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An integrated scattering feature with application to medical image retrieval☆

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ABSTRACT

Scattering transform has been successfully applied to medical image retrieval because it provides extensive semantic representations of an image. To efficiently handle the scattering transform results, the coefficient matrices are usually compressed to vectors. However, the existing features derived from the compressed vectors only consider one distribution information of the original image. To address this problem, this paper proposes an integrated scattering feature for medical image retrieval. The proposed method integrates two types of compressed scattering data from different perspectives, namely data concentration and canonical correlation analysis (CCA). For each integration model, we also give a corresponding feature representation strategy that takes account of more comprehensive characteristics of original medical image. Experiments on two benchmark medical computed tomography (CT) image databases demonstrate the superiorities of the proposed features over several state-of-the-art methods.

1. Introduction

Medical image retrieval (MIR) is an important topic in the fields of medical image analysis and pattern recognition owning to its extensive applications. The performance of a MIR system heavily depends on the used features. Drawing on the experience of general multimedia retrieval techniques [1–5], a great deal of algorithms have been developed to extract features of medical images. Because there are many texture-like regions on medical images, the existing features for traditional texture image representation are popularly used in several MIR systems. The well-known local binary pattern (LBP) [6,7] and its improvements [8–13] have achieved promising performance. The key idea of these methods is to develop different local encoding strategies to describe the local image contents from various perspectives.

Inspired by the success of deep learning techniques [14], the scattering transform [15], a variation of deep convolutional networks, has been used to derive features for MIR. In [16], the authors proposed a histogram of compressed scattering coefficients (HCSC) feature from medical images. HCSC first employs a projection operation to compress the scattering coefficient matrix to a vector by a given direction, and then describes the compressed vectors via the bag-of-words (BoW) model. Though HCSC has achieved satisfactory performance, it has following limitations. First, HCSC only considers one projection direction for compression such that just partial information of the image is used. Fig. 1 illustrates the vertical and

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horizontal projections of a scattering coefficient matrix. It can be seen that they contain different intensity distribution characteristics of the matrix, but only one of them is applied in HCSC. It is necessary to take account of all these information to derive features. Second, the derivation of codebook used in BoW model is time consuming because of the clustering operation, which adversely affects the efficiency of HCSC.

To address the above issues, we develop an integrated scattering feature for medical image retrieval in this paper. Rather than only considering one intensity distribution information of a scattering coefficient matrix, we first integrate two different intensity distribution information from following perspectives, namely data concentration and canonical correlation analysis (CCA) [17]. Two corresponding feature representations are also given, which include more comprehensive distribution information of the original image in contrast with some related features. The developed scheme is evaluated on two benchmark medical computed tomography (CT) image databases, and the comparison results demonstrate that it outperforms several state-of-the-art methods.

The remainder of this paper is organized as follows. Section 2 describes the proposed algorithm in detail, and Section 3 illustrates several comparison results obtained by the proposed algorithm. Section 4 finally presents some conclusions and future work.

2. Proposed approach

In this section, we will detail the proposed feature extraction approach for medical images. Considering a MIR system, let **A** denotes a collection of all training images. The proposed method consists of following modules, i.e., scattering coefficient extraction, scattering coefficient integration, and scattering feature representation, respectively.

2.1. Scattering coefficient extraction

As aforementioned, we first perform scattering transform to each image of **A** respectively to obtain their coefficients. Scattering transform is a cascade of the traditional wavelet transform and modulus operation, and it provides higher level representations that are more close to the semantic descriptions of the original image [15,16]. Given a 512×512 medical image, we can obtain several sub-images whose size is 64×64. Denote each sub-image by $\boldsymbol{I}_z(m, n)$, where $m = 1, \ldots, M, n = 1, \ldots, N,$ and $z = 1, \ldots, Z$. Note that $\{M, N\}$ is the size of $\boldsymbol{I}_z(m, n)$, and there is a total of Z sub-images generated from **A**.

To efficiently handle the obtained $\boldsymbol{I}_z(m, n)$, the projection operation is conducted here too. The simple vertical and horizontal projections are considered, which can be represented as follows:

$$\boldsymbol{I}_{z,v}(n) = \sum_{m=1}^{M} \boldsymbol{I}_z(m,n), \;\; n = 1, \ldots, N; \boldsymbol{I}_{z,h}(m) = \sum_{n=1}^{N} \boldsymbol{I}_z(m,n), \;\; m = 1, \ldots, M. \quad (1)$$

The two vectors, $\boldsymbol{I}_{z,\,v}$ and $\boldsymbol{I}_{z,\,h}$, are margin distributions of $\boldsymbol{I}_z(m, n)$, representing different characteristics of $\boldsymbol{I}_z(m, n)$ (see Fig. 1).

2.2. Scattering coefficient integration

In this work, we develop two ways to integrate $\boldsymbol{I}_{z,\,v}$ and $\boldsymbol{I}_{z,\,h}$ from following perspectives, namely data concentration and CCA.

2.2.1. Integration via data concentration

To take both information of $\boldsymbol{I}_{z,\,v}$ and $\boldsymbol{I}_{z,\,h}$ into account, the most intuitive way is to directly concentrate two vectors into one. This operation is commonly used in many real situations. Moreover, note that pooling technique is able to improve the data quality in the fields of image processing and pattern recognition. Here we also conduct the pooling operations to $\boldsymbol{I}_{z,\,v}$ and $\boldsymbol{I}_{z,\,h}$ before concentration.

Let $M_p = \lfloor \frac{M}{2} \rfloor$ and $N_p = \lfloor \frac{N}{2} \rfloor$, where $\lfloor \cdot \rfloor$ is a operator to round the element to the nearest integer towards minus infinity. Then the pooling operations are conducted as:

$$\boldsymbol{I}^p_{z,v}(n) = \mathcal{F}(I_{z,v}(2n-1), I_{z,v}(2n)), \;\; n = 1, \ldots, N_p, \quad (2)$$

$$\boldsymbol{I}^p_{z,h}(m) = \mathcal{F}(I_{z,h}(2m-1), I_{z,h}(2m)), \;\; m = 1, \ldots, M_p, \quad (3)$$

where $\mathcal{F}(x, y)$ is a pooling function. Eqs. (2) and (3) indicate that $\mathcal{F}(x, y)$ is employed to every two adjacent elements without any overlapping. Here we employ the maximum and average operations, namely $\mathcal{F}_1(x, y) = \max\{x, y\}$ and $\mathcal{F}_2(x, y) = (x + y)/2$ respectively. After pooling operation, we integrate the obtained vectors into the following form:

$$\boldsymbol{I}^p_z = [\boldsymbol{I}^p_{z,v}(1), \ldots, \boldsymbol{I}^p_{z,v}(N_p), \boldsymbol{I}^p_{z,h}(1), \ldots, \boldsymbol{I}^p_{z,h}(M_p)]. \quad (4)$$

It can be seen that $\boldsymbol{I}^p_z$ is with the same size of $\boldsymbol{I}_{z,\,v}$ or $\boldsymbol{I}_{z,\,h}$. Fig. 2 depicts the integration results of the corves shown in Fig. 1 via average and maximum pooling operations. It can be seen that $\boldsymbol{I}^p_z$ contains most distribution information of the original two curves, and there exists some differences in some local regions between two pooling results.