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IMPROVED NEURAL NETWORK TRAINING ALGORITHM FOR CLASSIFICATION OF COMPRESSED AND UNCOMPRESSED IMAGES

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ABSTRACT

For managing data in a smart card's limited memory, containing medical and biometric images, images compression is resorted to. For image retrieval, it is necessary that the classification algorithm be efficient to search and locate the image in a compressed domain. This study proposes a novel training algorithm for Multi-Layer Perceptron Neural Network (MLP-NN) to classify compressed images. MLP-NN is used for image classification. The most common training algorithm is Error Back Propagation algorithm (EBP) with a very poor convergence rate. Other second order approaches including Levenberg-Marquardt method and conjugate gradient method are better to train neural networks. This study proposes an improved training algorithm based on Levenberg-Marquardt method for Neural Network.

Keywords: *Image Classification, Compressed Images, Multi-Layer Perceptron Neural Network (MLP-NN), Levenberg-Marquardt method.*

1. INTRODUCTION

Digital images form the basis for visual information in medical and identification applications. Agencies maintain visual information documentation including photographs and fingerprints for identification/ verification purposes. Image retrieval searches an entire database (archives) to locate closest matching records. Face recognition is a much sought application. Locating the desired image in a large/varied collection resulted in many image retrieval systems being designed. Conventional image indexing methods are inadequate as the number of images to be indexed is huge thereby making it impractical and error prone [1]. Automatic image retrieval based on color, shape and texture is called Content Based Image Retrieval (CBIR). CBIR methods are similar to those in image processing. Image processing includes image enhancement, compression and interpretation while CBIR focuses on image retrieval in response to queries from a database.

A generic CBIRs process involves three stages [2]. The first involves features extraction from database images. Extracted features are further indexed and compiled in the database. The second stage involves the query image as input is extracted for features. The final stage includes comparison of extracted feature from query with feature database with the image being retrieved.

Smart Cards are micro-processor carrying tokens, which stores and process a varied range of data/applications. It is used in banking, healthcare cards, in mobile telecommunications, and also in broadcast service subscriber services. Similar in size to the plastic payment card of today, smart cards have microprocessor/memory chips embedded which when coupled with a reader, can process and serve many applications. Smart cards are used as credit cards, healthcare cards and public transport cards. They are now replacing documents like driver's license and insurance papers. Registration cards as smart cards can store/protect a huge amount of information [3]. The main drawback is the limited and expensive storage medium built into it. Images are compressed to manage data in a smart card's limited memory which has medical and biometric images.

This study focuses on image retrieval issues using compressed images and compression's impact on classification accuracy. This study proposes an improved training algorithm based on Levenberg-Marquardt method for MLP-NN which can classify a smart card's compressed images. This study's following sections deal with related works in

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literature, different techniques used for image classification and experimental results.

2. RELATED WORKS

A hybrid model of Artificial Neural Networks (ANN) using multiple linear regression models to get precise classification accuracy was proposed by Khashei, et al., [4]. The model can be used for a 2 class and multi class problems. A content based color image retrieval system based on Fast Compression Distance (FCD) concept was proposed by Cerra and Datcu [5]. Computationally less complex, it is capable of use on large data sets. An image indexing/retrieval system suiting JPEG2000 compressed images was presented by Tang, et al., [6]. The new method did not include total decompression. Histogram features were extracted from wavelet coefficients used for retrieval. Results prove improved retrieving accuracy than that of current algorithms.

Khashman and Dimililer [7] trained a neural network to relate radiograph image contents to optimum image compression ratio. When trained, the NN chose ideal Haar wavelet compression ratio of x-ray images on being presented to the network. Experiments suggest that the proposed system efficiently compresses radiographs with high image quality. The trained NN correctly recognized optimum compression ratios for 25 training images as expected, yielding 100% training set recognition. Testing the trained NN using 23 images from Test Set 1 not presented to the network earlier, yielded a 95.65% recognition rate, where 22 out of 23 images with known optimum compression ratios were assigned correct ratio. A minimum accuracy level of 89% was accepted in this work. Using this accuracy, the NN yielded 95.65% correct recognition rate among optimum compression ratios. The proposed method's successful implementation using NN was revealed by high recognition rates and minimal time costs when operating a trained NN.

An image retrieval technique for JPEG images in the compressed domain was proposed by Zargari, et al., [8]. Packet header information was decoded for image retrieval and performed better than the pixel based Gabor filter and other wavelet based retrieval procedures. Zargari, et al., [9] suggested a new compressed domain texture based visual information retrieval process. The new method is for spatially predicted I-frames in H.264 video coding standard. I-Frame coding uses various prediction modes to spatially predict pixels of a block from upper or left adjacent pixels. A block's selected prediction mode indicates how the block's pixels are related to neighbouring parts. A suggestion was that histogram of prediction modes be used as a compressed I-frames texture descriptor. As the method is based on independent I-Frame coded pictures, it can be used for H.264 coded videos analysis or I-frame based coded images image retrieval like advanced image coding. Simulation indicates the superior performance and lower computational load compared to a Gabor filter based efficient realization of pixel domain texture retrieval method. Also, it is robust to variations in image/coding parameters. Thus, this procedure is a tool for various applications visual information analysis.

Daugman and Downing [10] investigated three schemes for high iris images compression to assess their impact on recognition performance of algorithms deployed to identify people through this biometric feature. The authors presented schemes combining region-of-interest (ROI) isolation with JPEG and JPEG2000 compression at several levels, testing them with a public iris images database showing the possibility of compressing iris images to as little as 2000 bytes with lowered impact on recognition performance. Only 2% to 3% of bits in IrisCode templates were changed by this severe image compression. It also calculated entropy per code bit introduced by every compression scheme. Error tradeoff curve metrics document good recognition performance despite data size reduction by a net factor of 150, approaching image data and template sizes convergence.

3. METHODOLOGY

This investigation evaluates classification accuracy for compressed/uncompressed images. Images are decomposed through use of Symlet wavelets. It is proposed to use Embedded Zero trees of Wavelets (EZW) algorithm to compress images including photo of smart card holder, biometric information and medical images. Image features are extracted using Gabor filters. Uncompressed images and various compressed images classification accuracy for retrieval is evaluated by the suggested MLP-NN.

A. Image Decomposition

Symlets are near symmetrical wavelets proposed by Daubechies to modify the db family as properties of both wavelet families are similar. Symlets are compactly supported with least asymmetry with maximum vanishing moments for a specific support width [11].

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B. Image Compression

The Embedded Zero trees of Wavelets (EZW) algorithm provides an embedded bit stream from a frequency domain transformed image using DWT. The EZW algorithm generated bit stream represents a binary decisions sequence distinguishing an image from another which is null and grey thereby allowing an encoder to terminate encoding any time. This allows a target bit rate to be achieved correctly. Similarly, a decoder terminates decoding any time, to ensure progressive transmission.

Wavelets algorithm embedded zerotrees processes hierarchical wavelet image decomposition. EZW exploits image self-similarity by introducing a data structure named zero tree [12] the idea being that when a coefficient at a coarse scale is insignificant regarding a given threshold, then all similar orientation wavelet coefficients in same spatial location at finer scales will also be insignificant. In zerotree structure, a coefficient has four descendants at finer scales and not the coarsest scale. The LL sub band, has three descendants for each coefficient [13].

An initial threshold is chosen to perform embedded coding,

$$t_0 = 2^{(\log_2(max|h(x,y)|))}$$

where h(x, y) denotes a coefficient. The encoder alternates between dominant and subordinate pass till image is fully encoded or desired bit rate achieved. A dominant pass is succeeded by a subordinate pass where next most significant bit of coefficients in subordinate list is the output. The first T subtracted from a coefficient becomes T/2 the subordinate threshold. If coefficient is bigger than or equal to T/2, then a '1' is the output, or else '0' is the output.

C. Feature extraction

Texture is important in image analysis for classification/segmentation and image generation/ processing. Many texture feature extraction algorithms were developed for image classification. Gray scale texture features are subdivided into statistical and signal theoretic algorithms and classes selected based on underlying stochastic process or specific Fourier pattern. A Gaussian kernel function modulated by a sinusoidal plane wave in a spatial domain [14] is a 2D Gabor filter which are self-similar: all filters are generated from one mother wavelet through dilation or rotation. A one-dimensional Gabor filter is the multiplication of a cosine/sine (even/odd) wave with Gaussian windows as given below [15],

$$G_E(X) = \frac{1}{\sqrt{2\pi\sigma^2}} e \frac{-x}{2\sigma^2} \cos(2\pi w_0 x)$$

$$G_0(X) = \frac{1}{\sqrt{2\pi\sigma^2}} e \frac{-x}{2\sigma^2} \sin(2\pi w_0 x)$$

where w_0 defines centre frequency (frequency where the filter yields greatest response) and σ the spread of Gaussian window.

D. Classifier

A Multilayer perceptron (MLP) is a favored supervised learning network model. The NN consists of input layer, one/more hidden layer and output layer. Connections between layers are formed by connecting nodes from a given layer to neurons in next layer. The training phase adjusts each connection's scalar weights. Outputs are from the output nodes. Feature vector x is input at input layer and output representing a discriminator between its class and other classes. In training, training examples are fed and predicted outputs computed. The output is compared with target output and error measured is reverted back through network and weights adjusted [16].

The training set of size m is represented as $T_M = \{(x_1, y_1),.....,(x_m, y_m)\}$ where $x_i \in R^a$ are input vectors of dimension a and $y_i \in R^b$ are output vectors of dimension b and R represents a set of real numbers. Let f_w represent function with weight w for neural network. Supervised learning adjusts weight so that:

$$f_w(x_i) = y; \forall (x_i, y_i) \in T_M$$

After NN is trained, and tested on new samples, its output is correct to some extent. A common training algorithm is Error Backpropagation algorithm (EBP).

EBP poor convergence rate in NN is a major concern, with efforts being made to speed up the algorithm [17, 18]. Though many approaches were tried in literature [19-21], little improvement resulted. Second order approaches like Newton's method, conjugate gradient's or Levenberg-Marquardt (LM) optimization techniques achieved good improvement of realization performance. LM

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is highly efficient in realization accuracy [22] achievement. It combines Newton algorithm's speed and stability of steepest descent method. LM's major disadvantages are memory requirement to operate large Jacobians and need to invert large matrices.

For LM algorithm, performance index to be optimized is defined as

$$F(w)=\sum_{p=1}^{P}\left[\sum_{k=1}^{K}\left(d_{kp}-o_{kp}\right)^{2}\right]$$

where $w=\begin{bmatrix} w_1 & w_2 & \cdots & w_N \end{bmatrix}^T$ consists of all network weights, d_{kp} is desired value of k^{th} output and p^{th} pattern, o_{kp} is actual value of k^{th} output and p^{th} pattern, N is number of weights, P the number of patterns, and K the number of network outputs.

The above equation can be rewritten as

$$F(w)=E^T E$$

where

$$E=\begin{bmatrix} e_{11} & \cdots & e_{K1} & e_{12} & \cdots & e_{K2} & \cdots & e_{1P} \end{bmatrix}$$

$$e_{kp}=d_{kp}-o_{kp}, k=1,.....,K$$
$$p=1,.....,P$$

where E is cumulative error vector for patterns. The Jacobian matrix is defined as

$$J=\begin{bmatrix}
\frac{\partial e_{11}}{\partial w_1} & \frac{\partial e_{11}}{\partial w_2} & \cdots & \frac{\partial e_{11}}{\partial w_N} \\
\frac{\partial e_{12}}{\partial w_1} & \frac{\partial e_{12}}{\partial w_2} & \cdots & \frac{\partial e_{12}}{\partial w_N} \\
\vdots & \vdots & & \vdots \\
\frac{\partial e_{K1}}{\partial w_1} & \frac{\partial e_{K1}}{\partial w_2} & \cdots & \frac{\partial e_{K1}}{\partial w_N} \\
\vdots & \vdots & & \vdots \\
\frac{\partial e_{1P}}{\partial w_1} & \frac{\partial e_{1P}}{\partial w_2} & \cdots & \frac{\partial e_{1P}}{\partial w_N} \\
\frac{\partial e_{2P}}{\partial w_1} & \frac{\partial e_{2P}}{\partial w_2} & \cdots & \frac{\partial e_{2P}}{\partial w_N} \\
\vdots & \vdots & & \vdots \\
\frac{\partial e_{KP}}{\partial w_1} & \frac{\partial e_{KP}}{\partial w_2} & \cdots & \frac{\partial e_{KP}}{\partial w_N}
\end{bmatrix}$$

and the weights are calculated using

$$w_{t+1}=w_t-\left(J_t^T J_t+\mu_t I\right)^{-1} J_t^T E_t$$

where I is identity unit matrix, μ a learning parameter and J Jacobian of m output errors with respect to n weights of NN. For μ = 0 it becomes Gauss-Newton method. For very large μ LM algorithm becomes steepest decent or EBP algorithm. The μ parameter is automatically adjusted at every iteration to secure convergence. LM algorithm needs computation of Jacobian **J** matrix at every iteration step and inversion of $J^T J$ square matrix, the dimension of which is N X N. This is why for large size NN the LM algorithm is not practical.

The performance index F(w) to be minimized in EBP algorithm is defined as the sum of squared errors between target outputs and network's simulated outputs, namely:

$$F(w)=E^T E$$

where $w=\begin{bmatrix} w_1 & w_2 & \cdots & w_N \end{bmatrix}^T$ consists of all network weights, e is error vector comprising error for all training examples.

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When training with LM method, increment of weights Δw is obtained as follows:

$$\Delta w = \left[J^T J + \mu I \right]^{-1} J^T e$$

where J is the Jacobian matrix, μ the learning rate to be updated using β depending on outcome. Specifically, μ is multiplied by decay rate β (0<β<1) whenever F(w) decreases, whereas μ is divided by β whenever F(w) increases in a new step.

The standard LM training process is illustrated through the following pseudo-codes,

1. Initialize weights and parameter μ (μ=.01 is appropriate).

2. Compute sum of squared errors over inputs F(w).

3. Solve (2) to obtain increment of weights Δw

4. Recompute sum of squared errors F(w)

Using w + Δw as the trial w, and judge

IF trial F(w) < F(w) in step 2 THEN

w = w + Δw

μ = μ · β (β = .1)

Go back to step 2

ELSE

$$\mu = \mu / \beta$$

go back to step 4

END IF

E. Proposed Training Method

Though Levenberg-Marquardt method is considered efficient, computing large Jacobians needs a large memory. The large matrixes needed to be inverted for computation, results in bigger computation time. Hence, to reduce computation cost, the following changes are introduced in Levenberg-Marquardt method.

Performance index to be optimized in Levenberg-Marquardt algorithm is given as

$$F(w) = \sum_{c=1}^{C} \left[\sum_{i=1}^{I} \left(d_{ic} - o_{ic} \right) \right]$$

where w refers to all network weights. d_{ic} is desired/required value of i^{th} output and c^{th} pattern. o_{ic} is actual value.

The following performance index is introduced in Levenberg-Marquardt method

$$F(w) = \sum_{c=1}^{C} \left[\sum_{i=1}^{I} \left(d_{ic} - o_{ic} \right) \right]^2$$

This leads to major reduction in matrix size, thereby reducing computation cost.

4. RESULTS AND DISCUSSION

In this study, MRI image, passport photograph of card holder and fingerprint images obtained from FVC2006 competition were used to evaluate the proposed method. 50 images of Passport photograph, 50 MRI images of which 30 non-stroke images and 20 were stroke images and 50 images of fingerprint were used for evaluating the proposed method. Some of the images used are presented in Figure 1.

Summarized below are the steps followed:

1. Images were decomposed using Symlet 2, for decomposition level 2.

2. Compress images including photo of the smart card holder, biometric information and medical images using Embedded Zero trees of Wavelets (EZW) algorithm.

3. The classification accuracy for retrieval of uncompressed images and various compressed images is evaluated using the proposed MLP-NN.

Table I: Classification Accuracy

Classification Accuracy	**Biometric Verification**	**Stroke Classification**
No Compression	84	92
Symlet 2 Decomposition 2	84	94
EZW	89.14	93.1
Proposed MLP-NN	90.84	94.42

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Figure 1: Images used for the experimental setup

Figure 2 and table 1 show the classification accuracy obtained for different images.

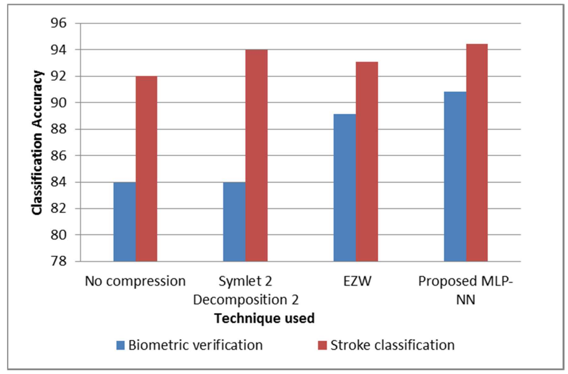

Figure 2: Classification Accuracy

It is observed that the classification accuracy achieved for the compressed images is better when compared to the accuracy of uncompressed images. For biometric images, the classification of the compressed image is improved by 8.14% when compared to uncompressed image. For the stroke classification, an improvement of 2.63% is observed.

5. CONCLUSION

This study evaluates classification accuracy for retrieving compressed image which are compared with uncompressed images classification accuracy. Medical image compression’s ultimate goal is performance of medical image matching from an online server with high resolution images. Experiments were undertaken using 50 images of a Passport photograph, 50 fingerprint images and 50 MRI images of which 20 were stroke and 30 non-stroke images. The images were decomposed using Symlet wavelets and Embedded Zero trees of Wavelets (EZW) algorithm compressed the images. Features extraction was through use of Gabor filters. The proposed MLP-NN was used for the classification retrieval accuracy of uncompressed images and various compressed images. Experiments revealed that classification accuracy for compressed images was better in comparison to accuracy of uncompressed images when images were decomposed using Symlet 2 at decomposition level 2.

REFRENCES:

[1] Da Silva Torres, R., & Falcão, A. X. (2006). Content-Based Image Retrieval: Theory and Applications. RITA, 13(2), 161-185.

[2] Gudivada, V. N., & Raghavan, V. V. (1995). Content based image retrieval systems. Computer, 28(9), 18-22.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[3] Mike Hendry "Multi application smart cards: Technologies and applications", Cambridge university press, 2007

[4] Khashei, M., Zeinal Hamadani, A., & Bijari, M. (2012). A novel hybrid classification model of artificial neural networks and multiple linear regression models. Expert Systems with Applications, 39(3), 2606-2620.

[5] Cerra, D., & Datcu, M. (2012). A fast compression-based similarity measure with applications to content-based image retrieval. Journal of Visual Communication and Image Representation, 23(2), 293-302.

[6] Tang, J., Zhang, W., & Li, C. (2005). An approach to compressed image retrieval based on JPEG2000 framework. In Advanced Data Mining and Applications (pp. 391-399). Springer Berlin Heidelberg.

[7] Khashman, A., & Dimililer, K. (2008). Image compression using neural networks and haar wavelet. WSEAS Transactions on Signal Processing, 4(5), 330-339.

[8] Zargari, F., Mosleh, A., & Ghanbari, M. (2008). A fast and efficient compressed domain JPEG2000 image retrieval method. Consumer Electronics, IEEE Transactions on, 54(4), 1886-1893.

[9] Zargari, F.; Mehrabi, M.; Ghanbari, M., "Compressed domain texture based visual information retrieval method for I-frame coded pictures," Consumer Electronics, IEEE Transactions on , vol.56, no.2, pp.728,736, May 2010

[10] Daugman, J., & Downing, C. (2008). Effect of severe image compression on iris recognition performance. Information Forensics and Security, IEEE Transactions on, 3(1), 52-61.

[11] Ahmed, S., Ahmad, S., Faruqe, M. O., & Islam, M. R. (2009, November). EMG signal decomposition using wavelet transformation with respect to different wavelet and a comparative study. In Proceedings of the 2nd International Conference on Interaction Sciences: Information Technology, Culture and Human (pp. 730-735). ACM.

[12] Shapiro, J. M. (1992, March). An embedded wavelet hierarchical image coder. In Acoustics, Speech, and Signal Processing, 1992. ICASSP-92., 1992 IEEE International Conference on (Vol. 4, pp. 657-660). IEEE.

[13] Bhattar, R. K., Ramakrishnan, K. R., & Dasgupta, K. S. (2002). Strip based coding for large images using wavelets. Signal Processing: Image Communication, 17(6), 441-456.

[14] Fogel, I., & Sagi, D. (1989). Gabor filters as texture discriminator. Biological cybernetics, 61(2), 103-113.

[15] Daugman, J. G. (1985). Uncertainty relation for resolution in space, spatial frequency, and orientation optimized by two-dimensional visual cortical filters. Optical Society of America, Journal, A: Optics and Image Science, 2, 1160-1169.

[16] Bello, M. G. "Enhanced training algorithms, and integrated training/architecture selection for multi layer perceptron networks," IEEE Trans. on Neural Net., vol. 3, pp. 864-875, 1992.

[17] Rumelhart, D. E., Hinton, G. E. and Williams, R. J, "Learning internal representations by error propagation," In Parallel Distributed Processing, Cambridge, MA: MIT Press, vol 1, pp. 318-362.

[18] Werbos, P. J. "Back-propagation: Past and future," Proceeding of International Conference on Neural Networks, San Diego, CA, 1, pp. 343-354, 1988.

[19] Samad, T. "Back-propagation improvements based on heuristic arguments," Proceedings of International Joint Conference on Neural Networks, Washington, 1, pp. 565-568, 1990.

[20] Bello, M. G. (1992). "Enhanced training algorithms, and integrated training/architecture selection for multilayer perceptron networks", *IEEE Trans. on Neural Networks*, **3,** 864-875.

[21] Miniani, A. A. and Williams, R. D. (1990). "Acceleration of back-propagation through learning rate and momentum adaptation", *Proceedings of International Joint Conference on Neural Networks*, San Diego, CA, **1,** 676-679.

[22] Salvetti, A. and Wilamowski, B. M., "Introducing Stochastic Process within the backpropagation Algorithm for Improved Convergence", presented at *ANNIE'94 – Artificial Neural Networks in Engineering*, St. Louis, Missouri, USA, November 13-16, 1994; also in *Intelligent Engineering Systems Through Artificial Neural Networks* vol **4**, pp. 205- 209, ed. C. H. Dagli, B. R. Fernandez, J. Gosh, R.T. S. Kumara, ASME PRESS, New York 1994.

[23] Hagan, M. T. and Menhaj, M., "Training feedforward networks with the Marquardt algorithm", IEEE Transactions on Neural Networks, vol. **5**, no. 6, pp. 989- 993, 1994.