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Tattoo Based Image Retrieval System Using Sketch to Tattoo

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***Abstract*— Tattoos plays a vital clue to the identification of suspects in criminal investigation. However it's one amongst distinctive symbol, to trace the illicit. Characteristic and taking moles on criminals' body, tattoos also are permanent distinctive identification currently each day. There's already some prosperous tries are created to develop looking out the info for tattoos to spot near-duplicate pictures of a question tattoo image. However several things, the supply image of the crime image isn't available clearly, that the search is within the kind of a sketch of tattoo or free-hand image of a tattoo. In our methodology, we've developed model mistreatment invariant options. Above all, tattoos square measure taken from each tattoo sketch and tattoo image mistreatment unattended learning technique and smart edge detector. A confined feature vector based mostly distributed illustration classification theme is then used for matching. Simulation results on identical pictures of one hundred tattoo sketches against a bunch set with 5000 tattoo pictures shows that the our approach got goodly sweetening (up to fifty seven correctness) compared to gift progressive of sketch to info image matching system.**

***Keywords*— Tattoo, t image retrieval, sketch tattoo**

I. INTRODUCTION

Tattoos on shape give vital clue to the identity of a suspect. whereas a tattoo isn't AN distinctive symbol, it narrows down the list of identities for the suspect. For these reasons, enforcement agencies are grouping tattoo pictures of the suspects at the time of booking. Many prosperous {attempts makes AN attempt tries} are created to style an automatic system to look a tattoo info to spot near-duplicate pictures of a question tattoo image. However, in several situations, the police investigation image of the crime scene isn't accessible, therefore the question is within the type of a sketch of a tattoo (as against a picture of a tattoo) drawn supported the outline provided by AN viewer. during this paper, we have a tendency to extend the potential of tattoo image-to-image matching by proposing a way to match tattoo sketches to tattoo pictures victimisation native invariant options. Specifically, tattoo shape is initial extracted from each tattoo sketch and tattoo image victimisation cagey edge detector.

Figure1: Tattoos Examples.

Local patterns area unit then extracted from tattoo form likewise as tattoo image (appearance) victimisation SIFT. a neighborhood feature based mostly distributed illustration classification theme is then used for matching. Experimental results on matching a hundred tattoo sketches against a gallery set with ten,100 tattoo pictures show that the planned technique achieves vital improvement (rank-200 accuracy of 57%) compared to a progressive tattoo image-to-image matching system (rank-200 accuracy of 19%).

II. RELATED WORK

Soft biometric traits, e.g. scars, marks, and tattoos area unit being more and more wont to complement primary biometric authentication systems supported fingerprint, face, or iris [14]. In fact, criminal investigations have leveraged soft biometric traits as so much back because the late nineteenth century. for instance, the primary personal identification system, the Bertillon system, tried to produce a definite and methodology to spot criminals by victimisation physical measurements of body components, particularly measurements of the top and face, likewise as recording individual scars, marks, and tattoos on the body. Thanks to the importance of soppy biometric traits, the U.S. Federal Bureau of Investigation (FBI) is developing consequent Generation Identification (NGI) system [28] for distinguishing criminals, wherever palm print, face, iris, and SMT are going to be wont to augment fingerprint proof.

Among varied soft biometric traits, tattoos, specially, have received substantial attention over the past many years thanks to their prevalence among the criminal section of the population and their strikingness in visual attention. Tattoos are used as an indication by people to differentiate themselves from others for thousands of years [1]. A recent survey by The

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Harris Poll shows that there has been an enormous increase in quality of tattoos among U.S. adults; regarding one in 5 U.S. adults have a minimum of one tattoo (21%) that is up from Sixteen Personality Factor Questionnaire once identical survey was conducted in 2003 [2].

A. Tattoo Sketch info

There is no operational tattoo sketch information set that we have a tendency to may realize from enforcement agencies. So, in our study, we have a tendency to construct an information set consisting of a hundred tattoo sketches drawn by 2 totally different subjects, every sketch correspond-ing to a celebrated tattoo image. A tattoo image was initial shown to a subject matter for one minute. 10 minutes later, the topic was asked to draw a tattoo sketch (a depiction image) on a white book consistent with his/her memory. The tattoo viewing time and therefore the time gap between viewing the tattoo and drawing the sketch were selected for advantage functions. The tattoo sketches drawn on the paper were then digitized with a scanner. additionally to those a hundred tattoo sketch and image pairs, we have a tendency to conjointly created use of an information set of ten,000 tattoo pictures pro-vided by the Michigan State Police to populate the gallery.

B. Sketch to Image Matching

In several visual perception tasks, alignment is that the key step. for instance, in face recognition, 2 eyes area unit unremarkably wont to normalize face pictures. However, since totally different faces have identical pure mathematics, face alignment will leverage this property throughout landmark detection and alignment. against this, objects in tattoo pictures will be of absolute form, that makes it tough to ascertain the correspondence for the tattoo sketch to image matching task, there area unit extra challenges, specifically the modality distinction and deformation between the 2 entities to be matched. this implies the utilization of native feature similarity in matching a tattoo sketch to a tattoo image. Specifically, it might be fascinating to see whether or not there exist some native patterns or structures that seem in each the sketch and therefore the image. The planned approach initial extracts the tattoo shapes from each the sketch and therefore the image us-ing a grip detector. native patterns area unit then detected from the sting map (tattoo shape) victimisation the SIFT operator [22]. Finally, native pattern based mostly distributed illustration classifier (SRC) [21, 31] is used to live the similarity between a tattoo sketch and a tattoo image.

III. SKETCH TO IMAGE MATCHING

A. Tattoo form extraction

Tattoo pictures that area unit captured victimisation digital cameras, sometimes contain a big quantity of texture data. However, careful texture will hardly be represented in hand drawn tattoo sketches. A tattoo sketch drawn supported statement provided by a witness primarily describes the form of the tattoo. this can be understand-able as a result of studies in human vision counsel that “simple cells” in striate cortex area unit answerable for edge detection, and area unit fairly sensitive to sharp changes in intensity [24]. Following this observation, we have a tendency to propose to match tat-too sketches to tattoo pictures by specializing in the matching of form (structure) information9. Feature illustration as mentioned within the on top of due to the presence of tattoo form deformation between tattoo sketch and image, it's difficult to ascertain a correspondence between their holistic shapes. we have a tendency to more illustrate this challenge, by overlapping a tattoo sketch with its corresponding tattoo image. against this, if we glance at the tattoo sketch and therefore the corresponding tattoo image in native neighborhoods, we discover that there area unit comparatively minor deformations between them (See the native patterns illustrated with red and blue circles. during this section, we have a tendency to propose a way to represent individual tattoo shapes supported their native patterns.

$$IM\text{ - LP}(x,y) = \log \frac{I(x \text{ AND } y)}{I(x) \times I(y)}$$

Here IM represents image matching, LP for local patterns input image x and target image y. Local pattern based methods have found considerable success in a variety of computer vision applications, like object recognition [22], image retrieval [17, 29], and image moseying [7]. The SIFT detector proposed by Lowe [22] is probably the most widely used local operator. SIFT pro-vides a description of an object in an image by detecting salient image regions (interesting points, or key-points). The salient image regions usually lie in high-contrast regions of the image, for example object edges, such that they can be repeatedly detected under changes in viewpoint that induces translation, rotation, and scaling of image, as well as noise and illumination variations.

A. Matching

Sparse Representation-based Classification (SRC) has been found to be very effective for face recognition [21, 31]. It was also reported in [21, 31] that a block or key point based SRC classifier is even more robust than SRC based on holistic gray scale images. Inspired by this idea, we propose to match tattoo sketch to tattoo image using a local pattern based SRC. Specifically, for a probe tattoo sketch, we de-note its local pattern features as Y = {y_i|i = 1, 2, · · ·, m}, where m is the number of local patterns, and y_i is a 128-dimensional feature vector.

$$. \; sim(Y^t_{i,j}, S_{i'}) = \sum_{\forall y^t_{i',l} \in S_{i'}} sim(y^t_{i,j}, w^t_{i',l})$$

$$score(Y^t_{i,j}) = \sum_{\forall i' \neq i} sim(y^t_{i,j}, S_{i'})$$

$$q^t_i = \arg\max_{y^t_{i,j}} score(y^t_{i,j})$$

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III. EXPERIMENTAL RESULTS

A. *Evaluation metrics*

Forensic scenarios with sketch matching (tattoo or face) generally involve an examination by the eyewitness or detective of the top few hundred retrieved tattoo images. Hence, the proposed tattoo sketch to image matching method is evaluated by examining the top-200 retrieval rate using a Cumulative Match Characteristic (CMC) curve. The accuracy of the proposed method is compared against a state-of-the-art image-to-image tattoo matching system, Tattoo-ID [16, 20].

B. *Robustness to deformations*

In this section, we evaluate the robustness of the pro-posed tattoo sketch to image matching approach against several common types of deformation. We consider three types of deformations, i.e., rotation, shear-warp, and twirl (See Fig. 11). Fig. 12 shows two tattoo sketches (A and B) that are first deformed, and then matched to the gallery tattoo images.

The matching scores and retrieval ranks for the two tattoo sketches with and without manual de-formations. For the rotated tattoo sketches, the matching scores range from 0.55 to 1.0, and the retrieval ranks range from rank-1 to rank-22, which demonstrates that the pro-posed approach is fairly robust against rotation[15]. View-point changes lead to shear-warp deformations between a left or right 90° rotation is exactly one of the 8 orientations of the SIFT descriptor. That is why the matching scores for tattoo sketches with 90° rotations are as high as the original tattoo sketch tattoo sketch and a tattoo image. Fig. 12 (b) shows that the proposed approach is robust to shear-warp deformations[16]. Compared with rotation and shear-warp, twirl is a more challenging deformation for tattoo sketch to image matching (See the tattoo sketches in the bottom row. However, the proposed approach can still match most (10 out of 12) of the deformed tattoo sketches within top-200 rank. These experiments reveal the effectiveness of local invariant features for tattoo representation.

Tattoos	Ranks	Tattoo(Input)	Target image
0	0	20	5
10	50	30	15
20	100	45	30
30	150	90	75
40	200	130	110
50	250	150	130
60	300	170	150
70	350	190	170

C. *Matching performance*

We evaluate the performance of the proposed approach by arching 100 tattoo sketches to 10,100 tattoo images. A state-of-the-art image-to-image tattoo matcher, called Tattoo-ID [20] is used as the baseline. As shown in Fig. 13, the matching rates of Tattoo-ID at rank-100 and rank-200 are 13% and 19%, respectively. The performance of Tattoo-ID demonstrates the difficulty of tattoo sketch-to-image matching. By contrast, the proposed system achieves significantly higher matching rates than Tattoo-ID. For example, the matching rates of our system at rank-100 and rank-200 are 48% and 57%, respectively.

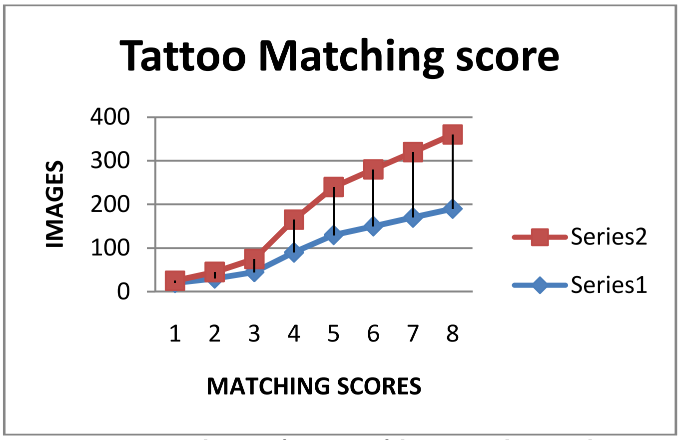

Fig2: Matching performance of the proposed approach

In fig, shows some examples of good and poor matching's by the proposed approach. Three good matches where rank-1 is the correct match. We can find that even in the presence of deformations, the matching score is high. We also noticed that while two tattoos may have several common local patterns, their global structures can be completely different. This suggests the exploration of structural constraints to further improve our method.

IV. CONCLUSIONS

Tattoos on human body provide valuable clue to establish the identity of a suspect or a victim of a crime. While tattoo images are routinely collected by law enforcement agencies, their use so far has been limited due to lack of automatic tattoo matching systems. Recent work on automatic tattoo matching, for instance [16, 20], has shown the ability to identify near-duplicate tattoos. We have extended the state-of-the-art in tattoo matching by devising a method to match tattoo sketch to tattoo image. We constructed a tat-too sketch database with 100 tattoo sketches, and proposed a scheme to match tattoo sketches to tattoo images using local invariant features. The proposed approach was found to be robust against deformations like rotation, shear-warp, and twirl. Our method significantly outperforms a state-of-the-art image-to-image tattoo matcher.

In our future work, we plan to enlarge the tattoo sketch database by using the Amazon Mechanical Turk (AMT) crowd sourcing service. We also would like to improve our approach by integrating human annotations of tattoos, and by

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introducing structural constraints between various local patterns extracted in both tattoo image and sketch. The differences between tattoo image-to-image matching and sketch-to-image matching will also be further investigated.

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