IET Biometrics

Review Article

Survey on features for fingerprint indexing

ISSN 2047-4938
Received on 14th December 2017
Revised 26th April 2018
Accepted on 27th May 2018
doi: 10.1049/iet-bmt.2017.0279
www.ietdl.org

Patrick Schuch[1,2] ✉
[1]*NISlab, NTNU, P.O. Box 191, Gjøvik N-2802, Norway*
[2]*DERMALOG Identification Systems GmbH, Department of Biometrics Research, Mittelweg 120, D-20419 Hamburg, Germany*
✉ *E-mail: patrick.schuch2@ntnu.no*

Abstract: Nowadays, several biometric databases already contain millions of entries of individuals. With an increasing number of enrolled individuals, the response time of queries grows and can become critical. Fingerprint indexing offers a set of techniques to reduce the workload of entries, which have to be compared thoroughly. This work surveys research on such techniques. It focuses on the features of fingerprints, which are used as input. This survey also provides an assessment of the quality of the body of research in this field. Deficiencies herein are identified, *e.g.* there is a lack of common datasets and metrics used for testing.

1 Introduction

Biometric systems are a widespread means for identification of individuals today. Response times of such systems mainly depend on three aspects: the response time for an individual comparison of two fingerprint (FP) samples, the size of the database to be searched, and the actual hardware used for biometric comparison. All three aspects result in the biometric system's throughput.

As biometric databases, in general, tend to grow over time, the throughput declines over time. Nowadays, there are biometric systems rolled out, which contain several million individuals. The most prominent and largest example is the Aadhaar project in the Republic of India. It already contains more than 100 million entries and targets over one billion people.

In general, classical FP comparison of FP minutiae is computationally expensive. This survey will refer to this exhaustive comparison as the *thorough comparison*. Besides scaling the hardware, there is another way to increase the throughput. While some FPs are very similar, some FPs are very different. When comparing FPs, only those comparisons are worth a closer look, where both FP samples are similar. For many comparisons, one can decide at the first glance that both FP samples are not mated. Thus, one does not need to perform the thorough comparisons on the entire database but only on a subset. This reduces the mean response time for an individual comparison indirectly. This reduction can be done by any kind of filtering the entire dataset for those, which are most likely relevant for the current identification query. The number of thoroughly evaluated entries is, therefore, reduced. This is usually expressed as the so-called *penetration rate*, i.e. what ratio of the dataset has to be compared thoroughly against. If the combination of time for the overhead of prefiltering and time for thorough comparison of the remaining entries reduces the mean response time, the throughput can be increased.

There are mainly two kinds of such prefiltering: *FP classification* (FC) and *FP indexing* (FI). The former clusters all FPs into distinctive classes. The most common clustering assigns one out of five pattern types to FPs. FC can reduce the mean response time. However, it has three drawbacks: the clustering may be ambiguous for many FPs, it may fail, if the FP sample contains only a small part of the finger's area, and the penetration rate is not very low due to the small number of classes. FI assigns one or more index values to each FP sample. Usually, a fixed number of features are concatenated to a *fixed-length* feature vector. This, in turn, allows a rough but computationally simple comparison. The comparison is no hard classification such as in FC. It is continuous, and therefore allows lower penetration rates. FI may, therefore, is superior to FC. The generation of fixed-length feature values is common also for other biometric traits. Examples are the so-called Iris-Code [1] for iris recognition or Eigen-Faces [2] for face recognition. For both biometric traits, such an indexing is distinctive enough to allow not only prefiltering but even identification.

Various approaches to FI have been proposed. This work surveys the research on this topic. It focuses on the features of the FP samples, which are used to generate the index vectors. There is no other survey on the features for FI yet. In addition, the quality of the body of research is assessed.

The rest of this work is organised as follows: Section 2 gives a short introduction into FI. The actual survey process is described in Section 3. Section 4 categorises and describes the reviewed research items. Section 5 gives an overview of the datasets and metrics, which have been used in the surveyed works. A summary with conclusions of this survey can be found in Section 6.

2 Indexing

The technique of FI consists of multiple processing steps. FP samples are taken as inputs. The final output is a candidate list $\mathscr{C}$.

FI makes use of an index generating function F, which maps an FP sample on an identifier. This identifier is called an *index* or an *index vector*. An ideal index would be unique for every FP. Thus, all FP samples of the same FP would be mapped to the same index. In general, the index generating function is not injective, i.e. one index may be assigned to more than one sample. It also is not surjective, i.e. more than one sample might be mapped to the same index vector. Thus, the index generating function is not distinctive enough to generate a unique index.

However, the similarity between indices indicates the likelihood of both being mated, i.e. from the same finger. The comparison of indices results in an indexing score s_i representing the likelihood. Without loss of generality one can assume that a higher score indicates a higher likelihood. This means that the order of the indexing scores matters. The actual values and relations in magnitude do not necessarily have an explicit meaning.

A requirement for FI is that the comparison of indices has to be way faster than the typical thorough comparison based on FP minutiae. This aspect of speed is usually achieved by two techniques: comparing index vectors of fixed length and a computationally simple comparison, *e.g.* L_2-norm of the difference between indices.

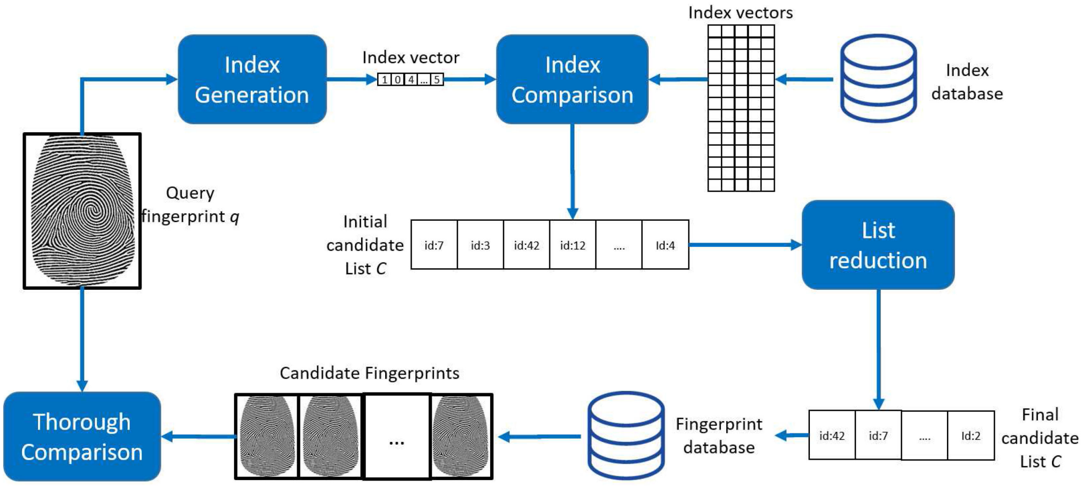


Fig. 1 *FP recognition workflow incorporating FI*

The result of an FI for a single query is a candidate list $\mathscr{C}$ of identities. This list $\mathscr{C}$ contains a subset of those candidates in the database, which are most likely targets for a given query sample. FI can be interpreted as a fast prefiltering before the thorough comparison will be performed. Fig. 1 visualises how FI can be integrated schematically into the entire biometric comparison workflow. The index generating function F generates an index $F(q)$ for a given query sample q. This index $F(q)$ is compared against the set of indices $\{F(\text{id}):\text{id} \in \text{DB}\}$ of all entries id in the database DB. Each comparison between two indices $F(q)$ and $F(\text{id})$ results in an indexing score $s_i[F(q), F(\text{id})]$. Then, an *initial candidate* list $\mathscr{C}$ of identities is generated. If applicable, the initial candidate list is reduced further in an additional *list reduction* process into a *final candidate list*. If no list reduction is applied, the initial candidate list can be passed as the final candidate list. For the sake of simplicity, this survey will only deal with the final candidate list and define it as the candidate list $\mathscr{C}$. Finally, all identities in the candidate list are evaluated by the thorough comparison against the query q. The final biometric decision is then carried out only on the remaining candidates. The candidate list $\mathscr{C}$ can be generated according to several policies. Each represents its own idea of how to use the indexing scores generated by the indexing. Cappelli *et al.* identified the five typical policies on how to reduce the candidate list $\mathscr{C}$:

- *Fixed threshold*: All indexing scores are compared against a fixed threshold θ. Only those candidates exceeding the threshold θ are added to the candidate list $\mathscr{C}$. Thus, the candidate list $\mathscr{C}$ is of variable length. In this case, the indexing score s_i is interpreted as a probability for being the mated comparison. Therefore, the fixed threshold θ represents some kind of probability, which is at least necessary for being a mated comparison
$$\mathscr{C} = \{\text{id}: s_i(F(q), F(\text{id})) > \theta, \text{id} \in \text{DB}\}$$
- *Top N ranking*: In this scenario, the candidate list consists of a fixed number N of candidates, which achieved the highest indexing scores for a single query q. The constant length of $\mathscr{C}$ allows a forecast on the runtime of an entire query. Only the order of the index scores is relevant in this case. The actual values of the index scores are irrelevant. This may help in more difficult comparisons, *e.g.* those in which indexing scores may be low due to bad quality.
- *Variable threshold on score differences*: The maximum indexing score $s_{\max}(q)$ for a query is identified. The candidate list $\mathscr{C}$ contains all candidates resulting in a comparison score not smaller than the maximum indexing score reduced by a given offset δ. This results in a candidate list $\mathscr{C}$ of variable length
$$\mathscr{C} = \{\text{id}: s(F(q), F(\text{id})) > s_{\max}(q) - \delta, \text{id} \in \text{DB}\}$$
- *Variable threshold on score ratio*: This approach is similar to the approach *Variable threshold on score differences*. The maximum indexing score $s_{\max}(q)$ for a query is identified. The list $\mathscr{C}$ contains all candidates resulting in an index score exceeding a given ratio ρ with respect to the highest found index score. This also results in a candidate list $\mathscr{C}$ of variable length
$$\mathscr{C} = \{\text{id}: s(F(q), F(\text{id}))/s_{\max}(q) > \rho, \text{id} \in \text{DB}\}$$
- *Oracle*: In this case, for every query, the candidate list is of exactly the optimal size, which is required to include the correct identity. This workflow would be to thoroughly compare the candidates in the candidate list until the correct one is identified. This implies a perfect thorough comparison. Therefore, this policy is mainly of the theoretical value.

Generating the candidate list can be quite time-consuming, *e.g.* if a very long list of indexing scores needs to be sorted. In such cases, the candidate list generation can take a large amount of the total time of the FI. The policy for the candidate list construction might, therefore, be considered as a critical component. All policies have their own reasoning and are reasonable to some degree. None of the policies is superior to the others by design. Every policy has its own to reasonable metrics.

Other forms of candidate list reduction are possible. For example, if one was able to decide or knew whether an FP sample belongs to a male or a female, one could reduce the candidate list by gender. Dantcheva *et al.* [3] provided a comprehensive review of such approaches.

3 Survey

3.1 Survey process

I decided to search for relevant works in the four most relevant archives in computer science which require a review: *IEEE Xplore*, *ScienceDirect* from Elsevier, *SpringerLink*, and Association for Computing Machinery (ACM). Table 1 reports the exact search phrases. Only original research works have been included in the survey. Therefore, some additional filtering had to be applied to the search results. The table also lists the number of research items found in the review.

The first screening was to sort out roughly the irrelevant works from all found results. This was done considering only publication titles and abstracts. Mainly, there have been two criteria for inclusion. First, a proposed approach had to be applicable to FP samples. Second, it is needed to generate a fixed-length index vector for samples or features, which could be used for FI. In case of doubt, research was kept for closer inspection during the second screening.

During the second screening, the remaining publications have been analysed thoroughly. Some works, which had not been sorted out before, have been filtered by this stage. No further criteria have been applied at this stage. Deficiencies in the quality of work have been captured by using a survey questionnaire (see Section 3.2.).

The reference lists of the most popular publications found during the regular survey have also been inspected. This allowed identifying additional relevant works, which had been missed by the search in the archives. Actually, this review is not complete with respect to all publications ever done in the domain of FI. The survey is limited by the described review process. To the best of my knowledge, no ground-breaking features for FI were missed by this review process.

3.2 Survey questionnaire

The approaches found during the survey have been evaluated according to a defined catalogue of aspects. Those aspects are:

- *[Level]*: *What is the level of detail?*: This aspect shall estimate how well the actual methods are described. This is very important for reproduction of the claimed results. The clearer and the more detailed the description is, the higher the chance of reproducibility. However, this aspect is subject to the opinion of the survey's author. This aspect's ratings range from a good level (○○●), over a fair level (○●○) to a bad level (●○○) of description.
- *[Repr]*: *Is the approach working in a local or a global manner?*: Some approaches inspect *local* structures, *e.g.* neighbourhoods of FP minutiae. Others use a *global* representation, *e.g.* the orientation field of the entire FP sample.
- *[Mod]*: *Which biometric modality is addressed?*: This aspect indicates whether an approach is bound to FP only. Some approaches are also proposed to be applicable for the modality *palm* (P) and some even to any modality (*).
- *[Multi]*: *Is a solution provided to process more than one finger at a time?*: Some biometric systems use more than one FPs as an identifier, *e.g.* all four FP of a hand. Checkmarks indicate whether the approach provides a solution for the combination of more than one FP.
- *[Index]*: *Is a single index generated for a sample or are there multiple indices for each feature?*: In general, a single index vector per sample allows a simpler comparison workflow, because in the other case special consolidations on the sub-results have to be performed. This aspect correlates slightly with the aspect of *Repr*: most local approaches generate indices per feature and most global approaches generate indices per sample. However, there are counterexamples.
- [$\mathcal{O}(\cdot)$]: *Is there any assessment of computational complexity?*: FI is meant to improve a system's throughput. A proposed approach shall, therefore, be evaluated on the effort which must be performed to apply the approach. An approach is even useless if it is so computationally expensive that there is no benefit in terms of the throughput at the end. Checkmarks indicate any assessment of the aspects.
- **[·]**: *Is there any assessment on time consumption?*: The aspects of computational complexity $\mathcal{O}(\cdot)$ and timing · strongly depend on each other. Nonetheless, the former is the more significant one. Checkmarks indicate any assessment of this aspect.
- *[Cit.]*: *How often has the work been cited?*: The number of citations can be interpreted as a rough indicator of the impact of an approach. The actual number of citations was measured on Google Scholar on 1st November 2017. The higher the count of citations, the more important a publication can be assumed. Google Scholar includes self-citations into the citation count. Self-citations distort this indicator.

An additional aspect would be the memory consumption of an approach. In general, this aspect is not addressed by the approaches. However, it can be derived by the reader.

4 Relevant approaches

The found approaches can be grouped into four domains of features: FP minutiae, FP ridges, orientation fields, and biometric scores. Each domain will be described in its own section as follows. Tables 2–6 give an overview of the found approaches with respect to the aspects monitored by the survey questionnaire.

4.1 Approaches using FP minutiae

The vast majority of approaches for FI uses FP minutiae (see Fig. 2) as a feature. Owing to the use of minutiae, all approaches in this domain are bound to the biometric modality of FPs. FP minutiae are also the most common features used for thorough comparison of FP samples.

Minutiae are well suited even for biometric identification. Thus, approaches using FP minutiae for FI make use of very descriptive and powerful features. Another advantage over other features is the fact that most of these approaches are applicable without any knowledge about the original FP sample. They can, therefore, be also applied to already deployed systems, in which no FP images are available.

A set of approaches is working on sets of few minutiae. For each set, features are calculated, which describe the relation of the minutiae. Germain *et al.* [12] were the first to propose triplets (see Fig. 2*b*) of FP minutiae. The triplets can then be represented by their geometric features, *e.g.* angles and side lengths. The number of possible combinations of minutiae to triplets is very large. When no restrictions on the triplets apply and an index is generated for every triplet, the number of triplet comparisons will be even larger. Therefore, restrictions seem reasonable. Kovács-Vajna [23], Bhanu and Tan [8], Reddy *et al.* [37], and Zhou *et al.* [45] proposed variations in the selection of relevant triplets and features to be extracted. These strategies allow keeping the number of triplets to a reasonable order. Ross and Mukherjee [38] enriched triplet features with the ridge curves associated with the vertices. The information on adjacent curves is, of course, a valuable information. By the way, this approach is quite similar to the methods' human examiners would apply. Biswas *et al.* [9] extended the features of triplets with information on the local *curvature* of the ridge structure. Each region in an FP sample has its own characteristic curvature. Thus, adding curvature information significantly increases the total information of a single minutia. The gain in information of course increases by using not one but three minutiae. Triplets become very descriptive in regions of strongly varying curvature. Khodadoust and Khodadoust [22] proposed to

Table 1 Number of relevant research items after the distinctive review stages and instructions for a reproducible review search

Archive	# Initial results	# After first screen	#After second screen	Search command	Additional filters
IEEE Xplore	139	40	31	`(((Fingerprint) AND Indexing) AND Biometric*)`	‘Conference Publications Journals’ or ‘Magazines’
ScienceDirect	52	21	16	`(‘Fingerprint Indexing’) and Biometric*`	‘Journals’
SpringerLink	33	15	11	`Biometric AND ‘Fingerprint Indexing’`	‘Conference Paper’ or ‘Article’
ACM	128	13	5	`(+Fingerprint+Biometric Indexing)`	*no filter*
from reference lists	n/a	n/a	19	n/a	n/a

Table 2 Approaches making use of minutiae

Authors	References	Approach	Level	Repr	Mod	Multi	Index	$\mathcal{O}(\cdot)$	⏱	Cit.
Bai *et al.*	[4]	*k*-nearest neighbours	○○●	local	FP	—	feature	—	✓	6
Bai *et al.*	[5]	statistics on MCC	○○●	local	FP	—	feature	—	—	0
Bebis *et al.*	[6]	Delaunay	○○●	local	FP	—	feature	✓	—	189
Benhammadi *et al.*	[7]	minutia code	○○●	local	FP	—	feature	—	—	68
Bhanu and Tan	[8]	triplets	○○●	local	FP	—	feature	—	✓	223
Biswas *et al.*	[9]	triplets	○●○	local	FP	—	feature	—	—	24
Cappelli *et al.*	[10]	MCC	○○●	local	FP	—	feature	—	✓	111
Chen *et al.*	[11]	matching of minutia subsets	○○●	local	FP	—	n/a	✓	✓	28
Germain *et al.*	[12]	triplets	○○●	local	FP	—	feature	—	✓	287
Gago-Alonso *et al.*	[13]	Delaunay triangulation	○○●	local	FP	—	sample	—	—	25
Hartloff *et al.*	[14]	sequences of minutiae	○○●	local	FP	—	feature	—	✓	13
Iloanusi	[15]	quadruplets	○○●	local	FP	✓	feature	—	✓	22
Iqbal and Namboodiri	[16]	triplets and quadruplets	○○●	local	FP	—	sample	—	✓	1
Jain and Prasad	[17]	geometric representation	○○●	global	FP	—	sample	✓	—	1
Jain and Prasad	[18]	geometric representation	○○●	global	FP	—	feature	—	—	2
Jayaraman *et al.*	[19]	minutia in relation to cores	○○●	global	FP	—	sample	✓	—	15
Khachai *et al.*	[20]	Delaunay triangulation	○○●	local	FP	—	feature	—	—	3
Khodadoust and Khodadoust	[21]	expanded Delaunay triangulation	○○●	local	FP	—	feature	—	✓	0
Khodadoust and Khodadoust	[22]	triplets of minutiae and cores	○○●	local	FP	—	feature	—	—	1
Kovacs-Vajna	[23]	triplets	○○●	local	FP	—	feature	—	✓	419
Kumar *et al.*	[24]	nearest neighbours	●○○	local	FP	—	sample	—	—	2
Le and Bui	[25]	triplets	○○●	local	FP	—	feature	✓	—	2
Le	[26]	hashing on neighbourhoods	○○●	local	FP	—	feature	✓	—	0
Li *et al.*	[27]	minutia discs	○○●	local	FP	—	feature	—	—	6
Li *et al.*	[28]	minutia discs	○○●	local	FP	—	sample	—	—	0
Liang *et al.*	[29]	Delaunay with minutia type	○○●	local	FP	—	feature	✓	—	38
Liang *et al.*	[30]	Delaunay with minutia type	○○●	local	FP	—	feature	✓	—	96
Liu *et al.*	[31]	minutiae and BioCode	○○●	global	FP	—	sample	—	—	23
Mansukhani *et al.*	[32]	trees of neighbourhoods	○○●	local	FP	—	feature	—	✓	21
Muñoz-Briseño *et al.*	[33]	low-order Delaunay triangles	○○●	local	FP	—	feature	—	—	2
Muñoz-Briseño *et al.*	[34]	Delaunay triangulation	○●○	local	FP	—	feature	—	—	2
Muñoz-Briseño *et al.*	[35]	extended Delaunay triangulation	○○●	local	FP	—	feature	—	✓	0
Nagati	[36]	minutiae around cores	○○●	local	FP	—	sample	—	—	0
Reddy *et al.*	[37]	triplets	○○●	local	FP	—	feature	—	—	1
Ross and Mukherjee	[38]	triplets with ridge curves	○○●	local	FP	—	feature	—	—	50
Vandana *et al.*	[39]	lower-order Delaunay triangles	○○●	local	FP	—	feature	—	—	8
Vij and Namboodiri	[40]	selection of quadruplets	○○●	local	FP	—	feature	—	✓	7
Wang *et al.*	[41]	spheric variation of LSH	○○●	global	FP	—	sample	—	✓	1
Wang *et al.*	[42]	shrinking of MCC	○○●	local	FP	—	sample	✓	—	9
Xu and Veldhuis	[43]	spectral representation	○○●	global	FP	✓	sample	—	—	2
Yang *et al.*	[44]	pixel look up via three minutiae	○●○	global	FP	—	sample	—	—	0
Zhou *et al.*	[45]	triplets	○○●	local	FP	—	feature	—	✓	8
Zhou *et al.*	[46]	alternative hashing for MCC	○○●	local	FP	—	feature	—	—	0

Table 3 Approaches making use of ridges/texture

Authors	References	Approach	Level	Repr	Mod	Multi	Index	$\mathcal{O}(\cdot)$	⏱	Cit.
Feng and Cai	[59]	ridge invariants	○●○	local	FP	—	feature	—	—	41
He *et al.*	[52]	SURF and DAISY features	○○●	global	*	—	sample	—	—	15
Komal *et al.*	[57]	radon transformation of core region	○○●	local	FP	—	sample	—	—	0
Jakubowski and Venkatesan	[60]	ridge crossing over random lines	○○●	global	FP	—	sample	—	—	3
Jazzar and Muhammad	[61]	Zernike moments	○○●	global	FP, P	✓	sample	—	✓	13
Liu *et al.*	[55]	region around singularities	○●○	global	FP	—	sample	—	—	53
Zegarra *et al.*	[56]	wavelets for core regions	○○●	local	FP	—	sample	—	—	45
Nanni and Lumini	[54]	various block-wise local descriptors	○○●	local	FP	—	feature	—	—	57
Shuai *et al.*	[49]	subset of SIFT of three impressions	○○●	global	FP	—	sample	—	—	67
Yang and Park	[58]	invariant moments	○○●	local	FP	—	sample	—	✓	97
Zheng *et al.*	[53]	SURF features	○○●	local	FP	—	sample	—	✓	4

use triplets containing two minutiae and a singularity as corners. This approach, of course, depends on a reliable detection of the FP singularities. Detection of the singularities is challenging especially for FP samples of bad quality. Singularities may not be detected at

Table 4 Approaches making use of biometric comparison scores

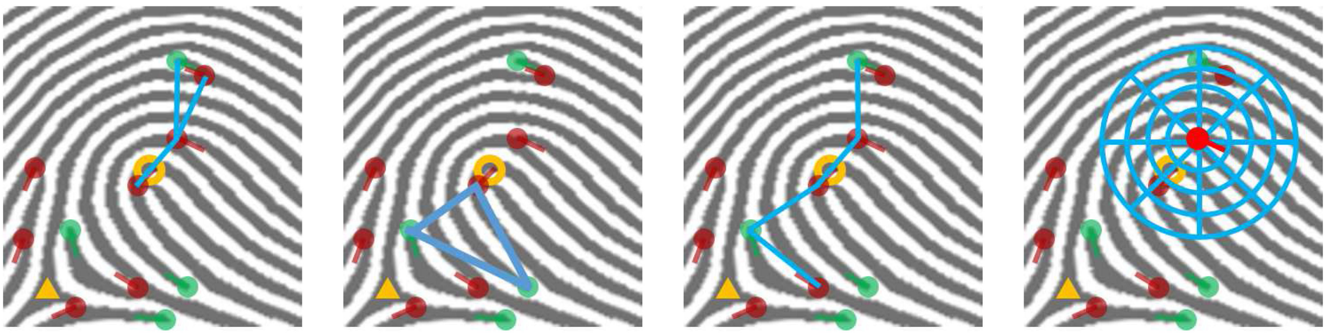
Authors	References	Approach	Level	Repr	Mod	Multi	Index	$\mathcal{O}(\cdot)$	⏱	Cit.
Gyaourova and Ross	[62]	bag of templates	○○●	global	*	—	sample	✓	—	44
Gyaourova and Ross	[63]	bag of templates	○○●	global	*	—	sample	—	—	25
Gyaourova and Ross	[64]	bag of templates	○○●	global	*	✓	sample	—	✓	50
Murakami and Takahashi	[67]	imitation of query	○○●	global	*	—	sample	—	✓	12
Cappelli *et al.*	[66]	evaluation on few scores	○○●	global	*	—	sample	—	✓	16

Table 5 Approaches making use of the orientation field

Authors	References	Approach	Level	Repr	Mod	Multi	Index	$\mathcal{O}(\cdot)$	⏱	Cit.
Jain *et al.*	[70]	FingerCode	○○●	global	FP	—	sample	—	—	1393
Kavati *et al.*	[71]	eight Gabor filters	○○●	global	FP	—	sample	—	✓	3
Leung and Leung	[72]	variation of FingerCode	○○●	global	FP	—	sample	✓	✓	31
Li *et al.*	[73]	symmetric filters	○○●	global	FP	—	sample	—	—	40
Liu *et al.*	[74]	local symmetries for alignment	○●○	global	FP	—	sample	—	—	14
Liu *et al.*	[75]	complex filters	○○●	global	FP	—	sample	—	—	34
Lumini *et al.*	[76]	PCA on orientation field	○○●	global	FP	—	sample	—	—	116
Maio and Nanni	[77]	variation of FingerCode	○○●	global	FP	—	sample	—	✓	25
Ross *et al.*	[78]	eight Gabor filters of tessellation	○○●	global	FP	—	sample	—	✓	465
Turky and Ahmad	[79]	self-organizing maps for representation of orientation field (OFs)	○●○	global	FP	—	sample	—	—	8
Xu and Hu	[80]	sparse representation	○○●	global	FP	—	sample	—	—	3
Yang *et al.*	[81]	invariant moments	○○●	global	FP	—	sample	—	✓	8

Table 6 Approaches making use of more than one characteristic

Authors	References	Approach	Level	Repr	Mod	Multi	Index	$\mathcal{O}(\cdot)$	⏱	Cit.
Bazen *et al.*	[88]	OF and minutiae	○○●	global	FP	—	sample	—	✓	2
de Boer *et al.*	[89]	OF, FingerCode, and triplets	○○●	global	FP	—	sample	—	—	104
Cappelli	[85]	OF and ridge frequencies	○○●	global	FP	—	sample	✓	✓	46
Cappelli and Ferrara	[86]	MCC, OF, and ridge frequencies	○○●	global	FP	—	sample	—	✓	23
Han *et al.*	[91]	minutiae and image	○●○	global	FP	—	sample	—	—	17
Jiang *et al.*	[83]	OF and ridge frequencies	○○●	global	FP	—	sample	—	✓	80
Lee *et al.*	[82]	OF and ridge frequencies	○○●	global	FP	—	sample	—	—	22
Liu *et al.*	[84]	OF and ridge frequencies	○○●	global	FP	—	sample	—	—	68
Pandey and Singh	[90]	triplets, MCC, and OF	○●○	global	FP	—	feature	—	—	0
Paulino *et al.*	[87]	triplets, MCC, OF, singularities, and ridge frequencies	○○●	global	FP	—	feature	—	—	22



a *b* *c* *d*

Fig. 2 *Minutiae is characteristic point on the ridge structure: endings (green) and bifurcations (red). Other characteristic points are the singularities: delta (orange triangle) and core (orange circle). Minutiae can be used for FI in various representations. Usually, neighbouring minutia is described in groups, e.g. nearest neighbours (3a), triplets (3b), or a sequence (3c). In some cases, the neighbourhood is sampled at a tessellation grid (3d)*
(a) Nearest neighbours, ***(b)*** Triplets, ***(c)*** Sequence, ***(d)*** Tessellation

all in partial FPs or in FPs with pattern types without singularities at all, i.e. *arches*.

Several approaches propose to use a Delaunay triangulation for selection of relevant triplets. Sampling triplets in such a manner is a special and popular strategy in triplet selection. Bebis *et al.* [6] were the first to use Delaunay triangulation. The advantage of using this sampling strategy is that a Delaunay triangulation generates unique sets of triplets. Even though the Delaunay triangulation may slightly differ, when the minutia positions are disturbed, most of the Delaunay triangulation usually works stable for most of the entire FP sample. Liang *et al.* [29, 30] proposed to variant integrate the minutia type as a feature. The type of a minutia can either be a so-called ridge *ending* or a ridge *bifurcation*. Adding such information to the description of minutiae can enhance the information significantly. However, distinguishing both types is challenging especially for FP samples of low quality.

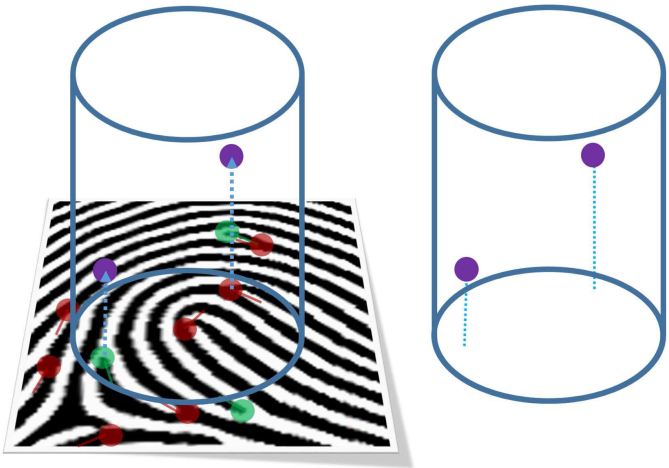


Fig. 3 *MCC encodes a neighbourhood of minutiae. Each neighbouring minutia (purple) is represented with its relative angle and position to a central minutia*

Vandana *et al.* [39] proposed to use triplets from a lower-order Delaunay triangulation. This approach increases the amount of generated triplets. The approach gets more tolerant to spurious and missing minutiae. Muñoz-Briseño *et al.* [34] additionally used distances to the next nearby singularity as a feature. This information can be interpreted as a rough indicator of the region in the FP sample. Again, detection of singularities can be challenging or even impossible. They further proposed two variations of the triplet selection by the Delaunay triangulation [33, 35]. Khodadoust and Khodadoust [21], Khachai *et al.* [20], and Gago-Alonso *et al.* [13] also proposed further variations of the Delaunay triangulation. Those approaches mainly deal with the challenges arising due to missing and spurious minutiae or from positional variations of the minutiae.

Some approaches use more than three minutiae. The more minutiae one use, the more informative the set of minutiae becomes. These approaches suffer from missing and spurious minutiae too. Vij and Namboodiri [40] and Iloanusi [15] proposed to use quadruplets of FP minutiae. In some cases of biometric comparisons, two FP samples from the same FP share only a small area. In such cases, finding shared quadruplets will be harder than finding shared triplets. Thus, the strong gain in information comes with drawbacks for mated comparisons with the small overlapping area. Iqbal and Namboodiri [16] proposed to combine triplets and quadruplets of minutiae and perform cascaded filtering on these. This approach, therefore, tries to combine the benefits from triplets and quadruplets. Cappelli *et al.* [10] proposed to represent minutiae and their relative neighbourhood in a compact form called *minutia cylinder code* (MCC). In this approach, a cylinder describes the relative position and relative angles of the neighbouring minutiae (see Fig. 3). The cylinders represent a special tessellation grid. Neighbouring minutiae are represented as Gaussians on the grid. This deals with the sampling errors on the grid and also enables tolerance to slight positioning errors of minutiae. Each plane in the cylinder represents a relative angle with respect to the central minutia. By the way, actually it is not a cylinder but a torus, which allows dealing with the cyclicity of angles. MCC is the only approach, which was evaluated at benchmark FP verification competition (FVC)-ongoing [47]. FVC-ongoing is the only available independent benchmark for FI. There is an software development kit (SDK) for MCC available by the way. MCC is the base for some variations. Wang *et al.* [42] proposed to reduce the size of the cylinders. Even though the original MCC has a compact format, only a small share of each cylinder is non-zero, i.e. the points where the neighbouring minutiae lie. This fact allows reduction of the size. The original MMC also has a straightforward tessellation grid. Sampling and quantisation leave space for improvement here. Bai *et al.* proposed, therefore, to use statistics on the cylinders for an improved quantisation of the cylinders [5]. Zhou *et al.* [46] proposed an alternative hashing for MCC. Li *et al.* [27, 28] proposed two variants of descriptions of neighbourhoods, described as *minutiae discs*. Neighbouring minutiae are represented here in polar coordinates. Polar coordinates enable a more natural dealing with positional and angular relations compared with Cartesian coordinates.

There are further approaches describing local neighbourhoods of minutiae (see Fig. 2*a*). Those approaches usually use the nearest neighbouring minutiae around a central minutia. These neighbourhoods, therefore, are local descriptions. Such descriptions can be interpreted as small puzzle pieces. Those usually allow how to deal with a biometric comparison of FP samples with a small overlap. In such cases, only very few puzzle pieces match between the FP samples. Kumar *et al.* [24] proposed to add some undefined features to minutiae. Mansukhani *et al.* [32] and Bai *et al.* [4] proposed to use trees for fast comparison of local minutia neighbourhoods. Hartloff *et al.* [14] used series of neighbouring minutiae and concatenated them into sequences (see Fig. 2*c*) of minutia. Those sequences have similar features such as triplets or quadruplets. The concatenation of minutiae to sequences can be interpreted as a sampling strategy of neighbours such as in the approaches using triplets. However, this approach might be promising for comparisons of mated FPs with very small overlaps. This interpretation of minutia sequences as *strings* allows using methods from string processing. Benhammadi *et al.* [7] proposed to describe the minutia by their surrounding local orientations in so-called *minutia code*. Local orientations give an idea, in which region of an FP the sampled minutia is in. The representation is especially expressive in regions of high curvature or near-orientation field singularities.

Some approaches deal in more detail with the index generation from the features. Le and Bui [25] and Le [26] improved the index generation, *e.g.* with error-correcting codes. Wang *et al.* [41] proposed a variation of locality-sensitive hashing (LSH) on FP minutiae.

There are also ideas, which only aim at a fast comparison but do not necessarily use a fixed-length representation. For example, Nagati proposed to use only the minutiae in the central region for a fast but thorough comparison [36]. This region usually contains the highest curvature and dynamic. One can assume that most of the information is clustered in this region. However, by doing so available information is discarded. The reduction to a quite small region automatically introduces the problems arising from the small overlap between FP samples. Jayaraman *et al.* [19] described the local neighbourhoods in the regions around the singularities. Chen *et al.* [11] proposed to compare just a subset of minutiae in a thorough manner. Both approaches suffer from the same drawbacks as the approach proposed by Nagati.

Other approaches use minutiae for a global representation. Jain and Prasad [17, 18] proposed two variations of a geometric representation of all minutiae of an FP sample. This representation is called *spiral tree* and can be used for feature extraction. The generated representation looks like a snail shell. This representation is quite helpful for visual inspection since it allows easy comparisons between two FP samples. Weaknesses of the

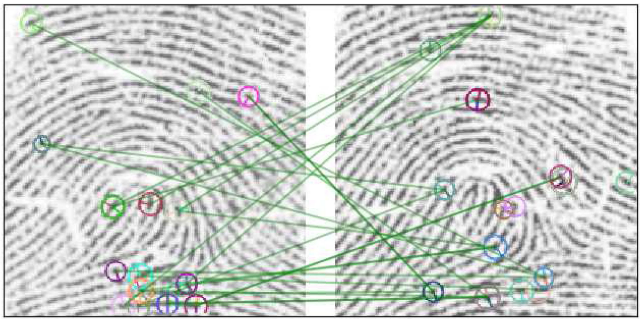


Fig. 4 *Scale-invariant features can describe textures (coloured circles). These descriptors can be matched (green lines) and may also be used for FI*

approach might be the detection of the innermost point of spiral tree and the disturbance from spurious and missing minutiae. Yang *et al.* [44] proposed to assign a value from a random look-up table and three pixels each to each pixel in an image. The random look up induces revocability. Xu and Veldhuis proposed to use a complex representation of the FP minutiae [43]. Each minutia is represented by a complex impulse in the image domain. A minutia's orientation is encoded into the phase of the impulse. By applying Fourier transformation and mapping to polar coordinates, this approach is invariant to translation and rotation. Fourier transformation enables the invariance to translations. Rotations in the image domain result in translations in the polar coordinates of the Fourier spectrum. These translations can be dealt with by application of correlation between two samples. Thus, this approach nicely uses signal processing techniques. Liu *et al.* [31] proposed to combine minutiae with a modification of *BioCode* (which originally included an additional token). External tokens induce extra effort for users but usually enable them to apply verification approaches rather than identification approaches, of course.

4.2 Approaches using FP ridges

Several approaches for FI make use of the ridges of the FP samples. Thus, those methods are dealing with the textures in an image. Such approaches usually assume that FPs actually look similar between multiple impressions. This assumption does only hold for some samples. Usually, two FP samples of the very same FP vary. The stronger the variation is, the less applicable those approaches are. Table 3 lists the found approaches. Four approaches propose to use local descriptors, which are commonly used for dealing with textures. Those techniques are often used for the task of image registration, which can be seen as a similar task to find out how two FP samples fit together. Shuai *et al.* proposed to use a fixed number of scale-invariant feature transform (SIFT) [48] features as a descriptor (see Fig. 4) [49]. SIFT features are scale invariant and were quite popular for matching two images, *e.g.* in computer vision with two cameras. Since actual sizes of structures in an FP are known due to known image resolutions and physiological limitations of FPs, the scale invariance of the SIFT features might be an unnecessary restriction of the feature description. For instance, a twice as large copy of an FP sample would match the original FP perfectly, while two samples of such scaling difference could never be originated from the same FP. FP samples of low quality usually differ strongly. Such variations make SIFT even less applicable. He *et al.* proposed a combination of speeded-up robust features (SURF) [50] and DAISY [51] features to describe the textures [52]. SURF features are similar to SIFT features, while replacement of internal filters leads to a speed up compared with SIFT features. The same restrictions as for SIFT features apply for SURF features as well. The speed up is mainly achieved during the feature index generation, in which timing is of little relevance. Zheng *et al.* [53] used only SURF features but combined it with clustering. Nanni and Lumini [54] proposed to use a selection of local descriptors for FI. Some other approaches focus on the description of a small region of the FP sample. Like in the approaches for FPs, the reduction to sub-region has always discarded information. Challenges from comparisons of samples with small overlap do also apply here. Those approaches usually detect the FP singularities first and process only the area around those singularities. Liu *et al.* [55] were the first to describe this central region. Zegarra *et al.* [56] proposed to use a wavelet decomposition to describe this region. Representation with wavelets usually requires a precise alignment of the input samples. Alignment is a research field on its own, which brings its own challenges. Wavelet approaches usually are also disturbed strongly by elastic transformations. Komal *et al.* [57] described the central region with a variation of the *radon* transformation. The radon transformation can be understood as a representation for lines. This makes it an appropriate means for the description of FP ridges. However, the flow of FP ridges is disturbed by FP minutiae. Yang and Park [58] proposed the usage of *invariant* moments in the central region. These moments are invariant to position, scale, and rotation. This makes a precise alignment irrelevant.

Three other texture-based approaches have been proposed. Feng and Cai [59] proposed to calculate so-called *ridge invariants* from the ridge structures. This approach is related to the minutia-based approaches as it describes ridges by minutia on them. However, the focus here is on the ridges. Indices are generated for lines, which cross over FP ridges. The ridges are identified by minutiae on them. This approach imitates the method a human examiner might use when he counts ridges between minutiae. The approach, therefore, also might deal well with elastic distortions of the FP since those disturbances cannot change the connections of ridges between minutiae. Jakubowski and Venkatesan [60] proposed to use the count of crossings of the ridge structure over several random lines. This method does not only describe the texture but also the orientations found in the FP samples. This approach would require an alignment. Otherwise, the approach would fail since the random lines would cross different ridges. This approach is not tolerant to elastic deformations. Jazzar *et al.* proposed to use *Zernike moments* for the description of an entire FP sample. Zernike moments are invariant to rotation by definition and can be modified to be also invariant to scaling and translation. Those moments are derived from a set of complex polynomials, which form an orthogonal base. This results in a compact description of the FP ridge structure.

4.3 Approaches using scores

All approaches in this domain of features make use of the conventional and thorough biometric comparison. Those approaches use the biometric comparison scores as a biometric feature on its own. The key to still achieve an improvement in throughput is to compare only a small fraction of the entire search database. The most charming aspect in such approaches is the fact that one incorporates the same technology as in the thorough comparison. What cannot be compared correctly during FI, will most likely not be compared correctly during the thorough comparison anyway. As the thorough comparison usually makes use of FP minutiae, these approaches can also be linked to the minutia-based approaches in Section 4.1. They make use and benefit indirectly from these descriptive features. Improvements over time made in the thorough comparisons may also result in improvements in such FI approaches. On the other hand, all approaches will suffer from the same challenges, which are also present during the thorough comparison. Most challenging here are partial FPs, which potentially result in mated comparisons with a small overlap. Table 4 gives an overview of the five approaches in this feature domain.

Gyaourova and Ross [62–64] proposed a total of three approaches, which are all quite similar in their basic idea to use a *bag of* approach. The idea here is to identify a set of samples in the search database, which represents some prototypes of FPs. All queries are compared only against this set (bag) of prototypical FPs. Each score is a single feature in the index (see Fig. 5). It is, therefore, a representation by means of the similarity to prototypes. It is assumed that all impressions of the same FP will result in similar biometric scores when compared with the prototypes. This approach is slightly related to the so-called *Doddington Zoo* [65] because it assumes that each FP will generate its individual

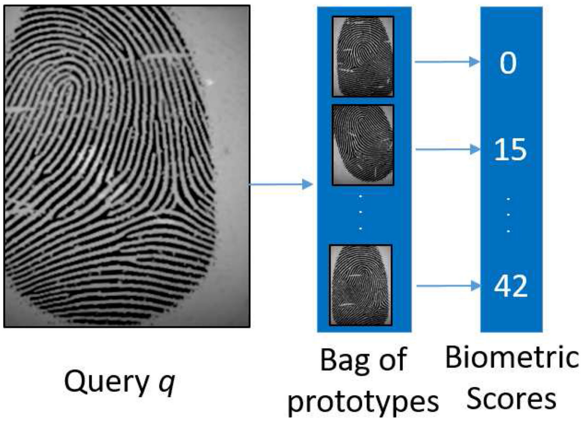


Fig. 5 *Biometric scores can be used for FI. Comparison against a set of prototypes will result in similar biometric scores for similar FPs*

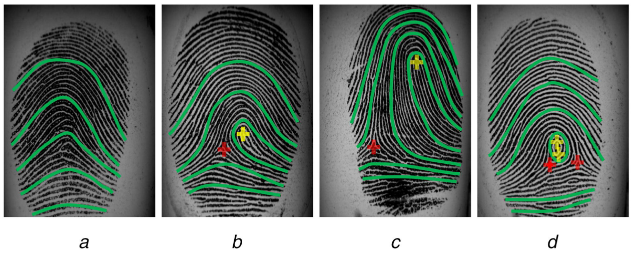


Fig. 6 *Orientation field describes the local orientations (roughly indicated as green lines) of the ridge structure. The orientation fields are dominated by the positional relation and the presence of singularities (yellow and red crosses). Orientation fields have already been used for FC, which classified each FP into a distinctive pattern-type class. Each pattern-type represents a large variation of orientation fields (compare Figs. 6b and c). Orientation fields can also be used for FI*
(a) Arch, ***(b)*** Right loop, ***(c)*** Right loop, ***(d)*** Whorl

biometric score distribution. The fixed number of thorough comparisons allows assumptions on the processing time. Partial FPs may result in small biometric scores for all pattern types. Depending on the policy for candidate list construction, partial FPs will then result in very long candidate lists or the correct identity might not be on the list at all. Cappelli *et al.* [66] proposed to perform only a few comparisons. The idea of Doddington's Zoo also applies in this case. For instance, there are some FPs matching well with many others. These are called chameleons. For so-called *ghost* FPs' mated and non-mated comparisons both result in low biometric scores. Murakami and Takahashi [67] proposed a slightly related approach. They used a few scores to imitate a search against an entire database. This approach strongly depends on the predictive power of those few scores.

4.4 Approaches using orientation fields

There are also approaches, which make use of the orientation field of the FP samples. The orientation field is a representation for the local orientations of the ridge structure. It is a so-called first-level feature. The orientation field is such a distinctive feature that it can be used especially for exclusion during FP comparison (see Fig. 6). However, estimation of the orientation field is no trivial task. The estimation may fail especially in regions of bad quality. Estimation of the orientation field is a research field on its own [68]. Moreover, orientation fields are also the most frequently used feature in FC approaches [69]. Approaches using the orientation field, therefore, have similar advantages and drawbacks as approaches in FC. The main advantage over FC is the fact that there is no hard classification in pattern types. FI allows continuous index vectors. This mainly allows dealing with two challenges in FC. First, even though the classification sorts into single classes, the classification is unambitious in some cases. There is a small inter-class variance for some classes of pattern types. The transition from one pattern type to another is continuous in those cases. Second, two FPs from the same pattern type may still have really different orientation fields. Actually, there is a quite large intra-class variance for some FP classes. For instance, singularities may be quite close to each other in one FP sample and far away in the other. Descriptive power is not used if one uses only hard classes such as in FC. Another advantage of using orientation fields for FI is the fact that orientations fields are smooth and can be modelled mathematically. This allows making estimations of what the orientation field looks such as in regions close to the area of the actual FP sample. This, in turn, allows dealing with biometric comparisons with a small overlap. However, this hypothetical advantage is not used by any approach. Another charming aspect of using orientation fields is the fact that the orientation field is visually perceivable and understandable for humans. One can easily see and tell, why FI using orientation fields works in some cases and fails in the other cases. Many approaches are neither invariant to rotation nor to translation. Therefore, those approaches rely on some kind of alignment before processing. All approaches use a global representation and generate a single index for each sample.

Jain *et al.* [70] proposed so-called *FingerCode*. The idea is to use eight *Gabor* filters for filtering the FP samples. The eight resulting filter responses are sampled at a tessellation grid over the FP sample. The tessellation grid is circular with its centre on a detected reference point. By doing so, all local orientations and their signal quality are encoded into a fixed-length vector. This fact makes the features of this approach very descriptive as it uses the advantages of the high intra-class variance. FingerCodes are an appropriate example for visually perceivable and understandable representation, as differences between different FingerCodes can easily be identified even by visual inspection. Ross *et al.* [78] proposed usage of a square tessellation. In addition, no reference point is required. The FP sample is instead aligned using information on the FP minutiae. This results in a more or less simple description of orientation field for the entire FP sample. Yang *et al.* used discrete wavelet transform instead of Gabors filters for [81]. Invariant moments around core regions are used to generate features. Maio and Nanni [77], Leung and Leung [72] and Kavati *et al.* [71] proposed further variations of the MinutiaCode approach.

Liu *et al.* proposed to use local symmetries for the alignment of the FP sample [55]. The aligned orientation field is then used to generate the index vector. Symmetries again are perceivable by humans, which facilitate understanding of this approach. Li *et al.* [73] used similar symmetric filters for a description of characteristics in the orientation field. Liu *et al.* [75] proposed to use complex filters on the orientation field to find singularities. Those singularities are used as features. Of course, challenges will arise, if no singularities are present, *e.g.* in small FPs.

Some approaches describe the orientation field more directly. Lumini *et al.* [76] proposed to use a *principal component analysis* (PCA) on the orientation field. With respect to orientation fields, this approach was the first to evolve from FC to continuous FI. This is a straightforward approach to generate a compact representation from an orientation field. Xu and Hu [80] proposed to use the method of *total variation* to reconstruct the assumed orientation field of an FP sample. Total variation is a popular method for modelling smooth vector fields such as an FP orientation field. It is quite tolerant to disturbances of the vector field. As orientation field estimation is no trivial task, this approach might be quite robust against quality variations between FP samples. This approach, therefore, makes use of the fact that FP orientation fields are smooth. Finally, a sparse representation is generated from the reconstructed orientation field. Turky and Ahmad [79] proposed to use *self-organising maps* for a description of the orientation field. The self-organising maps can also be finally used to for generation of the index vector. Self-organising maps have the capabilities to deal with disturbed inputs. This approach may, therefore, be appropriate for FP samples of low quality.

4.5 Hybrid approaches

A few approaches have been proposed, which use features from more than one domain. These approaches, in general, do not propose new features for generation of index vectors. They only combine features proposed by others. Owing to the combination of features and the fact that more information is processed, these approaches may achieve higher accuracies. Another advantage is of course that if a single sub-component such as the orientation field estimation is improved, the entire FI may be improved. On the other hand, such hybrid approaches may be prone to failures in the single sub-component. Such approaches may unintentionally combine not only the advantages but also the drawbacks of their sub-components. In some cases, each feature is indexed for its own, and in some cases the features are used jointly. All found approaches use a global representation of the features.

Even though these approaches do not provide any new features, they are still worth listing here. Lee *et al.* [82], Jiang *et al.* [83], Liu *et al.* [84], and Cappelli [85] proposed to use the orientation field and ridge frequencies (describing distances between neighbouring ridges) as features for FI. Later, Cappelli and Ferrara [86] extended this approach with the use of MCC. Paulino *et al.* [87] extended this approach even further. They proposed to use a combination of minutia triplet, MCC, the orientation field, FP singularities, and ridge frequencies. Bazen *et al.* [88] combined orientation fields and minutia. de Boer *et al.* [89] used orientation fields, FingerCode, and triplets for FI. Pandey *et al.* proposed to use minutia triplet, MCC, and the orientation field for FI [90]. All features are compared individually. In the end, a fusion of all three results is performed. Han *et al.* [91] proposed a hashing directly on the FP minutiae and enriched the minutiae information with features extracted from the FP image.

5 Usage of data and metrics

Standardisation organisation International Organization for Standardization (ISO) is currently working on the topic of indexing techniques. However by now, there is no standard to evaluate biometric indexing. Thus, there is also no standard test set. The surveyed works evaluated their proposed approaches on a multitude of different datasets. Table 7 gives an overview of the evaluations.

There are datasets publicly available for evaluation. The benchmark series FVC has four editions, which supply the following volumes of datasets: 2000 [92], 2002 [93], 2004 [94], and 2006 [95]. National Institute of Standard & Technology (NIST) provides a so-called special database NIST SD4 of rolled FPs [96]. There is a variant of this dataset available, which reassembles a natural distribution of pattern types: NIST SD4 *nat*. NIST also provides another dataset of rolled FP: NIST SD14. The University of West Virginia provides the multi-modal dataset WVU. This set also contains FP samples. All datasets have individual characteristics. Table 8 provides information on the characteristics of the datasets. Table 8 shows which approach has been evaluated on which dataset. Some approaches have been evaluated on the unknown, sequestered or only rarely used datasets. Those datasets are summarised to the category *Others*. Two datasets have been used for testing most often: FVC2002 DB1 and the NIST SD4 or rather its natural subset. Owing to their frequent usage, both can be seen as some kind of pseudo-standard test sets. In general, no reviewed work gave reasons for selection of the evaluated datasets.

When dealing with pattern recognition, *generalisation* is an important aspect. Generalisation indicates how well a task can be solved by an approach to unknown data. A method's degree of ability to generalise can be assessed typically in two ways. First, a strict splitting of the data into a part used for training and a part for testing. Second, testing on multiple different test sets may reveal the ability to generalise with respect to a larger variety of data. Achieving good results on a single dataset may just be a fluke.

Most of the approaches have a tunable parameter. However, in almost no case a training set to tune the parameters was declared. It is, therefore, unclear, whether or not a strict splitting of the data has been applied. This, in turn, allows doubts in the generalisation ability of most of the approaches. Many approaches have been tested only on one or two datasets. A larger variety of data would have been desirable. Unfortunately, only very few approaches have been tested thoroughly on a larger number of datasets.

FI is meant to be applied to large datasets. Unfortunately, no really large datasets are publicly available. Some approaches have been tested on large but sequestered datasets. This does not allow reproducibility of the claimed results.

Besides the aspect of datasets, metrics are also important when assessing an approach. There are several policies on how to generate the candidate list (see Section 2). Each policy has its own reasonable metrics. In general, no approach was evaluated with respect to all policies. Usually, only a single policy was evaluated. This results in a multitude of used metrics, which are not comparable directly. In addition, even the naming of the metrics is not following a standard. This results in the confusing usage of a multitude of synonyms for metrics. Two metrics and their synonyms are used most frequently: *penetration rate* and *error rate*. The penetration rate is the ratio between the length of the candidate list and the entire database. The error rate is the ratio of candidate lists, which do not contain the genuine candidate. Both rates usually depend on ranks in an ordered candidate list.

It is worth mentioning, that there is an independent benchmark for FI: FVC-ongoing [47]. This benchmark evaluates on a large, sequestered dataset. In addition, it would provide common metrics for evaluation. Thus, FVC-ongoing would allow reasonable comparison of approaches. Unfortunately, there is only one approach with published results.

6 Conclusion

FI can be a key processing step when dealing with large FP databases. Various approaches to FI have been proposed in the past. This work has surveyed the approaches, which have been found in the four relevant archives. The approaches can be grouped into five categories with respect to the features which are processed. Most approaches use FP minutiae as input features. A few approaches work on ridges/textures, orientation fields, or biometric scores. There are also some hybrid approaches.

It is almost impossible to identify a state of the art in FI for several reasons: first, there is no standard protocol or common metric. Usually, error rate is evaluated against penetration rate. Second, there is no standard dataset for evaluation. Even though, the datasets FVC2002 DB1 and the NIST SD4 are the most commonly used, only about half the approaches evaluate on these datasets. Some approaches even evaluated on sequestered data. Claimed results are, therefore, not reproducible at all. Only very few approaches have been evaluated on large datasets even though this would be the use case for FI. Third, there is a lack of independent external evaluation, even though the benchmark FVC-ongoing would be available for this very task.

The level of description of the proposed approaches is quite good in most of the reviewed works. This allows a fair chance of reimplementation of the approaches.

Unfortunately, several deficiency in the quality of the body of research has been observed. In almost all approaches, the methods have a tunable parameter. However, only in very few cases, the dataset used for optimisation of those parameters is declared. This lack of declaration makes it impossible for those approaches to claim separation of training and test data. Having no separation between training and test data allows no conclusion on a generalisation of the approaches. However, generalisation is an important aspect in pattern recognition.

The aspect of computational complexity is a central aspect of FI. Even approaches allowing lowest penetration rates are worthless if computation just takes too much time. A very large fraction of found publications simply neglect this aspect. After all, about half of the approaches report some kind of timing of their approaches – even though this is only a weak proxy for the computational complexity.

Bit sizes of index vectors are especially of interest when databases are large, which is essentially the use case for application of FI. Almost no approach explicitly reports this aspect. However,

Table 7 Checkmarks ✓ indicate reported results for a dataset. Brackets indicate that only a subset has been tested. Some approaches explicity state a training set or claim splitting training and test data

Feature	Reference	**FVC2000 DB1**	**FVC2000 DB2**	**FVC2000 DB3**	**FVC2000 DB4**	**FVC2002 DB1**	**FVC2002 DB2**	**FVC2002 DB3**	**FVC2002 DB4**	**FVC2004 DB1**	**FVC2004 DB2**	**FVC2004 DB3**	**FVC2004 DB4**	**FVC2006 DB1**	**FVC2006 DB2**	**FVC2006 DB3**	**FVC2006 DB4**	**NIST DB4**	**NIST DB4 natural**	**NIST SD14**	**WVU**	**Others**	**Training Set**	**Separation**
Minutiae	[4]					✓												✓		(✓)				
	[5]					✓												✓						
	[6]																					✓		
	[7]	✓	✓	✓	✓	✓	✓	✓	✓															
	[8]																	✓				✓		
	[9]																					✓		
	[10]		✓	✓		✓												✓	✓	✓			✓	✓
	[11]																					✓		
	[13]		✓	✓		✓				✓					✓			✓	✓	(✓)				
	[12]																					✓		
	[14]					✓	✓	✓	✓															
	[15]																					✓	✓	
	[16]					✓	✓	✓	✓														✓	✓
	[17]					✓	✓	✓	✓	✓	✓				✓								✓	✓
	[18]					✓	✓	✓	✓															
	[19]									✓	✓	✓												
	[20]																	✓						
	[21]		✓	✓		✓				✓								✓		(✓)				
	[22]		✓	✓		✓				✓								✓		✓				
	[23]																	✓						
	[24]																					✓		
	[25]									✓														
	[26]									✓														
	[27]					✓	✓			✓	✓				✓								✓	✓
	[28]					✓	✓								✓							✓		
	[29]		✓																			✓		
	[30]					✓				✓														
	[31]					✓	✓																	
	[32]					✓				✓												✓		
	[33]			✓		✓												✓		✓				
	[34]																	✓	✓					
	[35]														✓									
	[36]	✓																						
	[37]																					✓		
	[38]					✓	✓	✓	✓	✓	✓	✓	✓											
	[39]																					✓		
	[40]					✓	✓	✓	✓															
	[41]					✓																		
	[42]					✓														✓			✓	✓
	[43]						✓																	
	[44]						✓																	
	[45]		✓			✓														✓				
	[46]		✓			✓																		
Ridges	[48]					✓																		
	[49]		✓			✓																		
	[51]																					✓		
	[52]																					✓		
	[50]					✓																		
	[53]					✓																		
	[57]	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓										✓	✓
	[54]					✓	✓	✓	✓	✓	✓	✓	✓											
	[55]					✓	✓	✓	✓															
	[56]		✓			✓																		
	[58]																	✓					✓	✓
Scores	[62]																				(✓)			
	[63]																	✓			(✓)			
	[64]																				✓			
	[67]																					✓		
	[66]		✓	✓		✓												✓		✓				
OF	[70]																					✓		
	[71]																					✓		
	[72]		✓	✓		✓												(✓)						
	[73]																		✓					
	[74]		✓																					
	[75]																	✓	✓					
	[76]																	✓						
	[77]					(✓)	(✓)	(✓)	(✓)															
	[78]																					✓		
	[79]																					✓	✓	✓
	[80]		✓			✓																		
	[81]					✓																	✓	↯
Hybrid	[88]		✓				✓																	
	[89]		✓																					
	[85]		✓	✓		✓												✓	✓	✓			✓	✓
	[86]		✓	✓		✓												✓	✓	✓				
	[91]																							
	[83]						✓	✓											✓					
	[82]																		✓					
	[84]																	✓						
	[90]																					✓		
	[87]																			✓		✓		

Brackets indicate that only a subset has been tested. Some approaches explicitly state a training set or claim splitting training and test data.

Bold values indicate header columns and rows.

Table 8 Datasets used for evaluation

Dataset	Samples	Dimensions	Resolution	Data Origin	Ref
FVC2000 DB1	800	300×300	500dpi	Optical	[92]
FVC2000 DB2	800	364×254	500dpi	Capacitive	
FVC2000 DB3	800	478×448	500dpi	Optical	
FVC2000 DB4	800	320×240	∼500dpi	Synthetic	
FVC2002 DB1	800	388×374	500dpi	Optical	[93]
FVC2002 DB2	800	560×296	569dpi	Optical	
FVC2002 DB3	800	300×300	500dpi	Capacitive	
FVC2002 DB4	800	384×288	∼500dpi	Synthetic	
FVC2004 DB1	800	640×480	500dpi	Optical	[94]
FVC2004 DB2	800	364×328	500dpi	Optical	
FVC2004 DB3	800	480×300	512dpi	Thermal Sweeping	
FVC2004 DB4	800	384×288	∼500dpi	Synthetic	
FVC2006 DB1	1,680	96×96	250dpi	Capacitive	[95]
FVC2006 DB2	1,680	560×400	569dpi	Optical	
FVC2006 DB3	1,680	500×400	500dpi	Thermal Sweeping	
FVC2006 DB4	1,680	384×288	∼500dpi	Synthetic	
NIST DB4	4,000	512×512	500dpi	Ink-based	[96]
NIST DB4 natural	2,408	512×512	500dpi	Ink-based	
NIST SD14	54,000	768×832	500dpi	Ink-based	[97]
WVU	7,219	292×248	500dpi	Optical	[98]

thanks to quite good descriptions of the approaches, bit sizes are derivable.

7 References

[1] Daugman, J.: ‘How iris recognition works’, *IEEE Trans. Circuits Syst. Video Technol.*, 2004, **14**, (1), pp. 21–30

[2] Turk, M.A., Pentland, A.P.: ‘Face recognition using eigenfaces’. IEEE Computer Society Conf. Computer Vision and Pattern Recognition 1991. Proc. CVPR'91, Lahaina, USA, 1991, pp. 586–591

[3] Dantcheva, A., Elia, P., Ross, A.: ‘What else does your biometric data reveal? A survey on soft biometrics’, *IEEE Trans. Inf. Forensics Sec.*, 2016, **11**, (3), pp. 441–467

[4] Bai, C., Zhao, T., Wang, W., *et al.*: ‘An efficient indexing scheme based on *k*-plet representation for fingerprint database’. Int. Conf. Intelligent Computing, Fuzhou, China, 2015, pp. 247–257

[5] Bai, C., Wang, W., Zhao, T., *et al.*: ‘Learning compact binary quantization of minutia cylinder code’. 2016 Int. Conf. Biometrics (ICB), Halmstad, Sweden, 2016, pp. 1–6

[6] Bebis, G., Deaconu, T., Georgiopoulos, M.: ‘Fingerprint identification using Delaunay triangulation’. Proc. 1999 Int. Conf. Information Intelligence and Systems 1999, Bethesda, USA, 1999, pp. 452–459

[7] Benhammadi, F., Amirouche, M., Hentous, H., *et al.*: ‘Fingerprint matching from minutiae texture maps’, *Pattern Recognit.*, 2007, **40**, (1), pp. 189–197

[8] Bhanu, B., Tan, X.: ‘Fingerprint indexing based on novel features of minutiae triplets’, *IEEE Trans. Pattern Anal. Mach. Intell.*, 2003, **25**, (5), pp. 616–622

[9] Biswas, S., Ratha, N.K., Aggarwal, G., *et al.*: ‘Exploring ridge curvature for fingerprint indexing’. Second IEEE Int. Conf. Biometrics: Theory, Applications and Systems, 2008 BTAS 2008, Arlington, USA, 2008, pp. 1–6

[10] Cappelli, R., Ferrara, M., Maltoni, D.: ‘Fingerprint indexing based on minutia cylinder-code’, *IEEE Trans. Pattern Anal. Mach. Intell.*, 2011, **33**, (5), pp. 1051–1057

[11] Chen, F., Huang, X., Zhou, J.: ‘Hierarchical minutiae matching for fingerprint and palmprint identification’, *IEEE Trans. Image Process.*, 2013, **22**, (12), pp. 4964–4971

[12] Germain, R.S., Califano, A., Colville, S.: ‘Fingerprint matching using transformation parameter clustering’, *IEEE Comput. Sci. Eng.*, 1997, **4**, (4), pp. 42–49

[13] Gago-Alonso, A., Hernández-Palancar, J., Rodríguez-Reina, E., *et al.*: ‘Indexing and retrieving in fingerprint databases under structural distortions’, *Expert Syst. Appl.*, 2013, **40**, (8), pp. 2858–2871

[14] Hartloff, J., Dobler, J., Tulyakov, S., *et al.*: ‘Towards fingerprints as strings: secure indexing for fingerprint matching’. 2013 Int. Conf. Biometrics (ICB), Madrid, Spain, 2013, pp. 1–6

[15] Iloanusi, O.N.: ‘Fusion of finger types for fingerprint indexing using minutiae quadruplets’, *Pattern Recognit. Lett.*, 2014, **38**, pp. 8–14

[16] Iqbal, A., Namboodiri, A.M.: ‘Cascaded filtering for biometric identification using random projections’. 2011 National Conf. Communications (NCC), Bangalore, India, 2011, pp. 1–5

[17] Jain, A., Prasad, M.V.: ‘Clustering based fingerprint indexing using triangle spiral’. 2015 11th Int. Conf. Signal-Image Technology & Internet-Based Systems (SITIS), Bangkok, Thailand, 2015, pp. 81–88

[18] Jain, A., Prasad, M.: ‘A novel fingerprint indexing scheme using dynamic clustering’, *J. Reliab. Intell. Environ.*, 2016, **2**, (3), pp. 159–171

[19] Jayaraman, U., Gupta, A.K., Gupta, P.: ‘An efficient minutiae based geometric hashing for fingerprint database’, *Neurocomputing*, 2014, **137**, pp. 115–126

[20] Khachai, M.Y., Leshko, A., Dremin, A.: ‘The problem of fingerprint identification: a reference database indexing method based on Delaunay triangulation’, *Pattern Recognit. Image Anal.*, 2014, **24**, (2), pp. 297–303

[21] Khodadoust, J., Khodadoust, A.M.: ‘Fingerprint indexing based on expanded Delaunay triangulation’, *Expert Syst. Appl.*, 2017, **81**, pp. 251–267

[22] Khodadoust, J., Khodadoust, A.M.: ‘Fingerprint indexing based on minutiae pairs and convex core point’, *Pattern Recognit.*, 2017, **67**, pp. 110–126

[23] Kovács-Vajna, Z.M.: ‘A fingerprint verification system based on triangular matching and dynamic time warping’, *IEEE Trans. Pattern Anal. Mach. Intell.*, 2000, **22**, (11), pp. 1266–1276

[24] Kumar, D.G., Sudha, G., Revathi, B.: ‘An efficient space partitioning tree approach for indexing and retrieving fingerprint databases’. Proc. 2015 Int. Conf. Advanced Research in Computer Science Engineering & Technology (ICARCSET 2015), Unnao, India, 2015, p. 50

[25] Le, T.H., Bui, T.D.: ‘A codeword-based indexing scheme for fingerprint identification’. Tenth Int. Conf. Control, Automation, Robotics and Vision, 2008 ICARCV 2008, Hanoi, Vietnam, 2008, pp. 1352–1356

[26] Le, T.H.: ‘A fast and distortion tolerant hashing for fingerprint image authentication’. Proc. Int. Workshop on Computational Intelligence in Security for Information Systems CISIS'08, San Sebastián, Spain, 2009, pp. 266–273

[27] Li, G., Yang, B., Busch, C.: ‘A fingerprint indexing scheme with robustness against sample translation and rotation’. 2015 Int. Conf. Biometrics Special Interest Group (BIOSIG), Darmstadt, Germany, 2015, pp. 1–8

[28] Li, G., Yang, B., Busch, C.: ‘A fingerprint indexing algorithm on encrypted domain’. IEEE 2016 Trustcom/BigData/SE/I/SPA, Tianjin, China, 2017, pp. 1030–1037

[29] Liang, X., Asano, T., Bishnu, A.: ‘Distorted fingerprint indexing using minutia detail and Delaunay triangle’. Third Int. Symp. Voronoi Diagrams in Science and Engineering 2006 ISVD'06, Banff, Canada, 2006, pp. 217–223

[30] Liang, X., Bishnu, A., Asano, T.: ‘A robust fingerprint indexing scheme using minutia neighborhood structure and low-order Delaunay triangles’, *IEEE Trans. Inf. Forensics Sec.*, 2007, **2**, (4), pp. 721–733

[31] Liu, E., Liang, J., Pang, L., *et al.*: ‘Minutiae and modified biocode fusion for a fingerprint-based key generation’, *J. Netw. Comput. Appl.*, 2010, **33**, (3), pp. 221–235

[32] Mansukhani, P., Tulyakov, S., Govindaraju, V.: ‘A framework for efficient fingerprint identification using a minutiae tree’, *IEEE Syst. J.*, 2010, **4**, (2), pp. 126–137

[33] Muñoz-Briseño, A., Gago-Alonso, A., Hernández-Palancar, J.: ‘Fingerprint indexing with bad quality areas’, *Expert Syst. Appl.*, 2013, **40**, (5), pp. 1839–1846

[34] Muñoz-Briseño, A., Gago-Alonso, A., Hernandez-Palancar, J.: ‘Using reference point as a feature for fingerprint indexing’. Iberoamerican Congress on Pattern Recognition, Puerto Vallarta, Mexico, 2014, pp. 367–374

[35] Muñoz-Briseño, A., Gago-Alonso, A., Hernandez-Palancar, J.: ‘Fingerprint matching using a geometric subgraph mining approach’. Iberoamerican Congress on Pattern Recognition, Montevideo, Uruguay, 2015, pp. 160–167

[36] Nagati, K.A.: ‘A non-linear model for fingerprints matching based on minutiae core pairs interaction’. 2012 22nd Int. Conf. Computer Theory and Applications (ICCTA), Alexandria, Egypt, 2012, pp. 174–180

[37] Reddy, A., Jayaraman, U., Kaushik, V.D., *et al.*: ‘An efficient fingerprint indexing scheme’. Proc. Second Int. Conf. Soft Computing for Problem Solving (SocProS 2012), Jaipur, India, 28–30 December, 2012, 2014, pp. 723–728

[38] Ross, A., Mukherjee, R.: ‘Augmenting ridge curves with minutiae triplets for fingerprint indexing’. Proc. SPIE Conf. Biometric Technology for Human Identification IV, Orlando, USA, 2007, vol. **6539**, p. 65390C

[39] Vandana, D.K., Singh, D., Raj, P., *et al.*: ‘*Kd*-tree based fingerprint identification system’. Second Int. Conf. Anti-counterfeiting, Security and Identification 2008 ASID 2008, Guiyang, China, 2008, pp. 5–10

[40] Vij, A., Namboodiri, A.: ‘Fingerprint indexing based on local arrangements of minutiae neighbourhoods’. 2012 IEEE Computer Society Conf. Computer Vision and Pattern Recognition Workshops (CVPRW), Providence, USA, 2012, pp. 71–76

[41] Wang, Y., Yuen, P.C., Cheung, Y.-M.: ‘Hashing fingerprints for identity de-duplication’. 2013 IEEE Int. Workshop Information Forensics and Security (WIFS), Guangzhou, China, 2013, pp. 49–54

[42] Wang, Y., Wang, L., Cheung, Y.-M., *et al.*: ‘Learning compact binary codes for hash-based fingerprint indexing’, *IEEE Trans. Inf. Forensics Sec.*, 2015, **10**, (8), pp. 1603–1616

[43] Xu, H., Veldhuis, R.N.: ‘Binary spectral minutiae representation with multisample fusion for fingerprint recognition’. Proc. 12th ACM Workshop on Multimedia and Security, Rome, Italy, 2010, pp. 73–80

[44] Yang, B., Chen, Z., Busch, C.: ‘Raster image representation of fingerprint minutiae’. Proc. 2011 ACM Symp. Applied Computing, Taichung, Taiwan, 2011, pp. 8–12

[45] Zhou, W., Hu, J., Wang, S., *et al.*: ‘Fingerprint indexing based on combination of novel minutiae triplet features’. Int. Conf. Network and System Security, Xi'an, China, 2014, pp. 377–388

[46] Zhou, W., Hu, J., Wang, S.: ‘Enhanced locality-sensitive hashing for fingerprint forensics over large multi-sensor databases’, *IEEE Trans. Big Data*, 2017

[47] Dorizzi, B., Cappelli, R., Ferrara, M., *et al.*: ‘Fingerprint and on-line signature verification competitions at ICB 2009’. Int. Conf. Biometrics, 2009, pp. 725–732

[48] Lowe, D.G.: ‘Object recognition from local scale-invariant features’. Proc. Seventh IEEE Int. Conf. Computer Vision 1999, 1999, vol. **2**, pp. 1150–1157

[49] Shuai, X., Zhang, C., Hao, P.: ‘Fingerprint indexing based on composite set of reduced SIFT features’. 19th Int. Conf. Pattern Recognition 2008 ICPR 2008, 2008, pp. 1–4

[50] Bay, H., Ess, A., Tuytelaars, T., *et al.*: ‘Speeded-up robust features (SURF)’, *Comput. Vis. Image Underst.*, 2008, **110**, (3), pp. 346–359

[51] Tola, E., Lepetit, V., Fua, P.: ‘Daisy: an efficient dense descriptor applied to wide-baseline stereo’, *IEEE Trans. Pattern Anal. Mach. Intell.*, 2010, **32**, (5), pp. 815–830

[52] He, S., Zhang, C., Hao, P.: ‘Clustering-based descriptors for fingerprint indexing and fast retrieval’. Asian Conf. Computer Vision, 2009, pp. 354–363

[53] Zheng, R., Zhang, C., He, S., *et al.*: ‘A novel composite framework for large scale fingerprint database indexing and fast retrieval’. 2011 Int. Conf. Hand-based Biometrics (ICHB), Hong Kong, China, 2011, pp. 1–6

[54] Nanni, L., Lumini, A.: ‘Descriptors for image-based fingerprint matchers’, *Expert Syst. Appl.*, 2009, **36**, (10), pp. 12414–12422

[55] Liu, T., Zhu, G., Zhang, C., *et al.*: ‘Fingerprint indexing based on singular point correlation’. IEEE Int. Conf. Image Processing 2005 ICIP 2005, 2005, vol. **3**, pp. II–293

[56] Zegarra, J.A.M., Leite, N.J., da Silva Torres, R.: ‘Wavelet-based fingerprint image retrieval’, *J. Comput. Appl. Math.*, 2009, **227**, (2), pp. 294–307

[57] Komal, K., Albrecht, D., Bhattacharjee, N., *et al.*: ‘A region-based alignment-free partial fingerprint matching’. Proc. 14th Int. Conf. Advances in Mobile Computing and Multi Media, Singapore, 2016, pp. 63–70

[58] Yang, J.C., Park, D.S.: ‘A fingerprint verification algorithm using tessellated invariant moment features’, *Neurocomputing*, 2008, **71**, (10), pp. 1939–1946

[59] Feng, J., Cai, A.: ‘Fingerprint indexing using ridge invariants’. 18th Int. Conf. Pattern Recognition 2006 ICPR 2006, Hong Kong, China, 2006, vol. **4**, pp. 433–436

[60] Jakubowski, M.H., Venkatesan, R.: ‘Randomized radon transforms for biometric authentication via fingerprint hashing’. Proc. 2007 ACM Workshop on Digital Rights Management, Alexandria, USA, 2007, pp. 90–94

[61] Jazzar, M., Muhammad, G.: ‘Feature selection based verification/ identification system using fingerprints and palm print’, in (Eds.): ‘*Arabian journal for science & engineering*’, **vol. 38**, (Springer Science & Business Media BV, 2013), (4)

[62] Gyaourova, A., Ross, A.: ‘A novel coding scheme for indexing fingerprint patterns’, *Struct. Syntactic Stat. Pattern Recognit.*, 2008, pp. 755–764

[63] Gyaourova, A., Ross, A.: ‘A coding scheme for indexing multimodal biometric databases’. IEEE Computer Society Conf. Computer Vision and Pattern Recognition Workshops 2009 CVPR Workshops 2009, Miami, USA, 2009, pp. 93–98

[64] Gyaourova, A., Ross, A.: ‘Index codes for multibiometric pattern retrieval’, *IEEE Trans. Inf. Forensics Sec.*, 2012, **7**, (2), pp. 518–529

[65] Doddington, G., Liggett, W., Martin, A., *et al.*: ‘Sheep, goats, lambs and wolves: a statistical analysis of speaker performance in the NIST 1998 speaker recognition evaluation’, Technical Report National Institute of Standards and Technology, Gaithersburg MD, 1998

[66] Cappelli, R., Ferrara, M., Maio, D.: ‘Candidate list reduction based on the analysis of fingerprint indexing scores’, *IEEE Trans. Inf. Forensics Sec.*, 2011, **6**, (3), pp. 1160–1164

[67] Murakami, T., Takahashi, K.: ‘Fast and accurate biometric identification using score level indexing and fusion’. 2011 Int. Joint Conf. Biometrics (IJCB), Arlington, USA, 2011, pp. 1–8

[68] Maltoni, D., Maio, D., Jain, A.K., *et al.*: ‘*Handbook of fingerprint recognition*’ (Springer, London, 2009)

[69] Galar, M., Derrac, J., Peralta, D., *et al.*: ‘A survey of fingerprint classification part i: taxonomies on feature extraction methods and learning models’, *Knowl.-Based Syst.*, 2015, **81**, pp. 76–97

[70] Jain, A.K., Prabhakar, S., Hong, L., *et al.*: ‘Filter bank-based fingerprint matching’, *IEEE Trans. Image Process.*, 2000, **9**, (5), pp. 846–859

[71] Kavati, I., Prasad, M.V., Bhagvati, C.: ‘A new indexing method for biometric databases using match scores and decision level fusion’, in Kumar Kundu, Malay, Mohapatra, Durga Prasad, Konar, Amit*, et al.* (Eds.): ‘*Advanced computing, networking and informatics*’, vol. **1**, (Springer, 2014), pp. 493–500

[72] Leung, K., Leung, C.H.: ‘Improvement of fingerprint retrieval by a statistical classifier’, *IEEE Trans. Inf. Forensics Sec.*, 2011, **6**, (1), pp. 59–69

[73] Li, J., Yau, W.-Y., Wang, H.: ‘Fingerprint indexing based on symmetrical measurement’. 18th Int. Conf. Pattern Recognition 2006 ICPR 2006, Hong Kong, China, 2006, vol. **1**, pp. 1038–1041

[74] Liu, T., Zhang, C., Hao, P.: ‘Fingerprint indexing based on LAS registration’. 2006 IEEE Int. Conf. Image Processing, 2006, pp. 301–304

[75] Liu, M., Jiang, X., Kot, A.C.: ‘Fingerprint retrieval by complex filter responses’. 18th Int. Conf. Pattern Recognition 2006 ICPR 2006, 2006, vol. 1, pp. 1042–1042

[76] Lumini, A., Maio, D., Maltoni, D.: ‘Continuous versus exclusive classification for fingerprint retrieval’, *Pattern Recognit. Lett.*, 1997, **18**, (10), pp. 1027–1034

[77] Maio, D., Nanni, L.: ‘An efficient fingerprint verification system using integrated Gabor filters and Parzen window classifier’, *Neurocomputing*, 2005, **68**, pp. 208–216

[78] Ross, A., Jain, A., Reisman, J.: ‘A hybrid fingerprint matcher’, *Pattern Recognit.*, 2003, **36**, (7), pp. 1661–1673

[79] Turky, A.M., Ahmad, M.S.: ‘The use of SOM for fingerprint classification’. Int. Conf. Information Retrieval & Knowledge Management (CAMP) 2010, Toronto, Canada, 2010, pp. 287–290

[80] Xu, J., Hu, J.: ‘Multi-constrained orientation field modeling and its application for fingerprint indexing’. Int. Conf. Network and System Security, New York, USA, 2015, pp. 176–187

[81] Yang, J., Shin, J., Min, B., *et al.*: ‘Fingerprint matching using invariant moment FingerCode and learning vector quantization neural network’. 2006 Int. Conf. Computational Intelligence and Security, Guangzhou, China, 2006, vol. **1**, pp. 735–738

[82] Lee, S.-O., Kim, Y.-G., Park, G.-T.: ‘A feature map consisting of orientation and inter-ridge spacing for fingerprint retrieval’. Int. Conf. Audio- and Video-based Biometric Person Authentication, Hilton Rye Town, USA, 2005, pp. 184–190

[83] Jiang, X., Liu, M., Kot, A.C.: ‘Fingerprint retrieval for identification’, *IEEE Trans. Inf. Forensics Sec.*, 2006, **1**, (4), pp. 532–542

[84] Liu, M., Jiang, X., Kot, A.C.: ‘Efficient fingerprint search based on database clustering’, *Pattern Recognit.*, 2007, **40**, (6), pp. 1793–1803

[85] Cappelli, R.: ‘Fast and accurate fingerprint indexing based on ridge orientation and frequency’, *IEEE Trans. Syst. Man Cybern. B (Cybern.)*, 2011, **41**, (6), pp. 1511–1521

[86] Cappelli, R., Ferrara, M.: ‘A fingerprint retrieval system based on level-1 and level-2 features’, *Expert Syst. Appl.*, 2012, **39**, (12), pp. 10465–10478

[87] Paulino, A.A., Liu, E., Cao, K., *et al.*: ‘Latent fingerprint indexing: fusion of level 1 and level 2 features’. 2013 IEEE Sixth Int. Conf. Biometrics: Theory, Applications and Systems (BTAS), Arlington, USA, 2013, pp. 1–8

[88] Bazen, A., Veldhuis, R.N., Gerez, S.H., *et al.*: ‘Hybrid fingerprint matching using minutiae and shape’, in Sarfraz, Muhammad (Ed.): ‘*Computer aided intelligent recognition techniques and applications*’ (2005), pp. 119–129

[89] de Boer, J., Bazen, A.M., Gerez, S.H.: ‘Indexing fingerprint databases based on multiple features’. 14th Workshop on Circuits, Systems and Signal Processing, Technology Foundation (STW), Veldhoven, The Netherlands, 2001

[90] Pandey, N., Singh, S.: ‘Adaptive latent fingerprint indexing’. 2014 Fifth Int. Conf. Confluence the Next Generation Information Technology Summit (Confluence), Noida, India, 2014, pp. 509–514

[91] Han, F., Hu, J., Yu, X.: ‘A biometric encryption approach incorporating fingerprint indexing in key generation’, *Lect. Notes Comput. Sci.*, 2006, **4115**, p. 342

[92] Maio, D., Maltoni, D., Cappelli, R., *et al.*: ‘FVC2000: fingerprint verification competition’, *IEEE Trans. Pattern Anal. Mach. Intell.*, 2002, **24**, (3), pp. 402–412

[93] Maio, D., Maltoni, D., Cappelli, R., *et al.*: ‘FVC2002: second fingerprint verification competition’. Proc. 16th Int. Conf. Pattern Recognition 2002, Quebec, Canada, 2002, vol. **3**, pp. 811–814

[94] Maio, D., Maltoni, D., Cappelli, R., *et al.*: ‘FVC2004: third fingerprint verification competition’. Biometric Authentication, Hong Kong, China, 2004, pp. 1–7

[95] Cappelli, R., Ferrara, M., Franco, A., *et al.*: ‘Fingerprint verification competition 2006’, *Biometric Technol. Today*, 2007, **15**, (7), pp. 7–9

[96] Watson, C.I., Wilson, C.: ‘NIST special database 4’, *Fingerprint Database, Natl. Inst. Stand. Technol.*, 1992, **17**, p. 77

[97] Watson, C.I.: ‘NIST special database 14: mated fingerprint cards pairs 2 version 2,’ Technical Report, Citeseer, 2001

[98] Crihalmeanu, S., Ross, A., Schuckers, S., *et al.*: 'A protocol for multibiometric data acquisition, storage and dissemination', Technical Report, WVU, Lane Department of Computer Science and Electrical Engineering, 2007