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Survey of Palm Print Detection Techniques

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ABSTRACT

Todays, there are various of systems that requires high-level security methods. Due to the sophisticated methods of breaking the traditional security methods. One of the most advanced methods nowadays is handprint validation. Which is based on the features of the palm in hands. These feature could include the lines, valleys, hand texture, and other features. In this work, a survey of the latest works that are used for palm print detection and recognition

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1. Introduction

Nowadays, many threats of hacking and security intrusions are threatening different types of systems. These systems could be categorized into digital and physical [1]. The digital systems that involves software's installed on user devices such as smart phones or personal computers. The physical systems includes the hardware's that are attached to do a specific task, such as attendance devices, or electronic gates. Since the security breaches and threats are becoming more dangerous and sophisticated, the need for secure and efficient personal validation methods is necessary [2].

The most promising methods in user validation are those which are based on human biometrics [3]. Due to its high level security and resistant to hacking. And one of the most efficient biometric validation methods is the palm print [4]. Validation methods based on palm print are considered one of the most preferred methods among biometrics validation methods, due to its ease of use, its relatively simple hardware installation, and the increasing number of training dataset.

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In this paper, the cutting edge technologies and methods used in the palm print detection and recognition are described intensively. The techniques are usually follow two steps. The first step is detection the palm reign. Which is known as Region of Interest (ROI) Detection. Which the palm area is detected and selected first. In order to be processed later for recognition of the person. The ROI step could be divided into three parts, according to the methods used. The most promising methods are these based on segmentation, Machine Learning (ML), and Artificial Neural Network (ANN). The second step is the Feature Extraction and Matching. Which involves getting the features of the detected palm area from the previous step, and match it with the features stored in the database, in order to identify the person. Different techniques are used in this step. However, the Deep Learning algorithm of Convolutional Neural Network (CNN) is the most promising technique.

2. Region of Interest detection

Due to the inconsistency of the images in palm detection datasets, Region of Interest (ROI) detection is necessary. According to the published papers and proposed methods in the literature review, there are four categories ROI in palm print recognition are falling into:

2.1. Segmentation

In this type of ROI, segmentation is used to separate the hand from the background. This types of methods are based on accurate segmentation, and require a specific position and consistencies of the hand image.

In 2003, Zhang and others [5] used a method to determine the tangent line between the two side finger valleys in order to normalize the palm print's rotation and provide a reference point from which to extract a square region. Notice that the author used images in constrained environment.

Xiao and others [6] proposed a method that uses intersection of binarized hand with lines of specific orientations, giving the most promising points of the finger valleys. K-means clustering is used to get the clusters centres.

2.2. Machine Learning

In In this type of ROI techniques, Machine Learning algorithms are utilized to determine the ROI.

Shao and others [7] developed a multi-steps of ROI extraction. They started by using Histogram of Oriented Gradients (HOG) to detect the hand. And there is a moving window that moves along the image to detect the potential reigns. The sliding window output will be given to pre-trained SVM classifier to detect the ROI. After that, An Ensemble of Regression Trees (ERT) is used for the landmark regression task applied to all 14 key-points placed around the palm and base of fingers. Though its sophistication, this study didn't provide detailed results of the proposed method accuracy.

Ata and others [8], used different machine learning algorithms to compare their performance on palm print recognition. They used CASIA dataset, with total of 5502 images, from 312 persons. They applied image pre-processing steps first, which included the Gaussian filter. After that, RoI is detected in order to feed it into the machine learning algorithms. The used machine learning algorithms included the Artificial Neural Network (ANN), Support Vector Machine (SVM), Naïve Bias, K-Nearest Neighbour (KNN), Random Forest, Decision Tree, and Adaptive Boosting. As a results, ANN gained the best accuracy among the machine learning algorithms. Followed by Naive Bias, SVM, KNN, Random forest, Decision Tree, and Adaptive Boosting.

2.3. Artificial Neural Network

Artificial Neural Networks (ANN) is very powerful technique that is used to solve many types of problems. And one of the most powerful algorithms used for computer vision and image processing is Convolutional Neural Network (CNN).

Bao and others [9] used CASIA palm print dataset to detect the valley points of the hand figures. The proposed method is consisting of four Convolutional layers, and two Fully Connected layers, besides few Max-polling and DropOut layers.

Izadpanahkakhk and others [10] proposed a model consists of five Convolutional layers, and two fully connected layers. Besides Max-polling layer, and Local Response Normalization Layer (LRN). They tested the system with HKPU dataset. However, the dataset docent consist rotated palms.

Jaswal and others [11] used the Faster R-CNN with Resnet-50 architecture. Which consist of 87 layers. And they used three datasets in their research. Which are HKPU, CASIA and GPDS-CL1. Their results were 5% lower for CASIA dataset. This might be due to the rotation variation of this dataset.
Liu and Kumar [12] also used Fast R-CNN approach. They acquired several videos of palm prints in 11 environments (no other details provided) where the hand pose was varied (from spread to closed fingers, with several hand orientations). These acquisition sessions resulted in 30,000 images that were used for training and testing.

3. Feature Extraction and Matching

In order to extract and match the palm prints, further techniques are required. These techniques could be divided into the following:

3.1. Traditional approaches

The Artificial In this types of approaches, the most prominent are those which based on texture-based coding, line-like feature detection, or subspace learning.

In the approaches based on texture description, Chen and others [13] used a 2D Symbolic Aggregate approximation (SAX) for palm print recognition. The SAX represents a real valued data sequence using a string of discrete symbols or characters. Applied to grayscale images, it encodes the pixel values, essentially performing a form of compression. The low complexity and high efficiency of SAX make it suitable for resource-constrained devices.

Moreover, Ramachandra and others [14] used BSIF filters which they are trained on images from dataset to perform texture description. The ROI is convolved with the bank of filters and then binarized (using a specific threshold value), allowing for an 8-bit encoding.

On the approaches based on line orientation at pixel level, Guo and others [15] proposed Binary Orientation Cooccurrence Vector (BOCV) method. In which filter response of a Gabor filter bank and encoded every pixel relative to a specific threshold. In which L1 normalized prior to the encoding, after which the threshold values from each orientation were used to encode an 8-bit number corresponding to every pixel.

Ignat and Păvăloi [16] proposed a method based on Speeded-Up Robust Features (SURF) algorithm to detect the key points of the hand-palm. By using it, there are 64 or 128 key-points are detected. After that, the researchers proposed a method named FIKEN to select the most prominent key points. The used datasets are GPDS with 1000 images for 100 persons, IITD with 2601 images for 230 persons, and CASIA with 5502 images for 312 persons.

Iula and Micucci [17] proposed a sophisticated approach to detect the palm print. Their approach is based on the image of the palm captured by ultrasound device. They collected their own dataset, which contains 423 images, from 55 people. Different steps of image processing processes are used to generate unique template for each hand to match it with database.

3.2. Convolutional Neural Network approaches

CNN have the advantage of creating filters from the training images datasets. Unlike the traditional hand crafted filters, CNN is more powerful since they are based on real data, and much higher number could be created comparing with traditional manually crafted filters.

Dian [18] and others used AlexNet to extract the features of the images. And the features are matched by using Hausdorff distance.

Similarly, Tarawneh and others [19] used AlexNet, VGG16, and VGG19 to extract the features. They used COEP and MOHI datasets in their method. And used multi-class SVM classifier to match the palm prints.

Vijayakumar [20] proposed a method based on simple CNN. In which containing only convolutional layer, max-pooling, and fully connected layer. USM and SDUMLA-HMT datasets are used in this proposed work. The same CNN model is used for palm-print, iris, and figure print recognition. Highest accuracy value achieved is 94%.

Wang and others [21], proposed a method for palm print and palm vein recognition by using CNN. Their proposed model is motivated by ResNet18. Their proposed architecture is consist of 20 layers. With four different Multispectral combination. And the highest accuracy they get is 97.32%.

Jia and others [22] used CNN model to recognize the palm print. However, they didn't design the model manually. Instead, they used what is known as Neural Architecture Search (NAS). Which is an automatic technique that is used to design the CNN and ANN models, instead of the human crafted designs. Different NAS techniques are used to propose different CNN models. These models are tested by different datasets.

Gong and others [23] used AlexNet with PRelu to classify and recognize palm print. PolyU 2D+3D Palmprint Database is used, which contains 8000 images from 400 people. Besides PolyU Multi-Spectral Palmprint Database, which contains total of 24000 images, for 500 people. The highest accuracy get by the researchers is 99.96%.

In the work of Ito and others [24], they used encoder–decoder model with a pyramid pooling module in their design of CNN model. For the training and testing, they used 11k Hands datasets, with 11078 images for 189 people. Besides Places365 dataset, which contains 1825000 images, for 365 people. And Aoki Hands dataset, which contains 180 images, from 5 people. Different skip connections are used in the encoder-decoder configuration. The highest accuracy value they get is 98.9%.

4. Results

Table 1 shows a general overview of the papers related to the subject of personal identification systems based on palmprint. Regarding the used datasets, the most common are CASIA, HKPU, IITD, PolyU, and MBR. Besides some self-collected dataset by the researchers themselves. The used techniques are varied between the traditional image processing techniques, and machine learning based techniques.

Considering the variant of datasets and the obtained results, the methods based on machine learning approaches gave a better performance in terms of classification accuracy.

Table 1 – Summary of the cutting edges research's related to palmprint identification

Paper	Used dataset	Aim	Technique	Results
And an entry Online palmprint identification [5]	Collected by the researchers. With total of 193 images.	Detect and identify palmprints.	2D Gabor phase coding scheme for palmprint representation. And normalized Hamming distance for palmprint matching.	ROC 0.98 for verification.
Extracting Palmprint ROI From Whole Hand Image Using Straight Line Clusters [6]	Collected by the researchers. With total of 16000 images.	Extract the Region of Interest (ROI) for palmprint detection.	Gaussian smoothing is used as pre-process operation. Detect the palmprint features by using vertical line cluster, ray cluster, and k-means clustering respectively.	ARR (Accurate Recognition Rate) 0.99
Efficient Deep Palmprint Recognition via Distilled Hashing Coding [7]	Collected by the researches. With 30000 images.	Palmprint verification and identification.	Knowledge distillation using Deep hashing network.	Average accuracy for Knowledge distillation is 0.85
Toward Palmprint Recognition	CASIA dataset, with 5502 images.	Palmprint recognition.	Preprocessing steps. Followed by trying 7	The best performance is

Methodology Based Machine Learning Techniques [8]			different machine learning algorithms.	given by the Neural Network, with 1.0 AUC, 0.96 Sensitivity, and 1.0 Specificity.
Extracting region of interest for palmprint by convolutional neural networks [9]	CASIA dataset, with 5239 images.	Extract the Region of Interest (ROI) for palmprint detection.	Convolutional Neural Network (CNN)	Average correct matching rate of 0.99
Deep Region of Interest and Feature Extraction Models for Palmprint Verification Using Convolutional Neural Networks Transfer Learning [10]	HKPU version 2 dataset (7752 images), and Indian Institute of Technology Delhi (IITD) Touchless Palmprint Database (1150 images).	Region of Interest (ROI) detection, feature extraction, and palmprint verification.	Convolutional Neural Network (CNN), Transfer Learning, and Support Vector Machine (SVM).	0.987 AUC for HKPU database. And 0.997 for IITD database.
DeepPalm-A Unified Framework for Personal Human Authentication [11]	Poly-U, CASIA, and GPDS-CL1 datasets.	Extract the Region of Interest (ROI) for palmprint detection.	Region based Convolutional Neural Network (R-CNN)	0.99 accuracy for Poly-U and CASIA datasets. And 0.97 accuracy for GPDS-CL1.
Contactless Palmprint Identification Using Deeply Learned Residual Features [12]	IITD touchless palmprint database with 1150 images.	Palmprint Detection and Identification	Faster Region based Convolutional Neural Network (R-CNN)	The best result obtained is 0.99 for recall evaluation metric
Palmprint authentication using a symbolic representation of images [13]	PolyU Palmprint Database (7752 images), and CASIA dataset (5239 images).	Palmprint Detection and Identification	Symbolic Aggregate approximation (SAX)	0.99 accuracy
Robust palmprint verification using sparse representation of binarized statistical features [14]	PolyU palmprint database (3520 images), IIT Delhi palmprint database (1175 images), and Multi-Spectral PolyU palmprint database (500 images)	Palmprint Detection and Identification	Binarized Statistical Image features (BSIF), and Sparse Representation Classifier (SRC).	
Palmprint verification using binary orientation co-occurrence vector [15]	PolyU Palmprint Database (7752 images)	Palmprint Detection and Identification	Binary Orientation Co-Occurrence Vector (BOCV)	Best result obtained, is 0.0189 for ERR.
Keypoint Selection Algorithm for Palmprint Recognition with SURF [16]	GPDS (1000 images), IITD (2601 images), and CASIA (5502 images).	Detect the key points of the hand-palm.	Speeded-Up Robust Features (SURF)	
A Feasible 3D Ultrasound Palmprint Recognition System for Secure Access	Collected by the researches. With 423 images.	Palmprint Detection and Identification	2D Feature Extraction, and 3D Template Generation.	1.0 identification accuracy.

Control Applications [17]				
Contactless palmprint recognition based on convolutional neural network [18]	PolyU II, CASIA, and IITD databases	palmprint recognition	Convolutional Neural Network (CNN), AlexNet, and hausdorff distance.	Best result obtained is ERR of 0.044
Pilot Comparative Study of Different Deep Features for Palmprint Identification in Low-Quality Images [19]	MOHI palmprint image database (3000 images), and COEP database.	Palmprint Identification	Convolutional Neural Network (CNN), AlexNet, VGG-16, VGG-19, and Support Vector Machines (SVM)	
Synthesis of Palm Print in Feature Fusion Techniques for Multimodal Biometric Recognition System Online Signature [20]	MBR	Palmprint Identification	Convolutional Neural Network (CNN)	0.98 accuracy rate.
Multispectral Palm Print and Palm Vein Acquisition Platform and Recognition Method Based on Convolutional Neural Network [21]	PolyU	Palmprint feature extraction.	Convolutional Neural Network (CNN), and ResNet	Best RR is 0.97
2D and 3D Palmprint and Palm Vein Recognition Based on Neural Architecture Search [22]	PolyU II, PolyU M_B, HFUT, HFUT CS, and TJU-P.	Palmprint Identification	Neural Architecture Search (NAS), and Convolutional Neural Network (CNN)	ProxylessNAS gained 1.0 accuracy for PolyU M_N and FairNAS-A datasets, 0.98 for PolyU II dataset. And 0.99 for HFUT CS.
Palmprint Recognition Based on Convolutional Neural Network-Alexnet [23]	PolyU 2D+3D Palmprint Database, and PolyU Multi-Spectral Palmprint Database.	Palmprint Identification	Convolutional Neural Network (CNN), Alexnet,	Accuracy of 0.99
HandSegNet: Hand segmentation using convolutional neural network for contactless palmprint recognition [24]	PolyU-IITD contactless palmprint image dataset (PolyU-IITD)	Palmprint Identification	Convolutional Neural Network (CNN)	Accuracy of 0.98

5. Conclusions

This study is helpful in taking an overview of the used methods and datasets in palmprint identification and recognition. This is critical whenever new project is considered. So the researchers could consider the advantages and disadvantages of each method. Besides deciding whether to presume the proposed idea or not. Table 1 shows a summary of the investigated methods. Table 1 shows a summary of the cutting edge palmprint detection research's.

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