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Evolutionary optimization of a multiscale descriptor for leaf shape analysis

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A B S T R A C T

Shape analysis and recognition play an important role in the design of robust and reliable computer vision systems. Such systems rely on feature extraction to provide meaningful information and representation of shapes and images. However, accurate feature extraction is not a trivial task since it may depend on parameter adjustment, application domain and the shape data set itself. Indeed, there is a demand for computational tools to understand and support parameter adjustment and therefore unfold shape description representation, since manual parameter choices may not be suitable for real applications. Our major contribution is the definition of an evolutionary optimization methodology that fully supports parameter adjustment of a multiscale shape descriptor for feature extraction and representation of leaf shapes in a high dimensional space. Here, intelligent evolutionary optimization methods search for parameters that best fit the normalized multiscale bending energy descriptor for leaf shape retrieval and classification. The simulated annealing, differential evolution and particle swarm optimization methods optimize an objective function, which is based on the *silhouette* measure, to achieve the set of optimal parameters. Our methodology improves leaf shape characterization and recognition due to the intrinsic shape differences which are embedded in the set of optimized parameters. Experiments were conducted on public benchmark data sets with the normalized multiscale bending energy and inner-distance shape context descriptors. The visual exploratory data analysis techniques showed that the proposed methodology minimized the total within-cluster variance and thus, improved the leaf shape clustering. Moreover, supervised and unsupervised classification experiments with plant leaves accomplished high Precision and Recall rates as well as Bulls-eye scores with the optimized parameters.

1. Introduction

In computer vision, shape description consists of extracting feature for recognition, classification and exploratory data analysis. Feature extraction is widely applied to shape analysis and image processing and furthermore, it has been successfully used to solve a wide range of challenges in information science, biology, taxonomy, medicine and engineering (Anuar, Setchi, & Lai, 2013; Backhaus et al., 2010; Cesar Jr. & Costa, 1997; Chaki, Parekh, & Bhattacharya, 2015; Direkoglu & Nixon, 2011; Mokhtarian & Mackworth, 1986; Rossatto, Casanova, Kolb, & Bruno, 2011; Wang, Brown, Gao, & La Salle, 2015). Identification of plant species or leaf groups within a population is a challenging task since leaves of the same specie tend to subtly differ in size and shape due to the phenotypic plasticity. In plant taxonomy, leaf dimensions and shape are degrees of freedom by which plants adapt to their environment. Thus, a large range of variation can be found, even considering a given genotype and leaf position, depending on climate and resources (Dornbusch, Jillian, Baccar, Fournier, & Andrieu, 2011). Historically, sample specimens are stored in a herbarium

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for further identification, but with the advent of digital image technology it is now possible to create and publish leaf image data sets. Therefore, there is an increasing interest in deploying automated computational systems, which support taxonomists, who examine biological specimens, in the process of leaf-based plant species identification (Chaki et al., 2015; Cope, Corney, Clark, Remagnino, & Wilkin, 2012; Ghasab, Khamis, Mohammad, & Fariman, 2015; Wang et al., 2015).

A particularly important problem in shape analysis is to fit a shape descriptor to the application domain. In fact, this task comprises parameter adjustment of the shape descriptor and investigation about its structure and how it matches information knowledge, skill and perception of specialists.

Normally, parameter setting is an empirical task (Ling & Jacobs, 2007; Mokhtarian & Suomela, 1998; Wang, Bai, You, Liu, & Latecki, 2012). Paula Jr., Medeiros, Bezerra, and Ushizima (2013) have applied a brute force optimization scheme to effectively addressing parameter adjustment and achieved better results when adjusted shape descriptor parameters according to the database. In general, the design of shape descriptors or shape matching algorithms assigns parameter values regardless of the database. Alternatively, Bai, Yang, Latecki, Liu, and Tu (2010) proposed a method that computes image descriptors to regulate learned shape similarities. Thus, the learning context-sensitive shape similarity applies a supervised learning framework to search for the best learned parameters to calculate the affinity matrix (Bai et al., 2010).

An interesting approach to unfold the structure of a shape descriptor is to assess its performance in a subset of a data set due to the inherent complexity of the high dimensional representation that the descriptor provides. Data visualization techniques, which apply projection-based data, also known as manifold learning, are powerful tools to support this sort of assessment. Such tools provide a 2D representation of multidimensional data, which yields an informative panorama about its organization (Amorim et al., 2015). Moreover, these tools promote data exploration and support specialists to extract relevant data information.

Automatic parameter adjustment of a descriptor can be addressed as an optimization problem, where computational intelligence (CI) (Engelbrecht, 2007), a sub-branch of artificial intelligence, can be used. Studies in computational intelligence encompass bio-inspired algorithms, which present intelligent behavior to solve complex problems. In computer science, evolutionary computation (EC) consists of algorithms that mimic natural evolution processes of populations. The essence of an evolutionary approach to solve a problem is to equate possible solutions to individuals in a population, and to introduce a notion of fitness on the basis of solution quality (Eiben & Smith, 2015).

This paper introduces an optimization methodology to achieve parameter adjustment of the normalized multiscale bending energy (NMBE) (Cesar Jr. & Costa, 1997) tailored to leaf shape analysis. Our approach searches for the best set of descriptor parameters, which encompasses the intrinsic shape differences within a database, to perform leaf shape supervised classification and content-based image retrieval experiments. The main contribution of this work is to provide an optimization methodology for parameter adjustment of a multiscale shape descriptor to characterize plant leaves, which can also be adapted to deal with different objective functions, data sets and applications.

The remainder of this paper is organized as follows. The next section introduces materials and methods to support the proposed methodology that optimizes a multiscale shape descriptor. It also describes the evaluation methodology which comprises the self-organization map and multidimensional scaling. Section 3 presents the public Flavia leaf data set and discusses the classification and shape retrieval results as well as the visual exploratory cluster analysis. It also evaluates the computational cost of the proposed methodology. In Section 4, we draw conclusions and summarize our main contributions.

2. Materials and methods

The proposed methodology for shape descriptor optimization follows the schemes depicted in Fig. 1. The goal of the optimization procedure is to improve shape description and hence its ability to identify hidden and subtle shape features. In fact, what guides this optimization procedure is the minimization of the objective function *median* absolute deviation error (MAD) of the *silhouette* measure (Rousseeuw, 1987). We have chosen this objective function due to its robustness to outliers (Rousseeuw & Leroy, 1987) and, it is given by

$$\mathrm{MAD} = median\left(|s_i - 1|_{i=1,\,2,\,\cdots,\,L}\right), \tag{1}$$

where the set $S = \{s_1, s_2, \cdots, s_L\}$ comprises the computed *silhouette* values for L shape descriptors. The operators $|.|$ and $median()$ return the absolute value of an argument and the median of a set of values, respectively.

Silhouette (Rousseeuw, 1987) is a cluster quality measure that indicates the affinity degree of an object i with a particular class A, taking into account the average within-class and inter-class distances of this object to the others. This measure is defined as

$$s_i = \frac{b_i - a_i}{\max\,(a_i, b_i)} \in [-1, 1], \tag{2}$$

where a_i is the mean dissimilarity between the object i and the objects belonging to the same class A and b_i is the mean dissimilarity of the object i to the neighbor class closest to i, excluding its own class. *Silhouette* may assume values in the interval $[-1, 1]$, and furthermore, a negative value indicates that an object potentially belongs to its neighbor class. Differently, a positive value denotes that it belongs to the estimated class. A value close to zero indicates that the object is close to a boundary between two classes and hence there is uncertainty about which class it belongs to. The objective function (MAD) values lie within the interval [0, 2]. Accordingly, a value equal to zero for this function indicates a perfect cluster structure, while a MAD value close to 2 indicates a cluster structure with low intra-class similarity and high inter-class similarity.

The proposed methodology adjusts the parameters of the multiscale shape descriptor following the process in Fig. 1. The first step randomly selects a subset of sample leaf shapes from Flavia leaf data set and then it runs the optimization methodology to find the best set of scale parameters $\boldsymbol{\sigma}_{best} = (\sigma_1, \sigma_2, \cdots, \sigma_k)$ of the multiscale descriptor that minimizes the MAD function (Eq. 1). Finally, the set of feature vectors is evaluated qualitatively and quantitatively by applying manifold learning algorithms and performing supervised classification and content based image retrieval experiments.

The qualitative evaluation applies two manifold learning algorithms, namely the Kohonen clustering algorithm (Kohonen, Schroeder, & Huang, 2001) and the multidimensional scaling (MDS) (Cox & Cox, 2000). These algorithms generate 2D projections of the leaf description and display these projections in shape similarity maps. Actually, these maps provide graphical representations that support cluster analysis, since they illustrate how the multiscale descriptor spatially organizes leaf shapes in a 2D space.

The quantitative evaluation methodology of the cluster quality relies on the mean *silhouette* per shape class as a measure of the leaf cluster cohesion (Rousseeuw, 1987). Finally, Precision and Recall rates assess the performance of the optimized multiscale descriptor in supervised classification experiments, where the Naive Bayes (NB) (Fukunaga, 1990), K-nearest neighbors (Knn, $K = 5$) (Fukunaga, 1990; Webb, 2002), Fisher linear discriminant analysis