Chapter 34 Quantum Behaved Swarm Intelligent Techniques for Image Analysis: A Detailed Survey

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ABSTRACT

In this chapter, an exhaustive survey of quantum behaved techniques on swarm intelligent is presented. The techniques have been categorized into different classes, and in conclusion, a comparison is made according to the benefits of the approaches taken for review. The above-mentioned techniques are classified based on the information they exploit, for instance, neural network related, meta-heuristic and evolutionary algorithm related, and other distinguished approaches are considered. Neural Network-Based Approaches exhibit a few brain-like activities, which are programmatically complicated, for instance, learning, optimization, etc. Meta-Heuristic Approaches update solution generation-wise for optimization, and the approaches differ based on the problem definition.

INTRODUCTION

Image segmentation (Jahne, 1993; Jain, 1989) is a fundamental and significant technique in image processing. This technique is used to segregate an image into several non-overlapping consequential and homogeneous regions. The basic property of image segmentation is that each segmented region must share some common features of image, such as, texture, color or pixel intensity. Occasionally, the

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analogous grouping is known as clusters. A basic *prior* knowledge or even a presupposition about the image may be very useful for successful classification. This knowledge may help ones to find the appropriate features for this classification. Mathematically, let an image (I) is separated into *p* number of homogeneous, non-overlapping sub-regions viz., R_1, R_2, \ldots, R_p . Each pixel in image (I) must be allocated to only one R_k for $k = 1, 2, \ldots, p$. According to the rule of image segmentation, each R_k $(k = 1, 2, \ldots, p)$ must satisfy the following properties:

$$a)R_1 \cup R_2 \cup \ldots \cup R_n = I \tag{1}$$

$$b)R_i \cap R_j = \emptyset, i \neq j \tag{2}$$

$$c)i, j \in \{1, 2, \dots, p\}$$
(3)

In many occasions, segmentation was proved to be a useful and significant stair in image analysis. A good segmentation can reduce the computational overhead for the subsequent phases in image analysis. Segmentation is very useful for detecting and extracting the specific features of object from both graphic and nonnumeric data set. Segmentation has been successfully employed in different fields of application, such as, pattern recognition, surveillance, machine learning, medical sciences, artificial intelligence, economics, defense remote sensing to name a few. Segmentation techniques are generally classified into two classes viz., feature space based and image domain based (Lucchese & Mitra, 2001). Thresholding acts as a popular tool in image segmentation (Hammouche et al., 2008). One popular example of the former technique may be histogram thresholding whereas, region growing and merging, splitting and merging, edge detection based techniques may be some popular examples for later category (Lucchese & Mitra, 2001). Based on the characteristics of image pixel in its neighboring areas like discontinuity and resemblance, some segmentation techniques have been presented in (Freixenet et al., 2002). A review in this literature has been presented in (Gonzalez & Woods, 2002). Later, Bhattacharyya presented a detailed survey on different image thresholding and segmentation techniques based on classical and non-classical approaches (Bhattacharyya, 2011a).

Optimization can be described as an underlying way of finding feasible solutions of defined problems of various domains. Mathematically, it is defined as maximization or minimization function, subject to a group of constraints (if any). Optimization tries to discover best results (most acceptable) under the given circumstances. Two types of optimization can be defined based on the number of objectives (criteria) to be optimized. These are single objective optimization and multi-objective optimization. For the former type, the number of objectives to be optimized is solely one whereas, for the later type, minimum two objectives are optimized simultaneously. In multi-objective optimization, the number of objectives may vary subject to the nature of problem. In general, the objectives of conflicting type are used as fitness functions in this category (Deb et al., 2002). In general, in multi-objective optimization, multiple solutions are to be found out in chorus and the acceptable solutions are considered among them based on the importance of the unidentified objectives (Nocedal, 1999; Rao, 1996).

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