Latent Fingerprint Value Prediction: Crowd-based Learning

Tarang Chugh† chughtar@cse.msu.edu
Kai Cao† kaicao@cse.msu.edu
Jiayu Zhou† zhou@cse.msu.edu
Elham Tabassi‡ elham.tabassi@nist.gov
Anil K. Jain† jain@cse.msu.edu

†Department of Computer Science and Engineering, Michigan State University
‡National Institute of Information Technology

Introduction

- **Latent fingerprints:** partial fingerprint impressions accidentally left behind on the surface of objects when they are touched or handled
- Crucial source of evidence in forensic investigations

Fig. 1: Challenges in latent processing.

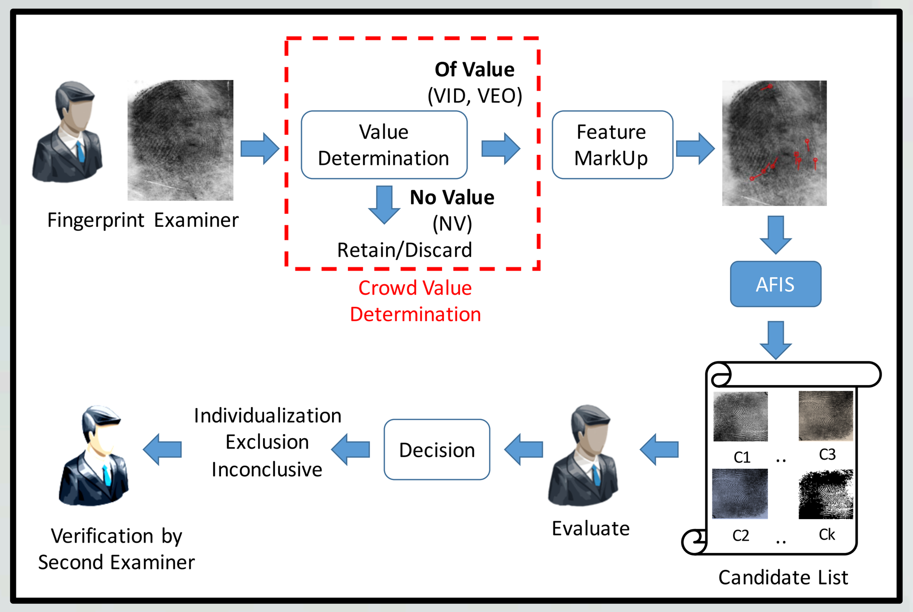


Fig. 2: Manual processing of a query latent by fingerprint examiners.

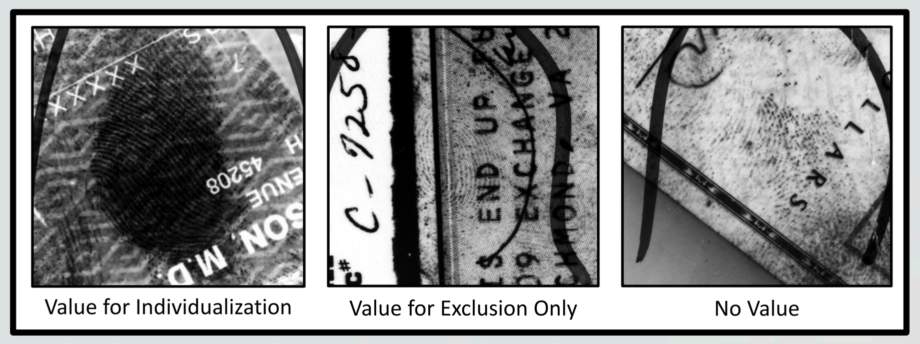


Fig. 3: Example latents determined to be VID, VEO and NV resp.

Challenges and Motivation

- Value determination is subjective with large intra- & inter-examiner variations
- Underlying bases used by examiners for value prediction are unknown
- Does not rank latents based on their value

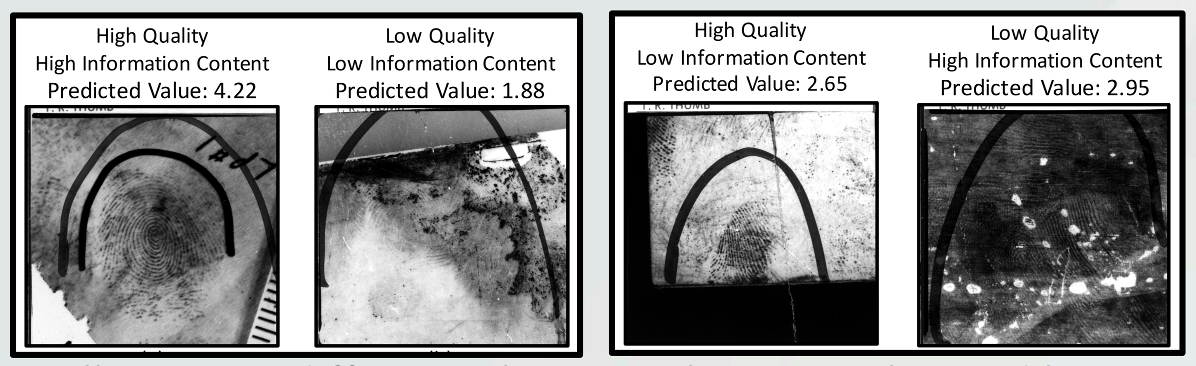


Fig. 4: Illustrating difference between latent quality and latent value.

Research Idea:

- Utilize the collective wisdom of fingerprint experts to reduce subjectivity & understand the underlying bases
- Learn a quantitative latent value predictor by relating the underlying basis with automatically extracted latent image features

Proposed Approach

- Designed a crowdsourcing tool, Fingerprint*Mash*, to collect labels indicating the quality and the quantity of information present in latent fingerprints

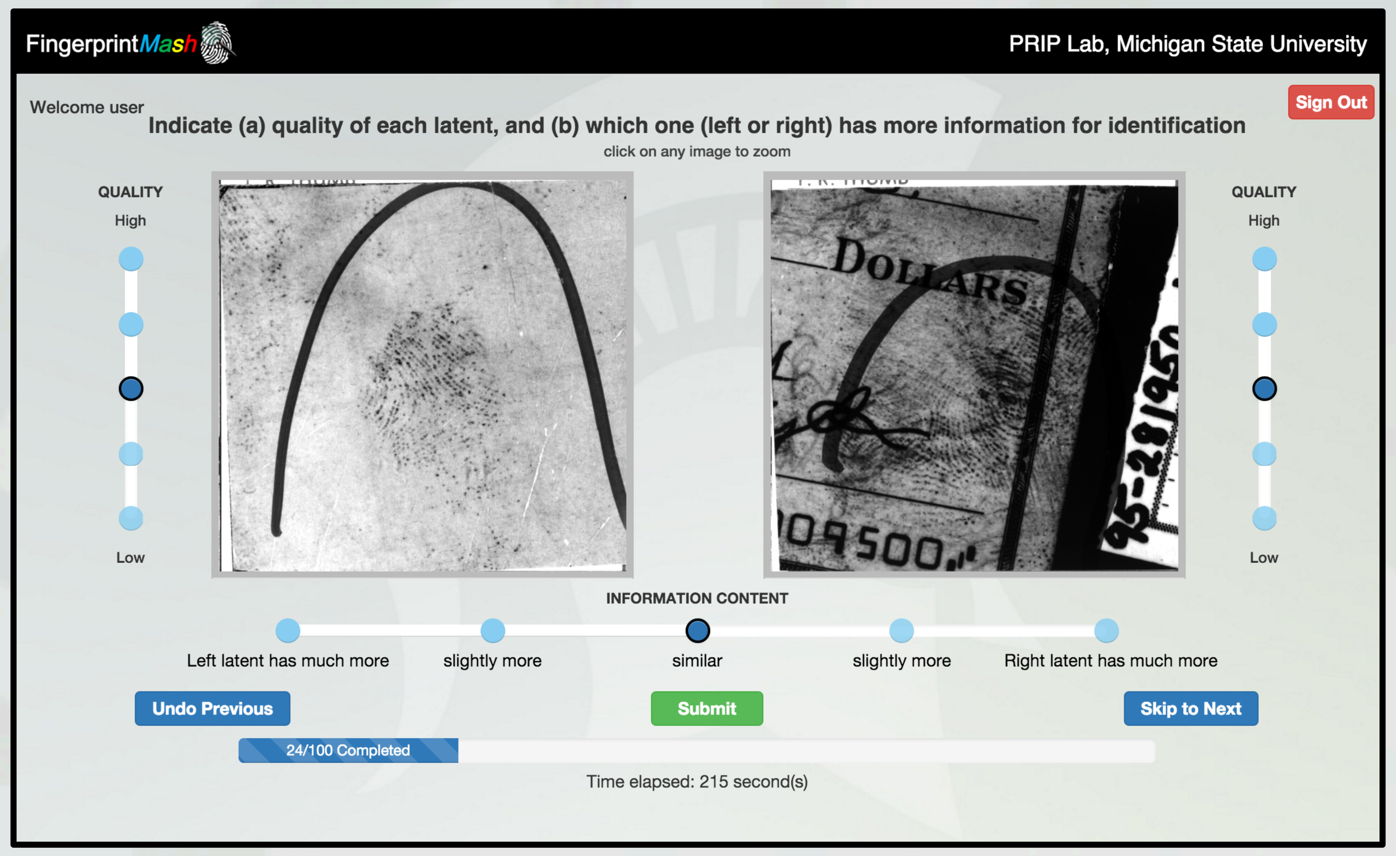


Fig. 5: Interface of the expert crowdsourcing tool, Fingerprint*Mash*. Available at: www.fingerprintmash.org

- Utilized Matrix Completion, Multidimensional Scaling and Lasso to learn a latent value predictor

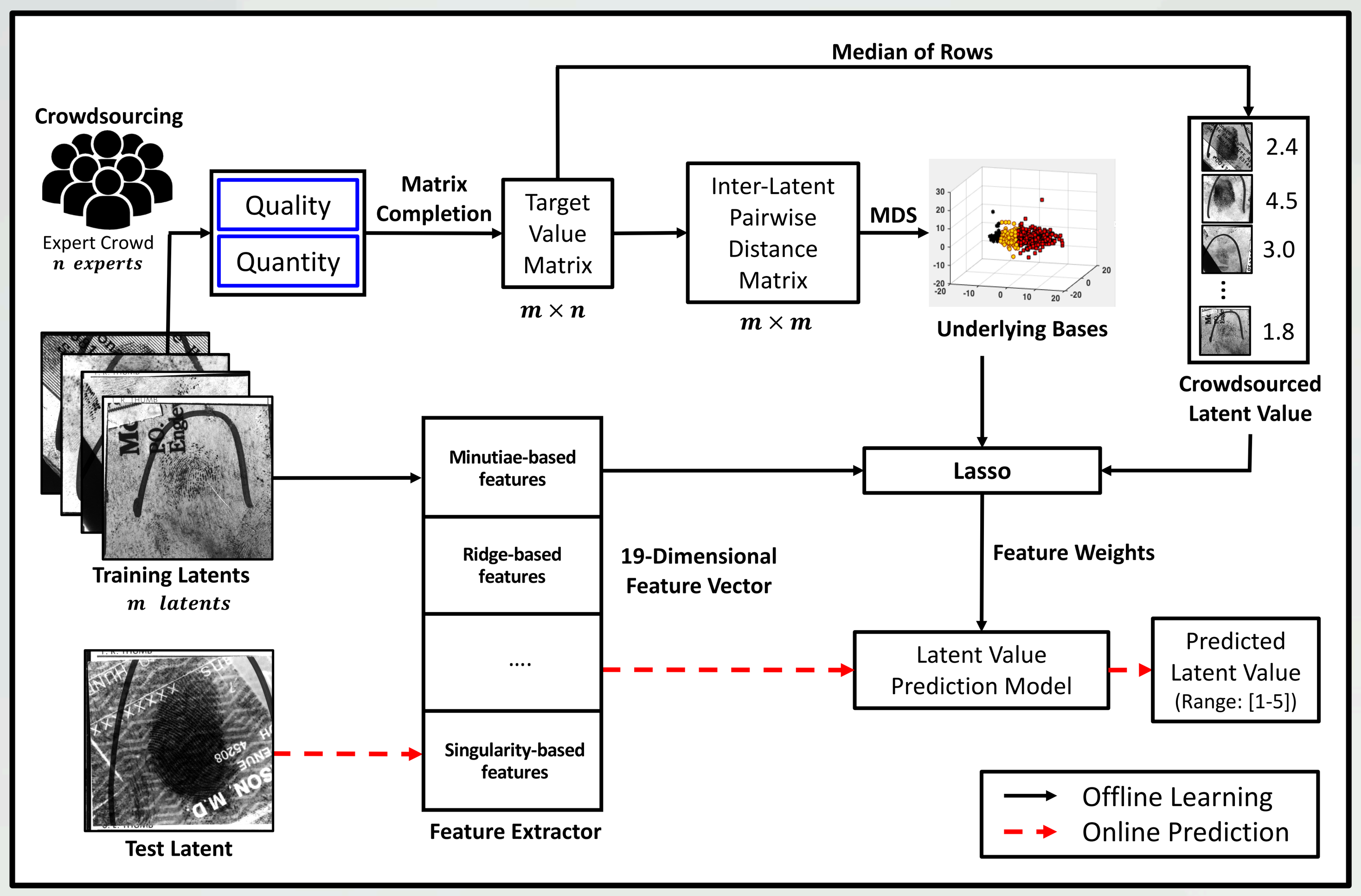
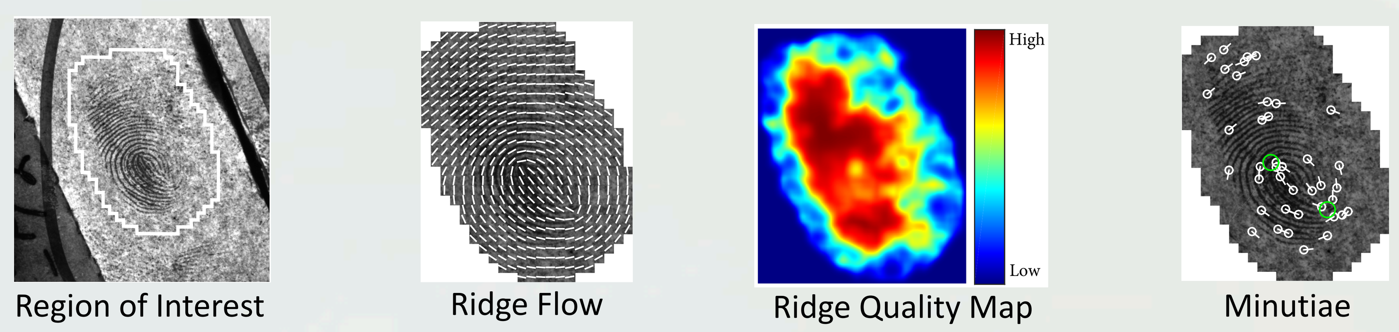


Fig. 6: Overview of the proposed crowdsourcing-based approach.



Bases	Minutiae Count	Minutiae Reliability	Area of fingerprint	Ridge Quality	Core and Delta	Ridge Flow
Basis I	0.68	0.31	0	0.2	0.4	0.19
Basis II	0	0	0.69	0	0.13	0.52

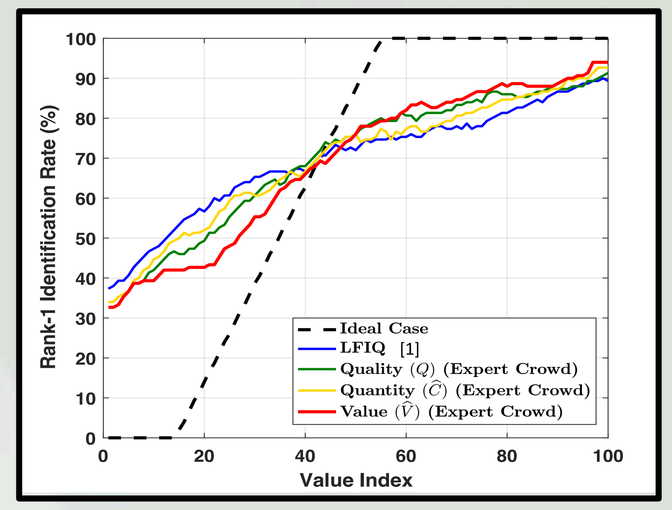
Fig. 7: Illustration of automatically extracted latent features and interpretation of bases.

Experimental Results

- **Latent Databases**

Database	#Latents	Latent Type	Used For
NIST SD27	258	Crime Scene	Training
MSP 258	258	Crime Scene	Training
MSP 400	400	Crime Scene	Testing
WVU subset	139	Laboratory	Testing
IIIT-D subset	2926	Laboratory	Testing

- **Reference Database:** 250K rolled prints from MSP
- **Evaluating crowdsourced latent value**



- Crowdsourced latent value successfully ranks latents;
- Ranking has higher correlation with Rank-1 identification rate

Fig.8: Rank-1 identification rate of a state-of-the-art AFIS for different latent value indices.

- **Evaluating Latent Value Prediction**

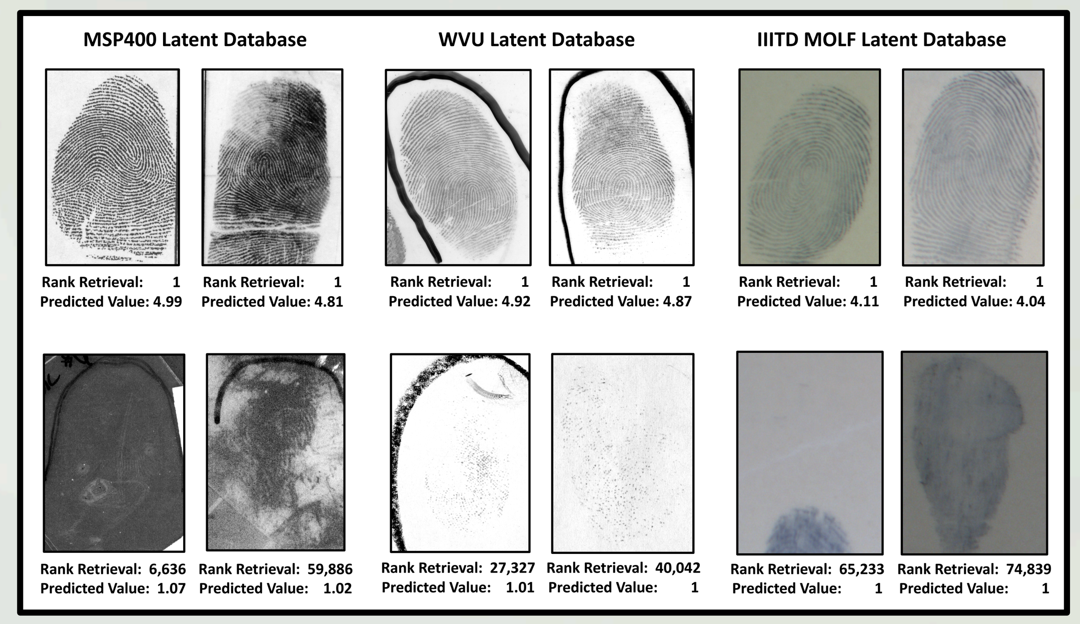


Fig.9: Top-2 and Bottom-2 latents from each of the three test datasets with their rank retrieval

Database	LFIQ [1]	Proposed Approach
MSP (400 latents)	0.49	0.70
WVU (139 latents)	0.47	0.73
IIIT-D (2,629 latents)	0.42	0.67

Table 2: Correlation between predicted latent value and AFIS performance.

[1] S. Yoon, K. Cao, E. Liu, and A. K. Jain, “LFIQ: Latent Fingerprint Image Quality,” in International Conference on Biometrics: Theory, Applications and Systems (BTAS), 2013, pp. 1–8.

Conclusion

- Crowdsourced latent value is more robust than prevailing value determination (VID, VEO and NV) and LFIQ for predicting AFIS performance.
- Two bases can explain expert value assignments which can be interpreted in terms of latent features.
- Our value predictor can rank a collection of latents from most informative to least informative.