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# A New Face Region Recovery Algorithm based on Bicubic Interpolation

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*Abstract*— Recently, researchers focused on face image manipulation detection and localization techniques because of their importance in image security applications. The previous research has not highlighted the recovery of the face region after manipulation detection. This paper presents a new face region recovery algorithm (FRRA) to be included in the face image manipulation detection algorithms (FIMD). The proposed FRRA consists of two main algorithms: face data generation algorithm and face region restoration algorithm. Both algorithms start by detecting the face region using Multi-task Cascaded Neural Network followed by a face window selection process. In the face data generation algorithm, the recovery information is generated from the shirked face window using bicubic interpolation technique. In the face region restoration algorithm, the face region zoomed using bicubic interpolation technique. The proposed FRRA has been tested and compared with previous recovery methods for different color face images, and the results proved that the FRRA could recover the face region with better visual quality at the same data length compared to previous methods. The main contributions of this research are a) the suggestion of including a face region recovery algorithm to FIMD, b) the study of previous recovery data generation algorithms for color face images, and c) introducing a new algorithm for generating the recovery data based on bicubic interpolation. In the future, the proposed algorithm can be included in the recent FIMD algorithms to recover the face region, which can be very useful in practical applications, especially those used in data forensics systems.

Keywords— Face image security; face image manipulation detection; bicubic interpolation; image forensics.

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## I. INTRODUCTION

Authors Digital face images are increasingly used and shared via networks for different purposes. The shared face images can increase the speed of various processes and documentation, facilitate working with different systems, overcome distance restrictions, share memories and personal information, access online applications, and many others. The shared face images can easily be manipulated using digital image processing applications, and the manipulations can be harmful or harmless based on the intentions of the manipulator [1]. The recent interest of the research community has been directed towards a type of manipulation called DeepFakes which utilizes deep-learning or machinelearning-based algorithms to create fake face images or videos that are hard to be recognized as fake information [2]-[6]. The images and videos generated from DeepFakes can be used for many harmful intentions which may threaten the lives of people and their financial or social situation [7]–[12].

Recently, several researchers introduced face image manipulation detection (FIMD) algorithms to check the authenticity of the image [13]-[18]. Most available techniques have been implemented based on machine learning or deep learning algorithms because they depend on the type of manipulation utilized to generate the fake image. These techniques can successfully detect specific types of manipulation under specific conditions, but they suffer from some limitations and may face several limitations. Some recently published review papers have been presented to illustrate the types of FIMD, their limitations, and challenges [19]–[23]. The review paper in [23] highlighted some of the challenges that can face FIMD techniques, such as: (a) the rapid development of face image processing applications, (b) the requirement of large and high-quality datasets for training, (c) the need for knowing the type of manipulation applied in order to choose the suitable detection technique, (d) the lack of generalization, (e) the lack of standard metrics, (f) the high complexity and time-consuming process required for training networks, (g) the generation of high-quality fake face images

which are difficult to be detected by the trained network, in addition to other challenges. Some solutions have been suggested to overcome the limitations and challenges [23]. One suggested strategy is to implement a face image authentication technique based on image watermarking.

A new FIMD technique based on face detection and image watermarking algorithms [24]. The face region is detected, and a binary mask image is generated to classify the image blocks into two groups belonging to the face region or outside the face region. The manipulation reveals data are extracted from the blocks that belong to the face region and embedded in the blocks outside the face region using Slantlet-based image watermarking [25]-[27]. The proposed technique outperforms previous detection techniques, which can detect and localize different face image manipulations with 100 % accuracy [24]. However, the face region's recovery has not been highlighted in this technique. It will be very useful for security and forensics applications to recover the original face region if manipulations exist. We suggest adding a data generation and recovery algorithm to the steps of the FIMD technique [24].

The recovery information has been generated using the average of  $4\times4$  blocks of pixels [28]–[30]. At the receiver side, the average value replaces the pixels in its related  $4\times4$  block. The recovery information has been generated using the average of  $2\times2$  blocks of pixels [31]. At the receiver side, the average value replaces the pixels in its related  $2\times2$  block. The method by Zain and Fauzi [31] recovered the image with better visual quality results compared to the average  $4\times4$  method. However, it was at the cost of increasing the number of bits generated in the recovery information. An Integer Wavelet Transform (IWT) based recovery information generation method has been applied [32]. Some other studies have been used to generate recovery information for grayscale medical images [28]–[32].

In this paper, a new face region recovery algorithm (FRRA) is presented in order to be included in the face image manipulation detection algorithms (FIMD). The proposed FRRA consists of two main algorithms: face data generation algorithm and face region restoration algorithm. Both algorithms start by detecting the face region using Multi-task Cascaded Neural Network (MTCNN) followed by the face window selection process. In the face data generation algorithm, the recovery information is generated from the shirked face window using the bicubic interpolation technique [33], [34]. In the face region restoration algorithm, the face region is zoomed using the bicubic interpolation technique. In order to compare the performance of the proposed FRRA with the previous methods, the average 2×2 and IWT-based algorithms have been applied to color face images. The main contributions of this work can be summarized as follows:

- The suggestion of including a face region recovery algorithm in the available FIMD techniques is a new idea that has not been highlighted in previous FIMD methods.
- The study of two previous recovery data generation algorithms for color face images.
- Introducing a new algorithm for generating the recovery data from the face region based on bicubic interpolation.

The rest of the paper is organized as follows: section 2 presents the related works; section 3 presents the proposed FRRA; section 4 illustrates the experimental results and discussion; finally, section 5 presents the conclusions of this work.

## II. MATERIALS AND METHOD

As mentioned in the introduction, the average  $2\times 2$  and IWT algorithms have been applied to generate the recovery information of the region of interest in grayscale medical images. The proposed research in this paper aims to introduce a face region recovery algorithm for color images. Therefore, the average  $2\times 2$  and IWT-based algorithms have been implemented to serve the aim of this research. The proposed FRRA consists of two main algorithms: the face data generation algorithm, which is applied on the sender side, and the face region restoration algorithm, which is applied on the receiver side.

The following subsections illustrate the steps of the implemented algorithms based on average  $2\times2$  and IWT. To test the visual quality of the recovered face region, the Peak Signal-to-Noise Ratio (PSNR) and the Structured Similarity Index (SSIM) between the original face region and the recovered face region have been calculated. Then the block diagrams of the proposed FRRA algorithms and their details are explained.

## *A.* Generating Recovery Data based on Average 2×2 Block

The proposed algorithms of generating the recovery information based on dividing the face region into nonoverlapping blocks, each of size  $2 \times 2$  pixels are illustrated in Fig 1 and can be summarized as follows:

1) The steps of the average  $2 \times 2$ -based recovery algorithm at the sender side:

- Step 1: Read the original face image.
- Step 2: Apply MTCNN to detect the face box.
- Step 3: Adjust the output of the MTCNN to select the face region.
- Step 4: Divide one channel from the face region into non-overlapping blocks of size 2×2 pixels.
- Step 5: Calculate the average of each block from Step 4.
- Step 6: Convert the average values to binary and concatenate the bits to generate one binary sequence.
- Step 7: Repeat step 4 to step 6 for the remaining channels of the face region.
- Step 8: Calculate the length of the resultant binary sequences.

2) The steps of average  $2 \times 2$ -based recovery algorithm at the receiver side are as follows:

- Step 1: Read the binary sequence for one channel.
- Step 2: Divide the binary sequence into nonoverlapping subsequences, each of length (8 bits).
- Step 3: Convert the binary subsequences to decimal to recover the average values.
- Step 4: Recover the channel of the face region by replacing the pixels in each (2×2) block with their average value.

- Step 5: Repeat step 1 to step 4 to recover the other two channels of the face region.
- Step 6: Calculate the PSNR and SSIM to test the visual quality of the recovered face region.



Fig. 1 Recovery algorithm based on average (2×2) block.

# B. Generating Recovery Data based on IWT

The proposed algorithms for generating the recovery information based on IWT are illustrated in Fig 2 and can be summarized as follows:



Fig. 2 Recovery algorithm based on IWT.

*1)* The steps of the IWT-based recovery algorithm on the sender side:

- Step 1: Read the original face image.
- Step 2: Apply MTCNN to detect the face box.

- Step 3: Adjust the output of the MTCNN to select the face region.
- Step 4: Select one channel from the face region.
- Step 5: Apply IWT to transform the selected channel into four subband coefficients (i.e., approximation (CA), horizontal (CH), vertical (CV), and diagonal (CD)).
- Step 6: Apply the pixel adjustment process to CA.
- Step 7: Convert the resultant coefficients from Step 6 to binary and concatenate the binary bits to obtain one binary sequence.
- Step 8: Repeat steps 4 to 7 for the remaining two channels.
- Step 9: Calculate the length of the resultant binary sequences.

2) The steps of the IWT-based recovery algorithm at the receiver side:

- Step 1: Read the binary sequence for one channel.
- Step 2: Divide the binary sequence into subsequences, each of length (8 bits).
- Step 3: Convert the binary subsequences to decimal to recover CA coefficients.
- Step 4: Set CH, CV, and CD to zeros.
- Step 5: Apply inverse IWT to recover the channel image.
- Step 6: Repeat steps 1 to 5 to the remaining two channels.
- Step 7: Calculate the PSNR and SSIM to test the visual quality of the recovered face region.

# C. The proposed FRRA algorithms

The proposed algorithms for generating the recovery information based on the bicubic interpolation technique are explained in the following subsections.

1) Face data generation algorithm: The input of the proposed algorithm for face data generation is the original face image, while the output of this algorithm is the generated binary sequence. The block diagram of this algorithm is shown in Fig 3, and the steps of the algorithm are as follows:

- Step 1: Read the original face image.
- Step 2: Apply MTCNN to detect the face box.
- Step 3: Adjust the output of the MTCNN to select the face region.
- Step 4: Apply bicubic interpolation with a scale value of 0.5.
- Step 5: Select one channel from the face region and convert it to binary, then concatenate the binary bits to obtain one binary sequence.
- Step 6: Repeat step 5 to the remaining two channels and calculate the length of the resultant binary sequences.



Fig. 3 Proposed face data generation algorithm.

2) Face region restoration algorithm: The input of the proposed algorithm for face region restoration is the binary sequence, while the output of this algorithm is the recovered face region. The block diagram of this algorithm is shown in Figure 4, and the steps of the algorithm are as follows:

- Step 1: Read the binary sequence for one channel.
- Step 2: Divide the binary sequence into subsequences, each of length (8 bits).
- Step 3: Convert the binary subsequences to decimal to recover resized channel.
- Step 4: Repeat steps 1 to 3 to recover the remaining two channels.
- Step 5: Apply bicubic interpolation with scale value (2) to the recovered resized face region.
- Step 6: Calculate the PSNR and SSIM to test the visual quality of the recovered face region.



Fig. 4 Proposed face region restoration algorithm.

## **III. RESULTS AND DISCUSSION**

Different test images have been used with different sizes to test the proposed algorithms' performance. Samples of the test images are shown in Fig 5, and their corresponding sizes are shown in Table I. The experiments have been conducted to test the performance of average  $2\times 2$ , IWT, and the proposed FRRA. PSNR and SSIM have been calculated to test the recovered face region's visual quality. The length of the binary sequence (Lseq) is also calculated to illustrate the number of recovery bits that are generated from each algorithm. The following subsections present the experiments and their results.

TABLE I
CORRESPONDING SIZES OF DIFFERENT IMAGE

Image name	Image size	Size of the face region
Img_1	570×1014×3	160×128×3

Img_2	600×1200×3	112×80×3
Img_3	1152×2048× 3	432 ×384× 3
Img_4	1152 ×2048× 3	288 ×224 ×3
Img_5	536× 1024× 3	144 ×144× 3
Img_6	600×1200×3	224 ×192× 3
Img_7	640 ×800× 3	80×64×3
Img_8	1669×2500×3	256×224×3
Img_9	455×728×3	128×128×3
Img_10	608×1080×3	224×176×3



# Fig. 5 Sample test images.

### A. Test of Average $2 \times 2$ algorithm

Img 8

In this experiment, the visual quality of the recovered face region using the average  $2\times 2$  algorithm is calculated using PSNR and SSIM. Table II presents the results for the ten face images shown in Fig 5. Samples of the recovered face regions using this algorithm are shown in Fig 6.

IABLE II
Test of visual quality and length of sequence for average (2×2)
ALGORITHM

Image name	PSNR	SSIM	Lseq
Img 1	30.6599	0.9054	122880
Img_2	35.4847	0.9921	53760
Img 3	35.5698	0.9809	995328
Img 4	31.5999	0.9702	387072
Img 5	27.589	0.9379	124416
Img 6	33.6023	0.9822	258048
Img <sup>7</sup>	25.2304	0.9329	30720
Img 8	30.5817	0.9465	344064
Img 9	29.4238	0.9694	98304
Img_10	36.7524	0.9857	236544

## B. Test of IWT Algorithm

In this experiment, the visual quality of the recovered face region using IWT algorithm is calculated using PSNR and SSIM. Different IWT types have been tested to choose the one with the best results. Table III presents samples of the PSNR results using different IWT types. The results proved that the best type of IWT is cdf 3.5. Table IV presents the experimental results for IWT cdf 3.5 for the test images shown in Fig 5. Samples of the recovered face regions using this algorithm are shown in Fig 7.

TABLE III
TEST OF VISUAL QUALITY FOR DIFFERENT IWT TYPES

Wavelet type	pe PSNR (dB) for sample test images					
~ 1	img_1	img_3	img_4	img_6	Img_9	Img_10
bior4.4	20.7739	14.3456	14.6716	14.1492	15.5878	28.7293
bior5.5	24.3623	18.0065	18.8657	17.415	17.7289	28.1301
cdf1.1	32.0368	37.178	33.5153	34.9857	30.2974	38.555
cdf1.3	31.9584	37.0745	33.4299	34.9069	30.2254	38.4432
cdf1.5	31.8989	37.0062	33.3642	34.8596	30.1664	38.3699
cdf2.2	32.0336	37.3676	33.2941	33.263	29.6802	38.6792
cdf2.4	32.0741	37.4101	33.3312	33.2974	29.717	38.7244
cdf2.6	32.079	37.4246	33.3373	33.3031	29.7214	38.7425
cdf3.1	32.7623	38.1706	34.5836	35.4071	30.3429	39.2822
cdf3.3	32.9486	38.3417	34.7419	35.5681	30.5224	39.4507
cdf3.5	32.9982	38.394	34.788	35.6123	30.5773	39.5158
cdf4.2	31.9031	37.0988	33.3159	33.397	29.5387	38.181
cdf4.4	32.1684	37.4017	33.5695	33.7094	29.8129	38.5064
cdf4.6	32.2646	37.5202	33.6766	33.8286	29.9253	38.6183
cdf5.1	31.1605	36.3035	33.2491	33.8112	28.7295	37.0632
cdf5.3	30.5142	35.307	32.6954	33.0712	28.0457	35.5718
cdf5.5	32.2911	37.0001	34.016	34.5233	29.7416	37.6252
cdf6.2	28.9913	33.5113	30.3685	30.808	27.007	33.8572
cdf6.4	30.1049	34.5366	31.3998	31.7553	28.0684	34.7971
cdf6.6	30.5497	34.9254	31.7538	32.1625	28.4905	35.1629
db2	32.7411	37.6525	34.4431	35.2105	29.9604	38.4108
db3	32.5144	36.8807	34.222	33.9149	28.7998	37.2864
db4	17.813	12.3985	12.4098	12.0537	13.5638	24.3623
db5	18.2894	12.6807	12.738	12.3717	13.9181	25.3898
db6	31.274	34.1777	32.7085	30.8518	26.2203	34.096
db7	12.9849	9.3611	9.0349	8.7506	9.8592	15.4542
db8	30.1001	32.0581	30.9866	29.0037	24.9296	31.9616
haar	32.0368	37.178	33.5153	34.9857	30.2974	38.555
sym2	32.7411	37.6525	34.4431	35.2105	29.9604	38.4108
sym3	14.6255	10.4511	10.2051	9.8947	11.1383	18.1427
sym4	32.3373	37.7897	33.7536	34.0072	30.0528	39.0601
sym5	32.856	37.8219	34.5598	35.3588	30.5005	38.7409
sym6	24.8445	26.9725	24.1389	20.751	18.4486	26.666
sym7	25.0551	27.7253	24.8635	21.3963	19.0716	27.48
sym8	13.9089	9.9403	9.6701	9.3589	10.4618	16.7156
Max. PSNR	32.9982	38.394	34.788	35.6123	30.5773	39.5158



Fig. 7 Sample results from IWT (cdf 3.5) algorithm.

TABLE IV TEST OF VISUAL QUALITY AND LENGTH OF SEQUENCE FOR IWT (CDF 3.5) AL GORITHM

ALGORITHM					
Image name	PSNR	SSIM	Lseq		
Img_1	32.9982	0.9337	122880		
Img_2	33.9581	0.9843	53760		
Img_3	38.394	0.9882	995328		
Img_4	34.788	0.9785	387072		
Img 5	29.8801	0.9526	124416		
Img_6	35.6123	0.9874	258048		
Img_7	26.268	0.9272	30720		
Img_8	31.6545	0.9546	344064		
Img_9	30.5773	0.9758	98304		
Img_10	39.5158	0.9891	236544		

# C. Test of the proposed FRRA

In this experiment, the visual quality of the recovered face region using FRRA is calculated using PSNR and SSIM. Table V presents the results for the ten face images shown in Fig 5. Samples of the recovered face regions using this algorithm are shown in Fig 8.

TABLE V

TEST OF VISUAL QUALITY AND LENGTH OF SEQUENCE FOR TRRA					
Image name	PSNR	SSIM	Lseq		
Img_1	33.0215	0.9326	122880		
Img_2	41.901	0.998	53760		
Img_3	38.5454	0.9884	995328		
Img_4	34.9665	0.9811	387072		
Img_5	29.9417	0.9543	124416		
Img_6	37.7847	0.9912	258048		
Img_7	26.4317	0.9439	30720		
Img_8	31.6808	0.9554	344064		
Img_9	31.3559	0.9787	98304		
Img_10	40.4415	0.9929	236544		



Fig. 8 Sample results from FRRA algorithm.

### D. Comparison between the proposed algorithms

This section presents a comparison of visual quality for average  $2\times2$  (AVG  $2\times2$ ), IWT (cdf 3.5), and FRRA. Table VI and Table VII compare PSNR results for the ten test images

shown in Fig 5, which proved that the best visual quality of the recovered face region has been obtained using FRRA.

TABLE VI Comparison of PSNR (db)					
Image name	Lseq	AVG 2×2	IWT cdf 3.5	Proposed FRRA	
Img_1	122880	30.6599	32.9982	33.0215	
Img_2	53760	35.4847	33.9581	41.901	
Img 3	995328	35.5698	38.394	38.5454	
Img_4	387072	31.5999	34.788	34.9665	
Img 5	124416	27.589	29.8801	29.9417	
Img 6	258048	33.6023	35.6123	37.7847	
Img <sup>7</sup>	30720	25.2304	26.268	26.4317	
Img 8	344064	30.5817	31.6545	31.6808	
Img 9	98304	29.4238	30.5773	31.3559	
Img 10	236544	36.7524	39.5158	40.4415	

## IV. CONCLUSION

The recent interest of the research community has been directed toward face image manipulation detection (FIMD) techniques where different algorithms have been presented. Recently, the watermarking based FIMD proved its efficiency in detecting and localizing various manipulations in the face image. However, the recovery of the original face image has not been highlighted. To improve the performance of the watermarking based FIMD technique, this paper highlighted the need for recovering the face region if manipulations exist using recovery algorithms based on average  $(2 \times 2)$ , IWT (cdf 3.5), and bicubic interpolation. The visual quality of the recovered face images using the proposed algorithms has been tested using PSNR and SSIM. The results proved that the proposed face region recovery algorithm using bicubic interpolation obtained the best results and can be considered in the future to be included in the FIMD technique.

TABLE VII Comparison of SSIM

Image name	AVG 2×2	IWT cdf 3.5	Proposed FRRA
Img_1	0.9054	0.9337	0.9326
Img_2	0.9921	0.9843	0.998
Img_3	0.9809	0.9882	0.9884
Img 4	0.9702	0.9785	0.9811
Img_5	0.9379	0.9526	0.9543
Img 6	0.9822	0.9874	0.9912
Img <sup>7</sup>	0.9329	0.9272	0.9439
Img 8	0.9465	0.9546	0.9554
Img 9	0.9694	0.9758	0.9787
Img_10	0.9857	0.9891	0.9929

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