

Intelligent watermarking of document images as a dynamic optimization problem

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Abstract—Intelligent watermarking (IW) allows adapting embedding parameter for each image and set of attacks using evolutionary computing. However, IW is not practical in real-world applications because of the computational cost of (evolutionary computing) algorithms that must be applied to optimize the parameters for each document image. It is however possible to formulate IW as a dynamic optimization problem (DOP), as similar images should result in similar fitness landscapes. Such formulation could allow a decrease in the computational burden of IW since dynamic optimization uses knowledge obtained in previous image optimizations in order to reduce the number of optimizations in some cases, replacing re-optimization by recalls to previously seen solutions. In this paper, a bi-tonal intelligent watermarking system is proposed and employed as a tool to characterize IW as a DOP. Proof of concept simulations using such approach resulted in a decrease of 93.5% in the computational cost with little impact on accuracy.

I. INTRODUCTION

Everyday, millions of transactions involving digitized physical documents are made across the globe. Since many of these documents contain sensitive information, the enforcement of the security of these images is considered a paramount issue. Digital watermarking, which consists of embedding information about a cover work (image) through manipulation of its signal (pixels, in the image case), has been successfully employed in the security enforcement of multimedia data. This is a non-intrusive process as it is subject to robustness and fidelity constraints.

Since watermarking involves a trade-off between robustness and fidelity, many authors have proposed using of evolutionary computing (EC) in order to optimize embedding parameters trade-off between both properties [10]. However, this is a very costly process because with algorithms for EC, a population of candidate solutions is optimized over several iterations and at least one embedding and detection operation is required per solution at each iteration. For example, the Genetic Algorithms (GA) intelligent watermarking method proposed by Shieh *et al* [9] involves a population of 10 candidate solutions, evolved up to 28000 generations for a single image, in some cases. For this reason, this process is only feasible for small databases (i.e. with no more than 10 images).

In practical applications (specially those involving long streams of document images) many of the images being

watermarked are similar in nature and it is expected that their underlying fitness landscapes also share some similarities. It is possible to decrease the computational burden in this scenario with dynamic optimization techniques.

This paper presents an intelligent bi-tonal watermarking system based on Particle Swarm Optimization (PSO) [8] and quantized odd-even embedding [5]. In this system, the selection of embedding parameters for different document images is formulated as a dynamic optimization problem. Using a database of document images, the performance of this system is assessed empirically, along with the possibility of exploring pre-existing solutions to avoid some costly re-optimizations.

II. IW AS A DYNAMIC OPTIMIZATION PROBLEM

The intelligent watermarking system proposed in this paper employs PSO in order to optimize the embedding parameters of the bi-tonal watermarking system seen in [5]. In this digital watermarking system, a bi-tonal image is partitioned into blocks of $B \times B$ pixels. Then, a flippability score is assigned to each pixel based on the properties of its neighbour pixels (i.e., a window of size $M \times M$) and the image is shuffled using a pseudo-random sequence based on a seed S in order to distribute flippable pixels across the image. The embedding is performed by flipping pixels in each block, pixels with highest score first. The number of black pixels is set to $2kQ$ to embed a ‘1’ or $(2k + 1)Q$ to embed a ‘0’, where Q is the quantization step size (and defines the robustness of the watermark) and k is merely a factor of the number of black pixels. Then, the image is de-shuffled. Detection is performed by partitioning the image in blocks of size $B \times B$, shuffling the pixels using the same seed S and verifying if the number of black pixels at each block is either $2kQ$ or $(2k + 1)Q$.

This watermarking system is optimized for the embedding of two watermarks – a robust and a fragile (whose Q parameter is fixed at 2), with the use of PSO, an EC technique inspired by the behaviour of flocks of birds. In PSO, a population (swarm) of candidate solutions (particles) evolves through a number of iterations. Each particle has a position and a velocity. At each iteration, the velocity of a particle (v_i) is computed based on

its previous velocity and on the best location visited by itself and by its best neighbour

$$v_{id} = \chi \times (v_{id} + c_1 \times r_1 \times (p_{id} - x_{id}) + c_2 \times r_2 \times (p_{gd} - x_{id})) \quad (1)$$

where χ is the constriction factor which ensures convergence [8], d is one of the dimensions of a particle, c_1 and c_2 are respectively the cognitive and social acceleration constants, r_1 and r_2 are two different random numbers in the interval $[0, 1]$, p_{id} is the best position visited by particle i at dimension d and p_{gd} is the best location ever visited by all neighbours of particle i . The neighbourhood can be either the whole swarm (G-Best) or a limited number of particles (L-Best). For better optimization results, c_1 and c_2 must be set to 2.05 and χ must be set to 0.7298 [8].

The new position of a particle is computed as

$$x_{id} = x_{id} + v_{id} \quad (2)$$

In the proposed method, a L-Best PSO [8] is employed in the optimization of the watermarking system described before. Four embedding parameters – B , M , S and ΔQ (the difference between the Q of the robust and fragile watermarks) – are optimized. The configuration of a particle and the corresponding embedding parameters employed in this system can be seen in Table I.

TABLE I: Configuration of a particle in the proposed system.

Parameter	Range (PSO)	Range (embedding)
B	{1, 2, 3, ..., 256}	{1, 2, 3, ..., 256}
ΔQ	{1, 2, ..., 75}	{2, 4, 6, ..., 150}
M	{1, 2, 3, 4}	{3, 5, 7, 9}
S	{0, 1, 2, ..., 15}	{0, 1, 2, ..., 15}

Both watermarks contain 936 bits and can be seen in Fig. 1. Then, the quality of the watermarked image is computed

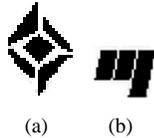


Fig. 1: Bi-tonal logos used as watermarks. (a) 26×36 BancTec logo (robust). (b) 36×26 Université du Québec logo (fragile).

using the Distance Reciprocal Distortion Measure (DRDM) [5] which employs a normalized weight matrix W , of size $m \times m$ (here, a window of 9×9 is employed) in order to measure the fidelity between two images (IA and IB)

$$d(IA, IB) = \frac{\sum_{i=0}^{IA_H-1} \sum_{j=0}^{IA_W-1} d_{i,j}(IA, IB)}{K} \quad (3)$$

where IA_W and IA_H are respectively the width and height of IA , K is the number of non-uniform (not all black or all

white pixels) blocks of size 8×8 in IA , and $d_{i,j}()$ is the distortion for pixel (i, j) computed as:

$$d_{i,j}(IA, IB) = \sum_{(k,l)=-\frac{m}{2}}^{\frac{m}{2}} [|IA_{i+k,j+l} - IB_{i+k,j+l}| \times W_{k+\frac{m}{2},l+\frac{m}{2}}] \quad (4)$$

Finally, the robust watermark (R_D) is detected and the inverse of the Bit Correct Ratio (BCR^{-1}) between the embedded and detected watermarks is computed in order to determine the watermark robustness:

$$BCR(R_E, R_D) = \frac{1}{N} \sum_{i=1}^N b_i \quad (5)$$

$$b_i = \begin{cases} 1, & \text{if } R_E[i] = R_D[i] \\ 0, & \text{if } R_E[i] \neq R_D[i] \end{cases}$$

where R_E is the embedded watermark, R_D is the detected watermark and N is the watermark length.

These two metrics (DRDM and BCR^{-1}) are combined with the use of Conventional Weighted Aggregation (CWA) [7]:

$$F = \sum_{i=1}^{N_{fitness}} \gamma_i f_i(x) \quad (6)$$

where γ_i is a non-negative weight (set to 0.5 for both metrics), $N_{fitness}$ is the number of fitness functions, $f_i(x)$ is fitness function i and $\sum_{i=1}^{N_{fitness}} \gamma_i = 1$. The DRDM is scaled by a factor of 10^2 (since the optimal DRDM is significantly smaller than the optimal BCR^{-1} [5]). Since PSO relies on real-valued encoding, each parameter has to be rounded before employed on embedding [7].

In a dynamic optimization problem, the location and/or value of the optimum change at unknown time intervals. A change can happen only in the location (Type I) of the optimum, on its value (Type II) or both (Type III) [6]. The two main issues regarding dynamic optimization are diversity and outdated memory. Regarding diversity, there are three main strategies – (1) to introduce diversity after the problem has changed, (2) to maintain diversity throughout the run and (3) to use multiple populations in order to keep track of multiple regions of the fitness landscape. Outdated memory can be tackled by either erasing memory or re-evaluating memory and setting it to either previous or current value (which one is better) [2].

In the practical applications, changes are not completely random as similar states tend to reappear overtime [1] (as in IW of document images). In such scenario, IW can be seen as the problem of optimizing a stream of similar problems.

III. SIMULATION RESULTS AND DISCUSSION

In order to validate this hypothesis, the bi-tonal watermarking system of section II was optimized using the aforementioned PSO method, for a stream of 61 pages from scientific

journals. The stream was divided in four blocks, where the first and third contain 15 pages of plain text, the second and fourth contain 15 and 16 pages of text and half-toned images, respectively. This is the Text/Image/Text/Image (TITI) database. Fig. 2 shows some images from this database.

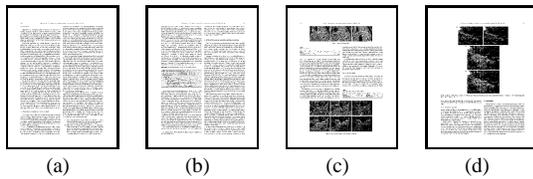


Fig. 2: Database samples. (a–b) Text. (c–d) Half-toned image.

This database is a subset of a larger database containing 317 images consisting of pages of articles (one page per image) from the Computer Vision and Image Understanding (CVIU) Journal, issues 113(1):1–157 and 113(2):159 – 316 obtained from CVIU’s web site. These articles were converted to bi-tonal format using the ImageMagick’s ¹ convert utility at 200 dpi.

A PSO swarm is formed with 50 particles (in the literature, swarm sizes vary between 20 and 50 particles [8]) and the neighbourhood size (k) is set to 3. Optimization stops whenever no improvement in global best fitness occurs during 50 iterations. For proof-of-concept simulations, all particles are randomized at each image transition (full optimization mode).

It was observed that the fitness of most of the 61 optimal solutions is very similar, and that the variations were mainly due to the DRDM, as the robustness remained stable for almost all solutions. Fig. 3 depicts the DRDM performance for the global best solutions for the 61 images.

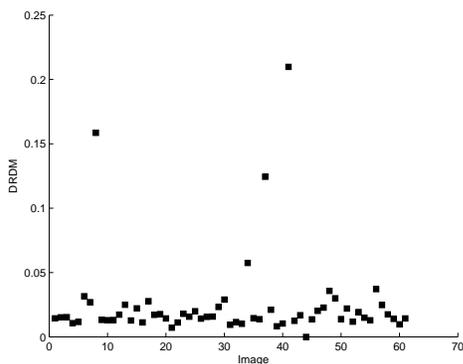


Fig. 3: DRDM values of the 61 optimal solutions.

This is the first indication that intelligent watermarking can be formulated as the optimization of a stream of related

¹<http://www.imagemagick.org>

problems. An analysis of the parameter space with the use of Sammon mapping [3] provides another perspective for this phenomenon. Fig. 4 shows a mapping of the 61 swarms obtained at the end of the optimization of each one of the images in the TITI database. It can be observed that there are two clusters of particles – the smallest one, with 637 particles (average fitness of 0.53 and standard deviation of 0.04) and the largest one with 2413 particles (average fitness of 0.74 and a standard deviation of 0.003). This means that after optimization, particles end up being distributed in the same manner for the 61 images. Thus, computational cost for an intelligent watermarking task could be decreased by using the knowledge of previous tasks.

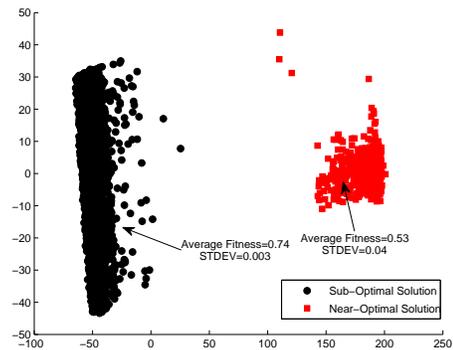


Fig. 4: Sammon mapping of the 61 swarms obtained.

Looking more closely to the near-optimal region for a few images (34–41, seen in Fig. 5), it is possible to observe that some variations in the global bests follow the categorization seen in [6]. In this figure, the circle size represents the DRDM measurement for that particle. In the variation between images 34 and 39, it can be observed that the particles are in the same location but with a significant variation in their fitness values (type II change). For images 37 and 39, a significant variation occurred for both, location and fitness value (type III change). Finally, for images 35 and 39, the variations in location and fitness values are both small.

Thus, it can be said that for the first case computational resources were wasted since the optimal solution is almost identical to previously-found solution (although the fitness value has changes). For the second case, re-optimization was justified. And for the third case, since the variation is small in fitness and parameter space, if the corresponding peaks overlap, computational cost could also be decreased by re-using previously acquired environment knowledge.

Although analysis of the global bests allows understanding how the optimum changes during image transitions, they provide little information about the environment. For this reason the 637 near-optimal solutions depicted in Fig. 4 were re-evaluated for images 34, 35, 37 and 39. The results can be observed in Fig. 6, where the X and Y coordinates represent

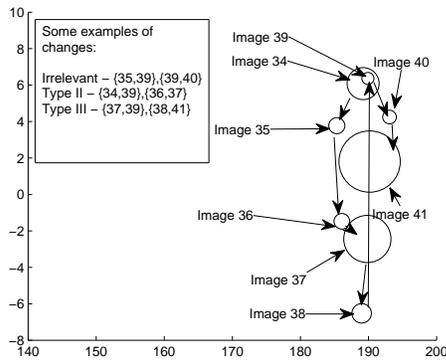


Fig. 5: Sammon mapping of the global bests for images 34 – 41.

Sammon mapping of solutions and the Z coordinate represents fitness value. It is possible to observe that in the first case (Figs. 6a and 6d), which represents a change of type II, there is a small variation for a few particles, but for the majority of the solutions in the valley, the fitness is roughly the same. If a solution is in the optimal location (valley), it is possible to use it for both images without any significant impact on accuracy. In the second case (Figs. 6c and 6d), it can be observed that the variation is very noticeable, which means solutions are not interchangeable. Finally, for the third case (Figs. 6b and 6d), the variation is not noticeable at all. Here, near-optimal solutions can be interchanged with practically no impact in accuracy.

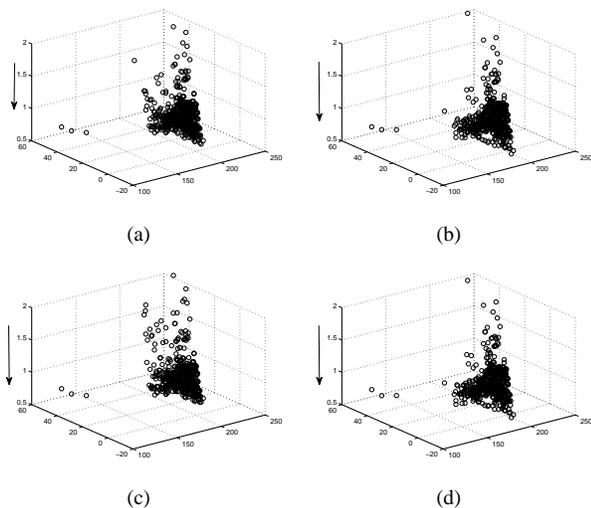


Fig. 6: Sampling of fitness landscape with near-optimal solutions. (a) Image 34. (b) Image 35. (c) Image 37. (d) Image 39.

IV. CONCLUSION

In this paper, the intelligent watermarking of document images was formulated as a dynamic optimization problem. Through empirical analysis of test images, it was possible to observe that images produce three different types of variations in the landscape. In two cases – the first, where only the value of the optimum changed and the third where neither the location nor the value changed – it is possible to avoid costly re-optimization operations.

Proof of concept simulations involving probes sampled in the near-optimal region and a change detection based on the Kolmogorov-Smirnov statistic at a confidence level of 0.05 resulted in a decrease of 93.5% in the computational cost with little impact on fitness performance – the MSE between the 61 solutions found by full optimization and the solutions obtained by this recall mechanism is only 0.2681. One common approach in the dynamic optimization literature [4] is to probe the unknown environment with the use of previously found solutions, compare both measurements (change detection) and re-use the previous solution directly in the new environment.

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