Information fusion approach for detection of brain structures in MRI

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ABSTRACT

This paper presents an information fusion approach for automatic detection of mid-brain nuclei (caudate, putamen, globus pallidus, and thalamus) from MRI. The method is based on fusion of anatomical information, obtained from brain atlases and expert physicians, into MRI numerical information within a fuzzy framework, employed to model intrinsic uncertainty of problem. First step of this method is segmentation of brain tissues (gray matter, white matter, and cerebrospinal fluid). Physical landmarks such as inter-hemispheric plane alongside numerical information from segmentation step are then used to describe the nuclei. Each nucleus is defined according to a unique description according to physical landmarks and anatomical landmarks, most of which are the previously detected nuclei. Also, a detected nucleus in slice n serves as key landmark to detect same nucleus in slice $n+1$. These steps construct fuzzy decision maps. Overall decision is made after fusing all of decisions according to a fusion operator. This approach has been implemented to detect caudate, putamen, and thalamus from a sequence of axial T1-weighted brain MRI's. Our experience shows that final nuclei detection results are highly dependent upon primary tissue segmentation. The method is validated by comparing resultant nuclei volumes with those obtained using manual segmentation performed by expert physicians.

Keywords: MRI segmentation, brain structures, information fusion

1. INTRODUCTION

Magnetic Resonance images (MRI) provide detailed anatomical information about the internal structures and substructures of the human body. Detection of internal structures in brain MRI is widely used to diagnose several brain diseases such as epilepsy, multiple sclerosis lesions, schizophrenia, and alcoholism. Moreover, accurate segmentation of brain structures is a fundamental issue in navigated brain surgery. Considering the fact that manual detection of brain structures is a very time-consuming task while subject to operator mistakes, the need to develop a reliable and accurate automatic technique has been emerged. A great deal of research activities is being carried out throughout the world to provide an environment in which physicians can rely on the computerized detection of brain structures.

Many of these automatic methods are based on image registration in which a digital brain atlas (source) is mapped onto the MRI (target) according to an appropriate transformation.[1, 2] To find a specific structure in the MRI, the corresponding labeled structure in the template atlas is mapped to the target image. This matching process can be based on physical point matching (landmark-based registration),[3] free form transformation,[4] geometric feature matching, or anatomical matching. In addition to image registration techniques, the segmentation process can be performed using dynamic contours and active shape models.[5]

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Recently, Barra and Boire[6] introduced a new approach to the detection of brain substructures using information fusion. Their method is based upon the theory of data fusion in image processing.[7] In this approach, the desired structures are described by means of symbolic information. The symbolic information consists of expert physicians' description of the structure. The uncertainty inherent in linguistic description is modeled by means of fuzzy theory. On the other hand, numerical information such as image statistical data, morphology, segmentation, and filtering are provided with image processing techniques. These two kinds of information are then fused according to an appropriate fusion operator, which provides the detection of the desired structure.

In this paper, some mid-brain substructures such as caudate, putamen, and thalamus nuclei are detected in a sequence of axial MRIs. The necessary anatomical information, obtained from both brain atlases and expert physicians, are fused into the image numerical information. We have used both anatomical and structural landmarks to detect the desired structures. Once a structure is detected, we have used it as a landmark to find other structures and/or the same structure in the preceding slice. The advantage of this method is that it is applicable to detect any uniquely describable structure.

In Section 2, we present the method formulation. In Section 3, we show experimental results for the detection of caudate, putamen, and thalamus in a sequence of axial MRI data. In Section 4, we discuss the validation results and present concluding remarks.

2. PROPOPSED METHOD

In this section, we first review the theory of information fusion in image processing briefly. Then we introduce the nuclei description. In Subsection 2.3, we reveal what mathematical fusion framework best fits our application. Finally, the system block diagram is shown and its blocks are discussed in detail.

2.1 Data fusion in image processing

A comprehensive review of the theory of information fusion in image processing has been presented by I. Bloch and H. Maître.[7] In their paper, image fusion is defined as the process that combines information obtained from different sources in order to make a decision. Generally speaking, all of the data that we are dealing with can be categorized either as *symbolic* or *numerical*. While numerical information is easy to understand, symbolic information requires more attention. Within an appropriate mathematical framework, the symbolic information would be quantifiable. For example, if the symbolic information is a general rule consisting of imprecision, a mathematical framework that models imprecision such as fuzzy theory is appropriate. A general image fusion problem statement can be as follows: Given L general heterogeneous sources of information, S_j ($0 \leq j \leq L$), a decision D_i^j ($0 \leq i \leq n$) is taken on element p according to source S_j. For each I, D_i is estimated after fusing the D_i^js according to a fusion operator F: $D_i = F(D_i^1, D_i^2, \ldots, D_i^L)$. A final decision is made on the resultant D_i. These steps can be summarized as follows:

a. Information modeling in a mathematical framework;
b. Estimation of the D_i^js;
c. Choosing an appropriate fusion operator;
d. Making the decision.

In our application, the heterogeneous sources of information (S_j) are the gray-level matrix of MRI, the result of the tissue segmentation, and the nuclei descriptions. Depending on the desired nucleus description, an associated set of decision maps (D_i^j) is acquired. We have then fused these decision maps by means of a fusion operator and have taken the decision based on the resultant D_i.

2.2 Nuclei description

Accurate detection of brain internal structures is still an open problem. The complexity arises from the inherent complexity of the brain. The advantage of using an information fusion approach is that once a structure is uniquely describable, it can be detected. We have used this approach to detect caudate, putamen, and thalamus nuclei. These structures are defined as follows:[8]

2.2.1 Topographical anatomy of caudate nucleus[8, 9]

Caudate nucleus is an elongated arcuate mass of gray matter related throughout its extent to the lateral ventricle, occupying the floor of the anterior or frontal horn and the roof of the temporal horn. Its anteriorly enlarged portion is termed the head and protrudes into the frontal horn of the lateral ventricle. At the interventricular foramen, the nucleus narrows to constitute the body of the nucleus, which lies dorsolateral to the thalamus and contiguous to the lateral wall of the lateral ventricle (Fig. 1a).[8] The anatomy of caudate nucleus reveals that it is a gray matter that is adjacent to frontal lobes of the lateral ventricle from one side and surrounded by white matter from the other side.[9]

2.2.2 Putamen[9]

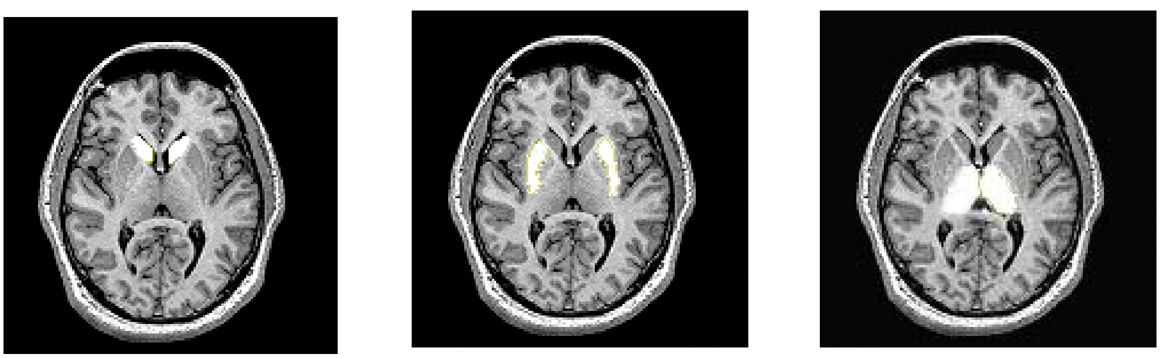
The putamen is a gray matter structure fully surrounded by white matter (internal and external capsules). It is the nearest mass of gray matter to the head of caudate nucleus and adjacent to globus pallidus. If the MR imaging resolution is not high enough, the globus pallidus is not observable. Moreover, the putamen is located almost at 1-1.5 cm of the caudate nucleus.

2.2.3 Anatomy of internal capsule[8]

The cerebral cortex is connected with the thalamus, the brainstem and the spinal cord by an extensive projection fiber system, which penetrates the white matter of Centrum semiovale of Vieussens and converges as the corona radiata toward the thalamus. At this level, these radiating fibers constitute a compact band interposed between the thalamus and the caudate on the medial side, and the lentiform nucleus on the lateral aspect. This mass of fibers is designated as the internal capsule.[8] We have used the internal capsule to locate the thalamus.

2.2.4 Thalamus[8, 9]

The thalami are the largest, most internal structures of the diencephalons, consisting of two oblique ovoid nuclear masses of gray matter situated at the rostral end of the midbrain on each side of the third ventricle. Each thalamus is about 3-4 cm long.[8] The lateral wall of the thalamus borders upon the internal capsule[9] (Fig. 1c). The thalamus is intrinsically more difficult to detect, since it is a relay station for the afferent tracts. This leads to a great amount of ambiguity at the edges of the detected nuclei. The higher the resolution (the shorter the thickness of an MRI), the better is the final detection of the thalamus from MRI.



(a) (b) (c)

Figure 1: Localization of some brain nuclei. (a) Caudate. (b) Putamen. (c) Thalamus.

2.3 Mathematical fusion framework

From the nuclei descriptions, which constitute important information, it can be seen that we need a mathematical framework to model uncertainty and imprecision. Fuzzy theory satisfies all the desired specifications in this regard.

2.3.1 Numerical information

The numerical information consists of the segmentation of the image according to a fuzzy classification algorithm. The classification algorithm is a revised version of fuzzy c-means (FCM) and is adapted to the MRI segmentation into 4 classes: Background, cerebrospinal fluid (CSF), gray matter, and white matter. In the standard version, the FCM iteratively minimizes the following cost function J:

$$J = \sum_{i=1}^{C} \sum_{j=1}^{N} u_{ij}{}^{m} d(x_j, c_i),$$

where u_{ij} is the class membership function, and $d(x_j, c_i)$ provides the Euclidean distance between each data x_j and each class center c_i. The fuzzification degree is m, and can take any number in the range of [2, 3] without significant difference in the results.

However, it was seen that FCM presents poor results for the accurate edge detection in the fuzzy neighborhoods where the white matter and gray matter meet. This is particularly because of the fact that the fibers (white matter) actually penetrate the gray matter structures. The partial volume effect intensifies this inappropriate segmentation. To overcome this flaw, once the preliminary segmentation is done, we re-segmented the combined white matter and gray matter classes. It is seen that, the gray matter itself consists of 2 combined classes. The results of the implementation of standard FCM (Fig. 2b) versus our modified version (Fig. 2c) are compared in Fig. 2.

(a) (b) (c)

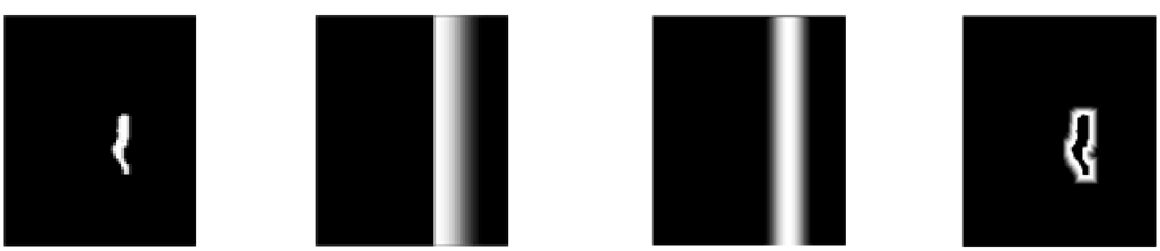
Figure 2: (a) Original T1-weighted MRI. (b) Segmentation results from the standard FCM method. (c) Segmentation results from our proposed modified FCM method.

2.3.2 Symbolic information

The nuclei descriptions, presented in Subsection 2.2, deal with uncertain data such as adjacent to, anterior to, and almost at d cm of. Hence, they are most efficiently implemented using fuzzy maps. The following fuzzy membership functions were used to implement such vague information:

- Adjacent to structure and at direction D (Fig. 3b)
- At distance d of the structure and at direction D (Fig. 3c)
- Exterior and adjacent to the structure (Fig. 3d)

To avoid complexity D is taken as D={right, left, up, down}). The results of the implementation of these fuzzy membership functions on a sample structure are shown in Fig. 3.



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

Figure 3: (a) A given structure S. (b) Adjacent at *right*. (c) Distance d at *right*. (d) Exterior and adjacent.

2.4 System block diagram

The proposed system block diagram is shown in Figure 4. After initial tissue segmentation (Fig. 2b), the misclassified areas around the edges where white matter and gray matter meet are refined (Fig. 2c). This numerical information is fused into the symbolic information, obtained from expert physicians, according to an Information Fusion Operator (IFO) to detect the desired nuclei. Each detected nuclei in slice *n* is the key landmark to detect the same nuclei in slice *n+1*.

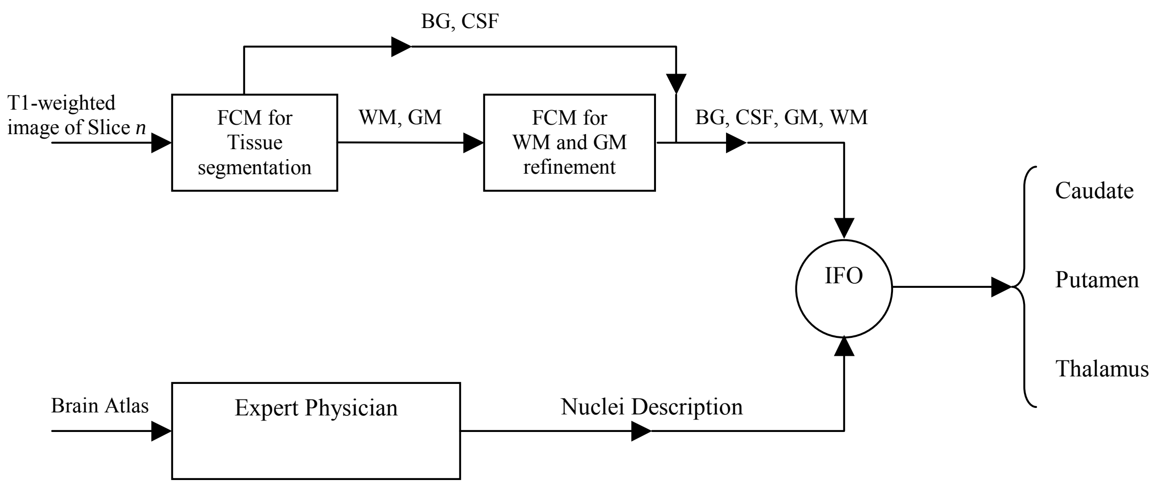


Figure 4: The system block diagram.

3. EXPERIMENTAL RESULTS

In this section, we show the results of our algorithm on a sequence of T1-weighted MRI. First, we introduce the data to which the algorithm has been applied. Then we present the experimental results for the detection of caudate, putamen, and thalamus. At the end of this section, a test is performed to quantitatively validate the results.

3.1 Data

The data has been acquired from *BrainWeb: Simulated Normal Brain Database.*[10, 11] The slice thickness is 1mm with 3% noise and 20% intensity non-uniformity in the axial plane. A sequence of 6 slices is used in which all the desired nuclei are present. Each slice is grabbed 2mm from the preceding slice, covering 1.2cm of the midbrain. Figure 5 shows the original data.

3.2 Nuclei detection

According to the nuclei descriptions presented in Section 2.2, right caudate, right putamen, and right thalamus are detected successfully from the left side of image. Figure 6 shows the detection of these nuclei in the MRI sequence.

3.3 Test of validity

To test the validity of the results, we asked 2 experts to segment each nucleus manually twice in each slice and then combined the results to generate a region for each nucleus. To this end, the pixels that were common in at least 3 segmentations were used in the definition of final regions. These regions were used to evaluate the results of the algorithm according to the following similarity measure:

$$Similarity = \frac{Area(I_{\exp} \cap I_{alg})}{Area(I_{\exp})}$$

where $I_{\exp}$ is the binary region mentioned above and $I_{a\lg}$ is the region resulted from the algorithm. Table 1 shows the quantitative measures of similarity of each nucleus to the expert-detected one. It is seen that the algorithm has a good performance for detecting these nuclei.

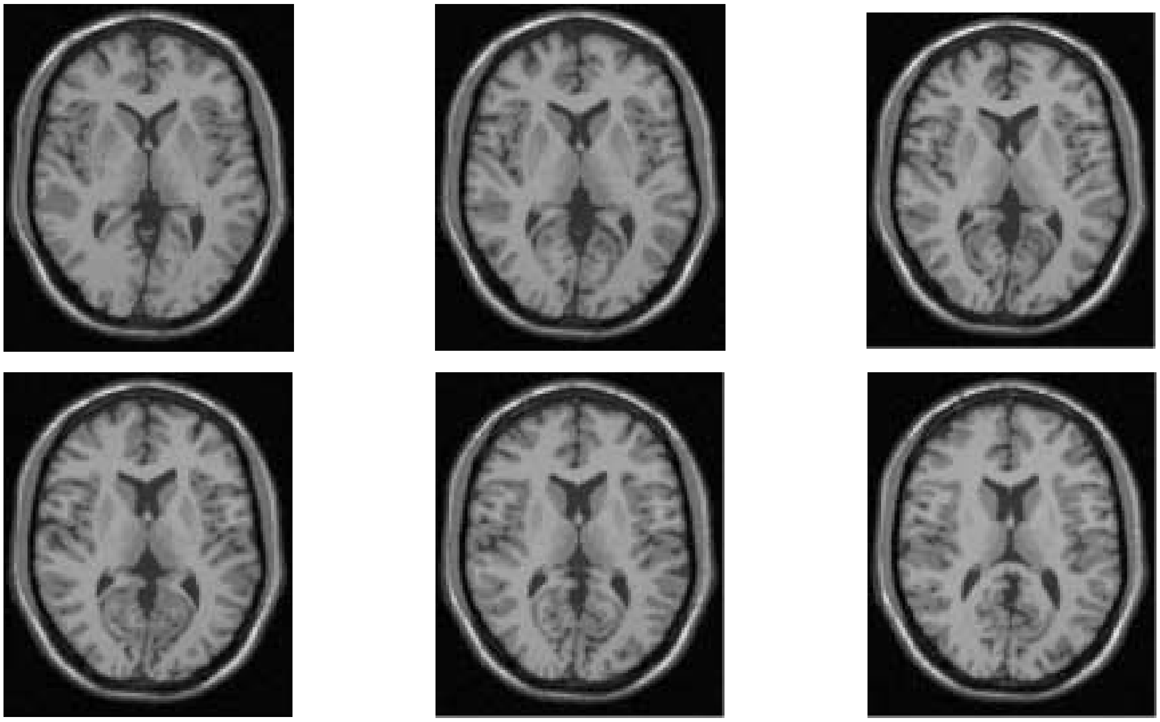


Figure 5: Original T1-weighted MR images.

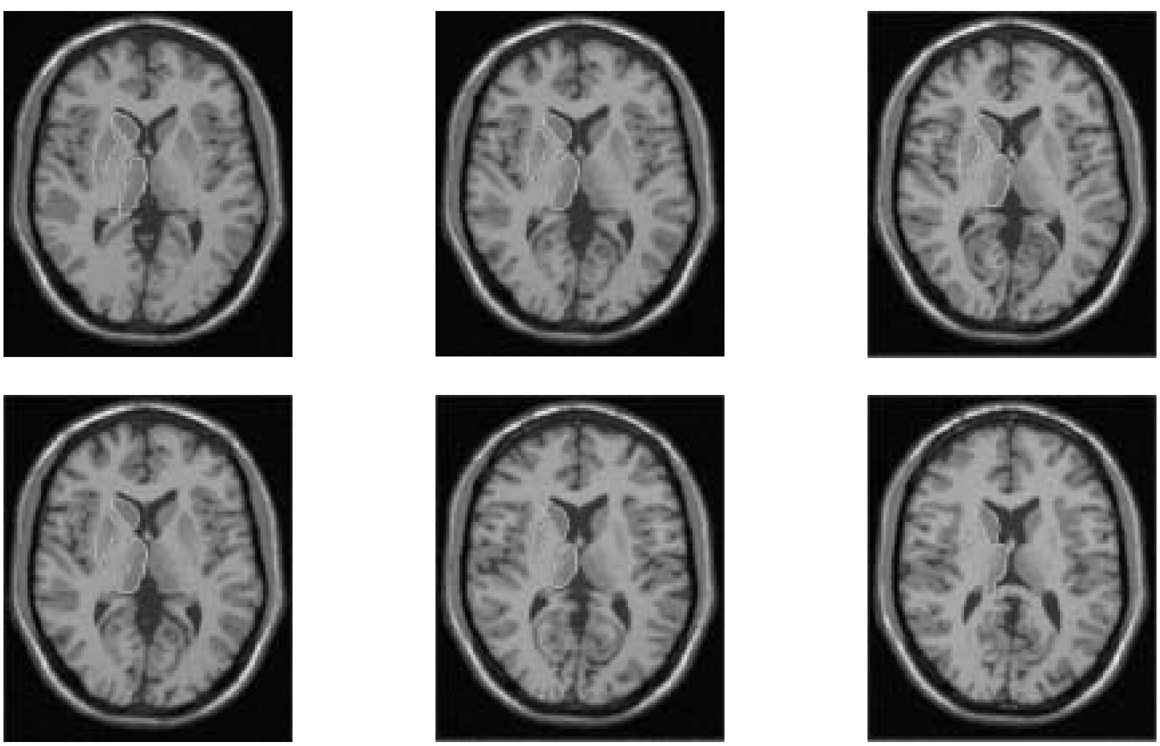


Figure 6: Detection of caudate, putamen, and thalamus nuclei by the proposed method.

Table 1: Similarity measure of the detected nuclei to the regions selected by experts.

Slice\Structure	Right Caudate (left side of image)	Right Putamen (left side of image)	Right Thalamus (left side of image)
Slice 1	92.7%	97.9%	88.0%
Slice 2	94.2%	98.8%	81.7%
Slice 3	97.3%	96.3%	89.3%
Slice 4	90.2%	88.0%	83.7%
Slice 5	99.5%	84.2%	82.6%
Slice 6	99.5%	17.0%	88.1%

4. CONCLUDING REMARKS

A method based on information fusion was proposed to detect midbrain structures from MRI automatically. Once a structure is uniquely describable, the algorithm finds the associated nucleus. We have implemented this approach to detect caudate nucleus, putamen, and thalamus. The test of validity shows that in most of the slices in which all three nuclei are present the algorithm is reliable. In the last slice, the putamen is almost disappearing and that is why a small similarity measure has been obtained.

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