Signal Processing 137 (2017) 213–222

Contents lists available at ScienceDirect

Signal Processing

journal homepage: www.elsevier.com/locate/sigpro

A new locally optimum watermark detection using vector-based hidden Markov model in wavelet domain

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ARTICLE INFO

Article history:
Received 2 April 2016
Revised 17 November 2016
Accepted 17 January 2017
Available online 4 February 2017

Keywords:
Statistical modeling
Watermark detection
Wavelet transform
Hidden Markov model

ABSTRACT

Watermark detection is a way of verifying the existence of a watermark in a watermarking scheme used for copyright protection of digital data. Statistical modeling of wavelet subband coefficients has been extensively used in watermark detection. The effectiveness of a watermarking scheme depends directly on how the wavelet coefficients are modeled. It is known that the vector-based hidden Markov model (HMM) is a very powerful statistical model for describing the distribution of the wavelet coefficients, since it is capable of capturing the subband marginal distribution as well as the inter-scale and cross orientation dependencies of the wavelet coefficients. In this paper, it is shown that modeling using the vector-based HMM gives a better fit for the empirical data in comparison to modeling with Cauchy, Bessel-K form (BKF) and generalized Gaussian (GG) distributions. In view of this, we propose a locally-optimum blind watermark detector using the vector-based HMM in the wavelet domain. In a Bayesian framework, closed-form expressions for the mean and variance of a test statistic are derived, experimentally validated and used in evaluating the performance of the proposed detector. Using a number of test images, the performance of the proposed detector is evaluated. It is shown that the proposed detector provides a detection rate higher than that provided by other detectors designed based on the Cauchy, Gaussian, BKF or GG distributions for the wavelet coefficients. The proposed detector is also shown to be highly robust against various kinds of attacks.

1. Introduction

Watermarking is a way of embedding a key into the original data in order to increase its security and facilitate copyright protection. Based on the domain used for embedding the watermark, image watermarking algorithms can be classified into two categories: spatial [1,42] and frequency [2–23]. Frequency domain techniques, such as watermarking based on discrete Fourier transform (DFT) [3], discrete cosine transform (DCT) [4–8,43,46] or digital wavelet transform (DWT) [8–21], have been used in recent works. Depending on the detection methods, existing watermarking schemes can also be classified into two major categories: informed detection, where the host signal is available at the detector during the watermark detection process, and blind detection, where the host signal is not available [18,44]. In order for a blind watermark detection to be realized, advantage is usually taken of the statistical properties of the image. Every image has certain features and characteristics. In statistical modeling, it is intended to capture these characteristics using a small number of parameters. In recent works, statistical image modeling has been focused mostly on transform domains in which the energy density has a more local structure. Among all the transforms employed, wavelet transform has received greater acceptance due to its multiresolution and compression properties. The wavelet subband coefficients were previously assumed to be independent and simply modeled by marginal statistics such as the Gaussian [20], generalized Gaussian (GG) [4,15–17,21,45], Cauchy [5,6,21] alpha-stable [5,6], Gauss-Hermite [9] and Bessel K-form (BKF) [13,14] and [25] distributions. The marginal PDFs cannot capture the dependency of the wavelet coefficients in a single subband or between subbands and therefore, such PDFs cannot be made to fit well the empirical PDF of the wavelet coefficients. However, the wavelet coefficients have strong dependencies across the scales. In view of this, joint statistical models in the wavelet domain, namely, hidden Markov models (HMMs) [26–34] and Markov random field (MRF) priors [35], have been proposed to capture the inter-scale dependencies of the wavelet coefficients. In the case of model-based detection algorithms, most of the existing methods in the wavelet domain are based on the assumption that the wavelet coefficients

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http://dx.doi.org/10.1016/j.sigpro.2017.01.019
0165-1684/

have Gaussian distribution so that the common correlation detector can be used for detection. However, correlation-based detectors are not optimal for non-Gaussian data and in addition, they ignore the dependencies among the wavelet coefficients. The use of optimal or locally-optimal (LO) detectors based on the signal statistics have been proposed and shown to provide significantly better detection results than that provided by correlation-based detectors in various transform domains [36,39]. In [16,17], LO detectors have been designed for watermarking schemes in which the DFT, DCT or DWT coefficients of images have been modeled by the GG distribution. In [4], GG modeling has been applied on DCT coefficients, and the detector has been designed based on a maximum likelihood decision rule. In [15], LO detector has been developed using GG modeling. However, it is difficult to determine its performance in general situations, since the asymptotic performance has not been provided in this work. In [5], the LO watermark detector has been designed by modeling the DCT coefficients using the Cauchy distribution. In [21], Cauchy and GG PDFs are applied to model the detail subband coefficients of DWT. In [13], LO watermark detector has been proposed in which the BKF distribution is used for modeling the DWT coefficients.

The performance of a statistical model-based detection of a watermark is highly influenced by the accuracy of the model itself. There are a number of distributions that have been used in watermark detection; however, there is still scope to explore further the suitability of distributions to improve the performance of watermark detectors. Some initial work in this direction can be found in [33]. The objective of the present work is to propose a locally optimum blind watermark detector using the vector-based hidden Markov model in the wavelet domain. We choose the wavelet domain over DFT or DCT since the former has the properties of localization, multi-resolution, human visual system modeling and compression, which are very relevant to watermarking. This model is shown to provide a good fit for the distribution of the wavelet coefficients in view of its ability to capture the inter-scale and cross orientation dependencies between the wavelet coefficients. A formulation for watermark detection is carried out using the log-likelihood ratio test. A closed-form expression for the test statistics of the receiver operating characteristic curve of the proposed detector is obtained. The performance of the proposed watermark detector is investigated through experiments and compared with those of the other existing detectors. The robustness of the proposed watermarking scheme against various attacks is also studied.

This paper is organized as follows. In Section 2, the suitability of the vector-based HMM for modeling of wavelet transform is studied. In Section 3 , watermark detector using the vector-based HMM is presented. Section 4 provides simulation results and Section 5 concludes the paper.

2. Wavelet domain hidden Markov model

Wavelet transform has some attractive features such as locality, multiresolution and compression, which make it a desirable choice in statistical signal processing. Beside these primary features, the wavelet transform also has the properties of non-Gaussianity (wavelet coefficients have peaky, heavy-tailed marginal distributions) and persistence across scales (large/small values of wavelet coefficients tend to spread across scales). Taking into account these properties of the wavelet transform, a hidden Markov model in the wavelet domain has been proposed in [26]. Wavelet transform of a typical signal consists of a small number of large coefficients and a large number of small coefficients, each coefficient can be considered as being in one of two states, “high” or “low” depending on the level of energy it contains. The result is a two-state mixture model for each wavelet coefficient called a two-state HMM. The two-state HMM models the non-Gaussian marginal PDF as a two-component Gaussian mixture. If a wavelet coefficient is small (large), its hidden state is labeled as small (high). The small state corresponds to the Gaussian component with a relatively small variance and captures the peakiness around the mean value, whereas the high state corresponds to the high variance Gaussian components, capturing the heavy tails. It should be noted that although each wavelet coefficient is conditionally Gaussian, due to the randomness of states, the overall density function is non-Gaussian. The two-state HMM can readily be extended to M-state HMM [26].

In an M-state HMM, for each wavelet coefficient x_{ij}, i and j representing the node and scale, respectively, there is a hidden state S_{ij} with the probability mass function $P(S_{ij}=m)=P_{ij}^m,\ m=1,2,\dots,M$. Conditioning on $S_{ij}=m$, x_{ij} follows a Gaussian density with mean μ_{ij}^m and variance $(\sigma_{ij}^m)^2$. The marginal distribution of the wavelet coefficients in the i^{th} node and j^{th} scale can be written as

$$f_X(x_{ij})=\sum_{m=1}^{M}\frac{p_{ij}^m}{\sqrt{2\pi}\sigma_{ij}^m}\exp\left\{\frac{-(x_{ij}-\mu_{ij}^m)^2}{2(\sigma_{ij}^m)^2}\right\} \tag{1}$$

where $\sum_{m=1}^{M}p_{ij}^m=1$. There is an inter-scale dependency between each of the wavelet coefficients at a coarse level, parent, and the corresponding four coefficients at the next level, children (see Fig. 1(a), scalar-based HMM). The persistence across scales is captured through state transition probability matrices, A_{ij} given by

$$A_{ij}=\begin{bmatrix} p_{ij}^{1\to1} & p_{ij}^{1\to2} & \dots & p_{ij}^{1\to M}\\ p_{ij}^{2\to1} & \ddots & & p_{ij}^{2\to M}\\ \vdots & & \ddots & \vdots\\ p_{ij}^{M\to1} & \dots & \dots & p_{ij}^{M\to M}\end{bmatrix}_{M\times M} \tag{2}$$

where $p_{ij}^{m\to m'}$ is the probability of a child coefficient being in state m given its parent coefficient in state m', $j=1,2,\dots,J$ and $m'=1,2,\dots,M$. By denoting the parent of the node i by $\rho(i)$ in the wavelet coefficient tree, we have

$$P(S_{ij}=m)=\sum_{m'}P(S_{\rho(i)}=m')\,P(S_{ij}=m|S_{\rho(i)}=m') \tag{3}$$

To reduce the number of the model parameters, we use the tied version of scalar-based HMM, i.e., all the nodes at the same scale j have the same statistics. Hence, we can write $A_{ij}=A_j,\ p_{ij}^m=p_j^m$, $\mu_{ij}^m=\mu_j^m$ and $\sigma_{ij}^m=\sigma_j^m,\ \forall i$. Thus,

$$p_j^m=\sum_{m'}p_{j-1}^{m'}\,p_j^{m\to m'},\forall j=2,3,\dots,J \tag{4}$$

If $p_j=[p_j^1,p_j^2,\dots,p_j^M]$, then $p_j=p_{j-1}A_j$. Thus,

$$p_j=p_1A_2A_3\dots A_j,\forall j=2,3,\dots,J \tag{5}$$

Therefore, the scalar-based HMM is defined by a set of model parameters for each orientation $d=LH,HL$ or HH, as

$$\Theta^d=\left\{p_1,A_2,\dots,A_J;\mu_j^m,\sigma_j^m,\forall j=1,2,\dots,J;\ m=1,2,\dots,M\right\}^d \tag{6}$$

To enhance the capability of the wavelet domain scalar-based HMM model to capture the cross-orientation dependency of the wavelet coefficients, grouping coefficients at the same location and scale into vectors, and then modeling them by a single multidimensional HMM has been proposed in [29]. This results in a single vector HMM Θ for the entire input image. If x_{ij}^d denotes the wavelet coefficients at orientation d, node i and scale j, the grouping process yields vectors of coefficients as $\mathbf{x}_{ij}=[x_{ij}^{LH},x_{ij}^{HL},x_{ij}^{HH}]^T$. The cross-correlation of these three wavelet coefficients for the