Evolving Texture Image Descriptors Using A Multitree Genetic Programming Representation

Harith Al-Sahaf, Bing Xue, and Mengjie Zhang
School of Engineering and Computer Science
Victoria University of Wellington, P.O. Box 600, Wellington 6140, New Zealand
{Harith.Al-Sahaf,Bing.Xue,Mengjie.Zhang}@ecs.vuw.ac.nz

ABSTRACT

Image descriptors play very important roles in a wide range of applications in computer vision and pattern recognition. In this paper, a multitree genetic programming method to automatically evolve image descriptors for multiclass texture image classification task is proposed. Instead of using domain knowledge, the proposed method uses only a few instances of each class to automatically identify a set of features that are distinctive between the instances of different classes. The results on seven texture classification datasets show significant, or comparable, performance has been achieved by the proposed method compared with the baseline method and six state-of-the-art methods.

CCS CONCEPTS

•**Computing methodologies → Genetic programming;** *Interest point and salient region detections; Matching;* Feature selection;

KEYWORDS

Genetic Programming, Multitree, Multiclass classification, Textures

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1 INTRODUCTION

Identifying a set of important image keypoints or regions of interest, e.g., lines, corners, and homogeneous regions, that can be used to categorise images into different groups is a crucial task in computer vision and pattern recognition. This task is often carried out by a domain expert in order to identify or design those keypoints. Detecting those keypoints in an image is the next step towards generating the feature vector. Image descriptors are models that aim at automatically detecting a set of predetermined keypoints in an image and generating the feature vector [5]. On the one hand, developing an image descriptor often requires domain expert to define the steps needed to detect those keypoint. Furthermore, the majority of the existing image descriptors are limited to detect only a specific set of keypoints.

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An early work by Ebner and Zell [4] used Genetic Programming (GP) to automatically evolve an interest point detector. Similarly, GP is used to automatically evolve interest point detectors in [7].

Inspired by structural genes in living organism, a multitree GP based method is proposed by Benbassat and Sipper [3] to the zero-sum, deterministic, full-knowledge board game of Lose Checkers. The method aimed at utilising GP for discovering effective strategies for playing the Lose Checkers game, where their experiment results show the effectiveness of this method.

Lee et al. [6] proposed a multitree GP based method to efficiently discover a set of patterns necessary for self-assembling swarm robots. Those patterns are then incorporate into the corresponding robot modules. The experiments in [6] reveal the effectiveness of their method.

Al-Sahaf et al. [1] proposed a GP based method that automatically evolves image descriptors. A special *code* node type is used in the function set that comprises a predefined number of children, which thresholds the values of its children and generates a binary code. Using the *code* node type in this method imposes the requirements for utilising strongly-typed GP to specify different restrictions.

The overall goal of this paper is to automatically evolve rotation-invariant image descriptors by utilising a multitree GP representation to the task of multiclass texture image classification. Furthermore, designing a new fitness function motivated by the margins concepts of support vector machines (SVM) that can handle having only two instances per class is also an objective of this paper.

2 MULTITREE GP IMAGE DESCRIPTOR

The proposed method *multitree GP rotation-invariant image descriptor* ($\text{MGPD}^{\text{ri}}_{t,w}$) uses a multitree representation for an individual instead of the single tree used by conventional GP. The terminal set is identical to that of GP-criptor$^{\text{ri}}$, whereas the function set comprises the four arithmetic operators +, −, × and /. The subscripts t and w specify the number of trees and sliding window size, respectively. The fitness function relies on the within-class and between-class distances, which is defined as

$$fitness = \alpha \times D_{\text{w}} + (1-\alpha) \times (1 - D_{\text{b}}) \tag{1}$$

$$D_{\text{w}} = \frac{1}{z} \sum_{\mathbf{u} \in \mathbf{R}} \sum_{\vec{u} \in \mathbf{u}} \max_{\vec{v}} \chi^2\left(\vec{u}, \vec{v}\right), \quad \left\{\vec{v} \in \mathbf{u}, \vec{u} \neq \vec{v}\right\} \tag{2}$$

$$D_{\text{b}} = \frac{1}{z\,(c-1)} \sum_{\mathbf{u} \in \mathbf{R}} \sum_{\mathbf{v} \in \mathbf{R} \setminus \mathbf{u}} \min_{\vec{u}, \vec{v}} \chi^2\left(\vec{u}, \vec{v}\right), \quad \left\{\vec{u} \in \mathbf{u}, \vec{v} \in \mathbf{v}\right\} \tag{3}$$

where $\alpha \in [0, 1]$ is a scale factor, a bold letter, e.g., $\mathbf{u}$ and $\mathbf{v}$, is a set of all instances corresponding to one class, z and c is, respectively, the total number of instances in the training set and number of classes, and $\mathbf{R} = \left\{\left(\vec{v}_i, \ell_i\right)\right\}$ where $i \in \{1, 2, \ldots, z\}$. Furthermore, χ^2

Table 1: The average accuracy (%) of 1-NN using seven image descriptors on the seven texture images datasets ($\bar{x} \pm s$).

	$LBP^{u2}_{8,1}$	$LBP^{u2ri}_{24,3}$	$CLBP_{24,3}$	$LBC_{24,3}$	$CLBC_{24,3}$	$DRLBP_{8,1}$	GP-criptor^{ri}	$MGPD^{ri}_{9,5}$
BrNoRo	83.99 ± 1.95 +	68.49 ± 3.18 +	82.37 ± 4.88 +	66.26 ± 2.80 +	63.62 ± 2.52 +	83.17 ± 2.49 +	90.92 ± 1.94 =	**91.97 ± 1.89**
BrWiRo	42.29 ± 1.66 +	67.63 ± 2.62 +	85.78 ± 2.70 +	64.49 ± 2.95 +	70.84 ± 3.19 +	69.65 ± 2.41 +	92.49 ± 1.14 =	**93.16 ± 1.21**
OutexTC00	87.88 ± 1.23 =	69.50 ± 2.88 +	81.00 ± 2.95 +	68.25 ± 3.81 +	72.79 ± 2.87 +	84.96 ± 1.79 +	87.68 ± 1.87 =	**88.70 ± 1.97**
OutexTC10	34.45 ± 1.79 +	64.50 ± 1.05 +	86.10 ± 2.39 =	60.50 ± 1.82 +	75.53 ± 2.24 +	63.97 ± 2.57 +	86.82 ± 1.93 =	**87.84 ± 2.01**
KySinHw	54.82 ± 2.18 +	81.76 ± 1.46 +	**97.31 ± 0.73** −	80.72 ± 1.51 +	89.03 ± 1.86 +	85.30 ± 2.32 +	94.06 ± 1.63 =	94.54 ± 1.73
KyNoRo	75.45 ± 1.96 +	67.41 ± 2.94 +	**90.56 ± 1.16** −	66.09 ± 2.76 +	76.67 ± 4.05 +	86.26 ± 1.14 =	86.66 ± 1.79 =	86.73 ± 1.73
KyWiRo	42.61 ± 1.84 +	69.46 ± 3.33 +	**88.97 ± 2.82** =	68.26 ± 3.59 +	76.58 ± 3.77 +	74.05 ± 2.07 +	88.51 ± 1.39 =	88.41 ± 1.45

is defined similar to [1]. To evolve a descriptor, $MGPD^{ri}_{t,w}$ randomly generates a population of individuals that will be improved over a number of generations. The fitness of each individual is evaluated, and individuals with good fitness value are more likely to be selected to generate offspring through crossover, mutation and elitism for the subsequent generation. When the last generation is reached, the best evolved program is returned. Generating a feature vector for an image by an evolved descriptor is similar to that of [1].

3 EXPERIMENTS DESIGN AND RESULTS

As in [2], seven image datasets for texture classification (BrNoRo, BrWiRo, OutexTC00, OutexTC10, KySinHw, KyNoRo and KyWiRo) are used here to assess the performance of $MGPD^{ri}_{t,w}$ and compared with that of the benchmark methods. The datasets differ in the number of classes, instances, dimensions, materials, and rotations. All those datasets comprise grey-scale images.

As the proposed method in this study ($MGPD^{ri}_{t,w}$) evolves dense image descriptors, standard benchmark and the-state-of-the-art dense hand-crafted image descriptors are used to assess the performance of $MGPD^{ri}_{t,w}$. Six hand-crafted image descriptors are used as benchmark methods: $LBP^{u2}_{p,r}$, $LBP^{u2ri}_{p,r}$, $CLBP_{p,r}$, $LBC_{p,r}$, $CLBC_{p,r}$, and $DRLBP_{p,r}$. Furthermore, GP-criptor^{ri} is also used in our experiments. Details of these methods can be found in [2].

The parameters in $MGPD^{ri}_{t,w}$ are as follows. The population size and number of generations are, respectively, 300 and 50. The mutation and crossover rates are set to 20% and 80%, and only the best individual is copied to the subsequent generation. A tournament of size 5 is used and the tree depth is set between 2 and 10. Furthermore, α, t and w are set to 0.1, 9 and 5, respectively.

Each row in Table 1 presents the mean ($\bar{x}$) and standard deviation (s) statistics for one dataset using the eight image descriptors. Mann-Whitney-Wilcoxon Test is used with 0.05 significance level, where "+", "−" and "=" are used to indicate that $MGPD^{ri}_{9,5}$ is, respectively, significantly better, significantly worse, and not significant compared with the corresponding method.

On BrNoRo, $MGPD^{ri}_{9,5}$ has achieved 91.97% accuracy, which has significantly outperformed all the other image descriptors apart from GP-criptor^{ri}. Moreover, the gap between $MGPD^{ri}_{9,5}$ and the benchmark methods ranging between 1.05% (GP-criptor^{ri}) and 28.35% ($CLBP_{24,3}$). Similarly, on BrWiRo $MGPD^{ri}_{9,5}$ shows the best performance (93.16%) and has significantly outperformed the competitor methods, apart from GP-criptor^{ri}.

On the OutexTC00 dataset and its rotated version OutexTC10, $MGPD^{ri}_{9,5}$ has, respectively, achieved 88.70% and 87.84% accuracy on average. $MGPD^{ri}_{9,5}$ shows better performance than $LBP^{u2}_{8,1}$ and GP-criptor^{ri} on OutexTC00 as well as $CLBP_{24,3}$ and GP-criptor^{ri} on OutexTC10, and has significantly outperformed the other competitor methods on these two datasets.

$MGPD^{ri}_{9,5}$ has the second best performance (94.54%) on the KySinHw dataset, which has significantly outperformed all the other benchmark methods, apart from $CLBP_{24,3}$ and GP-criptor^{ri}.

On the KyNoRo and KyWiRo datasets, $MGPD^{ri}_{9,5}$ has the second and third best performance that is 86.73% and 88.41%, respectively. It has significantly outperformed the other methods apart from the $CLBP_{24,3}$, $DRLBP_{24,3}$ and the GP-criptor^{ri} methods on KyNoRo. Furthermore, $MGPD^{ri}_{9,5}$ has significantly outperformed all the other benchmark methods apart from $CLBP_{24,3}$ and GP-criptor^{ri}, and shows a comparable (no significant difference) performance to both $CLBP_{24,3}$ (the best method) and GP-criptor^{ri}

4 CONCLUSIONS AND FUTURE WORK

A multitree GP has been successfully utilised in this study to automatically evolve image descriptors, which relies on the within-class and between-class distances and requires only two instances of each class. An evolved individual has the potential to extract similar feature vectors from instances belonging to the same class and dissimilar to those extracted from instances of the other classes. Experimental results on seven texture datasets show that the proposed method has significantly outperformed six hand-crafted image descriptors in most of the cases, and has better performance than GP-criptor^{ri}. In the future, we would like to use the proposed method for object classification and detection tasks.

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