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Online Sequential Extreme Learning Machine for watermarking in DWT domain

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ABSTRACT

Protecting and securing an information of digital media is very crucial due to illegal reproduction and modification of media has become an acute problem for copyright protection now a day. A Discrete Wavelet Transform (DWT) domain based robust watermarking scheme with Extreme Learning Machine (ELM), Online Sequential Extreme Learning Machine (OSELM) and Weighted Extreme Learning Machine (WELM) have been implemented on different color images. The proposed scheme which combine DWT with ELM, OSELM and WELM machine learning methods and a watermark or a tag or a sequence is embedded as an ownership information. Experimental results demonstrate that the proposed watermarking scheme is imperceptible/transparent and robust against image processing and attacks such as blurring, cropping, JPEG, noise addition, rotation, scaling, scaling–cropping, and sharpening. Performance and efficacy of algorithms of watermarking scheme is determined by measuring Peak Signal to Noise Ratio (PSNR), Bit Error Rate (BER) and Similarity parameter $SIM(X, X^*)$ and calibrated results are compared with other existing machine learning methods. As a watermark detector, machine learning techniques are used to learn neighbors relationship among pixels in a natural image has high relevance to its neighbors, so this relationship can be predicted by its neighbors using machine learning methods and watermark image can be extracted and detected and thereby ownership can be verified.

1. Introduction

In recent years, there has been a rapid development of multimedia including images, audio and video, are reprinted, duplicated and easily redistributed over internet which has become a very serious problem to protect intellectual property right (IPR) of digital media. Implementation of image processing applications must be completed within required time constraints. One such application is digital watermarking of color image in which embedding and extraction of tag or sequence or watermark must complete in minimum time complexity [5–9]. Although there are many other mechanisms like cryptography used for protection of digital data but this is a weak method to decrypt. The robust and imperceptible digital watermark schemes were developed to remove the drawbacks of cryptography techniques. Embedding and extraction processes should be optimized without loss of visual quality of image. A number of soft computing learning methods used to develop robust and imperceptible watermarking techniques [1–3]. In recent years, digital watermarking has received considerable attention for finding unauthorized use of digital media. In digital watermarking, a watermark or a trademark or a sequence is embedded into the image for copyright protection and embedded watermark can be extracted from the media in order to prove ownership. The number of color images are used for digital watermarking either in spatial domain or in frequency domain. In spatial domain, an intensity value of pixel is modified but watermarking in this domain is not robust while in frequency domain the coefficients of image are modulated by adding additional information and scheme becomes more imperceptible. There are number of methods based on frequency domain [2–11] used for digital watermarking for colored images in which watermark logo embedded into blue channel as human vision system (HSV) [42] as it is insensitive to blue channel. In image authentication techniques, where visually recognizable pattern is embedded as watermark in low frequency sub-band in DWT, gives a trade off between imperceptibility and robustness. A digital watermarking scheme must have following requirements (i) imperceptible or transparency (ii) difficult to extract without affecting quality of an image (iii) should have robustness against image processing, conventional and geometrical attacks. Therefore, developing a computational algorithm which exhibits these requirements is not an easy

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job. A number of information hiding schemes have been used and reported in the literature [13]. Recently, computational intelligence-techniques have been widely used and neural networks and support vector machine (SVMs) [14,15] have been dominant. However, these techniques have numbers of unavoidable drawbacks such as (i) slow learning speed due to increase of local minima's (ii) poor computational capability (iii) particularly standard variant of SVM training involves a quadratic programming problem, thereby computational complexity is unusually intense. SVM is used as regression problem for watermarking scheme of the image [16,18] for watermark embedding and extraction. The number of machine learning methods are used for digital watermarking of image in spatial as well as frequency domains. Most of the drawbacks in neural networks based back propagation and support vector machine, ELM based learning algorithm tries to address them. We have explored the possibility of ELM based methods for information hiding in natural images where every pixel has high relevance to its neighbors, it can be predicted by its neighbors pixel relationship [16] using ELM, OSELM and WELM and this pixels relevance help in extraction of watermark. The relationship among pixels can be memorized by the training process and it was found that this relationship found intact even though the natural images are subjected to some attacks such as image processing, blurring, cropping, JPEG compression, rotation, noise addition, scaling, scaling–cropping, and sharpening. So this feature can be used for robust digital watermark embedding and extraction combined with machine learning techniques used as relationship is intact despite of number of attacks and using this relationship, watermark can be extracted by predicting this relationship.

Rest of the paper is organized as follows. We briefly give theories about ELM, OSELM and Weighted ELM in Section 2. Watermarking schemes are described in Section 3. Experimental results are discussed in Section 4. Finally, concluded in Section 5.

2. Brief theories of learning machines

2.1. ELM

Over last decades, batch learning algorithms for machine learning have wide range of application in different kind of research areas, starting from pattern recognition [19,27], text classification [30], time series analysis [31,32] to watermarking and information hiding [16,29], etc. Huang et al. [20–26] proposed new machine learning algorithm, Extreme Learning Machine for single hidden layer feed forward neural networks (SLFNs). In this algorithm, input layer weights need not to be tuned iteratively and to be generated randomly, however, the output weights are determined analytically using least-squares method. This algorithm has fast learning speed and high learning accuracy with good generalization ability. ELM is a batch learning type of algorithm having single hidden layer feed forward neural networks (SLFNs). The nature of ELM has been investigated by using the interpolation and universal approximation capabilities [27]. Given N arbitrary distinct data samples $(x_i, t_i)_i^N$, where $x_i = [x_{i1}, \ldots, x_{in}]$ and $t_i = [t_{i1}, \ldots, t_{im}]$. The output function of SLFNs with $\hat{L}$ number of hidden nodes can approximate N input samples with zero error then β_i, a_i and b_i hold such that

$$f_L(x) = \sum_{i=1}^{\hat{L}} \beta_i g_i(x) = \sum_{i=1}^{\hat{L}} \beta_i G(a_i, b_i, x), \quad a_i \in \Re^n,\ b_i \in \Re,\ \beta_i \in \Re^m \tag{1}$$

where, g_i, denotes the output function $G(a_i, b_i, x)$ of ith hidden node and $a_i = [a_{i1}, \ldots, a_{in}]$ is the weight vector connecting ith hidden neuron and input neuron and b_i is the threshold of ith hidden neuron, are learning parameters of hidden nodes and $\beta_i = [\beta_{i1}, \ldots, \beta_{im}]$ is the weight vector connecting ith hidden node to output neuron. For additive nodes, the activation function $g(x) : R \to R$ for ith hidden node, g_i, is defined as

$$g_i = G(a_i, b_i, x) = g(a_i \cdot x + b_i), \quad a_i \in \Re^n,\ b_i \in \Re \tag{2}$$

The above two equations can be written in the matrix form as

$$H\beta = T \tag{3}$$

where H is called the hidden layer output matrix of the SLFNs [22] and β is the weight vector connecting the hidden node to the output node and T is the target vector written as

$$H_{N\times\hat{L}} = \begin{bmatrix} G(a_1, b_1, x_1) & \ldots & G(a_{\hat{L}}, b_{\hat{L}}, x_1) \\ \vdots & \ldots & \vdots \\ G(a_1, b_1, x_N) & \ldots & G(a_{\hat{L}}, b_{\hat{L}}, x_N) \end{bmatrix}$$

$$\beta_{\hat{L}\times m} = \begin{pmatrix} \beta_1^T \\ \vdots \\ \beta_{\hat{L}}^T \end{pmatrix} \quad \text{and} \quad T_{N\times m} = \begin{pmatrix} t_1^T \\ \vdots \\ t_{\hat{L}}^T \end{pmatrix} \tag{4}$$

As described in [25], the parameters of hidden layer nodes as weights a_i and bias b_i need not be adjusted again and again but these are randomly generated, assigned and fixed. Therefore, for known values of hidden layer output matrix H and output matrix T, the solution of output parameter, β, can be obtained as

$$\hat{\beta} = H^{\dagger} T \tag{5}$$

where $H^{\dagger}$ is the Moore–Penrose generalized pseudo inverse [36] of the hidden layer output. The orthogonal projection method can be used for determining Moore–Penrose generalized inverse as $H^{\dagger} = (H^T H)^{-1} H^T$ provided $H^T H$ is non-singular in nature. However, $H^T H$ may sometimes tends to be singular and in that case the orthogonal projection method may not be used for inverse calculation. It is important to note that singular value decomposition (SVD) [36] is always used for calculation of Moore–Penrose inverse and implementation of ELM. When the number of training data samples is higher than the number of hidden nodes, that is, $N > \hat{L}$, still input weights and biases can be generated randomly, assigned and fixed, an output weights by using same Moore-Penrose inverse of hidden nodes matrix H with a small nonzero training error. Therefore, it should be noted in conclusion about the theoretical aspect of ELM that the hidden node parameters a_i and b_i (input weights and biases or centres) of SLFNs need not be tuned during training and may simply be assigned with random values. One of the typical features about the implementation of ELMs is addition of random computational nodes in hidden nodes and hidden layer of SLFNs need not be tuned again and again as it is independent of input training data samples. Unlike traditional neural networks, ELM not only tends to reach the smallest training error but also the smallest norm of output weights that leads to better generalization performance of learning networks. Therefore, the output weight can be resolved using least-square method as ELM hidden layer parameters are fixed. Accordingly output estimation function (1) may be determined for ELM by

$$\begin{aligned} f_{(ELM)}(x) &= \sum_{i=1}^{\hat{L}} \beta_i g_i(x), \quad a_i \in \Re^n,\ b_i \in \Re,\ \beta_i \in \Re^m \\ &= \sum_{i=1}^{\hat{L}} \beta_i g(a_i \cdot x, b_i) \end{aligned} \tag{6}$$

The essence of ELM can be summarized as follows:

(1) The parameters of hidden layer of ELM need not be iteratively tuned [20,38].
(2) The training error $\|H\beta - T\|$ and norm of output weight $\|\beta\|$ need to be minimized [20,37,38].