system model of image retrieval using back propagation network. It offers a method of combining image features. Using combined rather than individual, features is especially for image databases, for which no single feature is outstanding.

Neural Network

The characteristics of biological neural networks serve as the inspiration for artificial neural networks. An artificial neural network is an information-processing system that has certain performance characteristics in common with biological neural networks have been developed as generalizations of mathematical models of human recognition or neural biology, based on the assumptions that:

1. Information processing occurs at many simple elements called neurons.
2. Signals are passed between neurons over connection links.
3. Each connection link has an associated weight, which, in a typical neural net, multiplies the signal transmitted.
4. Each neuron applies an activation function (usually nonlinear) to its net input (sum of weighted input signals to determine its output signals) to determine its output signal.

Neural network consists of a large number of simple processing elements called neurons, units, cells, or nodes. Each neuron is connected to other neurons by means of directed communication links, each with an associated weight. The weights represent information being used by the net to solve a problem. Neural nets can be applied to a wide variety of problems, such as storing and recalling data or patterns, classifying patterns performing general mappings from input patterns to output patterns, or finding solutions to constrained optimization problems [13].

Each neuron has an internal state, called its activation or activity level, which is a function of the inputs it has received .Typically, a neuron sends its activation as a signal to several

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other neurons. It is important to note that a neuron can send only one signal at a time, although that signal is broadcast to several to other neurons [14].

The most typical neural net setting, training is accomplished by presenting a sequence of training vectors, or patterns, each with an associated target output vector. The weights are then adjusted according to a learning algorithm. This process is known as supervised training.

In unsupervised training sequence of input vectors is provided, but no target vectors are specified. The net modifies the weights so that the most similar input vectors are assigned to the same output (or cluster) unit. The neural net will produce and exemplar (representative) vector for each cluster formed.

Methodology

Back propagation Neural Network

Two of the reasons for the "quiet years" of the 1970's were the failure of single layer perceptrons to be able to solve such simple problems (mappings) as the Xor function and the lack of a general method of training a multilayer net. A method for propagation information about errors at the output units back to the hidden units had been discovered in the previous decade, but had but gained wide publicity. This method was also discovered independently by David Parker and by LeCun before it became widely known.

Pattern Recognition

Many interesting problems fall into the general area of pattern recognition. One specific area in which may neural network applications have been developed is the automatic recognition of handwritten characters (digits or letters). The large variation in sizes, positions, and styles of writing make this a difficult problem for traditional techniques. It is a good example, however, of the type of information processing that humans can perform relatively easily.

General-purpose multilayer neural nets, such as the back propagation net (a multilayer net trained by back propagation), have been used for recognizing handwritten zip codes. Even when an application is based on a standard training algorithm, it is quite common to customize the architecture to improve the performance of the application. This back propagation net has several hidden layers, but the pattern of connections from one layer to the next is quite localized.

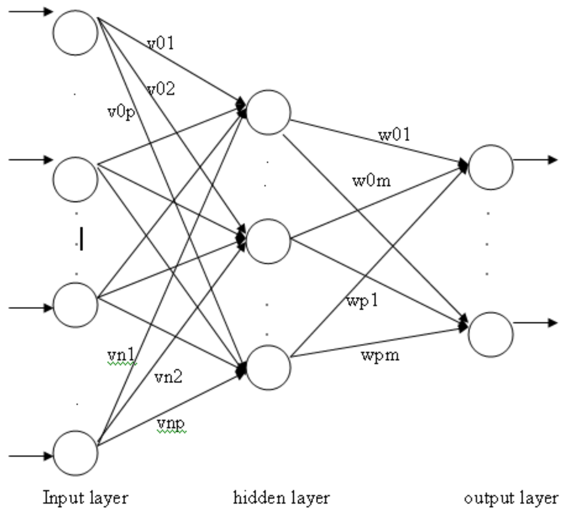
The training of a network by a back propagation involves three stages:

1. The feed forward of the input training pattern.
2. The calculation and back propagation of the associated error
3. And the adjustment of the weights.

After training, application of the net involves only the computations of the feed forward phase. Even if the training is slow, a trained net can produce its output very rapidly. Numerous variations of back propagation have been developed to improve the speed of the training process.

Although a single-layer net is severely limited into the mappings it can learn, a multiplayer net (with one or more hidden layers) can learn any continuous mapping to an arbitrary accuracy. More than one hidden layer may beneficial for some applications, but one hidden layer is sufficient.

Md. Rahman suggested the machine learning methods for image prefiltering, similarity matching using statistical distance measures, and a relevance feedback (RF) scheme. To narrow down the semantic gap and increase the retrieval efficiency, we investigate both supervised and unsupervised learning techniques to associate low-level global image features (e.g., color, texture, and edge) in the projected PCA-based eigenspace with their high-level semantic and visual categories [15].



Algorithm

Step 0. Initialize weights. (Set to small random values).

Step 1. While stopping condition is false, do Steps 2-9.

Step 2: For each training pair, do Steps 3-8.

Feed forward:

Step 3: Each input unit (X_i, i=1,…,n) receives input signal x_i and broadcasts this signal to all units in the layer above(the hidden units).

Step 4. Each hidden unit (Z_j,j=1,…,p) sums its weighted input signals,

$$z\_in_j = vo_j + \sum_{i=1}^{n} x_i v_{ij},$$

applies its activation function to compute its output signal,

$$z_j = f(z\_in_j),$$

and sends this signal to all units in the layer above(output units)

Step 5: Each output unit (Y_k, k=1,…, m) sums its input signals,

$$y\_in_k = wo_k + \sum_{j=1}^{p} z_j w_{jk},$$

applies its activation function to compute its output signal,

$$y_k = f(Y\_ink).$$

Back propagation of Error

Step 6. Each output unit (Y_k, k=1,…, m) receives a target pattern corresponding to the input training pattern, computes its error information term,

$$\delta_k = (tk - y_k)\, f'(y\_in_k),$$

calculates its weight correction term(used to update w_{ij} later),

$$\Delta w_{ik} = \alpha \delta k z_j,$$

calculates its bias correction term (used to update w_{ok} later),

$$\Delta w_{ok} = \alpha \delta_k,$$

and sends $\delta_{k\ to}$ units in the layer below.

Step 7. Each hidden unit (Z_j,j=1,…,p) sums its delta inputs(from units in the layer above),

$$\delta\_in_j = \sum \delta_k w_{ij},$$

multiplies by the derivative of its activation function to calculate its error information term,

$\delta=\delta\_in_j\, f\,'(z\_in_j)$,

calculates its weight correction term (used to update v_{ij} later),

$\Delta v_{ij}=\alpha\delta_j x_i$,

and calculates its bias correction term(used to update v_{oj} later),

$\Delta v_{oj}=\alpha\delta_j$.

Update weights and biases:

Step 8: Each output unit (Y_k,k=1,…,m) updates its bias and weights (j=0,…,p):

$W_{ik}(new)=w_{jk}(old)+\Delta w_{jk}$.

Each hidden unit (Z_j,j=1,…,p) updates its bias and weights (i=0,…,n):

$v_{ij}(new)=v_{ij}(old)+\Delta v_{ij}$.

Step 9: Test stopping condition.

Note that in implementing this algorithm, separate arrays should be used for the deltas for the output units (step 6,δ_k) and the deltas for the hidden units(step 7,δ_j).

An epoch is one cycle through the entire set of training vectors. Typically, many epochs are required for training a back propagation neural net. The foregoing algorithm updates the weights after each training pattern is presented. A common variation is batch updating, in which weight updates are accumulated over an entire epoch (or some other number of presentations of patterns) before being applied.

Note that f(y_in_k) and f(z_in_j) can be expressed in terms of y_k and z_j, respectively, using the appropriate formulas(depending on the activation function used)

The mathematical basis for the back propagation algorithm is the optimization technique known as gradient descent. The gradient of a function (in this case, the function is the error and the variables are the weights of the net) gives the direction in which the function increases more rapidly; the negative of the gradient gives the direction in which the function decreases most rapidly. A derivation of the weights clarifies the reason why the weight updates should be done after all of the δj and δk expressions have been calculated, rather than during back propagation .

Choices of initial weights and biases

Nguyen-widrow initialization:

The following simple modification of the common random weight initialization just presented typically gives much faster learning. The approach is based on a geometrical analysis of the response of the hidden neurons to a single input; the analysis is extended to the case of several inputs by using Fourier transforms. Weights from the hidden units to the output units (and biases on the output units) are initialized to random values between –0.5 and 0.5, as is commonly the case.

The initialization of the weights from the input units to the hidden units is designed to improve the ability of the hidden units to learn. This is accomplished by distributing the initial weights and biases so that, for each input pattern, it is likely that the net input to one of the hidden units will be in the range in which that hidden neuron will learn most readily. The definition as follows:

n number of input units,

p number of output units

β scale factor:

β=0.7 (p) 1/n

the procedure consists of the following simple steps:

for each hidden unit (j=1,…,p):

initialize its weight vector (from the input units):

vin(old)= random number between -05 and 0.5 (or between –γ and γ)

Compute |vj(old)| = V1j(old)2+V2j(old)2+ . . . +Vnj(old)2

Reinitialize weights:

Vij = βv_{ij}(old) / |vij(old)|

Set bias:

Voj = random number between β and –β.

The Nguyen- Widrow analysis is based on the activation function

$$\mathrm{Tanh}(x) = (e^{x}-e^{-x} /e^{x}+e^{-x})$$

How many training pairs there should be?

A relationship among the number of training patterns available, P, the number of weights to be trained, W, and the accuracy of classification expected, e, is summarized in the following rule of thumb. If there are enough training patterns , the net will be able to generalize as desired (classify unknown testing patterns correctly). Enough training patterns is determined by the condition

W/P=e

For example, with e=0.1, a net with 80 weights will require 800 traininig patterns to be assured of classifying 90% of the testing patterns correctly, assuming that the net was trained to classify 95% of the training patterns correctly.

INITWB By-weight-and-bias layer initialization function.

Syntax:

net = initwb(net,i)

Description:

INITWB is a layer initialization function which initializes

a layer's weights and biases according to their own initialization

functions.

INITWB(NET,i) takes two arguments,

NET - Neural network.

i - Index of a layer.

and returns the network with layer i's weights and biases updated.

Results and Discussions

In this neural approach, first the user can select the feature which will be used for comparison with the query image. Any one feature or combination of features may be selected for retrieval purpose.

Then the entire images are trained by using 800 epochs in the back propagation network. For training the image the error rate was set as 0.1. In this basis, the entire image database has been trained and the appropriate image which is matched with a query image has been retrieved from the database with in a short time.

Each and every feature has been selected individually and their performance has been calculated and given in Fig 4.1. It has been found by training all the images for the target value of 1. Finally the trained image which is similar to the query image has been retrieved from the image database using back propagation network.

The query image (Fig 4.2) has been selected initially by the user. Based on the query image, the other images are trained for the target 1 with the error rate 0.1. The image which is nearest to the target value has been retrieved as the resultant image (Fig 4.3) from the image database.

Fig. 4.1 Performance of images for error rate 0.1

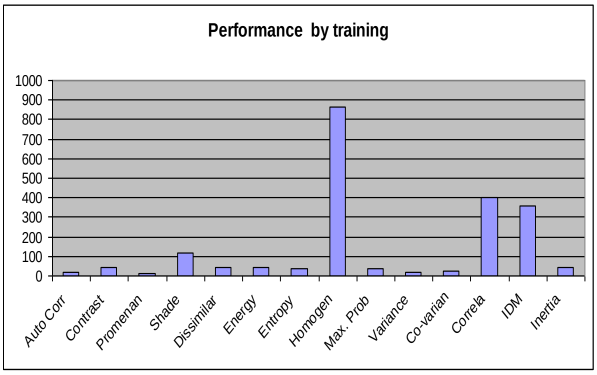


Fig 4.2 Query Image

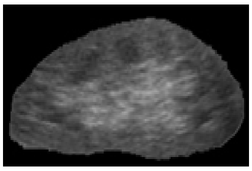
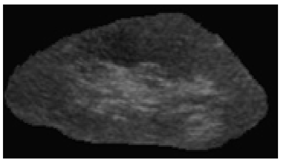


Fig 4.3 Resultant Image



Two statistical measures were computed to assess the system performance namely recall and precision. Recall consists of proportion of target images that have been retrieved among all the relevant images in the database. Precision consists of the proportion of target images that are retrieved up to the last correct one, which corresponds to 100% recall. A high value of precision indicates that the top ranked hits all contain target images.

In the case of back propagation method of Table 4.1, on average 83.04% of the images belong to the target class and target images represent 68.68% of all the images that need to be displayed in order not to miss any target. This result shows that our approach has better recall and precision performance compare to other methods.

Conclusion

An effective image retrieval system is developed based on the use of neural networks. It takes advantages of association ability of multilayer neural networks as matching engines which calculate similarities between a query image and the images stored in the database. It can automatically extract features of a user's drawn sketch during the retrieval phase and can store them as additional information to improve the performance. Based on the training given to the images with a target value and the error rate using back propagation network, the resultant image has been retrieved from the image database. The experimental result shows that our method has 83.04% recall and 68.68% precision which is better than the other methods.

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Table 4.1 Average Performance measure for query images

Method	Recall	Precision
Back Propagation Method	83.04%	68.68%
Linear Combining Method	77.84%	35.82%
Rank based Methods	8.91%	2.62%