Experiment and Analysis Services in a Fingerprint Digital Library for Collaborative Research

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Abstract. Fingerprint management systems support millions of images and complicated but imperfect image identification algorithms. The forensic community requires a set of digital library services to support large image collections, execute identification algorithms, and analyze experiments that test identification algorithms in development. We present a model and prototype system capable of testing and analyzing fingerprinting algorithms in terms of identification performance based on matches of a known image to partial images, distortions of the images, and sub-regions of the images. These services are provided based on our framework for composing a set of services and a fingerprint image collection. The prototype will be useful in collaborations connecting several algorithm development efforts, and in composing an experimentation workflow. We also describe extensions of these services into other domains.

Keywords: fingerprint collections, algorithms, experiments, analyses.

1 Introduction

Fingerprint identification has been a staple of forensics and criminal justice for more than a century. National fingerprint collections contain millions of images and are searched by extracting details on the unique ridge structure and minutiae. Minutiae are common features in a fingerprint. Developing algorithms for image retrieval, comparison, identification, compression, and analysis remains an active field. Fingerprint management systems have been developed to maintain recorded prints in civilian, military, and criminal collections in addition to crime scene collections. The FBI fingerprint system contains around 66 million criminal and 25 million civil images [4]. The largest fingerprint collections are proprietary or government-owned and are not released for public usage. Researchers currently lack a digital library (DL) for human training and the developing, testing,

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and training of fingerprint identification algorithms. Such a DL would be useful for studying and modifying existing algorithms that detect minutiae, ridges, sub-images, and full images. To support identification tasks, digital library services are required to expose large image collections, support algorithms, and maintain algorithm analysis experiments.

We propose a fingerprint digital library with services to manage collections, algorithms, analysis experiments, and experiment results as shown in Fig. 1. The provided services allow researchers to gauge the quality of matching algorithms for distorted and sub-region images. While the services are tailored to fingerprint images and specific algorithms in the prototype implementation, we propose a generic model for maintaining scientific data and plugging tools or algorithms into a testing environment. *The goal of this work is to present a model and prototype of an end-to-end image-based DL experimentation and analysis service.*

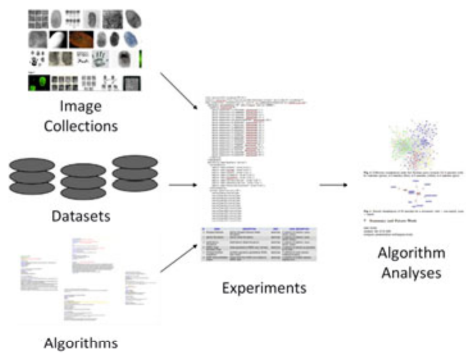

Fig. 1. Workflow framework: fingerprint images, feature or distortion datasets, and image-processing algorithms are used in experiments to analyze algorithm performance

This paper describes fingerprint images and collections in Section 2, algorithm and analysis services in Section 3, a proposed framework and prototype experiment DL in Section 4, and then a summary and plan for future work.

2 Fingerprint Image Collections

Current research into fingerprinting algorithms is hampered by the lack of a large, well-defined testing dataset and infrastructure for executing new or revised algorithms. Testing ridge mapping algorithms for quality assurance is currently a human-intensive endeavor due to computational errors because of fuzziness and blurriness in distorted images. On a similar note, ascertaining the quality of feature extraction algorithms also requires comparisons to human identified features.

2.1 Fingerprint Images

For over a century, fingerprints have been classified by features clear to human observers. Historical classifications of fingerprint features include combinations of arches, loops, and whorls. Finer-grained features are labeled minutiae, which are several points along fingerprint ridges. Ridge points include terminal ends, islands, and forking locations, called bifurcations, see Fig. 2. Fingerprint subregions can be differently affected by finger pressure, direction of movement, stretches, and humidity, with several levels of quality compared to an original print. Humidity levels include wet, proper, and dry, see Fig. 3.

Images used in fingerprinting are often not perfect specimens. In a forensic setting, crime scene evidence might be a partial, smeared, distorted, or overly humid fingerprint. In order to train algorithms and software with poor quality field images, distorted example images must be generated to analyze each potentially troublesome factor. Several types of distortions may transform high-quality fingerprint images on record to what are found as poor-quality images in actual evidence. A distorted image may have displacements in the x and y directions on a plane, a distortion common with partial images. Rotations and skin plasticity also distort images, as is shown in Fig. 4. Notice that when the skin's focal point of contact is where pressure is applied, rotations and plasticity will cause multiple portions of an image to be skewed differently.

In this study, we use real fingerprint images from Fingerprint Verification Competition (FVC) 2000 DB1 and DB2, consisting of 880 images (110 different individuals who are 20 to 30 year-old students, about 50% male). For latent image analysis, we used the National Institute of Standards and Technology (NIST) Special Database 27 as a real dataset of fingerprint minutiae from latent and matching tenprints. These datasets are widely used by researchers and trainers.

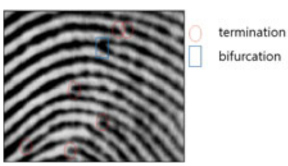

Fig. 2. Highlighted ridge termination and bifurcation minutiae

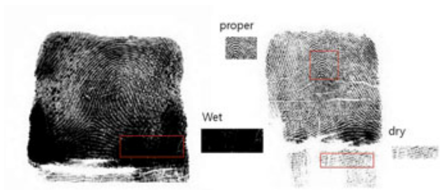

Fig. 3. Fingerprint humidity

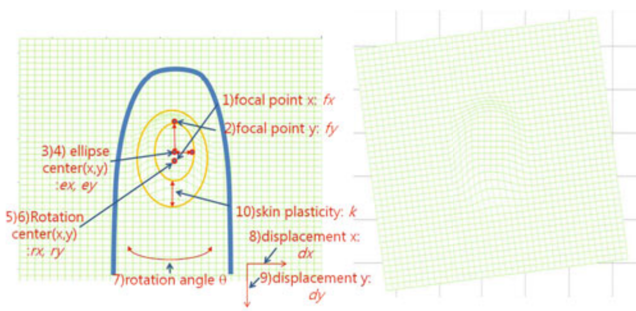

Fig. 4. Fingerprint distortion parameters indicated (left) and skin distortions [6] (rotation and translation) model example (right)

2.2 Distorted Image Collection

Four sources for fingerprint images include crime scenes, citizen databases, distortion collections, and training materials [4]. A fingerprint collection would be incomplete without numerous examples and combinations of classifications and minutiae. Our efforts presented here are to develop a DL for distorted images to be used in identification and matching algorithm analysis services for DLs that support the three other types of image sources.

A large set of distorted images from a known image is needed in order to test search algorithms. For the distortion parameters displayed in Fig. 4, the number of distorted images with full compositions of distortions will grow at a rate of 10^k, where k is the number of distinct levels selected for each distortion. For example, if $k = 5$, the levels of -8, -3, 2, 7, 12 pixels might be selected for x-axis displacement, and over 100,000 distorted images would be produced from the full-factorization of the ten parameters. Note that the number of levels could vary between distortion factors. Initial images in a distorted image collection come from human fingers, toes, palms, and foot pads. Assuming prints from entire palms and foot pads could be captured in one large image, a single human would produce 24 initial print images. Distorting each print over only five levels for the ten parameters leads to a sizable collection of 2,400,000 images per human.

Due to the extreme number of possible distorted images derived from a single human, especially as k grows large, high-quality algorithms need training to identify matches. A distortion collection is needed to build an algorithm testing platform with known fingerprint matches to test matching precision, recall, false negatives, false positives, and conditions that lead to low levels of certainty. Such a collection is useful in analysis to determine the contribution of each distortion in order to provide feedback to prediction algorithms. The collection we have developed uses a small set of initial images to allow for a larger number of distortion parameter levels. A system for managing distorted image collections also may determine which factors contribute to negatively impact matching algorithms. In order to conduct such analyses, each distorted image and sub- or partial image is stored with its generation parameters, provenance, and relationships to the unaltered initial image and other distorted images. Storage space plays a major factor in developing image collections. Currently, we have limited k to 5 as a terabyte of distorted images are generated per ten initial images.

3 Analysis and Experiment

To support a typical fingerprint algorithm analysis workflow, we have developed a DL services model and implemented a prototype instantiation. The workflow includes five stages: image harvesting, distortion image generation, algorithm execution, result harvesting, and algorithm performance analysis. With this model, researchers are able to investigate how an algorithm performs with synthetic, field-quality images. In particular, researchers are provided with an analysis framework that could be used to determine which image distortion parameters effect feature identification. The targeted workflow model framework pairs new algorithms with image collections to allow analysis on which image characteristics effect algorithm performance, as seen in Fig. 5. Previous work has defined the format for formally defining DL services that we will employ [2]. Formal definitions already exist for generic versions of several of our fingerprint-specific! services, e.g., searching and visualizing [2]. The services in the following section are implemented in the prototype's initial workflow.

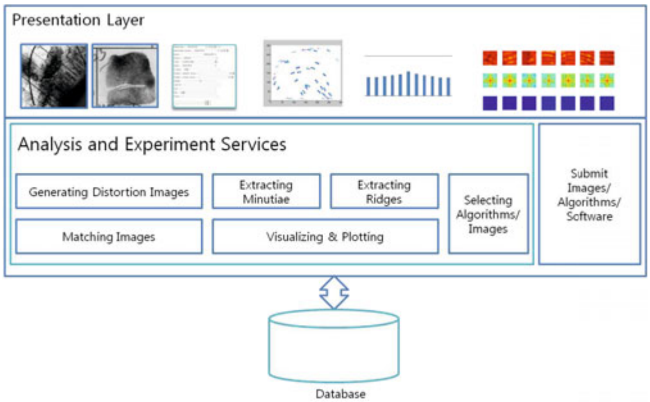

Fig. 5. Analysis and Experiment Services in DL framework

3.1 Analysis and Experiment Services

Analysis and Experiment Setting. Each algorithm to be used in experimentation requires an algorithm-specific description of which outputs to process for analysis. The minutiae extraction algorithm requires analysis on the number, pixel location, and quality of identified minutiae. The ridge tracing algorithm requires quantification and analysis on ridge identification. The matching algorithm requires analysis to determine if the set of selected minutiae was sufficient in making a match. One required step to begin an experiment is to set up all the input parameters using the 'Selecting algorithm/images' service to choose which images and algorithms should be selected in an experiment run.

Distortion Generation and Image Processing. After high-quality real-world fingerprint images are submitted, a distortion generation algorithm takes a set of values for the ten distortion parameters used in [6]. Each distorted image then is added to the DL collection along with a link to the original image and the parameters used in the image generation. In environments with low amounts of disk storage available, the image generator may be used to generate distorted images on a just-in-time basis, and images may be removed after usage though their metadata or generation script is archived.

For the image processing service, there are two approaches to the extraction of minutia and ridge features: *binarization* and *gray scale*. *Binarization* approaches typically use image processing techniques such as sharpening, histogram equalization, and enhancement, while *gray scale* approaches often exploit filtering with a Gabor filter to enhance gray scale fingerprint images. This service can be considered as a converting service, similar to the distortion service, and thus has the same 5S formalization [2]. See Table 1 for basic terms and definitions.

Table 1. Basic Terms and Definitions of 5S formalization [2]

Term	Definition	Term	Definition
DO_i, DO_j	digital objects i, $j \in C$	V	Vertex
C	a collection $\in$ $Coll$	Stm_i	$\Psi_{ij}.Dom$
$Coll$	a set of collections	$\Psi_{ij}.Dom$	V $\times$ Streams
stm_j	a stream	S^3	Streams $\cup$ Structures $\cup$ Spaces
st_j	a structure	tfr	$S^3\times$ Spaces
Ψ	V $\times$ Streams $\Rightarrow$ (N $\times$ N)	sp_j	a space j
St^2	a set of functions Ψ		

Informally, *distorting* and *image processing* take a digital object and produce a distorted version by changing its streams, structures, or structured streams as defined in the 5S framework [2], an alternative to the DELOS reference model[1].

Definition. *Distorting/image processing* is a service defined as $f : do_i \Rightarrow do_j$, given a digital object do_i. The input and output structures for this service are do_i and do_j. The pre-condition and post-condition for this service are $\exists C \in Coll : do_i \in C$ and $\exists C \in Coll : do_j \in C$.

Minutiae Extraction and Ridge Tracing. A minutiae extraction algorithm is used to identify the locations and quality of major features, e.g., ridge bifurcation and termination. A third algorithm attempts to automatically trace the ridges in images resulting from smears, partial-smudges, or high humidity. High humidity refers to an overly oily or wet print that causes ridges to run together.

Definition. These two feature extraction algorithms form a service, *extracting*, that can be informally defined as *given a digital object, produce a descriptor from the object that represents the digital object.* User input is required as stm_i and outputs are (st_j, Ψ_{ij}). Pre-condition and post-condition are $stm_i \in Streams$ and $st_j \in Structs; \Psi_{ij} \in St^2; stm_i \in \Psi_{ij}.Dom; st_j.V \in \Psi_{ij}.Dom$, respectively.

Matching and Searching. A fourth algorithm for *matching* and *searching* attempts to use 3, 6, or 9-point triangles of high-quality minutiae locations to identify matches between two images as groups of minutiae are less susceptible to distortions. This matching algorithm stems from attempts to reduce the effects of small distortions on the identification of minutiae location and quality.

Definition. This process can be defined as a *binary* operation service $f(do_i, do_j) = k,\ k \in R$, compared to a service such as rating and measuring which is a *unary* operation $f(do_i) = k, k \in R$, where a real number k is a similarity score.

[1] See www.delos.info

Evaluating. Evaluation is a critical service among these experimental services. Evaluation criteria can be 1) algorithm performance, 2) algorithm efficiency, 3) minutia reliability, and 4) image quality. First, performance metrics include indicators used in the FVC such as 1) number of rejected fingerprints during enrollment; 2) number of rejected fingerprints during genuine matches; 3) number of rejected fingerprints during impostor matches; 4) impostor and genuine score distributions; 5) FMR(t) / FNMR(t) curves, where FMR is the false match rate, FNMR is the false non-match rate, and t is the acceptance threshold; 6) ROC(t) curve, where ROC is a receiver operating characteristic; 7) equal-error-rate (EER), the value that EER would take if the matching failures were excluded from the computation of FMR and FNMR (EER*); 8) the lowest FNMR for FMR≤1%; 9) the lowest FNMR for FMR≤0.1%; 10) the lowest FNMR for FMR=0%; and 11) the lowest FMR for FNMR=0%. Second, metrics for measuring efficiency include 1) average enrollment time, 2) average matching time, 3) average and maximum template size, and 4) maximum amount of memory allocated. Third, minutia reliability and image quality can be measured with the combination of many different maps (e.g., low frequency, high frequency, and directional).

Definition. Given a digital object, an evaluating service produces an evaluation (i.e., a real number) for it. Input is do_i and output is (do_i, w_i). Pre-condition is $\exists C \in Coll : do_i \in C$ and post-condition is $w_i \in [a, b] \subset R$.

Visualizing and Plotting. Analysis results can be visualized by projection to measurable spaces. Visualization techniques can be used to analyze the appearance and disappearance of minutiae over distortion degrees.

Definition. Visualizing and plotting can be described as processes that, given a collection, produce visualizations such as charts, histograms, plots, or meshes. Input for a visualizing service is a collection C and a transformation k, and output is a space j. Pre-conditions and post-conditions are $C \in Coll$ and $tfr_k(C) = sp_j \in Metric$.

3.2 Example Experiment Scenarios

Using these services, we have carried out three pilot experiments to analyze the effects of distortion on image quality. These experiments were performed regarding *fingerprint sufficiency* to provide objective standards of image quality.

Matching Score Accuracy Experiment. The first experiment analyzed the effects of skin distortion, specifically rotation and x-axis and y-axis displacements, on matching scores. This experiment followed the path: $distorting \Rightarrow minutia\ extraction \Rightarrow matching \Rightarrow analysis \Rightarrow visualization$. An example experiment for y-axis displacement is illustrated in Fig. 6. These led to another experiment to answer: "how does the distortion (e.g., rotation and translation in the skin distortion model) affect the number of minutiae?"

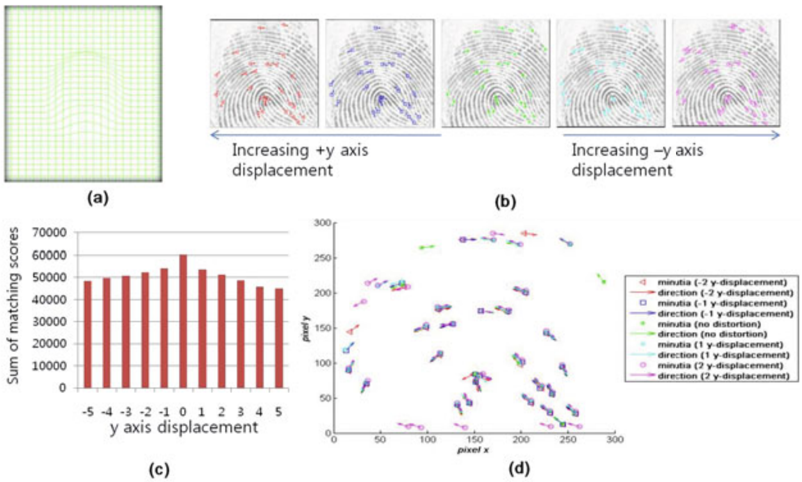

Fig. 6. Example analyzing effects of y-axis displacements on matching quality: (a) skin distortion model selected; (b) distorted images; (c) histogram of y displacement versus sum of matching score; (d) plotting of minutiae spatial distribution

Minutiae Count and Reliability. This experiment investigates the effects of distortions on minutiae count. We hypothesized that it would diminish the number of minutia points. For this experiment, we required minutia extraction services. This experiment was accomplished by following this path: *distorting* ⇒ *minutia extraction* ⇒ *analysis* ⇒ *visualization*. Fig. 7 shows that the number of minutiae increased as distortion increases.

Therefore, we investigated the effects of distortion on minutiae reliability, using the same experiment path used for the minutiae count test. In this case, minutia reliability was extracted and graphed to show the effects of distortion on extraction. In Fig. 8, the x-axis represents the amount of translation distortion ranging from -5 to +5 pixels for the x-axis and y-axis of a given image. (0,0) means no distortion in any image's axis, (0, -1) means y-axis distorted by -1. The y-axis represents reliability scaling from 0 (not reliable) to 100 (very reliable). We observed that average reliability and minutiae distortion are inversely related.

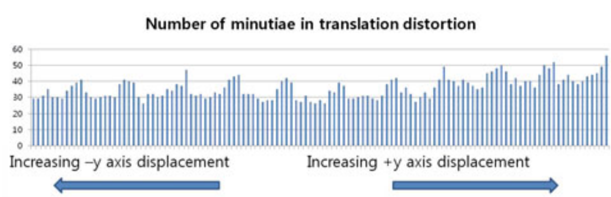

Fig. 7. Number of minutiae in translation distortion

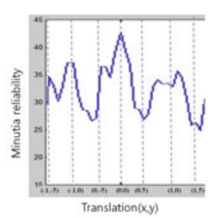

Fig. 8. Average minutiae reliability: images distorted by translation

Minutiae Plotting on Fingerprint. Plots for minutia reliability of each image follow the path: *distorting* ⇒ *minutia extraction* ⇒ *analysis* ⇒ *visualizing*. The results shown in Fig. 9 revealed that distortions have introduced false positive minutiae with low reliability, degrading the average minutia quality. The red points on the fingerprint image indicate low quality minutia points, whereas green points indicate high quality minutia points. The scale assigns red the lowest reliability and blue the highest.

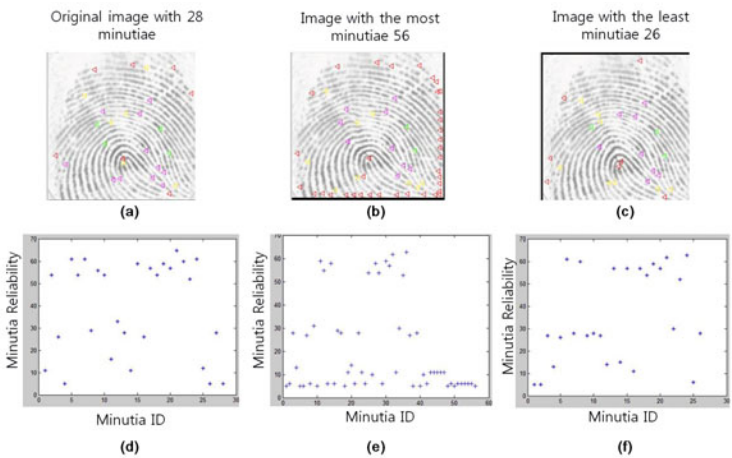

Fig. 9. Spatial distributions of minutia reliability: (a) original image with 28 minutiae; images which increased (b) and decreased (c) the most in minutia points after distortion (56 and 26 minutiae respectively); and (d)-(f) minutia reliability of each image

4 Framework and Prototype

We have designed a framework for workflowing image-based services, considering Kepler [5] and related existing systems.

4.1 Workflow, Experimentation, and Analysis Framework

When designing an image-based experiment, a user selects a collection of images and an algorithm to execute. Each algorithm in our framework is paired, by the algorithm developer, with an algorithm-specific analysis script to identify and extract the phenomenon being tested from the algorithm output. Our experimentation workflow involves executing each algorithm with a specific collection, e.g., a set of distorted images. After termination of the algorithm, the analysis service determines the differences in the algorithm results between the images. Metadata, such as distortion parameter values, then can be used to analyze each parameter's effect on the algorithm's results. Thus, the framework consists of building workflows of compositions of collections, algorithms, and analyses.

As an example workflow, the number of minutiae located and the assigned quality score (0.0 to 1.0) for each minutiae is provided by the minutiae extraction algorithm. An analysis script extracts the Cartesian location and assigned quality scores. The results from executing this algorithm on the entire set of distorted images from a base image then is matched with distortion parameters. The predefined analysis script is executed to specifically determine the statistical significance of each factor in hindering the identification of minutiae. This algorithm requires the distortion generation algorithm as a pre-requisite, forming a workflow involving several algorithmic executions and subsequent analysis.

4.2 Prototype Implementation

We have implemented a basic prototype of this framework to conduct experiments with the feature extraction algorithms previously mentioned. The prototype consists of DL services to manage a distorted image collection, select and execute an algorithm, and execute analyses. The analysis processes allows a researcher to hold several parameters constant by careful selection of distortion parameters, e.g., x-axis translation, rotations, and skin plasticity. We are developing a plug-in system for easier integration of new algorithms.

We have developed a collection of real-world images. For several selected images, we have generated a range of distorted images and produced a service for generating new distorted images as required. An experiment was successfully designed, executed, and analyzed to determine the effects of humidity, x-translations, y-translations, rotations, and skin plasticity on minutia extraction.

The prototype includes an online collection of original and distorted images and a system for selecting and composing service workflows. The Google chart API is used to present results of completed analysis tasks. A web-interface is used to browse the image collection, image information, distortion parameters used to generate specific images, extracted minutiae, and ridge information.

Currently, our prototype system contains 137,785 prints (FVC2000: 3520, FVC2002: 3520, SD27: 516, self-collected: 629, and distorted: 129,600). For the preliminary experiments, we generated distorted images from real fingerprints as described in Section 2.2. As a result of our experiments, the system yielded the following: 1) matching scores of a minutia extraction module MINDTCT and BOZORTH3 produced by National Biometric Image Sofware of BIST matching algorithm with distorted image sets (see Figure 6); 2) minutia counts of MINDTCT algorithm with distorted image sets (Figure 7); 3) minutia reliability of MINDTCT algorithm with distorted image sets (see Figures 8 and 9); and 4) improvement of schema presented in previous work [4].

Our framework is scalable but limited by file system storage space. Current terabyte storage devices can have roughly 1-10 billion images assuming 800 base images and 100,000 distortions at 100KB per file. Distorted image generation time is 1.0 sec. on a Pentium 4. Both time and space complexity are $O(n)$.

4.3 Other Applications

This framework, developed for fingerprint testing and analysis, can be applied to a broader set of domains. Hays and Efros [3] recognize the location pictured by a given image by extracting visual features of that image and matching them to a previous known geo-tagged image database. The most similar geo-tagged images retrieved tell at which point on Earth the given input image is located. Retrieval algorithms for this type of task are quite precise. A researcher might test different algorithms to check their sensitivity to distorted or rotated images using the proposed framework.

The problem of astronomical identification resembles fingerprint matching in the sense that once stars are extracted from an input image, they are matched to a guide stars catalogue. A great number of algorithms for this problem have been proposed, but as in the fingerprint domain, the precision of star identification is influenced by extraction of a star centroid and preprocessing of the raw image [7]. The study of how those factors influence the precision of proposed algorithms, similar to triangle minutiae matching, can benefit from this framework as well.

5 Related Work

FBI's Integrated Automated Fingerprint Identification System (IAFIS) is a large fingerprint management system, supporting search capabilities against both latent and ten prints, storing electronic images, and electronically exchanging fingerprints. However, it does not support a series of services for experiment digital libraries such as experiment setting, distorting, plotting, and visualizing. The Universal Latent Workstation (ULW) is the first latent workstation supporting interoperability and sharing latent identification services with local and state authorities, and with the FBI IAFIS, all with a single encoding.

Penatti et al. [9] proposed an experiment management tool, *Eva*, for evaluating descriptors in content-base image retrieval, providing image descriptors, and image management, to run comparative experiments. This tool has stimulated the development of our holistic DL experiment framework. Previous work also supported scientific communities in a web-based integration framework [10].

Fingerprint analysis has been challenged by various distortions such as merged prints, pressured impressions, humidity on fingertips, partial prints, or simultaneous prints. Distortions are likely to affect minutia extraction quality, ridge tracing quality, matching scores, and image quality. The Analysis, Comparison, Evaluation and Verification (ACE-V) and Scientific Working Group on Friction Ridge Analysis, Study and Technology (SWGFAST) groups (see swgfast.org) have worked on fingerprint analysis. Oliveira et al. [8] proposed a multiscale directional operator and morphological tools for reconnecting broken ridges in fingerprint images. Huang et al. [1] proposed singular point detection.

From the object perspective in very large digital libraries, Kozievitch et al. [4] proposed an solution to integrate four different very-large fingerprint digital libraries. A proposed compound object (CO) scheme uses the 5S framework, modeling different types of objects found in those DLs, to allow uniform use in an integrated DL. Our work is focused on designing a DL framework, from a services perspective, to deliver analytical results of an experiment that integrates related services designed by different researchers.

6 Summary and Future Work

Our main contribution is supporting collaborative research for researchers and trainers with services for generating distorted image datasets, testing different algorithms (e.g., for minutia detection and matching), and managing and workflowing scientific research datasets, algorithms, and analysis results.

We are integrating each implemented service under the proposed framework. We plan to verify this prototype in terms of algorithm correctness before and after integration. In addition, we will confirm that findings of experiments relate to the practice of researchers and fingerprint analysts. We also plan to incorporate (training and matching) algorithms from three other types of fingerprint DLs [4] with our collection of distorted images. Astronomy and geo-location identification domains provide a parallel corpus of algorithms that compare images based on feature extraction. Comparisons of these algorithms would be useful for cross-domain generalization.

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