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Fuzzy clustering to detect tuberculous meningitis-associated hyperdensity in CT images

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Abstract

Hyperdensity in head CT images has been shown to be a specific feature for diagnosing tuberculous meningitis (TBM) in children. We describe the extraction of hyperdense regions using fuzzy c-means clustering and fuzzy maximum likelihood estimation, thus providing a tool for the enhancement of an often subtle radiological feature. We calculate an asymmetry measure and confirm that normal and TBM images have different patterns of hyperdensity. Our results may be used in computer-assisted diagnosis of TBM.

Keywords: Tuberculous meningitis; Fuzzy clustering; Computed tomography; Computer-assisted diagnosis; Hyperdensity; Basal cisterns

1. Introduction

Tuberculous meningitis (TBM) results from the spread of tuberculosis to the central nervous system. Symptoms include fever, headache, nausea and drowsiness leading to stupor and coma. The clinical features of TBM are well recognized yet are considered non-specific and hence the disease is currently difficult to diagnose at an early stage; early diagnosis and treatment are, however, imperative given the high morbidity and mortality associated with this disease [1].

The gold standard for diagnosis of TBM is the identification of bacilli by microscopy after culture of cerebrospinal fluid (CSF), which takes several weeks [2]. Neuroradiology in the form of magnetic resonance imaging (MRI) and computed tomography (CT) has been used in disease management and in particular in the diagnosis and follow-up of those complications of TBM requiring surgery [3]. CT has been shown to be an important diagnostic method in identifying features suggestive of TBM, such as tuberculoma and post-contrast basal enhancement, and in assessing the complications of TBM, such as infarction and hydrocephalus [1,4].

Andronikou et al. [1] have shown that the presence of tuberculous exudates in the basal cisterns and Sylvian fissures, represented by hyperdensity on non-contrast CT scans, is a specific feature for diagnosing TBM; hyperdensity was confirmed using a manual image thresholding technique. Manual thresholding is operator-dependant and time-consuming, and junior radiologists or those not experienced in detecting TBM-related hyperdensity may have difficulty performing this task. In this paper we describe the use of fuzzy clustering [5] to segment hyperdensity in head CT images of children confirmed to have TBM; abnormal hyperdensity associated with TBM is compared with hyperdensity segmented from normal images.

Fuzzy clustering lends itself to applications in medical imaging where the boundaries of structures or areas of interest are often poorly defined. However, few CT segmentation algorithms based on fuzzy clustering have been reported; applications include automatic segmentation of spontaneous intracerebral hemorrhage [6]; detection of suspicious regions in the liver [7]; tissue classification for fusion of CT and magnetic resonance images of the brain [8]; segmentation of colonic polyps [9]; and segmentation of the lungs [10]. In contrast, fuzzy clustering of magnetic resonance images of the brain receives much attention [11].

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2. Materials and methods

2.1. Fuzzy c-means clustering

We make use of the unsupervised fuzzy clustering algorithm proposed by Gath and Geva [12]. The fuzzy c-means (FCM) algorithm [5] is used to provide an initial estimate of the cluster centers. FCM finds a fuzzy partition of the data set by minimizing the objective function $J_q(U, V)$ with respect to fuzzy memberships $u_{i,j}$ and centroids or feature vector means V:

$$Jq(U, V) = \sum_{j=1}^{N}\sum_{i=1}^{K}(u_{ij})^q d^2(X_j, V_i), \tag{1}$$

where $q > 1$ is a fuzziness index; X_j is the jth m-dimensional feature vector; V_i is the centroid of the ith cluster; u_{ij} is the degree of membership of the data point X_j in the ith cluster; $d^2(X_j, V_i)$ is a similarity measure between the cluster center V_i and the data point X_j; N is the number of data points; and finally $K \geqslant 2$ is the number of clusters. The membership matrix U is initialized randomly and the centroids and degrees of membership are updated iteratively as follows:

$$u_{ij} = \frac{[1/d^2(X_j, V_i)]^{1/(q-1)}}{\sum_{k=1}^{K}[1/d^2(X_j, V_k)]^{1/(q-1)}}, \tag{2}$$

$$\hat{V}_i = \frac{\sum_{j=1}^{N}(u_{ij})^q X_j}{\sum_{j=1}^{N}(u_{ij})^q}. \tag{3}$$

The termination criterion, $\max |u_{ij} - \hat{u}_{ij}| < \varepsilon$, with ε between 0 and 1, is used. The Euclidean distance is used as the similarity measure in FCM.

2.2. Fuzzy maximum likelihood estimation

The fuzzy maximum likelihood estimation (FMLE) algorithm [12] combines fuzzy logic with statistical clustering methods and yields better results than FCM in data sets with high levels of noise and where the clusters have differing densities and the data points are not equally distributed. FMLE requires well defined starting clusters as it searches for an optimum in a very narrow local region. FCM is therefore used to obtain good starting clusters before FMLE implementation.

An exponential distance measure, based on maximum likelihood estimation, replaces Euclidian distance as the similarity measure. This distance measure is used to calculate $h(i|X_j)$, the posterior probability:

$$h(i|X_j) = \frac{1/d_e^2(X_j, V_i)}{\sum_{k=1}^{K} 1/d_e^2(X_j, V_k)}, \tag{4}$$

$$d_e^2(X_j, V_i) = \frac{[\det(F_i)^{1/2}]}{P_i} \exp[(X_j - V_i)^{\mathrm{T}} F_i^{-1}(X_j - V_i)/2], \tag{5}$$

where F_i is the fuzzy covariance matrix of the ith cluster:

$$F_i = \frac{\sum_{j=1}^{N} h(i|X_j)(X_j - V_i)(X_j - V_i)^{\mathrm{T}}}{\sum_{j=1}^{N} h(i|X_j)} \tag{6}$$

and P_i is the *a priori* probability of selecting the ith cluster:

$$P_i = \frac{1}{N}\sum_{j=1}^{N} h(i|X_j). \tag{7}$$

The replacement of Eq. (2) in the FCM algorithm by Eq. (4) results in the FMLE algorithm.

2.3. Performance measures

Gath and Geva [12] introduced performance measures to evaluate the quality of the partitioning of the data with different numbers of clusters. They used three criteria to define optimal partitioning of the data: (1) clear separation between the resulting clusters; (2) minimal cluster volume; and (3) maximal number of data points concentrated around the cluster centroid. These criteria are embodied in the performance measures fuzzy hypervolume F_{HV} and partition density P_{D}:

$$F_{\mathrm{HV}} = \sum_{i=1}^{K}[\det(F_i)]^{1/2}, \tag{8}$$

$$P_{\mathrm{D}} = \frac{\sum_{i=1}^{K}\sum_{j=1}^{N} u_{ij}}{F_{\mathrm{HV}}}. \tag{9}$$

Plotting F_{HV} and P_{D} as a function of the number of clusters yields extrema at the optimal number of clusters. The optimal number of clusters will produce the minimum hypervolume and the maximum hyperdensity.

2.4. New cluster placement

New clusters must be added if the current number of clusters is not optimal. Placement of a new cluster affects the performance of the algorithm. Loncaric et al. [6] used the following placement strategy in fuzzy clustering of head CT images for intracerebral brain hemorrhage analysis, based on the notion that the new cluster should be placed where data points have a low degree of fuzzy membership:

$$p = \operatorname*{argmin}_j \max_i u_{ij}, \quad V_{k+1} = X_p, \tag{10}$$

where u_{ij} is the fuzzy membership to each cluster, i is the cluster number, and j is the position of the data point. V_{K+1} is the new cluster to be added, K is the current number of clusters, and X_p is the value of the data point whose position is specified by p.

2.5. Algorithm implementation

Preprocessing in the form of contrast stretching is applied to head CT images in order to improve the clustering speed of convergence; the highest and lowest 1% of input pixel intensities