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A Multi-model Restoration Algorithm for Recovering Blood Vessels in Skin Images

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Abstract — Blood vessels under skin surface have been used as a biometric trait for many years. Traditionally, they are used only in commercial and governmental applications because infrared images are required to capture high quality blood vessels. Recent research results demonstrate that blood vessels can be extracted directly from color images potentially for forensic applications. However, color images taken by consumer cameras are likely compressed by the JPEG compression method. As a result, the quality of the color images is seriously degraded, which makes the blood vessels difficult to be visualized. In this paper, a multi-model restoration algorithm (MMRA) is presented to remove blocking artifacts in JPEG compressed images and restore the lost information. Two mathematical properties in the JPEG compression process are identified and used to design MMRA. MMRA is based on a tailor-made clustering scheme to group training data and learns a model, which predicts original discrete cosine transform coefficients, from each grouped dataset. An open skin image database containing 978 forearm images and 916 thigh images with weak blood vessel information and a set of diverse skin images collected from the Internet are used to evaluate MMRA. Different resolutions and different compression factors are examined. The experimental results show clearly that MMRA restores blood vessels more effectively than the state-of-the-art deblocking methods.

Keywords: JPEG compression, biometrics, image restoration, deblocking, image quality, forensics

1. Introduction

Because of the recent advances of imaging technology, the number of evidence images, e.g., child pornographic images, is increasing dramatically [1-3]. Criminals in some of these images, e.g.,

pedophiles, usually show only skin with neither faces nor tattoos to avoid identification. This identification problem is not limited to child sexual abuse cases, but also includes masked gunmen, riots and terrorist attacks. Most of the traditional biometric traits, including face, fingerprint, DNA and palmprint are not applicable to these evidence images. Skin marks, scars, and androgenic hair patterns give valuable information for identifying the criminals [4-7]. However, they are insufficient to address the problem. Not every criminal has a unique scar, skin mark or androgenic hair pattern on a particular body site exposed in the images.

Hand veins, palm veins and finger veins have been widely studied for development of commercial biometric systems because they can be captured in contactless environments and are difficult to be forged [43-44]. Vein patterns are generally considered as a hard biometric trait. Infrared and laser imaging systems are required to capture this vascular information under skin, because they have high penetration ability, comparing to visible light. Recently some researchers attempt to visualize blood vessels hidden in color images for commercial biometric, healthcare and forensic applications [8-11]. Their results exposed the potential of using blood vessels for criminal and victim identification. However, most of evidence images in the cases mentioned above are taken by consumer cameras and compressed by the JPEG method [12]. Vascular information hidden in images can be seriously degraded by the JPEG method, which makes the visualization methods not work. Fig. 1 shows three images collected from the Internet as examples. The first column shows the original color images¹. The second column shows the corresponding visualized blood vessels [10]. The third and the last columns show their visualized blood vessels from the JPEG compressed versions with compression factors of 75 and 50 respectively. Blood vessels from the original images (the second column) are clear, but they are seriously degraded by the JPEG method (the third and last columns). Thus, to finally utilize blood vessels for identifying criminals and victims or searching suspects, vascular information should be restored before applying the visualization methods.

¹ The images were downloaded from the Internet and were originally compressed by JPEG method. To show the degradation effects, original (uncompressed) images were required. Thus, the downloaded images were resized to remove the compression effects and referred to as references.

Fig. 1 Illustration of vascular information degraded by the JPEG method. The first column is three original images collected from the Internet. The second column is the corresponding blood vessel patterns visualized by Zhang et al.'s method [10]. The third and the last columns show their visualized blood vessels from the JPEG compressed versions with compression factors of 75 and 50 respectively.

Though many deblocking methods have been proposed, they are not suitable to restore vascular information because they are designed for generic images. These methods attempt to remove blocking artifacts, but original information is not guaranteed to be restored. Some priors are imposed on some of these methods. However, they are not related to blood vessel quality. In fact, many of them further deteriorate the vascular information, which is already weakened by the JPEG method. An effective blood vessel restoration method should recover the original information and suppress the blocking artifacts as well. In this paper, statistics of skin images and mathematical properties in the JPEG method are used to design the proposed algorithm, multi-model restoration algorithm (MMRA), to remove blocking artifacts and recover blood vessels from JPEG compressed skin images. MMRA is an application-specific method [13-17], which uses prior knowledge from the JPEG compression process to cluster training sets and learn a model for each clustered dataset to perform restoration.

The rest of this paper is organized as follows. Section 2 briefly introduces the JPEG method and previous deblocking methods. Section 3 presents the proposed algorithm. Section 4 reports the experimental results and comparisons. Section 5 offers some concluding remarks.

2. The JPEG method and related works

The main steps of the JPEG method are illustrated in Fig. 2(a). Images are first transformed from the RGB color space into the YUV color space. The three channels are processed separately in the rest of the operations. As human vision is less sensitive to the chrominance channels, the U and V channels are down-sampled. Then, the three channels are divided into 8 by 8 blocks and each block is processed by the discrete cosine transform (DCT). The quantized DCT (QDCT) coefficients are computed by,

$$x_{zk}^j = [y_{zk}^j / q_{zk}], \quad (1)$$

where y_{zk}^j denotes the k^{th} DCT coefficient in the j^{th} block and the z channel; q_{zk} is a value from a predefined quantization table, Q_z ; $k \in \{1, 2, \dots, 64\}$; $z \in \{Y, U, V\}$ and $[]$ is a round operator. Finally, the QDCT coefficients are encoded to increase compression ratio without further information loss. As shown in Fig. 2(b), the DCT coefficients are arranged in a zigzag order in which a lower frequency coefficient has a lower order. The first element is a DC coefficient and the others are AC coefficients. Figs. 2(c) and (d) are two quantization tables for generating images with a quality factor of 50 [12], where Q_y is for processing the Y channel and Q_{uv} is for processing the U and V channels. Note that they are different. Most of the values in Q_{uv} are larger than the corresponding values in Q_y . As a result, the compressed U and V channels have more noticeable blocking artifacts than the compressed Y channel. In the JPEG compression process, the down-sampling operation removes information in the U and V channels; the block-based operations destroy data correlation between adjacent blocks, and the coarse quantization procedure eliminates high frequency information. These operations produce blocking artifacts and seriously deteriorate image quality, which makes blood vessel patterns hardly to be visualized.

1	2	6	7	15	16	28	29
3	5	8	14	17	27	30	43
4	9	13	18	26	31	42	44
10	12	19	25	32	41	45	54
11	20	24	33	40	46	53	55
21	23	34	39	47	52	56	61
22	35	38	48	51	57	60	62
36	37	49	50	58	59	63	64

(b)

16	11	10	16	24	40	51	61
12	12	14	19	28	58	60	55
14	13	16	24	40	57	69	56
14	17	22	29	51	87	80	62
18	22	37	56	68	109	103	77
24	35	55	64	81	103	113	92
49	64	78	87	103	121	120	101
72	92	95	98	112	100	103	99

(c)

17	18	24	47	99	99	99	99
18	21	26	66	99	99	99	99
24	26	56	99	99	99	99	99
47	66	99	99	99	99	99	99
99	99	99	99	99	99	99	99
99	99	99	99	99	99	99	99
99	99	99	99	99	99	99	99
99	99	99	99	99	99	99	99

(d)

Fig. 2 Introduction to the JPEG method. (a) is an illustration of the JPEG method. (b) is the zigzag order. (c) is the quantization table Q_y for the Y channel with a quality factor of 50 and (d) is the quantization table Q_{uv} for the U and V channels with a quality factor of 50.

Restoring blood vessels from JPEG images is challenging because vascular information in uncompressed images is weak already and the JPEG operations further deteriorate this information. Consequently, there is very little information in the compressed images available for restoration. Many methods have been proposed for removing JPEG artifacts. Based on the operations, they can be classified into two categories: the preprocessing approach and the postprocessing approach [18]. The preprocessing approach reduces the blocking artifacts before or during the compression process at the encoder end [19-23]. These methods are not applicable to evidence images because the images generated by consumer cameras are already compressed by the JPEG method. It is impossible to control imaging procedures in crime scenes. The postprocessing approach deals with JPEG images at the decoder end. Since blocking artifacts are high frequency noise, postfiltering methods were proposed to smooth them [24]. Adaptive filtering methods were further developed to avoid blurry effects [25-27]. Liaw et al. recovered the high frequency components to improve image quality by using classified vector quantization [28]. Overcomplete wavelet representations were adopted to reduce blocking artifacts [29-30]. From the perspectives of probability, the blocking artifact reduction problem was formulated as a maximum a posteriori (MAP) problem [31-33]. Projection onto convex sets (POCS) based methods were also proposed to suppress blocking artifacts [34-36]. Adaptive kernel regression method was employed in both the frequency and spatial domains to remove blocking artifacts [45]. A structure-texture decomposition based method was integrated into a contrast enhancement framework to suppress the artifacts boosted by image enhancement operations [46].

The JPEG deblocking methods introduced above are not ideal for recovering skin features, such as skin marks and blood vessels for forensic analysis because they were designed for generic images. Most of them do not make use of extra information. Some of them even further destroy the

information left in the JPEG compressed images. To overcome these drawbacks, learning based methods specially developed for skin image restoration were proposed. A knowledge-based (KB) method was proposed to recover skin marks in JPEG compressed skin images [37]. Previous works show that it is effective for restoring skin marks but not for blood vessels, because this method did not consider the cross block and cross channel dependence. Our previous work takes QDCT coefficients in compressed images as features and uses a regression method to estimate the original DCT coefficients in uncompressed images [38]. Though this method outperforms other methods for restoring vascular information in JPEG skin images, it does not take any mathematical properties of the JPEG compression process into consideration. To overcome the weaknesses of the previous methods, in this paper, a multi-model restoration algorithm (MMRA), which extracts cross block and cross channel information from large databases and makes use of the mathematical properties of the JPEG compression process, is developed and evaluated on one public skin image database and a set of skin images collected from the Internet with diverse quality.

3. The proposed algorithm based on multi-models

The quantization process described by Eq. 1 implies that given a QDCT coefficient x_{zk}^j and a quantization value q_{zk} , the range of the DCT coefficient y_{zk}^j can be determined. It is reminded that k, j and z are respectively indexes for DCT coefficients, blocks, and channels. y_{zk}^j is a real number between $(x_{zk}^j - 1/2) \times q_{zk}$ and $(x_{zk}^j + 1/2) \times q_{zk}$. It should be highlighted that the quantization tables can be obtained from the JPEG image headers. In other words, x_{zk}^j and q_{zk} are always known. In addition, when $x_{zk}^j \neq x_{zk}^i$, the ranges of their DCT coefficients, y_{zk}^j and y_{zk}^i , are not overlapping. These two properties imply that there is no point in using a regression method, which mixes training data with different values of x_{zk}^j together to learn a regression model for estimating y_{zk}^j . In this paper, this regression method is called a global method (GM). To make use of these two mathematical properties, a multi-model restoration algorithm is proposed.

3.1 Notations and statistics of skin QDCT coefficients

For purposes of presentation clarity, a set of notations is presented. Let (f_{zk}, y_{zk}) be a training datum for restoring a QDCT coefficient at location $k \in \{1, 2, \dots, 64\}$ in channel $z \in \{Y, U, V\}$, where f_{zk} is a column feature vector and y_{zk} is a target DCT coefficient from uncompressed images. Because all of the target values y_{zk} discussed below are from the same location k and the same channel z , the subscripts k and z are removed to simplify the notations. Let also the entire feature set and target set, respectively, be $F = \{f_1, \dots, f_n\}$ and $Y = \{y_1, \dots, y_n\}$, where n is the total number of training data for restoring a QDCT coefficient at location k in channel z . The feature set F and the target set Y are respectively organized as $\{F_1, \dots, F_M\}$ and $\{Y_1, \dots, Y_M\}$, where all $y_p \in Y_i$ have the same quantized value, i.e., $\lfloor y_p/q \rfloor = C_i$, $f_p \in F_i$ are the corresponding features and M is the number of different C_i in the training set. $C_i < C_j$ if $i < j$. $\varphi_i(\cdot, \theta)$ is a regression model controlled by a parameter vector θ and trained by $\{F_i, Y_i\}$.

For algorithm design, a statistical analysis on skin images was performed. Fig. 3 shows the probability of non-zero QDCT coefficients estimated from a public skin image database [40]. The quality factor of 50 was used in this statistical analysis. The y-axes are the probabilities of non-zero QDCT coefficients and the x-axes are their orders, given in Fig. 2(b). Most of the QDCT coefficients in the three channels are zero. The first DCT coefficients (the DC coefficients) in all of the channels have the highest probability of non-zero QDCT coefficients, i.e., almost one. Several other QDCT coefficients in the Y channel also have great probabilities of non-zero values. However, for the U and V channels, the probabilities of other non-zero QDCT coefficients are nearly zero. Figs. 4(a)-(c) show the distributions of the quantized DC (QDC) coefficient values of the Y, U and V channels, respectively. Figs. 4(a)-(c) point out that the QDC coefficient values in all of the channels are not uniformly distributed and the probability density in the tails is very low. Fig. 4(d) shows the distributions of the first five quantized AC (QAC) coefficients in the Y channel. As with the QDC coefficients, the QAC coefficients are not uniformly distributed and the probability density in the tails is also very low. Fig. 3 shows that the probabilities of non-zero QAC coefficients in the U and V channels are almost zero.

Fig. 3 (a)-(c) are the probabilities of non-zero QDCT coefficients in the Y, U and V channels respectively.

Fig. 4 The distributions of quantized DCT coefficients of the Y, U and V channels. (a)-(c) are the QDC coefficients in the Y, U and V channels respectively. (d) is the first five QAC coefficients in the Y channel.

3.2 Algorithm design

The proposed algorithm uses multiple $\varphi_i(\cdot, \theta)$, which are trained by different datasets, to perform the restoration. Thus it is named multi-model restoration algorithm (MMRA). The original training set $\{F, Y\}$ for restoring a QDCT coefficient at location $k \in \{1, 2, \dots, 64\}$ in channel $z \in \{Y, U, V\}$ is organized as $\{F_L, F_a, \dots, F_{a+m}, F_R\}$ and $\{Y_L, Y_a, \dots, Y_{a+m}, Y_R\}$, where $F_L = F_1 \cup \dots \cup F_{a-1}$ and $F_R = F_{a+m+1} \cup \dots \cup F_M$ are, respectively, training features for the left and right tails of the DCT distributions and $Y_L = Y_1 \cup \dots \cup Y_{a-1}$ and $Y_R = Y_{a+m+1} \cup \dots \cup Y_M$ are their corresponding target DCT coefficient values. Note that $F_i \cap F_j = \emptyset, \forall i \neq j; F = F_L \cup F_a \cup \dots \cup F_{a+m} \cup F_R$ and $Y = Y_L \cup Y_a \cup \dots \cup Y_{a+m} \cup Y_R$. Fig. 5 illustrates the training phase of the proposed algorithm. Each of the baseline regression models φ_i is trained by a dataset (F_i, Y_i) whose target range is the same. More precisely, $(C_i - 1/2) \times q \leq y_p \leq (C_i + 1/2) \times q, \forall y_p \in Y_i$ and $a \leq i \leq a + m; (C_1 - 1/2) \times q \leq y_p \leq (C_{a-1} + 1/2) \times q, \forall y_p \in Y_L$ and $(C_{a+m+1} - 1/2) \times q \leq y_p \leq (C_M + 1/2) \times q, \forall y_p \in Y_R$. Note that given a testing datum with its QDCT coefficient to be restored, these properties can be used to select the corresponding trained model without any error.

Fig. 5 Illustration of the training phase of the proposed multi-model restoration algorithm. The clustered training data in each set share the same predication range, e.g., $(C_i - 1/2) \times q \leq y_p \leq (C_i + 1/2) \times q, \forall y_p \in Y_i$ and $a \leq i \leq a + m$. Except for (F_L, Y_L) and (F_R, Y_R) , each clustered dataset (F_i, Y_i) is defined as $Y_i = \{y_p | [y_p/q] = C_i\}$, and $F_i = \{f_p | (f_p, y_p), y_p \in Y_i\}$, where $i = a, a + 1, \dots, a + m$, and $p = 1, 2, \dots, n$. $F_L = F_1 \cup \dots \cup F_{a-1}$ and $F_R = F_{a+m+1} \cup \dots \cup F_M$.

Assume that the regression model $\varphi(\cdot, \theta)$ is controlled by a parameter vector θ to predict y_i and it always achieves a global minimum training error for a given training set $\{F, Y\}$ and a predefined error function $\varepsilon(\cdot, \cdot)$, i.e., $\sum_{i=1}^n \varepsilon(y_i, \varphi(f_i, \theta_{\{F, Y\}})) \leq \sum_{i=1}^n \varepsilon(y_i, \varphi(f_i, \theta)), \forall \theta$, where $y_i \in Y, f_i \in F, n$ is the total number of data in F and $\theta_{\{F, Y\}}$ is the optimal parameter vector for the training set $\{F, Y\}$. It can be proven that the proposed MMRA outperforms a global regression method in terms of training error defined by ε i.e.,

$$\sum_{i=1}^n \varepsilon(y_i, \varphi(f_i, \theta_{\{F, Y\}})) \geq \sum_{j \in E} \sum_{y_i \in Y_j, f_i \in F_j} \varepsilon(y_i, \varphi(f_i, \theta_{\{F_j, Y_j\}})), \quad (2)$$

where E denotes the set $\{L, a, \dots, a + m, R\}$. The proof is given in Appendix A. Mathematically, if the training set is organized as $\{F_1, \dots, F_M\}$ and $\{Y_1, \dots, Y_M\}$, lower training error i.e.,

$$\sum_{j \in E} \sum_{y_i \in Y_j, f_i \in F_j} \varepsilon(y_i, \varphi(f_i, \theta_{\{F_j, Y_j\}})) \geq \sum_{j=1}^M \sum_{y_i \in Y_j, f_i \in F_j} \varepsilon(y_i, \varphi(f_i, \theta_{\{F_j, Y_j\}})), \quad (3)$$

can be achieved. The proof is similar to the one given in Appendix A. Training error does not necessarily represent generalization error, especially when the training set is small. To obtain low generalization error, which is well approximated by the training error, the size of each $\{F_i, Y_i\}$ should be taken into consideration. Fig. 4 shows that the probability density in the tails of the QDCT distributions is very low. In other words, the corresponding $\{F_i, Y_i\}$ do not have enough data to

achieve low generalization error. Thus, the training sets for the tails are grouped as $F_L = \{F_1 \cup \dots \cup F_{a-1}\}$, $F_R = \{F_{a+m+1} \cup \dots \cup F_M\}$, $Y_L = \{Y_1 \cup \dots \cup Y_{a-1}\}$ and $Y_R = \{Y_{a+m+1} \cup \dots \cup Y_M\}$.

The skin image analysis and compression test in [39] indicate that the first six coefficients in the Y, U and V channels play a critical role in blood vessel restoration. Their corresponding orders are 1-6 given in Fig. 2(b). Thus, the proposed algorithm only restores these critical DCT coefficients. The grouping scheme is applicable to all of these coefficient values except for non-zero quantized AC coefficient values in the U and V channels. Even if all non-zero quantized AC coefficient values in the U and V channels are included to form F_R and F_L , they are still too small. Our training database is already very large. The baseline regression method employed in the experiment cannot even use up all of the training data because their memory usage reaches the system limit. Thus, it is impossible to use all data directly to train the baseline regression method for restoring the non-zero quantized AC coefficients in the U and V channels. To handle this limit, the feature set F_{ac} sharing the same quantized DC values is used to train the baseline regression method for predicting the non-zero quantized AC coefficients in the U and V channels. More clearly, F_{ac} and the block being restored share the same quantized DC values.

Fig. 6 summarizes the proposed algorithm. It includes a training procedure and a testing procedure. In the training procedure, skin images are first extracted from the raw images and resized to remove the compression effects. These images are employed as original (uncompressed) images. After JPEG compression, image pairs, including uncompressed images and their compressed counterparts are obtained to form the training database. Then, feature vectors and target values are extracted from them separately. Before training the regression models, the data is reorganized according to the clustering rules discussed previously. Then, the regression models are trained using the corresponding datasets, e.g., $\{F_j, Y_j\}$. In the testing procedure, the same feature extraction operation is applied to the input testing image to generate the feature vectors. Then, regression models are selected to restore the DCT coefficients according to the QDCT coefficient values of the target block. Note that because of the properties discussed before, there is no error for the model selection.

Fig. 6 The schematic diagram of the proposed algorithm.

3.3 Features and regression models

The training data generation process for a block from U or V channel, which includes the target value generation from the uncompressed images and the feature generation from the compressed images, is illustrated in Fig. 7. Extracting the original critical DCT coefficients from the uncompressed images as target values is straightforward. The DCT coefficients can be obtained by applying DCT to the images in the YUV color space. According to the zigzag order (Fig. 2(b)), the first six critical DCT coefficients are extracted from the target block as target values. Since the quantization operation is a many-to-one mapping, there are many different uncompressed blocks corresponding to the same compressed block. Using information in one block and in one channel alone is not enough to provide accurate recovery. Thus, it is necessary to explore cross channel and cross neighbour information. The statistics given before show that a lot of QDCT coefficients are zero and therefore, for each block, six DCT coefficients (i.e., $x_{zk}^j \times q_{zk}$) whose orders are 1-6 (Fig. 2(b)) in the Y channel and three DCT coefficients whose orders are 1-3 (Fig. 2(b)) in the U and V channels are used to form the feature vectors for restoration (Fig. 7). For recovering the blocks in the U and V channels, 5 by 5 blocks in the U and V channels are used to generate features. The number of neighbor blocks is determined by

cross validation. Because of the down-sampling operation, each block in these two channels corresponds to four blocks in the Y channel. Thus, DCT coefficients from 100 blocks in the Y channel are used. Features from each block in the Y, U and V channels are concatenated to form the final feature vector with a size of 750 (Fig. 7). Because the down-sampling operation is applied to the U and V channels, the feature generation process for the U and V channels is different from that for the Y channel. In the feature generation process for the Y channel, DCT is directly applied to the compressed U and V channels without the down-sampling operation and therefore, each block in the Y channel has one corresponding block in the U and V channels. For each target block in the Y channel, features are extracted from 9 by 9 blocks in the Y, U and V channels and the final feature size is 972. These features are grouped according to the clustering rules given above for recovering different target DCT coefficients.

Fig. 7 Illustration of training data generation process for U and V channels.

The proposed MMRA employs the gradient boosting algorithm [41] as the baseline regression method φ , and the error function $\varepsilon(\cdot, \cdot)$ is defined as mean squared error. Gradient boosting is an ensemble technique to construct a strong model through combining many weak models and decision trees are the most widely used weak model. Gradient boosting solves the regression problem in an

iterative manner and a model is fit to minimize the gap between the predicted value and the true value in each step.

Given a training set, $\{F_j, Y_j\}$, where $F_j = \{f_1, \dots, f_n\}$, $Y_j = \{y_1, \dots, y_n\}$, and $j \in \{L, a, \dots, a + m, R\}$, the mean squared error function $\varepsilon(\cdot, \cdot)$ and the number of iterations T , gradient boosting optimizes φ through the process below.

1. The model $\varphi_0(f_i, \theta_0) = \omega_0, \forall f_i \in F_j, i = 1, 2 \dots n$, where ω_0 is computed through

$$\omega_0 = \arg \min_{\omega} \sum_{i=1}^n \varepsilon(y_i, \omega) = \arg \min_{\omega} \sum_{i=1}^n \|y_i - \omega\|^2. \quad (4)$$

2. For $t = 1$ to T ,

- a. The residuals are computed as, $R_{j,t} = \{r_{t,i} | r_{t,i} = y_i - \varphi_{t-1}(f_i, \theta_{t-1}), i = 1, 2 \dots n\}$.
- b. A regression tree $h_t(\cdot, \lambda_t)$, where λ_t is a parameter vector, is learned to fit the residuals $R_{j,t}$ using F_j as features.
- c. The model is updated through,

$$\varphi_t(\cdot, \theta_t) = \varphi_{t-1}(\cdot, \theta_{t-1}) + \gamma h_t(\cdot, \lambda_t), \quad 0 < \gamma < 1, \quad (5)$$

where γ is a predefined shrinkage parameter to prevent over fitting.

3. The final model is $\varphi(\cdot, \theta_{\{F_j, Y_j\}}) = \varphi_T(\cdot, \theta_T)$.

3.4 Post-processing

The restored images and the compressed images should have the same QDCT coefficients. Therefore, the recovered DCT coefficients should subject to a quantization constraint which is defined as

$$[\bar{y}_{zk}^j / q_{zk}] = x_{zk}^j, \quad (6)$$

where $\bar{y}_{zk}^j$ is the final restored DCT coefficient, and x_{zk}^j and q_{zk} are defined in Eq. 1. The predicted DCT coefficients, $\hat{y}_{zk}^j$ are further processed by,

$$\bar{y}_{zk}^j = \begin{cases} x_{zk}^j \times q_{zk} + q_{zk}/2, & \text{if } e_{zk}^j > q_{zk}/2, \\ x_{zk}^j \times q_{zk} - q_{zk}/2, & \text{if } e_{zk}^j < -q_{zk}/2, \\ \hat{y}_{zk}^j, & \text{otherwise,} \end{cases} \quad (7)$$

where $e_{zk}^j = \hat{y}_{zk}^j - x_{zk}^j \times q_{zk}$.

4. Experimental results

A public skin image database (NTU Forensic Image Database (NTUFID), including NTU Inner Forearm Image Database v1 and NTU Inner Thigh Image Database v1), [40] and a set of images collected from the Internet (NTU Internet Image Set v1 (NTUIIS²)) were used to evaluate the performance of the proposed algorithm. To test images with different compression levels, the compression quality factors of 50 and 75 were used in the experiments. These two quality factors were selected because some skin images collected from the Internet had quality factors lower than 75 and they are commonly employed to evaluate deblocking algorithms for generic images. Images in NTUFID were used to generate training data for evaluating MMRA on both the NTUFID and the Internet image set. The method reported in [10] was used to visualize blood vessels in these experiments.

NTUFID has four parts: a left forearm dataset, a right forearm dataset, a left thigh dataset and a right thigh dataset. Each limb in these datasets has two images, collected in two sessions with an interval of 11 days. Images in the left and right forearm datasets were, respectively, collected from 239 and 250 subjects. Images in the left and right thigh datasets were, respectively, collected from 230 and 228 subjects. In total, the database contains 1,894 images. The imaging configuration, such as the illumination and the background, was changed in the data collection. The poses of the subjects were not strictly restricted. The subjects were different in races and ages. The collected images were saved in the JPEG format with a high quality factor and without noticeable quality degradation. To construct testing and training databases for algorithm development and evaluation, the limbs were extracted from the raw images and aligned. Then, the limbs were further resized to remove the compression effects and referred to as the original (uncompressed) images. Fig. 8(a) gives some raw images in the datasets. The raw images show that the data collection process was not strictly controlled. It should be emphasized that evidences in cases of child sexual abuse and other sexual offenses are often high resolution close-up images.

² The dataset is available at <http://forensics.sce.ntu.edu.sg/>.

Fig. 8 Samples of the testing images. (a) raw images with background from the NTUFID and (b) images from the NTUIIS.

To obtain images with different resolutions, skin images in NTUFID are further downsampled to generate a lower resolution image database. To differentiate them, the database with the original scale is denoted as NTUFID_1 and the lower resolution one is denoted as NTUFID_2. Table 1 summarizes the databases.

Table 1. A summary of the databases

Datasets	Abbreviation	Number of limbs	NTUFID_1		NTUFID_2	
			Length (pixels)	Width (pixels)	Length (pixels)	Width (pixels)
Left forearm dataset	LF	239	958	393	480	185
Right forearm dataset	RF	250	1018	371	480	163
Left thigh dataset	LT	230	1127	651	512	288
Right thigh dataset	RT	228	1093	620	512	286

The Internet images in NTUIIS were taken by different persons using different cameras and compressed by the JPEG compression method with different quality factors. NTUIIS contains two parts: NTUIIS_1 and NTUIIS_2. Images in NTUIIS_1 were employed for visual comparison and objective evaluation based on quality indexes. To generate original (uncompressed) images for comparisons, they were resized to remove the compression artifacts and referred to as references. To show the restoration effects clearly, images were downsampled to a low resolution so that blood vessels were clear in the original images and JPEG compression artifacts were observable in the compressed images with the compression factors of 50 and 75. There are 44 images and 40 images in NTUIIS_1 for testing JPEG compression factors of 50 and 75, respectively. For each image in NTUIIS_2, there is one corresponding image from the same body part of the same subject. They were collected for objective evaluation based on blood vessel matching. Fig. 8(b) shows sample images in NTUIIS. It shows that the Internet images vary in terms of background, lighting, resolution, pose and body part, etc. In addition, it can be seen that the Internet images are very different from the images in NTUFID.

4.1 Visual comparisons

Figs. 9-10 show the restoration results from some Internet images in NTUIIS_1. The vascular patterns from the original images and the JPEG compressed images are shown as references. The state-of-the-art deblocking methods, including Foi et al.'s pointwise shape-adaptive DCT method (SADCT), which improves image quality both in terms of objective criteria and visual appearance [26], Sun et al.'s maximum a posteriori method based on a field of experts prior (FOE), which achieves higher PSNR gain and good visual quality [31], Tang et al.'s knowledge-based method (KB), which is specially designed for removing blocking artifacts and restoring biometric traits (e.g., skin marks) in skin images [37], Zhang et al.'s overlapped-block transform coefficient estimation (OBTCE) with block similarity method, which is one of the latest deblocking methods [33], Florentín-Núñez et al.'s adaptive kernel regression (AKR) based method, which operates in the both frequency and spatial domains [45] and Li et al.'s blocking artifact suppression method, which is specially designed for contrast enhancement framework (CEFAS) [46], were used for comparison. The skin prior learning algorithm given by Laurens van der Maaten [47] is used in FOE [31], except explicit indication. The state-of-the-art deblocking methods are selected for comparison because no other research team attempted to restore blood vessels in JPEG images and the most related works are deblocking methods for generic images. Fig. 9 shows the results restored from JPEG compressed images with a quality factor of 50 and Fig. 10 shows the results from JPEG compressed images with a quality factor of 75.

The results show that the SADCT method and the FOE method smooth the blocking artifacts effectively. However, they blur the blood vessels at the same time and some details are wiped away. The blurry effect is even more serious in the low resolution images. The OBTCE method does not improve the image quality significantly comparing with the blood vessels from the JPEG compressed images. The blocking artifacts are suppressed by the AKR and CEFAS methods, but some details of the blood vessels are missing. The KB method also can reduce the blocking artifacts, but it is not effective to restore the blood vessels. Some blood vessels are clear in the results from the compressed images but they are destroyed by the KB method. The proposed algorithm gives better performance than the existing deblocking methods in terms of visual effect. It reduces the blocking artifacts

effectively and recovers the deteriorated blood vessels in the Internet images, which are very different from the training images from NTUFID. More results are given in Appendix B.

Fig. 9 The restoration results from the JPEG compressed images with a quality factor of 50. (a)-(c) show three examples. The first row of each example shows the original color image, the uncovered vein patterns from the skin regions, the vein patterns from the JPEG compressed images with a quality factor of 50 and the restoration results from FOE [31] and SADCT [26] methods. The second row of each example shows the results from KB [37], AKR [45], OBTC [33], CEFAS [46] and MMRA. 'JPEG50' means the JPEG compression with a quality factor of 50.

Fig. 10 The restoration results from the JPEG compressed images with a quality factor of 75. (a)-(c) show three examples. The first row of each example shows the original color image, the uncovered vein patterns from the skin regions, the vein patterns from the JPEG compressed images with a quality factor of 75 and the restoration results from FOE [31] and SADCT [26] methods. The second row of each example shows the results from KB [37], AKR [45], OBTCE [33], CEFAS [46] and MMRA. ‘JPEG75’ means the JPEG compression with a quality factor of 75.

4.2 Objective evaluation based on the structural similarity (SSIM) index and PSNR

To evaluate the effectiveness of the proposed algorithm objectively, the structural similarity (SSIM) index [42] and PSNR, which are full reference image quality metrics, were utilized. Greater values of the SSIM index and PSNR indicate that the testing image and its reference image are more similar. In this evaluation, the vascular images from the uncompressed images were regarded as references. The vascular images from the JPEG compressed images and the images restored by the deblocking methods were regarded as testing images.

The mean SSIM indexes and the mean PSNR from the compressed Internet images in NTUHS_1 and the compressed NTUFID images with quality factors of 50 and 75 are given in Tables 2 and 3. The proposed MMRA performs the best in all the experiments in terms of PSNR. For NTUFID images, it also outperforms all the other methods in terms of SSIM. For the Internet images, it is the second best in terms of SSIM. Though CEFAS [46] obtains the highest SSIM for the Internet images, it is not stable. Its performs even worse than JPEG images in terms of both SSIM and PSNR for NTUFID. For the Internet images with quality factor of 50, PSNR from CEFAS is also lower than that from JPEG images without any processing. All the other methods also have a similar situation. In some experiments, they perform even worse than the JPEG images. The improvements from the proposed MMRA are more obvious for NTUFID than that from the Internet images because the Internet images are different from the training data. The aim of this paper is to restore JPEG images for visualizing clearer blood vessels. The SSIM and PSNR in the original color domain are not given in here because they do not measure the quality of blood vessels.

For readers who are interested in the SSIM and PSNR from the RGB domain, they are given in Appendix C. The results in Appendix C show that both the mean SSIM index and PSNR from the original and JPEG compressed images in the RGB domain are quite similar, which is consistent with human observation. Comparing with generic images, skin texture images are not sharp and more homogeneous, so the degradation from JPEG compression is less observable to human vision and less detectable for the quality indexes designed to mimic human vision in the RGB domain. Images in Fig. C1 in Appendix C have been highly compressed but it is hard for human vision to observe their JPEG artifacts. In the JPEG compression process, the U and V channels are compressed more seriously

than the Y channel because human vision is less sensitive to the U and V channels, which leads to the more serious degradation in the U and V channels. The analysis of blood vessel quality [39] shows that most of the vascular information exists in the U and V channels, while the Y channel only contains little vascular information. The degradation in the blood vessel images is more noticeable than that in the RGB domain because they rely on information in the U and V channels. Fig. C1 in Appendix C shows the visual effect of the degradation caused by JPEG compression in the RGB domain, the Y, U and V channels, and the vascular image. The original color image, the Y, U and V channels and the blood vessels from the original image are shown as references in the first row. The second row shows the corresponding compressed image with a quality factor of 50, the Y, U and V channels and the blood vessels from the compressed image. The figure shows that some blood vessels are visible in the U and V channels. It also can be seen that the degradation in the Y channel is not observable, while the blocking artifacts in the U and V channels and the vascular image are obvious.

Table 2. (a) Mean SSIM indexes and (b) Mean PSNR from the Interent images

	JPEG	#FOE [31]	SADCT [26]	KB [37]	AKR [45]	OBTCE [33]	CEFAS [46]	Proposed MMRA
JPEG50	0.4377	0.4490/0.4460	0.4458	<u>0.3271</u>	0.4541	0.4439	0.4621	0.4589
JPEG75	0.5099	0.5133/0.5120	<u>0.4736</u>	<u>0.3899</u>	0.5181	0.5138	0.5195	0.5164

	JPEG	#FOE [31]	SADCT [26]	KB [37]	AKR [45]	OBTCE [33]	CEFAS [46]	Proposed MMRA
JPEG50	24.13	<u>21.64/23.76</u>	<u>22.93</u>	<u>22.37</u>	<u>23.60</u>	<u>24.08</u>	<u>23.72</u>	24.21
JPEG75	25.28	<u>23.46/24.83</u>	<u>23.66</u>	<u>24.17</u>	<u>24.57</u>	25.35	25.44	25.81

The best method for each quality factor is highlighted. The methods with the mean SSIM or PSNR lower than those of the JPEG images are underlined.

Two FOE values are given. The first one is obtained from a prior learned through generic images and the other is obtained from a prior learned through NTUFID.

Table 3. (a) Mean SSIM indexes and (b) Mean PSNR from NTUFID

	JPEG	#FOE [31]	SADCT [26]	KB [37]	AKR [45]	OBTCE [33]	CEFAS [46]	Proposed MMRA
JPEG50	0.2674	<u>0.2654/0.2545</u>	<u>0.2585</u>	<u>0.2466</u>	0.3151	0.2716	<u>0.2635</u>	0.3431
JPEG75	0.3149	0.3170/ <u>0.3020</u>	<u>0.2905</u>	<u>0.3073</u>	0.3618	0.3271	<u>0.3044</u>	0.3868

	JPEG	#FOE[31]	SADCT [26]	KB [37]	AKR [45]	OBTCE [33]	CEFAS [46]	Proposed MMRA
JPEG50	14.82	<u>12.64/13.52</u>	<u>12.66</u>	19.24	17.16	<u>14.34</u>	<u>12.86</u>	20.43
JPEG75	13.81	<u>12.81/12.88</u>	<u>12.42</u>	17.67	15.23	13.90	<u>12.98</u>	18.62

The best method for each quality factor is highlighted. The methods with the mean SSIM or PSNR lower than those of the JPEG images are underlined.

Two FOE values are given. The first one is obtained from a prior learned through generic images and the other is obtained from a prior learned through NTUFID.

4.3 Objective evaluation based on blood vessel matching

In this subsection, an evaluation based on matching accuracy is reported. The three-step blood vessel matching method [10] was utilized to compute cumulative matching characteristic (CMC) curve as a performance index. The matching evaluation was performed on NTUFID_1 and NTUFID_2. Two-fold cross validation was adopted in the matching experiments. In the first set of experiments, the datasets collected in the first session were employed as the probe sets and the datasets collected in the second session were employed as the gallery sets. In the second set of experiments, the probe sets and the gallery sets were swapped. The average accuracy of the two folds is regarded as the final results. The matching results from NTUFID_1 and NTUFID_2 are shown in Figs. 11-12. The matching results from the original images and the JPEG compressed images are given as references. Besides the proposed MMRA, the KB, FOE, SADCT, OBTCE, CEFAS, AKR, GM and DT methods are given for comparisons. GM stands for a global method without using the clustering scheme proposed in this paper and DT refers to our preliminary approach using decision tree [38].

Fig. 11 shows that MMRA provides the best performance comparing other deblocking methods and the results from the JPEG compressed images for all the four limb datasets. It pinpoints that in most of the cases, the results given by the OBTCE, FOE, CEFAS and SADCT methods are lower than the JPEG images without any processing because they were in fact designed for generic images. The KB method designed for skin images can restore some blood vessels for all the datasets, except for the left forearm dataset. Fig. 12 shows that the proposed algorithm significantly improves the matching accuracy comparing the results from the JPEG compressed images. It also outperforms the other deblocking methods. The matching results show that MMRA is effective for restoring the degraded vascular information from JPEG compressed images.

Table 4 and Table 5 give the matching results in terms of rank-1 and rank-10 identification accuracy from NTUFID_1 and NTUFID_2 respectively. The term “rank-1 (rank-10) identification accuracy” refers to the percentage of input vascular patterns whose corresponding patterns in the database can be found within the top 1 (10) of the patterns given by the algorithm. Table 4 shows that in terms of the rank-10 identification accuracy, MMRA offers improvements of 17.79%, 24.20%,

15.65% and 19.74% for respectively the left forearm dataset, the right forearm dataset, the left thigh dataset and the right thigh dataset comparing with the JPEG compressed images with a quality factor of 50. Table 4 also shows that MMRA always outperforms the corresponding global regression method using the same baseline regression method. It indicates the effectiveness of the clustering scheme. Comparing the JPEG images without any processing in Table 5, MMRA offers, respectively, improvements of 13.39%, 19.20%, 15.66% and 20.61% in terms of the rank-10 identification accuracy for the left forearm dataset, right forearm dataset, left thigh dataset and right thigh dataset. The experimental results show that MMRA performs better than the other deblocking methods and effectively restores blood vessels. It offers the highest rank-10 matching accuracy in all the evaluations. In terms of rank-1 matching accuracy, GM gives the similar results. Note that the clustering scheme guarantees a lower error in terms of l_2 , which is not equivalent to the matching accuracy.

Table 4. Matching results from NTUFID_1

	LF		RF		LT		RT	
	<i>Rank-1</i>	<i>Rank-10</i>	<i>Rank-1</i>	<i>Rank-10</i>	<i>Rank-1</i>	<i>Rank-10</i>	<i>Rank-1</i>	<i>Rank-10</i>
Original	51.88	69.04	68.60	82.00	46.09	62.39	46.93	61.84
JPEG50	15.06	32.00	21.80	36.40	9.57	23.48	10.53	25.00
FOE [31]	12.55	29.08	17.20	30.40	6.74	21.30	7.02	21.93
SADCT [26]	11.72	25.73	14.40	28.40	7.17	17.17	5.48	20.39
KB [37]	11.92	26.15	20.40	36.80	9.13	24.13	12.28	29.82
AKR[45]	20.08	41.84	31.60	50.80	16.30	34.78	18.64	35.75
OBTCE [33]	13.60	30.96	18.80	34.80	8.48	22.39	9.87	25.66
CEFAS[46]	8.79	21.55	13.40	25.00	6.96	18.26	6.58	19.74
DT [38]	18.62	38.08	31.60	51.40	12.83	26.09	13.16	30.04
GM	28.24	48.54	39.40	59.00	20.00	35.65	23.25	42.11
Proposed MMRA	28.87	49.79	41.00	60.60	21.30	39.13	25.44	44.74

The highest matching accuracy, except for that from the original images, is highlighted.

Table 5. Matching results from NTUFID_2

	LF		RF		LT		RT	
	<i>Rank-1</i>	<i>Rank-10</i>	<i>Rank-1</i>	<i>Rank-10</i>	<i>Rank-1</i>	<i>Rank-10</i>	<i>Rank-1</i>	<i>Rank-10</i>
Original	46.86	64.44	62.60	80.20	46.74	62.82	49.56	64.25
JPEG75	16.11	29.08	13.80	30.20	3.91	13.04	4.17	16.67
FOE [31]	14.23	28.66	14.80	28.80	3.26	13.04	3.29	14.47
SADCT [26]	5.23	14.64	2.60	10.80	1.96	7.39	1.32	9.21
KB [37]	5.44	19.87	8.40	18.60	5.00	19.13	8.55	24.34
AKR[45]	19.46	36.82	20.20	38.60	6.52	21.74	12.94	26.75
OBTCE [33]	15.69	29.50	13.80	30.00	3.26	11.96	3.07	15.57
CEFAS[46]	13.60	25.31	10.40	25.00	2.39	10.00	2.19	12.06
DT [38]	18.20	31.78	18.40	34.20	4.57	17.61	7.46	17.76
GM	22.80	41.00	27.40	47.60	11.96	26.30	17.54	36.40
Proposed MMRA	22.59	42.47	27.00	49.40	11.74	28.70	17.98	37.28

The highest matching accuracy, except for that from the original images, is highlighted.

Fig. 11 The matching results from compressed images with a quality factor of 50. (a)-(d) respectively show the results from LF, RF, LT and RT.

Fig. 12 The matching results from compressed images with a quality factor of 75. (a)-(d) respectively show the results from LF, RF, LT and RT.

To match images collected from the Internet, NTUIIS_2, which contains image pairs from the same parts of the same subjects, was constructed. The forearms are extracted and formed two datasets: a left forearm dataset and a right forearm dataset. Their sizes are 156 and 162 images from 78 and 81 subjects respectively. Their quality factors range from 50 to 90. For each subject, two different images were collected so that image pairs can be constructed for matching. Note that two images from the same subject may have different compression quality factors and these images may include both left and right forearms. In the experiments, all the methods used for comparison and MMRA were directly applied to the Internet images without any preprocessing. More clearly, the methods are applied to remove the block artifacts which are not generated by any of our preprocessing but are originally in them. After applying the methods, the forearm skin regions were extracted and further processed for matching. For matching the left (right) forearm images, one image from each left (right) forearm is put into a probe set and the rest of the left (right) forearm images are mixed up the first session images in NTUFID_2 to form a gallery set. The sizes of the left forearm probe and gallery sets are 78 and 317 images and the sizes of the right forearm probe and gallery sets are 81 and 331 images. Fig. 13(a) shows that the proposed MMRA outperforms other deblocking methods in all the ranks and most of them perform even worse than the JPEG images without any processing when matching the left forearm images. MMRA offers 5% improvement comparing to JPEG images in terms of rank-10 matching accuracy. Fig. 13(b) shows the proposed MMRA, FOE, AKR, OBTCE, and CEFAS perform similarly in the first seven ranks, but the proposed MMRA outperforms the others in the rest of ranks.

These experimental results indicate that MMRA can restore JPEG images taken in uncontrolled environment and improve their matching performance.

³Fig. 13 Matching results from NTUIIS_2. (a) is the matching result from the left forearm set and (b) is the matching result from the right forearm set.

5. Conclusion and Discussion

In this paper, a multi-model restoration algorithm (MMRA) is presented for restoring JPEG skin images to visualize clear blood vessels. Two mathematical properties in the JPEG compression method are identified and used to derive MMRA. It has been proven that under a minor assumption, the data clustering scheme used in MMRA always offers lower training error than the corresponding global regression method. To extend this mathematical result for achieving lower generalization error, the size of training sets is taken into consideration and the training sets are re-organized. MMRA is evaluated on a public database with 1894 images from 947 limbs and also images collected from the Internet. To examine its effectiveness, images with different scales and different compression factors are tested. Matching accuracy, PSNR and SSIM index are used as performance indexes. The experimental results show clearly that MMRA outperforms the existing deblocking methods for different scales and different compression levels and effectively restores blood vessel information.

Some may believe that the quantization error is uniformly distributed and therefore, estimating the original DCT coefficients is impossible. If only one quantized DCT was used as an input feature and the quantization error was uniformly distributed, it would be no way to estimate the

³ The matching accuracy in Fig. 13 is higher than the previous experiments because the images have higher quality factors ranging from 50 to 90.

original DCT coefficients. The proposed algorithm can restore skin images because the input features are formed by the quantized DCT coefficients from one block and its neighbouring blocks and channels. Though the compression is performed block-by-block and channel-by-channel, the information in compressed images is across channels and across blocks. More clearly, blood vessels pass through many blocks and their information can be found in Y, U and V channels. To demonstrate that MMRA can reduce the QDCT coefficient error, Figs. 14-15 give the error distributions estimated from NTUFID before and after processing. They show that JPEG quantization errors in skin images are not uniformly distributed and MMRA can effectively reduce the errors.

Fig. 14 Quantized DC coefficient error distributions from JPEG compression with a quality factor of 50. (a)-(c) The error distributions from respectively the Y, U and V channels.

Fig. 15 Quantized DC coefficient error distributions from JPEG compression with a quality factor of 75. (a)-(c) The error distributions from respectively the Y, U and V channels.

The proposed algorithm has two potential applications. The first one is to obtain clearer blood vessels for manual comparison as supporting evidence in courts. Note that soft biometrics, e.g., height and skin color, is always used as supporting evidence even though they are not unique. Also note that fingerprint experts still compare latent prints manually. If clearer blood vessels are restored, they can provide high image quality for manual comparison as supporting evidence. In fact, clear blood vessel patterns have more information than many soft biometrics, e.g., skin color. The experimental results have shown that MMRA can improve visual quality. The second application is to shorten suspect lists. The experimental results show that MMRA can improve matching performance. It implies that it has

potential for shortening suspect lists. Using hidden vascular information in JPEG images for criminal and victim identification is a very new research direction, and further research is necessary.

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