Robust DWT-SVD Domain Image Watermarking based on Iterative Blending

Kodathala Sai Varun1, Ajay Kumar Mandava1, Rakesh Chowdary1

1 Department of Electrical, Electronics and Communication Engineering, GITAM School of Technology, GITAM, Bengaluru Campus, Karnataka, India

E-mail: kodathalasaivarun@gmail.com

Abstract. Copyright protection for digital multimedia has become a research hotspot in recent years. As an efficient solution, the digital watermarking scheme has emerged at the right moment. In this article, a highly robust and hybrid watermarking method is proposed. The discrete wavelet transform (DWT) and the singular value decomposition (SVD) as well as iterative blending are adopted in this method to insert and recover the watermark. To enhance the watermark imperceptibility, the second low-level (LL2) coefficients after SVD are modified using the watermark. Compared with the conventional DWT-SVD-based watermarking method and other watermarking techniques, the watermarked images obtained by the proposed method have higher image quality. In addition, the proposed method achieves high robustness in resisting various image processing attacks.

1. Introduction

Digital Image watermarking has gained interest due to both its abundance and the method of distribution. These methods guard against unauthorized access and misuse of digital information. Authentication, operator acknowledgment, material preservation, and trademark protection are all applications that involve these techniques. Watermarking approaches for digital images vary according to the working domain (spatial, frequency, or hybrid), the type of document (text, picture, audio, or video), the algorithm utilized (sequential or parallel), human perceptibility (visible or invisible), and the type of application (i.e., source or destination-based). This section summarizes current developments in this area and covers various strategies for digital picture watermarking based on the working domain. The techniques for watermarking of the spatial domain are too fragile to control. These methods are significantly less resistant to various forms of attacks than frequency-domain algorithms. These disadvantages have prompted researchers to investigate transform-domain watermarking techniques that more effectively conceal data in the transform space of a signal rather than in its time domain. This technique converts an image to the frequency domain using a predefined transform. The watermark is then embedded by altering the original image’s transform domain coefficients using various transformations, including the Discrete Cosine Transform (DCT), the Discrete Fourier Transform (DFT), the Discrete Wavelet Transform (DWT), and the Singular Value Decomposition (SVD). Finally, it extracts the watermark using an inverse transformation and a right key. Singular value decomposition (SVD) has gained much attention in watermarking theory due to its stability in signal processing. The SVD traditional robust watermark approach was introduced in [1] by Liu and Tan. By modulating the singular values of the image directly, the watermark is inserted into the carrier image. However, this approach is not safe enough and the watermark has a lot to do with image quality. To solve the problem there have been several robust watermarking processes that
combine SVD with other transforms including DWT and DCT based on hybrid transformation has been proposed. Lai and Tsai [2] proposed a DWT- SVD-based watermarking algorithm that inserts the watermark by changing the singular values of high-frequency sub-bands. Gupta and Raval suggested another DWT-SVD-based robust watermarking approach in [3]. The principal component of the watermark is then superimposed on the singular values of the diagonal high-frequency sub-band in this scheme (HH). However, experimental findings show that when the watermark images have been attacked, the extracted watermark has low image quality. Narula et al. compared the performance of the DWT and DWT-SVD watermarking schemes in RGB images in [4], concluding that the hybrid DWT-SVD based scheme outperforms the traditional DWT based scheme.

In [5], the authors suggested a DWT-based image watermarking scheme. In this paper, the watermark is incorporated into the first-level decomposition coefficients, however, the image quality degrades with increased quantization steps Jinyuan et al. [6] proposed a logistic map-based watermarking algorithm for digital images in the DWT domain. The watermark bit is then incorporated into the multilevel DWT coefficients. However, the PSNR of this approach is low, and the trade-off between robustness and imperceptibility is unsatisfactory. Asma et al. [7] proposed a DWT-based approach that uses alpha blending to insert a watermark bit into the low-frequency band. This form, however, is the least robust against Gaussian noise. Hsieh and Tseng [8] suggested the following steps for a DWT-based algorithm: The wavelet coefficients of an original image are decomposed. Then, to achieve a robust algorithm, a multi-energy watermarking scheme based on the suitable significant wavelet tree is used. Rastie et al. embedded the watermark using DWT, SVD, orthogonal-triangular decomposition, and chirpz-transform [9]. DWT is applied at two levels, and the LL sub-band is chosen to embed the watermark’s unique values. Roy et al. proposed a new watermarking approach based on the YCbCr colour space using DWT and SVD [10]. The Cb component is chosen and subdivided into four-level sub-bands. The HL sub-band is chosen to embed the watermark’s unique values. Lakritz et al. [11] proposed a dynamic watermarking which used three levels of DWT for the luminance value of the host image, and then he divided the sub-band LL into many blocks. A dynamic block is randomly picked for embedding using a pseudo-random generator. Ali et al. [12] proposed a DWT/SVD hybrid picture watermarking system. The host image is subjected to a two-level DWT, followed by SVD on all sub-bands. On each sub-band, the watermark is modified using 1-level DWT followed by SVD. The principal components for each sub-band in the watermark are then determined. Finally, in the converted host image, the primary components of each sub-band are incorporated in the singular values S of each sub-band. To achieve imperceptibility and robustness, DE is employed to obtain the best MSF. The principal components are employed instead of singular values, hence FPP is avoided. The hybrid SVD-Based image watermarking systems have been examined by W H. Alshoura et al. [13]. The survey focussed on SVD and hybrid frequency domains systems and assessed existing watermarking systems. The study involved SVD security vulnerabilities (FTP attacks), hybrid SVD classification, and SVD embedding comparison.

This paper is structured as follows. In Section 2, we go over the fundamentals of discrete wavelet transforms (DWT). In Section 3, we present our new DWT-based watermarking system. In Section 4, we carry out some numerical experiments with various image distortions and finally the conclusion.

Figure 1. 2 – Level DWT decomposition
2. The wavelet transform, SVD and iterative blending

In this section the mathematical description of Discrete Wavelet Transform (DWT), Singular Value Decomposition (SVD) and the Iterative blending is summed up concisely. The broad description about the techniques can be fetched from [14], [15] and [16].

2.1. The Wavelet Transform

Discrete wavelet transform is a technique which transforms image pixels into wavelets. These wavelets are then used for wavelet-based compression and coding. The DWT is defined as [17]:

$$W_{\varphi}(j_0, k) = \frac{1}{\sqrt{M}} \sum_{x} f(x) \varphi_{j_0, k}(x)$$  \hspace{1cm} (1)

In two-dimensional DWT, the matrix is decomposed into four sub-bands namely: LL, HL, LH, HH. The sub-band LL can be further decomposed to obtain second level of decomposition. The process is continued until the desired level of decomposition is reached. To preserve the properties of imperceptibility and robustness 2nd level decomposition is applied on both the host and watermark images and the second level - low level features (LL2 sub-bands) are used for embedding.

2.2. Singular Value Decomposition

Singular value decomposition (SVD) is a technique which is extensively used to decompose a matrix into several component matrices. SVD of a real matrix A is defined as

$$[A] = [U][S][V]^T$$ \hspace{1cm} (2)

Matrices [U] and [V] consists of left and right singular vectors of [A] and the diagonal elements of [S] are the singular values of [A]. The SVD is applied on the LL2 sub-bands and the corresponding singular matrices are used for embedding, the advantage of using SVD is the decomposed singular matrix is robust against geometric attacks.

2.3. The Iterative Blending

Zhang Gui-cang, Wang Rang-ding and Zhang Yujin [16] proposed a digital image information hiding technique using iterative blending in intensity domain. If H and W are host and watermark images respectively then the iterative embedded image E is given by

$$E(x, y) = (1 - \alpha^n) \ast H(x, y) + \alpha^n \ast W(x, y)$$  \hspace{1cm} (3)

Where $\alpha$ is the embedding strength parameter ($0 < \alpha < 1$) and n is the number of iterations. The embedding strength $\alpha$ decides the strength of watermark being embedded and n describes the host image concentration. The following are the properties of iterative blending:
1. The difference between embedded image $E$ and host image $H$ is inversely proportional to number of iterations and directly proportional to $\alpha$:

$$\Delta(E - H) \propto \frac{\alpha}{n} \quad (4)$$

2. The difference between extracted watermark $W'$ and original watermark $W$ is directly proportional to number of iterations and inversely proportional to $\alpha$:

$$\Delta(W' - W) \propto \frac{n}{\alpha} \quad (5)$$

3. From the property 1, the embedded image is equal to the host image as $n \rightarrow \infty$.

From the properties, parameters $\alpha$ & $n$ must be chosen wisely in order to maintain robustness and imperceptibility. This iterative blending algorithm is applied on the singular matrix in the transform domain to approach high robustness and imperceptibility. A new hybrid non-blind image watermarking system is proposed in this paper, which integrates DWT, SVD, and iterative blending and is robust to various attacks.

3. The proposed watermarking technique

In this section, the embedding and extracting process used to achieve high quality metrics are defined.

3.1. Embedding process

The embedding process requires pre-processing of both host and watermark images, the both images are converted to monochrome and default input size is set to [256,256] which can be varied. It is required to resize both the images to same dimensions. The detailed embedding process is given in Algorithm: 1.

| Algorithm 1: Watermark embedding process |
|------------------------------------------|
| Input:                                   |
| (i) Load Host Image $H$.                 |
| (ii) Load Watermark Image $W$.           |
| (iii) Choose embedding parameters $\alpha$, $n$. |

*Embedding Process*

(i) Apply DWT on Host image $H$ to get $LL$, $HL$, $LH$, $HH$.
(ii) Apply second level DWT on $LL$ sub-band to get $LL2$, $HL2$, $LH2$, $HH2$.
(iii) Apply SVD on $LL2$: $LL2 = U * S * V'$.
(iv) Apply DWT on Watermark image $W$ to get $LLw$, $HLw$, $LHw$, $HHw$.
(v) Apply second level DWT on $LLw$ sub-band to get $LLw2$, $HLw2$, $LHw2$, $HHw2$.
(vi) Apply SVD on $LLw2$: $LLw2 = Uw * Sw * Vw'$.
(vii) Modify $S$ matrix using: $S' = (1 - \alpha^n) * S + \alpha^n * (Sw)$.  
(viii) Reconstruct $LL2'$: $LL2' = U * S' * V'$.
(ix) Apply two times inverse DWT to construct Embedded Image $E$.

**Output: Embedded Image $E$**

3.2. Extraction process

The extraction process is inverse embedding process and detailed description is given in Algorithm: 2.
4. Experimental results

In this section proposed scheme is tested and compared with the results obtained using the techniques mentioned in [18][19][20]. The “Peppers” image is used as the host image with default size [256, 256] and “Cameraman” image is used as the watermark image with same size of [256, 256]. The original images are shown in Fig 3 and Fig 4.

4.1. Imperceptibility performance

In evaluation of imperceptibility performance of techniques, the host image is embedded with watermark image and the result image is compared with the host image without any attacks. The embedded image and extracted watermark using the proposed technique are shown in Fig 5 and Fig 6.
The imperceptibility performance is analysed using quality index metrics mentioned in Table 1.

The results of imperceptibility performance are given in Table 2 and relatively the proposed technique outperforms the existing techniques.

Table 1. Quality metrics for performance evaluation

| Quality Metric | Description | Formula | Best Value | Reference |
|----------------|-------------|---------|------------|-----------|
| ERGAS          | It computes the quality of embedded image in terms of normalized average error of each band of image. Increase in the value of ERGAS indicates disturbance in the embedded image, lower value of ERGAS indicates that the embedded image is similar to the base image. | $100 \frac{\text{BMSE}}{\text{mean}} \left( \sum_{m=1}^{M} \sum_{n=1}^{N} \frac{f_{m,n}}{} \right)$ | Lower value | (Du et al., 2007) [21] |
| MSE            | It computes the spectral difference between image pixel intensities, the lower value indicates better embedding. | $\frac{1}{N} \sum_{n=1}^{N} (L_n - I_n)^2$ | Lower value | (Pinki et al., 2016) [22] |
| MSSSIM         | The Multi Scale Structural Similarity Index for Motion Detection (MS-SSIM) quality metric is an extension of the SSI which computes these measures at various scales and combines them. | $\frac{1}{N} \sum_{n=1}^{N} \left( \sum_{m=1}^{M} \left( \frac{f_{m,n}}{} \right) - \left( \frac{I_{m,n}}{} \right) \right)^2$ | Higher Value (Close to unity) | (Z. Wang et al., 2006) [23] |
| PSNR           | It is extensively used metric which is computed by the number of gray levels in the image divided by the corresponding pixels in the base and the embedded images. When the value is high, the base and embedded images are similar. A higher value indicates superior embedding. | $\frac{1}{N} \sum_{n=1}^{N} \left( \sum_{m=1}^{M} \left( f_{m,n} - I_{m,n} \right)^2 \right)$ | Higher value | (Naidu, 2010) [24] |
| RASE           | The relative average spectral error (RASE) characterizes the average performance of a method by computing difference between intensities of base image and embedded image. The lower the value, the better the method | $\frac{1}{M} \sqrt{\frac{1}{N} \sum_{n=1}^{N} \text{RMSE}(B_n)^2}$ | Lower value | (Gonzalez et al., 2003) [25] |
| RMSE           | It is often used to visualise the difference between the base and embedded images by computing the variation in pixel intensities. RMSE gives spectral quality of embedded image. | $\frac{1}{M} \sqrt{\frac{1}{N} \sum_{n=1}^{N} \left( f_{m,n} - I_{m,n} \right)^2}$ | Lower value | (Zoran, 2009) [26] |
SAM
It computes the spectral angle between the pixel, vector of the base image and embedded image. It is performed on a pixel-by-pixel base. A value of SAM equal to zero denotes the absence of spectral distortion.

\[
\arccos \left( \frac{\langle V, V' \rangle}{\|V\|_2 \cdot \|V'\|_2} \right)
\]

Lower value
(Alparone et al., 2007)[27]

UQI
It is used to evaluate the amount of variation of relevant data from base image into embedded image. The range of this metric is -1 to 1. The value 1 indicates that the base and embedded images are similar.

\[
\frac{4\sigma_x \sigma_y (\mu_x + \mu_y)}{(\sigma_x^2 + \sigma_y^2)(\mu_x^2 + \mu_y^2)}
\]

Higher Value
(Close to unity)
(Alparone et al., 2008)[28]

VIFP
VIF measures the mutual information between the base image and embedded image, the higher value indicates the similarity between the images.

\[
\frac{\sum_{i,j} \log \left( \frac{f_i \cdot f_j}{g_i \cdot g_j} \right)}{\sum_{i,j} \log \left( \frac{f_i \cdot f_j}{g_i \cdot g_j} \right)}
\]

Higher Value
(Close to unity)
(Hamid et al., 2004)[29]

SSIM
SSIM compares the local patterns of pixel intensities between the base and embedded images. The range varies between -1 to 1. The value 1 indicates the base and embedded images are similar.

\[
\frac{2\mu_x \mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1} \cdot \frac{2\sigma_{xy} + C_2}{\sigma_{xx} + \sigma_{yy} + C_2}
\]

Higher Value
(Close to unity)
(Wang et al., 2004)[30]

Table 2. Imperceptibility performance of the algorithms.

| Quality Metric | E. Ganic et al. (Ref: 18) | Wai CK et al. (Ref: 19) | Rahman MN et al. (Ref: 20) | Rahman MN et al. (iterative) | DWT_SVD_LL2 | Proposed |
|----------------|--------------------------|------------------------|---------------------------|-----------------------------|-------------|----------|
| ERGAS          | 1676.35015               | 1034.48103             | 2017.96209                | 705.401570                  | 1985.690262 | 603.665425 |
| MSE            | 33.1715240              | 6.63858032             | 29.9302063                | 2.576126099                 | 29.06634521 | 2.11517334 |
| MSSSIM         | 0.99611094              | 0.99875304             | 0.99914262               | 0.999314262                | 0.99820678  | 0.99957755 |
| PSNR           | 32.9231493              | 39.9100514             | 33.3697065                | 44.02113243                 | 33.49689934 | 44.8773439 |
| RASE           | 241.960303              | 149.314475             | 291.267740                | 101.8159466                 | 286.6097018 | 87.1315989 |
| RMSE           | 5.75947254              | 2.57654426             | 5.47085060                | 1.605031495                 | 5.39132187  | 1.45436355 |
| SAM            | 0.0376152               | 0.01957114             | 0.01207048                | 0.012194174                | 0.01149176 | 0.01105131 |
| UQI            | 0.99887454              | 0.99958285             | 0.99821040                | 0.999770130                 | 0.99887497  | 0.99985400 |
| VIFP           | 0.80328039              | 0.82013331             | 0.90898915                | 0.897728713                | 0.912682022 | 0.91194932 |
| SSIM           | 0.98166270              | 0.99193288             | 0.99462302                | 0.995696637                 | 0.995626901 | 0.99686668 |

4.2. Robustness of technique under attacks
For the analysis of robustness performance, the embedded image is affected by various attacks and the attacked image is used in extraction process. The extracted watermarked image is compared with the original watermark using the same metrics mentioned in imperceptibility performance analysis. The attacks are gaussian blurring with kernel size: 5x5, poison noise, speckle noise, image sharpening, wiener filtering with kernel size: 3x3, average filtering with kernel size: 3x3, median filtering with kernel size: 3x3 and image resizing (256 to 128 and 128 to 256). The performance of proposed model under attacks are shown in Table 3.
Table 3. Performance of proposed algorithm against attacks.

| Attack                      | Attacked image | Extracted watermark |
|-----------------------------|----------------|---------------------|
| Gaussian blur               |                |                     |
| Image sharpening (0.8)      |                |                     |
| Average filter (3X3)        |                |                     |
| Median filter (3X3)         |                |                     |
| Weiner filter (3X3)         |                |                     |
| Speckle noise               |                |                     |
| Resizing (256-128-256)      |                |                     |
| Poisson                     |                |                     |

4.2.1. Gaussian Blur
Gaussian blurring is the outcome of blurring of an image using gaussian function which is implemented by convolving an image with FIR kernel of gaussian values. Mathematical function is given as

\[ P(x) = \frac{1}{\sigma \sqrt{2\pi}} e^{-(x-\mu)^2/2\sigma^2} \]
For inspecting the performance of watermarking technique, the embedded image is blurred using gaussian function and the extracted watermark is compared with the original watermark.

### 4.2. Image Sharpening

Image sharpening is used to grab features of an image by maintaining contrast levels of dark and bright. Image is convoluted with the kernel to obtain the smoothed image.

#### 4.2. Average Filtering

Average filtering is also referred as smoothing of image, the kernel performs the mean operation for neighbourhood pixels.

#### 4.2. Median Filtering

Average filtering is also referred as smoothing of image, the kernel performs the median operation for neighbourhood pixels.

#### 4.2.5. Wiener Filtering

The Wiener filter is the MSE-optimal stationary linear filter for images degraded by additive noise and blurring.

#### 4.2.6. Speckle noise

Speckle noise is defined as multiplicative noise, having a granular pattern it is the inherent property of SAR image.

### 4.2.7. Resize of image

The embedded image is resized into its lower dimension [128X128] and restored to its original dimension [256X256] to measure its scaling performance.

### 4.2.8. Poisson Noise

Poisson noise is a signal-dependent noise that can be seen on photon images, and is also called quantum noise.

#### Table 4. Performance of the algorithms under the attack of Gaussian Blur

| ALGORITHM | ORGAN | MSE | PSNR | SSIM | RASE | UQI | VIFP | QUALITY METRIC |
|-----------|-------|-----|------|------|------|-----|------|----------------|
| E. Garce et al. - LL (Ref: 18) | 19.9550 | 35.49 | 33.59 | 0.71 | 0.12 | 0.81 | 0.62 |
| E. Garce et al. - LL (Ref: 18) | 19.9550 | 35.49 | 33.59 | 0.71 | 0.12 | 0.81 | 0.62 |
| E. Garce et al. - LL (Ref: 18) | 19.9550 | 35.49 | 33.59 | 0.71 | 0.12 | 0.81 | 0.62 |
| E. Garce et al. - LL (Ref: 18) | 19.9550 | 35.49 | 33.59 | 0.71 | 0.12 | 0.81 | 0.62 |

#### Table 5. Performance of the algorithms under attack of Sharpen 80

| ALGORITHM | ORGAN | MSE | PSNR | SSIM | RASE | UQI | VIFP | QUALITY METRIC |
|-----------|-------|-----|------|------|------|-----|------|----------------|
| E. Garce et al. - LL (Ref: 18) | 19.9550 | 35.49 | 33.59 | 0.71 | 0.12 | 0.81 | 0.62 |
| E. Garce et al. - LL (Ref: 18) | 19.9550 | 35.49 | 33.59 | 0.71 | 0.12 | 0.81 | 0.62 |
| E. Garce et al. - LL (Ref: 18) | 19.9550 | 35.49 | 33.59 | 0.71 | 0.12 | 0.81 | 0.62 |
| E. Garce et al. - LL (Ref: 18) | 19.9550 | 35.49 | 33.59 | 0.71 | 0.12 | 0.81 | 0.62 |
### Table 6. Performance of the algorithms under the attack of Average filtering

| ALGORITHM | ERGAS | MSSIM | PSNR | SSIM | UQI | VOP | DOI |
|-----------|-------|-------|------|------|-----|-----|-----|
| E. Ganic et al. (L - Ref. 19) | 3.579295 | 0.80147597 | 35.592875 | 0.4557164 | 1.396428 | 0.4019052 | 10.18650452 |
| E. Ganic et al. (L - Ref. 18) | 3.579295 | 0.80147597 | 35.592875 | 0.4557164 | 1.396428 | 0.4019052 | 10.18650452 |

### Table 7. Performance of the algorithm under the attack of Median filtering

| ALGORITHM | ERGAS | MSSIM | PSNR | SSIM | UQI | VOP | DOI |
|-----------|-------|-------|------|------|-----|-----|-----|
| E. Ganic et al. (L - Ref. 19) | 3.579295 | 0.80147597 | 35.592875 | 0.4557164 | 1.396428 | 0.4019052 | 10.18650452 |
| E. Ganic et al. (L - Ref. 18) | 3.579295 | 0.80147597 | 35.592875 | 0.4557164 | 1.396428 | 0.4019052 | 10.18650452 |

### Table 8. Performance of the algorithm under the attack of wiener filter

| ALGORITHM | ERGAS | MSSIM | PSNR | SSIM | UQI | VOP | DOI |
|-----------|-------|-------|------|------|-----|-----|-----|
| E. Ganic et al. (L - Ref. 19) | 3.579295 | 0.80147597 | 35.592875 | 0.4557164 | 1.396428 | 0.4019052 | 10.18650452 |
| E. Ganic et al. (L - Ref. 18) | 3.579295 | 0.80147597 | 35.592875 | 0.4557164 | 1.396428 | 0.4019052 | 10.18650452 |

### Table 9. Performance of the algorithms under the attack of speckle noise

| ALGORITHM | ERGAS | MSSIM | PSNR | SSIM | UQI | VOP | DOI |
|-----------|-------|-------|------|------|-----|-----|-----|
| E. Ganic et al. (L - Ref. 19) | 3.579295 | 0.80147597 | 35.592875 | 0.4557164 | 1.396428 | 0.4019052 | 10.18650452 |
| E. Ganic et al. (L - Ref. 18) | 3.579295 | 0.80147597 | 35.592875 | 0.4557164 | 1.396428 | 0.4019052 | 10.18650452 |

### Table 10. Performance of the algorithms under the attack of resizing

| ALGORITHM | ERGAS | MSSIM | PSNR | SSIM | UQI | VOP | DOI |
|-----------|-------|-------|------|------|-----|-----|-----|
| E. Ganic et al. (L - Ref. 19) | 3.579295 | 0.80147597 | 35.592875 | 0.4557164 | 1.396428 | 0.4019052 | 10.18650452 |
| E. Ganic et al. (L - Ref. 18) | 3.579295 | 0.80147597 | 35.592875 | 0.4557164 | 1.396428 | 0.4019052 | 10.18650452 |
Table 1. Performance of the algorithms under the attack of poisson noise

| QUALITY METRIC | ALGORITHM | ERGAS | MSE | MSSSIM | PSNR | RASE | RMSE | SAM | UQI | VIFP | SSIM |
|----------------|-----------|-------|-----|--------|------|------|------|-----|-----|------|------|
| E. Ganie et al. – LI (Ref. 18) | 1.3955 | 0.0081 | 0.9988 | 50.94 | 2.34 | 17.60 | 0.00 | 0.99 | 0.80 | 0.98 |
| E. Ganie et al. – LI (Ref. 18) | 0.8514 | 0.0180 | 0.9707 | 47.93 | 2.78 | 19.65 | 0.00 | 0.97 | 0.80 | 0.80 |
| F. Gang et al. – LI (Ref. 14) | 1.2864 | 0.0066 | 0.9980 | 50.64 | 2.32 | 17.59 | 0.00 | 0.99 | 0.80 | 0.98 |
| F. Gang et al. – LI (Ref. 14) | 0.8514 | 0.0173 | 0.9703 | 47.80 | 2.76 | 19.63 | 0.00 | 0.97 | 0.80 | 0.80 |
| E. Ganie et al. – HH (Ref. 18) | 0.8134 | 0.0062 | 0.9981 | 50.67 | 2.32 | 17.65 | 0.00 | 0.98 | 0.80 | 0.80 |
| E. Ganie et al. – HH (Ref. 18) | 0.9245 | 0.0173 | 0.9703 | 47.80 | 2.76 | 19.63 | 0.00 | 0.97 | 0.80 | 0.80 |
| West C.K. et al. – LI (Ref. 19) | 0.8514 | 0.0177 | 0.9707 | 47.93 | 2.78 | 19.65 | 0.00 | 0.97 | 0.80 | 0.80 |
| West C.K. et al. – LI (Ref. 19) | 0.8514 | 0.0177 | 0.9707 | 47.93 | 2.78 | 19.65 | 0.00 | 0.97 | 0.80 | 0.80 |
| West C.K. et al. – HH (Ref. 19) | 0.8134 | 0.0062 | 0.9981 | 50.67 | 2.32 | 17.65 | 0.00 | 0.98 | 0.80 | 0.80 |
| West C.K. et al. – HH (Ref. 19) | 0.9245 | 0.0173 | 0.9703 | 47.80 | 2.76 | 19.63 | 0.00 | 0.97 | 0.80 | 0.80 |
| Rahman M.S. et al. (Ref. 20) | 1.0312 | 0.0083 | 0.9977 | 50.60 | 2.32 | 17.65 | 0.00 | 0.98 | 0.80 | 0.80 |
| Rahman M.S. et al. (Ref. 20) | 0.9245 | 0.0173 | 0.9703 | 47.80 | 2.76 | 19.63 | 0.00 | 0.97 | 0.80 | 0.80 |

5. Conclusions
In this paper, a new robust image watermarking system DWT-SVD domain based on iterative blending is proposed to solve the copyright protection problem of a picture. A series of simulation results indicate that the proposed watermarking scheme has good imperceptibility performance without sacrificing the image's quality. Furthermore, the adoption of iterative blending technique highly improved the hiding capacity of the proposed scheme.

6. References

[1] Liu, R.Z.; Tan, T.N.: An SVD-based watermarking scheme for protecting rightful ownership. (IEEE transactions, Multimedia, 4, 121–128 (2002))

[2] Lai, C.C.; Tsai, C.C.: Digital image watermarking using discrete wavelet transform and singular value decomposition.(IEEE transactions, Instrumentation and Measurement). 59, 3060–3063 (2010).

[3] Gupta, A.K.; Raval, M.S.: A robust and secure watermarking scheme based on singular values replacement. (Sadhana), 37, 425–440 (2012).

[4] Narula, N.; Sethi, D.; Bhattacharya, P.P.: Comparative analysis of DWT and DWT-SVD watermarking techniques in RGB images. (International Journal of Signal Processing, Image Processing and Pattern Recognition). , 8, 339–348 (2015).

[5] Preda, R.O. Self-recovery of unauthentic images using a new digital watermarking approach in the wavelet domain. (In Proceedings of the 2014 10th International Conference on Communications (COMM), Bucharest, Romania); pp. 1–4 (2014)

[6] Hu, J.; Shao, Y.; Ma, W.; Zhang, T.: A robust watermarking scheme based on the human visual system in the wavelet domain. (In Proceedings of the 2015 8th International Congress on Image and Signal Processing (CISP), Shenyang, China; pp. 799–803) (2015)

[7] Ahmad, A.; Sinha, G.; Kashyap, N. 3-level DWT Image watermarking against frequency and geometrical attacks. (International Journal of Computer Network and Information Security(IJCNIS)). 6, 58 (2014)

[8] Hsieh, M., Tseng, D., and Huang, Y. Hiding digital watermarks using multiresolution wavelet transform. (IEEE Transactions on Industrial Electronics), 48(5), 875–882 (2001).

[9] P. Rasti, G. Anbarjafari, and H. Demirel, ‘‘Colour image watermarking based on wavelet and QR decomposition,’’ in (Proceedings, 25th Signal Processing and Communications Applications Conference (SIU)), pp. 1–4 (2017).

[10] Roy, A. K. Maiti, and K. Ghosh,'An HVS inspired robust nonblind watermarking scheme in YCbCr color space,’’ (International Journal of Image and Graphics), vol. 18, no. 3, Art. no. 1850015 (2018).

[11] Y. Lakrisi, A. Saaidi, and A. Essahlouai,'Novel dynamic color image watermarking based on DWT-SVD and the human visual system,' Multimedia Tools and Applications., vol. 77, no. 11, pp. 13531–13555. (2018)

[12] M. Ali and C. W. Ahn,'An optimized watermarking technique based on self-adaptive DE in DWT-SVD transform domain,' Signal Process., vol. 94, pp. 545–556 (2014)

[13] W. H. Alshoura, Z. Zainol, J. S. Teh, M. Alawida and A. Alabdulatif, ‘‘Hybrid SVD-Based Image Watermarking Schemes: A Review,’’ in IEEE Access, vol. 9, pp. 32931–32968 (2021)
[14] Kenneth R. Castleman, *Digital Image Processing*, Tsinghua University Press, pp.331–339, (2003)

[15] B. Zhou and J. Chen.: *A Geometric Distortion Resilient Image Watermarking Algorithm Based on SVD*, Chinese Journal of Image and Graphics, **Vol. 9**, pp. 506–512 (2004)

[16] Zhang Gui-cang, Wang Rang-ding and Zhang Yu-jin.: *Digital Image Information Hiding Technology Based on Iterative Blending*, Chinese Journal of Computers, **Vol.25** No.5,pp.569–574 (2003)

[17] R. Gonzalez and R. Woods, *Digital Image Processing*, Prentice Hall, Englewood Cliffs, NJ, (2002).

[18] E. Ganic and A. M. Eskicioglu, *Robust DWT-SVD Domain Image Watermarking: Embedding Data in All Frequencies*, Proceedings of the ACM Multimedia and Security Workshop pp. 166-174, Magdeburg, Germany (2004)

[19] Wai CK, Ahmad NA.: *Robust DWT-SVD image watermarking with hybrid technique for embedding data in all frequencies*. AIP Conference Proceedings (2014)

[20] Rahman MM, Ahammed MS, Ahmed MR, Izhak MN.: *A semi blind watermarking technique for copyright protection of image based on DCT and SVD domain*. The Global Journal of Researches in Engineering **16**(7): 9–15. (2017)

[21] Du, Q., Younan, N.H., King, R., Shah, V.P.: *On the performance evaluation of pan-sharpening techniques*. IEEE Geosci. Remote Sens. Lett. **4**, 518–522 (2007)

[22] Pinki, D.R. Mehra, *Estimation of the image quality under different distortions*, Int. J. Eng. Sci., **8**, 17291–17296 (2016).

[23] Z. Wang, E. P. Simoncelli and A. C. Bovik, “Multiscale structural similarity for image quality assessment,” The Thirty-Seventh Asilomar Conference on Signals, Systems and Computers, pp. 1398–1402 Vol2 (2003).

[24] Naidu, V.P.S., *Discrete Cosine Transform-based Image Fusion*. Def. Sci. J. **60**, 48–54 (2010).

[25] M. Gonzalez-Audicana, J. L. Saleta, R. G. Catalan and R. Garcia, “Fusion of multispectral and panchromatic images using improved IHS and PCA mergers based on wavelet decomposition,” in IEEE Transactions on Geoscience and Remote Sensing, vol. **42**, no. 6, pp. 1291–1299,(2004).

[26] Zoran, L.F., *Quality Evaluation of Multiresolution Remote Sensing Image Fusion*. U.P.B. Sci. Bull., Ser. C **71**, 38–52 (2009).

[27] Alparone, L., Wald, L., Chanussot, J., Member, S., Thomas, C., Gamba, P., Bruce, L.M., *Comparison of Pansharpening Algorithms: Outcome of the 2006 GRS-S Data-Fusion Contest*. IEEE Trans. Geosci. Remote SENSINGI **45**, 3012–3021 (2007).

[28] Alparone, L., Aiazzi, B., Baronti, S., Garzelli, A., Nencini, F., Selva, M.: *Multispectral and Panchromatic Data Fusion Assessment Without Reference*. Photogramm. Eng. Remote Sens. **74**, 193–200 (2008)

[29] H. R. Sheikh and A. C. Bovik, “*Image information and visual quality, “* in IEEE Transactions on Image Processing, vol. **15**, no. 2, pp. 430-444 (2006)

[30] Wang, Z., Bovik, A.C., Sheikh, H.R., Member, S., Simoncelli, E.P., Member, S.*Image Quality Assessment: From Error Visibility to Structural Similarity*. IEEE Trans. IMAGE Process. **13**, 1–14 (2004).