Evaluation of Image Scrambling Degree with Intersecting Cortical Model Neural Network

Chunlin Li, Guangzhu Xu*, Chunxian Song and Jing Jing

College of Computer and Information Technology, China Three Gorges University, Yichang, Hubei of P.R. China
lichunlin0921@126.com, xugzhu@gmail.com, songchunxian0419@163.com, jingjinzhengxi@163.com

Abstract

Scrambling transformation plays an important role in information hiding application, so offering an effective evaluation method for scrambling algorithms is becoming increasingly necessary. The paper firstly analyzed the Arnold transformation process to get some universal rules about the periodicity of scrambling process, then used the improved Intersecting Cortical Model Neural Network (ICMNN) designed especially to extract 1D signatures of the original image and scrambled images which could effectively reflect the image structure changing processing. Finally L1 norm was adopted to evaluate the scrambling degree and the universal rules obtained above were used to verify the results. The experimental results showed that the proposed method could analyze and evaluate the scrambling degree efficiently and had a promising application future.

Keywords: *Arnold transformation, ICMNN, Signature, Scrambling degree*

1. Introduction

Image scrambling technology is a widely used in image encryption method by which the original image information can be hidden, so that the information will not be easily intercepted [1]. With the rapid development and wide application of computer network technologies, data transmission by the network has become very convenient and fast. People can transmit large amount of information through the network, so network security technologies are receiving more and more concern. There are many image scrambling algorithms, such as Arnold transformation [2], Fibonacci transformation[3], affine transformation [4], magic square transformation [5], Hilbert transformation [6] etc. Image scrambling technologies have been widely used in digital watermarking technology, and the watermarking information will be directly embedded into the image after scrambling transformation, which can accomplish image information hiding [7].

In general, the better an image is scrambled, the better the information is hidden. So the evaluation for scrambling degree has an important theoretical and practical significance in the information hiding field. But by now, there are still many problems to be solved in the current scrambling degree evaluation methods. In [8], a method based on the intensity differential and information entropy was proposed, which fully took the discreteness and randomness of image into account, but lacked of the direct extraction of image structural information.

* Corresponding author:Guangzhu Xu
Telephone number:86-15971636485

Statistical hypothesis testing was used in [9] to calculate the randomness of images, and image scrambling degree evaluation was obtained, though it considered the structure information of the image, the method would sometimes mistake a good scrambled image as a poor one, which made it difficult to evaluate the image scrambling degree properly. In [10], an image was divided into blocks, and the two-block bipartite graph and standard deviation were calculated, which could be used to evaluate the scrambling degree, but were only limited to the binary image scrambling degree evaluation. The mean square SNR and optimal image sub-block were combined in [11] and could be applied to colour images. This method can correctly evaluate the scrambling degree of image to a certain extent, but the results were still inconformity with visual perception for some special images, and lacked considering the global information in the image. Different from these methods, in [13] the Pulse Coupled Neural Network (PCNN) was applied to extract signatures [12, 14] of scrambling images, and information entropy was used to evaluate the scrambling degree. The PCNN [12] can both integrate the intensity and the surrounding structure information of the image pixels through its own connection units, using pulse output to express the image effectively, therefore it has potential to evaluate the image scrambling degree.

Though the PCNN has more advantages in scrambling evaluation than other methods, there are still some disadvantages, such as too many parameters to set, lower stableness, and single evaluation criteria. Moreover, the entropy series of PCNN can not reflect more information than the common signature of PCNN. In order to make the neural network be more suitable for scrambling evaluation, the paper used improved ICMNN to extract image signature, and introduced a parameter β to make the signature contain more structure information than before. Because the Arnold transformation has been continuously improved and widely used in practice [15], so the paper took Arnold transformation to carry on the scrambling experiments (the proposed algorithm is not limited to any scrambling method). In order to support the observations of our study, the entire periodical analysis and evaluation of Arnold transformation were also given.

2. The Scrambling Algorithm based on Arnold Transformation

Arnold transformation was proposed by Mathematician Arnold [16] in the study of ergodic theory. Assuming the original image size is N×N, (x, y) is the pixel coordinate, after the geometric transformation the pixel is moved to (x', y'). This geometric transformation can be described as follows [16]:

$$\begin{pmatrix} x' \\ y' \end{pmatrix} = \begin{pmatrix} a & b \\ c & d \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} (\bmod N) \tag{1}$$

3. Improved Intersecting Cortical Model Neural Network (ICMNN)

As an image processing engine, the ICMNN was first proposed [17] in the late 1990s. ICMNN can be seen as the simplified PCNN, which avoids complex parameters setting and effectively reduces the computation through simplifying the process.

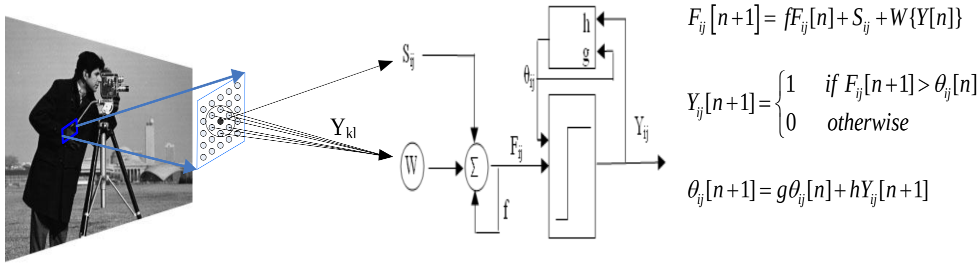


Figure 1. ICMNN and its Mathematical Equations

Figure 1. is an ICMNN neuron (in the middle part) and its mathematical model (as shown on the right side). In ICMNN, the state within all neurons (the results of feeding unit) is represented by a two-dimensional array F (initially $F_{ij} = 0$), while the threshold oscillator for all neurons is represented by a two-dimensional array θ (initially $\theta_{ij} = 0$). The f and g are the attenuation coefficients of feeding unit and threshold unit respectively (less than 1), and W is the connection weight with other adjacent neurons. The linking area can be circular or square one [18]. In this paper we select the widely used circular area and the connection weight W is inversely proportional to the distance between the center neuron and surrounding neurons.

Feature signature of ICMNN contains the structural and intensity information of images, but the amount of information is not easily controlled. Arnold transformation changes only the structural information of an image, and the total gray scale is not changed. In order to express more structural information, the improved ICMNN is proposed in this paper as follows:

$$F_{ij}[n+1] = S_{ij} \tag{2}$$

$$L_{ij}[n+1] = \alpha_l * L_{ij}[n] + V_l * W(Y[n])_{ij} \tag{3}$$

$$U_{ij}[n+1] = (1-\beta) * F_{ij}[n+1] + \beta * L_{ij}[n+1] \tag{4}$$

$$Y[n+1] = \begin{cases} 1 & if \quad U_{ij}[n+1] > \theta_{ij}[n] \\ 0 & otherwise \end{cases} \tag{5}$$

$$\theta_{ij}[n+1] = \alpha_\theta * \theta_{ij}[n] + V_\theta * Y_{ij}[n+1] \tag{6}$$

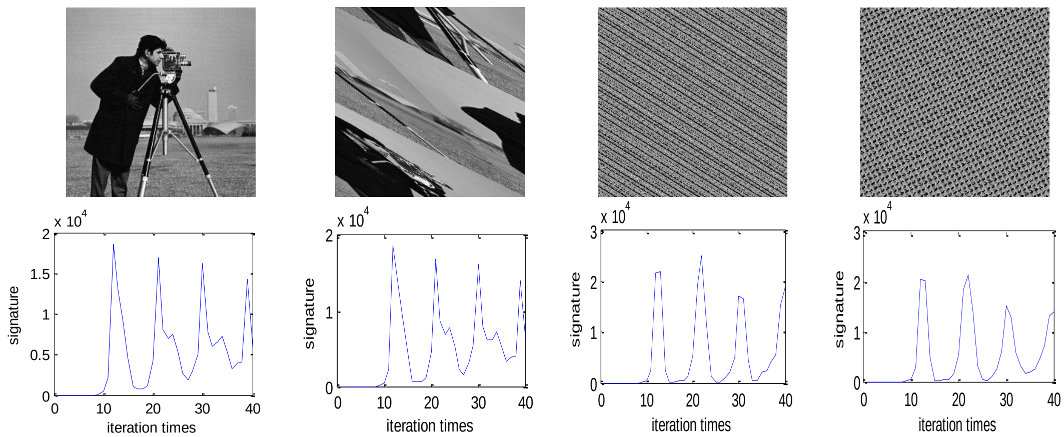
As can be seen from the above equations, the equation (2) is the feeding item which is only dependent on the value of image pixel. The linking item coming from other neurons can be calculated with equation (3). In order to get the inner state of an ICMNN neuron and strengthen structural information extracting ability of ICM, we introduced the parameter β ($\beta \in [0, 1]$) in equation (4), when β equals to 0, there is only the gray information in union unit, while β equals to 1, there is only the structural information in union unit. As we know, the structure information is related with intensity information. In the following experiments β =0.7, so more structural information can be gotten. Equation (5) and (6) have no essential difference with the original model.

4. Image Signature Extraction and Scrambling Degree Evaluation

ICMNN neuron is inspired by external input excitation and output coupling effect of neighboring neurons, and further affects other adjacent neurons. This is similar to the auto-wave [19] propagation coming from a central neuron or a group of neurons. Because of such auto-wave, adjacent neurons with similar state can be simultaneously inspired by the outside similar excitation, then producing a series of binary pulse images. By calculating the pulse numbers of each iteration output binary image, we can also transform the output pulse image into a 1D signal which can characterize the image partly. All pulses in each iteration output can be calculated as the signature [19] of an image as follows.

$$N = \sum Y_{ij} \tag{7}$$

Take the Cameraman image as an example to extract the signature, after certain iterations of Arnold transformation, there are a series of scrambled images. Here only several images are selected, which will be put into the ICMNN. The number of output pulses in the 40 iterations is showed in Figure 2.



(a) (b) (c) (d)

Figure 2. Scrambled images and their ICMNN Signatures (a) Original Image and its Signature; (b) the 1st Scrambled Image and its Signature; (c) the 5th Scrambled Image and its Signature; (d) the 12th Scrambled Image and its Signature

In Figure 2, the signatures which reflect the change of structural information are different from each other. The L1 norm is adopted to extract such difference between the original image and the scrambled images. At the same time, we also have done a lot of other metrics such as information entropy, Euclidean distance, correlation coefficient and so on. The experiment results show that L1 norm is simple and efficient to evaluate scrambling degree.

The difference between the signatures of the scrambled image and the original image can reflect the changing of structural information. the L1 norm is calculated by Equation (8), Y_K represents the feature signature of the Kth scrambling, Y_O is the feature signature of the original image, D_K represents the L1 norm of the Kth scrambled image.

$$D_K = \sum_{i=1}^{n} | Y_K - Y_O | \tag{8}$$

After obtaining the L1 norm of the scrambled image, it is normalized to clearly compare the scrambling degree of different scrambled images. The scrambling degree range is [0, 1], and the image with valve 1 of scrambling degree can be approximately seen as the best scrambling image.

5. Experimental Simulation and Analysis

In order to get some intuitive information about Arnold transformation, the paper designed scrambling transformation from a point to lines, through iterative process analysis, objective criteria for scrambling evaluation is obtained.

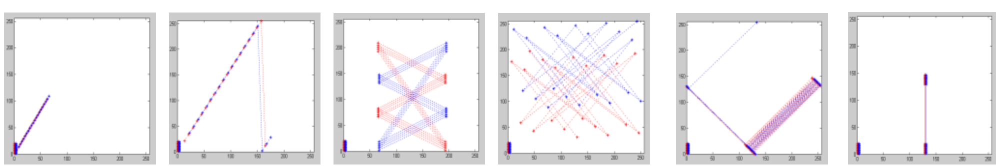
Now select an image which has only a point (1, 1) as the original image to carry on Arnold transformation. The size of the image is 124×124, and the image cycle of Arnold transformation is 15. Take the pixel whose coordinate is (1, 1) for a cycle iterations, and observe the whole process. In order to more clearly observe the coordinates changing in the iteration, the coordinates were listed in Equation (9).

$$\begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \rightarrow \begin{bmatrix} 2 \\ 3 \end{bmatrix} \rightarrow \begin{bmatrix} 5 \\ 8 \end{bmatrix} \rightarrow \begin{bmatrix} 13 \\ 21 \end{bmatrix} \rightarrow \begin{bmatrix} 34 \\ 55 \end{bmatrix} \rightarrow \begin{bmatrix} 89 \\ 20 \end{bmatrix} \rightarrow \begin{bmatrix} 109 \\ 5 \end{bmatrix} \rightarrow \begin{bmatrix} 114 \\ 119 \end{bmatrix}$$
$$\rightarrow \begin{bmatrix} 109 \\ 104 \end{bmatrix} \rightarrow \begin{bmatrix} 89 \\ 69 \end{bmatrix} \rightarrow \begin{bmatrix} 34 \\ 103 \end{bmatrix} \rightarrow \begin{bmatrix} 13 \\ 116 \end{bmatrix} \rightarrow \begin{bmatrix} 5 \\ 121 \end{bmatrix} \rightarrow \begin{bmatrix} 2 \\ 123 \end{bmatrix} \rightarrow \begin{bmatrix} 1 \\ 0 \end{bmatrix} \rightarrow \begin{bmatrix} 1 \\ 1 \end{bmatrix} \tag{9}$$

It is easy to find that the coordinate points are symmetrical about the point (114, 119) along the X-axis in Equation (9). By Arnold transformation for multiple points, the similar regularity can be found. Therefore, in the subsequent analysis, only the results during half-cycle were carried out according to the approximate symmetry of Arnold transformation.

For each image, each pixel has its own motion path, and the different paths cause the different scrambling degree of the whole image. To further analyze the effect of different iterations for the whole image, an image with two straight lines was used to carry on Arnold transformation.

Take an image with size of 256×256, whose Arnold transformation iteration cycle is 192, composed of two adjacent lines, and each line contains 20 pixels. After Arnold transformation, the iteration results are shown as Figure 3.



(a) the 2nd (b) the 3rd (c) the 48th (d) the 70th (e) the 95th (f) the 96th

Figure 3. Arnold Transformation Process of the Image

In the above analysis, Arnold transformation is approximate symmetrical about 1/2 cycle, so observing the half-cycle image is enough. Take six results images to analyze. The position of two lines in the lower left corner of the figure is the position of the original image, discrete points linked together are the points after corresponding iterations. Figure 3(a), (b), (e) and (f) are several iteration images ahead and around 1/2 cycle images of Arnold transformation. The distance between two lines becomes bigger with the number of iteration increasing, but they are still piecewise linear transformation and have relative stable distance. So it is easy to find that they are still two straight lines and maintain greater similarity with the original image. Figure 3(c) is the iteration image of 1/4 cycle, having a certain linear relationship with the original image, but this weak similarity is vulnerable to be affected by the image content. When other pixels with different gray values are inserted, the iteration image easily loses the similarity with the original image. Just as an image is added with noise, the more noise is added, the less similarity looks like. Figure 3(d) represents the middle iterative process of the image, with the number of iteration increasing, the distance between pixels of each line becomes bigger, and the distance between the lines is also widening, then the original linear relationship of the two lines does not exist, and the similarity also decreases.

The scrambling degree of an image's Arnold transformation has certain relationship with the content of the image itself. There is a stable local minimum value point at the half-cycle, while the appearance of local minimum value point in other places is unstable. This conclusion can support the results of scrambling evaluation method based on improved ICMNN below.

In order to verify the effectiveness of improved ICMNN, the above analysis was taken as a criterion, and the images after Arnold transformation were analyzed. There are 5 parameters in the model, we assign them by experience and certain experiments: $\beta = 0.7$, $\alpha_l = 0.5$, $\alpha_\theta = 1$, $V_l = 0.2$, $V_\theta = 0.4$, select the image Cameraman, as is shown in Figure3, whose size is 256×256, and the iteration cycle of Arnold transform is 192. The scrambling degree curve and some scrambled images are shown as Figure 4.

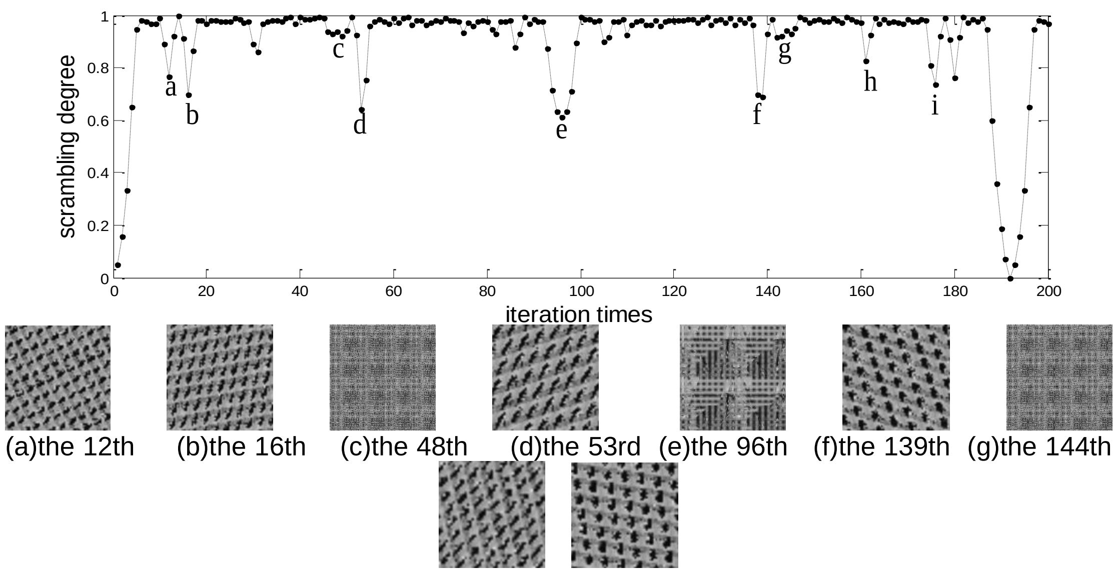
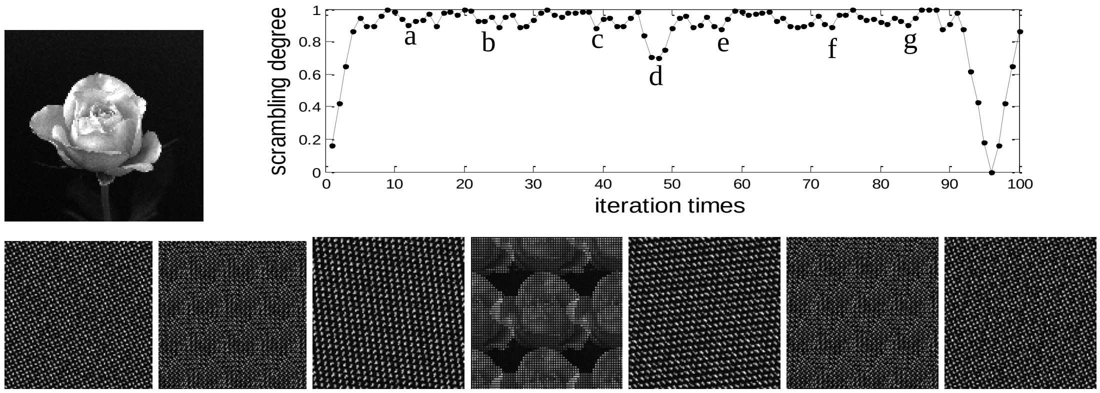


Figure 4. Scrambling Degree Curve and Scrambled Images

In the iteration curve of Figure 4, the local minimum value points emerged at the 12th, 16th, 53rd, 96th, 139th, 161st and 176th iteration, for analyzing position of the local minimum point, the corresponding images in the iterative process of Arnold transformation are shown in Figure 4. Note that, iteration images except for the 48th, 96th (1/2 cycle) and 144th are amplified. Take the 12th and 16th iteration images as examples to analyze, it can be seen from the images that the 12th and 16th iteration images have greater similarity with the original image, which like the original image after sampled, so the two minimum value point positions are consistent with vision. While the 48th (1/4 cycle) and 144th (3/4 cycle) images are less similar with original image than the 53rd and 139th images from visual view, so it is normal that minimum value points are not apparently here. Several other places of the local minimum value points are also consistent with scrambled images.

Take another image to extract its scrambling degree curve, as shown in Figure 5. Its size is 128×128, and Arnold transformation cycle is 96.



(a)the 12th (b)the 24th (c)the 39th (d)the 48th (e)the 57th (f)the 72nd (g)the 84th

Figure 5. Scrambling Degree Curve and Several Scrambled Images

For this image, the scrambling degree curve has a local minimum value point at the half-cycle, and has no apparent local minimum value point at other places. In the corresponding images, Figure 5(d) which is a half-cycle image has greater similarity with the original image than the other images.

The above results show that scrambling degree of Arnold transformation is consistent with visual effect and Arnold transformation analysis. Therefore, the improved ICMNN can effectively reflect scrambling degree of the scrambled images.

To provide an efficient, convenient and integrated environment, the scrambling degree of Arnold transformation evaluation system was created by user interface design of Matlab 7.0. By scrambling degree evaluation, the image with the highest scrambling degree is picked up, which is defined as the best scrambled image. The interface is shown as Figure 6.

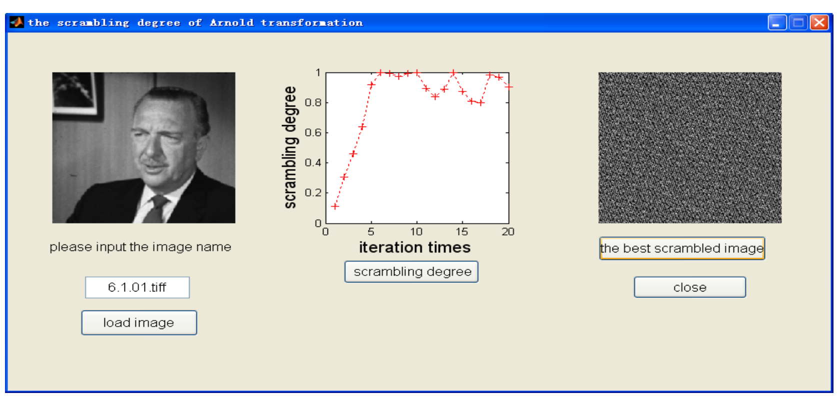


Figure 6. The Scrambling Degree Evaluation System of Arnold Transformation

In order to test the universality of the proposed method, this paper used improved ICMNN to evaluate scrambling degree of other different 50 images after Arnold transformation. We found that there frequently is a local minimum valve point at 1/2 cycle in Arnold transformation process, and the local minimum value points are unstable at the other places, which may occur or not. This can be explained by the previous analysis of Arnold transformation, the image of 1/2 cycle maintains more linear change of the original image information than other places, so it is subject to the impact of the image itself.

6. Conclusion

Compared with previous work, this paper mainly evaluated the scrambling degree of the whole cycle Arnold transformation by using improved ICMNN and L1 norm. By analyzing the Arnold transformation algorithm itself, objective evaluation information for scrambling degree of image was obtained, and the error caused by simple visual analysis is avoided. In former analysis, there will be the minimum value points of scrambling degree at the 1/4, 1/2, 3/4 cycle of scrambling transformation, but this paper found that because of double effect of the image information itself and scrambling transformation, the minimum value point may not occur in the 1/4 and 3/4 cycle, so it is unstable.

The improved ICMNN realized the scrambling degree evaluation of images, but only extracted indirect structure information, therefore we need to continue study direct structure information extracting method of scrambled images.

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Authors

Chunlin Li

She received her bachelor degree in North China Institute of Aerospace Engineering, 2010. Currently she is a Master candidate in China Three Gorges University and working for Institute of Intelligent vision and Image Information. Her areas of interest are neural network and its application, Images processing, Pattern recognition and Machine vision.

Guangzhu Xu

He is currently an associate Professor at University of China Three Gorges University, in the College of Computer and Information Technology & the Institute of Intelligent Vision and Image Information. He received his M.S. and Ph.D. degrees in Circuits & Systems and Radio Physics at Lanzhou University in 2004 and 2007. His main research interests are Biometrics, Computer vision and Pattern recognition.

Chunxian Song

She received her bachelor degree in North China Institute of Aerospace Engineering, 2010. Currently she is a master candidate in China Three Gorges University and working for Institute of Intelligent vision and Image Information. Her areas of interest are Iris recognition, Pattern recognition and Computer vision.

Jing Jing

She received her bachelor degree in China Three Gorges University, 2011. Currently she is a Master candidate in the university and working for Institute of Intelligent vision and Image Information. Her areas of interest are Images processing, Pattern recognition and Machine vision.