**ISSN** 1746-7659, England, UK
**Journal of Information and Computing Science**
Vol. 8, No. 1, 2013, *pp*. 027-040

# Vietnam License Plate Recognition System based on Edge Detection and Neural Networks

VinhDu Mai [1,2+] , Duoqian Miao [1] and Ruizhi Wang [1]

[1] Department of Computer Science and Technology, Tongji University, Shanghai 201804, P.R. China

[2] Electricity & Electronic Department, The University of Transport & Communications, Hanoi, Vietnam

(*Received August 05, 2012, accepted November 20, 2012*)

**Abstract.** This paper proposed an improved Automatic License Plate Recognition (ALPR) system for all types of Vietnam license plates (LP), which consists of three modules: license plate location (LPL), characters segmentation and characters recognition. In the LPL module, we have combined edge detection, image subtraction, mathematical morphology, radon transform, interpolation and specific characteristics of Vietnam LP to locate exact LP region. In the characters segmentation module, we have used peak-to-valley method and statistical parameters of Vietnam LP to segment characters & numbers in one-row & two-row types of Vietnam LP. In the characters recognition module, we have used a Multilayer Perceptron (MLP) neural network and back-propagation (BP) algorithm to recognize characters & numbers of Vietnam LP, two MLP networks used independent for characters & numbers and MLP has trained with noises in the training task. Character & number images processed by the pre-processing task, which obtained high quality of character & number images for the using network task to improve accuracy of the system. We have implemented our ALPR system on 700 Vietnam vehicle images taken from actual system with different conditions such as lightening conditions (night & day), license angles, illumination, size and type, colors and reflected light. Our method is more effective than some existing methods and efficiency of computing time & accuracy is improved and very satisfied for all types of Vietnam LP and Vietnam environment.

**Keywords:** *License plate location, Characters segmentation, Characters recognition, Automatic license plate recognition, Artificial neural network.*

## 1. Introduction

The Automatic License Plate Recognition (ALPR) system is very important part of the Intelligent Transportation System (ITS) which is very important for the development in the transport infrastructure on the world. Specially, in the developing countries such as Vietnam, where the ITS have been beginning to apply for some years ago. Usually, an ALPR system consists of three parts: 1) license plate location (LPL), 2) characters segmentation, 3) characters recognition.

In the LPL work, there are many techniques have been proposed such as: mathematical morphology and hat transform [1], edge detection, auto –correlation and morphology operation [2], local intensity variance & local vertical edge density and a model of edge densities [3]. Vertical sobel color edge detection & edge density analysis [4], color and shape information [7], hough transform and contour algorithm [8], vertical & horizontal edge detection [12,19], sharp spikes in the horizontal projection [13]. Hough transform and feature-salience theory [14], morphological operations, edge detection, normalized correlation coefficient [15], adaboost algorithm [21], morphological operations and edge detection [22]. Beside on that, there are some other technologies such as wavelets transform, template matching, SVM based method, neural network and genetic algorithm proposed for this work.

In the characters segmentation module, there are also some techniques to address this work such as: edge detection, color model transform, connected components analysis [4], an intelligent framework that outlines character of car LP by various illumination [5]. Horizontal projection [8,19], multi-clustering algorithm [10],

+ Corresponding author. Tel.: +86-13681639973.
*E-mail address*: maivinhdu@yahoo.com.

threshold and connected components [12], horizontal and vertical projections [13,15,18]. Color reverse, vertical edge detection, horizontal projection histogram, vertical projection [9], morphology operation and connected components [22].

In the characters recognition module, there are also many techniques to address this work such as: decision trees [6], color image processing [7], hidden markov model [8], support vector machine [9], multi-cluster and multilayer neural networks [10]. Least squares support vector machines [11], multi layer perceptron network [12,13], template matching [14,22], fuzzy multilayer neural network [15], bayesian framework [16], radial basis function neural networks [17]. And fuzzy method & template matching [18], extension theory [20], and OCR software [21].

Although, there are many method proposed for ALPR system. But, there are not single method can provide satisfactory performance in all the applications in various complicated background such as: uncertainty of edges, various types of plate, the plate is small, dim lighting, the images are fuzzy, low or high illuminated images, types of plate, colors, character fonts, syntax, size, spacing, angle of the LP, weather and environment, multi-rows. On the other hand, every researcher used various image sources, environment, quality of the images, parameters of the images are not same, and the vehicle images not collected in Vietnam. Therefore, most of the previous methods could not apply for all the countries, all the environments, all types of the LP and Vietnam LP.

To cope with these limitations, we have considered for the specific characteristics of Vietnam LP and Vietnam environment to propose a new method for the Vietnam ALPR system, which satisfied for all types of Vietnam LP and Vietnam environment, our ALPR system has main contributions as following:

- In the LPL module: We have combined morphology operation & subtract operation on the grayscale image, which very efficiency for complex background images, night & day images and different illumination, different light conditions, from that we have obtained the better image with new intensity values, which more satisfied for the image binarization to reduce candidate regions. And then we used opening operation on binary image to remove small objects (noise areas), using radon transform and interpolation method to find LP angle & rotating LP, and measuring properties of license plate regions to cut exactly for different Vietnam LP dimensions (one-row and two-row LP). Therefore, our method is more effective than some existing methods and very satisfied for Vietnam LP.
- In the characters segmentation module: We have considered statistical parameters of Vietnam LP and types of Vietnam LP (one-row LP and two-row LP) to propose an improved method to segment characters & numbers in one-row & two-row types of Vietnam LP based on the peak-to-valley method & statistical parameters of characters and digits. We also combined pre-processing (image quantization, normalized image, adjust horizontal contours, morphology opening to remove noises) to improved image quality and remove noise, our approach is very satisfied for all types of Vietnam LP.
- In the characters recognition module: We proposed an improved method to recognize characters & numbers of Vietnam LP by using a Multi-layer perceptron (MLP) neural network and back-propagation algorithm to recognize characters & numbers of the Vietnam LP. In the training task, we used two networks in training task for characters & numbers with noises, which the computing time and accuracy be improved, in the using network task, we used image processing technology for pre-processing to obtain high quality of characters & numbers before put them in the trained network to improve accuracy of the system

This paper is organized as follows: section 2 introduces license plate location, section 3 shows the characters segmentation, section 4 shows characters & numbers recognition, section 5 shows experimental results and section 6 is conclusions and the last is references.

## 2. License plate location (LPL)

### 2.1. Flowchart of LPL

Because of the vehicle images usually obtained from a complex background, so there are many areas like LP in the images. This paper used method in our last paper [24] by used Otsu method to convert gray-scale image to binary image & canny operator for the edge detection step. Specially, we used an arithmetic operation to decrease influence on lightening conditions, illumination and reflected light in the vehicle images. Then we used opening operation on binary image to remove small objects (noise areas), radon transform and interpolation method to find LP angle & rotating LP, and measuring properties of Vietnam LP regions to cut exactly of Vietnam LP (one-row and two-row LP), the proposed method has the flowchart in the Fig. 1.

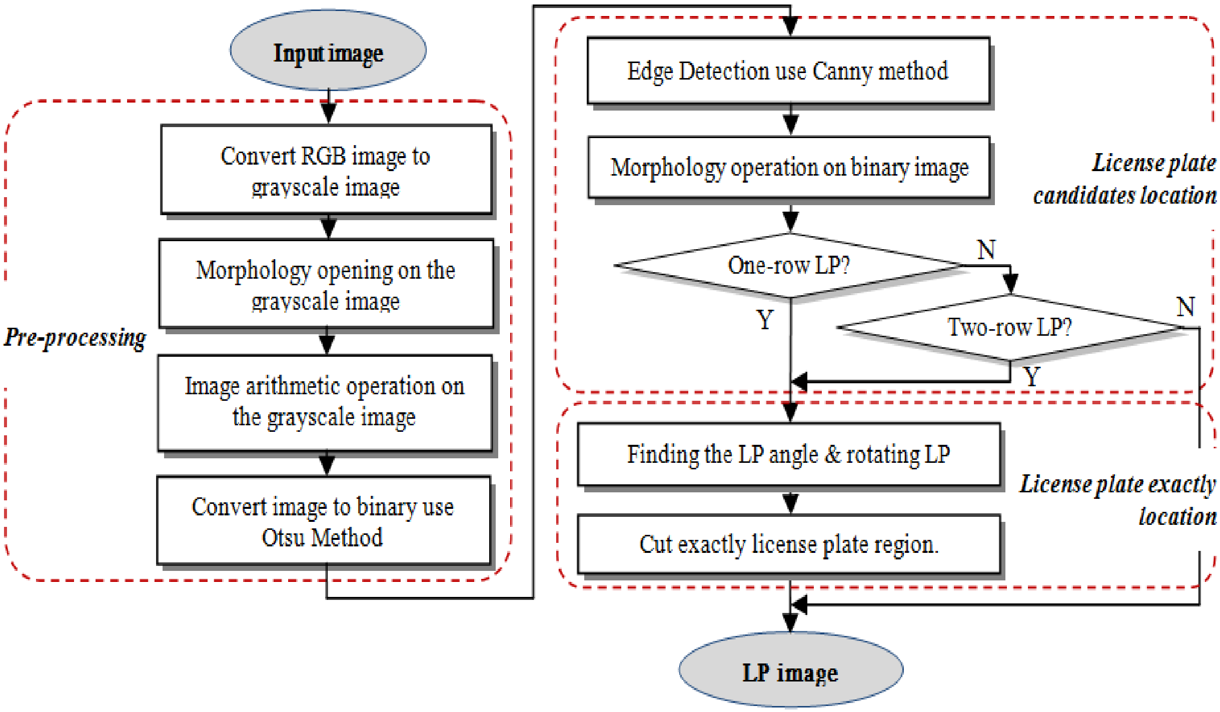



Fig. 1: Flowchart of proposed method for Vietnam LPL.

## 2.2. Pre-processing for LPL

*Image converting:* First, the origin RGB image in Fig. 2(a) is converted to grayscale image by forming a weighted sum of the R, G, and B components [12,17], with 8 bits per pixel, which allows 256 different intensities as Eq. (1), result is Fig. 2(b).

$$Y = 0.2989*R + 0.5870*G + 0.1140*B \tag{1}$$

*Morphological opening on the grayscale image:* we used morphological opening on the grayscale image, it is efficiently for the image subtraction step, with the structuring element (SE=25) by the Eq. (2), result is Fig. 2(c).

$$A \circ B = (A \Theta B) \oplus B \tag{2}$$

*Image subtraction on the grayscale image:* The image subtraction is very efficiency for complex background images, night & day images and different illumination, after that we obtained the better image with new intensity values and satisfied for the image binarization step to reduce LP candidate regions. The pixel subtraction operator takes two images as input and output image having pixel values are of the first image minus the corresponding pixel values of second image as Eq. (3), with $f_1(x,y)$, $f_2(x,y)$ are input, $g(x,y)$ is output, result is Fig. 2(d).

$$g(x,y) = f_1(x,y) - f_2(x,y) \tag{3}$$

*Convert to binary image by Otsu Method:* Fig. 2(d) is converted to binary image by Eq. (4), T is some global threshold that defined by Otsu's method [4,5,10]. Computing a global threshold (level) used to convert an intensity image to a binary image, this level is a normalized intensity value that lies in the range [0, 1], which chooses the threshold to minimize the intra-class variance of the black and white pixels, result is Fig. 2(e).

$$g(x,y) = \begin{cases} 1 \; if \; (x,y) \geq T \\ 0 \quad otherwise \end{cases} \tag{4}$$

## 2.3. License plate candidate location

*Edge detection use Canny operator:* The unit edge normal given by $\vec{n}(\vec{x}) = \vec{R}(\vec{x}) \big/ \left|\vec{R}(\vec{x})\right|$, this method [15,24] is search for maxima in the directional image derivative in the direction $\vec{n}(\vec{x})$. Search for local maxima of gradient magnitude $S(\vec{x}) = \left|\vec{R}(\vec{x})\right|$ in the direction normal to local edge, $\vec{n}(\vec{x})$, suppressing all responses except for local maxima. Steps of Canny edge detection algorithm as following:

- ***Step 1:*** Convolve with gradient filters (at multiple scales).

$$\vec{R}(\vec{x}) = \left(R_x(\vec{x}), R_y(\vec{x})\right) = \nabla G(\vec{x}, \sigma^2) * I(\vec{x}) \tag{5}$$

- ***Step 2:*** Compute response magnitude.

$$S(\vec{x}) = \sqrt{R_x^2(\vec{x}) + R_y^2(\vec{x})} \tag{6}$$

- ***Step 3:*** Compute local edge orientation (represented by unit normal).

$$\vec{n}(\vec{x}) = \begin{cases} \left(R_x(\vec{x}), R_y(\vec{x})\right) \big/ S(\vec{x}) & if \; S(\vec{x}) > threshold \\ \quad 0 & otherwise \end{cases} \tag{7}$$

- ***Step 4:*** Peak detection (non-maximum suppression along edge normal).
- ***Step 5:*** Non-maximum suppression through scales and hysteresis threshold along edges, result image is Fig. 2(f).

*Closing operation on binary image:* Closing operation [2,1,22,24] used to merge structures on a binary image. The closing of A by B obtained by the dilation of A by B, followed by erosion of the resulting structure by B as Eq. (8), where $\Theta$ and $\oplus$ denote erosion and dilation, output image is Fig. 2(g)

$$A \circ B = (A \oplus B) \Theta B \tag{8}$$

*Opening operation to remove noises:* We use this method [2,3,24] on binary image to remove objects. Their pixel areas on binary image that all connected components that fewer than [7 25] pixels to remove all of the regions (noises) that is not license plate candidates, output image is Fig. 2(h).

*Dilation operation:* Dilation operation [1,2,4,22,24] used to increase objects in the binary images, the positions where a given structure element fits. The dilation of A by the structuring element (SE) B is defined by Eq. (9), dilate is a function also known by the names "grow", "bolden", and "expand". It turns on pixels that near pixels that were on originally, thereby thickening the items in the image, result is Fig. 2(i).

$$A \oplus B = \bigcup_{b \in B} A_b \tag{9}$$

*Fixing the LP Region:* We measured properties of each connected component [2,3,19] on binary image. The fields of the structure array denote different properties of each region, selecting the LP from the candidates by chosen area that is the deepest region in the frame that has properties of the LP area, then find a set the coordinates of the LP region, result is Fig. 2(k).

## 2.4. License plate exact location

*Finding the LP angle & rotating LP:* Applying the radon transform [24] on an image $f(x,y)$ for a given set of angles can be thought of as computing the projection of the image along the given angles $\rho$, result is a new image $R(\rho,\theta)$ with lines in the Fig. 2(l).

$$\rho = x*\cos(\theta) + y*\sin(\theta) \tag{10}$$

$$R(\rho,\theta) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f(x,y)\,\delta(\rho - x\cos\theta - y\sin\theta)\,dxdy \tag{11}$$

*Rotating LP:* we used the interpolation method specified by bilinear interpolation [24], after rotating, result is the Fig. 2(m).

*Cut exactly LP region:* We find the coordinates of the LP rectangle, then we have four-element position vector [$x_{min}$ $y_{min}$ width height], specifies size & position of the crop rectangle, result is Fig. 2(n).

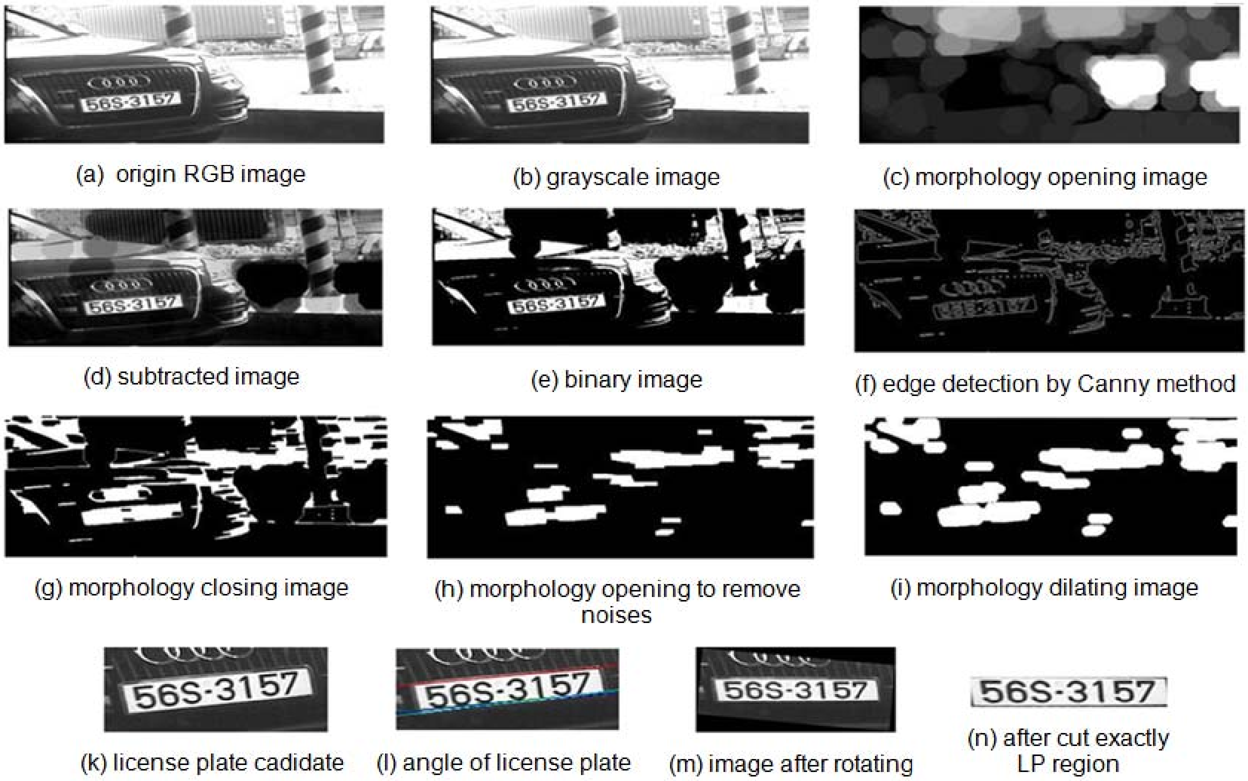



Fig. 2: Results of step-by-step for Vietnam license plate location

## 3. Characters segmentation

### 3.1 Flowchart of characters segmentation

In this work, we proposed a new method for one-row & two-row of Vietnam LP characters segmentation, which combined pre-processing to remove noises, normalized and then segment characters & numbers based on peak-to-valley method and according to the statistical parameters of Vietnam LP, flowchart of our method is Fig. 3(a).

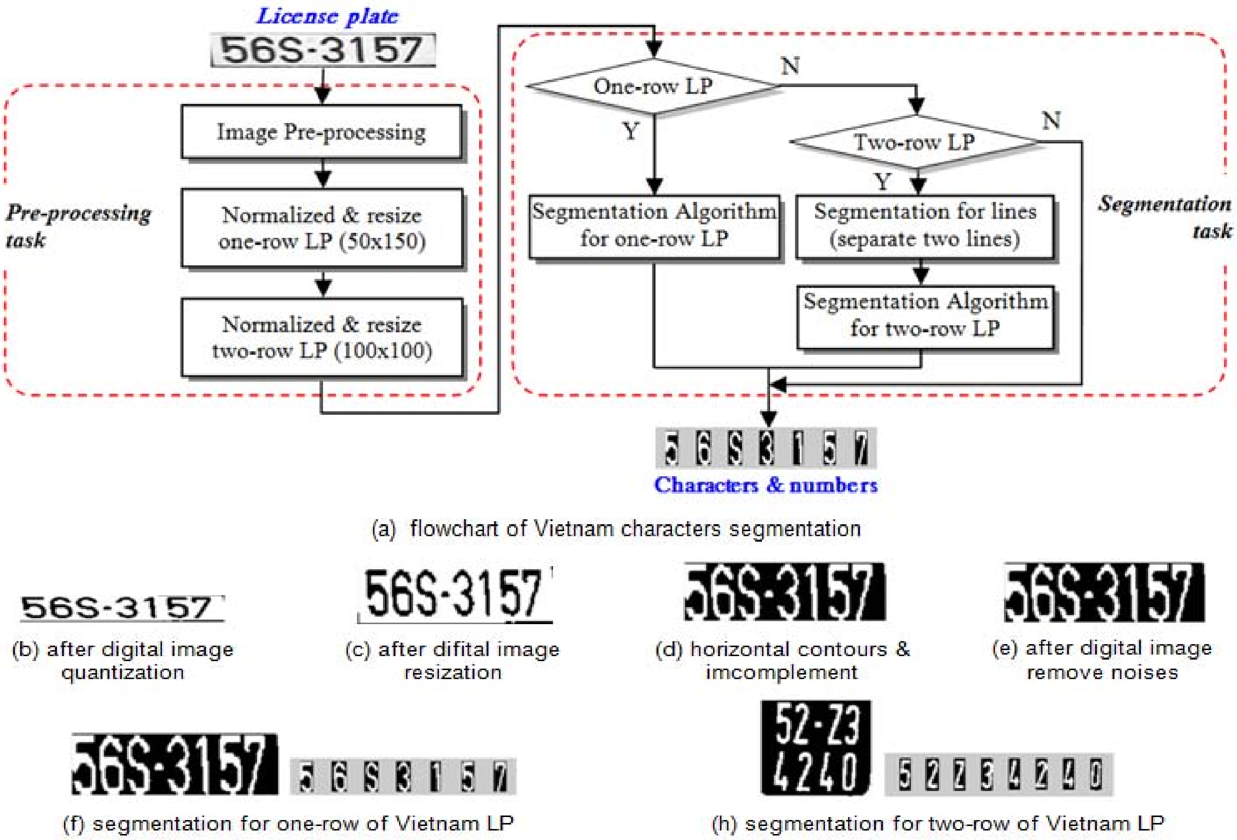



Fig. 3: Flowchart of Vietnam characters segmentation and results of segmentation work

### 3.2 Pre-processing for characters segmentation

*Image quantization & image resizing:* Quantization on gray image in Fig. 2(n), a black & white image determined by an adaptive threshold, we obtained Fig. 3(b). Then, the image is resized in parameter 50x150 pixels for one-row LP and 100x100 pixels for two-row LP, result is Fig. 3(c).

*Adjusting horizontal contours & imcomplement:* Determining the LP horizontal contours by computing the sum of the lines in Fig. 3(c), and in the complement of image, 0 become 1 and 1 become 0, black and white are reversed. Each pixel subtracted from the maximum pixel value and the difference used as the pixel value in the output image, result is Fig. 3(d).

*Morphology opening on binary image (remove noises):* Using morphology opening [2,3,24] on binary image to remove all connected components (noises) fewer than 10 pixels for one-row LP & two-row LP, result is Fig. 3(e).

### 3.3 Characters Segmentation

After pre-processing work, we need to divide two rows in the two-row LP type by computing and division in the vertical direction, and then characters segmentation work is finished by a peak-to-valley method for each row according to segmentation algorithm following:

*Segmentation Algorithm:* For this work, we used a method called “peak-to-valley” on binary image to segment characters in every line of the Vietnam LP, characters and numbers zone is detected using peak to valley function as Eq. (12).

$$Vp_{(x)} = \frac{V\left(l_p\right) - 2*V\left(x\right) + V\left(r_p\right)}{V\left(x\right) + 1} \tag{12}$$

where, $Vp_{(x)}$ is the vertical projection function at current x location, $l_p$ is peak position on the left side of x,

$r_p$ is the peak position on the right side of x. We search changes between peaks and valleys, and then count number of black pixels per column in the projection, each characters position found by steps bellowing:

**Step 1 -** Segmentation based on digit width & min area: Segmentation the characters in digital images according to the variable "digit width" and returns a matrix containing the two bounds of each digit. The function keeps in the result only segment whose "rectangular" areas are more than "min area".

- Summing the column of image: Sum of array elements, image is a matrix, treats the columns of image as vectors, returning a row vector of sums each column.
- Getting the segments in image: Peak-to-valley method is used for segmentation the characters in the image, get two bounds of the each digit segment according to the statistical parameter of digit width.
- Using the vector of the sums of the columns in the LP binary image supplied in the parameter. The function passes over the graph corresponding to this vector from left to right, bottom-up, incrementing at each recursive step the height that examined on the graph. It checks the bandwidth of the first part of the signal: if it is greater than digit width, the function is recursively called after incrementing the height that examined on the image. Otherwise, if the bandwidth is good, two bounds of the signal with this bandwidth taken as a digit segment, the function is recursively called for part of image, which is at right side of digit segment just found.
- Keeping in the result only of the segmentation whose rectangular areas is more than min area.

**Step 2 -** Keeping in results the seven segments with the largest area, we obtained result of segmentation in Fig. 3(f,h) with 50x150 pixels for one-row LP and 100x100 pixels for two-row LP.

# 4. Characters & numbers recognition

## 4.1. MLP architecture

MLP neural network is an important in the text recognition by [27,10,12]. In this paper, we proposed an improved method based on MLP neural network and back-propagation algorithm for training to recognize characters & numbers in the Vietnam LP, we used two network for characters & numbers, architecture of proposed method in the Fig. 4(a).

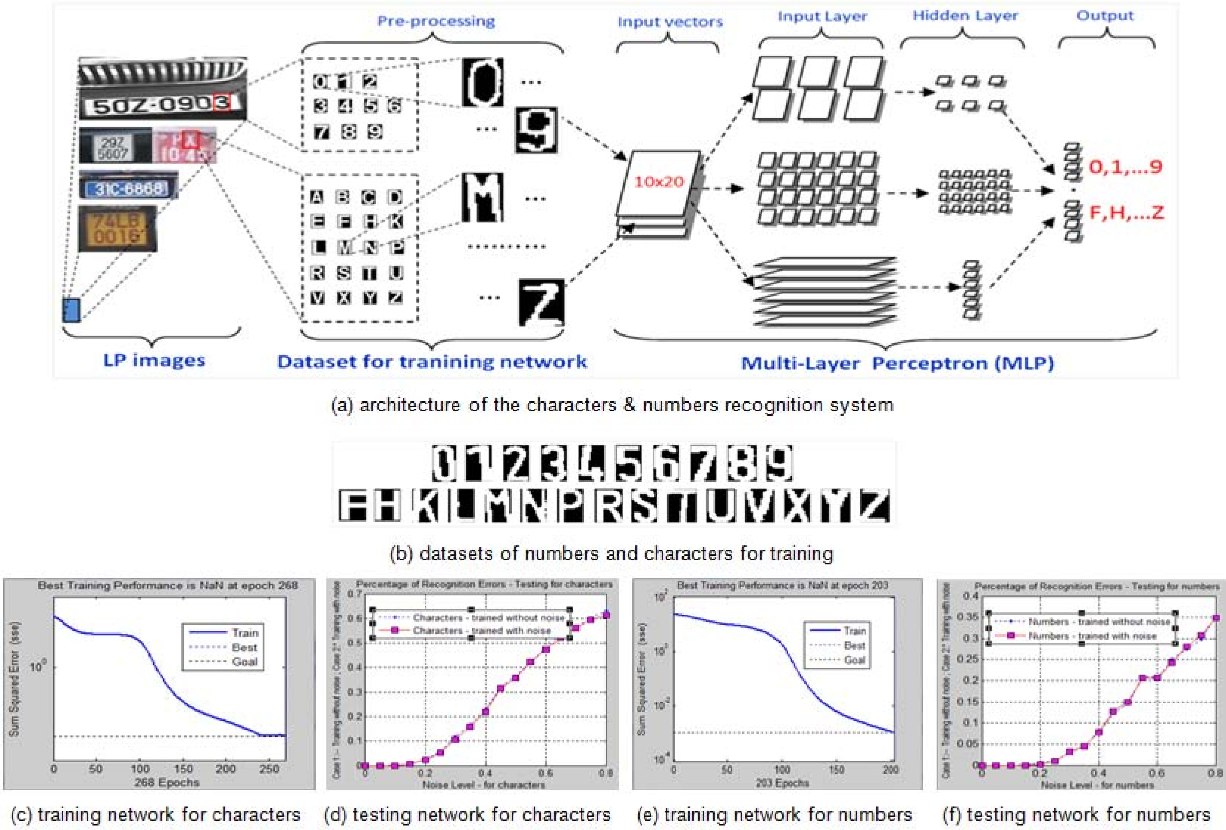


Fig. 4: MLP architecture, datasets for training, results of training and testing

*Datasets and pre-processing:* Datasets for training network are 15 characters and 10 numbers, which obtained from Vietnam LP images taken from the actual systems, all of characters & numbers resized in (10x20) pixels as Fig. 4(b) and they used for training network.

*Parameters of MLP:* Input vectors of character & number is $X_j = [x_0, x_1, ..., x_m]^T$, where $j = 1, 2, ..m$, weight vectors between input layer & hidden layer and between hidden layer & output layer are $W_{qj} = [w_{0q}, x_{1q}, ..., x_{mq}]^T$ and $W_{iq}(i = 1, 2, ...n)$, where $q = 1, 2, ..l$, $j = 1, 2, ...m$. Input liner function of network is $v_k = \sum_{i=0}^{l} w_{ik} x_i - \theta$, where $\theta$ is scalar bias. Activation function is sigmoid transfer function $f(v) = 1/(1+e^{-\lambda v})$, the log-sigmoid transfer function at the output layer was picked because its output range (0 to 1). Actual output of network is $Y_i(i = 1, 2, ...n)$, activation function is sigmoid transfer function $a = f(n) = 1/(1+e^{-x})$. Input signal for hidden layers is $netq = \sum_{j=1}^{m} v_{qj} x_j$, output signal of hidden layers is $z_q = a(netq) = (1-e^{-netq})/(1+e^{-netq})$, input signal of output layers are $neti = \sum_{q=1}^{l} w_{iq} z_q$, output signal of output layers are $y_i = a(neti) = (1-e^{-neti})/(1+e^{-neti})$. We will use a sum of mean squares error $E(w) = \frac{1}{2}\sum_{i=1}^{n}(d_i - y_i)^2$, where $w$ is weighted values, $d_i$ is desired output values, $y_i$ is actual output values of network. We will find a set of weighted values that $E(w)$ will be touch minimum value.

## 4.2. Training MLP network use back-propagation algorithm

In the training task, we used two MLP networks for characters & numbers training based on back-propagation algorithm [12] with noises. In each network, we will adjust the weights of each unit in such a way that the error between the desired output and the actual output reduced, we compute the error derivative of the weights. In other words, it must calculate how the error changes as each weight is increased or decreased slightly, steps for training task with input vector $X_j$ and desired output $D_j$, m input layers (m=200), l hidden layers (l=10), n output layers (n=15 for characters network, n = 10 for numbers network).

**Step 1:** Read input vector $X_i$ (for characters and numbers), all of samples have dimensions are (10x20) pixels and recorded in a two dimensions array [10 20]. Clear all previous values, and then initialize the weights vectors $W_{qj}$ and $W_{iq}$ and biases, learning rate $\eta$, error max $E_{\max}$, k=1 and E=0.

**Step 2:** Computing actual output of network from input signal of hidden layer is Eq. (13), output signal of hidden layer is Eq. (14), input signal of output layer is Eq. (15). Finally, we have output signal of output layer is Eq. (16).

$$netq = \sum_{j=1}^{m} v_{qj} x_j \tag{13}$$

$$z_q = a(netq) = (1 - e^{-netq}) \big/ (1 + e^{-netq}) \tag{14}$$

$$neti = \sum_{q=1}^{l} w_{iq} z_q \tag{15}$$

$$y_i = a(neti) = (1 - e^{-neti}) \big/ (1 + e^{-neti}) \tag{16}$$

**Step 3:** Computing for squared errors according to Eq. (17)

$$E(w) = \frac{1}{2} \sum_{i=1}^{n} (d_i - y_i)^2 \tag{17}$$

**Step 4:** Update of weigh matrix according to Eq. (18), and then based on the gradient method with delta rule in the Eq. (19), we computed weights values between hidden layer & output layers is updated by Eq. (20) and $\delta_{oi}(k)$ is error of output of output layer, this error will be calculate according to Eq. (21). The weight values between input layers and hidden layers that updated by Eq. (22), and $\delta_{nq}(k)$ is error of output of hidden layer calculated according to Eq. (23).

$$W(k+1) = W(k) + \Delta w_{iq}(k) \tag{18}$$

$$\Delta w_{iq}(k) = -\eta(\partial E \big/ \partial w_{iq}) = -\eta\left(\partial E \big/ \partial y_i \;\; \partial y_i \big/ \partial neti \;\; \partial neti \big/ \partial w_{iq}\right) = \eta * (d_i - y_i) * a'(neti) * z_q \tag{19}$$

where, $\partial E \big/ \partial y_i = -(d_i - y_i)$, $\partial y_i \big/ \partial neti = a(\sum_{q=1}^{l} w_{iq} z_q)'$, $\partial neti \big/ \partial w_{iq} = z_q$.

$$W_{iq}(k+1) = W_{iq}(k) + \eta * \delta_{oi}(k) * z_q(k) \tag{20}$$

where, $q = 1, 2, \ldots l$, $i = 1, 2, \ldots n$

$$\delta_{oi}(k) = \left(d_i(k) - y_i(k)\right) * y_i(k) * a'\left(neti(k)\right) = \left(d_i(k) - y_i(k)\right) * y_i(k) * \left(1 - y_i(k)\right) \tag{21}$$

where, $i = 1, 2, \ldots n$

$$v_{qj}(k+1) = v_{qj}(k) + \eta * \delta_{nq}(k) * x_j(k) \tag{22}$$

where, $q = 1, 2, \ldots l$, $j = 1, 2, \ldots m$

$$\delta_{nq}(k) = \left(\sum_{i=1}^{n} \delta_{oi}(k) * W_{iq}(k)\right) * a'\left(netq(k)\right) = \left(\sum_{i=1}^{n} \delta_{oi}(k) * W_{iq}(k)\right) * y_{nq} * \left(1 - y_{nq}\right) \tag{23}$$

where, $i = 1, 2, \ldots n$

**Step 5:** If the $E < E_{max}$ then end, else if we give k=1 and E=0 and return step 1.

We will create a network can handle noisy input vectors, so the network trained without noise input vectors first, and then the network is trained on noisy input vectors. After training done using back-propagation with 268 epochs for character network and 203 epochs for number network or until the network sum-squared error falls beneath 0.001, results of neural network training performance for the character and number in the Fig. 4(c,e).

## 4.3. Testing for MLP trained network

The reliability of the MLP network for characters & numbers recognition system is measured by testing the network with hundreds of input vectors in varying quantities of noises. Testing the network at various noise levels, noise with a mean of 0 and a standard deviation from 0 to 0.8 added to input vectors. The output is then passed through the competitive transfer function so that only one of the 15 outputs (representing the characters), has a value of 1. The solid line on the graph shows the reliability for the network trained with & without noise, the reliability of the same network when it had only trained without noise shown with a dashed line. Beside on that, MLP network could be trained on input vectors with greater amounts of noise if greater reliability were needed for higher levels of noise. Results of neural network testing for character and number with noise and without noise in the Fig. 4(d,f).

### 4.4. Using of network to recognize characters & numbers of Vietnam LP

After training and testing, we will use two trained networks to recognize all of the characters and numbers of Vietnam LP. Before put characters & numbers in to the trained network, we will use the image processing technology for pre-processing to obtain high quality of characters & numbers images (dilate the supplied image using a line structure element whose width is 2 pixels). For the characters recognition, the target vectors defined with a variable called target, each target vector is a 15-element vector with a 1 in the position of the character it represents, and 0's everywhere else. For the numbers recognition, the target vectors defined with a variable called target, each target vector is a 10-element vector with a 1 in the position of the number it represents, 0's everywhere else, we obtained the final results are number plates in the Fig. 5(a,b).

## 5. Experiment results

We implemented experiment with PC Intel(R) Core(TM)2 Duo CPU T7250 @2.00GHz, RAM 1.00 GB, Windows Vista Version 6.1 (Build 7600) 32-bit Operating System and MATLAB Version 7.8.0.347 (R2009a). We tested 700 Vietnam vehicle images (400 one-row type, 300 two-row type), which obtained from the actual system, these vehicle images are very different background such as illumination, license angles, size and type, dimensions from camera to vehicles, colors, light conditions in Vietnam environment, these vehicle images are RGB true-color image and in two format (800x600 pixels and 768x288 pixels).

In the license plate location module, most of limitations in the previous methods (restricted in case: uncertainty of edges, various types, low or high illuminated images, colors, sun light & night light) were solved by our proposed method by these reasons following. The first reason, we have used subtract operation on the grayscale image to obtain a better image with new intensity values that satisfied for the image binarization, this is reason why our proposed method is very efficiency for complex background images, night & day images and different illuminations. The second reason, we have chosen the good structuring element values (SE=25) in the morphological opening step and connected components value [7 25] pixels to remove all of the regions (noises) that is not license plate candidates. The third reason, we have chosen the good values in the fixing the LP region step, this values satisfied for Vietnam LP dimensions. We see that, the accuracy rates of our method are very high such as Table 1.

In the characters segmentation module, most of the previous methods only applied for the one-row LP. In our paper, we have proposed an improved method to segment characters & numbers in both one-row and two-row types of Vietnam LP based on the peak-to-valley method & statistical parameters of characters and digits. We combined pre-processing to improved image quality and remove noise before segmentation, our approach could applied for both one-row and two-row types of Vietnam LP with the accuracy rates are very high such as Table 1.

In the characters & numbers recognition module, we have used two networks to train for characters & numbers with noises, so the computing time and accuracy improved. In the using network, we have used the image processing technology for pre-processing to obtain high quality of characters & numbers before put in the trained networks, so accuracy rates of the our system are higher than some previous methods, we can see in the Table 1.

Table 1. Test results of LP Location task, LP Segmentation task, LP Recognition task

| | **LP Location** | | **LP Segmentation** | | **LP Recognition** | | **Overall ALPR system** | |
|---|---|---|---|---|---|---|---|---|
| | One-row LP | Two-row LP | One-row LP | Two-row LP | One-row LP | Two-row LP | One-row LP | Two-row LP |
| Image total | 400 | 300 | 400 | 300 | 400 | 300 | 400 | 300 |
| Correct rate | 389 | 291 | 395 | 293 | 390 | 291 | 683 | 681 |
| Error rate | 11 | 9 | 5 | 7 | 10 | 9 | 17 | 19 |
| Accuracy rate (%) | 97.25 | 97.00 | 98.75 | 97.67 | 97.50 | 97.00 | 97.57 | 97.28 |
| Average rate (%) | **97.13** | | **98.21** | | **97.25** | | **97.43** | |

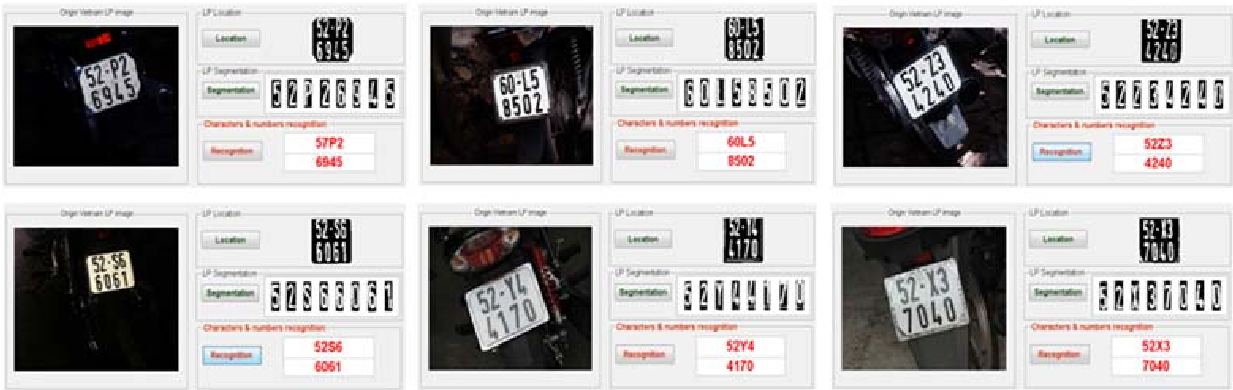
In Table 1, we have results for the testing of the overall our ALPR method, we see that the average accuracy of the overall ALPR system is very high. In Table 2, we have compared results of our proposed method to the some previous methods earlier, we see that the accuracy rate of our method is higher than most of previous works and the computing time of our method is improved.

Table 2. Comparison results of our method to some previous methods

| Ref. | Image total | Correct rate | Error rate | Average rate (%) | Computing time (s) |
|---|---|---|---|---|---|
| In Ref. [7] | No | No | No | 90.00 | 0.3 |
| In Ref. [8] | 795 | 738 | 57 | 92.85 | No |
| In Ref. [9] | No | No | No | 98.00 | 0.45 |
| In Ref. [10] | 1000 | 910 | 90 | 91.00 | No |
| In Ref. [11] | No | No | No | 94.00 | 0.87 |
| In Ref. [12] | 150 | 140 | 10 | 93.20 | No |
| In Ref. [13] | No | No | No | 80.00 | No |
| In Ref. [14] | 1176 | 1125 | 51 | 95.70 | 0.223 |
| In Ref. [15] | 180 | 157 | 23 | 87.22 | No |
| In Ref. [16] | 476 | 447 | 29 | 94.00 | No |
| In Ref. [17] | No | No | No | 88.30 | 0.2 |
| In Ref. [18] | 300 | 286 | 14 | 95.50 | 0.75 |
| In Ref. [21] | 594 | 515 | 79 | 86.70 | No |
| In Ref. [22] | 150 | 138 | 12 | 94.33 | No |
| **Our method** | **700** | **682** | **18** | **97.43** | **0.25** |

Fig. 5(a,b) have shown some experiment results of our ALPR system for both one-row types and two-row types Vietnam LP. We see that, our ALPR method is very satisfied for the Vietnam vehicle images, which obtained from the actual system, these vehicle images are very different background such as illumination, license angles, LP angle, size and type, dimensions from camera to vehicles, colors, lighting conditions in Vietnam environment.

(a) some of results for one-row Vietnam LP



(b) some of results for two-row Vietnam LP

Fig. 5: Recognition results for both one-row types and two-row types Vietnam LP

## 6. Conclusion

In this paper, we proposed an improved ALPR system for all types of Vietnam LP, which included of three modules: license plate location, characters segmentation and characters recognition. In the LPL module, we have combined edge detection, image subtraction, mathematical morphology, radon transform and interpolation method and considered to remove noises and specific characteristics of Vietnam LP to locate exactly LP region. In the characters segmentation module, we used peak-to-valley method and statistical parameters of Vietnam LP to segment characters & numbers in one-row & two-row types of Vietnam LP. In the characters recognition module, we used a MLP neural network and BP algorithm to recognize characters & numbers of Vietnam LP. Two networks for characters & numbers is trained with noises in the training task, character & number images were processed by the pre-processing to obtain high quality of character & number images in the using network task to improve accuracy of the system. We have tested our improved ALPR system on 700 Vietnam vehicle images taken from actual system with different conditions: lightening conditions (night & day), license angles, illumination, size and type, colors and reflected light. Our ALPR method is more effective than some existing methods earlier, the efficiency of computing time & accuracy is improved and very satisfied for all types of Vietnam LP and Vietnam environment.

## 7. Acknowledgements

This work supported by National Natural Science Foundation of China (No. 60970061, 61075056, 61103067) and the Fundamental Research Funds for the Central Universities.

## 8. References

[1] H.K. Sulehria, Y. Zhang, D. Irfan, Mathematical Morphology Methodology for Extraction of Vehicle Number Plates. International Journal of Computers 1, pp. 69-73, 2007.

[2] W. Pan, R. An, Morphology and auto -correlation based method of fast locating vehicle license plate. In: Proc. of the 2nd Internat. Conf. Advanced Computer Control, vol.3, pp. 116-119, 2010.

[3] V. Abolghasemi, A. Ahmadyfard, An edge-based color-aided method for license plate detection. Image and Vision Computing 27, pp. 1134-1142, 2009.

[4] B. Li, Z.Y. Zeng, J.Z. Zhou, An Adaptive Algorithm for License Plate Orientation and Character Segmentation. In: Proc. of the IEEE Pacific-asia. Work. on Computat. Intelli. Indust. Appli, pp.533-537, 2008.

[5] J.G. Park, An Intelligent Framwork of Illumination Effects Elimination for Car License Plate Character Segmentation. In: Proc. of the Internat. Conf. on Mach. Learn. Cyber, pp.1268-1272, 2010.

[6] A. Janota, J. Zahradník, J. Spalek, Attributes Selection for License Plate Recognition based on Decision Trees. Acta Electrotechnica et Informatica 4, pp. 1-7, 2005.

[7] Shi, X.F., Zhao, W.Z., Shen, Y.H., 2005. Automatic License Plate Recognition System Based on Color Image Processing. Springer-Verlag Berlin Heidelberg. LNCS 3483, 1159-1168.

[8] D.D. Tran, L.H.D. Tran, V.P. Tran, V.H. Nguyen, Building an Automatic Vehicle License-Plate Recognition System, In: Proc. of the Internat. Conf. in Comp. Science, pp.59-63, 2005.

[9] L.H. Zheng, X.J. He, Number Plate Recognition Based on Support Vector Machines. In: Proc. of the IEEE. Internat. Conf. on Video and Signal Based Surveillance, (AVSS'06), 2006.

[10] S.N.H.S. Abdullah, M. Khalid, R. Yusof, K. Omar, License Plate Recognition using Multi-cluster and Multilayer Neural Networks. In: Proc. of the Inform. Commun. Techno, pp.1818-1823, 2006.

[11] G.Y. Ge, J.J. Xu, M.H. Wang, On the Study of Image Characters Location, Segmentation and Pattern Recognition using LS-SVM. In: Proc. of the 6$^{th}$ World. Cong. on Intelli. Cont. Automation, pp.9650-9654, 2006.

[12] O. Khalipha, S. Khan, R. Islam, A. Shuleiman, Malaysian Vehicle number plate recognition. The International Arab Journal of Information Technology 4, pp. 359-364, 2007.

[13] F. Arya, I.S. Suwardi, License Plate Recognition System for Indonesian Vehicles. In: Proc. of the Internat. on Electrical Engineering and Informatics, pp.657-659, 2007.

[14] Z.X. Chen, G.Y. Wang, J.G. Liu, C.Y. Liu, Automatic License Plate Location and Recognition Based on Feature Salience. International Journal of Cumputational Cognition 5, pp. 1-9, 2007.

[15] O.O.V. Villegas, D.G. Balderrama, H.D.J.O. Domínguez, V.G.C. Sánchez, License Plate Recognition Using a Novel Fuzzy Multilayer Neural Network. International Journal of Computers 3, pp. 31-40, 2009.

[16] X. Fan, G.L. Fan, Graphical Models for Joint Segmentation and Recognition of License Plate Characters. IEEE Signal Processing Letters 16, pp. 10-13, 2009.

[17] W.H. Wang, License Plate Recognition Algorithm Based on Radial Basis Function Neural Networks. In: Proc. of the Internat. on Intellig. Ubiq. Comput. Education, pp.38-41, 2009.

[18] W.A. Faqheri, S. Mashohor, A Real-Time Malaysian Automatic License Plate Recognition (M-ALPR) using Hybrid Fuzzy. International Journal of Computer Science and Network Security 9, pp. 333-340, 2009.

[19] K. Deb, H.U. Chae, K.H. Jo, Vehicle License Plate Detection Method Based on Sliding Concentric Windows and Histogram. Journal of Computers 4, pp. 771-777, 2009.

[20] N.S. Pai, S.F. Huang, Y.P. Kuo, C.L. Kuo, License Plate Recognition Based on Extension Theory. In. Proc. of the Internat. on Comput. Commu. Cont. Automation, pp.164-67, 2010.

[21] L.H. Zheng, X.J. He, B. Samali, L.T. Yang, Accuracy Enhancement for License Plate Recognition. In: Proc. of the Internat. on Compu. Inform.Technology, pp.511-615, 2010.

[22] S.H. Kasaei, S.M. Kasaei, S.A. Kasaei, New Morphology-Based Method for Robust Iranian Car Plate Detection and Recognition. International Journal of Computer Theory and Engineering 2, pp. 264-268, 2010.

[23] P.L. Hsieh, Y.M. Liang, H.Y.M. Liao, Recognition of Blurred License Plate Images. Technical Report No. TR-IIS-10-003, April 28, 2010.

[24] V.D. Mai, D.Q. Miao, R.Z. Wang, H.Y. Zhang, An Improved method for Vietnam License Plate Location. In. Proc. of the Internat. on Multime.Technology , Vol.4, pp. 2942-2946, 2011.

[25] V.D. Mai, D.Q. Miao, R.Z. Wang, An Improved Method for Vietnam License Plate Location based on Mathematic Morphology & Measuring Properties of Image Regions. Applied Mechanics and Materials 105-107, pp. 1995-1999, 2012.

[26] D.Q. Miao, Q.G. Duan, H.Y. Zhang, J. Na, Rough Set based Hybrid Algorithm for Text Classification. Expert Systems with Applications 36, pp. 8932-8937, 2009.

[27] D.Q. Miao, Q.S. Tang, W.J. Fu, Fingerprint minutiae extraction based on principal curves. Pattern Recognition Letters 28, pp. 2184-2189, 2007.

[28] C.M. Liu, D.Q. Miao, C.H. Wang, Multi-resolution Character Recognition by Adaptive Classification. In: Proc. of the Internat. on Advan. Intelli. Comput. applications Vol.1, pp. 1182-1191, 2007.