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Texture-based segmentation of diffuse lesions of the brain's white matter

Frithjof Kruggel,[a,*] Joseph Suresh Paul,[a] and Hermann-Josef Gertz[b]

[a]*204 Rockwell Engineering Center, University of California, Irvine, CA 92697-2755, USA*
[b]*University of Leipzig, Leipzig, Germany*

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Diffuse lesions of the white matter of the human brain are common pathological findings in magnetic resonance images of elderly subjects. These lesions are typically caused by small vessel diseases (e.g., due to hypertension, diabetes), and related to cognitive decline. Because these lesions are inhomogeneous, unsharp, and faint, but show an intensity pattern that is different from the adjacent healthy tissue, a segmentation based on texture properties is proposed here. This method was successfully applied to a set of 116 image data sets of elderly subjects. Quantitative measures for the lesion load are derived that compare well with results from experts that visually rated lesions on a semiquantitative scale. Texture-based segmentation can be considered as a general method for lesion segmentation, and an outline for adapting this method to similar problems is presented.

Keywords: White matter; Lesion segmentation; MRI; Texture; Aging

Introduction

In elderly patients suffering from cognitive impairment, an important differential diagnosis with therapeutic implications is drawn between the presence of a neurodegenerative disease (e.g., Alzheimer's disease, AD), a cerebrovascular disease (e.g., a multiinfarct cognitive disorder), or a combination thereof. In magnetic resonance imaging (MRI) of the brain, cortical and hippocampal atrophy are found as well-known signs for AD (Wolf et al., 2003), while focal or diffuse lesions are signs of cerebrovascular disease (Englund, 2002; Erkinjuntti et al., 1996; Tullberg et al., 2002). Especially, "periventricular lesions" (PVLs) and "diffuse white matter hyperintensities" (DWMHs) are often found in the subcortical white matter (WM) (Bowen et al., 1990; Deary et al., 2003; Fazekas et al., 1987; Guttmann et al., 1998). The amount of these abnormalities is correlated with age and risk factors for diseases affecting small brain vessels such as hypertension and diabetes (Bowen et al., 1990; Englund, 2002; Fazekas et al., 1998; Tullberg et al., 2002), and increased in the presence of memory disorders or dementia (Bowen et al., 1990; de Groot et al., 2002; Deary et al., 2003; Desmond, 2002; Starr et al., 2003; Tullberg et al., 2002). PVLs are typically adjacent to the corner of the lateral ventricle, as "caps" on the frontal horns, or "bands" along the trigone and occipital horn (see Fig. 1). DWMHs are located in the deep white matter, and appear as faint, nodular or confluent, patchy lesions with fuzzy borders. For an excellent discussion of the neuropathological features of the lesions refer to (Braffman et al., 1988; Englund et al., 1988; Erkinjuntti et al., 1996; Fazekas et al., 1998).

Visual assessment of T_2-weighted MR images is still the most widely used practice for evaluating these lesions: Fazekas et al. (1987) proposed a semiquantitative rating 4-point scale (0: absence; 1: mild; 2: moderate; 3: severe). Intensity is the most important image feature employed in segmentation approaches, either by using MR contrast agents (e.g., in the case of multiple sclerosis lesions, Parodi et al., 2002), by acquiring special MR imaging protocols (e.g., a fast-fluid-attenuated inversion recovery (FLAIR) sequence, Gootjes et al., 2004), or by combining information from multiple protocols (e.g., T_1, T_2, and PD-weighting, Zijdenbos et al., 1994). Lesions are segmented as outliers of the intensity distribution in monomodal images (Jack et al., 2001), or by intensity-based classification in multimodal images (Anbeek et al., 2004; Admiraal-Behloul et al., 2005; Tullberg et al., 2002; Zijdenbos et al., 1994). Due to the partial volume effect, white matter lesions may have similar intensity values as grey matter, so the use of a white matter template (an atlas) was suggested to define the search space for lesions (Admiraal-Behloul et al., 2005; DeCarli et al., 2005). Besides these voxel-based approaches, the spatial homogeneity of lesion may be used as an additional segmentation criterion. These "region-growing" procedures typically require a seed point specified by an expert (Payne et al., 2002; Parodi et al., 2002; Gootjes et al., 2004). Finally, DeCarli et al. (2005) proposed a classification procedure that is based on the intensity distribution of the WM and the distance of a voxel to the next cerebro-spinal fluid (CSF) compartment. For a comprehensive comparison of current ap-

* Corresponding author. Fax: +1 949 824 1727.
E-mail address: fkruggel@uci.edu (F. Kruggel).
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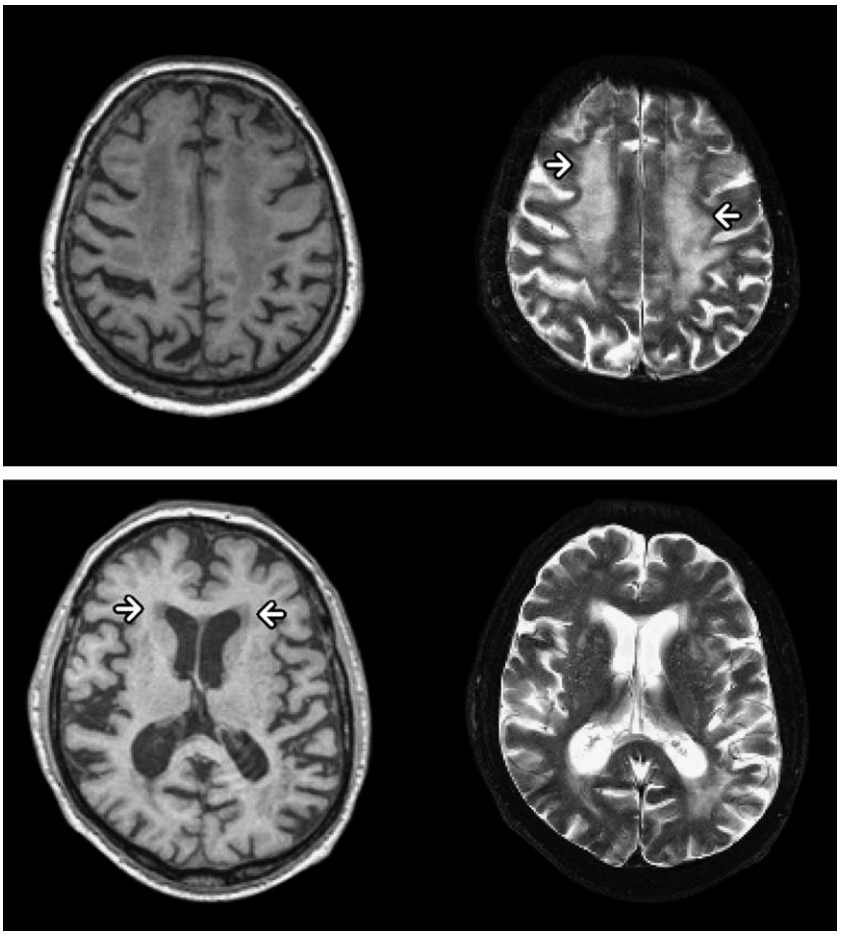

Fig. 1. T_1- (left) and T_2-weighted images (right) of diffuse white matter hyperintensities (DWMH, top) and periventricular lesions (PVL, right). Arrows point to example lesion areas.

proaches for segmenting WM hyperintensities, refer to Yoshita et al. (2005).

Because these lesions have an irregular shape and inhomogeneous structure (see Fig. 1), segmentation approaches based on intensity or shape alone may yield imprecise results. Thus, characterizing and classifying these unsharp, faint, inhomogeneous lesions by their textural characteristics appear promising. We briefly indicated this idea in Kovalev et al. (2001), and elaborate here on a detailed procedure for texture-based segmentation of WM lesions. Indeed, a wide variety of textures are encountered in biomedical images, and recent 3D CT and MRI images show rich correlates of the natural texture of organs: examples for oriented textures are muscles fibers or white matter tracts. The advantage over current intensity- or region-based approaches discussed above is that the intensity *pattern* of a lesion is classified here—and different lesion types may be discriminated by their different intensity pattern. The approach is applicable to mono- and multimodal images: using multiple weightings generally increases the sensitivity and specificity of lesion detection.

Intensity properties of textures may be described by a grey-level co-occurrence matrix (COM, refer to Rangayyan, 2005 for a detailed introduction). An element in this two-dimensional matrix represents the probability of occurrence of a pair of intensity levels i_1,i_2 of neighboring voxels v_1,v_2. Thus, the COM describes the joint intensity distribution of neighboring voxels. Other useful characteristics that describe textures include the gradient magnitude g_1,g_2 or the angle a_{12} between gradients at v_1,v_2. These multi-dimensional co-occurrence matrices were introduced by Kovalev and Petrou (1996), and applied to MRI data analysis in Kovalev et al. (2001). We denote an element of the COM as texture feature, and aim at segmenting lesions from normal tissue by discriminating their texture features.

Although we focus on the detection and segmentation of PVL and DWMH here, we emphasize that our approach is applicable for solving similar problems (e.g., the detection of WM lesions in multiple sclerosis, the segmentation of edema around tumor lesions and infarct zones), and is not limited to brain image data, or even MRI as imaging modality. Therefore, we describe a general procedure for computing texture properties from small subvolumes of an image, and develop a strategy for optimizing the discrimination between two or more texture descriptors (e.g., corresponding to WM, PVL, and DWMH). Vectors of texture features may be classified in high-dimensional space, and properties of lesions understood in terms of their distinctive features. We consider as specific strengths of this approach: (1) it is conceptually simple and easy to implement, (2) it is computationally efficient (e.g., it takes less than 60s typical computation time for a brain volume), (3) taking