CONVOLUTIONAL NEURAL NETWORKS FOR FACE RECOGNITION AND FINGER-VEIN BIOMETRIC IDENTIFICATION

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Dedicated to my beloved parents, husband and daughter.

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ABSTRACT

The Convolutional Neural Network (CNN), a variant of the Multilayer Perceptron (MLP), has shown promise in solving complex recognition problems, particularly in visual pattern recognition. However, the classical LeNet-5 CNN model, which most solutions are based on, is highly compute-intensive. This CNN also suffers from long training time, due to the large number of layers that ranges from six to eight. In this research, a CNN model with a reduced complexity is proposed for application in face recognition and finger-vein biometric identification. A simpler architecture is obtained by fusing convolutional and subsampling layers into one layer, in conjunction with a partial connection scheme applied between the first two layers in the network. As a result, the total number of layers is reduced to four. The number of feature maps at each layer is optimized according to the type of image database being processed. Consequently, the numbers of network parameters (including neurons, trainable parameters and connections) are significantly reduced, essentially increasing the generalization ability of the network. The Stochastic Diagonal Levenberg-Marquadt (SDLM) backpropagation algorithm is modified and applied in the training of the proposed network. With this learning algorithm, the convergence rate is accelerated such that the proposed CNN converges within 15 epochs. For face recognition, the proposed CNN achieves recognition rates of 100.00% and 99.50% for AT&T and AR Purdue face databases respectively. Recognition time on the AT&T database is less than 0.003 seconds. These results outperform previous existing works. In addition, when compared with the other CNN-based face recognizer, the proposed CNN model has the least number of network parameters, hence better generalization ability. A training scheme is also proposed to recognize new categories without full CNN training. In this research, a novel CNN solution for the finger-vein biometric identification problem is also proposed. To the best of knowledge, there is no previous work reported in literature that applied CNN for finger-vein recognition. The proposed method is efficient in that simple preprocessing algorithms are deployed. The CNN design is adapted on a finger-vein database, which is developed in-house and contains 81 subjects. A recognition accuracy of 99.38% is achieved, which is similar to the results of state-of-the-art work. In conclusion, the success of the research in solving face recognition and finger-vein biometric identification problems proves the feasibility of the proposed CNN model in any pattern recognition system.

ABSTRAK

Convolutional Neural Network (CNN) yang merupakan variasi kepada *Multilayer Perceptron* (MLP) telah menunjukkan kebolehan dalam kerja pengecaman yang rumit terutamanya dalam pengecaman corak visual. Walau bagaimanapun, senibina klasik CNN iaitu LeNet-5, yang merupakan asas kepada kebanyakan penyelesaian, mempunyai pengiraan intensif yang tinggi. CNN ini juga berhadapan dengan masa latihan yang terlalu lama disebabkan oleh bilangan lapisannya dalam lingkungan enam hingga lapan lapisan. Dalam kajian ini, model CNN dengan kurang kekompleksan telah dicadangkan untuk diaplikasi pada pengecaman muka dan pengesahan identiti biometrik urat jari. Senibina yang lebih ringkas telah diperolehi dengan cara mencantumkan lapisan *convolution* dan *subsampling* ke satu lapisan, dengan gabungan skim sambungan separa antara dua lapisan pertama dalam rangkaian. Keputusannya, jumlah lapisan telah dikurangkan kepada empat. Bilangan petak sifat pada setiap lapisan telah dioptimumkan berdasarkan kepada jenis pangkalan data yang digunakan. Kesannya, bilangan parameter rangkaian (termasuk *neuron*, parameter terlatih dan sambungan) nyata sekali dapat dikurangkan, terutamanya kebolehan generalisasi yang lebih baik. Algoritma *Stochastic Diagonal Levenberg-Marquadt* (SDLM) telah diubah suai dan diaplikasi dalam latihan rangkaian yang dicadangkan. Dengan algoritma ini, kadar pembelajaran titik tumpu telah dipercepatkan untuk tumpu dalam tempoh 15 *epoch*. Untuk pengecaman muka, CNN yang dicadangkan mencapai kadar pengecaman sebanyak 100.00% dan 99.50% masing-masing untuk pangkalan data AT&T dan AR Purdue. Masa pengecaman untuk AT&T adalah kurang daripada 0.003 saat. Keputusan yang diperolehi telah mengatasi kerja terdahulu. Tambahan pula, apabila dibandingkan dengan reka bentuk CNN yang lain, senibina CNN yang diusulkan mempunyai parameter rangkaian yang paling sedikit malahan ia mempunyai kebolehan generalisasi yang lebih baik. Satu skim latihan juga telah dicadangkan untuk mengecam kategori baru tanpa memerlukan keseluruhan latihan CNN. Dalam kajian ini, penyelesaian CNN untuk masalah pengesahan identiti biometrik urat jari juga telah dicadangkan. Sepanjang pengetahuan yang ada, tiada kerja sebelumnya yang dilaporkan mengaplikasi CNN untuk pengesahan identiti biometrik urat jari. Kaedah yang dicadangkan berkesan kerana algoritma pemprosesan mudah digunakan. Reka bentuk CNN diadaptasi pada pangkalan data urat jari, yang telah dihasilkan sendiri dan mengandungi 81 orang. Kejituan pengecaman sebanyak 99.38% telah dicapai, yang hampir sama dengan keputusan yang diperoleh daripada kerja terkini. Kesimpulannya, kajian ini telah berjaya menyelesaikan masalah pengecaman muka dan pengesahan identiti biometrik urat jari membuktikan bahawa CNN yang dicadangkan boleh dilaksanakan dalam sebarang sistem pengecaman corak.

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LIST OF ABBREVIATIONS

AI	–	Artificial Intelligence
ANN	–	Artificial Neural Network
BP	–	Backpropagation
CI	–	Computational Intelligence
CNNs	–	Convolutional Neural Networks
CMC	–	Cumulative Match Characteristic
DNN	–	Deep Neural Network
EBGM	–	Elastic Bunch Graph Matching
EER	–	Equal Error Rate
FERET	–	Face Recognition Technology
FAR	–	False Acceptance Rate
FRR	–	False Rejection Rate
FPGA	–	Field Programmable Gate Array
GA	–	Genetic Algorithm
GPU	–	Graphic Processing Unit
HD	–	Hausdorff Distance
HMM	–	Hidden Markov Model
LED	–	Light-Emitting Diode
LDA	–	Linear Discriminant Analysis
MATLAB	–	Matrix Laboratory
MSE	–	Mean Square Error
MHD	–	Modified Hausdorff Distance
MCDNN	–	Multi-column Deep Neural Networks
MLP	–	Multilayer Perceptron
MCPCNN	–	Multiple Circular Path Convolutional Neural Network
MSCNN	–	Multiscale Convolutional Neural Networks
NIR	–	Near Infrared
NNs	–	Neural Networks

ORL	–	Olivetti Research Laboratory
1D	–	One-Dimensional
OS	–	Operating System
PC	–	Personal Computer
PIN	–	Personal Identification Number
PCA	–	Principal Component Analysis
PNN	–	Probabilistic Neural Network
RAM	–	Random Access Memory
ROC	–	Receiver Operating Characteristic
RCNN	–	Recurrent Convolutional Neural Networks
RNN	–	Recurrent Neural Networks
ROI	–	Region of Interest
RBF	–	Radial Basis Function
RF	–	Receptive Field
RPROP	–	Resilient Backpropagation
SOM	–	Self-Organizing Map
SICoNNets	–	Shunting Inhibitory Convolutional Neural Networks
SCNN	–	Siamese Convolutional Neural Network
SDNN	–	Space Displacement Neural Network
SPCNN	–	Sparse Convolutional Neural Network
SDLM	–	Stochastic Diagonal Levenberg-Marquardt
SVM	–	Support Vector Machine
3D	–	Three-Dimensional
TDNN	–	Time Delay Neural Networks
2D	–	Two-Dimensional
US	–	United State
UTM	–	Universiti Teknologi Malaysia

CHAPTER 1

INTRODUCTION

1.1 Overview of Pattern Recognition

Pattern recognition continues to be an active area of research since half a century ago. The basic approach in pattern recognition is to transform raw images through a series of image processing algorithms before applying the final stage of classification. Examples of applications for pattern recognition includes: speech recognition, handwriting recognition, object recognition, etc. Figure 1.1 shows a common pattern recognition flow. The choice of sensors, preprocessing techniques and decision making techniques depend on the characteristics of the problem domain.

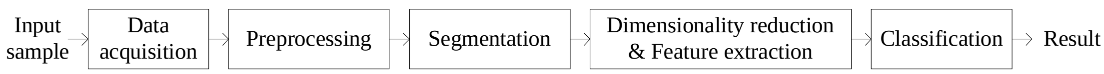

Figure 1.1: Typical pattern recognition flow

The first stage of a pattern recognition system is data acquisition. In this stage, raw data or images are collected from sensors or capture devices. Image preprocessing is then performed, where transformations such as image enhancement, image restoration, compression and morphological processing are applied [13]. Image enhancement is applied to highlight certain features of interest in an image by applying contrast transformation, Region of Interest (ROI) processing and noise filtering. Then the image is restored by improving its appearance. This involves recovering the original image that has been degraded by using a priori knowledge of the degradation phenomenon and applying the inverse process. Image restoration applies deblurring and noise reduction algorithm. Compression is then performed to remove redundant data in the image. Typically, the image is converted to image file formats such as JPEG (Joint Photographic Experts Group) image compression standard. In morphological processing stage, it involves with the techniques to extract image components that are useful in subsequent stages. Example of morphological processing includes dilation and erosion, opening and closing, hit or miss transform and basic morphology algorithms such as region extraction, region filling, extraction of connected component, convex hull, thinning, thickening, skeleton and pruning. These processes are applied to extract image components required in subsequent stages.

Commonly, segmentation is part of preprocessing techniques. However, in this thesis, segmentation is assumed as a separate process to ease the explanation of this thesis. In segmentation, the image is partitioned into its constitutional parts/regions. This is a critical stage in the process flow because, the more accurate is the segmentation process, the more likely is the recognition to succeed. The next stage in pattern recognition flow is feature extraction. In this stage, dimensionality reduction is applied to eliminate redundant information, and unique features that best describe the samples are extracted. The goal of feature extraction is to characterize an input sample with similar values in the same category and very different for input samples in different catogery. An effective feature extractor should be invariant to scaling, rotation and translation [14]. A common method to reduce dimension is Principal Component Analysis (PCA). Next, the extracted features are passed to a stage that classifies the resulting vectors into categories. Classifiers can be either rule-based or machine learning types (e.g., Neural Networks (NNs) or Support Vector Machine (SVM).

1.2 Neural Networks in Pattern Recognition Problems

NNs are suitable for pattern recognition because of the ability to learn that makes them ideal in handling non-linear problems that normally involve data that are noisy and imprecise, the noise in an image exists due to deformable nature of sensors or corruption by environmental noise, variability over time and occlusion by other objects. Research has shown that NNs play an important role in solving complex pattern recognition problem. However, NNs have complex architectures and requirements. Among these considerations include identifying the learning rate, finding the best weight initialization algorithm to apply, and obtaining the optimal set of weights. In addition, the optimal network topology is highly dependent on the complexity of the problem.

Recent work using NNs in pattern recognition have shown great promise. This is mainly due to the fact that NNs is an alternative computational approach for problems that do not have algorithmic solutions or too difficult to be expressed algorithmically [15]. The conventional approach is to use multilayer perceptron (MLP) NNs as a trainable classifier on the data output of the feature extraction stage. There are several drawbacks that arise with this approach [3]. First, when the problem domain changes, a re-design of the feature extractor are required. The performance of the MLP classifier is highly dependent on the ability of the designer to generate an appropriate set of features for input to the classifier. Hence, the effectiveness of the feature extractor greatly affects the success of the system. Secondly, the MLP classifier implements the full connection scheme with all the extracted features, that is, a totally flat structure with inputs all fully connected to the subsequent layers in the architecture. This result in the number of trainable parameters becoming extremely large. The presence of these free parameters causes the MLP to suffer from over-fitting conditions in training, hence reducing the generalization ability of the network. Thirdly, it offers little or no invariance to shifting, scaling, and other forms of distortion. Fourth, the topology of the input data is completely ignored, yielding similar training results for all permutations of the input vector.

1.3 Convolutional Neural Network

A variant of the MLPs that can circumvent the aforementioned drawbacks is known as Convolutional Neural Network (CNN). CNN was first introduced in 1990 by LeCun *et al.* [4] using the idea of Neocognitron by Fukushima to create a series of LeNet architectures. Recently, CNNs have shown great promise in solving complex pattern recognition problems, especially those involving visual processing tasks. CNN accepts raw data images with simple and minimal preprocessing such as ROI extraction and image resize. It is a hierarchical multilayered NN that combines noise filtering, dimensionality reduction, feature extraction and classification process in one trainable module. It trains the input samples in supervised mode using gradient descent learning algorithm, such as the stochastic mode standard back-propagation (BP) algorithm.

A CNN model applies the concepts of local receptive field, shared weights and spatial subsampling. With local receptive fields, neurons can extract salient visual features such as oriented edges, corners, borders, etc. Subsampling reduces the resolution of pixels into a much smaller resolution hence producing a dimensionality reduction effect, which results in ensuring geometric invariance in shift, scale and distortion. The use of shared weights (i.e. using the same set of weights for all features in a feature map) reduces the number of parameters in the system thus aiding generalization, and also minimizes the risk of over-fitting [3]. An example of a common CNN architecture is LeNet-5 [3], depicted in Figure 1.2. It normally consists of 6 to 8 number of layers. Other advantages of CNN include: (a) Whenever the problem domain changes, the only requirement is to adjust the number of feature maps in each CNN layer, and (b) CNN takes into consideration the topological properties of the input samples including deformations (translation, rotation and scaling) during the learning process. This results in a robust feature extraction process built in the system.

CNNs have shown success in solutions for a wide range of applications such as face detection [16–24], face recognition [25–29], gender recognition [30, 31], object recognition [32–34], character recognition [35, 36], texture recognition [37], etc. CNNs have also been applied in the biometric field to solve complex non-linear problem such as face recognition [38, 39] and fingerprint recognition [6].

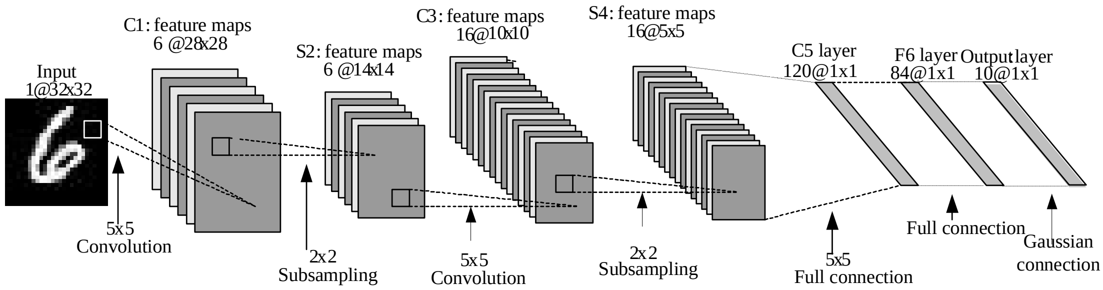

Figure 1.2: Example of CNN Architecture

1.4 Biometric Pattern Recognition

A biometric system is a subset of the pattern recognition problem. Biometrics can be defined as identification of humans by their distinctive characteristics or traits in the application of identification, access control and security. Today, biometric recognition techniques are replacing the traditional access control methods of token-based identification system (e.g., using driver's license or passport) and knowledge-based identification system (e.g., using password or personal identification number). The traditional methods have several disadvantages that can be overcome by employing biometric systems. For example, a driver's license or passport could be easily misplaced by the owner, stolen and forged by the impostor. In the case of password or personal identification number, it can be easily forgotten by the owner. Biometric methods increase security while decreasing the need for password or identity card. When biometric is used, that particular person must physically present since one's biometric traits can not be passed to another person.

Biometric features or identifiers can be classified into two categories: physiological and behavioral biometrics. A physiological biometric identifies a person by physical characteristic such as fingerprint, facial, hand geometry, iris, retina, vascular patterns, ear shape and DNA [2]. Behavioral biometric refers to voice, signature, keystroke and gait. The physiological biometric is a relatively more stable biometric identifier compared to behavioral biometric. Among these biometric methods, the face biometric recognition is currently a very active research topic. Its main advantage over others is that co-operative requirement from the person to be identified is not needed. A properly-designed system installed in public places can identify individuals among the crowd. Besides face biometrics, finger-vein biometric methods have also emerged as another promising biometric approach. Each people have unique vein patterns, and the patterns are stable, and cannot be deformed by the local environment as it is located beneath human skin.

A biometric system has two modes of functionality: verification (authentication) or identification. The former involves a one-to-one comparison while the latter involves a one-to-many comparison between the query image and the reference image stored inside a database. Figure 1.3 shows the taxonomy of existing biometric methods.

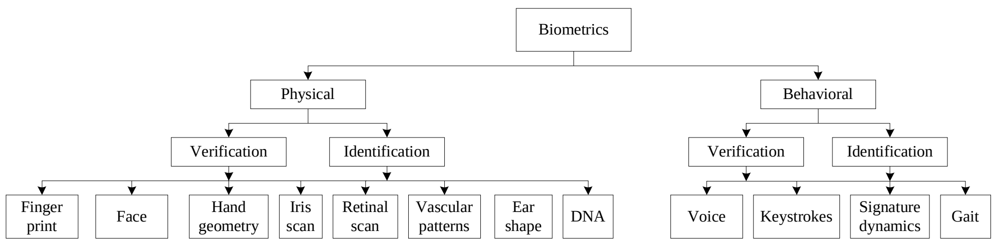

Figure 1.3: Taxonomy of biometric methods

Table 1.1 gives the comparison of some biometric development in terms of characteristic, defect sensitivity, security, sensor type and cost. The table shows that face and finger-vein applications have similar feature in terms of sensor and cost, but the finger-vein method has better security and less sensitive to defects. Common problem in capturing biometric data is that, the biometric trait cannot be captured precisely the same way twice [40, 41]. There will be variance at each time capture and also consists of noise. Therefore, the common biometric matching approach using similarity metric will result in creating fuzziness when measuring the similarity between two biometric samples. This problem makes Computational Intelligence (CI) methods an ideal approach for solving biometric problems. CI methods which includes NNs, fuzzy logic, evolutionary computing, etc., learns the biometric features adaptively making CI robust towards changes of biometric samples.

Table 1.1: Characteristic comparison of biometric application [1]

Type	Characteristic	Sensitive to defect	Security	Sensor	Cost
Voice	Natural/Convenient	Noise	Normal	Non-contact	Low
Face	Remote-controlled	Light	Normal	Non-contact	Low
Fingerprint	Widely application	Skin	Good	Contact	Low
Iris	High precision	Glasses	Excellent	Non-contact	High
Finger-vein	High security	Few	Excellent	Non-contact	Low

Table 1.2 provides the history of biometric system development, showing the start of research and the year of the first commercial effort. Among these applications, research on face biometric is among the earliest biometric application, but it continues to be very challenging and hence very active today due to several issues remaining unsolved. Research on face recognition has started in 1965, and has become significantly important since the nineties because, face is perhaps the most natural and practical biometric traits to capture since it does not need any cooperation by the subject. In addition, facial image is widely deployed in passports and national identification card. However, face recognition remains a most challenging problem. On the other hand, finger-vein methods only recently have shown promise in biometric solutions and hence currently is an active research topic in pattern recognition.

Table 1.2: History of some biometric development [2]

Technology	Approximate date of an early major paper or relevant patent	Approximate date of an early commercial implementation
Fingerprint (AFIS)	1962 paper	1979, 1985 Identix
Speaker	1963 paper, Pruzansky	1976, Texas Instruments
Face	1965, Helen Chan and Charles Bisson	1996, Cognitec, ZN, Identix
Hand	Mid-1960s	1986, IR Recognition Systems
Retina	1978	1984, EyeDentify, Inc.
Keystroke	1986, Patent, J. Garcia	2002 iMagic
Iris	1987, Patent, John Daugman	1995, Iridian
Vascular	1992, Dr K. Shimizu	Early-2000s
3D face	1992, G. Gordon	2001, A4 Vision
Palm	1994	1997
Finger Vein	2002	2004

1.4.1 Summary of Existing Face Recognizers

Once identifying the motivation of conducting the research, it is important to determine the status of current research for each problem. For face recognition problem, applying CNN as the face recognizer is not new, as among the earliest work is reported by Lawrence *et al.* in [39]. Table 1.3, gives the summary of existing works on CNN face recognition problem using various databases.

There are two general weaknesses of non-CNN methods for face recognition problem. Firstly, the efficiency of the classifier depends on how well the preprocessing and feature extraction algorithms are designed. Secondly, major re-design is required, whenever the database changes. Table 1.4 provides the summary of significant non-CNN methods for three standard face databases of AT&T, AR Purdue and FERET.

Table 1.3: Previous work on face recognition based on CNN

Reference/Year	**Database/ No. of subjects**	**No. of layers**	**Weaknesses**
Lawrence *et al.*,1997 [39]	AT&T/40	5	Complex, 2 types of NN, epochs do not include SOM
Fasel 2002 [42]	JAFFE/10	5	Complex, more than 100 epochs to converge
Duffner & Garcia, 2007 [43]	AT&T/40	6	Complex, more than 100 epochs to converge
Cheung, 2012 [38]	CAPTCHA/10	6	Complex, more than 5 layers
Khalajzadeh *et al.,* 2013 [15]	AT&T/40	4	Low accuracy

Table 1.4: Previous work on face recognition applying non-CNN methods

Reference/Year	**Approach**	**Number of Subjects**
AT&T face database		
Chengjun and Wechsler, 2003 [44]	ICA	40
Omaia *et al.*, 2009 [45]	DCT	40
Naseem *et al.*, 2010 [46]	Linear regression	40
Zhang *et al.*, 2010 [47]	Sparse representation	40
Huang, 2010 [48]	2D PCA-LDA	40
Rinky *et al.*, 2012 [49]	DWT	40
Mashhoorir *et al.*, 2013 [50]	2D-PCA	40
AR Purdue face database		
Roli and Marcialis, 2006 [51]	Semi-supervised PCA	100
Rose, 2006 [52]	Gabor and log-gabor filters	126
Song *et al.*, 2007 [53]	Parameterized direct LDA	120
Jiang *et al.*, 2011 [54]	K-SVD	100
Patel *et al.*, 2012 [55]	Dictionary-based Recognition	100
FERET face database		
Shih *et al.*, 2005 [56]	Fisherface	20
Rinky *et al.*, 2012 [49]	DWT	35

1.4.2 Summary of Work on Finger-vein Pattern Recognition

For finger-vein biometric identification problem, to date, there have been no reported work on applying CNN particularly for this problem. For comparison purpose, recent works are divided into CI and conventional methods as shown in Table 1.5 and Table 1.6 respectively. Table 1.5 for CI approach reports accuracies that are significantly high ($> 90\%$) for the number of subjects of at least 7. While for conventional method, most of the existing works employed more than 50 number of subjects as listed in Table 1.6. Hence, in this thesis, we have to ensure that the number of subjects and accuracy are higher than the mentioned number to make the proposed approach stands at the same level with other approaches.

Table 1.5: Accuracy achieved by CI approach for finger-vein identification system

Reference	Number of subjects	Number of test samples	Weaknesses
Zhang, Ma *et al.* 2006 [57]	400	3200	Less robust, NN detect horizontal line only
Wu and Ye 2009 [1]	25	500	Too few numbers of subjects
Wu and Liu 2011 [58]	10	100	Too few numbers of subjects SVM sensitive to noise
Wu and Liu 2011 [59]	10	100	Too few numbers of subjects Execution time too long
Hoshyar, Sulaiman *et al.* 2011 [60]	7	14	Too few numbers of subjects

Table 1.6: Detail information and accuracy achieved by conventional approach for fingervein identification system

Reference	No. of subjects	Number of test samples	Weaknesses
Liu *et al.*, 2010 [61]	164	-	The distance-based classifier is highly dependent on how well the preprocessing and feature extraction algorithms are designed
Kejun *et al.*, 2010 [62]	300	600	
Yang *et al.*, 2011 [63]	70	1050	
Beng and Rosdi, 2011 [64]	51	408	
Yang *et al.*, 2011 [65]	-	440	
Mobarakeh *et al.*, 2012 [66]	204	408	
Damavandinejadmonfared, 2012 [67]	204		
Yang and Shi, 2013 [68]	600	-	

1.5 Problem Statement

Recent researches have shown that Convolutional Neural Networks (CNNs) present an interesting and promising method for image processing, particularly in complex visual pattern recognition problems. CNN possesses key properties of translation invariance and spatially local connections (receptive fields and shared weights). It learns the data features adaptively making CNNs very robust towards any changes of captured images. Even though CNNs are reported to give promising results, there are several outstanding issues to be resolved with currently defined model/architectures.

In designing a NN architecture, generalization ability is the key performance measure to ensure efficient implementation of a NN system. This measure the ability of the NN to generalize from ”unseen” data, that is not used in the training of the network. A network is said to generalize if the input-output mapping computed by the network is near to the test set that are not seen during training. Generalization performance is measured by the classification accuracy. Generalization ability of a NN is mainly affected by the model complexity of the NN architecture. If there are high number of neurons, trainable parameters and connections, the generalization performance will degrade, and over-fitting of the data samples may occur. Over-fitting occurs when the network learns too many input-output mappings to a point when it starts to memorize the training data including the noise existing in the data. If too many parameters are used, the generalization performance degrade. If too little, the NNs does not learn adequately. Although CNN have reduce significant number of free parameters (unnecessary trainable parameters) compared to the conventional NNs, overfitting condition can still occur if the aforementioned parameters exceed the sufficient amount. Therefore, it is crucial that the optimal number of parameters is determined to ensure the best generalization ability can be obtained.

The performance of the NN is also evaluated for its convergence rate. Convergence rate is the speed taken by the learning process, measured by the number of epochs between current solution and global minima. To achieve a fast convergence rate, an appropriate learning algorithm must be used. Standard Backpropagation (BP) is the common learning algorithm to train a NN. BP is simple and efficient, but it is well-known for slow convergence speed and has a risk of getting stuck in local minima. This is due to the characteristics of the error surface that contains numerous flat and steep slopes. The network tends to oscillate around the flat area in the weight space which results in settling into a local minimum. This is because the gradient is sharp in some direction but slow in others. Even after long training time, the convergence is not guaranteed and it is normal to require thousands of iterations through the dataset. The convergence rate in standard BP is highly dependent on learning rate or step size. The learning rate is minimized at each epoch according to a specified constant. However, sometimes the value of learning rate is not suitable with the condition of the error surface in the weight space causing the network to bounce back and forth resulting in a slow convergence learning speed. In the ideal case, learning rate has to adapt with the condition of the error surface. For example, if the surface is steep, the learning rate should be reduced and act oppositely if flat surface area is reached. In order to satisfy this condition, a unique learning rate is required for each individual weight, and extensive adjustment of the learning rate parameter (step size) is required at each epoch. LeCun *et al.* [3] introduced the Stochastic Diagonal Levenberg-Marquardt (SDLM) learning algorithm to overcome the limitations by standard BP. It guarantees the convergence state is reached but high speed of convergence is not ensured. Hence, modification of SDLM is required, and thus is undertaken in this thesis.

As mentioned before, there will be variance of biometric images at each time capture and it also contains noise. In addition, a conventional biometric recognition system specifically identification mode, the template of an unknown subject is compared with the templates stored inside the database. A similarity algorithm is performed to find possible match of the unknown subject with the candidates stored in the database. If the similarity index exceeds a predefined threshold, a match is identified. The problem with this approach is that, with a specific threshold, there can be more than one match. The candidate list is shortlisted after the matching process but there is no guarantee that the ”true” match is found. Efficiency of the design is highly dependent on the quality of the feature extraction algorithm. Therefore, in order to cope with the variations of input images, CI method through CNN is seen as the best candidate to learn the samples adaptively. On the other hand, one method has been identified to bridge up the fuzziness of finding the true match of the query sample by using ”winner-take-all” rule. However, the number of neurons (classes) applied in this method is fixed during training. Hence, in order to make the network design generalizes to new samples from previously unseen categories, retraining the whole network is required. This will incur additional cost and execution time. Therefore, a simplified method that provides the ability to generalize to new samples from previously unseen categories is undertaken in this thesis.

In a conventional biometric system, the reliability of the system depends on the amount of noise exist in the system. The higher the noise, the less reliable is the system. The noise exists due to deformable nature of biometric traits, corruption by environmental noise, variability over time and occlusion by user’s accessories. In addition, a designer of conventional biometric recognition system will design an algorithm that is specific to the problem domain. If the problem domain changes, the image processing tasks will also change. In contrast, CNN offers unique features to deal with robustness issues. Noises that exist inside an image could be initialized to aid in speeding up the training convergence rate [5]. In addition, with an adjustment on the number of feature maps at each layer, a CNN architecture can be made suitable and generic to visual recognition problems [3]. Thus, a similar CNN architecture that has the ability to solve at least two pattern recognition problems is another aim in this thesis.

The performance of a face recognition system is challenged by several factors that include variations in pose, illumination, facial expressions, partial occlusions and other variations. The first factor is caused by illumination effect on facial images. Illumination can cause shadows that entail considerable variations of the facial appearance. The system is also affected by partial occlusions that means parts of facial features are covered by an object. For example, hand occluding part of the face or wearing sunglasses that covers the eyes. The third factor is facial expressions such as smile, laugh, anger, sad, surprise, disgust, and fright. The next factor is due to poses of the facial image. Certain poses will cause some of the facial features such as eyes or nose to be partially occluded. The current face biometric system works extremely well to frontal faces but performance may degrade when certain degree of poses exists [69]. For that reason, many applications limits themselves to frontal view image only or perform pose-specific processing that leads to multi-view face recognition approaches. In addition, efficient face biometric system should be robust to varying make-up, varying hair-cut, presence of facial hair (beard, mustache etc), varying aging, varying skin color, varying gender, varying races and varying ethnic origin. Figure 1.4 shows examples of the facial image variations that pose serious challenge to obtain high performance in face recognition. Therefore, the CNN design should provide the ability to cope with all the challenges mentioned.

The evaluation of the face recognizer is typically carried out using standard face databases, of which include AT&T, AR Purdue and FERET, etc. AT&T contains image of ”moderate challenge” which includes moderate degree of variation in poses (up to 20 degrees), lighting (dark homogenous background), facial expressions and head positions. On the other hand, AR Purdue represents image of ”complex challenge” which includes high degree of variation in facial expressions, lighting (illumination), partial occlusions (wearing sunglasses and scarf). The ”extreme challenge” database can be found in FERET which includes high degree of variation of facial expressions, appearances, illumination and poses (up to 90 degrees).

In the case of finger-vein biometric recognition, to date, there is no report

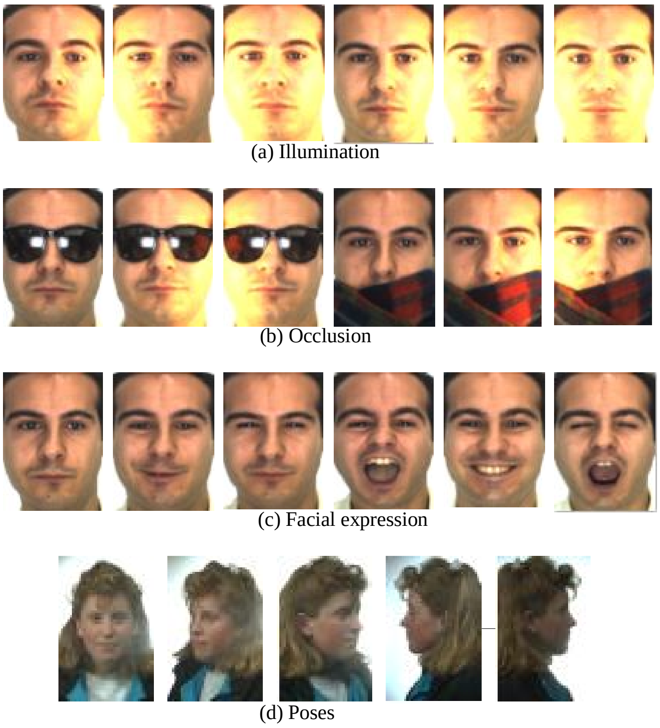

Figure 1.4: Challenges faced by biometric face recognition system

of current work that applied CNN in finger-vein recognition. Finger-vein biometric recognition system also encounters with several challenges. The quality of the captured images vary according to the surrounding of temperature, humidity, illumination and angle at each of acquisition of data samples, resulting in noisy images. In a conventional finger-vein recognition system, these image defects have to be reduced as much as possible by performing sophisticated image preprocessing tasks to enhance the quality of the image. This includes in deploying the costly local dynamic thresholding for as part of the preprocessing task. However, the trade-off of adding more and complex preprocessing tasks is the increase of processing time to classify the input sample. Hence, simpler and fewer preprocessing tasks are preferred. Figure 1.5 shows examples of the aforementioned challenges taken from four subjects of VeCAD-UTM finger-vein database, in which some of the samples encounter inapproprate lighting which causes the sample to appear darker (row number three) or brighter (row number four) than expected. The proposed method thus can overcome the challenges of image suffers from poor illumination.

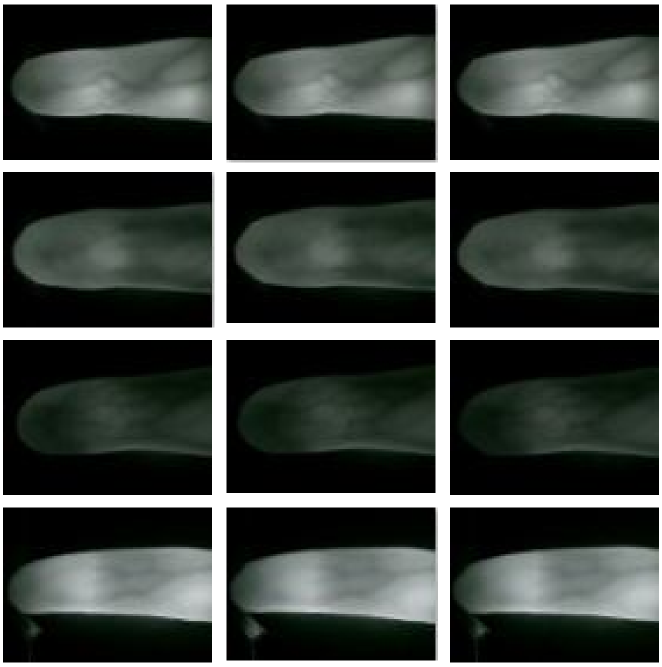

Figure 1.5: Inappropriate lighting in finger-vein samples of VeCAD-UTM finger-vein database

1.6 Research Objectives

The overall goal of this thesis is to propose novel CNN models for application in biometric pattern recognition problems. Hence, the main objectives of this thesis are:

1. To propose an improved Convolutional Neural Network (CNN) model for face recognition application that is optimized for performance and generalization ability under ”complex challenge” image conditions, which include varying facial expressions, illumination, partial occlusions and moderate degree of poses (up to 20 degrees).
2. To propose a novel CNN-based solution for finger-vein biometric identification problem.
3. To propose a second order backpropagation algorithm for training the proposed CNN with the optimization goals of fast convergence rate and higher generalization ability. The proposed training scheme will also allow the NN to be extended to recognize new subjects without retraining the whole system.

1.7 Scope of Work

The details of the software tools, performance measures and case studies are described as follows:

i. The proposed solution should outperform other existing previous work on (a) AT&T database that has moderate degree of poses, facial expressions and head pose and (b) AR Purdue that has high degree of facial expressions, illumination and partial occlusions. Note that, the database under the category of "extreme challenge" (includes high degree of variation of facial expressions, appearances, illumination and poses up to 90 degrees) specified by FERET database is out of the scope. Optimization in performance will include faster feed-forward execution speed and reduced model complexity.

ii. Finger-vein biometric identification will be evaluated on database developed in-house by VeCAD Laboratory from Universiti Teknologi Malaysia (UTM) (labelled as VeCAD-UTM finger-vein database).

iii. During training, the "winner-takes-all" rule assigns true match to the input or query sample. Therefore, common biometric performance measures such as False Rejection Rate (FRR), False Acceptance Rate (FAR), Equal Error Rate (EER) and Receiver Operating Characteristic (ROC) curve are not relevant. Hence, the only performance measure used in this research is accuracy or recognition rate to measure the system's performance.

iv. The software tools and design measurement for this research is as follows:

    a. Matlab is used to prepare of data samples, labels of data samples before training the NNs is carried out. All the graphs are plotted in Matlab.

    b. The proposed CNN model is developed in C/C++ and compiled with the GCC compiler under Ubuntu Linux.

    c. CNN simulation and training ran on a 2.5 GHz Intel i5-3210M quad core processor, 8GB RAM, with Ubuntu Linux.

1.8 Research Contributions

i. The proposed CNN model has fewest number of layers (i.e. four layers) and a reduced model complexity (less number of neurons, trainable parameters and connections) compared to existing works. This is done by fusing the convolution and subsampling layers to become one layer. The model complexity has further reduced by implementing partial connection scheme in between the first two layers.

ii. CNN models have been developed for face recognition and finger-vein biometric identification. The same architecture is applied for these two problem domains; that is the number of layers is the same, only the number of feature maps at each layer is optimized according to the problem domain. In addition, the preprocessing stage for both problems also differ due to different problem domain. This aspect of the design is novel, since with any other conventional pattern recognition methods, a major re-design is required whenever the problem domain changes. The optimization strategies resulted in a NN model with better generalization ability compared to other existing works, indicated by the recognition rate achieved - 100.00% (through *5-14-60* model) and 99.50% (through *15-45-130* model) on the AT&T and AR purdue databases respectively.

iii. The *15-45-130* model is chosen as the best model for face recognition problem since it manage to handle moderate degree of poses and high degree of facial expressions, illumination and partial occlusions. In conjunction with the reduced model complexity, ”winner-takes-all” approach and optimized number of feature maps at each layer, have contributed to an improved recognition time over the existing works. For instance, the recognition time obtained for AT&T database is less than 0.003 seconds which significantly improved over existing works.

iv. In this thesis, a new training algorithm based on SDLM [3] algorithm is proposed to enhance the speed of convergence. The original SDLM algorithm is modified by incorporating ”repeating scheme”. Convergence time of 15 epochs is achieved, which outperforms similar existing work.

v. This work proposes a training scheme to recognize new categories without full CNN training. This method involves the last two layers for retraining instead of the whole system. This is done by allowing the feature extraction layers to be generalized to new samples from previously unseen categories. The optimal weights from previous training are set fixed for layer one until three and new connections are established at the last layer to train a new classifier on top using the training images of the new dataset.

vi. Based on all known previous works, this work is among the first successful attempts of implementing CNN for finger-vein biometric case study. A novel approach is conducted by applying the proposed CNN model to classify finger-vein samples by excluding several sophisticated preprocessing stages such as angle normalization, contrast normalization, local binarization and noise removal techniques. The finger-vein recognition system has extremely few and simple image preprocessing tasks such as ROI detection, ROI extraction and image resizing yet managed to obtain high recognition rate through the database developed in-house known as VeCAD-UTM finger-vein database. An excellent recognition rate of 100.00% and 99.38% are achieved for 50 and 81 number of subjects through the *5-13-50* CNN model.

1.9 Thesis Organization

This thesis is organized into seven chapters. Chapter 1 describes briefly on the background of the research and related issues. The objectives, summary of related works, problem statements, scope of work, and contributions are explained clearly.

Chapter 2 describes variant type of CNN models and review of previous works on the selected case studies namely face and finger-vein biometric system.

Chapter 3 covers the underlying theories of CNN, learning algorithms and other related algorithms.

Chapter 4 describes on the methodology taken to emphasis the contributions of the research work, algorithms and implementation model of the proposed CNN.

Chapter 5 presents the experimental work and results for CNN in face recognition problems. Discussions and justification of the work are stated in this chapter.

Chapter 6 presents the experimental work and results for CNN in finger-vein recognition problems. Discussions and justification of the work are stated in this chapter.

Ultimately, the final chapter summarizes the thesis, re-stating the contributions and suggests ideas for future works and concludes the overall research work.

The proposed architecture is practical to small number of subjects that are less or equal to 100 numbers of subjects and it is known as discriminative approach. Beyond that number, training the NN becomes a time-consuming process. Therefore, a generative approach can be the best solution in providing scalability of the system towards increasing number of subjects. Generative approach produces generic distribution representing a particular class. Discriminative approach is also required in order to distinguish the subjects. Hence, a hybrid of discriminative and generative approach provides the best solution to cater increasing number of subjects. One possible CNN model to solve this problem is referred to as *Siamese* CNN as discussed in Section 2.4.1. In this model, whenever a new subject is added into the system, retraining is not required since a generic distribution is already obtained during the first training.

Recently, multimodal approach that combines two biometric applications has gained significant attention. The proposed NN can also be applicable to multimodal case studies such as combination of face and finger-vein by fusing the features of both applications at the input level. This approach is possible since the proposed CNN design has been proved to perform excellently on two case studies using the same number of layers.

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