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A quality guaranteed robust image watermarking optimization with Artificial Bee Colony

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ABSTRACT

Achieving robustness with a limited distortion level is a challenging design problem for watermarking systems in multimedia applications with a guaranteed quality requirement. In this paper, we provide an intelligent system for watermarking through incorporating a meta-heuristic technique along with an embedding method to achieve an optimized performance. The optimization objective is to provide the maximum possible robustness without exceeding a predetermined distortion limit. Hence, the quality level of the watermarking method could be guaranteed through that constraint optimization. A new fitness function is defined to provide the required convergence toward the optimum solution for the defined optimization problem. The fitness function is based on dividing its applied solution population into two groups, where each group is ranked according to a different objective. Thus, the multi-objectives in the problem are decoupled and solved through two single-objective sub-problems. Unlike existing watermarking optimization techniques, the proposed work does not require weighting factors. To illustrate the effectiveness of the proposed approach, we employ a recent watermarking technique, and then use it as the embedding method to be optimized. The Artificial Bee Colony is selected as the meta-heuristic optimization method in which the proposed fitness function is used. Experimental results show that the imposed quality constraint is satisfied, and that the proposed method provides enhanced robustness under different attacks for various quality thresholds. The presented approach offers a robust solution that can be applied to numerous multimedia applications such as film industry, intelligent surveillance and security systems.

1. Introduction

The widespread use of the internet has made the multimedia information easy to be shared and accessed. Hence, valuable data could be exposed to malicious manipulations or violation of intellectual property rights. Digital watermarking is one of the most popular ways for securing multimedia data over a shared medium. It has been the core of many applications such as: copyright protection, copy control, authentication, broadcast monitoring, ownership identification, and tamper detection (Fung, Gortan, & Godoy Jr, 2011; Husain, 2012; Liu & He, 2005; Olanrewaju, Khalifa, Hashim, Zeki, & Aburas, 2011; Preda & Vizireanu, 2010; Yusof & Khalifa, 2007). Watermarking is the process of embedding digital information, called the watermark, inside a cover digital content such as: image, video, audio, or text (Cox, Miller, Bloom, & Honsinger, 2002).

In robust watermarking design, it is challenging to achieve robustness along with high quality due to their conflict behavior with each other. The robustness is essential for many applications, while the quality is necessary for any watermarking method. However, applications may differ in their required quality level. Meta-heuristic optimization techniques can be utilized to search for embedding parameters that provide the best compromise between robustness and quality.

A meta-heuristic is an iterative process, which intelligently searches for the optimum solution inside a search space that contains all feasible solutions to an optimization problem. It must define a fitness function that measures the quality of any solution according to the design objectives. For multi-objective optimization problems, the fitness function is evaluated by measuring all objective functions. Then, a multi-objective optimization method is applied to rank the solutions, selected per iteration, according to their measured objectives (J. Wang, Peng, & Shi, 2011).

Existing work on watermarking optimization is versatile. Some existing watermarking optimization methods focus on optimizing a single objective only, and the other objectives are obtained

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through predetermined or adaptively evaluated embedding parameters. Farhan and Bilal (2011) introduced an optimized robust embedding technique in the wavelet domain. The quality was optimized by searching for the optimum locations, where coefficients were modified according to the watermark. Hence, the fitness function was evaluated based on the quality objective only, while the robustness was managed by a fixed embedding strength. The authors presented the quality performance only, but no attacks were considered for robustness evaluation.

Hammouri, Alrifai, and Al-Hiary (2013) proposed a watermarking scheme based on a meta-heuristic optimization method. The embedding was applied in the Discrete Wavelet Transform (DWT) domain. The optimum embedding positions were selected to enhance the robustness of the watermark against some of the common attacks. Thus, the authors represented the fitness of the solution by its achieved robustness, while the quality objective was considered by the embedding strength parameters that were evaluated adaptively.

To improve the performance of watermarking, both robustness and quality should be optimized. That is, we have a multi-objective optimization problem. Many existing methods (Ali, Ahn, & Siarry, 2014; Aslantas, 2009; Lai, Yeh, Ko, & Chiang, 2012; Lei, Wang, Chen, Ni, & Lei, 2013; Mishra, Agarwal, Sharma, & Bedi, 2014; Run, Horng, Lai, Kao, & Chen, 2012; Vahedi, Zoroofi, & Shiva, 2012; Y.-R. Wang, Lin, & Yang, 2011) use the weighted sum approach for optimization, where the objectives of the fitness function are combined additively using weighting factors. One limitation of this approach is that the optimum solution depends on the values of the weighting factors, which are determined experimentally or heuristically.

Recently, Abdelhakim, Saleh, and Nassar (2015) proposed a fitness function to optimize the embedding strength parameters that were employed for embedding each watermark bit individually. In this fitness function, the robustness of a watermark bit was estimated through the achieved quality value. Hence, a single metric reflects both robustness and quality, and thus no weighting factors were needed.

Loukhaoukha (2013) employed a simple optimization algorithm, where its fitness function was evaluated using the exponential weighted criterion. This approach has the same limitations encountered in the weighted sum approach. J. Wang et al. (2011) applied the Non-dominated Sorting Genetic Algorithm II (NSGA II), which is an efficient multi-objective optimization technique. The fitness function ranked the solutions according to the non-dominated sorting method. Hence, the fitness of each solution was its assigned rank. Better performance, in terms of both quality and robustness, was achieved compared to the weighted sum approach. However, it is more complex.

The problem of optimizing one objective while constraining the others, by predefined thresholds, is known as the e-constrain problem (Marler & Arora, 2004). This multi-objective optimization technique is suitable for watermarking applications that define a limit on some of the watermarking objectives. Huang and Wu (2009) presented a fidelity-guaranteed robust watermarking method for achieving a pre-defined quality. The selected solutions, per optimization iteration, were pre-processed before applied to the fitness function. Then the fitness of each solution was evaluated through a weighted sum approach.

In general, multi-objective optimization algorithms applied within robust watermarking are uncommonly utilized due to their complexity. The weighted sum approach is considered to be a simple multi-objective optimization method according to Marler and Arora (2004). However, it is usually referred to as a single-objective optimization (J. Wang et al., 2011), when applied within watermarking. Moreover, it is difficult to find the optimum weighting factors. Note that due to the required computations, optimized watermarking approaches are suited to delay-tolerant applications. However, the advances in microprocessors would reduce the computational delay, enabling wider range of applications.

In this paper, we consider a challenging watermarking problem of achieving robustness without degrading the quality level beneath a predetermined threshold. Here, we consider a fixed payload. As mentioned earlier, mitigating attacks is essential for many watermarking applications, some of which might have quality of service requirements regarding the image quality, such as in Broadcast monitoring (Fujiyoshi & Kiya, 2004; Tachibana, Fujiyoshi, & Kiya, 2004a,2004b).

Note that the higher the application's tolerance to distortion, the more robustness to attacks the system can be. Therefore, it is important to design the watermarking system to achieve the highest robustness based on the application's maximum allowable distortion limit. To solve this problem, we define a new fitness function to be applied within an optimization algorithm that is designed to maximize the robustness while guaranteeing a predetermined quality. The e-constrained optimization problem is solved through the proposed approach, which is simple, effective, and does not require weighting factors.

The rest of the paper is organized as follows. In Section 2, the Artificial Bee Colony is described. In Section 3, the process of embedding and extracting the watermark is illustrated. The proposed work is presented in Section 4. Experimental results are demonstrated in Section 5. Finally, the paper is concluded in Section 6.

2. Artificial Bee Colony (ABC)

The Artificial Bee Colony (ABC), introduced in Karaboga (2005), is a simple population-based optimization algorithm, where a solution population is updated in each iteration. It has been applied in many practical optimization problems (Akay, 2013; Draa & Bouaziz, 2014; Hanbay & Talu, 2014; Li, Li, & Gong, 2014). The ABC algorithm simulates the foraging behavior of the bee swarm, such that each food source represents a possible solution for the optimization problem, and the quality of the source indicates the fitness of the associated solution. The foraging process involves three groups of bees:

(1) Employed bees: They are responsible for collecting food from food sources, and carrying information about them.
(2) Onlookers: They search for food sources to exploit according to the information received from the employed bees.
(3) Scouts: They search randomly, the environment surrounding the hive, for new food sources.

The ABC algorithm converges toward the optimal or near-optimal solution through the operation of the three groups of bees. The main steps of the algorithm are explained as follows:

1. Initialization:

Generate randomly the initial solution population of size NS, where each solution X_i has a dimension of D i.e. $X_i = (x_{i,1}, x_{i,2}, \ldots, x_{i,D})$ and $i = 1,2, .., NS$. All Solutions are bounded between X_{min} and X_{max}, where $X_{min} = (x_{min,1}, x_{min,2}, \ldots, x_{min,D})$ and $X_{max} = (x_{max,1}, x_{max,2}, \ldots, x_{max,D})$. Solution $x_{i,j}$ is generated using the following equation:

$$x_{i,j} = x_{min,j} + rand(0,1) \cdot \left(x_{max,j} - x_{min,j}\right), \tag{1}$$

where $j = 1, 2, .., D$, and rand(0,1) is a random number between zero and one. After generating all NS solutions, their fitness values are calculated.

2. Employed bees phase:

Each employed bee updates its position (solution) to produce a new one.. The old solution is updated according to the following