Engineering Letters, 15:1, EL_15_1_18

Adaptive Wavelet-based-CMAC Network Predictor Design for Lossless Image Coding

Ching-Hung Lee, *Member, IAENG* and Bo-Hang Wang

***Abstract*— In this paper, we propose a novel wavelet-based-CMAC (WCMAC) network for predictive image coding. The Gaussian functions of traditional CMAC are replaced by wavelet functions. In addition, properties and advantages of fuzzy TSK- model are used to modify the activation functions of CMAC for obtaining high approximation accuracy and convergent rate. The WCMAC is employed to predict differential pulse code modulation (DPCM) of image compression. The WCMAC predictor can not only have accurate prediction, but also rather study and adapt to various and constant changing data. Experimental results and comparisons with other state-of-the-art lossless predictors are given to highlight the advantages of the proposed approach.**

***Index Terms*—CMAC, wavelet, image compression, lossless image coding.**

I. Introduction

With the improvement of the digital system and the development of the internet, the quality of the multimedia data which includes image, voice and video becomes more and more, therefore, the data compression becomes important. Image compression is the process of using fewer data to represent the original image [13, 27]. The compression process is called “lossless” if the reconstructed image is identical to the original one; otherwise, it is called “lossy” compression [5, 13, 24, 27]. Lossless image coding is used in a wide variety of applications such as medical imaging and remote sensing. Therefore, many state-of-the-art lossless image coders (or predictor) have been proposed [12-14, 18, 25, 28, 32, 34]. Among which, most of the results are obtained by adaptive approaches and predictive coding in spatial domain. It is known that predictive coding, such as DPCM, offers an attractive means especially for real-time applications and encoding of high-resolution images, thus it has been adopted in advanced image coding systems [1, 5, 6, 8, 13, 23, 24, 27, 29, 33-35]. In predictive image coding, we use the previously coded pixels, the so-called causal pixels, as the prediction inputs to predict the pixels to be encoded. Statistically, the entropy of the prediction errors will be smaller than that of the original image due to the high correlation between pixels. Therefore, the error (difference) between the original value and the predicted value are then entropy encoded to produce the bit stream.

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Though have low computational complexity, the result of lossless image predictors obtained by using linear regression is not as good as expected. Thus, some of the results using fuzzy logic and neural networks as the nonlinear predictors are proposed [1, 8, 16, 23, 26, 34]. As can be seen, the results obtained by the use of a nonlinear predictor are better than that of obtained by linear predictors. Besides, most of the adaptive neural network-based predictors are made of multi-layered perceptions and the network weights are adapted in the coding process using a predefined training area. However, an online adaptation process with a large training area and training cycles may results in a drastic increase in the computational complexity.

Cerbellar model articulation controller (CMAC) was developed by J.S. Albus in 1975 which is a perceptron-like associative memory that to formulate the processing characteristics of the cerebellum [2, 3, 7]. It performs nonlinear relationships from a broad category of functions. To take advantage of CMAC NN structure, the CMAC NNs are proposed for closed-loop control of complex dynamical systems [2, 4, 7, 10, 21]. Herein, a novel wavelet-based-CMAC (WCMAC) network for predictive image coding is presented. The Gaussian functions of traditional CMAC are replaced by wavelet functions. In addition, properties and advantages of fuzzy TSK- model are used to modify the activation functions of CMAC for obtaining high approximation accuracy and convergent rate. The WCMAC is employed to predict differential pulse code modulation (DPCM) of image compression. The WCMAC predictor can not only have accurate prediction, but also rather study and adapt to various and constant changing data. Finally, experimental results and comparisons to existing state-of-the-art lossless predictors will be given to highlight the advantages of the proposed approach.

The rest of the paper is organized as follows. Section II gives a description about the DPCM. The WCMAC network and its learning algorithm are presented in Section III. Section IV introduces the WCMAC network for DPCM system. Experimental results are shown in Section V to demonstrate the effectiveness of the proposed system. Finally, a concluding remark is given in Section VI.

II. Differential Pulse Code Modulation (DPCM)

Differential pulse code modulation (DPCM) has been used in a wide variety of applications such as image and speech compression [13, 18, 27]. Due to the high correlation between successive image samples, a relatively simple solution to

(Advance online publication: 15 August 2007)

remove the redundancy is to encode the differences between successive samples rather than the samples themselves. The resulting technique is called DPCM. Since the difference between samples is expected to be smaller than the actual sampled amplitudes, fewer bits are required to represent the difference. Thus, the concept of DPCM is to estimate the inter pixel redundancies of closely spaced pixels by extracting and coding only the new information between pixels. Only new information in the signal is encoded rather than the original signal. That is, the new information of a pixel is defined as the difference between the actual and predicted value of that pixel. In addition, predictive coding, such as DPCM, offers attractive means especially for real-time applications and encoding of high-resolution image.

Figure 1 shows the basic block diagram of a lossless predictive coding system. Both the predictors in the encoder and the decoder are identical. Figure 2 shows the two dimensional image in an $M \times N$ array. For convenience, we use the symbol p to denote the pixel $f(i,j)$ currently being encoded. The predicted value is generated using the previously decoded samples as the prediction inputs and rounded to the nearest integer $\hat{p}$. The output of the predictor is then subtracted from the original value to form the difference or prediction error.

$$e = p - \hat{p} \tag{1}$$

The prediction error in (1) is then entropy encoded to produce the bit stream for transmission or storage. The decoder in Fig. 1 reconstructs p from the received bit stream and performs the reverse operations.

$$p = e + \hat{p} \tag{2}$$

Obviously, the predictive DPCM removes the mutual redundancy between successive pixels by coding prediction errors. If the predictor is well designed, the entropy and the variance of the prediction error will be much smaller than that of the original image. The performance is essentially dependent upon the choice of the predictor. Recently, many approaches have been proposed for the predictor design [1, 5, 6, 12-14, 16-18, 23-29]. Most of which use a linear combination of the previously coded pixels to estimate the pixel to be encoded [24, 27]. Though with low complexity, the prediction result obtained by the use of linear predictors is not as good as expected. Thus, some approaches using fuzzy logic and neural networks as the nonlinear predictor have been proposed [1, 8, 17, 23, 26, 35]. Obviously, the results are better than that of obtained by the linear predictors. In this paper, we propose the use of WCMAC system to develop an adaptive linear-like predictor (Gaussian function and linear combination). As we will see in succeeding sections, the proposed system performs nonlinear prediction but with much reduced computational complexity just like a linear predictor.

III. WAVELET-BASED-CMAC (WCMAC) NETWORK

Cerebellar model articulation controller (CMAC) is a perceptron-like associative memory that was developed by J.S. Albus in 1975 to formulate the processing characteristics of the cerebellum [2, 3]. This model performs nonlinear relationships from a broad category of functions. CMAC NN has been applied in many real-world applications such as robotic control, signal processing, and pattern recognition by its fast learning, good generalization capability, and ease to implement [4, 7, 9-11, 18, 20, 21, 30].

In this paper, to achieve highly approximated accuracy and speed up the convergence, the traditional CMAC NN is modified as a novel wavelet-based CMAC NN. The major differences are: the Gaussian receptive fields functions are replaced by first order wavelet functions and the weight memory space are linear combination of input variables which took the advantages of TSK-type fuzzy model. Figure 3 depicts the proposed WCMAC system.

Herein, we indicate the signal propagation and the basic function of every node in each layer, $net_i^{(l)}$ denotes the net output, the superscript $^{(l)}$ indicates the lth layer and the subscript i indicates the ith input variable.

Layer 1:

For the ith node of layer 1, the net input and the net output are:

$$net_i^{(1)}(t) = x_i^{(1)}(t)$$

$$y_i^{(1)}(t) = f_i^{(1)}(net_i^{(1)}(t)) = net_i^{(1)}(t),\ i = 1,2,\cdots,n. \tag{3}$$

Each node of the first layer transports the input to the membership layer.

Layer 2:

Similar to the fuzzification of fuzzy logic system, the input/output relation is

$$net_j^{(2)}(t) = \frac{x_j^{(2)} - m_{ij}}{\sigma_{ij}}$$

$$y_j^{(2)}(t) = f_j^{(2)}(net_j^{(2)}(t)) = -net_j^{(2)}(t) \cdot e^{-\frac{(net_j^{(2)}(t))^2}{2}},\ j = 1,2,...,n. \tag{3}$$

Note that the Gaussian functions of this layer are replaced by the first order wavelet functions- Haar wavelet function. From the results of literature [19], the Haar functions are orthogonal basis, i.e., the Haar wavelet functions have the ability of universal approximation. By the property of universal approximation, the Haar wavelet functions are adopted to replace the Gaussian functions.

Layer 3:

The operation of each node is the product of inputs (similar to the fuzzy AND operation), i.e.,

$$net_k^{(3)}(t) = \prod_j w_{jk}^{(3)} x_k^{(3)}(t)$$

$$y_k^{(3)}(t) = f_k^{(3)}(net_k^{(3)}(t)) = net_k^{(3)}(t) \quad k = 1,2,\cdots,r. \tag{4}$$

Layer 4:

Each node calculates the linear combination of input variables, i.e., the consequent part of TSK-type fuzzy model. The details operation described below.

$$H = [1, x_1, x_2, \cdots, x_n]_{1\times(n+1)} \quad W_{jq} = [w_{0jq}, w_{1jq}, \cdots, w_{(n)jq}]^T$$

$$net_q^{(4)}(t) = \sum_{j=1}^{r} x_q^{(4)}(t) \times (W_{jq} \cdot H^T)$$

$$\begin{aligned} y_q^{(4)}(t) &= f_q^{(4)}(net_q^{(4)}(t)) = net_q^{(4)}(t) \\ &= \sum_{j=1}^{r} \left\{ net_q^{(4)}(t)[w_{0jq} + \sum_{i=1}^{n} w_{ijq} \cdot x_i(t)] \right\}, \quad q = 1,2,\cdots,r \end{aligned} \tag{5}$$

The function approximation properties of neural networks and fuzzy systems are well-known [19, 31]. Similarly, the WCMAC also has the universal approximation ability [4, 11]. By the way, the function approximation properties of the WCMAC can be guaranteed.

Herein, we use the well-known backpropagation learning algorithm to train the WCMAC. The general used update laws is

$$W(t+1) = W(t) + \eta(-\frac{\partial G}{\partial W}) \tag{6}$$

where G denotes the error function for training. First, the error cost function for tracking control is defined.

$$G = \frac{1}{2}\sum_q (y_d - y_q^{(4)})^2 = \frac{1}{2}\sum_q e^2 \tag{7}$$

where $y_q^{(4)}$ and y are WCMAC output and actual system output, respectively. By gradient method, the update laws of the WCMAC network parameters are obtained as bellows.

For W:

$$\begin{aligned} \Delta W_{jq} &= -\beta_W \frac{\partial G}{\partial W_{jq}} = -\beta_W \frac{\partial G}{\partial net_q^{(4)}} \frac{\partial net_q^{(4)}}{\partial W_{jq}} \\ &= -\beta_W (y_d - y_q^{(4)}) y_k^{(3)}(t) H^T \end{aligned} \tag{8}$$

where

$$\frac{\partial G}{\partial net_q^{(4)}} = \frac{\partial G}{\partial y_q^{(4)}} \frac{\partial y_q^{(4)}}{\partial net_q^{(4)}} = (y_d - y_q^{(4)}) \,. \tag{9}$$

For m and σ :

$$\begin{aligned} \Delta m_{ij} &= -\beta_m \frac{\partial G}{\partial m_{ij}} = -\frac{\partial G}{\partial net_j^{(2)}} \frac{\partial net_j^{(2)}}{\partial m_{ij}} \\ &= -\sum_q (y_d - y_q^{(4)})(W_{jq} \cdot H^T) y_k^{(3)} \beta_m \frac{2(m_{ij} - x_j^{(2)})}{\sigma_{ij}^2} \end{aligned} \tag{10}$$

$$\begin{aligned} \Delta \sigma_{ij} &= -\beta_\sigma \frac{\partial G}{\partial \sigma_{ij}} = -\frac{\partial G}{\partial net_j^{(2)}} \frac{\partial net_j^{(2)}}{\partial \sigma_{ij}} \\ &= \sum_q (y_d - y_q^{(4)})(W_{jq} \cdot H^T) y_k^{(3)} \beta_\sigma \frac{2(x_j^{(2)} - m_{ij})^2}{\sigma_{ij}^3} \end{aligned} \tag{11}$$

where

$$\begin{aligned} \frac{\partial G}{\partial net_j^{(2)}} &= \frac{\partial G}{\partial net_q^{(4)}} \frac{\partial net_q^{(4)}}{\partial y_k^{(3)}} \frac{\partial y_k^{(3)}}{\partial net_k^{(3)}} \frac{\partial net_k^{(3)}}{\partial y_j^{(2)}} \frac{\partial y_j^{(2)}}{\partial net_j^{(2)}} \\ &= \sum_q (y_d - y_q^{(4)})(W_{jq} \cdot H^T) y_k^{(3)}. \end{aligned} \tag{12}$$

Finally, the update laws are

$$\begin{aligned} W_{jq}(t+1) &= W_{jq}(t) + \Delta W_{jq} \\ m_{ij}(t+1) &= m_{ij}(t) + \Delta m_{ij} \\ \sigma_{ij}(t+1) &= \sigma_{ij}(t) + \Delta \sigma_{ij} \,. \end{aligned} \tag{13}$$

Remark 1. In this paper, the on-line (or real-time) learning performance is required for image compression. That is, the WCMAC network play the role of "adaptive predictor DPCM" and the WCMAC network is trained by only one cycle.

IV. DPCM USING WCMAC NETWORK

In this paper, we propose the use of the WCMAC network to design an adaptive DPCM predictor for image compression. The WCMAC network predictor is made adaptive to the varying statistics by learning from prediction errors using the gradient descent method to update network parameters continuously. In image coding systems, the pixels are usually encoded in a sequence such as from left to right and from top to bottom. Figure 4 (a) shows the raster scan order of a given image. By the results of [16], a block scanning method is proposed and the compression performance can be improved. Thus, we modify the order of the encoding sequence. Figure 4 (b) shows the scanning order of the proposed partition method. For natural images, the variations of the pixel values tend to be smooth within a small region. Therefore, the image is partitioned into $m \times n$ regions. Finally, we encode the image by the sequence of the partition regions. We will use a set of 6 test images to demonstrate the effectiveness of the proposed WCMAC network predictor.

The corresponding two-dimensional neighborhood of the pixel $f(i,j)$ (denotes p) is shown in Fig. 5, where i and j denotes the horizontal and vertical direction respectively. The four causal pixels as shown in Fig. 5 are used as the inputs of the WCMAC predictor, and the output is the predicted pixel of $f(i,j)$, i.e.,

$$x(t) = [N - NN \;\; W - WW] \tag{14}$$

When the pixel $f(i,j)$ is to be encoded, reconstructed values of its neighborhood on its left and top are also available in the decoder and the decoder can perform the same operations just like the encoder.

Besides, the gray levels of the test images are represented by 8 bits, i.e., [0 255]. To avoid being trapped in the saturation region in the first few steps while doing online training, the prediction inputs are always quantized and normalized, i.e.,

$$z(t) = \begin{bmatrix} z_1(t) & z_2(t) \end{bmatrix} = \frac{1}{\varepsilon}\begin{bmatrix} N - NN & W - WW \end{bmatrix} \tag{15}$$

where $\varepsilon = 255$. The output of WCMAC is also timed by ε. The on-line training scheme can be summarized as Fig. 6.

In addition, the quality of lossless predictive coding is evaluated by the entropy of the prediction error in bits per symbol $H(s)$ defined by [13]

$$H(s) = \sum_{i=1}^{n} - p(s_i)\log_2 p(s_i) \tag{16}$$

where $p(s_i)$ is the probability of occurrence of the symbol s_i. After on-line adaptation, the histogram of prediction error for image "Lena" is shown in Fig. 7. Thus, from Fig. 7, we observe that the probability of error around zero is very high. That is, the WCMAC predictor provides high accuracy of prediction and performs well.

V. Experimental Results

In lossless predictive coding of images, the predictor is designed to minimize the entropy of the prediction error such that a maximum compression ratio can be achieved. The performance of the proposed adaptive WCMAC predictor can be demonstrated by the following experimental results in comparison with other predictors. The highly approximation accuracy and faster convergent speed are also shown for "Pepper, Barbara, Sailboat, Lena, Lynda, Pentagon," images.

Table 1 gives the comparison of different approaches [23, 26]. Obviously, the proposed adaptive WCMAC predictor performs better than other fuzzy logic system or neural network nonlinear predictors with smaller entropies. These comparison results show the advantages of the proposed adaptive WCMAC approach.

VI. Conclusion

In this paper, we have proposed the use of an adaptive WCMAC network system for lossless image coding. A modified scanning order method has been designed to improve the compression performance. The adaptive WCMAC predictor has the following advantages- fast convergence and minimum parameters (use the matrix computation), high accuracy approximation, and easy to understand. The experimental results reveal that the adaptive WCMAC system has real-time training performance, and accurate prediction. Experimental comparisons with the most advanced methods in the literature have been presented to highlight the advantages of the proposed adaptive WCMAC scheme for data compression. Furthermore, the usefulness of the proposed approach has been demonstrated through experimental results and comparisons to existing state-of-the-art linear and nonlinear predictors.

Acknowledgment

The authors would like to thank the Guest Editor and anonymous reviewers for their valuable comments and helpful suggestions.

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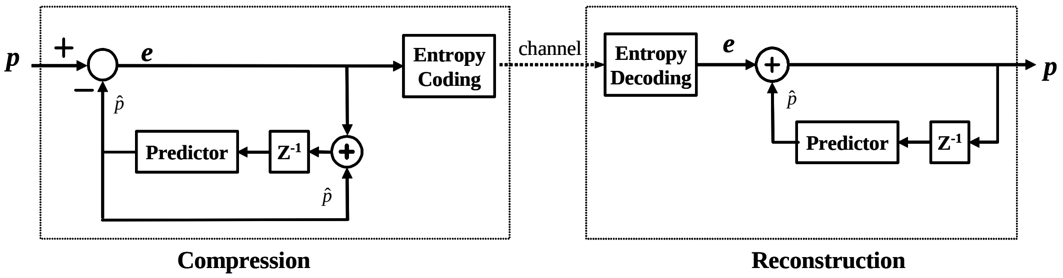

Figure 1: Block diagram of differential pulse code modulation (compression and reconstruction).

$f(1,1)$	$f(2,1)$	$f(3,1)$	…	$f(M\text{-}1, 1)$	$f(M,1)$
$f(1,2)$	$f(2,2)$	$f(3,2)$	…	$f(M\text{-}1,2)$	$f(M,2)$
$f(1,3)$	$f(2,3)$	$f(3,3)$	…	$f(M\text{-}1,3)$	$f(M,3)$
⋮	⋮	⋮	⋱	⋮	⋮
$f(1,N)$	$f(2, N)$	$f(3, N)$	…	$f(M\text{ -}1, N)$	$f(M, N)$

Figure 2: Two dimensional image- $M\times N$ array.

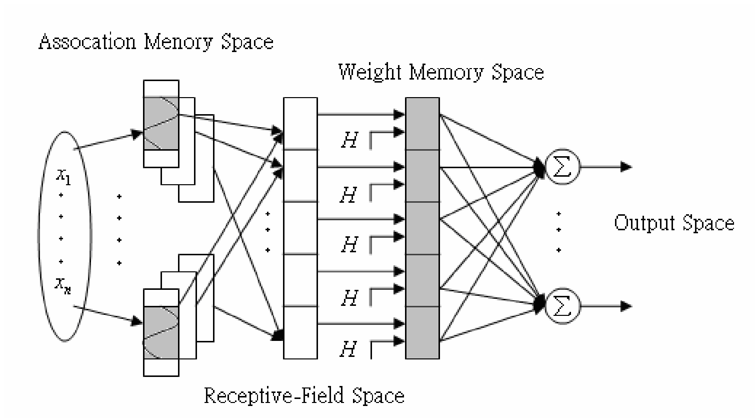

Figure 3: Wavelet- based CMAC network architecture.

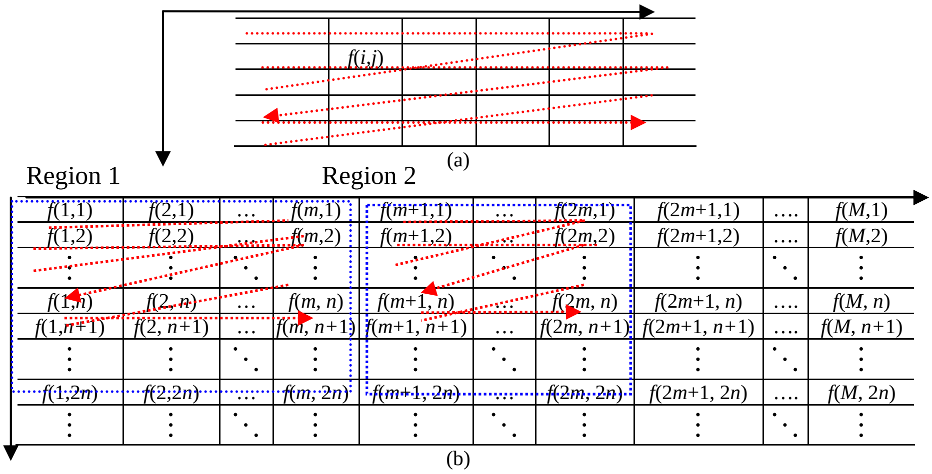

Figure 4: Scanning order of a two-dimensional image: (a) raster scan of an image (b) the used block scan method.

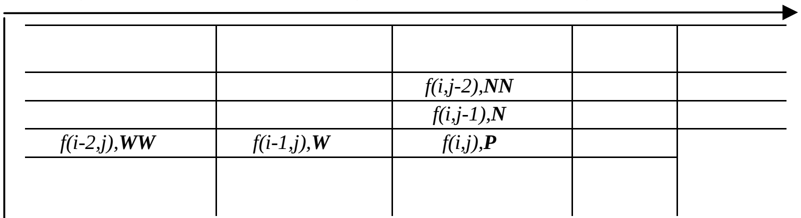

Figure 5: Two dimensional neighborhood of prediction inputs.

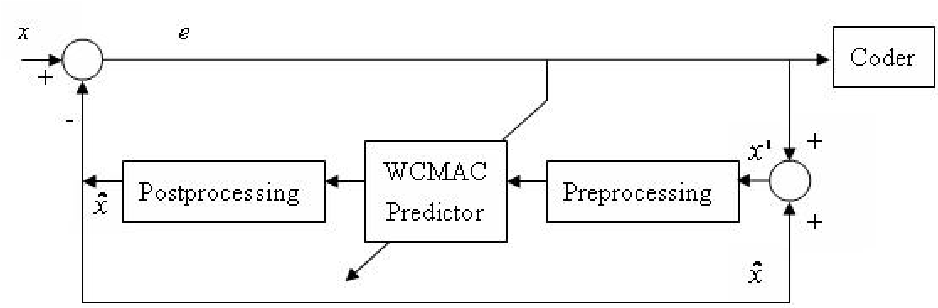

Figure 6: Training scheme of WCMAC predictor.

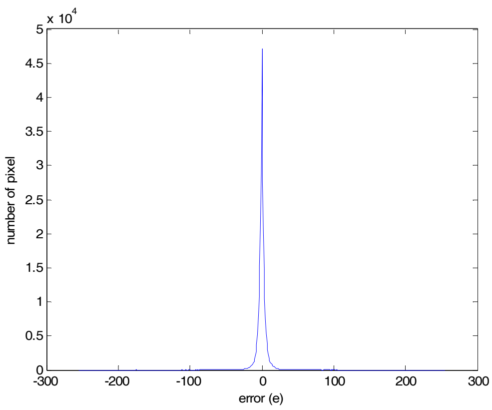

Figure 7: The histogram of prediction error for image Lena.

Table 1: Comparison results

Image	Predictive Median Hybrid Filters [26]				Neural Networks [23]		T-S Type Fuzzy neural Network [17]	WCMAC
	Type1	Type2	Type3	Type4	Type1	Type2		
Lena	4.56	4.32	4.51	4.53	4.54	4.64	4.49	**3.72**
Barbara	5.68	5.60	5.60	5.60	5.56	5.59	4.72	**4.24**
Sailboat	5.28	5.32	5.24	5.25	5.40	5.48	4.98	**4.51**
Pepper	4.92	5.05	4.91	4.95	5.37	5.31	4.42	**4.27**
Lynda	3.44	3.79	3.49	3.57	4.49	3.61	3.33	**2.80**
Pentagon	5.30	5.23	5.22	5.20	5.29	5.41	5.06	**4.54**
Avg.	4.86	4.93	4.83	4.85	5.11	5.00	4.5	**4.01**