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Based On Convolutional Neural Networks Dorsal Hand Vein Recognition for High Security Applications

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Abstract: **with the advent of high power, cheap computing and greater complexity, biometric authentication has become possible at every scale because of its safer nature and also user-friendly. According to different researchers, vein biometric is a good biometric trait among others such as fingerprint, palm and finger veins, eyes, voice, signature, gait and DNA for authentication systems. In this paper, PalmDorsal (Back of hand) vein pattern authentication using a Convoluted Neural Network (CNN) is proposed. The main advantage of CNN over other traditional approaches is its ability to simultaneously extract features, reduce dimensionality of data, and classifying it using single network structure. Also, the method requires only minimal steps for image pre-processing since the CNN is robust to noise.This paper proposes a new approach to authenticate the individuals based on the hand dorsal vein images and the knuckle shape features using CNN. The proposed system is a fully automated and it uses a contactless, low-cost near IR imaging device to capture hand vein images. The minutiae points: vein bifurcations and vein endings, are extracted from the hand vein image and along with them knuckle points are used to perform authentication. The matching scores are generated in two stages: (i) hierarchical matching score from the four sets of triplets generated from binarized vein image (ii) the knuckle tip distances and vein map length. The weighted average of the matching scores is used to authenticate an individual. The proposed system produced satisfactory results and provides a more user friendly way of authenticating individuals. In existing system palm vein recognition work has been done. And in proposed method dorsal recognition work has been done. We have to compare accuracy is improved than palm vein recognition. The proposed system developed on MATLAB 2013a version.**

Index Terms – Image Processing, Biometrics, Contactless hand based authentication, knuckle shape, hand dorsal veins **etc.**

1. INTRODUCTION

Biometric technology is an efficient personal authentication and identification technique. Biometric is the term used in computer science to refer to the field of mathematical analysis of unique human features. Biometric solutions have witnessed an accelerated pace of growth in the global market of security over the past several decades, mainly by increasing requirements in public security against terrorist activities, sophisticated crimes, and electronic frauds. The following are some of the security parameters that are associated with biometrics.

- Biometrics is based on the uniqueness of human features
- Since biometrics is associated with individual, it cannot be shared with others.
- Biometrics properties cannot be lost, unless a serious accident happens.
- It cannot be copied. As one of the main-stream branches, vein recognition has drawn much attention among researchers and diverse users.

Anatomically, veins are blood carrying vessels interweaved with muscles and bones, and the key function of the vascular system is to supply oxygen to each part of the body. The spatial arrangement of vascular network in the human body is stable andunique, and vein patterns of individuals are different, even between identical twins [1]. Biometrics is the science of identifying a person using its behavioural and physiological features [2]. Biometrics systems are classified in two categories that are physical and behavioural. Physical systems are related to the shape of the body such as fingerprints, face recognition, DNA, vascular patterns, iris of the eye etc. Behavioural biometrics system are related to behaviour of a person like voice, gait etc. In this paper, we focus on the vein or vascular pattern of the back of the hand (i.e., dorsal hand) because it is distinctly visible, easy to acquire, and efficient to process

It is also a best variant to biometric systems that require physical contact because it extracts the vein pattern, with the hand not in contact with the device instead hand is just easily stretched and the capturing of vein pattern is easily carried out. Since the system is based on three features like live body, internal veins and non-contact type, there is no possibility for forgery, and no misuse by evildoers, thus it can be used at places requiring high level of security. Despite the merits mentioned above, there are some challenges still needed to be sorted out in order to achieve greater performance required in real-world deployments of Palm-Dorsal vein biometric identification systems. First, poor lighting at the capturing device may cause the image to appear extremely dark or bright [4]. Secondly, in a Palm-Dorsal vein acquisition process, the position of the back of the hand and the camera is very close, which causes optical blurring on the captured image [5] and if the hand is not guided with a proper hand-docking frame, then a slight misalignment will be there, which may decrease the recognition rate [6] eventually causing the matching process to be inaccurate. Third fact is, each individual has different pressure levels in keeping the hand in a fisted position, resulting in varied size of palm dorsal surface. The resulting noise has to be removed as much as possible and traditional palm-vein recognition methods employ some complex image processing algorithms to overcome the issues mentioned. Several works in the literature have been focused on applying Computer Intelligence (CI) methods in biometric identification especially using CNN. Among the early works, face recognition research using CNN was reported by Lawrence et al. in 1997 [7]. In their work, input samples were first processed by a Kohonen self-organizing map neural network to reduce dimensionality, and then followed by the operation on a LeNet-5 CNN. Learning was performed using a standard back propagation algorithm. Their method had high complexity since two different neural networks were combined to perform the recognition tasks. From the recent researches, it has been inferred that the above-said problems can be solved by adapting to CI methods, which include neural networks [8], fuzzy logic, and evolutionary computing. A neural network is a cognitive model trying to simulate biological neurons inside human brain, typically known as a multilayer perceptron (MLP), which will work as a powerful classifier. The Neural Network (NN) is formed by several processing elements that provide the ability to do parallel processing, to handle noisy images and learn from experience.

Dorsal hand vein recognition technology is a kind of biometric recognition based on the characteristics of the dorsal hand vein. Compared with traditional biological features, the dorsal hand vein characteristics have more following advantages: The first one is uniqueness, even between the twins, there is still some difference in the dorsal hand veins; the second one is invariance, the dorsal hand vein of human is basically constant; the third one is difficult to forge, the dorsal vein is a kind of biological characteristic; the last one is the detection method is friendly, as the dorsal vein characteristics belong to the internal features, it is difficult to be damaged. Therefore, the technique of dorsal hand vein recognition has great research value and wide application prospect. Owing to the characteristic of deep learning that can automatically select the target feature, it performs well in solving the problem like visual recognition, speech recognition and natural language processing. Afterwards, among the common model of deep learning, CNN (Convolution Neural Network) which is inspired by the mechanism of natural visual cognition, gets the most thorough research. Its modern structure was established in the paper published by LeCun et al in the 1990s [1]. CNN can obtain the effective representation of the original image, and can recognize its visual regularity directly from the image pixels with very little pre-treatment.

The main contributions of this paper are as follows: z Proposed a method of dorsal hand vein recognition based on CNN, which use the depth feature of the dorsal hand vein is to identify; z The feature extraction method of CNN avoids cumbersome manual selection process and simplifies the pre-processing; z Analyzing the influence of the depth of the network and the amount of data to recognition rate, by comparing the recognition rate of the CNN model with different depth and the recognition rate of the varying expansion degrees of dorsal vein data

The organizational framework of this study divides the research work in the different sections. The Literature Review is presented in section 2. Further, in section 3 shown Concept of CNN and palm vein recognition is discussed in section 4 , proposed methodology is discussed in section 5 and In section 6, Simulation Results work is shown. Conclusion and future work are presented by last sections 7.

2. LITERATURE SURVEY

The important characteristic of hand vein patterns is stability, which means that the hand structure and hand veins configuration continue comparatively stable through the individual's life. For this reason, vein identification systems are considered as a promising and reliable biometric.

In this section, some of the vein identification systems are presented.

Huang et al. [5] proposed a method for dorsal hand vein identification. A new process integrating together holistic and local analysis then hierarchically joint with that from the surface modality, born by a reputable texture operator, that Local Binary Patterns (LBP), Binary Coding (BC) and graph for decision production by Factorized Graph Matching (FGM). Consequences attained are greater than the state-of-the-art ones so far described in works, which proves its efficiency.

Lee et al. [6] suggested a directional filter include different alignments that cutting hand vein patterns and encode hand vein features into binary code by the minimum directional filtering response (MDFR) and classification by Hamming Distance (HD). Also, there are many areas that not contain the vein in the image, which are not important for hand vein identification. To increase accurateness, the regions that not contain the vein are identified through calculating the modification of the minimum filtering. Their suggested approach achieves high accuracy that displays the method is effective for dorsal hand vein identification.

Trabelsi et al. [7] suggested a new hand vein pattern identification process for person recognition. Fixed static texture descriptor known as Circular Difference and Statistical Directional Patterns (CDSDP) is suggested to extract hand vein patterns and Artificial Neural Network (ANN), Feedforward Multilayer Neural Network (FMNN) for classification. The CDSDP is a neighboring circular change with weights combining the statistical directional data of vessels. Experimental display that descriptor depend on CDSDP has improved effective than the earlier descriptors that used in LBP.

Yun et al. [8] presented a novel hand vein identification system that depend on the linking lines of feature points. This way the feature points is the connection points with the endpoints of the dorsal hand vein image. They extracted the reference point from feature points that is connection points and the endpoints. Features that extracted are identified by calculating the comparative distances among the two feature points and the angles among the neighboring connections of this two feature points. Lastly, these two features are joint for hand vein identification. The process efficiently overcome the effect on the identification outcomes produced with image translation and rotation.

Chuang et al. [9] suggested local feature-based hand vein image process depend on minutiae features extraction from venous networks to study the greatest discriminative areas and features of dorsal hand veins for recognition. These minutiae feature contain end points and the curve lines among the two end points as measured beside the edge of the area of attention. In addition, suggest a dynamic pattern tree (DPT) to speed up matching presentation and estimate the feature points discriminatory power for verifying an individual's identity.

Zhu et al. [10] proposes an approach for dorsal hand vein recognition that use the texture with geometry features. They first segment the vein area then compute its skeleton in addition to the Energy Cost take out in the Thinning process (TEC) that used to decrease a number of incorrect candidates. Then texture and geometry clues are shown through Local Binary Patterns (LBP) and the diagram collected with the overpass points and endpoints of vein correspondingly and the two modalities are lastly joint for decision production.

A system that uses deep learning for dorsal hand vein recognition was proposed by Wan et al. [11] that depends on CNN, and extracts image by the region of interest (ROI) then preprocess this image with histogram equalization and Gaussian smoothing filter. The system extracts feature by using Convolution Architecture for Feature Extraction (Reference-CaffeNet), AlexNet and VGG and using logistic regression for classification. As a summary, the systems presented in [5-10] extracting features by using machine learning techniques that need to be identified by an expert and then hand-coded as per the domain and data type. As well as in [11] images have been processed before the features extraction by extracting the region of interest (ROI) then applied histogram equalization and Gaussian smoothing filter.

However, the proposed system in this paper is automatically learned how to extract features from original image without pre-processing based on deep learning. The CNN depth model is used to eliminate the work of selecting feature artificially. CNN can select and express the depth feature of the image automatically, thus ensuring the accuracy of the selection of image features and the validity of the representation.

3. CONVOLUTION NEURAL NETWORK

Convolution Neural Network (CNN) was proposed by LeCun in 1989 through LeNet-5 architecture, which was first applied in a handwriting recognition problem. It is a NN Variant that has been widely used for several applications such as face detection [8][9], gender, object, character and texture recognitions. CNN is a type of feedforward artificial neural network in which the connectivity patterns amongst its neurons are inspired by the organization of the animal visual cortex. LeNet-5 contains several important features; namely, convolution layers, sub sampling layers and two or three fully connected layers. Convolution and sub sampling layers are interleaved twice among each other and become the feature extraction layer arriving at a feature map, while the two or three fully connected layers become the MLP for the classification process. CNN combines segmentation, feature extraction and classification in a single trainable module with minimal pre-processing steps. CNN is normally trained with standard back propagation algorithm. The position and values of filters are automatically decided by the CNN during training process. Classification is performed during training, and at the end of training, the final weights obtained behave as a feature extractor to classify the query input sample To the best of our knowledge, this is the first attempt to apply a CNN for Palm-Dorsal vein pattern authentication. A well-known CNN architecture called LeNet-5 which was first applied in a handwriting recognition problem, consisted of seven layers performing convolution alternated with sub sampling operations.

The first convolution layer, which convolves the input with a convolution kernel, essentially acts an edge detector that extracts salient features of the input samples. The kernel, which is of size 5 x 5 in this case, consists of weighting coefficients that create blurring (low-pass filter), sharpening (high-pass filter), or edge enhancement effects. The convolution process is performed by moving a flipped kernel through the images and the resulting output is placed as a new pixel of a feature map at the succeeding layer. The second layer performs sub sampling, that is, a local averaging on a non overlapping small window size of 2 x 2 in this case. This operation reduces the resolution of the feature maps from the previous layer, essentially adding robustness against small distortions in translation, rotation, and scaling. The final two layers of this architecture are MLPs that act as classifiers. The CNN architecture proposed in this paper has convolution and sub sampling layers which were fused into one single layer. The idea of reducing the number of layers, known as fusion convolution or subsampling concept, was inspired by Simard et al. in 2002 [10]. This fusion significantly reduces the total number of layers in the CNN from seven to four, where seven layers are used in LeNet-5 architecture.

Advantages

As compared with other popular biometric traits, such as face or fingerprint, the hand vein has several distinguished merits. Comparatively, vein pattern based biometric systems have the following advantages [3].

- **Direct Liveness Detection:** Vein pattern can be obtained from a person who is alive.
- **Internal:** As the veins are hidden inside the body it is not damageable and non-wearable.
- **Highly Secure:** It is extremely difficult to counterfeit or duplicate.
- **Universality:** It can be obtained from anyone.
- **Consistency:** Vein patterns do not change with time.
- **Uniqueness:** Vein patterns are different for different individuals. Even identical twins have different pattern

4. PALM VEIN RECOGNITION

Fig. 1 depicts the schematic of the palm vein identification system. This study proposed improvements of computer vision algorithms presented in several studies. The research method can be divided into 2 parts: 1) image pre-processing, region of interest, and a 3) convolutional neural network (CNN).

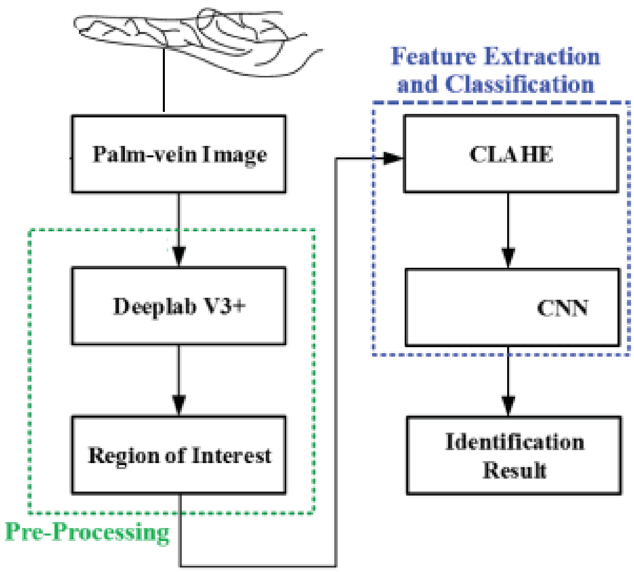

Fig.1: Existing System Block Diagram

5. PROPOSED METHOD

Dorsal hand vein pattern, shown in Fig. 2. is the network of blood vessels under body's skin. The vein pattern was used as a biometric technology in 1992. vein patterns are sufficiently dissimilar through persons, also they are stable unaffected via ageing and no important changed in adults through observing. The patterns of blood vein are unique for all parsons, even between twins. Contrasting other biometric characters, like face or fingerprint, vein patterns provide a detailed pattern that are unseen inside of a person body making them unaffected with the conditions of the outside skin (such as dirty hand).

Due to the deep learning characteristics which include extracting the aim feature automatically, it does fit to recognition systems such as visual identification, speech identification and natural language treating. Convolution Neural Network (CNN) is one of the public models of deep learning that inspired through the mechanism of normal visual perception that also becomes the greatest thorough research.

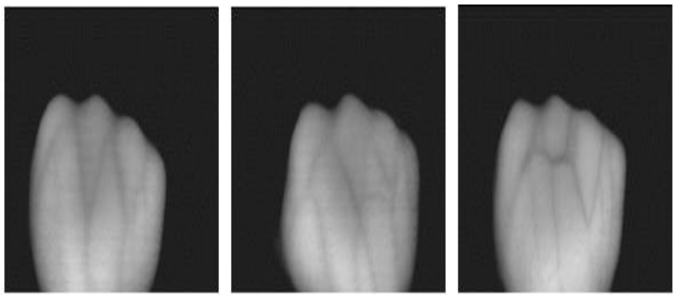

Fig.2: Dorsal Input images

In this paper, the process framework of vein recognition mainly includes the preprocessing of vein image, transforming the image data into the more efficient format in processing called LMDB (Lightning Memory-Mapped Database Manager); CNN network construction; network training; softmax logical regression classifier training and other steps. The processes are divided into training and identification; the process framework of identification is shown in Fig. 1.

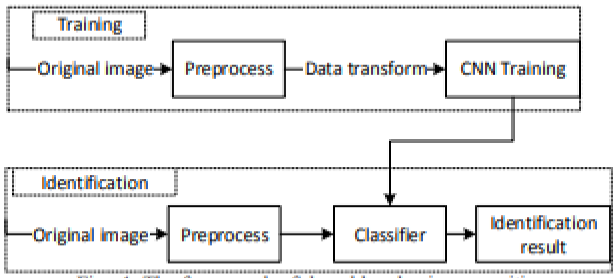

Fig.3: Proposed System Block Diagram

The data set used in this experiment is NIR (Near Infrared Reflection) vein image whose imaging resolution is not high, and need image preprocessing, which includes using centroid method to extract the image ROI (Region of Interest), using CLAHE (Contrast Limited Adaptive Histogram Equalization) [14] algorithm to enhance the contrast of the image.

A. ROI Extraction

The coverage area of the collected image is larger than that of the dorsal vein, and the centroid method take centroid of image as the standard of ROI extraction. (x0, y0) as the centroid of the dorsal hand vein image, the calculation process is shown in equation (1) (2):

$$x_0 = \frac{\sum_{i,j} i \times f(i,j)}{\sum_{i,j} f(i,j)} \tag{1}$$

$$y_0 = \frac{\sum_{i,j} j \times f(i,j)}{\sum_{i,j} f(i,j)} \tag{2}$$

After finding the centroid of image, taking a subgraph of 360×360 pixels as the center,

Evaluation parameters

In this paper, we use several evaluation standards to evaluate the proposed framework. The process of evaluating the model is one of the most important ways to measure the success of the model in the future and to obtain the best model for representing the data. Below is a detailed description of the metrics used in the evaluation process.

Accuracy: It is considered one of the most important methods used to judge the success of the model. It can be applied to calculate the accuracy of the proposed system of hand images, as follows: TN is the true negative states, FN are the false negative states, TP are the true positive states and FP are the false positive states.

$$Accuracy = \frac{TNT+P}{TP+FP+TN+FN}$$

Specificity: is the proportion of negative instances out of the total actual negative instances and it is calculated as following:

False Positive Rate (FPR): a ratio of the false negatives to the sum of the false negatives and true positives, calculated as following:

$$FPR = \frac{TP}{TP+FN}$$

Precision: the number of correct positive instances divided by the number of all positive instances returned by the model. It can be calculated as:

$$Precision = \frac{TP}{TP+FP}$$

Recall: also known as sensitivity is the number of correct positive instances divided by the number of all relevant samples. It is measure by the following equation:

$$Recall = \frac{TP}{TP+FN}$$

6. SIMULATION RESULTS

The simulation results simulated using MATLAB 2013a Version.

A. EXISTING SYSTEM

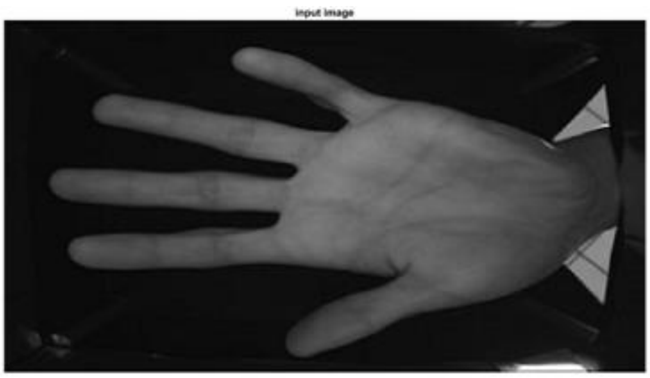

Fig.4: Palm Input image

Fig.5: Noise Suppressed Image

Fig.6: Binaraised Palm input image

Fig.7: Output image

B. PROPOSED METHOD

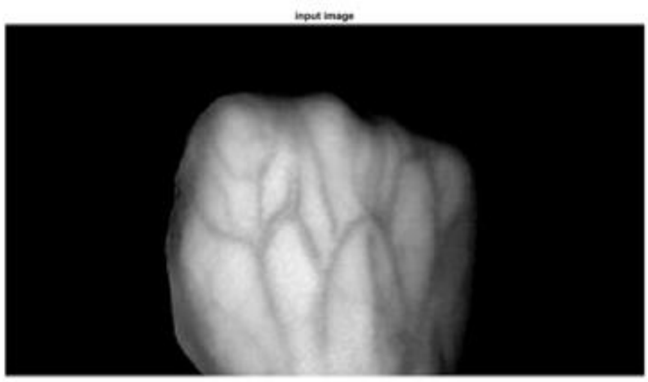

Fig.8: Dorsal Hand input image

Fig.9: Noise Suppressed Image

Fig.10: Binaraised Dorsal input image

Fig.11: Output image

C. Comparison Table

S.N	Parameter	Palm Veins	Dorsal Veins
1	Classifier	CNN	CNN
2	Accuracy	96.1538	98.3607
3	Precession	1	1
4	Sensitivity	0.8000	0.800
5	Specificity	6	6
6	FPER	0	0
7	Recall	1	1

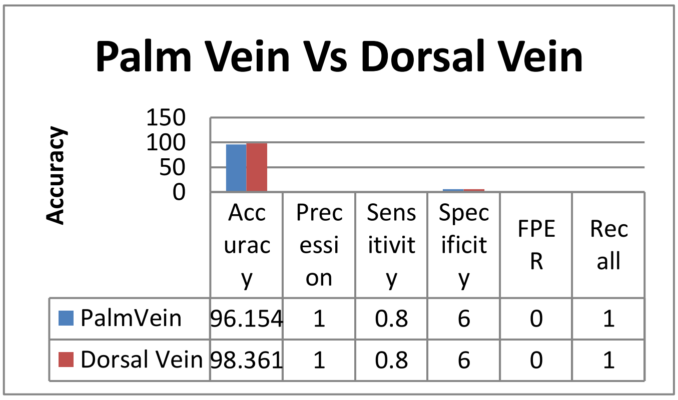

Fig.12: Comparison Graph between Palm Veins and Dorsal Veins
LCD

7. CONCLUSION

In this paper, a method of dorsal hand vein recognition based on convolution neural network in deep learning is proposed. CNN can learn images in end-to-end with a small amount of preprocessing, and parameter transfer makes feature extraction more efficient. The whole process not only guarantees the reliability of the feature, but also ensures the efficiency of recognition. The experimental results show that the recognition method based on convolution neural network is superior to most existing palm vein recognition using CNN methods, and deep learning method has advantages itself: high efficiency and feature selection is convenient. This method can be effective in practical application. With the development of deep learning technology and the expansion of the dorsal vein data set, the recognition rate will be further improved.

Future Scope

For future work, the proposed framework can be extended to solve more complicated recognition problems, such as age and gender recognition problems using hand images.

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