***Abstract*—There are many figure-ground image segmentation methods. Some of them are too simple and less accurate and some of them are solution complexity and computationally expensive, although having higher accurate. What if there is a method that can be less computationally expensive and higher accurate. A new genetic programming(GP) method is proposed for image segmentation, which can fulfill the requirement we mentioned.**

***Index Terms*—Figure-ground image segmentation, Genetic programming, Solution complexity**

I. INTRODUCTION

Image segmentation is one of the mot important and useful techniques in image processing. It can have robust and high degree of accuracy in results. [1]

In methodology, image segmentation is the art of dividing an image into many, smaller fragments or groups of pixels, and then each pixel in a digital image is assigned a specific label. Pixels with the same label have similarities in features. Image segmentation can be used to detect edges, boundaries, and outlines in an image. [2]

In image segmentation, figure-ground image segmentation is a method to separate the foreground objects or regions of interest from the background. It is an important step of preprocessing in the image processing, such as image editing. [3]

There are some existing methods. CNN has more accuracy in figure-ground segmentation but quite computation-expensive. And normally, it needs more instances to train the model than GP method and hard to interpret. There are also some simple image-segmentation method, such as thresholding, cannyedge and watershed. The disadvantage of these methods is they are less accuracy.

Genetic programming (GP) is a main branch of evolutionary computation techniques, which are inspired by biological evolution [4]. GP can automatically create a computer program/algorithm to solve the problem based on a high-level statement of the task. Considering the unsatisfactory performance of existing segmentation methods, GP has been introduced to evolve segmentors by existing works [5]–[8], which show that the segmentors produced by GP can produce promising results in certain image domains, e.g. texture images [5], [6], biomedical images [8] and object images [9].

II. BACKGROUND AND RELATED WORK

A. Genetic Programming (GP)

GP is one of the promising EC techniques and is a specical case of GA. GP and GA mainly differ in the representation scheme. GA uses strings of bits, integers, or real numbers to represent individuals. By contrast, GP mainly represents individuals as trees and is well suited for mapping functions, model development, nonlinear regression, and other related problems. Fonlupt and Koza17, 18 has pointed out various exciting problems, where GP produced human-competitive results. GP is a domain-independent method and can solve complex problems automatically.19 Moreover, pioneering works of Koza, Langdon, Poli, and Banzhaf has boosted research in the field of GP. [10]

B. Image Segmentation

The primary purpose of image segmentation is to segment out different gray levels of an image. If the pixels belonging to regions are homogeneous, then they are assigned the same label. Otherwise, various labels are attached. In other words, a good segmentation criterion is required to look for homogeneity within-region and heterogeneity between regions. [11]

C. GP for Image Segmentation

In the field of image processing, GP has been widely used to segment region of interest from images. In 1996, Poli developed filter for detecting enhanced features for image segmentation. Vojodi used GP to combine different and unrelated evaluation measures. They selected three evaluation measures, which are based on the layout of entropy, similarity within the region, and disparity between the areas for the creation of composite evaluation measures. [7]

In another technique, Song and Ciesielski used GP to evolve automatic texture classifiers, which were then used for texture segmentation. As opposed to conventional methods, their method does not require the manual construction of models to extract texture features because the classifier's input is raw pixels instead of features. In addition, the conventional methods are not universally applicable as they rely on the knowledge of the nature of texture, which may differ from region to region and image to image. [9]

GP can capture variation within images; that is why GP is popular in evolving a suitable image segmentation technique. However, GP-based techniques mainly developed vast and expansive segmentation algorithms. In this regard, Liang proposed a MOGP-based segmentation technique, in which classification accuracy and program complexity are included within the fitness function. Liang's method evolved a suitable solution with an optimal tradeoff between accuracy and program complexity. In another approach, the GP-based segmentation technique developed an accurate and reliable figure-ground segmentation. Their segmentation approach was evaluated against four different datasets. [12]

III. THE PROPOSED APPROACH

This section describes a new GP approach for image segmentation, including a function set, a number of image-related operators, and a new terminal set.

A. Program Structure

In order to realize automatic generate region, construction and segmentation at the same time, a multi-layer program structure is designed in the MLGP method. The program structure has three layers, namely the input layer, the region layer, the construction layer and the output layer. The program structure is shown in fig 1. A sample program that demonstrates how to construct multiple layers in a single program tree is also shown in fig 1. In the fig, each layer is shown in a different color.

Input: The input takes the RGB-image and constant parameters, known as ephemeral random constants, as inputs.

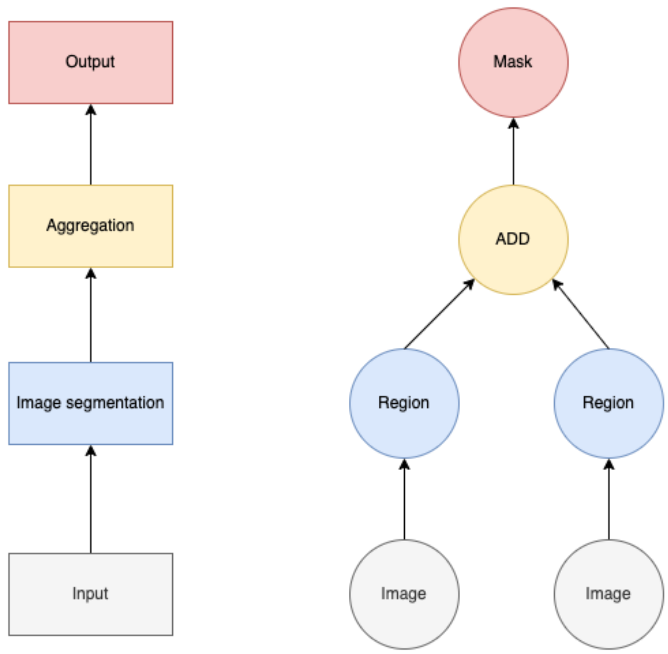

Fig. 1: **Program structure and an example program that can be evolved by MLGP**

Image segmentation: The Image segmentation aims to transfer input RGB-image to a ground image.

Aggregation: The region layer aims to construct ground image using commonly used arithmetic functions, i.e., +, , × and protected ÷, which are the commonly used functions in the classic GP method. With these functions, the ground image can be constructed into a better ground region.

The program structure of the proposed GP method is constructed according to the six layers in a bottom-up manner, as shown in Fig.1. It is a tree-based representation, where operators are used to form the internal nodes and terminals are used to form the leaf nodes. To deal with different tasks at each layer, a set of operators and terminals are employed. As the example program tree shown in Fig. 1, it has operators i.e. Thresholdling, Cannyedge, chanVese, Snakes, walk and terminals i.e. Image, X, Y, Z.

More details about the operators and terminals can be seen in Sect.III-C.

With the multi-layer program structure, MLGP can integrate different types of functions into a single tree and construct solutions for simultaneous region generation, construction, and output.

B. Terminal Set

The terminal set has four terminals, indicating the inputs of the MLGP approach. The terminals are Image, X, Y, Z. The data types and detailed information of these terminals are described in TableI. The image terminal represents the input RGB-scale image, which is a 3-D array with image pixel values in range [0, 255]. The X, Y and Z terminals are the parameters within a range from 0 to 1. In the MLGP approach, the values of X, Y and Z are randomly selected from their ranges at the initialisation step and changed by mutation during the evolutionary process.

C. Function Set

The function set of MLGP has region generation functions, and construction functions for each layer. The input type, output type and descriptions of these functions are listed in Table**??**. This section describes these functions.

Region Detection Functions: The region detection layer has six functions. Each function is a common method to do image segmentation and is also the baseline function. Each function takes image as input and returns a figure-ground image. In the function Thresholding, the X is terminal. In the function walk, the Y and Z are terminal. The values of these terminals are randomly generated from their pre-defined ranges.

Region Construction Functions : The region construction layer has three functions, i.e., ADD, ADD2 and weightedsum.

D. Fitness Function

In the MLGP approach, the fitness function(F) is the f1 score, which is good and commonly used for figure-ground image segmentation. The fitness function is defined as follows.

$$F = \frac{TP}{TP + \frac{1}{2}(FP + FN)} * 100\%$$

where TP, FP, and FN indicate the total numbers of true positives, false positives, and false negatives, respectively. TP indicates the positive samples are correctly classified into the positive class. FP indicates the positive samples are classified into the negative class and FN indicates the negative samples are classified into the positive class. The fitness function is to be maximised and the value range is in [0, 100].

IV. EXPERIMENT DESIGN

The section presents the benchmark datasets, baseline methods and parameter settings in the experiments.

A. Benchmark Datasets

Demonstrate the effectiveness of the proposed GP method on different image segmentation tasks, three different images datasets with different difficulty are used as benchmarks datasets. There datasets are Black Sea Sprat, Gilt-Head Bream and Hourse Mackerel[dataset]. These datasets represent 3 typical image segmentation tasks. Segment the specific fish from background. The difficulties of image classification varies with the datasets due to different variations such as scale, illumination, rotation in images. The images are RGB-scale images.

In the experiments, each dataset is spilt into the training set, the validation set and the test set, having 50%, 25%,

Terminal	Output type	Description
Image	Img	The input image. It is an array with values in the range of [0, 255]
X	Int 1	The parameter of Thresholding, it is in the range of range [0, 1]
Y	Int 2	The parameter of walk, it is in the range of range [0, 1]
Z	Int 3	The parameter of walk, it is in the range of range [0, 1]

TABLE I: Terminal set of MLGP

TABLE II: Dataset properties

Name	Size	Training set	Validation set	Test set
Sprat	100*100	1203	403	403
Gilt	100*100	1203	403	403
Hourse	100*100	1203	403	403

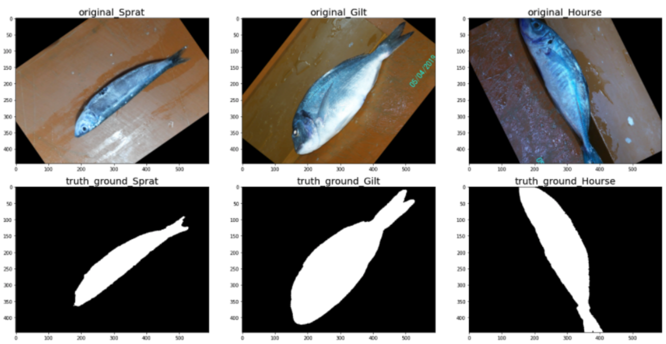

Fig. 2: **Example images of three datasets**

25% images respectively. The orginal images datasets are resized to 100*100 with high quality in order to maintain the image size consistent of each dataset and to reduce the computational cost.Details of the datasets are listed in table II. Several example images of the datasets are shown in fig 2.

B. Baseline Methods

To show the effectiveness of the proposed MLGP approach, six methods are used as baseline methods for comparisons. These methods are based on commonly used image segmentation methods.

C. Parameter Settings

All the algorithms which are related to GP are from DEAP(Distributed Evolutionary Algorithm in Python) package in Python. The Opencv and Skimage package are used to implement the baseline algorithms. The Parameter settings for algorithms are listed in table **??**. There are 30 times running with different random seeds for each algorithm on each dataset.

V. Results and Discussions

The experimental results of the MLGP approach and the six baseline methods are listed in Table V. The Wilcoxon rank-sum test with a 5% significance level is employed to compare the proposed approach with baseline methods. In Table V, the "+" symbol indicates that the proposed approach is significantly better than the compared method, the "" symbol indicates the proposed approach performs significantly worse than the compared method, and the "=" symbol indicates that the proposed approach achieves similar results to the compared method.

Method	Description
Thresholding	An image processing method that creates a binary image based on setting a threshold value on the pixel intensity of the original image.
Canny_edge	Canny Edge Detection is used to detect the edges in an image.
ChanVese	The Chan-Vese segmentation algorithm is designed to segment objects without clearly defined boundaries.
WaterShed	Watersheds separate basins from each other. The watershed transform decomposes an image completely and thus assigns each pixel either to a region or a watershed.
Snake	A snake is an energy minimizing, deformable spline influenced by constraint and image forces that pull it towards object contours and internal forces that resist deformation. Snakes may b as a special case of the general technique of matching a deformable model to an image by means of energy minimization.[14]
Walk	The random walker algorithm was initially motivated by labeling a pixel as object/background based on the probability that a random walker dropped at the pixel would first reach an object (foreground) seed or a background seed. However, there are several other interpretations of this same algorithm that have appeared.[15]

TABLE III: Baseline methods

Parameter	Value	Parameter	Value
Generations	50	Crossover rate	0.8
Population size	100	Mutation rate	0.19
Selection type	Tournament	Elitism rate	0.01
Tournament size	7	Tree-depth	2-6

TABLE IV: GP parameters

A. Compared with baseline methods

TableV lists all the test results of MLGP and the total 6 baseline methods on the three datasets. On the Sprat dataset,the results of the proposed method is shown as mean and its standard deviation.The proposed method achieves significantly better result in precision than any of the 6 baseline methods in 4 performance metrics. The performace of MLGP is better than other methods in 4 performance metrics but is worse than Walk in f1-score, Canny_edge in accuracy, Chanvese and walk in recall.

On the Gilt dataset, the proposed method achieves significantly better result in f1-score and precision than any of the 6 baseline methods in 4 performance metrics. The performace of MLGP is better than other methods in 4 performance metrics but is worse than Canny_edge and walk in accuracy and Chanvese in recall.

On the Hourse dataset, the performace of MLGP is better than any other methods in 4 performance metrics but is worse than ChanVese, WaterShed and Walk in f1-score, Walk in

Methods	F1-score	Accuracy	Recall	Precision
		Sprat		
MLGP	41.61 ±0.5	83.73 ±0.52	54.7 ±2.52	38.19 ±1.13
Thresholding	9.32 +	63.72 +	18.26 +	6.49 +
Canny_edge	31.02 +	85.48 -	34.15 +	29.42 +
ChanVese	22.67 +	40.0 +	87.41 -	13.29 +
WaterShed	35.8 +	77.85 +	52.77 +	30.95 +
Snakes	13.4 +	47.49 +	50.75 +	8.15 +
Walk	46.92 -	82.16 +	56.08 -	35.55 +
		Gilt		
MLGP	60.01 ±0.21	80 ±0.65	61.5 ±2.53	61.01 ±3.65
Thresholding	8.57 +	54.59 +	15.06 +	6.16 +
Canny_edge	30.61 +	81.89 -	29.06 +	32.97 +
ChanVese	31.38 +	46.02 +	87.36 -	19.43 +
WaterShed	40.25 +	75.37 +	53.09 +	35.51 +
Snakes	15.62 +	49.31 +	41.58 +	10.06 +
Walk	46.92 +	80.46 -	56.83 +	43.66 +
		Hourse		
MLGP	47.87 ±0.69	81 ±1.31	57.59 ±2.76	44.95 ±2.16
Thresholding	16.52 +	40.34 +	24.06 +	13.15 +
Canny_edge	34.74 +	75.88 +	26.76 +	51.16 -
ChanVese	51.85 -	64.26 +	77.43 -	40.46 +
WaterShed	52.09 -	78.76 +	46.0 +	66.32 -
Snakes	26.34 +	41.92 +	42.68 +	20.0 +
Walk	57.02 -	81.99 -	48.6 +	74.84 -

TABLE V: Four performance metrics of new GP method and the 6 baseline methods on the three datasets

accuracy, ChanVese in recall and Canny_edge, WaterShed and Walk in precision.

In summary, the comparisons and discussions show that the proposed MLGP approach is a promising approach for image segmentation. With a single-tree representation, the proposed MLGP approach can perform region detection, region construction, and segmentation simultaneously and automatically.

VI. Conclusions

In this paper, we proposed a new GP method for figure-ground image segmentation. The proposed methods were tested on three benchmark image datasets, i.e. Sprat, Gilt and Hourse datasets. They were compared with GP-based method and the reference method.

The results show that the new GP method performs better than the reference methods.

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