HFDSegNet: Holistic and Generalized Finger Dorsal ROI Segmentation Network

Gaurav Jaswal[1], Shreyas Patil[2], Kamlesh Tiwari[3] and Aditya Nigam[1]
[1]School of Computing and Electrical Engineering, Indian Institute of Technology Mandi, India
[2]Department of Electrical Engineering, Indian Institute of Technology Jodhpur, India
[3]Department of Computer Science and Information Systems, Birla Institute of Technology and Science Pilani, India

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Abstract: The aforementioned works and other analogous studies in finger knuckle images recognition have claimed that the precise detection of true features is difficult from poorly segmented images and the main reason for matching errors. Thus, an accurate segmentation of the region of interest is very crucial to achieve superior recognition results. In this paper, we have proposed a novel holistic and generalized segmentation Network (HFDSegNet) that automatically categorizes the given finger dorsal image obtained from multiple sensory resources into particular class and then extracts three possible ROIs (major knuckle, minor knuckle and nail) accurately. To best of our knowledge, this is the first attempt, an end-to-end trained object detector inspired by Deep Learning technique namely faster R-CNN (Region based Convolutional Neural Network) has been employed to detect and localize the position of finger knuckles and nail, even finger images exhibit blur, occlusion, low contrast etc. The experimental results are examined on two publicly available databases named as Poly-U contact-less FKI data-set, and Poly U FKP database. The proposed network is trained only over 500 randomly selected images per database, demonstrate the outstanding performance of proposed ROI's segmentation network.

1 INTRODUCTION

Biometry based authentication solutions have been used in large scale security and privacy applications like mobile device, surveillance etc (Jain et al., 2004). As for as features of Palmer region of hand is concerned, palm-print, fingerprint, palm vein and hand geometry are the ideal biometric traits (Bera et al., 2014). In earlier studies, fingerprint provided the basis for personal identification. Apart from its extensive usages, fingerprint requires high quality images ($> 400dpi$) for accurate results as well as its features deteriorate with sharp cuts/ injuries which limit its role in certain commercial applications (Kumar and Kwong, 2013). Also, the quality of fingerprint of laborers or cultivators is not very good to be used for recognition (Jaswal et al., 2017b). Similarly, instead of having the bigger ROI region, a palm consist of limited systematic line features and may undergone impostor attacks because most of the time people leave their palm print or fingerprint unintentionally. While, geometrical features of palm/ finger are not very much unique for identification (). The vein traits in hand are distinctive, difficult to spoof but requires extra imaging devices (Kumar and Prathyusha, 2009). On the contrary, the skin patterns over finger dorsal surface are unaffected or naturally preserved. (Jaswal et al., 2016).

1.1 Finger Knuckle Anatomy and Challenges

The basic epidermis structure appearing on the dorsal surface of finger is named as finger knuckle image (FKI) pattern (Zhang et al., 2010). It mainly consists of rich convex like lines, corner points, skin folds, and gray-mutation regions specifically around the finger joints. The three joints in a finger lie in between one of three bone groups called as the distal, proximal, and middle phalanx (Kumar and Xu, 2016). The epidermal cells near knuckle mature very early stage of development and rarely change during an adult's life. Its failure to enroll rate (FTE) is observed to be lower and can be acquired easily using an inexpensive setup with lesser user cooperation (Jaswal et al., 2017a). Moreover, the dorsal knuckle patterns are invariant

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to emotions/ behavioural aspects and cannot be easily manipulated (Kumar and Xu, 2016). However, there exist several challenge in FKI recognition that are to be solve for superior performance: (1) Track the middle knuckle line for FKI registration because the position of fingers deviate during contact-less acquisition. (2) Control varying illumination and lighting affects for outdoor conditions (3) Automatically segment the major, minor finger knuckle and nail ROI's consistently (4) Improve the matching accuracy of major, minor finger knuckle and nail recognition. (5) Develop non-uniform databases in which images incorporate the real world situations such as non-stretch palm or bending of fingers.

1.2 Problem Statement

Beside the possibility of simultaneous acquisition and highly stable patterns of major and minor finger knuckles, FKI is still not enough mature to be used solely in personnel security applications like mobile devices, forensic etc. Grouping of a major, and minor finger knuckles may take the advantage to improve the performance of single modality based FKI recognition systems. However, the performance is often affected by inconsistent ROI segmentation, varying lighting situations, sensor accuracy etc and it is important to minimize these factors at initial level. Specifically, it can be summarize that the performance of consistent ROI extraction performs a key part in the performance of a biometric system, since the successive processing units has to work over the extracted ROI region. Therefore, the exact ROI segmentation of major and minor knuckles is very crucial for doing point-wise correspondence of image patches. In view of above mentioned FKI challenges, this work has been proposed to automatically segment the major and minor (upper) finger knuckles on PolyU FKI data set using deep learning criteria. Moreover, we have investigated the possibility of another region of interest near finger nail as a part of finger dorsal feature which have not yet attracted the attention. Till date no other work has been reported that exploits nail feature over this data-set.

Contribution: We present a two fold problem, as image classification network (handled via ResNet) for categorizing the multi sensory input data and as ROI segmentation for extraction of four (1-PolyU FKP; 3-PolyU FKI) ROI's (handled via Modified R-CNN. Our proposed holistic and generalized Finger Knuckle Segmentation Network (HFDSegNet) provide a single fully automated network for finger knuckle image ROI extraction that can be trained and perform well for two type of finger knuckle databases. In this architecture, a trained ResNet50 model (He et al., 2016) is first used to identify the object class of the given finger knuckle. The classified finger image is further given as input to a modified deep learning network which actually provides three region of interest in that image as shown in Fig. 1. In practice, the deep learning network has been trained almost similar to state-of-art faster R-CNN (Girshick et al., 2014) by explicitly reformulate the layers as learning functions. Also, it can further classify the extracted ROI's of particular data-set into respective classes (major or minor or finger nail), so that it can later be matched with the appropriate gallery sample. For more rigorous experimentation, we have involved two publicly available finger knuckle databases i.e., PolyU contactless finger knuckle image (FKI) database (56, 6 13) and PolyU finger knuckle print (FKP) data-set (55, 2009). To the best of our knowledge, this is the first holistic deep learning architecture utilized to classify and localize the ROI of any type of finger knuckle image. One of the major implementations breakthrough achieved wad that we have managed to train the entire network with only 500 images per dataset whereas generally any deep learning network takes huge amount of data to train. The performance of ROI segmentation algorithm is measured in terms of IOU, accuracy, precision, and recall. The remainder of article is organized into following main sections: Section 2 summarizes the state-of-art studies for FKI recognition. In section 3, the proposed ROI extraction algorithm is presented including image classification and training/testing strategy. Then, experimental results and comparative analysis are presented in section 4. Finally, the important findings and future scope are drawn in the last section.

2 RELATED WORK

The present state of art studies in the area of finger knuckle recognition can be mainly grouped into following main implementations: ROI extraction, quality assessment, ROI enhancement, feature extraction and finally, the most crucial matching.

2.1 ROI Extraction

In real sense, major finger knuckle is the most studied biometric identifier among knuckle print studies whereas minor finger knuckle and nail are still not much explored. Most of the major knuckle ROI extraction methods are based on local convexity characteristics of the line patterns on the middle knuckle region. In (Zhang et al., 2010), authors computed

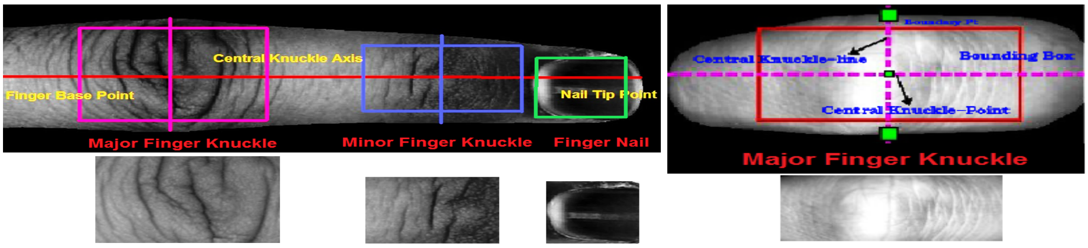

Figure 1: Finger Knuckle Image Annotation: (a) PolyU FKI Sample, (b) PolyU FKP Sample.

convexity magnitude to detect the center of the middle finger joint and for that encoded image pixels as (1, -1). In (Nigam et al., 2016), authors proposed an idea to locate middle knuckle point by which finger knuckle ROI can be segmented consistently. They used magnitude responses of two curvature Gabor filters with fine tune parameters to locate central knuckle line. In (Kumar and Xu, 2016), authors proposed ROI segmentation framework for major and minor finger knuckles using local image processing operations on contact-less images.

2.2 Feature Extraction/Classification

In (Zhang et al., 2009), authors proposed competitive code in which orientation information of major knuckle pattern is extracted through the use of gabor filter. In (Kumar and Ravikanth, 2009), authors resolved the problems occurring in finger knuckle recognition due to challenging knuckle images. In (Kumar and Prathyusha, 2009), authors stated biometric fusion of knuckle shape and vein features to validate the identity of individuals. In (Kumar, 2012), first time ever the usages of upper minor finger knuckles for personnel identification is presented. In another hand dorsal study (Kumar, 2014), importance of lower minor finger knuckles and palm dorsal region for personal authentication is discussed. In (Jaswal et al., 2017a), authors presented a score level fusion of multiple texture features obtained from local transformations schemes and performed multi-scale based matching. In latest work (Chlaoua et al., 2018), authors extracted the middle knuckle features by deep learning based PCANet model as well as performed hashing and multi-class classification. In another latest work (Zhai et al., 2018), authors made efforts to improve recognition performance of hand crafted features and proposed Convolutional Neural Network (CNN) architecture with data augmentation and batch normalization.

3 PROPOSED ROI EXTRACTION NETWORK

There have been no research work till now that adopts deep methods for FKI ROI segmentation. We propose an end-to-end deep network architecture for FKI ROI segmentation that can efficiently minimize the poor segmentation results. The main aim of proposed ROI extraction approach is to consistently segment the fixed size ROI's from PIP, DIP, and finger nail regions. For this, a two stage end-to-end network (HFDSegNet) has been trained using modified faster RCNN, which takes any finger as input and results into different type of ROI regions.

3.1 HFDSegNet: The Network Architecture

Various deep learning methods have been developed and achieve significant progress in object classification and localization. The goal of any image classification challenge is to train a model that can correctly classify an input image. The proposed HFDSegNet consists of two main stages: (i) Object classification- ResNet and (ii) Object localization- Modified R-CNN. In this work, we have two state-of-art finger knuckle databases available, namely PolyU FKP and PolyU contact-less FKI database.

3.1.1 Classification Network: ResNet-50

The proposed HFDSegNet is trained in such a way that first it categorize the given input image into either Class-1 (PolyU FKP) or Class-2 (PolyU contact-less FKI) database for the purpose of next level processing. For this, a well known state-of-art model ResNet50 has been used because it is very easy to implement and train. There are other ResNet (ResNet101, ResNet-152) variants are available but this particular model more correctly classifies the given input image into two categories.

3.1.2 ROI Segmentation: Modified R-CNN with Inception-v3

To keep in mind time complexity of existing ROI networks like YOLO, R-CNN etc, we have selected a network which has the most optimum ratio of the time consumed, the computations performed and the accuracy required in the field of biometrics. Therefore, a network inspired from Faster R-CNN architecture has been presented that gives much better accuracy as well as transferable features than current state-of-art studies. As shown in Fig 2, proposed modified R-CNN comprises of three major modules such as:

1. **Shared Layers of Inception-V3:** In this work, a set of convolutional layers are selected form a pre-trained network namely Inception-V3 for extraction of best possible line features. we have truncated the pre-train Inception-v3 network by detaching the whole fully connected layers. Thus, we have only left with 2D convolution layers for extraction of feature map. Now at first level of the detection, we take the output feature map of last convolution layer of Inception with dimension $17 \times 17 \times 768$. Since, last layers of Inception-v3 is helpful to provide mixed kind of knuckle features, so we only take feature map from last 2D convolution layer. Further, we lower the total number of channels from 768 to 128 (using 1×1 convolutions) for memory requirement. Till this level, we have only concentrated on global knuckle features. However for localization of different traits, context information also play a crucial part. As context information is important hence we have included three context layers with 7×7, 5×5 and 3×3 filters. However, small sequential filters take few hyper-parameters than large filters, so we consider small filters. The context information of three types of filters will further merged and given as input to classification and regression head which will give the classification score and regression output respectively. Up to this level, first we take the feature map of last layer of Inception, then we apply Max-pooling over that for getting more global features, finally this output feature map has been given to context module.
2. **Region Proposal Network (RPN):** RPN is a network that takes in an input of size 3*3 from the feature map obtained from the shared layers. It then considers several anchor boxes of different scales and aspect ratios, so as to select the best fit anchor box for every ground truth bounding box. The anchor boxes are chosen to be scale and shape invariant. By default, three aspect ratios and three scales are considered, yielding nine anchor boxes at each (3×3) patch position. Later on, it selects the coordinates of these anchor boxes by regressing them w.r.t the ground truth bounding box. The similarity between the anchor and the bounding boxes are measured using Intersection over Union (IOU). For each of the bounding box, at-least one anchor has to be chosen. These anchor boxes are further pruned to one (in case if they are more) per bounding box, using non-maximum suppression(NMS). The RPN network, gives an output of 4K and K values, signifying the coordinates of the K anchor boxes (4 values per box) and the probability (one value per box) of box existence respectively.
3. **ROI Pooling and Classification (Conv2D-512 Filters, Relu) and Regression (Conv2D-2048 Filters, Relu) Heads:** An arbitrary sized matrix given as input (as previously defined by RPN) to ROI pooling to reduce the dimension of feature maps. It maps the RPN region into a fixed size (14×14) vector, and applies max pooling over such a re-sized grid. It is easy to back propagate through this layer as it is just a max pooling applied over to different regions of a feature map. Finally, the network turns into two heads predicting the class scores and bounding box coordinates. The multiple regions obtained after ROI pooling are finally fed to a network consisting of a few convolutional layers and a few fully connected layers to predict the class scores and the bounding box coordinates.

3.2 Testing and Training Strategy

The training and testing strategy were performed in two phases to ascertain the usefulness of proposed KHSegNet for the ROI segmentation.

3.2.1 Training

1. **Ground Truth Generation:** The ground truth with respect to two type of finger knuckle images has been generated using (Kumar and Ravikanth, 2009; Nigam et al., 2016) respectively. This is performed because the RPN is trained as a regressor and the probabilities and the coordinates of the anchor boxes have to be generated so as to provide a ground truth for calculating the loss. The RPN, outputs 4K and K values corresponding to K anchor boxes for each $n \times n$ input. For generating the ground truth for the RPN we have used IOU as a similarity measure between the anchor boxes and the bounding boxes provided as ground truth for probability prediction. The anchor boxes

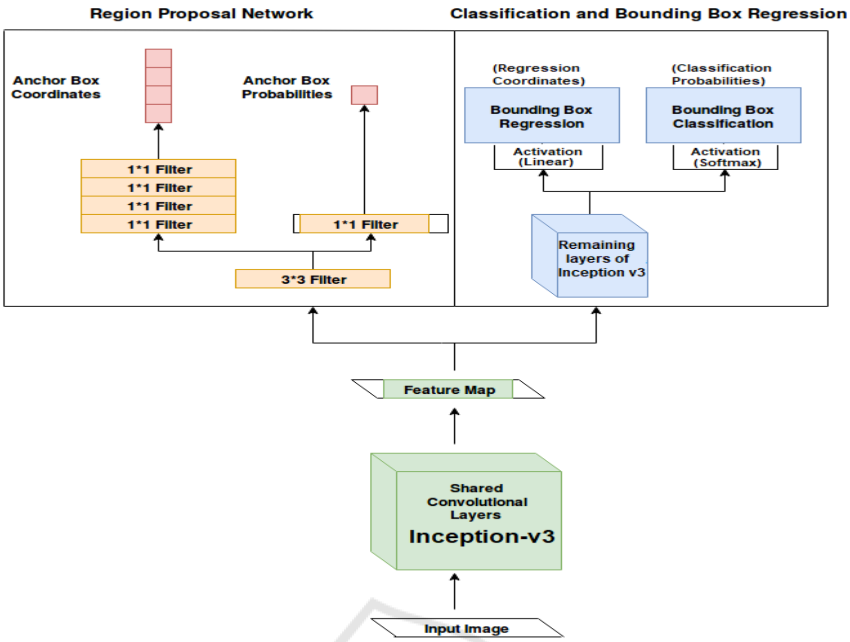

Figure 2: ROI segmentation Architecture: Modified R-CNN.

with the maximum IOU while compared with the ground truth are given high probabilities, termed “positive”. It is ensured that each of the bounding boxes has to have at-least one positive anchor box corresponding to it.

2. **Training RPN Network:** Initially, we have trained the region proposal network along with the shared layers using the above computed ground truths for the RPN. We are training modified R-CNN from scratch rather than considering pre-trained weights in order to make out the trained model as problem specific as possible. One has to notice that RPN along with the shared layers has to be trained as an end-to-end network so as to achieve good performance.

3. **Training Classification and Regression Heads:** In the next step, we have to train the classification and the regression heads using the obtained region proposals. This also has to be carried out in end-to-end fashion through ROI pooling layer and shared convolutional layers.

4. **Fine Tuning RPN, Classification and Regression Heads:** Once we have trained the shared layers for RPN and both heads (as in Steps (2),(3)), the best possible and discriminative features have been learned at shared layers attaining the maximum accuracy. But the problem is, that RPN is trained as end-to-end in Step (2), along with shared layers. Hence, we have fine tuned the RPN layers keeping the shared layers frozen, in order to learn the anchor box prediction and their probabilities. Similarly, the classification and regression heads has to be fine tuned in order to take a different feature map as an input, keeping the weights of shared layers frozen, to get satisfactory results.

5. **Losses:** In order to train proposed HFDSegNet, the four type of training losses are considered: (i) RPN regression loss, (ii) RPN classification loss, (iii) Final regression loss and (iv) final classification loss. For each epoch, RPN network is first trained and then the final regression and classification heads is trained. The loss functions considered for trait classification and RPN classification are “categorical cross-entropy” and “binary cross entropy” respectively. In addition, mean squared error (MSE) loss function has been used for regression of both region proposal network as well as bounding boxes.

Size Invariant Network: Our network can take input of any size (size invariant), mainly because of this tweaked implementation of RPN and the classification and regression heads. The region proposal network has been implemented as convolutional layers and the ground truth is corresponding to the image size, making our RPN size invariant. In the case of classification and regression heads, the ROI pooling layer serves this purpose, as the pooling layers take in any arbitrary sized region of interest (ROI) and pools it into a fixed sized output as discussed above. This fixed sized output has been fed to a network consisting of convolutional and fully connected layers, making the classification and regression heads size invariant too. All the network hyper-parameters, have been selected "empirically" by maximizing the system performance over a validation set.

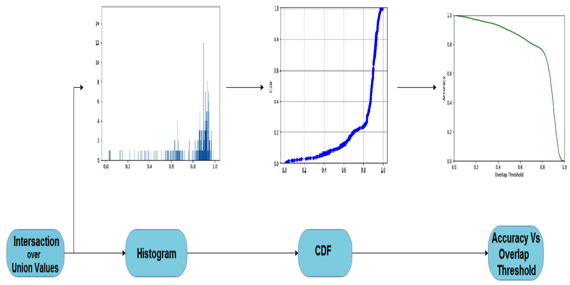

Figure 3: Steps involved for generating Accuracy Vs IOU Graph

3.2.2 Testing

In case of class-2 database, We have used only 500 images for training while around 2015 images has been used for testing in order to generate the response of proposed HFDSegNet. Likewise, the equal number of 500 images of class-2 database has been selected for training. The trained network has been tested by evaluating IOU, that we have used to obtain the accuracy of our proposed network. It is the most widely used evaluating parameter, to check the efficiency of any algorithm/ network, for object localization. Iterative thresholding has been applied to over each of the traits individually, as well over all the traits to determine the individual trait as well as overall performance analysis.

(a) Accuracy Vs IOU Graph: To visualize system performance, we have plotted a graph, showing accuracy at each threshold for each trait as well as overall, as shown in Fig. 3. The IOU ranges from 0 to 1. Where 0, indicates that the boxes do not match at all and 1 indicates that the boxes are perfectly matched. When the threshold is high the number of images (in %) having IOU more than the threshold will be less, where as it is 100% at 0 threshold. Such a graph can be plotted as follows : Compute IOU of predicted and ground truth boxes. The predicted boxes having the same ground truth along with their respective distance has been considered to match the boxes in images containing multiple boxes. Generate a histogram over IOU values at an step of 0:00001 so as to get a smooth curve. Normalize it, so as to get a probability distribution function (PDF) and compute its cumulative distribution function (CDF). Accuracy at each IOU threshold (i_t) can be defined as : $Accuracy = \frac{\#\ test\ images\ with\ IOU\ >= i_t}{\#\ test\ images}$ and can be computed using the Eq. (1), as shown in Fig. 4.

$$Accuracy = 1 - cdf + Value\ of\ histogram \quad (1)$$

(b) Precision and Recall: In addition to the accuracy values, precision and recall has also been calculated for the proposed network validation as defined in Eqs. (2), (3).

$$Precision = \frac{\#\ of\ correct\ boxes\ predicted}{Total\ No.\ of\ boxes\ predicted} \quad (2)$$

$$Recall = \frac{\#\ of\ correct\ boxes\ predicted}{Total\ No.\ of\ Ground\ truth\ boxes} \quad (3)$$

Precision and recall are calculated so as to validate our approach, while calculating accuracy we only consider the true predicted boxes and not all the predicted boxes. Similarly the intersection over union values calculated are with respect to the ground truth bounding boxes, but it may so happen that all the ground truth boxes are not considered while calculating accuracy, therefore we take into account this detail while computing the recall values.

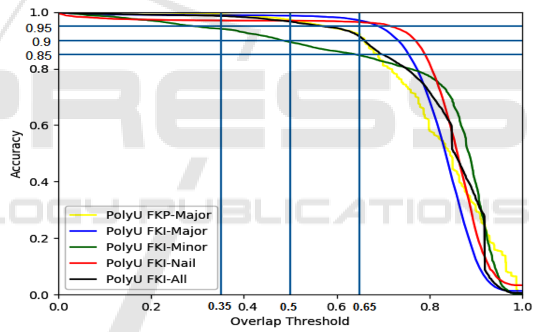

Figure 4: The Accuracy Vs. Overlap Threshold Graph.

4 EXPERIMENTAL RESULTS AND DISCUSSION

This section presents a detail of evaluation parameters, datasets and the testing protocol by which we eveluate the performance of proposed HKSegNet Segmentation network. For datasets, the two publicly available finger knuckle databases: PolyU FKP dataset (55, 2009) and PolyU Contactless FKI dataset (56, 6 13) have been used.

[a] Test-1: In the first test, training for each database is done using 500 images taken randomly. The combined Accuracy Vs. Overlap Threshold graph is shown in Fig. 4, where different colours have been used to plot the curves for different ROI's. One can observe that the network produces high accuracy

Table 1: The Accuracy, Precision and Recall Values at different Overlap (IOU) thresholds.

Biometric Traits	**Accuracy**			**Precision**			**Recall**		
	Overlap IOU Threshold			Overlap IOU Threshold			Overlap IOU Threshold		
	0.35	**0.5**	**0.65**	**0.35**	**0.5**	**0.65**	**0.35**	**0.5**	**0.65**
PolyU FKP	99.56	98.52	93.15	99.04	98.62	96.97	90.27	8.38	88.12
Major FKI	99.18	98.94	97.88	98.05	97.96	97.34	97.75	97.66	96.68
Minor FKI	95.42	89.36	86.09	95.27	90.22	86.21	97.19	89.30	85.64
Nail	97.82	98.10	97.96	97.62	97.33	97.12	98.25	97.58	97.44
All	99.15	97.36	92.46	98.89	97.76	90.87	98.55	95.09	91.05

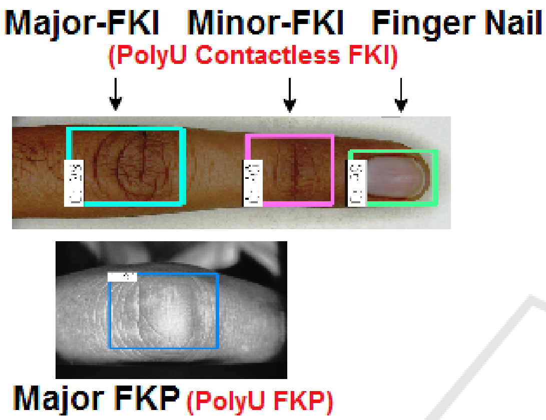

Figure 5: ROI obtained for various finger knuckle images using HFDSegNet.

even up to 0.5 overlap IOU threshold for almost all the images. A slight accuracy drop has been observed when overlap IOU threshold becomes more than 0.3, especially for minor knuckle (Green curve). But, one can see that it drops gradually. It may be the case as the curvature features are largely missing in that region. While the performance of finger nail (Red curve) is surprisingly observed good, as it sustains the uniformity up to 0.65 IOU. Similarly the accuracy vs overlap threshold graph for major knuckle shows that it outperforms its counterparts at every IOU threshold level. The prime reason behind this is that finger knuckle image contains features that are easily distinguishable from the others under their respective region of interests. The PolyU FKI (Blue curve) maintains constant accuracy (97.88%) up to 0.65 IOU while it drops somewhat earlier for PolyU FKP images. Since, line features are evenly distributed in case for PolYU FKP samples and most of the previous approaches tried to obtain the centre line or the center point (Zhang et al., 2010; Nigam et al., 2016). Network may not be able to capture such a symmetry in the finger image. However, this type of accuracy is considered to be very good in object recognition literature. From Fig 4 one can infer that the proposed network has been performing very well across all the samples. Some network predictions are depicted in Fig 5. We obtain only major finger knuckle ROI using PolyU FKP data-set while three ROI's i.e., major, minor finger knuckles including finger nail are obtained from PolyU FKI database.

[b] Test-2: To best of our knowledge, this is the first ever proposed FKI biometrics deep learning segmentation network. Table 1, shows the values obtained for Accuracy, Precision and Recall for the all experiments performed. Hence, we have not compared our results with any other method. Although, one can compare it with the existing techniques, such as (Kumar and Ravikanth, 2009; Zhang et al., 2010; Nigam et al., 2016), but such comparison may not be justified due to two reasons : (i) They had been tested only over single trait (we have performed multi-class classification) and (ii) None of them had used deep learning. Still we have observed that the proposed network performs better that previous individual trait techniques.

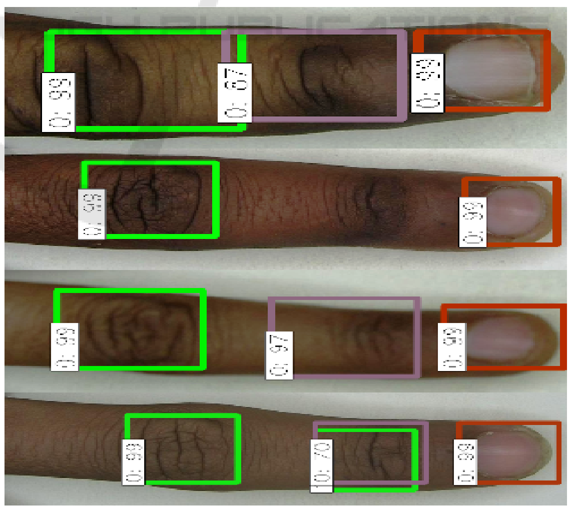

Figure 6: Failed ROI Images in case of Minor Finger Knuckle.

[c] Pros and Cons of the Proposed Network: We have tried to train HFDSegNet on nail bed, which contains useful structural information. A set of few images over which the proposed HFDSegNet failed to segment are shown in Fig 6. The algorithm mainly fails for Minor FKI due to blurriness, presence of artifact/ minor cuts and scrapes etc. While, the results for major knuckle and finger nail are much more consistent. One most important point to mention is that our network has just been trained over 500 random images and performs much better than other existing state-of-the-art ROI extraction algorithm.

5 CONCLUSION AND FUTURE SCOPE

In this paper, we have proposed a end-to-end network for extracting ROIs from any finger knuckle image. To best of our knowledge, this is the first holistic architecture proposed so far, segmenting three ROIs namely major finger knuckle, minor finger knuckle and finger nail in the image. We have explored the possibility to extract a complete information from a finger dorsal region so that it can enumerate the recognition performance of state-of-art FKI recognition systems. This method provides rotation and translation error free results and capable of localizing regions in case of challenging finger kuckle images. The proposed holistic ROI segmentation network has been trained with around 500 images and produces very satisfactory and consistent results. Experimental results on two FKI data-sets show that our method outperforms state-of-the-art finger knuckle segmentation approaches in terms of segmentation accuracy. This work on holistic finger knuckle segmentation, opens up the vast opportunities in the field of multi-biometric authentication systems. In future work, we will try to compute the recognition performance over these extracted ROI's.

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