The Impact of Tattoo Segmentation on the Performance of Tattoo Matching

Huang Yi, Peicong Yu, Xingpeng Xu, and Adams Wai Kin Kong
School of Computer Engineering, Nanyang Technological University
Nanyang Avenue, Singapore, 639798
{yhuang, pcyu, xpxu, adamskong}@ntu.edu.sg

***Abstract* —** Tattoos are an important trait for criminal and victim identification and have been widely used by law enforcement agencies around the world. To facilitate it, tattoo images of prisoners, gangsters and other suspects are collected regularly. Up until now, these tattoo images are still manually annotated by law enforcement officers and text-based searching is used to retrieve tattoos of criminals and victims. Researchers have applied image-based matching methods to tattoos. Tattoo images collected from prisoners and crime scenes always include background and body sites other than tattoos. The aim of this paper is to evaluate how these non-tattoo regions impact on the performance of the image based matching methods. In this paper, SIFT and SURF are used as the matching methods. Four experimental settings are designed and over 4000 tattoo images are used in this evaluation. The experimental results pinpoint clearly that non-tattoo regions have negative impact on the matching performance and imply that tattoo matching will benefit from accurate tattoo detection.

Keywords—tattoo segmentation, tattoo detection, tattoo matching, biometrics, criminal and victim identification

I. INTRODUCTION

With the popularity of digital cameras, high quality images are being constantly taken in every corner of the world. Some of these images are vital for law enforcement agencies because they capture the acts of crimes, criminals and victims. Tattoos are an important clue for criminal and victim identification and have been regularly used by law enforcement agencies. In some countries, tattoos are very popular. For example, over 49% populations in the age group of 18-29 in USA have tattoos and over 21% populations in the same age group in UK have tattoos [1]. Though tattoo may not be considered as unique as fingerprint because different persons can have the same tattoo, they provide crucial insight when the primary biometric traits, e.g., face and fingerprint are not available. Fig. 1 shows a masked rioter with a tattoo on his left forearm.

To use tattoos for criminal and victim identification, tattoo images are regularly collected from prisoners, gangsters and other suspects. These images are manually annotated and text-based searching methods are used to retrieve tattoos of criminals and victims. This approach is still widely used by many police departments. The annotation process is time consuming and has unavoidable inconsistency though some agencies have employed certain standards e.g., the NIST tattoo annotation standard.

To match tattoo images collected from crime scenes with tattoo images collected from ex-offenders, gangsters or other suspects, researchers applied the general image matching methods to tattoos. Jain et al. applied content-based image retrieval (CBIR) techniques for automatic tattoo matching, where low-level image features e.g., color, shape and texture, and a histogram intersection method were, respectively, used for representation and similarity measure [3]. In their work, tattoo patterns were segmented from the skin by thresholding the gradient, followed by morphological closing and opening. Acton and Ross tackled the tattoo segmentation problem [4]. They made use of active contour for tattoo segmentation and proposed a global image feature approach, which improved matching performance. Their input images were roughly segmented, in which most background and irrelevant information has been removed. Fig. 2 shows an example of their input images. In order to address the problem of semantic gap, Lee et al. adopted the concept of visual similarity for image retrieval and examined the use of SIFT features for matching [5]. Though the performance was improved, this approach was still hindered by the number of false matches in SIFT-based matching. Lee and Jain indicated that although the local descriptors like SIFT can achieve a promising performance, they suffered from the scalable problem [6]. Therefore, they proposed an ensemble ranking approach to obtain more accurate retrieval results for a large scale database by combining the rankings from multiple bag-of-words models. In tattoo matching, one important procedure is tattoo segmentation. Besides the two segmentation methods mentioned above, Allen et al. proposed an unsupervised tattoo segmentation method which splits each tattoo image into clusters through a bottom-up process [7]. The clusters containing the skin were merged through learning and the tattoo pattern was distinguished from other skin tissues via a top-down prior in the image itself. Detecting and classifying tattoos from uncontrolled and uncooperative images is another challenge. To address this problem, Heflin et al. [8] introduced a new methodology for detecting and classifying tattoos found in the unconstrained imagery typical of forensics scenarios. Another application of content-based tattoo image retrieval is sketch-to-image matching, which is especially important when the query image is not available. Han and Jain [9] proposed a method to match tattoo sketches with tattoo images using local invariant features. Huynh et al. [10] noted that police and prison departments do not have a systematic way to collect tattoo images. They still employ a manual and very time consuming approach. To address this problem, Huynh et al. developed a full-body imaging system which included an automatic and systematic routine for collecting and processing tattoos and other biometric traits, e.g. androgenic hair, skin marks and veins, for criminal identification [12-14].

Fig. 1. A masked rioter with tattoo. [2]

Fig. 2. Examples of input images.

(a) (b) (c)

Fig. 3. (a) a simulated tattoo image collected in police departments. (b) a tattoo image from a crime scenes [17]. (c) a tattoo image collected from victim [18].

(a) (b)

Fig. 4. Tattoo images. (a) original images. (b) segmented tattoo images.

All those works mentioned above were based on roughly segmented tattoo images. Fig. 2 gives 4 examples of their input images. However, images taken from prisoners, gangsters and crime scenes may contain a lot of irrelevant information, e.g., background and other body sites. Fig. 3(a) shows a simulated image collected in police departments. The simulation process is based on our experience working with Singapore Police Force. Figs. 3(b) and (c) show tattoo images collected from a crime scene and a victim. How this irrelevant information impacts on the performance of tattoo matching is not yet known. The aim of this paper is to investigate the impact of tattoo segmentation on the performance of tattoo image matching. In this paper, the term segmented tattoo images refers to cropped tattoo images, where most of the irrelevant information is removed. Some examples are given in Fig. 4. To perform this study, Scale-Invariant Feature Transform (SIFT) and Speeded Up Robust Features (SURF) [15-16] are used to match tattoo images and four different settings are designed: both probe and gallery sets with segmentation, both probe and gallery sets without segmentation, and probe set with segmentation and gallery set without segmentation and vice versa.

The rest of this paper is organized as follows. Section 2 briefly introduces SITF and SURF and presents the testing databases and experimental settings. Section 3 reports the experimental results and discusses the impacts of our findings. Section 4 gives conclusive remarks.

II. Testing Methods, Databases and Experiemntal Settings

Scale-Invariant Feature Transform (SIFT) and Speeded Up Robust Features (SURF), which are invariant to image scaling and rotation, and partially invariant to change in illumination and 3D camera viewpoint, are popular local feature detectors and descriptors for object recognition. They detect repeatable salient points in images and subsequently encode their local image appearance into descriptors.

In SIFT, keypoints are detected using scale-space extrema of difference-of-Gaussian convolved images. Subsequently the gradient magnitude and orientation at the neighbourhood of each keypoint is summarized into orientation histogram and concatenated into 128 dimensional feature vectors.

In contrast, SURF makes uses of determinant of Hessian to detect interest points. And Harr wavelet responses are extracted from the neighbouring region, which result in a descriptor of length 64. SURF has been shown to offer similar performance as SIFT with a faster operational speed [11]. Matching pairs can be found by comparing the Euclidean distance between the features descriptors from two different images.

The testing database contained two sets of tattoo images. One set was composed of 4,332 tattoo images. The other set was collected by our research group in collaboration with Singapore Police Force. It consisted of 200 tattoo images from 100 subjects. Corresponding images from the same subject were captured in two different sessions with an interval ranging from one to two weeks. The images collected in one of the session formed the probe sets and the images collected in the other session were combined with the other 4,332 images to form the gallery sets. To investigate the impact of tattoo segmentation in the matching performance, we manually cropped the tattoos from the original images. The original images with background were referred as images without segmentation while the cropped tattoo images were referred as images with segmentation. Four different settings were designed and tabulated in Table I. All the probe and gallery sets contained, respectively, 100 and 4,432 images. Both SIFT and SURF features were investigated for their matching performance on the four settings.

TABLE I. EXPEIRMENT SETTINGS

	Probe set	Gallery set
Setting 1	Without segmentation	Without segmentation
Setting 2	Without segmentation	With segmentation
Setting 3	With segmentation	Without segmentation
Setting 4	With segmentation	With segmentation

III. RESULTS AND DISCUSSION

Fig. 5 and Fig. 6 show, respectively, the cumulative matching characteristic (CMC) curves of tattoo images matching using SIFT and SURF for the four settings. The best matching result was obtained from using segmented tattoo images in both gallery and probe sets (Setting 4) for both SIFT and SURF features.

Table II lists the detailed matching accuracy using SIFT features. The rank-1 and rank-10 accuracies achieved with segmented tattoo images (Setting 4) using SIFT features were 0.70 and 0.83 respectively. For SIFT features (referring to Fig. 5), the matching results deteriorate when images without segmentation were used (Setting 2, 3 and 4). In terms of rank-1 accuracy, the deterioration was in the range of 2%-12% and in terms of rank-10 accuracy was in the range of 4%-8%. These results indicate that the irrelevant information, e.g., limbs and background, provides incorrect SIFT matching points. Among the settings using tattoo images without segmentation (Setting 1, 2 and 3), none of them consistently performs better than others.

Table III lists the detailed matching accuracy using SURF features. The best matching result was obtained in Setting 4, where both probe and gallery sets were segmented tattoo images. The rank-1 and rank-10 accuracies achieved with segmented tattoo images (Setting 4) were 0.61 and 0.82 respectively. For SURF features (referring to Fig. 6), the results were better when segmented tattoo images were used in the probe sets as in Setting 3 and 4, regardless the type of images used in the gallery sets. For SURF features, using segmented tattoo images in the probe sets have great impact on matching results. The rank-1 accuracies of Setting 3 and 4, which used images with segmentation in probe sets, were 0.5 and 0.61, respectively, while the rank-1 accuracies of Setting 1 and 2, which used images without segmentation in probe sets, were only 0.13 and 0.06 respectively. Results from SIFT and SURF indicate that tattoo segmentation has positive impact on the matching.

TABLE II. ACCURACY OF MATCHING USING SIFT

SIFT	Rank-1	Rank-5	Rank-10	Rank-50
Setting 1	0.58	0.71	0.75	0.86
Setting 2	0.68	0.77	0.79	0.84
Setting 3	0.61	0.73	0.75	0.84
Setting 4	**0.70**	**0.78**	**0.83**	**0.92**

TABLE III. ACCURACY OF MATCHING USING SURF

SURF	Rank-1	Rank-5	Rank-10	Rank-50
Setting 1	0.13	0.21	0.24	0.47
Setting 2	0.06	0.24	0.32	0.46
Setting 3	0.50	0.73	0.75	0.83
Setting 4	**0.61**	**0.78**	**0.82**	**0.86**

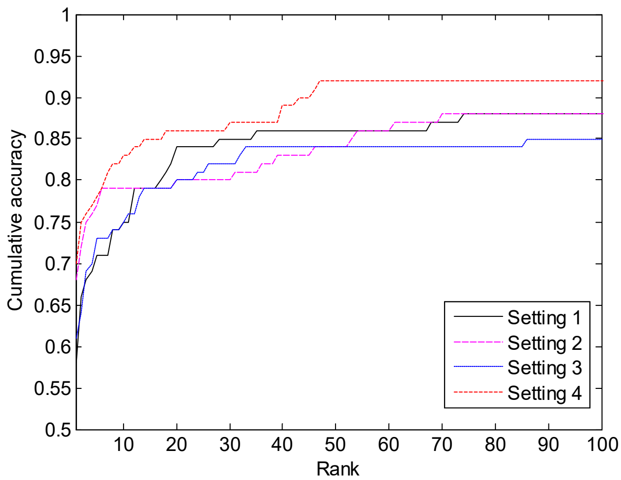


Fig. 5. CMC curves of tattoo images mathcing using SIFT.

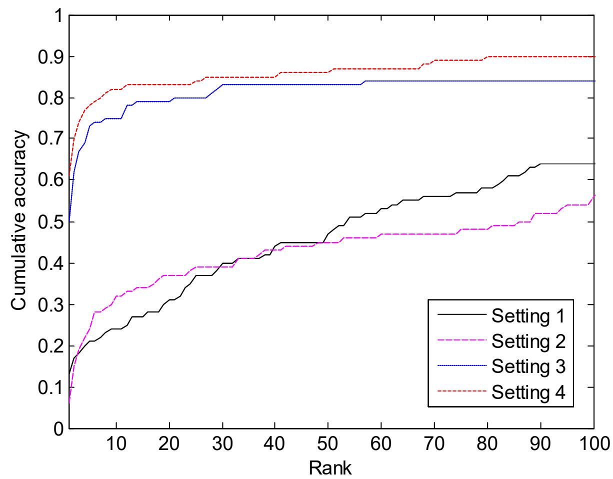
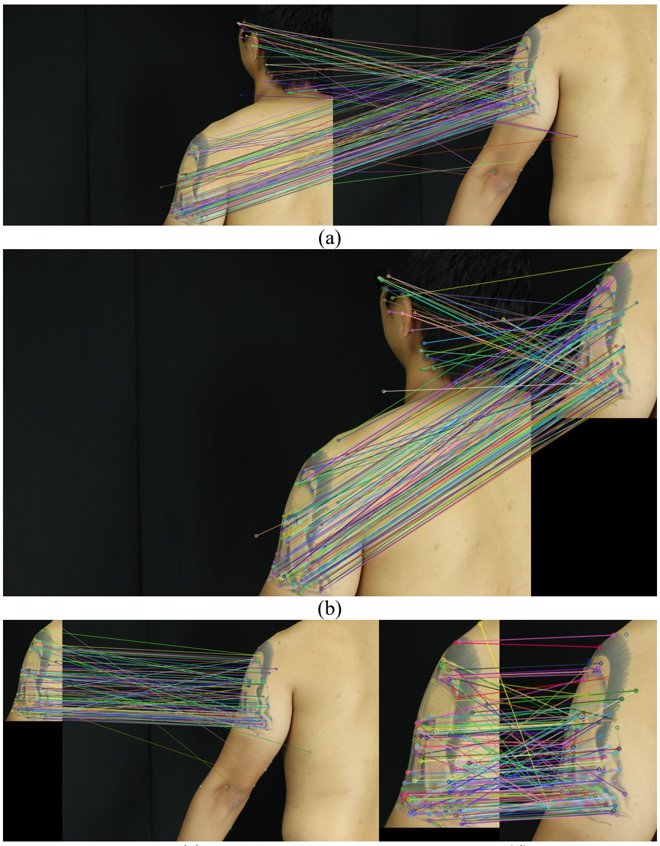


Fig. 6. CMC curves of tattoo images mathcing using SURF.

Figs. 7(a)-(d) are respectively resultant images from Setting 1-4 using SIFT features. Figs. 7(a) and (b) show that the edges of the hair generated a lot of false correspondences. Fig. 7(c) shows that the arm and back produced some false correspondences. As with Figs. 7(a)-(c), Fig. 7(d) has false correspondences within the tattoo, but almost no false correspondences outside the tattoo. These figures demonstrate that the irrelevant information, e.g. arm and hair, provides false correspondences and deteriorates the matching quality.



(a) (b) (c) (d)

Fig. 7(a)-(d) SIFT correspondences from Setting 1-4, respectively.

IV. Conclusion

Tattoos are an important biometric trait for criminal and victim identification and have been widely used by law enforcement agencies around the world. Though image retrieval methods have been applied to tattoo retrieval, the impact of tattoo segmentation has not been studied. Tattoo images collected from prisoners, suspects, and crime scenes always have irrelevant information, e.g., background and limbs. This paper investigated the impact of tattoo segmentation on the performance of tattoo matching through four experimental settings. The experimental results pinpointed clearly that tattoo segmentation has positive impact on the matching performance. Comparing with tattoo matching, only very limited works are related to segment tattoos from the unprocessed images [8, 10]. More effort should be put on this research direction.

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