行政院國家科學委員會補助專題研究計畫成果報告

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自動化復發性鼻部腫瘤偵測系統

計畫類別：x□**個別型計畫**　　　□**整合型計畫**

計畫編號：NSC　89－2213－E　－041-008-

執行期間：　89 **年** 8　　**月**　1　**日至**　90　**年**　7　**月**　31　**日**

計畫主持人：黃文楨

共同主持人：詹寶珠

本成果報告包括以下應繳交之附件：

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執行單位：嘉南藥理科技大學　資訊管理系

中　華　民　國　　90　**年**　　9　**月**　　26　**日**

行政院國家科學委員會專題研究計畫成果報告
自動化復發性鼻部腫瘤偵測系統
Automatic Recurrent Nasal Tumor Detection System

計畫編號：NSC NSC 89－2213－E －041-008-
執行期限：89 年 8 月 1 日至 90 年 7 月 31 日

主持人：黃文楨　嘉南藥理科技大學 資訊管理系
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一、中文摘要

鼻咽部位 inverted papilloma 是在鼻腔中常見的體內異常生長物，由於其高復發性，因此如果能得到較好的腫瘤偵測結果，對於手術實施的成功率的提昇就顯的非常重要。 Gadolinium- enhanced MRI 在復發性直腸的腫瘤的偵測上已被廣泛的使用。然而到目前為止，尚無一種方法可以有效率且自動的辨識出鼻咽部位的不正常組織究竟是腫瘤或是纖維化。

本計劃的目的就是要發展出一套可以有效率且自動的辨識出鼻咽部位的不正常組織究竟是腫瘤或是纖維化的診斷系統。此系統包含一種新模組稱為『相對灰階變化模組 Relative Intensity Change (RIC)』，用來比對連續磁振影像(MR)的相對應點的灰階變化。另一新模組為『時空型類神經網路 Spatiotemporal Neural Network (STNN)』用來分辨不正常組織究竟是腫瘤或是纖維化。然後應用以知識為基礎的精緻化程序 (a knowledge-based refinement process)來進一步擷取或過濾出腫瘤或是纖維化的正確位置。 RIC 的曲線在時空類神經網路中，用來表示腫瘤或纖維化的時空資訊 (spatiotemporal information)，並用來訓練時空型類經網路中腫瘤及纖維化所代表的權數(tap-weight)考量。RIC 曲線經由 STNN 運算的結果將被指定為 colormap 的指標: 紅色代表腫瘤而綠色代表纖維化。 最後所偵測出的腫瘤或纖維化的區域將會和原始的 MR 影像融合以利視覺的辨識。

關鍵詞：Nasal inverted papilloma, Gadolinium-enhanced MRI, 影像分割，時空型類神經網路

Abstract

Nasal inverted papilloma is a relatively common neoplasm of the nasal cavity, and because of its high recurrence rate, it is important to obtain better detection results for surgery. Gadolinium- enhanced MRI had been widely used in detection of recurrent rectal tumor. However, there still isn't an efficient and automatic method to identify the tumors and fibrosis in the nasal cavity.

The purpose of this research is to develop an automatic diagnosis system for distinguishing between tumor and fibrosis in the nasal region. The proposed system is composed of a new model, Relative Intensity Change (RIC), for point matching among the consecutive MR image sequence, and a Spatiotemporal Neural Network (STNN) for distinguishing between the tumor and fibrosis. Then, a knowledge-based refinement process is applied for extracting the tumor/fibrosis. The RIC curves were embedded in the STNN to represent the spatiotemporal information of tumors and fibrosis with consideration of the tap-weighted. The outputs of proposed STNN were assigned for the index of colormap: red is expressed for tumor and green is expressed for fibrosis. Finally, the tumor/fibrosis areas are displayed by colors and fused to the original MR image for facilitating visual interpretation.

Keywords： Nasal inverted papilloma, Gadolinium-enhanced MRI, segmentation

二、緣由與目的

Nasal inverted papilloma is a relatively common neoplasm of the nasal cavity, and because of its high recurrence rate, it is important to obtain better detection results for surgery [1]. In order to locate the precise tumor site, physicians usually need to integrate the information acquired from two or more examinations using different imaging modalities. This involves registration of images with different dimension, orientation, and acquisition tilt angle, a rather tedious process [2-5]. Recently, a new image modality called Gadolinium-enhanced MRI has been developed and widely used in the *diagnosis* of recurrent rectal tumor [6]. In Gadolinium-enhanced MRI, images are captured following a sequence of time stamps after the administration of contrast material. The contrast material not only causes the intensities of lesion images different from normal tissues, the differences also response on temporal images. Based on both the spatial and the temporal

differences, lesion position and the type of diseases, fibrosis or tumor, are identified.

In our previous works [7], where the region of interest (ROI) is pre-selected by users, followed by an active contour technique, so called snake, to extract a more precise ROI. For each pixel inside the ROI region, its temporal intensity values are converted into a temporal curve called relative signal intensity (RSI) [6], which is then fitted into a curve of three adjustable parameters -- A (enhancement amplitude) and Tc (tissue distribution time), and C (first-order washout rate). Combination of the best obtained A, Tc and C gives indication of the possibility that the pixel is a tumor or a fibrosis pixel. The three-parameter mathematical model [6 ,12] is fitted to the MR imaging enhancement time-intensity curves. To facilitate visual interpretation, the values of A (amplitude) and Tc (tissue distribution time) are mapped into colored imaging representation of the recurrent nasal tumor. While its results are acceptable, this approach is limited in three respects: First, finding the ROI is done in a semi-automatic manner, which implies that physicians must identify the suspicious lesion a priori. Thus, lesion detection is actually not conducted in this work. Second, the RSI curves in the same region often vary considerably making the identification of tumor or fibrosis less accurate. Third, the method can only detect the recurrent nasal tumor but not fibrosis.

To rectify these limitations, an automatic diagnosis system based on a spatiotemporal neural network for distinguishing between tumor and fibrosis in nasal regions is proposed. Spatiotemporal neural networks[8-9] were developed to process data of spatial and temporal information, and have been successfully used in various applications, such as speech recognition and pattern recognition. However, their medical application is relatively new. Applications of different temporal characteristics require different spatiotemporal neural network architectures. Thus, the network architecture used in [8-9] cannot be applied to our application. Therefore, a specifically designed spatiotemporal neural network is proposed for capturing the spatiotemporal information of tumor and fibrosis after contrast administration. The spatiotemporal information is evaluated by a new quantitative evaluation method called relative intensity change (RIC). The deviations of the RIC curves are smaller than RSI curves. Therefore, this new quantitative method can provide more accurate evaluation for dynamic MR images.

三、結果與討論

To show that the proposed automatic NP diagnosis system (Auto-NPDS) has good capability of detection and distinguishing between tumor and fibrosis, four cases including two tumor cases and two fibrosis cases were tested. Images for these experiments were taken from the radiology departments of Kaohsiung Veteran General Hospital. The MRI scanner is General Electric Signa. The image size is 256 by 256 and the gray level is 256.

The proposed Auto-NPDS is compare with K-mean-based, Principal-component-analysis-based, and Eigenimage-filtering-based methods. In the evaluations, the most appropriate parameters (e.g. threshold) for each method to gain the best detection results in these testing images are obtained by trail-and error. In our experiments, the suspicious tumor and fibrosis are conspicuousness in second PCA image. For eigenimage-filtering-based method, the desired feature is selected from the suspicious tumor and fibrosis, and the undesired features are selected from other tissues.

Figure 1 show the cases of postoperative recurrent papilloma. Figures 1(a-g) are motion-corrected results of T1-weighted MR images, which show isointense mass in the left paranasal maxillary sinus and ostiomeatal complex region. From Fig. 1(h), the detected result of k-means is messy. Fig. 1(i) and Fig. 1(j) show the detection results of tumor by PCA-based and eigenimage-filtering-based methods, respectively. From Figs. 1(h-j), it can be seen that eigenimage-filtering-based method can obtain more accurate detected result than k-means and PCA-based methods. Even so, the over-detection phenomenon in the surrounding tissues of nasalcavity is seriously. In addition, all of these three compared methods couldn't distinguish between tumor and fibrosis. Especially, we need select the desired feature and undesired features carefully in the eigenimage-filtering based method. It is implies that doctors need recognize the regions of tumor/fibrosis previously. The STNN detected result shown in Fig. 1(k) reveals a red color-coded tumor, which was proven by operation. The image after knowledge-based refinement is shown in Fig. 1(l). It clearly shows that more precise tumor was detected in the proposed auto-NPDS.

四、計畫成果自評

Gadolinium- enhanced MRI had been widely used in detection of recurrent rectal tumor. However, there still isn't an efficient and automatic method to identify the tumors and fibrosis in the nasal cavity.

In this research, we have developed a spatiotemporal- neural-network-based automatic NP diagnosis system (Auto-NPDS) for distinguishing the tumor and fibrosis in the nasal regions. A more accurate evaluation method called relative intensity change (RIC) for dynamic MR images is proposed. The RIC curves were embedded in the STNN to represent the spatiotemporal information of tumors and fibrosis with consideration of the tap-weighted. The outputs of proposed STNN were assigned for the index of colormap: red is expressed for tumor and green is expressed for fibrosis. A knowledge-based refinement module is proposed to extract precise tumor/fibrosis areas. Finally, the tumor/fibrosis areas are displayed by colors and fused to the original MR image for facilitating visual interpretation

The experimental results enhance clinical diagnosis and greatly increase the accuracy of detecting recurrent nasal tumor/fibrosis. However, the number of fibrosis is still small. Thus, our future work is to collect more recurrent nasal fibrosis cases for testing.

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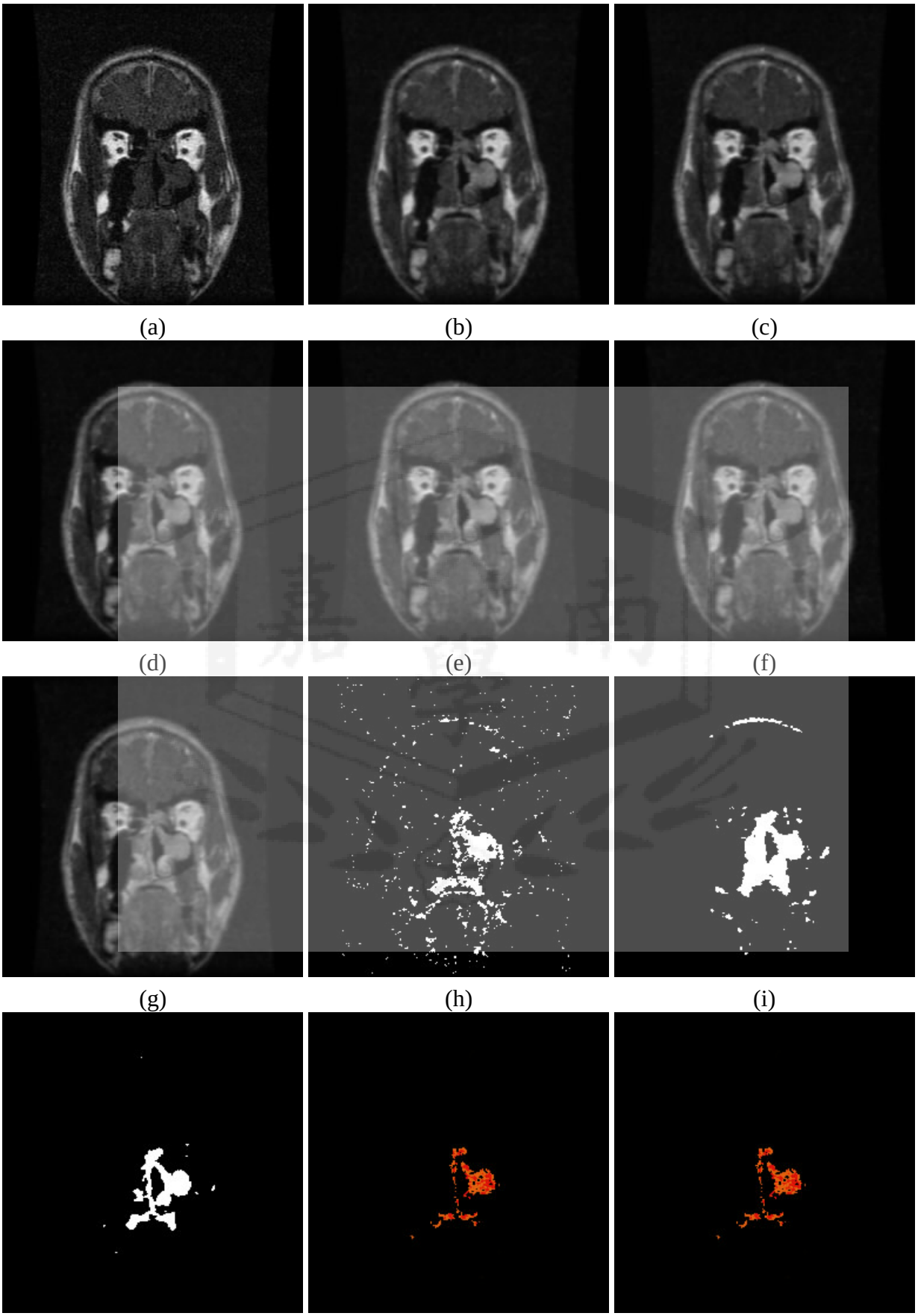
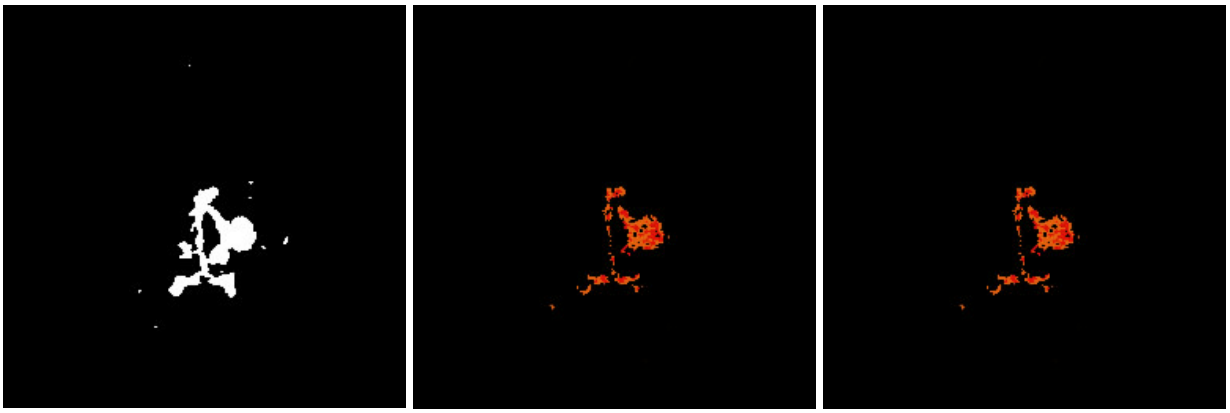


(a) (b) (c)

(d) (e) (f)

(g) (h) (i)

(j) (k) (l)



(j) (k) (l)

Figure 1. A case of postoperative recurrent papilloma. (a-g) Motion correction results of T1-weighted MR images show isointense mass in the left paranasal maxillary sinus and ostiomeatal complex region, (h) The detection result by K-mean (i) The detection result by principle component analysis of 2nd pca (j) The detection result by eigenfilter (k) The image done by STNN reveals a red color-coded tumor, which was proven by operation. (l) Image after knowledge-based refinement is shown.