Fuzzy Rough Set Based Image Watermarking Approach

Musab Ghadi[1(✉)], Lamri Laouamer[1,2], Laurent Nana[1], and Anca Pascu[1]

[1] Lab-STICC (UMR CNRS 6285), University of Bretagne Occidentale, Brest, France
e21409716@etudiant.univ-brest.fr, {Laurent.Nana,Anca.Pascu}@univ-brest.fr
[2] Department of Management Information Systems, Qassim University, Buraydah, Kingdom of Saudi Arabia
laoamr@qu.edu.sa

Abstract. Computational intelligent techniques can be useful in developing efficient watermarking approaches that are able to maintain and reduce risks to integrity, confidentiality, and availability of information and resources in computer and network systems. This paper aims to develop a new spatial domain-based watermarking approach that uses the fuzzy rough set to select well thought out blocks to embed secret data with acceptable rate of imperceptibility and robustness against different scenarios of attacks. The proposed model focuses on analyzing the host image to discover specified features in some blocks that in turn will be considered in the watermarking process. These features include the characteristics of the Human Visual System (HVS) regarding the color sensitivity and the textured/semi-smooth regions, where embedding the watermark in low color sensitivity to the human eye and more textured regions gains high imperceptibility and robustness. The experiment results show that the proposed approach gives interesting and remarkable results to preserve the image authentication.

Keywords: Intelligent techniques · Watermarking · Fuzzy rough set · Imperceptibility · Robustness · Attacks

1 Introduction

Digital watermarking is one of the appropriate solutions, which can contribute significantly to the authentication of the transmitted text, images, and videos on the Internet. Many watermarking approaches are proposed both in spatial and frequency domains [1–5]. taking into account the complexity of modern systems and the diversity of attacks are needed. Computational intelligent techniques exhibit many capabilities to adapt and provide multimodal solutions for these complex systems. The scope of computational intelligent methods involves fuzzy logic, genetic algorithm, artificial neural network, and rough set. Some frequency domain-based watermarking approaches use these techniques with a goal to develop an efficient watermarking approach using Discrete Cosine Transform

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(DCT), Discreet Wavelet Transform (DWT), and Singular Value Decomposition (SVD) [4,5]. Intelligent techniques in spatial domain based watermarking approaches have not been widely used. Few works such as those proposed in [6–8] explore the artificial neural network and rough set principles. This paper aims to develop a new spatial domain watermarking approach based on the fuzzy rough set technique by selecting particular blocks to embed secret data with an acceptable rate of imperceptibility by achieving a remarkable robustness against different kind of attacks and maintaining a low process complexity. The rest of this paper is organized as follows: In Sect. 2, we present a literature review. Section 3, illustrates the rough set principle. Then, the system model is illustrated in Sect. 4. The experiments result is presented in Sect. 5 and a comparative study is conducted in Sect. 6. Finally, we conclude the presented approach in Sect. 7.

2 Literature Review

This section presents a literature review on spatial and frequency domain-based digital image watermarking approaches using computational intelligent techniques in both watermark embedding/extraction processes.

In the case of spatial domain, authors in [6] proposed an efficient watermarking approach that embeds an encoded watermark image in the image blue components. The different intensities of the original blue components are used as a feature to train an Artificial Neural Network (ANN) and extract the attacked watermark image. The experiments result showed that the Bit Correct Rate (BCR) ratio ranged between [57.23–100]% and the Peak Signal-to-Noise Ratio (PSNR) ranged between [10.03–39.6] dB. As well, authors in [8] proposed a fragile watermarking scheme that operates in spatial domain based on the K-means method. The proposed scheme computes the distance between each 2×2 block and its centroid to find the feature sequence that XOR-ed with random sequence number to generate a 8 authenticated bits that replace the Least Significant Bits (LSBs) in each 2×2 block of the original image. This model was tested in tamperproofing under a variety of attacks like cut-paste and collage attacks. The experiments result showed that the PSNR ratio reached the 46.2 dB. For the case of frequency domain, a probabilistic neural network technique was proposed in [9] based on a DWT watermarking scheme. As well, a genetic algorithm was applied to develop an SVD-based watermarking scheme in [10] and a DCT-based scheme in [11]. In addition, [12] utilized a fuzzy rough set to design a DWT-based watermarking scheme.

3 Rough Set Principle

Rough set is one of the computational intelligent tools that deals with the induction of concept approximation to process information in a database. It is concerned with classification and analysis of imprecise and incomplete information

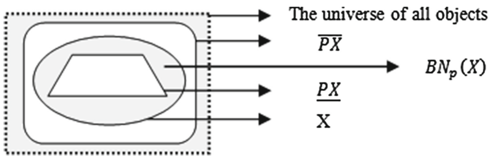

Fig. 1. The three approximation regions in rough set theory

or knowledge to facilitate the tasks of feature selection and knowledge discovery [13, 14]. The imprecision and uncertainty in rough set theory is expressed by boundary region of a set. Rough set technique is based on sets of objects (U) and attributes (A) that represent an information system I such as I = (U,A), where X $\subseteq$ U and P$\subseteq$A. The system table is built such as its rows correspond to objects U and columns correspond to attributes A. Based on the defined attributes P, the rough set can approximate X using only the information contained in P by defining three regions, as illustrated in Fig. 1; (1) The B-upper region $\overline{PX}$, which is the set of all of objects that can be possibly classified as member of X with respect to P. It can be denoted by $\overline{PX} = \{x|\text{p(x)} \bigcap \text{X} \neq \phi\}$. (2) The B-lower region $\underline{PX}$, which is the set of all objects that can be classified with certainly as member of X regarding P, and certainly belong to the subset of interest. It can be denoted by $\underline{PX} = \{x|\text{p(x)} \subseteq \text{X}\}$. (3) The boundary region BNp(X), represents the set of all of objects, which cannot be classified neither in $\overline{PX}$ nor $\underline{PX}$. If the BNp(X) is empty, then the set is called 'Crisp set'. Otherwise, if the BNp(X) is non-empty, then the set X is called 'Rough set' in other terms BNp(X) = $\overline{PX}$-$\underline{PX}$ [14].

4 System Model

The proposed system considers two types of colored image: semi-smooth and textured images to construct a system table, where any colored image I consists of three components R, G, and B that can be converted to YCbCr components to display each of luminance component(Y), blue-difference (Cb), and red-difference (Cr). Then the proposed model exploits the low HVS sensitivity to the blue component (Cb) [6] and the highly textured regions in the original image to be concerned in the embedding process. Selecting those attributes is justifited by the availability of imperceptibility and robustness against attacks [6, 11].

4.1 Construct an Information System for both Semi-smooth and Textured Images

Table 1 below, illustrates the information systems for both semi-smooth and textured images by taking into account that the average value of 8×8 block pixels in Cb matrix corresponds to Cb attribute and the range of the DC coefficient in each block corresponds to DC coefficient attribute. The decision of the information system is based on two thresholds: T1 that corresponds to the average value

Table 1. Information systems of semi-smooth and textured images

Information system of semi-smooth images				*Information system of textured images*			
Class (C)	C_b	DC coefficient	Decision (D)	Class (C)	C_b	DC coefficient	Decision (D)
1	$X \leq 127$	0	Yes	1	$X \leq 127$	0	No
2	$X > 127$	0	Yes	2	$X > 127$	0	No
3	$X \leq 127$	[1-3]	Yes	3	$X \leq 127$	[1-3]	No
4	$X > 127$	[1-3]	Yes	4	$X > 127$	[1-3]	Yes
5	$X \leq 127$	[4-5]	Yes	5	$X \leq 127$	[4-5]	Yes
6	$X > 127$	[4-5]	No	6	$X > 127$	[4-5]	Yes
7	$X \leq 127$	[6-7]	No	7	$X \leq 127$	[6-7]	Yes
8	$X > 127$	[6-7]	No	8	$X > 127$	[6-7]	Yes
9	$X \leq 127$	[8-9]	No	9	$X \leq 127$	[8-9]	Yes
10	$X > 127$	[8-9]	No	10	$X > 127$	[8-9]	Yes
11	$X \leq 127$	[10-11]	No	11	$X \leq 127$	[10-11]	Yes
12	$X > 127$	[10-11]	No	12	$X > 127$	[10-11]	Yes

of Cb component and T2 corresponds to the range of DC coefficient in any 8×8 block. By demonstrating the information systems in Table 1 for semi-smooth and textured images respectively, we can find that the decision for semi-smooth images depends on T1 $\leq$ 127 and T2 = [4-5]. This can be theoretically justified by noting that the probability to see an increasing value in the average Cb in each block is very low, particularly when the average value did not exceeded 127, compared to when the average value of Cb is greater than 127. As well as regard, the value of DC coefficient where the probability to see a change in DC coefficient may be increased if the DC coefficient becomes greater than or equal to [4,5]. On the other hand, the decision regarding the textured images depends on T1 > 127 and T2 = [1-3]. This can be justified by the fact that embedding watermark in more textured regions is imperceptible and highly robust against attacks. So the probability to see an increasing value in the average of Cb for each block in the textured images is very low, particularly when the average value exceeds 127 and the value of DC coefficient is equal to or greater than [1–3].

4.2 The Employment of Rough Set Technique

From the information systems illustrated in Table 1, we can build a unified information system as illustrated in Table 2 to be manipulated in one of computational intelligent technique to deal with a variety of images regardless of its nature. Rough set is our choice to deduce a concepts approximation of existing information in our model. By rough set, we can extract the CD-upper approximation $\overline{CD}$, the CD-lower approximation $\underline{CD}$, and the boundary BNc(D) regions as following:

$$Yes \rightarrow \{1, 3, 5, 7, 8, 9, 10, 12, 14, 16, 18, 20, 22, 24\}$$

$$NO \rightarrow \{2, 4, 6, 11, 13, 15, 17, 19, 21, 23\}$$

$$Yes \setminus No \rightarrow \{1, 2, 3, 4, 5, 6, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24\}$$

$$\overline{CD} \rightarrow \{1, 2, 3, 4, 5, 6, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 7, 8, 9, 10\}$$

Table 2. Information systems of semi-smooth and textured images

Class (C)	C_b	DC coefficient	Decision (D)	Class (C)	C_b	DC coefficient	Decision (D)
1	$X \leq 127$	0	Yes	13	$X \leq 127$	[6-7]	No
2	$X \leq 127$	0	No	14	$X \leq 127$	[6-7]	Yes
3	$X > 127$	0	Yes	15	$X > 127$	[6-7]	No
4	$X > 127$	0	No	16	$X > 127$	[6-7]	Yes
5	$X \leq 127$	[1-3]	Yes	17	$X \leq 127$	[8-9]	No
6	$X \leq 127$	[1-3]	No	18	$X \leq 127$	[8-9]	Yes
7	$X > 127$	[1-3]	Yes	19	$X > 127$	[8-9]	No
8	$X > 127$	[1-3]	Yes	20	$X > 127$	[8-9]	Yes
9	$X \leq 127$	[4-5]	Yes	21	$X \leq 127$	[10-11]	No
10	$X \leq 127$	[4-5]	Yes	22	$X \leq 127$	[10-11]	Yes
11	$X > 127$	[4-5]	No	23	$X > 127$	[10-11]	No
12	$X > 127$	[4-5]	Yes	24	$X > 127$	[10-11]	Yes

$$\underline{CD} \rightarrow \{7, 8, 9, 10\}$$

$$BNc(D) \rightarrow \{1, 2, 3, 4, 5, 6, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24\}$$

Then our model concerned with those blocks that are matching the condition for any rough set element (i.e. inside the BNc(D) set).

4.3 Parsing JPEG Bitstream

As proposed in [15], the JPEG file structure is constructed by combining many segments that represent the bitstream file for any image. Each 8×8 DCT block was compressed by 1 DC and possibly 63 AC coefficients. In our model, we parse the encoded data to find the DC coefficient category based on Huffman table that is illustrated in [16].

4.4 Model Initialization

The proposed model has to read the Cb component from the RGB image to build an avg_matrix and category_matrix that define the attributes of the pre-arranged information systems to deduce the decision in the proposed model. The initialization process is illustrated in Fig. 2.

4.5 Watermark Embedding Process

After defining the avg_matrix and category_matrix from Cb matrix of RGB image, we can check whether the given block of Cb matrix matches the rough set rules by means of BNc(D) set or not. Subsequently, any satisfied block will be in-queued in rough set RS queue, and will be embedded with a watermark w by a linear interpolation equation. This equation gives us the ability to control the visibility/invisibility of embedded watermark by factor t. The obtained

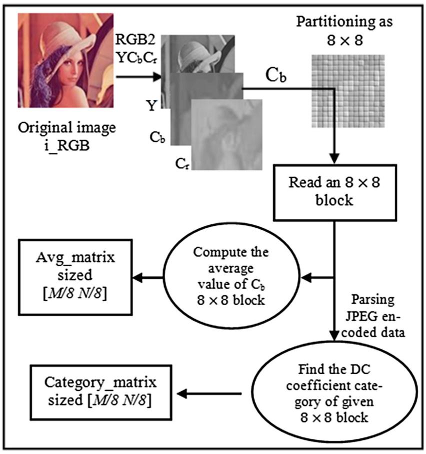

Fig. 2. Model initialization structure

watermarked image *iw_cb* is illustrated in Eq. (1), and the embedding process is illustrated in Fig. 3.

$$i_w = (1 - t)w + t * i\,, \quad 0 < t < 1 \tag{1}$$

where i is a squared size *Cb* component of the RGB image, w is the watermark image sized 8×8, and t is the linear interpolation factor. The value of the linear interpolation factor t reflects the degree of visibility/invisibility of the embedded watermark in the original image within three cases.

Case 1 (visible case): if t closes to 0, then $\mathrm{i}_w = \underbrace{(1 - t) * w}_{\text{goes to 1}} + \underbrace{(t * i)}_{\text{goes to zero}}$. The result will be as $\mathrm{i}_w = \mathrm{w}$, which means that w is the dominant in i_w.

Case 2 (invisible case): if t closes to 1, then $\mathrm{i}_w = \underbrace{(1 - t) * w}_{\text{goes to zero}} + \underbrace{(t * i)}_{\text{goes to 1}}$. The result will be as $\mathrm{i}_w = \mathrm{i}$, which means that i is the dominant in i_w.

Case 3 (semi-visibility case): if $t \in [0.4 - 0.6]$, then w will be clear with some visibility degrees. So, in our experiments we used $t = 0.98$, since the invisibility is achieved if t is closes to 1. After embedding the watermark, the resulting *iw_cb* matrix and the RS queue would be sent to the receiver via public network, which requires to concatenate the *Y* and *Cr* of the original image with *iw_cb*. The Receiver will receive the attacked *iwa_RGB* image and the attacked RS queue, because the RS may be also prone to different attacks, we need to secure it. One-Time Pad (OTP) algorithm can be a best choice to encrypt it due to its unbreakability.

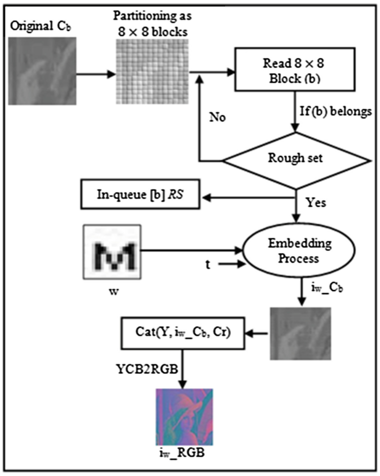

Fig. 3. Embedding process framework

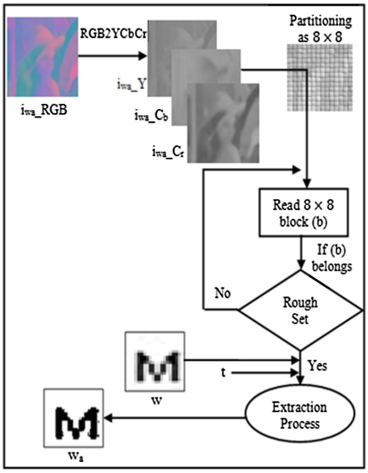

Fig. 4. Extraction process framework

4.6 Watermark Extraction Process

The watermark extraction will be applied on the attacked watermarked image *iwa_RGB* in order to extract the attacked watermark w_a also via linear interpolation as illustrated in Eq. (2).

$$w_a = (1/t)w - (1-t)/t * i_w a\,, \quad 0 < t < 1 \tag{2}$$

where w_a is the extracted attacked watermark image, *i_wa* is the attacked watermarked image, and $t = 0.98$. The extraction process is illustrated in Fig. 4.

5 Experiments Result

The proposed model processed a square color images sized 128 × 128 as an original image and 8 × 8 watermark image. The resulted watermarked images are exposed to a variety of attacks including: geometric attack (i.e. such as rotation) and non-geometric attacks (i.e. like JPEG compression, Gaussian noise, and median filtering) by StirMark Benchmark v.4 [17]. Figure 5 illustrates a sample of the processed images. The tests are conducted on these seven images that are in turn partitioned as 8 × 8 blocks and a watermark image w sized 8 × 8 is embedded in particular blocks of the original images that satisfy the rough set rules.

To evaluate the performance of our model, we applied three metrics (i.e. PSNR, Bit Error Rate (BER), and Correlation Coefficient (CC) [6,11]), where the PSNR and CC measured the robustness and the similarity between the original watermark w and all extracted attacked watermark w_a, while the BER metric measured the stabilization (i.e. the number of correct bits that can be extracted from the attacked watermarked image). Due to the large number of

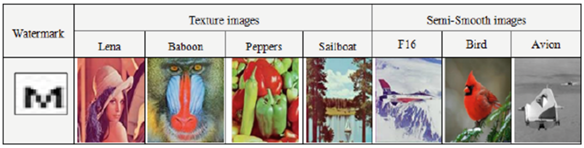

Fig. 5. Samples of original images and the watermark images

Table 3. Average results for PSNR, BER, and CC for processed images

Images name	Robustness against attacks					
	Attacks	JPEG_80	Medain_9	Noise_10	Rot_10	Rot_45
Lena	PSNR	45.5	45.54	44.8	45.17	44.75
	BER	0.18	0.18	0.19	0.18	0.18
	cc	1	1	1	1	1
Baboon	PSNR	44.5	44.45	43.8	44.2	44.0
	BER	0.19	0.19	0.19	0.19	0.19
	cc	1	1	0.99	1	1
Peppers	PSNR	45.2	45.17	44.6	44.8	44.5
	BER	0.18	0.18	0.19	0.18	0.19
	cc	1	1	0.99	1	1
Sailboat	PSNR	44.8	44.9	44.1	44.5	44.2
	BER	0.19	0.19	0.19	0.19	0.19
	cc	1	1	1	1	1
F16	PSNR	43.4	43.4	43.4	43.5	43.6
	BER	0.20	0.20	0.20	0.20	0.19
	cc	1	1	1	1	1
Bird	PSNR	45.2	45.2	44.1	44.8	44.5
	BER	0.19	0.19	0.19	0.19	0.19
	cc	1	1	1	1	1
Avion	PSNR	43.5	43.5	43.5	43.6	43.7
	BER	0.20	0.20	0.20	0.19	0.19
	cc	1	1	0.99	1	1

blocks that satisfy the rough set rules, our experiment's result are displayed in average as showed in Table 3.

The results of PSNR, CC, and BER are very interesting, where the PSNR ratio ranges between (43.4–45.5) dB and the CC ratio is equal to 1 in most cases, while the BER ratio ranges between (18–20) %. By comparing the results with the different kind of attacks, we can note that the result involved with Noise_10 and Rot_45 are the least ones in terms of PSNR, while JPEG_80 and Median_9 present the same results in PSNR, CC, and BER. From the displayed

Table 4. Comparisons of the CC of the proposed model and other related approaches

Image's name	Attacks	Metric	Han et al. [11]	Lu et al. [18]	Proposed model
Lena image	JPEG_80	cc	NA	0.98	1
	Noise_10	cc	0.92	0.91	1
	Median_9	cc	0.87	0.95	1
Baboon image	JPEG_80	cc	NA	0.99	1
	Noise_10	cc	0.91	0.91	1
	Median_9	cc	0.82	0.93	1
F16 image	JPEG_80	cc	NA	0.99	1
	Noise 10	cc	0.91	0.94	1
	Median 9	cc	0.82	0.91	1

Table 5. Comparisons of PSNR of the proposed model and the model in [11]

Attacks	Metric	Han et al. [11]	Proposed model
Lena	PSNR	42.54	43.9
Baboon	PSNR	41.5	43.5
F16	PSNR	42.7	42.6

Table 6. Comparisons of BER of the proposed model and the model in [6]

Image		Lena image		Baboon image		F16 image	
Attacks	Metric	Findik et al. [6]	Proposed model	Findik et al. [6]	Proposed model	Findik et al. [6]	Proposed model
JPEG_80	BER	0.40	0.156	0.42	0.159	0.29	0.16
Noise_10	BER	0.07	0.156	0.13	0.159	0.07	0.16
Rot_10	BER	0.08	0.155	0.12	0.159	0.08	0.16
Rot_45	BER	0.15	0.156	0.19	0.157	0.14	0.158

results we can also conclude that our proposed model is compatible to deal with both textured and semi-smooth images. This will give us a sense that the rough set-based watermarking technique is very useful to achieve the robustness and imperceptibility in terms of stabilization and similarity.

6 Comparative Study

In this section we compare the results achieved by the proposed model with those of other interesting related approaches. An adaptive work has been made on our model to be compatible with other related work, in terms of the host image and watermark sizes. All of these approaches involved a particular computational intelligent technique. Our comparisons held on three images (i.e. Lena, Baboon

Table 7. Clarification of the Weakness/strength of the obtained approaches comparing with our model

The model	Is our model outperforming the obtained approach? And in which terms?	The evidence of the weakness/strength of the obtained approaches comparing with our model
Findik et al. [6] (2011)	Our model outperform [6] in terms of BER in case of high scale factor of attacks.	The weakness of this technique appears in embedding a watermark image in blue components of the host image, without consideration to the nature of embedding region (i.e. textured or smooth).
Han et al. [11] (2016)	Our model outperform [11] in terms of CC and PSNR	The weakness of this technique appears in embedding watermark in the DC coefficient of all DCT blocks, without consideration to the HVS sensitivity properties.
Lu et al. [18] (2006)	Our model outperform [18] in terms of CC.	The weakness of this technique appear in selecting the textured regions by considering the green and red components of the host image, which is not suitable for availability of imperceptibility and robustness against attacks, since the HVS sensitivity is rematkable in cases of choosing red and green components comparatively to the blue component.

and F16) with different attacks scenario. Firstly, our results are compared with [11,18] in terms of CC. Secondly, our results are compared with [11] in terms of PSNR and finally, our results are compared with [6] in terms of BER. Tables 4, 5 and 6 present these results, followed by a discussion in Table 7. Through Tables 4, 5 and 6, we can note that our model outperformed [11,18] models, in terms of

CC under Noise_10 and Median_9 attacks, whereas in the case of JPEG_80 the CC in all approaches are convergent. Our model also enhanced a robustness ratio by (1–2) dB in all attacks scenario comparing with [11]. Similarly, the BER was enhanced by 25 % with JPEG_80 attack, and it is approximately the same in Rot_45 attack. In terms of Noise_10 and Rot_10, the results of BER ratio in [6] outperformed our model by 10 %. This is due the low noise and rotation used factors. However, we think that our model is more practical than model in [6], especially with the high used factors in noise, rotation, or JPEG attacks, which appear clearly in the case of Rot_45 attack.

7 Conclusion

This paper aims to develop a new spatial domain-based watermarking approach that utilizes the fuzzy rough set technique by selecting many blocks to embed secret data with acceptable rate of imperceptibility and robustness against different kinds of attacks. Based on the proposed model structure, we can conclude that the rough set-based watermarking model in spatial domain is capable to achieve a significant rate of robustness and imperceptibility with means of similarity and stabilization. The experiment's result showed that the results of PSNR, CC, and BER are very interesting. This gives a sense that the rough set-based watermarking can serve significantly in achieving both watermark imperceptibility and robustness.

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