國 立 交 通 大 學

電子工程學系 電子研究所

碩 士 論 文

基於深度卷積神經網路之
手勢辨識技術研究

Hand Gesture Recognition based on Deep Convolutional Neural Network

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中 華 民 國 一 〇 三 年 七 月

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摘要

在這篇論文中，我們提出了一個使用任意單一攝影機在不同角度下仍能遠距離辨識多重手勢的技術。此技術不需固定攝影機角度，不需要由特定使用者操作，且能分辨多種手勢。此技術在影片中自動找出使用者的手的位置，並判斷使用者想傳達的訊息，希望能進行遠距離的操作以及在任何背景之下皆能達到手勢辨識的效果。在此設定議題下，為了能在複雜背景與不同視角拍攝的情況下有效的找到手部出現的區域以及辨識使用者所傳達的訊息，我們不採用易被複雜背景所誤導膚色資訊且不使用事先設定之特徵萃取技術，而是利用卷積神經網路有效且準確的學習不同手勢所擁有的特徵，並結合不同形狀與大小的特徵，以找到能分離不同手勢最佳的特徵空間，再利用深度神經網路找出特徵之間的關係以及不同手勢與各特徵的連接，藉此達到手部偵測與多重手勢辨識的成果。此外，我們也利用影片中已經得到的手部位置與移動資訊加上手勢辨識結果，推測之後較有可能出現手部的區域以及最佳的手勢辨識結果。

Hand Gesture Recognition based on Deep Convolutional Neural Network

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Abstract

In this thesis, we propose an algorithm which recognize hand gestures with a single camera under different view-points within a range remotely. The algorithm can recognize multi-gestures without fixing view-point of the camera or a particular user controlling. In order to find the hand position and recognize the gestures from the video automatically and efficiency in the clutter background under different view-points within a range, we don't take the skin color as the information which is easily influence by the clutter background, nor do we use the specific feature extraction processing. Instead, we use the convolutional neural network to learn the features in the hand gesture image and combine the different kernel sizes to get the best feature space for separating different gestures. Then we use the deep neural network to find the relationship between the hand features and the gesture classes. Under this setting, we are able to locate the hand and recognize multi hand gestures. Furthermore, with the help of the temporal information for the hand position and motion getting from the video, we are able to infer the most possible area where the hand would appear and the best recognition result.

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Chapter 1. Introduction

In the technological era, computers play an important role in our daily lives. Our most common way to communicate with computer is through the mouse and keyboard. However, we want to interact with computer directly instead of using mechanical devices. The progress of computer vision and machine learning algorithms enable us to interact with computer in novel ways, such as Kinect. We can use our hand gesture to convey our thought intuitively.

Hand gesture recognition system can be categorized into three stages: detection, tracking and recognition. We want to know the position of our hand in an image, then track the movement of hand and the moving trajectory. Finally, the computer must understand the meaning of user expression. Traditionally, people usually find skin color in the image with simple background and investigate the appearance of skin color part to determine where the hand is. Based on the temporal information obtained from acquired trajectory and result, predict the hand movement. At last, we use some classification methods to identify the gesture we express. However, the variant of appearance of hand is complicated since our hand is composed of five fingers and a palm. In addition, a finger has two knuckles to change the exterior of our hand. Furthermore, the shape of hand will be significantly different as the view point is changing. If the image has a complex background, it will influence the result of hand gesture recognition. Therefore, finding a robust classifier against complex background is difficult when using a simple model. Traditional machine learning method like support vector machine and random forest may not apply to multiple hand gestures and out-of-plane rotation of hand. As with the rapid development of deep learning algorithm, we want to use deep learning algorithm to find a robust classifier of hand gesture.

In this thesis, we want to identify four different gestures, stop, pointer, ok and wave in the clutter background at a remote distance. We propose a hand gesture recognition algorithm in which the detection and recognition stage is based on convolutional neural network and deep neural network. These two methods are widely used in handwritten digit recognition recently. We modify the convolutional neural network to apply it to the hand gesture data set. Combining convolutional neural network and deep neural network to build our classification model for multiple hand gestures and the hand detector. Due to the dramatic change of hand shape and appearance, the points to track are not easy to choose. Therefore, nowadays tracking algorithms are not robust of hand tracking. Therefore, we rely on the detection achievement and adding some basic tracking technique to improve the detection accuracy and reduce the computation time.

In our algorithm, we first use convolutional neural network [1]**錯誤! 找不到參照來源。** to extract the feature of an image, and transform RGB images to the feature space. Then use these features of hand as the input of deep neural network. At deep neural network stage, we use unsupervised learning method : Restricted Boltzmann Machine (RBM) [3] to pre-train the relationship within the low level local features. Combine the local features into global features at RBM training stage. Then add labeled data to do the supervised fine-tuning stage to get the classification model. After we get the hand position in the frame and the gesture it represents, we can only search for the neighbor region to find the hand position in the next frame. In order to improve the accuracy, we calculate the patch similarity of adjacent region to correct the position of the hand. After we get the detection and tracking results, we will do some refinement to get the most reliable position and gesture class in the video frame.

The thesis is organized as follows. We will introduce some other hand gesture recognition technique in Chapter 2. After that, we will describe our proposed method and learning algorithm to do the hand gesture recognition in detail in Chapter 3. Then some experiment results are shown in Chapter 4. Finally, we provide our conclusion in Chapter 5.

Chapter 2. Related Works

The main purpose of hand gesture recognition is to convey user's expression for the computers. The rapid development of vision based hand gesture recognition increase the possibility of remote control human computer interface. There are two different ways to do the hand gesture recognition. One way is using some additional equipment to help doing the recognition, such as Microsoft Kinect and the MIT colored glove. Another way is using the appearance of hand to classify different gestures in which extracting some specific feature in the image. The classification accuracy has been strongly associated with the feature extraction.

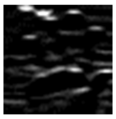
In this section, we introduce two different methods of using the appearance of hands to recognize different gestures. The first method introduced in section 2.1 extracts different orientation edges from hand images and trains the classification model by the random forest algorithm. In section 2.2, the second method extracts the hand contour and complex moments in hand images as the feature vector. They use the neural network algorithm to classify the images into different hand gestures.

2.1 Hand Gesture Recognition by using Random Forest

In [10], they propose a single-camera hand gesture recognition algorithm for human-computer interface. The hand gesture recognition algorithm is composed of three parts. First, they us eight pre-defined edge filters to generate the corresponding edge maps for the hand images. Second, they use randomized pooling cell method to learn more efficient cells for the hand images. They get image feature vectors by concatenating feature vectors in some different size and shape cells. Finally, they use these feature vectors to train a random forest model for hand gesture recognition.

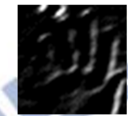
At first, they use 360° orientation edge filters to generate the corresponding edge maps for the hand images. They quantize 360 degrees into 8 bins, then get eight filtered images for all edge filters. The eight edge filters and the examples of the corresponding edge maps for an hand image are shown in Figure 2-1.

0	0	0	0	0
-1	-1	-1	-1	-1
0	0	0	0	0
+1	+1	+1	+1	+1
0	0	0	0	0



(a) 0^0-sensitive.

0	0	0	-1	0
0	-1	-1	0	+1
0	-1	0	+1	0
-1	0	+1	+1	0
0	+1	0	0	0



(b) 45^0-sensitive.

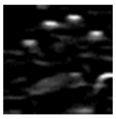
0	-1	0	+1	0
0	-1	0	+1	0
0	-1	0	+1	0
0	-1	0	+1	0
0	-1	0	+1	0

(c) 90^0-sensitive.

0	+1	0	0	0
-1	0	+1	+1	0
0	-1	0	+1	0
0	-1	-1	0	+1
0	0	0	-1	0

(d) 135^0-sensitive.

0	0	0	0	0
+1	+1	+1	+1	+1
0	0	0	0	0
-1	-1	-1	-1	-1
0	0	0	0	0

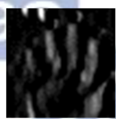


(e) 180^0-sensitive.

0	0	0	+1	0
0	+1	+1	0	-1
0	+1	0	-1	0
+1	0	-1	-1	0
0	-1	0	0	0

(f) 225^0-sensitive.

0	+1	0	-1	0
0	+1	0	-1	0
0	+1	0	-1	0
0	+1	0	-1	0
0	+1	0	-1	0



(g) 270^0-sensitive.

0	-1	0	0	0
+1	0	-1	-1	0
0	+1	0	-1	0
0	+1	+1	0	-1
0	0	0	+1	0

(h) 315^0-sensitive.

Figure 2-1 Eight edge filters and the corresponding edge maps for the image “Five”.

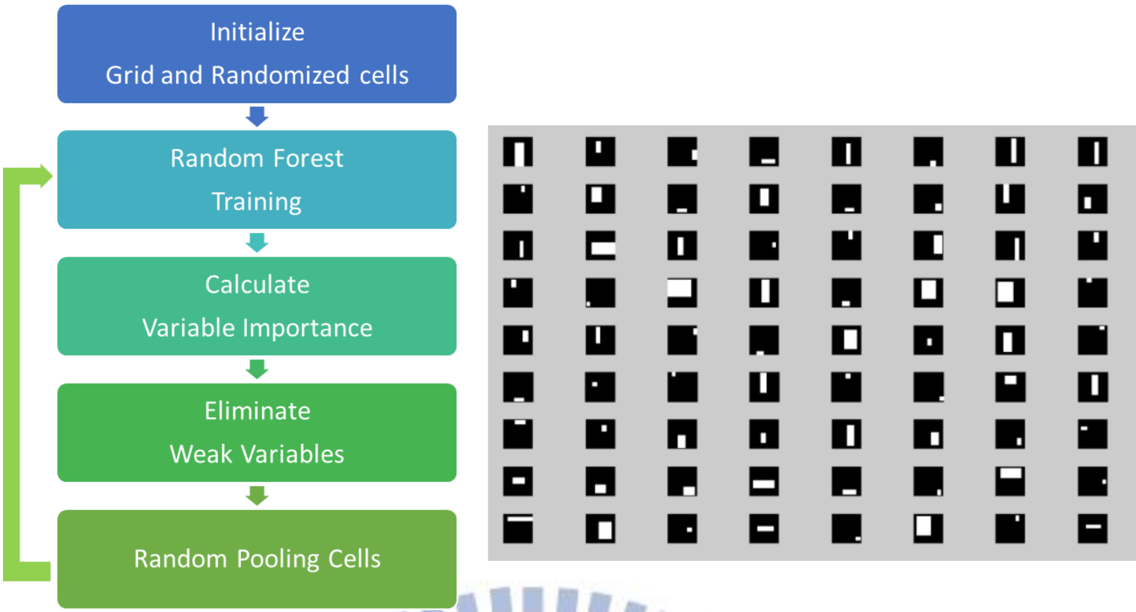
After generating the edge maps, they use the structure of randomized pooling cells to calculate feature vectors [9]. Unlike tradition grid cells, they use more efficient cells to calculate the edge information for the hand images. Figure 2-2(a) shows traditional grid cells for the hand image. It partitions the image into equal size and extract the edge information in each cell. However, in [9], they use randomized pooling cells to get edge information more efficiency instead of grid cells. The training procedure of random forest with randomized pooling cell is mentioned in [9]. Figure 2-2(b) represents the training result for pooling cells which can extract the edge information more efficient for the hand image. After that, the feature vectors of hand images are concatenated by the feature vectors in all cells.

(a) Grid pooling cells. (b) Randomized pooling cells.

Figure 2-2 Compare traditional grid cells and randomized pooling cells for hand image.

As mentioned in [9], their proposed method of random forest with randomized pooling cell training procedure is shown in Figure 2-3(a). First, they choose some grid cells and some randomized cells. Use these cells to calculate the feature vector of hand images and train the hand gesture classifier by random forest. After that, they calculate the variable importance at the training stage for the feature vectors and eliminate some weak variables. They eliminate weak variables and resample different rectangular to get more informative cells iteratively. Finally, they can get the most efficient cells to extract the edge information from hand images. Figure 2-3(b) shows the final randomized pooling cells by random forest training stage.

This hand gesture recognition is good at two class recognition. It can classify the “five” gesture with background and the “zero” gesture with background respectively. The error rate for two class recognition is about 1 to 2 percent. However, it might get much higher error rate when the hand gesture classes increased. The error rate for three class recognition may be 5 percent or higher. Therefore, we want to obtain a more robust multi-gesture classifier for hand images.



(a) (b)

Figure 2-3 (a) Training procedure of random forest with randomized pooling cells.
(b) The final trained random pooling cells for hand image.

2.2 Hand Gesture Recognition by Neural Network

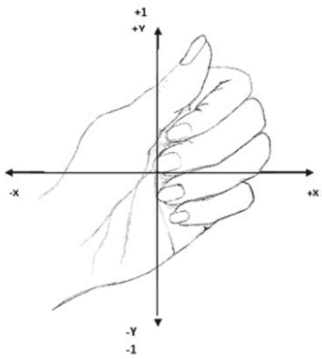
In [8], they proposed a novel technique to do the hand gesture recognition. They infer that the Neural Network has many benefits at pattern analysis. First, Neural Network learns to recognize the pattern which exist in the data set instead of some image processing technique which analyze specific behavior of the model. Second, Neural Network is more robust in different environment than some specific image processing system which is limited to the situation they were designed.

The hand gesture recognition process consist three stages: pre-processing, feature extraction and classification. Furthermore, they consists of two phases: training (learning) and classification (testing). Overview of gesture recognition system is seen as Figure 2-4. They introduced two different ways to extract features for input hand images, that is geometric feature (hand contour) and invariant features (complex moments).

Figure 2-4 Overview of hand gesture recognition system.

At pre-processing stage, they segment the input image into background and objects at first. They use a thresholding algorithm for segmentation of hand gesture images [13]. In order to eliminate some errors produced by segmentation algorithm, they use a median filter to reduce noise. Furthermore, for geometric feature (hand contour), they use edge detection to extract the hand contour For invariant feature (complex moments), they use image trimming to eliminate redundant margins and image scaling combine coordinate normalization to let the origin point coordinates be at the center of the image as shown in Figure 2-5(a).

At feature extraction stage, for the first method, they extract hand contour by edge map. Then do the feature image scaling to get an 32*32 image and shift the hand gesture section to the origin point. Furthermore, they use general feature to be an additional information for height and width offset of the hand gesture image. Figure 2-5(b) shows the example of height and width offset matrix, which the hand gesture has the width near to 2^3 and the height near to 2^5. For the second method, they calculate the complex moments from zero-order to ninth-order for each hand gesture image.



(a)

	2^0	2^1	2^2	2^3	2^4	2^5
2^0	0	0	0	0	0	0
2^1	0	0	0	0	0	0
2^2	0	0	0	0	0	0
2^3	0	0	0	0	0	1
2^4	0	0	0	0	0	0
2^5	0	0	0	1	0	0

(b)

Figure 2-5 (a) Central coordinates normalization. (b) Example of general features matrix.

At the last stage, that is classification stage, they use a simple one hidden layer neural network with back-propagation learning algorithm. Input layer has 1060 nodes or 10 nodes for two method. Hidden layer has 100 nodes and output layer, the recognition layer, has 6 nodes for 6 different hand gestures. The recognition rate is 70.83% for the first method and 86.38% for the second method.

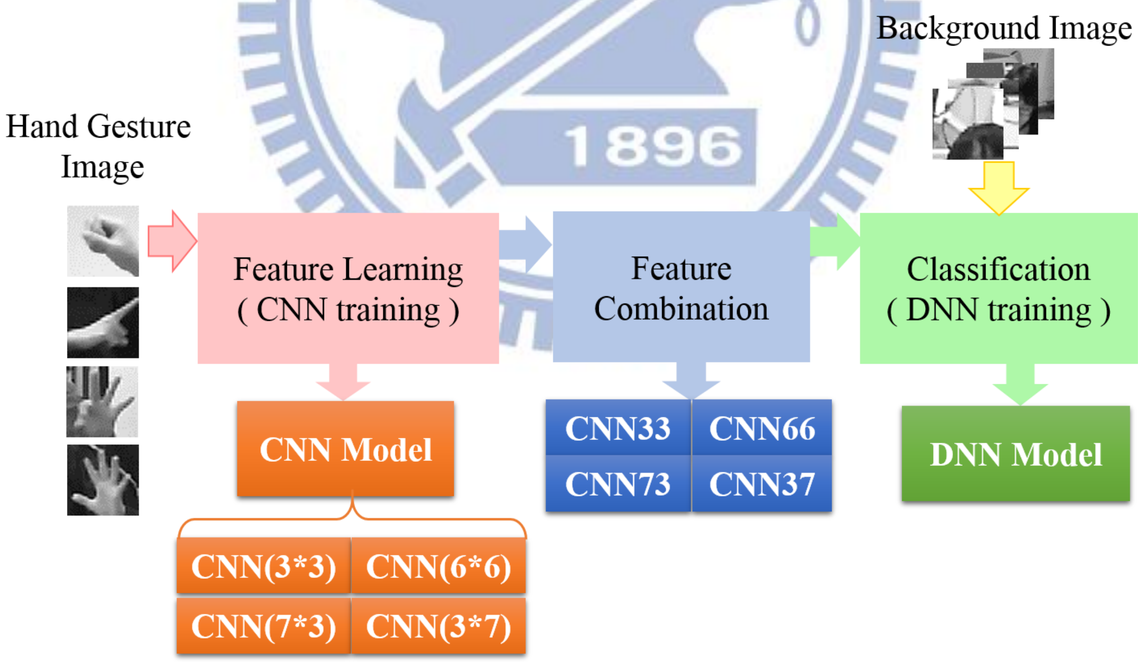
This paper introduce a simple neural network training for hand gesture recognition. It also pointed out the advantage of learning algorithm. However, this paper still use some image processing like edge detection to get the feature of data set. In our method, we use convolutional neural network to extract feature from training data set. It might get more robust recognition systems for changing environment.

Chapter 3. Proposed Method

The purpose of our system is to detect the hands position and recognize the meaning of user represent in a video captured by arbitrary camera and viewpoints within a range. The most difficult part is the clutter background and multi-class gestures classification. We want to figure out four different kinds of hand gestures: stop, pointer, ok and wave. Because of the complex background which might have some other skin color like objects with the remote distance of hand and camera, we won't use the skin color clue to do the image pre-processing. To build a more robust hand gesture recognition model, our training data is from arbitrary viewpoints within a range, different users and clutter background. Furthermore, we extract the feature in training data set by learning features from convolutional neural network, instead of specific pre-defined image processing technique like edge, corner, contour and silhouette. In order to find the relationship between local features extract from convolutional neural network, we use the unsupervised learning algorithm, deep neural network to recognize four different hand gestures. First find the internal structure in the local features and combine low level features into high level features at pre-training stage. After that, find the relationship between input features and output targets at fine-tuning stage. Furthermore, in order to solve the extremely variant shape of hand gestures, we modify the convolutional neural network to applicable to the multi-class hand gestures. At testing stage, we add some tracking technique to assist the detection result in correcting the hand position in the video frame. We also do some refinement to improve our hand gesture recognition accuracy.

The overall proposed algorithm procedure is shown in Figure 3-1, Figure 3-1(a) shows the training stage of proposed algorithm and Figure 3-1(b) shows the testing stage of proposed algorithm. In training stage, we have three steps, learning features, feature combination and classification. In the testing stage, we not only extract the features and classify the gestures by two model we get from training stage but also combining the detection and tracking result to correct the recognition result.

We will describe the data set we use for convolutional neural network (CNN) and deep neural network (DNN) in Section 3.1. In Section 3.2, we will describe the learning algorithm of convolutional neural network and deep neural network, which we need to learn the features in hand gesture data set and classify different gestures in feature space. We do some modification for the hand gesture data set at the feature extraction stage by using convolutional neural network. In Section 3.3, we will introduce our modification and how to combine the convolutional neural network and deep neural network for doing the hand gesture recognition. Also, we will add some tracking technique to improve the hand gesture recognition accuracy in video testing. At last, in Section 3.4, we will use the temporal information and compare the confidence of detection result and tracking result to do the refinement stage.



(a)

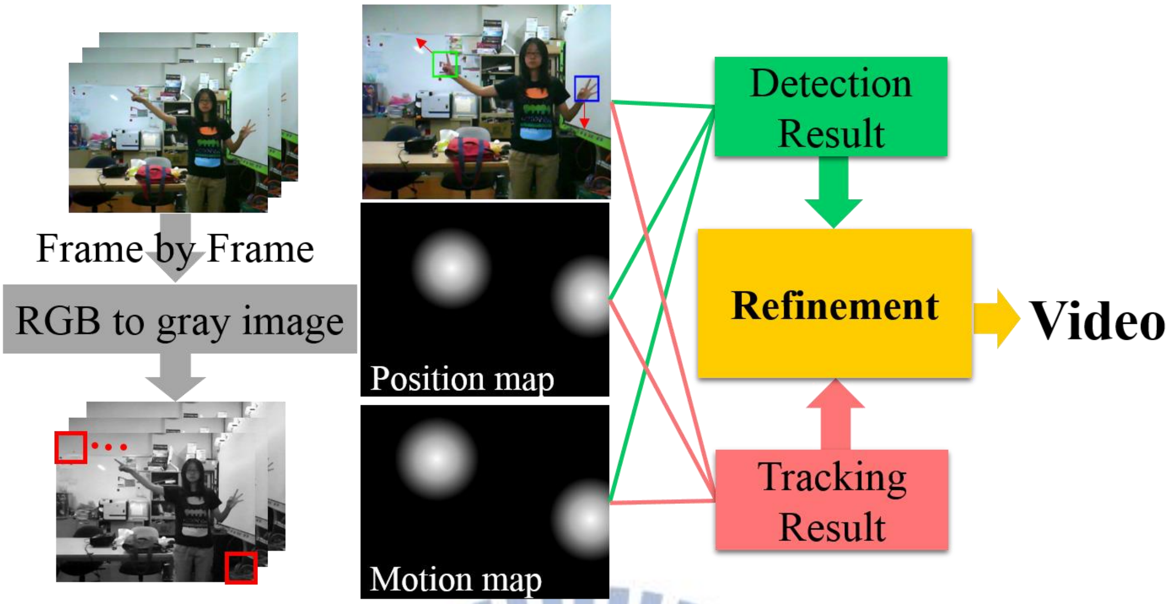


Figure 3-1 (a) Training procedure of our proposed algorithm.
(b) Testing procedure of our proposed algorithm.

3.1 Data Set

We will provide two different data set for convolutional neural network and deep neural network respectively. For convolutional neural network, we take amount of hand image for four different gestures. After we extract features from the learning algorithm of convolutional neural network, we might transform the hand gesture images from RGB color space to the feature space. In order to detect the hand in the video frame and recognize the hand gestures at once, we also transform the background from the RGB color space to hand gesture's feature space. The training data set for deep neural network will be the feature space of both hand gesture image and background images.

3.1.1 Data set for Convolutional Neural Network

We take images from arbitrary camera, viewpoints within a range and different clutter background. The image size is 50*50 pixel by pixel for all gestures. We use particle filter to automatically extract the hand part in the image. This makes a lot of mistakes, so that we choose the successful hand images by artificial selection. We use the fist to represent stop meaning, one finger to represent pointer meaning, three fingers to represent ok meaning and all fingers with the palm to represent wave meaning. In order to have the same number of right hand image and left hand image, we flip all the hand image we have. Each gestures have 6400 hand images for training data set, in other words, there are 25600 hand images. We have 3742 hand images for testing data set. Figure 3-2 are ten examples of hand gesture image in the training data set for each gestures and the last row are examples of background image for deep neural network.

Figure 3-2 Row one is the examples of stop gesture.
Row two is the examples of pointer gesture.
Row three is the examples of ok gesture.
Row four is the examples of wave gesture.
Row five is the examples of background image.

3.1.2 Data set for Deep Neural Network

After we extract the feature from convolutional neural network, we add the background image into the training data set, as shown in the last row of Figure 3-2. We have 25600 background images in the training data set and 6400 background images in the testing data set. We transform the RGB color space to the feature space for all training data. There are some examples of training data set in Figure 3-3. There are four hand gesture features and background features, each column illustrate the same gestures. The order for the gestures are stop, pointer, ok and wave. The last column is the background image's features. Each row represent the same kernel size for feature extraction in convolutional neural network. There are 3*3, 6*6, 7*3 and 3*7 four different kinds of kernel size represented in sequence.

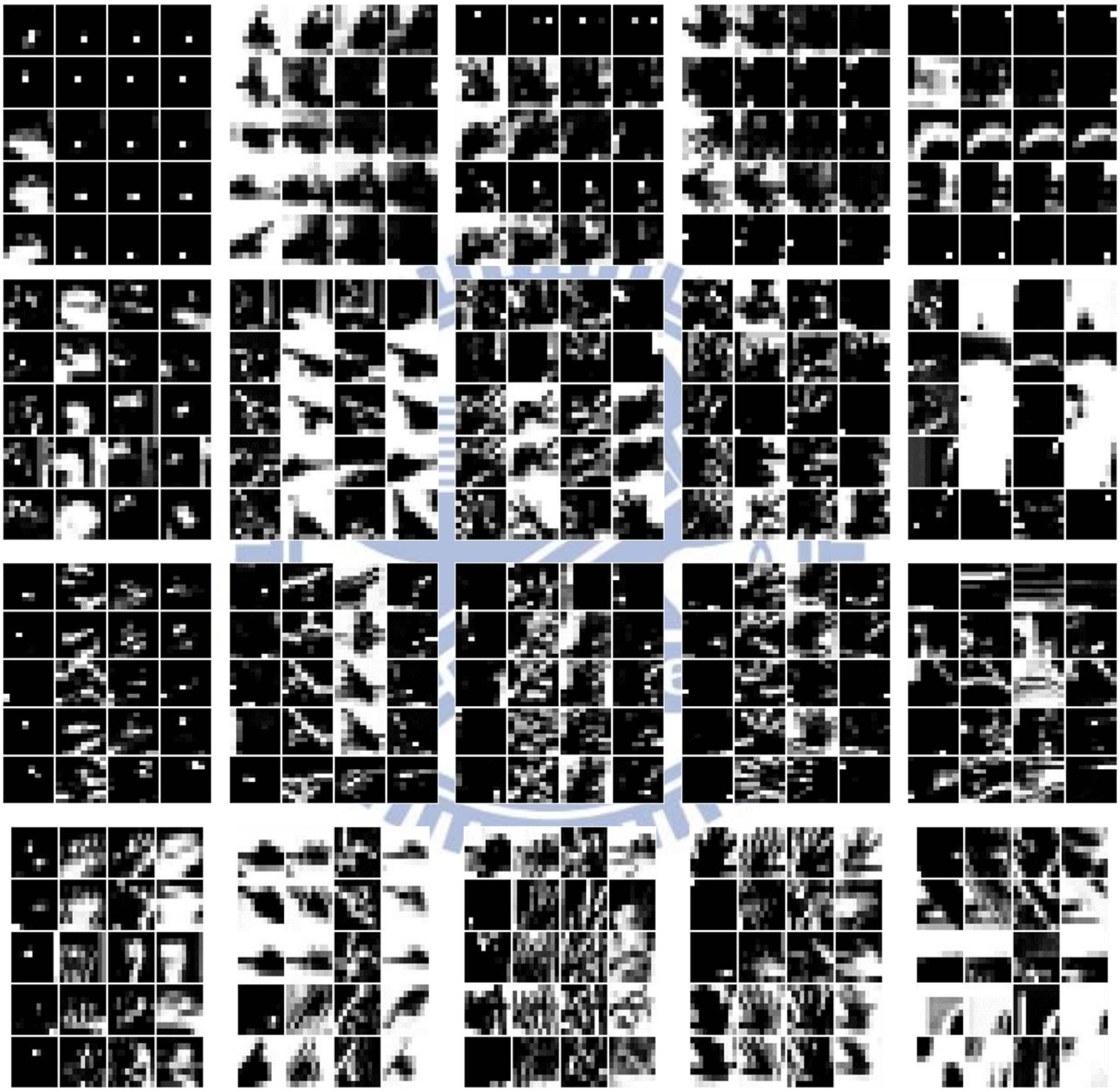


Figure 3-3 For each row, there are, 3*3, 6*6, 7*3 and 3*7, four different kinds of kernel size. For each column, there are stop, pointer, ok, wave and background five different kinds of input images.

3.2 Basic concept of two learning algorithm

We will introduce two learning algorithm we need for feature extraction and hand gesture classification. We will describe the architecture of the learning algorithm at first. After that, we will explain the basic concept of the learning algorithm.

3.2.1 Convolutional Neural Network

Convolutional neural network is a learning procedure which can extract some regular pattern or specific feature in a large amount of image which called training data set. The main idea of convolutional neural network is shared weight and translation invariance. Traditional neural network connect all input nodes with all hidden nodes. Therefore, when input image has a corner at left top and a corner at right bottom will make large difference for the learning weight. Convolutional neural network pose the shared weight concept to learn some regular pattern in the image. When image has repeated feature, the model might learn only one feature to represent it. Furthermore, convolutional neural network add a pooling layer after a convolutional layer, which can let the model be confronted with translation invariance. The pooling layer calculate the mean of no overlap patch in the feature map which is represent the appearance probability of feature. In section 3.2.1.1, we will introduce the architecture of convolutional neural network and describe each layer in detail. We will also brief introduce the basic learning algorithm of convolutional neural network in section 3.2.1.2.

3.2.1.1 Architecture of Convolutional Neural Network

Convolutional neural network has four different type of layers: input layer, convolution layer, pooling layer and fully-connected layer. Figure 3.4 is an example of convolutional neural network learning architecture. The convolutional neural network tool we use is from matlab deep learning toolbox provided by Palm[1].

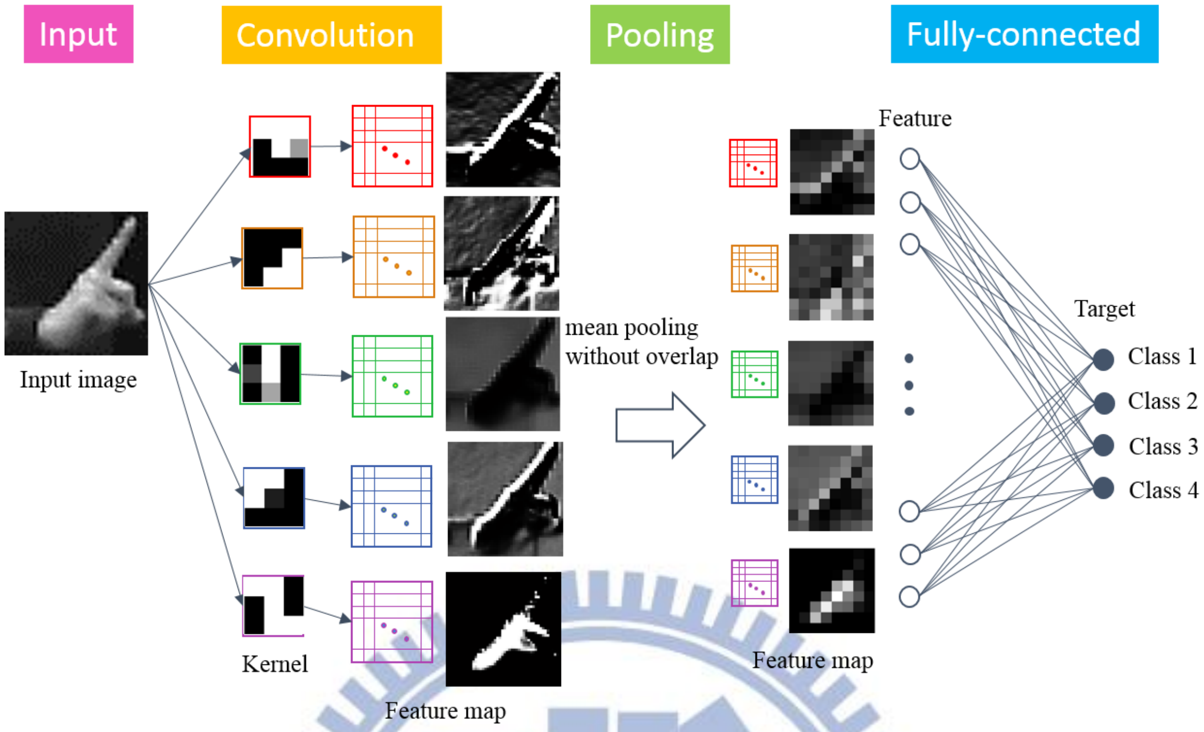


Figure 3-4 Example of convolutional neural network architecture.

Input layer

For 2D image processing, the input layer might be a gray-level image which normalized from zero to one.

Convolution Layer

In convolution layer, we can assume the number of kernel we need to learn in the image training data set. Traditional neural network will fully connect all input layer with a hidden node. A hidden node which connect with all input nodes represent the image appearance. The larger value the hidden node is, the more similar between input image and weight appearance. Figure 3.5(a) shows an input image as an example. If we want the hidden node can represent the input image appearance, the weight appearance might be complex, which shows in Figure 3.5(b). However, convolutional neural network use shared weight to represent regular pattern arise from input image. A hidden node only connect a local patch in the image and let the node connected weight, which called kernel, to shows the local feature learn from the input image. Using a feature map corresponding to a kernel to record the appearance of the local feature in the whole image. Do the convolution function between input image patch and kernel, the larger the result value, the more similar between local patch and kernel appearance. Figure 3.2(c) shows an example of a specific kernel and its correspondence feature map.

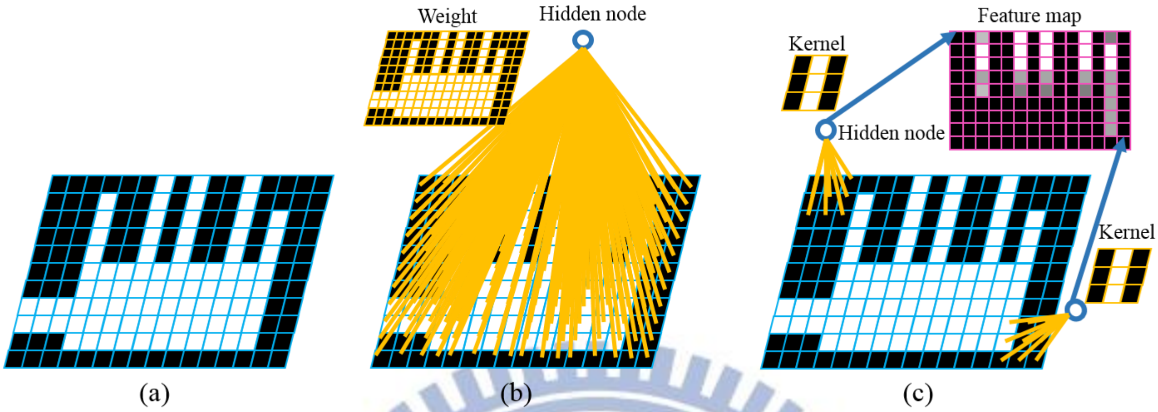


Figure 3-5 (a) An example of input image.
(b) Neural network : A hidden node with its fully-connected weight which might learns from the input image data set.
(c) Convolutional neural network : A hidden node with its local-connected weight which might learns from the input image data set.

Furthermore, if a hidden node is fully-connected with the input image, the weight number which we need to learn might be larger and more complex than the local feature learned from convolutional neural network. Hence, convolutional neural network might save some computation because of learning local and regular features in input image data set.

For the convolution layer, the feature map size will be (N-M+1) by (N-M+1), where the input image is N by N and the kernel size is M by M.

Pooling layer

After convolution layer, we will get a feature map corresponding to a specific kernel mask. A node in the feature map represent the proportion of a local patch is similar as the specific feature which the kernel shows. However, the adjacent nodes will corresponding to two overlap region. For different input image, even the local feature appeared at different nearby patch, we want to get the same feature map to against the translation of local feature. Hence, we cut the feature map to some non-overlap patch and calculate the mean of a local patch in the feature map. Then a node in the pooling feature map will represent the proportion of the feature appeared in a larger patch. There is a simple example at Figure 3.6. Even though the input image has the same appearance with translation, we can consider them to be the same appearance. This is an advantage that neural network might not have.

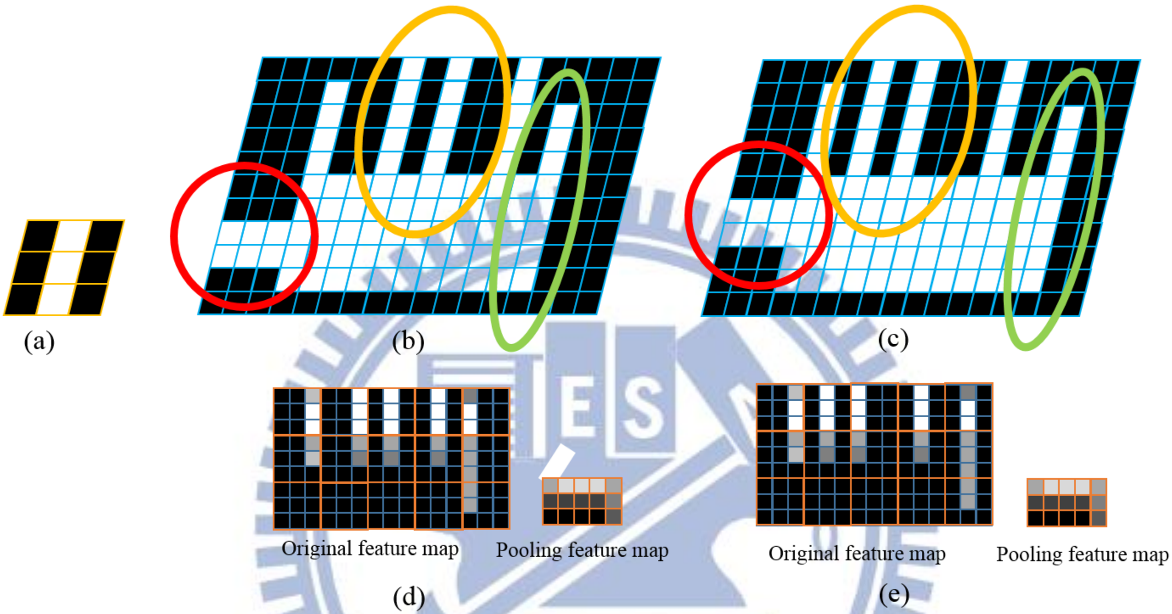


Figure 3-6 (a) An example of a specific kernel.
(b)&(c) Two different input image with same appearance but some local translation feature (as circled region).
(d)&(e) Two feature map corresponding to two input image and its pooling result.

For the pooling layer, the feature map size will be down-sample from (N-M+1) by (N-M+1) to ((N-M+1)/scaling factor) by ((N-M+1)/scaling factor). We usually choose the factor of (N-M+1) to get the down-sampled feature map with integer size.

Fully-connected layer

In the last layer, we will arrange all feature map to an one column feature. In addition, we might have a target layer to do the final classification. All nodes in the feature column will connect to all the target nodes, as Figure 3-4 shows.

3.2.1.2 Learning algorithm of Convolutional Neural Network

Convolutional neural network use the same learning algorithm as traditional neural network, which is back-propagation algorithm. The main concept of back-propagation is minimize the error function of the training model. We can modify the weight in each layer to get lower and lower error score. Gradient descent is the optimization method we use in the learning algorithm. [14] might discuss all the derivation and implementation of convolutional neural network in detail.

The error function of convolutional neural network is as equation (3-1). N means the total number of input image in the training data set. C means the output target has C classes. t_k^n is the target of kth image in nth class is 0 or 1. y_k^n is the calculation result of kth image in nth class. Consider with respect to a single training data, the error function can be seen as equation (3-2).

$$Error^N = \frac{1}{2}\sum_{n=1}^{N}\sum_{k=1}^{C}(t_k^n - y_k^n)^2, \quad (3\text{-}1)$$

$$Error^n = \frac{1}{2}\sum_{k=1}^{C}(t_k^n - y_k^n)^2, \quad (3\text{-}2)$$

We have different function operator in different layer. Therefore, the parameter update in each layer might be difference. We will introduce them all in the following.

Back-propagation in fully-connected layer

We define the function operator in the last layer to be as equation (3-3). x^l denotes the current layer *l* output, as last layer been layer L , input layer been layer 1. $f(.)$ is the activation function we choose. W^l is the weight and b^l is the bias in layer *l*.

$$x^l = f(a^l), \ \text{ with } a^l = W^l x^{l-1} + b^l, \quad (3\text{-}3)$$

The gradient of current layer is back-propagated from next layer as traditional neural network.

$$\frac{\partial E}{\partial W} = \frac{\partial E}{\partial a}\frac{\partial a}{\partial W} = x^{l-1}(\delta^{l})^{T}, \;\; with \;\; \delta^{l} = (W^{l+1})^{T}\delta^{l+1} \odot f'(a^{l}), \tag{3-4}$$

where $\odot$ denotes element-wise multiplication operator.

$$\frac{\partial E}{\partial b} = \frac{\partial E}{\partial a}\frac{\partial a}{\partial b} = \delta^{l}. \tag{3-5}$$

Back-propagation in pooling layer

The pooling layer produce a down-sampled feature maps. The function operator in convolution layer is defined in equation (3-6).

$$x_j^l = f(a^l)\,,\; with \;\; a^l = \;\beta_j^l \cdot down(x_i^{l-1}) + b_j^l, \tag{3-6}$$

where $down(.)$ represents a non-overlapped sub-sampling function. Each output map might have its own multiplicative bias β and an additive bias b.

We need to update both multiplicative bias β and additive bias b in this layer. The gradient can be compute as fully-connected layer.

$$\frac{\partial E}{\partial b_j} = \textstyle\sum_{u,v}(\delta_j^l)_{uv}\,, with\; \delta_j^l = f'(a^l) \odot (k_j^{l+1} * \delta_j^{l+1}) \tag{3-7}$$

$$\frac{\partial E}{\partial \beta_j} = \frac{\partial E}{\partial a}\frac{\partial a}{\partial \beta_j} = \textstyle\sum_{u,v}(\delta_j^l \odot d_j^l)_{uv}\,, with\; d_j^l = down(x_i^{l-1}) \tag{3-8}$$

Back-propagation in convolution layer

The output feature map will combine several feature maps. The function operator in convolution layer is defined as equation (3-9), where S_j represents a subset of input maps, * denotes convolution operator.

$$x_j^l = f(a^l), \;\; with \;\; a^l = \textstyle\sum_{i \in S_j} x_i^{l-1} * k_{ij}^l + b_j^l \tag{3-9}$$

The gradient of current layer might be sum over the next layer's gradient corresponding to units that connected to the node of interest in the current layer. The update function of kernel and corresponding bias describe in equation (3-10) and (3-11), where p_i^{l-1} is the patch in previous layer which multiplied element-wise by k_{ij}^{l} during convolution. β_j^{l+1} denotes the next pooling layer parameter. $up(.)$ denotes an up-sampling operation.

$$\frac{\partial E}{\partial k_{ij}^{l}} = \sum_{u,v} (\delta_j^l)_{uv} (p_i^{l-1})_{uv} \text{ , with } \delta_j^l = \beta_j^{l+1} \left(f'(a^l) \odot up\left(\delta_j^{l+1}\right) \right) \tag{3-10}$$

$$\frac{\partial E}{\partial b_j} = \sum_{u,v} (\delta_j^l)_{uv} \tag{3-11}$$

3.2.2 Deep Neural Network

The reason we introduce "deep" neural network, not traditional neural network, is the high complexity of training data set. While the object we want to distinguish being more variability, we need more hidden nodes and more layers to learn the model. However, traditional learning algorithm is not efficiency for deep neural network architecture. For example, when we use back-propagation algorithm to update our learning weight, we have the gradient from later layer propagate to previous layer. The gradient might be tiny as propagating to the front layer. This causes the weight update stagnant at local optima. Furthermore, the traditional learning algorithm require labels to calculate error function and get gradient of weight to update the model. The back-propagation algorithm find the relationship between input feature and output target instead of finding the internal structure in training data set. Deep neural network is an unsupervised learning method which learns the model without target. We can find the exist structure behind the input data set.

Hinton introduced a new learning method to train the model layer-by-layer instead of learning the whole deep architecture once [5]. This algorithm has two stage : unsupervised pre-training and supervised fine-tuning. At first, they take the whole deep architecture apart to train two layers as a Restricted Boltzmann Machine (RBM) which uses an unsupervised training algorithm. As the previous layer complete the pre-training stage, the output of previous layer will be the input of the next layer RBM training. Figure 3-7(a) shows the architecture of whole deep neural network. Figure 3-7(b) shows the layer-wise pre-training architecture. After that, we can get the initial weight of every layer and do supervised fine-tuning to get the relationship between input image and output target by updating the weight slightly, shows in Figure 3-7(c). We will introduce the structure of Restricted Boltzmann Machine (RBM) which is suitable for binary visible and Gaussian Restricted Boltzmann Machine which is suitable for real-valued visible both in section 3.2.2.1. In section 3.2.2.2, we will describe the learning algorithm of pre-training and fine-tuning in detail.

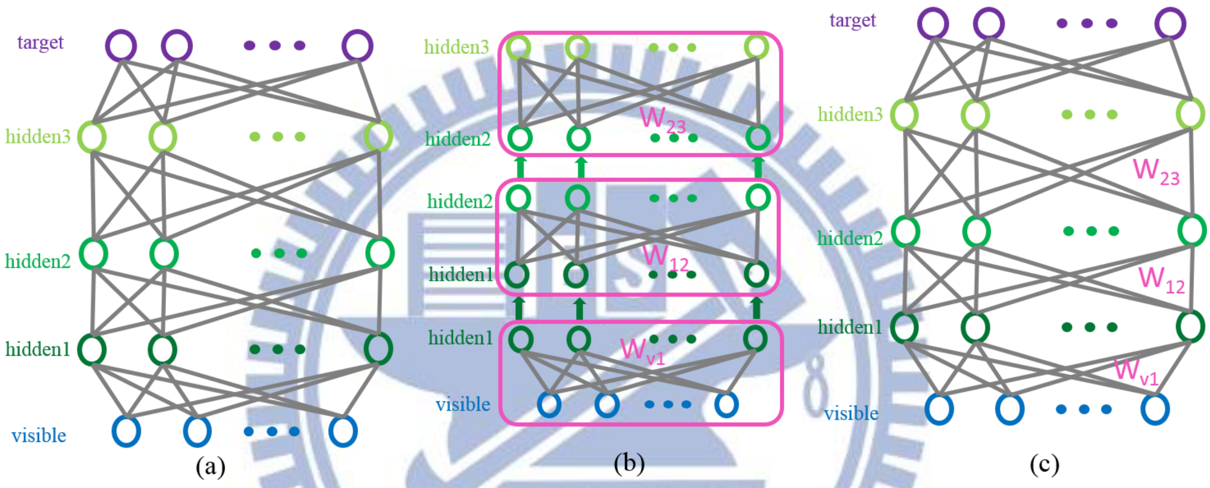


Figure 3-7 (a) The whole architecture of deep neural network.
(b) Layer-wised pre-training architecture.
(c) Supervised fine-tuning architecture.

3.2.2.1 Restricted Boltzmann Machine

Restricted Boltzmann Machine is a two layer and undirected model without intra-layer connections. The bottom layer called visible layer is a set of binary units $v \in \{0,1\}$ and the top layer called hidden layer is a set of binary units $h \in \{0,1\}$. We will use Gaussian Restricted Boltzmann Machine if the bottom layer is a set of real-valued units $v \in [0,1]$ which we will describe later. The structure of RBM is shown in Figure 3-6(b) pink circled.

RBM is an energy-based model, the energy of a pair of (v,h) is defined in equation (3-12), where b , c denotes the bias of the visible and hidden layers respectively and W represents the weights connecting hidden and visible units. The probability distribution of the pair of (v,h) is defined in equation (3-13), where the constant Z is the normalization term.

$$\mathrm{Energy}(\mathrm{v},\mathrm{h}) = -b^T v - c^T h - v^T W h \tag{3-12}$$

$$\mathrm{P}(\mathrm{v},\mathrm{h}) = \frac{1}{Z}\left(e^{-Energy(v,h)}\right) \tag{3-13}$$

Since there is no connection within hidden layer and within visible layer, and the hidden layer and visible layer are conditionally independent given one-another. Using these two property, we can get the conditional distribution for each layer as equation (3-14) and (3-15), where $sigm(x) = \frac{1}{(1+e^{-x})}$ is a sigmoid function and M , N denotes the number units in visible layer and hidden layer Respectively.

$$\mathrm{P}(\mathrm{h}|\mathrm{v}) = \prod_j^N P\left(h_j = 1\middle|v\right),\ with\ P\left(h_j = 1\middle|v\right) = sigm(c_j + W_j v) \tag{3-14}$$

$$\mathrm{P}(\mathrm{v}|\mathrm{h}) = \prod_i^M (v_i = 1|h),\ with\ P(v_i = 1|h) = sigm(b_i + W_i h) \tag{3-15}$$

As mentioned previously, we use Gaussian Restricted Boltzmann Machine for real-valued visible. The energy function and the conditional distribution is defined as equation (3-16) to equation (3-18).

$$\mathrm{Energy}(\mathrm{v},\mathrm{h}) = -\sum_i^M \frac{(v_i - b_i)^2}{2{\sigma_i}^2} - \sum_j^N c_j h_j - \sum_i^M \sum_j^N \frac{v_i}{\sigma_i} W_{ij} h_j \tag{3-16}$$

$$\mathrm{P}(\mathrm{h}|\mathrm{v}) = \prod_j^M \left(h_j = 1\middle|v\right),\ with\ P\left(h_j = 1\middle|v\right) = sigm\left(c_j + \sum_i^N \frac{v_i}{\sigma_i} W_{ij}\right) \tag{3-17}$$

$$\mathrm{P}(\mathrm{v}|\mathrm{h}) = \prod_i^N P\left(v_j = 1\middle|h\right),\ with\ P\left(v_j = 1\middle|h\right) = Normal\left(v_i \middle| b_i + \sigma_i \sum_j^M h_j W_{ij}\right) \tag{3-18}$$

3.2.2.2 Learning algorithm of Deep Neural Network

We have two stage for the learning algorithm, unsupervised pre-training and supervised fine-tuning. The first stage might get the relationship between the input features and get more efficient initial weight for learning an optimal model after the second stage.

Unsupervised pre-training

We want to minimize the energy function of the RBM, on the other hand, we want to maximize the log-likelihood given a training data v with model parameters θ. By using gradient ascent method, we can get the learning rule for the model parameters. The first term of equation (3-20) denotes the data-term which takes expectation over the training data set empirical distribution P(h|v). The second term denotes the model-term which takes expectation over the model distribution P(v,h).

$$\ln \mathrm{P}(\mathrm{v}|\theta) = \ln \frac{1}{Z}\sum_h e^{-Energy(v,h)} = \ln \sum_h e^{-Energy(v,h)} - \ln \sum_{v,h} e^{-Energy(v,h)} \tag{3-19}$$

$$\frac{\partial}{\partial\theta}\ln \mathrm{P}(\mathrm{v}|\theta) = -\sum_h P(h|v)\frac{\partial}{\partial\theta}Energy(v,h) + \sum_{v,h} P(h,v)\frac{\partial}{\partial\theta}Energy(v,h) \tag{3-20}$$

$$\Delta\mathrm{W} = \epsilon(E_{data}[\mathrm{v}h^T] - E_{model}[\mathrm{v}h^T])\ , with\ \epsilon\ is\ the\ learning\ rate \tag{3-21}$$

$$\Delta\mathrm{b} = \epsilon(E_{data}[\mathrm{v}] - E_{model}[\mathrm{v}]), with\ \epsilon\ is\ the\ learning\ rate \tag{3-22}$$

$$\Delta\mathrm{c} = \epsilon(E_{data}[\mathrm{h}] - E_{model}[\mathrm{h}]), with\ \epsilon\ is\ the\ learning\ rate \tag{3-23}$$

We use Gibbs sampling to approximate the model-term because of its difficulty. According to the Markov chain Monte Carlo (MCMC) algorithm, we can sample the hidden nodes by the visible nodes then sample the reconstruct visible nodes by the sampled hidden nodes. We will do this procedure until the Markov chain converge in order to get the model-term. The architecture of MCMC with Gibbs sampling is shown in Figure 3-8(a). However, it is not efficient to run a MCMC to converge in an update step. In [5], Hinton propose a fast algorithm which is called Contrastive Divergence. This method shows that the effect of sampling until the Markov chain converge and sampling once might get close result. Therefore, the update function can be approximated as equation (3-24) to equation (3-26). Figure 3-8(b) shows the architecture of Contrastive Divergence algorithm.

$$\Delta\mathrm{W} = \epsilon(E_{data}[\mathrm{v}h^T] - E_{reconstruct}[\mathrm{v}h^T])\ , with\ \epsilon\ is\ the\ learning\ rate \tag{3-21}$$

$$\Delta\mathrm{b} = \epsilon(E_{data}[\mathrm{v}] - E_{reconstruct}[\mathrm{v}]), with\ \epsilon\ is\ the\ learning\ rate \tag{3-22}$$

$$\Delta c = \epsilon(E_{data}[h] - E_{reconstruct}[h]), with\ \epsilon\ is\ the\ learning\ rate \quad (3\text{-}23)$$

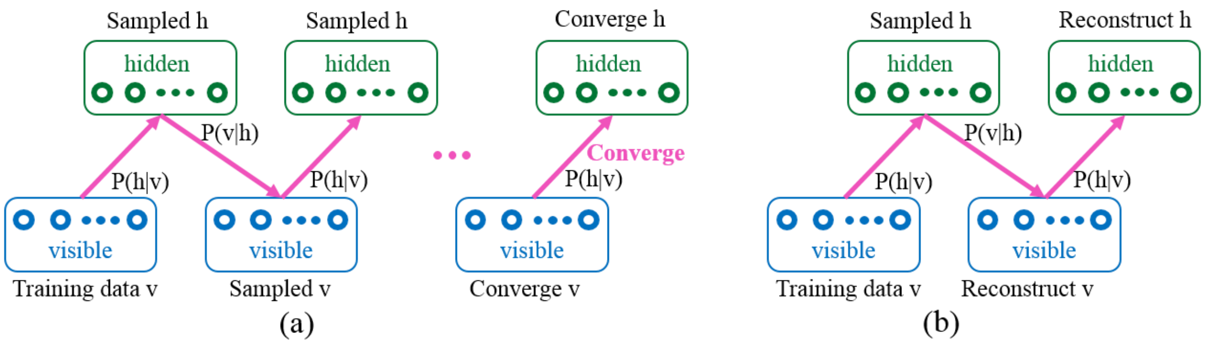


Figure 3-8 (a) Architecture of MCMC by using Gibbs sampling.
(b) Architecture of Contrastive Divergence algorithm

We will train the RBM layer-wise staring from visible layer and hidden layer one. When we get the weight W^1 between visible layer v and hidden layer one h^1, we treat the real-valued probabilities of the conditional distribution $E[P(h^1|v; W^1)]$ as the visible units in the second RBM and so on. After we get all trained weight between layers, we can do the next stage, supervised fine-tuning.

Supervised fine-tuning

We learned the internal structure of the training data set in the previous stage. Next, we want to learn the relationship between input training data set and the output targets for classifying the different class in the training data set. We use the back-propagation algorithm to learn the overall optimization solution.

3.3 Applicable to Hand Gesture Recognition

As we mentioned before, the hand has extremely distinct shape and appearance from different gestures. Using traditional convolutional neural network or traditional deep neural network is not enough. We combine these two learning algorithms and modify them to be better than before. We will describe our modification in Section 3.3.1. In Section 3.3.2, we will introduce the way we combine these two learning algorithms to do the hand gesture recognition.

In order to improve the accuracy in the video testing, we add some tracking technique described in Section 3.3.3.

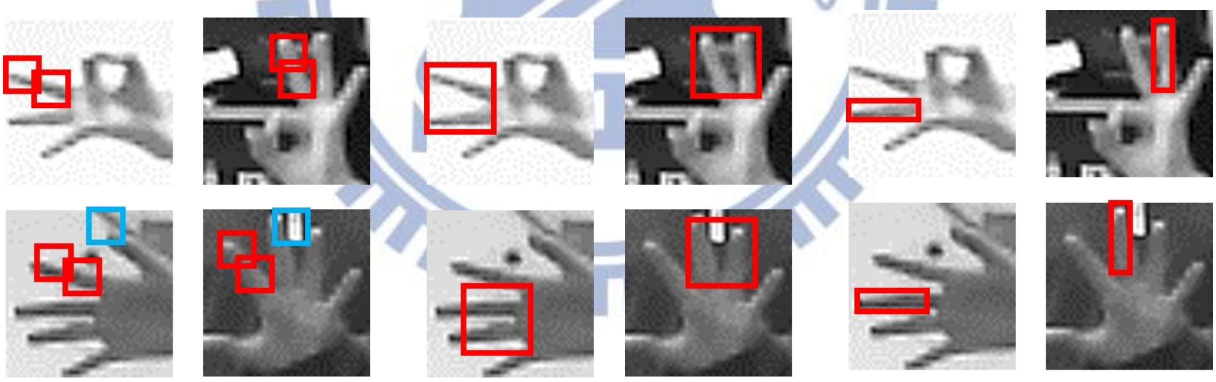
3.3.1 Feature Extraction by Convolutional Neural Network

We want to use convolutional neural network to learn the feature from training data set directly. Traditional convolutional neural network have the features for single kernel size and it is restricted to be square and the down-sampling scaling factor for feature map's width and height are limited to be the same. As we observe the training data set of the hand gestures, we find that hands can be composed of fingers and a palm. Fingers are different orientation, different length, long and narrow strip. Palm is a larger rectangle which width and height ratio is extremely different from the fingers. Furthermore, the four hand gestures we need to classify are composed of different number of fingers and the open or close palm. Therefore, the features we want to learn in the hand gesture training data set might be modify to some long and narrow strips and some rectangles close to square. In order to cope with the different kernel size for width and height, we also modify the down-sampling scaling factor could be distinct for the width and height. Also, we want to represent the hand gestures by more different kernel size to get a more robust feature space of the hand gestures. Therefore, we need some algorithm to choose better features of different kernel size and combine different kernel size feature to find more robust feature space for hand gestures.

The convolutional neural network architecture we attempt is shown in Figure 3-4. We set one convolution layer and one pooling layer to get the local features of the hand gesture images. Also, we don't use the last full-connected layer for the hand gesture classification. We only extract the feature vector from the output of the pooling layer. The pooling scaling factor might be cope with the kernel size we choose at the convolution layer. We will have a summary of the choice for kernel size and corresponding pooling scaling factor in the following section.

3.3.1.1 Non-square kernel size and pooling scaling factor

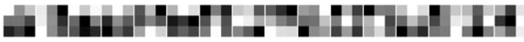
The important issue at convolutional neural network learning is the choice of kernel size. If the kernel size might be square, a larger square or a smaller square is not the best choice. As using the smaller one, it will turn on some position of the feature map because of the clutter background, which is shown in Figure 3-9 (a). The blue rectangles are the clutter background features we don’t need and red rectangles are the hand features we want. In Figure 3-9(b), we can discover that a larger block might get a complex feature to cope with the multiple fingers. However, if we have a complex feature, it might not represent the hand gestures good for the different hand gestures. Different number of fingers in the patch and the close or open palm might need different features to represent. These will reduce the effect we want to have in the learning feature stage of convolutional neural network. We want to learn the local features of the hand gestures not the global features in the whole image. For a specific long and narrow block, we can represent the fingers more efficient, as shown in Figure 3-9(c).



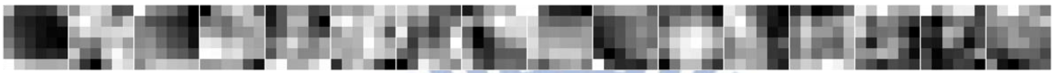
(a) (b) (c)

Figure 3-9 (a) The kernel of convolutional neural network is a small square.
(b) The kernel of convolutional neural network is a large square.
(c) The kernel of convolutional neural network is a long and narrow stipe.

For the feature of the palm and the fist, we use some small block to get the features of the edges and corners. Because of the complexity of hand shape variance, we needs not only long and narrow strip but also different kernel size combination to get more robust feature space. As we have different viewpoints of the hand gestures, we not only need long and narrow rectangles but also need short and wide rectangles for different orientation fingers. However, convolutional neural network could not tolerate the different kernel size learning at once, we need to train the different kernel size feature one by one. Figure 3-10 shows four different kernel size features for the hand gesture training data set. The kernel size are 3*3, 6*6, 7*3, 3*7 pixel by pixel in Figure 3-10(a) to (d). Each row has sixteen features learned by the convolutional neural network.



(a)



(b)

(c)

(d)

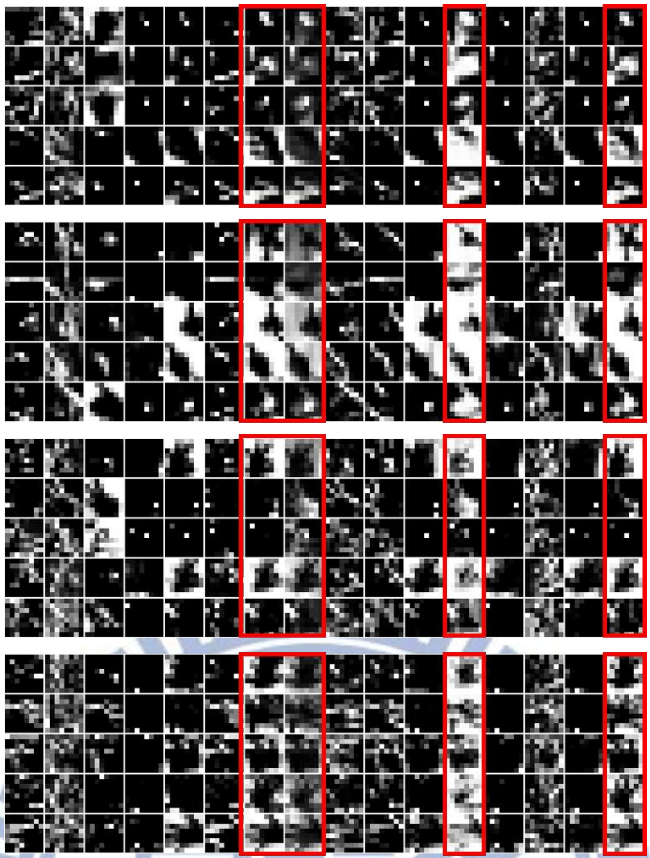
Figure 3-10 (a) The convolutional neural network feature learned by 3*3 kernel size.
(b) The convolutional neural network feature learned by 6*6 kernel size.
(c) The convolutional neural network feature learned by 7*3 kernel size.
(d) The convolutional neural network feature learned by 3*7 kernel size.

After the convolution layer, we have the pooling layer to down-sample the feature map we get from previous layer. The pooling concept might let the convolutional neural network to be translation invariance as we mention in Section 3.2.1. We calculate the mean of a local patch of the feature map to indicate the feature is existence or not at a small region in the original input image as shown in Figure 3-4. The pooling scaling factor is limited as the same for width and height in the conventional convolutional neural network. We modify it to coordinate the long and narrow rectangles and the short and wide rectangles of kernel we learned for the hand gesture. Therefore, we can down-sample for different scaling factor for the feature map width and height. Also, we choose a large scaling factor to let the feature map be more translation invariance. The corresponding scaling factor for four different kernel size is shown in Table 3-1. The unit for the kernel size and scaling factor are pixels.

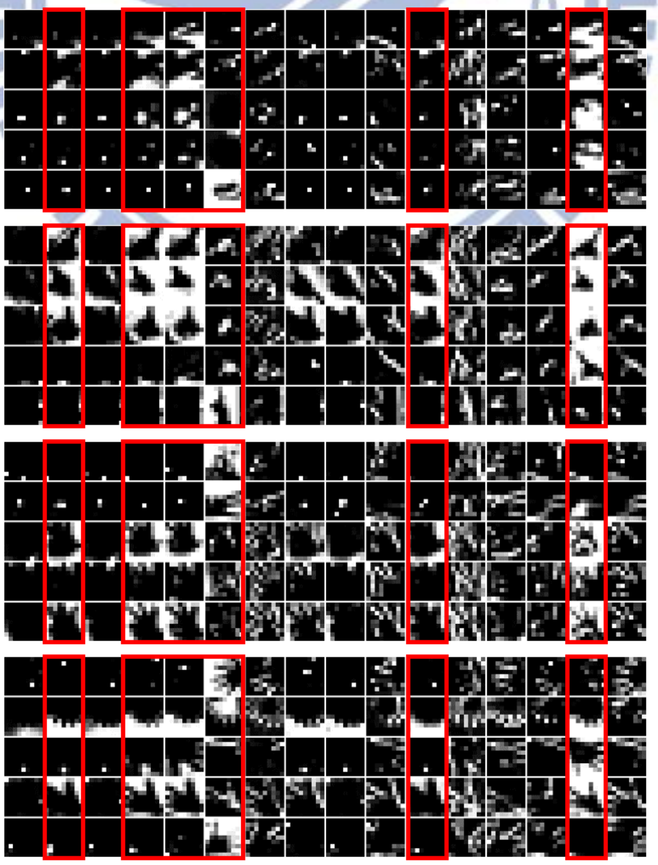
	1		2		3		4	
	Width	Height	Width	Height	Width	Height	Width	Height
Kernel Size	3	3	6	6	7	3	3	7
Scaling Factor	6	6	5	5	4	6	6	4

Table 3-1 Different kernel size correspond to different pooling scaling factor.

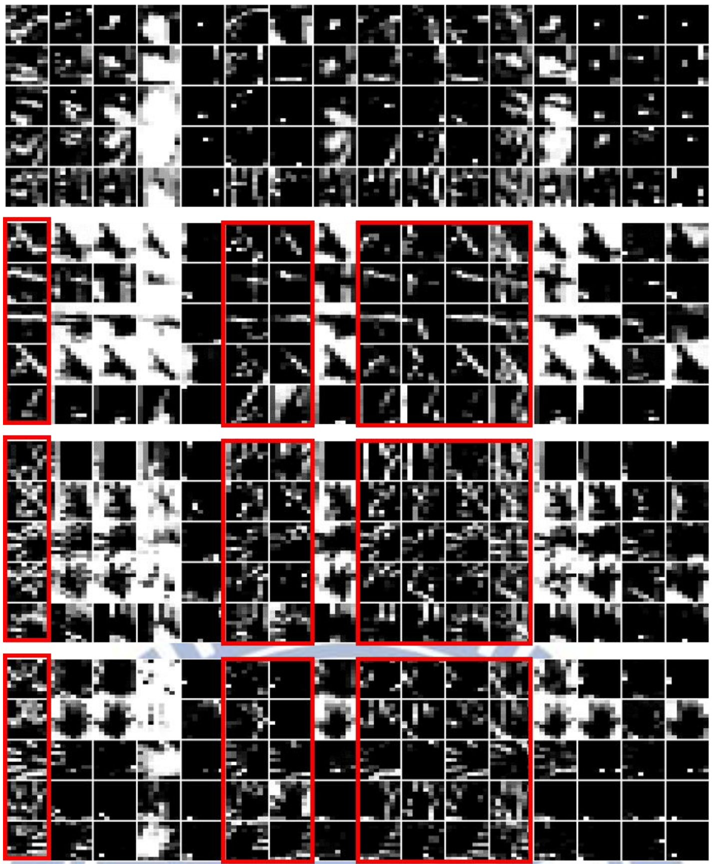
The feature maps of different kernel size we get from convolutional neural network after pooling layer are shown in Figure 3-14(a) to (d). We random choose some example from training data set to get the feature maps for the four different gestures, each gestures has five example images. The top to down blocks are the stop gesture, pointer gesture, ok gesture and wave gesture. We can figure out that a long and narrow kernel size, such as 3*7 and 7*3 might be good at fingers feature, as the red circled region in Figure 3-11 (c) and (d). The small square kernel size, 3*3 and 6*6, might get the rough contour of the hand gesture, as the red circled region in Figure 3-11(a) and (b).



(a)



(b)


(c)

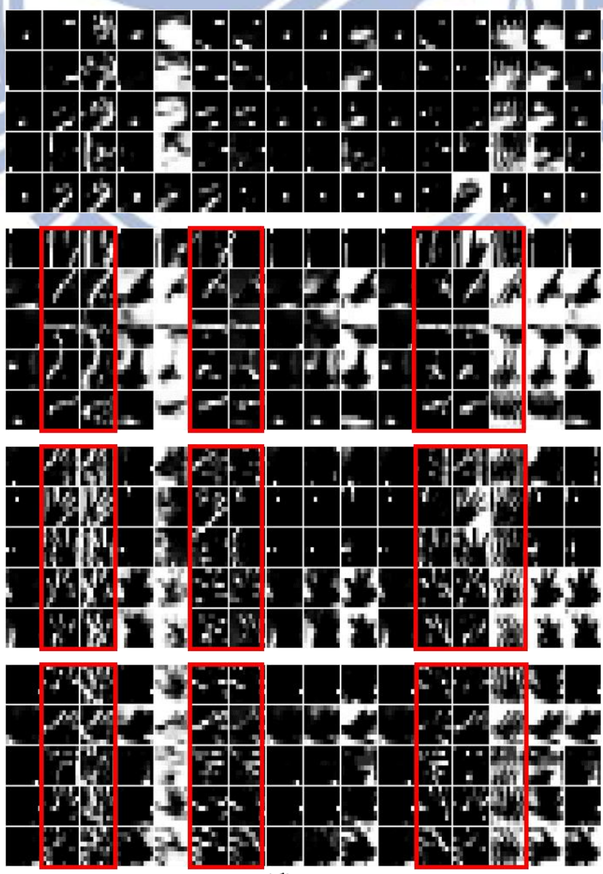

(d)

Figure 3-11 (a) The feature map of kernel 3*3, red circled region show the rough contour of hand gestures.
(b) The feature map of kernel 6*6, red circled region show the rough contour of hand gestures.
(c) The feature map of kernel 7*3, red circled region show the finger feature.
(d) The feature map of kernel 3*7, red circled region show the finger feature.

3.3.1.2 Combination of different kernel size feature

Because of the complex shape and extremely variant of appearance for the hand gestures, the features might be different size, such as small square, large square and rectangles. Figure 3-10 shows some example for different kernel size for the hand gestures. Therefore, we want to use different kernel size to express the hand gesture features as shown in Figure 3-12. For vertical fingers, horizontal fingers, fist and palm, we need different kernel size to represent its local feature. We design four different kernel size, 3*3, 6*6, 3*7 and 7*3. We will train sixteen kernels for a specific kernel size, then choose four of them. The reason why we need to train sixteen kernels then choose four of them rather than only train four kernels for one kernel size is the overall kernel number. If we only set four kernels for the convolutional neural network model, the model might learn more complex feature than we set sixteen kernels for it. It expect use four features to represent the whole training data set. However, we have sixteen feature to represent the training data set not four. The features we want to learn is the simple, local feature, not the complex and global feature. Figure 3-13 shows the different between four features and sixteen features for a convolutional neural network model. Figure 3-13(a) shows the features we learned for sixteen kernels and choose four of them and the corresponding feature maps. Figure 3-13(b) shows the features we learned for only four kernels and the corresponding feature maps. We can figure out that for four specific kernel, we get a more complicated feature maps. We couldn’t easily determine the gestures for ok and wave as shown in red rectangles of Figure 3-13(b).

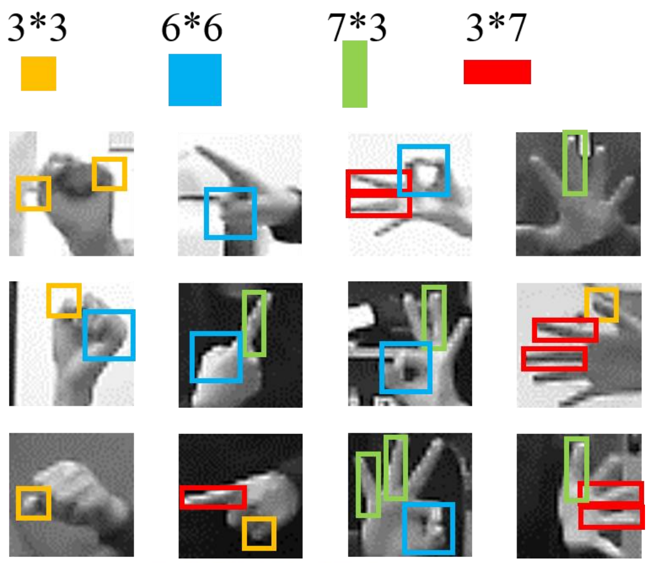


Figure 3-12 The different kernel size we need for hand gesture images.

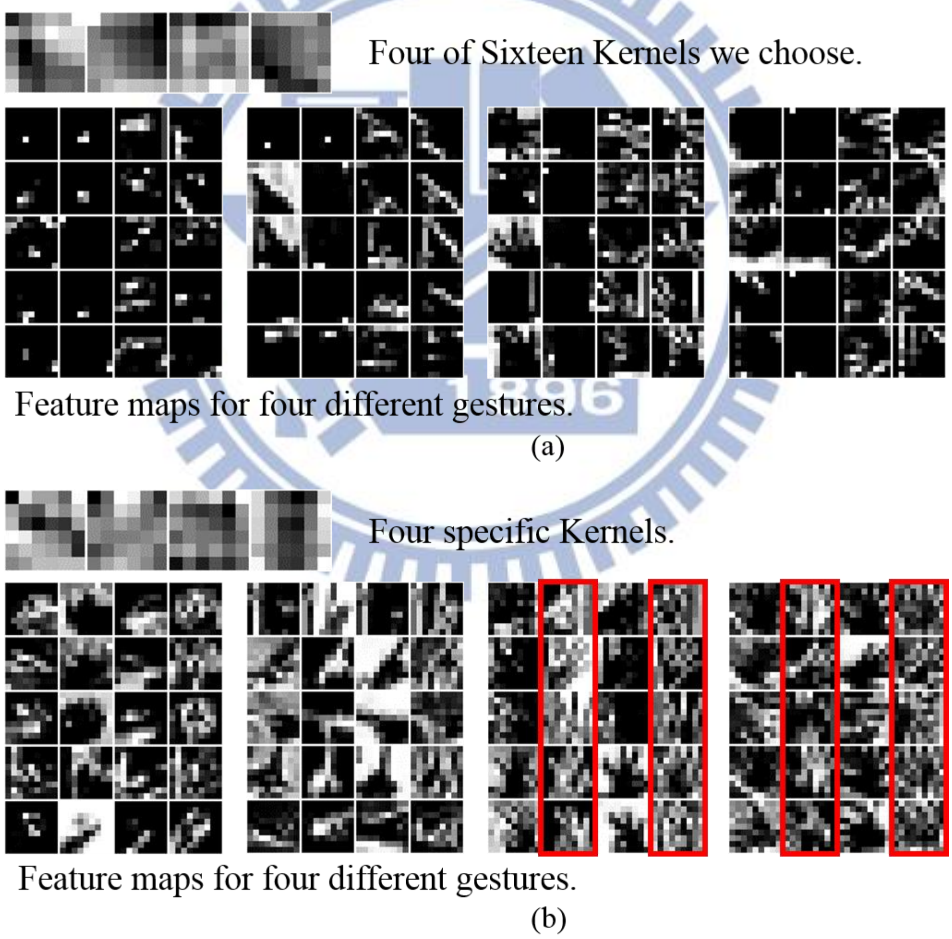


Figure 3-13 (a) Four of sixteen kernels we choose and corresponding feature maps for stop, pointer, ok and wave gestures.

(b) Four specific kernels and corresponding feature maps for stop, pointer, ok and wave gestures.

As record in Table 3-1, we have four different convolutional neural network for four different kernel size. For kernel 3*3, the feature map at the convolution layer is 48*48. After the pooling layer, the down-sampled feature map is 8*8 because of the scaling factor is 6*6. For kernel 6*6, the feature map at the convolution layer is 45*45. After the pooling layer, the down-sampled feature map is 9*9 because of the scaling factor is 5*5. For kernel 7*3, the feature map at the convolution layer is 44*48. After the pooling layer, the down-sampled feature map is 11*8 because of the scaling factor is 4*6. For kernel 3*7, the feature map at the convolution layer is 48*44. After the pooling layer, the down-sampled feature map is 8*11 because of the scaling factor is 6*4. We transform the feature map from two dimension to one dimension vector and concatenate four different kernel size to get our overall feature vector. The feature vector dimension is 1284. (((8*8)*4) + ((9*9)*4) + ((11*8)*4) + ((8*11)*4) = 1284)

As we have sixteen features for a specific kernel size and four different kernel size, we need some algorithm to choose the best combination for different kernel size. We take an intuitive idea to solve it. The criteria we choose are the more far from different gestures and more close for same gestures in the feature space. The concept is shown in Figure 3-14. Figure 3-14(a) shows the feature space we prefer to and Figure 3-14(b) shows the feature space which the gestures is not easy to separate. We random sample four of sixteen features for a specific kernel size and combine four different kernel size to get a feature vector with different kernel size. Then calculate the difference map in different gestures of the specific kernel. Also, we calculate the difference map in same gesture of the specific kernel. After we get the difference map, we calculate the variance of the map and compute the ratio of the variance for same gestures and the variance for different gestures as equation (3-24). We choose the smallest value of the ratio to get a feature space with large distance from the different gestures and close in the same gestures. There are some examples in Figure 3-15.

$$\text{Ratio} = \frac{variance(Difference\ map\ of\ same\ gestures)}{variance(Difference\ map\ of\ different\ gestures)} \tag{3-24}$$

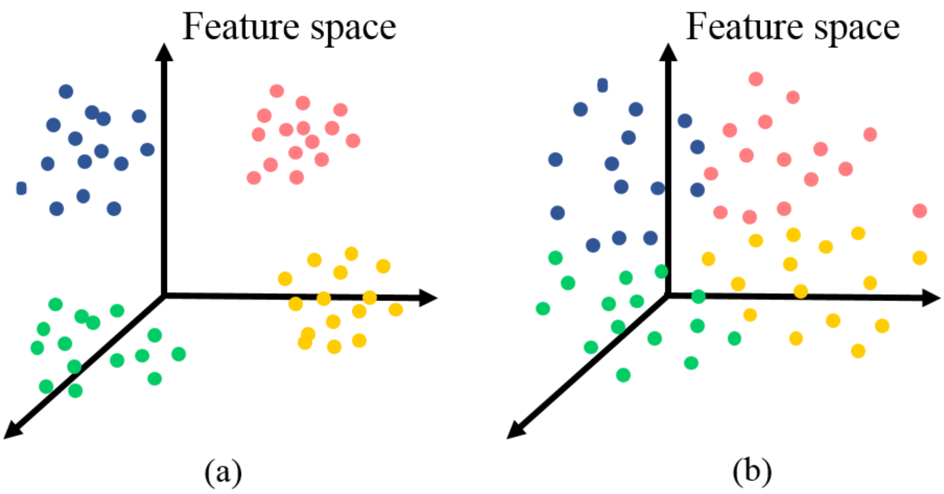


Figure 3-14 (a) The schematic diagram of feature space which is easy to separate.
(b) The schematic diagram of feature space which is not easy to separate.

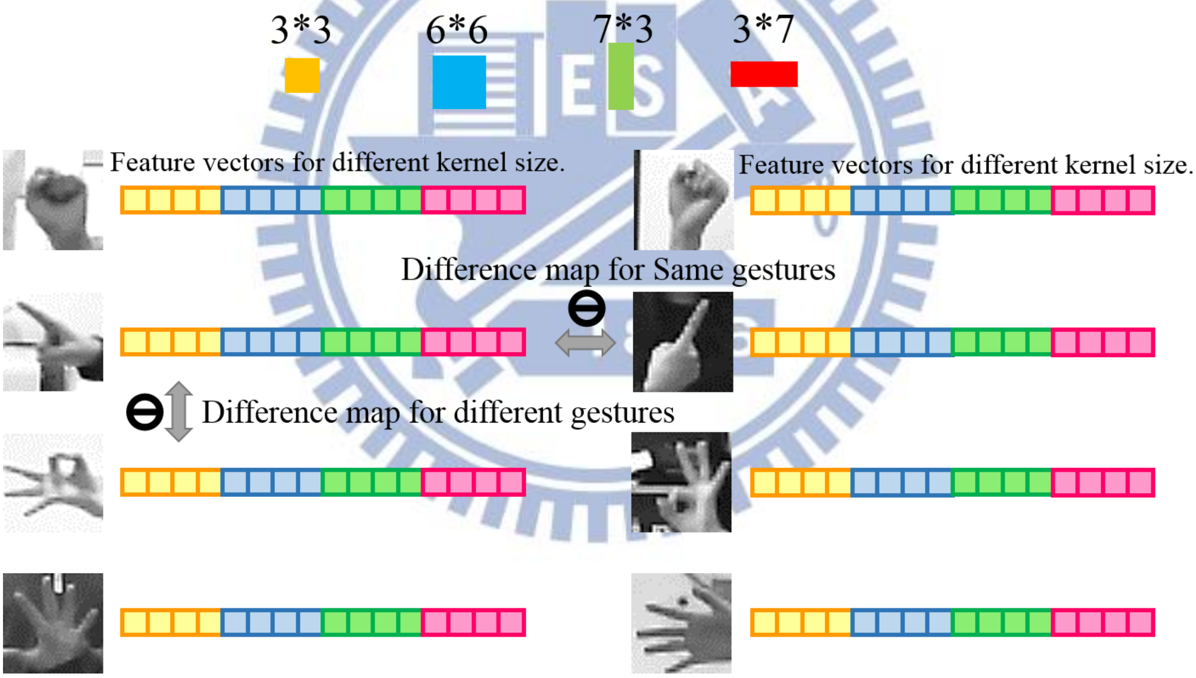


Figure 3-15 The feature vectors combining different kernel size for the hand gestures.

3.3.2 Deep Convolutional Neural Network Classification

After we get the transformation between RGB color space and hand gesture feature space, we can transform all image training data set from convolutional neural network to our feature training data set for deep neural network. Figure 3-11 shows all sixteen kernels we learned from convolutional neural network by a specific kernel size. We choose four of them by the algorithm as mentioned before. Our training data set for deep neural network is shown in Figure 3-3. The architecture of our deep neural network model is shown in Figure 3-17(a). Our feature vector combines four different kernel size and each kernel size has four features. The input feature dimension is 1284 and output target is 5(four gestures and background). The model with layers of size 1284-1024-1024-1600-5. Also, we apply a sigmoid function after the hidden units and a softmax function after the target units as the activation function, as shown in Figure 3-17(b). Equation (3-25) and (3-26) are the formula of sigmoid function and softmax function respectively.

$$\mathrm{sigmoid}(\mathrm{x}) = \frac{1}{1+exp^{-x}} \tag{3-25}$$

$$\mathrm{softmax}(\boldsymbol{x})_i = \frac{exp^{x_i}}{\sum_{k=1}^{K} exp^{x_k}}, \text{for K is the dimension of } \boldsymbol{x} \tag{3-26}$$

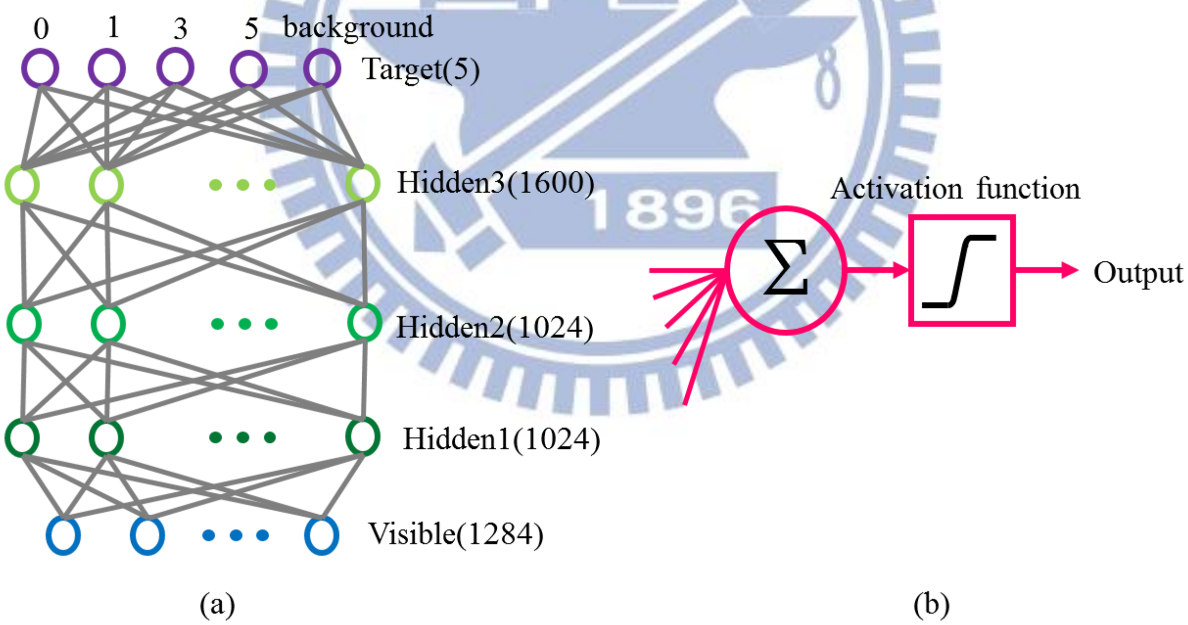


Figure 3-16 (a) Our deep neural network model architecture.
(b) The example of the activation function after the hidden node.

The deep neural network training procedure is mentioned as Section 3.2.2. We have two stages, that is, unsupervised pre-training stage and supervised fine-tuning. We trained the neural network model layer-wise by using Restricted Boltzmann Machine and adopt the contrastive divergence algorithm to update the weight between two layers. The basic concept for Restricted Boltzmann Machine is to find the hidden nodes which can represent the visible nodes better. As we use the hidden nodes to re-sample the visible nodes, we can figure out whether these hidden nodes could represent these visible nodes or not by calculating the different between visible nodes and the re-sampling visible nodes. After several times updating, we can get the hidden nodes which can represent our visible nodes. We might get some combination for the input features, on the other words, more global features be composed of the local features in the visible layer. As we trained the first two layers of the model, we might use visible nodes and the trained weight between visible nodes and hidden one nodes to get the output of hidden layer one nodes. Then we do the second two layers training by setting the hidden one nodes as the visible nodes, and so on. Finally, we have trained all the weights between any two layers. After that, we stack the two layer-wise structure to be a deep neural network architecture. At the supervised fine-tuning stage, we use the back-propagation algorithm to minimize the error function by updating the weight we get from previous stage. We adjusted the weight slightly, to get the best solution of this neural network model. At last, we could have a classifier for hand gesture recognition by using the deep neural network model.

3.3.3 Tracking Technique

The purpose of an object tracker is to find the object position from previous frame to next frame. The tracking method might get the trajectory of the object in every frame which we are interested. In [15], according to different object representation, the tracking method can be categorized into three types, point tracking, kernel tracking and silhouette tracking. Their common goal is finding the most possible position of the object in next frame from the information of the previous frame. The first one might use the previous frames position and motion to match the point which represent the interested object from previous frame to next frame. The second one adds some patch similarity to match the object more reliable. The third one might find the optimum solution of the silhouette or contour matching. Figure 3-17(a) to (c) briefly illustrate the three tracking method. The dot arrow denote the previous motion estimation and the dash arrows denote the predict motion for the next frame. The solid nodes denote the previous hand gesture position and the light-colored nodes denote the predict hand position. Because of the complex changes for the hand shape from different gestures, there isn't a robust tracking method for the hand gestures. Therefore, we only use the basic concept of the tracking technique in our hand gesture recognition algorithm.

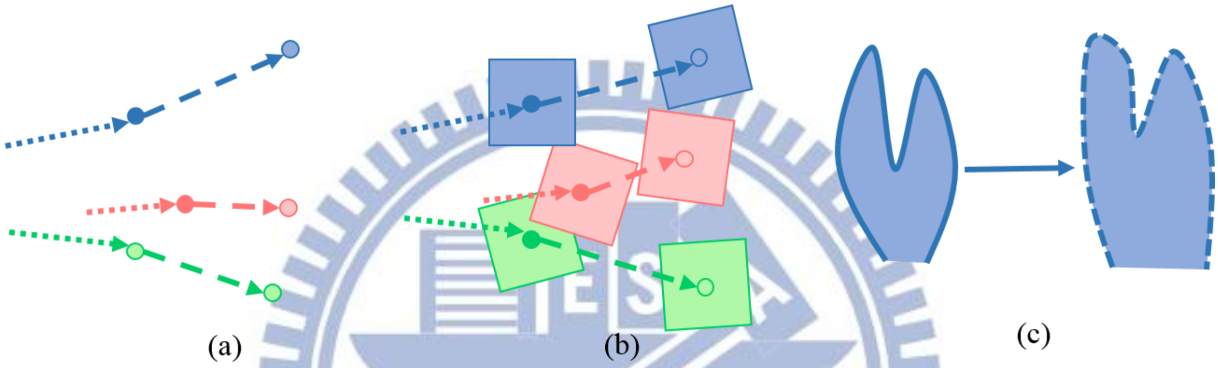


Figure 3-17 (a) The example of point tracking method.
(b) The example of kernel tracking method.
(c) The example of silhouette tracking method.

The idea of our tracking algorithm are the constraints of the searching region of our detection algorithm and using a simple two dimension correlation of two patches to find the similarity of them. Because of the video will have about thirty frames in a second, the hand position won't be distance from two successive frame. Also, the motion of previous two frame and next two frame won't be a lot of difference. We restrict the searching region of our detection by using convolutional neural network and deep neural network. The searching region will adjusted according to the motion estimation. For example, as we estimate the object move from the bottom left corner to the top right corner, the range we search at the top right corner will larger than the bottom left corner to cope with the object trajectory. We estimate the object motion by assuming it will be the same as previous motion. The previous motion could get from our hand gesture recognition result for the previous frames. Figure 3-18 shows an example of searching region adjustment and the motion estimation for our proposed method. In Figure 3-18, the blue dash block is the adjustment of searching region for the detection algorithm and the green arrow is our motion estimation result. For the similarity issue, we use the two dimension correlation function for the target patch and a testing patch. The target patch is the hand gesture we find in the previous frame whether getting by detection or by tracking. The testing patches are the adjacent region of the target patch. The two dimension correlation function is described in equation (3-27),

$$corr2 = \frac{\sum_i \sum_j (A_{ij} - \bar{A})(B_{ij} - \bar{B})}{\sqrt{\sum_i \sum_j (A_{ij} - \bar{A})^2} \sqrt{\sum_i \sum_j (B_{ij} - \bar{B})^2}}, \tag{3-27}$$

where A denotes the target patch and B denotes the testing patch. A_{ij} is the pixel at the i row and j column in the target patch and same as B_{ij}. $\bar{A}$ and $\bar{B}$ are the mean of the target patch and testing patch respectively. We have an example target patch and some testing patches to shown the correlation between two patches in Figure 3-18.

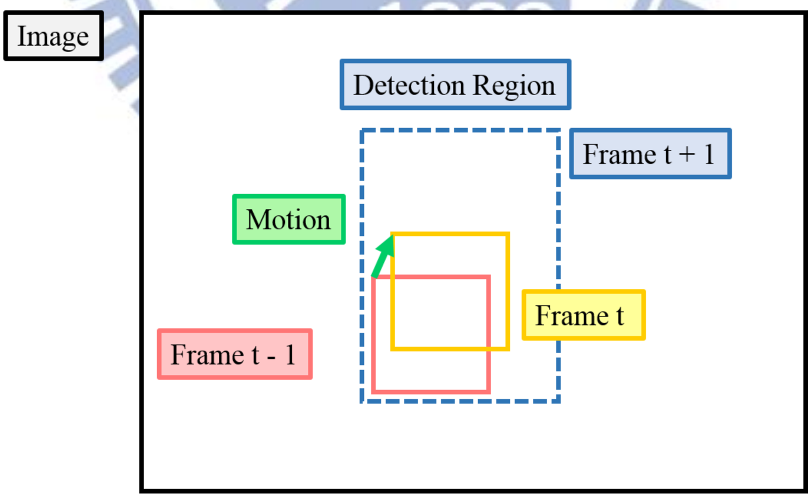


Figure 3-18 An example for the detection region adjustment and the motion estimation result.

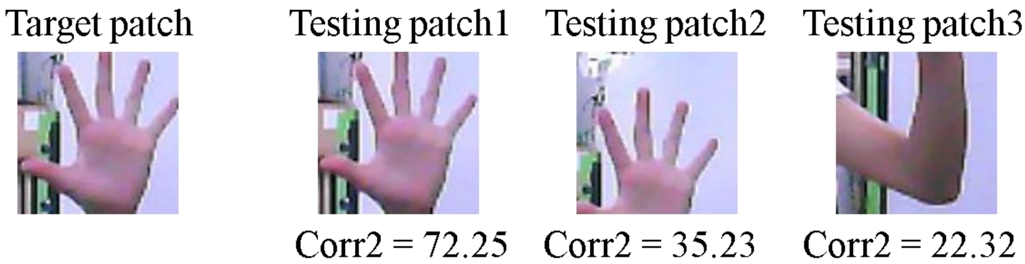


Figure 3-19 The example of target patch and three testing patch with its two dimension correlation for the target patch.

In order to reinforce the hand position constraint, we use two maps, position map and motion map to weighted the result of detection and tracking. The position map is obtained from the previous hand gesture recognition result. We use a two dimension Gaussian distribution to model the position map for the previous hand gesture recognition is one and drop to the surrounding. Also, the motion map is obtained from the previous hand gesture recognition result add the displacement we predict by motion estimation. The previous position add the displacement is set to one and drop to the surrounding as a two dimension Gaussian distribution. Figure 3-20 shows an example of the position map and motion map. The blue point and green point in the position map are the previous hand gesture recognition result. The red arrows in the motion map are the motion estimation result for the previous frame.

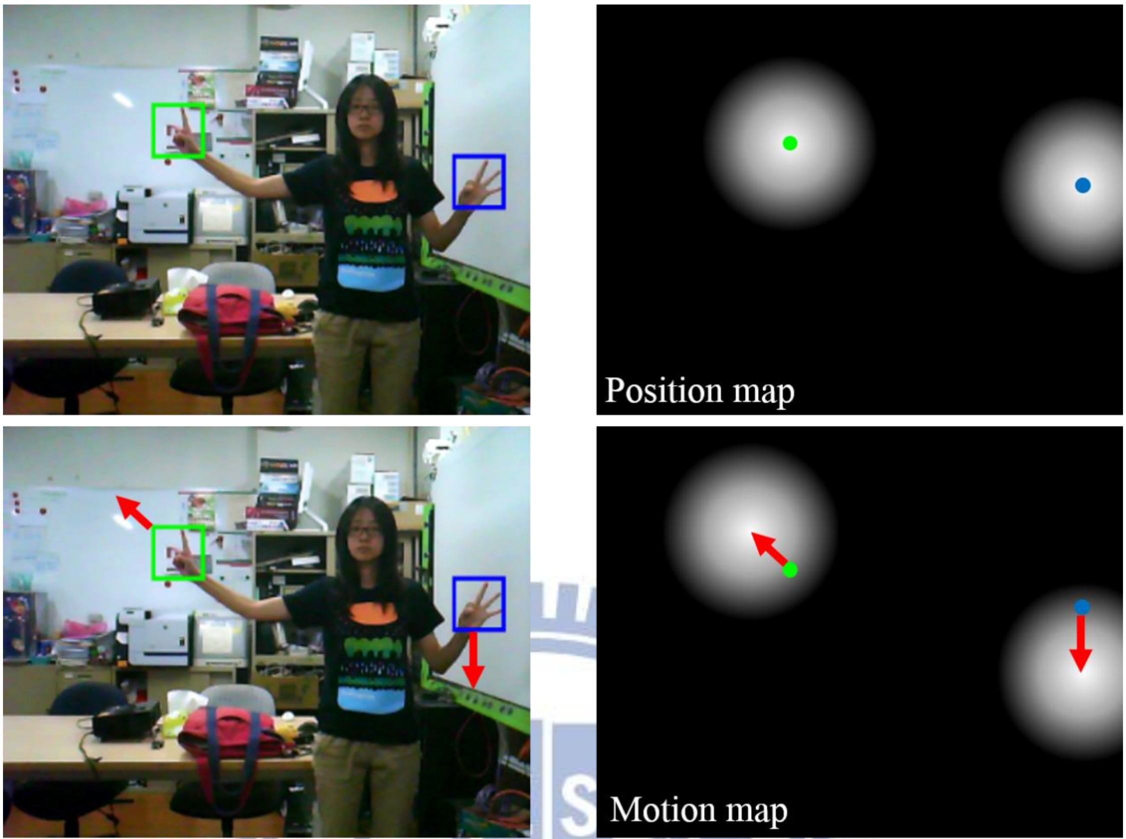
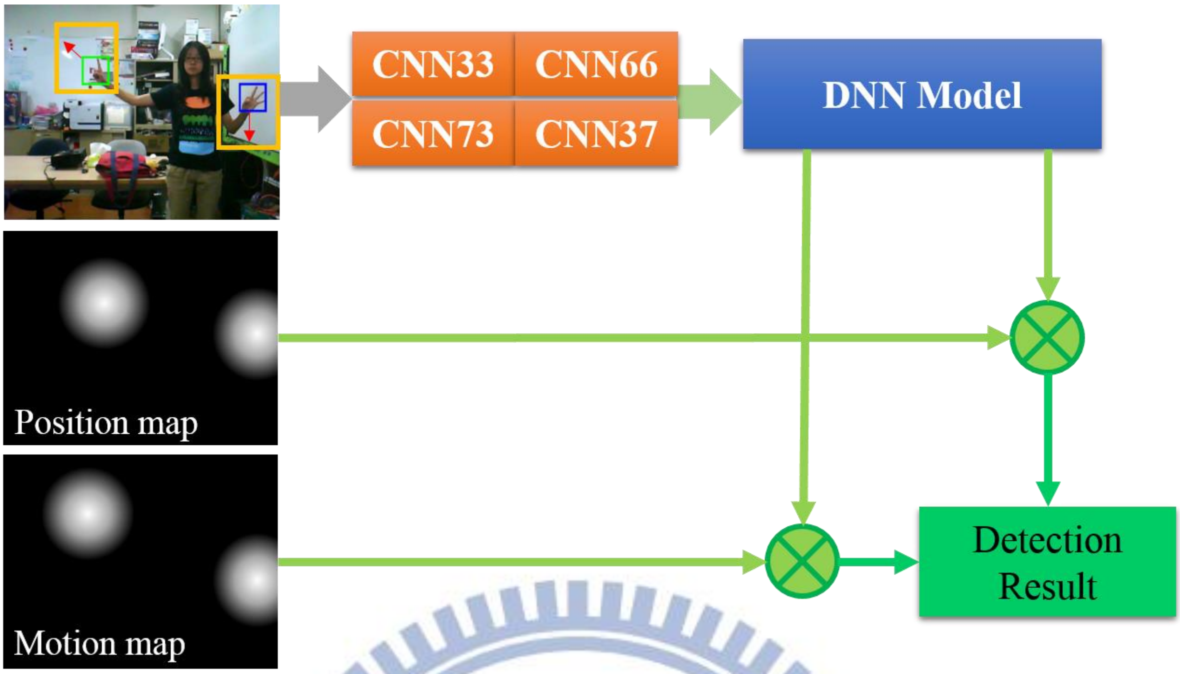


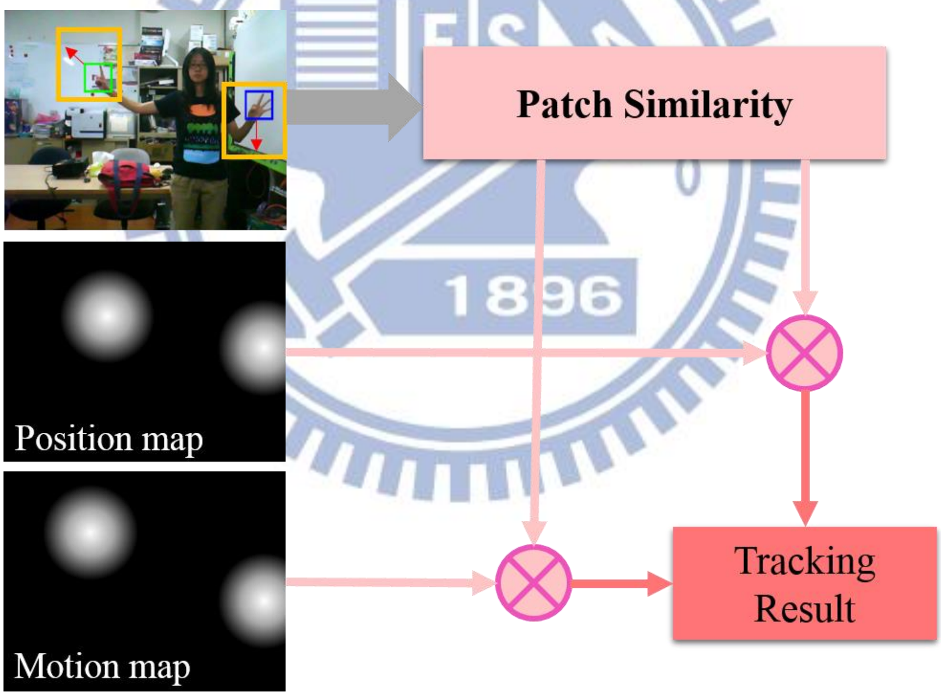
Figure 3-20 The examples for the position map and the motion map.

3.4 Refinement

The last stage of our hand gesture recognition algorithm is refinement. We have to choose the result from the detection algorithm and the tracking algorithm. The first refinement step is the weighted score for both detection and tracking result. The weighted are the position map and the motion map. The closer the local patch and the previous hand gesture recognition result the higher weighted it has. After we get the weighted score for both detection and tracking result, we will find the highest two scores to represent the right hand result and left hand result. Figure 3-21 is the flowchart of the weighted score for detection and tracking result. This step is established under the constraint of the hand position won’t extremely change in the successive frames.



(a)



(b)

Figure 3-21 (a) The flowchart for the weight score of detection result.
(b) The flowchart for the weight score of tracking result.

Secondly, we use the temporal information to improve the stability of our hand gesture recognition results. The idea of our proposed refinement for temporal domain is the records of the temporal gesture recognition result and calculate for the most probable gesture. We record seven frames to average the score for four different gestures. The closer to the frame we want to figure out the hand gestures in the temporal domain, the higher weighted we multiply to the score of detection or tracking result we choose. Figure 3-22 is an example for the temporal information refinement in our proposed method. The rows under the arrow is the result of our choice for the detection and tracking result in the temporal domain from ten frames before the frame we are processing. The square above the arrow is the refinement result in the frame we are processing. We can see that even the result in the processing from is distinct from previous few frames, we can use the temporal information to correct the result. This information is under the limitation of the hand shape would not dramatic change.

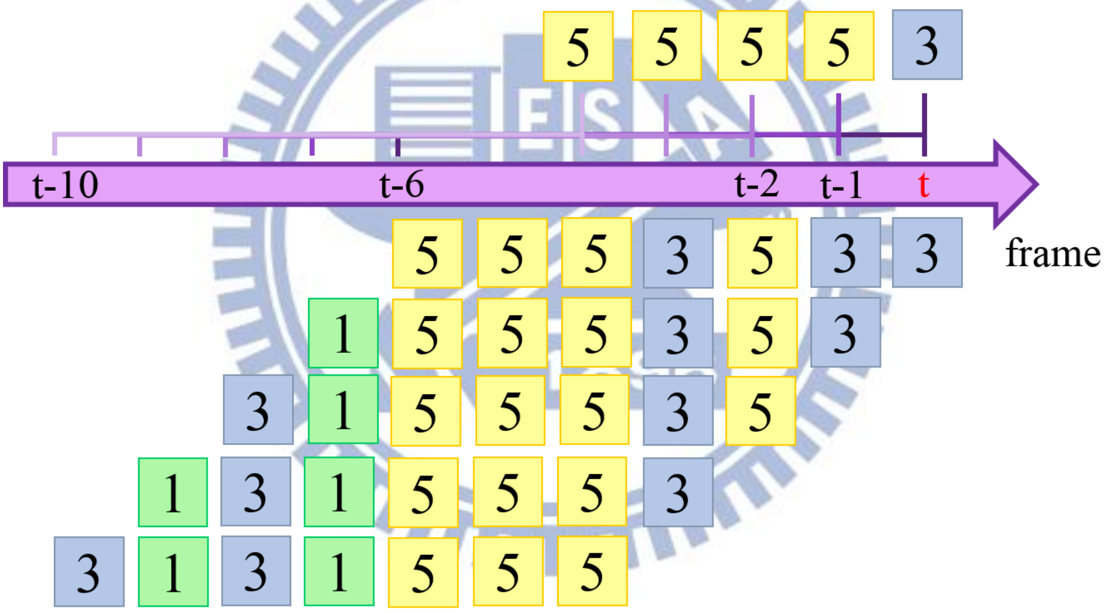


Figure 3-22 The example of the temporal information refinement of our proposed method.

Chapter 4. Experimental Results

We have several technique combine in our proposed algorithm. We will compare the detection and recognition accuracy for traditional convolutional neural network, traditional deep neural network and our proposed deep traditional neural network. As we combine the detection and tracking algorithm, we can save times for computation. We will compare the time savings for detection without tracking and detection with tracking. Also, detection accuracy might be improve when combining the tracking technique, we will have some example frames for the improvement. Furthermore, we will do the same tracking technique for both traditional convolutional neural network and traditional deep neural network and compare the frames of three methods. We have two videos for testing. The first video is a person stands in front of the camera and the background is clutter but static. The second video is a person sits in front of the camera and the background is clutter but having some moving people and hands.

4.1 Detection accuracy

The detection accuracy is defined as whether the hand gesture recognition is the same as the target or not. We test both training data set and testing data set. The training data set has 6400 images for each gestures and 25600 images for the background and the testing data set has about 1000 images for each gestures and 6400 images for the background. We trained the traditional convolutional neural network model, traditional deep neural network model and our proposed deep convolutional neural network model for the same training data set. Then test these three models for the same testing data set. We calculate the accuracy for different gestures and for background independent. Table 4-1 shows the accuracy rate for three different training models when testing the training data set. Table 4-2 shows the accuracy rate when testing the testing data set. We can see that the accuracy might improve as we combine the convolutional neural network and deep neural network and using different kernel size for feature learning.

	0	1	3	5	background	total
DCNN	99.92	99.75	99.87	99.94	100.0	99.94
CNN	96.33	64.73	91.23	91.03	98.74	92.29
DNN	98.91	98.23	99.52	98.70	99.83	99.36

Table 4-1 Accuracy rate for training data set.

	0	1	3	5	background	total
DCNN	98.89	96.07	96.17	98.61	99.55	98.77
CNN	94.07	55.58	88.40	91.28	98.42	92.12
DNN	94.81	92.98	94.20	94.34	98.14	96.63

Table 4-2 Accuracy rate for testing data set.

Furthermore, we test the hand gesture recognition model for the real video frames. We shows the most probable two results for the hand gesture recognition in a frame in order to represent the right hand and the left hand. Figure 4-1(a) shows some frames in the first video we test for our proposed method, traditional convolutional neural network and traditional deep neural network. Figure 4-2(b) shows the test result for video 2. The square means the hand position we find and the red square denotes the stop gesture, the green square denotes the pointer gesture, the blue square denotes the ok gesture and the pink square denotes the wave gesture. Two videos are from different view-point and different background. We can see that our proposed deep convolutional neural network can detect the hand and recognize the gestures best. The row is the same frame for our proposed method, traditional convolutional neural network and traditional deep neural network respectively.

(a)

(b)

Figure 4-1 (a) Example frames for our proposed method, convolutional neural network and deep neural network in a row of video 1.

(b) Example frames for our proposed method, convolutional neural network and deep neural network in a row of video 2.

4.2 Combine Tracking and Detection

As the detection test for all the patch in a frame is not efficient and the clutter background might influence the hand gesture recognition result, we use the tracking technique to save time and improve the accuracy. Table 4-3 shows the computation time for our proposed deep convolutional neural network (DCNN), traditional convolutional neural network (CNN) and traditional deep neural network (DNN) for detection only and detection combine tracking technique. We can see that adding tracking technique could reduce the computing time to about 1 second per frame.

	Detection Only	Detection & Tracking
DCNN	6.12 sec/frame	1.09 sec/frame
CNN	4.30 sec/frame	0.85 sec/frame
DNN	2.16 sec/frame	0.88 sec/frame

Table 4-3 The computing time for detection only and detection combine tracking.

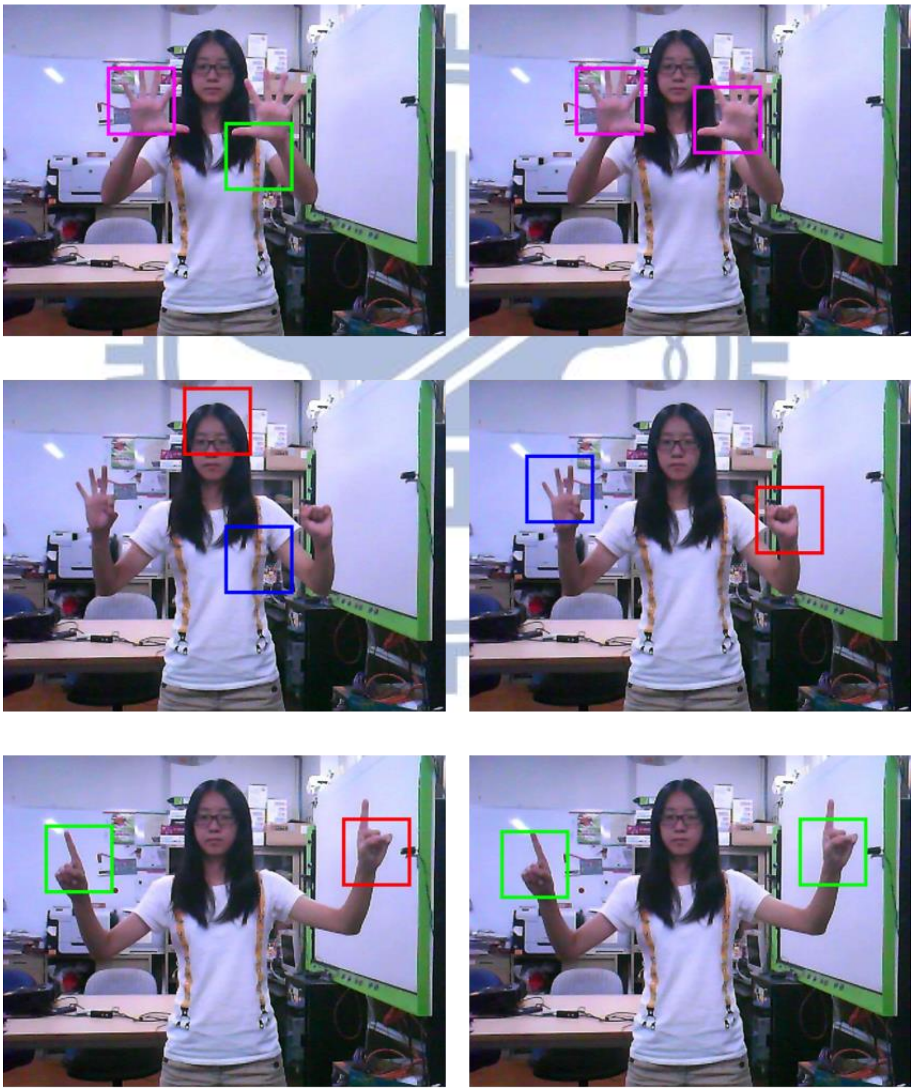
We also have some example frames to compare the hand gesture recognition result for using tracking technique or not, shows in Figure 4-2(a) and Figure 4-2(b). The left column is the result of detection algorithm and the right column is the detection combine tracking algorithm. We calculate the frame accuracy rate for both detection algorithm and detection combine tracking algorithm as shown in Table 4-4 and Table 4-5. We can see that combining detection and tracking not only reduce the computing time but also improve the frame accuracy. The hand detection accuracy denotes that the hand position is correct whether the gesture recognition is correct or not. The gesture recognition accuracy denotes that based on the hand position is correct, we could recognize the gesture. The hand gesture recognition accuracy denotes that we have both correct hand position and gesture recognition.

	Hand detection accuracy		Gesture recognition accuracy		Hand gesture recognition accuracy	
	Left	Right	Left	Right	Left	Right
Detection Only	69.35 %	79.84 %	92.64 %	49.83 %	64.25 %	39.78 %
Detection &Tracking	97.85 %	93.55 %	76.10 %	62.64 %	74.46 %	58.60 %

Table 4-4 The hand gesture recognition accuracy for detection only and detection combine tracking of video 1.

	Hand detection accuracy		Gesture recognition accuracy		Hand gesture recognition accuracy	
	Left	Right	Left	Right	Left	Right
Detection Only	82.68 %	65.09%	54.60 %	76.21 %	45.14 %	49.61 %
Detection &Tracking	94.75 %	95.54 %	56.79 %	65.38 %	53.81 %	62.47 %

Table 4-5 The hand gesture recognition accuracy for detection only and detection combine tracking of video 2.



(a)

(b)

Figure 4-2 (a) Example frames for detection only algorithm and detection combine tracking algorithm in a row of video 1.
(b) Example frames for detection only algorithm and detection combine tracking algorithm in a row of video 2.

4.3 Video comparison

The last comparison is using the detection and tracking algorithm and instead of our proposed deep convolutional neural network algorithm, we use traditional convolutional neural network and traditional deep neural network to combine with our tracking technique. We calculate the frame accuracy for hand detection, gesture recognition and hand gesture recognition as the previous section. The accuracy rate shows in Table 4-6 and Table 4-7. We also have some example frames for both video and for these three algorithms as shown in Figure 4-3(a) and Figure 4-3(b). The figure shows the same frame for our proposed method, traditional convolutional neural network algorithm and traditional deep neural network algorithm in a row respectively. We can see that the proposed deep convolutional neural network (DCNN) could detect the hand position best and almost recognize the hand gestures correct than two other method which is the traditional convolutional neural network (CNN) and traditional deep neural network (DNN).

	Hand detection accuracy		Gesture recognition accuracy		Hand gesture recognition accuracy	
	Left	Right	Left	Right	Left	Right
DCNN	97.85 %	93.55 %	76.10 %	62.64 %	74.46 %	58.60 %
CNN	87.37 %	91.12 %	62.15 %	55.75 %	54.30 %	50.80 %
DNN	87.63 %	79.57 %	60.12 %	33.45 %	52.69 %	26.61 %

Table 4-6 The hand gesture recognition accuracy for our proposed deep convolutional neural network, traditional convolutional neural network and traditional deep neural network of video 1.

	Hand detection accuracy		Gesture recognition accuracy		Hand gesture recognition accuracy	
	Left	Right	Left	Right	Left	Right
DCNN	94.75 %	95.54 %	56.79 %	65.38 %	53.81 %	62.47 %
CNN	81.63 %	94.23 %	53.70 %	70.19 %	43.83 %	66.14 %
DNN	83.46 %	92.65 %	38.99 %	63.46 %	32.55 %	58.79 %

Table 4-7 The hand gesture recognition accuracy for our proposed deep convolutional neural network, traditional convolutional neural network and traditional deep neural network of video 2.


(a)


(b)

Figure 4-3 (a) Example frames for our proposed deep convolutional neural network, traditional convolutional neural network and traditional deep neural network combining our tracking technique in a row of video 1.
(b) Example frames for our proposed deep convolutional neural network, traditional convolutional neural network and traditional deep neural network combining our tracking technique in a row of video 2.

Chapter 5. Conclusion

We proposed a hand gesture recognition algorithm which could be used in the human-computer interface. We use some intuitive gestures to convey the user's thought and interact with the computer. We defined more than two gestures to recognize and expect that the interface won't be limited for a specific viewpoint, user, camera and background. We collect the hand images from different users, viewpoints, camera and arbitrary background. We try to use the convolutional neural network for feature extraction. In order to cope with the complicated hand gestures, we modify the traditional convolutional neural network and combine different kernel size convolutional neural network model to do the feature extraction. After that, we use the deep neural network to classify the gestures in the feature space. We use the unsupervised pre-training and supervised fine-tuning to fine the combination of local feature and to find the relationship between the features and the target gestures. Also, we add some tracking technique to reduce the computing time and to improve the hand gesture recognition accuracy. Therefore, we could detect the hand position and recognize the hand gesture in any video we want to process.

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