Image Reranking Using Semantic Signatures

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ABSTRACT:

Elastic distortion of fingerprints is one of the major causes for false non-match. While this problem affects all fingerprint recognition applications, it is especially dangerous in negative recognition applications, such as watchlist and deduplication applications. In such applications, malicious users may purposely distort their fingerprints to evade identification. In this paper, we proposed novel algorithms to detect and rectify skin distortion based on a single fingerprint image. Distortion detection is viewed as a two-class classification problem, for which the registered ridge orientation map and period map of a fingerprint are used as the feature vector and a SVM classifier is trained to perform the classification task. Distortion rectification (or equivalently distortion field estimation) is viewed as a regression problem, where the input is a distorted fingerprint and the output is the distortion field. To solve this problem, a database (called reference database) of various distorted reference fingerprints and corresponding distortion fields is built in the offline stage, and then in the online stage, the nearest neighbor of the input fingerprint is found in the reference database and the corresponding distortion field is used to transform the input fingerprint into a normal one. Promising results have been obtained on three databases containing many distorted fingerprints, namely FVC2004 DB1, Tsinghua Distorted Fingerprint database, and the NIST SD27 latent fingerprint database.

EXISTING SYSTEM:

- Fingerprint matcher is very sensitive to image quality as observed where the matching accuracy of the same algorithm varies significantly among different datasets due to variation in image quality. A fingerprint recognition system can be classified as either a positive or negative system. In a positive recognition system, such as physical access control systems, the user is supposed to be cooperative and wishes to be

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identified. In a negative recognition system, such as identifying persons in watch lists and detecting multiple enrollment under different names, the user of interest (e.g., criminals) is supposed to be uncooperative and does not wish to be identified.

- In Existing System, since existing fingerprint quality assessment algorithms are designed to examine if an image contains sufficient information (say, minutiae) for matching, they have limited capability in determining if an image is a natural fingerprint or an altered fingerprint. Obliterated fingerprints can evade fingerprint quality control software, depending on the area of the damage. If the affected finger area is small, the existing fingerprint quality assessment software may fail to detect it as an altered fingerprint.

DISADVANTAGES OF EXISTING SYSTEM:

- Distortion rectification (or equivalently distortion field estimation) is viewed as a regression problem, where the input is a distorted fingerprint and the output is the distortion field.
- They require special force sensors or fingerprint sensors with video capturing capability
- They cannot detect distorted fingerprint images in existing fingerprint databases.
- They cannot detect fingerprints distorted before pressing on the sensor.
- However, allowing larger distortion in matching will inevitably result in higher false match rate. For example, if we increased the bounding zone around a minutia, many non-mated minutiae will have a chance to get paired.
- In addition, allowing larger distortion in matching will also slow down the matching speed.

PROPOSED SYSTEM:

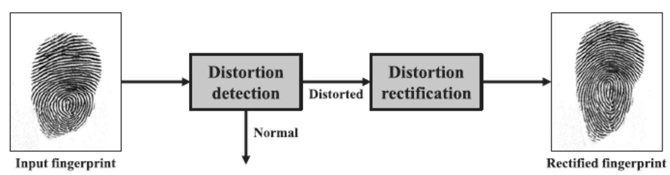
- In Proposed System was evaluated at two levels: finger level and subject level. At the finger level, we evaluate the performance of distinguishing between natural and altered fingerprints. At the subject level, we evaluate the performance of distinguishing between subjects with natural fingerprints and those with altered fingerprints

- This paper described a novel distorted fingerprint detection and rectification algorithm. For distortion detection, the registered ridge orientation map and period map of a fingerprint are used as the feature vector and a SVM classifier is trained to classify the input fingerprint as distorted or normal.
- A nearest neighbor regression approach is used to predict the distortion field from the input distorted fingerprint and then the inverse of the distortion field is used to transform the distorted fingerprint into a normal one.

ADVANTAGES OF PROPOSED SYSTEM:

- Fingerprint rectification algorithm consists of an offline stage and an online stage. In the offline stage, a database of distorted reference fingerprints is generated by transforming several normal reference fingerprints with various distortion fields sampled from the statistical model of distortion fields.
- The proposed distortion rectification algorithm by performs well by performing matching experiments on various databases.
- The proposed algorithm can improve recognition rate of distorted fingerprints evidently.

SYSTEM ARCHITECTURE:



.INTRODUCTION

WEB-SCALE image search engines mostly use keywords as queries and rely on surrounding text to search images. They suffer from the ambiguity of query keywords, because it is hard for users to accurately describe the visual content of target images only using keywords. For example, using “apple” as a query keyword, the retrieved images belong to different categories (also called concepts in this paper), such as "red apple," "apple logo," and "apple laptop." In order to solve the ambiguity, content- based image retrieval [1], [2] with relevance feedback [3], [4], [5] is widely used. It requires users to select multiple relevant and irrelevant image examples, from which visual similarity metrics are learned through online training. Images are re-ranked based on the learned visual similarities. However, for web-scale commercial systems, users' feedback has to be limited to the minimum without online training.

Our Approach

In this paper, a novel framework is proposed for web image re-ranking. Instead of manually defining a universal concept dictionary, it learns different semantic spaces for different query keywords individually and automatically. The semantic space related to the images to be re-ranked can be significantly narrowed down by the query keyword provided by the user. For example, if the query keyword is "apple," the concepts of "mountain" and "Paris" are irrelevant and should be excluded. Instead, the concepts of "computer" and "fruit" will be used as dimensions to learn the semantic space related to "apple." The query-specific semantic spaces can more accurately model the images to be re-ranked, since they have excluded other potentially unlimited number of irrelevant concepts, which serve only as noise and deteriorate the re-ranking performance on both accuracy and computational cost.

RELATED WORK

The key component of image re-ranking is to compute visual similarities reflecting semantic relevance of images. Many visual features [36], [37], [38], [39], [40] have been developed in recent years. However, for different query images, the effective low-level visual features are different. Therefore, Cui et al. [6], [7] classified query images into eight predefined intention c categories and gave different feature weighting schemes to different types of query images. But it was difficult for the eight weighting schemes to cover the large diversity of all the web images. It was also likely for a query image to be classified to a wrong category. In order to reduce the semantic gap, query-specific semantic signature was first proposed in [41]. Kuo et al. [42] recently augmented each image with relevant semantic features through propagation over a visual graph and a textual graph which were correlated. Another way of learning visual similarities without adding users' burden is pseudo relevance feedback [43], [44], [45]. It takes the top N images most visually similar to the query image as expanded positive examples to learn a similarity metric. Since the top N images are not necessarily semantically-consistent with the query image, the learned similarity metric may not reliably reflect the semantic relevance and may even deteriorate re-ranking performance. In object retrieval, in order to purify the expanded positive examples, the spatial configurations of local visual features are verified [46], [47], [48]. But it is not applicable to general web image search, where relevant images may not contain the same object.

APPROACH OVERVIEW

The diagram of our approach is shown in Fig. 3. It has offline and online parts. At the offline stage, the reference classes (which represent different concepts) related to query keywords are automatically discovered and their training images are automatically collected in several steps. For a query keyword (e.g., "apple"), a set of most relevant keyword expansions (such as "red apple" and "apple macbook") are automatically selected utilizing both textual and visual information. This set of keyword expansions defines the reference classes for the query keyword. In order to automatically obtain the training examples of a reference class, the keyword expansion (e.g., "red apple") is used to retrieve images by the search engine based on textual information again. Images retrieved by the keyword expansion ("red apple") are much less diverse than those retrieved by the original keyword ("apple"). After automatically removing outliers, the retrieved top images are used as the training examples of the reference class. Some reference classes (such as "apple laptop" and "apple macbook") have similar semantic meanings and their training sets are visually similar. In order to improve the efficiency of online image re-ranking, redundant reference classes are removed. To better measure the similarity of semantic signatures, the semantic correlation between reference classes is estimated with a web-based kernel function. For each query keyword, its reference classes forms the basis of its semantic space. A multi-class classifier on visual and textual features is trained from the training sets of its reference classes and stored offline. Under a query keyword, the

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semantic signature of an image is extracted by computing the similarities between the image and the reference classes of the query keyword using the trained multiclass classifier. If there are K types of visual/textual features, such as color, texture, and shape, one could combine them together to train a single classifier, which extracts one semantic signature for an image. It is also possible to train a separate classifier for each type of features. Then, the K classifiers based on different types of features extract K semantic signatures, which are combined at the later stage of image matching. Our experiments show that the latter strategy can increase the re-ranking accuracy at the cost of storage and online matching efficiency because of the increased size of semantic signatures.

SEMANTIC SIGNATURES

Given M reference classes for keyword q and their training images, a multi-class classifier on the visual features of images is trained and it outputs an M-dimensional vector p, indicating the probabilities of a new image I belonging to different reference classes. p is used as the semantic signature of I. The distance between two images Ia and Ib are measured as the L1-distance between their semantic signatures pa and pb,

CONCLUSION AND FUTURE WORK

We propose a novel framework, which learns query-specific semantic spaces to significantly improve the effectiveness and efficiency of online image re-ranking. The visual features of images are projected into their related semantic spaces automatically learned through keyword expansions offline. The extracted semantic signatures can be 70 times shorter than the original visual features, while achieve 25-40 percent relative improvement on reranking precisions over state-of-the-art methods.

In the future work, our framework can be improved along several directions. Finding the keyword expansions used to define reference classes can incorporate other metadata and log data besides the textual and visual features.For example, the co-occurrence information of keywords in user queries is useful and can be obtained in log data. In order to update the reference classes over time in an efficient way, how to adopt incremental learning [72] under our framework needs to be further investigated.

Although the semantic signatures are already small, it is possible to make them more compact and to further enhance their matching efficiency using other technologies such as hashing [76]

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