行政院國家科學委員會專題研究計畫 期末報告

使用最低相關 LBPH 影像紋理特徵之瞌睡偵測系統

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中 文 摘 要 ： 近年來，瞌睡偵測研究廣泛應用於駕駛瞌睡偵測與遠距教學系統中，而其中眼睛狀態的辨識是建立瞌睡偵測研究裡不可或缺的基礎。然而，傳統之眼睛狀態辨識很容易受光照變化或頭髮/眼鏡遮蔽的干擾。因此本計劃提出一項創新之影像特徵，稱為最低相關之 LBPH 紋理特徵(Least Correlated LPBH)，能夠在光照變化及穿戴眼鏡情形下正確的辨識眼睛狀態。接著將此影像紋理特徵使用獨立成分分析方法(Independent Component Analysis) 產生低維度且具統計獨立特性之特徵向量，最後依據此新特徵向量來訓練支持向量機(Support Vector Machine)，訓練出眼睛狀態辨識之分類器。最後於本計畫，我們依據心理學家在瞌睡偵測研究中的眨眼生理反應，設計出四個法則配合前述的眼睛狀態分類器，來辨識人在正常、困倦及瞌睡狀態時，眼睛狀態變化之轉移模式，從而建構完整之瞌睡偵測系統。本瞌睡偵測系統可在兩秒內判定瞌睡與否，辨識正確率 98%，每張畫面的眼睛辨識時間需 0.08 秒。

中文關鍵詞： 瞌睡偵測、眼睛狀態、最低相關局部二值化圖樣統計直方圖(Least Correlated LPBH)、獨立成分分析(ICA)、支持向量機(SVM)

英 文 摘 要 ： In recent years, the drowsiness detection is widely applied to the driver alerting or distance learning. The drowsiness recognition system is constructed on the basis of the recognition of eye states. The conventional methods for recognizing the eye states are often influenced by the illumination variations or hair/glasses occlusion. In this project, we propose a new image feature called ’least correlated LBP histogram (LC-LBPH)’ to generate a high discriminate image features for establishing a robust eye states recognition system. Then, the method of independent component analysis (ICA) is used to derive the low-dimensional and statistical independent feature vectors. Finally, support vector machines (SVM) is trained to identify the eye states. Furthermore, we design four rules to recognize three eye transition patterns which define the normal (consciousness), drowsiness, and sleeping situations. Experimental results show that the eye-state recognition rate is about 0.08 seconds per frame and the drowsiness recognition accuracy approaches 98%.

英文關鍵詞： drowsiness recognition, eye state, LC-LBPH, ICA,
support vector machine

(二)中、英文摘要及關鍵詞 (keywords)。

近年來，瞌睡偵測研究廣泛應用於駕駛瞌睡偵測與遠距教學系統中，而其中眼睛狀態的辨識是建立瞌睡偵測研究裡不可或缺的基礎。然而，傳統之眼睛狀態辨識很容易受光照變化或頭髮/眼鏡遮蔽的干擾。因此本計劃提出一項創新之影像特徵，稱為最低相關之 LBPH 紋理特徵(Least Correlated LPBH)，能夠在光照變化及穿戴眼鏡情形下正確的辨識眼睛狀態。接著將此影像紋理特徵使用獨立成分分析方法(Independent Component Analysis) 產生低維度且具統計獨立特性之特徵向量，最後依據此新特徵向量來訓練支持向量機(Support Vector Machine)，訓練出眼睛狀態辨識之分類器。最後於本計畫，我們依據心理學家在瞌睡偵測研究中的眨眼生理反應，設計出四個法則配合前述的眼睛狀態分類器，來辨識人在正常、困倦及瞌睡狀態時，眼睛狀態變化之轉移模式，從而建構完整之瞌睡偵測系統。本瞌睡偵測系統可在兩秒內判定瞌睡與否，辨識正確率 98%，每張畫面的眼睛辨識時間需 0.08 秒。

關鍵字：瞌睡偵測、眼睛狀態、最低相關局部二值化圖樣統計直方圖(Least Correlated LPBH)、獨立成分分析(ICA)、支持向量機(SVM)

In recent years, the drowsiness detection is widely applied to the driver alerting or distance learning. The drowsiness recognition system is constructed on the basis of the recognition of eye states. The conventional methods for recognizing the eye states are often influenced by the illumination variations or hair/glasses occlusion. In this project, we propose a new image feature called “least correlated LBP histogram (LC-LBPH)” to generate a high discriminate image features for establishing a robust eye states recognition system. Then, the method of independent component analysis (ICA) is used to derive the low-dimensional and statistical independent feature vectors. Finally, support vector machines (SVM) is trained to identify the eye states. Furthermore, we design four rules to recognize three eye transition patterns which define the normal (consciousness), drowsiness, and sleeping situations. Experimental results show that the eye-state recognition rate is about 0.08 seconds per frame and the drowsiness recognition accuracy approaches 98%.

Keywords: drowsiness recognition, eye state, LC-LBPH, ICA, support vector machine

(三)報告內容：包括前言、研究目的、文獻探討、研究方法、結果與討論（含結論與建議）等。

3.1 前言

在此計畫中我們提出創新的最低相關局部二值化圖樣統計直方圖（LC- LBPH）來擷取出具高鑑別度之影像特徵。接著，我們使用獨立成分分析（ICA）方法用於建構低維度且具統計獨立特徵向量。最後，訓練支持向量機(SVM)來辨識眼睛的狀態。根據有關人類眨眼動作的研究文獻和我們的觀察，我們定義了三種眼睛的運動模式，分別來表示正常狀態（有意識）、瞌睡狀態及熟睡狀態。於此計畫中，我們提出四個辨識規則來辨識之。實驗結果顯示，本瞌睡偵測系統可在 2 秒內判定瞌睡與否，辨識正確率為 98%，每張畫面的眼睛狀態辨識時間需 0.08 秒。

3.2 研究目的及文獻探討

近年來，瞌睡偵測系統被廣泛應用於駕駛瞌睡偵測[1]與遠距教學系統中[2]。瞌睡偵測方法的研究可分為基於感測器和基於電腦視覺這兩種方法。在基於感測器的方法中，腦波圖（EEG）[3]和眼電圖（EOG）[4]是用記錄生理信號的方式來檢測睡眠狀態。然而，基於感測器的方法往往是侵入式的，相對的，基於視覺的方法則是從數位視覺信號中截取圖像的特徵或人類行為特徵等，是屬於非侵入性的方法。在本計畫中，我們將專注開發出一款基於以視覺為基礎之眼睛狀態辨識技術，並以此技術發展瞌睡偵測系統。

基於視覺之瞌睡偵測系統還可再進一步分為基於模板和基於影像特徵這兩種方法。在基於模板的方法中，是利用眼睛圖像模板的構造，來定位眼睛的位置，並確定眼睛的形狀，Horng [5]使用皮膚顏色來檢測出人臉區域，然後應用邊緣的資訊來定位眼睛的位置，之後利用動態模板追蹤眼球之運動狀態，來檢測疲勞程度。Fernandes [6]利用 AdaBoosting 演算法[7]來偵測人臉並使用照度分佈特徵來定位出眼睛的中心點。然後，使用模板比對技術來辨識出眼睛狀態。Khan[8]應用 SMQT 特徵和 SNoW 分類器來檢測出人臉和眼睛區域，使用眼睛開闔時的模板交互比對來辨識瞌睡。Liu [9]從連續的影像去分析眼睛的開闔與嘴巴張開程度，用此來辨識瞌睡。然而，基於模板的方法很容易受光照變化或頭髮/眼鏡的干擾。

在基於特徵的方法中，Vural [10]和 Fan [11]應用整體空間分析來分析全臉部區域，並取得 Gabor 小波特徵[12] ，然後應用 AdaBoost 分類器檢測疲勞程度。此外於研究[13-14]中，局部二值化圖樣（LBP）的編碼被使用來擷取影像紋理特徵，並結合 AdaBoost 或是 SVM 演算法來辨識瞌睡。除了灰階影像的分析，Wang [15] 在疲勞感測系統中，使用了色彩關係圖特徵(color correlogram)與 AdaBoost 分類器來檢測眼睛狀態。此外，Wu [16]使用粒子濾波器來追蹤眼睛的位置，同時使用主成分分析(PCA analysis)來擷取特徵，之後使用 logistic regression 偵測眨眼的動作。Lastly [17]使用 RNDA 來擷取影像特徵，並用多視角對人臉和眼部檢測，來辨識出人臉區域與眼睛區域。在基於特徵的方法中，主要是要考量所使用之影像特徵是否會受到光照變化或頭髮/眼鏡的干擾，以及對於眼睛運動狀態之鑑別度。同時，因為其高維度的特徵向量，所以會有龐大的訓練資料量，同時也需要很高的計算成本。

為了改善上述問題，我們提出了一種新的基於影像特徵的方法來辨識眼睛運動狀態。首先，我們提出創新的最低相關局部二值化圖樣統計直方圖（LC- LBPH）

來擷取出具高鑑別度之影像特徵。接著，我們使用獨立成分分析（ICA）方法用於建構低維度且具統計獨立特徵向量。最後，訓練支持向量機(SVM)來辨識眼睛的狀態。根據有關人類眨眼動作的研究文獻[18-19]和我們的觀察，我們定義了三種眼睛的運動模式，分別來表示正常狀態（有意識）、瞌睡狀態及熟睡狀態。於此計畫中，我們提出四個辨識規則來辨識之。實驗結果顯示，本瞌睡偵測系統可在 2 秒內判定瞌睡與否，辨識正確率為 98%，每張畫面的眼睛狀態辨識時間需 0.08 秒。下列流程圖是我們提出的瞌睡偵測系統和眼睛狀態分類器的訓練過程。(如圖 1 所示)

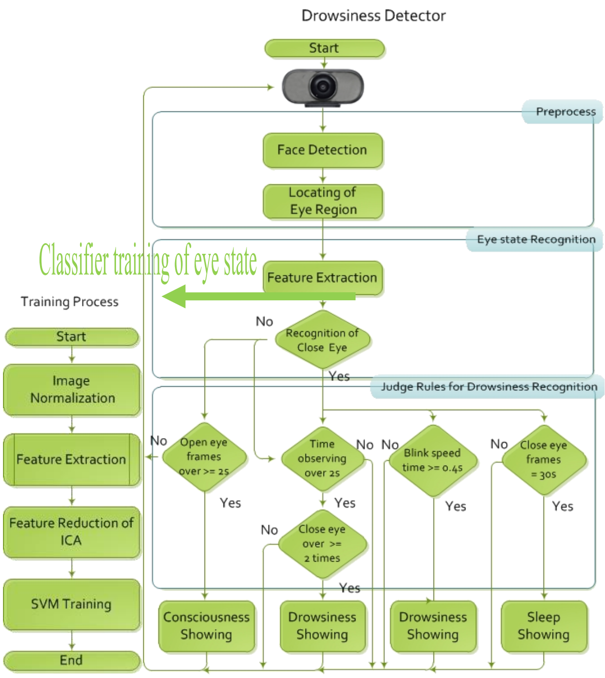


Figure 1　The left side indicate the training phase for the eye state classifier and the right side indicate the recognition phase for the drowsiness recognition.

Reference

[1] M. J. Flores and J. M. Armingol, “Real-TimeWarning System for Driver Drowsiness Detection Using Visual Information,” Journal of Intelligent and Robotic Systemst, vol. 59, no. 2, pp. 103–125, August 2010.

[2] K. Hwang and C. Yang, “Learner attending auto-monitor in distance learning using image recognition and Bayesian Networks,” Expert Systems with Applications, vol. 36, no. 9, pp. 11461–11469, November 2009.

[3] M. V. M. Yeo, X. Li, K. Shen, and E. P.V. W. Smith, “Can SVM be used for automatic EEG detection of drowsiness during car driving,” Safety Science, vol. 47, no. 1, pp. 115–124, January 2009.

[4] A. Picot, A. Caplier, and S. Charbonnier, “Comparison between EOG and high frame rate camera for drowsiness detection,” Applications of Computer Vision (WACV), pp. 1-6, December 2009.

[5] W. Horng and C. Chen, “A Real-Time Driver Fatigue Detection System Based on Eye Tracking and Dynamic Template Matching,” Tamkang Journal of Science and Engineering, vol. 11, no. 1, pp. 65-72, March 2008.

[6] T. Fernandes, A. F. Henzen, A. F. Charão, F. K. Schneider, H. R. Gamba and P. M. Gewehr, “Image Processing-Based Eyelid State Detection,” Springer Word Congress on Medical Physics and Biomedical Enginering IFMBE Proceedings, vol. 25/5, pp. 145-148, Sep. 2009.

[7] P. Viola and M. J. Jones, “Robust Real-Time Face Detection,” International Journal of Computer Vision, vol. 57, no. 2, pp. 137-154, May 2004.

[8] M. I. Khan and A. B. Mansoor, “Real Time Eyes Tracking and Classification for Driver Fatigue Detection,” Springer International conference on Image Analysis and Recognition, vol. 5112/2008, pp. 729-738, April 2008.

[9] H. A. M. Noor and R. Ibrahim, “Fatigue Detector Using Eyelid Blinking and Mouth Yawning,” Springer Computer Vision and Graphics, vol. 6375/2010, pp. 134-141, September 2010.

[10] E. Vural, M. Çetin, A. Erçil, G. Littlewort, M. Bartlett and J. Movellan, “Machine Learning Systems for Detecting Driver Drowsiness,” Springer In-Vehicle Corpus and Signall Processing for Driver Behavior, pp.97-110, Feb. 2009.

[11] X. Fan, Y. Sun, B. Yin, and X. Guo, “Dynamic Human Fatigue Detection Using Feature-Level Fusion,” ELSEVIER Pattern Recognition Letters, vol. 31, no. 3, pp. 234-243, February 2010.

[12] L. Wiskott, J.-M. Fellous, N. Kuiger, and C. von der Malsburg, “Face recognition by elastic bunch graph matching,” IEEE Transactions Pattern Analysis and Machine Intelligence, vol. 19, no. 7, pp. 775-779, Jul 1997.

[13] Y. Wu, T. Lee, Q. Wu, and H. Liu, “An Eye State Recognition Method for Drowsiness Detection,” IEEE 71st Vehicular Technology Conference, pp. 1-5, June 2010.

[14] C. Xu, Y. Zheng, and Z.Wang, “Eye state detection by boosting local binary patter histogram featus,” 15th IEEE International Conference on Image Processing, pp. 1480 - 1483, Oct. 2008.

[15] H. Wang, L.B. Zhou, and Y. Ying, “A novel approach for real time eye state detection in fatigue awareness system,” IEEE Conference on Robotics Automation and Mechatronics, pp. 528-532, June 2010.

[16] J.Wu and M. M. Trivedi, “Simultaneous Eye Tracking and Blink Detection with Interactive Particle Filters,” EURASIP Journal on Advances in Signal Processing, vol. 2008, no. 2008, pp. 0-17, January 2008.

[17] P. Wang and Q. Ji, “Multi-view face and eye detection using discriminant features,” ELSEVIER Computer Vision and Image Understanding, vol. 105, no. 2, pp. 99-111, February 2007.

[18] W. J. Freed, J. E. Kleinman, C. N. Karson, S. G. Potkin, D. L. Murphy, R. J. Wyatt, “Eye-blink rates and platelet monoamine oxidase activity in chronic schizophrenic patients,” Biological Psychiatry, vol. 15, no. 2, pp. 329-332, Apr. 1980.

[19] B.W. Shahani, “The human blink reflex,” J Neurol Neurosurg Psychiatry, vol. 33, no. 6, pp. 792-800, December 1970.

[20] Intel's open source computer vision library. http://www.intel.com/technology/computing/opencv/index.htm.

[21] T. Ojala, M. Pietikainen, and T. Maenpaa, “Multiresolution Gray-Scale and Rotation Invariant Texture Classification with Local Binary Patterns,” IEEE Transaction on Pattern Analysis and Machine inTelligence, vol. 24, no. 7, pp. 971-987, July 2002.

[22] P. Wang and Q. Ji, “Learning Discriminant Features for Multi-View Face and Eye Detection,” IEEE Computer Society Conference on Computer Vision and Pattern Recognition, vol. 1, pp. 373-379, June 2005.

[23] A. Hyvärinen and E. Oja, “Independent Component Analysis:Algorithms and Applications,” Neural Networks, vol. 13, no. 4-5, pp. 411-30, May-Jun 2000.

[24] A. Hyvarinen, “Fast and Robust Fixed-Point Algorithms for Independent Component Analysis,” IEEE Transactions on Neural Networks, vol. 10, no. 3, pp. 626-634, May 1999.

[25] The FastICA MATLAB package. (2005, Oct.) Independent Component Analysis (ICA) and Blind Source Separation (BSS). [Online]. HYPERLINK "http://www.cis.hut.fi/projects/ica/fastica/" http://www.cis.hut.fi/projects/ica/fastica/

[26] C. J.C. Burges, “A Tutorial on Support Vector Machines for Pattern Recognition,” Data Mining and Knowledge Discovery, vol. 2, no. 2, pp. 121-167, June 1998.

[27] G. Pan, L. Sun, Z. Wu, and S. Lao, “Eyeblink-based Anti-spoofing in Face Recognition from a Generic Webcamera,” 11th IEEE International Conference on Computer Vision, pp. 1-8, Oct. 2007.

[28] D. J. Hand, “Measuring classifier performance: a coherent alternative to the area under the ROC curve,” Journal of Machine Learning, vol. 77, no. 1, pp. 103-123, March 2009.

3.3 研究方法

本計畫研究方法及進行步驟分為下列步驟

1. 發展最低相關局部二值化圖樣統計直方圖影像特徵（Least Correlated LBPH Feature , LC- LBPH）
2. LC- LBPH 特徵之獨立成分分析（ICA）
3. 瞌睡偵測(Drowsiness Recognition)

1. 發展最低相關局部二值化圖樣統計直方圖影像特徵（Least Correlated LBPH Feature , LC- LBPH）

1.1 人臉與眼睛辨識

要有效率地辨識眼睛狀態，一個強大且快速的人臉辨識技術是必須的。Viola [7] 將 boost 分類器串聯起來，以更準確並有效地辨識人臉。這些分類器在人臉區域中，使用大小 20×20 到 90×90 的滑動視窗來搜尋 Haar-like 特徵，Haar-like 特徵是從人臉區域中的每個位置擷取其紋理資訊，而每個紋理資訊有不同紋理分佈。(見圖 1) 在我們的眼睛狀態辨識系統中，我們使用了 Intel 的電腦影像視覺函式庫[20]之開放原始碼中的 Adaboost 演算法，來偵測人臉與嘴的區域，如此可以增加眼睛定位的準確性。下圖為部分人臉辨識的結果(如圖 2 所示)，此外，用 Adaboost 演算法偵測嘴的區域，它會位於在人臉區域的下半部。(如圖 2 所示)

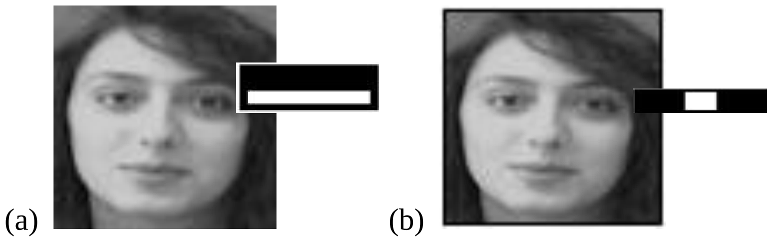


Figure 1　The Haar-like features shown in (a) and (b) are extracted on eyes region.

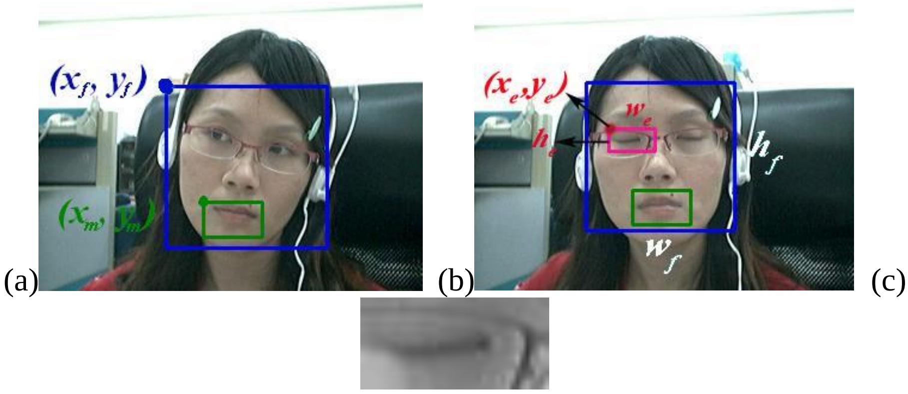


Figure 2 (a) Face and mouth regions are detected in a video sequence. (b) Eyes position is located according to the rules in Eq. (1). (c) The eye region is cropped from the face region.

在精細的測量下，我們發現眼睛區域與人臉的寬度與長度有固定的幾何關係(如圖3所示)。因此，可以按照下列幾項簡單的規則定位出眼睛的位置:

1. 根據偵測到的人臉區域，記錄其左上角角點(x_f, y_f)、臉的寬度 w_f 及臉的高度 h_f。

2. 根據偵測到的嘴巴區域，記錄其左上角角點(x_m, y_m)，眼睛區域的左上角角點(x_e, y_e)。眼睛的位置可以依下列公式計算得知：

$$(x_e , y_e) = (x_m - 0.16\, w_f , y_f + 0.16h_f +20) \quad (1)$$

3. 眼睛區域的寬度和高度可依 $w_e = 1.6 \times 0.16 \times w_f$ 與 $h_e = 0.16\, h_f$ 決定之。

1.2 最低相關局部二值化圖樣統計直方圖影像特徵(LC- LBPH)

為了描述一個較大區域的紋理分佈，一個稱為局部二值化圖樣統計直方圖(LBPH) [21]的新影像特徵被提出。藉著延伸 LBP 的概念，LBPH[21]的運算子被提出來用以描述如圖 3 所示的各種紋理圖案。而如圖 4 所示的編碼模式，特徵從 bin0 到 bin57 表示 0 - 1 轉換的數量少於 2（LBP- U2）的樣式， 0-1 轉換數量大於 2 的視為 bin58。

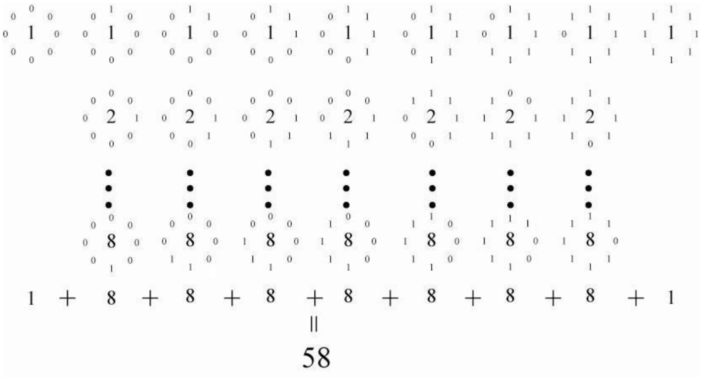


Figure 3 By rotating the 9 unique codes we can construct 58 code patterns [21]

然而，在我們仔細的實驗觀察下，原始的 LBPH 特徵，對眼睛的開闔狀態不能提供滿意的辨識鑑別度。為了提高 LBPH 特徵的辨識鑑別度，我們變動 LBPH 的建構方式，由下列參數描述之。第一個參數為於眼睛影像內分割成多掃描區塊(scanning block)且於此區塊內變動 mask 移動型態，它可以建構在掃描區塊內不同空間解析之 LBPH 特徵，而 LBPH 特徵是在每個掃描區塊內計算累積得之(如圖 4 所示)。第二個參數為的變動掃描區塊的移動距離，它可決定掃描區塊的移動距離(如圖 5 所示)。第三個參數為 LBP 運算子的遮罩移動距離，它可以決定在掃描區塊或影像中的遮罩移動距離(如圖 6 所示)。第四個參數為 LBP 的類型，其可以決定不同的 LBP 圖樣運算子(如圖 7 所示)。第五個參數為影像解析度參數，利用不同的影像解析度來調整辨識度(如圖 8 所示)。

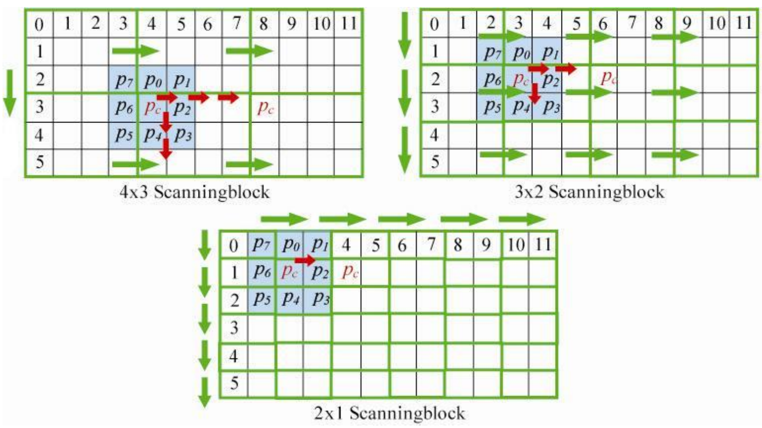


Figure 4 The parameter of scanningblock type can provide the function of multi-resolution scanning.

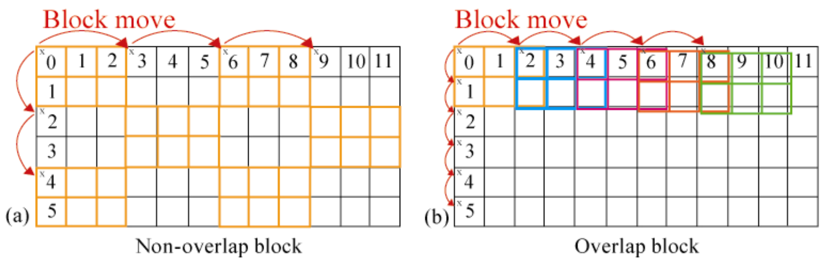


Figure 5 The parameter for block moving distance that is used to determine the moving distance.

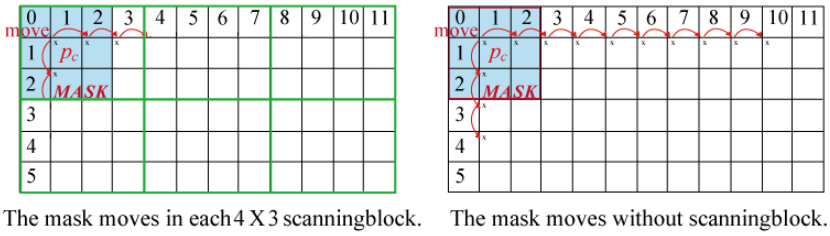


Figure 6 The mask moving distance parameter that is used to indicate moving distance of mask.

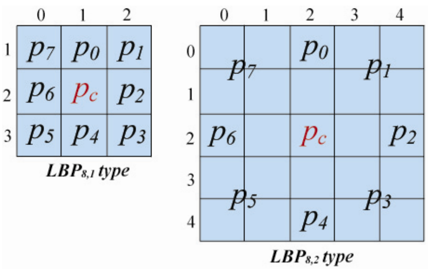


Figure 7 The parameter of LBP is used to indicate the radius for constructing the LBP code.

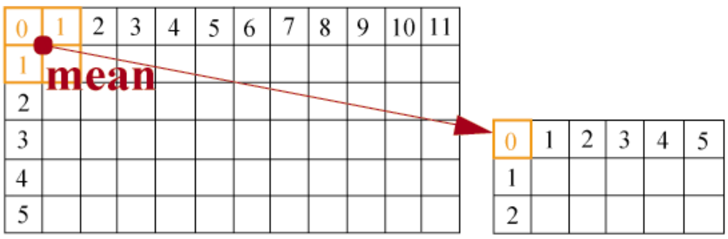


Figure 8 The parameter for image decimation is used to indicate different image resolutions.

這些參數可用於分析何種參數組合，對於眼睛的開闔狀態鑑別可以提供最低相關局部二值化圖樣統計直方圖特徵（見表 1）。如圖 9 所示，我們使用開闔狀態之眼睛影像建構的最低相關局部二值化圖樣統計直方圖(LC-LBPH)特徵。相關係數定義於(2)式中，用來評估相關的程度。

$$R(X,Y) = \frac{C(X,Y)}{\sqrt{C(X,X)C(Y,Y)}} = \begin{bmatrix} r_{1,1} & \cdots & r_{1,59} \\ \vdots & \ddots & \vdots \\ r_{59,1} & \cdots & r_{59,59} \end{bmatrix} \quad (2)$$

其中 X 與 Y 分別表示眼睛闔上與眼睛睜開的特徵矩陣，C 表示共變異數的函數，而 R 代表相關係數矩陣。相關係數的意義在表 2 中有說明。

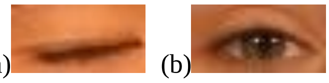
(a) (b)


Figure 92　Test images for analyzing the least correlated LBPH features.

Table 1. The various kinds of parameter combinations for constructing the least correlated LBPH.

LBP-operator Mode	Mode	1	2	3	4	5	6
	Scanningblock type	9*4⊕13*6⊕ 19*9[HYPERLINK \l "XuC08" 14]	1×1 pixel				
	Image decimation	no decimation	2×2	2×2	4×4	2×2	2×2
	Block Moving Distance	Half block-size	0 pixel				
	Mask Moving Distance	1 pixel	2 pixel	1 pixel	1 pixel	1 pixel	2 pixel
	LBP Type	$LBP^{u2}_{8,1}$	$LBP^{u2}_{8,1}$	$LBP^{u2}_{8,1}$	$LBP^{u2}_{8,1}$	$LBP^{u2}_{8,2}$	$LBP^{u2}_{8,2}$
	Correlation coefficients	0.5341	0.4996	0.4820	0.4760	0.4649	**0.4300**

Table 2. Interpretation of the correlation coefficients

Correlation	None	Small	Medium	Large (strong)
Positive	0.0 ~ 0.09	0.1 ~ 0.3	0.3 ~ 0.5	0.5 ~ 1.0
Negative	−0.09 ~ 0.0	−0.3 ~ −0.1	−0.5 ~ −0.3	−1.0 ~ −0.5

在表 1 中，Mode 1 的 LBPH 是從多解析度掃描過程[14]中獲得的，而 Mode 2 到 Mode 6 的 LBPH，是用基於區塊的掃瞄過程與表格 2 中列出的可靠區塊大小建構而成。根據表格 1 的分析，我們發現，在 Mode 6 的參數可以提供最低的相關值。因此，在 Mode 6 的參數可以提供最低的相關之 LBPH 被稱為「最低相關局部二值化圖樣統計直方圖(LC-LBPH)」。

2. LC- LBPH 特徵之獨立成分分析（ICA）

由於 LC – LBPH 的特徵向量之統計分佈數據並非屬於高斯分佈，且它擁有 59 維度。因此，在本計畫中，我們選擇使用獨立成分分析(ICA)，以降低 LC – LBPH 的特徵維度，並找出有效的且統計獨立之特徵成分。在本計畫中，我們使用 Matlab™ 25]來實現快速獨立成分分析(FastICA)演算法，用以計算獨立成分分析

(ICA)的轉換矩陣 ***W***，來得到新的特徵向量[HYPERLINK \l "Hyv99" 24]。

$$\boldsymbol{S} = \boldsymbol{W}\boldsymbol{X} = \boldsymbol{A}^{-1}\boldsymbol{X} \tag{6}$$

其中，***X*** 是 LC- LBPH 特徵向量組成的矩陣，對於計算未知的轉換矩陣 ***W***，反矩陣 ***A*** 可經由四階統計量(kurtosis)23]估算得出。然後，新的 LC- LBPH 特徵，便可從公式(6)計算得知。演算法敘述如下:

1. 使用主成分分析(PCA)的方法來得到不相關的特徵向量。
2. 使用快速獨立成分分析(FastICA)演算法[23, 25]，來計算轉換矩陣 ***W***。
3. 將每個最低相關局部二值化圖樣統計直方圖（LC- LBPH）特徵向量轉換成低維度特徵向量。

在產生 ICA 特徵向量訓練過程中，我們使用 RPI ISL 眼睛訓練資料庫[HYPERLINK \l "GPa" 22]內共 300 張解析度為 40×20 的測試用眼睛影像，如圖 10 所示。

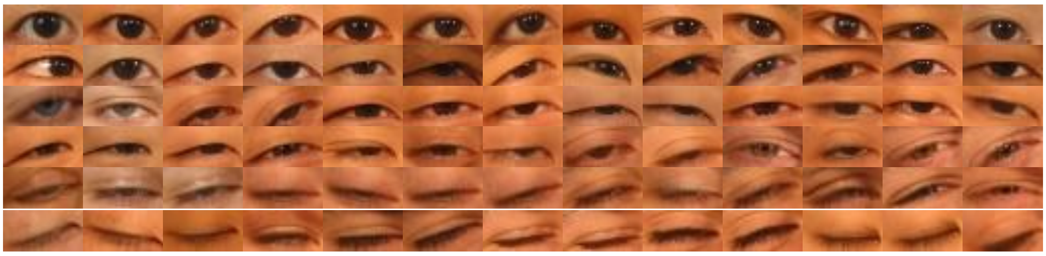


Figure 10 Training samples are selected from the 300 training set.

為了分析特徵向量維度的鑑別度，經過初步實驗(如表 3 所列)，不同維度所顯示眼睛狀態辨識率顯示於圖 11。最好的維度是 10。最後，我們在支持向量機(SVM)中使用它來訓練眼睛狀態分類器。

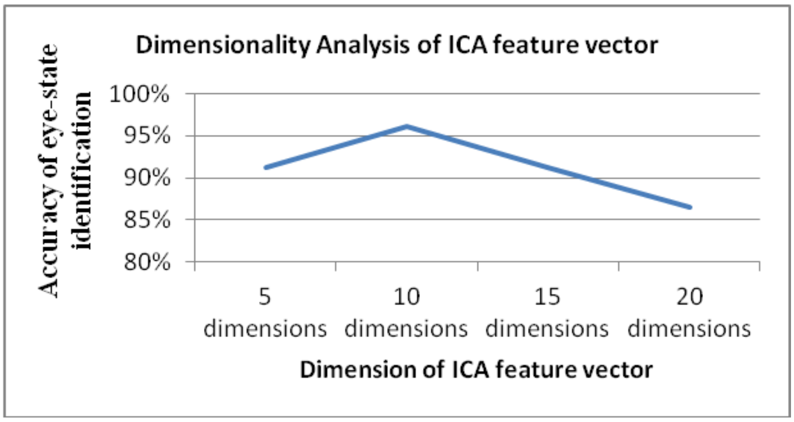


Figure 31 Accuracy analysis of the ICA features for LC-LBPH.

Table 3 Dimensionality analysis of ICA feature vector.

ICA feature vector with **5** dimensions		
Confusion matrix	True Positive (open)Rate	True Negative (close) Rate
False Positive Rate	0.8947	0.1053
False Negative Rate	0.0099	0.9901
Accuracy Rate	***0.9122***	

ICA feature vector with **10** dimensions		
Confusion matrix	True Positive (open)Rate	True Negative (close) Rate
False Positive Rate	0.9496	0.0504
False Negative Rate	0.0264	0.9736
Accuracy Rate	***0.9616***	
ICA feature vector with **15** dimensions		
Confusion matrix	True Positive (open)Rate	True Negative (close) Rate
False Positive Rate	0.8999	0.1001
False Negative Rate	0.0363	0.9637
Accuracy Rate	***0.9116***	
ICA feature vector with **20** dimensions		
Confusion matrix	True Positive (open)Rate	True Negative (close) Rate
False Positive Rate	0.8487	0.1513
False Negative Rate	0.0594	0.9406
Accuracy Rate	***0.8655***	

3. 瞌睡偵測(Drowsiness Recognition)

3.1 支持向量機(Support vector machine)

支持向量機(Support vector machine)已廣泛用於回歸分析、數據分析、圖型識別和分類。支持向量機(SVM)的概念是要找到一個超平面，能夠最大化各個類別最近點之間的邊緣[26]。在這邊，眼睛狀態辨識的支持向量機(SVM)分類器可以寫成：

$$\mathrm{H}(x_j) = \sum_{i=1}^{N} \boldsymbol{\alpha}_i \boldsymbol{y}_i \, \mathrm{k}(s_i, \boldsymbol{x}_j) + b$$

其中 k()是一個線性核心函數。每一個向量 x_j 代表由 LC-LBPH 特徵所產生的獨立成分分析(ICA)特徵向量，而 y_i 代表分類索引。 當支持向量 s_i、權重 $_i$, 和偏量 b 經由訓練後，函數 H 就能將每一個輸入的向量 x_j 分類。 如果 $H(x_j) \geq 0$，則 x_j 被分類為第一類別的成員，除此之外則被分類為第二類別的成員。在我們的眼睛狀態分類器的訓練過程中，以 200 個獨立成分分析(ICA)特徵向量用來訓練支持向量機(SVM)分類器。

在分類器測試過程中，我們從 RPI ISL 的資料庫中採用了 303 張闔眼和 1348 張睜眼的眼部影像。表格 4 列出為眼睛狀態辨識的正確辨識率和不正確辨識率。

Table 4 Confusion matrix for eye state recognition

	True Positive(close) Rate	True Negative Rate
False Positive Rate	0.9736	0.0264
False Negative(open) Rate	0.0504	0.9496
	Accuracy Rate : 0.9616	

3.2 瞌睡偵測系統

瞌睡偵測正確率有很大程度是取決於眼睛狀態轉移型態之辨識。於本計畫裡，分別對於清醒狀態、瞌睡狀態和睡眠狀態，眼睛狀態的轉移型態做仔細 觀察。在圖 26 中，兩種典型的眼睛狀態轉移型態可被歸類為瞌睡類別;兩種特有的眼睛狀態轉移型態可被分別歸類為清醒類別和睡眠類別。每一種眼睛狀態的轉移都是經由眨眼的頻率和速度所形成的。首先，一個正常人眨眼的瞬間通常是 0.2 秒到

0.4 秒，然後眨眼的時間間隔大約是 2 秒到 8 秒。其次，當人感到疲勞或瞌睡時，眨眼頻率將變為圖 12 中「Drowsiness#1」的情形。在「Drowsiness#1」的情況下，2 秒之內眨眼的次數會多於三次以上。在「Drowsiness#2」的情況下，眼睛閉起的速度將變得非常緩慢，甚至隨時間而超過 0.4 秒。如果闔眼的時間超過 30 秒，則確定為睡眠的情形，如圖 12 所示的「Sleeping」。

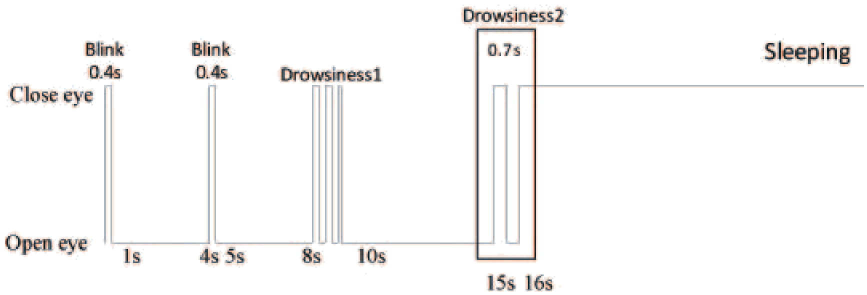


Figure 12 The waveform for showing the eye state transitions for drossiness and sleep.

圖 13 為描述瞌睡偵測的流程圖。 我們對於瞌睡偵測設計四條判斷規則，規則說明如下。

1. 如果偵測到睜眼的狀態的時間間隔超過 2 秒，則判斷這個人為清醒狀態。
2. 如果偵測到闔眼的狀態的畫面張數大於 1.5 秒，如圖 26 的「Drowsiness1」模式所示，則瞌睡偵測系統發出警報。
3. 如果偵測到闔眼的狀態的畫面張數大於 0.4 秒，如圖 26 的「Drowsiness2」模式所示，則瞌睡偵測系統發出警報。
4. 如果偵測到闔眼的狀態的畫面張數大於 30 秒，如圖 26 的「Sleeping」模式所示，則瞌睡偵測系統發出警報。

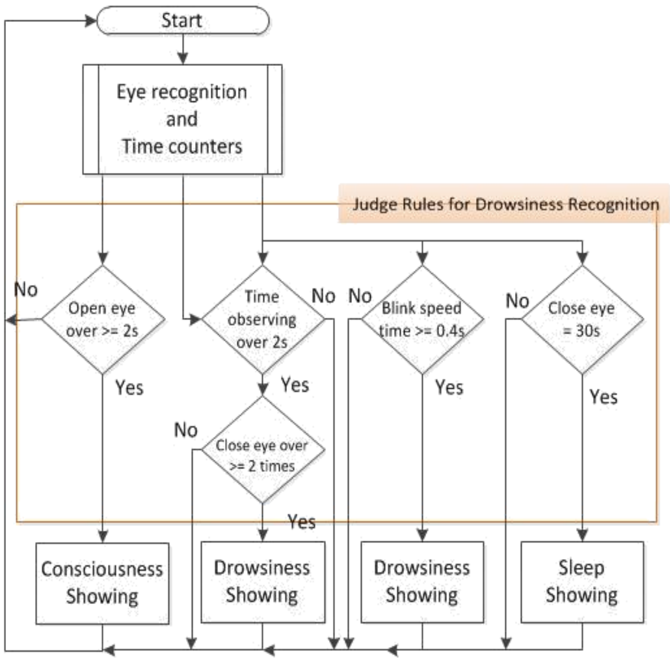


Figure 13 Flowchart for drowsiness recognition rules.

3.4 結果與討論

本計畫已完成之工作項目及成果為：

1. 訓練與測試資料庫

於本計畫，我們採用 RPI ISL 的眼睛訓練資料庫(RPI ISL Eye Training Database)[22]和浙江大學的眨眼資料庫(ZJU Eyeblink Database)[27]，使用了300個訓練資料和1651個測試資料。在RPI ISL眼睛訓練資料庫中包括被裁剪成不同大小、狀態和方向的左右眼影像。

2. 眼睛狀態和瞌睡偵測的分析

我們研發以 LC-LBPH 影像特徵及應用獨立成分分析(ICA)所得之特徵向量，訓練支持向量機(SVM)分類器。眼睛狀態辨識正確率為 98.63％。 此外在表格 5 中對於兩種眼睛狀態辨識方法進行了比較。很顯然，我們的眼睛狀態辨識方法比 Flores 的方法[1]更為準確。

Table 5 Accuracy-rate comparison of Eye-state recognition

Method	Number of test video	Accuracy Rate
Flores's method [1]	5	95.59%
LC-LBPH + SVM	5	98.63%

關於瞌睡偵測的成果，我們找了 30 名學生來進行測試。 在實驗分析中，我們在三十秒之內計算學生的狀態是否在打瞌睡。在表格 6 中，所列的是我們的方法和 Fan 的方法，實驗以 30 個人來檢測疲勞的準確性分析。 實驗的結果顯示，我們的方法優於 Fan 的方法。 每種方法的 ROC 位置如圖 14 所示。瞌睡偵測系統從 USB 數位網路攝影機中獲取即時的視頻畫面，並在作業系統為 Microsoft Windows XP、CPU 為 Intel Core2 Quad 以及 3GB 記憶體的機器下處理。眼睛狀態辨識速度大約是每張畫面 0.08 秒。 圖 15 與圖 16 為瞌睡偵測系統的實際示範。

Table 6　Accuracy comparisons for drowsiness detection

Method	Accuracy Rate
PCA + HMM	76%
PCA + LDA	81%
Fan’s method I [11]	91%
Fan’s method II[11]	96%
LC LBPH + SVM	*98%*

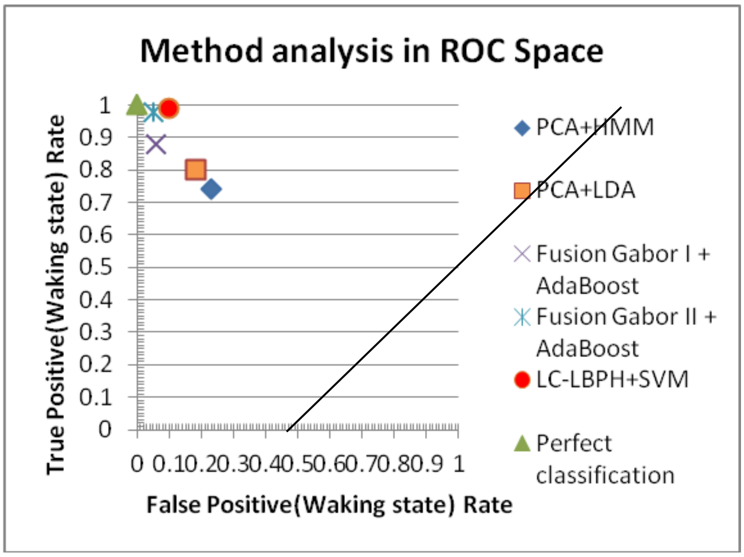


Figure 14 Method comparisons for drowsiness detection and fatigue monitoring [11]

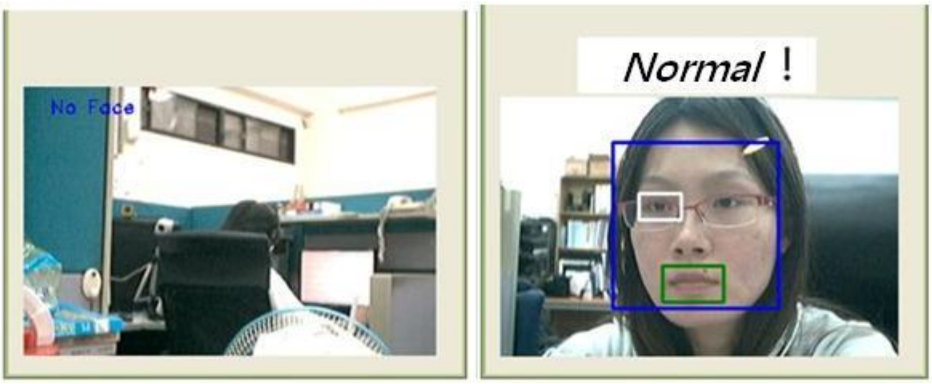
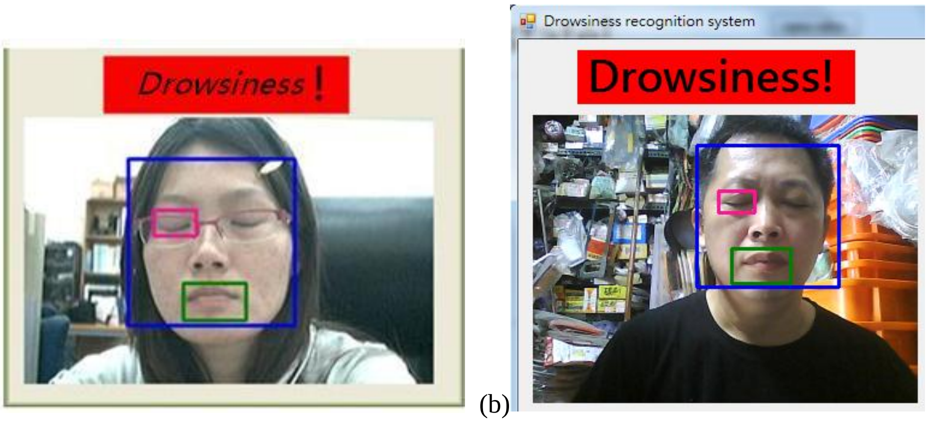


Figure 15 Demonstration of drowsiness recognition.



(a) (b)

Figure 16 (a) System recognizes the drowsiness state. (b) Drowsiness is recognized under the non-uniform illumination.

國科會補助專題研究計畫出席國際學術會議心得報告

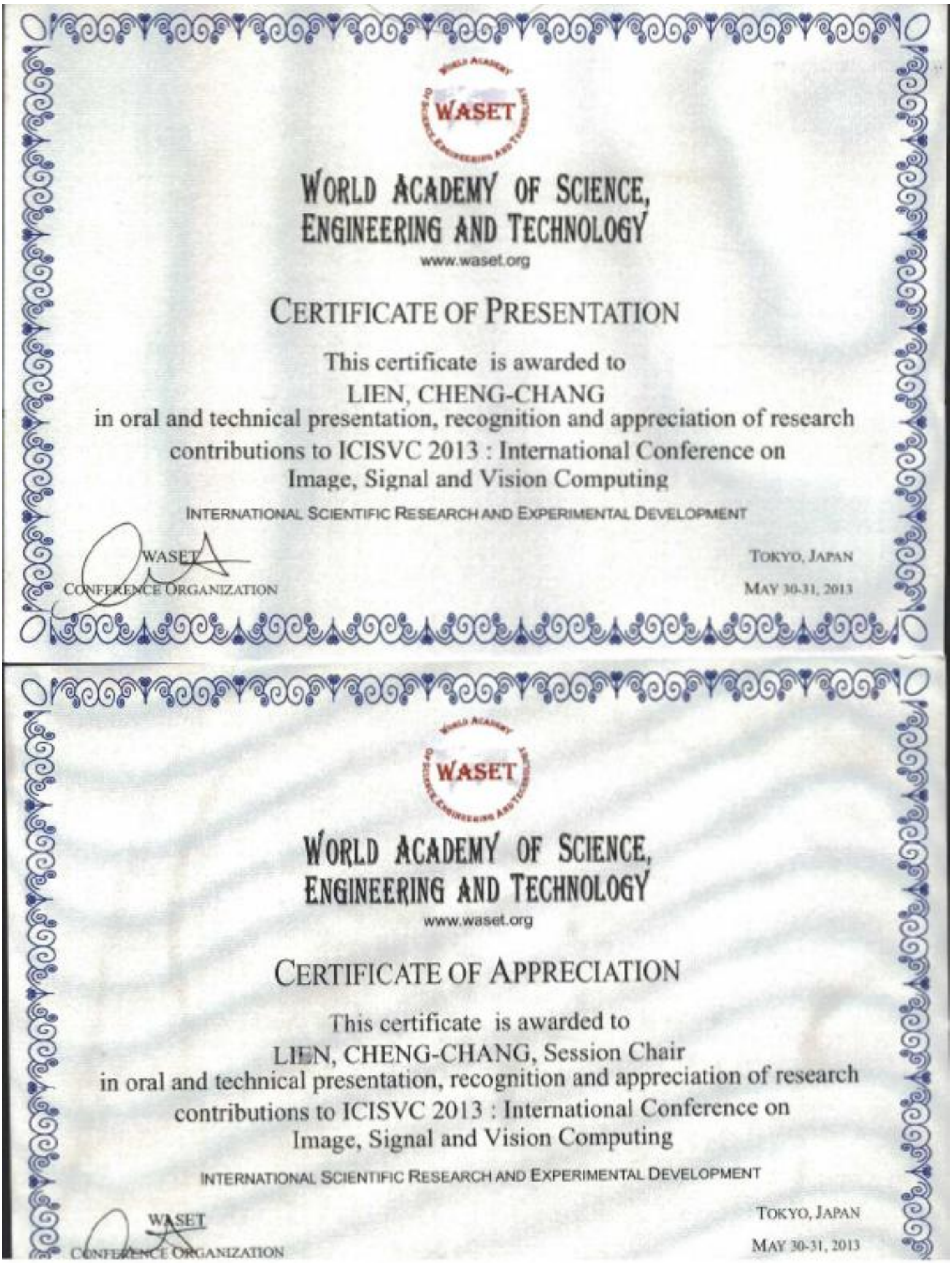
日期：___年___月___日

計畫編號	NSC 101-2221-E-216 -035 -		
計畫名稱	使用最低相關LBPH影像紋理特徵之瞌睡偵測系統		
出國人員姓名	連振昌	服務機構及職稱	中華大學資訊工程學系 副教授
會議時間	102 年 5 月 30 日至 101 年 7 月 31 日	會議地點	日本 東京
會議名稱	（中文)2013 國際影像、訊號及視覺學術研討會 （英文）ICISVC 2013 : International Conference on Image, Signal and Vision Computing		
發表題目	(中文)以 Surf 特徵點為基礎之目標物追蹤 (英文) Surf-Badge-Based Target Tracking		

一、參加會議經過

這一次赴日本東京參加 ICISVC 2013 會議，除了發表論文” Surf-Badge-Based Target Tracking”外並擔任 session chair，主持近 2.5 小時之議程，議程內約有十篇論文發表，並與大會議程主席交流對會議看法。佐證資料如下圖所示。

此次赴日本東京參加 ICISVC 2013 會議之目的在於了解吸收國際最新研究方向及技術發展新知，對於規劃日後研究方向有甚大助益。



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二、與會心得

此次赴日本東京參加 ICISVC 2013 會議之目的在於了解吸收國際最新研究方向及技術發展新知，對於規劃日後研究方向有甚大助益。

三、發表論文全文或摘要

Surf-Badge-Based Target Tracking

Cheng-Chang Lien, Shin-Ji Lin, Cheng-Yang Ma, and Yu-Wei Lin

***Abstract*—With the great demand for constructing a safe and security environments, video surveillance becomes more and more important. In order to detect each individual target under serious occlusions, we propose a SURF-badge-based target tracking method to overcome the occlusion problem. First, the blob-based object detection and verification is used to initialize the object tracking scheme. Second, the moving object region is segmented into three portions for locating the SURF feature points as the badge of moving object. Finally, the dynamic updating of the SURF feature points is applied for the purpose of robust target tracking. The experimental results show that the accuracy of individual tracking under serious occlusions can be higher than 90% and the efficiency can approach 10-12 fps.

***Keywords*—Video surveillance, occlusion, blob-based-detection, target tracking, SURF.

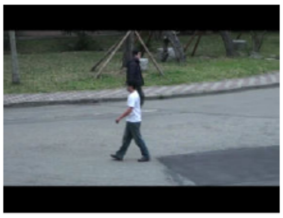
I. Introduction

RECENTLY, with the rapid development of video processing technologies, some new visual applications are emerging, e.g., video content searching [1], video indexing [2], video classification [3], and intelligent video surveillance [4-5]. Especially, in the intelligent video surveillance [4], human are tracked and their activities are recognized and monitored.

In the conventional blob-based object detection systems, some typical methods are applied to extract the moving objects, e.g., background subtraction [6], optical flow [7-9], frame difference analyses [10], and codebook model [11]. In [6], the regions of moving objects may be acquired precisely by using the method of background subtraction but it is extremely sensitive to the illumination and the background variations. In [7-9], the optical flow method is used to independently track each object with the low-level feature. Applying frame differencing method [10] may be adaptive to the illumination changes, but the moving objects are extracted incompletely when the objects move slowly. In [11], the codebook method can overcome the problems of background or illumination variations, but this method is difficult to detect and track the targets in the situation of partial occlusion.

Hence, conventional video surveillance systems [12-13] often may face the following problems. First, target detection can't be accurate under the light variation environment or clustering background. Especially, the light reflection, back-lighted and shadow problems can influence the target detection seriously. Second, multiple targets tracking become difficult on a crowd scene because the split and merge or occlusions among the tracked targets occur frequently and irregularly. Third, it is difficult partition the tracked targets from a merged image blob and then the target tracking may fail. Finally, the tracking efficiency and precision are reduced by the inaccurate foreground detection.

In the novel video surveillance application, one of the most challenging problems is the target tracking under the serious occlusion condition shown in Fig. 1. Generally, serious occlusions make the conventional blob-based target detection/tracking methods failed. For example, the tracked person can be partially occluded by other persons and only part of region can be served as a cue for continuous tracking. Hence, target tracking may face the problems of frequent partial occlusions that can make the target segmentation very difficult. Therefore, in this study, the SURF-badge-based target tracking method is proposed to tackle the occlusion problems.



(a)

(b)

(c)

Fig. 1 Target occlusion situations (a) People are walking crossover, (b) People is occluded by the tree, (c) People is occluded by the car

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The block diagram of the proposed system is shown in Fig. 2. In Fig. 2, the blob-based foreground detection is applied to detect the candidate object regions and then the object verification scheme with the moving trajectory length is utilized to extract the real objects. In the following, the SURF-badge-based target tracking is activated to track each individual object. In the target tracking, the object region is divided into three equal portions. In each portion, the SURF feature points are detected as the badge of this object and recorded for object tracking under the partially occluded conditions. Finally, the matching and dynamic updating for the SURF feature points are continuously applied for the purpose of robust target tracking.

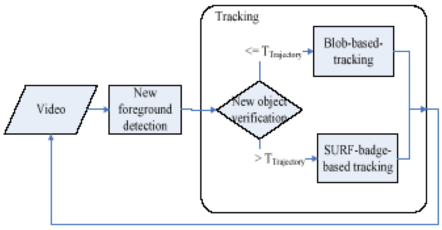

Fig. 2 The block diagram of the SURF-badge-based target tracking system

II. Object Detection And Surf Badge Locating

In this section, the method of target tracking consists of two phases. First, the moving objects will be detected with the blob-based object detection method. Second, the SURF feature points served as the badge for each moving object are located for continuous object tracking. Fig. 3(a) shows that a moving object is detected by the blob-based object detection method and Fig. 3(b) shows that the SURF feature points are detected and located in the moving object.

(a) (b)

Fig. 3 (a) Example of blob-based object detection, (b) SURF feature points (red dots) are located in the object region.

A. Blob-Based Object Detection

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Given an image sequence captured by a fixed camera over a time period, the intensity variation for each pixel can be modeled by the Gaussian distribution function. Furthermore, by the carefully observation, the intensity variations of the pixels in the regions of moving objects may be modeled by the flat Gaussian distribution functions. Hence, the mixture of Gaussians (MOG) [14], [16] may be used to model the intensity variation for each pixel that may belong to the backgrounds or the moving objects over a time period. The blob-based foreground detection is illustrated in Fig. 4.

(a) (b)

Fig. 4 Example of blob-based object detection (a) Original image, (b) The detected objects

B. Badge Locating

In general, the blob-based object detection methods [15] can extract the moving objects on the less crowded scene. However, when the moving objects are frequently partially occluded the conventional blob-based methods are difficult to track each individual object because of the inaccurate segmentation of each individual object. To overcome this problem, the SURF badge is located on the detected objects for continuous and robust tracking of each moving object.

There are three typical point-based features which are Kanade-Lucas-Tomasi (KLT) [7], Scale Invariant Feature Transform (SIFT) [8] and Speeded-Up Robust Features (SURF) [9]. The KLT does not address the issue of scale, translation, and rotation invariant feature description when tracking in the image sequences. Therefore, we don't use the KLT feature as the target badge. Both descriptors in SIFT and SURF have the properties of rotation, translation and scaling invariants. Based on the SIFT algorithm, the SURF improve the efficiency by box filtering and integral image calculation for the Hessian matrix and Haar wavelets. In this study, we apply the SURF to develop the point-based target tracking scheme. There are three main processes in the SURF algorithm, which are:

1. Given a point $p=(x, y)$ in an image I, the Hessian matrix $H(p,\sigma)$ at the scale σ is defined as:

$$H(p,\sigma)=\begin{bmatrix} L_{xx}(p,\sigma) & L_{xy}(p,\sigma) \\ L_{xy}(p,\sigma) & L_{yy}(p,\sigma) \end{bmatrix}, \quad (1)$$

where the elements in H denote the convolutions of the Gaussian second order derivatives $g_{xx}(\sigma)$, $g_{xy}(\sigma)$, $g_{yx}(\sigma)$, and $g_{yy}(\sigma)$ with the image I at the point p. In contrast to SIFT method which approximates Laplacian of Gaussian (LoG) with the Difference of Gaussians (DoG), SURF approximates the second order Gaussians derivatives [17] with the box filters (mean or average filter). The locations and scales of interest points are selected based on the determinant of the Hessian matrix. The interest points are detected by applying the non-maximum suppression in a

$3\times3\times3$ neighboring space and searching the local extremes in the different scale spaces.

2. In the SURF algorithm, a circular region around the detected interest points is constructed to compute a unique orientation for gaining the rotation invariance property. With the dominant orientation, the SURF descriptor is constructed by extracting square regions around the interest points. The region is split up regularly into smaller 4×4 sub-regions. In each sub-region, the Haar wavelet responses in both horizontal and vertical directions d_x and d_y are used to extract the underlying intensity pattern (first derivatives) described by a feature vector $V = \left(\sum d_x, \sum d_y, \sum|d_x|, \sum|d_y|\right)$. Finally, the SURF descriptor with length 64 is constructed.
3. The matching process is performed by finding the nearest neighbor of each descriptor. The Euclidean distance used to measure the dissimilarity between two SURF descriptors is defined as:

$$\mathrm{Dist}(p^q, p^c) = \| V^{(p^q)} - V^{(p^c)} \|_e \tag{2}$$

Let $F_q=\{p_1^q, p_2^q,..., p_M^q\}$ and $F_c=\{ p_1^c, p_2^c,..., p_N^c\}$ represent SURF feature points sets of the query and current images respectively. For a feature p_k^q in F_q, the matching point is found when the ratio of dissimilarity measure between its nearest and second nearest feature points in F_c is satisfied with the criteria in (3).

$$\frac{\mathrm{Dist}(p_k^q, p_{NN}^c)}{\mathrm{Dist}(p_k^q, p_{SN}^c)} < Threshold \tag{3}$$

The example of SURF feature points matching is shown in Fig. 5. The matched SURF feature points are served as the badge of the detected object.

Fig. 5 SURF feature points matching between the successive images

III. TARGET TRACKING WITH THE SURF BADGE

In this section, a novel target tracking scheme with the SURF badge is proposed which aims at improving the tracking robustness when the objects are partially occluded. The system block diagram of the proposed target tracking scheme is shown in Fig. 6. In Fig. 6, the left side denotes the blob-based object detection and verification and right side denotes the target tracking scheme with the SURF badge. It is obvious that both the blob-based and point-based methods are interactive and corporative in our proposed system. The detail descriptions are given in the following sections.

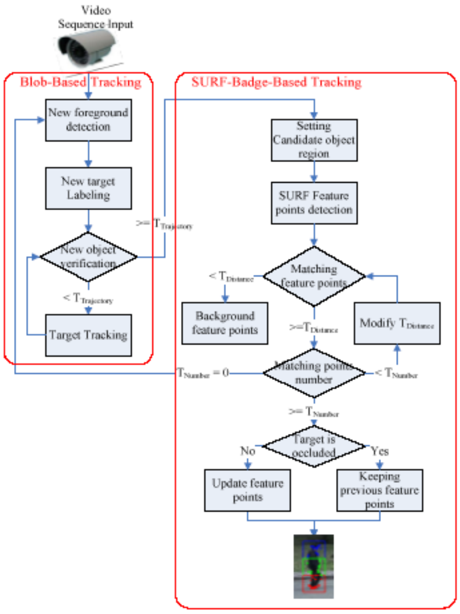


Fig. 6 The flowchart of the target tracking scheme with the SURF badge

A. Object Detection and Verification

In our system framework, we firstly detect the foreground area with the blob-based object detection method. Each foreground area is described by a vector with four components: the center, width and height of the region, which is represented as: $\{O_t^i = [x, y, w, h]^T, i=1,..., N\}$ where t denotes the time information (frame number) and N denotes the total number of blob-based object detection at frame t.

If the object area is detected and classified as a single moving object [16], this object will be tracked for a certain time interval to verify whether it is a true moving object or not. First, we calculate the trajectory length of the moving object O_t^i. Second, if the length of the trajectory is larger than a threshold $T_{Trajectory}$, then O_t^i is identified as a true moving object shown in Fig. 7.

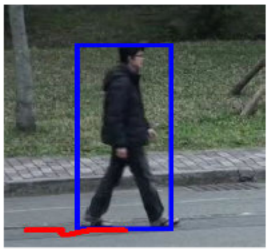
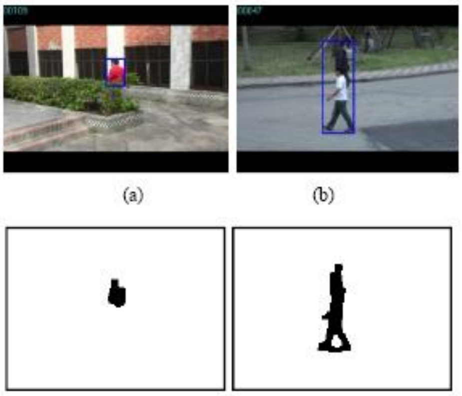


Fig. 7 Blue rectangle denotes the object region O_t^i. Red line denotes the trajectory of the moving object



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

Fig. 10 Object moves with partial occlusion (a) Moving object is occluded by the tree, (b) Two people are partially occluded, (c) The image blob for (a), (d) The image blob for (b). Blue rectangle denotes the candidate object region O_t^1

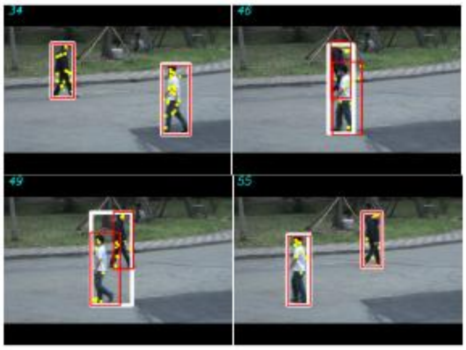


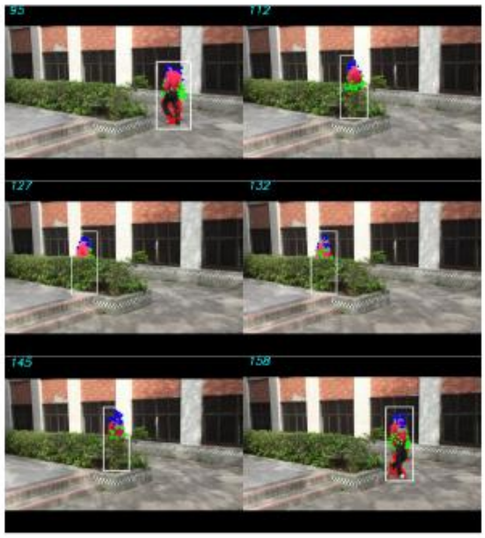
Fig. 11 Target tracking using the proposed scheme are illustrated on frames 34, 46, 49 and 55. In these frames, white rectangle denotes the blob-based object detection result, yellow dots denote the SURF matching feature points, and red rectangle denotes the final tracking results

IV. Experimental Results

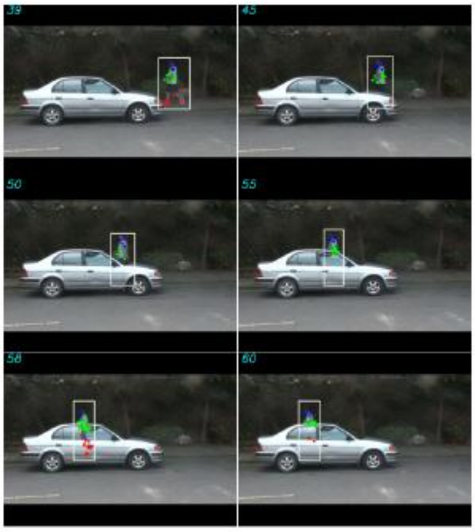
In the experiments, the proposed algorithm is executing on the PC with core 2. First, the SURF badge locating is used to identify the moving targets. Second, the SURF-badge-based target tracking method is used to track the detected targets. All the test videos are recorded within the open space in Chung-Hua University.

A. SURF Feature Points Detection on the Moving Objects

We detect the SURF feature points on the moving object by using SURF algorithm. The detected SURF feature points form a set F that is used to serve as the badge of the detected object. In Fig. 12, we illustrate that the detected SURF feature points are located on the moving object within the successive frames. In these figures, red, green and blue dots denote the detected SURF feature points on different body portions. It is obvious that although the SURF feature points on the low portions are missing, the moving object can be still tracked successfully based on the SURF point matching on the upper portion. Fig. 13 shows the SURF matching process. The dynamic updating of the SURF feature points described in (4) is applied for the robust tracking. In Fig. 13, the SURF feature points are matched between the successive images with the formula in (3). The threshold in (3) is set as 0.6.

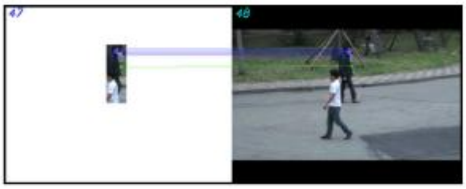


(a)

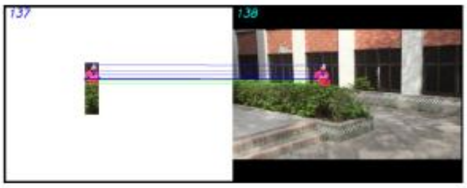


(b)

Fig. 12 Feature points detection on the moving object under normal or occluded conditions (a) Target is occluded by the tree, (b) Target is occluded by the car



(a)



(b)

(c)

Fig. 13 The SURF feature points matching between successive frames

B. Accuracy Analysis for the Target Tracking Using the SURF-Badge-Based Method

In order to evaluate the accuracy of the proposed method, we compare the proposed method to the blob-based method in [16]. The test video sequence is shown in Fig. 15. Table I shows the accuracy analysis for the method in [16] and ours. It can be seen that the tracking accuracy outperforms the blob-based method in [16]. Fig. 14 illustrates the tracking accuracy comparison between the blob-based and surf-badge-based methods. When the tracked targets occluded each other, the blob-based method can't segment the individual object within the merged image blob. On the contrary, the occlusion problem can be overcome with the aids of SURF badges. In Fig. 15, we can see that each individual target can tracked successfully under the partial occlusion situation. The tracking accuracy is analyzed with the Euclidean distance for the center position of tracked target and ground truth position. The experimental results show that the proposed SURF-badge-based method can track the target with higher accuracy than the conventional methods. The efficiency of the proposed algorithm can approach 10-12 frames per second with the resolution of 640×480.

TABLE I
THE TRACKING ACCURACY ANALYSIS BETWEEN THE BLOB-BASED AND SURF-BADGE-BASED METHODS

Method	Blob-Based-tracking	Our proposed Method
Ground truth	293	293
Correct	268	275
Correct Rate	91%	93%

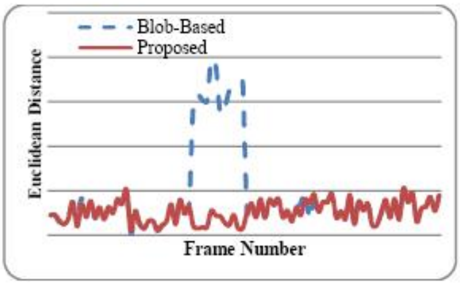


Fig. 14 Tracking accuracy analysis.

Fig. 15 Video sequence used to test the tracking accuracy

V. Conclusion

In this paper, we propose a SURF-badge-based target tracking method to overcome the occlusion problem. First, the blob-based object detection and verification is used to initialize the object tracking scheme. Second, the moving object region is segmented into three portions for locating the SURF feature points as the badge of moving object. Finally, the dynamic updating of the SURF feature points is applied for the robust tracking. The experimental results show that the accuracy of individual tracking under serious occlusion can be higher than 90% and the efficiency can approach 10-12 fps. The future works focus on the refining the tracking accuracy for the multiple targets' segmentation and tracking.

References

[1] J. Assfalg, A. D. Bimbo, and M. Hirakawa, "A mosaic-based query language for video databases," *IEEE International Symposium on Visual Language*, pp. 31-38, 2000.

[2] S. Dagtas, W. Al-Khatib, A. Ghafoor, and R.L. Kashyap, "Models for Motion-Based Video Indexing and Retrieval," *IEEE Transactions on Image Processing*, vol. 9, no.1, pp. 88-101, 2000.

[3] M. Petkovic and W. Jonker, "Content-based video retrieval by integrating spatio-temporal and stochastic recognition of events," *IEEE Workshop on Detection and Recognition of Events in Video*, pp.75-82, 2001.

[4] I. Haritaoglu, D. Harwood, and L.S. Davis, "W4: Who? When? Where? What? A real time system for detecting and tracking people," *Third IEEE International Conference on Automatic Face and Gesture Recognition*, 1998. Proceedings, pp. 222-227, 1998.

[5] C.W. Lin, Z.H. Ling, Y.C. Chang, and C.J. Kuo, "Compressed-domain fall incident detection for intelligent home surveillance," *IEEE International Symposium on Circuits and Systems*, 2005. ISCAS 2005, vol. 4, pp. 3791-3784, 2005.

[6] C.R. Jung, "Efficient Background Subtraction and Shadow Removal for Monochromatic Video Sequences," *IEEE Transactions on Multimedia*, vol. 11, no. 3, pp. 571-577, 2009.

[7] J. Shi and C. Tomasi, "Good features to track," *Proceedings of the IEEE Computer Vision and Pattern Recognition*, pp. 593-600, 1994.

[8] D. G. Lowe, "Distinctive Image Features from Scale-Invariant Keypoints," *International Journal of Computer Vision*, vol. 60, no. 2, pp. 91-110, Jan 2004.

[9] H. Bay, A. Ess, T. Tuytelaars, and L.V. Gool, "Speeded-Up Robust Features," *Proceedings of the 9th European Conference on Computer Vision*, vol. 3951, pp. 404-417, May 2006.

[10] S. Wang, X. Wang, and H. Chen, "A stereo video segmentation algorithm combining disparity map and frame difference," *International Conference on Intelligent System and Knowledge Engineering*, vol. 1, pp. 1121-1124, 2008.

[11] A. Ilyas, M. Scuturici, and S. Miguet, "Real Time Foreground-Background Segmentation Using a Modified Codebook Model," *IEEE International Conference on Advanced Video and Signal Based Surveillance*, pp. 454-459, 2009.

[12] C. Wren, A. Azarbayejani, T. Darrell, and A. Pentland, "Pfinder: Real-Time Tracking of the Human Body," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 19, no. 7, pp. 780-785, July 1997.

[13] M. Xu, J. Orwell, L. Lowey, and D. Thirde, "Architecture and Algorithms for Tracking Football Players with Multiple Cameras," *Image and Signal Processing, IEE Proceedings*, vol. 152, no. 2, pp. 232-241, April 2005.

[14] Y. Ren, C.S. Chua, and Y.K. Ho, "Motion detection with non-stationary background," *International Conference on Image Analysis and Processing*, pp. 78-83, 2001.

[15] Ethem Alpaydin: Introduction to Machine Learning. MIT Press, Cambridge (2004).

[16] C.C. Lien, C.C. Han, J.H. Tang, and J.C. Wang, "A Multiple Target Tracking System with Close-up Zooming Using the Cooperative Cameras," *Journal of Information Technology and Application*, pp. 215-227, 2006.

[17] L. M. J. Florack, B. M. Ter Haar Romeny, J. J. Koenderink, and M. A. Viergever, "General intensity transformations and differential invariants," *Journal of Mathematical Imaging and Vision*, vol. 4, no. 2, pp. 171-187, 1994.

[18] Z. H. Khan and I.Y.-H. Gu, "Joint Feature Correspondences and Appearance Similarity for Robust Visual Object Tracking," *IEEE Transactions on Information Forensics and Security*, vol. 5, no. 3, pp. 591-606, 2010.

四、建議

無

五、攜回資料名稱及內容

論文光碟片

六、其他

　無

國科會補助計畫衍生研發成果推廣資料表

日期:2013/10/31

<table>
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101 年度專題研究計畫研究成果彙整表

計畫主持人：連振昌　計畫編號：101-2221-E-216-035-

計畫名稱：使用最低相關 LBPH 影像紋理特徵之瞌睡偵測系統

成果項目			量化：實際已達成數（被接受或已發表）	量化：預期總達成數(含實際已達成數)	量化：本計畫實際貢獻百分比	單位	備註（質化說明：如數個計畫共同成果、成果列為該期刊之封面故事...等）
國內	論文著作	期刊論文	0	0	100%	篇	
		研究報告/技術報告	0	0	100%		
		研討會論文	0	0	100%		
		專書	0	0	100%		
	專利	申請中件數	0	0	100%	件	
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		博士生	0	0	100%		
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國外	論文著作	期刊論文	1	1	100%	篇	Cheng-Chang Lien, Cheng-Ta Hsieh and Ming-Hsiu Tsai,’’Vehicle Counting without Background Modeling,’ accept to publish in Journal of Marine Science and Technology. (SCIE)（通訊作者）
		研究報告/技術報告	0	0	100%		
		研討會論文	2	2	100%		[1]Cheng-Chang Lien, Kuan-Lin Yu, Cheng-Ta Hsieh, Yan-Fan Chen, and Chien-Hsiang Wang,’ Blur Image

							Using Iterative Super-pixels Grouping Method,' International Conference on Machine Learning and Cybernetics (ICMLC) 2013, Tianjin China, pp. 1161-1167, July 14-17, 2013. (EI) [2]Cheng-Chang Lien, Shin-Ji Lin, Cheng-Yang Ma, and Yu-Wei Li,' Surf-Badge-Based Target Tracking,' ICISVC 2013 : International Conference on Image, Signal and Vision Computing, Tokyo, Japan, May 30-31, pp. 1309-1315.
		專書	0	0	100%	章/本	
	專利	申請中件數	0	0	100%	件	
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	技術移轉	件數	0	0	100%	件	
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		博士生	0	0	100%		
		博士後研究員	0	0	100%		
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其他成果 (無法以量化表達之成果如辦理學術活動、獲得獎項、重要國際合作、研究成果國際影響力及其他協助產業技術發展之具體效益事項等，請以文字敘述填列。)	本計畫之研究成果正與123視科技公司洽談合作

	成果項目	量化	名稱或內容性質簡述
科教處計畫加填項目	測驗工具(含質性與量性)	0	
	課程/模組	0	
	電腦及網路系統或工具	0	
	教材	0	
	舉辦之活動/競賽	0	
	研討會/工作坊	0	
	電子報、網站	0	
	計畫成果推廣之參與（閱聽）人數	0	

國科會補助專題研究計畫成果報告自評表

請就研究內容與原計畫相符程度、達成預期目標情況、研究成果之學術或應用價值（簡要敘述成果所代表之意義、價值、影響或進一步發展之可能性）、是否適合在學術期刊發表或申請專利、主要發現或其他有關價值等，作一綜合評估。

1. 請就研究內容與原計畫相符程度、達成預期目標情況作一綜合評估

■達成目標

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與一二三視科技公司洽談合作

3. 請依學術成就、技術創新、社會影響等方面，評估研究成果之學術或應用價值（簡要敘述成果所代表之意義、價值、影響或進一步發展之可能性）（以 500 字為限）

近年來，瞌睡偵測系統被廣泛應用於駕駛瞌睡偵測與遠距教學系統中。瞌睡偵測方法的研究可分為基於感測器和基於電腦視覺這兩種方法。在基於感測器的方法中，腦波圖（EEG）和眼電圖（EOG）是用記錄生理信號的方式來檢測睡眠狀態。然而，基於感測器的方法往往是侵入式的，相對的，基於視覺的方法則是從數位視覺信號中截取圖像的特徵或人類行為特徵等，是屬於非侵入性的方法。在本計畫中，我們將專注開發出一款基於以視覺為基礎之眼睛狀態辨識技術，並以此技術發展瞌睡偵測系統。