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Training Samples-Optimized Dictionary Learning for Magnetic Resonance Super-Resolution Imaging

Hayder Simavat[1*], Umran Shifalan [2]

[1] Electrical Engineering and Computer Science Department, Izmir Institute of Technology, Turkey, Izmir
[2] Engineering and Applied Informatics Department, Izmir Institute of Technology, Turkey, Izmir

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Abstract

Sensorineural hearing loss is a condition characterized by damage to the inner ear or nerve pathways connecting it to the brain, resulting in hearing impairment. Cochlear implants have been developed as a solution for children with bilateral or unilateral sensorineural hearing loss. However, the success of cochlear implant surgery relies on the presence and functionality of the cochlear nerve. Therefore, accurate segmentation and measurement of the cochlear nerve are crucial for surgeons to predict the outcome of the cochlear implant procedure. In this study, we propose a modified region growing segmentation algorithm that accurately segments the cochlear nerve region. The segmentation accuracy is assessed using various parameters, including Jaccard, Dice, False Positive Dice, and False Negative Dice. Additionally, the segmented region is measured using long diameter, short diameter, and cross-sectional area. Statistical analyses, such as intra/inter-observer correlation and limits of agreement, are conducted on the cross-sectional area of the cochlear nerve to assess the reproducibility of the automated measurement. This automated segmentation and measurement approach holds promise for predicting the outcome of cochlear implantation in individuals with sensorineural hearing loss.

Keywords: MR super-resolution, dictionary learning, sparse reconstruction, training samples optimization

I. Introduction

Dictionary learning methods have found applications in various fields, such as medical image classification, data classification, face recognition, face identification, diagnostic magnetic resonance image super-resolution, image representation, joint sparse principal component analysis, patch alignment, object tracking, MR spectroscopy quantification, and medical image super resolution[1]. The construction of a sparse representation model relies heavily on dictionary learning, which is a critical issue. In image reconstruction based on dictionary learning, both the sparse coefficients and the dictionary itself play important roles in achieving high-performance reconstructions [2].

Sparse representation-based signal representation involves approximating a signal using a linear combination of other signals, known as atoms, from a set of signals called dictionaries. Therefore, the quality of signal sparse coding is influenced by the choice of dictionary [3]. Optimizing dictionary learning has garnered attention in various signal processing domains, including images and audio. The prevalent approach for learning dictionaries involves solving an iterative minimization problem. In the sparse coding stage, the dictionary is fixed in advance while the sparse coefficients are solved, and in the dictionary update stage, the dictionary is generated based on the obtained coefficients [4]. Several dictionary learning methods have been proposed for the sparse coding stage. For instance, the Orthogonal Matching Pursuit (OMP) method has been applied to Method of Optimal Directions (MOD)-based dictionary learning, and the Iterative Shrinkage Thresholding (IST) algorithm has been used for Majorization Method (MM)-based dictionary learning. Additionally, Maximum A Posteriori (MAP)-based dictionary learning employs the gradient descent method and dictionary column normalization [5]. However, these methods do not take into account uncertain parameters, such as the regularization parameter. Another class of dictionary learning methods involves machine learning-based approaches, including K-Singular Value Decomposition (K-SVD) and frame design techniques [6]. Previous works have also focused on extracting features from edges, textures, and structures for dictionary generation, as well as constraint-based dictionary training and iteration-based sparse domain image deblurring using a single high-resolution dictionary. While these methods directly sparse code from the dictionary update, they fail to fully and quickly extract the potential expressive information of the dictionary [7]. In this paper, we propose a training sample selection approach to enhance dictionary learning performance.

consistency method and effectively distinguishes global diversity by calculating the maximum first and second-order gradients.

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