COLOUR SPREAD TRANSFORM DATA HIDING CAPACITY USING COMPLEX WAVELETS

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ABSTRACT
Information theoretic methods of calculating the capacity of data hiding schemes allow for objective comparisons of watermarking algorithms. This paper applies these methods to the case of colour image watermarking, using a dual tree complex wavelet transform and non redundant complex wavelet transform along with a spread transform data hiding algorithm to compare levels of capacity between the two most commonly used uncorrelated colour spaces. The information theoretic model used involves the use of game theory applied to optimize the embedding and attack strategy across parallel Gaussian channels. The two most popular uncorrelated colour spaces YUV and YIQ are compared.

1. INTRODUCTION
Data hiding refers to the imperceptible hiding of data in digital media. In recent years wavelets have gained considerable popularity in the field of digital data hiding, the discrete wavelet transform (DWT) however suffers from various problems such as lack of shift invariance and directional selectivity, several complex wavelet transforms have been proposed to overcome these difficulties [1,2]. As demonstrated in the following section complex wavelets can provide separable diagonal orientations unlike the DWT. Using an information theoretic modelling of wavelet subbands [3], the upper limits of data hiding capacity can be derived for different wavelet transforms facing an optimized scaled additive white Gaussian noise attack (SAWGN).

Little attention has been given in the literature to the case of embedding in colour images. Gilani et al. [4] have demonstrated empirically that uncorrelated colour spaces such as YUV and YIQ can produce better results than uncorrelated colour spaces but to this date no information theoretic analysis has been performed to determine which of these colour spaces is better for embedding.

2. COMPLEX WAVELET TRANSFORMS
Most recent schemes have taken place in the Discrete Wavelet Transform (DWT) domain, but this domain suffers from some problems – first, it lacks directional selectivity, this means that it is unable to differentiate between opposing diagonals. Second it also lacks shift invariance so small changes in the signal cause large changes in the wavelet coefficients.

2.1 Dual Tree Complex Wavelet Transform
The Dual Tree Complex Wavelet Transform (DTCWT) was developed to overcome these difficulties [1]. The disadvantage of this transform is the increased redundancy (4:1 for 2-D signals), for this reason the real version of the transform is used which has a controllable redundancy of 2:1 for 2-D signals.

The DTCWT uses two DWTs acting in parallel on the same data. One acts upon the even samples of the data while the other acts upon the odd. The DTCWT produces six different subbands orientated at 15°, 75°, 45°, -15°, -75° and -45° (figure 1). As a result the DTCWT can discriminate between opposing diagonals unlike the DWT, in addition the directionality in the horizontal and vertical directions is also improved.

2.2 Non Redundant Complex Wavelet Transform
Fernandes et al. [2] have recently developed a non-redundant complex wavelet. It makes use of a triband filter-bank where the data is downsampled by 3 at each stage. The filter-bank uses both real and complex filters that are applied to real and complex inputs respectively.

This allows for a non-redundant complex wavelet transform (NRCWT) using a complex wavelet filter and real scaling filter. The subbands produced are orientated at 0°, 90°, 45° and -45°, both real and imaginary. While not providing as much directionality as the DTCWT it doesn’t have
the disadvantage of redundancy. It is able, unlike the DWT, to separate the diagonal features of an image (figure 2).

3. SPREAD TRANSFORM DATA HIDING

Although it is claimed in [5] that the solution to the Gaussian watermarking game given is a general one, Eggers and Girod [6] have shown that solutions for the sub-optimal scheme spread transform can actually produce higher capacity estimates. For this reason capacities are calculated for the specific spread transform embedding case.

Spread transform data hiding was originally proposed by Chen and Wornell [7] as an extension of quantization index modulation (QIM) where data is quantized using a scalar quantizer \( \Delta \) to carry data. It applies QIM in a lower dimensional space across several samples in an effort to combine the advantages of QIM and spread spectrum methods. Quantization is applied to vectors composed of host samples rather than individual host samples as defined in (1).

\[
X^{ST} = \sum_{n=1}^{N} x_n v_n \tag{1}
\]

Where \( X^{ST} \) represents host samples, \( v \) a key dependent vector and \( N \) the length of the vector used. Letting the watermark MSE be equal to \( D_1 \), the attacker distortion equal to \( D_2 \) and the watermark to noise ratio (WNR) equal to \( 10 \log_{10}(D_1 / D_2) \), Eggers and Girod [6] show that the effective gain in WNR over QIM when using spread transform is equal to:

\[
WNR_N = WNR_1 + 10 \log_{10} N \tag{2}
\]

and that the capacity \( C \) of spread transform data hiding can be calculated from the capacity of embedding without spread transform \((r=1)\) as follows:

\[
C^{AWGN}_{ST,1} = \max_a I(y; d) \tag{4}
\]

where \( y \) is the data received by the decoder, \( d \) is equal to 0 or 1 for binary data embedding and \( I \) is the mutual information. (4) is solved through a comparison of the PDFs of the transmitted and received data. Finally the power of the watermark distortion is given by (5).

\[
E[q^2] = \frac{\Delta^2}{12} \tag{5}
\]

The advantage of spread transform is its complete independent of interference from the host image. It also offers capacities that are generally higher than spread spectrum for low to moderate levels of attack.

4. PARALLEL GAUSSIAN CHANNELS

To derive capacity limits it is necessary to divide the source image into separate channels. To divide the wavelet coefficients of an image into separate channels the model proposed by Lopresto et al. [8] has been used. Within this scheme wavelet subbands are modeled as Gaussian distributions with zero mean and variance dependent upon the coefficient’s location within the wavelet subbands to create independent parallel channels. The coefficients’ variances lie in a quantization band \( k \) where \( 1 \leq k \leq K \). The channels are designated as follows:

- Apply 5 levels of DWT or DTCWT. Due to the greater downsampling by 3 at each level of the NRCWT only 3 levels of decomposition are used.
- Calculate the local variance in a 5x5 window for finer detail levels and 3x3 window for coarser levels (level 3 for NRCWT, levels 4&5 for DWT).
- The natural logarithm of each variance is quantized using \( K \) levels and step size \( \Delta \). A channel then consists of all coefficients with the same quantized variance within each subband.

The quantizer step size \( \Delta \) is determined by the range of variances in the subband decomposition.

In this work, \( K \) equal to 256 as in [3,9] is used. The 256 channels are calculated for each colour band leading to 768 channels in total. The estimated 256 parallel Gaussian channels are shown in figures 3, 4 and 5 for the DTCWT decomposition of the YUV components of the ‘Lena’ image, where coefficients in channel 1 are represented as black while those in channel 256 are represented as white.

\[
C^{AWGN}_{ST,1} = \max_a I(y; d) \tag{4}
\]

Figure 3 - 256 Parallel Gaussian Channels for Y component of ‘Lena’ Image
Simpler images like ‘Lena’ will tend to have lower rates for higher power channels, while textured images like ‘Baboon’ will tend to have high power channels with high rates.

Each channel is assumed to be i.i.d and Gaussian with zero mean and variance \( \sigma_j^2 \). Each channel has an inverse sub-sampling rate \( r_k \). For all transforms channels are critically sampled so that:

\[
\sum_{k=1}^{K} r_k = 1
\]

5. CAPACITY ESTIMATION

The problem of finding the capacity can be viewed as a game across the parallel gaussian channels [3,9] where both embedder and attacker attempt to maximize their advantage in every channel. For the capacity estimates to be meaningful distortion constraints are imposed upon both the embedder and the attacker. For the channel model under consideration the embedder and attacker distortions are given as:

\[
\sum_{k=1}^{K} r_k \theta_k e_k = D_1
\]

\[
\sum_{k=1}^{K} r_k \theta_k a_k = D_2
\]

where \( \theta \) is the distortion modifier for the channel \( j \) dependent upon the orientation and level of the coefficients in the channel, \( e \) and \( a \) are the weighted MSE of the attack and embedding strategy respectively.

The three distortions placed upon both sides are:

\[
0 \leq e_k
\]

\[
e_k \leq a_k
\]

\[
a_k \leq p_k
\]

where \( p_k \) is the original power of the channel \( k \). The capacity of the parallel Gaussian channels is then given by the maximization-minimization relation shown in (12).

\[
C = \max \min \sum_{k=1}^{K} r_k C_{SAWGN}^{SAWGN} (p_k, e_k, a_k)
\]

The solution to (12) for SAWGN attacks is given in the following sub-section.

5.1 Optimization for SAWGN attacks

The SAWGN attack involves both the addition of AWGN noise and amplitude scaling by both the embedder and attacker. This differs from the analysis in [3] in that amplitude scaling is applied at both attacker and embedder, but as in practice embedding distortion is a small fraction of the original power in a channel this has little effect on the results.

For optimized scaling at both embedder and attacker the effective ratio \( \zeta \) of the embedding distortion to the attacker distortion is given by (13) regardless of embedding algorithm being used.

\[
\zeta_k = \frac{e_k (p_k - a_k)}{p_k (a_k - e_k)}
\]

Eggers and Girod [6] solve (12) through the use of a lagrainge multiplier \( \lambda \) that controls the magnitude of attack across all channels. For any given channel \( k \) this gives:

\[
\frac{\partial C_{SAWGN}^{SAWGN} (p_k, e_k, a_k)}{\partial a_k} + \theta_k \lambda = 0
\]

For low WNRs the optimum strength of the attack for each channel for ST-SCS is derived in (15) and (16):

\[
a_k = e_k \pm \sqrt{\frac{C_{SAWGN}^{SAWGN} (e_k)}{\zeta_{krit}}} \frac{e_k}{\lambda e_k (p_k - e_k)}
\]

\[
10 \log_{10} (\zeta_{krit}) = 0.01
\]

The optimization of the embedding is more complicated and can not be derived analytically due to the numerical computation of the capacity for ST-SCS. An optimization algorithm is used to derive the capacity through simulated annealing instead.
Figure 6&7 – Channels from DWT decomposition of Y(solid), I(dashed) and Q(dotted) of ‘Lena’ image and ‘Baboon’ image respectively

Figure 8 – Channels from DWT decomposition of Y(solid), I(dashed) and Q(dotted) of ‘Peppers’ image

5.2 Application to Colour Images
Moulin [10] provides a framework for the application of the Gaussian watermarking game to the case of colour images. Individual colour pixels are modelled as vectors of 3 values. An image with N colour pixels can then be modelled as being a vector of 3N values.

The MSE between two colour images can then be calculated using (17).

\[
D_{colour} (I^N, I'^N) = \frac{1}{N} \sum_{k=1}^{K} \sum_{n=1}^{N_k} \left| I(n) - I'(n) \right|^2
\]  

The procedure outlined at the beginning of the chapter can hence be used by applying the constraints \( D_{y} / 3 \) and \( D_{q} / 3 \) for each individual colour subband. Due to the high degree of statistical correlation between subbands in colour spaces such as RGB statistically uncorrelated colour spaces must be used. The two most widely used colour spaces YUV and YIQ are analysed.

Figures 6, 7 & 8 show the channel distributions of the colour bands with the channel powers (x-axis) and channel rates (y-axis).

6. RESULTS
For calculation of capacities the level of embedder distortion \( D_y \) is set to the values used in [3,9]. The filters used for the DWT are 9/7 linear phases in both cases, specialized filters are used for the DTCWT and NRCWT.

The well known test images Lena, Baboon and Peppers are used for the capacity estimates. Light to moderate attack levels are applied and capacities obtained through the solution of (12) for each of the YIQ and YUV colour bands. Results are obtained for images of size 512x512, except for the NRCWT. Due to the triband structure of the NRCWT filter bank, images of size 513x513 must be used instead, obtained results are extrapolated through multiplication by \( \frac{513}{512} \) for comparison purposes.

Results for the colour images as a whole are also given in bold. The YUV colour space produces superior results to the YIQ colour space in the case of the Baboon image while YIQ produces the better results in the case of Peppers. For Lena YIQ performs worse for low distortion but better for moderate distortion.
7. CONCLUSIONS

As expected the complex wavelet give superior capacities compared to the DWT. This is because they can better represent the energy of the colour subbands due to their improved directionality. The further improvement offered by the NRCTW can be attributed to its superior ability to represent textured areas of an image.

Whether the YIQ or YUV colour space produces the better results varies. This is due to the variation of colour in the image with Baboon having dominant blue and red areas that are represented well by the U and V subbands. By contrast the Peppers image is better represented by the orange-blue I band and the purple-green Q band. The results suggest that the appropriate colour space to use in embedding should be varied according to the colour content of the image.

REFERENCES


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