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Review

Revisiting overlapped fingerprint separation methods and their key requirements for forensic systems

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ABSTRACT

At crime scenes, overlapped fingerprints are frequently found on commonly used surfaces, requiring separation methods for reliable person identification with forensic systems. While various methods for separating overlapped fingerprints have been developed in recent years, their practical usefulness has not been adequately evaluated due to a lack of practical requirements.

This paper presents a comprehensive overview of overlapped fingerprint separation methods, based on a meta-study analyzing 33 methods published between 2010 and 2024 (i.e., 15 years). Additionally, we identified ten key requirements to strengthen the transfer of scientific methods to forensic practice. Our analysis shows a significant trend towards hybrid and AI-based approaches for fingerprint separation, offering both new opportunities (e.g., efficiency, accuracy) and challenges (e.g., reliability, explainability). Unfortunately, we found that current separation methods cannot yet be satisfactorily evaluated in terms of their practical usability for forensic systems. This limitation results from the fact that most existing studies only address some of the identified requirements or only to a certain extent, which significantly hinders their practical implementation.

The study emphasizes the need for a more practice-oriented approach in evaluating fingerprint separation methods. To enhance their real-world applicability, we strongly encourage researchers to address the ten identified requirements, contributing to a facilitated transfer of theoretical methods into real-world forensic systems.

1. Introduction

The accurate identification of a person is a fundamental part of any criminal investigation. In this context, biometrics are an essential tool as they provide a set of methods to identify people based on their behavioral or physiological characteristics, such as DNA, voice, or fingerprints [1,2]. Fingerprints are widely regarded as one of the most important physiological characteristics due to the pattern of ridges and valleys of the skin surface [3,4]. In particular, fingerprints meet four widely accepted requirements for biometric identifiers, including: *(1) uniqueness*, i.e., they are distinctive to every person [5,6], *(2) measurability*, i.e., they can be acquired and digitized [3,4], *(3) persistence*, i.e., their properties remain permanent over time [7,8], and *(4) universality*, i.e., (nearly) all persons own a fingerprint [3,4].

Fingerprints are used worldwide in, for example, forensic laboratories and are accepted by courts of law after a review by forensic experts [9–12]. They can be lifted from surfaces by various methods, for example, dusting or ninhydrin [13]. After lifting, they are typically matched against stored fingerprints from datasets [14] after manual or automatic analyses of extracted characteristic points of the ridges and valleys, so-called minutiae [15]. However, several problems have arisen over time regarding the reliable and accurate recognition and analysis of such points and patterns, such as unclear ridge structures of fingerprints, complex background patterns, or handling overlapped fingerprints [16,17].

1.1. Problem statement

Overlapped fingerprints usually appear on surfaces where one or more people have touched an object once or several times [18,19]. These situations occur particularly on crime scenes, for example, when door handles or weapons are used in a crime. This is why separation

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methods are crucial to provide accurate results of individual fingerprints that can be used for person identification or authentication [20]. However, fingerprint-related forensic systems are typically developed under the assumption that fingerprint images only contain one single fingerprint [18,21]. This assumption leads to the problem that these “common” extraction methods cannot be applied unchanged to overlapped fingerprints [19]. To solve this problem, various separation methods for overlapped fingerprints have been developed in recent years [22].

Unfortunately, current methods and associated research studies typically lack comparable evaluations regarding their actual usefulness and practicability in forensic systems, for example, automatic fingerprint identification systems (AFIS) [21]. *We argue that this issue is due to a lack of uniform evaluation criteria, i.e., missing requirements*. The definition of such requirements, for example, similar to the requirements for biometric identifiers, is essential to determine which separation method is the best solution in a specific forensic scenario (e.g., a burglary).

1.2. Goal and research questions

Our main goal is to provide *a comprehensive overview of the current state-of-the-art in the field of overlapped fingerprint separation and to define key requirements for uniform method evaluations*. In this way, we aim to strengthen the transfer of theoretical methods into forensic practice. To achieve our goal, we rely on the following Research Questions (RQ):

- **RQ1:** *What are the key requirements for evaluating methods of separating overlapped fingerprints?*
  This question aims to identify and define the key criteria necessary to effectively evaluate the methods used to separate overlapped fingerprints, ensuring that they meet practical and biometric system standards in forensic practice. Moreover, we investigate to what extent current separation methods already mention the identified requirements, assessing their general practical orientation and discussing shortcomings related to their transfer into real-world forensic scenarios.

- **RQ2:** *What are current state-of-the-art trends regarding the separation of overlapped fingerprints?*
  We aim to explore and summarize the latest advancements and predominant methods in the field of overlapped fingerprint separation, highlighting relevant trends since 2010 oriented towards traditional, hybrid, and AI-based methods.

1.3. Contributions

To answer our research questions, we conducted a meta-study of overlapped fingerprint separation methods available since 2010, based on a Systematic Literature Review (SLR) methodology according to Kitchenham et al. [23]. Please note that our study is designed as a research synthesis and does not include primary experimental work. We highlight that our study offers the most comprehensive review in this field to date. In our study, we summarize and critically discuss relevant findings on these separation methods and the requirements they already target. More specifically, we contribute the following with our study:

- We define ten key requirements of separation methods for overlapped fingerprints, indicating recommendations for standardized system evaluations in forensics.
- We systematically analyze and describe current separation methods according to their procedures for separating fingerprints. In this way, we provide an extensive and essential overview of current methods, highlight the most significant ones, and show how they evolved over the years.
- We thoroughly discuss the insights obtained from our analysis and the identified requirements.

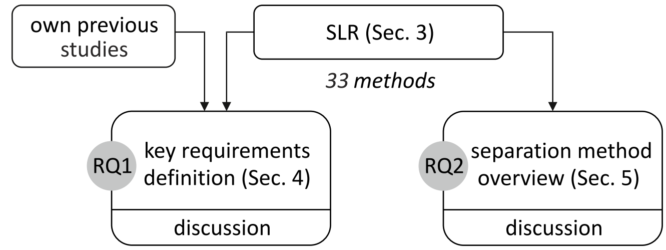

Fig. 1. Methodological workflow of the paper, combining insights from previous studies and an SLR.

Overall, our results show the complexity and importance of current separation methods as well as the existing issues regarding their practice orientation and actual implementation. The requirements defined in our study aim to provide an initial decision-making aid for the selection of suitable methods forensic practice. Note that although AFIS are often referenced as example applications, we argue that the reviewed methods and requirements can also support related biometric systems or one-to-one forensic comparison.

1.4. Structure

The article is structured as follows: In Section 2, we present the essential terms and the traditional approach to separate overlapped fingerprints. After that, we describe the meta-study design and its conduct in Section 3. In Section 4, we introduce ten key requirements and examine to what extent they are mentioned in current research to answer **RQ1**. Then, an overview of the most relevant separation methods is given in Section 5 and answer **RQ2**. In Section 6, we consider relevant threats to validity. Finally, after describing relevant related work in Section 7, concluding comments and suggestions for further research are given in Section 8. For a better overall understanding, the methodological structure of our study is illustrated in Fig. 1.

2. Background

In this section, we provide key background information on latent and overlapped fingerprints. In particular, we focus on essential processing steps of fingerprint separation methods to provide an understanding of typical characteristics.

2.1. Latent fingerprints

Latent fingerprints, also known as finger marks or latents, are (partial) fingerprints lifted from surfaces of objects at a crime scene [24]. Typically, latents are created by sweat, which accumulates in the ridges of the skin and is partially or completely transferred to a surface by contact with an object.

There is a variety of challenges and issues that can possibly affect the usability of latent fingerprints, for example, in the context of an AFIS or associated fingerprint identification hardware in a criminal investigation [25]. A typical issue of latents is the poor quality of their ridge impressions [26,27]. In addition, lifting a fingerprint can result in further loss of quality, such as background noise or non-linear distortion [24,28]. However, the quality of latent fingerprint images is essential for subsequent processing steps as they are matched against stored fingerprints to identify a person. In this context, the accuracy of the processing methods, such as concrete algorithms for separating overlapped fingerprints, decreases more and more the worse the quality of the latent is and vice versa. Consequently, the selection of appropriate methods based on uniform requirements is essential to allow the highest possible usability of a fingerprint-related method, for example, integrated into an AFIS [4].

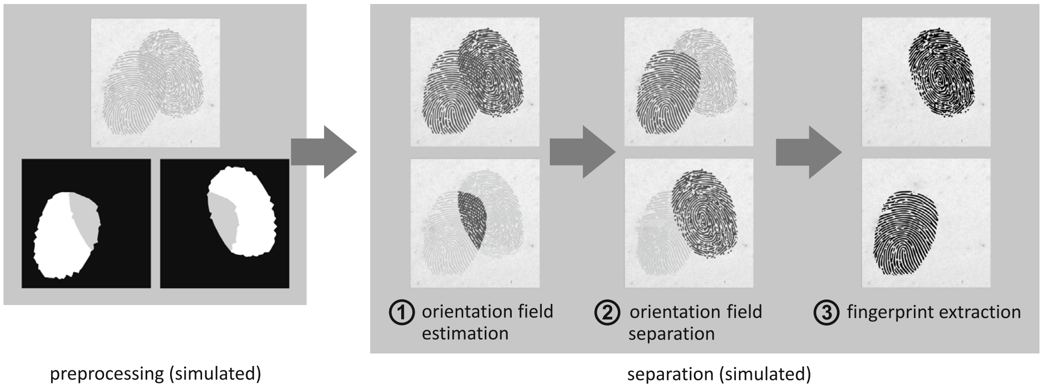

Fig. 2. An example of a typical (i.e., traditional) solution for automated overlapped fingerprint processing including pre-processing and the separation process with (1) OF estimation, (2) OF separation, and (3) fingerprint extraction. The fingerprints used were simulated and the process illustrated by the authors.

2.2. Overlapped fingerprints

As already described in the previous sections, overlapped fingerprints can often be found on surfaces of frequently used objects, such as door handles, light switches, or computer keyboards. Moreover, they can occur when residue fingerprints are left on the surface of fingerprint sensors [18,29]. Based on the assumption by Chen et al. [18], the term *overlapped fingerprints* is always understood as two overlapped fingerprints, since the separation of more than two fingerprints is typically too complex. Although this definitional assumption and the associated basic approach were made almost 15 years ago, they are still used as an essential basis in current methods [30,31].

As shown in Fig. 2, the *traditional* approach for separating overlapped fingerprints consists of three essential processing steps [20]. After splitting the fingerprint image into foreground and background, a pre-processing step called segmentation, the overlapped fingerprints are typically separated in three steps: (1) orientation field (OF) estimation (i.e., masking two non-overlapped OF of the non-overlapped fingerprint as well as the overlapped region of both fingerprint), (2) OF separation (i.e., separating the overlapped region into two fingerprint components), and (3) fingerprint extraction (i.e., filtering and separating individual fingerprints) [18,32]. All steps typically include several intermediate processing steps to eliminate errors and achieve the best possible results, such as smoothing methods (e.g., low-pass filtering) [33]. Generally, in this work, we use the term *traditional* to denote methods that implement these processing stages explicitly via primarily manually, deterministic procedures, even if individual steps are refined or extended.

Unsurprisingly, the traditional three-step procedure presented cannot be entirely applied to all existing methods, in particular to *Artificial Intelligence-based* (AI-based) separation methods. AI-based methods are typically based on machine-learning algorithms (e.g., supervised-learning methods) that learn core separation representations from data and merge several steps in a black-box environment (e.g., via learning-based or end-to-end pipelines) and rely on different terminologies [31, 34]. Similar issues arise in the context of *hybrid* methods that usually merge traditional and AI-based methods. Here, we refer to hybrid methods as approaches that retain at least one explicit traditional processing component (e.g., OF estimation, filtering) while augmenting or substituting other components with learning-enabled modules [21,22]. Nevertheless, such methods typically still roughly follow the traditional separation approach, emphasizing the great value of the traditional procedure to date as well as its various implementations during the last years (cf. Section 5).

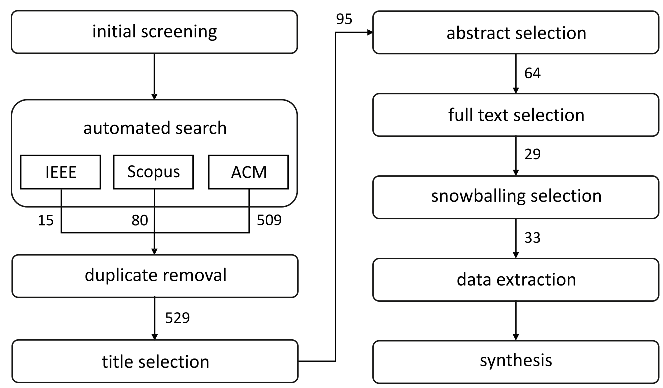

Fig. 3. Methodological overview of the meta-study according to Kitchenham et al. [23], including the numbers that indicate the amount of selected publications.

3. Methodology

After describing the basics of fingerprints and processing steps to separate overlapped fingerprints, we present the methodological background of our meta-study. In particular, we focus on the study design as well as its conduct and results.

3.1. Study design

We based our meta-study on the widely accepted guidelines for SLR by Kitchenham et al. [23], which provide the methodological framework for the subsequent steps (cf. Fig. 1). Following these guidelines, we detail the SLR design in the next paragraphs, including the initial screening procedure, search strategy, inclusion criteria, and data extraction.

Initial Screening. To ensure the need for our study, i.e., that there is a sufficient and relevant body of knowledge and research interest in the research field of separation methods for overlapped fingerprints, we conducted an initial screening. In particular, we focused on the literature databases Scopus, IEEE Xplore, and the ACM Digital Library. These databases include peer-reviewed literature from a variety of publishers. Thus, we could reduce the threat of missing potentially relevant papers. Moreover, we could assess a high publication quality. In this context, we applied the following search string:

`separation AND overlapped AND fingerprint`

Based on this general search string we achieved more than 1500 publications. Consequently, we identified a considerable research interest regarding the separation of overlapped fingerprints.

We note that we are aware of existing overviews, especially the review study by Stojanović et al. [21] that covers research until 2016. However, our study differs from this and other studies referenced therein, since we cover a larger period of time as well as all available and more recent methods. Moreover, we have another focus, since we provide insights in both separation methods and practical requirements.

An initial screening of the publications found in this step showed that requirements for separation methods had not been addressed in detail to date. Thus, we argue at this point that there is a relevant shortcoming in research that impairs the transfer of theoretical knowledge into forensic practice, for example, an AFIS in a forensic use case.

Search Strategy. In a next step, we defined a more detailed search string for an automated search on Scopus, IEEE Xplore, and the ACM Digital Library:

`(‘‘overlapped’’ OR ‘‘overlapping’’) AND fingerprint AND (‘‘separation’’ OR ‘‘separating’’)`

Moreover, we improved the completeness and quality of our search strategy, for example, regarding repeatability or consistency, by applying one iteration of forward and backward snowballing [23,35].

Inclusion Criteria. To identify appropriate literature, we defined the following inclusion criteria:

- The literature is written in English.
- The literature has been published between 2010 and 2024.
- The literature is a peer-reviewed conference paper or journal article.
- The publication is longer than three pages.
- The literature reports one or more separation methods for overlapped fingerprints.

Based on these criteria, we aim to ensure that all included publications are relevant to our research objectives. The time frame was intentionally chosen as the first internationally relevant method was published in 2010 by Chen et al. [20]. The key findings of their method are still used today as the basis for the majority of separation methods.

We excluded all publications that (briefly) explained methods in terms of hardware or chemical processes [36,37], as a part of a larger system or approach [38], or only separation pre-processing or post-processing steps [39,40]. Moreover, we excluded literature reviews, surveys, or mapping studies that include an overview or a comparison of separation methods [21,22]. These are described in more detail in Section 7 in the context of related work.

Data Extraction. To extract relevant data from the selected literature, we defined the following extraction criteria besides typical bibliographic data, such as publication year, author, or title:

- **Requirements**, i.e., which requirements regarding separation methods are addressed, for example, accuracy [18], robustness [41].
- **Separation type**, i.e., the classification of a separation method into a traditional, hybrid, or AI-based method.
- **Separation procedures**, i.e., methods used to separate overlapped fingerprints.
- **Fingerprint samples used**, i.e., which type of fingerprints are used to evaluate the proposed method, for example, real [42] (i.e., latent fingerprints lifted under varying conditions) or simulated [29] (i.e. synthetically generated under controlled conditions).
  real [42] or simulated [43].

Based on these criteria we can assess the structure and practical application relevance of the considered methods. However, we do not focus on mathematical specifications or particular implementations of the methods and do not consider country-specific decision thresholds to maintain methodological generality. Consequently, this work's objective is to give a comprehensive overview of current separation methods and to identify requirements that are as generally applicable as possible, i.e., providing a high transferability to real-world biometric systems. In addition, we aim to identify recent trends regarding the separation process of actual methods.

3.2. Study conduct

The study was carried out on August 25, 2025. By using the search string, the first author identified a total of 604 publications (15 in IEEE Xplore, 80 in Scopus, and 509 in the ACM Digital Library). After a duplication removal, the number of publications was reduced to 529 articles. Next, we did a title and abstract selection by applying the already presented inclusion criteria, reducing the included literature to 95 (titles) and 64 papers (abstracts). Thereby, we were able to reduce the number of publications to 29 scientific papers after a full-text review. In the next step, by applying forward and backward snowballing, i.e., analyzing papers that cited the already included methods and the references of the included papers [44], we were able to identify four more papers meeting our inclusion criteria. So, after a discussion involving the first and the third author a final number of 33 methods was selected. A methodological overview of the meta-study and the selection steps, including the numbers that indicate the number of publications, is shown in Fig. 3.

After the selection process, the first author created a spreadsheet for the data extraction according to our defined extraction criteria and performed an open-coding-oriented process. In this way, we were able to identify specific requirements of data that matched our database. After that, we classified recurring information in our dataset. Moreover, we synthesized common themes for each data category by relying on an open-card-sorting-oriented method [45]. The first author discussed all results with the second and the third author. Conflicts, particularly in the context of identified separation methods and requirements, were resolved in discussion until a consensus on a decision was achieved. The third author took random samples (ten publications) to evaluate interpretations and assignments. To support the reproducibility of this meta-study, we provide a transparent description of the search strategy, inclusion criteria, data extraction process, as well as the analysis file in the context of the supplementary material.

4. RQ1: Key requirements

After presenting our methodology, we introduce the key requirements of separation methods that we identified in the literature. More specifically, we define ten requirements for latent fingerprint separation methods, describe to what extent they are already mentioned in the literature, and discuss these findings. In this way, we answer **RQ1**.

4.1. Requirements definition

Requirements are essential to achieve defined goals for any system. The practicability of requirements is of particular importance as this property has a great impact on how appropriately a system is designed for users and their practical environment [46]. In the context of overlapped fingerprints, the fulfillment of specific requirements indicates which separation algorithm should be chosen for forensic practice. To find out which requirements may be most applicable, we built on two information sources: (1) the results of the meta-study (cf. Section 4.2) and (2) our own previous studies.

In previous work, we identified seven requirements for separation methods. In particular, these requirements are based on interviews with forensic experts who work with diverse fingerprint data in their daily work [47]. Thus, it is ensured that they are well-founded and practice-oriented. Finally, we added three more requirements that we identified as relevant by analyzing the literature in terms of the meta-study. Note that the associated analyses of the literature and the examination of to what extent existing methods address the requirements follow after the requirements definition in Section 4.2.

Overall, we defined ten requirements of separation methods for overlapped fingerprints, including *accuracy, integrity, usability, sustainability, singularity, explainability, reproducibility* (based on previous work), as well as *efficiency, robustness*, and *human intervention* (based on the SLR results):

- **Accuracy:** The separation of two overlapped fingerprints has to be performed in a way that guarantees a correct assignment of the same non-overlapped fingerprints. Consequently, the accuracy is essential as it shows the correctness of the produced results of a separation algorithm [47]. The separation accuracy is closely linked to the frequently mentioned matching accuracy [48–50]. However, they do not mean the same. The matching accuracy refers to the applied matching algorithm after the separation process [51]. In general, accuracy can also referred to as one indicator of an appropriate performance for a particular target application [3,10].

- **Integrity:** The separation of overlapped fingerprints has to be always complete. Accordingly, both fingerprints have to be completely separated from each other and not only partially. This is especially important for the algorithm's credibility and prevents the fingerprints from being analyzed by other methods which would be time-consuming or potentially error-prone [52]. The integrity is related to accuracy due to its dependence on the best possible separation accuracy [47].

- **Usability:** It is essential that an algorithm is easy to use not only for its developers but also for later users, especially forensic experts [3]. In this context, an algorithm should not require too many parameters that make the forensic application unpractical for the user [47]. Usability can also be interpreted in the context of a forensic system and its user interface [53,54]. There already exist several norms and guidelines to assess the usability of a system such as the NIST definition of usability or ISO 9241-11 [55,56], including the assessment of a system's efficiency [57].

- **Sustainability:** One of the most practice-relevant properties of biometric classifiers such as fingerprints is sustainability, also referred to as permanence [10,58]. Thus, while using a separation algorithm, fingerprints are not allowed to be modified or destroyed, so that potentially other algorithms can work with the fingerprint image [47]. Since this can be caused by unsuitable methods, it is important to use appropriate methods [59]. These methods are called non-destructive methods [60]. This characteristic is of greatest relevance not only in the context of algorithms but also to the physical methods for detecting fingerprints [61,62].

- **Singularity:** Singularity means that only one single image is allowed to be used as input for the separation algorithm. This requirement is of high practical relevance, as multiple (overlapped) fingerprints of the same persons are only rarely found at one crime scene [47].

- **Explainability:** The results of static separation methods can often not be traced. However, the explainability of separation results is essential for the use of the results in court [47]. The more complex the separation processes are, the more important explainability becomes, especially when they include AI-enabled components [63,64]. Explainability can be supported by validating (intermediate) processing decisions or separation results, for example, through post-hoc visualization of decision-relevant regions (e.g., minutiae) [65].

- **Reproducibility:** The reproducibility of separation results is essential to compare whether the method always produces the same result [47]. For instance, this requirement is important to objectively measure the outcome of a method, i.e., in the context of automated minutiae extraction [33,66].

- **Efficiency:** The efficiency of an algorithm shows the relation between the accuracy, the fulfillment level of specific goals, and the resources used to achieve these goals [67]. This requirement can be used to evaluate several steps or an overall algorithm. Like the separation accuracy, the separation efficiency is closely linked to the matching efficiency and thus the application performance [3,10]. In this context, the overall separation and matching efficiency measures the time an algorithm takes to produce the highest possible quality separation of two separated fingerprints and match them against fingerprints in a database [16,68].

- **Robustness:** The requirement robustness refers to the ability of an algorithm to work correctly even under poor conditions. For instance, the orientation field estimation has to be robust even when the image quality of real latent fingerprints is poor [33]. Robustness is related to accuracy as it affects further processing steps like enhancement methods and, in particular, the quality of the final results of a separation algorithm [51].

- **Human intervention:** The level of human intervention is strongly related to the fact that processing steps like marking region masks are usually done manually by forensic experts [16]. This manual work is time-consuming and can lead to several errors which can affect other requirement fulfillments, such as accuracy or efficiency [9]. By completely automating these processes, for example, in terms of an AFIS, the mentioned problems can be addressed [66,69]. However, to actually consider a fingerprint application automated, it is necessary that human interventions are as rare as possible [18].

4.2. Literature results

This section describes details to what extent the identified literature mentions the identified requirements (cf. Table 1).

All but two publications (94%) mention requirements for their methods. The requirements addressed most frequently are *integrity*, *sustainability*, *singularity*, and *reproducibility*, which are implicitly described by all authors. Accordingly, they are not mentioned directly, but can be clearly assigned based on the procedures and results described. The most frequently mentioned requirement is *accuracy*, which was addressed in 24 methods (73%). This requirement is typically related to method evaluations. Efficiency, often strongly related to effectiveness, is described in 23 papers (70%). *Human intervention* was discussed by 15 researchers (45%) in terms of manual work, for example, by manually marking the region masks [30]. We identified 13 papers in which the *robustness* of the method was relevant (39%). The authors often considered this requirement in connection with the poor image quality of real latent fingerprints. Since *efficiency*, *robustness*, and *human intervention* are of particular relevance due to their frequent occurrence, we include them in the key requirements described in Section 4.1.

Table 1
Fulfillment of requirements by analyzed methods (n = 33).

Requirement	n (%)	References
accuracy	24 (73)	[17–20,29,30,34,41–43,52,69–81]
integrity	33 (100)	[17–20,29–31,34,41–43,52,61,69–88]
usability	4 (12)	[31,75,81,87]
sustainability	33 (100)	[17–20,29–31,34,41–43,52,61,69–88]
singularity	33 (100)	[17–20,29–31,34,41–43,52,61,69–88]
explainability	0 (0)	not mentioned
reproducibility	33 (100)	[17–20,29–31,34,41–43,52,61,69–88]
efficiency	23 (70)	[17–20,29,31,34,41,43,61,69–73,75,77–81,86,88]
robustness	13 (39)	[17,19,29,31,41–43,69,72,73,78,80,81]
human intervention	15 (45)	[17,29,30,41,43,52,69,71–74,76,80,82,85]

Interestingly, *usability* was only mentioned four times (12%) and none of the publications refer to *explainability*.

We also identified more requirements, for example, security, sensitivity, and simplicity. Note that we do not include them in our requirements as they relate more to the general system perspective and are not explicitly focused on the separation methods (e.g., more context to matching).

RQ1 – Key requirements: *We defined ten requirements for separation methods of overlapped fingerprints, including: accuracy, integrity, usability, sustainability, singularity, explainability, reproducibility, efficiency, robustness, and human intervention. Accuracy is the most frequently mentioned in the literature, whereas integrity, sustainability, singularity, and reproducibility are implicitly described by all authors, indicating their fundamental importance. The frequent discussion of efficiency, robustness, and human intervention highlights their critical role in developing reliable systems. Explainability is not addressed, pointing to an area for future research to enhance in particular the transparency of AI-based methods.*

4.3. Discussion

The results of our research have shown the great relevance of the problem identified: Separation methods for overlapped fingerprints typically do not adhere to practical requirements. During the SLR we encountered a variety of shortcomings. In order to fully evaluate a method regarding its practical suitability, not only requirements but also methods to measure the requirements are needed. Since the requirements also influence themselves, the development of potential metrics in terms of a requirements evaluation framework is complex and requires profound research. For instance, theoretical methods for evaluating accuracy [21,47] or customizable matching software, such as VeriFinger SDK, to test the accuracy or robustness of methods already exist [74,89]. However, such methods or systems are typically not comparable (i.e., do not rely on comparable requirements and associated metrics) or are not applied in a comparable way (i.e., different evaluation settings).

Likewise, the requirements introduced are formulated as generally as possible. Consequently, the introduced requirements have to be always related to the entire separation method. However, every method should also be evaluated ambivalently. Accuracy, for instance, demonstrates that this requirement can be applied not only to the entire algorithm, but also to the results of individual components of the approach, such as OF estimation, OF separation, or fingerprint matching. Therefore, this case exemplifies the complexity of potential evaluation metrics.

Our study shows that some requirements, including sustainability and integrity, are not explicitly mentioned in the articles. However, this does not mean that they have not been considered, forgotten, or that they are less relevant. For example, in the case of sustainability, it can be assumed that all methods met this requirement, assuming that the fingerprints were not lifted by powder. This issue can be explained by the fact that separation methods typically work with digital equivalents of latent overlapped fingerprints (i.e., non-destructive methods) which often have been lifted by using powder, which is by far the cheapest method [60]. Other popular methods relate to generating digital equivalents by using chromatic light [90].

Moreover, we found that no method refers to more than five requirements. This issue demonstrates that they are not yet sufficiently addressed. So, some developers already address the requirements accuracy, efficiency, and robustness in terms of their research objectives. For instance, the authors Jeyanthi et al. [29,43] considered half of the requirements. However, we cannot conclude that their methods are actually suitable for practical use. Overall, many developers neglect other highly relevant requirements, such as usability, robustness, or human intervention (cf. Table 1). Accordingly, the use of separated fingerprints for court is barely possible. Based on this finding, we can identify a significant shortcoming in theory, in particular regarding the practical relevance of the considered methods. This gap indicates that the generation of credible separation results can hardly be achieved in practice. Moreover, we assume that the requirements mentioned as research objectives were only partly understood as requirements. This issue indicates that the definition of requirements in the context of a comprehensive requirements engineering process has not been conducted in most cases.

Nevertheless, we note that the requirements may vary in importance depending on the concrete use case and the objective of each separation method. In this context, some requirements, such as explainability, may increase in importance in the next few years considering the growing number of black-box AI systems [91]. In contrast, other requirements, such as human intervention, may decrease in importance due to the emerging role of automated AI systems. However, assessing their actual importance is outside our current study's scope.

We also identified an issue regarding the significance of the publications we examined. In this context, it is striking that many papers claimed to outperform previous methods in terms of requirements such as accuracy or robustness. However, these statements were mostly proven in non-comparable evaluations. This lack of comparability can largely be attributed to heterogeneous evaluation metrics and experimental setups across studies. In particular, different works assess performance at different stages of the processing pipeline (e.g., separation accuracy versus matching accuracy), often relying on non-uniform datasets, tools, or thresholds. Consequently, claims of superiority must

Table 2
Method comparison of separation methods for overlapped fingerprints.

Year	Authors and references	Method type	Samples
2010	Chen et al. [20]	traditional	real and simulated
2011	Chen et al. [18]	traditional	real and simulated
2011	Shi et al. [70]	traditional	real and simulated
2011	Kargel et al. [71]	hybrid	real
2012	Qian et al. [82]	traditional	real and simulated
2012	Ananth et al. [83]	traditional	real
2012	Reka et al. [84]	traditional	real and simulated
2012	Feng et al. [19]	traditional	real and simulated
2012	Zhao and Jain [17]	hybrid	real and simulated
2013	Qian et al. [52]	traditional	real and simulated
2013	Jeyanthi et al. [29]	traditional	simulated
2014	Qian et al [85]	traditional	real and simulated
2014	Zhang et al. [41]	hybrid	real
2014	Zhang et al. [72]	hybrid	real
2014	Vanitha et al. [86]	traditional	real and simulated
2015	Jeyanthi et al. [43]	hybrid	simulated
2015	Mahajan et al. [73]	traditional	real and simulated
2016	Stojanović et al. [74]	AI-based	real and simulated
2016	Pawar et al. [69]	traditional	real and simulated
2017	Neha et al. [42]	traditional	real
2017	Hung et al. [75]	hybrid	real
2018	Stojanović et al. [30]	AI-based	real and simulated
2018	Huang et al. [77]	traditional	real and simulated
2018	Yih et al. [34]	AI-based	real
2019	Stojanović et al. [76]	AI-based	real and simulated
2020	Yoo et al. [31]	AI-based	real
2021	Sommit and Chitaree [87]	hybrid	real
2022	Akiba et al. [61]	hybrid	real
2022	Akiba et al. [88]	hybrid	real
2022	Sen et al.[78]	hybrid	simulated
2023	Chegur et al. [79]	AI-based	simulated
2023	Su et al. [80]	hybrid	simulated
2024	Johnson and Chitra [81]	AI-based	simulated

be interpreted with caution, as they are frequently based on fundamentally different evaluation criteria. Only Stojanović et al. [74] performed a comparable evaluation including five methods but only focused on the matching accuracy. Unfortunately, this evaluation was conducted in 2016 and does not reflect the actual variety of methods. This issue emphasizes the need for a comprehensive and comparable investigation of existing methods based on requirements. However, there is no standardized basis for the evaluation of methods to date, especially regarding our introduced requirements. In detail, we did not find literature that defines the requirements for overlapped fingerprint separation. Without a standardized basis for evaluation based on clearly described requirements, it is not possible to assess which method offers the maximum advantage for practical use in forensic systems, for example, in a criminal investigation.

5. RQ2: Separation methods

After describing the key requirements of separation methods and to what extent they are mentioned in the literature, we give a comprehensive overview of the method landscape for separating overlapped fingerprints. Precisely, we first describe the SLR results, then go into detail with regard to the most significant methods, and finally discuss our findings. Consequently, in this section, we answer **RQ2**.

5.1. Results

Publication years. Considering the publication years of all methods, about half of the methods (52%) were published between 2010 and 2015 (i.e., before the AI-based methods). During this period, there were up to five papers (2012) published in this field. From 2016 onward, the number of publications per year decreased continuously, except in 2018 (three papers). From 2019 to 2021 we could only find one new method per year. Surprisingly, there were six new methods between 2022 and 2024. Interestingly, none of the methods refer to the traditional approach. An overview of the distribution of the methods according to their classification is presented in Fig. 4.

Method types. As shown in Table 2, 36% of the methods (12/33) follow the meta-method (i.e., *traditional method*) proposed by Chen et al. [18], i.e., they are based on local or fast Fourier analysis for OF estimation, (constrained) relaxation labeling for OF separation, and tuned Gabor filters for fingerprint extraction. Although the last paper based on this method was published in 2018, we identified that this method was most frequently used between 2010 and 2015 (71% of the methods published in this time period). Since 2016, several *AI-based methods* have emerged. These are typically based on several variants of neural networks, such as convolutional neural networks (e.g., [34]). Considering only the methods published since 2016, 44% of the papers are based on neural networks. Interestingly, AI-based methods usually do not longer rely on the traditional three separation steps (cf. Fig. 2) as they merge these steps or create even new steps, i.e., these methods are only roughly comparable with the traditional procedure. Nevertheless, they often reference the traditional method because of its widespread use and understanding [30,74]. Besides these trends, we identified several methods that we call *hybrid methods*. These methods typically emerged only once [29,43,71] or for a limited time frame, for example, three methods (16%) by Zhao and Jain [17,41,72] based on (orientation) models between 2012 and 2014. Overall, 11 methods (33%) rely on hybrid procedures. Interestingly, we identified distinct temporal trends across the different separation approaches: traditional methods (e.g., Chen et al. [18]) peaked around 2012; AI-based methods (e.g., Stojanović et al. [76]) peaked later, around 2018; and hybrid approaches (e.g., Akiba et al. [61]) showed their strongest growth around 2022.

Fingerprint samples. Referring to the type of fingerprints used (cf. Table 2), 26 methods (82%) were tested on real or both real and simulated fingerprints, for example, [61] focused only on real samples. Only six methods (18%) refer to simulated fingerprints, for example, based on the NIST Special Database [77].

5.2. Significant separation methods

In the following, we present a broad overview of relevant separation methods. Specifically, we aim to provide basic, high-level insights into the research landscape based on brief, easily understandable method descriptions and describe major differences of traditional, hybrid and AI-based methods.

5.2.1. Traditional methods

Chen et al. [18,20] presented a separation method based on local Fourier analysis for OF estimation and relaxation labeling for OF separation in 2010 and 2011. They used Gabor filters [92] tuned to the separated OFs to extract the individual fingerprints. To evaluate their method, they used both real and simulated fingerprints. Their work can be seen as the first important and most widespread general method of the last decade. Moreover, a variety of methods is based on the work by Chen et al. [20] or improved versions, i.e., the combination of local Fourier analysis, relaxation labeling, and tuned Gabor filters [19,52,69,70,73,77,82–86]. Usually, these methods adapt various method parameters, the exact application of specific methods, or apply additional pre-processing or post-processing steps to improve the basic approach, especially in terms of accuracy and efficiency.

Jyanthi et al. [29] described a method based on relaxation labeling for OF separation in 2013. Moreover, the authors use local Fourier analysis and Sobel filters for OF estimation. They also implemented Gabor filters for enhancement. In 2015, Jeyanthi et al. [43] extended their work with a focus on practical usability in an AFIS. In this work, they apply a convolutional neural network (CNN) to determine whether

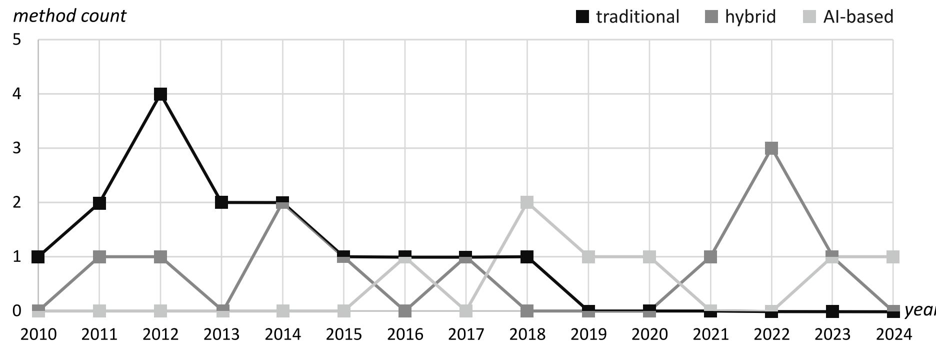

Fig. 4. Distribution of overlapped fingerprint separation methods over time (2010–2024), classified according to method types (i.e., traditional, hybrid, AI-based methods).

an image contains a single fingerprint or two overlapped fingerprints. They evaluated their method on real overlapped fingerprints.

Neha et al. [42] introduced a separation method to develop a precise and powerful authentication system in 2017. After several enhancement steps by utilizing histogram equalization and fast Fourier transform, the image is binarized to estimate the OF. After that, Gabor filters are used to extract the fingerprint components. Neha et al. [42] evaluated their method with real overlapped fingerprints.

5.2.2. Hybrid methods

Kargel et al. [71] proposed a statistical method based on expectation maximization in 2011. Their method focuses on a maximum a posteriori estimation of the individual fingerprints and the mixing coefficients which are calculated by an expectation maximization algorithm. They tested their method with real fingerprints. However, fingerprints with strong differences in contrast are needed to produce reliable results. Overall, the method follows the work by Tonazzini et al. [93] regarding the separation of overlapping text patterns. Consequently, they do not follow the traditional three processing steps of traditional fingerprint separation approaches.

Zhao and Jain [17] based their separation method on a model-based approach. They separate the OF based on modeling the OF and predicting the unknown OF with the help of orientation cues. The fingerprint extraction is made with tuned Gabor filters. Overall, they focus on the robustness of the overall separation process. This method was tested on real and simulated fingerprints.

Zhang et al. [41,72] described a method based on an adaptive orientation model fitting for OF separation in 2014. OF estimation and fingerprint extraction are based on tuned Gabor filters. The authors evaluated their method on real fingerprints. At that time, they concluded that their method with its model-based method achieved the state-of-the-art in terms of accuracy. However, we argue that their assumption probably no longer holds up today, but it underlines the great efficiency of this method.

Hung et al. [75] developed a method in 2017 focusing on the separation and reconstruction of overlapped fingerprints. Precisely, they apply Bandelet transform and a combination of Bandelet image inpainting and contourlet transform to separate the fingerprints. They evaluated their method on real overlapped fingerprints.

Sommit and Chitaree [87] presented a separation method based on spatial filtering and Fourier transform in 2021. Their method does not follow the traditional three separation steps. Instead, they converted the overlapped fingerprints (considered as spatial domain patterns) to spatial frequency domain patterns. Next, Sommit and Chitaree [87] use spatial filters to delete unwanted components, i.e., the respective unwanted fingerprint. Finally, the modified pattern is converted back to spatial domain patterns to extract the separated fingerprint. They evaluated their method on real fingerprints.

Akiba et al. [61,88] proposed a separation method based on the fingerprints' fluorescence spectra in 2022. Assuming that fingerprint fluorescence spectra of multiple subjects differ from each other, the authors used a hyperspectral imager based on principal component analyses (PCA) and multivariate curve resolution–alternating least squares (MCR-ALS). These methods produce high-contrast images of the overlapped fingerprints, leading to a differentiation of both fingerprints. The authors evaluated their method on real overlapped fingerprints.

Su et al. [80] developed a method for separating overlapped fingerprints using deep learning-oriented methods in 2023. After fingerprint segmentation using a U-Net model, the fingerprint separation algorithm applies Gaussian blurring, binarization, and morphological operations to isolate the overlapping and non-overlapping areas of the fingerprints. Finally, an ellipse mask is generated to extract each fingerprint separately. This method was successfully tested based on simulated samples.

5.2.3. AI-based methods

Stojanović et al. [30,74,76] published three separation methods based on a CNN with error back-propagation between 2016, 2018, and 2019. The researchers estimate the OF using local Fourier analysis adopted from Jain and Feng [51]. The OF are separated based on a pre-trained FFNN including a global-based enhancement model. Stojanović et al. [74] proposed tuned Gabor filters to extract the fingerprint components. Based on the qualitative evaluation results with real and simulated fingerprints, this method can be considered the first working machine learning-based separation method and one of the state-of-the-art algorithms for real overlapped fingerprints. The method of Stojanović [74] is usually used as an important reference algorithm of later AI-based methods in the context of fingerprints [31,94,95].

Yih et al. [34] proposed a separation method based on CNN in 2018. The developers trained their CNN on overlapped and non-overlapped fingerprints to detect overlapped and non-overlapped regions. If a part of the fingerprint image is overlapped, an erased mark is set. If not, a reserved mark is set. Finally, the overlapped range is erased so that a non-overlapped image is created. Yih et al. [34] evaluated their method on real fingerprints.

Yoo et al. [31] published a separation method based on a four-layer CNN in 2020. The authors first trained their CNN based on synthesized single fingerprints. Based on the U-Net CNN architecture, their method called FinSNet can segment the regions and separate the OF, including the extraction of the fingerprint. Yoo et al. [31] evaluated their method on real fingerprints. They conclude that their method offers several advantages in terms of computational efficiency compared to the methods by [30,74,76].

Chegur et al. [79] introduced a method for separating overlapped fingerprints utilizing deep learning in 2023. Their methodology commences with pre-processing steps such as converting to grayscale and reducing noise. The overlapped areas are identified, marked, and subsequently cropped. Gaussian blurring, erosion, and dilation are performed to separate the fingerprints. Each fingerprint is isolated with an elliptical mask and then reconstructed through a convolutional autoencoder. Chegur et al. [79] tested their method based on simulated fingerprints.

Johnson and Chitra [81] proposed a method for separating overlapped fingerprints, palm prints, and finger knuckles in 2024. Their method starts by estimating the regions of interest from fingerprint images. Noise in the fingerprint images is removed using bilateral filters, followed by contrast enhancement to improve the clarity of the ridges. The overlapped fingerprints are then separated using a clustering technique based on their own Brownian Motion-enabled k-means algorithm, which partitions the fingerprint images into distinct clusters. This separation facilitates the extraction of significant features for further processing. They evaluated the method based on simulated fingerprints.

5.3. Discussion

Our study shows several key trends and correlations. These trends can be mainly categorized based on the type of method, their evolution over time, and the context of their development and application.

Overall, the field of fingerprint separation methods has seen a clear evolution from traditional methods, which rely on well-defined procedural steps based on the first approach by Chen et al. [18], to AI-based methods that offer more flexibility and adaptability in a more black-box environment. This transition highlights the increasing role of machine learning and deep learning in forensic science, initiated by Stojanović et al. [74]. In addition, we argue that hybrid methods represent a bridge between traditional and AI-based methods, incorporating properties of both to address specific challenges in fingerprint separation.

In general, the integration of AI tasks, such as classification or clustering [96], has not only introduced new methods but also reshaped the research landscape, as evidenced by the decline in traditional method publications and the rise of AI-based methods. The shift to AI-based methods has significant implications for forensic science. AI algorithms can potentially handle more complex overlapping patterns with greater accuracy [30]. It is conceivable that AI technology could also be used to separate more than two overlapped fingerprints, which is still the established definition of overlapped fingerprints [18]. In this way, the adoption of AI can streamline forensic system workflows, reducing the time required to process and analyze fingerprint data, thereby speeding up investigations and the delivery of justice. However, while AI-based methods offer significant potential, their development and implementation pose various challenges, such as the need for large fingerprint datasets and computational resources. Fluctuations in the number of publications and the publication of hybrid methods suggest ongoing adjustments and refinements in these methods. In this context, the increasing complexity of AI-based methods requires the collaboration of forensic experts as well as system developers. Such interdisciplinary efforts can drive innovation and improve the robustness and applicability of new methods. Collaboration with legal experts is also essential to ensure that new methods meet standards based on key requirements and are admissible in court.

Note, that AI-based methods must be rigorously tested to ensure they do not introduce (critical) errors or biases (e.g., against specific demographic groups) [97]. We strongly emphasize that only proven and explainable methods as part of reliable forensic systems (e.g., AFIS) can be used in court without any doubt. The accuracy, trust, and fairness of separation methods are essential to avoid incorrect separations and identifications. Interestingly, in particular, we expect that issues related to fairness [98] may lead to an increasing relevance of explainable AI-based separation methods. Generally, in the context of the ten requirements identified in this study, AI-based separation methods must not be viewed as substitutes for human examiners but as tools that strengthen requirement fulfillment, particularly with respect to accuracy, reproducibility, and robustness. At the same time, their integration must ensure that human experts remain able to verify, interpret, and ultimately endorse the results. This is especially critical given the requirements of explainability and integrity, which cannot be guaranteed without expert oversight. Thus, effective fingerprint separation in forensic practice requires a "human–AI partnership" in which automated methods improve efficiency while forensic examiners maintain responsibility for validating the separation results and ensuring their admissibility in court.

Finally, we found that most methods were evaluated based on real fingerprints or both real and simulated ones. In most cases, however, it was found that the methods for real fingerprints provide poorer results than for simulated fingerprints, i.e., they only partially fulfill robustness requirements or only within a certain range. Not surprisingly, this effect can be attributed to the fact that real fingerprints introduce variability at multiple processing stages, such as OF estimation or segmentation, which is typically absent or strongly reduced in simulated data and can directly affect separation results. However, to enable higher transferability of theoretical methods into practice, high variability of real fingerprints has to be taken into account. Therefore, we argue that most of the separation methods are currently not practicable for application in a real-world environment.

> RQ2 **– Separation methods:** *Fingerprint separation methods have evolved from traditional techniques which dominated until 2015, typically local Fourier analysis, relaxation labeling, and Gabor filters, to AI-based methods since 2016 that use neural networks for greater accuracy and efficiency. Hybrid methods, which combine traditional and artificial intelligence approaches, emerged sporadically to address specific challenges (e.g., combining local Fourier analysis and neural networks). Although AI methods offer significant potential today, they require extensive computing resources and rigorous testing to ensure trust and fairness.*

6. Threats to validity

We identified several issues that could affect the internal and external validity of our work's results.

6.1. Internal validity

There are some issues regarding the different use of terms and definitions that could affect internal validity. For example, the requirements effectiveness and efficiency are used as synonyms in some papers. Here, it is not verifiable whether the authors of the papers use them intentionally or not. We have not included effectiveness in our requirements, as this would mean that the best possible results would be achieved regardless of the effort needed [99]. We argue that the requirement efficiency already includes the highest possible quality of results but at the lowest possible effort. Thus, efficiency is much more practice-oriented than effectiveness. In addition, it was not always possible to clarify whether the method authors actually refer to separation or matching. This issue mainly concerns to efficiency. Moreover, we identified a lack of consistency and completeness in depth of content. In some papers, methods are described in great detail, but in others only briefly. Therefore, it is sometimes quite unclear how exactly the proposed methods work. For this reason, our paper could not provide a uniform evaluation of the presented methods. In addition, method-related requirements were partly well described or only mentioned very briefly. Therefore, all results can only be considered as trends. However, this does not change the shortcomings identified in our article. Nevertheless, it could affect the internal validity of the results. We are aware that not all publications can be classified appropriately based on the traditional three steps. However, due to its widespread usage and referencing its usage is still reasonable and helps to sufficiently understand the basic structure of all methods.

6.2. External validity

Not surprisingly, our search strategy may have missed potential publications due to the specific keywords used. Nevertheless, in experimental iterations we also tested other related terms (e.g., finger mark), which indeed yielded a larger number of search results; however, these additional results did not include any further peer-reviewed publications that met our inclusion criteria. Of course, this does not mean that we identified all suitable publications. Moreover, we only focused on the separation methods for overlapped fingerprints. However, we cannot exclude that there are more methods that are only part of a bigger system. Considering more general publications or methods in the field of biometrics, in particular fingerprints, could increase the external validity. A similar problem arises regarding the identification of requirements. In this context, we have already built on two information sources including an expert interview [47]. However, considering requirements in other biometric fields, such as iris verification, or interviewing even more experts from different countries could lead to additional insights.

7. Related work

We found three related publications that focus on actual scientific work in the field of fingerprint separation.

Pawar et al. [69] presented a literature survey, in addition to their own separation approach. In their literature survey, they explicitly describe the motivation, methods, results, and conclusion of five methods published between 2010 and 2014. Stojanović et al. [21] published a review of methods for latent overlapped fingerprint separation with a special focus on the processing steps before feature extraction. Seven separation methods published between 2008 and 2016 are described and compared. The use of artificial or real fingerprints by the methods has been specifically mentioned. The authors describe the impact of methods to evaluate five methods. They conclude that all methods, datasets, and quality metrics summarized, show that there is still a great field for further research. As part of this research, automatic methods for fingerprint segmentation and the development of larger publicly available datasets are mentioned. The review by Gundgurti et al. [22] describes and compares 19 segmentation and separation methods published between 2010 and 2016. The methods, databases used, and results of the presented works are described. They conclude that AFIS have been improved, but it is still a difficult problem to separate overlapped fingerprints because of poor image quality or complex structures of the background or fingerprint ridges. Besides these review publications, we found literature that presents the already mentioned general requirements for biometric identifiers, for example, Jain et al. [3] or Saini et al. [10]. These requirements are not directly applicable to separation methods. However, they provide a partial basis for our identified requirements, for example, regarding accuracy, efficiency, or usability.

In contrast to all related work found, we provide a more comprehensive literature study in terms of the considered time period (i.e., 15 years of research) and the number of included methods (i.e., 33 methods). We argue that our study is particularly high-contributing because we compare traditional, hybrid, and AI-based methods, including those that have been recently published until 2024. In contrast to our review, the most recent detailed reviews by Gundgurti et al. [22] and Stojanović et al. [21] only include studies until 2016, whereas our work clarifies that 2016 can only be considered as the beginning AI-based method trend. Moreover, none of the publications focuses on practical requirements to ensure a relevant basis for a comparable evaluation of separation methods. Thus, we argue that our work is the most comprehensive and practice-oriented study in the area of systematic reviews for overlapped fingerprints so far.

8. Conclusion

In this article, we presented ten requirements for separation methods and a comprehensive review of 33 separation methods for overlapped fingerprints. We conclude that the requirements introduced provide a strong practical relevance. They can be seen as the first basis for the evaluation standardization of separation methods. Based on the study results, we identified several shortcomings regarding practice orientation and comparable evaluations. Due to the great importance of fingerprints for forensic systems and criminal investigations, comparability should be ensured to choose the best possible method for practical application. Our work is intended to provide an essential basis for further research on requirements and metrics for overlapped fingerprint separation methods. In addition, we highlighted current research directions in the area of fingerprint separation methods by identifying trends, particularly with respect to the great potential of AI-based methods but also their risks concerning robustness, explainability, and fairness. Overall, we strongly recommend research on the following research questions:

- How can the requirements be measured and validated comprehensively?
- How can a framework based on the requirements for evaluating separation algorithms be described?
- For which parts of a separation method may the requirements have the greatest impact?

Our work demonstrates a great need for a standardized evaluation based on requirements to evaluate methods on a comprehensive and comparable basis. Moreover, we emphasize the immense relevance of requirements engineering as a link between theoretical methods and forensic systems in practice. The identification of specific requirement fulfillment could lead to a new level of practice-orientation and credibility of separation methods in criminal investigations, for example, based on highly flexible hybrid or AI-based methods.

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Richard May: Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Methodology, Investigation, Data curation, Conceptualization. **Marco Filax:** Writing – review & editing, Validation, Supervision, Methodology, Conceptualization. **Fabian Theuerkauf:** Writing – review & editing, Validation, Conceptualization. **Frank Ortmeier:** Writing – review & editing. **Thomas Leich:** Writing – review & editing, Supervision, Project administration, Conceptualization.

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Data availability

The analysis file created during the study is available online.

References

[1] A.K. Jain, J. Feng, A. Nagar, K. Nandakumar, On matching latent fingerprints, in: Conference on Computer Vision and Pattern Recognition Workshop, CVPRW, IEEE, 2008, pp. 1–8.
[2] R. Bolle, J. Connell, S. Pankanti, N. Ratha, A. Senior, Guide to Biometrics, Springer Science & Business Media, 2013.
[3] A.K. Jain, P. Flynn, A.A. Ross, Handbook of Biometrics, Springer Science & Business Media, 2008, pp. 1–42.
[4] D. Maltoni, D. Maio, A.K. Jain, S. Prabhakar, Handbook of Fingerprint Recognition, Springer, 2009.
[5] R.M. Bolle, A.W. Senior, N.K. Ratha, S. Pankanti, Fingerprint minutiae: A constructive definition, in: International Workshop on Biometric Authentication, Springer, 2002, pp. 58–66.
[6] R.E. Gaensslen, Fingerprints, in: Forensic Science, CRC Press, 2014, pp. 341–364.
[7] A.K. Jain, L. Hong, S. Pankanti, R. Bolle, An adentity-authentication system using fingerprints, Proc. IEEE 85 (9) (1997) 1365–1388.
[8] E. Mordini, S. Massari, Body, biometrics and identity, Bioethics 22 (9) (2008) 488–498.
[9] M.B. Thompson, J.M. Tangen, D.J. Mccarthy, Expertise in fingerprint identification, J. Forensic Sci. 58 (6) (2013) 1519–1530.
[10] M. Saini, A. Kumar Kapoor, Biometrics in forensic identification: Applications and challenges, J. Forensic Med. 1 (2) (2016) 1–6.
[11] L. Levanon, G. Tully, Fingerprint analysis and reporting in legal trials: a critical re-evaluation, in: Crim. Law Forum, 2025, pp. 1–32.
[12] J. Levinson, E. Buchnik, B. Ariel, A.J. Domb, Scientific evidence in courts of law: An overview, Judic. Indep.: Cornerstone Democr. (2024) 140–164.
[13] A. Sharma, M. Kaur, Automatic segmentation for separation of overlapped latent fingerprints, Int. J. Comput. Sci. Eng. 6 (7) (2018) 484–490.
[14] X. Liu, K. Raja, R. Wang, H. Qiu, H. Wu, D. Sun, Q. Zheng, N. Liu, X. Wang, G. Huang, et al., A latent fingerprint in the wild database, IEEE Trans. Inf. Forensics Secur. 19 (2024) 3703–3718.
[15] L. Hong, A. Jain, Fingerprint enhancement, in: Automatic Fingerprint Recognition Systems, Springer, 2004, pp. 127–143.
[16] A.K. Jain, J. Feng, Latent fingerprint matching, IEEE Trans. Pattern Anal. Mach. Intell. 33 (1) (2011) 88–100.
[17] Q. Zhao, A.K. Jain, Model-based separation of overlapping latent fingerprints, IEEE Trans. Inf. Forensics Secur. 7 (3) (2012) 904–918.
[18] F. Chen, J. Feng, A.K. Jain, J. Zhou, J. Zhang, Separating overlapped fingerprints, IEEE Trans. Inf. Forensics Secur. 6 (2) (2011) 346–359.
[19] J. Feng, Y. Shi, J. Zhou, Robust and efficient algorithms for separating latent overlapped fingerprints, IEEE Trans. Inf. Forensics Secur. 7 (5) (2012) 1498–1510.
[20] F. Chen, J. Feng, J. Zhou, On separating overlapped fingerprints, Conf. Biom.: Theory, Appl. Syst. (BTAS) (2010) 1–6.
[21] B. Stojanović, O. Marques, A. Neskovic, Latent overlapped fingerprint separation: A review, Multimedia Tools Appl. 76 (15) (2017) 16263–16290.
[22] P. Gundgurti, P. Pattan, P. Gundgurti, A review of digital latent fingerprint image processing with a special focus on techniques for separation of overlapped fingerprint images, in: System Reliability, Quality Contol, Safety, Maintenance and Management: Applications to Electrical, Electronics and Computer Science and Engineering (ICICCT), Springer Singapore, 2019, pp. 287–299.
[23] B.A. Kitchenham, D. Budgen, O.P. Brereton, Evidence-based Software Engineering and Systematic Reviews, Taylor and Francis, 2015.
[24] K. Cao, E. Liu, A.K. Jain, Segmentation and enhancement of latent fingerprints: A coarse to fine ridge structure dictionary, IEEE Trans. Pattern Anal. Mach. Intell. 36 (9) (2014) 1847–1859.
[25] K. Deepika, G. Shivakumar, A robust deep features enabled touchless 3D-fingerprint classification system, SN Comput. Sci. 2 (4) (2021) 1–8.
[26] N.P. Ramaiah, A.T. Rao, C.K. Mohan, Enhancements to latent fingerprints in forensic applications, Conf. Digit. Signal Process. (DSP) (2014) 439–443.
[27] U.U. Deshpande, V. Malemath, S.M. Patil, S. Chaugule, et al., Latent fingerprint identification system based on a local combination of minutiae feature points, SN Comput. Sci. 2 (3) (2021) 1–17.
[28] K. Cao, A.K. Jain, Automated latent fingerprint recognition, IEEE Trans. Pattern Anal. Mach. Intell. 41 (4) (2019) 788–800.
[29] S. Jeyanthi, N.U. Maheswari, R. Venkatesh, Separation and recognition of overlapped latent images, Conf. Comput. Commun. Netw. Technol. (ICCCNT) (2013) 1–6.
[30] B. Stojanović, O. Marques, A. Neskovic, Machine learning based overlapped latent fingerprints segmentation and separation, IEEE Telecommun. Forum (TELFOR) (2018) 1–8.
[31] D. Yoo, J. Cho, J. Lee, M. Chae, B. Lee, B. Lee, FinSNet: End-to-end separation of overlapped fingerprints using deep learning, IEEE Access 8 (2020) 209020–209029.
[32] J. Zhang, R. Lai, C.C.J. Kuo, Latent fingerprint detection and segmentation with a directional total variation model, Conf. Image Process. (ICIP) (2012) 1145–1148.
[33] J. Feng, J. Zhou, A.K. Jain, Orientation field estimation for latent fingerprint enhancement, IEEE Trans. Pattern Anal. Mach. Intell. 35 (4) (2012) 925–940.
[34] C.H. Yih, J.L. Hung, J.A. Wu, L.M. Chen, Overlapped fingerprint separation based on deep learning, ACM Int. Conf. Proceeding Ser. (2018) 14–18.
[35] S. Jalali, C. Wohlin, Systematic literature studies: Database searches vs. backward snowballing, in: Symposium on Empirical Software Engineering and Measurement, ESEM, IEEE, 2012, pp. 29–38.
[36] J.-H. Yang, S.-J. Choi, J.J. Yoh, Towards reconstruction of overlapping fingerprints using plasma spectroscopy, Spectrochim. Acta Part B: At. Spectrosc. 134 (2017) 25–32.
[37] J.-H. Yang, J.J. Yoh, Reconstruction of chemical fingerprints from an individual's time-delayed, overlapped fingerprints via laser-induced breakdown spectrometry (LIBS) and raman spectroscopy, Microchem. J. 139 (2018) 386–393.
[38] M. Schott, R. Merkel, J. Dittmann, Sequence detection of overlapping latent fingerprints using a short-term aging feature, Work. Inf. Forensics Secur. (WIFS) (2012) 85–90.
[39] J. Zhang, R. Lai, C.-C.J. Kuo, Adaptive directional total-variation model for latent fingerprint segmentation, IEEE Trans. Inf. Forensics Secur. 8 (8) (2013) 1261–1273.
[40] Y. Zhu, X. Yin, X. Jia, J. Hu, Latent fingerprint segmentation based on convolutional neural networks, in: Workshop on Information Forensics and Security, WIFS, IEEE, 2017, pp. 1–6.
[41] N. Zhang, X. Yang, Y. Zang, X. Jia, J. Tian, Overlapped fingerprints separation based on adaptive orientation model fitting, Conf. Pattern Recognit. (ICPR) (2014) 678–683.
[42] N. Neha, P. Gundewar, Overlapped fingerprint separation for fingerprint authentication, Int. J. Eng. Res. Appl. 7 (6) (2017) 47–49.
[43] S. Jeyanthi, N. Uma Maheswari, R. Venkatesh, Neural network based automatic fingerprint recognition system for overlapped latent images, J. Intell. Fuzzy Syst. 28 (6) (2015) 2889–2899.
[44] C. Wohlin, Guidelines for snowballing in systematic literature studies and a replication in software engineering, in: International Conference on Evaluation and Assessment in Software Engineering, EASE, ACM, 2014.
[45] T. Zimmermann, Card-sorting: From text to themes, in: Perspectives on Data Science for Software Engineering, 2016, pp. 137–141.
[46] A. Van Lamsweerde, Goal-oriented requirements engineering: A guided tour, Conf. Requir. Eng. (RE) (2001) 249–261.
[47] M. Filax, Bewertungsmetriken zur verifizierten Separation von überlagerten Fingerspuren, (Masterthesis), Otto-Von-Guericke-University Magdeburg, Magdeburg, 2013.
[48] S. Xie, J. Yang, D. Park, S. Yoon, J. Shin, Fingerprint quality analysis and estimation for fingerprint matching, IntechOpen State the Art Biom. (2011) 3–24.
[49] Z. Yao, J.-M.L. Bars, C. Charrier, C. Rosenberger, A literature review of fingerprint quality assessment and its evaluation, IET Biom. 5 (3) (2016) 243–251.
[50] S. Yoon, K. Cao, E. Liu, A.K. Jain, LFIQ: Latent fingerprint image quality, Conf. Biom.: Theory, Appl. Syst. (BTAS) (2013) 1–8.
[51] A.K. Jain, J. Feng, Latent palmprint matching, IEEE Trans. Pattern Anal. Mach. Intell. 31 (6) (2009) 1032–1047.
[52] K. Qian, M. Schott, J. Dittmann, Separation of contactless captured high-resolution overlapped latent fingerprints: Parameter optimisation and evaluation, Work. Biom. Forensics (IWBF) (2013) 1–4.
[53] V. Matyáš, Z. Říha, Biometric authentication—Security and usability, in: Advanced Communications and Multimedia Security, Springer, 2002, pp. 227–239.
[54] D.T. Toledano, R. Fernández Pozo, Á. Hernández Trapote, L. Hernández Gómez, Usability evaluation of multi-modal biometric verification systems, Interact. Comput. 18 (5) (2006) 1101–1122.
[55] R. Blanco-Gonzalo, R. Sanchez-Reillo, J. Liu-Jimenez, C. Sanchez-Redondo, How to assess user interaction effects in biometric performance, in: Conference on Identity, Security and Behavior Analysis, ISBA, IEEE, 2017, pp. 1–6.
[56] R. Blanco-Gonzalo, C. Lunerti, R. Sanchez-Reillo, R.M. Guest, Biometrics: Accessibility challenge or opportunity? Plos One 13 (3) (2018) 1–20.
[57] J. Ward, C. Riley, G. Johnson, Posture, position & biometrics: Guidelines for self-service technology, in: Conference of the Ergonomics Society on Contemporary Ergonomics, CE, Taylor & Francis, 2008, pp. 121–126.
[58] A.K. Jain, L. East, B. Ruud, S. Pankanti, H. Yorktown, Introduction to biometrics, Biom.: Pers. Identif. Networked Soc. (2002) 1–43.
[59] H.C. Lee, R.E. Gaensslen, Advances in Fingerprint Technology, CRC Press, 2001.
[60] M. Filax, A. Kenner, S. Wabnitz, B. Landmesser, M. Ulrich, T. Leich, Farbige Daktyloskopie: Verifizierte Separation überlagerter Fingerspuren, Kriminalistik 68 (5) (2014) 297–302.
[61] N. Akiba, A. Nakamura, T. Sota, K. Hibino, H. Kakuda, M.C. Aalders, Separation of overlapping fingerprints by principal component analysis and multivariate curve resolution—Alternating least squares analysis of hyperspectral imaging data, J. Forensic Sci. (2022).
[62] E.R. Menzel, Fingerprint Detection with Lasers, Marcel Dekker, 1999.
[63] H. Garg, A way towards explainable AI using neuro-fuzzy system, in: Conference on Information Systems and Computer Networks, ISCON, IEEE, 2021, pp. 1–6.
[64] A. Preece, Asking 'Why' in AI: Explainability of intelligent systems–perspectives and challenges, Intell. Syst. Acc. Financ. Manag. 25 (2) (2018) 63–72.

[65] E. Manai, M. Mejri, J. Fattahi, Fingerprint fraud explainability using grad-cam for forensic procedures, in: New Trends in Intelligent Software Methodologies, Tools and Techniques, IOS Press, 2024, pp. 457–470.
[66] S. Pankanti, S. Prabhakar, A.K. Jain, On the Individuality of Fingerprints, IEEE Trans. Pattern Anal. Mach. Intell. 24 (8) (2002) 1010–1025.
[67] D.T. Toledano, R. Fernandez Pozo, A. Hernandez Trapote, L. Hernandez Gomez, Usability evaluation of multi-modal biometric verification systems, Interact. Comput. 18 (5) (2006) 1101–1122.
[68] D. Peralta, I. Triguero, R. Sanchez-Reillo, F. Herrera, J.M. Benitez, Fast fingerprint identification for large databases, Pattern Recognit. 47 (2) (2014) 588–602.
[69] A. Pawar, M. Madankar, Improved algorithm for separating latent overlapped fingerprints, Int. J. Comput. Sci. Netw. 5 (2) (2016) 286–293.
[70] Y. Shi, J. Feng, J. Zhou, Separating overlapped fingerprints using constrained relaxation labeling, Conf. Biom. (IJCB) (2011) 1–8.
[71] R. Kärgel, S. Giebel, M. Leich, J. Dittmann, Separation and sequence detection of overlapped fingerprints: Experiments and first results, in: Optics and Photonics for Counterterrorism and Crime Fighting, International Society for Optics and Photonics, 2011, pp. 1–11.
[72] N. Zhang, Y. Zang, X. Yang, X. Jia, J. Tian, Adaptive orientation model fitting for latent overlapped fingerprints separation, IEEE Trans. Inf. Forensics Secur. 9 (10) (2014) 1556–6013.
[73] S.K. Mahajan, P.S. Joshi, Separation of overlapped fingerprints for forensic application, Int. J. Technol. Res. Eng. 2 (9) (2015) 1741–1743.
[74] B. Stojanović, A. Neskovic, O. Marques, A novel neural network based approach to latent overlapped fingerprints separation, Multimedia Tools Appl. 76 (10) (2016) 12775–12799.
[75] K.M. Hung, L.M. Chen, W.L. Lin, A Novel Overlapping Fingerprint Partition and Reconstruction Based on Vector Flow Method, Proc. IEEE Int. Congr. Adv. Appl. Informatics (IIAI) (2017) 841–846.
[76] B. Stojanović, O. Marques, A. Neskovic, Machine learning based separation of overlapped latent fingerprints, in: Segmentation and Separation of Overlapped Latent Fingerprints, Springer, 2019, pp. 45–51.
[77] H.C. Huang, C.T. Hsieh, M.N. Hsiao, C.H. Yeh, A study of automatic separation and recognition for overlapped fingerprints, Appl. Soft Comput. J. 71 (1) (2018) 127–140.
[78] S. Sen, M. Paul, R. SinhaRoy, C.K. Sengupta, Overlapped fingerprint separation using graph based model, in: Silchar Subsection Conference, SILCON, IEEE, 2022, pp. 1–5.
[79] P. Chegur, N. Patil, N. Doddamani, P. Thakkannavar, N.T. Pendari, M. Maralappanavar, S. Ingalagaon, Separation of overlapped fingerprint images using deep learning, in: International Conference on Advances in Electronics, Communication, Computing and Intelligent Information Systems, ICAECIS, IEEE, 2023, pp. 233–238.
[80] S.-G. Su, Y.-H. Cheng, Y.-L. Lin, H.-C. Hsu, Overlapping fingerprint segmentation and separation based on deep learning, in: International Conference on AI-Generated Content, AIGC, Springer, 2023, pp. 256–265.
[81] J. Johnson, R. Chitra, Multimodal biometric identification based on overlapped fingerprints, palm prints, and finger knuckles using BM-KMA and CS-RBFNN techniques in forensic applications, Vis. Comput. (2024) 1–15.
[82] K. Qian, M. Schott, W. Schöne, M. Hildebrandt, Separation of high-resolution samples of overlapping latent fingerprints using relaxation labeling, in: Optics, Photonics, and Digital Technologies for Multimedia Applications II, International Society for Optics and Photonics, 2012, pp. 1–9.
[83] R.P. Ananth, J. Nalini, H. Ajai, Overlapped fingerprint separation and feature enhancement using gabor filter, Digit. Image Process. 4 (4) (2012) 198–201.
[84] R. Reka, S. Uma, Automatic overlapped fingerprint separation, Int. J. Commer. Bus. Manag. 1 (1) (2012) 34–39.
[85] K. Qian, M. Schott, W. Zheng, J. Dittmann, Context-based approach of separating contactless captured high-resolution overlapped latent fingerprints, IET Biom. 3 (2) (2014) 101–112.
[86] J. Vanitha, S. Thilagavathi, Separation of overlapped fingerprints for forensic application, Int. J. Adv. Res. Electr. Electron. Instrum. Eng. 3 (6) (2014) 1741–1743.
[87] N. Sommit, R. Chitaree, The overlapped latent fingerprint separation by using Fourier optics (FO), in: J. Phys.: Conf. Ser., vol. 2145, IOP Publishing, 2021, pp. 1–8.
[88] N. Akiba, A. Nakamura, T. Sota, K. Hibino, H. Kakuda, K. Tsuchiya, K. Tanabe, Examination of fingerprint separation methods based on hyperspectral data measured from latent overlapping fingerprints, in: Counterterrorism, Crime Fighting, Forensics, and Surveillance Technologies, vol. 12275, SPIE, 2022, pp. 58–62.
[89] A. Sankaran, T.I. Dhamecha, M. Vatsa, R. Singh, On matching latent to latent fingerprints, in: Conference on Biometrics, IJCB, IEEE, 2011, pp. 1–6.
[90] R. Merkel, S. Gruhn, J. Dittmann, C. Vielhauer, A. Bräutigam, On non-invasive 2D and 3D chromatic white light image sensors for age determination of latent fingerprints, Forensic Sci. Int. 222 (1–3) (2012) 52–70.
[91] D. Minh, H.X. Wang, Y.F. Li, T.N. Nguyen, Explainable artificial intelligence: A comprehensive review, Artif. Intell. Rev. (2022) 1–66.
[92] R. Mehrotra, K.R. Namuduri, N. Ranganathan, Gabor filter-based edge detection, Pattern Recognit. 25 (12) (1992) 1479–1494.
[93] A. Tonazzini, L. Bedini, E. Salerno, A Markov model for blind image separation by a mean-field EM algorithm, IEEE Trans. Image Process. 15 (2) (2006) 473–482.
[94] A.A.J. Al-Saedi, A. Ibrahim, Fingerprint recognition by using convoloutional neurla network and support vector machine classification, in: Symposium on Multidisciplinary Studies and Innovative Technologies, ISMSIT, IEEE, 2020, pp. 1–4.
[95] B. Stojanović, O. Marques, A. Nešković, Deep learning-based approach to latent overlapped fingerprints mask segmentation, IET Image Process. 12 (11) (2018) 1934–1942.
[96] R. May., T. Niemand., P. Scholz., T. Leich, Design patterns for monitoring and prediction machine learning systems: Systematic literature review and cluster analysis, in: International Conference on Software Technologies, ICSOFT, SciTePress, 2023, pp. 209–216.
[97] J.W. Gichoya, K. Thomas, L.A. Celi, N. Safdar, I. Banerjee, J.D. Banja, L. Seyyed-Kalantari, H. Trivedi, S. Purkayastha, AI pitfalls and what not to do: mitigating bias in AI, Br. J. Radiol. 96 (1150) (2023) 1–8.
[98] K. Lai, S.N. Yanushkevich, V. Shmerko, Fairness, bias and trust in the context of biometric-enabled autonomous decision support, in: Transactions on Computational Science XL, Springer, 2023, pp. 66–87.
[99] V. Potočan, Business operations between efficiency and effectiveness, J. Inf. Organ. Sci. 30 (2) (2006) 251–262.