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METHOD FOR SELECTING THE STRENGTH OF UNSHARP MASKING PRE-FILTER USED TO ENHANCE THE DETECTION RATE OF DCT-DOMAIN IMAGE WATERMARKS

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Abstract. This work investigates the improvement of digital watermark detection robustness by applying image sharpening prior to the detection stage for an algorithm through the use of DCT-domain for both embedding and detection. Watermark detection is treated as a binary classification problem, enabling the use of the recall metric to evaluate the quality of detection. The recall metric is calculated on a set of test images by embedding and detecting the watermark with unsharp masking applied as a pre-filtering step. A method for selecting the optimal sharpening strength coefficient is proposed, based on maximizing the recall metric under fixed embedding and detection parameters. Computational experiments across a range of distortions demonstrate that pre-filtering with the optimal sharpening strength coefficient determined by the proposed method increases the true positive detection rate for most tested distortions without increasing the number of false positive detections.

Keywords: digital watermark, discrete cosine transform, unsharp masking, recall, content protection

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МЕТОД ОПРЕДЕЛЕНИЯ КОЭФФИЦИЕНТА УВЕЛИЧЕНИЯ РЕЗКОСТИ ИЗОБРАЖЕНИЯ, ПОЗВОЛЯЮЩИЙ ПОВЫСИТЬ УСТОЙЧИВОСТЬ ЦИФРОВЫХ ВОДЯНЫХ ЗНАКОВ, ВСТРОЕННЫХ В ДКП-ОБЛАСТИ

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Аннотация. В данной работе исследуется повышение устойчивости обнаружения цифровых водяных знаков (ЦВЗ) путем увеличения резкости изображения перед этапом обнаружения для алгоритма, использующего при встраивании и обнаружении область коэффициентов дискретного косинусного преобразования. Задача обнаружения ЦВЗ рассматривается как задача бинарной классификации, что позволяет использовать метрики качества бинарных классификаторов, в частности метрику полноты. Значение метрики полноты вычисляется на наборе тестовых изображений путем встраивания и последующего обнаружения ЦВЗ с предварительным увеличением резкости. Предложен метод выбора оптимального коэффициента увеличения резкости, основанный на максимизации значения метрики полноты при фиксированных параметрах встраивания и обнаружения. Результаты вычислительного эксперимента показывают, что предварительное увеличение резкости изображения перед обнаружением ЦВЗ с использованием коэффициента, выбранного предложенным методом, повышает число истинно положительных обнаружений для большинства протестированных искажений и не приводит к увеличению количества ложно положительных срабатываний.

Ключевые слова: цифровой водяной знак, дискретно косинусное преобразование, нерезкое маскирование, полнота, защита от несанкционированного копирования

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Introduction

A digital watermark is information embedded into host digital content (a container). The purpose of watermarking includes copyright protection, authentication, and traceability of digital media [1]. Over the past decades, a wide range of watermarking algorithms has been proposed [2, 3]. In this work, we focus on algorithms designed for digital images.

During the embedding stage the watermark is inserted into the container. Watermark embedding is paired with a detection algorithm, designed to verify the presence of a specific watermark within the analyzed container. Between the embedding and detection stages, the container can be modified by a range of distortions. These distortions may arise from unintentional factors such as signal processing operations occurring during transmission or losses in communication channels, as well as from attempts to remove the watermark.

Within a broad class of algorithms [4], the digital watermark is a pseudo-random sequence embedded into the container. Watermark detection is performed by calculating the correlation between the tested container and the watermark. The container is marked as watermarked when the correlation exceeds the selected detection threshold.

The correlation calculated between watermark and watermarked container for a watermark embedding and detection algorithm depends on both the embedding parameters and the distortions affecting the container. Distortions often decrease the correlation [5], resulting in undetected watermarks and reduced detection rates. However, certain types of distortions can increase the correlation, which improves detection performance. As described in [6–8], the use of sharpening filters as a pre-filtering step during the watermark detection stage improves the performance of the detection process.

In [6], the authors propose applying a linear unsharp masking filter before the watermark extraction in a spatial-domain correlation based watermarking scheme. The authors experimentally test the proposed method on a few images under several distortions and show that applying linear unsharp masking filtering prior to the extraction leads to better visual quality of the recovered watermark compared to the baseline method.

In [7], the authors propose using adaptive unsharp masking as a pre-filtering step before watermark detection. The proposed method adjusts the sharpening strength locally based on the contrast levels of the image. The authors demonstrate that using the proposed method can improve objective quality metrics for watermarking algorithm operating in the Discrete Cosine Transform (DCT) domain.

In [8], the authors propose a pre-filtering step applied before watermark extraction in a DCT-domain watermarking scheme. The pre-filtering process involves using an unsharp masking filter in combination with a Laplacian of Gaussian filter. The authors demonstrate that the proposed pre-filtering improves the quality of the extracted watermark compared to schemes without pre-filtering.

In our work we consider the use of an unsharp masking [9] which is a one of classical sharpening filters as a pre-filter applied to the watermarked container on the detection stage. The sharpened image is then used for watermark detection. Sharpening can be applied with different strength coefficients. In this paper, the impact of the sharpening strength coefficient to detection performance is evaluated. A method is proposed for determining the optimal sharpening strength coefficient through computational experiments with a software implementation of a watermarking algorithm. The founded optimal coefficient is then evaluated by testing detection rates on a set of images and range of distortions.

Methods

DCT-domain image watermarking

For embedding the watermark by the DCT based watermarking algorithm [10], the original image is divided into blocks of 8x8 pixels. A DCT is applied to each block. The transformed block of DCT coefficients is then converted into a sequence of 64 elements using ZigZag scanning [11], which reorders the DCT coefficients from low to high frequencies. In each sequence, the most significant low-frequency DCT coefficients are discarded. The remaining DCT coefficients are concatenated into a single sequence C_o. The length of C_o is n. The watermark W_r is a sequence of length n with elements generated according to the normal distribution $N(0, 1)$. The watermark W_r is embedded into the sequence C_o by equation (1). The modified blocks are transformed by inverse DCT to obtain the watermarked image.

$$C_w = C_o + \alpha W_r, \tag{1}$$

where C_w, C_o, $W_r \in R_n$, $n \in N$, $\alpha \in R$.

To detect the watermark W_r the normalized correlation (2) is calculated between W_r and the sequence of DCT coefficients C extracted from image.

$$\tilde{C}[i] = \frac{C[i]}{\sqrt{\sum_{j=1}^{n} C[j]^2}}, \quad \tilde{W}_r[i] = \frac{W_r[i]}{\sqrt{\sum_{j=1}^{n} W_r[j]^2}}, \quad Z_{nc}(C, W_r) = \sum_{i=1}^{n} \tilde{C}[i]\tilde{W}_r[i], \tag{2}$$

where C, $W_r \in R_n$, $n \in N$.

To determine the watermark W_r present in the image C the equation (3) with selected threshold detection threshold $\theta \in R$ is used:

$$Z_{nc}\left(C, W_r\right) > \theta. \tag{3}$$

Unsharp masking filter

Sharpening is a filtering method used in image processing and digital photography [9]. The primary goal of sharpening is to increase the contrast between adjacent pixels in the image. Sharpening is achieved by amplifying high-frequency components which correspond to high-intensity parts of the image, while leaving low-frequency regions unaffected. Unsharp masking is a classical tool for sharpening enhancement.

The process of unsharp masking involves generating a low-frequency (blurred) version of the image, which is used as a low-pass image approximation. Subtracting low-pass image approximation from the original image produces the high-frequency part of the image. The unsharp masked image is obtained by adding a high-frequency part scaled by sharpening strength coefficient to the original image.

In our work, the unsharp filter implemented in FFmpeg[1] is used for unsharp masking. The code of unsharp masking filter is based on the blurring algorithm described in [12]. The unsharp filter in FFmpeg has a sharpening strength coefficient limited to a maximum value of 5. For testing unsharp masking on higher sharpening strength coefficients, it is necessary to remove this restriction. The patch of FFmpeg code for removing this restriction can be found in the repository[2].

Method for selecting the optimal sharpening strength for watermark detection

Digital watermark detection can be considered as a binary image classification problem, which allows using the binary classification metrics to evaluate performance of detection. In this work, the optimal sharpening strength coefficient is determined by maximizing the recall metric [13] calculated by equation (4). The choice of this metric is motivated by the fact (as will be demonstrated in the following experiment) that changes in sharpening strength coefficient affect the number of correctly classified actual positives (true positive detections), while having no impact on the number of incorrectly classified actual negatives (false positive detections). This allows avoiding the need to prepare images for false positive detection analysis, thereby reducing the overall computational cost of the experiment.

$$\text{Recall} = \frac{TP}{TP + FN}, \tag{4}$$

where TP is the number of watermarked images in which the watermark was detected, FN is the number of watermarked images in which the watermark was not detected.

To perform the experiment for evaluating the quality of sharpening strength coefficient, it is needed to select a detection threshold θ. For the following experiments, the detection threshold is selected as the value below which false positive watermark detections begin to occur. To select this threshold, a computational experiment on the image set is conducted. A random watermark is embedded into each image in the set, and the correlation is calculated between the watermarked image and another watermark that was not embedded into that image. The maximum value from these calculated correlations is selected as the detection threshold.

[1] A complete, cross-platform solution to record, convert and stream audio and video. [online] Available: http://ffmpeg.org (Accessed 01.11.2025)

[2] GitHub – anjin-viktor/detect-with-unsharp: This repository contains Python scripts, C++ implementation of watermarks, and evaluation results used in the paper "Selecting the optimal unsharp masking strength for DCT-domain watermark detection via Recall metric optimization" · GitHub. [online] Available: https://github.com/anjin-viktor/detect-with-unsharp (Accessed 25.11.2025)

Although the detection threshold selected by the described algorithm was chosen to avoid false positives on the used set of images, the selected detection threshold can produce false positives on other images or randomly generated watermarks.

To evaluate the quality of sharpening strength and calculate recall metric, the experiment is conducted on a set of images. Random watermarks are generated and embedded into every image in the set. Since the detection rate is high for undistorted watermarked images, all watermarked images are distorted using a selected filter. After distortion, each image is processed by an unsharp masking filter with the evaluated sharpening strength. Watermark detection is then performed on the unsharp masked images, and the count of true positive detections is calculated. After processing all images in the set, the recall metric is calculated.

The recall metric calculated by the described algorithm for a watermarking algorithm with fixed embedding and detection parameters depends on the set of images, the filter applied to introduce distortions, and the sharpening strength coefficient used in the unsharp masking pre-filtering. The set of images and the distortion filter are selected once before the experiment. As a result, after all other parameters are fixed, the recall metric can be considered as a function of the sharpening strength coefficient.

The optimal value of sharpening strength is determined by maximizing the recall metric calculated by the described algorithm. This can be done by iterating through values of sharpening strength starting from 0 (which correspond to no unsharp masking) up to the point where a stable decrease in the recall metric is observed. When recall metric calculated by described algorithm has a single extremum, the methods for optimizing unimodal functions [14] can be used to select optimal value of sharpening strength.

Method for evaluating watermark detection performance with unsharp masking pre-filtering at selected optimal sharpening strength coefficient

To evaluate the selected sharpening strength coefficient, an experiment is conducted on a set of images. During the experiment, the counts of true and false positive detections are calculated with and without pre-filtering using the selected optimal sharpening strength coefficient.

A random watermark is generated and embedded into each image in the set. Filters are applied to the watermarked images to introduce distortions. The distorted by filters watermarked images are used for watermark detection, both with and without pre-filtering by unsharp masking at the selected optimal sharpening strength coefficient. The watermark detection is performed using detection thresholds selected while finding optimal value of sharpening strength. To evaluate false positive detections, watermark detection is performed using a different watermark that was not embedded in the images. The result of the experiment is the number of true positive and false positive detections.

Results and discussion

The C++ implementation of the watermarking algorithm, along with the Python scripts for running the experiments, plotting the figures and the obtained results, are available in the repository[3].

The computational experiments were conducted using the DCT-domain watermarking algorithm [10] with an embedding coefficient $\alpha = 0.5$, $\alpha = 1$ and $\alpha = 3$. All of these coefficients can be described as robust enough. The coefficient of $\alpha = 0.5$ introduces very small distortions that are imperceptible to the human eye after embedding. The coefficient $\alpha = 1$ produces minor distortions that are slightly noticeable. The coefficient $\alpha = 3$ produces distortions which are visible on some regions of images, but these distortions do not interfere with the overall perception of the image. Table 1 presents the average objective quality metrics PSNR [16] and VMAF [17], calculated between the original and watermarked images on set with 2500 images.

[3] GitHub – anjin-viktor/detect-with-unsharp: This repository contains Python scripts, C++ implementation of watermarks, and evaluation results used in the paper "Selecting the optimal unsharp masking strength for DCT-domain watermark detection via Recall metric optimization" · GitHub. [online] Available: https://github.com/anjin-viktor/detect-with-unsharp (Accessed 25.11.2025)

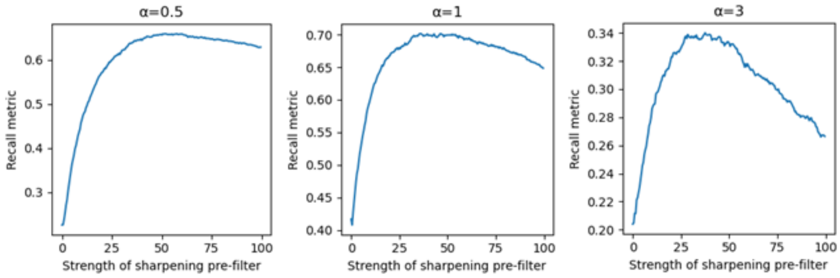

Fig. 1. Recall metrics calculated on 2500 images

Table 1

The average objective quality metrics of distortions introduced by watermarking

α	**PSNR**	**VMAF**
0.5	52.8	97.39
1	50.5	97.36
3	43.4	97.15

The computational experiment for selecting the detection thresholds was conducted using 2500 images from Flickr8K [15]. The detection threshold values $2.02*10^{-8}$, $1.64*10^{-8}$ and $2.03*10^{-8}$ were selected for $\alpha = 0.5$, $\alpha = 1$ and $\alpha = 3$ accordingly.

With these detection thresholds, the algorithm for selecting optimal value of sharpening strength coefficient was conducted using 2500 images from Flickr8K [15]. For introducing distortion to the watermarked images, the dctdnoiz filter from FFmpeg[4] was used with the filtering strength 7, 15, 45 for embedding coefficient $\alpha = 0.5$, $\alpha = 1$ and $\alpha = 3$ accordingly.

The results of the experiment are presented as a plot in Fig. 1. The X-axis represents the sharpening strength coefficient, varying from 0 (no sharpening) to 100. The Y-axis represents the recall metric calculated during experiments for corresponding sharpening strength coefficient.

The results of the experiment of evaluating the recall metric show that applying unsharp masking as pre-filtering step before watermark detection improves watermark detection performance. In the experiment with $\alpha = 0.5$ the recall value without sharpening (strength = 0) is 0.22. As the sharpening strength increases, the recall metric rises and reaches a maximum value of 0.66 at sharpening strength 52. Beyond this point, the recall value declines slowly. In the experiment with $\alpha = 1$ the recall metric without pre-filtering by unsharp masking is 0.43, and the maximum of recall is 0.70 which is achieved at the sharpening strength coefficient 35.5. Beyond this point, the recall decreases more rapidly compared to the $\alpha = 0.5$. For $\alpha = 3$ the value of recall metric without pre-filtering is 0.20, and the maximum recall is 0.34 which is achieved at the sharpening strength coefficient 37. Beyond this point, the recall metric also declines.

Based on the results of experiment, it can be observed that applying a unsharp masking as pre-filtering step before watermark detection improves detection performance up to an optimal sharpening strength coefficient, beyond which additional sharpening degrades detection accuracy. The optimal sharpening strength coefficient varies depending on the embedding coefficient α. The results also show that recall metric calculated over 2500 images has several local extremums, which prevents the use of fast optimization methods [14] designed for unimodal functions. Increasing the number of

[4] A complete, cross-platform solution to record, convert and stream audio and video. [online] Available: http://ffmpeg.org (Accessed 01.11.2025)

images can make plot of recall metric smoother and make the function unimodal, but this will lead to increasing the computational cost of experiment.

The obtained optimal sharpening strength coefficients were used to evaluate the performance of watermark detection with unsharp masking pre-filtering. The evaluation was performed using the Flickr30K [18] dataset which contains 31783 images. During the evaluating, the selected earlier detection thresholds were used ($2.02*10^{-8}$, $1.64*10^{-8}$ and $2.03*10^{-8}$ for $\alpha = 0.5$, $\alpha = 1$ and $\alpha = 3$ accordingly). The results of the experiment are presented in Table 2.

The following FFmpeg[5] filters were used to introduce distortions into watermarked images:

- Blurring: "unsharp=7:7:-1:7:7:-1";
- Denoising using the Non-Local Means: "nlmeans=s=15";
- Pixelization: "pixelize=w=2:h=2";
- JPEG transcoding with quantizer 10;
- Contrasting: "colorlevels=rimin=0.3:gimin=0.3:bimin=0.3:rimax=0.7:gimax =0.7:bimax=0.7";
- Noising: "noise=alls=100:allf=u".

In Table 2, the first column “Filter” specifies the FFmpeg filter used to introduce distortion in images. The column “Embedding coefficient α” specifies the value of embedding coefficient α. The “Unsharp masking pre-filter” column describes whether unsharp masking pre-filtering with the optimal sharpening strength coefficient was applied or not during watermark detection. The column “True positive (%)” contains the percentage of correctly detected watermarks for the corresponding configuration. The “False positive” column contains the number of false positive detections obtained under the corresponding configuration.

The results of the experiment show that applying an unsharp masking as pre-filter before watermark detection with the optimal sharpening strength coefficient selected by the proposed method improves the true positive rate in most cases. For low embedding coefficient $\alpha = 0.5$, the percentage of true positive detections increases significantly under most distortions, except noising, where it decreases from 99.61% without pre-filtering to 79.90% with pre-filtering. For embedding coefficient $\alpha = 1$ sharpening pre-filtering also improves detection performance for most distortions, except blurring, where the performance slightly decreases. For embedding coefficient $\alpha = 3$, the effect of sharpening becomes negligible, because the percentage of true positive detections after introducing distortions by selected filters is close to 100% without pre-filtering. However, in this case slight degradation in accuracy is observed for distortions introduced by JPEG transcoding and blurring.

Across all tested conditions, the false positive rate remains low, indicating that improvements in detection accuracy do not come at the cost of an increased count of false positive detections.

The correlations obtained during watermark detections in the experiment were used to plot Receiver Operating Characteristic (ROC) curves [19]. The ROC curve is a tool for evaluating the performance of results of binary classification. It represents the trade-off between true positive and false positive detections. In other words, the ROC curve provides a tool for evaluation of watermark detection robustness by plotting how reliably watermarks can be detected. The ROC curves were generated using the roc_curve function from the scikit-learn library [20], based on the correlations calculated during experiment between the watermarked container and the embedded and non-embedded watermarks. The resulting curves were visualized using Matplotlib [21].

The ROC curves shown in Fig. 2 demonstrates that applying unsharp masking filter with the selected optimal sharpening strength coefficient as a pre-filter step at the watermark detection stage after distortion by Non-Local Means denoising improves the true positive detection rate for the same false positive rate. The plot for $\alpha = 3$ is zoomed in, since the true positive detection rate is high and the difference between the curves is not visible over the full [0, 1] range. The curve corresponding to pre-filtering (orange dashed line) is located above the curve corresponding detection without pre-filtering

[5] A complete, cross-platform solution to record, convert and stream audio and video. [online] Available: http://ffmpeg.org (Accessed 01.11.2025)

Table 2

Percentage of true positive and count of false positive detections for watermark detection under distortions with and without unsharp masking pre-filtering

Filter	Embedding coefficient α	Unsharp masking pre-filter	True positive (%)	False positive
Blurring	0.5	no	22.52	6
		yes	25.42	8
	1	no	93.11	18
		yes	92.53	18
	3	no	99.99	8
		yes	99.98	8
Denoising with Non-Local Means	0.5	no	9.25	13
		yes	47.0	10
	1	no	67.13	22
		yes	87.22	27
	3	no	99.07	15
		yes	99.69	11
Pixelization	0.5	no	27.51	6
		yes	96.81	7
	1	no	95.20	30
		yes	99.97	20
	3	no	100	9
		yes	100	9
JPEG transcoding	0.5	no	0.93	12
		yes	1.00	5
	1	no	23.93	21
		yes	25.90	23
	3	no	93.26	9
		yes	92.84	8
Contrasting	0.5	no	96.20	11
		yes	99.24	5
	1	no	99.82	21
		yes	99.97	17
	3	no	99.99	10
		yes	100	8
Noising	0.5	no	99.61	6
		yes	79.90	7
	1	no	100	24
		yes	99.99	22
	3	no	100	11
		yes	100	12

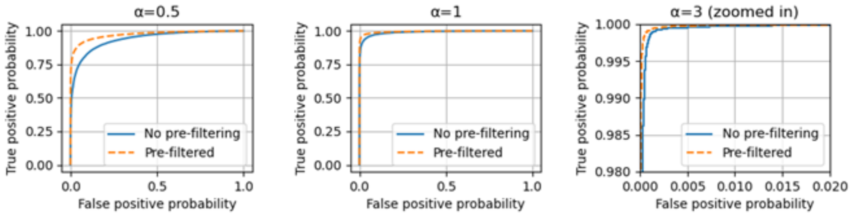

Fig. 2. ROC curves for detection with and without unsharp masking pre-filtering after Non-Local Means denoising

(blue solid line). This indicates that the use of unsharp masking as a pre-filtering step with optimal sharpening strength coefficient increases the watermark detection accuracy without introducing false positives in these cases.

An important observation is that pre-filtering does not introduce false positive detections. This suggests that a combined detection scheme that uses detection on both pre-filtered and non-filtered images can improve robustness across a wide range of distortions. When the detection modules with and without pre-filtering are considered as classifiers, the combined detection scheme can be implemented using classifier fusion [22]. An evaluation of such combined detection schemes is beyond the scope of the current paper.

Conclusion

This paper investigated the use of unsharp masking as a pre-filtering step during watermark detection in a DCT-domain correlation-based image watermarking algorithm [10]. A computational method was proposed for selecting the optimal sharpening strength coefficient by maximizing the recall metric of watermark detection on a set of images. The results of a computational experiment show that the recall metric increases with sharpening strength coefficient up to an optimal sharpening strength coefficient, beyond which unsharp masking degrades the accuracy of watermark detection. The optimal sharpening strength coefficient depends on the embedding coefficient α.

Evaluation of the sharpening strength coefficient selected by the proposed method for DCT-domain watermark embedding and detection algorithm confirmed that pre-filtering with the optimal sharpening strength improves the true positive detection rate across most of tested distortions without increasing the false positive rate. However, for some distortions (JPEG transcoding at high embedding coefficient α, noise at low embedding coefficient α), the detection rate decreases after pre-filtering.

ROC curve analysis of the data collected during optimal sharpening strength coefficient evaluation confirmed that sharpening pre-filtering enhances detection performance by increasing the true positive rate for the same false positive rate for most of tested distortions. These results demonstrate that unsharp masking on selected using the proposed method optimal sharpening strength coefficient improves the robustness of watermark detection when applied as pre-filtering step before watermark detection for DCT-domain watermark embedding and detection algorithm.

Since pre-filtering by unsharp masking on optimal sharpening strength coefficient does not introduce false positives detections, a combined detection scheme using both filtered and non-filtered images can be used to improve detection robustness across a wider range of distortions.

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