Recognition of Indonesian Vehicle Registration Plate by Discrete Cosine Transform and Radial Basis Function Network

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***Abstract*—A car has a unique label called a license plate or a vehicle registration plate. A vehicle registration plate (VRP) in Indonesia consists of a series of alphanumeric. The aim of this research is to recognize the VRP from a frontal image of a car. Image processing techniques are done to identify the VRP, by converting to grayscale image, transforming into binary image by using adaptive threshold, applying region labeling, filtering and others image processing techniques. Features of a character from VRP are taken by applying the Discrete Cosine Transform (DCT) then the character is recognized by Radial Basis Function network (RBF). Some experiments are conducted to determine the number of DCT is needed for each character and to know how well the system to recognize the VRP. System uses 63 DCTs to each character and recognizes the VRP with percentage is about 96%.**

***Index Terms*—Discrete cosine transform, radial basis function network, vehicle registration plate.**

I. Introduction

Basically they are four types of Indonesian VRP. Firstly, commercial and public vehicle has a yellow background and black numbering and letters. Secondly, private vehicle has a black background with white numbering and letters. Thirdly, government vehicle has red background with white numbering and letters. Lastly, dealer plate has white background with red numbering and letters. This is usually for new vehicles that still have no legal issue from government and it is no allowed to be in public road. Besides these normal plates, there are also military plates for Army, Navy, Air Force, and also the Police. While diplomatic corps get special white plates and black numbering with "CD" prefix.

VRP has been an important key function in an intelligent transportation system and it is mainly composed of three processing modules. That is, VRP detection, character segmentation, and character recognition. In the literature, there have been a number of techniques [1]-[10] proposed for VRP detection. The major features used for VRP detection include colors [2], corners [3], vertical edges [4], symmetry and projections of vertical and horizontal edges [5], OCR [8]-[10], and so on.

For example, Kim *et al.* [2], used color information and neural networks to extract VRP from images. However, color is not stable when lighting conditions have changes. On the other hand, Dai *et al*. [6] used the projections of edges with different orientations for determining peaks of the histograms as possible locations of VRP. Moreover, Yu and Kim [4] proposed an edge-matching algorithm for grouping all possible positions of VRPs. When the scene is complex, many unrelated edges will disturb the determination of the correct positions of VRP for the above approaches.

Continuing VRP detection is to segment each character from the extracted VRP for character recognition. Past works [1]-[10] on character segmentation assume that there is no occlusion between any two adjacent characters. Then, different characters can be well segmented using a vertical projection technique.

This paper presents an approach for not only detecting Indonesia private VRP but also recognizing each character in that VRP. Adaptive threshold technique for producing binary image and region labeling and filtering image techniques are used for VRP detection. Whereas DCT is chosen to take the features of a character and RBF Network is applied to recognize the character.

II. Theoritical Framework

A. Indonesia Vehicle Registration Plate

Vehicle Registration Plate is produced and registered by police department. The specification of the VRP is depicted in Table I.

TABLE I: Indonesia Vehicle Registration Plate

Spesification	Dimention in mm
Thickness	1
2 or 3 wheeled vehicle	275 × 110
4 or more wheeled vehicle	430 × 135

Fig. 1. An example of private vehicle registration plate.

The normal scheme of VRP comprises a one or two letters identification for the regencies, followed by an up to four digit number to uniquely identify the vehicle, and the last one up to three letters are the serial code or district identification. The expiry date of the license is embossed along the bottom

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and some on the top of the plate. At the middle of the plate number, the numbers are usually random or being requested by the vehicle owner and has a maximum nowadays of four digits, Fig. 1.

B. Detecting VRP

Lukas *et al*., [11], proposed adaptive threshold and region labeling by using integral image and image filtering techniques for detecting the VRP. The result is quite good 95% of the sample plates are able to be detected. A sample result is shown in Fig. 2.

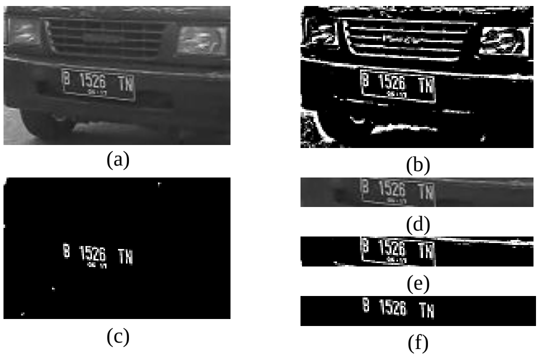

Fig. 2. Processing one sample image.
(a) Image data (b) Binary image data (c) VRP image (d) Grayscale VRP (e) Binary VRP (f) VRP binary image.

Adaptive threshold typically takes a grayscale or color image as input and, in the simplest implementation, outputs a binary image representing the segmentation. For each pixel in the image, a threshold has to be calculated. If the pixel value is below the threshold it is set to the background value, otherwise it assumes the foreground value.

The assumption behind the method is that smaller image regions are more likely to have approximately uniform illumination, thus being more suitable for threshold. The threshold for each single pixel is found by calculating the pixel value mean of the image region of that pixel. The drawback of this method is that it is computational expensive and, therefore, integral image is applied.

Region labeling scans an image and groups its pixels into components based on pixel connectivity, i.e. all pixels in a region share similar pixel values and are in some way connected with each other. Once all groups have been determined, each pixel is labeled with a graylevel or a color according to the component it was assigned to. The most common strategy leads to a two-pass algorithm [10]. This algorithm uses a data structure to record label equivalence information. It scans the image once to assign provisional labels and discover the label equivalence information, and scans the image a second time to assign the final labels. In this research, the input image is binary image and the pixel connectivity is 4. Therefore there are only two pixel values, 1 for the foreground and 0 for the background. 4-connectivity uses only North and West neighbors of the current pixel because the scanningprocess moves from left to the right and top to the bottom.

The vertical projection of the image isa graph, which represents an overall magnitude of theimage according to the axis *y* whereasthe horizontalprojection mapped to the axis *x*.If we compute the vertical projection of theimage after region labeling processing, the magnitude of certain pointrepresents the occurrence of vertical region at that point. This method can be used to determine the candidate of the VRP area.

C. Discrete Cosine Transform

Discrete Cosine Transform (DCT) is a transform coding mostly used in signal processing or digital image processing. It is derived from the Discrete Fourier Transform (DFT). Suppose there are 1-D sequence of length *N*, *x*(*m*), then the DCT of 1 D of length N is written in (1)

$$C[u] = \alpha(u)\sum_{m=0}^{N-1} x(m)\cos\left[\frac{(2m+1)\pi}{2N}u\right], u = 0, 1, \dots, N-1$$

$$x[m] = \sum_{m=0}^{N-1} \alpha(u)C(u)\cos\left[\frac{(2m+1)\pi}{2N}u\right], m = 0, 1, \dots, N-1$$

$$\alpha[u] = \begin{cases} \sqrt{\frac{1}{n}} & u = 0 \\ \sqrt{\frac{2}{n}} & u \neq 0. \end{cases} \quad (1)$$

It is clear that for $u = 0$, the first transform coefficient isthe average value of the sample sequence. This value is referred to as the DC Coefficient. All other transform coefficients are called theAC Coefficients [9]. The 2-D DCT is adirect extension of the 1-D case and is given as (2) from [12], [13].

$$C[u,v] = \alpha(u)\alpha(v)\sum_{m=0}^{N-1}\sum_{n=0}^{N-1} x(m,n)\cos\left[\frac{(2m+1)\pi}{2N}u\right]\cos\left[\frac{(2n+1)\pi}{2N}v\right]$$

$$x[m,n] = \sum_{m=0}^{N-1}\sum_{n=0}^{N-1} \alpha(u)\alpha(v)C(u,v)\cos\left[\frac{(2m+1)\pi}{2N}u\right]\cos\left[\frac{(2n+1)\pi}{2N}v\right]$$

$$\alpha[u] = \begin{cases} \sqrt{\frac{1}{N}} u, v = 0 \\ \sqrt{\frac{2}{N}} \ u, v \neq 0 \end{cases}; \alpha[v] = \begin{cases} \sqrt{\frac{1}{N}} u, v = 0 \\ \sqrt{\frac{2}{N}} \ u, v \neq 0 \end{cases} \quad (2)$$

DCT has important properties:de-correlation, energy compaction, domain scaling, separability, and symmetry.De-Correlation means that there is no correlation in calculating among all the DCT coefficients. Therefore, all DCT coefficients can be calculated independently. DCT exhibitsexcellent energy compaction for highly correlated images. Efficacy of a transformation scheme can be directly gauged by its ability to pack input data intoas few coefficients as possiblewithout introducing visual distortion in the reconstructed image significantly. DCT is not scaling invariant. It can be seen from the property in (3). If the scaling of the *x* and *y* axis of an image are *a* and *b* which are greater than 1, then the frequency spectrum of that image is higher but the amplitude is lower. This implies that in an image recognition system, all of the images that are used for training or identification have to be uniform.

$$f(ax, by) \leftrightarrow \frac{1}{|a||b|} C\left(\frac{w}{a}, \frac{w}{b}\right) \quad (3)$$

Separability means that the DCT coefficients can be computed intwo steps by successive 1-D operations on rows and columns of an image. The arguments presented can be identically applied for theinverse DCT computation. It is stated in (4):

$$C[u,v] = \alpha(u)\alpha(v)\sum_{m=0}^{N-1} cos\left[\frac{(2m+1)\pi}{2N}u\right]\sum_{m=0}^{N-1} x(m,n)cos\left[\frac{(2n+1)\pi}{2N}v\right] \quad (4)$$

Another look at the row and column operations in Equation (4) reveals that these operations are functionally identical. Such a transformation is called a symmetric transformation. A separable and symmetric transform can be expressed in Equation (5) from [14]

$$T = AfA \quad (5)$$

where A is an an $N \times N$ symmetric transformation matrix with entries $a\,(i, j)$ given by (6) and f is the $N \times N$ image matrix

$$a(i,j) = \alpha(j)\sum_{j=0}^{N-1} \cos\left[\frac{(2j+1)\pi}{2N}i\right] \quad (6)$$

D. Radial Basis Function Network

The idea of Radial Basis Function (RBF) Networksderives from Multi-Layer Perceptron (MLP) networks but RBFNetworks take a slightly different approach. They have five main features. They are two-layer feed-forward networks. The hidden nodes implement a set of radial basis functions (e.g. Gaussian functions). The output nodes implement linear summation functions as in an MLP. The network training is divided into two stages: first the weights from the input tohidden layer are determined, and then the weights from the hidden to output layer.The training/learning is very fast.Configuration of RBF Network for P input nodes with Q hidden nodes and R output nodes can be seen in Fig. 3.

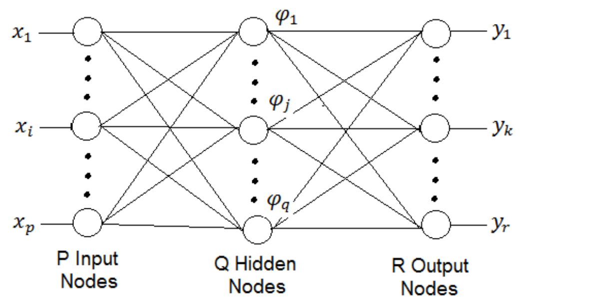

Fig. 3. RBF network configuration.

TABLE II: SUCCESSFUL RECOGNITION OF DATA TRAINING FOR 16 DCTS

0	1	2	3	4	5	6	7	8	9	A	B
78	93	100	100	95	100	59	95	47	79	100	93
C	D	E	F	G	H	I	J	K	L	M	N
100	67	100	100	86	100	100	100	92	100	100	86
O	P	Q	R	S	T	U	V	W	X	Y	Z
90	100	100	80	100	100	75	100	100	100	100	100

The goal of RBF is to find a function$f: x^P \rightarrow y^r$so that it can interpolate of a set of N data points in a multi-dimensional space of the Pdimensional input vectors $X^* = \{x_i^*: i = 1, 2, \dots, P\}$ to be mapped onto the corresponding target output $y^* = \{y_k^*: k = 1, 2, \dots, R\}$. Radial Basis function of every hidden node has a center, x_c, and a variance. The output of every hidden node is in the form $\varphi(\|x - x_c\|)$, $\varphi(a) = exp\left(-\frac{a^2}{2\sigma^2}\right)$. The output of the mapping is then taken to be linear combination of the basis function, (7). The weights of RBF Network are represented by W_{kj}

$$y_k^* = f(x^*) = \sum_{j=1}^{q} W_{kj}\varphi_j\left(\left\|x^* - x_{c_j}\right\|\right) \quad (7)$$

III. SYSTEM DESIGN

Block diagram of the system is presented in Fig. 4, [11]. Image source is captured from IP camera in the distance about 3 m, with the height 90 cm from the ground and 145^0 from normal line of the camera. The output of image preparation is image data. It is done not only by converting from image source (704 × 432 pixels) to greyscale image but also cropping out 1/8 area of the top and the bottom of the image to focus the VRP area. The output of Image filtering is VRP binary Image, Fig. 2f. There are three main processes in VRP Identification. They are cropping each character in the VRP, Calculating DCT Coefficients of the character and recognizing the character by RBF Networks.

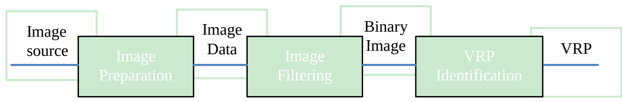

Fig. 4. Block diagram of the system.

TABLE III: SUCCESSFUL RECOGNITION OF DATA TRAINING FOR 61-71 DCTS

	Number of DCTs										
C	61	62	63	64	65	66	67	68	69	70	71
0	89	89	89	89	89	89	89	89	89	89	83
1	91	91	91	91	91	91	91	91	91	91	91
2	100	100	100	100	100	100	100	100	100	100	100
3	93	97	97	93	97	93	93	93	97	97	97
4	95	95	95	95	95	95	95	95	95	95	95
5	95	95	95	95	95	95	95	95	95	95	95
6	100	100	100	100	100	100	100	100	100	100	100
7	100	100	100	100	100	100	100	100	100	100	100
8	75	75	75	75	75	75	75	75	75	72	72
9	100	100	100	100	100	100	100	100	100	100	100
A	100	100	100	100	100	100	100	100	100	100	100
B	98	98	98	98	98	98	98	98	98	98	98
C	100	100	100	100	100	100	100	100	100	100	100
D	83	83	100	100	100	100	100	100	100	100	100
E	100	100	100	100	100	100	100	100	100	100	100
F	100	100	100	100	100	100	100	100	100	100	100
G	100	100	100	100	100	100	100	100	100	100	100
H	100	100	100	100	100	100	100	100	100	100	100
I	100	100	100	100	100	100	100	100	100	100	100
J	100	100	100	100	100	100	100	100	100	100	100
K	100	100	100	100	100	100	100	100	100	100	100
L	100	100	100	100	100	100	100	100	100	100	100
M	100	100	100	100	100	100	100	100	100	100	100
N	100	100	100	100	100	100	100	100	100	100	100
O	100	100	100	100	100	100	100	100	100	100	100
P	100	100	100	100	100	100	100	100	100	100	100
Q	100	100	100	100	100	100	100	100	100	100	100
R	100	100	100	100	100	100	100	100	100	100	100
S	100	100	100	100	100	100	100	100	100	100	100
T	100	100	100	100	100	100	100	100	100	100	100
U	75	75	75	75	75	75	75	75	75	75	75
V	100	100	100	100	100	100	100	100	100	100	100
W	100	100	100	100	100	100	100	100	100	100	100
X	100	100	100	100	100	100	100	100	100	100	100
Y	100	100	100	100	100	100	100	100	100	100	100
Z	100	100	100	100	100	100	100	100	100	100	100

Every character in VRP is normalized in the form 35 × 15 pixels. Therefore, system has 525 DCT coefficients. Feature of a character is chosen in the form of *P*DCT coefficients. Since system has 510 characters to be trained then matrix data training for the RBF is in size 510 × P. Number of hidden node is chosen 36 nodes same as number of output nodes. Then for every character, there will be 36 outputs from hidden layer. From the 510 training data can be performed matrix H, the size 510 × 36, as the output of hidden nodes. It is also the output matrix, Y, in the size 510 × 36. Then the matrix weight of RBF network is calculated in (8).

$$W = (H^T H)^{-1} H^T Y \quad (8)$$

TABLE IV: CHARACTER RECOGNITION OF 64 VRPS

Data VRP									Recognized as								Data VRP									Recognized as							
N	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	N	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
1	A	8	7	A					A	B	7	A					3	B	4	5	D	F				B	4	5	D	F			
2	B	1	3	8	6	I	Q		B	1	3	8	6	I	Q		3	B	5	7	3	D				B	5	7	3	D			
3	B	1	4	5	2	J	K		B	1	4	6	2	J	K		3	B	2	3	7	4	C	G		B	2	3	7	4	C	G	
4	B	1	5	2	6	T	N		B	1	5	2	6	T	N		3	B	2	5	4	G	H	E		B	2	5	4	G	H	E	
5	B	1	5	3	T	R	P		B	1	5	3	T	R	P		3	B	2	6	0	5	Q	Q		B	2	6	0	5	Q	Q	
6	B	1	1	2	F	G	P		B	A	1	2	F	G	P		3	B	2	8	6	2	P	R		B	2	8	6	2	P	R	
7	B	1	2	8	1	N	V	H	B	1	2	8	1	N	V	H	3	B	2	8	6	4	I	R		B	2	8	6	4	I	R	
8	B	1	2	8	4	N	F	W	B	1	2	8	4	N	F	W	4	B	6	3	3	G	O	D		B	6	3	0	G	O	D	
9	B	1	2	9	5	K	K	D	B	1	2	9	5	K	K	D	4	B	8	0	4	0	W	J		B	B	0	4	0	W	J	
1	B	1	3	1	6	C	F	T	B	1	3	1	6	C	F	T	4	B	8	2	0	9	N	X		B	B	2	0	9	N	X	
1	B	1	3	2	1	S	O	P	B	1	3	2	1	S	O	P	4	B	8	2	7	1	X	J		B	B	2	7	1	X	J	
1	B	1	3	2	6	B	Z	O	A	I	3	2	6	B	Z	O	4	B	8	2	7	9	C	V		B	8	2	7	9	C	V	
1	B	1	3	4	8	C	F	G	B	1	3	4	8	C	F	G	4	B	8	4	6	0	O	T		B	8	4	6	D	O	T	
1	B	1	3	6	9	B	Z	Z	B	I	3	6	9	B	Z	Z	4	B	8	6	7	0	K	J		B	8	6	7	0	K	J	
1	B	1	3	6	9	U	K	J	B	1	3	6	9	U	K	J	4	B	8	7	1	5	U	O		B	8	7	1	5	U	O	
1	B	1	3	7	3	S	Z	R	B	1	3	7	3	S	Z	R	4	B	8	8	8	T	J	P		B	8	8	8	T	J	P	
1	B	1	3	7	4	T	F	I	B	1	3	7	A	T	F	I	4	B	9	0	2	3	C	A		B	9	0	2	3	C	A	
1	B	1	4	3	3	G	F	A	B	1	4	3	3	G	F	A	5	F	1	2	0	5	A	U		F	1	2	0	5	A	0	
1	B	1	4	3	3	N	K	F	B	1	4	3	3	N	K	F	5	L	1	9	8	4	F	Z		L	1	9	8	4	F	Z	
2	B	1	4	3	3	P	Z	H	B	1	4	3	3	P	Z	H	5	B	1	7	5	5	S	O	M	B	1	7	5	5	S	O	M
2	B	1	4	4	0	C	F	I	B	1	4	4	D	C	F	I	5	B	1	7	5	8	C	K	B	B	1	7	5	8	C	K	B
2	B	1	0	8	9	C	F	P	B	A	0	8	9	C	F	P	5	B	1	8	0	8	B	K	D	B	1	B	0	8	B	K	D
2	B	1	0	9	3	C	E	R	B	1	0	9	3	C	E	R	5	B	1	8	2	9	T	O	Q	B	1	B	2	9	T	O	Q
2	B	1	1	2	6	W	F	X	B	1	1	2	6	W	F	X	5	B	1	8	2	9	U	Z	I	B	1	8	2	9	U	Z	I
2	B	1	5	5	0	S	Y	D	B	1	5	5	0	S	Y	D	5	B	1	8	3	5	K	K	V	B	1	B	3	5	K	K	V
2	B	1	2	4	7	B	O	N	B	1	2	4	7	B	O	N	5	B	1	8	4	0	B	K	V	B	I	8	4	0	B	K	V
2	B	1	5	6	8	B	K	N	B	1	5	6	8	B	K	N	5	B	1	8	5	3	B	Z	H	B	1	8	5	3	B	Z	H
2	B	1	5	7	7	B	J	F	B	1	5	7	7	B	J	F	6	B	1	8	6	7	B	Z	K	B	1	8	6	7	B	Z	K
2	B	1	5	8	2	G	F	B	B	1	5	8	2	G	F	B	6	B	1	9	1	0	B	O	S	B	1	9	1	0	B	O	S
3	B	1	6	2	5	T	Z	M	B	1	6	2	5	T	Z	M	6	B	9	7	2	7	C	C	A	B	9	7	2	7	C	C	A
3	B	1	6	3	3	B	J	I	B	1	6	3	3	B	J	I	6	B	1	9	9	0	C	F	F	B	1	9	9	0	C	F	F
3	B	1	7	2	3	B	Z	X	A	1	7	2	3	B	Z	X	6	B	1	7	3	1	S	F	Z	B	1	7	3	1	S	F	Z

IV. EXPERIMENTS AND DISCUSSIONS

Three experiments are conducted. First experiment is to determine the successful recognition for every training character with a certain number of DCT Coefficient. Table II shows that using 16 DCT coefficients, the smallest successful recognition is character 8. That is 47%. Out of 32 data training for character 8, 15 are recognized as 8 and 14 as B.

Second experiment is to determine the smallest number of DCT Coefficients so that the recognition of the training all characters data is the highest. Table III is successful recognition of each character with number of DCTs from 61 to 71 Coefficients.

It can be seen that with 61 DCTs, character "3" is successful identified with 93% whereas with 63 DCTs is 97%. Character D is recognized as D with 62 DCTs is 83% whereas with 63DCTs is 100%. From Table III, the minimum number of DCTs with the best recognition for all characters is 63. Therefore, the feature of a character is represented with 63 numbers of DCT Coefficient. Fig. 5 shows that character "8" is still the lowest successful recognition compares with others.

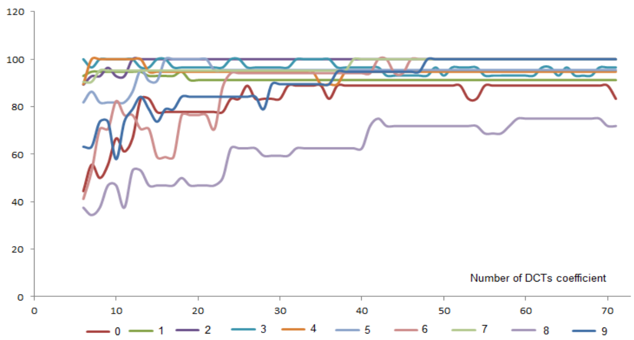

Fig. 5. Successful recognition for numeric 0 to 9.

TABLE V: UNSUCCESSFUL RECOGNITION CHARACTERS

Karakter	Total	0	6	8	A	B	D	I	Total	%
0	16						2		2	88%
1	54				2			3	5	91%
3	29	1							1	97%
4	18				1				1	94%
5	21		1						1	95%
8	30					7			7	77%
B	75				2				2	97%
U	4	1							1	75%

Third experiment is to know the recognition percentageof each character. Fig. 6 shows all 64 data image sources. From

64 image sources, they consist of 490 characters. Recognition result of each image is tabulated in Table IV. Out of 64 image sources, 20 of them are recognized incorrectly fully. Each of them only one or two characters are not identified correctly. All characters that not recognized 100% correctly are depicted in Table V. In general, level of character recognition is about 96%.

Fig. 6. The 64 input image source.

V. Conclusion

System is able to recognize Indonesian Private Vehicle Registration Plate with character recognition in each plate with accuracy is about 96%. However, research should be done in order to identify other types of Indonesian VRP and also increased the degree of accuracy.

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