Bandwidth oriented Image Compression using Neural Network with ASAF

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Abstract—We have applied the adaptive slope of activation function in the supervised learning algorithm for multilayer feedforward neural networks to get the bandwidth based demand of image compression in multimedia based applications. Developed solutions have applied to compress and decompress the gray scale as well as color images also. The Proposed solution has also contained a smoothing approach, which applied after decompression process to avoid the distortion at the edge of pixels blocks and it has observed that with the higher value of compression, usefulness of smoothing process is increased. The algorithm is applied successfully to classic linearly nonseparable benchmark, XOR problem, to understand the fundamental benefit of adaptive slope in activation function. The algorithm has successfully tested in the presence of different requirement of image transmission bandwidth, and results have shown that proposed solution has better compression quality along with faster convergence.

Index Terms—Artificial neural networks, Feedforward neural networks, Levenberg–Marquardt (LM), Back Propagation (BP), Adaptive Slope based architecture (ADSL), Constant (Fixed) Slope of activation function(FXSL)

I. Introduction

Artificial neural networks (ANN) have been an robust area of research in the last era and many attainments have been materialized. After any improvement in the techniques and algorithms, the question comes to the application. Feedforward neural networks (FNN) are broadly used to solve compound problems in analyzing non-linear multivariate data, non-linear signal processing, system modeling, identification, and pattern classification. One of the features of the FNN is its learning (or training) capacity. By training, the neural network can give accurate answers not only for learned examples, but also for the models similar to the learned examples, showing its strong associative ability and rational ability which are suitable for solving nonlinear, large, complex classification and function estimate problems. The Back Propagation (BP) algorithm is a classical method for training FNN. The Back Propagation (BP) algorithm is based on the gradient descent optimization technique. Even though the general achievement of this algorithm it may unite to a local minimum of the mean squared-error objective task and requires a huge number of learning iterations to adjust the weights of the FNN. Many attempts have been made to speed up the error BP algorithm. The most renowned algorithms of this type are the Conjugate Gradient Training Algorithm and Levenberg–Marquardt (LM) training algorithm. The computational difficulty of the Conjugate Gradient Algorithm is comprehensively dependent on the line search methods. The LM algorithm has a faster speed than gradient and hardly stuck in the local minimum. But it requires more memory and computational time. In this paper, Adaptive Slope of Activation Function has developed for the image compression which has the fixed ratio of compression.

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II. Literature survey

In [1] use of neural networks in image processing has been done and discussed and possible future role of neural networks, especially feed-forward neural networks, Kohonen feature maps and Hopfield neural networks. [2] has presented reviews over applications of soft computing in the area of medical image processing, where advantage is taken from the ability of fuzzy logic to work with imprecise information, the ability of neural networks to learn a system's behavior from representative examples and the ability of evolutionary algorithms to optimize complex systems, particularly when no mathematical model is available. Modeling of the processing occurring at retina level and in the V1 visual cortex has been discussed in [3] and shown the advantages of using such a modeling in order to develop efficient and fast bio-inspired modules for low level image processing. [4] Has described an image processing approach to the 3D shape recovery based on neural networks that tackles the major bottleneck in the current reverse engineering process, namely the lack of a rapid link between the physical object and its design representation. Given that neural networks have been widely reported in the research community of medical imaging, [5] provided a focused literature survey on recent neural network developments in computer-aided diagnosis, medical image segmentation and edge detection towards visual content analysis, and medical image registration for its pre-processing and post-processing, with the aims of increasing awareness of how neural networks can be applied to these areas and to provide a foundation for further research and practical development. A Cellular Neural Network (CNN) based edge detector optimized by Differential Evolution (DE) algorithm has presented in [6]. Cloning template of the proposed CNN has applied adaptively tuned by using simple training images. In [7] a combination of algorithms useful for image compression standard has discussed. Predictive Vector Quantization (PVQ) developed, which based on competitive neural networks quantizer and neural networks predictor. Additionally, the noiseless Huffman coding is used. The problem of image compression by using Artificial Neural Networks (ANN) has discussed in [8] by reducing the original feature spaces, that allows to eliminate the image redundancy and accordingly leads to their compression. Two variants of the neural networks: two layers ANN with the self-learning algorithm based on the weighted informational criterion and auto-associative four-layer feedforward network have been proposed and analyzed. A subclass of recurrent neural networks, called Pixel Neural Networks (PNN) has discussed in [9]. It appears that PNN networks can represent real-life images and fractal compression operators can be implemented by networks from the special subclass FBPNN. A Bacterial Foraging Algorithm (BFA) based neural network has presented in [10] for image compression. To improve the quality of the decompressed images, the concepts of reproduction, elimination and dispersal in BFA have introduced into neural network. In [11], an algorithm named the Predictive Vector Quantization (PVQ) has proposed for video compression. Into this scheme of image compression a competitive neural networks quantizer and a neural networks predictor are incorporated.in [12] , Magnitude Sensitive Image Compression (MSIC), approach has applied for selective image compression. The algorithm uses MSCL neural networks (in direct and masked versions). These kind of neural networks tend to focus the learning process in data space zones with high values of a user-defined magnitude function. In [13] , digital image compression have done using Deep Neural Networks (DNNs),which has applied two different DNN architectures, employing the hyperbolic tangent neurons and the other engaging the logistic sigmoid neurons. In [14], authors have proposed the method to predict the personalized emotion perceptions of images for each individual viewer. Different types of factors that may affect personalized image emotion perceptions, including visual content, social context, and temporal evolution, and location influence, ware jointly investigated. [15] Has proposed a method for hyper spectral image classification based on Deep Stacking Network (DSN), which owns advantages to other deep models for its simplicity when processing in batch-mode learning - not requiring stochastic gradient descent that other DNNs require. The feature extraction is gradually obtained by employing nonlinear activation function on the hidden layer nodes of each module. CNNs are an effective tool that has previously been used in image processing of several biomedical imaging modalities. In [16], work has done to explore the effectiveness of CNNs when trained to act as a pre-segmentation pixel classifier that determines whether a pixel is an edge or non-edge pixel. In [17], an image stitching method has been proposed, which utilizes Scale-Invariant Feature Transform (SIFT) feature and Single-Hidden Layer Feedforward Neural Network (SLFN) to get higher precision of parameter estimation. In [18], authors have investigated the use of Deep Convolutional Neural Network (DCNN) for scene classification.

III. Adaptive of Activation Function

Weight update equation for Back Propagation, the rate of the update is proportional to the derivative of the nonlinear activation function. A typical activation function for neurons in MLP NN is of sigmoid type with bell-shaped derivatives. During training of the neural network, the output of the linear combiner may fall in the fullness region of the stimulation function. The derivative of the activation task in that region is very small and since the weight updates depends directly on the magnitude of the derivative, the rate of learning turn out to be tremendously slow, it may take many iterations before the output of the linear combiner moves out of the fullness region. A possible solution of this problem is to increase the region of non-saturated region by decreasing the slope of activation function. However decreasing the slope will make the system more closer to linear model, which in effect diminish the advantage of having the multilayer network. Hence there is an optimum value of slope needed at each iteration as according to the landscape define by the error function. Again the value of slope for activation function is not same for all the neurons. Complexity involved with MLP does not to have all the slopes values before training commence hence there is need to provide the adaptive mechanism which has to take care of slopes of activation function. The process for adaption of slopes can be derived simultaneously with weights optimization in terms of minimization of error function. Specifically, the slopes are to be chosen so as to minimize the performance criterion

$$E_q = \frac{1}{2}\left(d_q - x_{out}^{(s)}\right)^T \left(d_q - x_{out}^{s}\right)$$

$$= \frac{1}{2}\sum_{h=1}^{n}\left(d_{qh} - x_{out,h}^{s}\right)^2 \qquad (1)$$

Where s denotes the number of layers in the network and $d_q \in \Re^{n\times 1}$ and x_{out}^s are the derived and actual output, respectively of the network due to q^th training pattern. Consider an activation function of the sigmoid type given by Eq.2

$$f(u,k) = \frac{1}{(1+e^{-ku})} \qquad (2)$$

Where **u** is the input to the nonlinearity and **k** is the slope parameter which has to be adjusted so that Eq.1 has to minimize. Considering the nonlinearity of the i^th neuron in the s^th layer of the network, gradient approach can be applied by obtaining

$$k_i^s(t+1) = k_i^s(t) - \beta\frac{\partial E_q}{\partial k_i^s} \qquad (3)$$

Using the chain rule, the second term on the right side in Eq.3 can be rewritten as

$$\frac{\partial E_q}{\partial k_i^s} = \frac{\partial E_q}{\partial u_i^s}\frac{\partial u_i^s}{\partial x_{out,i}^s}\frac{\partial x_{out,i}^s}{\partial k_i^s}$$

$$= -\delta_i^s \frac{1}{\partial x_{out,i}^s / \partial u_i^s}\frac{\partial x_{out,i}^s}{\partial k_i^s} = -\delta_i^s \frac{f_k(u,k)}{f_u(u,k)} \qquad (4)$$

Where δ_i^s is the local error for the i^th neuron of the s^th layer, and $f_k(u,k)$ and $f_u(u,k)$ denote the partial derivatives of the activation function with k and u respectively.

Hence the slope of the activation function can be defined by

$$k_i^s(t+1) = k_i^s(t) + \beta\delta_i^s \qquad (5)$$

To increase the stability, momentum term is also added.

A. Learning algorithm with adaptive activation function slopes

1. Initialize the weights in the network according to standard initialization process.
2. From set, the set of training data, derive the network response.
3. Compare the desired network response with the actual output of the network and the local error is computed according to

   For output layer:

   $$\delta_i^s = \left(d_q - x_{out,i}^s\right) g(u_i^s)$$

   For hidden layer:

   $$\delta_i^s = \sum_{h=1}^{n2} \delta_h^{s+1} w_{hi}^{s+1}\, g(u_i^s)$$

4. The weights of the network are updated according to

   $$w_{ij}^s(t+1) = w_{ij}^s(t) + \mu\delta_i^s x_{out,j}^s$$

5. The slope of the activation function are updated according to

   $$k_i^s(t+1) = k_i^s(t) + \beta\delta_i^s + \alpha[k_i^s(t) - k_i^s(t-1)]$$

6. Stop the iteration if network converged, else go back to step 2.

Experimental results

XOR classification problem: The network of XOR problem consists of two input nodes, two hidden nodes and one output node. Performance of obtained result has shown in Table 1.it is clear that there are more accurate result have obtained by Adaptive Slope based architecture (ADSL) in compare to result obtained with Constant (Fixed) Slope of activation function(FXSL), equal to 1.Total number of applied iterations was 5000 for both cases and from Fig1. it can observe that more faster convergence achieved with ADSL.

Table1: XOR Performance comparison

INPUT	TAR GET	ACHIEVED FXSL	ACHIEVED ADSL	ERROR FXSL	ERROR ADSL
0 0	0	0.0119	0.0047	-0.0119	-0.0047
0 1	1	0.9873	0.9948	0.0127	0.0052
1 0	1	0.9873	0.9948	0.0127	0.0052
1 1	0	0.0159	0.0068	-0.0159	-0.0068
MSE		1.0e-003 *0.1796	1.0e-003 * 0.0307		

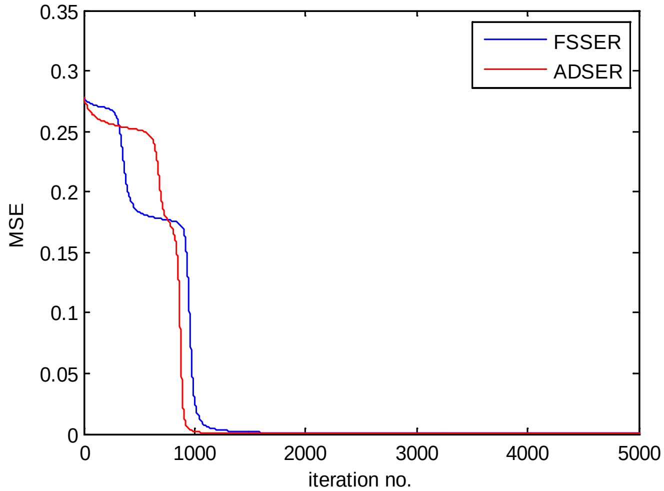

Fig.1 Convergence characteristic for XOR problem

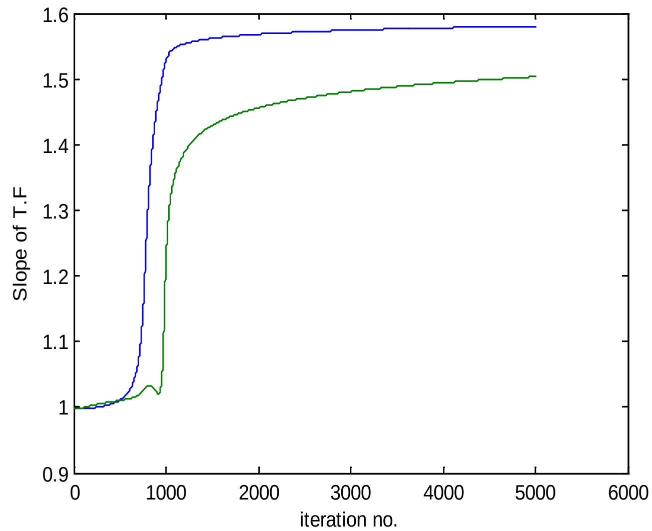

Fig.2 Slope variation in hidden nodes function

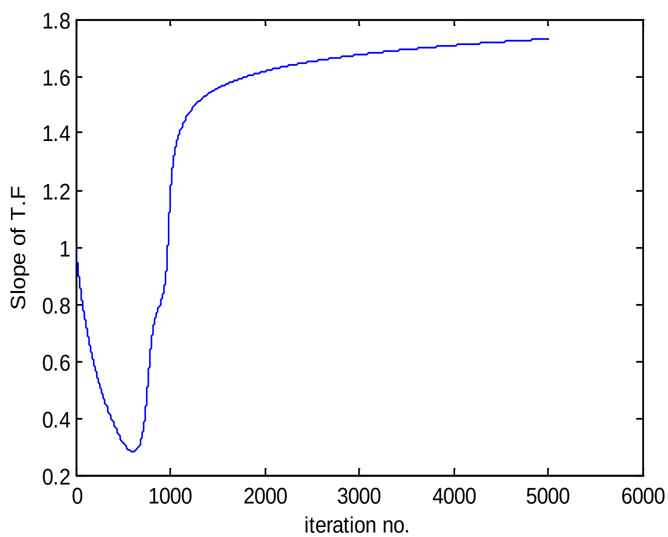

Fig.3 Slope variation in output node function

Adaptive characteristics in slope for hidden nodes and output nodes activation function have shown in Fig.2 and in Fig.3 and final iteration numeric values of slope have shown in Table2.

Table2: Final slope value for XOR problem

Slope (hidden nodes) =	1.5803 1.5033
Slope(output layer nodes)=	1.7308

Image compression

There are three different compression ratio have applied in this paper, 75%,87.5% and 93.75% and obtained performances have shown in Table3,Table5 and in Table 7.Obtained values of slope under different conditions are also shown in Table 4,Table 6 and in Table 8.It is easily possible to change the compression ratio in neural network by changing the number of hidden nodes involved with hidden layer. For compression ratio 75%,there are four hidden nodes, while 2 hidden nodes required to deliver the compression ratio of 87.5% and only one node is necessary for 93.75% compression ratio. Training has applied with Lena gray scale image, with formation of block size 4*4, in result, there 16 input nodes and 16 output nodes required. Learning characteristics for different compression ratio have shown in Fig.4, Fig.5 and in Fig.8.It is clear that there is more faster convergence with adaptive slope of activation function in all cases and improvement observed in PSNR values without exception.

Table 3: Performances of image quality in dB for 75% compression ratio

%Compression75	FSNN	ADSNN	ADSCNN	MSE(FX)	MSE(AD)
Gray image					
Lena	30.4185	32.0131	30.6064	6.2855 e-004	5.2936 e-004
Alina	29.5632	30.8049	30.1002		
Vegetable	28.0988	29.2497	28.5038		
Boat	27.0732	28.2155	27.1060		
Color image					
Lena	28.7710	29.7836	28.9214		
Vegetable	26.6878	27.6563	27.0619		

Table 4: Activation function slope for 75% compression ratio

Slope (hidden nodes) [0.5273 0.6232 0.8074 0.6189]
Slope(output layer nodes) [-2.2086 2.0938 -1.8030 1.8052 2.1207 1.7177 1.8425 1.8998 1.9199 1.7924 1.8200 2.0183 1.9674 1.8024 1.8838 2.0702]

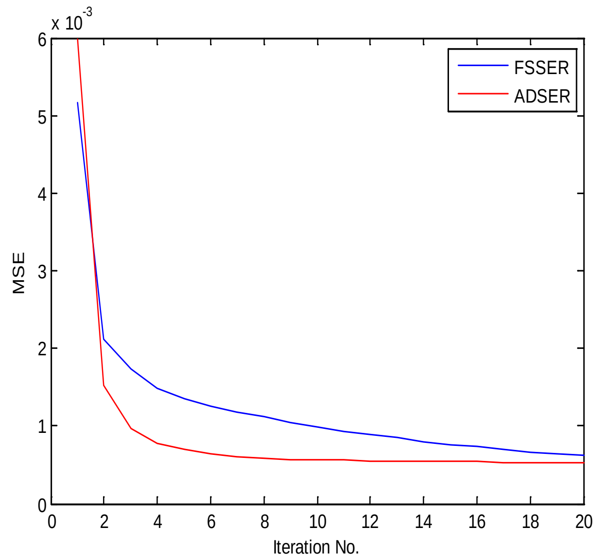

Fig.4 Convergence characteristic in 75% compression ratio

Table5: Performances of image quality in dB for 87.5% compression ratio

%Compression 87.5000	FSNN	ADSNN	ADSCNN
Gray image			
Lena	28.3168	29.0938	29.0673
Alina	27.9209	28.8658	29.2253
Vegetable	26.2143	26.7760	26.9301
Boat	25.1351	25.7561	25.7075
Color image			
Lena	27.1899	27.8201	27.7927
Vegetable	25.1652	25.6486	25.7461

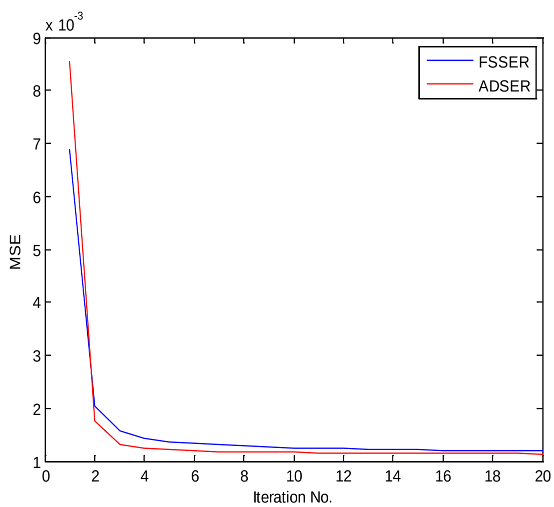

Fig.5 Convergence characteristic in 87.5% compression ratio

Table 6: Activation function slope for 87.5% compression ratio

Slope (hidden nodes) [0.4006 0.5410]
Slope(output layer nodes) [2.1426 2.1097 2.1315 2.0449 2.0673 2.1758 2.0876 2.0453 2.0158 2.2579 2.2543 2.0496 -2.1679 2.3487 2.2052 2.3044]

Table 7: Performances of image quality in dB for 93.75% compression ratio

%Compression93.75	FSNN	ADSNN	ADSCNN	MSE(FX)	MSE(AD)
Gray image					
Lena	25.8510	26.5276	27.2544	2.2135 e-003	2.1760e-003
Alina	26.4722	27.4254	28.2990		
Vegetable	24.5541	25.1172	25.7048		
Boat	23.3842	24.0569	24.3228		
Color image					
clena	25.2667	25.8426	26.3306		
cvegt	23.7631	24.2860	24.7011		

Table 8: Activation function slope for 93.75% compression ration

Slope (hidden nodes) [0.3723]
Slope(output layer nodes) [2.0789 2.1471 2.1124 2.1702 2.1258 2.2264 2.2427 -2.0979 2.1579 2.2141 2.2245 2.1887 2.1360 2.1511 2.0675 2.0249]

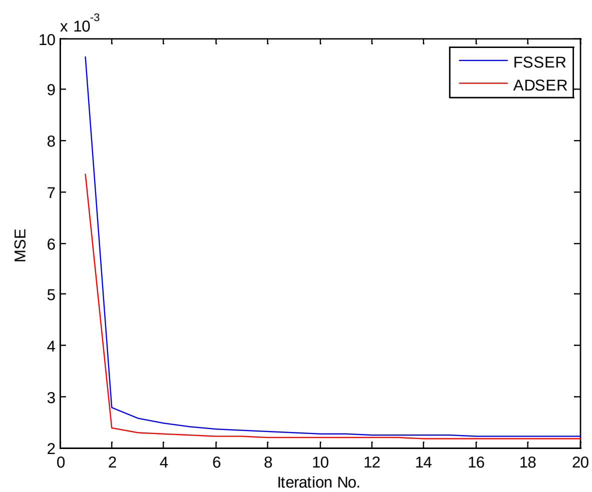

Fig.8 Convergence characteristic in 93.75% compression ration

Original	FSNN	ADSNN	ADSCNN

Fig.6 Decompressed gray scale images at compression ratio 87.5%

Original	FSNN	ADSNN	ADSCNN

Fig.7 Decompressed color images at compression ratio 87.5%

There is smoothing process applied once decompressed process is over. It is observe that as compression ratio is going more, smoothing process is more beneficial. In smoothing process, neighboring blocks boundary pixels are extracted and a mean value is replaced in horizontal as well vertical direction.

Conclusion

To handle the multimedia bandwidth constrained, where maximum resource utilization is the primary goal, fixed compression ratio is the better choice and in this research it has achieved with the help of feedforward architecture which has the adaptive slope of their activation function. Simultaneous optimization has applied for weights and slope value to make learning faster and deeper. Proposed solution has also capability to compress and decompress the color image also without any limitations. Proposed solution has achieved the better decompress image quality even there is very compression ratio.

References

[1]. M. Egmont-Petersen, D. de Ridder H. Handels," Image processing with neural networks—a review", Elsevier, Pattern Recognition, Volume 35, Issue 10, Pages 2279–2301, October 2002

[2]. I. Aizenberg, N. Aizenberg, J. Hiltner, C. Moraga, E. Meyer zuBexten, Erratum to "Cellular neural networks and computational intelligence in medical image processing", Image and Vision Computing, Volume 19, Issue 13, Page 1019, 1 November 2001.

[3]. A. Benoit,A. Caplier, B. Durette, J. Herault, "Using Human Visual System modeling for bio-inspired low level image processing", Computer Vision and Image Understanding, Volume 114, Issue 7, Pages 758–773, July 2010.

[4]. QingjinPeng, Martin Loftus, "Using image processing based on neural networks in reverse engineering", International Journal of Machine Tools and Manufacture, Volume 41, Issue 5, Pages 625-640, April 2001.

[5]. J. Jiang, P. Trundle, J. Ren, "Medical image analysis with artificial neural networks", Computerized Medical Imaging and Graphics, Volume 34, Issue 8, Pages 617-631, December 2010.

[6]. AlperBaştürk, EnisGünay, "Efficient edge detection in digital images using a cellular neural network optimized by differential evolution algorithm",Expert Systems with Applications, Volume 36, Issue 2, Part 2, Pages 2645-2650, March 2009.

[7]. Robert Cierniak,"An Image Compression Algorithm Based on Neural Networks",Artificial Intelligence and Soft Computing - ICAISC 2004,Volume 3070, Pages 706-711.

[8]. Yevgeniy Bodyanskiy, Paul Grimm, Sergey Mashtalir, Vladimir Vinarski, "Fast Training of Neural Networks for Image Compression",Advances in Data Mining. Applications and Theoretical Aspects,Volume 6171 of the series Lecture Notes in Computer Science Pages 165-173,2010.

[9]. Wladyslaw Skarbek,"Image Compression Using Pixel Neural Networks",Soft Computing for Image Processing,Volume 42 of the series Studies in Fuzziness and Soft Computingpp 162-182,2000

[10]. Ying Chu, Hua Mi, Zhen Ji, "BFA based neural network for image compression", Journal of Electronics (China),May 2008, Volume 25, Issue 3, Pages 405–408,2008

[11]. Robert Cierniak, Michal Knop,"Video Compression Algorithm Based on Neural Networks",Artificial Intelligence and Soft Computing,Volume 7894 of the series Lecture Notes in Computer SciencePages 524-531,2013

[12]. Enrique Pelayo,, David Buldain,, Carlos Orrite, "Selective Image Compression Using MSIC Algorithm",Computational Intelligence,Volume 613,Pages 419-436, 20 November 2015

[13]. FarhanHussain, "Exploiting deep neural networks for digital image compression",Web Applications and Networking (WSWAN), IEEE, 2015.

[14]. Sicheng Zhao; Hongxun Yao; YueGao; Guiguang Ding; Tat-Seng Chua,"Predicting Personalized Image Emotion Perceptions in Social Networks",IEEE Transactions on Affective ComputingYear: 2016, Volume: PP, Issue: 99 ,Pages: 1 - 1, October 2016.

[15]. Mingyi He; Xiaohui Li; Yifan Zhang; Jing Zhang; Weigang Wang, "Hyperspectralimage classification based on deep stacking network" IEEE International Geoscience and Remote Sensing Symposium (IGARSS),Pages: 3286 - 3289, 2016

[16]. Shaima I. Jabbar; Charles R. Day; Nicholas Heinz; Edward K. Chadwick,"Using Convolutional Neural Network for edge detection in musculoskeletal ultrasound images", International Joint Conference on Neural Networks (IJCNN),Pages: 4619 - 4626, 2016.

[17]. Min Yan; Qian Yin; Ping Guo, "Image stitching with single-hidden layer feedforward neural networks", International Joint Conference on Neural Networks (IJCNN) ,Pages: 4162 - 4169, 2016.

[18]. Gong Cheng; Chengcheng Ma; Peicheng Zhou; Xiwen Yao; Junwei Han, "Scene classification of high resolution remote sensing images using convolutional neural networks",IEEE International Geoscience and Remote Sensing Symposium (IGARSS),Pages: 767 - 770, 2016.

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