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RESEARCH ARTICLE

Construction of Rolled Digital for Newborns Using Image Registration

Construção de Digitais Roladas de Recém-nascidos Utilizando Registro de Imagem

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Abstract: This work aimed to reconstruct rolled fingerprint images from multiple flat fingerprints using image registration and composition techniques. The methodology involved selecting high-quality frames through a quality network, the application of preprocessing with remapping, cropping the area of interest, and adjusting colors. In addition to image registration steps, like key point identification, feature matching, and image distortion. Results indicated that while classical image registration had limitations, the composition technique significantly increased the number of features extracted, enhancing fingerprint identification. It was demonstrated that the composition method effectively captures important fingerprint details, offering a potential improvement in newborn biometric identification.
Keywords: Fingerprint — Newborn — Image Registration — Composition

Resumo: Este trabalho teve como objetivo reconstruir imagens de impressões digitais roladas a partir de múltiplas impressões digitais planas, utilizando técnicas de registro e composição de imagens. A metodologia envolveu a seleção de quadros de alta qualidade por meio de uma rede de qualidade, a aplicação de pré-processamento com remapeamento, recorte da área de interesse e ajuste de cores. Além disso, foram realizadas etapas de registro de imagem, como identificação de pontos-chave, correspondência de características e correção de distorção. Os resultados indicaram que, embora o registro clássico de imagens apresentasse limitações, a técnica de composição aumentou significativamente o número de características extraídas, aprimorando a identificação por impressões digitais. Demonstrou-se que o método de composição captura de forma eficaz detalhes importantes das impressões digitais, oferecendo uma potencial melhoria na identificação biométrica neonatal.
Palavras-Chave: Impressões Digitais — Recém-nascidos — Registro de Imagem — Composição

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1. Introduction

Biometric recognition systems are essential for individual identification and security, with fingerprints being the primary method due to their uniqueness [1]. This technique authenticates individuals based on unique patterns called minutiae [1], allowing for precise and reliable identification [2]. However, capturing fingerprints can be challenging in certain scenarios, such as with newborns, due to their small size, reduced ridge depth, and lack of cooperation. Standard sensors, typically designed for adults with a resolution of 500 ppi, struggle to capture the fine details of newborn fingerprints [3]. While higher-resolution sensors exist, they tend to be more expensive.

Additionally, the verification (match) rates for adult fingerprints can reach 98.68%, while for newborns (up to six months of age), the match rate drops to 64.27% [4]. This significant disparity shows, it is necessary to find solutions that improve the match rate in babies. One way to improve this is by overcoming the inherent difficulties of capturing high-quality fingerprints images in newborns.

In adults, fingerprint capture is done using the rolled method, which covers the entire surface of the finger, resulting in well-formed minutiae and satisfactory identification. For newborns, a pressed method is used due to their behavior and fingerprint irregularities. However, this method captures fewer identifying characteristics and is further limited by the

[1] Specific and unique characteristics that allow the individual identification of a person from their fingerprints.

low resolution of the scanners [3]. The comparison highlights the importance of rolled fingerprints, as they provide more detailed information, suggesting that reconstructing rolled fingerprints from pressed ones could improve match rates in newborns.

Image registration methods match images from different angles and positions to obtain rolled fingerprints. SURF is an example of an algorithm that identifies relationships between objects in the same scene [5]. In systems capturing infant fingerprints, video recordings with multiple frames of the same fingerprint allow for the application of registration methods. This work uses image registration to construct a composite fingerprint from high-resolution frames to obtain the rolled fingerprint.

This work aims to develop an algorithm that identifies the best parts of a fingerprint from multiple images and performs image registration of them. By enhancing the quality of the resultant composite images, this approach aims to contribute to more accurate and reliable fingerprint matching for newborns.

2. Related Works

In literature, to understand and explain the state of the art, most research on image registration for fingerprint recognition focuses on adults. Additionally, the construction of rolled fingerprints mostly converges into mosaics, considering small-area sensors [6]. As a result, various impressions of the same finger on small-area sensors often share limited overlap. This area is crucial for enhancing fingerprint recognition performance [6].

The ICP (Iterative Closest Point) algorithm, used for aligning three-dimensional geometric models, iteratively searches for the closest point sets and calculates the transformation using covariance matrices until the error change is below a threshold T [7]. Its purpose is to find the transformation matrix that defines the spatial relationship between two fingerprints [8]. Both ICP and image mosaicking improved fingerprint verification accuracy, though image size became a critical factor in the decision [7].

The authors in Ref. [6] presented a method for constructing rolled fingerprints using image registration based on a MRF (Markov Random Field) model. This approach establishes dense correspondences between images, allowing extensive distortions to create accurate rolled fingerprints while preserving geometric properties compared to ink-based prints. Comparative experiments demonstrated the method's efficiency.

In another study [9], the IFViT (Interpretable Fixed-length Representation for Fingerprint Matching via Vision Transformer) approach is introduced. It consists of two stages: a dense registration module with a Siamese network based on ViT for capturing long-range dependencies and providing interpretable matches, followed by extracting and matching fixed-length representations. Extensive experiments show that IFViT improves both performance and interpretability in fingerprint matching.

Another paper presents a non-minutia-based method for latent fingerprint registration that uses dense patch alignment and uniformly sampled points as key points instead of minutiae [10]. It generates similarity scores through pairwise comparisons and uses spectral clustering for consistent correspondences. Experiments on the NIST27 and MOLF databases show state-of-the-art performance, especially in challenging scenarios [10].

Compared to others, our study's distinguishing factor lies in its focus on infant fingerprints, a challenge that has been relatively unexplored in biometrics. Additionally, a classic image registration method was employed to simplify the process. This combination allows for a more practical and accessible approach to handling the unique characteristics of infant fingerprints.

3. Background

3.1 Recognition using fingerprints

The fundamental task in identity management is linking individuals with their data [11]. Biometric recognition through fingerprints uniquely identifies a person using the ridges and valleys on their fingertips, including distinctive minutiae [12]. Fingerprints are segmented into foreground (the fingertip contact area) and background (the noisy edges) to improve matching accuracy [13]. A fingerprint segmentation algorithm enhances the identification process's precision [13].

Minutiae are classified based on three parameters: position, orientation, and type. Position and orientation refer to the minutia's location and direction, while type classifies minutiae as bifurcation, island, lake, independent ridge, and others [14].

3.2 Types of fingerprint capture

A fingerprint acquisition can be done in two main ways: rolled or flat, depending on the individual's needs and conditions [15].

A rolled fingerprint involves rolling the finger over a surface to capture the entire area of interest, including ridges and minutiae, and is commonly used in criminal identification [11]. In contrast, a flat fingerprint is obtained by pressing the finger against a surface, capturing a smaller area, and is often used in authentication systems [16].

3.3 Image registration

Image registration is a key process in computer vision that overlays multiple images of a scene into a unified coordinate system. These images can be captured at different times, by various sensors, or from different perspectives [17]. The process consists of three stages: keypoint detection and feature description, matching these features, and image warping.

3.3.1 Keypoint detection and Feature description

A keypoint marks significant aspects of an image, such as corners and edges, and is paired with a descriptor robust to transformations like changes in position, scale, and illumination [17]. Feature description defines decision points at each keypoint using techniques resistant to scale, noise, rotation, and illumination, ensuring accurate matching [18]. Various algorithms support keypoint detection and feature description.

- SIFT (Scale-Invariant Feature Transform) is a keypoint detection algorithm used to identify similar objects across multiple images. The process involves four phases: constructing the scale space, detecting extrema, localizing keypoints, and assigning orientations [19]. Although slower than some other algorithms, SIFT is effective for object detection in high-resolution images [19].

- ORB (Oriented FAST and Rotated BRIEF) is a high-speed binary descriptor that combines the FAST keypoint detector with the BRIEF descriptor. While FAST efficiently detects corner keypoints, it lacks an orientation operator, unlike SIFT and SURF [20]. Conversely, BRIEF shares many characteristics with SIFT, including resilience to lighting variation, blur, and perspective distortion.

- KAZE is a 2D feature detection and description algorithm that uses nonlinear scale spaces, unlike methods using Gaussian blur [21]. It employs linear diffusion filtering for adaptive blurring, improving localization accuracy and preserving object contours [21]. Although KAZE has a moderate computational cost, its accelerated version, AKAZE [22], enhances performance by using the determinant of the Hessian matrix and a filtering structure called FED [23].

3.3.2 Feature matching

BFMatcher (Brute-Force Matcher) is an algorithm that links identified pairs of keypoints in two images, determining correspondences based on the smallest distance between their descriptors. It assigns each keypoint to its top k best matches by exploring all possibilities to find the best correspondences [24].

3.3.3 Image warping

Image warping involves deforming an original image into a target image based on corresponding points, correcting geometric distortions from imperfect imaging systems [25] [26]. This distortion is represented by a homography, defined by a 3x3 matrix with eight parameters, with RANSAC (Random Sample Consensus) commonly used for this process.

4. Methods

This work aims to improve the matching of newborn fingerprints through image registration, seeking to construct rolled fingerprints from flat ones captured across multiple frames of the same finger. The steps include video collection in hospitals, selection of the best frames, keypoint extraction, feature matching, and data comparison for result analysis. Figure 1 provides an overview of these steps.

This work is divided into four experiments: image registration without and with preprocessing, with preprocessing and segmentation, and image composition. The first three experiments involve video collection, frame separation, keypoint extraction, and feature matching. In the composition experiment, only collection and separation are performed, without using the image registration technique.

4.1 Experiment I: Image registration without preprocessing

In this initial experiment, data is collected using a high-resolution scanner that captures various parts of the same finger from a newborn male 24 hours after birth. The video used in the experiments is 1 minute and 2 seconds long, with image dimensions of 4160x3104 pixels.

After data collection, the next step was to obtain the video content and separate it into 628 frames. This separation is carried out using Python[2], leveraging functions such as VideoCapture from OpenCV[3] and arrays from NumPy, which allowed for easy and quick manipulation and visualization of any frame. These tools enabled the manual selection of some frames for image registration.

In this stage, image registration began, regardless of position. The key points in the images are identified and extracted using AKAZE because it has a more optimized version that is available in the OpenCV library. Initially, the algorithm received the frame images and converted them to grayscale since it operates on monochromatic images to simplify processing and improve feature detection accuracy. The algorithm's settings included adjusting the threshold to balance sensitivity, avoiding noise inclusion, and configuring diffusivity to control image smoothness, enhancing accuracy in noisy conditions. After this, AKAZE used a descriptor to detect and compute common points through descriptive vectors representing local image features. Finally, the algorithm marked the points in both images.

After the extraction stage, the feature-matching stage began. The brute-force matcher with the k-nearest neighbors (KNN) classifier is initially used. The brute-force matcher is configured to directly compare all key point descriptors of one image with all descriptors of another figure, finding the best matches based on minimum distance—an effective approach due to its simplicity and precision. KNN was used with $k = 2$, meaning that the two closest descriptors are identified for each key point descriptor. This setting is chosen to apply the distance ratio technique, which helps filter ambiguous matches and improves matching robustness by considering the ratio between the distances of the two-nearest neighbors. The distance ratio was used to validate the matches, where only matches with a distance ratio less than 0.75 are considered valid because it helps ensure that only strong and clear matches are

[2] ⟨https://www.python.org/⟩
[3] ⟨https://opencv.org/⟩

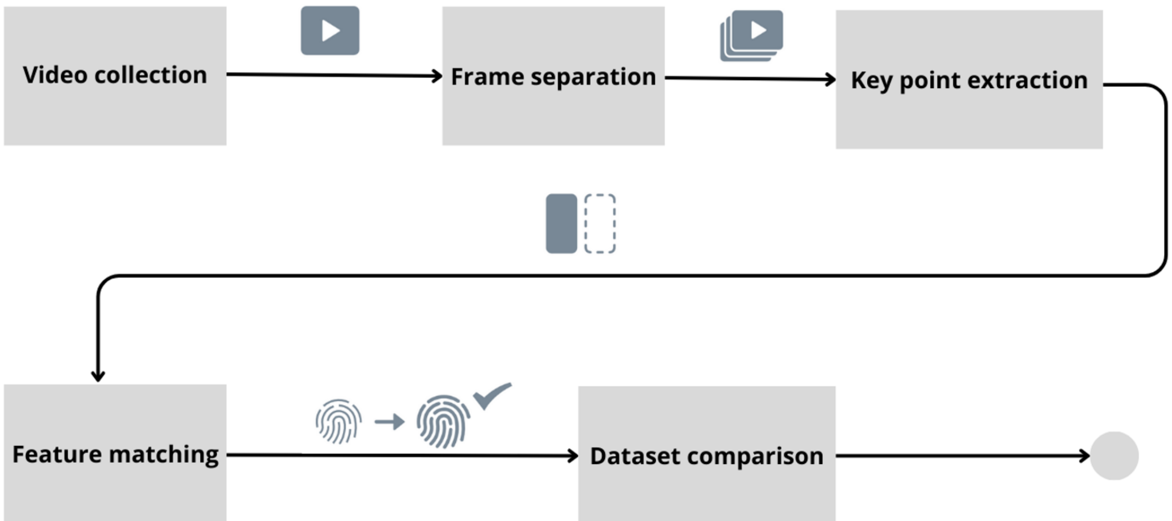

Figure 1. Proposed research protocol

accepted, eliminating false positives and increasing the overall process precision.

The corresponding points obtained served as input for the transformation matrix, which is calculated using the RANSAC method to ensure robustness against outliers. The transformation matrix was then used to align the images, correct distortions, and allow for image composition.

4.2 Experiment II: Image registration with preprocessing

In this second experiment, the same video collection step is reused. However, some changes are implemented in the frame separation step. Using Python and functions, such as OpenCV VideoCapture and NumPy array, the frames are separated once again. Next, the frames with the best quality were selected using the neural network with proprietary license, provided by [14] which assigns values between 0 (lower quality) and 1 (higher quality) to the images.

It is important to note that before the quality assessment, the frame undergoes a cropping procedure between the separation and obtaining the score. Then, the frame goes through a coordinate remapping performed using the cv2.remap function from the OpenCV library, which applies a geometric transformation to the pixels of the image. The function uses two maps (map1 and map2) to define how the pixels of the original frame should be repositioned in the remapped image. These maps specify the new coordinates for each pixel, allowing for precise adjustments as needed. The remapping ensures that the frame has the correct configuration for subsequent processing by the network.

After assigning scores, it was necessary to identify when the finger was in contact with the sensor (flat fingerprint) and when the finger was removed. Some tests using derivative methods and filters yielded unsatisfactory results. Finally, a simple analysis method was used, which consisted of checking for a considerable cluster of white pixels in the frame and normalizing the values. This cluster indicates that the finger is in contact with the scanner sensor; otherwise, the finger is not in contact.

With the pixel color analysis and application of a low-pass filter, it was possible to smooth the data, reduce the influence of rapid variations, and maintain slower changes. Specifically, the method transforms the list into a binary list, mapping values above a threshold to 1 and values below to 0. A sliding window is then used to calculate the average of these binary values, resulting in a smooth curve with values between 0 and 1. This method was useful for identifying the moments when the finger was in contact with the sensor throughout the video, which initially had a noisy and highly variable signal. When the fingerprint is visible, *i.e.*, in contact with the sensor, the red line remains at a quality level between 0.6 and 1.0. The score of 0.6 is the minimum quality threshold here because it was identified as the point where the quality of matches is acceptable after normalization. This behavior coincides with the highest-scoring frames by the blue line in the same range between 0.6 and 1, indicating that these are the best-quality moments. When the red line drops to a score of 0, the finger is removed and only rises again when repositioned.

4.3 Experiment III: Image registration with preprocessing and segmentation

All previous steps, from collection to preprocessing, are repeated in the third experiment. Additionally, the segmentation technique is introduced, which is a fundamental process in analyzing and processing fingerprint images. This process involves separating or extracting regions of interest from the image, usually the area containing the ridge and valley patterns used for individual identification and verification. Moreover, it enhances image quality, as filtering and enhancement techniques can be applied to improve the sharpness and contrast of the ridges and valleys, facilitating the detection and extraction of minutiae [13].

For the tests, the SEGV4 segmenter is used to improve the quality of the fingerprints and the image registration. It is an algorithm used to process images by separating the relevant area of the fingerprint (where the ridges and valleys are) from other parts of the image, such as the background or noise. The main objective is to isolate the fingerprint itself. Some settings are necessary for the algorithm to perform the segmentation, such as selecting the appropriate resolution, which is set at 3000 ppi.

4.4 Experiment IV: Image composition

This additional composition stage, using masks and ROIs, was specifically conducted in the fourth experiment. Initially, using the OpenCV, NumPy, and Matplotlib libraries, the images are loaded and converted to grayscale, just as in the other experiments, to facilitate processing. Then, dilation and erosion operations are applied to create masks that highlight certain features of the images. These masks are combined according to a condition that ensures only pixels present in one or two of them, but not all three, are included in the resulting image. This procedure is done to emphasize distinct regions in at least one or two of the original images. Finally, the result is generated by summing the regions of the original images based on the masks. Pixels that do not meet the specified condition are set to zero. Additionally, the final result sets the pixels in all three original images to white.

In the final step of the experiment, image comparison was performed based on the number of features present in a single frame's fingerprint and the result obtained from summing the frames. A minutiae identification tool called MINDTCT is used due to its precision in results, free and open-source nature. This tool takes an image as input and saves a file containing information on X and Y positions, angles, and quality of the minutiae. The X and Y positions can vary according to the image's width and height, while the angle can vary between 0 and 180 degrees and the quality between 1 and 100. The experiment's main interest is determining the number of features represented by each line of the file. The detector processes the input image, converts it to grayscale, and then calculates the four mentioned variables.

5. Results and Discussion

5.1 Experiment I: Image registration without preprocessing

Experiments with keypoint detection were conducted using the AKAZE algorithm, an optimized and accelerated version of KAZE, as presented in Section 4. For this, a video with proprietary license provided by [14] and the Python OpenCV library is used. A frame from the video captures the moment when the finger makes contact with the scanner sensor, thereby capturing a region of the fingerprint. Without preprocessing, this image is manually selected and fed into the algorithm, identifying and highlighting several key points. These points can represent potential minutiae, which are crucial features for identification. However, an additional challenge is observed, as some points are marked outside the region of interest. Moreover, the fingerprint quality made it difficult to distinguish between ridges and valleys.

After detecting the key points in the fingerprint, two additional frames were randomly selected, each with a different position and angle. These new frames also had their key points identified and highlighted. Then, the images are submitted to the BFMatcher, which evaluates the shortest distance between the descriptors of each pair of key points and matches them by drawing lines between them. Many connected points are observed, including those outside the areas of interest of the fingerprints, which do not contribute to the process. Additionally, there were noticeable connecting lines that crossed, linking points in the upper areas of one fingerprint to points in the lower areas of another. This pattern was unexpected, as the goal was to find common points between the images.

Based on the previous steps of keypoint detection and feature matching, it was possible to construct a rolled fingerprint image from three flat fingerprint images. However, it is still necessary to preprocess the information in the scenes, preserving important parts such as potential minutiae regions and eliminating dispensable elements like noise. The result of overlaying the fingerprints has some parts of the image remain saturated, which can still hinder the recognition of features such as valleys and ridges. This saturation has been observed since the image capture and is attributed to both the size of the fingerprint and the pressure applied during contact with the sensor. Parts such as the center of the composition are less affected, but overall, the result is still considered unsatisfactory.

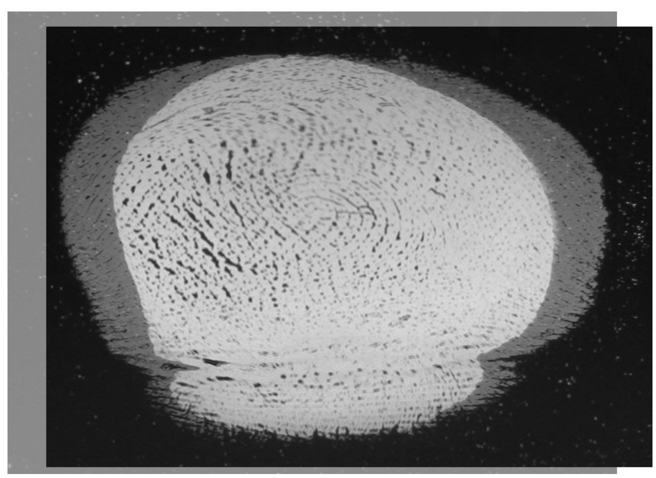

Figure 2. Rolled fingerprint constructed from three flat fingerprints

5.2 Experiment II: Image registration with preprocessing

Three frames were randomly chosen from each contact region to ensure a balanced distribution, facilitating image registration and avoiding an excessive number of frames that could complicate the process. Although the selection was random, it was based on the scores assigned by the quality network, which included cropping the area of interest, coordinate remapping, and color inversion.

Figure 3. Preprocessed frames

With the three frames selected from each contact region and the preprocessing completed, as illustrated in Figure 3, it was possible to move forward with the registration technique.

Finally, the image registration was performed using the classic method, with AKAZE detecting the key points and BFMatcher matching the features. The results are presented in the Figure 7 from the supplementary material [4], where it can be observed that the image registration yielded unsatisfactory results, which were demonstrated by the level of detail, as well as the corners and edges present in the images.

5.3 Experiment III: Image registration with preprocessing and segmentation

In this third experiment, the images resulting from the preprocessing were segmented. The SEGV4 segmenter was used, which takes the images and a resolution of 3000 ppi as input and provides the segmented images as output, as presented in Figure 8 from the supplementary material.

Again, as observed in Figure 9 from the supplementary material, even though the fingerprint characteristics (ridges and valleys) are more noticeable than the previous experiment, the image registration still failed. Despite overlapping the frames, the algorithm somehow merged them, but not satisfactorily. It is possible to see how the images are in different planes and positions.

5.4 Experiment IV: Image composition

In this fourth experiment, during the preprocessing phase, only remapping was performed, as illustrated in Figure 10 from the supplementary material. It is noticeable that the fingerprints are not cropped to the region of interest and that there are some streaks on the sides and a point, both due to the sensor's opening.

After remapping the images, segmentation and composition were carried out. However, shortly after completing this process, white spots were observed on the fingerprint that the segmenter had not previously identified. These areas were subjected to summation using masks created from the inverted grayscale images with a rectangular kernel of size (25, 25). This kernel size is chosen to enhance the regions of interest in the images, smooth the edges, and ensure the coalescence of relevant areas, thereby facilitating the analysis and combination of the resulting images. This attempt to sum the edges of the three images resulted in the emergence of some grooves and an increase in the contact area of the fingerprint, as can be seen in Figures 4.

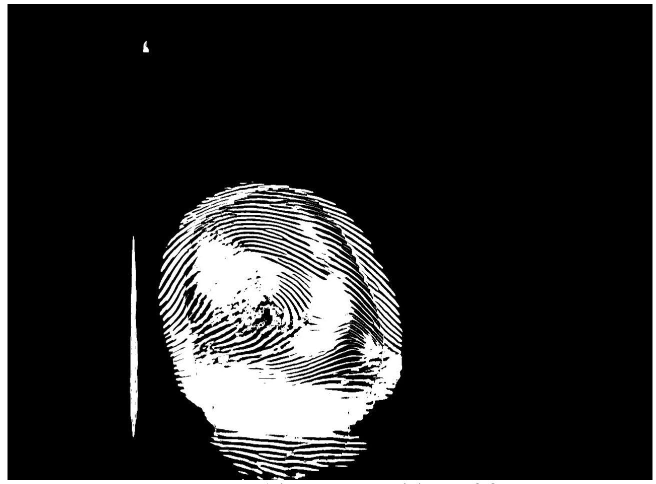

Figure 4. Resulting composition of frames

When analyzing these results, evaluating whether the technique provided any advantage or improvement became crucial. To perform this evaluation, MINDTCT assessed the number of features found in the individual frames, which results in a composed image. The features quantities are shown in Tables 1 and 2 .

The values presented in Table 1 correspond to three randomly selected frames from each contact, their resulting composition. The values in Table 2 follow the same pattern but use a different set of three frames.

Contact (flat)	1st Frame	2nd Frame	3rd Frame	Image composition
First	41	42	57	68
Second	39	64	38	122
Third	55	41	64	184

Table 1. Number of features extracted (first sample)

Contact (flat)	1st Frame	2nd Frame	3rd Frame	Image composition
First	34	47	42	103
Second	48	41	43	104
Third	47	64	44	166

Table 2. Number of features extracted (second sample)

After analyzing the tables, it was found that the results are promising: the composition of the three images resulted in an increase in the contact area of the fingerprint and the appearance of points that were not previously present. It is evident from the table that the number of extracted features increased with the composition of the images. This increase is significant as it demonstrates that the technique contributed

[4] https://github.com/WesleyCatuzzo/Papers-Supplementary-Material

to identifying important features of the fingerprint, which are crucial for matching and identification.

6. Conclusion

This paper presented that biometric identification, especially through fingerprints, offers high precision and security, making it especially important in the healthcare sector for newborns. Fingerprints possess unique characteristics, including minutiae, valleys, and ridges. Due to the size of newborn fingers and their behavior, fingerprints are typically captured as pressed images, although rolled captures provide more detail. The work aims to develop an algorithm that identifies the best parts of multiple pressed fingerprint images and uses image registration to create high-quality artificial rolled fingerprints.

Image registration is a technique that uses feature matching to compose an image from others in different positions, effectively supported by Python and its libraries. A significant challenge encountered was the lack of specific research on fingerprints using this technique, which is primarily applied in medical imaging, particularly with computed tomography. While positive results have been limited, they are considered promising. Most objectives were achieved, including frame extraction and selection, testing classic image registration techniques, and preparing compositions for neural network inputs. However, further testing with neural networks and additional improvement tests are still needed.

Neural networks play a promising role in enhancing image registration. These NN models complex patterns between images, enabling a more precise and robust composition. Techniques such as convolutional networks can be employed to align flat fingerprint images, automatically identifying feature correspondences. Additionally, NNs offer greater adaptability to variations in noise or deformation, common challenges encountered in this work, thereby improving the quality and reliability of the registration process. Residual Aligner Networks (RAN) can be an interesting option, as they have shown good results in abdominal and cranial images, spatially covariant image registration with text prompts.

Future efforts should focus on refining the project by exploring and testing new approaches. This includes comparing datasets using TAR/FAR and CMC, utilizing convolutional networks, including the models mentioned earlier, to analyze composite images, and assessing feature extraction validity. The goal is to enhance the techniques developed to achieve more robust and applicable results in the biometric identification of newborns.

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Author contributions

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