行政院國家科學委員會專題研究計畫 成果報告

醫學影像資料庫自動檢索系統之研製
研究成果報告(精簡版)

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I. Introduction

Content-based image retrieval (CBIR) is the current trend of designing image database systems as opposed to text-based image retrieval [2, 21, 11, 16, 19, 22, 42]. Rather than proceeding via a manually generated text-based description, CBIR works by matching the query image against each database image according to the contents of images. CBIR approach can discriminate images and retrieve desired images from the database based on their visual contents such as shapes [2, 21, 26], colors [11, 30], textures [10, 19], or spatial relationships among objects [5, 6, 15, 16, 17, 22, 24, 35, 42]. In such systems, more objective low-level image descriptions can be automatically extracted by machines and subsequently used as indexing tools or discriminating features for image retrieval.

One of the primary tools used by physicians is the comparison of previous and current medical images associated with pathologic condition. The benefits emanating from the application of content-based approaches to medical image retrieval range from clinical decision support to medical education and research [44]. As the amount of pictorial information stored in medical databases is growing, efficient image indexing and retrieval becomes very necessary.

Different from the general-purpose ones, medical image retrieval systems utilize the retrieval with pathology bearing regions (PBR) that is highly localized. To retrieve similar images efficiently, we develop a medical image representation which can capture lesion colors, tumor shapes, sizes, and spatial relationships between canonical organs and abnormal objects. The image representation has the properties of image scaling-, translation- and rotation-invariance, and these properties are necessary for an image database system with good accuracy. The proposed image retrieval system is not only consistent with human's perception, but also is powerful in terms of accuracy and flexibility.

The rest of this project is structured as follow. Section II outlines the related works. The proposed medical image representation is presented in Section III. The proposed pattern similarity scheme for medical image retrieval is presented in Section IV. The experimental results of the proposed scheme are apposed in Section V. Finally, Section VI summarizes the conclusions.

II. Related works

For the early versions of image retrieval systems, images in the database are usually indexed by their semantic keywords. Although such an approach can be used in small image databases, both efficiency and effectiveness are decreased for large image databases because a limited number of keywords are insufficient to describe the content of different types of images. Besides, different users may use different keywords to interpret the same visual content of an image. Therefore, the performance of this approach to image retrieval is very sensitive to the keywords employed by the user and the system.

In recent years, there is a growing need for retrieving images based on image's visual contents. Content-Based Image Retrieval (CBIR) approach can discriminate images and retrieve desired images from the database based on their visual contents such as shapes [2, 21, 26], colors [11, 30], textures [10, 19], or spatial relationships among objects [5, 6, 15, 16, 17, 22, 24, 35, 42]. In such systems, more objective low-level image descriptions can be automatically extracted by machines and subsequently used as indexing tools or discriminating features for image retrieval.

In medical images, the contour of abnormal object contains much important information for making diagnosis of disease [9]. The shape of tumor is the important feature for judging it as malignant or benign, and the size of tumor is the key indicator of tumor spread. Spatial relationship is another important feature for medical image retrieval. Because the location of lesion or tumor is uncertain, we can retrieve the similar pictures for physicians by the spatial relationship among the tumor and organs. Different spatial knowledge representation methods have been proposed for capturing and representing spatial relations between objects in a picture. Chang et al. [5] proposed the 2D string as a spatial knowledge representation to capture the spatial information about the content of a picture. The basic idea of 2D string is to project the objects of a picture along the *x*- and *y*-axis to form two strings representing the relative positions of objects in these two directions. Since a 2D string preserves the spatial relationships between any two objects in a picture, it has the advantage of facilitating spatial reasoning. Moreover, since a query picture [7] can also be represented as a 2D string, the problem of similarity retrieval becomes a problem of 2D string subsequence matching. Chang et al. [6] extended the idea of 2D strings to form 2D G-strings by introducing several new spatial operators to represent more relative positional relationships among the objects in a picture. The 2D G-string representation embeds more information about spatial relationships between objects, thus the capability of spatial reasoning based on 2D G-strings becomes more general and powerful.

Following the same theory, Lee and Hsu [24] proposed the 2D C-string representation based on a special cutting mechanism for objects. Since the number of objects' subparts generated by this new cutting mechanism is reduced significantly, the length of the string representing a picture becomes much shorter while still preserving the information about spatial relationships among objects. The 2D C-string representation is more economical in terms of storage space efficiency and navigation complexity in spatial reasoning.

The 2D C^+-string representation [17] was proposed later by adding relative metric information to 2D C-strings. As a consequence, reasoning about relative sizes and locations of objects, as well as the relative distance between objects in a symbolic picture becomes possible.

Chang [4] proposed a structure called 9DLT to encode the spatial relationship between objects in terms of nine directions. Let us consider a symbolic image containing four components (or symbols) *A*, *B*, *C* and *D* as shown in Fig. 1. We may use nine directional codes as shown in Fig. 2 to represent the pair-wise spatial relationships between *y*, a referenced component, and *x*, a contrasted component. So we have a 9DLT matrix T for the symbolic image of Fig. 1 as shown in the Fig. 3.

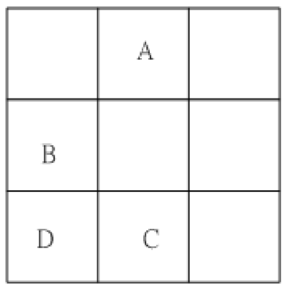

Figure 1: A symbolic image.

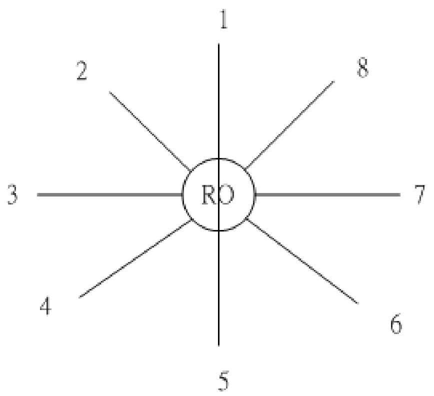

Figure 2: The direction codes.

$$
T = \begin{array}{c} \\ A \\ B \\ C \\ D \end{array} \begin{array}{c} \begin{array}{cccc} A & B & C & D \end{array} \\ \begin{pmatrix} - & - & - & - \\ 8 & - & - & - \\ 1 & 2 & - & - \\ 8 & 1 & 7 & - \end{pmatrix} \end{array}
$$

Figure 3: The 9DLT matrix of Fig. 1.

The representation of spatial relations proposed by Zhou and Ang [41] combines the nine directional relations proposed in 9DLT with the five topological relations, namely, disjoint, meet, partly-overlap, contain, and inside. Instead of combining the nine directional relations with the five topological relations, the 2D-PIR proposed by Nabil et al. [29] combines the 13 projection interval relations with the topological relations.

In addition to above representations of spatial relation, there are many image representations coded by directional relations. They may be divided into two categories: triangular models and rectangle-shaped partition. The triangular model [37] defines every directional area as a triangular area for determining the directional relationship between two objects from each other. The model can determine if one object is in a given direction from another object as shown in Fig. 4.

Except the above methods, two other direction models, direction-relation matrix [13] and 9D-SPA [20], based on rectangle-shaped partition were also proposed. They partition the whole space around a reference object and record into which direction tiles an extended target object falls as shown in Fig. 5. They can provide better approximations for spatial relations between objects with complex structures including shapes such as concave regions or objects with holes. The 9D-SPA method [20] can even support an efficient indexing structure to facilitate search in similarity retrieval.

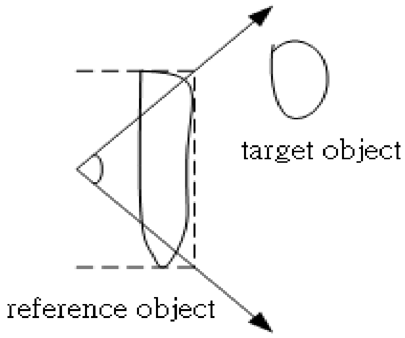

Figure 4: The triangular model for determining the directional relationship between two objects.

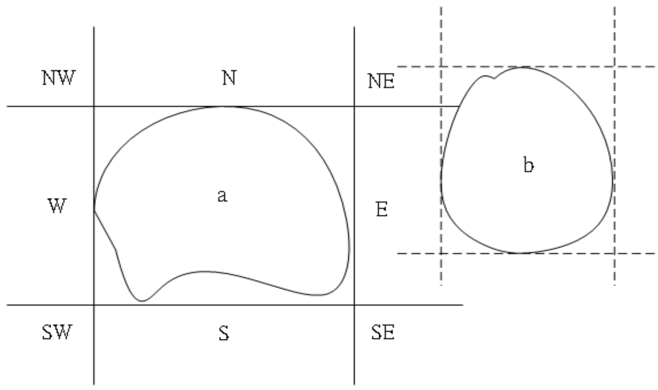

Figure 5: Capturing the direction relation between objects *a* and *b*, based on rectangle-shaped partition.

III. Image representation

To represent a picture using our method, the picture has to be preprocessed first. Assume that the objects in a picture can be identified by some image segmentation and object recognition procedures. Various techniques of image segmentation and object recognition can be found in [43].

In general, there is a dominant object in a medical image, which is the important part for diagnosis. In this project, a new image representation is developed for diagnosis on liver tumor, so the tumor is the dominant object here. To reduce the time complexity and achieve a good effectiveness, the image representation is focused on the tumor, and based on the features of factors in diagnosis. The features include the gray level, size and shape of the tumor and the spatial relationship between canonical organs and the tumor. These features included in the image representation are defined and described as follows:

- gray level of the tumor:

  Since the gray level of tumor is different from canonical organs, the feature is one of the important factors for diagnosis. We define the feature *gl* as the average gray level of the tumor, where $gl \in [0, 255]$.

- Size of the tumor:

  The size of tumor is another important feature for diagnosis. Since the properties of translation-, rotation-, and size-invariance of an image representation are very important for accuracy in CBIR system, the size of tumor is defined as: *size*=the area of tumor/the area of liver, where $size \in [0, 1]$.

- The shape of tumor:

  According to the properties of tumors, since malignant tumors would grow speedily, and violate or stress the canonical tissue, the shape of malignant tumor would have sticks as the roots of tree. So the property is an important indicator to judge whether the tumor is malignant. The shape of tumor defined in this paper is calculated by following steps:

  Step 1. Compute the location of the tumor's centroid, then compute the distance *D* between the tumor's centroid and boundary in each angle θ.

  Step 2. Draw the diagram of curve based on the values of θ and *D*, and the *x* axis and *y* axis represent the θ and *D* respectively. Figure 6 shows two different kinds of diagrams of curve, where *Area*(*A*) and *Area*(*B*) represent the areas included by real line in (a) and (b) respectively, and *MBR*(*A*) and *MBR*(*B*) represent the areas of minimum bounding rectangle included by dash line respectively.

  Step 3. $shape = \frac{MBR(A) - Area(A)}{MBR(A)}$, where *A* denotes the tumor.

  The more the shape of tumor is quasi-circular shown as Fig. 6(a), the value of shape will be closer to 0; when the shape of tumor is more irregular shown as figure 6(b), the value of shape is more closer to 1. So we can diagnose the degree of malignance of tumor by the value of shape.

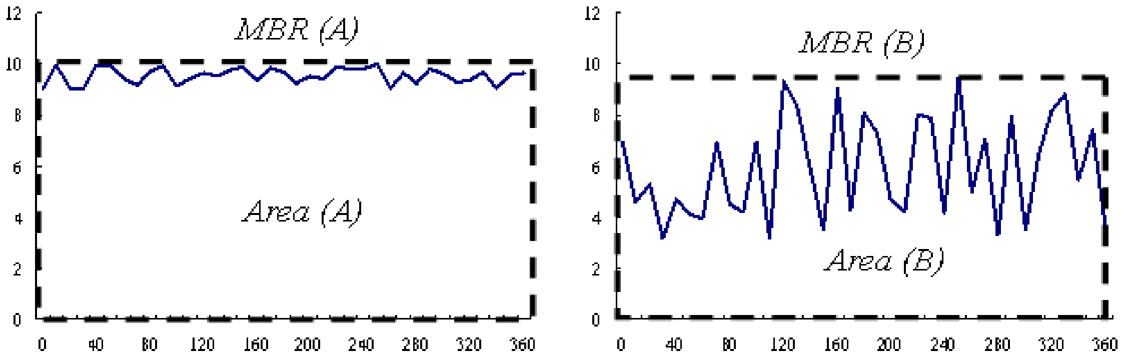

Figure 6: the curve diagrams of two different shapes of tumors. (a) quasi-circular shape of a tumor, (b) the irregular shape of a tumor.

- The location of tumor:

  We define the location of tumor β as the relative angle of the tumor among itself, liver and spine, and it is computed by following steps:

  Step1. Compute the centroid of tumor, liver and spine respectively.

  Step2. Draw a line called 0°-line from the centroid of liver to the spine's.

  Step3. Draw a line from the centroid of liver to the tumor's. Then compute the angle β between this line and the 0°-line in counterclockwise direction, where $\beta \in [0, 359]$.

  So the image representation for any image P is defined as: $R_P = \{(P_{gl}, P_{size}, P_{shape}, P_{\beta})\}$

For example, Figure 7 is a liver MRI and its segmented form. We can get the image representation of Figure 7 by above method. P_{gl}=90.82, P_{size}=0.0316, P_{shape}=0.123, P_{β}=296.187. So the image representation of Figure 7 can be calculated: $R_P = \{(90.82, 0.0316, 0.123, 296.187)\}$.

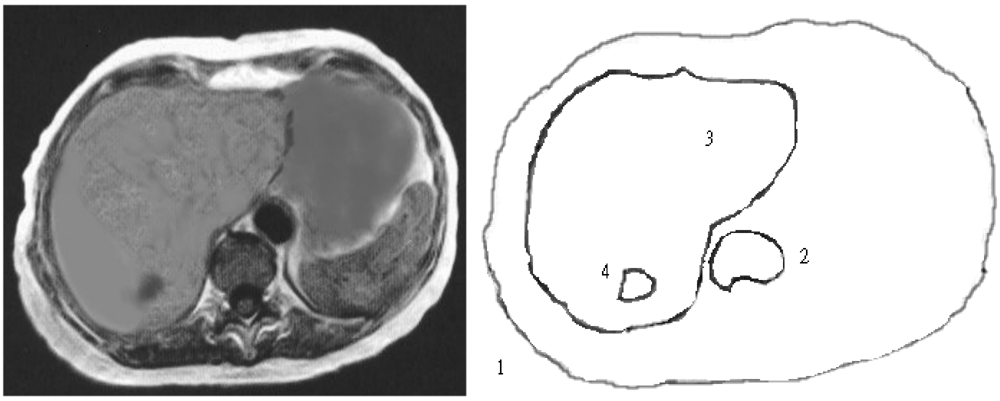

Figure 7: a liver MRI (left) and its segmented form (right).

The image representation has the properties of image scaling-, translation- and rotation-invariance, and these properties are necessary for an image database system with good accuracy.

IV. Similarity Measures and Similarity Retrieval

In this section, we present the similarity measures and retrieval method based on our image representation. The similarity measures are proposed based on the four features described above: grey level, size, shape and location. We first compute the difference degree between query picture and database picture on each feature, and the difference degree is normalized to the range of [0, 1]. Then we assign weight value for each feature according to user's requirement, and the sum of weight values must be 1. For example, if the user only cares the shape of tumor, we can assign the weight of shape as 1, and all other weights as 0. Finally, we can get the difference degree between the query picture and database picture by summing up the weighted difference on each feature, and the similarity measures have the flexibility to meet user's different requirements.

For convenience of explanation, let us introduce the following notations before giving the precise definitions for similarity measures.

- Q_{gl}, Q_{size}, Q_{shape} and Q_{β} (R_{gl}, R_{size}, R_{shape} and R_{β}): the values of gray level, size, shape and location in the image representation of query picture (database picture) respectively.

- D_{gl}, D_{size}, D_{shape} and D_{β}: the gray level-difference measure, size-difference measure, shape-difference measure and location-difference measure between query picture and database picture respectively.
- w_{gl}, w_{size}, w_{shape} and w_{β}: the weights of gray level, size, shape and location respectively, where $w_{gl} + w_{size} + w_{shape} + w_{\beta} = 1$.

Now, we can describe the similarity measures defined in this paper as follows.

- $D_{gl} = (Q_{gl}-R_{gl})/255$ (2)
- $D_{size} = Q_{size}-R_{size}$ (3)
- $D_{shape} = Q_{shape}-R_{shape}$ (4)
- $D_{\beta} = (Q_{\beta}-R_{\beta})/359$ (5)

To compare the similarity between query picture and database picture, the difference score *difference* is defined as:

- $difference = w_{gl} \times D_{gl} + w_{size} \times D_{size} + w_{shape} \times D_{shape} + w_{\beta} \times D_{\beta}$
  where $w_{gl} + w_{size} + w_{shape} + w_{\beta} = 1$, and $difference \in [0, 1]$. (6)

The weights are used to meet user’s requirement flexibly. For example, when the user’s query is only focused on the shape of tumor, w_{shape} is set to 1, and other weights are all 0.

Now we use the pictures shown in Fig. 8 to illustrate the effectiveness of our similarity measures. Based on the above similarity measuring equations and the rationale, we can calculate the values of *difference* for database pictures p_2, p_3, p_4, p_5 and p_6 with respect to the query picture p_1. The results obtained are shown in Table 1.

Table 1: values of *difference* for pictures p_2, p_3, p_4, p_5 and p_6 with respect to p_1.

difference	picture p_2	picture p_3	picture p_4	picture p_5	picture p_6
D_{size}	0.3176	0.2528	0.4224	0.36	0.3968
D_{shape}	0.2904	0.2544	0.1184	0.0536	0.2376
D_{β}	0.202625	0.194375	0.132875	0.1325	0.282

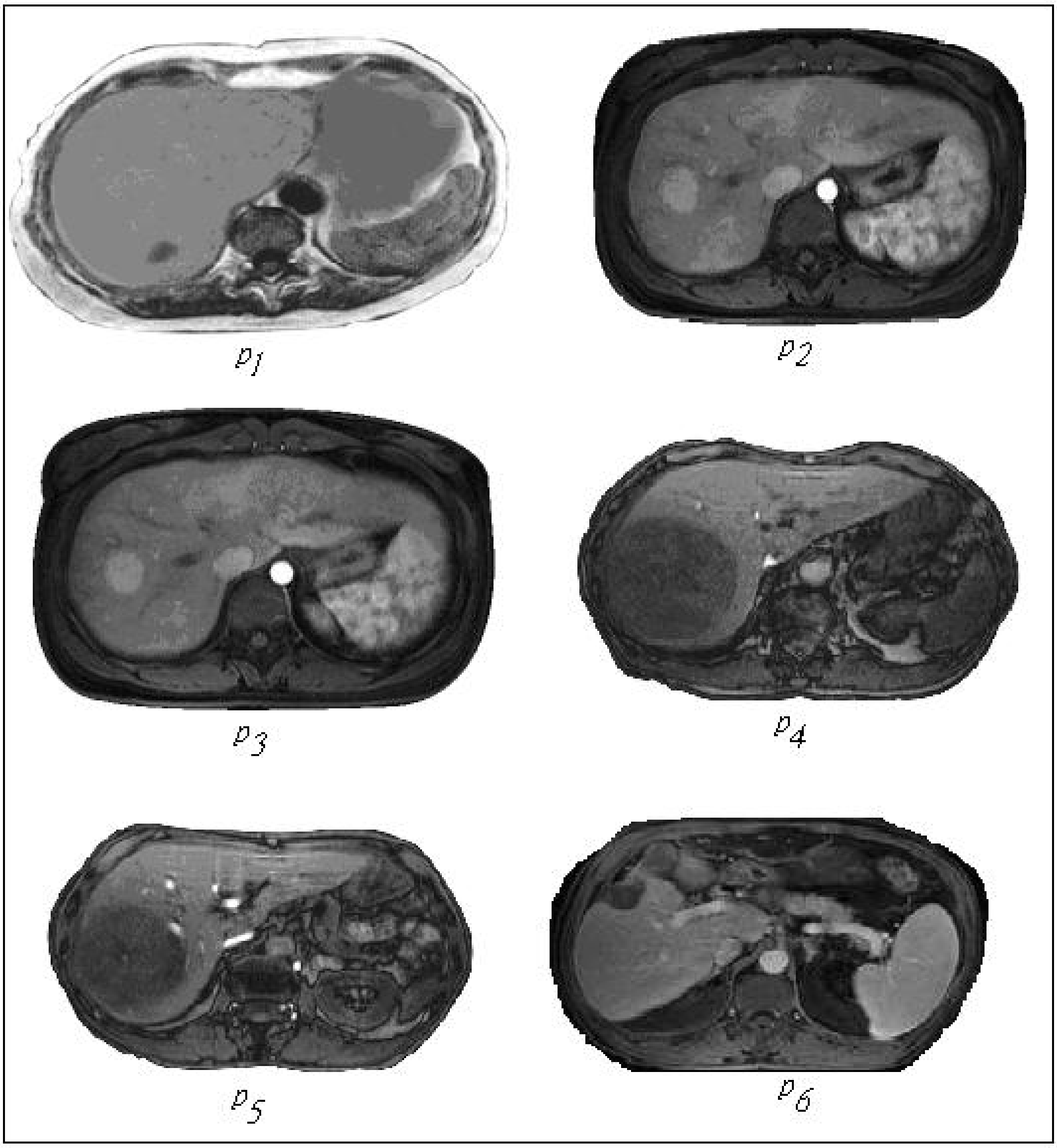

Figure 8: An example for similarity measurement.

When the user's query is only focused on the size of tumor, the above result implies that picture p_2 is most similar to picture p_1 among these pictures, because the value of

D_{size} for picture p_2 with respect to p_1 is minimal. Besides, the value of D_{size} for picture p_4 with respect to p_1 is maximal, it implies that picture p_4 is most different to picture p_1 among these pictures. In addition, when the user's query is only focused on the shape of tumor, the above result implies that picture p_5 is most similar to picture p_1 among these pictures, since the value of D_{shape} for picture p_5 with respect to p_1 is minimal, the reason is the tumors in other pictures are all almost circle not as in picture p_1. Finally, we can see when the user's query is only focused on the location of tumor, the pictures p_5 and p_4 are more similar to picture p_1 than others and picture p_6 is most different from picture p_1. The values of D_{β} in Table 1 are consistent with above result. In conclusion, the results obtained from our similarity measures defined in this section are consistent with the human visual system, and we can present the physician with a selection of similar cases with known diagnoses by our system.

V. Conclusion

In this project, a new image information system is developed for diagnosis on liver tumor. In the system, the emphasis is on the development of an efficient and practical database for recognizing and retrieving patterns in medical images that represent pathological processes. Different from the general-purpose ones, medical image retrieval systems utilize the retrieval with pathology bearing regions (PBR) that is highly localized. To retrieve similar images efficiently, we develop a medical image representation which can capture the color, shape and size of tumor and the spatial relationship between canonical organs and abnormal objects. Besides, the image representation has the properties of image scaling-, translation- and rotation-invariance, and these properties are necessary for an image database system with good accuracy. To satisfy physician's different requirements, the flexible similarity measures and the retrieval method based on our image representation are also proposed. Examples are used to show that the results obtained from the proposed similarity measures are consistent with human's perception, and the proposed image retrieval system is powerful in terms of accuracy and flexibility. Finally, the system proposed can present the physician with a selection of similar cases with known diagnoses for the assistance in diagnosing and therapy planning.

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無衍生研發成果推廣資料

98年度專題研究計畫研究成果彙整表

計畫主持人：徐麗蘋			計畫編號：98-2218-E-040-002-				
計畫名稱：醫學影像資料庫自動檢索系統之研製							
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	1	1	100%		IMP2009
		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	1	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%		
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	0	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%		

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。)	目前已於計畫執行完成後,將實驗結果及更新之方法撰寫為英文期刊論文,正於最後英文潤飾中,即將投稿於SCI期刊.

	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）

1.本計畫有部份成果已於 98/12/12 發表於國內研討會(IMP2009).

2.目前已於計畫執行完成後,將最後實驗結果及更新方法整理撰寫英文期刊論文,現做最後潤稿中,準備投稿 SCI 期刊.

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）

在學術理論方面：本計劃研發出適用於醫學腫瘤影像的特徵萃取、影像表示法模型建構及影像檢索之技術與方法，並即將研究成果發表於國際知名期刊(最後潤稿中)。而應用方面：本系統可將醫師所需的醫學影像利用快速檢索的方式，從影像資料庫中擷取類似病情之相關影像，提供醫師在診斷與治療方面有重大參考價值之工具。