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Image feature selection using genetic programming for figure-ground segmentation

Yuyu Liang*, Mengjie Zhang, Will N. Browne

School of Engineering and Computer Science, Victoria University of Wellington, PO Box 600, Wellington 6140, New Zealand

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ABSTRACT

Figure-ground segmentation is the process of separating regions of interest from unimportant background. One challenge is to segment images with high variations (e.g. containing a cluttered background), which requires effective feature sets to capture the distinguishing information between objects and backgrounds. Feature selection is necessary to remove noisy/redundant features from those extracted by image descriptors. As a powerful search algorithm, genetic programming (GP) is employed for the first time to build feature selection methods that aims to improve the segmentation performance of standard classification techniques. Both single-objective and multi-objective GP techniques are investigated, based on which three novel feature selection methods are proposed. Specifically, one method is single-objective, called PGP-FS (parsimony GP feature selection); while the other two are multi-objective, named nondominated sorting GP feature selection (NSGP-FS) and strength Pareto GP feature selection (SPGP-FS). The feature subsets produced by the three proposed methods, two standard sequential selection algorithms, and the original feature set are tested via standard classification algorithms on two datasets with high variations (the Weizmann and Pascal datasets). The results show that the two multi-objective methods (NSGP-FS and SPGP-FS) can produce feature subsets that lead to solutions achieving better segmentation performance with lower numbers of features than the sequential algorithms and the original feature set based on standard classifiers for given segmentation tasks. In contrast, PGP-FS produces results that are not consistent for different classifiers. This indicates that the proposed multi-objective methods can help standard classifiers improve the segmentation performance while reducing the processing time. Moreover, compared with SPGP-FS, NSGP-FS is equally capable of producing effective feature subsets, yet is better at keeping diverse solutions.

1. Introduction

Figure-ground image segmentation can be regarded as a special case of image segmentation. It only identifies regions of interest and considers other parts as the background, thus producing binary images as the result. Figure-ground segmentation is an important topic, as many tasks in computer vision and image processing, e.g. robot grasping and image editing, are only interested in certain regions of images and use it as a preprocessing step to isolate these regions (Zou et al., 2014). It is difficult to achieve accurate segmentation performance especially for images with high variations (Liang et al., 2015, 2017), e.g. in terms of object shapes and background regions. In these cases, effective image features that can capture distinguishing information are necessary. However, image features extracted by existing feature descriptors often contain noisy/redundant features, which feature selection (FS) can help remove, thus improving the segmentation performance.

One challenge in FS is the large search space of possible feature subsets, so effective search methods are crucial. Generally, existing FS algorithms use three types of search methods, e.g. exhaustive, sequential and random methods, to search for good feature subsets (Liu and Yu, 2005). FS using the exhaustive search methods, e.g. breadth first search, evaluates all possible combinations of the original features exhaustively, and then find the best subset. The exhaustive search has a high computational cost and may lead to the over-fitting problem (Nagata et al., 2015). Sequential search methods, such as forward selection and backward selection (Zhou and Hansen, 2006), aim to produce a good solution in a reasonable time by trading off accuracy and optimality for speed. Random search methods initially randomly select a feature subset, then two ways are applied to search for an optimal subset (Kumar and Minz, 2014). One is to use a completely random method to generate the next subset, such as the Las Vegas algorithm. However, it assumes that the run time is infinite, which is not realistic. As the Las Vegas algorithm cannot discover a good feature

* Corresponding author.

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subset in the allocated time, it often performs poorly. The other is to include heuristic knowledge in the search process, such as evolutionary computation (EC) techniques.

EC techniques have the potential to solve problems with large search spaces efficiently, and can be applied to a wide range of optimisation problems (Nag and Pal, 2016), e.g. feature selection. EC techniques can be mainly categorized into three groups (Borenstein and Ullman, 2008): evolutionary algorithms (e.g. genetic algorithms and genetic programming), swarm intelligence (e.g. particle swarm optimisation and bee algorithm) and others (e.g. memetic algorithms). Compared with other EC techniques, GP is more flexible (Espejo et al., 2010), as it can utilize complex and variable-length representations, such as trees. The flexibility of GP makes it possible to evolve better solutions than those designed by experts. GP has been applied to feature selection (Nag and Pal, 2016; Smart and Burrell, 2015; Davis et al., 2006; Muni et al., 2006), and promising results have been achieved.

Existing GP based FS methods can be divided into three categories based on the evaluation of selected feature subsets, which are the filter, the wrapper and the embedded approaches (Xue et al., 2016), which are described in detail in Section 2.1. For the filter approach, the avoidance of learning algorithms in the evaluation loop makes it challenging to evaluate the feature subsets, as it ignores the actual performance of the selected features for a given task (e.g. a classification problem). In contrast, the wrapper approach generally produces better performing feature subsets than the filter approach (Xue et al., 2016). Moreover, the embedded approach is more complex conceptually, and modifications to the learning algorithm may cause poor performance (Maldonado and Weber, 2011). Therefore, we only investigate the wrapper feature selection methods in this work.

1.1. Goals

The paper (Liang et al., 2016) published in “ IEEE Congress on Evolutionary Computation 2016” is our initial work of feature selection. In paper (Liang et al., 2016), GP is used to evolve segmentation algorithms rather than for the purpose of feature selection. Based on the GP-evolved solutions, a simple feature selection is conducted by selecting the features with high occurrence rates. In contrast, this paper employs GP for the first time to develop feature selection methods for figure-ground segmentation tasks, which aims to produce effective feature subsets to help improve segmentation performance on complex images (e.g. images with high variations). Three novel wrapper FS methods using both single-objective and multi-objective GP techniques, i.e. PGP-FS (parsimony GP FS), NSGP-FS (nondominated sorting GP FS) and SPGP-FS (strength Pareto GP FS), have been developed. Specifically, PGP-FS is single-objective; while NSGP-FS and SPGP-FS are multi-objective, which are based on two multi-objective techniques respectively, i.e. NSGA-II (nondominated sorting genetic algorithm) and SPEA2 (strength Pareto evolutionary algorithm). The generated feature subsets from the three proposed methods will be studied and compared with two standard selection methods (sequential forward and sequential backward methods) and the whole feature set. Specifically, we investigate the following objectives:

1. explore whether the proposed methods can produce effective feature subsets for complex segmentation tasks,
2. compare the single-objective method (PGP-FS) with the multi-objective methods (NSGP-FS and SPGP-FS),
3. investigate which one of the two multi-objective methods (NSGP-FS and SPGP-FS) performs better.

The rest of the paper is organised as follows. Section 2 provides the introduction to feature selection and existing works that utilize GP to select features. Section 3 describes the related methods, i.e. the feature extraction and the pixel classification based figure-ground segmentation method. In Section 4, the new feature selection methods are described. Section 5 provides the experimental preparation. In Section 6, the results are presented, and conclusions and future work are shown in Section 7.

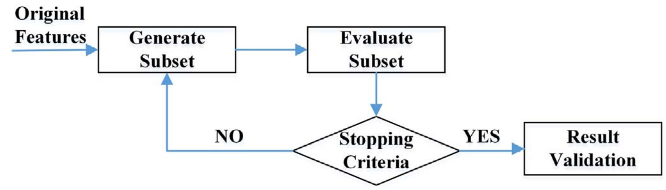

Fig. 1. A general feature selection process (Dash and Liu, 1997).

2. Background

2.1. Feature selection

Feature selection (FS) is the process of selecting a feature subset from a large space of possible subsets (Saeys et al., 2007). There are three major steps in a general feature selection procedure, i.e. generating subsets, evaluating subsets and checking whether the stopping criteria has been met (Dash and Liu, 1997). As shown in Fig. 1, firstly the possible feature subsets are produced by search methods, then the subsets are evaluated. Two classes of evaluation criteria are widely-used, i.e. independent criteria (e.g. distance measures between feature subsets) and dependent criteria (e.g. classification performance using feature subsets for given classification tasks). The former suits a filter model, while the latter suits a wrapper model (described later in this section). Stopping criteria include that the addition or deletion to the subset of features does not obtain significant difference in the performance or the search reaches a predefined minimum number of features or maximum number of iterations.

Based on the evaluation methods used for feature subset creation, feature selection methods can fall into one of three branches (Xue et al., 2016), i.e. the filter, the wrapper or the embedded approaches. Wrapper methods employ a classification algorithm to evaluate the goodness of the selected subsets (Talavera, 2005). In contrast, filter methods evaluate the subsets dependent on general characteristics of the training data rather than the feedback of an inductive algorithm (Sánchez-Maroño et al., 2007). Similar to the wrapper approach, the embedded approach is directed by an inductive algorithm for the subset evaluation, but the classification algorithm is the learning algorithm itself (Xue et al., 2016). In other words, embedded methods select features and build a learning model in one step, while filter and wrapper methods realize this in two steps: firstly select features, then conduct the model learning. Note that not all learning algorithms can conduct the embedded feature selection, which is based on learning characteristics of the algorithms and whether they have an integrated mechanism for implicit selection of features. Only GP and learning classifier system (LCS) among current EC techniques can be used for the embedded feature selection (Xue et al., 2016).

2.2. GP for feature selection

As an evolutionary computation technique, GP has the ability to deal with a large search space. Recent works (Nag and Pal, 2016; Smart and Burrell, 2015; Davis et al., 2006; Ahmed et al., 2013) on GP based feature selection are described as follows, which shows GP's potential for feature selection. However, all these papers address the classifica-