Improving Image Filters with Cartesian Genetic Programming

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Abstract: The automatic construction of an image filter is a difficult task for which many recent machine learning methods have been proposed. However, these approaches, such as deep learning, do not allow for the filter to be understood, and they often replace existing filters designed by human engineers without building on this expertise. Genetic improvement offers an alternative approach to construct understandable image filter programs and to build them by improving existing systems. In this paper, we propose a method for genetic improvement of image filters using Cartesian Genetic Programming. We introduce two operators for genetic improvement which allow insertion and deletion of a node in the graph in order to quickly improve a given filter. These new operators are tested in three different datasets starting from published or engineered filters. We show that insertion and deletion operators improve the performance of CGP to produce newly adapted filters.

1 INTRODUCTION

The automatic construction of image filters through machine learning has led to a number of novel applications. A common algorithm for this problem type is deep convolutional neural networks which learn a sequence of parameterized filters and which can total millions of parameters (He et al., 2016). While the performance of these methods on large datasets is impressive, surpassing human performance on visual recognition tasks (He et al., 2015), an important obstacle in the application of these models is their lack of interpretability. Furthermore, these systems are often used to replace systems designed by human experts and are unable to benefit from computer vision expertise. Previous work have been published in which Genetic Algorithms are used to improve the appearance and the visual quality of images characterized by a bimodal gray level intensity histogram, by strengthening their two underlying subdistribution (Rundo et al., 2019). Additional work have been done using genetic programming in the field of video change detection to automatically select the best algorithms, combine them in different ways, and perform the most suitable post-processing operations on the outputs of the algorithms (Bianco et al., 2017). Finally, a system for the automatic generation of computer vision algorithms at interactive frame rates using GPU accelerated image processing has been developed using genetic programming (Ebner, 2009) and work have been done to evolve object detectors using GPU processing (Ebner, 2010). Genetic programming offers an attractive alternative for this machine learning task. By combining low-level and high-level image processing functions, a filter can be constructed which is fully understandable and auditable. The set of functions can be chosen by experts to meet computational or legibility requirements and can build on expert functions like those in the OpenCV[1] library used in this work. Furthermore, existing image filters can be formulated as starting points for optimization; genetic improvement of software has demonstrated that evolution can build upon human-designed programs to improve their efficiency and fix bugs (Arcuri and Yao, 2008). This allows for a final program which is higher performing than the original human-designed code, but which remains understandable and explainable by human experts.

In this work, we use Cartesian Genetic Programming (CGP) (Miller, 1999), a popular form of graph

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genetic programming, to improve on existing image filters and to generate new filters. In CGP, programs are represented as graphs of functions, which allows for encoding existing filters through modifying the program graph. We propose novel genetic operators specifically for genetic improvement in CGP, demonstrating that inserting nodes into the program graph can improve evolution based on filter accuracy. We study standard CGP, CGP with a starting population of experts, and the proposed mutation operators on a set of image masking benchmarks, two from previous work on CGP (Leitner et al., 2012) and one new benchmark on urban traffic. Our evolution allow to quickly improve an image filter designed by a human with basic knowledge.

This article is structured as follows. In Section 2, we illustrate Cartesian Genetic Programming and its application to image processing; we then review genetic improvement. In Section 3, we describe the proposed node insertion and node deletion operations for genetic improvement with CGP. We present the image processing tasks and experimental parameters in Section 4, using tasks and image functions from existing work in image processing using CGP. In Section 5, we compare different evolutionary processes, starting from random populations and from expert filters, and using the proposed operators. We also study the resulting image filters, demonstrating the transparency of program graphs created by CGP. Finally, in Section 6, we discuss possible applications of this method and define future directions for this research.

2 RELATED WORKS

This work builds on two extensive bodies of genetic programming literature: Cartesian Genetic Programming (Miller, 1999), specifically its application to image processing and a study of possible genetic operators, and genetic improvement, the optimization of expert-designed programs through evolution.

2.1 Cartesian Genetic Programming

Cartesian Genetic Programming (CGP) is a form of Genetic Programming (GP) in which programs are represented as directed, often acyclic graphs indexed by Cartesian coordinates. CGP was invented by Miller and Thomson (Miller et al., 1997; Miller, 1999; Miller and Thomson, 2000) for use in evolving digital circuits, but has since been applied in a large number of domains (Miller, 2011). CGP is used in (Khan et al., 2011) to evolve neural networks, in (Harding et al., 2013) for object detection in image processing, and in (Kalkreuth et al., 2016) for image noise reduction. Its benefits include node neutrality, being the encoded parts of the genome that do not contribute to the interpreted program, node reuse, and a fixed representation that reduces program bloat (Miller, 2001). A recent review of CGP is given in (Miller, 2019).

In CGP, functional nodes, defined by a set of evolved genes, connect to program inputs and to other functional nodes via their Cartesian coordinates. The outputs of the program are taken from any internal node or program input based on evolved output coordinates. CGP nodes are arranged in a rectangular grid of R rows and C columns. Nodes are allowed to connect to any node from previous columns based on a connectivity parameter L which sets the number of columns back a node can connect to. In this work, as in many others (Miller, 2019), $R = 1$, meaning all nodes are in a single row.

The CGP genotype consists of a list of node genes; each node in the genome encodes the node function, the coordinates of the function inputs (here referred as Connection 0 and Connection 1), and optionally parameters for the node function. Connection 0 and Connection 1 can be outputs of previous nodes or program inputs. Finally, the end of the genome encodes the nodes which give the final program output. By tracing back from these output nodes, a single function can be derived for each program output, offering a concise and legible program representation.

The genes in CGP are optimized through using the 1+λ algorithm. A population of λ individuals are randomly generated and evaluated on a test problem. Evaluation is performed by decoding the program graph from the individual genotype and applying the program to a specific problem such as image masking, as in this work. The best individual based on this evaluation is retained for the next generation. A mutation operator is applied to this individual to create λ new individuals; in CGP, the mutation operator randomly samples a subset of new genes from a uniform distribution. This new population is evaluated and the best individual is retained for the next generation; this iterative process continues until a configured stopping criterion is satisfied.

2.2 Cartesian Genetic Programming for Image Processing

An important choice in using CGP is the set of possible node functions. In the original circuit design application, the node functions were logic gates such as AND and NOR. Applications of CGP in game playing and data analysis use a standard set of mathematical functions such as $x+y$, $x*y$, and $cos(x)$ for a node with inputs x and y. Function sets must be defined such that outputs of any node will be valid for another node; in mathematical functions, this is often guaranteed by restraining the domain and range of the functions between -1 and 1.

Cartesian Genetic Programming for Image Processing (CGP-IP) is an adaption of CGP which uses image processing functions and which applies programs directly to images (Harding et al., 2006). The inputs and outputs of the evolved functions are images which allows for consistency between node functions; each node function is defined to input an image of a fixed size and output an image of the same size. CGP-IP has previously used a set of 60 functions (Harding et al., 2012b) from OpenCV, a standard and open-source image processing library.

In previous work (Harding et al., 2006), CGP-IP has used an island population distribution algorithm. In this method, multiple populations compete inside "islands" which are independent $1+\lambda$ evolutionary algorithms. A migration interval parameter dictates the frequency of expert sharing between the islands, allowing for synchronization of the best individual across islands. Island models have been demonstrated as an alternative to the Genetic Algorithm and aid in preserving genetic diversity (Whitley et al., 1998). Their use in CGP-IP has shown improvement compared to the $1+\lambda$ algorithm.

CGP-IP individuals are evaluated by applying the evolved filter to a set of images, comparing them to target images, and computing a difference metric between the output image from the evolved filter and the target, such as the mean error or Matthews Correlation Coefficient (MCC) (Matthews, 1975). In this paper, we use MCC, which measures the quality of binary classification and has been showed particularly adapted to classification tasks using CGP (Harding et al., 2012a). Calculations are based on the confusion matrix, which is the count of the true positives (TP), false positives (FP), true negatives (TN) and false negatives (FN):

$$mcc = \frac{TP*TN - FP*FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \tag{1}$$

A MCC with a score of 1 corresponds to a perfect classification, 0 to a random classifier, and -1 to a fully inverted classification. Our fitness function for evolution is defined as follows:

$$fitness = 1 - mcc. \tag{2}$$

In this work, evolution is therefore used to *minimize* the objective function, searching for programs with a higher MCC.

2.3 Genetic Improvement

Genetic Improvement (GI) is a relatively recent field of software engineering research that uses search to improve existing software. Using handwritten code as a starting point, GI searches the space of program variants created by applying mutation operators. The richness of this space depends on the power and expressivity of the mutation operators, which can modify existing code by changing functions or parameters, add new code, and, in some cases, remove parts of a program. Over the past decade, the GI field has greatly expanded and current research on GI has demonstrated many potential applications. Genetic improvement has been used to fix software bugs (Arcuri and Yao, 2008; Langdon and Harman, 2015), to drastically speed up software systems (Langdon and Harman, 2015; White et al., 2011), to port a software system between different platforms (Langdon and Harman, 2010), to transplant code features between multiple versions of a system (Petke et al., 2014), to grow new functionalities (Harman et al., 2014) and more recently to improve memory (Wu et al., 2015) and energy usage (Bruce et al., 2015).

The majority of Genetic Improvement work uses Genetic Programming to improve the programs under optimisation (Arcuri and Yao, 2008; Langdon and Harman, 2010; Langdon and Harman, 2015; Petke et al., 2014; White et al., 2011). In most methods, applying GI to an existing program is done by encoding the existing program within a GP tree and then computing the corresponding genome. GP mutation operators are applied to the encoded program to generate adjacent programs. For this purpose, the program encoding and operators must be defined both to be suited to the initial program to be improved and with additional functions to allow evolution to improve the functional graph. The fitness used during the evolutionary optimization of the program can be based on various metrics, such as program length, efficiency, relevance to given test cases, or others (Arcuri and Yao, 2008; Langdon and Harman, 2010; White et al., 2011).

In this work, we propose operators for genetic improvement in CGP. To our knowledge, this is the first use of CGP for GI, as the majority of GI literature uses tree representations of programs instead of graphs. The proposed node insertion and deletion mutation operators are similar to existing mutation operators for tree-based GI but are studied here in the context of graph evolution.

3 GENETIC IMPROVEMENT IN CGP-IP

In this section, we deal with insertion and deletion operators specifically designed for GI with CGP. In the standard CGP,the evolution is only based on the injection of random mutation to node genes which is equivalent to connections or functions. Genomes are of constant sizes and adding and/or removing functional nodes inside the graph can be difficult for the evolution to finish. To this end, previous work has proposed self-modifying genomes (Harding et al., 2011) which use functions which can add or remove nodes but only while the graph is executing. In our proposal we do insertion and deletion of node using mutation operators in order to change the size of the graph during it's evolution. These operators are designed to maintain the active subgraph of a program, i.e. they are not destructive. Source code of the implementation in Python for our CGP-IP can be found here[2].

A mutation consists of applying one of the three following operators: node insertion, node deletion or standard parameter modification using a uniform distribution. The node operators have configurable mutation rates r_{ins} and r_{del} corresponding to the probability of the application of these mutation operators. If one of these structural operators is applied, it will be the only mutation performed; otherwise, standard parameter modification mutation occurs. In this work, $r_{ins} = 0.1$ and $r_{del} = 0.1$ for all experiments.

3.1 Node Insertion

The node insertion operator adds a new node between two connected nodes in the active graph of a CGP individual. To allow for node insertion, we change the total possible graph length of a CGP individual, $R*C$ or the number of columns C in this case, and adapt this value during evolution. In order to preserve the structure of the program, the connections of other nodes in the genome are adjusted after a node insertion. As described in Algorithm 1 and illustrated in Figure 1, the connection genes of all nodes after the inserted node are increased by 1. This preserves the existing connections in the graph and simply inserts the new node between two previously connected random nodes. We study two possible insertions: using an identity (NOP) function, this action does not immediately change the program graph, and using a random function, which can.

[2]https://github.com/julienbiau/CGP-IP-GI

Algorithm 1: Insertion of a node with a random function.

```
Data: nodes is an array containing all nodes
      NOP_insertion is a boolean
Result: node inserted at position index
index = getRandomActiveNode();
nodes.insert(index,copyNode(nodes[index]));
// connection 0 of next node is linked to
// inserted node
nodes[index+1].conn0 = 1;
// connection 1 of next node is increasing by
// 1 to maintain his links after insertion
nodes[index+1].conn1 = nodes[index+1].conn1
  + 1;
if NOP_insertion then
    // set a NOP function
    nodes[index].function = NOP;
else
    // set a Random function
    nodes[index].function =
      getRandomFunction();
end
for $i \leftarrow index$ to $nodes.length$ do
    if $i - nodes[i].conn0 < index$ then
        nodes[i].conn0 = nodes[i].conn0 + 1;
    end
    if $i - nodes[i].conn1 < index$ then
        nodes[i].conn1 = nodes[i].conn1 + 1;
    end
end
for $i \leftarrow 0$ to $outputs.length$ do
    if $nodes.length - outputs[i] < index$ then
        outputs[i] = outputs[i]+1;
    end
end
```

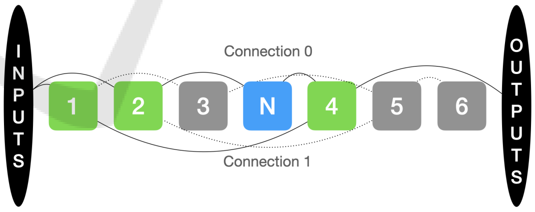


Figure 1: Graph with an random node N inserted at index 4.

3.2 Node Deletion

The node deletion operator removes a node from the active graph of a CGP individual, as shown in Figure 2. After a node deletion we adjust the rest of the genome to ensure that other parts of the graph are not impacted. Specifically, as described in Algorithm 2, all nodes which connected to the removed node are in turn connected to the Connection 0 input of the removed node, and all nodes after the selected node have their connection genes decremented by 1.

These operators does induce a global benefit to the CGP evolution by growing a topology over the evolu-

Algorithm 2: Deletion of a node.

```
Data: nodes is an array containing all nodes
Result: node deleted at position index in the graph
if $active\_nodes.length > 1$ then
    index = getRandomActiveNode();
    for $i \leftarrow 0$ to $outputs.length$ do
        if $nodes.length - outputs[i] == index$ then
            outputs[i] = outputs[i]+nodes[index].conn0;
        end
    end
    for $i \leftarrow 0$ to $active\_nodes.length$ do
        if $i - nodes[i].conn0 == index$ then
            nodes[i].conn0 = nodes[i].conn0 + nodes[index].conn0;
        end
    end
    for $i \leftarrow index$ to $nodes.length$ do
        if $i - nodes[i].conn0 < index$ then
            nodes[i].conn0 = nodes[i].conn0 - 1;
        end
        if $i - nodes[i].conn1 < index$ then
            nodes[i].conn1 = nodes[i].conn1 - 1;
        end
    end
    nodes.remove(index);
end
```

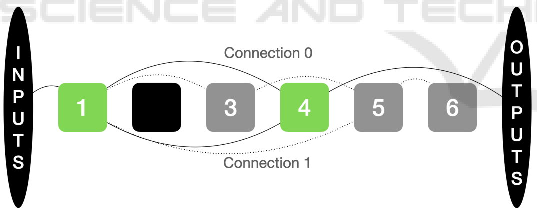


Figure 2: Graph with a deletion of node 2.

tion instead of searching in a graph with a fixed maximum size. However, we more specifically study this in the case of Genetic Improvement, where existing image filters can be improved through the node insertion and deletion operators.

4 EXPERIMENTS

To evaluate the insertion and deletion operators in the context of genetic improvement, we study the effect of using filter made using human expert as the starting point and using the proposed structural mutation operators. Specifically, we compare the following configurations:

Baseline: standard CGP-IP. Starting chromosome is randomly defined at the beginning. Insertion and deletion mutations are disabled.
Fixed Size: standard CGP-IP, but active nodes in the initial population are exclusively composed of function extracted from an expert filter and are positioned at the beginning of the graph. Inactive node are randomly decided after active nodes in the graph. Insertion and deletion mutations are disabled.
Fixed Size with NOP: standard CGP-IP, but active nodes in the starting population are composed of functions extracted from an expert filter and are intertwined with NOP function between each Connection 0 input. For example, if the filter contains 10 functions, the initial genome will be composed of 20 actives nodes (10 nodes with functions and 10 NOP nodes). Inactive nodes are randomly added after the active nodes. Insertion and deletion operators are disabled.
Adapting with NOP: The initial genome is built as in the **fixed size** method, ie with an expert individual. Insertion and deletion operators are enabled. If an insertion occurs, only NOP function are inserted.
Adapting with Random: The initial genome is built, as can be seen in the **fixed size** method. Insertion and deletion operators are enabled. If an insertion occurs, the function of the inserted node is randomly selected from the function library.
Adapting, No Expert: Starting chromosome is randomly defined at the beginning. Insertion and deletion mutations are enabled. If an insertion occurs, the function of the inserted node is randomly selected from the function library.

These configurations allow for detailed and independent study of the two proposed CGP-IP improvements in this work: genetic improvement of existing image filters and structural mutation operators of node insertion and deletion. The **fixed size** configurations isolate the possible benefit of building atop already designed image filter individuals, with the difference that the expert experience is encoded in the starting genome. The three adapting configurations allow for study of the node insertion and deletion operators, in particular for their use for genetic improvement. Once again, the distinction between additional random genetic information and NOP is made; for the node insertion operator, this difference determines if the functional phenotype of the CGP-IP individual is modified by node insertion (**adapting with random**) or if the insertion mutation is only structural (**adapting with NOP**). Finally, the **adapting, no expert** configuration allows for independent study of the benefits of the node insertion and deletion operators when starting from random genes, as in **baseline** CGP-IP.

4.1 CGP-IP Parameters

In this work, we have used the following parameters for CGP-IP:

- R: the number of rows in CGP is 1
- C: the number of columns in CGP is set to 50 for all experiments, but can change with the node addition and deletion operators
- r_{mut}: mutation rate for each gene is 0.25
- r_{ins}: node insertion mutation operator rate is 0.1
- r_{del}: node deletion mutation operator rate is 0.1
- Number of islands: the number of parallel $1+\lambda$ evolutions is 4
- λ: the population size on each island is 4
- Synchronisation interval between islands: number of generations before islands compare their fitness to update them with the best chromosome is 20
- Number of generations: 1000 for the Mars task and 2000 for the Lunar and Urban Traffic tasks

Each node of the graph is encoded with 8 parameters (see table 1). The function allele represents an index in the list of image processing functions. The second allele, Connection 0, is a connection with a previous node where output will be taken as input for the function. The third allele, Connection 1, is a connection with a previous node where output will be taken as input for the function (not all functions used connection 1). The fourth, fifth and sixth alleles, Parameters 0, 1 and 2, are real numbers that are the first, second and third parameters of the function. These alleles are not necessarily used as not all functions have three parameters. For example, Gabor Filter parameters are only used with Gabor filter functions. During the evolution process, mutation can occur either on function index, on connection or on parameters.

Table 1: Parameters of a node.

Parameter	**Type**	**Range**
Function	INT	# of function
Connection 0	INT	# of node/input
Connection 1	INT	# of node/input
Parameter 0	REAL	$[-\infty,\infty]$
Parameter 1	INT	[-16, 16]
Parameter 2	INT	[-16, 16]
Gabor Filter Freq.	INT	[0, 16]
Gabor Filter Orien.	INT	[-8, 8]

4.2 Image Processing Functions

The function we designed herewith is based on the CGP-IP function set (Harding et al., 2006). However, new functions have been added to the OpenCV library since this previous work. In addition to the existing list of image processing function (Harding et al., 2012b) already in CGP-IP, we have added the OpenCV functions watershed and distance transform.

4.3 Datasets

In this work, we aim to construct an image filter which provides a binary classification of an input image, allowing for the recognition of a desired object type. We use three different datasets for this task: images from Mars rovers, which was used in (Leitner et al., 2012), a similar Lunar dataset, and an Urban Traffic dataset, which is a new application for CGP-IP.

4.3.1 Mars Dataset

The Mars dataset is based on 5 images extracted from 1449 images that compose the McMurdo Panorama (Figure 3) taken by the rover Spirit on Mars[3].

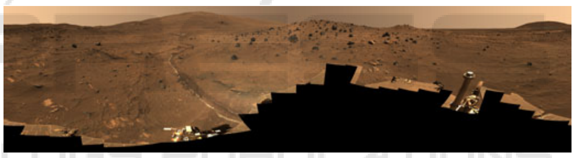
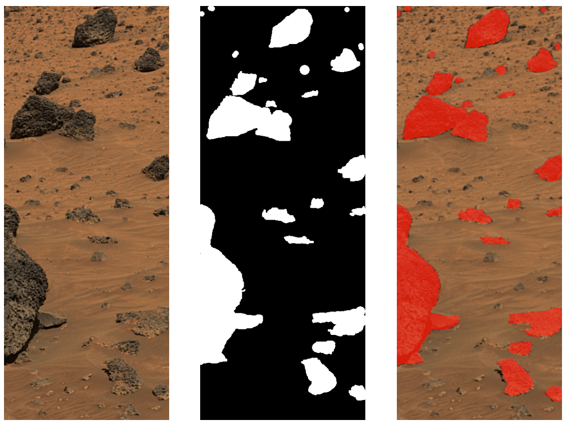


Figure 3: Full image from the Spirit rover.

The purpose of applying our algorithm on this dataset is to extract rocks from the images. Input images (Figure 4.A) have a resolution of 347x871 pixels and show rocks on the martian terrain. The target output is a binary mask (Figure 4.B), which identifies pixels with rocks as 1 and other pixels as 0. Figure 4.C display the overlay result.

For this dataset, we use an expert filter proposed by (Leitner et al., 2012), described in Listing 1 and displayed in Figure 5. This filter was generated using CGP-IP on the same dataset and has already a high accuracy, this allows us to study if further improvement using node addition and deletion is possible. For this dataset, we use 1000 generations for evolution and run 6 independent trials; given the starting point, 1000 generations was determined to be enough for establishing a convergence.

[3]http://pancam.sese.asu.edu/mcmurdo_v2.html



A : Input B : Output C : Overlay

Figure 4: An example from the Mars image dataset. The objective is to identify the rocks in the image.

```
def base_chromosome(input):
    # input is composed of R[0], G[1],
    B[2], H[3], S[4], V[5]
    node0 = cv2.GaussianBlur(input
    [5],(3,3))
    node1 = np.sqrt(node0)
    node2 = input[4]
    node3 = cv2.unsharpen(node2,13)
    node4 = node1*7.001
    node5 = cv2.bilateralfilter(node4
    ,9)
    node6 = normalize(node5)
    node7 = node3*4.03
    node8 = node7 + node6
    node9 = cv2.bilateralfilter(node8
    ,11)
    node10 = cv2.threshold(node9
    ,177.24,255)
    return node10
```

Listing 1: Python encoding of the Mars gene base.

4.3.2 Lunar Dataset

The Lunar dataset[4] is based on 5 images extracted from 9,766 realistic renders of rocky lunar landscapes, and their segmented equivalents (the 3 classes are the sky, smaller rocks, and larger rocks). This dataset was created by Romain Pessia and Genya Ishigami of the Space Robotics Group[5], Keio University, Japan. As with the Mars dataset, the new purpose of using this dataset here is to extract rocks from the images. The input images have a resolution of 720x480 pixels (Figure 6.A) and the target output images (Figure 6.B) classify the large rocks in the image.

[4]https://www.kaggle.com/romainpessia/artificial-lunar-rocky-landscape-dataset

[5]http://www.srg.mech.keio.ac.jp/index_en.html

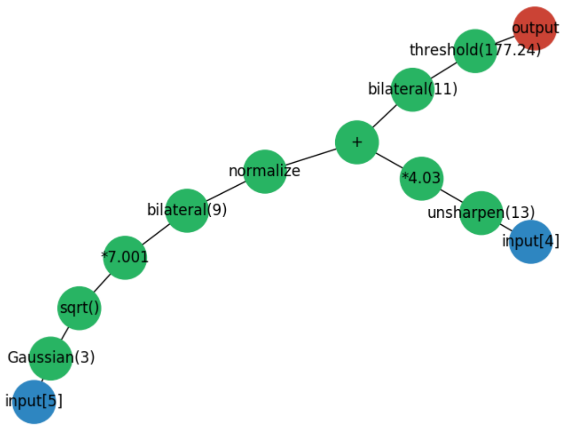
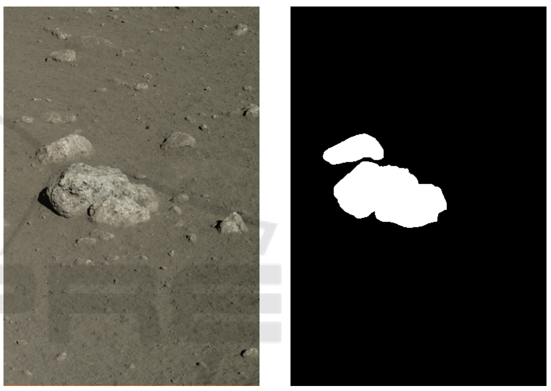


Figure 5: Graph of the Mars gene evolved with CGP-IP (Leitner et al., 2012).



A : Input B : Output

Figure 6: An example from the Lunar image dataset.

We use the same filter proposed by (Leitner et al., 2012) and used on the Mars dataset for this dataset (5). This allows us to study the adaptation of a filter from one dataset to another, where the size and color of the image changes, and where the target landscape is very different. For this dataset, evolution is run for 2000 generations on 6 independent trials.

4.3.3 Urban Traffic

To achieve this new purpose, we apply CGP-IP to identifying moving objects in a city landscape. Using this dataset allows to build a filter that extracts and follows the specific objects in the video. To do so, the filter needs to find each objects that exhibit a movement between individual frame in a frame to frame comparison. The dataset was made using video from urban traffic livestream cameras[6] and output masks were generated using Mask-RCNN (He et al., 2018) to keep only relevant objects. We use videos of 5 min-

[6]https://camstreamer.com/live/streams/14-traffic

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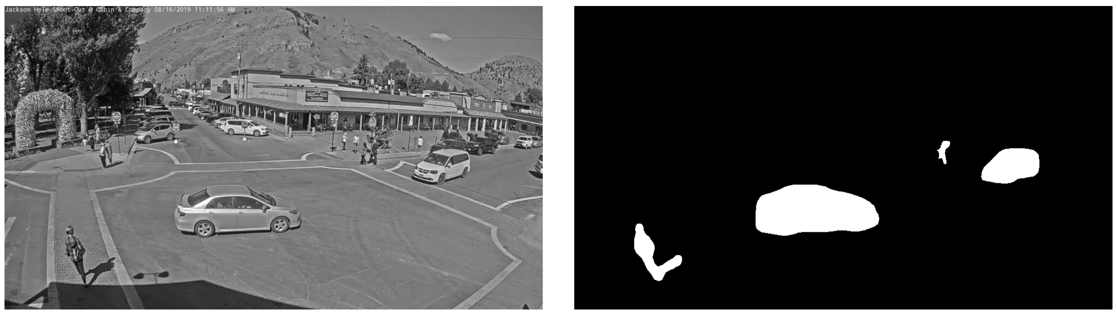

Figure 7: Example from the Urban Traffic image dataset.

utes in length, with 16 bit RGB color and a resolution of 1024x576 pixels. The images are then converted into grayscale for input and a sequence of 5 images are processed together by the evolved filter (Figure 7.A). The target classification (Figure 7.B) identifies large objects such as pedestrians and vehicles.

The expert filter used in this dataset was designed by engineers. It works by first subtracting the previous image from the current one, then by applying erode and dilate function to remove noise. The filter is detailed in Listing 2 and shown in Figure 8. For this dataset, evolution was run for 2000 generations over 6 independent trials.

```python
def base_chromosome(input1,input2):
    # input1 is composed of R[0], G[1],
     B[2]
    # input2 is composed of R[0], G[1],
     B[2]
    node0 = input1[0] + input1[1]
    node1 = node0 + input1[2]
    node2 = node1 / 3
    node3 = input2[0] + input2[1]
    node4 = node3 + input2[2]
    node5 = node4 / 3
    node6 = node5 - node2
    node7 = cv2.threshold(node6,50,255)
    node8 = cv2.dilate(node7)
    node9 = cv2.dilate(node8)
    return node9
```

Listing 2: Python encoding of the Urban Traffic gene base.

5 RESULTS

The results over the three datasets is dealt with hereafter. CGP-IP is able to construct image filters which accurately classify the desired objects in all cases, but the adaptive structure configurations show a clear benefit when compared with baseline CGP-IP.

Figure 9 shows evolution over 2000 iterations on the Mars dataset. **Adapting with random** converges more rapidly and towards better classification than the

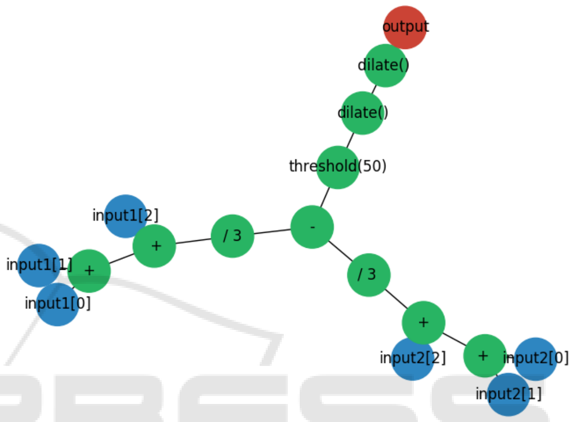

Figure 8: Graph of the Urban Traffic gene, human designed.

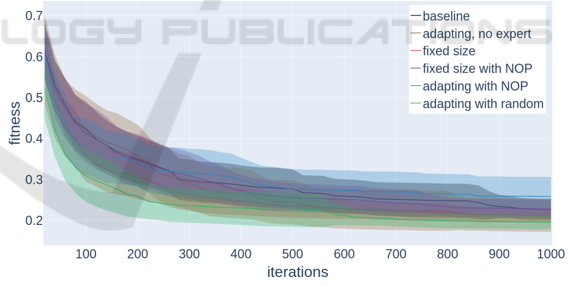

Figure 9: Average and standard deviation of fitness accuracy for Mars over 40 runs.

other methods. The other configurations show little difference. **Adapting with NOP** ends with the worst fitness, with an accuracy inferior to both **adapting with random** and **fixed size with NOP**. This demonstrates that adding nodes alone is not advantageous; rather, the addition of nodes which change the phenotype program should be preferred.

The similarity of the results with the Mars dataset is not a surprise given that the expert individual was the result of a previous CGP-IP experiment. However, it is notable that both **baseline** and **adapting, no expert**, which do not use this starting point, converge to match the other individuals.

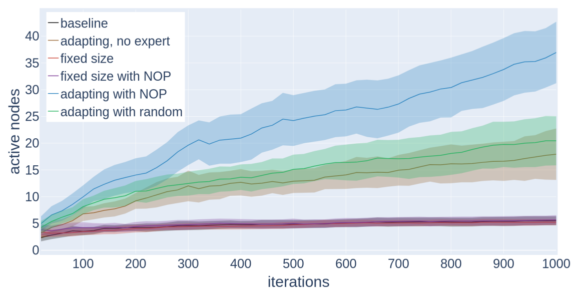

Figure 10: Average and standard deviation of actives nodes for Mars overs 40 runs.

Figure 10 displays the active graph size for the Mars dataset. **baseline**, **fixed size** and **fixed size with NOP** slowly increase to 5/6 actives nodes. For **adapting with NOP**, the actives nodes constantly increase throughout evolution. **Adapting with random** and **adapting, no expert** converge to similar size due to using the same addition operation. It is clear that the insertion operation results in a larger graph than uniform random mutation, even though there is a deletion operator also present.

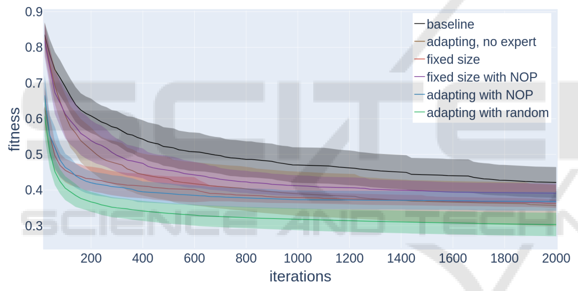

Figure 11: Average and standard deviation of fitness accuracy for Lunar overs 40 runs.

Figure 11 displays evolution over 2000 generations on the Lunar dataset. **Adapting with random** performs better and quicker than five others with a better variance and ttest p-value of less than $1e^{-5}$. **Baseline** starts slower than the five other experiments with a higher variance and worse final performance. While **adapting, no expert** does eventually converge to similar accuracy as other configurations which start with an expert, the benefit of starting with an expert is demonstrated through the suboptimal performance of **baseline**. It should also be noted that the expert used on this dataset was initially trained on the Mars dataset,this does show that a filter is efficiently applicable from one task to another.

Figure 12 shows that **baseline**, **fixed size** and **fixed size with NOP** increase slowly to 7 actives nodes. For this dataset, the adaptive configurations with random function insertion grow larger than when adding NOP, which is the opposite of the node size

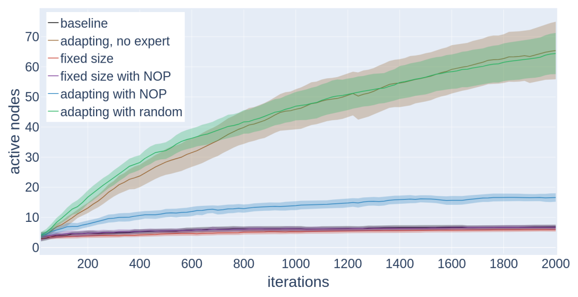

Figure 12: Average and standard deviation of actives nodes for Lunar overs 40 runs.

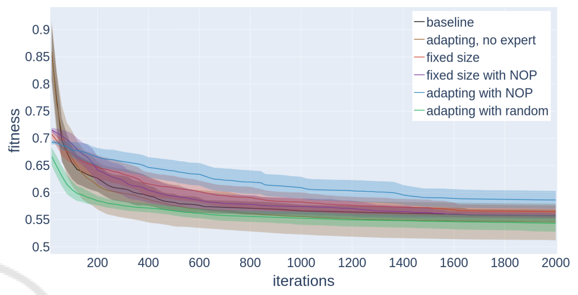

Figure 13: Average and standard deviation of fitness accuracy for Urban Traffic over 40 runs.

behavior for the Mars dataset. The adapting graphs reach enormous sizes after 2000 generations, oversizing the initial maximum graph size settled to 50.

Figure 13 shows that the evolution of the fitness function over 2000 iterations on the Urban Traffic dataset. **Adapting with random** outperforms and converges faster than **baseline**, **fixed size**, **fixed size with NOP** and **adapting with NOP** (p-value of Student t-test $<1e^{-5}$ both at iteration 300 as well as at iteration 2000). It is important to note that the standard deviation over the 40 runs is somewhere small with this method in comparison to other methods. This should be interpreted as proof that the **adapting with random** not only does perform better than other but also that to solution of similar quality independently of the randomness of the evolutionary process. **Adapting, no expert** performs slower than **adapting with random** but achieve a better fitness after 700 iterations and continue to decrease. This demonstrates a potential disadvantage of starting with an expert individual, which is early convergence based on this individual and lack of exploration when compared to a random initialization.

Figure 14 shows that **fixed size** and **fixed size with NOP** reduces the graph cardinal down to 7 active nodes. Here, as in the Lunar dataset, the random node insertion configurations continue to grow throughout evolution although their is a clear compression step visible after nearly 500 generations for **adapting, no expert** this in turn does demonstrate the benefit of the

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Table 2: Average fitness and standard deviation of each experiment on each dataset.

	Lunar	Mars	Urban traffic
Baseline	0.42 (0.09)	0.23 (0.05)	0.56 (0.02)
Adapting, no expert	0.36 (0.12)	0.21 (0.08)	0.55 (0.07)
Fixed sized	0.36 (0.02)	0.21 (0.04)	0.56 (0.02)
Fixed size with NOP	0.39 (0.05)	0.23 (0.04)	0.56 (0.01)
Adapting with NOP	0.37 (0.05)	0.26 (0.1)	0.59 (0.03)
Adapting with random	**0.3 (0.07)**	**0.2 (0.03)**	**0.54 (0.03)**

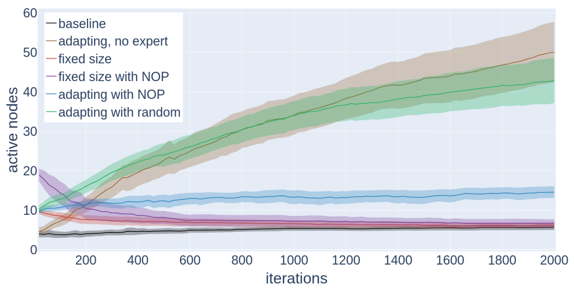

Figure 14: Average and standard deviation of actives nodes for Urban Traffic over 40 runs.

deletion operator.

To summarize: each experiment (Table 2), **adapting with random** performs better and quicker than standard CGP-IP with a lower variance and a ttest p value less than 1e-5. Our evolution with random function outperform the standard CGP-IP (**baseline**) and **fixed size with NOP** in each case. **Adapting with NOP** converges a bit faster but ends with an inferior accuracy. As expected, the **baseline** chromosome converge slower with a higher variance than the others. The proposed mutation operators (insertion of NOP and random function) greatly increase the number of active nodes in the graph unlike standard CGP-IP, where the number of active nodes is relatively stable. With Urban traffic dataset, **adapting, no expert** performs better than **adapting with random** after 700 iterations this emphases that it is important to start from an efficient base chromosome, otherwise genetic improvement will be outperformed by the classic evolution done with a random chromosome.

6 CONCLUSION

In this paper, we propose mutation operators for CGP-IP for use in the context of genetic improvement. To this end, our algorithm adds new functions in a graph and keeps existing connections intact. We have tested CGP-IP with these operators on 3 datasets and have shown that it consistently outperforms standard CGP-IP, increasing the convergence speed and final accuracy on all datasets.

Our method has the additional interest to slowly but constantly increase the number of active nodes. This allows evolution to access new research space leading to better accuracy. This conclusion is in line with previous work on incremental growth of neural networks (Stanley and Miikkulainen, 2002) or gene regulatory networks (Cussat-Blanc et al., 2015). For example, the NeuroEvolution of Augmenting Topologies (NEAT) (Stanley and Miikkulainen, 2002) algorithm demonstrates that increasing program complexity throughout search can improve the optimization. That is consistent with the results in this work, both when starting with an expert-designed image filter and when using a random initial population.

An avenue for exploration with this method is the reduction of graph complexity over time. While the node insertion operators are clearly beneficial for evolution, they reintroduce the problem of bloat into CGP. We aim to study the different mutation rates to see if large graphs can be automatically avoided in evolution.

In practice, this method can be used to converge quickly to a better solution using a efficient human designed filter than when starting from a random chromosome. This allows for application of this method which builds on existing image processing pipelines, especially those which use CGP-IP.

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