# Advanced Multi-Perspective Enrolment in Finger Vein Recognition

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***Abstract*—Finger vein recognition deals with the recognition of subjects based on their venous pattern within the fingers. It has been shown that its recognition accuracy heavily depends on a good alignment of the acquired samples. There are several approaches that try to reduce the impact of finger misplacement. However, none of these approaches is able to prevent all possible types of finger misplacements. As finger vein scanners are evolving towards contact-less acquisition, alignment problems, especially due to longitudinal finger rotation, are becoming even more important. Along with rotation detection and correction, capturing the vein pattern from multiple perspectives, as e.g. in multiple-perspective enrolment (MPE, [1]), is a way to tackle the problem of longitudinal finger rotation. Involving multiple cameras increases cost and complexity of the capturing devices, and therefore their number should be kept to a minimum. Perspective multiplication for MPE (PM-MPE, [2]) successfully reduces the number of cameras needed during enrolment while keeping the recognition rates at a high level. So far, (PM-)MPE has only been applied using Maximum curvature features (MC, [3]). This work analyses further approaches to improve the their recognition rates and investigates the applicability of (PM-)MPE to recognition schemes using features other than MC.**

***Index Terms*—Finger vein recognition, longitudinal finger rotation, rotation invariant recognition system**

## I. Introduction

Vascular pattern based biometric systems, commonly denoted as vein biometrics, offer several advantages over other well-established biometric recognition systems. In particular, hand and finger vein systems have become a serious alternative to fingerprint based ones for several applications. Vein based systems use the structure of the blood vessels inside the human body, which becomes visible under near-infrared (NIR) light. As the vein structure is located inside the human body, it is resistant to abrasion and external influences on the skin. Furthermore, a lifeness detection to detect presentation attacks can be performed easily [4].

The performance of finger vein recognition systems suffers from different internal and external factors. Internal factors include the design and configuration of the sensor itself, especially the NIR light source and the camera module. External factors include environmental conditions (e.g. temperature and humidity) and deformations due to misplacement of the finger, typically including shifts, tilt, bending and longitudinal rotation. Performance degradations caused by various types of finger misplacement are not new and have been addressed in several publications. The need for a robust finger vein image normalisation including rotational alignment has already been mentioned by Kumar and Zhou in 2012 [4]. Chen *et al.* [5] state that deformation correction can be done either during pre-processing, feature extraction or comparison. Moreover, the physical design of the sensor, e.g. [6], [7], can help to avoid misplacements of the finger. In [8] the authors showed that longitudinal finger rotation has a severe influence on the recognition performance of a finger vein recognition system. There are several approaches that try to reduce the influence of these issues in traditional single perspective systems during the processing of the vein patterns, e.g. [4], [5], [9]–[13]. Other systems try to utilize multi-camera capturing devices to overcome the problem of longitudinal finger rotation. Bunda [14] and Sonna Momo *et al.* [15] propose multi-perspective recognition systems using capturing devices that acquire the vascular template from three different perspectives at the same time. Kang *et al.* [16] proposed a finger vein recognition system in the 3D space. Prommegger and Uhl [1] introduced two methods that make finger vein recognition fully invariant against longitudinal rotation. Both methods acquire multiple perspectives during enrolment, while only one perspective is captured during recognition. The first approach, multi-perspective enrolment (MPE), compares the probe image to all acquired enrolment perspectives, while the second approach, perspective cumulative finger vein templates, generates a single template that holds the vein pattern all around the finger. In [2] the number of cameras needed during enrolment for MPE has successfully been reduced by introducing pseudo perspectives.

This article is an extension to the work presented in [1] and [2]. While in [1] and [2] only one recognition scheme, *Maximum curvature* (MC, [3]), was applied, this work analyses the applicability of (PM-)MPE to recognition schemes using features other than MC. The schemes under investigation are the *Wide Line Detector* (WLD, [9]), *Finger Vein Recognition With Anatomy Structure Analysis* (ASAVE, [13]) and a *SIFT*-based recognition scheme (SIFT, [17]). Furthermore, two additional adoptions to increase the performance of MPE and PM-MPE are analysed. The first approach strives to improve the performance of MPE by changing the position of the enrolment cameras, while the second method adopts PM-MPE by adding extra pseudo perspectives between two enrolment cameras. All experiments are carried out using the *PLUSVein*

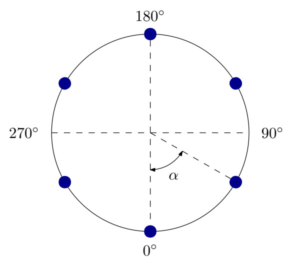


Fig. 1. Rotational shift of enrolment cameras for MPE: MPE as proposed in [1] (left) always includes the palmar view (0°), whereas for the proposed method (right) the start position is shifted by $\varphi$.

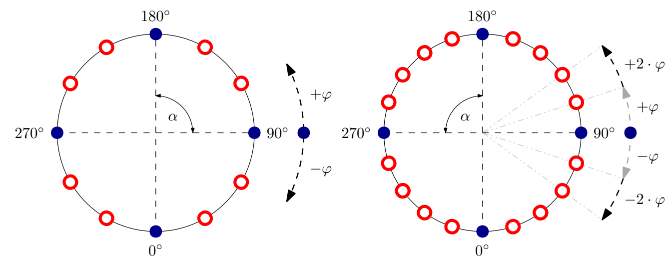


Fig. 2. Camera positioning for PM-MPE for a rotational distance of 90° between two adjacent enrolment perspectives. The filled blue dots are cameras, the red circles represent pseudo perspectives. The left image (originally published in [2]) shows the position of the pseudo perspectives as proposed in [2], the right side visualizes the principle of adding additional pseudo perspectives.

*finger rotation data set* (PLUSVein-FR) [18]. This article focuses on further analyses on and limitation of (PM-)MPE. Comparisons to methods that represent the state of the art in rotation invariant finger vein recognition have been omitted as such an analysis has already been carried out in the original publications [1], [2].

The reminder of this paper is organized as follows: In section II perspective shift for (PM-)MPE is described. Section III holds some details on PM-MPE and section IV the proposed approach to introduce additional pseudo perspectives. The experimental set-up together with its results are described in Section V. Section VI concludes the paper along with an outlook on future work.

## II. Perspective Shifts for Multi-Perspective Enrolment

The positioning of the enrolment cameras around the finger can be an influential factor for the recognition performance of the system. Two aspects need to be considered: (1) the performance of the different perspectives itself and (2) the rotational distance of the probe sample to the nearest enrolment perspective. For (1) it has been shown that finger vein recognition systems perform best around the palmar and dorsal view and worst around 90° and 270° [18]. For (2) it has been shown in [12] that state of the art recognition systems cannot compensate rotational distances exceeding 30°.

MPE and PM-MPE, as proposed in [1] and [2], start the positioning of the enrolment cameras always at the most commonly used palmar perspective. For some configurations, i.e. MPE 60°, this leads to the simultaneous occurrence of (1) inferior performing perspectives and (2) the maximum distance of the probe sample to the acquired enrolment perspectives. By rotating the acquired enrolment perspectives with an rotation angle of $\varphi$, the two negative impact factors should be separated. Fig. 1 visualizes the idea for MPE 60°. The right image shows the positioning of the enrolment cameras for MPE as proposed in [1]: They are linearly spaced around the finger starting at the palmar view (0°) with a rotational distance between two adjacent cameras of $\alpha = 60°$. The perspectives acquired during enrolment are: 0°, 60°, 120°, 180°, 240° and 300°. The maximum distance of the recognition perspective and the closest enrolment perspective is reached exactly in-between two enrolment perspectives. As a consequence of this positioning, for the worst performing perspectives (90° and 270°, [18]), the distance to the nearest enrolment camera reaches its maximum of 30°. In the left image the enrolment cameras are shifted by an angle of $\varphi = 30°$. Due to this shift, there are enrolment cameras at 90° and 270°, and hence, the negative impact factors do not occur simultaneously any more.

## III. Perspective Multiplication for Multi-Perspective Enrolment

PM-MPE, as proposed in [2], combines MPE and the fixed angle rotation compensation method of [12] to reduce the number of perspectives needed during enrolment. At enrolment $n$ perspectives with a rotational distance of $\alpha$ are acquired. PM-MPE adds two pseudo perspectives between two adjacent cameras by rotating every perspective with an rotational angle of $\pm\varphi = {}^{\alpha}/_{3}$ in both directions. For authentication, just as for traditional single-perspective finger vein recognition schemes, only a single perspective is acquired and compared to all enrolled perspectives and the generated pseudo perspectives. This leads to $3{*}n$ comparisons for each authentication attempt. The left image of Fig. 2 shows the positions of the enrolment cameras and pseudo perspectives for $\alpha = 90°$ between two adjacent enrolment perspectives. The solid blue dots represent perspectives actually acquired during enrolment. As for MPE, they are spread linearly around the finger at 0°, 90°, 180° and 270°. The remaining perspectives (red circles) are generated by rotating the acquired finger vein images by a rotation angle of $\varphi = {}^{90°}/_{3} = 30°$ in both directions. It was shown in [2] that by applying PM-MPE, the distance of the enrolment perspectives can be increased while keeping the recognition performance at a high level.

## IV. Generation of Additional Pseudo Perspectives for PM-MPE

The improvement in recognition performance of PM-MPE compared to MPE is based on the reduction of the horizontal shift executed during comparison. Deviating from PM-MPE, the approach proposed here, PMx-MPE, adds more than two pseudo perspectives between two enrolment perspectives. Each perspective is rotated $m$ times with multiples of $\varphi$ in both directions, where $\varphi = {}^{\alpha}/_{(2*m+1)}$. As a result of the additional pseudo perspectives, the rotational distance between the perspectives used for recognition is lower than for PM-MPE.

| Enrolment Perspectives | | Distance between adjacent perspectives | | | | # of comparisons | | | | Max distance recognition $\leftrightarrow$ enrolment | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | MPE | PM-MPE | PM2-MPE | PM3-MPE | MPE | PM-MPE | PM2-MPE | PM3-MPE | MPE | PM-MPE | PM2-MPE | PM3-MPE |
| $n$ | $\alpha$ | $\alpha$ | $\varphi = \alpha/3$ | $\varphi = \alpha/5$ | $\varphi = \alpha/7$ | $n$ | $3 \cdot n$ | $5 \cdot n$ | $7 \cdot n$ | $\alpha/2$ | $\varphi/2$ | $\varphi/2$ | $\varphi/2$ |
| 24 | 15° | 15° | - | - | - | 24 | - | - | - | 7.5° | - | - | - |
| 12 | 30° | 30° | 10° | - | - | 12 | 36 | - | - | 15° | 5° | - | - |
| 8 | 45° | 45° | 15° | 9° | - | 8 | 24 | 40 | - | 22.5° | 7.5° | 4.5° | - |
| 6 | 60° | 60° | 20° | 12° | 8.6° | 6 | 18 | 30 | 42 | 30° | 10° | 6° | 4.3° |

TABLE I

DISTANCE BETWEEN ADJACENT (PSEUDO) PERSPECTIVES, NUMBER OF COMPARISONS NEEDED DURING RECOGNITION AND MAXIMUM DISTANCE OF THE PROBE SAMPLE TO THE NEAREST (PSEUDO) PERSPECTIVE FOR MPE, PM-MPE, PM2-MPE AND PM3-MPE.

Therefore, the horizontal shifts during comparison can be reduced. According to the results of [19], this should lead to a better separation of genuine and impostor scores, which in turn results in a better recognition performance. The right side of Fig. 2 shows the principle for $\alpha = 90°$ and $m = 2$, which results in $2 * m = 4$ pseudo perspectives between two adjacent enrolment perspectives. Each acquired perspective is rotated by $\pm\varphi$ and $\pm 2 * \varphi$. The distance between two perspectives is $\varphi = 90°/5 = 18°$ instead of 30° as for PM-MPE in [2].

A drawback of the additional pseudo perspectives is that the number of comparisons during recognition increases. Instead of $3 * n$ comparisons as for PM-MPE, the additional perspectives results in $(2 * m + 1) * n$ comparisons. The experiments in the section V-D should show if adding more pseudo perspectives improves the recognition rates and if so, if this improvement justifies the added computational cost for generating the additional pseudo perspectives during enrolment and comparisons during recognition. Table I contains detailed information about various settings (different numbers of enrolment cameras) of MPE and the PM-MPE. This includes the number of perspectives involved, the distance between the cameras, the maximum rotational distance between a probe sample with an arbitrary rotational position of the finger and the closest enrolment perspective and the number of comparisons needed for one recognition attempt.

## V. EXPERIMENTS

The experiments are split into two parts: In the first part, the influence of perspective shifts, as explained in section II, is evaluated. The second part analyses the impact of the number of generated pseudo perspectives between two adjacent enrolment perspectives which is described in section IV.

### A. Recognition Tool Chain

The finger vein recognition tool-chain consists of the following components: (1) For *finger region detection* and *finger alignment* an implementation that is based on [20] is used. (2) The *ROI extraction* differs from [20]: instead of cutting out a defined rectangle within the finger, similar to [9], a normalization of the finger to a fixed width is applied. (3) To improve the visibility of the vein pattern *High Frequency Emphasis Filtering* (HFE) [21], *Circular Gabor Filter* (CGF) [22] and simple *CLAHE* (local histogram equalisation) [23] are used during *pre-processing*. (4a) For the simple vein pattern based feature methods, MC and WLD, the binary feature images are compared using a correlation measure, calculated between the input images and in x- and y-direction shifted and rotated versions of the reference image as described in [24]. (4b) The more sophisticated vein pattern based method, ASAVE, applies feature extraction and comparison as proposed in [13], and (4c) the SIFT based approach as described in [17], respectively. An implementation of the recognition tool-chain together with the used configurations and results are available for download on http://www.wavelab.at/sources/Prommegger20a.

### B. Experimental Protocol

For the experiments, the data set is split into tow subsets, one for enrolment and one for authentication. The enrolment subset contains two samples, the subset for authentication three samples. To quantify the performance, the EER, the FMR100 (the lowest FNMR for FMR $\leq$ 1%), the FMR1000 (the lowest FNMR for FMR $\leq$ 0,1%) as well as the ZeroFMR (the lowest FNMR for FMR = 0%) are used. For the evaluation, the experiments follow the test protocol of the FVC2004 [25].

Due to the high number of results generated during the experiments, only the EER values are visualized in the article. The detailed individual results for all performance descriptors for all perspectives and recognition schemes can be downloaded on http://www.wavelab.at/sources/Prommegger20a.

### C. Baseline Results

In order to have a reference for the quantification of MPE and PM-MPE results, the intra-perspective performance (IPP) of all 73 perspectives, without applying any rotation compensation methods and by applying CPN [1], is evaluated. For this calculations every perspective is considered as its own data set, which implies, that every perspective is its own independent classical single perspective recognition system where enrolment and probe image are acquired from the same perspective. As a result of this, rotational differences between the samples due to finger misplacement, i.e. longitudinal finger rotation, are subject to the same degradations as presented in [8]. Although the results of the different perspectives are presented together, they are completely independent from each other. Therefore, no rotational invariance can be concluded from the presentation of the intra-perspective results. As MPE and PM-MPE aim to generate rotation invariant recognition results for a single finger vein image acquired from any perspective during recognition, results close to or even better than the intra-perspective results without rotation correction can be considered as good performance.

### D. Perspective Shifts for Multi-Perspective Enrolment

The idea behind perspective shifts for MPE is to mitigate the prominent performance drops at 90° and 270° for MPE 60° and PM-MPE 60° by separating the two negative impact factors: (1) largest rotational distance to the perspective acquired

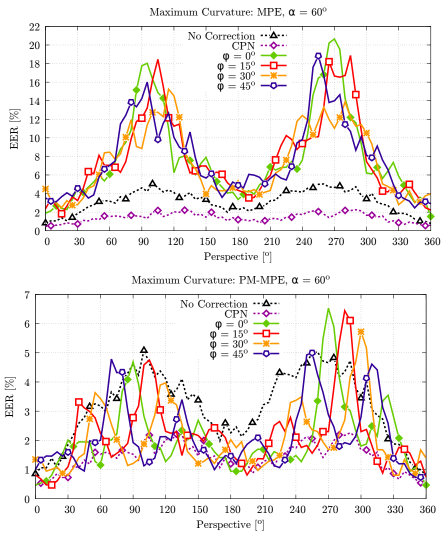


Fig. 3. Performance results (EER) for MPE (top) and PM-MPE (bottom) applying rotational shifts to the enrolment perspectives.

during enrolment and (2) inferior performing perspectives. This separation is achieved by rotating the enrolment cameras by an angle of $\varphi$ (see Fig. 1). The experiments are carried out for MPE 60° and PM-MPE 60° using four different $\varphi$, namely 0° (no shift), 15°, 30° and 45°. With a shift of $\varphi = 30°$ there are enrolment cameras at 90° and 270°. This results in a separation of the two negative factors.

Fig. 3 depicts the results for MPE 60° and PM-MPE 60°. The shift of the enrolment cameras only leads to a shift of performance drop by the same angle $\varphi$, which is particularly evident in the PM-MPE plot (bottom). This indicates that the influence of the distance to the enrolment perspective is greater than that of the inferior perspectives. Prommegger *et al.* showed in [18] that MC cannot compensate longitudinal finger rotation $> 30°$. Considering these results, one can conclude that for MC a rotational distance of $\alpha > 60°$ between enrolment perspectives is not useful.

### *E. Pseudo-Perspectives in Perspective Multiplication for Multi-Perspective Enrolment*

The experiments in this part serve two goals: They analyse (1) the impact of the number of generated pseudo perspectives between two adjacent enrolment perspectives and (2) the applicability of (PM-)MPE to recognition schemes using other features than MC. The schemes used are two simple vein pattern based ones using the well known MC and WLD features and a more sophisticated one, namely ASAVE. In addition, a keypoint based scheme (SIFT) is analysed. The rotational distance between two adjacent enrolment perspectives is $\alpha = 45°$ and 60°. The number of inserted pseudo perspectives between two cameras are 0 (MPE, [1]), 2 (PM-MPE, [2]), 4 (PM2-MPE) and 6 (PM3-MPE, only for $\alpha = 60°$). The latter two have not been applied before.

Fig. 4 shows the performance results (EER) of the vein pattern based methods (note the different scaling of the plots). The simple vein pattern based methods, MC (left column) and WLD (middle), behave similar: For $\alpha = 45°$ (top row), the EERs for MPE follow pretty much the intra-perspective results. They achieve the best results in the palmar region (around 0°) and the dorsal region (around 180°). The EERs inbetween are inferior, hitting its highest values around 90° and 270°. Introducing two pseudo perspectives (PM-MPE) noticeable improves the performance. The perspectives furthest away from the enrolment perspectives exhibit a noticeable performance degradation. These drops in the recognition performance are more prominent for MC and are visible as spikes in the EER curve at e.g. 67.5° and 292.5°. Generating four pseudo perspectives between two adjacent enrolment cameras still improves the performance, but not to the same degree as from MPE to PM-MPE. For $\alpha = 60°$ (bottom row), the performance of MPE delivers worse results than the intra-perspective results. Especially striking is the prominent performance degradation at 90° and 270°. Again, introducing pseudo perspectives improves the recognition results. Similar to MPE 45°, also MPE 60° shows drops in the performance for the perspectives with the maximum distance to the enrolment cameras. PM-MPE outperforms the intra-perspective results except for some regions with a large distance to the enrolment cameras, e.g. for MC at 270° and WLD around 300°. In turn with the results for PM2-MPE 45°, also PM2-MPE 60° shows a slight improvement compared to PM-MPE 60°. Introducing even more pseudo perspectives (PM3-MPE 60°) does not further improve the recognition performance.

When using MPE 45° in combination with ASAVE (left column), the performance is again similar to the intra-perspective results. Introducing pseudo perspectives still improves the results, but not to the same extend as for MC and WLD. The lower performance increase is reasonable as ASAVE has an integrated image alignment based on the vein backbone of the finger vein images. The creation of pseudo perspectives is in principle only an (albeit inaccurate) attempt to better align the images. Since ASAVE has already integrated such an alignment, the potential for improvement is lower. For more information on ASAVE, the interested reader is referred to the original article [13]. At a rotational distance of $\alpha = 60°$ similar results are given, although with slightly higher EERs. For ASAVE also the trend of the intra-perspective comparisons is interesting. Contrary to all other recognition schemes under investigation, the best results are achieved around 45° and 315°

The last studied recognition scheme is a keypoint based system using SIFT descriptors as features. SIFT is, to some degree, invariant against certain variations in the image, e.g. changes in the illumination, and some transformations, e.g. translation, rotation or scaling. Therefore, the introduction of pseudo perspectives should not have an positive effect on the recognition performance of the system. Fig. 5 depicts the trend of SIFT's EER. The achieved EERs for MPE are higher than for the intra-perspective comparisons. For both, $\alpha = 45°$ and 60°, the spikes between the enrolment perspectives are apparent. This is in line with the results of [12] where the authors showed that applying SIFT together with elliptic pattern normalization, which is similar to the used CPN, shows

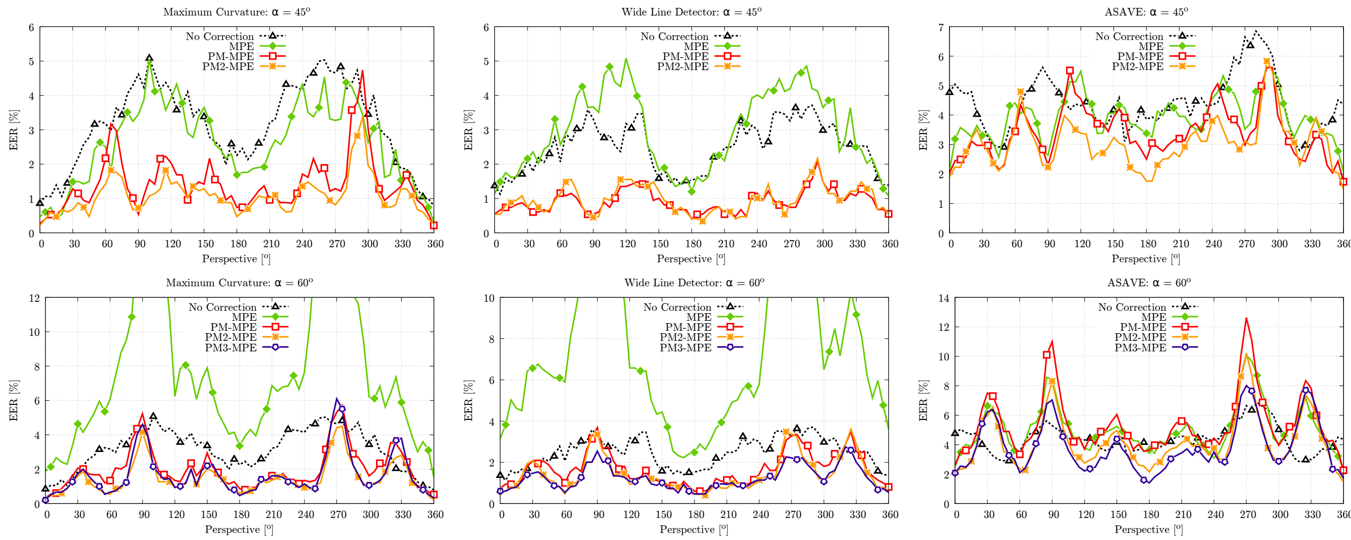


Fig. 4. Performance results (EER) for MC (left), WLD (middle) and ASAVE (right) using different rotational distances between adjacent enrolment perspectives: $\alpha = 45°$ (top), $\alpha = 60°$ (bottom).

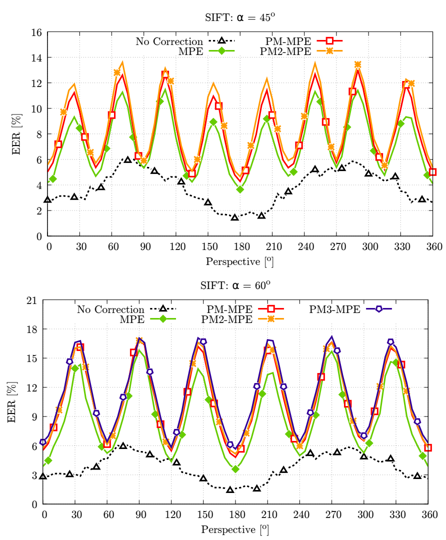


Fig. 5. Performance results (EER) for SIFT applying MPE, PM-MPE, PM2-MPE and PM3-MPE for $\alpha = 45°$ and $60°$.

a higher performance degradation compared to simple vein pattern based systems. It delivers only good recognition rates for rotational distances $< \pm 15°$. The maximum distance for $\alpha = 45°$ and $60°$ is 22.5° and 30°, respectively. This implies that in areas exceeding this 15°, the rotation can no longer be compensated. As expected, the introduction of additional pseudo perspectives does not improve the recognition rates, in contrary, they got slightly worse.

## VI. Conclusion

The analysis of the different recognition schemes in section V-D showed that simple vein pattern based systems benefit most from the insertion of pseudo perspectives. For schemes that have already some kind of image alignment included, the benefit of adding additional perspectives is lower. As already shown in [2], MC benefits from introducing two pseudo perspectives (PM-MPE) between two neighbouring enrolment cameras. Using four additional perspectives (PM2-MPE), results into another slight improvement. Adding more perspectives (PM3-MPE) does not further improve the performance. WLD, the second simple vein pattern based algorithm, shows the same behaviour but with better results for methods using perspective multiplication. For ASAVE, a more sophisticated vein pattern based method, applying MPE also results in rotation invariant recognition results. As ASAVE pre-aligns the images using their vein backbone, introducing pseudo perspectives has not the same impact as for the simple methods MC and WLD.

The last method examined, a SIFT-based approach, does not seem to be suitable for (PM)-MPE. The achieved recognition rates are noticeable worse than those of the intra-perspective comparisons. Furthermore, this approach is more sensitive to longitudinal rotation than vein pattern based methods.

For the analysis of perspective shifts, we changed the camera positions from 0° (original setting from [1] and [2]) to 45° in steps of 15°. The experiments showed that a shift of the enrolment perspectives did not result in an improvement of the recognition performance in regions with a high rotational distance to the enrolment cameras. The performance drop is only shifted with the same angle as the enrolment cameras were rotated. This indicates that the influence of an inferior intra-perspective performance is less than the impact of a large rotational distance to the enrolment cameras. This holds true for both, MPE and PM-MPE. Considering these results along with those of [12], rotational distances of $\alpha > 60°$ between the enrolment perspectives are not useful.

For the analysis of introducing additional pseudo perspectives for PM-MPE, we inserted different numbers of pseudo perspectives between adjacent enrolment cameras. The experiments showed that simple vein pattern based systems benefit most from the insertion of pseudo perspectives. For schemes that have already some kind of image alignment included, the benefit of adding additional perspectives is lower. MC and WLD benefit from introducing two pseudo perspectives (PM-MPE) between two neighboring enrolment cameras. Using four additional perspectives (PM2-MPE) results into another slight improvement. Adding more perspectives (PM3-MPE) does not further improve the performance. ASAVE, a more sophisticated vein pattern based system, still benefits from the use of PM-MPE, the impact of the introduction of additional perspectives is limited. The SIFT-based recognition system does not benefit from the introduction of pseudo perspectives at all.

Adding pseudo perspectives during enrolment introduces computational cost for their generation during enrolment and the additional comparisons for every recognition attempt. With standard applications, enrolment is carried out once while recognition is executed numerous times. Therefore, the additional costs during registration are not so decisive, especially not if it reduces the number of acquired perspectives and thus the cost and complexity of the capturing device. This applies e.g. for PM-MPE 60°: compared to MPE 45° one can save two cameras while achieving similar recognition rates. Compared to MPE the number of comparisons for a recognition attempt are trippled for PM-MPE, quintupled for PM2-MPE and increased by seven times for PM3-MPE. The performance gain for PM-MPE justified this extra effort. When looking at the results of PM2-MPE and PM3-MPE, the extra effort is not justifiable.

In our future work, we aim to further improve the invariance of finger vein recognition with respect to longitudinal finger rotation. We will experiment with different camera settings, e.g. multi perspective enrolment combined with multi perspective authentication. Furthermore, we will try to improve the results for perspective cumulative finger vein templates as proposed in [1].

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