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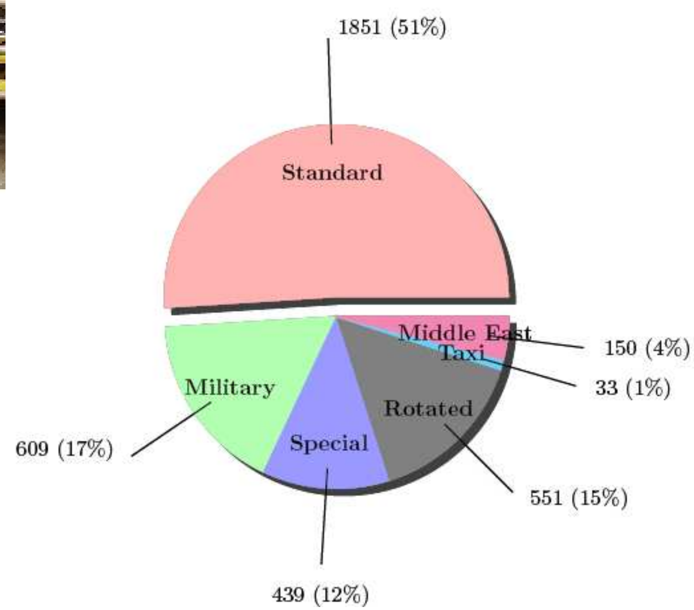
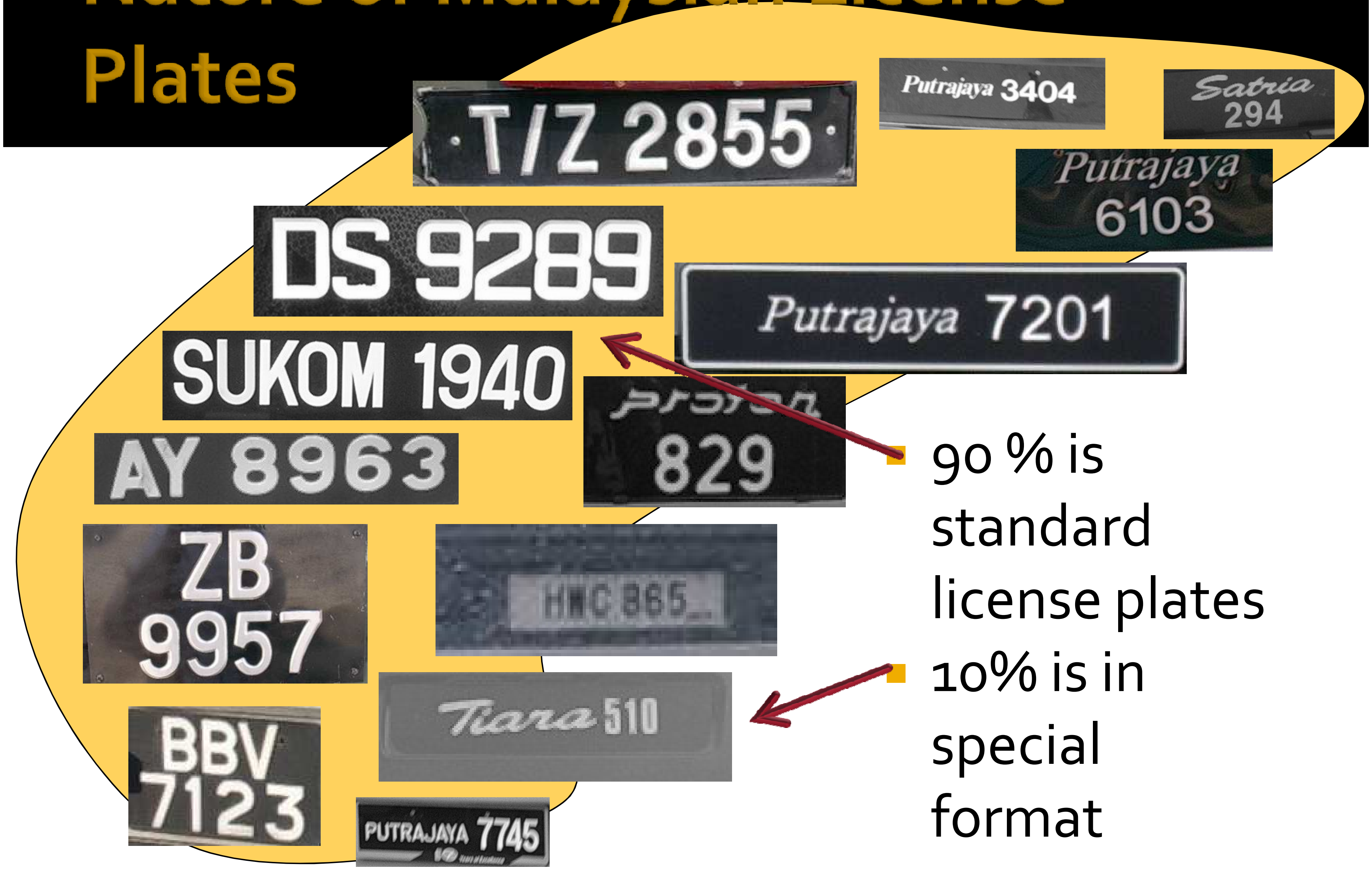
Intelligent License Plate Recognition System based on Multi-Feature and Support Vector Machine

Nature of frontal and back of Malaysian car images

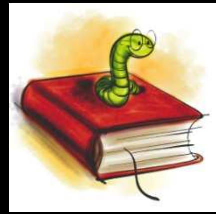


Nature of Malaysian License Plates



- 90 % is standard license plates
- 10% is in special format

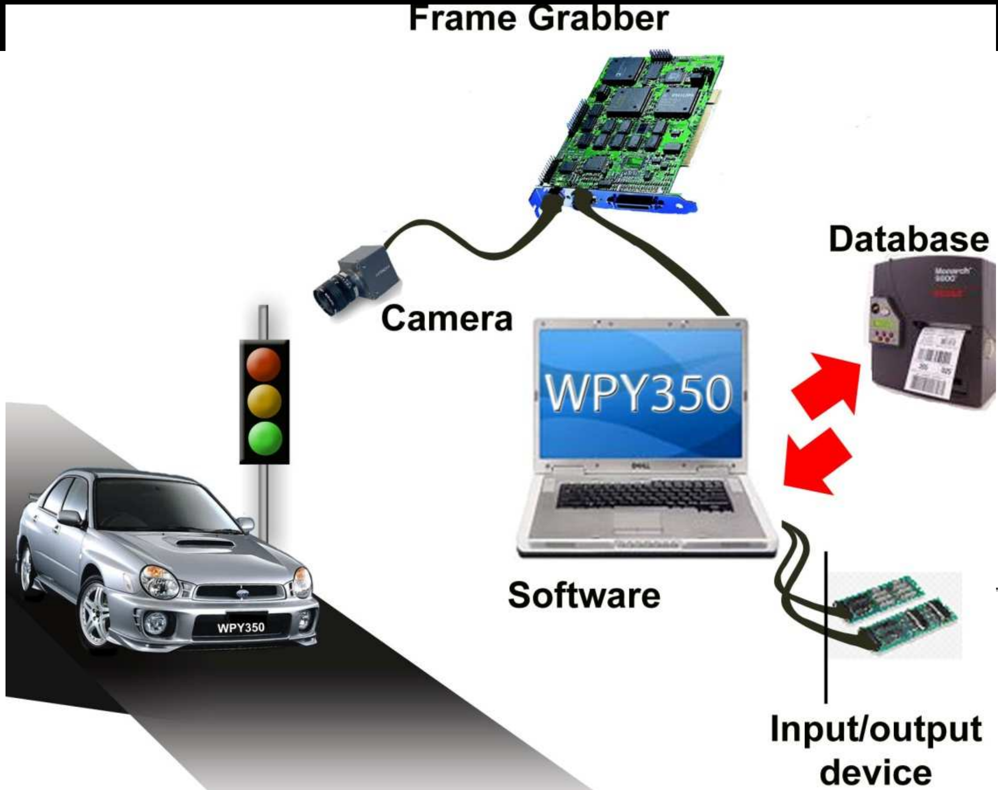
State of the Art

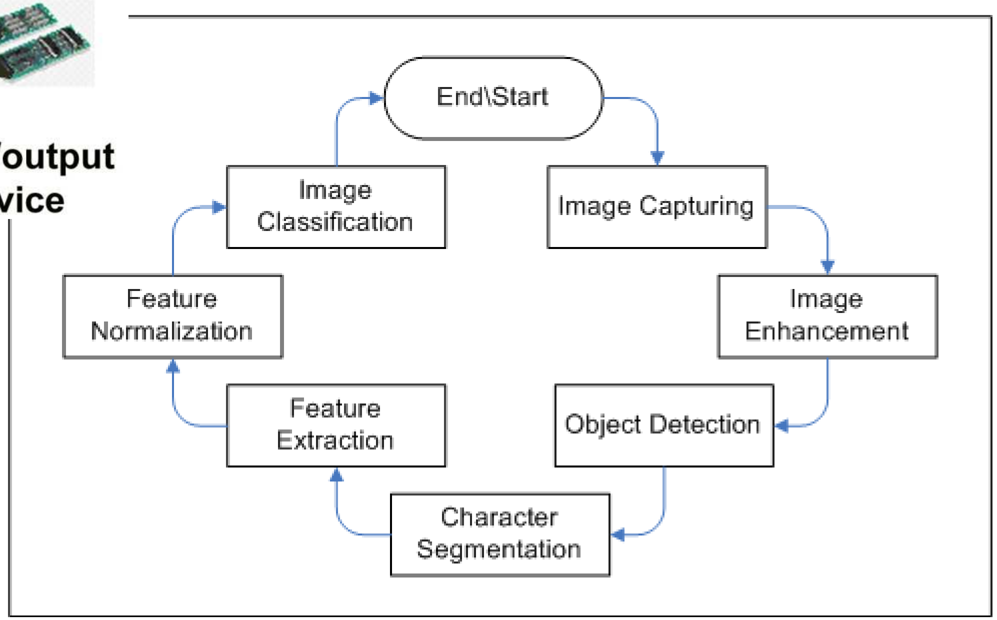


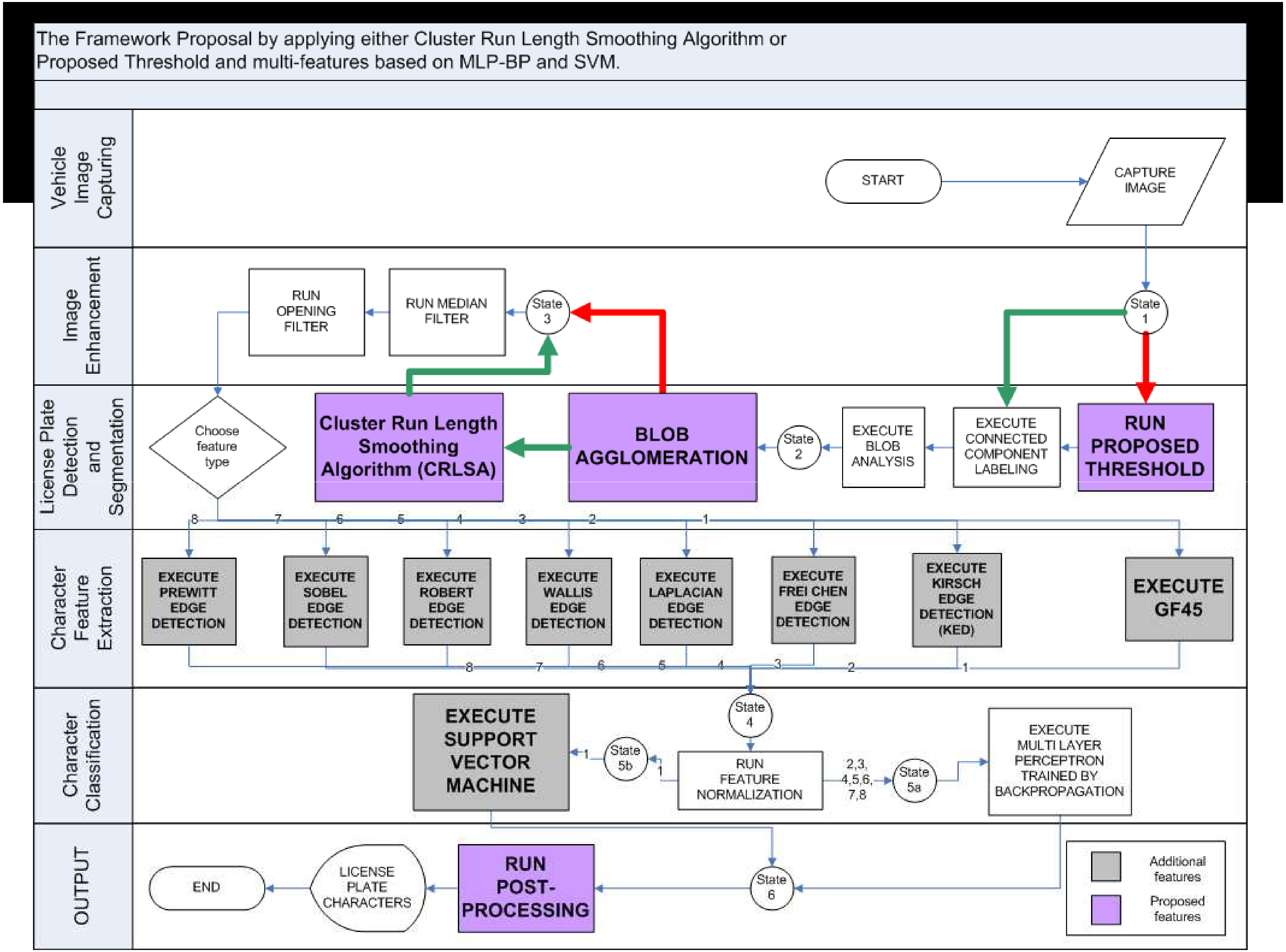
- Definitions: Car plate recognition, plate number recognition, vision plate, automatic number plate recognition and etc. (Hofman, Y., 2004)
- Most of the research has shown that classification rate was higher than detection rate. Therefore, license plate detection is a crucial research because it correlates with problem statements.
- Some research have been conducted world wide.

Year	Designer	License format	Techniques	Accuracy
1998	**Hans. A. Herg et. al**	Dutch	Histogram, Hotelling Transformation	98.7 %
1999	**T.Naito et..al.**	Japanese	Templat matching	97%
2003	**Shen-Zen Whang and His Jian Lee**	Taiwanese	Sobel, disciriminant function	96.60%
2003	**M.Safraz et.al**	Arabic	Sobel, templat matching	95.24%
2004	**Tomohiko Nukano et.al**	Malaysian	NN Threshold	87.3%

LPR system lifecyle

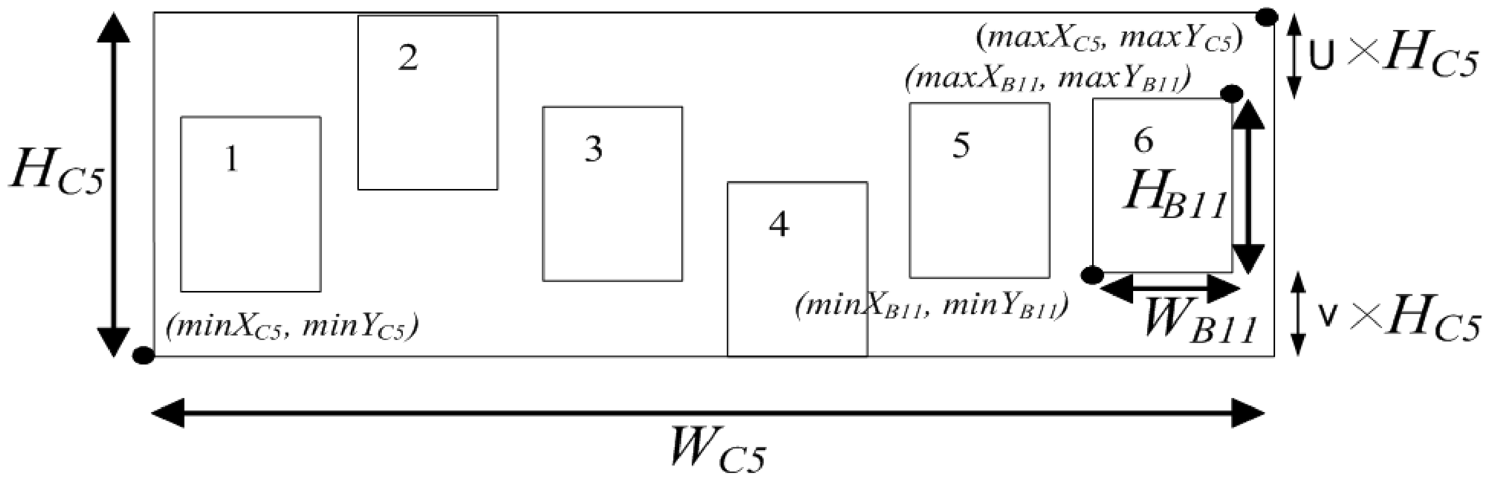





The Framework Proposal by applying either Cluster Run Length Smoothing Algorithm or Proposed Threshold and multi-features based on MLP-BP and SVM.
Vehicle Image Capturing
Image Enhancement
License Plate Detection and Segmentation
Character Feature Extraction
Character Classification
OUTPUT
START
CAPTURE IMAGE
State 1
State 3
RUN MEDIAN FILTER
RUN OPENING FILTER
Choose feature type
Cluster Run Length Smoothing Algorithm (CRLSA)
BLOB AGGLOMERATION
State 2
EXECUTE BLOB ANALYSIS
EXECUTE CONNECTED COMPONENT LABELING
RUN PROPOSED THRESHOLD
EXECUTE PREWITT EDGE DETECTION
EXECUTE SOBEL EDGE DETECTION
EXECUTE ROBERT EDGE DETECTION
EXECUTE WALLIS EDGE DETECTION
EXECUTE LAPLACIAN EDGE DETECTION
EXECUTE FREI CHEN EDGE DETECTION
EXECUTE KIRSCH EDGE DETECTION (KED)
EXECUTE GF45
State 4
EXECUTE SUPPORT VECTOR MACHINE
State 5b
RUN FEATURE NORMALIZATION
2,3, 4,5,6, 7,8
State 5a
EXECUTE MULTI LAYER PERCEPTRON TRAINED BY BACKPROPAGATION
END
LICENSE PLATE CHARACTERS
RUN POST-PROCESSING
State 6
Additional features
Proposed features

Blob agglomeration

- $|H_{current} - H'| <= (U+V) \times H_{current}$
- $|minY_{current} - Y'| <= (U+V) \times H_{current}$

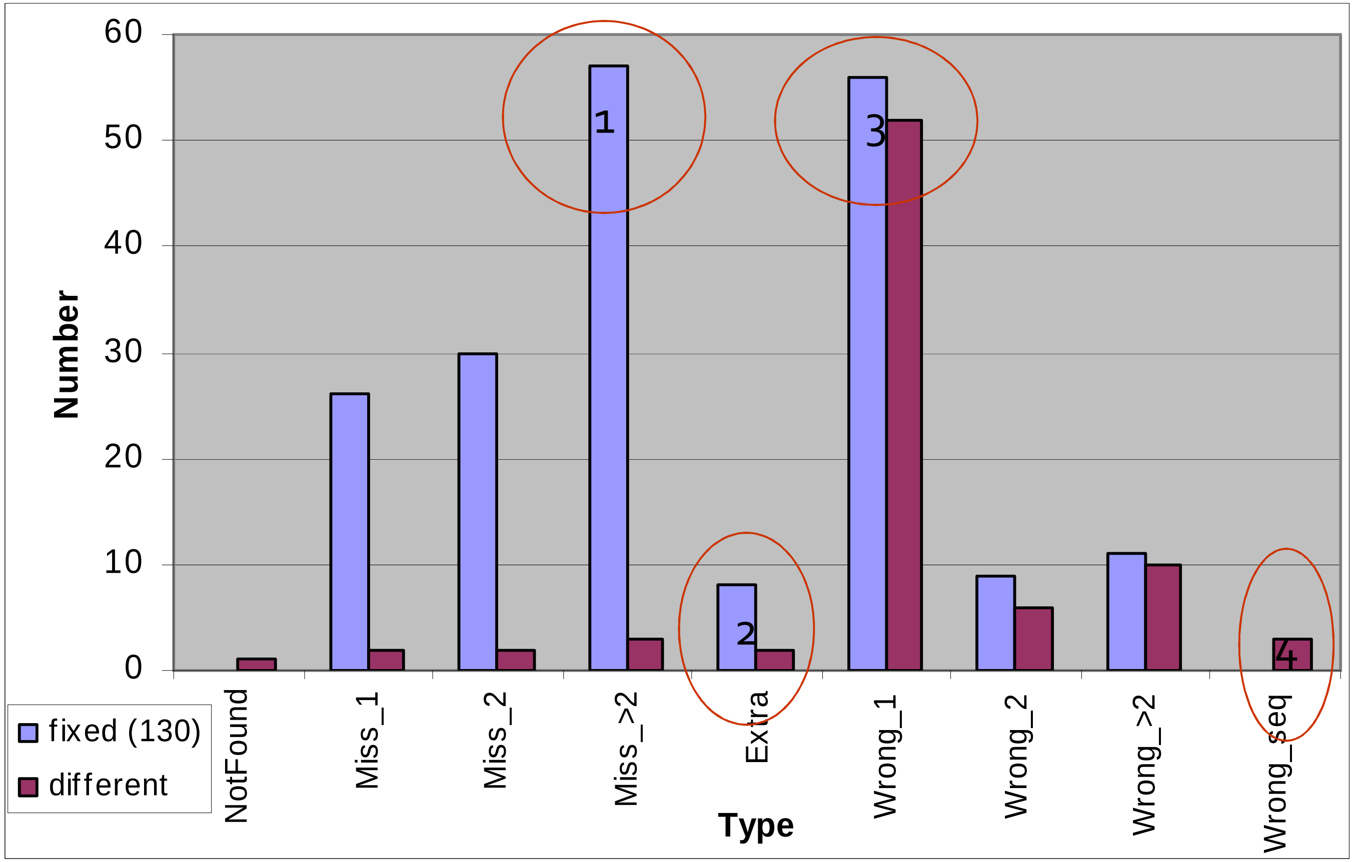


Prior LPR results (Siti Norul Huda et.al, 2006)

	threshold		average
	fixed (130)	manual	
total sample data	1000	1000	1000
no of correct	803	919	861
correct percentage	**80.3 %**	**91.9 %**	**86.%**
segmentation error	121	10	65.5
Segmentation error percentage	**61.4 %**	**12.3 %**	**36.9 %**
classification error	76	71	73.5
Classification error percentage	**38.6 %**	**87.7 %**	**63.1 %**

Abdullah, S. N. H. S.; Khalid, M.; Yusof, R. & Omar, K. License Plate Recognition Using Multi-classifier and Neural Network *2nd IEEE International Conference on Information & Communication Technologies: from Theory to Applications (ICTTA'06)*, **2006**, 659-660. (CD Proceedings)

Prior result: Error analysis



Why ?

1. Connected characters
2. Symbol or sign on LP.
3. Cannot distinguish slanting characters, fails to detect similar look characters. Ex: 3->8, B->8, 6->G or 4->A etc.
4. This problem occurs on 2 line LP.

Other issues

- Illumination often distracts determining object from the source image (Petrou and Bosdogianni, 2000)
- Improper segmentation technique contributes reduction in recognition rates (Lee et al.,2004).
- Otsu Thresholding technique applied statistical approach in calculating acceptable threshold value based on histogram projection. It only suitable in solving threshold localization process which makes it less accurate on globalization process.
- Therefore, an alternative method is required to improve the segmentation process.

Three main objectives:

1. To develop an enhance license plate detection (LPD),
2. To develop an alternative feature extraction and compare it with different classification techniques
3. To determine adaptive threshold value for image segmentation.

Hence, this research consists of three contributions:

1. Cluster Run Length Smoothing Algorithm for Object Detection

2. Enhance Geometry FeatureTopological Analysis for feature extraction

3. Determining Adaptive Threshold for Image Segmentation

First contribution
Objective: To develop an enhance license plate detection (LPD)

Cluster Run Length Smoothing Algorithm for Object Detection

Abdullah, S. N. H. S.; Khalid, M.; Yusof, R. & Omar, K.
Cluster Run Length Smoothing Algorithm (CRLSA) for License Plate Detection *Proceedings of the 25th International Multi-Conference on Artifical Intelligence and Applications (IASTED 2007)*, **2007**, 323-328

Abdullah, S. N. H. S.; Khalid, M.; Yusof, R. & Zainal, N.F.A. 2009. License plate detection and segmentation using cluster run length smoothing algorithm. IEEE Potential Journal. (Accepted for publish)

State of the art

- Run Length Smoothing Algorithm (RLSA) has been used widely in optical character recognition (OCR) process especially in document analysis [Strouthopoulos et al. 1999].
- Normally RLSA is only applied after horizontal or vertical projection to recognize the block segmentation and the transformation are only concerned on two dimensional image (black – white) [Gatos & Papamarkos, 2001]

Strouthopoulos, C.; Papamarkos, N. & Chamzas, C.
PLA using RLSA and a neural network
Engineering Applications of Artificial Intelligence, **1999**, *12*, 119-138
Gatos, B. & Papamarkos, N.
Applying fast segmentation techniques at a binary image represented by a set of non-overlapping blocks
Proceedings. Sixth International Conference on Document Analysis and Recognition, 2001., **2001**, 1147 - 1151

State of the art

TABLE I
PREVIOUS RESULTS USING DIFFERENT APPROACHES IN OBJECTION DETECTION PHASE.

Techniques	Accuracy	Designed by	License Background color
Clustering	89.63% - 97.78%	[5]	black
Square or contour	nil	[23]	yellow
Morphology	98.38%	[1]	yellow
Hough Transform	92.20%	[2]	yellow
Radon Transform	96.20%	[22]	yellow

[5] Siah, Y. K. A design of an intelligent license plate recognition. *Universiti Teknologi Malaysia,* **2000**

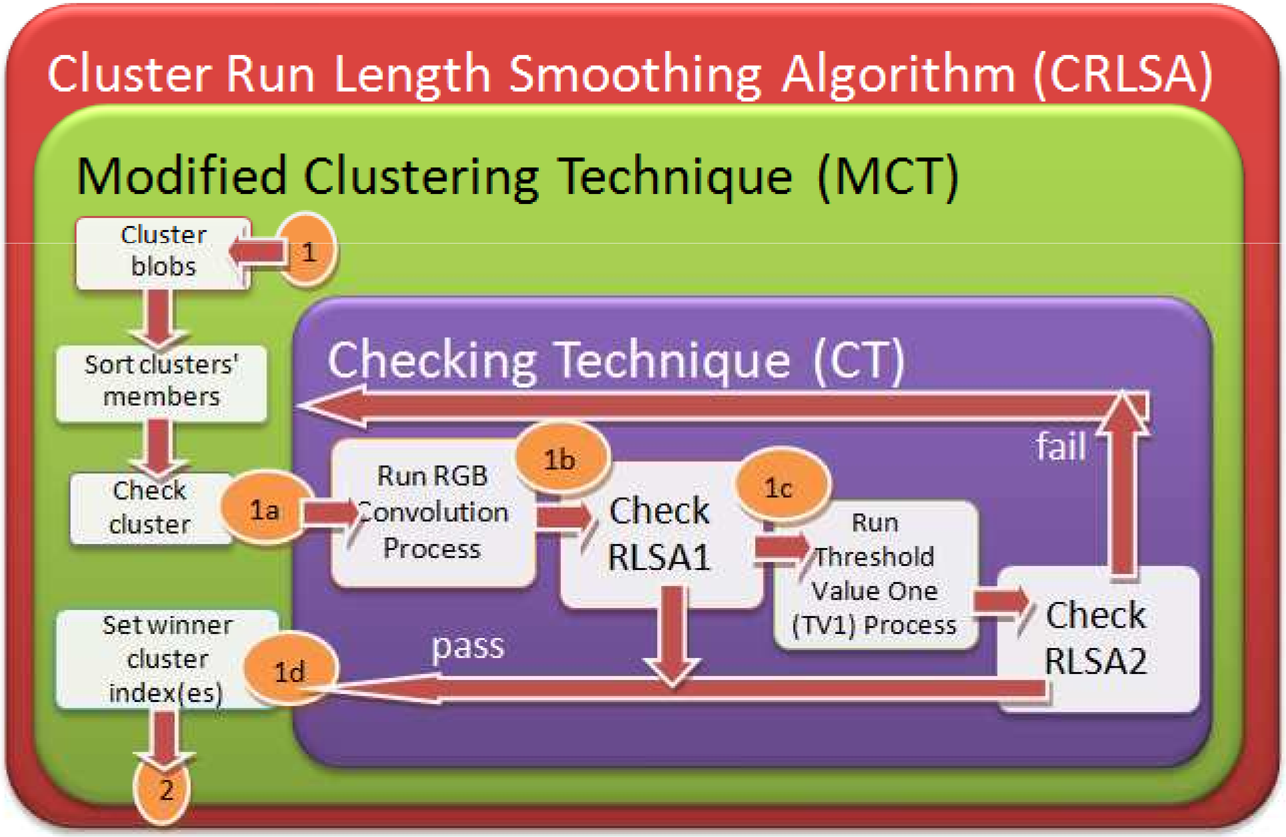
[23] Saldago, L.; Menende, J.; Rendon, E. & Garcia., N. Automatic car plate recognition through vision engineering. *Proceedings of IEEE 33rd Annual 1999 International Carnahan Conference on security technology,* **1999**, 71-76.

[1] Han, P.; Han, W.; Wang, D. & Zhai, Y. Car License Plate feature extraction and recognition based on multistage classifier. *International conference on Machine Learning and Cybernetics,* **2003**, *1*, 128-13

[2] Miyamoto, K.; Nagano, K. & Tamagawa, M. Vehicle license-plate recognition by image analysis *Proceedings of IEEE International Conference on Industrial electronics, Control and Instrumentation*, **1991**, *3*, 1734-1738

[22] Kong, J.; Liu, X.; Lu, Y.; Zhou, X. & Zhao, Q. Zhang, S. & Jarvis, R. *(ed.)* Robust License Plate Segmentation Method Based on Texture Features and Radon Transform AI 2005: Advances in Artificial Intelligence *Springer-Verlag Berlin Heidelberg,* **2005**, *3809/2005*, 510-519

Proposed Method: Cluster Run Length Smoothing Algorithm



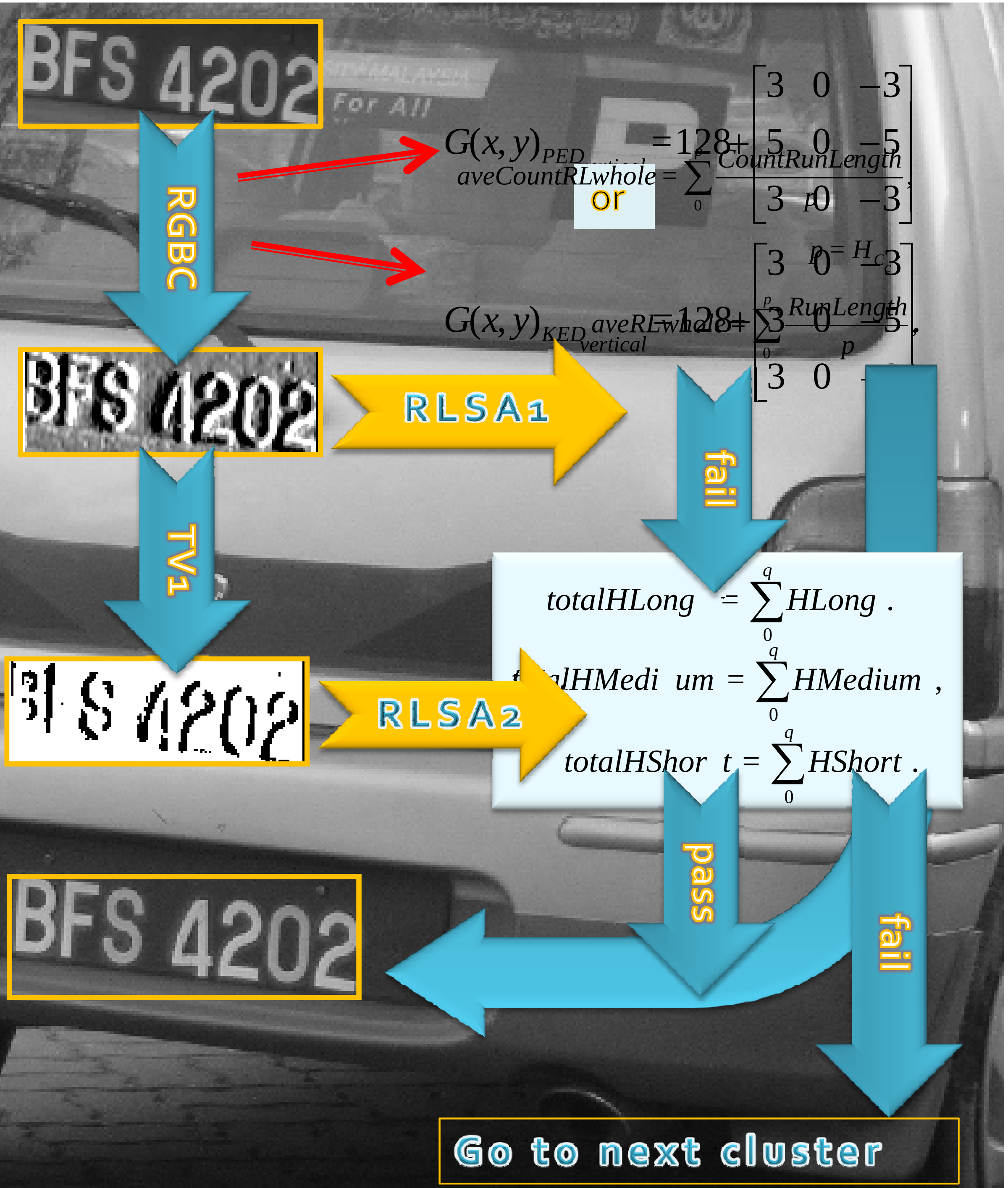
The proposed technique where:

- The CT sub-module comprises three main processes:

(a) Run RGB Convolution (RGBC) and Check the First Run Length Smoothing Algorithm (RLSA1),

(b) Run Threshold Value One (TV1) and Check the Second RLSA (RLSA2),

(c) Get winner cluster indexes.



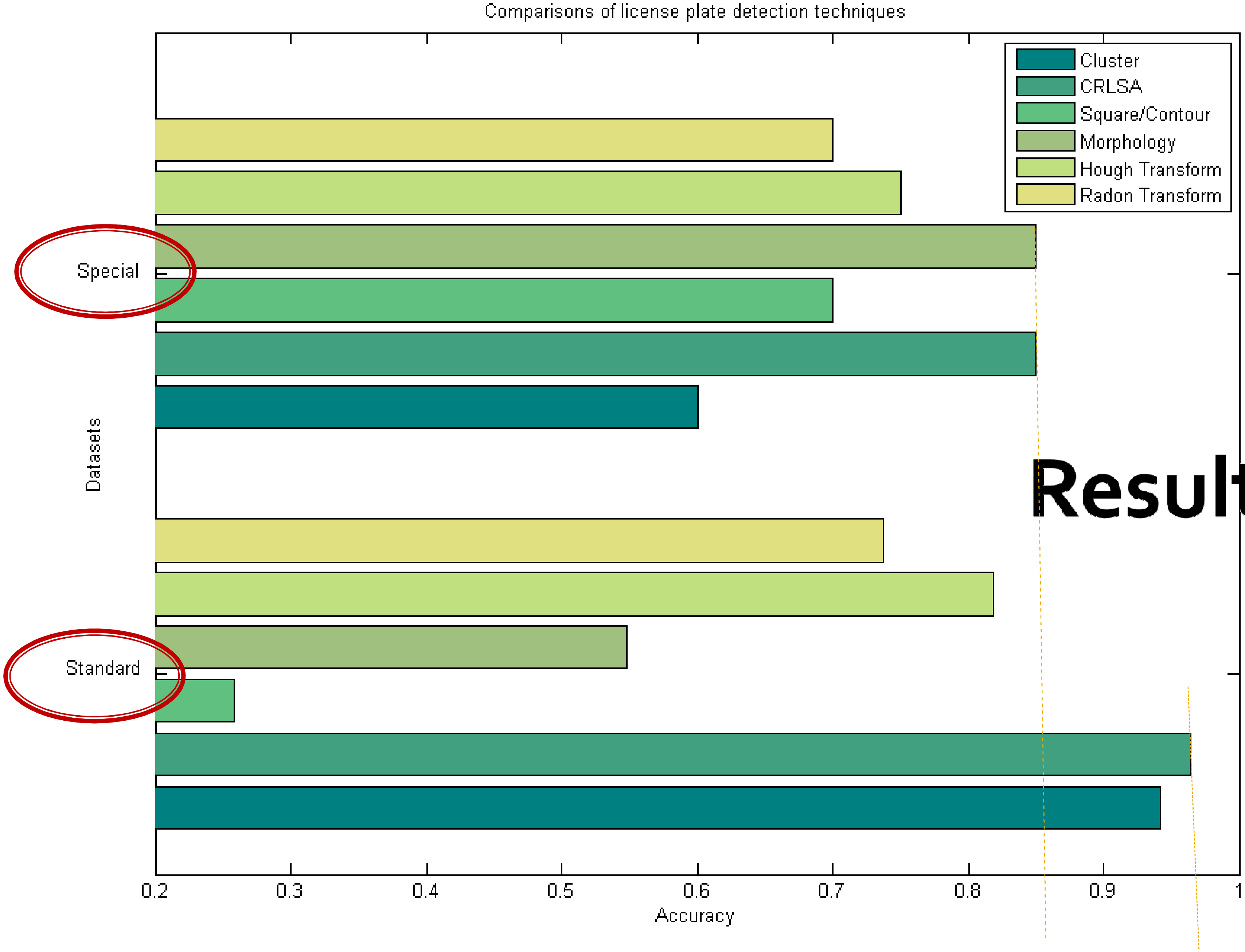
Results

TABLE III

EXPERIMENT RESULTS OF DIFFERENT LPD TECHNIQUES.

Malaysian license plate	**CLUSTERING**		**CRLSA**		**SQUARE/CONTOUR**	
	standard	Special	standard	Special	standard	Special
Non detect	72	8	44	3	916	6
Detect	1163	12	1191	17	319	14
Total image	1235	20	1235	20	1235	20
Detect %	0.941700405	0.6	0.96437247	0.85	0.258299595	0.7
Non detect %	0.058299595	0.4	0.03562753	0.15	0.741700405	0.3
Malaysian license plate	**MORPHOLOGICAL**		**HOUGH TRANSFORM**		**RADON TRANSFORM**	
	standard	Special	standard	Special	standard	Special
Non detect	571	3	232	5	340	6
Detect	692	17	1050	15	956	14
Total image	1263	20	1282	20	1296	20
Detect %	0.547901821	0.85	0.819032761	0.75	0.737654321	0.7
Non detect %	0.452098179	0.15	0.180967239	0.25	0.262345679	0.3

Results


Comparisons of license plate detection techniques
Cluster
CRLSA
Square/Contour
Morphology
Hough Transform
Radon Transform
Special
Standard
Datasets
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
Accuracy

Conclusion & Future Work

- Benefits:
  - Even though the original image of the back or frontalcar is having fusion problems such as illumination, blur, rotated, skewed, CRLSA can still successfully detect the locations of the license plate.
  - CRLSA is able to detect the precise location of the license plate even though the license plates's characters are connected or too close to each other.
- Limitations:
  - Processing time. RGB convolution with a edge detector is time consuming
  - Memory allocation. Quite often memory leaks when using RGB convolution because it requires high storage.
- Future Works:
  - Instead of using RGB Convolution using individual pixels, why not apply feature vectors.
  - Introduce new algorithm for adaptive thresholding.

Second contribution
Objective 2: To develop an alternative feature extraction and compare it with different classification techniques

Enhance Geometry FeatureTopological Analysis for feature extraction

Third contribution
Objective 3:To determine adaptive threshold value for image segmentation.

Determining Adaptive Threshold for Image Segmentation

State of the art

- Thresholding is a straightforward technique in transforming a gray scale image into a binary image that can facilitate the segmentation process. If $\hbar$, is the input image, the value of the output image $\wp$, at position (*x*, *y*), given a threshold Ω, is:

$$\wp(x,y) = \begin{cases} 1 & \text{if} \quad \hbar(x,y) \geq \Omega, \\ 0 & \text{else} \quad \hbar(x,y) < \Omega. \end{cases}$$

- Other methods for calculating the threshold namely the method of local entropy, proposed by Shanon [10] and Otsu[11].
- Otsu Thresholding is a favourite optimization thresholding method (Siah, 2000; Shapiro et al., 2006; Kahraman et al., 2003). It adopts primitive mean, μ, (Equation 2.8a) and variance, σ^2, (Equation 2.8b) calculations from histogram distributions , ρ_i, of an image, ρ where i is from 0 until g of gray level values.

$$\mu \equiv \frac{\sum_{i=0}^{g} i\rho_i}{\sum_{i=0}^{g} \rho_i}. \qquad (2.8a)$$

$$\sigma_i^2 = \frac{\sum_{i=0}^{g} (i-\mu)^2 \rho_i}{\sum_{i=0}^{g} \rho_i}. \qquad (2.8b)$$

[10] Yan, C.; Sang, N. & Zhang, T. Local entropy-based transition region extraction and thresholding *Pattern Recognition Letters*, **2003**, *24*, 2935 - 2941
[11] Noboyuki Otsu, 1979. A Threshold Selection Method from Gray-Level Histograms, *IEEE Transactions on System, Man and Cybernetics*, Vol SMC-9 (1):62-66.

Proposed threshold technique:

The proposed threshold (PT) consists of three steps:

(1) Identify the type of image according to its histogram,

(2) Calculation of blob distributions for various threshold values

(3) Selection of thresholds.

1

Identify the type of image according to its histogram

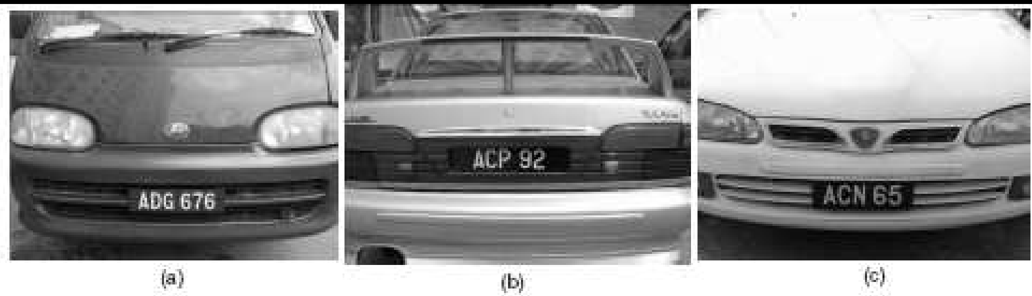


Figure 4.12 Examples of (a) 'dark', (b) 'medium' and (c) 'fair' for the original license plate images.

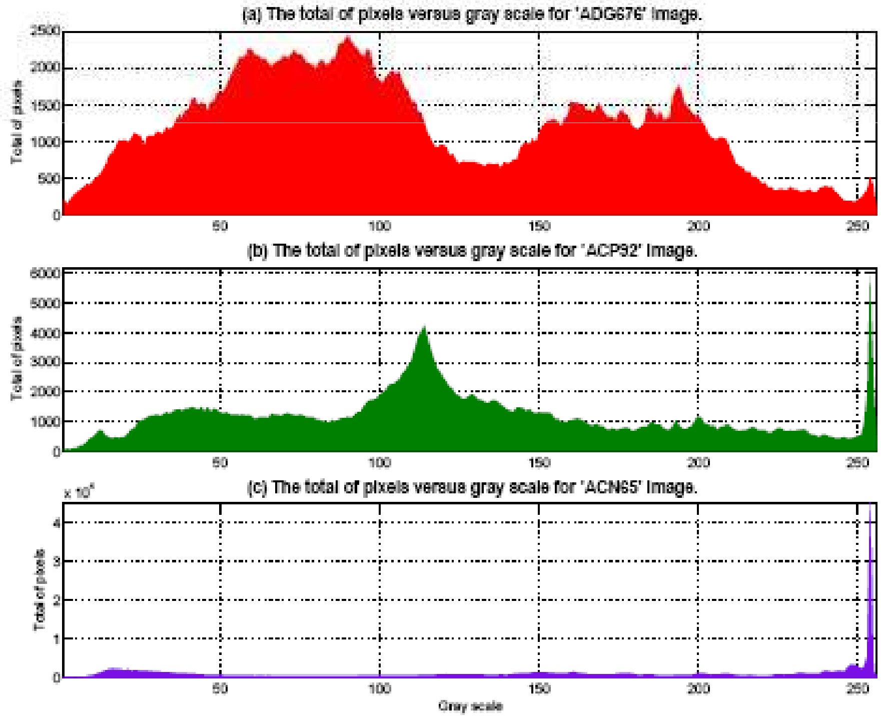


Figure 4.13 The histogram distribution, $\rho_{(0,1,\ldots,255)}$, for the (a) 'ADG676', (b) 'ACP92' and (b) 'ACN65' car image.

2 Calculation of blob distributions for various threshold values

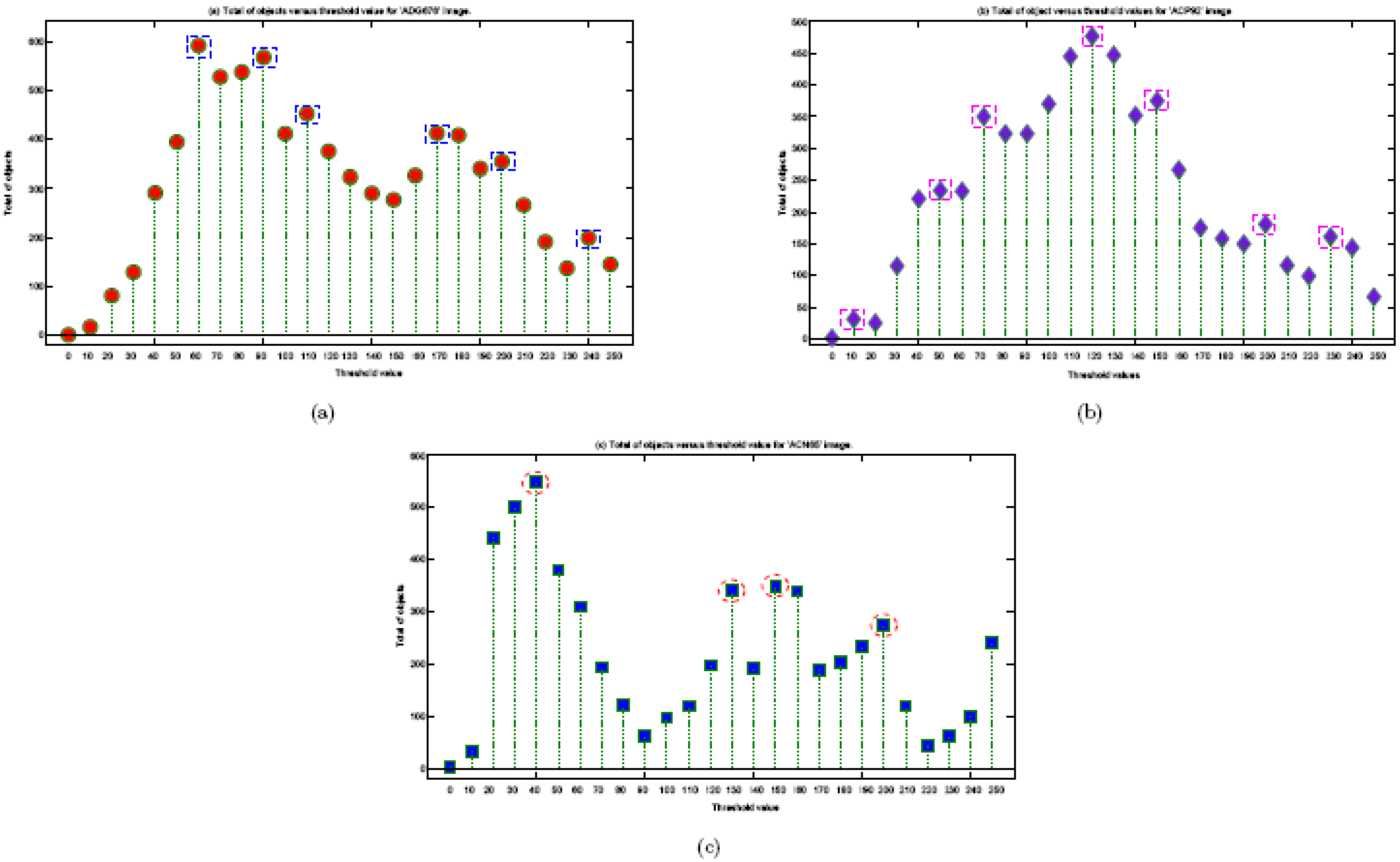
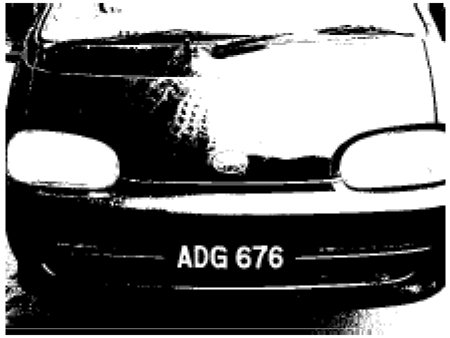


Figure 4.14 Graphs of the total of objects, $\Omega_{(0,1,\ldots,k-1)}$, versus the threshold value, $(0, 1\ldots, k-1)$, are the range of 10 from 0 to 255 for (a) 'ADG676', (b) 'ACP92', and (b) 'ACN65' image.

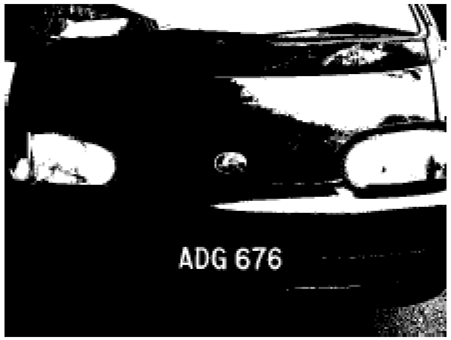
3 Selection of thresholds

Ω $peak_0$=60

Ω $peak_1$=90



Ω $peak_2$ =110



Ω $peak_3$ =170

Ω $peak_4$ =200

Ω $peak_5$ =240

$$\Omega_{Select_{(0,1,\ldots,q-1)}} = \begin{cases} \Omega_{Peak_{(0,1,\ldots,p-1)}}, (\Omega_{(q-1)} = 130) & \text{if} \quad medium \\ \Omega_{Peak_{(0,1,\ldots,p-1)}} & \text{else} \quad (fair \cup dark) \end{cases}$$

Results on License Plate Recognition (LPR)

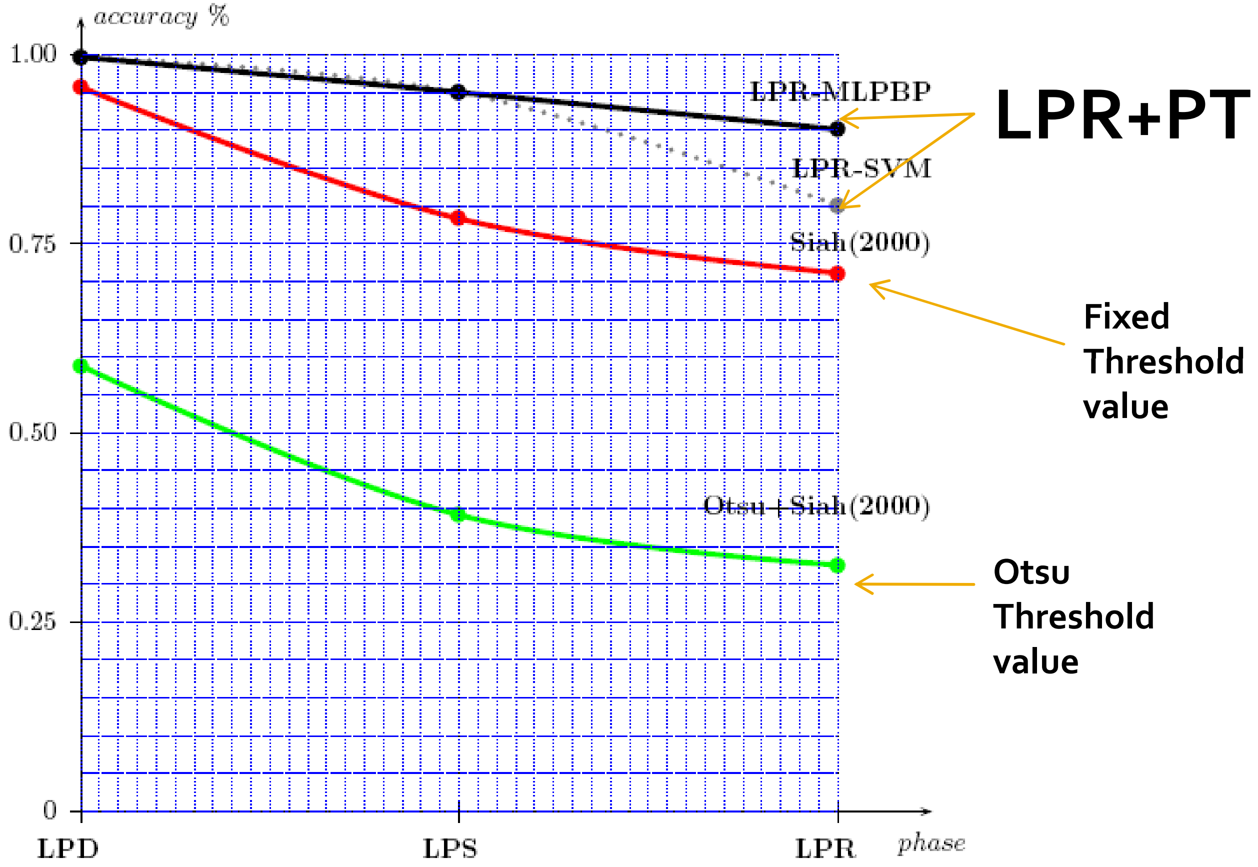
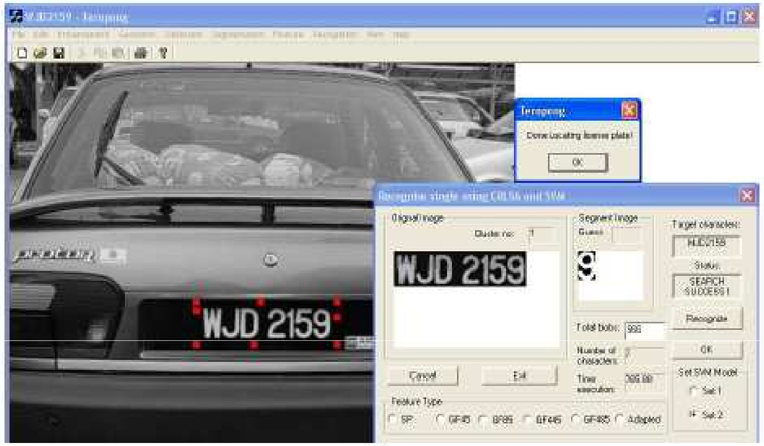


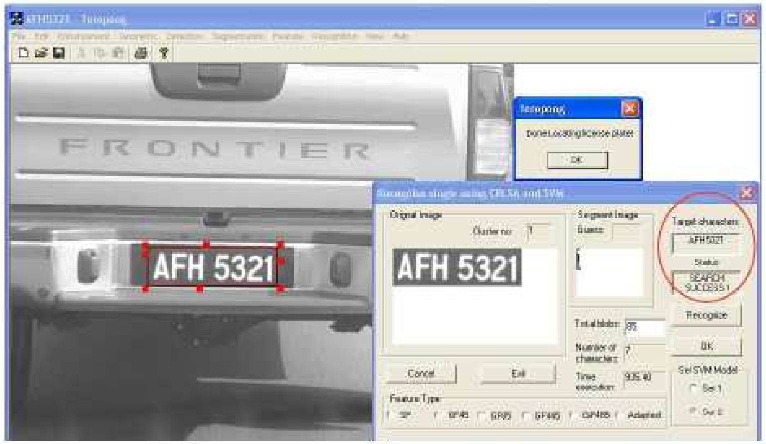
Figure 6.9 LPD, LPS and LPR accuracy rates for Otsu+Siah (2000) framework, Siah (2000) framework and the Framework Proposal.

Examples on screen shot LPR using Heuristic Threshold



(a)

(b)



(c)

(d)

Conclusion

- Advantages :
  - The proposed framework has significantly increased the LPD and LPS accuracy rate and it can give an alternative way to the LPR system.
  - The proposed threshold gives an alternative solution to obtain better threshold value(s) based on rule of thumb.
  - The proposed threshold equally treats all global and local maximum values of the probability density. Unlike Otsu, which only selects the global maximum value as the best threshold value which might not necessarily be true.
- Disadvantages
  - The proposed framework is prone to detect unnecessary blobs and signs together with the license plate characters.
  - Still not robust enough for real time applications due to overall LPR processing time because it suggests a selection of threshold values.

Future works

- Apply two dimensional blob distributions and apply mean and standard deviations to select only one threshold values.
- Apply local entropy to select the best peaks of the blob distributions.