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## A new detector for contourlet domain multiplicative image watermarking using Bessel K form distribution  $\dot{\mathbf{r}}$



Mehdi Rabizadeh<sup>a</sup>, Maryam Amirmazlaghani <sup>b,</sup>\*, Mahmoud Ahmadian-Attari <sup>a</sup>

<sup>a</sup> Department of Electrical Engineering, K. N. Toosi University of Technology, Tehran, Iran b Department of Computer Engineering and Information Technology, Amirkabir university of Technology, Tehran, Iran

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#### ABSTRACT

This paper proposes a novel multiplicative contourlet domain watermark detector. We use contourlet transform since this transform represents image edges sparsely and this makes it suitable for human visual system. Watermark detection can be formulated as a binary statistical decision problem, so, its performance is dependent on the accuracy of statistical modeling. Studying the statistical properties of contourlet coefficients, we demonstrate the high efficiency of Bessel K form (BKF) distribution to model these coefficients. Consequently, we design an optimal detector for multiplicative watermarking based on using the Maximum Likelihood (ML) decision rule and BKF distribution. Also, we derive its receiver operating characteristics analytically. Experimental results demonstrate the high efficiency of the proposed scheme under different types of attacks. Finally, we compare our proposed detector with other related detectors experimentally using Monte Carlo simulations and verify the performance improvement in utilizing the new strategy.

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### 1. Introduction

Due to the global use of the internet to distribute digital media, copyright protection has become increasingly important. Digital watermark is a pattern of bits inserted into multimedia data such as image, audio or video  $[1,2]$  to identify the ownership. A watermarking scheme consists of two steps: watermark embedding and watermark extraction. Perceptual transparency, data rate, and robustness against attacks are three major requirements of any watermarking system. There is a trade-off among these requirements [\[3–5\]](#page--1-0).

According to the watermark role, watermarking methods can be classified into two categories: (i) watermark detection in which the watermark detector should decide whether a received media contains a watermark or not, (ii) watermark decoding in which the watermark bits should be decoded correctly. This paper focuses on watermark detection for copyright protection.

To protect the copyright information, different watermarking methods have been proposed. Generally, two categories of the watermark embedding methods have been used: quantization based [\[6\]](#page--1-0) and spread spectrum (SS) based approaches [\[7\]](#page--1-0). Spread

⇑ Corresponding author.

E-mail address: [mazlaghani@aut.ac.ir](mailto:mazlaghani@aut.ac.ir) (M. Amirmazlaghani).

spectrum methods usually use a transformed domain to embed the watermark and are more robust against many types of attacks [\[7\]](#page--1-0). Usually the transforms are Discrete Cosine Transform (DCT), Discrete Fourier Transform (DFT), Discrete Wavelet Transform (DWT) [\[7,8\],](#page--1-0) and the contourlet transform [\[9\].](#page--1-0) Spread spectrum embedding methods are commonly classified into additive and multiplicative embedding. To efficiently embed the watermark, the power of the watermark should be proportional to the corresponding media featured samples. Multiplicative embedding provides image content dependent watermark so it is preferred to additive watermarking for copyright protection. In this paper, a multiplicative watermarking technique has been applied.

Various methods have been used to implement multiplicative watermarking schemes in different transform domains. For example, in  $[10,11]$  a correlation detector has been used for multiplicative watermark detection which is suboptimal. In [\[8\],](#page--1-0) a robust optimum detector for the multiplicative watermarking in the DCT, DWT and DFT domains has been proposed with the assumption of Generalized Gaussian (GG) distribution for the high frequency coefficients of DCT and DWT. Solachidis and Pitas [\[12\]](#page--1-0) have designed an optimum detector for multiplicative watermarking in the DFT domain for colored signals. In [\[13\]](#page--1-0), the locally optimum detector for Barni's multiplicative watermarking scheme using HVS in the wavelet transform domain [\[14\]](#page--1-0) has been introduced.

This paper has been recommended for acceptance by M.T. Sun.

The kernel of DWT is suitable for representing one-dimensional discontinuities. However, wavelets fail to represent singularities, when the dimension increases. The limited capability in capturing directional information is one major drawback of two dimensional wavelet transform. To overcome this problem, many researches have been performed on multiscale and directional representations that can capture the intrinsic geometrical structures such as as dual-tree complex wavelet [\[15\],](#page--1-0) ridgelets [\[16\],](#page--1-0) curvelets [\[17\],](#page--1-0) shearlets [\[18\]](#page--1-0), and contourlets [\[19,20\].](#page--1-0) The curvelet is a nonadaptive technique for multi-scale object representation. It is a tight frame of stretched oscillatory functions at different scales, that generates a fundamentally optimal approximation rate [\[17\].](#page--1-0) Shearlet transform provides the same optimal approximation properties. It is a natural extension of wavelets to accommodate the fact that multivariate functions are typically governed by anisotropic features such as edges in images.

To provide a better discrete implementation of the curvelets, the contourlet transform has been recommended. Contourlet Transform (CT) proposed by Do and Vetterli  $[19]$  is implemented using Pyramidal Directional Filter Bank (PDFB). The main advantage of contourlet transform over other directional representations is that it allows to include different directions for different scales of a given image while achieving nearly critical sampling [\[19\].](#page--1-0) This transform employs iterated filter banks, which makes it computationally efficient.

Also, contourlet transform provides the spreading property that is of great importance in the field of watermarking. In the other words, embedding the watermark into a specific contourlet subband results in spreading out the watermark in all subbands during the reconstruction of the watermarked image [\[21\]](#page--1-0).

Due to the good properties of the contourlet transform, some watermarking algorithms have been proposed in this domain [9,21-25]. In  $[9,22,23]$ , the additive watermarking methods are investigated, while Refs. [\[21,24\]](#page--1-0) have proposed the multiplicative watermarking approaches. Li et al. [\[24\]](#page--1-0) has suggested a Maximum Likelihood (ML) detector for multiplicative watermarking in the contourlet transform domain that is optimal only when the contourlet coefficients follow a Gaussian distribution. But, it is well known that these coefficients do not have Gaussian distribution, hence their receiver is sub-optimum. Sadreazami et al. [\[21\]](#page--1-0) has proposed a statistical detector based on alpha-stable distribution that doesn't have a closed form in general.

In this paper, to achieve an optimal detector for contourlet domain multiplicative watermarking, we use statistical decision approach. So, the choice of decision rule and statistical model are two determinant factors. Since detection of the watermark in the contourlet domain can be formulated as detecting a weak signal in noise, we use Bayesian loglikelihood ratio test (LLRT) to design the optimal detector [\[7\]](#page--1-0), hence, we should propose an efficient statistical distribution for the contourlet coefficients.

In [\[26,27\]](#page--1-0), Bessel K form (BKF) distribution has been proposed for band-pass filtered images. So, we are encouraged to use BKF for the contourlet coefficients. We confirm the compatibility between these coefficients and Bessel K form (BKF) distribution using different approaches such as comparing the histograms, kolmogrov-smirnov test, and bootstrapping. It should be mentioned that BKF distribution has been applied for the wavelet coefficients of images in [\[28,29\].](#page--1-0) In these papers, using BKF, optimum and locally optimum (LO) watermark detectors have been designed. But, both of these detectors are based on the additive watermark detection in the wavelet domain. Here, we design a contourlet domain multiplicative watermark detector based on BKF distribution. To assess the performance of the proposed detector, we calculate the receiver operating characteristics (ROC) analytically. Simulation results prove the validity of the analytical derivations and the high efficiency of the proposed method under different kinds of attacks.

The major contributions of this paper can be summarized as follows:

(i) Designing an optimal LLRT detector for multiplicative contourlet domain watermarking based on BKF distribution and achieving a closed form test statistic (ii) Calculating the ROC and analyzing the detector performance analytically based on statistical modeling of log-likelihood ratio.

The rest of this paper is organized as follows. Section 2 describes the statistical modeling of the contourlet coefficients using BKF distribution. The proposed contourlet domain multiplicative watermarking method based on BKF has been explained in Section [3](#page--1-0). Section [4](#page--1-0) analyzes the performance of the proposed detector analytically. Section [5](#page--1-0) provides the simulation results. In this section, the experimental performance of the proposed detector is evaluated and compared with other related detectors. Finally, concluding remarks are given in Section [6.](#page--1-0)

#### 2. Statistical modeling

In this section, first, we review the BKF distribution and a method to estimate the parameters of this distribution. Then, we discuss about the contourlet transform and study the compatibility between contourlet coefficients and the BKF.

#### 2.1. A brief of Bessel K forms density

A random variable f follows a Bessel K forms (BKF) distribution if [\[26,27,30\]:](#page--1-0)

$$
\mathbf{P}_f(f;c,p) = \frac{1}{\sqrt{\pi} \Gamma(p)} \left(\frac{c}{2}\right)^{-\frac{p}{2}-\frac{1}{4}} \left|\frac{f}{2}\right|^{p-\frac{1}{2}} K_{p-\frac{1}{2}}\left(\sqrt{\frac{2}{c}} |f|\right) = \text{BKF}(f,c,p) \tag{1}
$$

where  $\Gamma(.)$  denotes the gamma function and  $K_v(.)$  is the vth order modified Bessel function.  $p > 0$  and  $c > 0$  are the shape and scale parameters, respectively. Eq. (1) defines a Bessel K Form model when the mean of  $f$  is zero. But, in the Bessel K Form regression model, the mean of fis not zero. In this case, we have

$$
\bm{P}_f(f;c,p) = \frac{1}{\sqrt{\pi}\Gamma(p)} \left(\frac{c}{2}\right)^{-\frac{p}{2}-\frac{1}{4}} \left|\frac{f-\mu}{2}\right|^{p-\frac{1}{2}} K_{p-\frac{1}{2}}\left(\sqrt{\frac{2}{c}}|f-\mu|\right),
$$

where  $\mu$  denotes the mean of distribution. For  $p = 1$ , the BKF density simply reduces to the double exponential pdf. If  $p > 1$ , we get closer to the Gaussian distribution. If  $p < 1$ , the pdf becomes sharply peaked and the tails are heavier. The parameters pand c can be estimated using the second- and fourth-order moments of  $x$  according to

$$
\hat{p} = \frac{3}{Kurt(X) - 3}, \quad \hat{c} = \frac{Var(X)}{\hat{p}}\tag{2}
$$

In which  $Kurt(X)$  and  $Var(X)$  are:

$$
Var(X) = \kappa_2 = pc, \quad Kurt(X) = \frac{\kappa_4}{\kappa_2} + 3 = \frac{3}{p} + 3
$$
 (3)

and  $\kappa$  statistics can be estimated using unbiased cumulants estimators [\[30\]](#page--1-0)

$$
\hat{\kappa}_2 = \frac{n}{n-1} \hat{M}_2
$$
\n(4)

$$
\hat{\kappa}_4 = \frac{n^2 \left[ (n+1)\hat{M}_4 - 3(n-1)\hat{M}_2^2 \right]}{(n-1)(n-2)(n-3)}
$$
(5)

where  $\hat{M}_i$  is the ith sample central moment and n is the number of samples.

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