

行政院國家科學委員會專題研究計畫 成果報告

多攝影機視訊監控與人物外貌辨識 研究成果報告(精簡版)

計畫類別：個別型
計畫編號：NSC 99-2218-E-468-005-
執行期間：99年02月01日至99年11月15日
執行單位：亞洲大學資訊工程學系

計畫主持人：林智揚

計畫參與人員：碩士班研究生-兼任助理人員：劉于菁
大專生-兼任助理人員：張朝欽
大專生-兼任助理人員：尤淨存
大專生-兼任助理人員：張偉文
大專生-兼任助理人員：謝慧萍
博士班研究生-兼任助理人員：蔡濠全

報告附件：出席國際會議研究心得報告及發表論文

處理方式：本計畫可公開查詢

中華民國 100 年 01 月 09 日

行政院國家科學委員會補助專題研究計畫 成果報告
 期中進度報告

多攝影機視訊監控與人物外貌辨識

計畫類別： 個別型計畫 整合型計畫

計畫編號：NSC－99－2218－E－468－005

執行期間：99年2月1日至 99年11月15日

計畫主持人：林智揚

共同主持人：

計畫參與人員：張朝欽、尤淨存、謝慧萍、張偉文、劉于菁、蔡濠全

執行單位：亞洲大學資訊工程學系

成果報告類型(依經費核定清單規定繳交)： 精簡報告 完整報告

本成果報告包括以下應繳交之附件：

- 赴國外出差或研習心得報告
- 赴大陸地區出差或研習心得報告
- 出席國際學術會議心得報告
- 國際合作研究計畫國外研究報告

處理方式：除除列管計畫及下列情形者外，得立即公開查詢

涉及專利或其他智慧財產權， 一年 二年後可公開查詢

中華民國 100 年 1 月 10 日

行政院國家科學委員會專題研究計畫成果報告

多攝影機視訊監控與人物外貌辨識

Human Appearance Identification Based on a Robust Multi-camera Surveillance System

計畫編號：NSC - 99 - 2218 - E - 468 - 005

執行期限：99年2月1日至99年11月15日

主持人：林智揚

執行機構及單位名稱：亞洲大學資訊工程學系

[註]:本計畫內容已發表於國際會議:**Chih-Yang Lin**, Chao-Chin Chang, Wei-Wen Chang, Meng-Hui Chen, and Li-Wei Kang, "Real-Time Robust Background Modeling Based on Joint Color and Texture Descriptions," *Proceedings of The Fourth International Conference on Genetic and Evolutionary Computing (ICGEC 2010)*, Shenzhen, China, December 13-15, pp. 622-625, 2010.

■ Abstract

Background construction is the base of object detection and tracking for the machine vision system. Traditional background modeling methods often require complicated computations and are sensitive to illumination changes and shadow interference. In this paper, we propose a block-based background modeling method, which fully utilizes the color and texture characteristics of each incoming frame. The proposed method is quite efficient and is capable of resisting illumination changes and shadow disturbance. Experimental results show that our method is suitable for real-world scenes and real-time applications.

Keywords-component; Background modeling; motion detection; Gaussian mixture modeling

■ 中文摘要

背景建立法是機器視覺系統中遺物動偵測與追蹤的基礎。傳統背景建立法模型通常需要很複雜的計算量，並且容易受到光線變化、雜訊、與陰影的干擾。在本篇論文中，我們提出一個以區塊為基礎之背景模型建立法，對每一張攝像進來的影像，同時擷取顏色與紋理的資訊。我們所提的方法十分的有效率，並且可以抵抗光線變化、雜訊、與陰影的干擾。實驗結果顯示我們的方法非常適合應用於真實的監控環境。

關鍵字：背景模型；移動物偵測；高斯混合模型

計畫緣由及目的

Object detection is a very important task in video surveillance. In general, background modeling is utilized for

distinguishing between foreground and background. With a robust background model, the objects can then be successfully extracted from the background.

In literature, a number of methods for detecting moving objects have been proposed, where many different features are employed for background modeling. The most frequently used features are based on color information. For example, a color statistical approach [13] accomplished background subtraction without being affected by shadow; furthermore, the algorithm is also implemented by a DM270 iMX and DSP subsystem [9] for DV applications. In addition to the running statistics (e.g. average) of neighboring frames, a one-Gaussian adaptive modeling method is also a popular approach that can be found in [14].

However, one-Gaussian modeling cannot cope with dynamic background changes. Therefore, the Gaussian mixture modeling (GMM) approach [11-12, 15] was developed by means of using more than one Gaussian model for each pixel. Pixel values that do not fit the model would be recognized as foreground areas. One of the examples using GMM was developed (three Gaussian) for traffic monitoring [4]. Other discussions on implementation using GMM can be found in [2] and [10], which provide details of Stauffer and Grimson's algorithm [12].

Motion-based and edge-based methods are other approaches for background modeling. The motion-based method [13] utilizes optical flow to detect salient motion over frames. This approach usually suffers from complicated computations. The edge-based method [8] considers only edge information in frames and constructs edge histograms as a feature description for background modeling. The histogram-matching process determines the performance of this method.

Recently, Heikkilä and Pietikäinen [5-6] proposed a texture-based background construction method using local binary patterns (LBPs). LBPs have the property of tolerance for illumination changes. However, LBPs are not robust as shown when the central pixel value used in LBP is affected by noise or swaying trees, the corresponding LBP histogram would not be stable. This would increase the possibilities of false positive and false negative cases, respectively. Besides, the overlapping block strategy and histogram-matching process proposed in [5-6] make their method inefficient.

In this paper, we propose a hybrid method for background modeling based on the texture and color information from each frame. Instead of using LBPs, we propose a new texture descriptor, the idea of which is inspired by BTC (block truncation coding), [3] to enhance the tolerance of illumination changes and shadow interference. Furthermore, the background model integrated color and texture can effectively resist noise disturbance. Due to the computational simplicity of the proposed method, our background modeling has high efficiency and is suitable for real-time applications.

The remainder of this paper is organized as follows. First, we briefly review Heikkilä and Pietikäinen's method in Section 2. Then, in Section 3, we present our new background-modeling scheme based on texture and color descriptions. Empirical results and discussions are given in Section 4, and the conclusions are presented in Section 5.

2. 文献探討

The texture-based method proposed by Heikkilä and Pietikäinen [5-6] first partitions each image frame into overlapping blocks so that the extracted shape of the moving object can be more accurately described. Then, the pixels in each block produce a histogram according to their LBP values. An example of an LBP value for a pixel is illustrated in Fig. 1. Assume that the pixel value is 6 and its surrounding pixels are 5, 9, 3, and 1 in counterclockwise order. If the central pixel is greater than its neighbor, a bit 1 can be generated; otherwise, bit 0 is produced. Fig. 1(b) shows the result of the binary pattern, which indicates that the value of LBP is 2.

The histograms of each block support the background modeling. The history of each block histogram is modeled by K weighted histograms for the purpose of multi-model backgrounds. When a new block histogram comes in, the histogram compares with the K weighted histograms and performs background updating. The update process is similar to Stauffer and Grimson's method [12]. In the updating process, only B ($\leq K$) histograms are selected as the background model. If the incoming histogram is similar to a model histogram, the new block is regarded as a background block; otherwise, it is recognized as a foreground block.

3. 研究方法

In this section, we describe the proposed texture descriptor, texture-based background modeling, and finally the proposed motion detection method based on joint color and texture descriptors.

A. Texture Description

When a camera captures an image, the frame is first divided into non-overlapping blocks with a size of $n \times n$ pixels. For each block, the mean value m is calculated and defined as follows:

$$m = \frac{1}{n \times n} \sum_{i=1}^n \sum_{j=1}^n x_{ij}, \quad (1)$$

where x_{ij} indicates the pixel value in the position (i, j) of the block.

The output of each image block is a binary bitmap BM with a size equal to the block. The bitmap is generated by Eq. (2), where bit "1" in a BM denotes that the corresponding pixel value of the block is greater than m ; otherwise, the bit is set to 0. Therefore, the set of BM 's is the texture descriptor for an input frame.

$$b_{ij} = \begin{cases} 1, & \text{if } x_{ij} > m, \\ 0, & \text{otherwise,} \end{cases} \quad (2)$$

where b_{ij} means the bit in the position (i, j) of a BM .

B. Texture-based Background Modeling

In the beginning, each input frame is divided into non-overlapping blocks, and each block is transformed into a bitmap according to the proposed texture descriptor. Note that since the pixels in a smooth block are sensitive to their mean value, the corresponding texture description may not be robust. In order to solve this problem, we change the bitmap generation equation slightly from Eq. (2) to Eq. (3). The value TH_{smooth} is usually set to 8 according to our experimental results.

$$b_{ij} = \begin{cases} 0, & \text{if } x_{ij} < m + TH_{smooth}, \\ 1, & \text{otherwise.} \end{cases} \quad (3)$$

In addition, the captured image in a real surveillance system is a color image, so each block should have three masks for red, green, and blue channels, respectively. For convenient description, one block is represented by only one mask. It is straightforward to extend the idea to three masks for each block. Fig. 2 shows the image generated by the proposed texture descriptor. The fact that the texture of the image in Fig. 2 is clearly presented proves the validity of this descriptor.

We now consider how to use the feature vector to construct the background model. The background model for each block consists of K weighted bitmaps, $\{BM_1, BM_2, \dots, BM_K\}$, where each weight is between 0 and 1, and the K weights have a sum of 1. The weight of the k^{th} bitmap is denoted as w_k . When a new block BM_{new} comes in, BM_{new} is

compared with the K bitmaps by the following similarity equation, where m is in the range of $[1, K]$:

$$Sim(BM_{new}, BM_m) = \sum_{i=1}^n \sum_{j=1}^n (b_{ij}^{new} \cap b_{ij}^m). \quad (4)$$

If $\max_m Sim(BM_{new}, BM_m)$ is greater than a predefined threshold TH_D , the block BM_{new} matches BM_m in the background model, and the update process will be invoked; otherwise, BM_{new} is regarded as a foreground block, and the unmatched process will be launched. The complexity of the above distance calculation is quite low since it requires only bit operations.

The update and unmatched processes are derived from Stauffer and Grimson's method [12]. When an incoming block is considered as a background block, the weights of the background model are updated by:

$$w'_K = \alpha M_K + (1 - \alpha) w_K, \quad (5)$$

where α is the learning rate and M_k is 1 for the best-matched bitmap and 0 for the others.

The learning rate determines the speed of adaptation. That is, larger learning rates result in faster adaptations. As to each bit b_{ij}^m of the best-matched bitmap BM_m , the update rules are given in Eqs. (6) and (7). In Eq. (6), when t is greater than a predefined threshold T , t should be set to T to meet the self-adaptation requirement.

$$p_{ij}^{m'} = (1 - \frac{1}{t}) p_{ij}^m + \frac{1}{t} b_{ij}^{new}, \quad \text{where } t \text{ represents the } t\text{th} \quad (6)$$

frame and $p_{ij}^m = 0$ in the initial stage.

$$b_{ij}^{m'} = \begin{cases} 0, & \text{if } p_{ij}^{m'} \leq 0.5, \\ 1, & \text{otherwise.} \end{cases} \quad (7)$$

If the incoming block is a foreground block, the unmatched process replaces the bitmap that has the lowest weight in the background model with the incoming block. Then, the weight of the new block is set to a low initial weight of 0.01 in our experiments. Finally, the weights of the background model are renormalized in order to have a sum of one.

In the above description, the incoming block may match the bitmap with a low weight and is regarded as a background block. However, the low weight means that the corresponding bitmap has a low probability of being a background block. To solve this problem, the weights of the background model are sorted in decreasing order, and only the first B bitmaps are selected as the background model, such that:

$$\sum_{i=1}^B w_i > TH_B, \quad \text{where } TH_B \text{ is a predefined threshold.} \quad (8)$$

C. Motion Detection Based on Joint Color and Texture Background Models

The proposed method is to detect moving objects in the captured frames based on the constructed background models. In Section 3.2, we have proposed a texture-based background modeling method for moving object detection. However, a false negative may occur when the texture description of the moving object is similar to that of the background. Such a case can be greatly alleviated with the help of a color background model. The construction of a color background model for each block is done by using the Stauffer and Grimson's algorithm [12], where the input for a block is the mean vector containing R, G, and B channel mean values calculated by Eq. (1), respectively.

After the color background model is constructed, the moving objects can also be detected. The final result of motion detection is the intersection of CM and TM , where CM and TM represent the detection results using the color and texture models, respectively.

4. 結果

The performance of the proposed method is compared with two state-of-the-art approaches [5, 12] using several video sequences. The video sequences were acquired from real indoor and outdoor environments. The simulated environment for the experiments is equipped with a 1.8 GHz Core 2 Intel processor and 2 GB of memory. The image resolution was set to 320×240 pixels. All algorithms were implemented in C++.

For the sake of labeling and segmenting the foreground pixels, the connected components algorithm [1, 7] is applied to each background modeling method. The parameters used in the experiments are listed as in Table 1, where α is the learning rate, TH_B is used in Eq. (10), K denotes the number of Gaussians, X represents the fact that the parameter is not required in this method, BS means the block size, and $LBP_{P,R}$ is only used in Heikkilä and Pietikäinen's method [5-6] and represents using radius R to find P neighbors such as the example shown in Fig. 1(a).

The performance comparisons of these three methods are presented in Table 2, where the last row denotes the connected components labeling (CCL) method that is also involved in the background construction. From this table we can observe that the proposed method is much faster than other methods because the proposed block-based approach requires only bit operations. Heikkilä and Pietikäinen's method is slowest since they divide each frame into overlapping blocks, and the size of the LBP histogram significantly affects the performance.

Figs. 3 and 4 show the indoor scenes with some illumination changes, where people were walking towards the camera. The detection results can be observed that Stauffer and Grimson's method [12] is very sensitive to illumination changes, and Heikkilä and Pietikäinen's method [5-6] also suffers from noise interference. On the contrary,

the proposed method has a better ability to resist illumination changes because we simultaneously consider the color and texture information and gather more information from an area instead of a single pixel. Since the non-overlapping block approach is adopted, the contour of the proposed method is coarser than that of the compared methods.

More detection results of the outdoor scenes compared with Stauffer and Grimson's method are shown in Figs. 5 and 6. Although the proposed method may result in more holes on the inner areas of the moving object, such an effect can be eliminated by the morphology operations, as shown in Fig. 6.

5. 討論

In this paper, we proposed a joint color- and texture-based method for background modeling. The proposed method has the following advantages: (1) tolerance for illumination changes, (2) low computations, and (3) easy implementation. The experimental results show that our method is quite efficient (a frame rate of 62.5 can be achieved). Since the proposed method possesses a very high frame rate, it is quite suitable for real-time applications or low-power computation systems such as cell phones and personal digital assistants (PDAs).

ACKNOWLEDGMENT

This work was supported by National Science Council, Taiwan, under Grants NSC 99-2218-E-468-005 and NSC 99-2815-C-343-017-E.

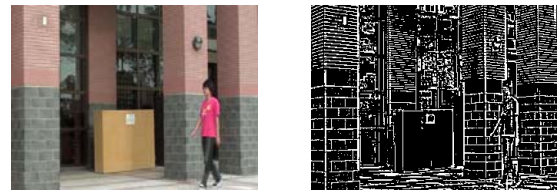
6. 參考資料

- [1] F. Chang, C. J. Chen, and C. J. Lu, "A Linear-Time Component-Labeling Algorithm Using Contour Tracing Technique," *Computer Vision and Image Understanding*, vol. 93, no. 2, pp. 206-220, 2004.
- [2] Y. Dedeoglu, B. U. Töreyn, U. Güdükbay, and A. E. Çetin, "Silhouette-Based Method for Object Classification and Human Action Recognition in Video," *Proceedings of ECCV Workshop on Computer Vision in Human-Computer Interaction*, Graz, Austria, pp. 64-77, 2006.



(a) Neighbors of the central pixel (b) Binary pattern
Fig. 1. An example of generating LBP.

- [3] E. J. Delp and O. R. Mitchell, "Image Compression Using Block Truncation Coding," *IEEE Transactions on Communications*, vol. 27, no. 9, pp. 1335-1341, 1979.
- [4] N. Friedman and S. Russell, "Image Segmentation in Video Sequences: A Probabilistic Approach," *Proceedings of the 13th Conference on Uncertainty in Artificial Intelligence*, San Francisco, pp. 175-181, 1997.
- [5] M. Heikkilä and M. Pietikäinen, "A Texture-Based Method for Modeling the Background and Detecting Moving Objects," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 28, no. 4, pp. 657-662, 2006.
- [6] M. Heikkilä, M. Pietikäinen, and J. Heikkilä, "A Texture-Based Method for Detecting Moving Objects," *Proceedings of British Machine Vision Conference*, British, pp. 187-196, 2004.
- [7] R. Lumia, L. Shapiro, and O. Zuniga, "A New Connected Components Algorithm for Virtual Memory Computers," *Computer Vision, Graphics, and Image Processing*, vol. 22, no. 2, pp. 287-300, 1983.
- [8] M. Mason and Z. Duric, "Using Histograms to Detect and Track Objects in Color Video," *Proceedings of the 30th on Applied Imagery Pattern Recognition Workshop*, Washington, DC, USA, pp. 154-159, 2001.
- [9] T. Matsuyama, T. Ohya, and H. Habe, "Background Subtraction for Non-Stationary Scenes," *Proceedings of the 4th Asian Conference on Computer Vision*, Taipei, Taiwan, pp. 662-667, 2000.
- [10] O. W. Power, "Understanding Background Mixture Models for Foreground Segmentation," *Proceedings of Image and Vision Computing*, Auckland, New Zealand, pp. 267-271, 2002.
- [11] C. Stauffer and W. E. L. Grimson, "Adaptive Background Mixture Models for Real-Time Tracking," *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, Fort Collins, Colorado, USA, pp. 246-252, 1999.
- [12] C. Stauffer and W. E. L. Grimson, "Learning Patterns of Activity Using Real-Time Tracking," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 22, no. 8, pp. 747-757, 2000.
- [13] L. Wixson, "Detecting Salient Motion by Accumulating Directionally-Consistent Flow," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 22, no. 8, pp. 774-780, 2000.
- [14] C. R. Wren, A. Azarbayejani, T. Darrell, and A. P. Pentland, "Pfinder: Real-Time Tracking of the Human Body," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 19, no. 7, pp. 780-785, 1997.
- [15] Z. Zivkovic, "Improved Adaptive Gaussian Mixture Model for Background Subtraction," *Proceedings of the 17th International Conference on Pattern Recognition*, Cambridge, UK., pp. 28-31, 2004.



(a) Original image (b) Texture description
Fig. 2. The proposed texture descriptor.

TABLE I. The parameter values used in the experiments

Parameters	α	TH_B	K	BS	TH_{smooth}	TH_D	$LBP_{P,R}$
Stauffer and Grimson's method	0.005	0.9	3	X	X	X	X
Heikkilä and Pietikäinen's method	0.005	0.9	3	4x4	8	0.65	$LBP_{4,2}$
Proposed method	0.005	0.9	3	4x4	8	0.75	X

TABLE II. Frame rates using different methods

Methods	Stauffer and Grimson's method	Heikkilä and Pietikäinen's method	Proposed method
Frame rate	20.94	3.54	57.55
Frame rate with CCL	20.01	3.38	45.32



Fig. 3. Detection results of the first sequence: (a) original image, (b) Stauffer and Grimson's method, (c) Heikkilä and Pietikäinen's method, and (d) proposed method.

Fig. 4. Detection results of the second sequence: (a) original image, (b) Stauffer and Grimson's method, (c) Heikkilä and Pietikäinen's method, and (d) proposed method.

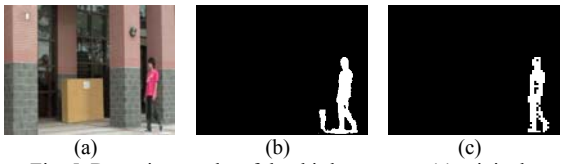


Fig. 5. Detection results of the third sequence: (a) original image, (b) Stauffer and Grimson's method, and (c) proposed method.



Fig. 6. Detection results of the fourth sequence: (a) original image, (b) Stauffer and Grimson's method, (c) proposed method, and (d) proposed method with morphology.

國科會補助專題研究計畫項下出席國際學術會議心得報告

日期： 100年 1月 10日

計畫編號	NSC - 99 - 2218 - E -468 - 005		
計畫名稱	多攝影機視訊監控與人物外貌辨識		
出國人員姓名	林智揚	服務機構及職稱	亞洲大學 資訊工程學系 助理教授
會議時間	99年11月4日至99年11月6日	會議地點	日本福岡
會議名稱	(中文) (英文) The Fifth International Conference on Broadband and Wireless Computing, Communication and Applications (BWCCA2010)		
發表論文題目	(中文) (英文) Noise-resistant Joint Fingerprinting and Decryption Based on Vector Quantization		

出席2010年第5屆 International Conference on Broadband and Wireless Computing, Communication and Applications 報告

報告人：林智揚
亞洲大學資訊工程學系 助理教授
TEL：(04)23323456 轉 20102
FAX：(4)23320718
E-mail：andrewlin@asia.edu.tw

一、緣由

BWCCA 2010(International Conference on Broadband and Wireless Computing, Communication and Applications)已舉辦五年之久，今年在日本福岡的福岡工業大學舉辦。

此 Conference 從 182 篇投稿論文中接受了 53 篇論文，主軸主要針對網路應用等議題進行討論，包括網路安全、多媒體安全，無線網路、異質性網路等議題。由於網路的普及，目前電腦的使用大部分已跟網路世界密不可分，探討網路上相關的研究與議題，有其必要性。BWCCA 會議每年舉行一次，其目的就是讓電腦專家們共同參與討論他們的研究成果。今年是五屆，很幸運地，今年我們的論文被接受並應邀參加，除了發表最近的研究成果外，也聽取了相關領域教授們所提出的研究報告

二、參加會議經過

今年的第5屆 International Conference on Broadband and Wireless Computing, Communication and Applications (BWCCA 2010)是由日本福岡的福岡工業大學主辦。本次會議，在日本福岡的福岡工業大學舉行。此次會議投稿的論文篇數共有 182 篇文章，最後錄取的文章篇數 53 篇，錄取率低於 30%。為了確保論文的品質，每篇文章均經由 3 位以上的議程委員仔細評審過，整個審查制度可以說是相當地嚴謹。我們的論文被安排在此會議下之 International Workshop on Cloud, Wireless and E-Commerce (CWECs 2010) 中。

本會議可以說是一個非常盛大的國際學術研討會，會議日程從 2010 年 11 月 4 日至 11 月 6 日。參加會議的人數很多，他們來自各個不同的機構，有學術機構、研究機構、產業機構、政府機構。從第一天開幕起就十分熱鬧，到最後一天仍有不少人參與會議的研討，可以說是相當成功的一次國際學術會議。會議的論

文均被收錄在論文集，而此論文集由 IEEE CS Press 所出版。

本次會議本人所發表的論文為：**Noise-resistant Joint Fingerprinting and Decryption Based on Vector Quantization**，安排在大會中第三天上午，Session 名稱為：**Image Secret, Sensor Network, and Computer Security**，此 session 共 9 篇論文發表，包含了網路安全與多媒體安全相關議題。本篇論文主要探討監控環境中，隱私權保護相關議題，發表時間約 20 分鐘，現場討論熱烈。

三、與會心得

從本次的會議，我們可以發現相關領域仍存在許多有趣的研究問題，而這些問題也將是未來熱門的研究重點。藉由本次會議的交流，我們可以和許多國家的研究人員，進行研究與資訊上的交流，是一個非常難得的經驗。而本人在會議期間，與發表人員互動良好，也因此認識多位來自不同國家的研究人員，整個過程非常圓滿順利。

- 攜回資料：**Proceedings of the 5th International Conference on Broadband and Wireless Computing, Communication and Applications** 論文集光碟片一片。

國科會補助計畫衍生研發成果推廣資料表

日期:2011/01/09

國科會補助計畫	計畫名稱: 多攝影機視訊監控與人物外貌辨識
	計畫主持人: 林智揚
	計畫編號: 99-2218-E-468-005- 學門領域: 圖形辨識
無研發成果推廣資料	

99 年度專題研究計畫研究成果彙整表

計畫主持人：林智揚		計畫編號：99-2218-E-468-005-				計畫名稱：多攝影機視訊監控與人物外貌辨識	
成果項目		量化			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）	
		實際已達成數（被接受或已發表）	預期總達成數（含實際已達成數）	本計畫實際貢獻百分比			
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	2	0	100%		
		專書	0	0	100%		
	專利	申請中件數	0	0	100%	件	
		已獲得件數	0	0	100%		
	技術移轉	件數	0	0	100%	件	
		權利金	0	0	100%	千元	
	參與計畫人力 （本國籍）	碩士生	1	0	100%	人次	
		博士生	1	0	100%		
		博士後研究員	0	0	100%		
		專任助理	0	0	100%		
國外	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	2	0	100%		
		專書	0	0	100%		章/本
	專利	申請中件數	0	0	100%	件	
		已獲得件數	0	0	100%		
	技術移轉	件數	0	0	100%	件	
		權利金	0	0	100%	千元	
	參與計畫人力 （外國籍）	碩士生	0	0	100%	人次	
		博士生	0	0	100%		
		博士後研究員	0	0	100%		
		專任助理	0	0	100%		

<p>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。)</p>	<p>擔任 The Fourth International Conference on Genetic and Evolutionary Computing (ICGEC 2010)國際會議之 Session Chair</p>
--	---

	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

未達成目標（請說明，以 100 字為限）

實驗失敗

因故實驗中斷

其他原因

說明：

2. 研究成果在學術期刊發表或申請專利等情形：

論文： 已發表 未發表之文稿 撰寫中 無

專利： 已獲得 申請中 無

技轉： 已技轉 洽談中 無

其他：（以 100 字為限）

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）

本計畫特別針對監控系統議題研究，並完成穩健性背景建立法之開發。背景建立法是機器視覺系統中遺物動偵測與追蹤的基礎。傳統背景建立法模型通常需要很複雜的計算量，並且容易受到光線變化、雜訊、與陰影的干擾。在本計畫中，我們提出一個以區塊為基礎之背景模型建立法，對每一張攝像進來的影像，同時擷取顏色與紋裡的資訊。我們所提的方法十分的有效率，並且可以抵抗光線變化、雜訊、與陰影的干擾。實驗結果顯示我們的方法非常適合應用於真實的監控環境。