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Image Pattern Recognition using Evolutionary Algorithm

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Abstract: - The goal of this paper is to investigate and explore evolutionary algorithm performance in image processing. We have made attempt to introduce image pattern recognition by using evolutionary technique. Initially the shape, color and texture feature is extracted from given query image and also for the databases images in a similar manner. Subsequently similar images are retrieved utilizing evolutionary algorithm. Thus by means of evolutionary algorithm required relevant image patterns are retrieved from a large image database based on a given query. The evolutionary algorithm is applied to decide the most plausible matching.

Keywords – *Image feature, evolutionary, feature selection, classification*

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I. Introduction

After a long incubation in academia and in very specialized industrial environments, in the last ten to fifteen years research and development of image processing and computer vision applications have become mainstream industrial activities. Apart from the entertainment industry, where video games and special effects for movies are a billionaire business, in most production environments automated visual inspection tools have a relevant role in optimizing cost and quality of the production chain as well. Evolutionary approach is a relatively recent and fast developing approach to automatic programming [1, 2,3]. In evolutionary approach, solutions to a problem can be represented in different forms but are usually interpreted as computer programmes. Darwinian principles of natural selection and recombination are used to evolve a population of programmes towards an effective solution to specific problems.

Designing a computer application to whatever field implies solving a number of problems, mostly deriving from the variability which typically characterizes instances of the same real-world problem. Whenever the description of a problem is dimensionally large, having one or more of its attributes out of the "normality" range becomes almost inevitable. A rather wide range of well-established and well-explored image processing and computer vision tools is actually available, which provides effective solutions to rather specific problems in limited domains, such as industrial inspection in controlled environments. However, even for those problems, the design and tuning of image processing or computer vision systems is still a rather lengthy process, which goes through empirical trial-and-error stages, and whose effectiveness is mostly based on the skills and experience of the designer in the specific field of application.

From the point of view of artificial intelligence (AI), which focuses on mimicking the high-level intelligent processes which characterize living beings, genetic and evolutionary computation, as the other soft computing paradigms, is a way to provide computers with natural skills (self-improvement, learning, generalization, robustness to variability, adaptively, etc.) based on nature-inspired paradigms.

EC paradigm has both exploration (random) and exploitation (knowledge-based) components, associated to specific user-defined parameters which the user can set. This makes EC paradigms particularly flexible, as they allow users to balance exploitation and exploration as needed. This translates into highly effective and efficient searches by which good solutions can be found quickly.

The common components of these techniques are *populations* (that represent sample points of a search space) that evolve under the action of stochastic operators. Evolution is usually organized into *generations* and copies in a very simple way the natural genetics. The engine of this evolution is made of (i) *selection*, linked to a measurement of the quality of an individual with respect to the problem to be solved, (ii) *genetic operators*, usually *mutation* and *crossover* or *recombination*, that produce individuals of a new generation.

II. IMAGE PATTERN RECOGNITION

Traditionally, most research on object recognition involves four stages: *preprocessing*, *segmentation*, *feature extraction*, and *classification* [4, 5]. The preprocessing stage aims to remove noise or enhance edges. In the segmentation stage, a number of coherent regions and "suspicious" regions which might contain objects are usually located and separated from the entire images. The feature extraction stage extracts domain specific features from the segmented regions. Finally, the classification stage uses these features to distinguish the classes of the objects of interest. The features extracted from the images and objects are generally domain specific such as high-level relational image features. Data mining and machine learning algorithms are usually applied to object classification Image pattern recognition, also called automatic image recognition or automatic target recognition, is a specific field and a challenging problem in computer vision and image understanding. This task often involves *object localization* and *object classification*. Object localisation refers to the task of identifying the positions of the objects of interest in a sequence of images either within the visual or infrared spectral bands. Object classification refers to the task of discriminating between images of different kinds of objects, where each image contains only one of the objects of interest. Traditionally, most research on object recognition involves four stages: *preprocessing*, *segmentation*, *feature extraction*, and classification. The preprocessing stage aims to remove noise or enhance edges. In the segmentation stage, a number of coherent regions and "suspicious" regions which might contain objects are usually located and separated from the entire images. The feature extraction stage extracts domain specific features from the segmented regions. Finally, the classification stage uses these features to distinguish the classes of the objects of interest. The features extracted from the images and objects are generally domain specific such as high-level relational image features. Data mining and machine learning algorithms are usually applied to object classification.

GENETIC OPERATORS:

Evolutionary algorithms are search strategies that is applicable to wide range of problems..The algorithm evolves with some stochastic rules. The three main genetic rules are selection, crossover and mutation.

The evolutionary algorithm may be built with these rules. These rules are nothing but the genetic operators. That is 1) crossover 2) mutation and 3) selection.

Crossover operator combines the information of two or more individual. Two selected parent chromosomes are separated at a particular point and their adjacent substrings are separated.

Mutation step is carried out by flipping bits of a chromosome. A single bit is selected randomly and inverted at a particular probability.

Selection operator that using the objective function evaluation of all individual in the population replicates some of them and eliminates other ones, generating next population.

Evolutionary algorithm may contain other type of rules such as niche, local search. It is known that specific operator structure and operator parameter tuning should be employed for each class of problems in order to get computational efficiency.

The probabilities for crossover and mutation are decided with regard to the real life evolution principles, where mutation occurrences are rare.

In practice it is very difficult to design a optimal set of genetic operators

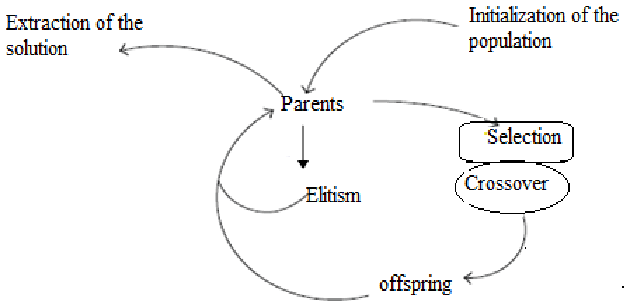

Figure 1. Evolutionary process

The evolutionary algorithms are naturally attractive as feature selectors, because they allow the size of the evolving feature sets to shrink and grow as the space is explored and do not require pre specification of the size of the optimal feature set.

EVOLUTIONARY ALGORITHMS IN FEATURE SELECTION

Features are nothing but a attributes that represent a object. If image is there we can select color,shape as feature. Feature selection is one of the important stage in image pattern recognition. As there may be number of features. But all the feature are not required for the problem at hand. If redundant features are there that can increase the computing time needed to extract the features. Redundant features can occupy more space also. It is advised to select relevant feature set. Feature redundancy problem can be overcome in this stage. If features are less, less training example will be required. Each feature has value associated with it. This value is nothing but a cost associated with it.

By applying domain knowledge, we can eliminate irrelevant features. Relevant feature selection can improve the learning accuracy.

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Feature selection stage contain three steps.

1) Generating a feature set containing a subset of original features.
2) Evaluating the feature subset and their utility. Based on the evaluation some features may be discarded.
3) Deciding whether the selected set is good enough. Otherwise feature selection algorithm iterates until some stoping criteria is met.

Feature selection may be supervise or un supervise. Feature selection is done in an offline manner. since execution time of algorithm is not important as compare to classification performance. If feature set is of moderate size then execution time become important.

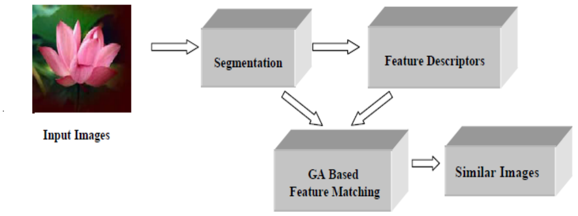

Figure 2. Overview of pattern recognition system using evolutionary algorithm

Evolutionary Algorithms in Classification

Classification tasks arise in a very wide range of applications, such as detecting faces from video images, recognizing words in streams of speech, diagnosing medical conditions from the output of medical tests, and detecting fraudulent credit card fraud transactions [6,7, 8]. In many cases, people (possibly highly trained experts) are able to perform the classification task well, but there is either a shortage of such experts, or the cost of people is too high.

Song [9–10] used tree-based genetic programming for a series of object image texture classification problems, such as classification of bitmap patterns, Brodatz textures, and mashing images.

Rule-Based Systems Representing concepts as sets of rules has long been popular in machine learning, because, among other properties, rules are easy to represent and humans can interpret them easily. In East here are two main ways to represent rule sets. In the "Michigan" approach, each individual in the population represents one fixed length rule, and the entire population represents the target concept. In contrast, in the "Pittsburgh" approach, each variable-sized individual represents an entire set of rules. The two representations have their merits and drawbacks and have been used successfully in classifier systems, which are rule-based systems that combine reinforcement learning and evolutionary algorithms.

The basic loop in a classifier system is that the system is presented with inputs from the environment, the inputs are transformed into messages that are added into a message list, and the strongest rules that match any message in the list are fired (possibly adding more messages to the list or acting on the environment). Rules are assigned a fitness value based on a reward returned by the environment. Evolutionary Algorithms and Neural Networks Genetic algorithms and artificial neural networks (ANNs) have been used together in two major ways. First, EAs have been used to train or to aid in the training of ANNs. In particular, Enslave been used to search for the weights of the network, to search for appropriate learning parameters, or to reduce the size of the training set by selecting the most relevant features.

III. Performance Of Evolutionary Algorithms

Evolutionary algorithms are proving themselves in solving real problems in data mining, especially in cases where the data is noisy, or requires the solution of a multi-objective optimisation problem.

It can be shown that different random sequences.

Sequences are used during the evolution, the final results may effectively be very close but not equal.

Some algorithm may be slow but converge fast.one way to measure the success performance is to investigate expected number of evaluation.

Several authors expressed that evolutionary algorithms can be very time consuming. Only a small sample of pixels could be used in order to reduce the time required. We should keep a global population of fit individuals, which can be used to seed the genetic algorithm for each image. This not only makes the system adaptive, but also reduces the computation time. If we exploit the inherent parallelism in genetic algorithms, we can reduce the time for edge detection operators in image analysis. In addition, we also hinted that using representations that are more appropriate for the problems at hand or designing custom operators could result in a more scalable algorithm.The efficiency of an evolutionary algorithm strongly depends on the parameter setting: successive populations (generations) have to converge toward what is wished, that is, most often the global optimum of a performance function.

IV. Conclusion

First of all, it has been made evident, if necessary, that evolutionary schemes are efficient in image analysis basic tasks, as far as we deal with complex optimization problems. In computer vision and, more generally, in pattern recognition applications, such as tracking, surveillance, industrial inspection, and quality control, detection of specific objects of interest (targets, defects, etc.) is often performed by examining arrays of relatively simpler data.

In this approach, the learning/evolutionary process is terminated when one of the following conditions is met.

(i) The classification problem has been solved on the training set, that is, all image objects of interest in the training set have been correctly classified without any missing objects or false alarms for any class.

(ii) The accuracy on the validation set starts falling down.

(iii) The number of generations reaches the predefined number, *max-generations*.

Evolutionary computation, describes the field of investigation that concerns all evolutionary algorithms and offers practical advantages to several optimization problems. The advantages include the simplicity of the approach, its robust response to changing circumstances, and its flexibility and so on.

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