Completely Contactless and Online Finger Knuckle Identification

Zhenyu ZHOU

July 1, 2022

1 Abstract

2 Introduction

Biometrics is the use of the human body's inherent physiological and behavioral characteristics for person identification. For the physiological characteristics, there are many human characteristics such as retina, iris, face, fingerprints and palm prints; as far as the behavioral characteristics, the available features include gait recognition, voice and other behavioral characteristics. As for the finger knuckle, it has also attracted many researchers devoted to it, because it is easier to expose, easier to collect, and it has also been proven to be unique and stable [15].

Many early works on biometric recognition of finger knuckle, ranging from coding-based methods, subspace methods and texture analysis methods to 3D shape patterns based on 3D image reconstruction and different methods have been used to achieve highly accurate recognition results. Most of the current finger knuckle biometric identification systems are based on the contact method.

However, as for the contactless and online finger knuckle identification topic, it is a relatively new field, but should be studied extensively because it is more security and more hygienic, especially now with COVID-19. Although many methods have obtained good recognition accuracy, the finger knuckles are easily deformed under practical application scenarios, and the finger knuckle features will change accordingly. Thus, the matching accuracy will be degraded. Because of the above problems, there are corresponding studies to solve the finger knuckle deformation problem and provide new data sets and new methods [16].

Moreover, in the actual application scenario, the data collected will be affected by various noisy backgrounds, different lighting, various camera focus and resolution, thus affecting the actual real application scenario. Of course, these problems can be solved to some extent. For example, to solve the difference of finger knuckle characteristics due to different lighting when taking pictures, FFT can be used to extract the frequency information from the pictures. For the deformation problem of finger knuckles, one can use adopt to select fixed key points and perform key points matching between corresponding images, use local feature descriptors for these key points to calculate the matching score, and finally, use the average matching score as the final matching score [16]. In conclusion, if we want to perform contactless finger knuckle recognition in a real-world scenario, the most critical problem comes from two aspects: how to efficiently perform finger knuckle segmentation and correction, and the second one is how to match with high accuracy in real-world applications.

3 Our Work

Contactless finger knuckle matching research has not only received much input from researchers, but also there are a large number of different corresponding datasets available. This paper uses the major finger knuckle for contactless biometrics, and between proximal phalange and middle phalange are called major finger knuckle. From the beginning, we have taken the application scenario out of the experimental environment and jumped into the wild, which is a real contactless way in the real scenario. We also created our cross-platform finger knuckle recognition system software, which is no longer an experimental result on data, but a working recognition software. From object detection, ROI extraction to feature extraction, a series of traditional image processing algorithms are replaced by neural networks.

A new finger knuckle object detection algorithm is used, which can automatically extract the region of interest of finger knuckle based on the YOLOv5 [37] model framework and integrates the rotation prediction function of the target object prediction frame. The angle information of the finger knuckle can be obtained. A factor to be considered in the target matching algorithm is the rotation angle of the target object. Suppose the angle information of the target is not known. In that case, it is necessary to match multiple times within 360 degrees in the figure, which is not only time consuming, but also the matching accuracy decreases, so the angle regression based on the horizontal bounding box using CSL [42], which in turn he angle information of the target object can be obtained. It is beneficial to the matching speed and accuracy of the matching algorithm and the automatic target segmentation using the object detection model to extract the ROI region of the major finger knuckle. The feature extraction step is also obtained based on the ResNet neural network model [7], and the matching algorithm uses the pixel-to-pixel minimum variance as the matching score. When calculating the pixel-to-pixel minimum variance, the pixel-to-pixel deviation can be compensated to some extent using pixel panning due to the offset, distortion and even the extraction of the ROI of the finger knuckles. In this paper, we have verified the theory and experimented with the whole process and created a cross-platform GUI based on the Qt Creator platform.

Chapter 2 will explain the public database of finger knuckles, the custom training data for finger knuckle detection models in the wild case, and the training database for feature extraction models. Chapter 3 introduces the finger knuckle detection model and how to implement the detection of finger knuckle angle information. For a complete biometric process, the segmentation is followed by the feature extraction process and the feature matching process, introduced in Chapter 4. Chapter 5 is the software production of finger knuckle recognition by connecting the whole process in series.

4 Contactless Finger Knuckle Segmentation

4.1 Challenges of Finger Knuckle Segmentation

As the most important module of a biometric system, the accuracy of the corresponding segmentation region of interest is crucial and affects the accuracy of the subsequent modules. A suitable ROI segmentation method can effectively improve the efficiency of matching and the accuracy of the matching algorithm. For the efficiency of the matching algorithm, there are two factors that can determine the matching efficiency, one is the size of the region of interest, and the other is the matching angle range. Whether local feature-based or holistic feature-based recognition algorithms, they both operate after the region of interest segmentation. The size of the region of interest should be comparable to the size of the actual target object at the pixel level so that the size obtained after segmentation will not have redundant pixel information, which will reduce the pixel values to be computed for both the extraction and the subsequent matching sessions. Since the target object has an angular rotation problem, the matching process generally requires simultaneous matching in multiple angular ranges, and the number of pixels to be computed increases exponentially. If the algorithm of ROI segmentation is accurate enough and the accuracy of the rotation is also high enough, this will naturally improve the detection efficiency. For the problem of improving the matching accuracy, if the accuracy of the region of interest is high enough, the background interference information extracted will be correspondingly more petite, and the pixel signal of the target object obtained is enough, the signal-to-noise ratio will be high, and the matching accuracy will be improved accordingly.

However, most of the current finger knuckle segmentation approaches are based on contact finger knuckle segmentation. Even for the contactless finger knuckle segmentation problem, their [16], [2] approach is to fix the finger knuckle position in the image when taking the finger knuckle data, and if the finger appears in the image in a different position or if there are multiple fingers, the problem of not detecting the finger knuckle or missing the finger knuckle is likely to occur. This segmentation is prone to errors, and this is not the only problem. Most importantly, the traditional segmentation algorithm cannot correctly segment the finger knuckles in the presence of complex background interference, multiple finger knuckles in the same field of view, obscured finger knuckles or bent finger knuckles. Since the subsequent operations of the finger knuckle recognition algorithm are based on the segmented image, the segmentation of finger knuckles affects the accuracy of finger knuckle recognition. It is vital to improving the efficiency of segmenting the finger knuckle region in any scenario.

5 Contactless Finger Knuckle Detection

This paper studies the finger knuckle region and uses the corresponding finger knuckle crease patterns as features of the finger knuckles. So the region of interest to be extracted is the part that can represent the skin crease patterns on the back of the finger. As mentioned in Section 3.1, it is difficult to use traditional object segmentation methods to automatically segment finger knuckles for applications such as in the wild. Even though there have been corresponding conventional algorithms implemented to automatically segment the finger knuckle region independent of the finger knuckle position pose [16], the method used in this paper requires fixing the position of the finger knuckles appearing in the image and is a Fixed ROI extraction.

In order to solve the problem of finger knuckle detection in the real world, this paper chooses to use neural network models instead of traditional segmentation algorithms. Models of neural network models for object detection have achieved great success, whether it is the sliding window detection algorithm, the 2-stage series of R-CNN models [6], [5], [26], or the 1-stage YOLO series [25], [23], [24], [1] and SSD models [17] up to the current position, and even the anchor-free based object detection algorithm [40] as well. Each of these models has its advantages. For the 2-stage model, the object detection accuracy is guaranteed, the 1-stage based model is a speedup based on the positive accuracy, and the anchor-free is a further improvement in the detection speed. In this paper, the latest version of the YOLO model series, YOLOv5 [37], is used as the network model for finger knuckle detection because the YOLO series is famous for its fast detection speed and high accuracy. The module adopts various latest network modules, and the YOLOv5 model has a variety of model structures to meet different accuracy and speed requirements. For the YOLOv5 model, the number of layers of each submodule is varied to cope with different speed and accuracy requirements, while the overall structural component modules remain unchanged. The YOLOv5 neural network model used as a finger knuckle detection has good results in the wild, the prediction bounding boxes of YOLOv5 are based on a horizontal bounding box for regression.

Although the results have been good for finger knuckle detection, they are not sufficient for the segmentation operation of finger knuckles. There are two main problems for rotating finger knuckles segmentation. The first problem is that when the horizontal bounding box is used to predict the object, the size of the bounding box is a minimum external horizontal rectangle for the size of the object. In such a case, when there is a rotation of the object, which is not horizontal for the picture, the horizontal box will have much more background for the detected object, and in the case that the target object is crowded, it is easy to eliminate the neighbouring of the horizontal bounding boxes are eliminated. As shown in Figure **??** (a), due to the rotation of the finger and the density of the finger, the prediction bounding box of the middle finger knuckle and the major finger knuckle of the ring finger have overlapped, so it is easy to be deleted during the non-max suppressing process, even if CIOU [47] or DCOU [48] is used. As shown in Figure **??** (b), after changing the threshold of IOU in the non-max suppressing process, the major finger knuckle of the ring finger is not detected.

The second problem is that for the segmentation operation if the horizontal box is used directly to carry out the segmentation operation, it is the same as shown in Figure **??** (c)-(i), which is the region of interest of the finger knuckle corresponding to the segmentation in Figure **??** (a). However, the segmentation to the background interference has a lot, and it is not considered a good finger knuckle segmentation operation. In order to solve the above problem, a rotated prediction bounding box was then used to deal with the background region minimally while predicting the target object's position, and the rotated bounding box could be used as the orientation detection finger knuckle. The subsequent finger knuckle matching process also needs to use the finger knuckle orientation information for the correction operation.

6 Contactless Finger Knuckle Recognition

7 Background of Finger Knuckle Recognition

The finger knuckle recognition algorithm has attracted much attention and input from researchers, from 2D to 3D. As a result, the corresponding algorithms have achieved high accuracy and efficiency and have been able to cope with differences in finger knuckle features due to ambient light and slight deformation of the finger knuckles. These feature extraction algorithms have been able to extract fairly robust features. These methods use different feature description operators for different feature extraction methods, so the corresponding matching methods also vary. Even a combination of multiple matching methods can be used to enhance the high accuracy of the matching results, such as using both 2D images and 3D images reconstructed from 2D images for extracting finger knuckle features and matching for finger knuckle recognition [3].

There are generally two main types of recognition algorithms for recognition algorithms: one is holistic-based, and the other is local feature-based. For holistic-based, the entire image information in the ROI region is used, and for local feature-based, in short, the domain feature information of the pixels is used. The broad category can be divided into subspace and spectral representation methods for holistic-based [41], [22], [20]. Sub-space methods are generally used for data dimensionality reduction and noise reduction [44], such as the use of principal component analysis to reduce the dimensionality of multidimensional data. In contrast to spectral representation methods, image space transformation can be performed as well as image feature enhancement and correlation coefficients for feature extraction [9]. For example, using the Fourier transform to transform the image from the spatial domain to frequency domain information can process frequency information that cannot be processed in the spatial domain.

For global information, algorithms exist relatively for processing local features, which are called local feature-based approaches. For the processing of local information, there are many algorithms, including, for example, extracting information about the gradient of the image edges, obtaining the boundary points, using other edge extraction algorithms such as Hough change. There are also coding-based methods and texture description methods. According to this classification, the method used in this paper uses local feature-based methods and is inspired by coding-based methods for extraction and matching methods. For example, a 1D log-Gabor filter was used to extract the finger knuckles' features and for the matching phase, the hamming distance was used here for the matching score calculation since it is a local feature-based method [21]. Alternatively, a 2D Gabor filter is used to extract the domain orientation information features of the finger knuckles, and an angular distance calculation is used to calculate the similarity between the different features for the matching score [19]. High recognition accuracy has been achieved for these matching algorithms, even up to 98.67% [41].

8 Contactless Finger Knuckle Feature Recognition Based on Deep Neural Network

Although good accuracy has been achieved for finger knuckle recognition algorithms, as mentioned at the beginning of the paper, they have some limitations for real contactless or real application scenarios. For example, they cannot cope with various complex or contactless sampling scenarios, or they cannot cope with changes in finger knuckle characteristics due to environmental changes, resulting in poor matching accuracy. However, there is no lack of research on contactless scenes. For example, there has been a study to deal with the deformation problem caused by knuckle bending in contactless scenes, and the paper [16] first matches on two images for a selected fixed number $32 * 32$ of point pairs for coping with the deformation problem and then uses local feature descriptors on each point pair for matching. Even early work considered application scenario using cell phones for finger knuckle recognition [2], but for finger knuckle segmentation using fixed finger position in the centre of the image is not very convenient for the user, for recognition phase log-Gabor is used for feature extraction, and Hamming distance is used for matching.

How to efficiently perform finger knuckle matching, as the various matching algorithms presented in the previous paper, we can use to the application scenario of this paper. However, these algorithms have a source of a problem that these algorithms have to keep changing their corresponding filters and even the corresponding detection parameters under the actual application scenario, or a slight change of the scenario [46]. The contactless matching accuracy will be degraded for the contactless scenario if the finger knuckle recognition algorithm verified in the contactless scenario is used directly.

9 Matching Contactless Finger Knuckle

One of our contributions is the online finger knuckle identification. In this kind of situation, we choose the Residual Feature Network (RFNet) [18] as our feature extraction backbone, because the model not only is lightweight enough, but it achieves state-of-the-art performance on the palmprint dataset. Meanwhile, the paper [18] uses the soft-shifted triplet loss function, called SSTL to train the model and matching two features for dealing with translation problem. However, in generally, feature maps of the same class will not only just shift along two axes, but also will have local deformable transformation. For solving it, we propose a new loss and also a new matching method, called translation and rotation triplet loss function (TRTL). With the TRTL, the feature maps can be translated along the x-axis and y-axis, and can be rotated clockwise and counterclockwise. Then we will get the minimal value after translation and rotation as the similarity scores.

9.1 Translated and Rotated Triplet Loss Function

As for a new loss function, the most important point is whether it can be differentiable. With a differentiable loss, the back propagation process can proceed smoothly, and the learnable parameters can be updated to get the minimal loss. In this section, we will discuss the derivation of the TRTL loss function. Because our neural networks were trained using the architecture of triplet network [28], we used TRTL as loss function to update convolutional kernel of our models.

In generally, the TRTLoss is still a variant of triple loss, so that the TRTLoss can be written as a format of triple loss function as the Equation 1. As for the N, it means the batch size during training iteration, and $T(I^a)$ is the output template of input anchor image I^a through neural network. The hard margin parameter m can determine the distance between different class cluster by pushing them away during training process.

$$TRTL = \frac{1}{N}\sum_{i}^{N}[L(T(I_i^a), T(I_i^p)) - L(T(I_i^a), T(I_i^n)) + m]_+ \tag{1}$$

In order to adapt to tasks with different degrees of deformation, and balance performance and speed, we set translation and rotation ranges as a hyperparameter. The $L(T_1, T_2)$ will get the minimal distance of two templates $D_{w,h,\theta}(T_1, T_2)$ after translation and rotation in the range $-W{\le}w{\le}W$, $-H{\le}h{\le}H$, $-\Theta{\le}\theta{\le}\Theta$, called minimal translation and rotation distance (MTRD). Meanwhile, the distance $D_{w,h,\theta}(T_1, T_2)$ calculates the pixel-wise MSE value when template T_1 is translated w pixel along x-axis and h pixel along y-axis and rotated θ angle in the Equation 3.

$$L(T_1, T_2) = \underset{-W\le w\le W, -H\le h\le H, -\Theta\le\theta\le\Theta}{min} D_{w,h,\theta}(T_1, T_2) \tag{2}$$

$$D_{w,h,\theta}(T_1, T_2) = \frac{1}{|C_{w,h,\theta}|}\sum_{(x,y)\in C_{w,h,\theta}} (T_1^{(w,h,\theta)}[x, y] - T_2[x, y])^2 \tag{3}$$

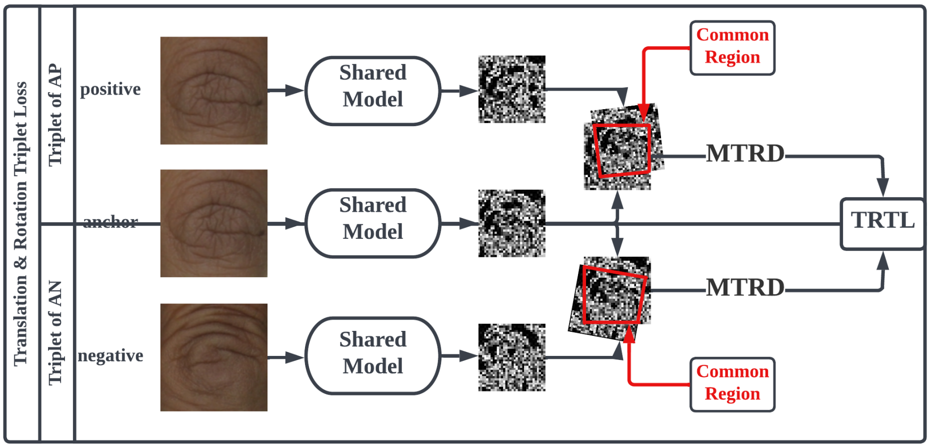


Figure 1: An overview of how to use our translation and rotation triplet loss function (TRTL) to train the triplet neural network. We will use the minimal translation and rotation distance (MTRD) to calculate the similarity of two output templates, the common region is the red box after shifting and rotating. During matching process instead of training process, we also use the MTRD to calculate matching scores.

In terms of $C_{w,h,\theta}$, it represents the common region between two templates after one template shifted along x-axis with w, shifted along y-axis with h, and rotated with θ, as showed in the Figure 1. As for the (T_a, T_p) pair, we can assume when the T_a is rotated angle of θ_{ap} and shifted with (w_{ap}, h_{ap}) pixels can get the minimal $D_{w_{ap},h_{ap},\theta_{ap}}(T_a, T_p)$, then $L(T_a, T_p) = D_{w_{ap},h_{ap},\theta_{ap}}(T_a, T_p)$. Meanwhile, with the $(w_{an}, h_{an}, \theta_{an})$, the (T_a, T_n) pair can get the minimal $D_{w_{an},h_{an},\theta_{an}}(T_a, T_m)$.

$$\frac{\partial Loss}{\partial T_i^p} = \begin{cases} 0, if(x, y) \notin C_{w_{ap},h_{ap},\theta_{ap}} \; or \; Loss = 0 \\ \frac{-2(T_i^a[[x_{w_{ap}}, y_{h_{ap}}]*M(\theta_{ap})]-T_i^p[x,y])}{N|C_{w_{ap},h_{ap},\theta_{ap}}|}, otherwise \end{cases} \tag{4}$$

The $M(\theta_{ap})$ is the rotation matrix.

$$\frac{\partial Loss}{\partial T_i^n} = \begin{cases} 0, if(x,y) \notin C_{w_{an},h_{an},\theta_{an}} \; or \; Loss = 0 \\ \frac{-2(T_i^a[[x_{w_{an}},y_{h_{an}}]*M(\theta_{an})]-T_i^n[x,y])}{N|C_{w_{an},h_{an},a_{an}}|}, otherwise \end{cases} \tag{5}$$

As for the $T_i^a[x,y]$ derivation, because we shift and rotate the anchor in the above formula, we can inversely shift and rotate the positive and negative input feature.

$$\begin{aligned} \frac{\partial Loss}{\partial T_i^a[x,y]} = -\frac{\partial Loss}{\partial T_i^p[[x-w_{ap},y-h_{ap}]*M(-\theta_{ap})]} + \\ \frac{\partial Loss}{\partial T_i^n[[x-w_{an},y-h_{an}]*M(-\theta_{an})]} \end{aligned} \tag{6}$$

10 Experiments and Results

We choose the baseline model is the RFNet [18], its performance can outperform DenseNet-BC [11], CompCode [13], DoN [46], Ordinal Code [30], and RLOC [12] algorithms on the palmprint verification problem. For proving TRTL loss function performance, we will compare its performance with Soft-Shift Triplet (STTL)[18] loss function on different public finger knuckle database based on the RFNet [18]. With TRTL loss function, the RFNet is represented by RFNet-TRTL, on the country, RFNet-STTL represents with STTL loss function. Compare to convolution layer or dilated convolution [43], the deformable convolution [49] can solve local deformable by sampling different location and different weight. We also replace the RFNet convolution layer with deformable convolution layer called DeConvRFNet. As for the RFNet and DeConvRFNet, we will firstly pretrain on the HKPolyU Finger Knuckle Images Database (V1.0) [33] as the pretrained weights.

Meanwhile, we will also compare with the FKNet [4] which get the state-of-the-art performance on 3D finger knuckle identification, and EfficientNetV2-S [31]. FKNet performance on the 3D finger knuckle database, 2D finger knuckle and even palmprint database can over SGD [3], CR_L1_DALM, CR_L2 [45], ResNet-50 [7], VGG-16 [29], AlexNet [14], DenseNet-121 [11], and SE-ResNet-50 [10]. Both of FKNet and EfficientNetV2-S are classification neural network. As a classification neural network, it commonly has a problem when the number of classes of testing dataset is not as same as the training set classes, result in fine-tuning on the testing set. Therefore, we use the vector before soft-max layer as the feature vector, and then calculate the MSE of two feature vectors as the similarity score during matching finger knuckle. We use the ResNet-50 pretrained weights as the FKNet initial weights, and use the pretrained weights on the ImageNet21K as the initial weights of EfficientNetV2-S.

We also want to show the performance of TRTL and SSTL on the EfficientNetV2-S model, therefore we keep the same architecture and just change the FC layer of the head part with convolution layer for fitting TRTL and STTL. The changed EfficientNetV2-S model with TRTL called EfficientNetV2-S-TRTL, and with STTL called EfficientNetV2-S-STTL. As same as the EfficientNetV2-S model, we also use the pretrained model weights on the ImageNet21K dataset. In generally, public finger knuckle database already offer segmented finger knuckle images, but we use our YOLOv5-CSL model to segment finger knuckle as our training and testing data during our experiment.

10.1 Model Complexity Analysis

As a completely contactless and online finger knuckle identification, we must choose a model that can meet the requirements of matching speed while ensuring matching accuracy, and even sacrifice matching accuracy for a certain matching speed. We have listed learnable weights of each model, and the corresponding feature extraction time and matching time on the Table 1.

Model	Prams (M)	Input Size	Template Size	FLOPs (B)	Feature Extraction (s)	Matching (s)
DeConvRFNet-STTL	0.36M	128x128	32x32	1.29B		
DeConvRFNet-TRTL	0.36M	128x128	32x32	1.29B		
EfficientNetV2-S [31]	20.18M	300x300	classes	5.40B		
EfficientNetV2-S-STTL	20.00M	300x300	9x9	5.38B		
EfficientNetV2-S-TRTL	20.00M	300x300	9x9	5.38B		
FKNet [4]	7.28M	96x64	classes	0.28B		
RFNet-STTL [18]	0.46M	128x128	32x32	1.39B	0.0062s	0.049s
RFNet-TRTL	0.46M	128x128	32x32	1.39B	0.0062s	

Table 1: Comparison time and space complexity of different neural network. Time complexity is the average time of 10k images on the Ubuntu 22.04 with GeForce RTX 2080 GPU. When the template size is classes, it means the training set classes number.

......

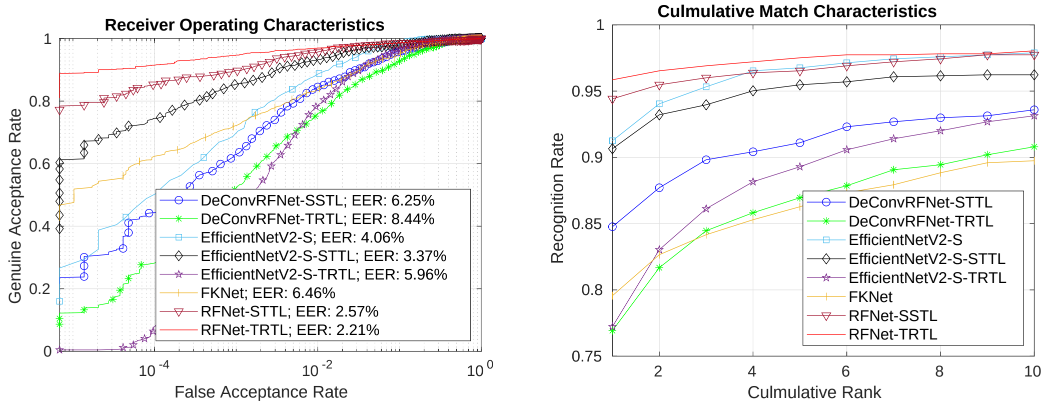
10.2 Within Database Performance Evaluation

10.2.1 Contactless Finger Knuckle Image Database (Version 3.0)

The finger knuckle database [34] can offer contactless finger knuckle of 221 subjects, but only 104 subjects have second session samples. For each session, each subject can offer 6 samples. It is worth mentioning that the finger knuckle sample provided by this database is more challenging and closer to real world scenarios, because the finger knuckle will bend from 0 to 90 degree result in crease deformation.

One-Session Protocol

As for the one-session protocol, I firstly fine-tuned models on the second session 104 subjects dataset, totally $104 * 6 = 624$ images as the testing set. Then use the first session 221 subjects as the testing set result in $221 * 6 = 1326$ genuine matching scores and $221 * 220 * 6 = 291720$ imposter matching scores. From the Figure 2, we can easily find the RFNet is the best model not only on the ROC but also on the CMC. In terms of the baseline model RFNet, our loss function TRTL can improve the matching accuracy when compare to the STTL loss function. Although the finger knuckle of the database with deformation while bend from 0 to 90 degree, the EER of the RFNet-TRTL can arrive at 2.21%. And as top-2 ranking, the RFNet-TRTL recognition rate is about 0.97 on the CMC. As for the rest model, EfficientNetV2-S model performance is better than FKNet and DeConvRFNet. From the performance result, if we just change the convolution layer with deformable convolution, it cannot overcome finger knuckle deformation, even the performance is dropped.

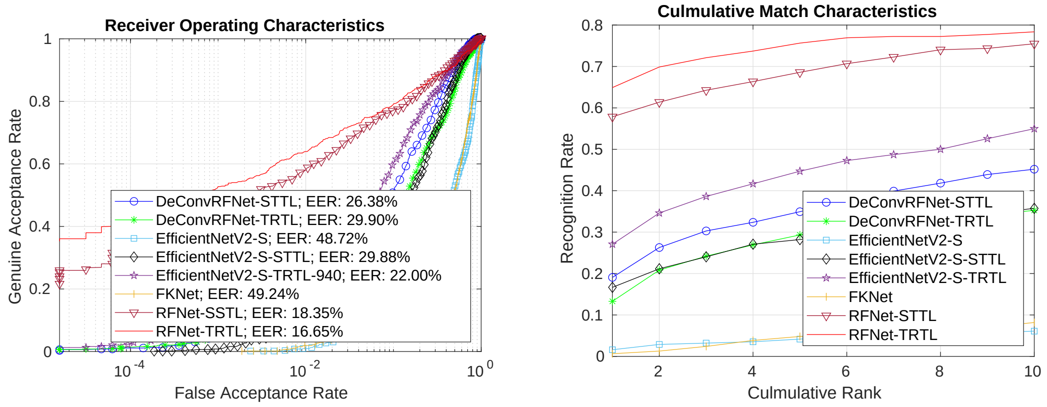


(a) (b)

Figure 2: Comparative ROC (a) and corresponding CMC (b) for one-session on the contactless finger knuckle image database [34].

Two-Session Protocol

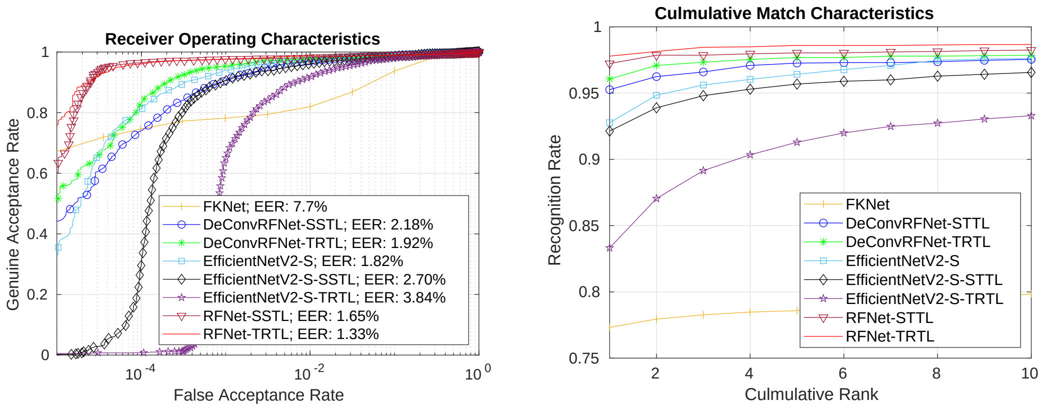
We fine-tune models on the first session subjects who don't provide second session samples, and use two-session protocol to evaluate my model performance on the first session subjects who can offer two-session data. In totally, it will generate $104 * 6 = 624$ genuine scores, and $104 * 103 * 6$ imposter scores. Just like said before, the FKNet and EfficientNetV2-S are classification networks, we use output feature vector to calculate MSE as the matching score. Because the degree of deformation vary on the two-session data, the verification and identification scenarios is more complexity than one-session protocol. Due to these factors, the accuracy on the two-session protocol is much lower than the one-session protocol. However, the RFNet is still the best model, even its EER is half of the EER of other models. Meanwhile, our TRTL loss function still work better than the STTL loss function, with 16.65% and 18.35% respectively on the ROC. As for the CMC, when the cumulative rank value is 2, recognition rate of RFNet-TRTL can arrive at 0.7. From the ROC and CMC Figure 3, we can also get that the STTL and TRTL triplet loss function are better than classification task, because the FKNet and EfficientNetV2-S have the lowest accuracy.



(a) (b)

Figure 3: Comparative ROC (a) and corresponding CMC (b) for two-session on the contactless finger knuckle image database [34].

10.2.2 Index Finger Knuckle of Contactless Hand Dorsal Image Database



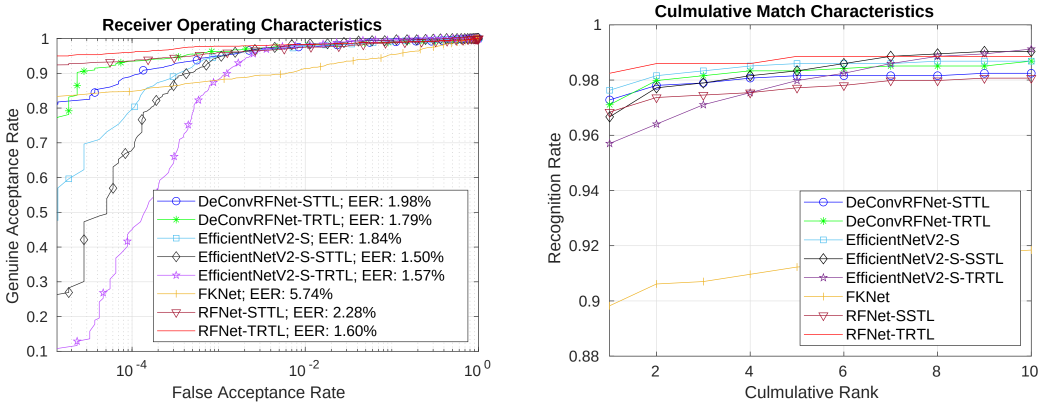
(a) (b)

Figure 4: Comparative ROC (a) and corresponding CMC (b) for one-session on the contactless hand dorsal image database [35].

As for the experiment, the dataset [35] totally contains 712 subjects, and each subject have 5 finger knuckle samples. And we fine-tuned our models on the first sample of each subject, and then use the rest four sample as the testing dataset. For protocol on the database, we use protocol as same as protocol of the FKNet [4]. At the evaluation process, it has $712 * 4 = 2848$ genuine matching scores, and has $712 * 711 * 4 = 2024928$ imposter matching scores. The performance of RFNet-TRTL and RFNet-STTL is similar, but the RFNet-TRTL is slightly better than RFNet-STTL depend on the EER value on ROC. And on the CMC, the RFNet-TRTL still get the best accuracy. We can notice that the FKNet get the worst result when compare to other models. The EfficientNetV2-S model is still better than the FKNet, because EfficientNetV2-S is deeper than FKNet with MBConv block. MBConv block is more robust than the original residual block.

10.2.3 2D Forefinger of 3D Finger Knuckle Database

The HKPolyU 3D Finger Knuckle Images Database [32] can offer reliable 3D finger knuckle pattern (surface normal vector, depth, or curvature) from 2D finger knuckle images, therefore we use its 2D images as our evaluation database. 190 subjects of the database have two-session finger knuckle samples, and 38 subjects offer one-session images. In this kind of situation, two-session protocol is not fit on the database, then we use one-session protocol to evaluate performance. We use the first session 190 subjects images to fine-tune models and then to test on the second session 190 subjects. It has $190 * 6 = 1140$ genuine matching scores and $190 * 189 * 6 = 215460$ imposter matching scores. From the ROC and CMC, we can get a conclusion that the performance of RFNet, DeConvRFNet, and EfficientNetV2-S are similar. However, the FKNet is still the worst one, which EER is 5.74% and the CMC is lower than others. The unchanged thing is that the RFNet with TRTL loss still get the best performance with 1.60% EER, even for the recognition rate on the CMC.



(a) (b)

Figure 5: Comparative ROC (a) and corresponding CMC (b) for one-session on the 3D finger knuckle database[32].

10.3 Cross Database Performance Evaluation

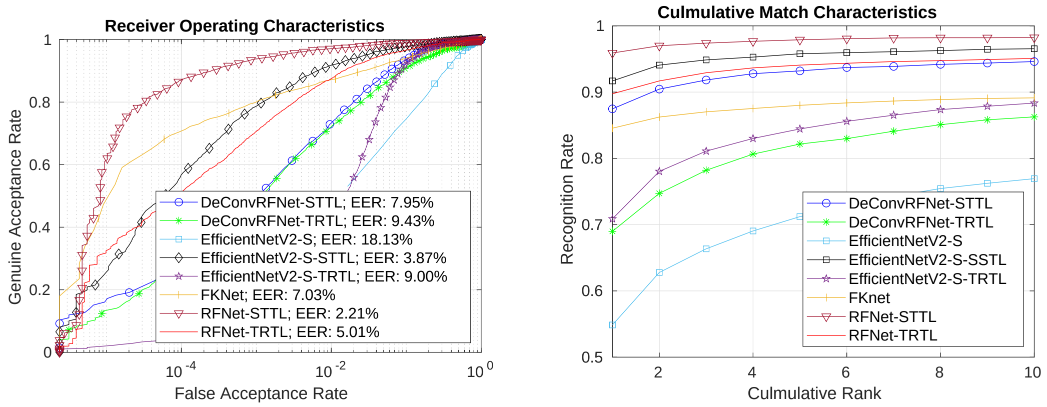
From the within database experiment, we can clearly get a conclusion that the TRTL loss function can increase the performance compare to the STTL loss function, and the RFNet is better than the DeConvRFNet, EfficientNetV2-S, and FKNet. Meanwhile, the FKNet performance is the worst one. In this section, we will compare these models' performance on the cross database experiment. For these cross database experiment, it can get the generalization ability of neural network, because these data can be regard as unseen data.

As for the cross database experiment, I firstly pre-trained our models on the Finger Knuckle Images Database V1, and then fine-tuned models on the Finger Knuckle Images Database V3 (with deformation). In the next step, we use our models to test all the finger knuckle of the Hand Dorsal Images Database and the Tsinghua Finger Vein and Finger Dorsal Texture Database (THU-FVFDT3) [36]. Although the THU-FVFDT3 database can offer two-session samples with interval several seconds, but strictly speaking, it is not two-session database. Therefore, I just use the training set of the database (THU-FVFDT-FDT3_Train) as our evaluation dataset.

10.3.1 Hand Dorsal Images Database

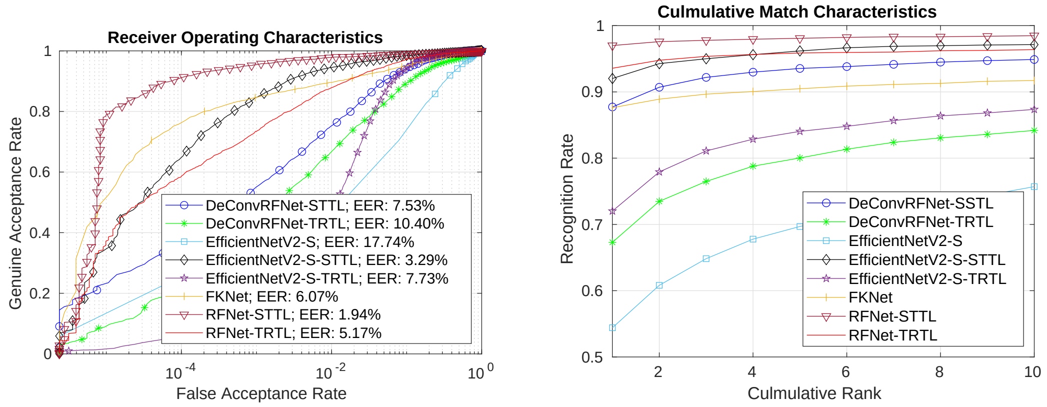
Index Finger Knuckle and Middle Finger Knuckle

The database totally has 712 subjects, and each subject has 5 samples of hand dorsal image. Therefore, it will have $712 * 5 = 3560$ genuine matching scores and $712 * 711 * 5 = 2531160$ imposter matching scores for index and middle finger knuckle. Figure 6 is the performance result on the index finger, and Figure 7 is the performance result on the middle finger knuckle. From Figure 6 and Figure 7, all models' cross database performance is similar on the database regardless which finger. We should also notice that STTL is better than TRTL on the cross database experiment, while within database, the TRTL is better than STTL. It shows that the generalization ability of TRTL is not better than STTL to some extent. However, the RFNet-STTL outperform the rest models depend on the ROC and CMC. Even better than FKNet and EfficientNetV2-S, both of them are classification models.



(a) (b)

Figure 6: Comparative ROC (a) and corresponding CMC (b) for one-session of the index finger knuckle on the contactless hand dorsal image database [35].



(a) (b)

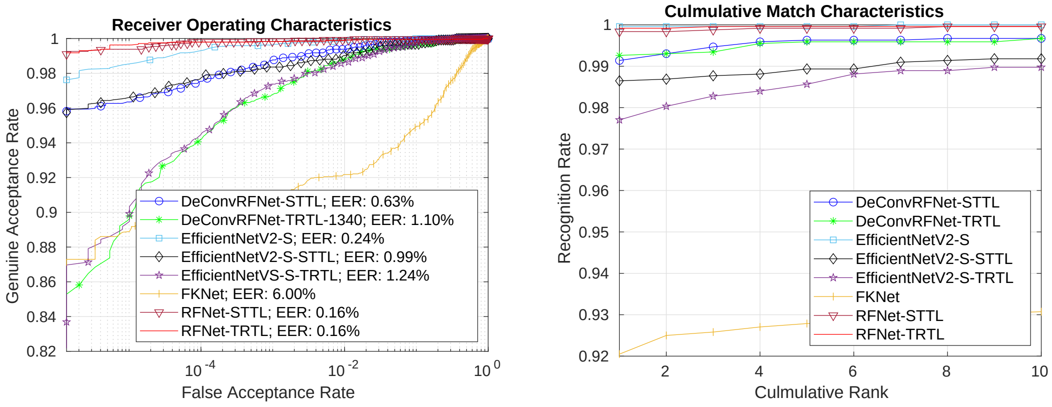
Figure 7: Comparative ROC (a) and corresponding CMC (b) for one-session of the middle finger knuckle on the contactless hand dorsal image database [35].

10.3.2 Tsinghua Finger Vein and Finger Dorsal Texture Database

The database [36] has 610 subjects, and each subject can offer 4 samples. From the finger dorsal texture images, we can use our YOLOv5-CSL model to segment finger knuckle images as our testing set. Then as the cross database experiment, it will have $610 * 4 = 2440$ genuine matching scores and $610 * 609 * 4 = 1485960$ imposter matching scores. In this database, all models can get very high matching performance from the Figure 8, even the worst FKNet can arrive at 6.00% EER on the database. The RFNet with TRTL and STTL get the same accuracy, in terms of the CMC, the recognition rate almost arrive at 100%.

10.4 3D Finger Knuckle Images Database

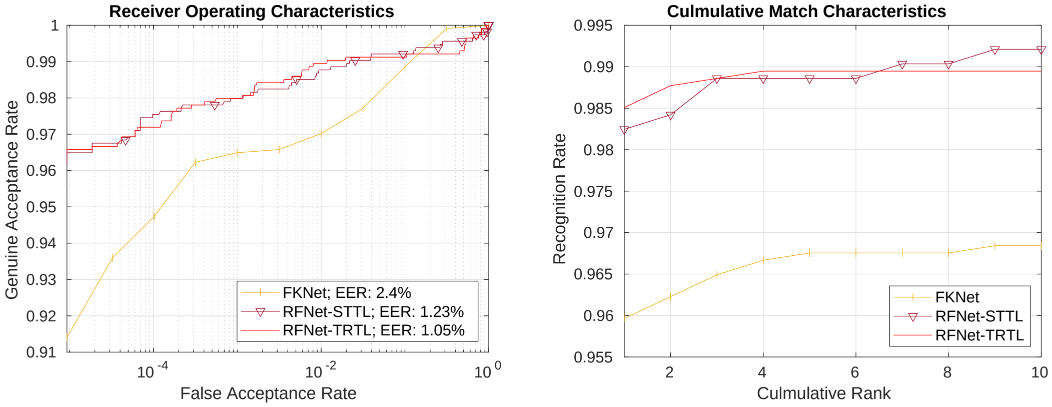
The 3D finger knuckle images database [32] can offer robust 3D information which can be invariant to changed illuminations, for example, the depth information of the crease of finger knuckle. With the 3D finger knuckle database, the FKNet is the state-of-the-art. Meanwhile, RFNet with TRTL loss function can get the best performance on the within database experiments



(a) (b)

Figure 8: Comparative ROC (a) and corresponding CMC (b) for one-session of the finger dorsal texture images [36].

and cross database experiments when compare to the FKNet on the 2D finger knuckle database. Therefore, we compare the RFNet with FKNet on the database to show the identification performance on 3D finger knuckle database. As for the protocol, it will generate $190 * 6 = 1140$ genuine matching scores, and $190 * 189 * 6 = 215,460$ imposter matching scores from matching matrix. From the Figure 9, RFNet-TRTL still can get the best performance for finger knuckle verification and identification. Form the ROC curve, the EER of the RFNet-TRTL can increase to 1.05% while the EER of the FKNet is 2.4%. Not only on the 2D finger knuckle database, but also on the 3D finger knuckle database, the RFNet-TRTL can outperform the state-of-the-art results.



(a) (b)

Figure 9: Comparative ROC (a) and corresponding CMC (b) for one-session of the 3D finger knuckle database [32].

10.5 Discussion

We have compared the identification performance of RFNet with EfficientNetV2-S, DeConvRFNet, and FKNet on the 2D and 3D finger knuckle database, and on the within database and cross database experiments. Due to deeply learned residual features of the RFNet which have already outperformed the state-of-the-art results on the palmprint, it still can get the best performance on the finger knuckle crease when compare to the rest models from above experiment results. Because finger knuckle is very prone to flexing, causing crease texture distortion, if just shift the template, it cannot solve the deformation problem with rotation. Therefore, we design our new TRTL to further solve the problem. With our TRTL loss function when train RFNet and MTRD when matching finger knuckle, the RFNet can increase matching accuracy regardless on the ROC and CMC based on the STTL. Especially on the Finger Knuckle Images Database (Version 3.0) which offer bending finger knuckle with complexity deformation, RFNet-TRTL improved performance is relatively more compare to other database from the Figure 2 and Figure 3. Two-session protocol is more complexity because of changing finger knuckle crease and more complexity deformation when matching process. Form the Figure 3 (a) ROC and (b) CMC, our TRTL with RFNet get the best matching and recognition performance. Meanwhile, our TRTL not only work on the RFNet, but also can work on the DeConvRFNet from the Figure 4 and Figure 5, with TRTL loss function, the matching and recognition performance also can increase.

From these experiment results, we can also get a conclusion is that EfficientV2-S model is better than FKNet from the within database experiment, and even on the Tsinghua finger knuckle database. EfficientNetV2 model can outperform the ResNet on the ImageNet [27], in other words, the EfficientNetV2 model can extract robust feature than ResNet on the ImageNet. Because EfficientNetV2 replace the residual block with inverted residual block, and use MBConv as a block unit. As for MBConv block, it uses depth-wise convolutions to decrease training weights and use Squeeze-Excited block as channel attention. Meanwhile, the depth of EfficientNetV2-S is deeper than the FKNet. On the contrary, the FKNet use the ResNet-50 fist conv3 as the feature extract model. EfficientNetV2 use the more light, advance and efficient module than ResNet.

However, TRTL generalization ability is lower than STTL loss from the cross database experiment, except on the Tsinghua database. On the cross hand dorsal database, Figure 6 and 7, EER of RFNet with TRTL performance will drop from about 2.0% to 5.0%. As for the rest model, performance with TRTL also drop with corresponding value when compare to STTL. But in the within database experiment, these model with TRTL loss is better than STTL loss. It shows our TRTL can affect the back propagation during training process to the different model weights, in other words. And another phenomenon is that EfficientNetV2-S with SSTL and TRTL cannot work. From the Table 1, if the input image size is 300x300, EfficientNetV2-S with STTL and TRTL will output 9x9 template size. The output feature size is too small when use the STTL and TRTL loss function, inversely, the performance will drop while translation and rotation.

10.6 Ablation Study

From

....

11 Online Contactless Finger Knuckle Identification

With TRTL loss, the RFNet [18] can outperform state-of-the-art methods. In the previous section, we have estimated its verification and identification performance on different public finger knuckle database, including within-db and cross-db experiments. As for a completely contactless and online finger knuckle identification, the finger knuckle detector is a very important module for automatically detect and segment finger knuckle region. However, as for traditional segmentation algorithm, they cannot correctly segment the finger knuckles in the presence of complex background interference, multiple finger knuckles in the same field of view, obscured finger knuckles or bent finger knuckles. Meanwhile, as for neural network, the current based on YOLO [25], [23], [24], [1], [37] and R-CNN [6], [5], [26], [8] series object detection and segmentation approaches cannot simultaneously obtain the angle of finger knuckle and the segmentation with high precision. Especially, the angle of the finger knuckle is a vital factor for identification. If we can get the angle of finger knuckle, we can use angle information to align two feature maps for increasing matching accuracy and efficiency. For solving above problems, we propose rotated bounding box detection based on YOLOv5 model for segmenting and getting angle information.

11.1 Contactless Finger Knuckle Detection

11.1.1 Rotated Bounding Box Based on YOLOv5

In order to solve the problem of finger knuckle detection in the real world, we choose to use YOLOv5 model because the YOLO series is famous for its fast detection speed and high accuracy. Especially, the YOLOv5's [37] speed can meet our online detection requirements.

Rotated Bounding Box

However, the YOLOv5 just detect horizontal bounding boxes which cannot offer angle information and will segment a lot of background information. In order to solve these above problem, a rotated bounding box will be predicted instead of horizontal bounding box. As analyzed in this paper [42], the rotated bounding boxes loss will mainly come from angular periodicity and the exchangeability of edges. When use the long side definition of rotated bounding box, it can deal with the exchangeability of edges problem. Meanwhile, using classification task to predict angle can make model easier to train. A periodic coding method called Circular Smooth Label (CSL) [42] soft coding can also solve the problem that One-Hot cannot distinguish class relationship. Formula 7 $g(x)$ is the window function to smooth One-Hot label, and r is a window function of the radius.

$$CSL(x) = \begin{cases} g(x), & \theta - r < x < r + \theta \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

Furthermore, in this paper, we used the Gaussian function for the Equation 7 window function, a commonly available function, and used a window radius of 6 to smooth the labels.

Loss function

The original YOLOv5 loss function can have three components. The formula can be simply written as $Loss = CIOU\_Loss + Loss_{conf} + Loss_{class}$. Since the rotated bounding box is based on the modification of YOLOv5, only the angle classification loss is added more. So the total loss function is as expressed in Equation 8, with the addition of $Loss_{angle}$ to YOLOv5 loss function.

$$Loss = CIOU\_Loss + Loss_{conf} + Loss_{class} + Loss_{angle} \tag{8}$$

$$\begin{aligned} Loss_{angle} = \sum_{i=0}^{S^2} I_{ij}^{obj} \sum_{a \in [0,180)} [\hat{P_i(a)} log(P_i(a)) + \\ (1 - \hat{P_i(a)}) log(1 - P_i(a))] \end{aligned} \tag{9}$$

11.1.2 Contactless Finger Knuckle Dataset

Our task is to detect finger knuckles in the contactless and online scenario, but by understanding current public finger knuckle database, their data are collected at specific conditions such as certain angle, certain light. In this kind of situation, this kind of data cannot represent real images of finger knuckle in real world. In order to address the shortcomings of current public finger knuckle dataset for contactless detection, we use a web crawler to get images from the Unsplash [38] where the keywords are finger knuckles. The Unsplash is an image site that offers uploads and downloads, and uses a copyright license that allows users to download and use them for free or even for commercial use [39]. We have downloaded 2347 images, there are 738 images without knuckles, and these images can be used as background training, and the rest 1609 images that contain at least one finger knuckle are the positive samples for the network model. In the network training process, we use crawled images, 169 finger knuckle images from the HKPolyU Finger Knuckle Database (V1.0) [33], and 64 finger knuckles images from the HKPolyU Hand Dorsal Database [35] as for the training set. And we use the rest data as testing set to evaluate performance. The most important part is the data augmentaion which conatains flip, rotation, resize, translate and mosaic.

11.1.3 Contactless Finger Knuckle Detection

Detection Performance

The YOLOv4 model predict horizontal bounding box, while the remaining YOLOv5 model predict rotated bounding box with CSL classification, called YOLOv5-CSL. We can see the performance difference between these variations of the YOLOv5 model from the Table 2. Among the downloaded 2580 images, 100 images were randomly selected as the testing set.

Model	Inference Time/ms (1024x1024)	Number of Layers	mAP^{val} 0.5	AP of Major FK	AP of Minor FK
YOLOv5x-CSL	41.395	407	**89.9**	**89.6**	**90.1**
YOLOv5m-CSL	36.252	263	85.7	88.9	80.4
YOLOv4	25.992	161	70.7	83.6	57.7

Table 2: Comparison of the accuracy of the different models of the YOLO series for the detection of the finger knuckle.The calculated values of mAP were measured at a detection threshold of 0.4 as well as an IOU threshold of 0.5.

Segmentation Performance

This section aim to compare quality of finger knuckle between YOLOv5-CSL segmented and dataset offered. Because the segmented finger knuckle on the 3D Finger Knuckle Dataset already have high quality, I mainly test on the Index Finger Knuckle of Hand Dorsal Dataset and the Finger Knuckle Dataset V3 (with deformable).

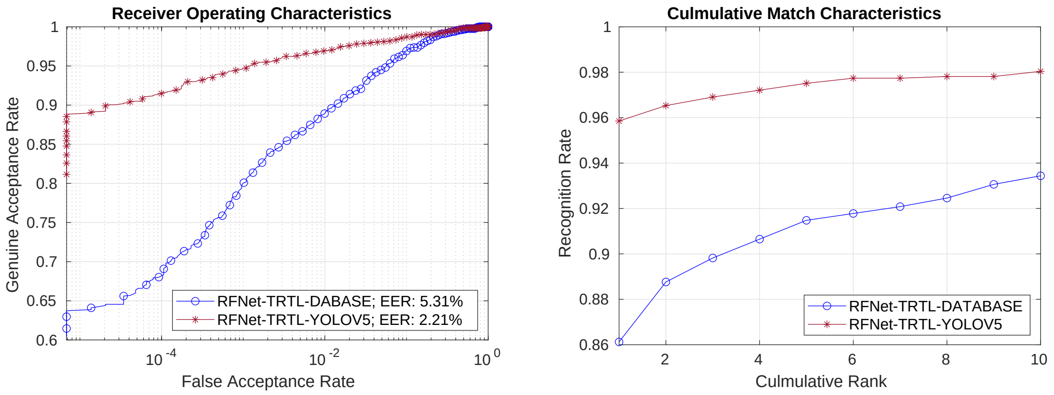


Figure 10: Compare performance on the Finger Knucle V3 Dataset (with deformable)

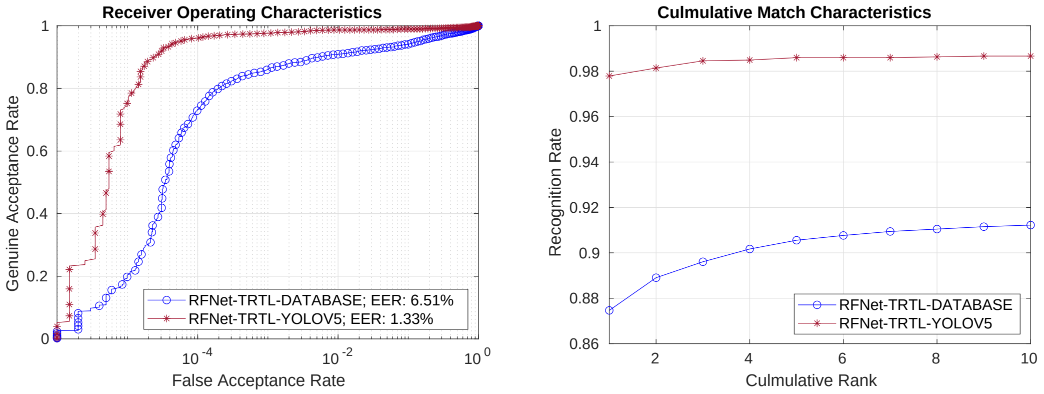


Figure 11: Compare performance on the Index Finger of the Hand Dorsal Image Database.

From the above figures, we can clearly get the conclusion that quality of segmented finger knuckle of YOLOv5 is better than the segmented finger knuckle of dataset through the ROC curve and CMC curve. Especially on the Hand Dorsal Image Database, the EER value can drop from 6.51% to 1.33%.

11.2 Online Contactless Finger Knuckle Identification Performance

....

12 Conclusions and Future Work

13 References

[1] Alexey Bochkovskiy, Chien-Yao Wang, and Hong-Yuan Mark Liao. “Yolov4: Optimal speed and accuracy of object detection”. In: *arXiv preprint arXiv:2004.10934* (2020).

[2] KamYuen Cheng and Ajay Kumar. “Contactless finger knuckle identification using smartphones”. In: *2012 BIOSIG-Proceedings of the International Conference of Biometrics Special Interest Group (BIOSIG)*. IEEE. 2012, pp. 1–6.

[3] Kevin HM Cheng and Ajay Kumar. “Contactless biometric identification using 3D finger knuckle patterns”. In: *IEEE transactions on pattern analysis and machine intelligence* 42.8 (2019), pp. 1868–1883.

[4] Kevin HM Cheng and Ajay Kumar. “Deep feature collaboration for challenging 3D finger knuckle identification”. In: *IEEE Transactions on Information Forensics and Security* 16 (2020), pp. 1158–1173.

[5] Ross Girshick. “Fast r-cnn”. In: *Proceedings of the IEEE international conference on computer vision*. 2015, pp. 1440–1448.

[6] Ross Girshick et al. “Rich feature hierarchies for accurate object detection and semantic segmentation”. In: *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2014, pp. 580–587.

[7] Kaiming He et al. “Deep residual learning for image recognition”. In: *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2016, pp. 770–778.

[8] Kaiming He et al. “Mask r-cnn”. In: *Proceedings of the IEEE international conference on computer vision*. 2017, pp. 2961–2969.

[9] Pablo Hennings, Marios Savvides, and BVK Vijaya Kumar. “Verification of biometric palmprint patterns using optimal trade-off filter classifiers”. In: *International Conference Image Analysis and Recognition*. Springer. 2005, pp. 1081–1088.

[10] Jie Hu, Li Shen, and Gang Sun. “Squeeze-and-excitation networks”. In: *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2018, pp. 7132–7141.

[11] Gao Huang et al. “Densely connected convolutional networks”. In: *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2017, pp. 4700–4708.

[12] Wei Jia, De-Shuang Huang, and David Zhang. “Palmprint verification based on robust line orientation code”. In: *Pattern Recognition* 41.5 (2008), pp. 1504–1513.

[13] AW-K Kong and David Zhang. “Competitive coding scheme for palmprint verification”. In: *Proceedings of the 17th International Conference on Pattern Recognition, 2004. ICPR 2004.* Vol. 1. IEEE. 2004, pp. 520–523.

[14] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. “Imagenet classification with deep convolutional neural networks”. In: *Advances in neural information processing systems* 25 (2012).

[15] Ajay Kumar. “Importance of being unique from finger dorsal patterns: Exploring minor finger knuckle patterns in verifying human identities”. In: *IEEE transactions on information forensics and security* 9.8 (2014), pp. 1288–1298.

[16] Ajay Kumar. “Toward pose invariant and completely contactless finger knuckle recognition”. In: *IEEE Transactions on Biometrics, Behavior, and Identity Science* 1.3 (2019), pp. 201–209.

[17] Wei Liu et al. “Ssd: Single shot multibox detector”. In: *European conference on computer vision*. Springer. 2016, pp. 21–37.

[18] Yang Liu and Ajay Kumar. “Contactless palmprint identification using deeply learned residual features”. In: *IEEE Transactions on Biometrics, Behavior, and Identity Science* 2.2 (2020), pp. 172–181.

[19] Rajiv Mehrotra, Kameswara Rao Namuduri, and Nagarajan Ranganathan. “Gabor filter-based edge detection”. In: *Pattern recognition* 25.12 (1992), pp. 1479–1494.

[20] Abdallah Meraoumia, Salim Chitroub, and Ahmed Bouridane. “Fusion of finger-knuckle-print and palmprint for an efficient multi-biometric system of person recognition”. In: *2011 IEEE International Conference on Communications (ICC)*. IEEE. 2011, pp. 1–5.

[21] Abdallah Meraoumia, Salim Chitroub, and Ahmed Bouridane. “Personal Recognition by Finger-Knuckle-Print Based on Log-Gabor Filter Response”. In: ().

[22] Shubhangi Neware, Kamal Mehta, and AS Zadgaonkar. “Finger knuckle identification using principal component analysis and nearest mean classifier”. In: *International Journal of Computer Applications* 70.9 (2013).

[23] Joseph Redmon and Ali Farhadi. “YOLO9000: better, faster, stronger”. In: *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2017, pp. 7263–7271.

[24] Joseph Redmon and Ali Farhadi. “Yolov3: An incremental improvement”. In: *arXiv preprint arXiv:1804.02767* (2018).

[25] Joseph Redmon et al. “You only look once: Unified, real-time object detection”. In: *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2016, pp. 779–788.

[26] Shaoqing Ren et al. “Faster r-cnn: Towards real-time object detection with region proposal networks”. In: *Advances in neural information processing systems* 28 (2015), pp. 91–99.

[27] Olga Russakovsky et al. “Imagenet large scale visual recognition challenge”. In: *International journal of computer vision* 115.3 (2015), pp. 211–252.

[28] Florian Schroff, Dmitry Kalenichenko, and James Philbin. “Facenet: A unified embedding for face recognition and clustering”. In: *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2015, pp. 815–823.

[29] Karen Simonyan and Andrew Zisserman. “Very deep convolutional networks for large-scale image recognition”. In: *arXiv preprint arXiv:1409.1556* (2014).

[30] Zhenan Sun et al. “Ordinal palmprint represention for personal identification [represention read representation]”. In: *2005 IEEE computer society conference on computer vision and pattern recognition (CVPR’05)*. Vol. 1. IEEE. 2005, pp. 279–284.

[31] Mingxing Tan and Quoc Le. “Efficientnetv2: Smaller models and faster training”. In: *International Conference on Machine Learning*. PMLR. 2021, pp. 10096–10106.

[32] *The HKPolyU 3D Finger Knuckle Images Database:* `https://www4.comp.polyu.edu.hk/~csajaykr/3DKnuckle.htm`.

[33] *The HKPolyU Contactless Finger Knuckle Images Database (V-1.0):* `http://www4.comp.polyu.edu.hk/~csajaykr/fn1.htm`.

[34] *The HKPolyU Contactless Finger Knuckle Images Database (Version 3.0) :* `https://www4.comp.polyu.edu.hk/~csajaykr/fn2.htm`.

[35] *The HKPolyU Contactless Hand Dorsal Images Database:* `http://www4.comp.polyu.edu.hk/~csajaykr/knuckleV2.htm`.

[36] *Tsinghua University Finger Vein and Finger Dorsal Texture Database (THU-FVFDT3):* `https://www.sigs.tsinghua.edu.cn/labs/vipl/thu-fvfdt.html`.

[37] Ultralytics. *YOLOv5*. `https://github.com/ultralytics/yolov5`. 18 May 2020.

[38] Unsplash. *Unsplash*. `https://unsplash.com/`.

[39] Unsplash. *Unsplash.com*. ”Unsplash License”. Retrieved 11 January 2017.

[40] Ying Xin et al. “PAFNet: An Efficient Anchor-Free Object Detector Guidance”. In: *arXiv preprint arXiv:2104.13534* (2021).

[41] Wankou Yang, Changyin Sun, and Zhenyu Wang. “Finger-knuckle-print recognition using Gabor feature and MMDA”. In: *Frontiers of Electrical and Electronic Engineering in China* 6.2 (2011), pp. 374–380.

[42] Xue Yang and Junchi Yan. “Arbitrary-oriented object detection with circular smooth label”. In: *European Conference on Computer Vision*. Springer. 2020, pp. 677–694.

[43] Fisher Yu and Vladlen Koltun. “Multiscale context aggregation by dilated convolutions”. In: *arXiv preprint arXiv:1511.07122* (2015).

[44] David Zhang, Xiaoyuan Jing, and Jian Yang. *Biometric image discrimination technologies*. IGI Global, 2006.

[45] Lin Zhang et al. “3D palmprint identification using block-wise features and collaborative representation”. In: *IEEE transactions on pattern analysis and machine intelligence* 37.8 (2014), pp. 1730–1736.

[46] Qian Zheng, Ajay Kumar, and Gang Pan. “A 3D feature descriptor recovered from a single 2D palmprint image”. In: *IEEE transactions on pattern analysis and machine intelligence* 38.6 (2016), pp. 1272–1279.

[47] Zhaohui Zheng et al. “Distance-IoU loss: Faster and better learning for bounding box regression”. In: *Proceedings of the AAAI Conference on Artificial Intelligence*. Vol. 34. 07. 2020, pp. 12993–13000.

[48] Zhaohui Zheng et al. “Enhancing geometric factors in model learning and inference for object detection and instance segmentation”. In: *IEEE Transactions on Cybernetics* (2021).

[49] Xizhou Zhu et al. “Deformable convnets v2: More deformable, better results”. In: *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. 2019, pp. 9308–9316.