Object Detection in Multi-modal Images Using Genetic Programming

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Abstract

In this paper, we learn to discover composite operators and features that are synthesized from combinations of primitive image processing operations for object detection. Our approach is based on genetic programming (GP). The motivation for using GP-based learning is that we hope to automate the design of object detection system by automatically synthesizing object detection procedures from primitive operations and primitive features. There are many basic operations that can operate on images and the ways of combining these primitive operations to perform meaningful processing for object detection are almost infinite. The human expert, limited by experience, knowledge and time, can only try a very small number of conventional combinations. Genetic programming, on the other hand, attempts many unconventional combinations that may never be imagined by human experts. In some cases, these unconventional combinations yield exceptionally good results. To improve the efficiency of GP, we propose soft composite operator size limit to control the code bloat problem while at the same time avoid severe restriction on the GP search. Our experiments, which are performed on selected regions of images to improve training efficiency, show that GP can synthesize effective composite operators consisting of pre-designed primitive operators and primitive features to effectively detect objects in images and the learned composite operators can be applied to the whole training image and other similar testing images.

Keywords: object detection, genetic programming, composite feature, ROI extraction.

1. Introduction

In recent years, with the advent of newer, much improved and inexpensive imaging technologies and the rapid expansion of the Internet, more and more images are becoming available. Recent developments in image collection platforms produce far more imagery than the declining ranks of image analysts are capable of handling due to the speed limitation of human beings in analyzing images. Relying entirely on human image experts to perform image processing, image analysis and image classification becomes more and more unrealistic. Building automatic object detection and recognition systems to take advantage of the speed of computer is a viable and important solution to the increasing need of processing a large quantity of images efficiently.

Designing automatic object detection and recognition systems is one of the important research areas in computer vision and pattern recognition [1, 2]. The major task of object detection is to locate and extract regions of an image that may contain potential objects so that the other parts of the image can be ignored. It is an intermediate step to object recognition. The regions extracted during detection are called regions-of-interest (ROIs). ROI extraction is very important in object recognition, since the size of the image is usually large, leading to the heavy computational burden of processing the whole image. By extracting ROIs, the recognition system can focus on the extracted regions that may contain potential objects and this can be very helpful in improving the recognition rate. Also by extracting ROIs, the computational cost of object recognition is greatly reduced, thus, improving the recognition speed. This advantage is particularly important for real-time applications, where the recognition accuracy and speed are of prime importance.

However, The quality of object detection is dependent on the type and quality of features extracted from an image. There are many features that can be extracted. The question is what are the appropriate features or how to synthesize features, particularly useful for detection, from the primitive features extracted from images. The answer to these questions is largely dependent on the intuitive instinct, knowledge, previous experience and even the bias of algorithm designers and experts in object recognition by computer.

In this paper, we use genetic programming (GP) to synthesize composite features, which are the output of composite operators, to perform object detection. A composite operator consists of primitive operators and it can be viewed as a way of combining primitive operations on images. The basic approach is to apply a composite operator on the original image or primitive feature images generated from the original one; then the output image of the composite operator, called composite feature image, is segmented to obtain a binary image or mask; finally, the binary mask is used to extract the region containing the object from the original image. The individuals in our GP based learning are composite operators represented by binary trees whose internal nodes represent the pre-specified primitive operators and the leaf nodes represent the original image or the primitive feature images. The primitive feature images are pre-defined, and they are not the output of the pre-specified primitive operators.

2. Motivation and Related Research

2.1. Motivation

In most imaging applications, human experts design an approach to detect potential objects in images. The approach can often be dissected into some primitive operations on the original image or a set of related feature images obtained from the original one. It is the expert who, relying on his/her rich experience, figures out a smart way to combine these primitive operations to achieve good detection results. The task of synthesizing a good approach is equivalent to finding a good point in the space of *composite operators* formed by the combination of primitive operators.

Unfortunately, the number of ways of combining primitive operators is almost infinite. The human expert can only try a very limited number of conventional combinations. However, a GP may try many unconventional ways of combining primitive operations that may never be imagined by a human expert. Although these unconventional combinations are very difficult, if not impossible, to be explained by domain experts, in some cases, it is these unconventional combinations that yield exceptionally good results. The inherent parallelism of GP and the high speed of current computers allow the portion of the search space explored by GP to be much larger than that by human experts. The search performed by GP is not a random search. It is guided by the fitness of composite operators in the population. As the search proceeds, GP gradually shifts the population to the portion of the space containing good composite operators.

2.2. Related Research and Contributions

Genetic programming, an extension of genetic algorithm, was first proposed by Koza [3] and has been used in image processing, object detection and object recognition. Harris et al. [4] applied GP to the production of high performance edge detectors for 1D signals and image profiles. The method is also extended to the development of practical edge detectors for use in image processing and machine vision. Poli [5] used GP to develop effective image filters to enhance and detect features of interest or to build pixel-classification-based segmentation algorithms. Bhanu and Lin [6] used GP to learn composite operators for object detection. Their initial experimental results showed that GP is a viable way of synthesizing composite operators from primitive operations for object detection. Stanhope and Daida [7] used GP to generate rules for target/clutter classification and rules for the identification of objects. To perform these tasks, previously defined feature sets are generated on various images and GP is used to select relevant features and methods for analyzing these features. Howard et al. [8] applied GP to automatic detection of ships in low-resolution SAR imagery by evolving detectors. Roberts and Howard [9] used GP to develop automatic object detectors in infrared images.

Unlike the work of Stanhope and Daida [7], Howard et al. [8] and Roberts and Howard [9], the input and output of each node of the tree in our system are images, not real numbers. The primitive features defined in this paper are more general and easier to compute than those used in [7, 8]. Unlike our previous work [6], we take off the hard size limit of composite operator and use a soft size limit to let GP search more freely while at the same time prevent the code-bloat problem. The training in this paper is not performed on a whole image, but on the selected regions of an image and this is very helpful in reducing the training time. Of course, training regions must be carefully selected and represent the characteristics of training images [10]. Also, two other types of mutation are added to further increase the diversity of the population. Finally, more primitive feature images are employed. The primitive operators and primitive features designed in this paper are very basic and domain-independent, not specific to a kind of imagery. Thus, our system and methodology can be applied to a wide variety of images. We show results using synthetic aperture radar (SAR), infrared (IR) and color video images.

3. Technical Approach

In our GP based approach, individuals are composite operators represented by binary trees. The search space of GP is the space of all possible composite operators. The space is very large. To illustrate this, consider only a special kind of binary tree, where each tree has exactly 30 internal nodes and one leaf node and each internal node has only one child. For 17 primitive operators and only one primitive feature image, the total number of such trees is 17^{30}. It is extremely difficult to find good composite operators from this vast space unless one has a smart search strategy.

3.1. Design Considerations

There are five major design considerations, which involve determining the set of terminals, the set of primitive operators, the fitness measure, the parameters for controlling the evolutionary run, and the criterion for terminating a run.

- **The Set of Terminals:** The set of terminals used in this paper are sixteen primitive feature images generated from the original image: the first one is the original image; the others are mean, deviation, maximum, minimum and median images obtained by applying templates of sizes 3×3, 5×5 and 7×7, as shown in Table 1. These images are the input to composite operators. GP determines which operations are applied on them and how to combine the results. To get the mean image, we translate the template across the original image and use the average pixel value of the pixels covered by the template to replace the pixel value of the pixel covered by the central cell of the template. To get the deviation image, we just compute the pixel value difference between the pixel in the original image and its corresponding pixel in the mean image. To get maximum, minimum and median images, we translate the template across the original image and use the maximum, minimum and median pixel values of the pixels covered by the template to replace the pixel value of the pixel covered by the central cell of the template, respectively.

Table 1. Sixteen primitive feature images used as the set of terminal

No.	Primitive feature image	description	No.	Primitive feature image	description
0	PFIM0	Original image	8	PFIM8	5×5 maximum image
1	PFIM1	3×3 mean image	9	PFIM9	7×7 maximum image
2	PFIM2	5×5 mean image	10	PFIM10	3×3 minimum image
3	PFIM3	7×7 mean image	11	PFIM11	5×5 minimum image
4	PFIM4	3×3 deviation image	12	PFIM12	7×7 minimum image
5	PFIM5	5×5 deviation image	13	PFIM13	3×3 median image
6	PFIM6	7×7 deviation image	14	PFIM14	5×5 median image
7	PFIM7	3×3 maximum image	15	PFIM15	7×7 median image

- **The Set of Primitive Operators:** A primitive operator takes one or two input images, performs a primitive operation on them and stores the result in a resultant image. Currently, 17 primitive operators are used by GP to form composite operators, as shown in Table 2, where A and B are input images of the same size and c is a constant (ranging from –20 to 20) stored in the primitive operator. For operators such as ADD, SUB, MUL, etc., that take two images as input, the operations are performed on the pixel-by-pixel basis. In the operators MAX, MIN, MED, MEAN and STDV, 3×3, 5×5 or 7×7 neighborhood are used with equal probability.

Table 2. Seventeen primitive operators

No.	Operator	Description
1	ADD (A, B)	Add images A and B.
2	SUB (A, B)	Sub image B from A.
3	MUL (A, B)	Multiply images A and B.
4	DIV (A, B)	Divide image A by image B (If the pixel in B has value 0, the corresponding pixel in the resultant image takes the maximum pixel value in A).
5	MAX2 (A, B)	The pixel in the resultant image takes the larger pixel value of images A and B.
6	MIN2 (A, B)	The pixel in the resultant image takes the smaller pixel value of images A and B.
7	ADDC (A)	Increase each pixel value by c.
8	SUBC (A)	Decrease each pixel value by c.
9	MULC (A)	Multiply each pixel value by c.
10	DIVC (A)	Divide each pixel value by c.
11	SQRT (A)	For each pixel with value v, if v ≥ 0, change its value to $\sqrt{v}$. Otherwise, to $-\sqrt{-v}$.
12	LOG (A)	For each pixel with value v, if v ≥ 0, change its value to ln(v). Otherwise, to –ln(-v).
13	MAX (A)	Replace the pixel value by the maximum pixel value in a 3×3, 5×5 or 7×7 neighborhood.
14	MIN (A)	Replace the pixel value by the minimum pixel value in a 3×3, 5×5 or 7×7 neighborhood.
15	MED (A)	Replace the pixel value by the median pixel value in a 3×3, 5×5 or 7×7 neighborhood.
16	MEAN (A)	Replace the pixel value by the average pixel value of a 3×3, 5×5 or 7×7 neighborhood.
17	STDV (A)	Replace the pixel value by the standard deviation of pixels in a 3×3, 5×5 or 7×7 neighborhood.

- **The Fitness Measure:** The fitness value of a composite operator is computed in the following way. Suppose *G* and *G'* are foregrounds in the ground truth image and the resultant image of the composite operator respectively. Let *n(X)* denote the number of pixels within region *X*, then *Fitness = n(G∩G') / n(G ∪ G')*. The fitness value is between 0 and 1. If *G* and *G'* are completely separated, the value is 0; if *G* and *G'* are completely overlapped, the value is 1.

- **Parameters and Termination:** The key parameters are the population size M, the number of generation N, the crossover rate, the mutation rate and the fitness threshold. The GP stops whenever it finishes the pre-specified number of generations or whenever the best composite operator in the population has fitness value greater than the fitness threshold.

3.2. Selection, Crossover and Mutation

GP searches through the space of composite operator to generate new composite operators, which may be better than the previous ones. By searching through the composite operator space, GP gradually adapts the population of composite operators from generation to generation and improves the overall fitness of the whole population. More importantly, GP may find an exceptionally good composite operator during the search. The search is done by performing selection, crossover and mutation operations. The initial population is randomly generated and the fitness of each individual is evaluated.

- **Selection:** The selection operation involves selecting composite operators from the current population. In this paper, we use tournament selection, where a number of individuals are randomly selected from the current population and the one with the highest fitness value is copied into the new population. The size of tournament is 5.
- **Crossover:** To perform crossover, two composite operators are selected on the basis of their fitness values. The higher the fitness value, the more likely the composite operator is selected for crossover. These two composite operators are called parents. One internal node in each of these two parents is randomly selected, and the two subtrees rooted at these two nodes are exchanged between the parents to generate two new composite operators, called offspring. The offspring are composed of subtrees from their parents. If two composite operators are somewhat effective in detection, then some of their parts probably have some merit. The reason that an offspring may be better than the parents is that recombining randomly chosen parts of somewhat effective composite operators may yield a new composite operator that is even more fit in detection.

It is easy to see that the size of one of the offspring (i.e., the number of nodes in the binary tree representing the offspring), may be greater than both parents. So if we do not control the size of composite operator by implementing crossover in this simple way, the sizes of composite operators will become larger and larger as GP proceeds. This is the well-known code bloat problem of GP. It is a very serious problem, since when the size becomes too large, it will take a long time to execute a composite operator, thus, greatly reducing the search speed of GP. Further, large-size composite operators may overfit the training data by approximating various noisy components of the image. Although the results on the training image may be very good, the performance on the unseen testing images may be bad. Also, large composite operators take up a lot of computer memory. Due to the finite computer resources and the desire to achieve a good running speed (efficiency) of GP, we must limit the size of composite operator by specifying its maximum size. In our previous work [6], if the size of one offspring exceeds the *maximum size* allowed, the crossover operation is performed again until the sizes of both offspring are within the limit. Although this simple method guarantees that the size of composite operator won't exceed the size limit, it is a brutal method since it sets a hard size limit. The hard size limit may greatly restrict the search performed by GP, since after randomly selecting a crossover point in one composite operator, GP cannot select some nodes of the other composite operator as a crossover point in order to guarantee that both offspring won't exceed the size limit. However, restricting the search may greatly reduce the efficiency of GP, making it less likely to find good composite operators.

One may suggest that after two composite operators are selected, GP may perform crossover twice and may each time keep the offspring of smaller size. This method can enforce the size limit and will prevent the sizes of offspring composite operators from growing large. However, GP will now only search the space of these smaller composite operators. With small number of nodes, a composite operator may not capture the characteristics of objects to be detected. How to avoid restricting the GP search while at the same time prevent code-bloat is the key to the success of GP and it is still a subject of intensive research. The key is to find a balance between these two conflicting factors.

In this paper, we set a composite operator size limit to prevent code-bloating, but unlike our previous work, the size limit is a soft size limit, so it restricts the GP search less severely than the hard size limit. With soft size limit, GP can select any node in both composite operators as crossover points. If the size of an offspring exceeds the size limit, GP still keeps it and evaluates it later. If the fitness of this large composite operator is the best or very close to the fitness of the best composite operator in the population, it is kept by GP, otherwise, GP randomly selects one of its sub-trees of size smaller than the size limit to replace it in the population. In this paper, GP discards any composite operator beyond the size limit unless it is the best one in the population.

- **Mutation:** In order to avoid premature convergence, mutation is introduced to randomly change the structure of some individuals to maintain the diversity of the population. Composite operators are randomly selected for mutation. There are three types of mutation invoked with equal probability:
  1. Randomly select a node of the binary tree representing the composite operator and replace the subtree rooted at this node, including the node selected, by another randomly generated binary tree
  2. Randomly select a node of the binary tree representing the composite operator and replace the primitive operator stored in the node with another primitive operator of the same number of inputs as the replaced one. The replacing primitive operator is selected at random from all the primitive operators with the same number of input as the replaced one.
  3. Randomly select two subtrees within the composite operator and swap these two subtrees. Of course, neither of the two sub-trees can be the sub-tree of the other.

3.3. Steady-state and Generational Genetic Programming

Both steady-state and generational genetic programming are used in this paper. In *steady-state GP*, two parent composite operators are selected on the basis of their fitness for crossover. The children of this crossover replace a pair of composite operators with the smallest fitness values. The two children are executed immediately and their fitness values are recorded. Then another two parent composite operators are selected for crossover. This process is repeated until crossover rate is satisfied. Finally, mutation is applied to the resulting population and the mutated composite operators are executed and evaluated. The above cycle is repeated from generation to generation. In *generational GP*, two composite operators are selected on the basis of their fitness values for crossover and generate two offspring. The two offspring are not put into the current population and won't participate in the following crossover operations on the current population. The above process is repeated until crossover rate is satisfied. Then, mutation is applied to the composite operators in the current population and the offspring from crossover. After mutation is done, selection is applied to the current population to select some composite operators. The number of composite operator selected must meet the condition that after combining with the composite operators from crossover, we get a new population of the same size as the old one. Finally, combine the composite operators from crossover with those selected from the old population to get a new population and the next generation begins. In addition, we adopt an elitism replacement method that keeps the best composite operator from generation to generation.

- **Steady-state Genetic Programming:**

0. randomly generate population P of size M and evaluate each composite operator in P.

1. for gen = 1 to N do // N is the number of generation

2. keep the best composite operator in P.

3. repeat

4. select 2 composite operators from P based on their fitness values for crossover.

5. select 2 composite operators with the lowest fitness values in P for replacement.

6. perform crossover operation and let the 2 offspring replace the 2 composite operators selected for replacement.

7. execute the 2 offspring and evaluate their fitness values.

8. until crossover rate is met.

9. perform mutation on each composite operator with probability of mutation_rate and evaluate mutated composite operators.

10. After crossover and mutation, a new population P' is generated.

11. let the best composite operator from population P replace the worst composite operator in P' and let P = P'.

12. if the fitness value of the best composite operator in P is above fitness threshold value then

13. stop.

endif

14. check each composite operator in P. if its size exceeds the size limit and it is not the best composite operator in P, replace it with one of its subtree whose size is within the size limit.

endfor // loop 1

- **Generational Genetic Programming:**

0. randomly generate populations of size M and evaluate each composite operator in P.

1. for gen = 1 to N do // N is the number of generation

2. keep the best composite operator in P.

3. *perform crossover on the composite operators in P until crossover rate is satisfied and keep all the offspring from crossover separately.*
4. *perform mutation on the composite operators in P and the offspring from crossover with the probability of mutation rate.*
5. *perform selection on P to select some composite operators. The number of selected composite operator must be M minus the number of composite operators from crossover.*
6. *combine the composite operators from crossover with those from P to get a new population P' of the same size as P.*
7. *evaluate offspring from crossover and the mutated composite operators.*
8. *let the best composite operator from P replace the worst composite operator in P' and let P = P'.*
9. *if the fitness of the best composite operator in P is above fitness threshold then*
10. *stop.*

    endif
11. *check each composite operator in P. if its size exceeds the size limit and it is not the best composite operator in P, replace it with one of its subtree whose size is within the size limit.*

endfor // loop 1

4. Experiments

Various experiments are performed to test the efficacy of genetic programming in extracting regions of interest from real synthetic aperture radar (SAR) images, infrared (IR) images and RGB color images. The size of SAR images is 128×128, except the tank SAR images whose size is 80×80, and the size of IR and RGB color images is 160×120. GP (in subsections 4.1 and 4.2) is not applied to the whole training image, but only to a region or regions carefully selected from the training image, to generate the composite operators. The generated composite operator is then applied to the whole training image and to some other testing images to evaluate it. The advantage of performing training on a small selected region is that it can greatly reduce the training time, making it practical for the GP system to be used as a subsystem of other learning systems, which improve the efficiency of GP by adapting the parameters of GP system based on its performance. Our experiments show that if the training regions are carefully selected from the training images, the best composite operator generated by GP is effective. In the following experiments in sections 4.1 and 4.2, the parameters are: population size (100), the number of generations (70), the fitness threshold value (1.0), the crossover rate (0.6), the mutation rate (0.05), the maximum size of composite operator (30), and the segmentation threshold (0). In each experiment, GP is invoked ten times with the same parameters and the same training region(s). The coordinate of the upper left corner of an image is (0, 0). The ground truth is used only during training, it is not needed during testing. We use it in testing only for evaluating the performance of the composite operator on testing images.

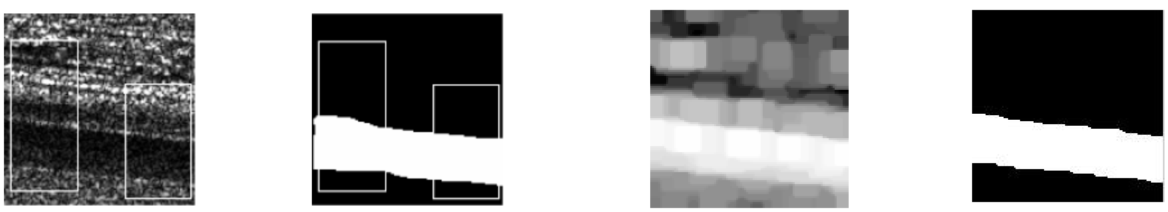
4.1. SAR images

Five experiments are performed with real SAR images. The experimental results from one run and the average performance of ten runs are reported in Table 3. We select the run in which GP finds the best composite operator among the composite operators found in all ten runs. The first two rows show the fitness value of the best composite operator and the population fitness value (average fitness value of all the composite operators in the population) on training region(s) in the initial and final generations in the selected run. The numbers in the parenthesis in the "f_{op}" columns are the fitness values of the best composite operators on the whole training image (numbers with a * superscript) and other testing images in their entirety. The last two rows show the average values of the above fitness values over all ten runs. The regions extracted during the training and testing by the best composite operator from the selected run are shown in the following examples.

Table 3. The performance of our approach on various examples of SAR images.
(f_{op} = fitness of the best composite operator, f_p = fitness of population, *: indicate fitness on training images, $f_{initial}$ = fitness in the initial generation, f_{final} = fitness in the final population)

	Road		Lake		River		Field		Tank	
	f_{op}	f_p	f_{op}	f_p	f_{op}	f_p	f_{op}	f_p	f_{op}	f_p
$f_{initial}$	0.68	0.28	0.56	0.32	0.65	0.18	0.53	0.39	0.51	0.16
f_{final}	0.95 (0.93*, 0.9, 0.93)	0.67	0.97 (0.93*, 0.98)	0.93	0.90 (0.71*, 0.83)	0.85	0.78 (0.89*, 0.80)	0.64	0.88 (0.88*, 0.84)	0.80
Ave. $f_{initial}$	0.55	0.27	0.59	0.32	0.48	0.18	0.54	0.37	0.61	0.17
Ave. f_{final}	0.83	0.60	0.95	0.92	0.85	0.77	0.76	0.59	0.86	0.68

- **Example 1 — Road Extraction:** Three images contain road, the first one contains horizontal paved road and field (Fig 1(a)); the second one contains unpaved road and field (Fig 8(a)); the third one contains vertical paved road and grass (Fig 8(d)). Training is done on the training regions of training image shown in Figure 1(a) and testing is performed on the whole training image and testing images. There are two training regions, locating from (5, 19) to (50, 119) and from (82, 48) to (126, 124), respectively. Figure 1(b) shows the ground truth provided by the user and the training regions. The white region corresponds to the road and only the training regions of the ground truth are used in the evaluation during the training. Figure 2 shows the sixteen primitive feature images of the training image.



(a) paved road vs. field (b) ground truth (c) composite feature image (d) ROI extracted

Figure 1. Training SAR image containing road.

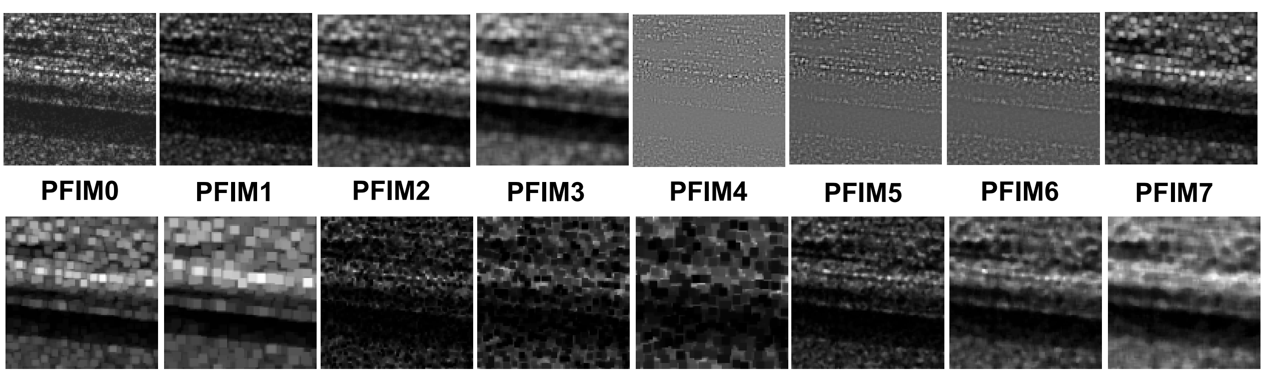


Figure 2. Sixteen primitive feature images of training SAR image containing road.

The generational GP is used to synthesize a composite operator to extract the road and the results of the 6th run are reported. The fitness value of the best composite operator in the initial population is 0.68 and the population fitness value is 0.28. The fitness value of the best composite operator in the final population is 0.95 and the population fitness value is 0.67. Figure 1(c) shows the output image of the best composite operator on the whole training image and Figure 1(d) shows the binary image after segmentation. The output image has both positive pixels in brighter shade and negative pixels in darker shade. Positive pixels belong to the region to be extracted. The fitness value of the extracted ROI is 0.93. The best composite operator has 17 nodes and its depth is 16. It has only one leaf node containing 5×5 median image. The median image is less noisy, since median filtering is effective in eliminating speckle noises. The best composite operator is shown in Figure 3, where PFIM14 is 5×5 median image. Figure 4 shows how the average fitness of the best composite operator and average fitness of population over all 10 runs change as GP explore the composite operator space. Unlike [6] where the population fitness approaches the fitness of the best composite operator as GP proceeds, in Figure 4, population fitness is much lower than that of best composite operator even at the end of GP search. It is reasonable, since we don't restrict the selection of crossover points. The population fitness is not important since only the best composite operator is used in testing. If GP finds one effective composite operator, the GP learning is successful. The large difference between the fitness of the best composite operator and the population indicates that the diversity of the population is always maintained during GP search, which is very helpful in preventing premature convergence. 10 best composite operators are learned in 10 runs.

After computing the percentage of each primitive operator and primitive feature image among the total number of internal node (representing primitive operator) and total number leaf node (representing primitive feature image), we get the utility of these primitive operators and primitive feature images, which is shown in Figure 5(a) and (b). MED (primitive operator 15) and PFIM5 (the 6th primitive feature image) have the highest frequency of utility. Figure 6 shows the output image of each node of the best composite operator shown in Figure 3. From left to right and top to bottom, the images correspond to nodes sorted in the pre-traversal order of the binary tree representing the best composite operator. The output of the root node is shown in Figure 1(c), so Figure 6 shows the outputs of other nodes. The primitive operators in Figure 6 are connected by arrow. The operator at the tail of an arrow provides input to the operator at the head of the arrow. After segmenting the output image of a node, we get the ROI (shown as the white region) extracted by the corresponding subtree rooted at the node. The extracted ROIs and their fitness values are shown in Figure 7. If an output image of a node has no positive pixel (for example, the output of MEAN primitive operator), nothing is extracted and the fitness value is 0; if an output image has positive pixels only (for example, PFIM14 has positive pixels only), everything is extracted and the fitness is 0.25. The output of the root node storing primitive operator MED is shown in Figure 1(d).

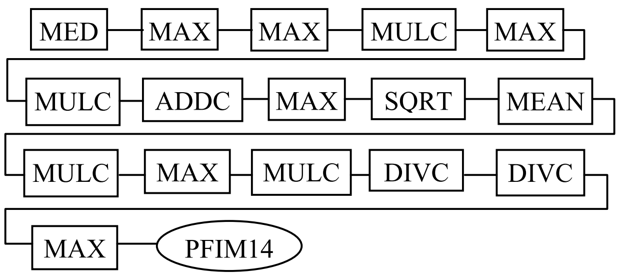


Figure 3. Learned composite operator tree.

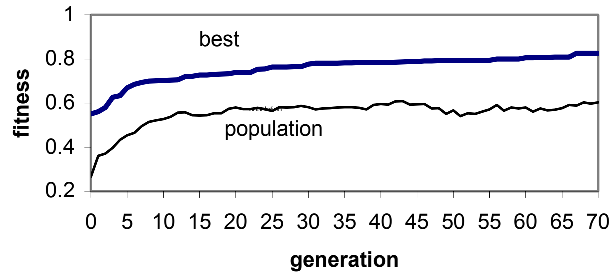


Figure 4. Fitness versus generation (road vs. field).

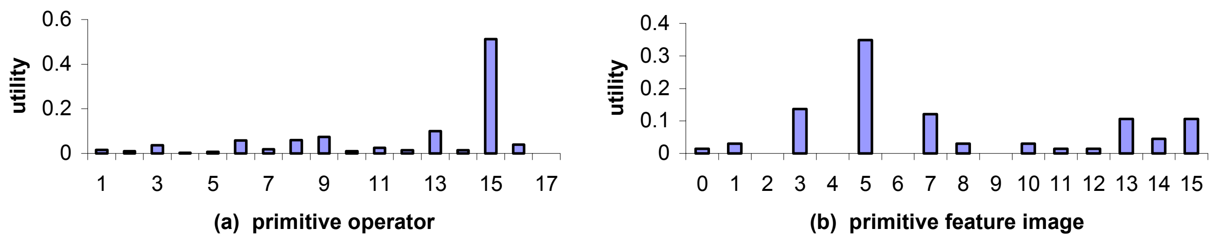


Figure 5. Utility of primitive operators and primitive feature images.

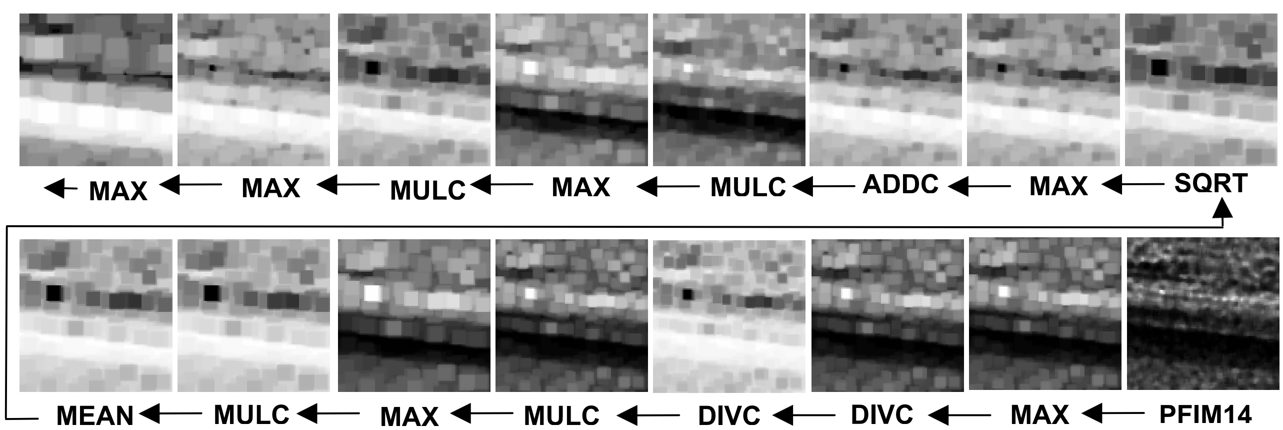


Figure 6. Feature image output by the nodes of the best composite operator.

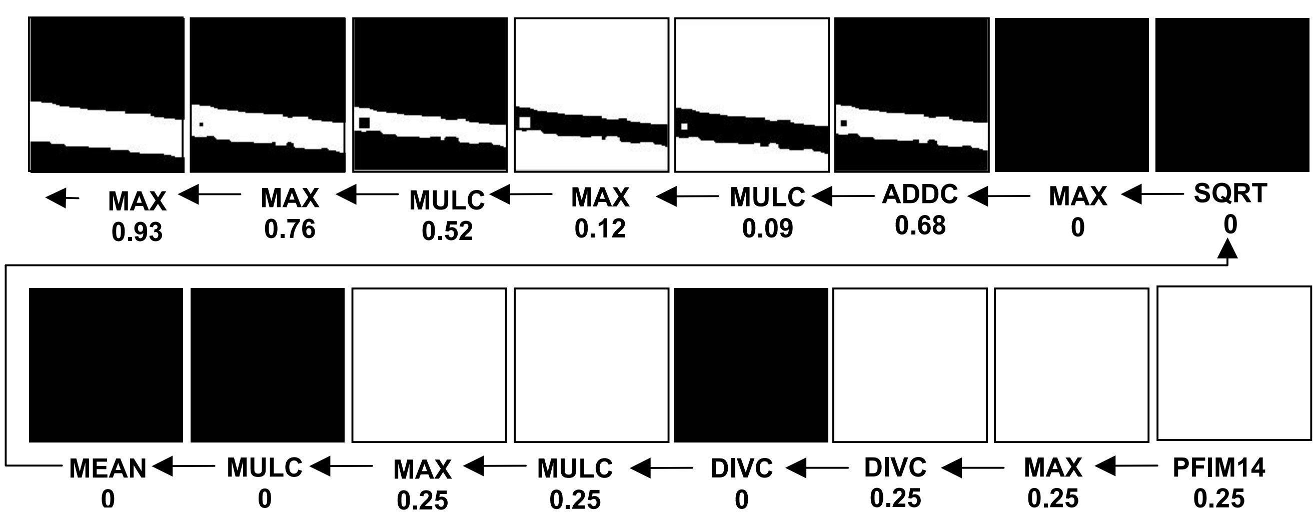
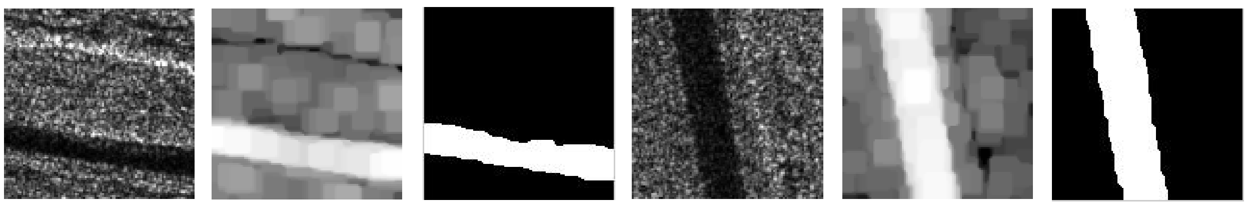


Figure 7. ROI extracted from the output image of nodes of the best composite operator. (The fitness value is shown for the entire image.)

We applied the composite operator obtained in the above training to the other two real SAR images shown in Figure 8(a) and 8(d). Figure 8(b) and 8(e) show the output of the composite operator and Figure 8(c) shows the region extracted from Figure 8(a). The fitness value of the region is 0.90. Figure 8(f) shows the region extracted from Figure 8(d) and the fitness value of the region, which is 0.93.



(a) unpaved road vs. field (b) composite feature image (c) ROI extracted (d) paved road vs. grass (e) composite feature image (f) ROI extracted

Figure 8. Testing SAR image containing road.

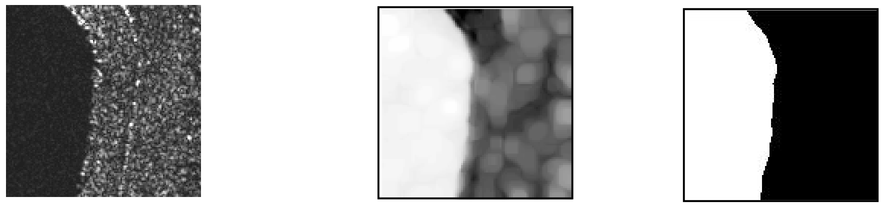
- **Example 2 — Lake Extraction:** Two SAR images contain lake (Fig 9(a), 10(a)), the first one contains a lake and field, and the second one contains a lake and grass. Figure 9(a) shows the original training image containing lake and field and the training region from (85, 85) to (127, 127). Figure 5(b) shows the ground truth provided by the user. The white region corresponds to the lake to be extracted. Figure 10(a) shows the image containing lake and grass.

(a) lake vs. field (b) ground truth (c) composite feature image (d) ROI extracted

Figure 9. Training SAR image containing lake.

The steady-state GP is used to generate the composite operator and the results of the 9th run are reported. The fitness value of the best composite operator in the initial population is 0.56 and the population fitness value is 0.32. The fitness value of the best composite operator in the final population is 0.97 and the population fitness value is 0.93. Figure 9(c) shows the output image of the best composite operator on the whole training image and Figure 9(d) shows the binary image after segmentation. The fitness value of the extracted ROI is 0.93.

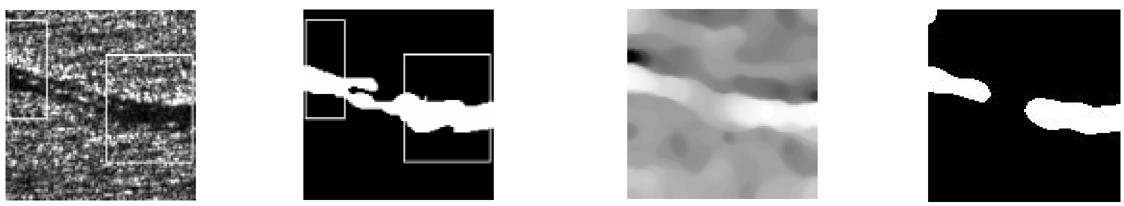
We apply the composite operator to the testing image containing lake and grass. Figure 10(b) shows the output of the composite operator and Figure 10(c) shows the region extracted from Figure 10(a). The fitness of the region is 0.98.



(a) lake vs. grass (b) composite feature image (c) ROI extracted

Figure 10. Testing SAR image containing lake.

- **Example 3 — River Extraction:** Two SAR images contain river and field. Figure 11(a) and 11(b) show the original training image and the ground truth provided by the user. The white region in Figure 11(b) corresponds to the river to be extracted. The training regions are from (68, 31) to (126, 103) and from (2, 8) to (28, 74). The testing SAR image is shown in Figure 14(a).



(a) river vs. field (b) ground truth (c) composite feature image (d) ROI extracted

Figure 11. Training SAR image containing river.

The steady-state GP was used to generate the composite operator and the results from the fourth run are reported. The fitness value of the best composite operator in the initial population is 0.65 and the population fitness value is 0.18. The fitness value of the best composite operator in the final population is 0.90 and the population fitness value is 0.85. Figure 11(c) shows the output image of the best composite operator on the whole training image and Figure 11(d) shows the binary image after segmentation. The fitness value of the extracted ROI is 0.71. The best composite operator has 29 nodes and its depth is 19. It has five leaf nodes and all contain 7×7 median image. There are more than ten MED operators that are very useful in eliminating speckle noises. It is shown in Figure 12. Figure 13 shows how the average fitness of the best composite operator and average fitness of population over all 10 runs change as GP explores the composite operator space.

We apply the composite operator to the testing image containing a river and field. Figure 14(b) shows the output of the composite operator and Figure 14(c) shows the region extracted from Figure 14(a) and the fitness value of the region is 0.83. There are some islands in the river and these islands along with the river around them are not extracted.

```
(MED (MED (MED (ADD (MED (STDV (MED
PFIM15))) (MED (MED (MED (MED (MED
(MIN2 (MED PFIM15) (MED (MED (MED
(MIN2 (MED PFIM15) (MED (MED (MIN2
PFIM15 (SUBC (DIVC PFIM15)))))))))))))))))))
```

Figure 12. Learned composite operator tree in LISP notation.

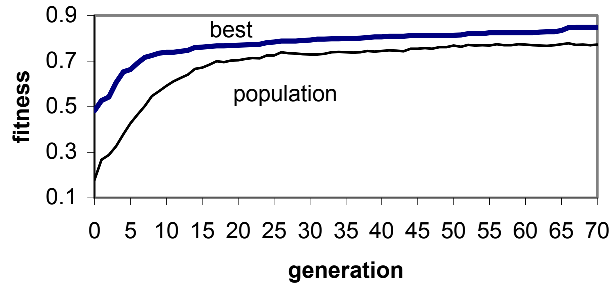
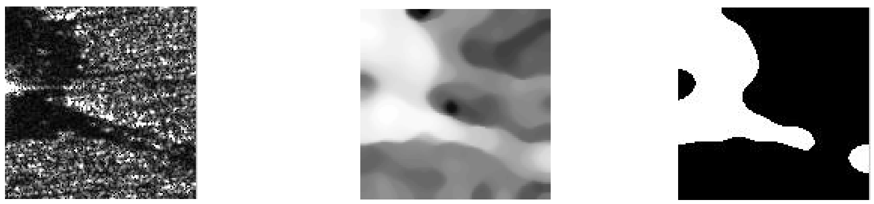


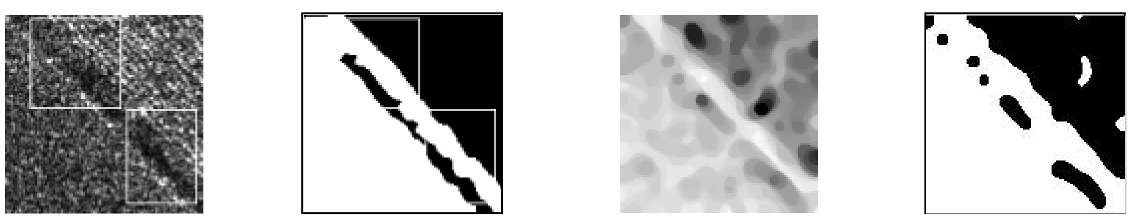
Figure 13. Fitness versus generation (river vs. field).



(a) river vs. field **(b) composite feature image** **(c) ROI extracted**

Figure 14. Testing SAR image containing river.

- **Example 4 — Field Extraction:** Two SAR images contain field and grass. Figure 15(a) and 15(b) show the original training image and the ground-truth. The training regions are from (17, 3) to (75, 61) and from (79, 62) to (124, 122). We consider extracting field from a SAR image containing field and grass as the most difficult task among the five experiments, since the grass and field are similar to each other and some small regions between grassy areas are actually field pixels.



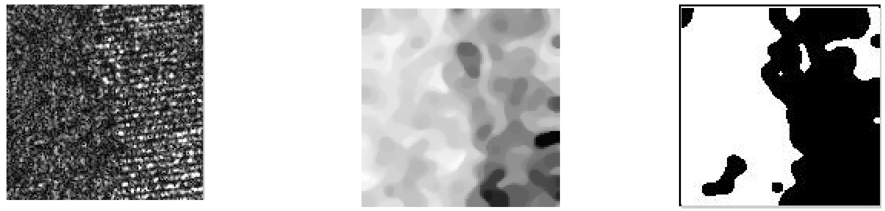
(a) field vs. grass **(b) ground truth** **(c) composite feature image** **(d) ROI extracted**

Figure 15. Training SAR image containing field.

The generational GP was used to generate the composite operator and the results from the second run are reported. The fitness value of the best composite operator in the initial population is 0.53 and the population fitness value is 0.39. The fitness value of the best composite operator in the final population is 0.78 and the population fitness value is 0.64. Figure 15(c) shows the output image of the best composite operator on the whole training image and Figure 15(d) shows the binary image after segmentation. The fitness value of the extracted ROI is 0.89.

We apply the composite operator to the testing image containing field and grass shown in

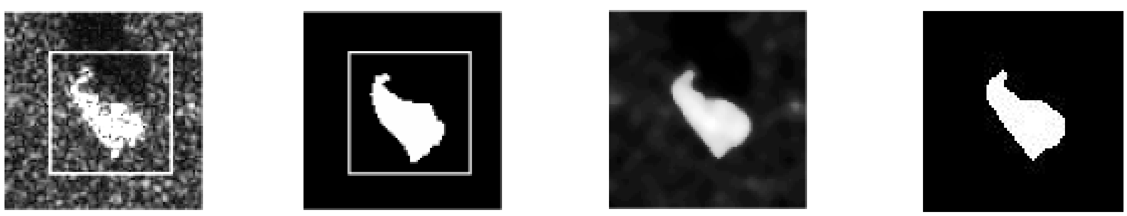
Figure 16(a). Figure 16(b) shows the output of the composite operator and Figure 16(c) shows the region extracted from Figure 16(a). The fitness value of the region is 0.80.



(a) field vs. grass (b) composite feature image (c) ROI extracted

Figure 16. Testing SAR image containing field.

- **Example 5 — Tank Extraction:** We use SAR images of T72 tank that are taken under different depression and azimuth angles and the size of the images is 80×80. The training image contains T72 tank under depression angle 17° and azimuth angle 135°, which is shown in Figure 17(a). The training region is from (19, 17) to (68, 66). The testing SAR image contains a T72 tank under depression angle 20° and azimuth angle 225°, which is shown in Figure 20(a). The ground-truth is shown in Figure 17(b).



(a) T72 tank (b) ground truth (c) composite feature image (d) ROI extracted

Figure 17. Training SAR image containing field.

The generational GP is applied to synthesize composite operators for tank detection and the results from the first run are reported. The fitness value of the best composite operator in the initial population is 0.51 and the population fitness value is 0.16. The fitness value of the best composite operator in the final population is 0.88 and the population fitness value is 0.80. Figure 17(c) shows the output image of the best composite operator on the whole training image and Figure 17(d) shows the binary image after segmentation. The fitness value of the extracted ROI is 0.88. The best composite operator has 10 nodes and its depth is 9. It has only one leaf node, which contains the 5×5 mean image. It is shown in Figure 18. Figure 19 shows how the average fitness of the best composite operator and average fitness of population over all 10 runs change as GP proceeds.

```
(MED (SQRT (MULC (MULC (SUBC (MULC
(SQRT (SUBC (SQRT PFIM2)))))))))
```

Figure 18. Learned composite operator tree in LISP notation.

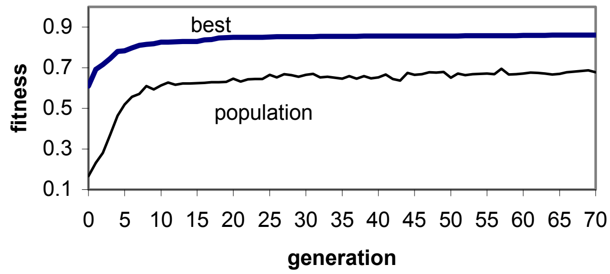
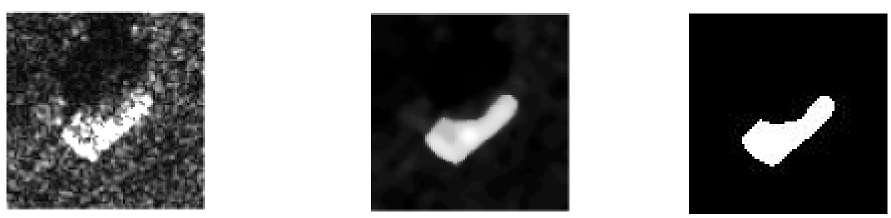


Figure 19. Fitness versus generation (T72 tank).

We apply the composite operator to the testing image containing T72 tank under depression angle 20° and azimuth angle 225°. Figure 20(b) shows the output of the composite operator and Figure 20(c) shows the region corresponding to the tank. The fitness of the extracted ROI is 0.84. Our results show that GP is very much capable of synthesizing composite operators for target detection. With more and more SAR images collected by satellites and airplanes, it is impractical for human experts to scan each SAR image to find targets. Applying the synthesized composite operators on these images, regions containing potential targets can be quickly detected and passed on to automatic target recognition systems or to human experts for further examination. Concentrating on the regions of interest, the human experts and recognition systems can perform recognition task more effectively and more efficiently.



(a) T72 tank **(b) composite feature image** **(c) ROI extracted**

Figure 20. Testing SAR image containing tank.

4.2. IR and RGB Color Images

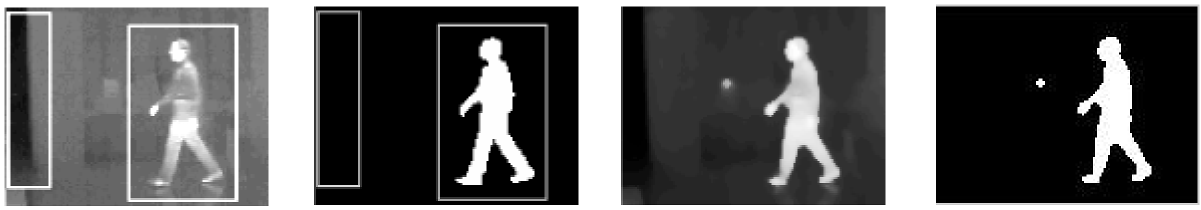
One experiment is performed with IR images and one is performed with RGB color images. The experimental results from one run and the average performance of ten runs are reported in Table 4. As we did in Subsection 4.1, we select the run in which GP finds the best composite operator among the composite operators found in all the ten runs. The regions extracted during the training and testing by the best composite operator from the selected run are shown in the following examples.

Table 4. The performance of our approach on examples of IR and RGB color images. (f_{op} = fitness of the best composite operator, f_p = fitness of population, *: indicate fitness on training images, $f_{initial}$ = fitness in the initial generation, f_{final} = fitness in the final population)

	IR Image — People		Color Image — Car	
	f_{op}	f_p	f_{op}	f_p
$f_{initial}$	0.56	0.23	0.35	0.18
f_{final}	0.93 (0.85*, 0.84, 0.81, 0.86)	0.79	0.84 (0.82*, 0.76)	0.79
Ave. $f_{initial}$	0.59	0.21	0.47	0.18
Ave. f_{final}	0.85	0.65	0.72	0.67

- **People Extraction in IR Images:** In IR images, pixel values correspond to the temperature in the scene. We have four IR images with one used in training and the other three used in testing. Figure 21(a) and (b) show the training image and the ground truth. There are two training regions from (59, 9) to (106, 88) and from (2, 3) to (21, 82), respectively. The left training region contains no pixel belonging to the person. The reason for selecting it during training is that there are major changes of pixel intensities among the pixels in the region. Nothing in this region should be detected. The fitness of composite operator on this region is defined as one minus the percentage of pixels detected in the region. If nothing is detected, the fitness value is 1.0. Averaging the fitness values on the two training regions, we get the fitness during training. When the learned composite operator is applied to the whole training image, the fitness is computed as a measurement of the overlap between the ground truth and the extracted ROI, as we did in the previous experiments. Three testing IR images are shown in Figure 24(a), (d) and (g).

The generational GP is applied to synthesize composite operators for person detection and the results from the third run are reported. The fitness value of the best composite operator in the initial population is 0.56 and the population fitness value is 0.23. The fitness value of the best composite operator in the final population is 0.93 and the population fitness value is 0.79. Figure 21(c) shows the output image of the best composite operator on the whole training image and Figure 21(d) shows the binary image after segmentation. The fitness value of the extracted ROI is 0.85. The best composite operator has 28 nodes and its depth is 13. It has nine leaf nodes and is shown in Figure 22. Figure 23 shows how the average fitness of the best composite operator and average fitness of population over all the 10 runs change as GP proceeds.



(a) person (b) ground truth (c) composite feature image (d) ROI extracted

Figure 21. Training IR image containing person.

(SQRT (SQRT (SUBC (SQRT (MAX2 (MAX2 PFIM1 (SUB (MAX2 PFIM14 PFIM15) (DIV (MULC (SQRT (MAX (MAX (ADD PFIM12 PFIM15))))) PFIM9))) (DIV (MULC (SQRT (MAX (ADD PFIM12 PFIM9)))) PFIM9))))))

Figure 22. Learned composite operator tree in LISP notation.

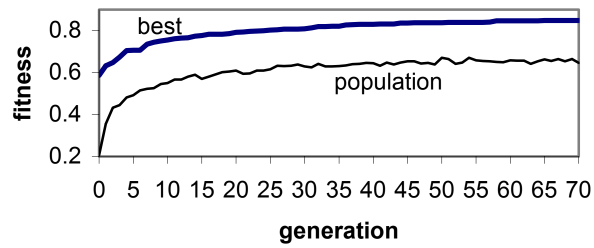


Figure 23. Fitness versus generation (T72 tank).

(a) person (b) composite feature image (c) ROI extracted

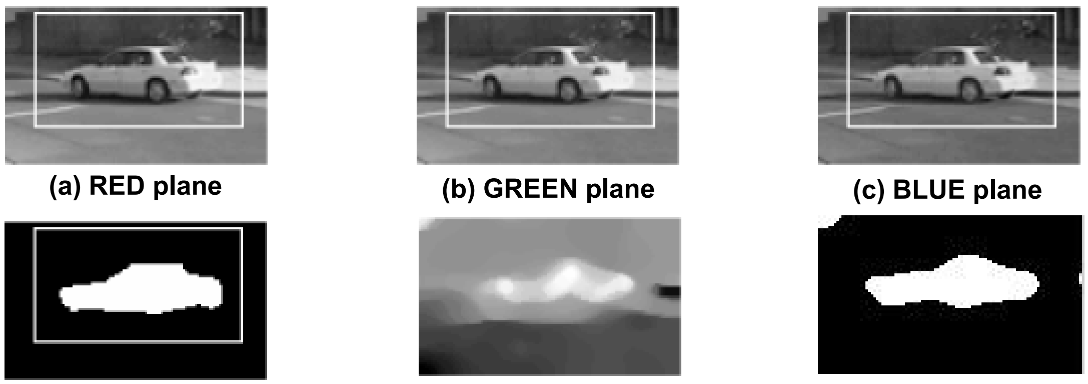
(d) person (e) composite feature image (f) ROI extracted

(g) person (h) composite feature image (i) ROI extracted

Figure 24. Testing IR images containing person.

We apply the composite operator to the testing images shown in Figure 24. Figure 24(b), (e) and (h) show the output of the composite operator and Figure 24(c), (f) and (i) show the ROI extracted. Their fitness values are 0.84, 0.81 and 0.86 respectively.

- **Car Extraction in RGB Color Image:** GP is applied to learn features to detect car in RGB color images. Unlike previous experiments, the primitive feature images in this experiment are RED, GREEN and BLUE planes of RGB color image. Figure 25(a), (b) and (c) show the RED, GREEN and BLUE planes of the training image. The ground truth is shown in Figure 25(d). The training region is from (21, 3) to (91, 46).



(a) RED plane **(b) GREEN plane** **(c) BLUE plane**

(d) ground truth **(e) composite feature image** **(f) ROI extracted**

Figure 25. Training RGB color image containing car.

The steady-state GP is applied to synthesize composite operators for car detection and the results from the fourth run are reported. The fitness value of the best composite operator in the initial population is 0.35 and the population fitness value is 0.18. The fitness value of the best composite operator in the final population is 0.84 and the population fitness value is 0.79. Figure 25(e) shows the output image of the best composite operator on the whole training image and Figure 25(f) shows the binary image after segmentation. The fitness value of the extracted ROI is 0.82. The best composite operator has 44 nodes and its depth is 21. It has ten leaf nodes with one of them containing GREEN plane and the others contain BLUE plane. It is shown in Figure 26, where PFG means GREEN plane and PFB means BLUE plane. Figure 27 shows how the average fitness of the best composite operator and average fitness of population over all 10 runs change as GP proceeds.

```
(MED (MED (MED (MULC (MUL (SUB (MIN
(MEAN (MAX2 (MED (ADDC (MAX2 (ADDC
(ADDC (MED (MAX2 (MED (MED (MAX2 (MED
(ADDC PFB)) PFB))) PFB)))) PFB))) (MED
PFG)))) (ADDC (MAX2 (ADDC (ADDC (MED
(MAX2 (MED (MED (MAX2 (MED (ADDC PFB))
PFB))) PFB)))) PFB))) (ADDC PFB))))))
```

Figure 26. Learned composite operator tree in LISP notation.

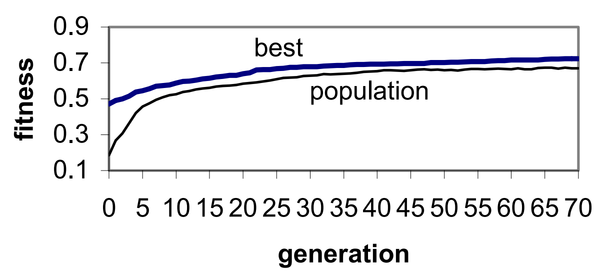
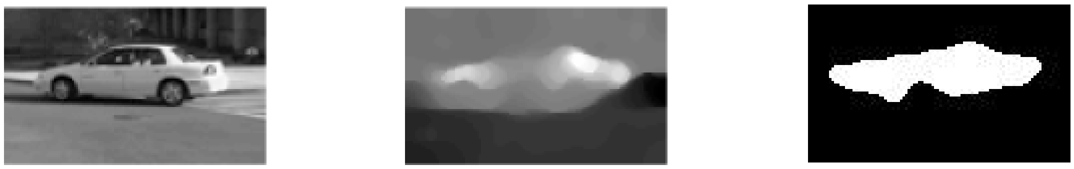


Figure 27. Fitness versus generation (T72 tank).

We apply the composite operator to the testing image whose RED plane is shown in Figure 28(a). Figure 28(b) shows the output of the composite operator and Figure 28(c) shows the ROI extracted. The fitness value of extracted ROI is 0.76.



(a) RED plane (b) composite feature image (c) ROI extracted

Figure 28. Testing RGB color image containing car.

4.3. Comparison

In [6], we applied genetic programming to learn composite operators for object detection. This paper is an advancement to our previous work. The major differences between the method presented here and that in [6] are:

1) Unlike [6] where a whole training image is used during training, GP runs on carefully selected region(s) in this paper to reduce the training time.
2) Hard size limit on the composite operator is replaced by soft size limit in this paper. This removes the restriction on the selection of crossover point in the parent composite operators to improve the search efficiency of GP, as stated in subsection 3.2.
3) Only the first mutation type in subsection 3.2 and only the fist seven primitive feature images are used in [6]. With more mutation types and more primitive feature images used, the diversity of the composite operator population can be further increased.

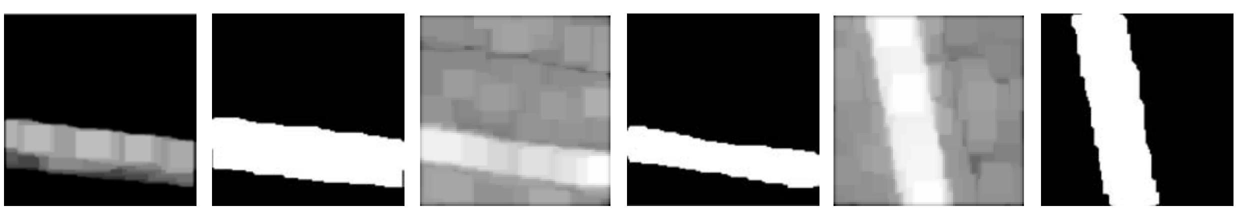
We summarize the experimental results on REAL SAR images in [6] for the purpose of comparison. The parameters are: population size (100), the number of generations (100), the fitness threshold value (1.0), the crossover rate (0.6), the mutation rate (0.1), the maximum size (number of internal node) of composite operator (30), and the segmentation threshold (0). In each experiment, GP is invoked ten times with the same parameters. The experimental results from one run and the average performance of ten runs are reported in Table 5. We select the run in which GP finds the best composite operator among the composite operators found in all ten runs to report. The numbers in the parenthesis in the "f_{op}" columns are the fitness values of the best composite operators on the testing SAR images.

Table 5. The Performance of Genetic Programming on Various Examples of SAR Images.

(f_{op} = fitness of the best composite operator, f_p = fitness of population, *: indicate fitness on training images, $f_{initial}$ = fitness in the initial generation, f_{final} = fitness in the final population)

	Road		Lake		River		Field	
	f_{op}	f_p	f_{op}	f_p	f_{op}	f_p	f_{op}	f_p
$f_{initial}$	0.47	0.19	0.65	0.42	0.43	0.21	0.62	0.44
f_{final}	0.92* (0.92, 0.89)	0.89	0.93* (0.92)	0.92	0.74* (0.84)	0.68	0.87* (0.68)	0.86
Ave. $f_{initial}$	0.47	0.18	0.73	0.39	0.37	0.11	0.65	0.41
Ave. f_{final}	0.81	0.76	0.92	0.87	0.68	0.58	0.84	0.77

- **Road Extraction:** Figure 1(a) shows the training image and Figure 8(a), (d) show the testing images. The generational GP was used to generate a composite operator to extract the road. The fitness value of the best composite operator in the initial population is 0.47 and the population fitness value is 0.19. The fitness value of the best composite operator in the final population is 0.92 and the population fitness value is 0.89. Figure 29(a) shows the output image of the best composite operator in the final population and Figure 29(b) shows the extracted ROI. We applied the composite operator obtained in the above training to the two testing SAR images. Figure 29(c) and (d) show the output image of the composite operator and the ROI extracted from Figure 8(a). The fitness value of the extracted ROI is 0.92. Figure 29(e) and (f) show the output image of the composite operator and the ROI extracted from Figure 8(d). The fitness value of the extracted ROI is 0.89.



(a) composite feature image **(b) ROI extracted from Figure 1(a)** **(c) composite feature image** **(d) ROI extracted from Figure 8(a)** **(e) composite feature image** **(f) ROI extracted from Figure 8(d)**

Figure 29. Results on SAR images containing road.

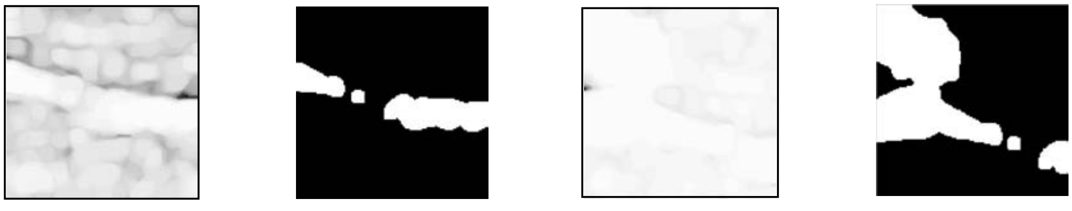
- **Lake Extraction:** Figure 9(a) shows the training image and Figure 10(a) shows the testing image. The steady-state GP was used to generate the composite operator. The fitness value of the best composite operator in the initial population is 0.65 and the population fitness value is 0.42.

The fitness value of the best composite operator in the final population is 0.93 and the population fitness value is 0.92. Figure 30(a) shows the output image of the best composite operator in the final population and Figure 30(b) shows the extracted ROI. We applied the composite operator to the testing SAR image. Figure 30(c) and (d) show the output image of the composite operator and the extracted ROI with fitness value 0.92. In Figure 30(a) and (c), pixels in the small dark regions have very low pixel values (negative values with very large absolute value), thus, making many pixels near the borders of the image appear bright, although these pixels have negative pixel values.

(a) composite feature image (b) ROI extracted from Figure 5(a) (c) composite feature image (d) ROI extracted from Figure 6(a)

Figure 30. Results on SAR images containing lake.

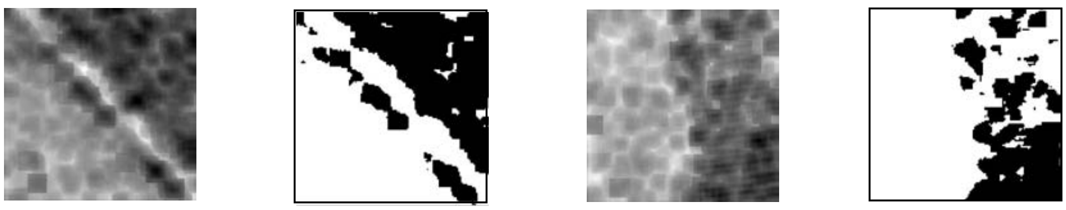
- **River Extraction:** Figure 11(a) shows the training image and Figure 14(a) shows the testing image. The steady-state GP was used to generate the composite operator. The fitness value of the best composite operator in the initial population is 0.43 and the population fitness value is 0.21. The fitness value of the best composite operator in the final population is 0.74 and the population fitness value is 0.68. Figure 31(a) shows the output image of the best composite operator in the final population and Figure 31(b) shows the extracted ROI. We applied the composite operator to the testing image. Figure 31(c) and (d) show the output image of the composite operator and the extracted ROI with fitness value 0.84. Like Figure 30(c), pixels in the small dark region have very low pixel values (negative values with very large absolute value), thus, making many pixels with negative pixel values appear bright,



(a) composite feature image (b) ROI extracted from Figure 7(a) (c) composite feature image (d) ROI extracted from Figure 10(a)

Figure 31. Results on SAR images containing river.

- **Field Extraction:** Figure 15(a) shows the training image and Figure 16(a) shows the testing image. The generational GP was used to generate the composite operator. The fitness value of the best composite operator in the initial population is 0.62 and the population fitness value is 0.44. The fitness value of the best composite operator in the final population is 0.87 and the population fitness value is 0.86. Figure 32(a) shows the output image of the best composite operator in the final population and Figure 32(b) shows the extracted ROI. We applied the composite operator to the testing image. Figure 32(c) and (d) show the output image of the composite operator and the extracted ROI with fitness value 0.68.



(a) composite feature image **(b) ROI extracted from Figure 11(a)** **(c) composite feature image** **(d) ROI extracted from Figure 12(a)**

Figure 32. Results on SAR images containing field.

From Tables 3 and 5 and associated figures, it can be seen that if the training regions are carefully selected and represent the characteristics of training images, the composite operators learned by GP running on training regions are effective in extracting the ROIs containing the object and their performances are comparable to the performances of composite operators learned by GP running on the whole training images. By running on the selected regions, the training time is greatly reduced. Table 6 shows the average running time of GP running on selected regions (Region GP) and GP running on the whole training images (Image GP) over all ten runs and the time is measured in second. Since the number of generation in [6] is 100 and the number of generation in this paper is 70, the running time of "Image GP" in Table 6 is the actually running time of "Image GP" times 0.7. It can be seen that the training time using selected training region is much shorter than that using the whole image.

Table 6. Average running time of Region GP and Image GP.

	Road	Lake	River	Field
Region GP	12876	2263	6560	9685
Image GP	23608	9120	66476	21485

5. Conclusions

In this paper, we use genetic programming to synthesize composite operators and composite features to detect potential objects in images. We use soft composite operator size limit to avoid code-bloating and severe restriction on GP search. Our experimental results show that the primitive operators and primitive features defined by us are effective. GP can synthesize effective composite operators for object detection by running on the carefully selected training regions of training image and the synthesized composite operators can be applied to the whole training image and other similar testing images. We don't find significant difference between generational and steady-state genetic programming algorithms. GP has well known code bloat problem. Controlling code bloat due to the limited computational resources inevitably restricts the search efficiency of GP. How to reach the balance point between these two conflicting factors is critical in the implementation of GP. In the future, we plan to address this problem by designing new fitness functions based on the minimum description length (MDL) principle to incorporate the size of composite operator into the evaluation process. Also, we will extend this work by discovering features within the regions of interest for automated object recognition.

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