Implementation of HDR for Image Acquisition on a Finger Vein Scanner

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***Abstract*—A novel approach to finger vein image acquisition consists of capturing a multi-intensity sequence of images and merging them into a single HDR image to record a maximum amount of vein detail.**

Two HDR methods are proposed and evaluated: basic scalar weighting which maximizes entropy, and weighting with a moving mean filter which increases local contrast and background homogeneity. Both methods show promising vein recognition results: a higher level of vein detail was detected using both Maximum Curvature and Repeated Line Tracking than with a single LDR finger vein image. A small-scale vein matching experiment with 3 samples of 4 different fingers from the same person gave no false positives or negatives, and showed improvement compared to using single LDR image. Further testing with large datasets is required in order to draw broader conclusions about recognition performance.

***Index Terms*—biometrics, finger vein, exposure fusion, NIR imaging, High Dynamic Range (HDR)**

I. Introduction

Finger veins are gaining traction as a promising biometric, since they can uniquely identify an individual and, unlike fingerprints, are virtually impossible to spoof or forge due to being subcutaneous. Finger veins can be acquired in a cheap and non-invasive manner, using Near-Infrared (NIR) technology. Indeed, NIR light is absorbed by hemoglobin in the blood but passes through bone and surrounding tissue. Finger veins thus can be captured by an NIR sensor as dark patterns by shining NIR light through the finger.

Despite its advantages, finger vein recognition also poses many technical challenges. In order to be viable as a secure and convenient personal identification method, finger vein recognition should be an accurate and timely process. That is, vein features should be faithfully identified and extracted, despite variations in finger thickness & size, vein thickness, finger displacement/rotation, and lighting conditions. The identification process is performed in real-time - ideally, the user should not have to wait more than a few seconds to obtain a matching score.

A crucial factor in the quality of finger vein images is the illumination of the finger. In the finger vein scanner developed by the DMB group, illumination is controlled by a strip of NIR LEDs placed above the finger. In the previous implementation, illumination is controlled using a feedback loop: images are acquired with varying LED intensities until homogeneous illumination of the finger is obtained, after which only the final image is used for vein recognition. However, this implementation is slow and wasteful, as many acquired images are discarded in the process, and the level of vein detail in resulting images is unsatisfactory.

This paper proposes an alternative approach, which records several finger vein images at different exposures and combines them all into a single High Dynamic Range (HDR) image. HDR imaging is typically used in photography to recover detail, contrast and depth in over- and under-exposed areas, resulting in a very visually pleasing image which is faithful to how the human eye would have perceived the scene. However, in the context of finger vein recognition, HDR is applied with the aim of condensing more vein information into one image and recovering vein detail across the whole finger.

To this end, we formulate the following main research question: *How can High Dynamic Range imaging be implemented to improve the quality of finger vein images?* which we break down into the following sub-questions:

- *How can the current setup be improved to acquire better vein images?*
- *How can the camera settings and illumination be controlled to acquire images with different exposures?*
- *How can multiple Low Dynamic Range images of different exposures be combined to create a High Dynamic Range image?*
- *What criteria should be used to evaluate the quality of the acquired vein images?*
- *To what extent does High Dynamic Range translate to recognition performance?*

II. Background & State of the art

A. Acquisition of finger vein images

The most widely used and documented acquisition method is the light transmission method: the finger is placed between the sensor and a near-infrared light source, such that IR light penetrates the finger from the top. This method has the potential of producing high contrast vein images.[2].

In their white paper[4], Hitachi also documents two other configurations: bottom lighting and side-lighting. In the case of a bottom lighting setup, the sensor and light source are placed on the same side, under the finger. This method is much less intrusive to the user than the light transmission method, as their finger is not ”hidden” by the light source; however, it offers much poorer performance. The side-lighting method was proposed by Hitachi as a compromise: light sources are placed on each side of the finger, and the sensor is placed below it. These two methods are more sensitive to ambient light and require complex adaptive control of illumination[3].

B. Evaluation of finger vein image quality

Assessing the quality of finger vein images is necessary for quantitative comparison of different acquisition setups and image processing techniques. It is also interesting to investigate to what extent different quality metrics relate to finger vein recognition performance.

Many different image quality metrics are featured in scientific literature. We list several of the most basic ones here. We can distinguish two types of metrics: statistical measures and co-occurrence based metrics. Statistical measures give insight into how pixels are distributed over the intensity range, but are independent of how pixels are distributed spatially over the image. Co-occurrence based metrics, on the other hand, depend on spatial distribution and thus can give textural information about the image.

Statistical measures:

- *Mean gray value:* computed by summing the value of all pixels in the image and dividing by the number of pixels. This gives information about the global brightness level of the image. A mean gray value close to the extremities of the intensity range (0 and 255 for an 8-bit image) indicates under- or over-exposure, and thus detail loss.
- *Standard deviation:* indicates how pixel intensities are distributed around the image. It gives an indication about the global contrast level.
- *Entropy:* is a measure of how much information is contained in an image. A predictable, flat image has low entropy while an image with many unpredictable ransitions between pixel values has a high entropy. In theory, high entropy vein images are desirable, since we want to maximize the amount of vein information. However high level of entropy in a vein image may also be due to noise or undesirable finger features (eg. ridges, joints, fingerprints, finger edges).

Co-occurrence based metrics:

- Local contrast: is a measure of intensity differences between neighbouring pixels. Although this parameter may indicate strong contrast between veins and surrounding tissue, it is also very sensitive to noise and saturation.
- Energy: can be described as the amount of work performed to obtain the image. The energy is maximum for a constant image.
- Correlation: measures the dependence of pixel intensities and that of neighbouring pixels.
- Homogeneity: homogeneity is desirable in finger vein images, since it indicates that variations in finger thickness are not prominent in the image. However, high homogeneity may also indicate a complete lack of detail or complete under/over-exposure.

As shown in [13], these metrics, although commonly used, are quite limited as vein quality assessment criteria. Many studies combine these metrics (”score fusion”) or develop novel methods for more accurate quality evaluation of finger vein images.

Furthermore, it is unclear how these metrics each exactly translate to recognition accuracy. Many papers about finger vein image quality enhancement seem to consider a high quality vein image to be an image where veins clearly stand out to the human eye. As such, histogram equalization is often mentioned in literature as an effective quality enhancement technique, since it enhances global contrast. However, insight is lacking about whether contrast enhancement truly improves the accuracy of vein pattern extraction and matching.

C. Vein recognition & matching

Acquired vein images must first be normalized to correct for any differences in finger orientation/position or image resolution. The region of interest (ROI) must then be localized and extracted; in this process, the background around the finger and the extremities of the finger (which contain little to no vein information) are discarded.

The next step is extracting the vascular pattern in the form of a binary image. Many finger vein recognition methods have been proposed in literature. Some of the most widely used vein recognition methods in scientific literature are Maximum Curvature (MC), Principal Curvature (PC), Repeated Line Tracking (RLT), and Wide Line Detection.

The Maximum Curvature method takes cross-sectional profiles of a vein images in four directions, and looks for local maximum curvature along each profile. The idea is that since veins in the image manifest as sharp transitions in pixel intensity, the curvature along the profile is highest when a vein is crossed. Each detected center point is weighted with a score, based on the width and curvature of the dent, indicating how probable it is that it is located on a vein. Filtering is then applied in order to connect vein centers and eliminate noise. Lastly, the vein pattern is binarized via thresholding.[6] Repeated Line Tracking also looks at cross-sectional profiles.

After vein pattern extraction, the last step consists of comparing the extracted binary vein pattern to previously captured patterns in a database. A matching score can then be given to the vein pattern.

For measuring vein matching performance, the Equal Error Rate (EER) is typically used. As illustrated in 1, the EER is equal to the error rate for which the False Acceptance Rate and False Rejection Rate are equal. Biometrics applications aim to reduce the EER to zero, such that there is no overlap between the acceptance and rejection curve, thus yielding 100% matching accuracy.

D. High Dynamic Range imaging

The dynamic range of an image is commonly defined as the ratio between its highest and lowest intensity value. Camera sensors have a limited dynamic range, and thus are unable to capture the full dynamic range of scenes with large variations in brightness; brightness levels outside of the camera’s dynamic range appear saturated in the captured image (under-exposed or over-exposed). Recording the full range of an HDR scene with an LDR sensor requires taking multiple captures at different exposures. This acquisition process is known as exposure bracketing. The image sequence must then be combined into a single image, such that all areas are properly exposed. The resulting image is an HDR image, and

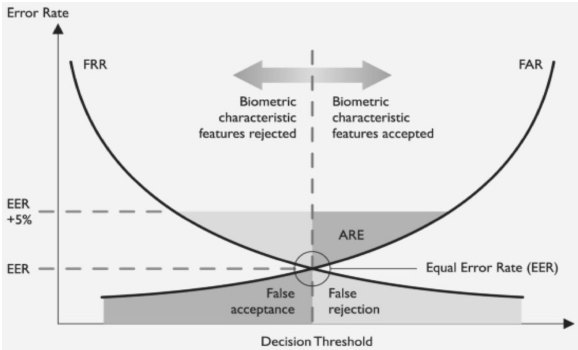


Fig. 1: Diagram showing the relation between EER, FAR and FRR. Source: https://www.tractica.com/biometrics/in-biometrics-which-error-rate-matters/

thus cannot be viewed on a typical LDR screen. For viewing purposes, the HDR image must be ”compressed” or converted into an LDR image - this is known as tone-mapping.

1) Exposure bracketing: Constructing an HDR image requires taking a sequence of images at different exposures. The exposure of acquired images can be varied from the camera itself, through the following settings, commonly known as the ”exposure triangle”:

- Shutter speed: longer shutter speeds result in brighter images, since the camera is exposed to light for a longer period of time; however controlling exposure in this manner has the disadvantage of introducing motion blur.
- ISO, which determines the light sensitivity of the camera. High ISO allows proper exposure in low-light conditions but tends to introduce visible noise in images; low ISO produces smoother images, but requires a high level of ambient lighting for proper exposure.
- Aperture is a property of the camera lens; a wider aperture allows more light to enter the camera, and also reduces the depth of field.

Merging images with different depths of field or noise levels would result in undesirable artifacts, since the content of the images is fundamentally different. This is why, when taking a sequences of images for HDR reconstruction, the exposure is traditionally controlled by adjusting shutter time, while the the ISO and aperture settings are kept fixed.

2) Constructing an HDR image: Constructing an HDR image from a sequence of multiple input images essentially amounts to taking a weighted average of these images. Images are inversely weighed based on their exposure level, such that details captured at lower exposures appear in the high end of the final image’s intensity range and vice-versa. State-of-the art methods in the field of photography first compute the Camera Response Function which relates scene radiance (ie. the amount of incoming light) to measured intensity values. This function is used to compensate for non-linearities introduced by the camera sensor and image compression. The goal is to approximate the amount of light that originally hit the camera sensor at each pixel location, to produce an HDR image which is as faithful as possible to the captured scene. An extensive review of CRF calculation and HDR weighting methods is given in [1].

3) Tone-mapping: The most basic tone-mapping method consists of linearly scaling the HDR image down to a LDR (usually 8-bits). However, this uniform distribution produces an image which is appears very flat and is not ”visually meaningful”[1]. Non-linear tone-mapping, which emphasizes intensity variations is much more commonly used. Non-linear tone-mapping methods often involve some form of histogram adjustment.

E. HDR imaging for finger vein recognition

In the context of finger vein recognition, there is very little documented use of HDR imaging or exposure fusion. In fact, illumination for finger vein acquisition as a whole is not a widely researched topic.

One approach[10], proposed by L. Chen et al., consists of acquiring images at different exposures, dividing each image into ten vertical segments, and reconstructing a single image by combining the best segments. Although this is an interesting fusion method if homogeneous illumination cannot be obtained, the result is not an HDR image.

A previous student at DMB[**?**] attempted to implement HDR imaging using constant illumination and varying shutter speed for exposure bracketing. Results are underwhelming due to the poor acquisition method.

III. Implementation

A. Setup improvement

The finger vein scanner developed at the DMB group uses a top-lighting setup: the finger is placed between the sensor and a near-infrared light source. The sensor used is a 5 Mega Pixel RB-Camera-WW from Joy It, which was chosen by previous student[12] for its low cost, Raspberry Pi compatibility and its large field of view. The camera lens has a fixed aperture (f-number of 2,35). As the camera does not have a built-in IR filter, an IR filter was added under the finger. Illumination control, image acquisition and vein recognition were all performed on a computer running Matlab, which controls the on-board Raspberry Pi remotely.

As can be seen in the top image of Figure 2, acquiring images using the original setup and original code gives unsatisfactory results: vein details are poorly visible due to low contrast between veins and surrounding tissue. In an attempt to improve the quality of acquired images, the following changes were made to the finger vein scanner:

- Shielding from ambient light was added by placing black paper around the scanner. This provides more predictable lighting conditions and seems to reduce scattering in the finger.
- The IR filter, which easily collects dirt and scratches, and introduces glare (see Appendix D), was removed. The IR filter proved to be unnecessary when the dark housing is used, since the amount of non-IR light entering the camera is minimal.
- Reflective material around the camera (eg. flatcables) was shielded as much as possible, as these seem to contribute to scattering in the finger.

- The zoom of the camera lens was manually adjusted such that veins appear in focus.

A major drawback of the previous software implementation is that exposure settings were set automatically by the camera: increasing the intensity of the LEDs did not cause an increase in image brightness, as the camera compensated for the increased light by lowering its exposure. As acquiring images from Matlab using the Raspberry Pi Camera Board module does not allow low-level manual control of camera settings like ISO and shutter, the illumination control and image acquisition parts of the code were re-written in Python to run on the Raspberry Pi itself in order to be able to fix the camera exposure.

For camera settings, we minimize noise by fixing the ISO to the minimum setting, and finding the highest shutter speed for which the image brightness is satisfactory in high light conditions.

The result of these improvements is shown in the bottom image of Figure 2. Although contrast between veins and surrounding tissue is still quite low, vein details are much more visible with the new setup. Blurring of veins due to scattering is reduced, and homogeneity is increased, especially in the joint areas.

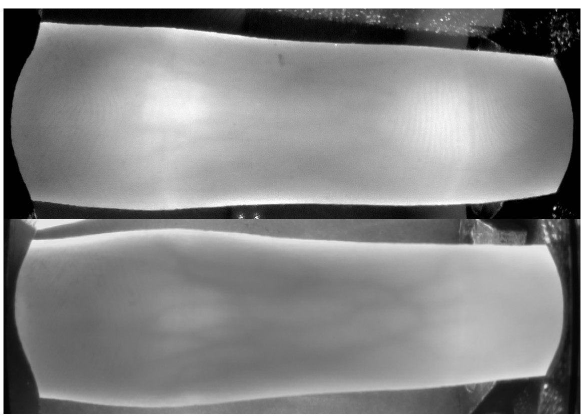


Fig. 2: Acquired vein images of the same finger using the old setup (top) and the improved setup (bottom)

B. Illumination control for multi-exposure image acquisition

In a finger vein scanner setup, we have direct control over the amount of light that the camera is exposed to. Exposure bracketing can be done by adjusting the intensity of the IR LEDs, thus allowing the shutter speed to be fixed. This avoids the problem of motion blur caused by lowering the shutter speed.

A suitable illumination pattern for the LED strip is determined based on typical joint locations of each finger. Infrared light passes through joints much more easily than muscle, and the base of the finger is much thicker than the tip. Thus, to obtain homogeneous brightness along the finger, LEDs placed above joints and at the tip of the finger are kept dim relative to LEDs at the base or between the phalangeal joints. To illustrate this, the illumination pattern used for the index finger is shown in Figure 3.

Fig. 3: Relative LED intensities used for the index finger. Each LED is represented as a cell in the row.

The intensity of the LEDs is set to the minimum at start-up, and is increased by a scalar value between each capture, until the maximum possible intensity has been reached. Images are taken in rapid succession to avoid finger displacement between images which would introduce blur when super-imposing them in the HDR reconstruction.

A resulting set of images is shown in Figure . As can be seen in the corresponding histogram (Figure 5), the acquired images cover the full 8-bit dynamic range, with no saturation.

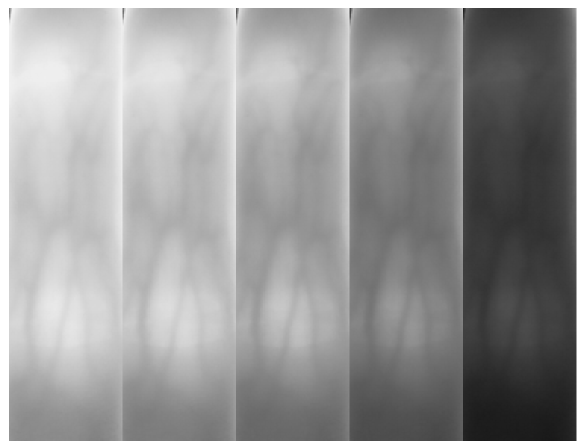


Fig. 4: Multi-exposure sequence of finger vein images. Note: Only 5 of the 21 images in the sequences are shown for the sake of conciseness.

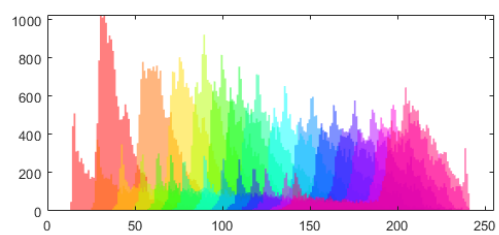


Fig. 5: Histogram of multi-exposure sequence. Each image in the sequence is shown in a difference color.

C. Normalization

Edges on each side of the finger are detected using Lee's method, implemented by Bram Ton[8]. From this finger outline, the orientation of the finger is estimated by fitting a line through the middle of the finger's extremities. Any deviation from a horizontal orientation is corrected with an affine transformation.[9] This process is shown in Figure 6.

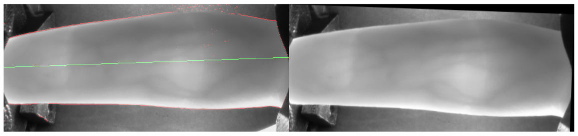


Fig. 6: Finger edge detection and affine transformation for normalization.

The image is then cropped down and scaled to a preset ROI of 106x361 pixels, such that it contains no background or finger edges. Without this step, finger edges or elements around the finger could be detected as veins and skew vein matching results.

D. Methods for HDR reconstruction

The main question here is how should the input images be weighed in order to maximize the amount of vein detail in the output image?

1) Basic HDR implementation with scalar weights: A very simple HDR implementation consists of weighing each input image with a single scalar value, with the weighting factor being the inverse exposure level. Here we estimate the exposure value by computing the mean gray value of the image. The image is also weighted with a box function, such that if an image's mean value lies outside the box's range, indicating under- or over-exposure, it is simply discarded from the HDR reconstruction. The result is seen in Figure 8.

This method is limited, since the brightness and level of vein detail often depends on the location on the finger: some portions of the finger may be poorly illuminated while others may feature high levels of vein detail. Thus, a better implementation consists of assigning location-dependent weights instead of a single global weight per image.

2) HDR reconstruction using moving mean filtering for background illumination suppression: Instead of using a single global exposure value per image, the exposure is computed locally by estimating the background illumination of the finger vein image. The background illumination pattern of can be estimated by low-pass filtering it; this essentially produces a matrix of 'local exposures'.

For smoothing the image, a moving mean filter is chosen. Mean filters are very sensitive to outliers, which is desirable in this case since we do not want veins (outliers) to appear in the background illumination estimation. Mean filters also have the advantage of being fast to compute (as opposed to Gaussian filters, for instance).

To avoid boundary effects around the edges of the image, the moving mean filter is applied on the original acquired image rather than the cropped version. The resulting filter image is then cropped to match the size of the cropped version. This way, boundary effects are simply cropped out.

For the HDR reconstruction, each LDR image in the input sequence is divided by the filtered version of itself. This suppresses low-frequency variations in intensity over the image, resulting in a homogeneous background. The effect of different moving mean window sizes can be seen in Figure 7. The smaller the window, the flatter the background but if the window size is chosen smaller than the minimum vein width, small veins are suppressed. As seen in the bottom image, using a non-square window gives a textured "ridge and valley" effect. Based on measured vein widths, a window of [7 7] is chosen.

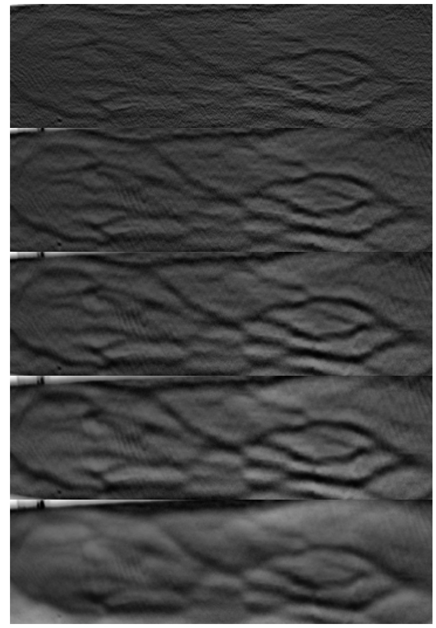


Fig. 7: Tone-mapped output of HDR reconstruction with mean filtering for different mean filter windows. From top to bottom: [2 2], [5 5], [7 7], [10 10], [10 2]

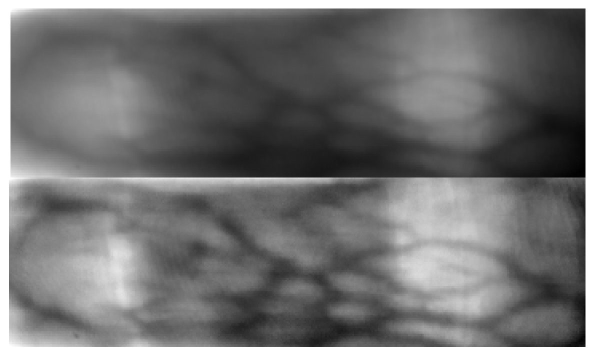


Fig. 8: Tone-mapped output of HDR reconstruction with 15 images used as input. Top: linear tone-mapping. Bottom: Matlab tonemap function

E. Tone-mapping

In the context of vein recognition, tone-mapping bears little relevance as vein extraction is executed on the HDR image itself. However, tone-mapping is required for visual assessment of the HDR reconstruction. Linear tone-mapping gives a better representation of what the vein extraction algorithm "sees". However, as seen in Figure 8 (top image), it produces images that look very flat and in which vein details are barely visible. Thus, for display purposes in this paper, the Matlab `tonemap` function is used, which uses a non-linear contrast-enhancing technique (bottom image).

IV. Experimental setup

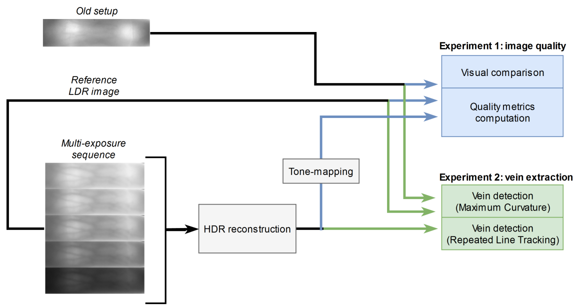


Fig. 9: Block diagram illustrating the first two experiments

A. Image quality evaluation

Objectives: The goal of this experiment is to compare the quality of

- images taken with the old setup vs. the improved setup
- HDR reconstructions with that of a single LDR image taken with the improved setup

Method: The image quality is evaluated in two ways:

- visually, that is, by displaying the image and observing characteristics of the image such as vein contrast, blur, noise or homogeneity
- using qualitative metrics which have been outlined in section II.B. Details on how each metric was computed are given in Appendix B

Data: A finger vein image is taken with the old setup and old adaptive illumination algorithm. Using the improved setup and method outlined in III-B, a multi-exposure sequence of images, is required, and two HDR reconstructions are made (one for each method). From the input sequence, a single image is chosen to be the reference LDR; we (subjectively) choose the "best" one in the sequence ie. the one with the most visible vein detail.

Presentation of results: Resulting images are displayed side-by-side for visual comparison. For displaying the HDR images, non-linear tone-mapping is used. Qualitative metrics are displayed in a table, with the maximum values for each row in bold for readability. Histograms are also plotted for each image for better insight into how pixels are distributed; this is especially useful for HDR images as only a tone-mapped version can be displayed.

Results of this experiment are shown in Table I and Figure 10.

B. Accuracy of vein extraction

Objectives: High image quality alone may not necessarily lead to high recognition performance. In order to draw conclusions about whether the proposed HDR algorithm is a promising method, a separate experiment must be conducted to evaluate whether this method leads to a higher level of detail being detected, and to a higher vein matching accuracy compared to the use of a single LDR image.

Method: For this experiment, two different vein recognition algorithms are used: Maximum Curvature and Repeated Line Tracking. A Matlab implementation was developed by Bram Ton[11], based on the work of Miura[6] [7]. Parameters for the recognition algorithm are chosen based on the observed width of the veins in pixels. The number of iterations used for RLT is kept quite low (1000) to limit computation time.

Data: The same images as in the first experiment are used.

Presentation of results: Resulting binary vein patterns are displayed side-by-side for visual comparison.

Prediction: We expect that a higher level of detail will be detected in HDR reconstructions than in the LDR reference image, since background illumination has been suppressed and since the reconstructions contain vein information from many different images.

Results of this experiment are shown in Figure 11.

C. Matching performance

Objectives: The performance of a finger vein identification device is ultimately determined by how accurately the system can identify whether two vein patterns belong to the same finger. The goal of this experiment is to take a first step in evaluating how well the proposed HDR reconstruction methods translate to improved matching performance, compared to using only the best LDR image in the sequence.

Data & Method: Four different fingers are used for this experiment (the index and middle finger on each hand of the same person). Each finger is scanned on three different occasions: the finger is removed from the scanner, and placed again between each measurement, to ensure some dissimilarity between captures of the same finger. In each measurement, a multi-exposure sequence is captured in quick succession, as outlined in section III-B. Similarly to the previous experiment, from this sequence, two HDR reconstructions are made (basic HDR reconstruction & HDR reconstruction with moving mean), and the best LDR image in the sequence is selected for comparison. Binary vein patterns are extracted using both MC and RLT. Each possible pair of images is given a matching score, using normalized 2D cross-correlation (implemented by Bram Ton). Since each finger was scanned on 3 (separate) occasions, each pattern has 2 expected matches and 9 expected mismatches in the full dataset.

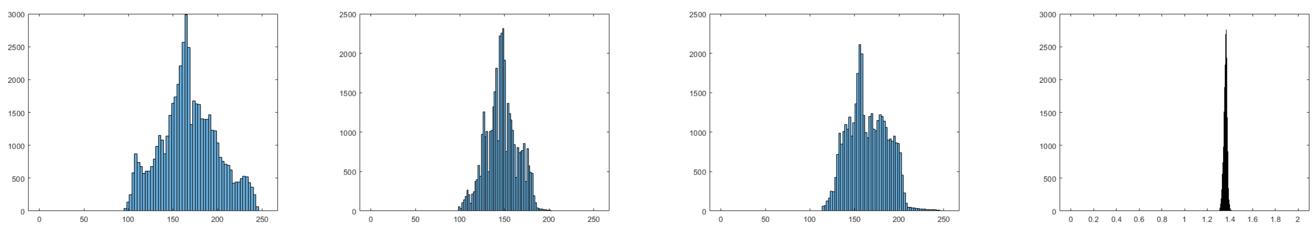
Presentation of results: For each group (LDR, basic HDR reconstruction & HDR reconstruction with moving mean) and for each recognition algorithm (Maximum Curvature, Repeated Line Tracking), matching scores are plotted in a histogram. Histograms are color-coded: separate colors are used for expected matches (patterns from the same finger) and expected mismatches (patterns from different fingers). Overlap between the two colors would indicate a false positive or negative. Matching scores between the RLT and MC pattern for each finger vein image are also computed to give an indication of how accurately veins can be extracted for each method.

Results of this experiment are shown in Figure 12.

V. RESULTS

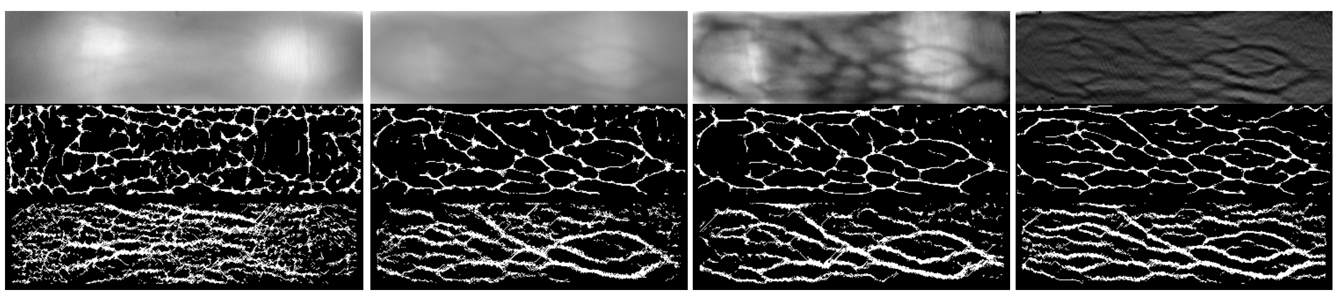
	Global metrics		Textural metrics			
	Standard dev.	Entropy	Local contrast	Homogeneity	Energy	Correlation
LDR - Old setup	**13.7737**	6.9336	5.1560	0.5935	0.0119	0.9992
LDR - Improved setup	10.8490	6.1205	5.7198	0.7070	**0.0178**	0.9989
HDR basic	12.0861	**7.2226**	2.3098	0.6236	0.0017	**0.9995**
HDR moving mean [5 5]	0.0132	4.5080	**15.5661**	**0.8057**	0.0006	0.9956

TABLE I: Image quality metrics for different LDR and HDR images. Maximum values in each column are shown in bold.



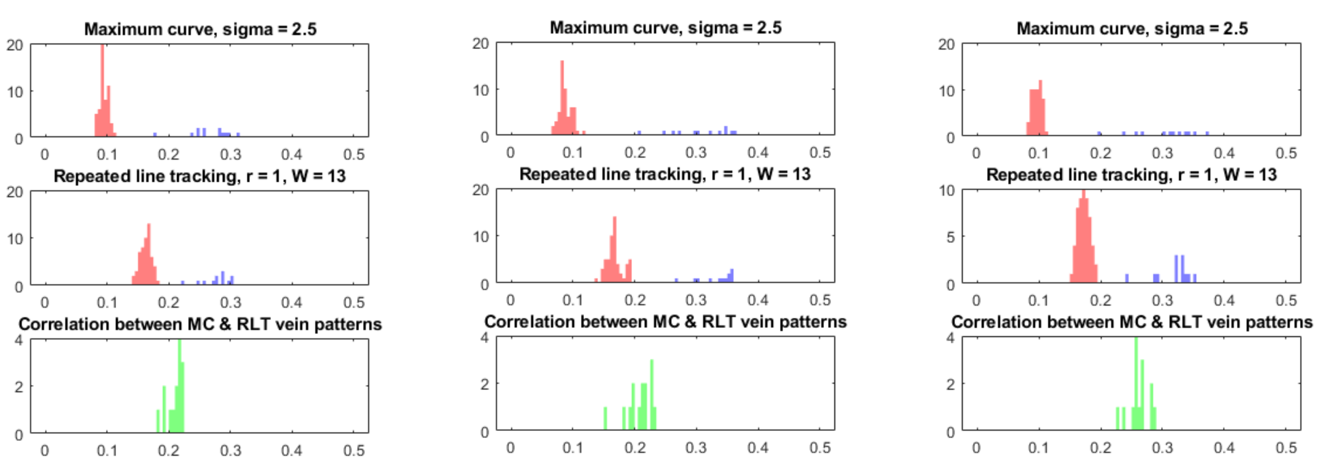
(a) LDR image from old setup (b) LDR image from improved setup (c) Basic HDR reconstruction (d) HDR reconstruction with moving mean

Fig. 10: Histograms of the four vein images shown in Figure 11. Note that the scale of the x-axis for image (d) was greatly reduced for readability.



(a) LDR image from old setup (different finger) (b) LDR images from improved setup (c) Basic HDR reconstruction (d) HDR reconstruction with moving mean

Fig. 11: Vein image (top), Maximum Curvature (middle) sigma = 3, Repeated Line Tracking (bottom), r = 1 W = 13



(a) LDR images from improved setup (b) Basic HDR reconstruction (c) HDR reconstruction with moving mean

Fig. 12: Histogram of matching scores in vein matching experiment. Vein patterns from different fingers are shown in red, vein patterns from the same finger are shown in blue.

VI. Discussion

A. Vein image quality and vein extraction

The result of merging a multi-exposure sequence of LDR images into a single HDR images can be seen in Figure 10 (c): the original intensity range in (b) appears much ”fuller” in (c), and slightly wider, as information from other LDR images has been added. As expected, the image produced with the basic HDR reconstruction method has the highest entropy, as it contains information from all (properly exposed) LDR images in the input sequence. The moving mean HDR method yields the lowest entropy, as low-frequency information along the finger has been removed to obtain a homogeneous background.

When comparing extracted vein patterns in Figure 11, the level of vein detail and clarity both using Maximum Curvature and Repeated Line Tracking, increases from left to right, with the moving mean HDR method showing the best results, especially around the base and tip of the finger. This is reflected by textural quality metrics: both the homogeneity and local contrast are highest for this method, which yields a ”cleaner” vein cross-sectional profile - the profile is globally flat (homogeneity) with sharp dips when a vein is crossed (local contrast). Vein extraction accuracy is also reflected in the bottom graphs (in green) of Figure 12: matching scores between MC and RLT patterns are highest in (c), confirming that veins are detected most reliably with this HDR method.

It is interesting to note that standard deviation (which we perceive as global contrast) does not appear to be a good predictor of finger vein image quality: the image taken with the old setup shows the worst results in terms of vein extraction ((a) in 12) despite having the highest standard deviation (I), while the intensity of image (d) is concentrated around a very small portion of the intensity range, yet vein details are detected much more accurately. This suggests that whether vein detail can be distinguished by the naked eye bears little importance for vein recognition, as long as the vein detail is present in the image.

B. Vein matching

In the vein experiment shown in 12, patterns from different fingers (in red) are successfully contained within a small range. The highest matching scores are obtained with the method in (c). For HDR images, the distance between the mean acceptance and rejection rates is higher than for LDR images, indicating higher matching accuracy. With Maximum Curvature: no significant difference is observed between the two HDR methods, and with Repeated Line Tracking, method (b) seems to perform slightly better, despite method (c) showing better vein detection performance in 11. A possible explanation is that detecting fine vein details is not necessarily beneficial in terms of matching, unless these details can be consistently captured across acquisition sessions. To test this, RLT and MC parameters could be adjusted such that only the major vein features are extracted.

We also observed that matching pairs (shown in blue in Figure 12) with the lowest matching scores have noticeable differences in orientation. This suggests that improved normalization (which would correct finger angle differences more accurately) and/or using a matching algorithm that is sensitive to rotational differences would improve the acceptance rate of matching vein patterns. Currently, 2D cross-correlation is used as a vein matching algorithm, which is very basic and only accounts for translative offsets. For normalization, parameters should be adjusted (as can be seen in Figure 6, the finger outline is not perfectly detected) or alternative methods should be explored.

Finger images analyzed in this paper were all from the same person; robustness of the proposed HDR reconstructions to variations in finger thickness, finger size was not investigated. Furthermore, due to the very small sample size of the vein matching experiment, no general claims can be made about the matching accuracy. Thorough and reliable evaluation of vein recognition accuracy requires a much larger sample size. As no available vein image database contains multi-exposure sequences (which are necessary for HDR reconstruction), a new database should be constructed.

VII. Conclusion

Some limitations of the existing image acquisition implementation were first identified, and several adjustments were made, both in hardware and in software, in order to acquire higher quality input images. Results show that these changes have starkly improved the homogeneity and level of detected vein detail in acquired images.

Multi-exposure image sets were then acquired by adjusting both the intensity and pattern of the illumination. In order to combine a multi-exposure sequence into a single image, a novel method was developed, which uses a mean filter as a weighting factor in the HDR reconstruction to emphasize vein details while homogenizing surrounding tissue in the background.

A first step in the direction of testing recognition performance was made, by visually evaluating the accuracy of extracted vein patterns, and by computing vein matching scores between different datasets. Results suggest that HDR imaging is a promising technique for finger vein image identification.

VIII. Recommendations

The quality of a HDR reconstruction is ultimately limited by the quality of the LDR images used as inputs. Thus, a significant portion of this project was spent trying to improve the quality of acquired images by adjusting the finger vein scanner setup and the camera settings. However, this was mostly done via trial-and-error, and subjective/visual evaluation of image quality. A more extensive and systematic analysis of how these parameters affect image quality is necessary to find the optimal configuration. Some questions to explore further include: is an IR filter necessary at all? If so, where should it be positioned in relation to the camera and finger? What is the effect of ambient light and different housing materials/surfaces on finger images?

Ideally, movement of the finger on the scanner should be more limited, to avoid significant variations in displacement or rotation between acquired image datasets. This could be achieved by narrowing the scanner area, and deepening the notch at the base and edge of the finger to limit finger rolling. Another option would be to implement a feedback mechanism which measures the finger position/orientation and prompts the user to adjust it.

The optimal image resolution for image acquisition and vein recognition should also be investigated: high resolutions allow for higher level of detail but greatly increase computation time.

As far as HDR reconstruction is concerned, it would be interesting to investigate the optimal number of input images and illumination algorithm for image acquisition. The illumination algorithm used for this paper was quite basic and manually tailored to each new finger. The next logical step is to develop an adaptive illumination algorithm which requires no manual intervention. Furthermore, the software implementation is currently divided between the Raspberry Pi and an external computer; a fully embedded Python implementation, which builds upon the existing Python illumination control & image acquisition code would be ideal.

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Appendix

A. *Source code*

All the source code used & developed for this project can be found at https://github.com/glhr/HDR-Finger-vein.

B. *Calculation of quality metrics*

Since these metrics are sensitive to noise, which would skew results, we first filter the input image with a Gaussian filter with a very small standard deviation such that vein features are conserved.

For the formulas below, we use the definitions specified in [14].

We take $I(x, y)$ to be pixel intensity at position (x, y), and X and Y to be the width and height of the image.

1) *Statistical metrics:*

Mean gray value μ:

$$\mu = \frac{1}{XY}\sum_{x=1}^{X}\sum_{y=1}^{Y} I(x, y)$$

Variance σ^2 & standard deviation σ:

$$\sigma^2 = \frac{1}{XY}\sum_{x=1}^{X}\sum_{y=1}^{Y}(I(x, y) - \mu)^2$$

Dynamic range:

$$\frac{\max I(x, y)}{\min I(x, y)}$$

We take k to be the pixel intensity, ranging from 1 to K, with $p(k)$ the probability that intensity k occurs.

Entropy:

$$Z = \sum_{k=1}^{K} p(k)\log_2 p(k)$$

2) *Co-occurence based metrics:*

These are described in [13] and computed using Matlab's `graycoprops` function.

C. *Camera settings*

See Table II.

D. *Finger vein scanner*

See Figure 13.

E. *Graphical tool*

A graphical tool was developed in Matlab for comparing the image quality and extracted vein pattern of two vein images. Images can be cropped using sliders. The image quality metrics described in this paper are automatically computed when loading an image, and displayed in a table. The maximum value in each row is shown in red for readability. Parameters for Maximum Curvature and Repeated Line Tracking can also be adjusted.

	Previous setup	**Proposed setup**
Resolution	1920x1080	800x600
Brightness	52	50
Contrast	90	0
Sharpness	0	0
Saturation	0	-100
Exposure mode	night	off (fixed by ISO & shutter time)
Shutter speed	N/A	maximum
ISO	N/A	100 (minimum)
Metering mode	average	N/A
AWB mode	auto	auto

TABLE II: Comparison of camera settings used in the previous and new implementation

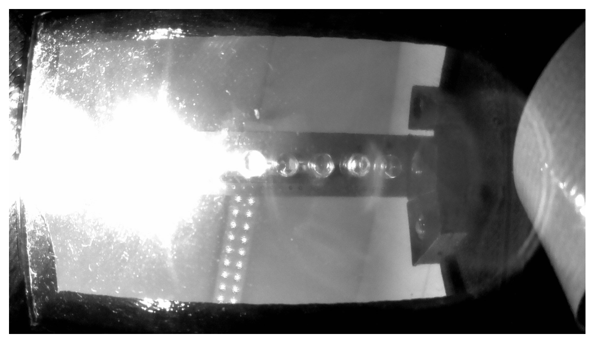

Fig. 13: Image taken by the finger vein scanner with 4 LEDs on, and the IR filter present.

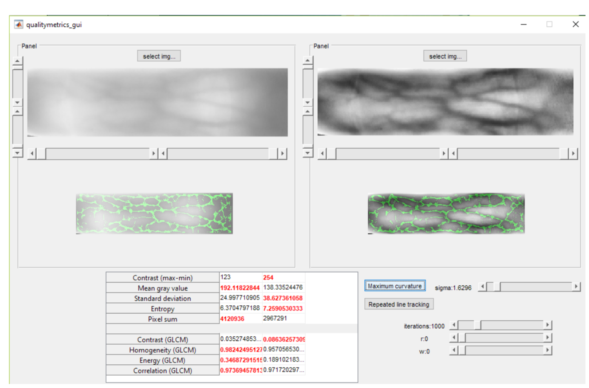

Fig. 14: Screenshot of the graphical tool