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Deep learning compact binary codes for fingerprint indexing

Key words: Fingerprint indexing; Minutia cylinder code; Deep neural
network; Multi-index hashing

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Motivations

1. With the growth of large-scale fingerprint databases, identifying a query fingerprint often incurs significant consumption of time and memory and even may not get a reliable result.
2. Fingerprint indexing is the most common solution. However most of earlier methods focus on the real-valued features, which are computationally expensive, consuming time, and memory.
3. The binary representation saves the loss of memory which is fast in terms of computation and robust to local variations.
4. Deep learning technique has strong ability of the feature representation and various successful applications.

Main ideas

1. According to the characteristics of MCC, we propose a creative and novel feature learning method based on deep learning techniques and learn to obtain an effective and discriminative DCBMCC for fingerprint indexing. It combines independence, balance, and similarity-preservation properties.
2. We design a fast and exact fingerprint indexing scheme based on the MIH algorithm in the Hamming space. This approach is quite suitable for fingerprint indexing, since it has the large-scale database and extremely high accuracy which is required in critical security applications.

Method

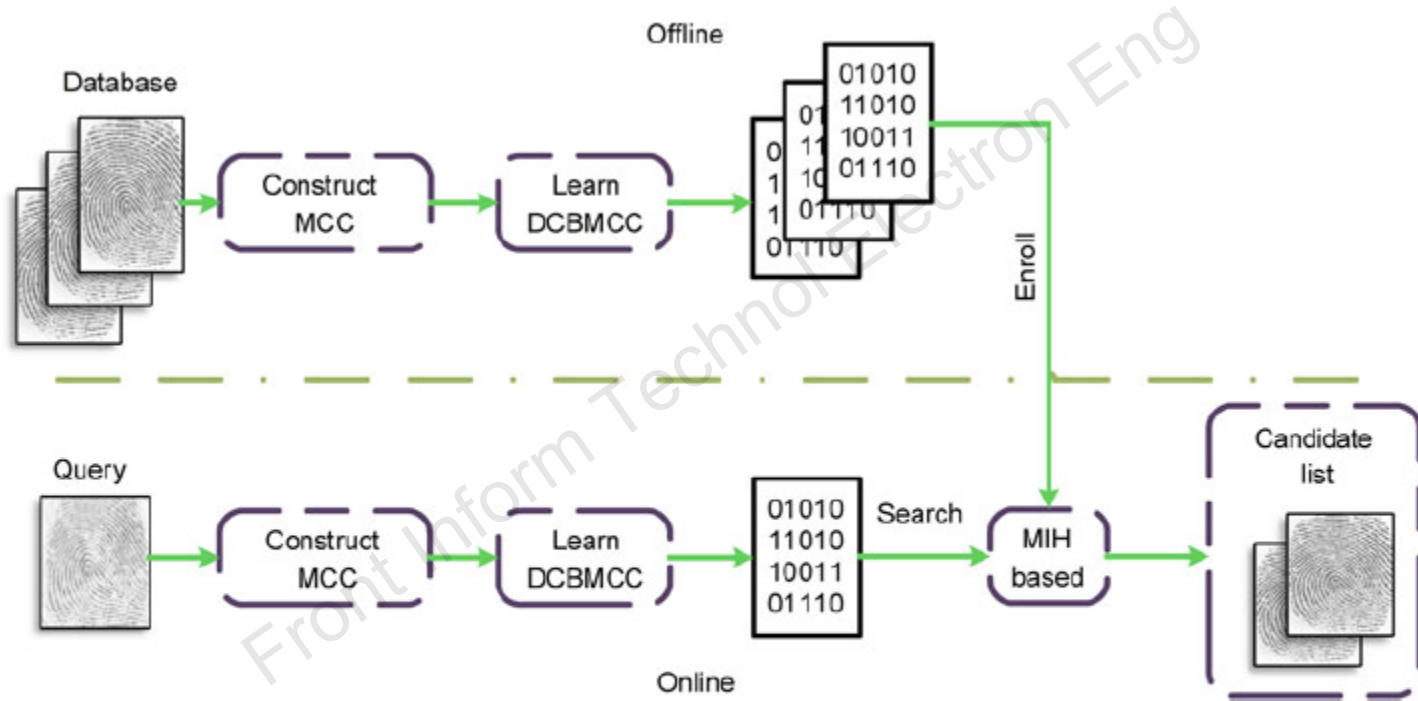


Fig. 1 Flowchart of the proposed deep compact binary minutia cylinder code based on the multi-index hashing (DCBMCC-MIH) approach. First, we extract and construct the real-valued MCC. Then we learn to obtain the binary DCBMCC. Eventually, an MIH-based fingerprint indexing scheme further speeds up the exact search in the Hamming space

Method

$$\begin{aligned} \min_{W, c, B} \quad J = & \frac{1}{2m} \|X - W^{(n-1)}B - c^{(n-1)}\mathbf{1}_{1 \times m}\|_F^2 \\ & + \frac{\lambda_1}{2} \sum_{l=1}^{n-1} \|W^{(l)}\|_F^2 + \frac{\lambda_2}{2m} \|A^{(n-1)}\mathbf{1}_{m \times 1}\|_2^2 \\ & + \frac{\lambda_3}{2} \left\| \frac{1}{m} A^{(n-1)} (A^{(n-1)})^T - I \right\|_F^2 \\ & + \frac{\lambda_4}{2m} \|A^{(n-1)} - B\|_F^2 \\ & + \frac{\lambda_5}{2m} \text{tr}(A^{(n-1)} P (A^{(n-1)})^T) \\ \text{s.t.} \quad & B \in \{-1, 1\}^{L \times m}. \end{aligned} \tag{9}$$

Major results

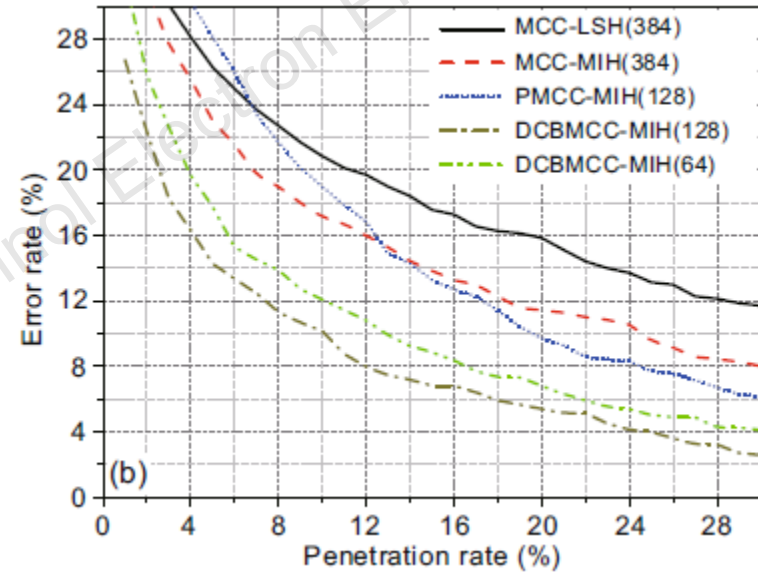
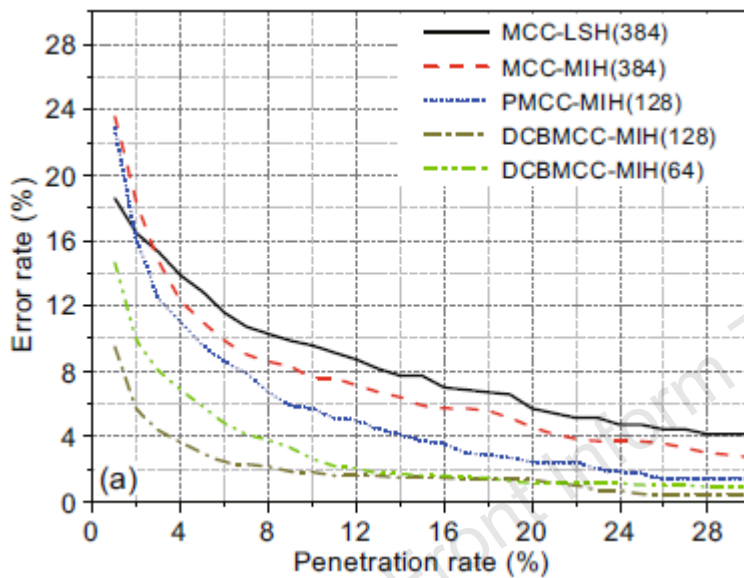


Fig. 3 Fingerprint indexing performance on the FVC2000 DB2 (a) and DB3 (b)

Major results

Table 2 Comparison with the existing L2H and CBMCC methods

Dataset	Average penetration rate (%)				
	SH	ITQ	SPH	CBMCC	Ours
FVC2000 DB2	4.10	3.05	2.89	2.28	1.63
FVC2000 DB3	7.74	5.04	5.11	4.89	4.07
FVC2002 DB1	2.25	2.11	2.16	1.58	1.49
FVC2002 DB4	4.07	3.82	3.71	2.64	2.32
FVC2004 DB2	7.39	5.79	6.07	5.14	4.58
FVC2004 DB3	6.29	4.53	4.39	3.80	3.59
NIST DB4	3.95	2.66	2.62	2.15	1.95
NIST DB14	4.07	2.84	2.90	2.17	1.97

Bold numbers denote the best results

Conclusions

1. We have proposed a deep neural network and a learning algorithm to learn binary features (DCBMCC).
2. The network constrains the penultimate layer to output the binary codes and incorporates small quantization error, similarity preservation, independence, and balance properties.
3. The MIH based fingerprint indexing method further speeds up the exact search in the Hamming space.
4. Numerous experiments illustrate that the proposed approach has excellent performance in fingerprint indexing.