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Two-Tier genetic programming: towards raw pixel-based image classification

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ABSTRACT

Classifying images is of great importance in machine vision and image analysis applications such as object recognition and face detection. Conventional methods build classifiers based on certain types of image features instead of raw pixels because the dimensionality of raw inputs is often too large. Determining an optimal set of features for a particular task is usually the focus of conventional image classification methods. In this study we propose a Genetic Programming (GP) method by which raw images can be directly fed as the classification inputs. It is named as *Two-Tier GP* as every classifier evolved by it has two tiers, the other for computing features based on raw pixel input, one for making decisions. Relevant features are expected to be self-constructed by GP along the evolutionary process. This method is compared with feature based image classification by GP and another GP method which also aims to automatically extract image features. Four different classification tasks are used in the comparison, and the results show that the highest accuracies are achieved by Two-Tier GP. Further analysis on the evolved solutions reveals that there are genuine features formulated by the evolved solutions which can classify target images accurately.

1. Introduction

The aim of this investigation is to propose a Genetic Programming (GP) methodology for image classification by which the conventional feature extraction step can be avoided. The importance of image classification is self-evident in the recent years as machine vision and image processing applications are widely and increasingly spread into our daily lives. For example an ordinary modern point-and-shoot camera can classify the presence or absence of human faces in real time. By image classification personal hand-held mobile-phones can be turned into a museum guide and an information booth. Museum visitors may access information of a displayed item simply by showing it to their phones. Image classification is frequently found in commercial applications as well, for example identifying pedestrians in security surveillance systems, labeling type of cells or detecting anomaly in medical imaging systems, and differentiating various terrains in satellite imagery applications.

Other than image acquisition, the two main components in a conventional image classification approach are feature extraction and classification. The classification is based on the features been extracted. In other words, the image classifier does not directly operate on the input image itself, but on some kind of feature values. Feature extraction is actually a transformation process which converts images into corresponding feature values. The main purpose of this process is dimensionality reduction, as an image often contains a large number of pixels of which many are redundant in term of the contribution towards classification. There are numerous image features available in the literature, for example features based on edges or contours; features based on image histograms, features extracted from transformed domains such as Fourier domain; Wavelet domain and Hough domain; features generated by templates; texture features and so on. Distinctive characteristics of images from different classes are expected to be captured in these features, so that the images would be labeled accurately by a classifier. Without features conventional classifiers would not be able to perform well on images especially when these images are from real world scenarios.

The negative side of feature extraction process is that domain knowledge is required. Features are often constructed to fit a specific application. If not so, then the designer of this application needs to select a set of existing features suited for the task. Therefore understanding of the application itself is essential, either for designing features or for choosing features. As the result, features are problem dependent. There is no universal features applicable for all kinds of applications. One workaround for the domain dependence issue is generating a large set of features to cover all

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the possible good ones, then performing feature selection on them to pick out the prominent features. This approach is computationally expensive. Additionally the classification accuracy would largely rely on the performance of the feature selection algorithm. A domain independent image classification method is therefore highly desirable, which is exactly the motivation of the GP method presented in this study.

Fundamentally GP is an evolutionary method for automatic program generation. A solution built by GP is essentially a computer program. As a powerful problem solving paradigm, it has been adapted into many complex domains such as timetable scheduling, circuit design, and stock market prediction (Poli et al., 2008). The programs generated by GP are often creative, and not thought about by human experts. Some solutions found by GP are even patentable. It also has been used for various image related tasks such as image segmentation (Poli, 2000), edge detection (Fu, Johnston, & Zhang, 2011), texture analysis (Song & Ciesielski, 2008), motion detection (Pinto & Song, 2009) and finding interest points (Olague & Trujillo, 2011). These studies show that GP can achieve better or at least comparable results in these tasks without providing much domain knowledge. In the domain of image classification, GP has also demonstrated its advantages in performance. Zhang et al. were able to classify haemorrhage and micro aneurysms in retina images by GP (Zhang, Ciesielski, & Andreae, 2003). Bhanu and Lin trained GP programs to identify road, like and field regions from radar images (Lin & Bhanu, 2005). Song et. al used GP to classify texture images (Song, Ciesielski, & Williams, 2002). It can be seen that GP is able to construct classifiers which are comparable to conventional classifiers such as decision trees. However most of these previous works require domain dependent features as well. GP is just responsible to generate the classifiers.

1.1. Goals of this study

In this paper we aim to enable GP to build classifiers based on raw pixels instead of feature values. The feature extraction process happens implicitly inside of a GP program. Hence no domain knowledge would be required in this approach. The specific research questions of this study are as follows:

- How can image classification problems be represented in GP to generate classifiers which operate directly on raw image pixels rather than extracted feature values?
- How would this approach perform on a collection of image classification tasks especially when compared with other approaches?
- How would the evolved GP classifiers achieve good accuracies? Can this approach automatically evolve genuine features relevant to a problem without human intervention?

1.2. Organization

The rest of this paper is organized as such: Section 2 briefly discusses GP and the related previous work. Section 3 presents the GP methodology called Two-Tier GP. In Section 4 four image classification tasks are introduced. It also describes the features manually designed for these domains. Section 5 reports the experiments along with the corresponding results. Section 6 is the study on some of the evolved GP classifiers to reveal the captured features. This paper is concluded in Section 7.

2. Background

Genetic Programming (GP), pioneered by John Koza Koza (1992), is a member of Evolutionary Computing methods. It has been successfully applied into many domains and proven as a powerful problem-solving paradigm (Poli et al., 2008). The key aspect of GP is to evolve programs as the solutions for a particular problem. Each solution is represented as a program tree in Lisp S-expression as shown in Fig. 1. The expression in the figure is actually $((x - y) * z) + (x * (y * y))$, which can be written as Lisp S-expression $(+ (* (- x\ y) z)(* x(* y\ y)))$.

During the evolutionary process of GP, a group of program trees are *randomly* generated as the initial population. They are evaluated against the problem to be solved, in our case an image classification task. Each program is assigned with a fitness value which is its performance on solving the task. A program with better fitness is more likely to be selected for reproducing the next generation. This implements the survival-of-the-fittest principle proposed by Darwin. Selected programs may swap their tree branches to generate new programs. This is known as *crossover* in GP. A selected program may randomly change its branch to create a new program. This is known as *mutation*. A selected program may also be directly copied into the new generation. This is known as *elitism*. The new population produced by crossover, mutation and elitism will be evaluated against the same fitness measure. The more successful programs, or individuals, are more likely to form their own offspring. Such a process is iterative and will stop if one of the termination conditions is met. For instance, a perfect solution is found, or the maximum number of generations is reached. A suitable representation, including a set of *functions* (internal nodes on a program tree) and a set of *terminals* (leaf nodes), is critical in the success of GP evolution.

GP methodology itself is domain independent. It has been adapted into many domains including classification (Espejo, Ventura, & Herrera, 2010). Image classification is also an area that GP has been extensively studied (dos Santos, Ferreira, da Silva Torres, André Gonçalves, & Lamparelli, 2011; Li, Ma, & Zhao, 2008; Bhowan, Zhang, & Johnston, 2010; Pasolli, Melgani, Donelli, Attoui, & de Vos, 2008). Song et al. used GP for texture classification which is based on raw image pixel values rather than on texture features. Their approach can handle this complex task well (Song, Loveard, & Ciesielski, 2001). Bhowan et al. studied the use of GP approach to classify images in unbalanced dataset (Urvesh et al., 2010). Their results suggest that GP is capable of handling this difficult problem.

As mentioned previously, image classification often consists of two parts: feature extraction and classification. GP can no only deal with classification, but also address the feature extraction component (Alden Tackett, 1993; Kowaliw, Banzhaf, & Harding, 2009; Szymanski et al., 2002; Guo & Nandi, 2006). For example Guo and Nandi developed a GP-based approach to extract features which actually outperformed the features designed by domain experts (Guo, Jack, & Nandi, 2005). Furthermore the time required for feature extraction was significantly reduced because of these GP generated features. Zhang and Rockett proposed a GP-based methodology to extract features for edge detection (Zhang & Rockett, 2005). The one-dimensional feature vector generated by their GP method performed better than the classical Canny algorithm.

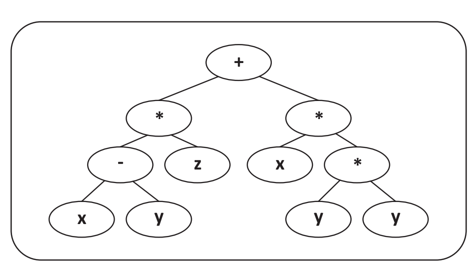

Fig. 1. An example of program tree in GP.