REVIEW

An investigation of latent fingerprinting techniques

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Abstract

Background: Latent fingerprints are the unintentional impressions that are left at crime scenes, which are considered to be highly significant in forensic analysis and authenticity verification. It is an extremely crucial tool used by law enforcement and forensic agencies for the conviction of criminals. However, due to the accidental nature of these impressions, the quality of prints uplifted is generally inferior.

Main body: In order to improve the overall fingerprint recognition performance, there is an insistent need to design novel methods to improve the reliability and robustness of the existing techniques. Therefore, a systematic review is presented to study the existing methods for latent fingerprint acquisition, enhancement, reconstruction, and matching, along with various benchmark datasets available for research purposes.

Conclusion: The paper highlights multiple challenges and research gaps using comparative analysis of existing enhancement, reconstruction and matching approaches in order to augment the research in this direction that has become imperative in this digital era.

Keywords: Latent fingerprint, Enhancement, Segmentation, Matching, Reconstruction

Background

Human fingerprints, since long have been used as crucial evidence for criminal investigation. Advancements in technology have enabled to improve the efficiency of the scientific procedure for evidence collection and analysis. Simultaneously, the rise in the number and diversity of crimes committed by criminals has become a challenging task for intelligence agencies to convict a criminal. It has been observed that perpetrators of the crime have also changed their methods of committing a crime, and they equally exploit technological advancements. With the increased digitization, criminals are now more into hacking, phishing, malware attacks, etc.. To deal with these upcoming security threats, it became imperative to secure ourselves from these new-age threats. One such method of defending ourselves is biometrics, which relies on intrinsic physical or behavioural traits of human beings for authentication purposes. Unique physical characteristics like fingerprints, palm prints, iris, facial recognition, etc. are widely used today for solving criminal cases in today's digital society (Singla et al., 2020). Solo or multiple traits can be used for authentication purposes. Even today, fingerprints are appreciated as highly significant and remain the most commonly accepted traits, among all, due to their uniqueness. Therefore, fingerprint recognition is widely used in the banking industry, securing areas of national interest, passport control, securing E-commerce, identifying missing children, etc.. In most of the above applications, the fingerprints are captured in a controlled environment for recognition purposes.

In real-world scenarios, the fingerprints recovered, particularly by law enforcement agencies, are unintentional and are left at crime scenes by chance. In such circumstances, latent fingerprinting is the mechanism that is available to recover the chance impression from a crime scene by legal authorities. These prints require

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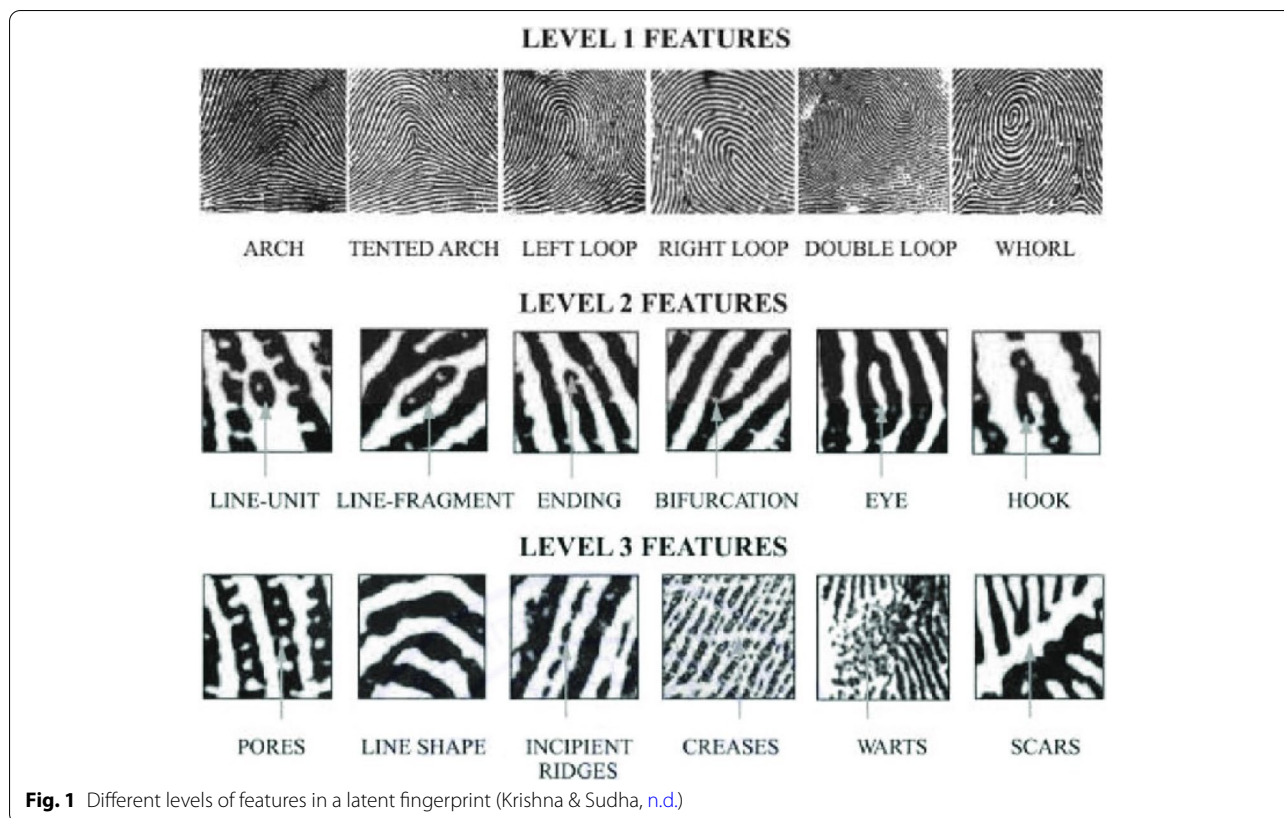
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Fig. 1 Different levels of features in a latent fingerprint (Krishna & Sudha, n.d.)

further processing for the identification of criminals. Due to the unintentional and uncontrolled nature of these impressions, we encounter a whole lot of challenges like inefficient capturing and upliftment of fingerprints, partial prints, complex background noise, manual marking of minutiae, one-time upliftment of prints in some techniques, enhancement of poor-quality ridge, reconstruction of the incomplete image, etc.. These challenges provide a lot of scope in improving the performance of the fingerprint recognition system. Recently, India launched the world's largest fingerprint database (i.e. Aadhaar), signifying the importance of fingerprint-based recognition even today (Singla et al., 2020; Krishna & Sudha, n.d.) The key objective of the paper is to acquaint the reader with the basic concepts of latent fingerprinting, along with some of the latest available approaches that are required for the enhancement, reconstruction, and matching of the lifted fingerprints. The research gaps and limitations are highlighted, providing scope for further improving the latent fingerprinting tools and techniques.

The primary task related to latent fingerprinting technology involves matching, reconstruction and enhancement. Matching deals with comparing the ground truth latent features with the features recovered from the sample under consideration. For matching to be performed efficiently, it is imperative to extract quality features from the sample which could be ensured by applying novel reconstruction and enhancement techniques which are discussed in the following sections.

Matching of the latent fingerprint is done using unique features which are categorized into three different levels, namely, level 1, level 2 and level 3(Fig. 1) (Jain & Feng, 2010a). Level 1 features are the most basic features that can be derived from a latent fingerprint sample like the arch, left loop, right loop, whorl, etc.. They are visible to our naked eyes and helps in visual inspection and manual matching of fingerprints. Further, we have level 2 features comprising ridge endings, bifurcations, hook, etc.. They are more sophisticated features than level 1 features. Sometimes due to poor quality of evidence, these features may not be extracted efficiently due to smudging of ridges. Hence, an appropriate reconstruction and enhancement is required to eliminate spurious features. Level 3 features are the most defining features that can help us enhance our performance enormously. They are permanent features that we can recover from a sample like pores, line-shape, scars, etc.. However, it is difficult to extract such features because of resolution constraints.

Usually, a combination of the above features is used for appropriate matching results.

The processing of latent fingerprint images follows a sequence of steps as depicted in Fig. 2. The first step is the image acquisition phase, wherein we uplift the latent fingerprint using various techniques, discussed in the Main text section of our paper. This captured image is further used in the enhancement phase in which the quality of an image is improved by noise removal, sharpening of an image, adjusting the brightness of the image, etc.. Image enhancement makes it easier to identify key features in an image. The next step is image restoration in which an image that is degraded due to blur, noise, dirt, scratches, etc. is recovered to extract accurate features from the image. Matching is the final step in which the features that are recovered from an image is matched with the ground truth using various matching techniques and algorithms.

Main text
Latent fingerprint upliftment approaches
Latent fingerprint upliftment from different surfaces is the first step in the processing of latent fingerprints. Since different surfaces possess different properties (texture, porosity, etc.), we require different techniques for latent fingerprint upliftment which are discussed in Table 1. This is the most vital step among all the preprocessing steps because the quality of latent prints uplifted at this stage is further used for enhancement, reconstruction and matching. If the uplifted prints are of good quality, the chances are that the results after preprocessing will be far better than if the prints are of poor quality. Further, the number of minutiae that we are able to extract from an image directly depends on the quality of prints obtained, which further affects the matching performance. To get quality results, we must be handing our evidence with the utmost care and uplift the prints with as much care as we can. In this section, we are going to discuss some of the available techniques for fingerprint upliftment.

Latent fingerprint enhancement approaches
After capturing the fingerprint evidence using various methods as discussed above, the next step is to enhance the image. In a real-world crime scenario, it is commonly observed that the uplifted evidence is not of good quality. So to get relevant information from the image, we need to enhance it using various approaches as discussed in Table 2.

In 2021, a generative adversarial network (GAN)–based latent fingerprint enhancement model was proposed (Joshi et al., 2021). The advantage of the proposed approach is that it helps preserve the ridge structure along with the minutiae details which helps in improving the enhancement of the fingerprint sample. Further, a novel Lindeberg's automatic scale selection method (Agarwal & Bansal, 2021) is introduced by the author. This method is based on the utility of level 3 features for the enhancement of latent fingerprints. In a recent paper by *Gupta et al.*, it introduces a new approach for enhancement and reconstruction of using two dictionaries. First dictionary is orientation based, while another is composed using continuous phases. The ridge pattern is reconstructed using a continuous phase-based dictionary (Gupta et al., 2020). Further, the AM–FM model is used for field correction. A novel approach for enhancement using progressive generative adversarial network (GAN) is proposed in (Gupta et al., 2020). A high-quality latent fingerprint image is obtained using two stages. In the first stage, Progressive Offline Training (POT) is used, while in the second phase, the Iterative Online Testing (IOT) module is used. Next, an algorithm is proposed by *Horapong et al.* based on matched filter and sparse autoencoder (Horapong et al., 2020). This method is devised for poor-quality or partially missing fingerprints. The given algorithm improves on the friction ridges using the frequency domain of the latent fingerprint. Further, a conditional generative adversarial network-based latent fingerprint enhancement algorithm is proposed by (Joshi et al., 2021). The proposed latent fingerprint enhancement model preserves ridge structure including minutiae and removes structured and nonstructured background noise present in a latent fingerprint.

In 2019, a fingerprint enhancement approach was proposed by *Jhansirani et al.* in which a combination of total variation model and sparse representation with multi-scale patching is used. In this method, the image is divided into two components, texture and cartoon components, using the total variation (TV) model (Jhansirani & Vasanth, 2019). In this algorithm, cartoon components are removed as non-fingerprint patterns, and texture components are classified as the informative structure of small patterns. Attributes of ridge structures like ridge frequency and orientation are obtained with the help of the Gabor function. Further, using a set of distinct fingerprint pattern dictionaries are created. Enhancement and restoration of ridge structures are done using multiscale patch-based sparse representation along with the understanding of dictionaries. For matching and identification purposes, the author used the Levenberg–Marquardt algorithm (Jhansirani & Vasanth, 2019) for training the neural networks. The advantage of the proposed algorithm is that it reduces the distortion and further enhances the fingerprint pattern which leads to increasing the recognition rate. A generative adversarial network-based latent fingerprint
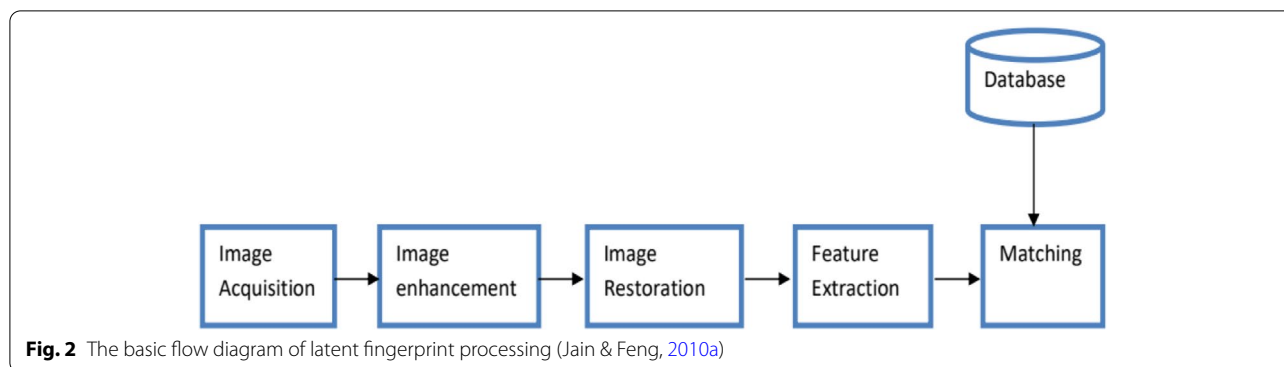
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Fig. 2 The basic flow diagram of latent fingerprint processing (Jain & Feng, 2010a)

Table 1 Various approaches for fingerprint upliftment

Approach	Description	Surfaces
Power method (Sodhi & Kaur, 2001)	Powder of contrasting colour with respect to its surface is used.	Used on dry, smooth, non-adhesive surfaces
Ninhydrin (Jasuja et al., 2009a; Yang & Lian, 2014; Jasuja et al., 2009b)	"Ruhemann's Purple" which is a purple colour product is obtained after the reaction.	Useful on porous surfaces—especially paper
1,8 Diazafluoren-9-one (DFO) (Xu et al., 2012; Luo et al., 2013)	It is a variant of ninhydrin. The print glows when exposed to blue-green light.	DFO helps to develop weak blood stains
Iodine (Kelly et al., 2012)	We get a yellow-brown product when sprayed on the print.	Useful on non-metallic surfaces, fresh prints on porous and nonporous
Cyanoacrylate (glue fuming) (Wargacki et al., 2007)	Whitish deposits are obtained when cyanoacrylate reacts with print.	Useful on most nonporous and some porous surfaces. Gives good results on styrofoam and plastic bags
Small particle reagent (Jasuja et al., 2008)	Grey deposits are obtained when it reacts with latent prints.	Used on relatively nonporous and smooth surfaces, including wet ones

enhancement algorithm is proposed by Joshi et al.. The main objective of the proposed approach is to boost the quality of ridge structure quality. Using this approach the ridge structures are preserved along with improving the quality of fingerprint images. The IIITD Multisensor Optical and Latent Fingerprint database (IIITD-MOLF) and the IIITD Multi-surface Latent Fingerprint database (IIITD-MSLFD) (Joshi et al., 2019a) are the datasets that are used in this paper for conducting experiments. The performance of the latent fingerprint recognition can be improved by making use of enhanced images with standard feature extraction as suggested by the author. Further, an enhancement approach was proposed by (Manickam & Devarasan, 2019) using an intuitionistic fuzzy set. For matching and enhancement purposes, the model proposed by the author requires the manual marking of the region of interest. The given approach is divided into two stages. Firstly, fingerprint contrast enhancement is done using an intuitionistic fuzzy set. Further, the level 2 features are extracted for matching purposes. The core of the given technique is based on minutia points which looks over *n* number of images. The matching score is calculated by the author using the Euclidean distance.

A novel approach was proposed by *Manickam et al.* which is based on Scale-Invariant Feature Transformation (SIFT) (Manickam et al., 2019a). The model deals with two phases. In the first phase, contrast enhancement of latent prints is done using an intuitionistic type 2 fuzzy set. In the next phase, the SIFT features are extracted which are further used for matching purposes. With the help of the Euclidean distance, the matching scores are calculated. A hybrid model is presented by (Liban & Hilles, 2018) which is a fusion of the edge directional total variation (EDTV) model and quality image enhancement with lost minutia reconstruction. The database used by the author for testing purposes is NIST SD27. The objective of the paper was to enhance input image as well as de-noise latent fingerprints. The observation made by the author is that the performance of the proposed technique is superior to good-quality latent fingerprint as compared with bad and ugly–quality images. Also, it was perceived that the matching accuracy is improved by about 30% using the given approach. The algorithm proposed by *Xu et .al.* in 2017 constructs minutia and ridge dictionaries (Liu et al., 2014). The prior knowledge of both ridge and minutia are utilized along with the

Table 2 Available latent fingerprint enhancement approaches

Ref.	Year	Description	Database	Limitation	Results
(Joshi et al., 2021)	2021	Direct de-noise the fingerprints and reconstruct the missing ridge structure without explicitly estimating the orientation field using GAN's	IIITD-MOLF IIITD-MSLF	GAN's are difficult to train as they require a large dataset for accurate results.	NFIQ (lower score means better quality) = 2.64
(Agarwal & Bansal, 2021)	2021	The fusion of pores and minutiae at score level is used to re-rank the minutiae-based latent matcher	IIITD latent fingerprint database LivDet 2015 database	Less number of minutiae are used. Additional features such as ridge flow map and ridge quality map can improve the performance.	True detection rate RT = 82.89% Average of the false detection rate RF = 21.2%
(Gupta et al., 2020)	2020	Enhancement and reconstruction of image using the minutiae density and the orientation field direction	Fingerprint verification competition 2002 (FVC2002) and fingerprint verification competition 2004 (FVC2004)	Only local orientation patterns are considered in the proposed method.	Type I attack: $TARa$ = 97.95% on FVC2002 and 94.09% on FVC2004 Type 2 attack: TAR = 49.25% and 50.02% on FVC2002 and FVC2004
(Huang et al., 2020)	2020	A generative adversarial network (GAN) is proposed for the enhancement of latent fingerprint images.	NIST SD27 dataset, NIST SD14		Identification rate (%): Cumulative match characteristics all = 50% Cumulative match characteristics good = 77% Cumulative match characteristics bad = 45% Cumulative match characteristics ugly = 29%
(Horapong et al., 2020)	2020	Two-Stage Spectrum Boosting with Matched Filter and Sparse Autoencoder is used for enhancement	IIT-D MOLF latent fingerprint database	The proposed method depends on high ridge signal strength initially to boost ridge spectra.	Identification rate (%) Rank 20 = 43%
(Joshi et al., 2021)	2020	A conditional generative adversarial network-based latent fingerprint enhancement algorithm is proposed.	IIITD-MOLF and IIITD-MSLF database	The proposed algorithm generates spurious features when the ridge information is insufficient	NFIQ (lower score means better quality) = 2.64
(Jhansirani & Vasanth, 2019)	2019	Image enhancement is done using the Gabor function via multiscale patch-based sparse representation	NIST SD27	Dictionary creation and lookup is slow	The best training performance is 7.8717e obtained at epoch 10.
(Joshi et al., 2019a)	2019	Latent fingerprint enhancement algorithm based on generative adversarial networks is used	IIITD-MOLF database and IIITD-MSLFD database	Spurious features are generated when the ridge information is insufficient.	Matching results: Rank-50 accuracy of 35.66% (DB 1) 30.16% (DB 2)
(Manickam & Devarasan, 2019)	2019	An intuitionistic fuzzy set is used for contrast enhancement of fingerprints	Fingerprint verification competition-2004 and IIIT-latent fingerprint database	Imperfect matching in case of presence of background noise and nonlinear ridge distortion	Matching scores IIIT-latent fingerprint = 0.2702 FVC2004 database 1 = 0.1912 FVC2004 database 2 = 0.2008
(Manickam et al., 2019a)	2019	Scale-Invariant Feature Transformation (SIFT) is used for the enhancement of an image.	FVC2004 and IIIT-latent fingerprint	Does not work well with very poor and partial prints	Linear index of fuzziness IIIT-latent fingerprint = 0.2702 FVC2004 database 2 = 0.2008

Table 2 (continued)

Ref.	Year	Description	Database	Limitation	Results
(Liban & Hilles, 2018)	2018	A hybrid model that is a combination of edge directional total variation model (EDTV) and quality image enhancement with lost minutia reconstruction is used.	NIST SD27 database for testing RMSE, PSNR to measure performance.	Results are not good with ugly images Overlapping images not considered	RMSE average = 0.018373 (good-quality image) PSNR average = 82.99068 (good-quality image)
(Chaidee et al., 2018)	2017	The spectral dictionary is used for enhancement	NIST SD27	Failure due to the wide bandwidth of filter which leads to noise leakage into enhancement process	Identification rate good-quality print = 76% bad quality = 59% ugly quality = 35%
(Liu et al., 2014)	2014	Multiscale Patch Based Sparse Representation used for enhancement	NIST SD27	Global ridge structures are ignored Do not work well for low-quality fingerprints	Identification rate = approx. 64%
(Cao et al., 2014)	2014	Ridge structure dictionary is used for enhancement	NIST SD27 and WVU DB	Confidence measure is poorly defined for the segmentation and enhancement results. Computational efficiency of the algorithm is low	Identification rate NIST SD27 = 71% WVU DB = 78%
(Zhang et al., 2013)	2013	Adaptive directional total variation model	NIST SD27		Identification accuracy less than 12% (rank20)
(Feng et al., 2012)	2012	Prior knowledge-based approach	NIST SD27	The speed of the proposed algorithm is slow with low-quality latents	Identification rate: good-quality print = 60% bad quality = 24% ugly quality = 11%
(Yoon et al., 2011)	2011	Enhancement using hypothesized orientation fields	NIST SD27	Human markup of minutiae is required. Performance is poor for bad and ugly-quality latents. Latent quality assessment is not automatic	Identification rate good-quality print = 66% bad quality = 50% ugly quality = 40%
(Yoon et al., 2010)	2010	Polynomial model and zero pole model	NIST SD27	Uses fixed ridge frequency	Identification accuracy = 35% (rank1)

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proposed two-step multiscale patch-based sparse representation for enhancement purposes. Enhancement of ridges is done using ridge dictionaries, whereas minutia is enhanced using both the dictionaries. The main objective of the author was to overcome the limitations of the widely used Gabor function. One of the major limitations is that Gabor functions are not capable of capturing the details of bifurcation of ridges as well as endpoints. From the results, it is evident that the two-step SR algorithm exceeds the performance of SR only by using the Gabor dictionary.

The algorithm proposed by *Yoon et al.* is based on the reconstruction of an image using orientation guided sparse representation and a TV image decomposition model (Feng et al., 2012). The first step of the proposed approach is to disintegrate the latent image into cartoon and texture components. In the next step, computation of the reliability and orientation field of the texture image is done. In the final step, to deal with low-reliability regions, a redundant dictionary that is based on sparse representation is used iteratively to reconstruct the image. This dictionary is created using the Gabor function and local ridge orientations. The enhancement algorithm proposed by (Yoon et al., 2011) is based on a multiscale patch-based sparse representation and total variation model. Firstly, the latent fingerprint is decomposed into texture and cartoon components using a total variation model. The cartoon component is removed as structural noise because it contains most of the patterns that are not required. In the next stage, weak latent fingerprints are enhanced, with the proposed multiscale patch-based sparse representation method, which is present in texture components. Using the Gabor elementary functions, dictionaries are constructed to capture ridge structures. Good-quality latent images are reconstructed using multiscale patch-based sparse representation. The advantage of using this algorithm is that along with the removal of overlapping noise, it also helps to enhance and restore the distorted ridge structures. The algorithm proposed by the author is based on prior knowledge of latent fingerprints. A dictionary is created using good-quality reference patches. Loopy belief propagation is used for orientation field estimation. This prior knowledge helps us to reconstruct our latent fingerprint.

A robust orientation field estimation algorithm is proposed in which an image is divided into multiple image blocks using a short-time Fourier transform. Further in this approach, a set of hypothesized orientation fields are created using randomized Ransac (Chaidee et al., 2018). The author has proposed an algorithm that is used in the pre-enhancement phase to obtain better results (Cao et al., 2014). In this approach, a dictionary is created using spectral responses of the Gabor filter. This

dictionary helps improve the high curved ridges. Most of the present algorithms are not able to achieve and preserve this information. The approach proposed in this paper is dictionary based. The paper aims to achieve "lights-out" latent identification systems. Background noise is removed using the total variation (TV) decomposition model (Yoon et al., 2010). Ridges are reconstructed using the dictionary which is created using good-quality patches. The author in this approach proposed a novel orientation estimation algorithm for enhancement of latent fingerprints. A commercial fingerprint SDK is used in this approach for estimation purposes. An adaptive directional total variation (ADTV) model is proposed by the author in this approach of enhancement of latent fingerprints (Zhang et al., 2013). In this approach, the latent images are divided into two layers (i.e. cartoon and texture). The latent print is present in the texture component whereas unwanted noise is present in the cartoon layer. This decomposition helps in the enhancement and segment of the latent print.

Latent fingerprint reconstruction approaches

Image reconstruction is a fundamental step in improving the quality of an image. Generally, the evidence recovered from crime scenes is of poor quality, blured, incomplete, etc.. So to extract minutiae efficiently from the evidence, it becomes essential to first reconstruct the image. Various reconstruction techniques are discussed in this section along with their comparison in Table 3.

Wong and Lai in 2020 proposed a CCN-based method for reconstruction and enhancement of latent fingerprints. The recovery of ridge structures is done by learning from corruption and noises encountered at various stages in fingerprint processing (Wong & Lai, 2020). The CNN model consists of two streams that help in reconstruction. The enhancement of an image is improved using orientation fields. A generative adversarial network (GAN)–based data augmentation scheme to improve reconstruction is proposed by (Lee et al., 2020). In the given approach, the clean fingerprints are converted to their corresponding latent one which is augmented with an unpaired large-scale clean dataset for the reconstruction purpose. Further, a novel algorithm is proposed by (Xu et al., 2020) which uses machine learning and skeleton image features for the reconstruction of the image. Also, a new method is proposed by the author for generating more natural images using the Pix2Pix model. The work proposed by (Joshi et al., 2019b) is based on generative convolutional networks. This approach helps in predicting the gaps, holes, and missing parts of the ridge structures, as well as helps in filtering the noise from minutiae. The testing of the proposed method is done

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using various standard methods of feature extraction like MINDTCT followed by MCC and BOZORTH3.

A conditional generative adversarial network (cGAN) approach is given by Liu et al. which helps in the direct reconstruction of latent fingerprints (Dabouei et al., 2018). The cGAN approach has been modified by the author so that it can be used for the task of reconstruction. In order to ensure that the orientation and frequency information is used in the generation process, three additional ridge maps are created. This prevents the model from generating false minutiae as well as avert the model from filling missing areas that are large in size. To protect ID information in the course of the reconstruction process, a perpetual ID preservation approach is used. An artificially generated latent fingerprint database is used for guessing missing information. An algorithm based on dictionary-based learning and sparse coding for the latent fingerprint is proposed by (Li et al., 2018). Also, an algorithm has been proposed for the estimation of orientation fields. In the first step using the total variation model, the texture image is acquired by decomposing the latent fingerprint image. It has been observed that a great reduction in the structural noise is observed from a texture image. To estimate local ridge orientation for texture images, a multiscale sparse coding method is presented. In order to create a dictionary, good-quality fingerprint patches of multiscale are used, to get prior information. Also, sparse coding is repeatedly applied with varying patch sizes to amend the distorted and corrupted orientation fields. The advantage of using this approach is that it helps to repair corrupted orientations as well as reduce noise. This algorithm helps to preserve the details of singular regions. Further, a convolutional neural network (ConvNet)–based approach is proposed by (Cao & Jain, 2015) for estimating latent orientation field. In order to achieve it, ConvNets are trained using 128 representative orientation patterns.

The authors Zhou et al. present an analytical framework for latent fingerprints (Kaushal et al., 2016). The reconstruction approach adopted by the paper is based on a combination of two approaches (i.e. exemplar inpainting and partial differential equation). These two approaches are used for the reconstruction of distorted images. The binarization approach is used for the matching of fingerprints. In this approach, the author (Zhou et al., 2016) proposes triplets of minutiae to improve the performance of the algorithm. Author claims of improvement in the performance after the addition of new triplet features. Further performance has been improved by combining global features and triplet features. The paper (http://www.ijirset.com/upload/2017/may/269_Criminal. pdf, 2019) proposes an algorithm based on prior knowledge. In this approach, two dictionaries are created. One

is based on a continuous phase patch and another is prepared using an orientation patch. For correction of orientation field, the latter of the two dictionaries is used and for the reconstruction of ridge pattern, the former is used. A model-based partial fingerprint reconstruction algorithm is proposed by the author (Zhou et al., 2013). The objective of the approach is to complete ridge information. This approach helps to reduce the index list before matching.

A fingerprint orientation model based on 2D Fourier expansions (FOMFE) is proposed in this paper (Wang et al., 2007) which is independent of prior knowledge. The biggest advantage of the proposed approach is its low computational cost and also that it can handle a very large database. This approach is very helpful in applications such as fingerprint indexing.

Latent fingerprint matching approaches

Latent fingerprint matching is the final step in the processing of our fingerprint image. At this stage, the matching between the original and the ground truth image is done using various approaches as mentioned in Table 4.

Malemath et al. proposed a latent minutiae similarity (LMS) algorithm and clustered latent minutiae pattern (CLMP) algorithm (Deshpande et al., 2020). The former algorithm is used for solving the geometrical constraints between the pairs of nearest points around a minutia, whereas the latter one is based on the arrangement of minutia and its patterns.

The matching technique proposed by (Manickam et al., 2019b) uses Scale-Invariant Feature Transformation (SIFT) for matching and enhancement purposes. The approach comprises two stages—in the first stage, contrast enhancement is performed using type 2 fuzzy sets. In the next step, the SIFT features are extracted for further matching purposes. A deep learning-based approach is put forward by Zheng et al. for matching latent with rolled fingerprints (Ezeobiejesi & Bhanu, 2018). This approach is based on the resemblance of patches and the minutiae which are present on the consistent patches. For enhancing the learning, the deep learning network is used. The distance metric learned with a convolution neural network is used for calculating the similarity score. With the fusion of minutiae and patch similarity score, the matching score has been calculated. The Minutia Spherical Coordinate Code (MSCC)–based matching algorithm is proposed by (Lin & Kumar, 2018). This algorithm is the improvement of the Minutia Cylinder Code (MCC). Every minutia is represented by a binary vector using 288 bits. The MCC algorithm was represented using 448 or 1792 bits. The advantage of using this approach is its compact representation. A greedy

Table 3 Available latent fingerprinting reconstruction approaches

Ref.	Year	Description	Database	Limitation	Results
(Wong & Lai, 2020)	2020	CNN-based fingerprint reconstruction from the corrupted image	MOLF, FVC2002 DB1 and FVC2004 DB1	Unsuccessful in extremely low contrast and noisy images	Accuracy = 84.10%
(Lee et al., 2020)	2020	Deep Neural Network–based approach for recovery of latent fingerprints	NIST Special Database 4		At reconstruction weight = 150 FMR0.01% = 66% FMR0.1% = 93% FMR 1% = 100%
(Xu et al., 2020)	2020	Generative adversarial network (GAN) based data augmentation scheme to improve the reconstruction	NIST SD14 and MOLF DB 1,2,3 were used at the augmentation stage.		Matching accuracy (%) NIST SD27: Rank25 = 82.17% IIITD: Rank25 = 95.12% MOLF DB4: Rank25 = 45.88%
(Joshi et al., 2019b)	2019	Reconstruction is done using generative convolutional networks.	Gallery datasets like Lumidigm, Secugen, Crossmatch are used	False minutiae generation is a challenge	Rank 25 Lumidigm = 16.14% Secugen = 13.27% Crossmatch = 12.66%
(Dabouei et al., 2018)	2018	ID preserving generative adversarial network is used for partial latent fingerprint reconstruction	IIIT-Delhi latent fingerprint database and IIIT-Delhi MOLF database	Minutiae are not directly extracted from the latent input fingerprints.	Rank 10 accuracy = 88.02% (IIIT-Delhi latent fingerprint database) rank 50 accuracy = 70.89% IIIT-Delhi MOLF matching
(Li et al., 2018)	2018	Multiscale dictionaries with texture components are used.	NIST SD27	Computation for false minutiae removal and repetitive minutiae removal is very high.	The average orientation estimation error (in degrees) is 16.38
(Kaushal et al., 2016)	2016	An analytical framework is proposed	NIST SD-27	Different filter used for different images	False acceptance rate = 27%
(Zhou et al., 2016)	2016	Partial fingerprint indexing–based algorithm is proposed	FVC 2000 DB2a, FVC2002 DB1a and NIST SD14	Indexing is difficult to apply on a very large database	Average penetration rate on FVC2002 DB1a when hit rate is 100% = 3.51%
(Cao & Jain, 2015)	2015	ConvNet–based approach for latent orientation field estimation	NIST SD27	When latent overlaps with strong background noise, global orientation patch dictionary and ridge structure dictionary approaches do not work well	The average root-mean-square deviation (RMSD) is 13.51 as compared with other algorithms.
(http://www.ijirset.com/upload/2017/may/269_Criminal.pdf, 2019)	2015	Dictionary-based approach	FVC2002, NIST SD4,	Dictionary lookup is a slow process	Improvement in reconstructed image (visual inspection)
(Zhou et al., 2013)	2013	Reconstruction of partial fingerprints	Self-created images	Tested on few images only that are of good quality	Improvement in reconstructed image (visual inspection)
(Wang et al., 2007)	2007	FOMFE-based approach is proposed	FVC2002 Db1a database and NIST Special Database 14 (SDB14)		At feature vector length = 15 Penetration rate = 0.21

Table 4 Available latent fingerprint matching approaches

Ref.	Year	Description	Database	Limitation	Results
(Deshpande et al., 2020)	2020	A clustered minutiae-based scale and rotation invariant fingerprint matching method is proposed	FVC2004 and NIST SD27 criminal fingerprint databases	Matching efficiency is poor in cases where sufficient clustered minutiae set is obtained.	97.5% and 100% of Rank-1 identification accuracy respectively on plain FVC2004 dataset. Rank-1 identification accuracy of 88.8% and 93.80% respectively on NIST database (LMS, CLMP algorithms)
(Manickam et al., 2019b)	2019	Matching using SIFT feature	FVC2004 and IIIT-latent fingerprint	Database size is small. The feature set used is small.	Linear index of fuzziness IIIT-latent fingerprint = 0.2702 FVC2004 database 1 = 0.1912 FVC2004 database 2 = 0.2008
(Ezeobiejesi & Bhanu, 2018)	2018	Matching is patch-based using a deep learning approach.	NIST SD27	The approach does not work well with mixed image resolutions	Rank-20 identification rate = 93.65%
(Lin & Kumar, 2018)	2018	Minutia Spherical Coordinate Code is used for matching	AFIS data and NIST special data27	There are many redundancies in MCC and MSCC's feature	Rank-1 recognition rate = 49.2%
(Ezhilmaran & Adhiyaman, 2017)	2017	Descriptor-based Hough transform used for matching	(NIST SD27 and WVU latent databases	Latent matching is slow	Rank-1 accuracy = 53.5%
(Zhou et al., 2017)	2017	The fusion of various extended features to improve performance	NIST SD4, SD14, and SD27 databases	The separation of feature extraction and matching in automatic systems leads to some information loss.	Rank-1 identification rate of 74% was achieved
(Medina-Pérez et al., 2016)	2016	Local and global matching	NIST SD27(A)	Approaches used for level 2 and level 3 matching are different which decreases accuracy	Rank-1 identification accuracy of 74%
(Zheng et al., 2015)	2015	CovNet and Dictionary-based approach	NIST SD27 and WVU latent databases	Recognition performance can be improved. Speed of feature extraction and comparison can be raised	Superior performance of texture (virtual minutiae) template on bad and ugly images (i.e. 47.1%; good-quality image is 83%)
(Cao et al., 2014)	2014	Extended features used for performance enhancement	NIST SD27	Differences in the approach used by latent experts and automatic matches. Prone to false minutiae and distortions. Information loss due to separation of automatic matching and feature extraction.	Identification rate Good images = 90% Bad images = 85% Ugly images = 71%
(Lan et al., 2019).	2014	A new feature Distinctive Ridge Point (DRP) is proposed	NIST14 and NIST4	High ridge point dependence with minutiae.	Rank-1 accuracy = 70.9%
(Jain & Feng, 2010b)	2014	Algorithm based on directional information	FVC2004 DB1, Tsinghua Distorted Fingerprint database, NIST SD27 database and NIST SD30 database.	Do not consider the rotation and translation of the whole image	Identification rate using Correlation score = 80% Verifinger score = 82%
(Feng, 2012)	2012	Descriptor-based Hough transform algorithm	NIST SD27 and WVU latent database	Do not work well with overlapping fingerprints	Identification rate = 67%

Table 4 (continued)

Ref.	Year	Description	Database	Limitation	Results
(https://www.nist.gov/itl/iad/image-group/nist-special-database-2727a, 2019)	2012	Two minutiae-based descriptors are proposed	FingerPass and Multi-Sensor Optical and Latent Fingerprint	For different sensor technology, performance is not good. Poor performance when fingerprints were distorted	False matching rate = 1.166% Equal error rate = 0.41%
(Jain & Feng, 2010b).	2010	Fusion of minutiae	NIST SD27	Orientation field reconstruction to be improved	Identification rate = 65% (manually marked minutiae)
(Jain & Cao, 2015)	2009	Fusion of plain and rolled finger-prints	ELFT-EFS Public Challenge Dataset	Does not appear to be a common practice in law enforcement	Rank-1 identification rate of 83.0%
(Feng et al., 2009)	2009	Fusion of plain and rolled finger-prints	NIST SD27	The distortion between rolled and plain fingerprints is not taken into account. Manual extraction of level 1 and level 2 features	Rank-1 identification rate = 83.0%
(Feng & Jain, 2008)	2008	Filtering-based approach	NIST SD27	Singular point detection is not accurate. More filtering approaches can be used to improve performance. Background database is small	Rank-1 matching accuracy = 73.3%

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alignment approach is used to restore minutiae pairs that are lost at the original stage.

A robust descriptor–based alignment algorithm is proposed by Paulino et al. which is based on the Hough transform (Ezhilmaran & Adhiyaman, 2017). Minutiae along with orientation fields are used by the author to draw a similarity between the fingerprints. Manual marking of the minutiae is performed in this algorithm due to which it is easy for application purposes. The orientation fields of latent fingerprints are reconstructed from minutiae. A novel fingerprint matching system is proposed by (Zhou et al., 2017). In the proposed approach the latent fingerprint images found at crime scenes are matched to the rolled fingerprint database of law enforcement agencies. Along with minutiae, other features like ridge wavelength map, skeleton, singularity, etc. are used to enhance the performance.

Further, a novel approach is proposed by Cao et al. in which extended features are used for improving the matching performance (Medina-Pérez et al., 2016). An automated latent fingerprint recognition system is proposed by (Zheng et al., 2015). Convolutional neural networks (ConvNets) are used for enhancing the matching performance. Fusion of rank, score and feature–based approach is proposed by (Jain & Cao, 2015) to boost the performance of the proposed approach. The approach proposed by the author (Cao et al., 2014) uses extended features like ridge quality map, ridge wavelength map, etc. along with minutiae. This system is created for matching crime scene fingerprints with rolled fingerprints. To gain insights into how performance changes with the addition of extended features, these features are added incrementally to the system. The conclusion drawn by the author is that among extended features, the most useful are singularity, ridge quality map, and ridge flow map. In this paper, a descriptor-based Hough transform algorithm is proposed (Feng, 2012). In this method, the comparison between latent prints is done after aligning the fingerprints using the proposed algorithm. One of the disadvantages of this approach is the requirement of manual markup. The approach proposed by the author is exclusively for matching partial fingerprints. In this paper, a new fingerprint feature is proposed by the author (i.e. Distinctive Ridge Point (DRP)) (Lan et al., 2019). This feature along with existing features are used for matching performance improvement. A novel algorithm is proposed in this paper (Jain & Feng, 2010b) for latent fingerprint matching. The core of the proposed algorithm is directional information. Estimation of distortion is done by merging image fields with the traditional model. This approach leads to a simple model with effective use of directional information.

The matching approach proposed in this paper (Jain & Feng, 2010b) merges manually marked minutiae with minutiae that are extracted automatically. The reconstruction is done using singular points and manually marked minutiae. Ridge frequency is used for the enhancement of latent prints. The main objective of the proposed approach is to enhance the speed of the matching system. Three filtering stages are proposed in this algorithm (Feng & Jain, 2008). Singular points, pattern type and orientation fields are utilized in this filtering system. The approach proposed in this paper fuses rank, score and features (Feng et al., 2009) to enhance the performance of the system as followed in many existing fusion-based approaches followed in image and video forensics (Kaur & Gupta, 2019). The main aim of fusion is to retrieve a high-quality fingerprint. Along with minutiae, the author proposes to use some extended features like quality maps, etc. to improve the performance of the system. An automatic fingerprint verification method is proposed by *Feng et al.*. Two minutiae-based descriptors are proposed by the author that are histograms of gradients and binary gradients. The false minutiae are handled using an orientation descriptor. Fusion of scores obtained from all the descriptors are done to achieve the desired performance.

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Databases available

The fingerprint database is generally classified into three categories – rolled, plain and latent fingerprint database (Singla et al., 2020). For forensic applications, mainly rolled and latent fingerprints are used, whereas for commercial applications, plain fingerprints are used. To capture latent fingerprints, range of methods like chemical, powder or simply photography is done. Plain fingerprints are prints of our fingers taken using sensors that are mostly used as ground truth. Rolled prints, on the other hand, are obtained by simply rolling fingers from one side to another. Various databases available related to latent fingerprints are listed in Table 5 as follows— NIST27 (https://www.nist.gov/itl/iad/image-group/nist-special-database-2727a, 2019), WVU latent databases (https://databases.lib.wvu.edu/, 2019), FVC2004 databases (http://bias.csr.unibo.it/fvc2004/download.asp, 2019), IIIT latent fingerprint database (http://www.iab-rubric.org/resources/molf.html, 2019), IIITD Multi-surface Latent Fingerprint database (IIITD-MSLFD) (http://www.iab-rubric.org/resources/molf.html, 2019), IIIT Simultaneous Latent Fingerprint (SLF) database (http://www.iab-rubric.org/resources.html, 2019), Multisensor Optical and Latent Fingerprint database (Sankaran et al., 2015), Tsinghua Latent Overlapped Fingerprint database (http://ivg.au.tsinghua.edu.cn/dataset/TLOFD.php,

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2019) and ELFT-EFS Public Challenge database (https://www.nist.gov/itl/iad/image-group/nist-evaluation-latent-fingerprint-technologies-extended-feature-sets-elft-efs, 2019).

Research gaps and challenges
To improve the authentication results and reliability of fingerprint recognition, we need a lot of improvement at various stages like enhancement, reconstruction, and matching. Some of the major challenges encountered are as follows.

- Even today, the marking of fingerprint features is done by an expert which opens a new sphere for improvement (i.e. automation of fingerprint marking) (Jhansirani & Vasanth, 2019).
- The fingerprints recovered from the crime scenes are generally of very poor quality (background noise, partial prints, etc.) which requires a lot of preprocessing to get desired results (Feng et al., 2012).
- Another major challenge is concerning the surface from which the fingerprints are uplifted. Different

surfaces require different methods based on their texture, colour, porous/nonporous surface, etc.
- Fingermark age determination is among the recent challenges have attracted many researchers as its reliable estimation is a difficult task. Factors like environmental conditions, substrate properties, donor features, etc. influence the composition and components of the fingerprint which hinders its effective determination (Chen et al., 2021).

Conclusions
To enhance the robustness and efficiency of various security applications, there is a dire need for a novel approach for latent fingerprint recognition. Various image processing techniques can be applied at the enhancement and reconstruction phase to improve robustness and efficiency at the matching stage. Some of the recent methods are trying to utilize deep learning techniques like GAN's to enhance the quality of fingerprint features. In addition, researchers are also trying to improve the results of latent fingerprint matching using various fusion

Table 5 Available latent fingerprint datasets

Dataset	Description
NISD27 (https://www.nist.gov/itl/iad/image-group/nist-special-database-2727a, 2019)	258 samples of grayscale fingerprint images. Includes both 500 pixels per inch (PPI) and 1000 PPI samples. Manually annotated features are also available for sample images. Can be used for rolled fingerprint matching.
WVU latent databases (https://databases.lib.wvu.edu/, 2019)	Collection of 449 images. Contains exemplars of 500 and 1000 PPI marked features that are available. The database can be used for latent to rolled fingerprint matching.
FVC2004 databases (http://bias.csr.unibo.it/fvc2004/download.asp, 2019)	Collection of 1440 impressions. The database is constructed using 120 fingers with 12 impressions per finger. DB1 and DB2 were collected using optical sensors DB3 collected using thermal sweeping sensor DB4 collected using synthetic fingerprint generation sensors
IIIT latent fingerprint database (http://www.iab-rubric.org/resources/molf.html, 2019)	The database is a collection of 15 subjects (for each subject, there are 10 fingerprints). Grayscale images are scanned using a 500-PPI scanner. The size of each image is 4752 × 3168 pixels
IIIT Simultaneous Latent Fingerprint (SLF) database (http://www.iab-rubric.org/resources.html, 2019)	The database contains a simultaneous fingerprint of 15 subjects. Fingerprint images are obtained using the black powder technique.
IIITD Multi-surface Latent Fingerprint database (IIITD-MSLFD) (http://www.iab-rubric.org/resources.html, 2019)	Consists of 551 latent fingerprints samples. Includes 500 DPI samples. Samples of 51 subjects are captured Eight different surfaces are used for capturing fingerprints (e.g. Ceramic mug, plate, steel glass, book cover, etc.)
IIITD Multisensor Optical and Latent Fingerprint database (Sankaran et al., 2015)	The database contains 19,200 fingerprint samples. One-hundred subjects were used for the construction of the database. Methods like CrossMatch L-Scan Patrol, Secugen Hamster, etc. are used
Tsinghua Latent Overlapped Fingerprint database (http://ivg.au.tsinghua.edu.cn/dataset/TLOFD.php, 2019)	Consists of 12 plain fingerprints and 100 latent fingerprints which are overlapped Optical fingerprint scanners are used to capture the dataset Includes 500 PPI samples
ELFT-EFS Public Challenge database(https://www.nist.gov/itl/iad/image-group/nist-evaluation-latent-fingerprint-technologies-extended-feature-sets-elft-efs, 2019)	The database contains 1100 images. Includes both 500 pixels per inch (PPI) and 1000 PPI samples. level 1, level 2, as well as level 3 features, can be extracted using this database

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techniques. This paper presents various aspects of latent fingerprinting which can be used to improve recognition and authentication results. Research in this domain may help us fortify ourselves from emerging digital era threats which is imperative to maintain the security and integrity of any nation.

Abbreviations
DRP: Distinctive ridge point; DFO: 1,8 Diazafluoren-9-one; ConvNets: Convolutional neural networks; MSCC: Minutia spherical coordinate code; MCC: Minutia cylinder code; LMS: Minutiae similarity; CLMP: Clustered latent minutiae pattern algorithm; SIFT: Scale-invariant feature transformation; GAN: Generative adversarial network; EDTV: Edge directional total variation model; cGANs: Conditional generative adversarial networks; IIITD-MSLFD: IIITD multi-surface latent fingerprint database; IIIT SLF: IIIT simultaneous latent fingerprint (SLF) database; POT: Progressive offline training; IOT: Iterative online testing; IIITD-MOLF: IIITD multisensor optical and latent fingerprint database; TV model: Total variation model; LMS algorithm: Latent minutiae similarity; CLMP algorithm: Clustered latent minutiae pattern; NIST: National Institute of Standards and Technology.

Authors' contributions
This article was conceptualized and designed by RD, MdK and MvK. Relevant literature was searched by RD. RD drafted the manuscript which was further edited and reviewed by MdK and MvK. The authors read and approved the final manuscript.

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Not applicable

Declarations

Ethics approval and consent to participate
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Competing interests
The authors declare that they have no competing interests.

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