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Copyright Protection of Image Learning Objects using Wavelet-based Watermarking and Fuzzy Logic

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Abstract – *An adaptive watermarking algorithm is presented which exploits a biorthogonal wavelets-based human visual system (HVS) and a Fuzzy Inference System (FIS) to protect the copyright of images in learning object repositories. Specifically, the HVS relies on the linear-phase property of biorthogonal wavelet filters (symmetric wavelets) in order to efficiently extract the masking information, while taking into account the local characteristics of the image. The FIS is utilized to compute the optimum watermark weighting function that would enable the embedding of the maximum-energy and imperceptible watermark. The experimental results achieved demonstrate that the proposed algorithm is robust against both, signal processing and geometric attacks.*

Keywords – *Image watermarking, biorthogonal wavelets, human visual system, fuzzy inference system.*

I. INTRODUCTION

The recent advances in multimedia technology gave rise to the concept of multimedia learning which plays an important role in providing a technology-enhanced learning environment. The paradigm of learning objects within the multimedia area has consequently emerged in order to serve this purpose. A multimedia "learning object" can be defined as a type of media that conveys certain knowledge. This media may be time dependent such as audio, video, and animations, or time independent, such as images and text. In this paper, we deal with the content protection of multimedia learning objects, more specifically, with image learning objects. This work is part of a bigger research project currently being developed at DISCOVER laboratory [1], which deals with the creation, search and delivery of advanced multimedia learning objects. The content protection of the learning objects is performed using digital watermarking. Digital watermarking is the process of embedding some predefined information (such as the owner's tracking and copyright information) directly into the digital data in an inconspicuous manner. Moreover, a watermark is a digital signal or pattern embedded in a digital content. In this paper, we consider watermarking of digital images. There are two important requirements that must be respected in order to perform effective watermarking. The watermark must remain imperceptible to the human visual system, and in consequence, it must not degrade the perceptual quality of the original image. Furthermore, the watermark must be robust against unintentional or intentional attacks. Transform domain watermarking techniques such as those based on the discrete cosine transform (DCT) [2], [12] and discrete wavelet transform (DWT) [3], [4], [5] are generally more robust against signal processing and geometric transformations. In addition, adaptive watermarking techniques can be easier to perform in the transform domain [6]. Moreover, although DCT-based watermarking has been widely exploited in the literature, wavelet-based techniques have proved to be generally more effective for several important reasons [5]. First, the wavelet transform has multiresolution hierarchical characteristics. Furthermore, its ability to decompose an image into bands that vary in both spatial frequency and orientation (vertical, horizontal and diagonal) has made it of great relevance when modeling the anisotropic properties of a Human Visual System (HVS). Moreover, the watermark embedding and detection processes may be performed at lower image resolutions, which could significantly decrease the computational load.

Several previous image-adaptive wavelet based watermarking schemes have been proposed in the past few years. Kaewkamnerd and Rao [8] proposed an image watermarking technique that exploits a HVS in order to adaptively embed a watermark in the two-dimensional DWT. The watermark embedding is performed in the higher level subband of the wavelet transform, even though this can clearly change the image fidelity. In order to avoid perceptual degradation of the image, the watermark insertion is carefully performed while using a HVS. Their approach relies on the HVS suggested in [7] that takes into account the background luminance, the frequency sensitivity (resolution bands and their orientation), as well as the texture using the multiresolution structure of the wavelet transform. However, the detection process is achieved through comparison with the original image, making this technique undesirable in certain scenarios e.g. storage of the original images can be significant when a database contains a large number of images. In addition, the HVS investigated in this technique was modeled specifically to solve the problem of DWT coefficients quantization for compression purposes, making it less accurate for the watermarking problem. Barni et al. [3] proposed a new approach to perform robust image watermarking using the characteristics of a HVS. First, the embedding process is performed solely at the first decomposition level of the wavelet transform. In addition, similarly to Kaewkamnerd and Rao's technique illustrated above, they exploit the HVS suggested in [7], however, slight modifications are performed to the model in order to better represent the behavior of the HVS to image watermarking. Furthermore, Barni et al.'s watermark detection process is performed without any reference to the original image, thus it is referred to as a blind detection scheme. In addition, the detection threshold (used to detect whether a watermark is present in an image) can be adaptively computed from each image without any knowledge of the watermark embedding strength. An important disadvantage of this technique is its vulnerability against severe lossy compression. Also, the approach they follow in order to compute the watermark weighting function is a crude approximation (a simple product expression of the data extracted from the HVS model) and can be improved from a theoretical point of view. Lou and Yin [9] propose an adaptive image watermarking algorithm that relies on a fuzzy clustering technique. The watermark is adaptively embedded in significant DWT coefficients that are selected in the higher level subband of the wavelet transform. In order to adjust the watermarking strength, a fuzzy c-means (FCM) clustering approach is used to classify the local characteristics of an image extracted by means of a HVS. The visual model suggested in this method takes into account the frequency sensitivity, the local luminance and texture, as well as the entropy sensitivity. There are several drawbacks to this scheme. The most important is that the HVS properties are not determined using the multiresolution structure of the wavelet transform, e.g. in order to determine the texture activity in the neighborhood of a pixel at a specific resolution level, only the subband in which the watermarking will be performed is considered (rather than considering the subbands with all three orientations in order to accurately locate the edge and texture patterns in an image).

In this paper, we deal with the copyright protection of image learning objects (i.e. images). The proposed consists of an adaptive wavelet-based watermarking algorithm that is based on the model of a HVS and a Fuzzy Inference System (FIS). The primary novelty of this algorithm resides in the way a Sugeno-type fuzzy model is exploited in order to determine a valid approximation of the quantization step of each DWT coefficient given the local image characteristics. Furthermore, the HVS properties are modeled using biorthogonal wavelets to improve watermark robustness and imperceptibility. This information is utilized by the algorithm to compute the optimum watermark weighting function that would enable the maximum energy and imperceptible watermark.

II. PERCEPTUAL WATERMARK EMBEDDING

The wavelet domain's excellent spatio-frequency localization property has made it very appropriate to locate the image regions where disturbance can be adequately hidden. Moreover, this property has made the wavelet transform a great candidate when modeling a HVS, as the latter has localized responses in both space and frequency domains [10]. Furthermore, accurate modeling of the HVS using biorthogonal wavelets is performed in order to accurately adapt the watermark strength according to the local characteristics of the image.

A. Watermark Embedding

The watermark embedding process first decomposes the image into four levels using the discrete wavelet transform. The local characteristics of the image are subsequently extracted using the model of the HVS, and the quantization step of each DWT coefficient is then computed using the FIS in order to generate the watermark weighting function. Then, the watermark which consists of a binary pseudo random sequence (BPRS) is embedded into the lowest level subbands (X_0^0,X_0^1,X_0^2). Moreover, the watermark insertion is performed as follows:

$$\widetilde{X}_0^\theta(i,j) = X_0^\theta(i,j) + \beta\alpha^\theta(i,j)x^\theta(i,j), \tag{1}$$

where $X_0^\theta(i,j)$ corresponds to the DWT coefficient of the original image, $\widetilde{X}_0^\theta(i,j)$ denotes the watermarked DWT coefficients of the subband at resolution level 0 and orientation θ, β is a scaling a factor, whereas $\alpha^\theta(i,j)$ denotes the watermark weighting function computed based on the local characteristics of the image. Finally, the inverse DWT is performed in order to generate the watermarked image.

B. The Estimation of the Human Visual System

The adaptive watermarking strength can be adjusted based on the relation between the DWT coefficients and a model of the HVS. In [7], Lewis and Knowles introduce a HVS in order to perform DWT coefficients quantization for image compression, where the quantization steps are adjusted according to the human eye's sensitivity to noise. In [3], Barni et al. introduce some modifications to the HVS introduced in [7] and attempt to better fit its behavior to image watermarking. In the proposed, the HVS suggested in [3] is improved using symmetric biorthogonal wavelets (rather than asymmetric orthogonal wavelets). This modification is significant as human vision is less tolerant to asymmetric error than symmetric one, it is therefore desirable to use symmetric biorthogonal wavelets when modeling a HVS [13]. In addition, the weighting function will be modified as the quantization step for each DWT coefficient will be approximated using a fuzzy logic technique. The aforementioned visual model takes into account the eye sensitivity to different resolution bands (and their orientation), the background luminance as well as the local texture activity. First, the human eye sensitivity to orientation and noise can be computed as in Equ.(2). This equation takes into consideration that the human visual system is less sensitive to disturbances in higher resolution bands and those bands with 45 orientations.

$$F(l,\theta) = \left\{ \begin{array}{ll} \sqrt{2}, & \text{if } \theta = 1 \\ 1, & \text{otherwise} \end{array} \right\} \cdot \left\{ \begin{array}{ll} 1.00, & \text{if } l = 0 \\ 0.32, & \text{if } l = 1 \\ 0.16, & \text{if } l = 2 \\ 0.10, & \text{if } l = 3 \end{array} \right\}, \quad (2)$$

Subsequently, the eye's sensitivity to image brightness can be computed as in Equ.(3). It takes into account that the eye is less sensitive to noise in regions of the image where the brightness is very high or very low.

$$L_l(i,j) = \frac{1}{256} \sum_{(x,y)\in\eta} X_3^3\Big(x + \Big\lfloor \frac{i}{2^{3-l}} \Big\rfloor, y + \Big\lfloor \frac{i}{2^{3-l}} \Big\rfloor\Big), \quad (3)$$

where

$$\eta = \{(x,y)|(x,y) \in (-1,0),(0,-1),(0,0),(1,0),(0,1)\}, \quad (4)$$

Finally, the local texture activity can be computed as in Equ.(5). This measure takes into account that the human eye is less sensitive to regions of the image with strong texture, more specifically, to areas near the edges.

$$T_l(i,j) = \sum_{k=0}^{3-l} \frac{1}{16^k} \sum_{\theta=0}^{2} \sum_{(x,y)\in\eta} \Big[X_{k+l}^{\theta}\Big(x + \Big\lfloor \frac{i}{2^k} \Big\rfloor, y + \Big\lfloor \frac{i}{2^k} \Big\rfloor\Big)\Big]^2 \cdot Var\Big\{X_3^3\Big(x + \Big\lfloor \frac{i}{2^{3-l}} \Big\rfloor, y + \Big\lfloor \frac{i}{2^{3-l}} \Big\rfloor\Big)\Big\}_{(x,y)\in\eta}, \quad (5)$$

where $X_3^3(i,j)$ corresponds to the DWT coefficient at position (i,j), resolution level 3, with orientation 3. The local texture is therefore computed by the multiplication of two expressions. The left expression is used to determine the local mean square value of the DWT coefficients in all the detail subbands (represents the distance from the edges), whereas the right expression consists of the local variance of the low-pass subband (represents the texture activity) [3].

C. *Perceptual Weighting by means of an FIS*

The Fuzzy inference system, also known as a fuzzy expert system, is a widely accepted computing framework based on the popular concepts of fuzzy set theory, fuzzy if-then rules and fuzzy reasoning [14]. The FIS is recognized to provide simple and fuzzy approaches in order to perform the mapping from a given set of inputs to another set of outputs without the extensive use of mathematical modeling concepts. Generally, a fuzzy inference system is composed of four different function blocks: a fuzzifier, a knowledge base, a fuzzy inference engine and a defuzzifier (see Fig. 1). The fuzzifier transforms crisp inputs into fuzzy sets. The knowledge base encompasses a database and a rule base. In this scenario, the database defines the membership functions of the linguistic variables "Luminance" and "Texture", as it is illustrated in Fig. 2. The rule base consists of a set of IF-THEN rules that can be given by a human expert or can also be extracted from the linguistic description of the data. A typical fuzzy if-then rule has an antecedent (or premise) part as well as a consequent (or conclusion) part. A fuzzy rule in a Sugeno fuzzy model (exploited in this scheme) has the following form $if\ x\ is\ A\ and\ y\ is\ B\ then\ z = f(x,y)$, where A and B are fuzzy sets in the antecedent part, whereas $z = f(x,y)$ is a polynomial in the input variables x and y. This polynomial function is typically defined such that it can appropriately illustrate the output of the model within the fuzzy region described by the corresponding antecedent part of the rule. The set of fuzzy rules that have been defined in this scheme are illustrated in Table I (where x and y correspond to the luminance values $L_l(i,j)$ and the texture values $T_l(i,j)$, respectively. Furthermore, The fuzzy inference engine is a generic control mechanism that exploits the fuzzy rules and the fuzzy sets defined in the knowledge base in order to reach a certain conclusion. Lastly, a defuzzifier in a typical FIS is used to convert fuzzy outputs of the fuzzy rules into crisp output values. In the case of the Sugeno fuzzy model investigated here, the consequent part of each fuzzy rule is described by a nonfuzzy equation of the input variables, thus the defuzzification process is not required. The Sugeno model is suited to represent the behavior of a nonlinear system as it interpolates between multiple linear models. This FIS is therefore ideal to model the watermark weighting function, as it can incorporate the fuzzy and nonlinear aspect of human vision.

Finally, The overall output of the system is consequently obtained as the weighted average of all rule outputs and it is computed as follows:

$$S^{\theta}(i,j) = \frac{\sum_{i=1}^{N} w_i z_i}{\sum_{i=1}^{N} w_i}, \quad (6)$$

where N corresponds to the number of rules depicted in Table I, whereas w_i is the firing strength that weights output z_i of rule i. Moreover, in the case investigated here, the overall output $S^{\theta}(i,j)$ denotes the quantization step within a subband at orientation θ, and location (i,j). This is obtained according to the local noise sensitivity of the original image extracted using strictly its local texture and luminance masking information.
An updated quantization step is subsequently computed where the frequency sensitivity is considered as follows:

$$q_l^{\theta} = \beta \cdot S^{\theta}(i,j) \cdot F(l,\theta), \quad (7)$$

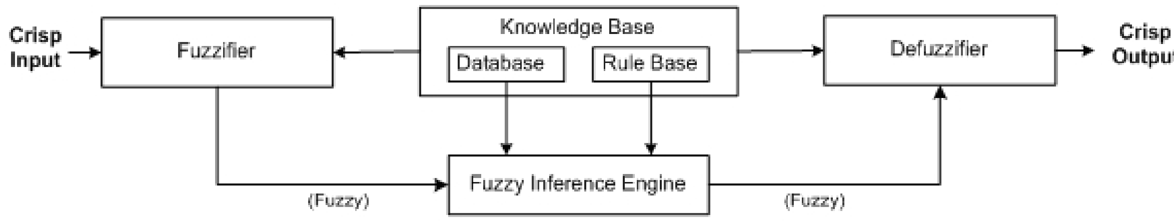


Fig. 1. General block diagram of a Fuzzy Inference System.

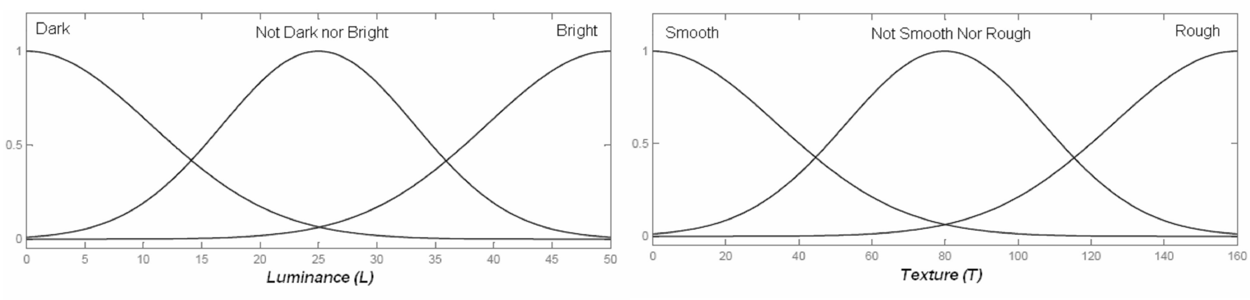


Fig. 2. Membership functions depicting the linguistic variables Luminance and Texture.

TABLE I
FUZZY INFERENCE RULES

Rule	Rule Description
1	IF ($L_l(i,j)$ is *dark* AND $T_l(i,j)$ is *smooth*) THEN $z_1 = a_1 y + b_1 x + c_1$
2	IF ($L_l(i,j)$ is *dark* AND $T_l(i,j)$ is slightly *rough*) THEN $z_2 = a_2 y + b_2 x + c_2$
3	IF ($L_l(i,j)$ is *dark* AND $T_l(i,j)$ is *rough*) THEN $z_3 = a_3 y + b_3 x + c_3$
4	IF ($L_l(i,j)$ is *slightly bright* AND $T_l(i,j)$ is *smooth*) THEN $z_4 = a_4 y + b_4 x + c_4$
5	IF ($L_l(i,j)$ is *slightly bright* AND $T_l(i,j)$ is *slightly rough*) THEN $z_5 = a_5 y + b_5 x + c_5$
6	IF ($L_l(i,j)$ is *slightly bright* AND $T_l(i,j)$ is *rough*) THEN $z_6 = a_6 y + b_6 x + c_6$
7	IF ($L_l(i,j)$ is *bright* AND $T_l(i,j)$ is *smooth*) THEN $z_7 = a_7 y + b_7 x + c_7$
8	IF ($L_l(i,j)$ is *bright* AND $T_l(i,j)$ is *slightly rough*) THEN $z_8 = a_8 y + b_8 x + c_8$
9	IF ($L_l(i,j)$ is *bright* AND $T_l(i,j)$ is *rough*) THEN $z_9 = a_9 y + b_9 x + c_9$

where β is a global scaling parameter. It can thereafter be assumed that disturbances with values lower than $q_l^\theta/2$ should remain imperceptible. The watermark weighting function is therefore computed as follows:

$$\alpha_l^\theta = q_l^\theta/2. \tag{8}$$

III. WATERMARK DETECTION

The detection process consists of the cross-correlation between the watermarked image and the pseudorandom sequence, thus this procedure is performed without any knowledge of the original image [3] (also known as blind watermarking detection). This is described as follows:

$$\rho = \frac{1}{3MN} \sum_{\theta=0}^{2} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} \widetilde{X}_0^\theta x^\theta(i,j), \tag{9}$$

where ρ is the computed detection value that's typically compared to a threshold T_ρ in order to determine whether a watermark is present in the image. In order to determine the adaptive threshold T_ρ, Barni et al. [3] adopted the Neyman-Pearson criterion: rather than minimizing the overall error probability, maximize the probability of detection while not allowing the probability of false detection exceed a certain predefined constant value. Consequently, the threshold T_ρ depends only on the statistics of the watermarked image, and can be computed as follows:

$$T_\rho = 3.97\sqrt{2\widehat{\sigma}_\rho^2}, \tag{10}$$

where,

$$\widehat{\sigma}_\rho^2 \approx \frac{1}{(3MN)^2}\sum_{\theta=0}^{2}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(\widetilde{X}_0^\theta(i,j))^2, \tag{11}$$

IV. EXPERIMENTAL RESULTS

The watermarking algorithm was tested using a 256×256 gray scale image of Baboon Fig. 3(a). For the experimental results presented here, the biorthogonal (2,2) wavelets [11] were used to compute the DWT. The Peak Signal to Noise Ratio (PSNR) was measured in order to evaluate the imperceptibility of the watermark as well as the degradation of the watermarked images. Furthermore, several experiments were performed in order to demonstrate the robustness of the algorithm under various attacks, including lossy JPEG compression, additive Gaussian noise, as well as cropping. As aforementioned, the watermark in our proposed scheme consists of a binary pseudo random sequence (± 1).

A. An adaptive and Imperceptible Watermark

As aforementioned, the proposed adaptive watermarking scheme computes a watermark weighting function using a HVS and a FIS. Moreover, pixel-based masking is performed while taken into account the texture and the luminance information of all image subbands. In Fig. 3(b), the watermark weighting function of the baboon image is displayed (at level = 0, and orientation = 1), it is evident that an accurate and a smooth representation of the adaptive watermark weights is presented. In order to examine the imperceptibility constraint, a watermark with maximum tolerable strength was embedded in the Baboon image while taking into consideration the watermark invisibility criterion. The invisibility was evaluated by a human observer at distance equal to six times the size of the image (as in [3]). The resultant watermarked image is shown in Fig. 3(c) with a PSNR as low as 36.7 dB. Furthermore, the difference images between the watermarked and original image is illustrated in Fig. 3(d). It can be observed that the algorithm can accurately model the regions in which the watermark insertion is performed, as it takes full advantage of the image adaptive HVS-FIS strategy. The watermark is constrained within the highly non-uniform regions of the image, in order to preserve the imperceptibility criterion.

B. JPEG Compression Attack

Lossy compression algorithms such as JPEG are commonly used for efficient storage and transmission of images over the Internet. It is therefore crucial to examine whether the proposed watermarking scheme can survive JPEG compression attacks. In order to perform this experiment, the watermarked image shown in Fig. 3(c) was compressed using different quality factors. The results are presented in Fig. 4(a), where the detection response is plotted against the JPEG quality factor, along with the watermark detection threshold and the second highest response of the detector (the highest among the remaining 999 randomly generated watermarks introduced to the detector). The detection results are satisfactory, even when the watermarked image is considerably degraded when compressed with a quality factor as low as 15.

C. Cropping Attack

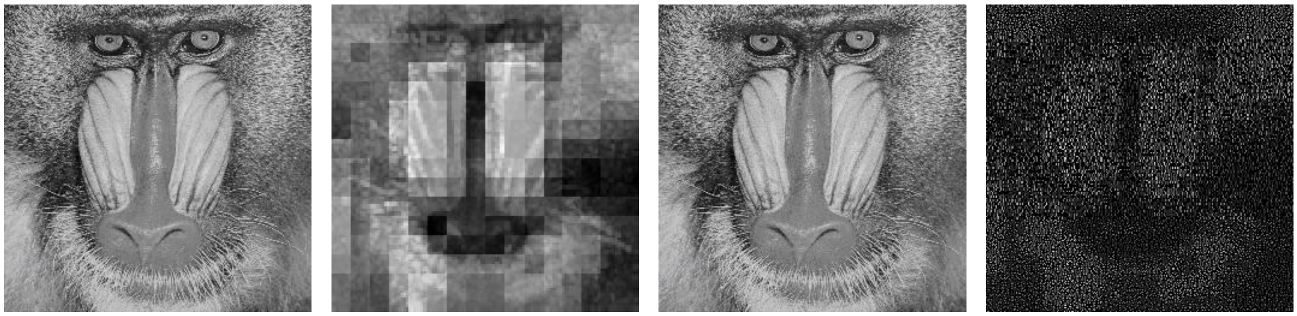
Image cropping is another geometric attack that may occur to a watermarked image. The response of the watermark detection is shown in Fig. 4(b), where the detection response is plotted against the cropped area. The results demonstrate the excellent robustness of the watermarking algorithm with respect to cropping.

D. Additive Gaussian Noise Attack

The watermarking scheme was also tested under additive Gaussian noise pollution, with zero mean and distinct variance values. The watermark detector response when the watermarked image is introduced to additive Gaussian noise with different variance values is shown in Fig. 4(c). The results demonstrate that this scheme is significantly robust against additive Gaussian noise.

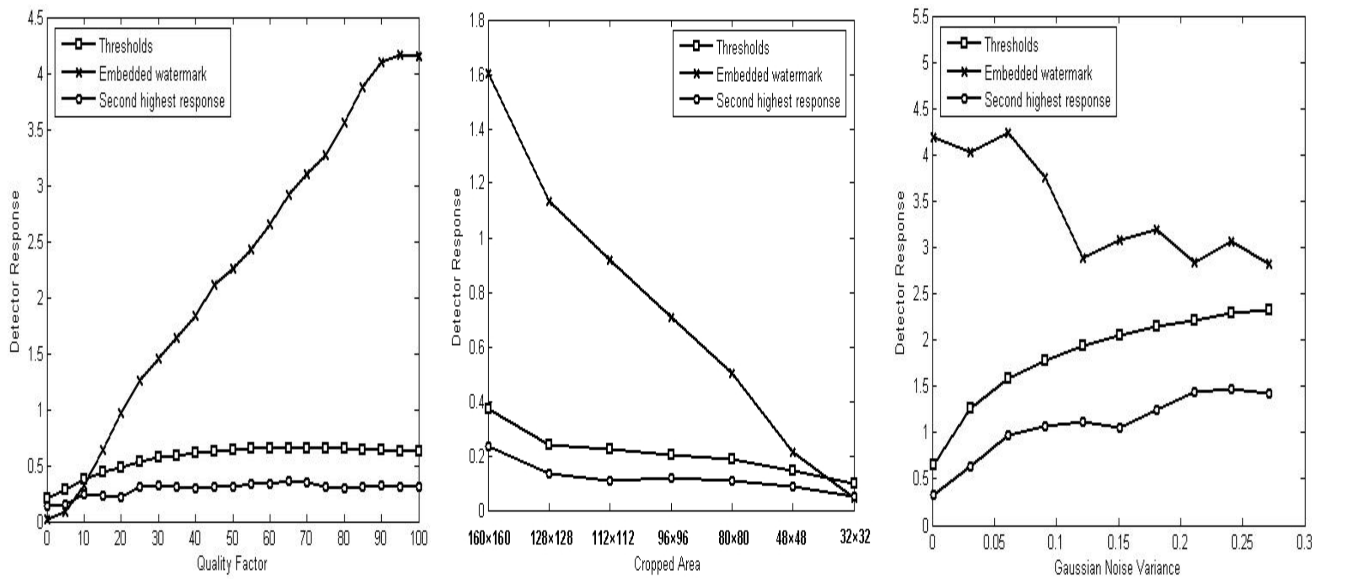
V. CONCLUSION

In this paper, we investigated the copyright protection of learning objects, more specifically, image learning objects. To achieve this goal, a novel image watermarking algorithm was illustrated where the watermark is adaptively embedded in higher resolution subbands of the discrete wavelet transform. Moreover, a biorthogonal wavelets-based HVS is exploited in order to accurately adapt the watermarking strength according to the local characteristics of the image. In addition, a Sugeno fuzzy model is used to compute the watermark weighting function, as it can accurately model the nonlinear relationship that exists between the HVS masking properties. Another important advantage of a Sugeno-type fuzzy model as opposed to other FIS models such as the Mamdani FIS [14], is its computational efficiency. The primary drawback of this algorithm is its vulnerability against geometric attacks such as Rotation, Scaling and Translation (RST). This is due to the fact that the DWT domain is not RST-invariant. Moreover, the watermarking algorithm is not very robust against low-pass filtering. This



(a) (b) (c) (d)

Fig. 3. (a) Original Image of Baboon (b) image of the weighting function (resolution level 0), (c) watermarked image PSNR = 36.7, (d) difference between the watermarked image and the original image.



(a) (b) (c)

Fig. 4. Plot of the detector response to the embedded watermark (cross markers), of the threshold (square markers), and of the second highest detector response (circle markers). (a) JPEG compression attacks, (b) Cropping attacks, (c) Additive Gaussian noise attacks.

can however be remedied by either attempting to embed in lower resolution subbands, and/or embed in selected significant (high magnitude) DWT coefficients. However, in the latter case, the detector will no longer be blind as certain knowledge about the original image (the selected DWT coefficients) will be required. Finally, the experimental results proved that the proposed algorithm is robust against signal processing attacks (such as lossy compression, and additive Gaussian noise) and geometric attacks (such as cropping attacks). The future work is to attempt to improve the robustness of this algorithm against low-pass filtering attacks.

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