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Quantum evolutionary clustering algorithm based on watershed applied to SAR image segmentation

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ABSTRACT

The goal of segmentation is to partition an image into disjoint regions. In this paper, the segmentation problem based on partition clustering is viewed as a combinatorial optimization problem. A new algorithm called a quantum evolutionary clustering algorithm based on watershed (QWC) is proposed. In the new algorithm, the original image is first partitioned into small pieces by watershed algorithm, and the quantum-inspired evolutionary algorithm is used to search the optimal clustering center, and finally obtain the segmentation result. Experimental results show that the proposed method is effective for texture image and SAR image segmentation, compared with QICW, the genetic clustering algorithm based on watershed (W-GAC) and K-means algorithm based on watershed (W-KM).

1. Introduction

Clustering [1,9,6,10,21] is an important unsupervised classification technique, which is a widely used in data mining, and classification. The existing clustering algorithms include partitional clustering, hierarchical clustering, density-based clustering, grid-based clustering, model-based clustering, as well as clustering technology combining with fuzzy theory [17], graph theory [18], and subspace learning [4,19,20]. There is some novel clustering methods lately, such as spectral clustering [23], fast gradient clustering [25] and manifold elastic net [26].

Texture feature is the most important intrinsic attributes of an image [5]. Texture is considered to be the interpretation of distinction between different attribute of images. Nearly three decades, researchers presented many segmentation algorithms based on texture feature, which can be divided into two categories: supervised learning method and unsupervised learning method. But supervised learning method applied to image segmentation problem leads to the same target area looks different even in the same image, thus, not all the categorical features of target area can be contained. In this case, unsupervised learning method applied to segmentation, and so called clustering method, will be more effective. Unsupervised segmentation can be generally divided into two categories: hierarchical clustering and partition clustering. Partition clustering is a division of data into different groups according to given rules.

In this paper, the segmentation problem using partition clustering is viewed as a combinatorial optimization problem, which is in accordance with some specific criterions that the image dataset will be partition into different category. But the existing optimization methods e.g., conventional genetic algorithms (CGAs) are often time-consuming, the convergence speed of which is slow and easy to trap in local optimal value. For solving above problems, a novel optimization method is introduced based on some concepts of quantum computing, called a quantum-inspired evolutionary algorithm (QEA) [7]. In particular, in QEA the representation is investigated to represent the individuals to explore the search space with a small number of individuals, and to exploit the global optimal solution in the search space within a short span of time, respectively. But for complex image, based on pixel clustering methods to solve image segmentation, it is often time-consuming. Watershed algorithm [22,2] has the advantage of a region growing algorithm, while still making use of boundaries information, as captured by the gradient surface, which is so simple and effective that it has been widely used image segmentation tool [8,15,14]. However, the gradient transformation is sensitive for noise, and can manifest itself as over segmentation. In the paper [13], QICW have been proposed for segmentation. But QICW needs to set more parameters. This paper proposes a novel algorithm for segmentation called a quantum evolutionary clustering algorithm based on watershed (QWC), which aims to search for the optimum clustering center quickly and effectively, locate edge position accurately, and improve the performance of image segmentation. In QWC, we use watershed algorithm to partition the original image into small blocks in this paper, for one thing, it can accelerate the

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convergence speed, for another, it is a region growing algorithm, while still making use of edge information, as captured by the gradient surface. And QWC is based on the concept and principles of quantum computing, such as the quantum bit and the superposition of states. QWC is also characterized by the representation of the individuals, the evolution mechanism, and the population dynamics. Unlike the binary, numeric coding, the coding manner of QWC is quantum individual coding, which can represent any states, thus has better diversity. And the quantum mutation and crossover operation can expedite the speed of evolution and avoid the prematurity in the whole procedure effectively.

The rest of this paper is organized as follows. Section 2 gives the related works about the image segmentation. In Section 3, the proposed method has been described in details. Section 4 shows the experimental results. Finally, Section 5 represents the conclusion of this paper.

2. Related works

2.1. Watershed segmentation strategy

Watershed segmentation algorithm [22] is a kind of region extraction algorithms, which is so simple and effective that it has been a widely used image segmentation tool. Watershed algorithm has the advantage of regional growth, namely spatially consistence, with boundaries forming a closed and connected set as well as making full use of edge information captured by the gradient surface. However, the gradient transformation is sensitive to noise, and can manifest itself as over-segmentation. This proposed algorithm will make use of the over-segmentation to supply reduced samples for the next phase of the quantum evolutionary clustering algorithm. The applied watershed segmentation strategy includes four steps.

Step 1: Simplify the image:
The purpose of simplifying the image is to remove the interference caused by noise and other unimportant details, as well as to smooth the image. Here the commonly used tool – Median Filter is adopted.
Step 2: Compute morphological gradient image:
Morphological gradient [24] image reflects the gray change in the image. At the edge of acute gray change, the gradient values also change a lot and vice-versa. The definition of morphological gradient image is that dilating transformation subtracting eroding transformation:

$$\text{grad}(f) = (f + s) - (f \Theta s). \tag{1}$$

where + represents the dilating transformation while Θ eroding transformation, and s is the structuring element.
Step 3: Compute the floating point activity image:

$$\text{fimg}(f) = \text{grad}(f) \times \text{grad}(f)/255.0. \tag{2}$$

Step 4: Get the initial segmentation result according to the watershed algorithm.

2.2. Discrete wavelet transformation

The discrete wavelet transformation (DWT) is regarded as the most useful technique for frequency analysis of signals that are localized in time or space. It decomposes signals into basis functions that are extension and translations of a signal prototype wavelet function.

The discrete wavelet transformation permits the analysis of the signal in many frequency bands or at many scales [12]. In practice, multiresolution analysis is carried out using two channels filter banks composed of a low-pass and a high-pass filter and each filter bank is then sampled at a half rate of the previous frequency. The down sampling procedure keeps the scaling parameter throughout successive wavelet transformation. Therefore, the original image is decomposed with n layers; there will be texture features with $3n+1$ dimensions $\{f_1, f_2, \ldots, f_{3n+1}\}$, where f_i is the energy of ith sub-band, which is calculated as follows:

$$f = \frac{1}{M*N}\sum_{i=1}^{M}\sum_{j=1}^{N}|x(i,j)|. \tag{3}$$

Here, $M*N$ is the size of sub-band, (i,j) represents the index for sub-band coefficient. In this paper, the DWT is used to decompose images into three layers.

3. Two-stage image segmentation approach

In this section, the proposed algorithm, quantum evolutionary clustering algorithms based on watershed (QWC) will be described in detail. First, the original image is partitioned into small pieces by using the watershed strategy. And then, these primitive regions are used to construct a graph representation of the image, the final segmentation is performed by the quantum evolutionary clustering algorithm.

Fig. 1 shows the overall structure of quantum evolutionary clustering algorithm based on watershed (QWC). The overall procedure of QWC is summarized as follows, in which $Q(t)$, $P(t)$ and b, respectively denote the population based on qubit at the tth generation, the population based on classical bit at the tth generation, and the best individual based on classical bit in the tth generation's population.

Quantum evolutionary clustering algorithm based on watershed:

Step 1: Input the image, the watershed algorithm is used to get the over segmentation result.
Step 2: Compute the block feature: First, extract the wavelet properties of each pixel, and then take the mean value of wavelet characteristics as the feature of each irregular region.
Step 3: Initialize the cluster centers $Q(t)$ and b; α_i^t and β_i^t $(i=1, \ldots, N)$ of all the $q_j^t (j=1, \ldots, M)$ are initialized with the same probability of $1/\sqrt{2}$.
Step 4: Observe the $Q(t)$ by collapsing the qubit representation into the binary representation $P(t)$.

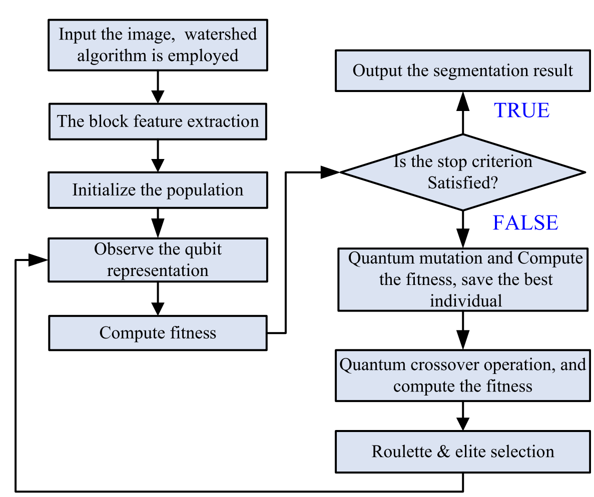

Fig. 1. Overall structure of QWC.