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Robust image watermarking based on Tucker decomposition and Adaptive-Lattice Quantization Index Modulation

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ABSTRACT

In this paper, a robust blind image watermarking scheme with a good rate distortion-robustness tradeoff is proposed by adopting both Tucker Decomposition (TD) and Adaptive-Lattice Quantization Index Modulation (A-LQIM). Inspired by the good properties provided by TD, such as content-based representation and stable decomposition under distortions, the core tensor of TD is computed from the host image to carry watermarks. The two coarsest coefficients in each frontal slice of the core tensor are considered as a host vector, into which one watermark bit is embedded by using Lattice Quantization Index Modulation (LQIM). In order to further improve the watermarked image quality, an A-LQIM method is proposed to control the embedding strength on each host vector by approximately minimizing the Structural SIMilarity (SSIM)-measured perceptual distortion. Optimal parameters for each embedding are obtained according to the host image. Experimental results have demonstrated that the proposed scheme provides high robustness against common attacks without degrading the image quality compared with state-of-the-art schemes.

1. Introduction

Digital watermarking can be applied to protect the copyright or verify the content of multimedia such as images and video. This paper focuses on robust image watermarking, which embeds information into images without causing perceptual degradation, while ensuring a considerable resistance to various unintentional distortions and malicious channel attacks. Such a watermarking scheme should achieve high robustness and imperceptibility simultaneously. Consequently, a good design needs to carefully handle the tradeoff between these two requirements.

Broadly, watermarks are often embedded in two types of domains: spatial and transform domains. Benefiting from the higher robustness, the latter type, such as Discrete Cosine Transform (DCT) [1], Finite RIdgelet Transform (FRIT) [2], and Discrete Wavelet Transform (DWT) [3–5], is preferred in the literature. Unlike the transforms mentioned above, Singular Value Decomposition (SVD) is content-dependent, which alleviates the degradation of image quality caused by image processing [6]. However, SVD is sensitive to noise. As a result, SVD-based watermarking schemes are often fragile (e.g., [7]). Some approaches try to employ side information to improve robustness (e.g., [8,9]), which, however, limits their

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applications in practice. Moreover, mistakenly sharing information may incur a high false positive [10,11].

As generalized versions of SVD, tensor decompositions preserve SVD's characteristics such as content-dependence. They have also been applied in watermarking on video [12,13], color images [14,15], multispectral images [16], etc. However, little attention has been paid to the characteristics of tensor decompositions that benefit their applications in watermarking. These schemes simply employ embedding strategies similar to SVD-based schemes. As a result, they are not blind. Some of them even suffer from the risk of high false positives (e.g., [12,14,15]). There are two major tensor decomposition methods: CANDECOMP/PARAFAC decomposition [17] and Tucker Decomposition (TD) [18]. It has been shown that the former is unstable under even a small perturbation [19]. However, we find that the analytic solution of the latter, known as High Order SVD (HOSVD) [20], is stable under many attacks. Inspired by this new observation, a robust and blind image watermarking scheme that adopts TD is proposed.

Quantization Index Modulation (QIM) [21] is an important tool for blind watermarking. It is usually extended to the vector case by using sparse QIM or Lattice QIM (LQIM) for a better performance [21,22]. Therefore, we choose the vector QIM to embed watermark bits. The perceptual adaptation is necessary for practical watermarking schemes in order to achieve a better tradeoff between robustness and imperceptibility. For this purpose, some QIM-based approaches employed nonuniform quantization [23,24], or perceptually shaped the projection vector in sparse QIM [25]. However, these are few adaptive extensions for LQIM, whereas LQIM is especially suitable for high dimensional host vectors [26]. QIM usually employs distortion compensation to improve the distortion-robustness tradeoff. The Distortion Compensated-QIM (DC-QIM) can even achieve an optimum performance with respect to the Mean Square Error (MSE)-based measurement [21]. Inspired by this, this paper introduces an Adaptive-LQIM (A-LQIM) method to perceptually modulate distortion compensation on individual host coefficients. In addition, the detector of A-LQIM is blind and formed as simply as that in DC-LQIM.

In this paper, a novel TD-based image watermarking scheme is proposed. The host image is folded and decomposed by TD to generate a core tensor. Though this manipulation reduces the correlation length of the image in the 2 classical directions, it improves the stability of the decomposition considerably. Then the two coarsest coefficients in each frontal slice of the core tensor are employed to embed one watermark bit, where the embedding is performed by LQIM. Experimentally we find that the blocking artifacts incurred by watermark embedding can be captured well with the Structural SIMilarity (SSIM)-based measurement [27]. Furthermore, this measurement can be well approximated by the weighted Sum of Squared Errors (wSSE). As a result, an extension of LQIM, namely A-LQIM, is introduced to optimize the local embedding strength according to wSSE. The embedding parameters are also optimized according to the host image. The embedded watermark can be blindly extracted without knowledge (or estimated knowledge) of the host image.

The rest of this paper is organized as follows. In Section 2, the generation of cover in the tensor decomposition domain is introduced and some new characteristics of the tensor decomposition employed are discussed. In Section 3, the perceptual measurement is defined, based on which A-LQIM is proposed. Section 4 optimizes the embedding parameters, including the quantization radius and maximum self-noise, and presents the designed watermarking scheme. Theoretical analysis and experimental results are reported and discussed in Section 5, which is followed by a conclusion drawn in Section 6.

2. Cover in tensor decomposition domain

An L-th-order tensor means a data array in L dimensions. By fixing all but two indices, we get the slices of a tensor. For example, the horizontal, lateral, and frontal slices can be obtained by fixing the first, second, and third indices of a third-order tensor, respectively. The matricization of a tensor is the process of reordering the elements of a tensor into a matrix, and the mode-k product of a tensor with a matrix, denoted by $\times_k$, is defined as a matrix multiplying the mode-k matricized tensor. More mathematical definitions can be found in [19].

We consider a block-wise watermarking scheme and construct a tensor that consists of image splits. The host image is partitioned into non-overlapping blocks first. Then these blocks are folded as frontal slices to construct a third-order tensor. Assuming that the size of a block is $l_1 \times l_2$, an $l_a \times l_b$ sized image can generate a tensor of size $l_1 \times l_2 \times l_3$ where $l_3 = \lfloor \frac{l_a}{l_1} \rfloor \times \lfloor \frac{l_b}{l_2} \rfloor$.

Given tensor $\mathfrak{T} \in \mathbb{R}^{l_1 \times l_2 \times l_3}$, tensor decomposition can be employed to apply factor analysis [19]. There is no unique way for tensor decomposition, of which a type of Tucker Decomposition (TD) tries to find the factorization

$$\mathfrak{T} = \mathfrak{C} \times_1 U_1 \times_2 U_2 + \mathfrak{E} \tag{1}$$

where the factor matrices $U_k \in \mathbb{R}^{l_k \times \tilde{l}_k}, \tilde{l}_k < l_k, k = 1, 2,$ are the solution of

$$\min_{U_1, U_2, C_k} \sum_{k=1}^{l_3} \left\| T_k - U_1 C_k U_2^T \right\|_F^2$$

$$\text{s.t.} \quad U_1^T U_1 = I_{\tilde{l}_1}, \quad U_2^T U_2 = I_{\tilde{l}_2} \tag{2}$$

where $\|\bullet\|_F$ denotes the Frobenius norm. Matrices $T_k \in \mathbb{R}^{l_1 \times l_2}$ and $C_k \in \mathbb{R}^{\tilde{l}_1 \times \tilde{l}_2}$ are the k-th frontal slices of tensors $\mathfrak{T}$ and $\mathfrak{C}$, respectively. C_k does not need to be diagonal. $I_{\tilde{l}_k}$ is the identity matrix of size $\tilde{l}_k \times \tilde{l}_k$. Factor matrices U_1 and U_2 span the spaces of the horizontal and vertical directions, respectively, and the core tensor $\mathfrak{C} \in \mathbb{R}^{\tilde{l}_1 \times \tilde{l}_2 \times l_3}$ describes the correlation among factor matrices, whose coefficients can be seen as the Singular Values (SVs). The analytic solution of Eq. (2) is given in [20], which also shows that, for any $\tilde{l}_k < l_k$, TD provides the best low rank approximation of $\mathfrak{T}$ under Frobenius norm metric.