A KNOWLEDGE-BASED ALGORITHM TO REMOVE BLOCKING ARTIFACTS IN SKIN IMAGES FOR FORENSIC ANALYSIS

[1]Chaoying Tang, [1]Adams Wai-Kin Kong, IEEE Member, and [2]Noah Craft

[1]School of Computer Engineering, Nanyang Technological University, Nanyang Avenue, Singapore, 639798;
[2] Los Angeles Biomedical Research Institute at Harbor-UCLA Medical Center, 1000 West Carson St, Torrance, CA 90502

ABSTRACT

Identifying criminals and victims in evidence images, where their faces are covered or obstructed, is a challenging task. In the legal case, United States v. Michael Joseph Pepe (2008), Craft and Kong, who served as expert witnesses, used nevi to identify a pedophile in evidence images. Their expert opinions were challenged, partially because the blocking artifacts generated by the standard JPEG algorithm adversely affected the visibility of the nevi. In addition to this case, a huge amount of JPEG compressed child pornography is posted on-line every day. Although many methods have been proposed to remove blocking artifacts, they are ineffective for our target application. In this paper, a knowledge-based algorithm, which simultaneously removes JPEG blocking artifacts, and recovers skin features, is proposed. Given a training dataset which contains original and compressed skin images, the relationship between original blocks and compressed blocks can be established. This prior information is used to infer original blocks of compressed evidence images. An indexing mechanism is also proposed to deal with large datasets efficiently. Extensive experiments are conducted on images with different characteristics and compression ratios. Both visual comparison and subjective evaluation demonstrate that the proposed algorithm is more effective than other methods.

Index Terms— pornography, skin mark, biometrics

1. INTRODUCTION

Recent technological advances have led to a proliferation of digital media, which can be used as hints for investigation and evidence in legal cases. Enhancing capability of processing this media for criminal and victim identification is becoming an important task. In some cases (e.g. child pornography and masked gunman), faces of criminals cannot be seen, because they are covered or obstructed. Biometric traits on the skin (e.g. skin marks) become important features for criminal identification. Craft and Kong were recruited by the U.S. Department of Justice as expert witnesses for a legal case, United States v. Michael Joseph Pepe (2008), which involved sexual acts with seven pre-teen girls in Cambodia [1]. Craft, who is a certified dermatologist, was required to identify skin marks in digital images (evidence images) collected from a crime scene and skin marks of the suspect, Pepe, for verification, because the face of the criminal in the evidence images could not be observed. Although prosecuted under the “Prosecutorial Remedies and Other Tools to end the Exploitation of Children Today” or PROTECT Act of 2003, the suspect was returned to the U.S., convicted, and faced up to 210 years in prison, unfortunately, Craft’s identification was challenged, partially because the visibility of skin marks was adversely influenced by blocking artifacts. In addition to this case, an enormous amount of child pornography has been posted on the Internet. Although there is no statistics about the percentage of this child pornography compressed by the JPEG algorithm, it would not be a small number, because the JPEG algorithm is an international standard and has been widely installed in digital cameras.

Using biometric traits on the skin for criminal and victim identification highly depends on the quality of evidence images, because the size of these traits in the images is usually very small. Even worse, these evidence images are always compressed by the JPEG algorithm. The blocking artifact is a well-known problem caused by this algorithm. As a result, vein patterns can be broken, and skin marks can be blurred, or even totally removed, especially under high compression ratios. Therefore, it is necessary to remove the blocking artifacts before any forensic analyses.

Many post-processing methods have been developed for removing the blocking artifacts in generic images. They cannot utilize prior knowledge from target images. In fact, these methods make the situation even worse, because they generally smooth images, including the biometric traits, to alleviate blocking artifacts. In addition, the difference between original (uncompressed) images and their resultant images may be even larger than that between original images and compressed images in terms of quantized Discrete Cosine Transform (QDCT) coefficients.

In this paper, we develop a new algorithm, which simultaneously removes blocking artifacts, and recovers skin features. We use a non-parametric approach to extract prior knowledge from skin images. A one-pass algorithm is developed to make inference based on this prior knowledge. We also develop an indexing mechanism to increase its speed. The rest of this paper is organized as follows. Section 2 introduces a representation of prior knowledge from skin images. Section 3 presents the one-pass algorithm and the indexing mechanism. Section 4 reports experimental results. Section 5 offers some concluding remarks.

2. A REPRESENTATION OF PRIOR KNOWLEDGE IN SKIN IMAGES

2.1. Database

To exploit prior knowledge in skin images, we construct a large database composed of skin images collected from different body sites, including the hand, arm, foot, leg, chest and back. The database consists of two parts. The first part (Asian database) was collected in Singapore from Asians with both genders and diverse ages, occupations and body mass indexes. The second part (Caucasian database) was collected in the US from Caucasians. The two parts have different imaging configurations such as camera models, illumination condition and image distance. We use 75% of the images in the Asian database to form a training set. The remaining 25% are put into the first testing set, and the images in the Caucasian database are considered as the second testing set. Because Caucasians have more skin marks, we use the second testing set to evaluate the performance of the proposed algorithm on skin marks. It should be noted that the images in the training and testing sets are from different individuals, with both genders and different ages.

For the training set, because a large part of the raw images is background, we crop sub-images with 256×256 pure skin pixels from them. This relatively small size not only reduces redundant information, but also improves the speed of the algorithm. Then we use the JPEG algorithm to compress them. Finally the training set contains 5,662 image pairs. Each pair has one original image and the corresponding JPEG compressed image. By cutting the image pairs into 8×8 pixel blocks, we have 5,797,888 block pairs in the training set. By choosing different compression quality factors, we can obtain different training sets.

2.2. Representation of Training Blocks

The relationship between an original block and its compressed result is that they have the same QDCT coefficients. In general, only several coefficients in the upper left corner of a QDCT matrix are non-zero integers. We call them effective coefficients, and use them to form an index vector. Fig. 1 illustrates a QDCT matrix, the effective coefficients and the corresponding index vector. Because the quantization is a many-to-one mapping, different original blocks can have the same QDCT coefficients and index vector. This many-to-one block relationship implies that only the local information inside one block is not sufficient to uniquely determine corresponding original blocks. We should also consider the relationship between neighboring blocks. These block and neighborhood relationships represent the prior knowledge of skin images.

3. A DEBLOCKING ALGORITHM BASED ON PRIOR KNOWLEDGE

3.1. A One-pass Algorithm

Assume that a compressed image is processed block by block in a raster-scan order – from left to right and from top to bottom. In other words, for a target compressed block, three upper and one left neighboring blocks have already been processed, while the other four neighboring blocks have not, as is illustrated in Fig. 2. We use the spatial information in the processed blocks (blocks 1-4 in Fig. 2) and the frequency information in the to-be-processed blocks (blocks 5-8 in Fig. 2) as constraints to search the best original block in the training set. More clearly, we use the pixels in the processed blocks that connect to the target block as a spatial neighborhood, and the index vectors in the to-be-processed blocks as a frequency neighborhood. We call them the hybrid neighborhood of the target block. For each original block in the training dataset, we supplement its hybrid neighborhood from its source image. In this way, each record in the training set contains an original block, its hybrid neighborhood, and its compressed block. In the testing stage, for a target block w, we use its index vector to find a group of candidate original blocks, $G(w) = \{z \mid QDCT[z] = QDCT[w]\}$. Then we search an optimal candidate according to the hybrid neighborhood of the target block. This search is carried out in two steps. Firstly, we use the frequency neighborhood to narrow down the group i.e.,

$$G'(w) = \{u \in G(w) \mid F_w = F_u\}, \tag{1}$$

where $F_w(F_u)$ represents the frequency neighborhood of $w(u)$. If it is an empty set, we search 20 candidate blocks from $G(w)$ whose frequency neighborhoods are the nearest to F_w to form G'. Then we use the spatial neighborhood to find the optimal original block t^*, i.e.,

$$t^* = \underset{t \in G'(w)}{\operatorname{argmin}}\, d(S_t, S_w), \tag{2}$$

where $S_w(S_t)$ represents the spatial neighborhood of $w(t)$, and d represents $L1$-norm.

3.2. An Indexing Mechanism

To make inference based on prior knowledge, a large training dataset is essential. Our training dataset contains more than 5 million block pairs. It would be extremely time-consuming to search the entire dataset for each testing block. We propose an indexing mechanism, which uses a multi-dimensional structure to store the information of each original block in the dataset, to speed up the searching. The number of dimensions corresponds to the length of index vectors, and each entry represents one index vector and stores the information of the corresponding original blocks, including their positions in the source images, and their hybrid neighborhoods. For a testing block, its index vector immediately leads us to the corresponding entry in the structure.

This indexing mechanism cannot be used directly in the Y component, because its quantization steps are much smaller than those in U and V components. As a result, the number of different index vectors is too large to be stored in a multi-dimensional structure, due to a memory constraint. We preprocess the Y components of the original images by normalizing their intensity values to zero mean and unit variance. Then we recalculate their index vectors, whose varying range decreases dramatically. This normalization step clusters the index vectors in Y components into a limited number of groups, and therefore, they are possible to be stored in a multi-dimensional structure. In each entry of the subsequent structure, we add the non-normalized index vectors as extra information to distinguish individual blocks. This indexing mechanism makes it possible to handle such a large dataset quickly and efficiently.

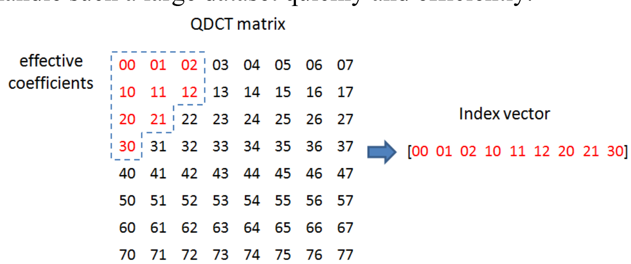

Fig. 1 Illustration of QDCT matrix, effective coefficients, and index vector

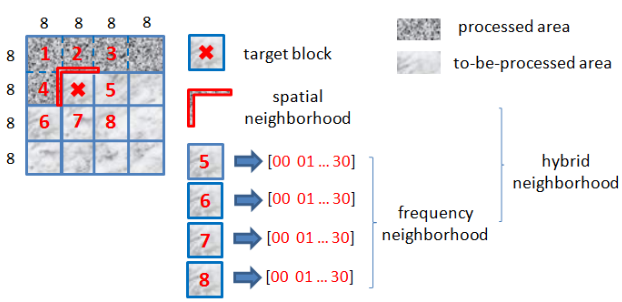

Fig. 2 Illustration of hybrid neighborhood

4. EXPERIMENTAL RESULTS

We compare the proposed algorithm with the popular deblocking methods: Sun et al.'s maximum a posteriori method based on a Field of Experts prior (FOE) which achieves higher PSNR gain [2], Foi et al.'s Pointwise Shape-adaptive DCT method (SADCT) which is one of the latest deblocking techniques [3], Luo et al.'s adaptive processing method (ADPROC) which is efficient at reducing blocking artifacts in smooth regions [4], and Chou et al.'s nonlinear filtering method (NLF) which is fast and robust to different images and quantization strategies [5]. These methods and the proposed algorithm were tested on the two testing sets. The average compression ratios of the two sets are 72.55 and 126.93, respectively. As a result, most skin features were destroyed or completely removed.

Fig. 3 offers four sets of skin images for visual comparison, where the 1st-3rd columns are respectively Y, U and V components, and the 4th column is color images. Their compression ratios are respectively 76.12, 71.50, 78.13, and 115.32. The red circle denotes a skin mark recognized by a medical student under supervision of Craft. The 1st row is original images, the 2nd row is compressed images, the 3rd-6th rows are respectively the results from FOE [2], SADCT [3], ADPROC [4], and NLF [5] methods, and the last row is the result from the proposed algorithm. This figure shows that FOE and SADCT methods have strong smoothing effect, which even removes the skin features; ADPROC and NLF methods have less smoothing effect, but they do not change the compressed images very much; and the proposed algorithm not only removes the blocking artifacts, but also recovers lost skin information including the skin mark.

To quantify these visual comparisons, we carry out a subjective evaluation. We do not use image quality indexes because forensic identification is still based on human, not machine. It is well-known that human is still much better than machine in fingerprint matching. In real cases such as the one mentioned in the first section, law enforcement agents including the U.S. Department of Justice recruit certified dermatologists to recognize skin marks.

Twenty-two observers participated in this experiment. Two of them had dermatological knowledge (one was certified dermatologist, Craft, and the other was a MD student); twelve of them were familiar with image processing; and the rest of them had computer science background. These observers were asked to rate the images using a 10-point scale. For each testing group, we presented an original uncompressed image (as reference), the corresponding compressed image, and the 5 resultant images (4 from the other methods and 1 from the proposed algorithm) to the observers. The experiment was carried out in Y, U, V components and color images. In each case, 125 resultant images were evaluated. Totally 500 images were evaluated, with 65% from the first testing set and 35% from the second testing set. We asked the observers to rate Y, U, and V images according to their similarity with the reference. High grade represents more similarity between reference images and resultant images. For color images, skin marks in reference images were highlighted. An example is given in Fig. 3. Observers are required to compare skin marks. As with the Y, U and V images, the same grading scheme was employed. Ten observers participated in the Y, U and V evaluation, and the other ten participated in the color evaluation, while the two dermatological professionals participated in all the evaluation. The average scores from the professionals and from other participants are given in Table 1 and Table 2, respectively. They show clearly that the proposed algorithm provides the greatest visual quality improvement. These results pinpoint clearly that the proposed algorithm is effective not only for generic skin images, but also for skin marks. They further confirm our visual comparison in Fig. 3.

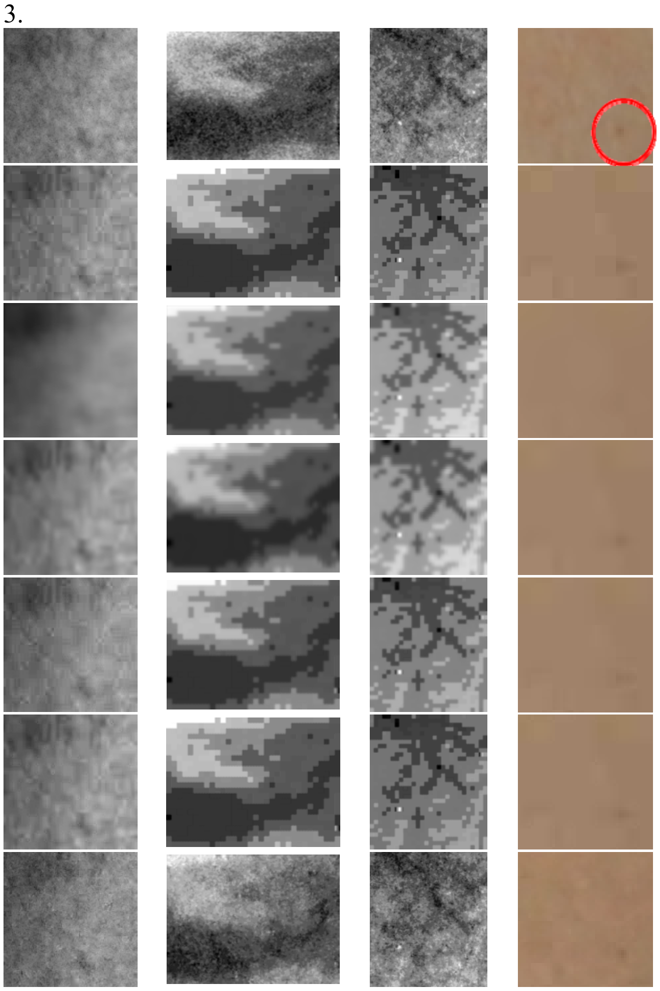

Fig. 3 Evaluation of deblocking performance.
The 1^{st}~3^{rd} columns are respectively Y, U and Y components and the 4^{th} column is color images. The 1^{st} row is original images, the 2^{nd} row is compressed images, the 3^{rd}~6^{th} rows are respectively results from FOE [2], SADCT [3], ADPROC [4], and NLF [5] methods, and the last row is the results from the proposed algorithm.

Table 1. Subjective evaluation results from experts

	Y	U	V	Color
Compressed	5.2600	2.7250	2.5250	4.6500
FOE [2]	2.1600	2.7500	2.6000	3.0625
SADCT [3]	4.0200	2.6500	2.3500	4.7375
ADPROC [4]	4.8600	2.6750	2.6000	4.8250
NLF [5]	5.3200	2.7000	2.6250	5.4625
proposed	**8.1000**	**6.9750**	**6.8750**	**7.0875**

Table 2. Subjective evaluation results from other participants

	Y	U	V	Color
Compressed	5.1840	3.1900	3.1150	4.4075
FOE [2]	2.3600	2.8400	3.2700	2.1875
SADCT [3]	4.2360	2.8050	3.0050	4.3100
ADPROC [4]	5.1860	2.9500	3.1700	3.8050
NLF [5]	5.3480	3.0000	2.9700	4.2775
proposed	**8.1240**	**7.5200**	**7.5850**	**6.7800**

5. CONCLUSION

In this paper, we propose a new algorithm to remove JPEG blocking artifacts in skin images for forensic analysis. It extracts prior knowledge of skin images from a training dataset, and uses it to infer original blocks in compressed evidence images. A one-pass algorithm is developed, and an indexing mechanism is also proposed to speed up the algorithm. Both visual comparison and subjective evaluation demonstrate that the proposed algorithm outperforms other deblocking methods. It not only removes blocking artifacts, but also recovers the lost skin information. The visual quality of biometric features such as skin marks is significantly improved.

6. ACKNOWLEDGEMENTS

We would like to thank the U.S. Department of Justice, the U.S. Immigration and Customs Enforcement, and the Singapore Police Force for their legal and forensic discussions. We also would like to thank the Singapore Prison Service for their assistance in the data collection.

7. REFERENCES

[1] Yahoo! News, May 29 2008, “LA Jury Convicts Ex-Marine in Sex Tourism Case”, http://news.yahoo.com/s/ap/20080530/ap_on_re_us/sex_tourism_1.

[2] D. Sun and W. Chan, “Postprocessing of Low Bit-Rate Block DCT Coded Images Based on a Fields of Experts Prior”, IEEE TIP, vol.16. no.11, pp.2743- 2751, 2007.

[3] A. Foi, V. Katkovnik, and K. Egiazarian, “Pointwise Shape-adaptive DCT for High-Quality Denoising and Deblocking of Grayscale and Color Images”, IEEE TIP, vol.16, no.5, pp.1395-1411, 2007.

[4] Y. Luo and R. K. Ward, “Removing the Blocking Artifacts of Block-Based DCT Compressed Images”, IEEE TIP, vol.12, no.7, pp.838-842, 2003.

[5] J. Chou, M. Crouse, and K. Ramchandran, “A Simple Algorithm for Removing Blocking Artifacts in Block-Transform Coded Images”, in Proceedings of ICIP vol.1, pp.377-380, 1998.