Recent Developments in Program Synthesis with Evolutionary Algorithms

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Abstract—The automatic generation of computer programs is one of the main applications with practical relevance in the field of evolutionary computation. With program synthesis techniques not only software developers could be supported in their everyday work but even users without any programming knowledge could be empowered to automate repetitive tasks and implement their own new functionality. In recent years, many novel program synthesis approaches based on evolutionary algorithms have been proposed and evaluated on common benchmark problems. Therefore, we identify in this work the relevant evolutionary program synthesis approaches and provide an in-depth analysis of their performance. The most influential approaches we identify are stack-based, grammar-guided, as well as linear genetic programming. Further, we find that these approaches perform well on benchmark problems if there is a simple mapping from the given input to the correct output. On problems where this mapping is complex, e.g., if the problem consists of several subproblems or requires iteration/recursion for a correct solution, results tend to be worse. Consequently, for future work, we encourage researchers not only to use a program’s output for assessing the quality of a solution but also the way towards a solution (e.g., correctly solved sub-problems).

Index Terms—Program synthesis, Evolutionary algorithms, Genetic programming, Benchmarks

I. INTRODUCTION

Automatic program synthesis differs from the conventional programming of computer programs primarily in the definition of the specification of the functionality. While the structures of a programming language, such as control structures, must be known by the programmer in conventional programming, automatic program synthesis aims, i.a., to enable also non-programmers to define new functionality, as natural language descriptions or input/output examples can be used for specification [1].

In evolutionary computation, especially genetic programming (GP) is known for the automatic generation of computer programs. For the program specification and the training process, usually input/output examples are used by GP. However, combinations of, e.g., natural language descriptions and input/output examples for the synthesis of programs can also be found in the GP literature [2]. Since the first GP paper by Cramer in 1985 [3], GP has been applied to many programming problems including sorting and searching [4], parity [5], and even quantum computing problems [6]. Often, especially in the older GP literature, domain-specific languages similar to S-Expressions are used [7], [8]. In recent work, real-world programming languages like C/C++ [9], Java [10], and above all Python [11], [12] are used with higher frequency. Nevertheless, also Push [13], a language specially designed for GP and not for practical software development, has been used regularly in recent years for program synthesis [14], [15].

However, evaluating the performance and ensuring the comparability of novel approaches is still challenging in GP. This is true especially for program synthesis, since the application possibilities are almost unlimited and the used methods can be very complex. A step towards better comparability has been made by Helmuth and Spector [16] in 2015 with the general program synthesis benchmark suite. This benchmark suite consists of 29 problems of different complexity, is not limited to a specific programming language, and has been widely used in the literature since its publication. The program synthesis benchmark suite is therefore well suited as a starting point for our survey covering the recent developments in program synthesis based on evolutionary algorithms.

In this work, we identify the currently relevant approaches for program synthesis with evolutionary algorithms and provide an in-depth analysis of the performance of the recent approaches on the problems defined in the general program synthesis benchmark suite. Based on this analysis, we discover the current challenges of program synthesis and suggest directions for future research.

For the survey, we considered all papers citing the general program synthesis benchmark suite. From those 89 papers, we identified 54 in-scope papers which are studying program synthesis using problems from the benchmark suite. As main evolutionary approaches, we identified stack-based GP (using mostly Push as representation language), grammar-guided GP, and linear GP. For the benchmark problems, we found that most problems from the benchmark suite can already be solved with evolutionary computation. Only for three problems, no successful results have yet been reported. However, the success rates (percentage of runs where a solution was found solving all considered cases correctly) differ from problem to problem and also depend on the program synthesis approach used. To assist researchers as well as practitioners in the development of novel program synthesis techniques, we provide for each benchmark problem a list of references solving the problem. Thus, for similar problems (e.g., similar in the used data types or complexity), one can orientate on the methods from the literature.

In Sect. [11] we present work on recent program synthesis approaches not based on evolutionary algorithms, to give the
A Python function that calculates the average of a list of numbers.

```python
def average(numbers):
    total = 0
    for number in numbers:
        total += number
    return total / len(numbers)
```

A Python function that calculates the sum of a list of numbers.

```python
def sum(numbers):
    total = 0
    for number in numbers:
        total += number
```

Fig. 1: Example of a text completed by GPT-3 using a response length of 64. The given phrase is printed in **bold** font and the line breaks correspond to the output in the GPT-3 playground.

reader a broader introduction into the field. We categorize the presented approaches by the type of the definition of the user’s intent. Section III describes the methodology used for the survey in detail and provides some descriptive statistics about the in-scope papers. In Sect. IV we present the relevant evolutionary approaches used for program synthesis identified in the survey. In Sect. V we analyze the performance of these approaches on the problems from the general program synthesis benchmark suite before concluding the paper in Sect. VI.

## II. Definition of User’s Intent

In programming languages, every element has its exactly defined semantics. However, in automatic program synthesis, we often have to deal with more ambiguous and incomplete definitions of the user’s intent like, e.g., natural language descriptions or input/output examples. In this section, we present recent work from the program synthesis domain using different types of program specifications. In contrast to the classification by Gulwani [1], we mention and discuss in this section different approaches for program synthesis which are possibly suitable to be combined with or to extent evolutionary algorithms in the future. Furthermore, we focus on approaches that can also be applied by users with little or even no programming experience.

### A. Natural Language Descriptions

For a user, the most intuitive way of defining the required functionality of a computer program is giving a description in natural language. Consequently, using natural language descriptions for program specifications is a relevant area in program synthesis research. For example, Desai et al. [17] automatically train a dictionary to find a relation between the words in the given textual description and the available program elements (terminals in the used grammar). Other work uses methods based on neural networks to process the natural language input [18], [19].

A recent prominent example, where program synthesis was not the explicitly intended application but which still obtains surprising results in this domain, is the large-scale language model GPT-3 proposed by Brown et al. [20]. Figure 1 shows an example of a textual description of a programming task completed by GPT-3. The given phrase is printed in **bold** font. The remaining text (including the presented line breaks) corresponds to the output obtained in the GPT-3 playground. In the example, the given phrase requests a Python function that should be able to calculate the average of a given list. GPT-3 did not only complete the given phrase in a reasonable way but also continues with presenting a useful solution for the problem. After adding the correct line breaks and indentations, the returned program would be executable in a Python environment. As we set the response length to 64, GPT-3’s output continues but the most relevant output was already given in first place. However, even if the returned program is the one most users would expect for the given problem, the given phrase still reveals a challenging problem for program synthesis based on natural language descriptions. The word `average` is ambiguous as it could not only refer to the arithmetic mean but also, e.g., to the harmonic or geometric mean. So the ideal program synthesis approach would include a dialog system to resolve such ambiguities together with the user.

So in practice, the first applications for general (not domain-specific) program synthesis will be support systems that help programmers in everyday software development by making meaningful suggestions. A recent example is GitHub Copilot [1] which was trained on a large amount of source code.

### B. Input/Output Examples

To define the intended functionality for a computer program with input/output examples, a user has to provide a set of inputs together with the related pre-calculated outputs as training data just as for classical supervised machine learning tasks like regression or classification. So the challenge for a program synthesis method is to construct a program, as general as possible, that maps correctly all given inputs to their respective outputs.

As the search space of programs is huge (and must be explored to find a program that fulfills the input/output examples), we find in the literature work that presents methods to reduce the search space [21], [22]. An example where such a program synthesis method based on input/output examples is used in practice also by non-programmers is Flash Fill [23], a tool integrated in Microsoft Excel. With Flash Fill, a user can automate repetitive string transformation tasks (e.g., concatenating or extracting sub-strings) by providing examples. This synthesis process works quickly and therefore does not interfere with the daily workflow in Excel.

For further examples and an in-depth introduction to, i.a., program synthesis based on input/output examples, we refer

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1 GitHub Copilot: [https://copilot.github.com/](https://copilot.github.com/)
the reader to the excellent online material of a program synthesis lecture by Solar-Lezama [24].

C. Other Types of Definition

An approach similar to using input/output examples, but which involves the programmer more intensively in the process, is sketch-based program synthesis [25], [26]. Instead of expecting that the program synthesis method generates the entire source code from scratch, the programmer provides, in addition to a reference implementation or assertions/unit tests for checking the program’s correctness, also the unfinished source code of a program containing placeholders. So the programmer provides the basic structure of the program (including loops and conditionals) and the synthesizer solves the complex details to substitute the placeholders.

Another way for users to define their required functionality is to explicitly demonstrate the specific task by giving a step-by-step instruction from problem to solution. Here, the task for the synthesizer is to abstract from the demonstration to provide a general solution that works also in other situations [27]. An example, where this demonstration principle is combined with traditional programming is Sikuli [28]. With Sikuli, programmers can easily interact with existing graphical user interfaces by integrating screenshots in their source code which makes it comfortable to describe repetitive tasks.

III. METHODOLOGY AND ANALYSIS

The general program synthesis benchmark suite by Helmuth and Spector [16] contains a curated list of 29 benchmark problems intended for programming novices. In addition to the problem descriptions, the benchmark suite defines also how the training and test data sets should be structured, to ensure that the necessary edge cases are contained in the data sets. The training/test set definitions are described in more detail in the benchmark suite’s associated technical report [29]. As problems from the benchmark suite have been widely used in recent work, the paper is well suited as a starting point for our survey.

As literature pool, we considered all work citing the benchmark suite paper [16] or the associated technical report [29]. To find the work citing the benchmark suite, we used Google Scholar. From this pool, we selected only research articles and PhD theses written in English which make use of at least one problem from the benchmark suite.

For the literature pool, we found 89 distinct papers (May 2021) citing the benchmark suite and/or the associated technical report on Google Scholar. From these papers, we selected 54 as in-scope papers with regard to the previous definition. Papers that only cite the benchmark suite as related work without using one of the benchmark problems were not considered.

Figure 2 shows the number of published in-scope papers per year from 2015 to 2020. In 2015, the two papers defining the program synthesis benchmark suite and two additional papers were published. After that, the number of publications increased in each of the following years up to 14 published in-scope papers in 2020, confirming the relevance of program synthesis in evolutionary computation and the influence of the benchmark suite.

Figure 3 shows the distribution of the in-scope papers over the scientific venues. With 27 publications, the Genetic and Evolutionary Computation Conference (GECCO) is represented most frequently – these include 17 publications in the companion proceedings. The second most frequent venue is the workshop Genetic Programming Theory & Practice (GPTP) with nine publications. Furthermore, three PhD theses are also within the scope of this survey.

During the analysis of the in-scope papers, we also identified the three evolutionary computation approaches for program synthesis used most frequently: stack-based GP, grammar-guided GP, and linear GP. Figure 4 shows the distribution of the in-scope papers over the identified program synthesis approaches. Papers that include only the results from other approaches (already reported in other papers) are counted only for the group for which they provided an in-depth analysis and/or performed own experiments. For stack-based GP, we identified 37 papers where most of them are based on the stack-based programming language Push as representation
Stack-based GP (37) supported data type (e.g., INTEGER supports different data types by providing a stack for each turn, is based on the Push programming language [13] which must be supported. Application like general program synthesis, multiple data types for regression problems) [30], [32]. However, for a broader stack-based GP used only one stack for numeric values (e.g., the instruction is simply skipped [30], [31]. Early work on the number of values available on the required stacks), then an instruction’s requirements cannot be fulfilled by the values is executed, it takes its inputs from the appropriate stacks. If the data from the program’s instructions. When an instruction

A. Stack-Based GP

In stack-based GP, stacks are used to handle and separate the data from the program’s instructions. When an instruction is executed, it takes its inputs from the appropriate stacks. If an instruction’s requirements cannot be fulfilled by the values on the stacks (e.g., if an instruction’s arity is larger than the number of values available on the required stacks), then the instruction is simply skipped [30], [31]. Early work on stack-based GP used only one stack for numeric values (e.g., for regression problems) [30], [32]. However, for a broader application like general program synthesis, multiple data types must be supported.

In the papers that are in the scope of this survey, primarily PushGP is used as stack-based GP approach. PushGP, in turn, is based on the Push programming language [13] which supports different data types by providing a stack for each supported data type (e.g., INTEGER, FLOAT, BOOLEAN) as well as for the program instructions itself (e.g., EXEC) [31].

The structure of a Push program is straightforward as it consists either of an instruction, a literal, or a combination of both in an arbitrary length. Furthermore, a Push program may contain brackets, provided that they are used in a balanced way (same number of opening and closing brackets) [31].

The instructions in Push are all strongly typed and follow a simple naming convention. An instruction’s name is a combination of the type it uses as input (the stack from which the arguments are taken) and a phrase describing what the instruction does. For example, the instruction INTEGER.MIN takes the top two items from the INTEGER stack and pushes the minimum of them back to this stack. To change the program flow during run-time (as done by control structures in common programming languages like Java or Python), Push provides instructions like EXEC.IF or EXEC.DO*TIMES which operate directly on the EXEC stack [31].

To describe the execution of a Push program, we give an example using the Smallest problem from the program synthesis benchmark suite. To solve the Smallest problem, a program should be found that returns the smallest of four given integer values [16]. As we already introduced the INTEGER.MIN instruction, which calculates the minimum of two values, such a program can be easily constructed by simply nesting the INTEGER.MIN instruction multiple times.

\[(1 \ 2 \ INTEGER.MIN) \ (3 \ 4 \ INTEGER.MIN) \ INTEGER.MIN\]

Fig. 4: Distribution of the in-scope papers over program synthesis approaches.

IV. PROGRAM SYNTHESIS APPROACHES BASED ON EVOLUTIONARY ALGORITHMS

During the analysis of the in-scope papers, we identified three main approaches based on evolutionary algorithms for program synthesis. In this section, we give an introduction to these approaches and highlight papers with promising and novel ideas which could be relevant for future program synthesis research.

A. Stack-Based GP

In stack-based GP, stacks are used to handle and separate the data from the program’s instructions. When an instruction is executed, it takes its inputs from the appropriate stacks. If an instruction’s requirements cannot be fulfilled by the values on the stacks (e.g., if an instruction’s arity is larger than the number of values available on the required stacks), then the instruction is simply skipped [30], [31]. Early work on stack-based GP used only one stack for numeric values (e.g., for regression problems) [30], [32]. However, for a broader application like general program synthesis, multiple data types must be supported.

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Fig. 5: Source code of an example Push program solving the Smallest problem.

Figure 5 shows the source code for a Push program that calculates the minimum of four integer values. The subordinate steps of the program are shown in brackets. First, the minima of 1 and 2 and then of 3 and 4 are calculated. After that, the minimum of the two minima is returned. Figure 6 shows how this works using an EXEC and an INTEGER stack. In the first step, the complete program (instructions and literals) is pushed to the EXEC stack (step 1). As the top two elements are literals of type integer, these elements are pushed to the INTEGER stack since literals from the EXEC stack are always pushed to their associated stack (step 2). After that, the top element on the EXEC stack is the instruction INTEGER.MIN which takes the values 1 and 2 (the top two elements) from the INTEGER stack as input. After the instruction is executed, it is removed from the EXEC stack and the result (min(1, 2) = 1) is pushed to the INTEGER stack (step 3). The next steps are similar to the previous ones. Again, the literals (values 3 and 4) are pushed to the INTEGER stack (step 4) and then INTEGER.MIN replaces the top two items with the resulting value. So on the INTEGER stack are now the values 3 and 1 which are the results from the previous calculations (step 5). Next, the last INTEGER.MIN instruction on the EXEC stack takes these intermediate results (step 5) and replaces them with the result. So, finally, the EXEC stack is empty and the final result is on the INTEGER stack (step 6).

For further illustrative examples (using different instructions and other data types/stacks), we refer the reader to the slides of one of the recent GECCO tutorials presenting the fundamentals of Push [33] as well as the online Push programming language description [34]. Additionally, the online Push interpreter can be used to illustrate the execution of small Push programs.

\(^2\)Online Push interpreter: [https://lspector.github.io/interpush/](https://lspector.github.io/interpush/)
achieved success rates, Plush and Plushi perform similar for program synthesis when used with PushGP [38].

Based on linear genomes, also a new mutation operator has been introduced: Uniform Mutation by Addition and Deletion (UMAD) [39]. In contrast to classical mutation operators (like sub-tree mutation) which always replace existing code blocks, UMAD adds code to the existing program instead of replacing it and randomly deletes code items in a second step. This means that a program can be supplemented or changed in several places without simply replacing large parts of the program. As the success rates could be notably improved with UMAD on several benchmark problems, it became the quasi-standard mutation operator in PushGP for program synthesis (i.a., it is used in [40], [41], and [42]).

In addition to representation and variation, also the selection of favorable individuals is substantial for the success of a program synthesis method based on evolutionary computation. Common selection methods like tournament selection are based on a fitness function which, in the program synthesis domain, combines the error achieved on the training cases. The disadvantage here is that the structural information of the training data is lost due to the compression to a single fitness value [43]. Contrary, with lexicase selection [44], [45], the information of the individual training cases is used. For the selection of a solution, the training cases are shuffled and every solution in the population is evaluated on the first one. Only the solutions with the exact lowest error are kept and tested on the next training case. This procedure continues until either all training cases have been used for evaluation or only one single solution is left. If there is still more than one solution, a random solution of the remaining ones is selected, otherwise the last remaining solution is the selected one.

Using PushGP, lexicase selection variants have been in recent work often compared to other selection methods (e.g., tournament selection) and achieved best success rates on many program synthesis benchmark problems [16], [29], [46], [47], [48], [49], [50], [51], [52], [53], [45].

In summary, stack-based GP has made a lot of progress in the past few years. However, a weakness of approaches like PushGP, is the used representation language (Push), as it is not relevant in practical software development. An encouraging counterexample is the work by Pantridge and Spector [54] presenting Code Building GP. Although the approach is based on stack-based principles, the authors demonstrate that simple Python code can also be generated. For future research, we therefore suggest to focus more on the generation of code in practically relevant programming languages, so that programmers in real-world software development can also benefit from the success achieved by stack-based approaches for program synthesis.

### B. Grammar-Guided GP

With grammar-guided GP approaches [55], [56], programs can be evolved in a programming language relevant in real-world software development (e.g., Python) in a relatively simple manner. Using a context-free grammar, elements like functions, variable assignments, and control structures can be easily supported.

In standard GP [55], trees are usually used for program representation and variation as a tree representation is inherent in computer programs in common programming languages. This is also obvious in the exemplary Push program presented in Fig. 5. However, tree-based variation operators introduce a bias into the search as, e.g., the probability that a program element is changed during variation depends on the element’s position in the tree [36]. Consequently, to enable the use of more uniform variation operators for program synthesis, Helmuth et al. [36] introduced Plush (Linear Push) which is based on linear genomes. With Plush, the variation operators are applied to the linear genomes but before evaluation, the program is translated to a standard Push program. To express a program’s structure, Plush uses so-called epigenetic markers which are used during the translation process. Another linear genome representation used in the literature is Plushi, introduced by Pantridge and Spector [37], which uses a similar strategy to describe a program’s structure. Also in terms of the
Figure 7 shows an example context-free grammar supporting Python functions, where the non-terminals are shown in angle brackets (e.g., `<program>`) and choices are separated by the pipe symbol. To keep the example grammar small, it supports only a few functions/operators and individual numeric values have been omitted in the grammar. However, the grammar is still expressive enough to support a solution for the Smallest problem from the benchmark suite similar to the example presented for Push (see Figs. 5 and 6). The first production rule (lines 1-3) defines the function’s signature, the body `<stmt>`, the return type `<int>`, and the initialization for the supported variables. The second production rule (lines 4-6) defines variable assignments, as well as control structures (if and while). In order to enable functions with any number of code lines, the first choice allows to double the non-terminal `<stmt>` which can be repeated as often as needed to generate the desired number of code lines. To define code blocks as well as code lines and to support the indentation style of the Python programming language, the grammar contains `NEWLINE`, `INDENT`, and `DEDENT` markers just as used in the official Python grammar specification.\footnote{Python grammar: https://docs.python.org/3/reference/grammar.html}

These markers are of course replaced accordingly before a program is evaluated. The remaining production rules (lines 7-12) provide the supported variables, functions and operators.

```
1  <program> ::= def smallest(int1, int2, int3, int4): NEWLINE INDENT int5, int6, int7 =
2     int(), int(), int() NEWLINE bool1, bool2, bool3 = bool(), bool(), bool()
3     NEWLINE <stmt> return <int>
4  <stmt> ::= <stmt><stmt> | <bool_var> = <bool> NEWLINE | <int_var> = <int> NEWLINE |
5     if <bool>: NEWLINE INDENT <stmt> DEDENT | while <bool>: NEWLINE INDENT
6  <stmt> DEDENT
7  <int_var> ::= int1 | int2 | int3 | int4 | int5 | int6 | int7
8  <int_op> ::= <int> <int_op> <int> | min(<int>, <int>) | max(<int>, <int>)
9  <bool_var> ::= bool1 | bool2 | bool3
10 <bool_op> ::= == | > | < | != | >= | <=
11 <bool> ::= True | False | <bool_var> | <bool> <bool_op> <bool> | <int> <bool_op> <int>
```

To build a program based on this genome and the grammar in Fig. 7 we start with the first production rule (lines 1-3). As this rule has only one choice (no decision needed), no gene of the genome is used. So in the current state, the phenotype contains two non-terminals: `<stmt>` and `<int>`. As we satisfy the non-terminals always from left to right, we consider `<stmt>` first. The production rule for `<stmt>` (lines 4-6) has five choices and the first gene is 12, so we calculate 12 mod 5 = 2 to find the choice which replaces the non-terminal. As we start to count with zero, we replace `<stmt>` with `<int_var> = <int> NEWLINE`. So the next non-terminal to replace is `<int_var>`. As the next gene is 25 and the production rule for `<int_var>` (line 7) has seven choices, we calculate 25 mod 7 = 4 and replace the non-terminal which leads to `<int5 = <int> NEWLINE. In the next step, we replace `<int>` with `min(<int>, <int>)` as the relevant gene is 30 and the production rule (line 9) has four choices. The next gene (42) nests the second `min()` function inside the first one which leads to `int5 = min(min(<int>, <int>), <int>)` NEWLINE. With the next four genes (20, 0, 80, and 15), the nested `min()` function is filled with variables so the current state is `int5 = min(min(int1, int2), <int>)` NEWLINE. With the next gene (26), the third and last `min()` function is added and again with the next four genes (16, 2, 92, and 17) the missing variables are added which leads to `int5 = min(min(int1, int2), min(int3, int4)). Finally, the last non-terminal `<int>` after the given return statement is still missing. As the next genome contains the value 44 and the relevant production rule (line 9) has four choices, we calculate 44 mod 4 = 0 and select `<int_var>`. After that, we calculate 11 mod 7 = 4 and replace the last non-terminal with `int5` as the production rule (line 7) has seven choices and the current gene is 11. Figure 9 shows the resulting Python source code with replaced markers. Since there are no open non-terminals in the source code, the remaining genes of the genome are not used.

As GE’s genotype-phenotype mapping uses linear genomes, the standard variation operators of genetic algorithms can be used\footnote{Python grammar: https://docs.python.org/3/reference/grammar.html}. However, the mapping process is not always successful as it is possible that all genes of the genome are consumed but the phenotype still contains unresolved non-

Fig. 7: A simplified context-free grammar suitable for the Smallest problem. To keep the example small, the number of functions has been reduced and numerical values have been omitted in the grammar.

Fig. 8: An example GE genome encoding a solution for the Smallest problem.

A well-known grammar-guided GP approach suitable for program synthesis is grammatical evolution (GE)\cite{57, 58}. For program representation, GE uses a linear genome consisting of numbers which can then be mapped to the phenotype (the resulting program) using the context-free grammar. An example genome, encoding a solution for the Smallest problem by nesting the `min()` function multiple times, is given in Fig.8.
should focus more on improving the generalizability of lex-
successful solutions with lexicase selection, future research
is unknown. However, since we also find on average most
technique that makes it difficult to overfit to individual training
selection) the fitness value serves as a built-in regularization
during the selection process. In contrast, for selection methods
when lexicase selection is used [62]. This is not surprising, as
the generalization rate is low on these benchmark problems
often generalize poorly to unseen test cases. In particular,
return value) the solutions that are found on the training cases
low output cardinality (especially for problems with a Boolean
recent work shows that for some benchmark problems with a
variants of lexicase selection [11], [63], [62], [64]. However,
Sect. IV-A), on average best success rates are achieved using
the right selection method is important for the quality of the
functions that are required more
terms. Such invalid solutions are likely if the grammar
contains many non-terminals (e.g., because of many high-
arity functions in the grammar) [59]. In recent work, Sobania
and Rothlauf [60] showed that consecutively applying small
mutations (randomly replacing one gene) to a GE genome,
encoding a correct solution for a program synthesis problem,
leads to a high percentage of invalid solutions after just a few
mutation steps.

A possibility to prevent invalid solutions through an unsuccess-
genotype-phenotype mapping is to use a tree repre-
sentation which is already given by the grammar’s structure.
Hence, tree representations have been often used in recent
work using grammar-guided GP approaches (i.a., they are used in [11], [61], and [62]).

Additionally, the size of the grammar is also important for
the quality of the grammar-guided GP system, as with an
increasing grammar the search space grows rapidly. To provide
small grammars that are still suitable for program synthesis,
Forstenlechner et al. [11] suggested to define grammars for
each data type together with a main grammar covering a
program’s basic structure. These grammars can then be put
together according to the modular principle, e.g., based on
the input and output data types defined for the considered
problem. Hemberg et al. [2] incorporated the textual problem
descriptions to optimize their grammar-guided GP approach.
For example, they use specific words in the problem’s descrip-
text as an indicator for functions that are required more
likely for a working solution.

Also for grammar-guided GP approaches, the choice of
the right selection method is important for the quality of the
found solutions. Just like for the stack-based approaches (see
Sect. V-A), on average best success rates are achieved using
variants of lexicase selection [11], [63], [62], [64]. However,
recent work shows that for some benchmark problems with a
low output cardinality (especially for problems with a Boolean
return value) the solutions that are found on the training cases
often generalize poorly to unseen test cases. In particular,
the generalization rate is low on these benchmark problems
when lexicase selection is used [62]. This is not surprising, as
lexicase selection makes use of the individual training cases
during the selection process. In contrast, for selection methods
that are based on a compressed fitness value (like tournament
selection) the fitness value serves as a built-in regularization
 technique that makes it difficult to overfit to individual training
cases as the individual performance on certain training cases
is unknown. However, since we also find on average most
successful solutions with lexicase selection, future research
should focus more on improving the generalizability of lex-
icase to enable an even broader application of this selection
method.

Just like for all program synthesis methods, also for
grammar-guided GP approaches the quality of the generated
source code is an important factor for its practical usage. To
actively use grammar-guided GP for program synthesis in real-
world software development projects, human programmers
expect the synthesized source code to be clearly structured,
readable, and maintainable. However, the source code gen-
erated by state-of-the-art GP methods strongly differs from
human-generated source code [65]. So in addition to finding
semantically correct programs, a challenge for future GP-based
program synthesis research is it also to generate programs that
follow a human-like coding style as suggested in [65] and [66].

C. Linear GP and Further Approaches

In the third relevant group of approaches in the in-scop-
papers, methods based on linear GP are used to solve problems
from the program synthesis benchmark suite [67], [68], [69],
[70], [71]. Similar as in Assembler programming, the data is
stored in registers and the provided functions operate on these
registers. E.g., the value stored in a register can be incremen-
ted or decremented by an Inc or Dec function, respectively,
or a value can be explicitly stored in a specific register with a
SetReg function [67]. As small changes in a genome may
easily destroy the connection between functions and the related
registers, Lalejini and Ofria [69] used a tag-based memory
in their linear GP approach. Instead of directly accessing a
memory cell by its index (as in index-based memory), the
memory cell with the smallest Hamming distance compared
to a given binary address (e.g., defined in the program) is
selected which makes programs more stable to small changes
during evolution.

In addition to the previously mentioned approaches stack-
based GP, grammar-guided GP, and linear GP, we also iden-
tified a paper by Lynch et al. [72] that proposes an approach
that could be a relevant direction for future program synthesis
research. The authors use a variational autoencoder [73] to
learn the representation of programs which are sampled using
a context-free grammar definition. After that, they search with
an EA in the autoencoder’s latent space for programs that solve
the considered benchmark problem.

V. BENCHMARK PROBLEMS: STATUS QUO

Over the last decades, the benchmark problems used for
program synthesis with evolutionary algorithms are often very
similar (e.g., in terms of complexity) and related to the
problems used today. For example, Krawiec and Swan [88]
searched, i.a., for programs that count the number of zeroes
or determine the maximum value of a stack of integers,
Shirakawa et al. [89] used basic problems like Fibonacci
or reversing a list, and Pillay [90] used, as in the general
program synthesis benchmark suite [16], also benchmark
problems suitable for programming lectures. However, due
to the different benchmark problems used in publications,
it is difficult to achieve comparability between different
approaches. A first step towards better comparability was made

```python
def smallest(int1, int2, int3, int4):
    int5, int6, int7 = int1, int2, int3
    bool1, bool2, bool3 = bool1, bool2, bool3
    int5 = min(min(int1, int2), min(int3, int4))
    return int5
```

Fig. 9: Resulting Python function based on the given grammar solving the Smallest problem.
TABLE I: In-scope papers reporting successful solutions for problems from the benchmark suite.

| Benchmark problem       | Stack-based GP | Grammar-guided GP | Linear GP & other | Σ  |
|-------------------------|----------------|-------------------|-------------------|----|
| Number IO               | [16], [29], [74], [48], [39], [75], [76]. | [11], [12], [78], [7], [63], [60], [54]. | [69]. | 20 |
| Small or Large          | [16], [29], [74], [48], [39], [75], [76]. | [11], [61], [79], [12], [2], [63]. | [68]. | 18 |
| For Loop Index          | [16], [29], [74], [48], [39], [75], [76]. | [11], [61], [12], [2], [63]. | [68], [69], [70]. | 18 |
| Compare String Lengths  | [16], [29], [74], [48], [39], [75], [76]. | [11], [61], [79], [78], [2], [63]. | [68]. | 24 |
| Double Letters          | [16], [29], [46], [74], [48], [39], [75], [76], [40], [42], [41], [38]. | [11], [12], [61], [60], [54], [68]. | [68], [69]. | 20 |
| Collatz Numbers         | -              | -                 | -                 | 0  |
| Replace Space with Newline | [16], [29], [74], [48], [39], [75], [76]. | [11], [61], [79], [12], [2], [63]. | [68], [69]. | 20 |
| String Differences      | 40             | -                 | -                 | 1  |
| Even Squares            | [16], [29], [74], [48], [75], [40]. | [11], [61], [2], [63]. | - | 10 |
| Wallis Pi               | -              | -                 | -                 | 0  |
| String Lengths Backwards| [16], [29], [46], [74], [48], [39], [75], [76]. | [11], [61], [79], [78], [2], [63]. | [68]. | 24 |
| Last Index of Zero      | [16], [29], [74], [48], [39], [75], [76], [50], [51], [54], [41], [71], [49]. | [11], [61], [12], [2], [63]. | [68], [69]. | 24 |
| Vector Average          | 40             | -                 | -                 | 23 |
| Count Odds             | [16], [29], [74], [48], [39], [75], [76], [36], [50], [51], [76]. | [11], [61], [79], [12], [2], [63]. | [68], [69]. | 24 |
| Mirror Image            | [16], [29], [74], [48], [39], [75], [76], [50], [51], [76], [52], [53], [42], [80]. | [11], [61], [12], [2], [63]. | [68], [69]. | 24 |
| Super Anagrams          | [39], [76], [40], [42], [38]. | [11], [61], [79], [78]. | [61]. | 9  |
| Sum of Squares          | [16], [29], [74], [48], [39], [75], [76], [40], [42], [41], [38]. | [11], [61], [79], [12], [2], [63]. | [68], [69]. | 24 |
| Vectors Summed          | [16], [29], [74], [48], [39], [75], [76]. | [11], [12], [2], [63]. | [68], [69]. | 24 |
| X-Word Lines            | [16], [29], [74], [48], [39], [75], [76], [50], [51], [81], [76]. | [11], [61], [79], [12], [2], [63]. | [68], [69]. | 24 |
| Pig Latin               | -              | -                 | -                 | 2  |
| Negative to Zero        | [16], [29], [46], [74], [48], [39], [75], [76]. | [11], [61], [79], [12], [2], [63]. | [68], [69]. | 24 |
| Scrabble Score          | [16], [29], [74], [48], [39], [75], [76], [76], [50]. | [11], [61], [2], [63]. | - | 17 |
| Word Stats              | -              | -                 | -                 | 0  |
| Checksum                | [74], [73], [76], [40], [42], [33]. | [11], [61], [2]. | - | 8  |
| Digits                  | [16], [29], [74], [48], [39], [75], [76], [40], [53], [42], [38]. | [11], [61], [79], [12], [2], [63]. | [68], [69]. | 24 |
| Grade                   | [16], [29], [74], [48], [39], [75], [76], [40], [53], [42], [38]. | [11], [61], [79], [12], [2], [63]. | [68], [69]. | 24 |
| Median                  | [16], [29], [74], [48], [39], [75], [76], [40], [53], [42], [38]. | [11], [61], [79], [12], [2], [63]. | [68], [69]. | 24 |
| Smallest                | [16], [29], [74], [48], [39], [75], [76], [52], [40], [42], [80], [45]. | [11], [61], [2], [63]. | - | 25 |
| Syllables               | [16], [29], [46], [82], [47], [48], [48]. | [11], [61], [2], [63]. | [68], [69]. | 24 |
A Collection of Successful Program Synthesis Approaches

Most state-of-the-art evolutionary program synthesis approaches focus on generating solutions at the function-level. Structures above, such as class hierarchies or the general software architecture, are left to human programmers. A property of functions that are implemented in real-world software development is that their structure is kept simple. Regularly, they consist only of a few lines of code (LOC) and are often limited to a low number of loops and conditionals, which can be confirmed by analyzing the source code from software repository hosting services like GitHub [65]. However, the automatic generation of such small programs is still a challenging task even if the required structure (LOC, number of loops, and conditionals) for the benchmark problems used in the literature is similar to the functions implemented in practice. To support researchers and programmers in developing novel program synthesis approaches, we selected from all in-scope papers and for every of the 29 benchmark problems a list of papers that report to have found successful solutions. Table I shows the references to these papers for every benchmark problem ordered by the used evolutionary program synthesis approach. In addition, we present for each benchmark problem the number of assigned papers. The benchmark problems are presented in the same order as in the benchmark suite paper [16].

We see that there are in-scope papers that report successful solutions for almost all benchmark problems. Most successes are reported for the Replace Space with Newline problem with 30 occurrences. With 28, the second most number of successes are reported for the Negative to Zero and the Smallest problem. For the problems Collatz Numbers, Wallis Pi, and Word Stats, there is so far no paper that reports that a working solution has been found.

The distribution of the number of in-scope papers solving individual benchmark problems offers already a first approximation for the difficulty level of these problems. Based on the reported successes, we expect the problems for which so far no successful solutions have been found to be the most difficult ones. We also expect the problems String Differences, Pig Latin, Checksum, and Super Anagrams to be challenging, as only a low number of in-scope papers report to have found successful solutions.

So far, for the other benchmark problems, we cannot make an estimation of their difficulty level, as Table I contains no information about the exact success rates. Furthermore, the number of in-scope papers could possibly also be related to the personal preferences of the respective researchers. Consequently, we provide in the next part an in-depth analysis of the success rates achieved on the benchmark problems in the literature.

B. Analyzing Problem Difficulty

To assess the difficulty of the benchmark problems and to discuss current challenges in program synthesis based on evolutionary algorithms, we analyze for each benchmark problem the success rates reported by the in-scope papers. Here, the success rate denotes the percentage of runs in which a program is found that works correctly on all considered cases. All in-scope papers that report the exact success rates in numerical form (e.g., in tables) are taken into account for the analysis. Success rates that are only reported in graphical form (e.g., plotted) and therefore cannot be determined exactly are not included. Results that were re-used in follow-up papers or only cited (duplicated results) are also not included. Since some of the in-scope papers do not describe how exactly the success rates are calculated, e.g., whether they are determined on the training or the test set, the results of all papers are included (including also the results of papers that explicitly describe that only the training data is used as for example in [46]) in order to be able to achieve a consistent evaluation. If a paper reports success rates for the training and the test set, we use only the results reported for the test set. We do not expect this to have a significant impact on the overall results but we should keep in mind that the averaged results may tend to be better then they really are.

Table II shows the median, the interquartile-range (IQR), and the maximum of the success rates in percent reported by the in-scope papers for every benchmark problem. In order to be able to discuss the connection between a problem’s structure and its difficulty, the table shows also the input and output types defined for each problem (as used in frameworks like PonyGE2 [91]). Furthermore, we mark for each benchmark problem if a successful solution requires iteration/recursion or at least a specialized function that abstracts from the required iteration/recursion (like for example a replace() function for strings).

As expected, the results show that the benchmark problems for which no or only a small number of in-scope papers report to have found successful solutions (see Table I) are among the problems with the lowest median success rates. Additionally, also for Small Or Large, Double Letters, Even Squares, Count Odds, Vectors Summed, X-Word Lines, and Scrabble Score, we observe median success rates below 10. Best median success rates are achieved for Number IO, Smallest, and Median with 96, 78, and 62, respectively. But where does this huge difference come from? Why can some benchmark
TABLE II: Median, interquartile-range (IQR), and maximum of the success rates reported by the in-scope papers, as well as the defined input and output types for each problem from the benchmark suite. Furthermore, we mark for each benchmark problem if a successful solution requires iteration or recursion (or a specialized function).

| Benchmark problem                     | Success rate | Input types | Output types | Iteration/Recursion |
|---------------------------------------|--------------|-------------|--------------|---------------------|
|                                       | Median (IQR) | Maximum     |              |                     |
| Number IO                             | 96.0 (12.0)  | 100.0       | int, float   | float              | x                    |
| Small or Large                        | 6.0 (7.5)    | 92.0        | int          | str                | x                    |
| For Loop Index                        | 40.0 (53.5)  | 88.0        | int, int, int| int[]              | ✓                    |
| Compare String Lengths                | 20.0 (38.75) | 95.0        | str, str, str| bool               | ✓                    |
| Double Letters                        | 1.0 (16.0)   | 87.0        | str          | str                | ✓                    |
| Collatz Numbers                       | 0.0 (0.0)    | 0.0         | int          | int                | ✓                    |
| Replace Space with Newline            | 51.0 (56.0)  | 100.0       | str          | str, int           | ✓                    |
| String Differences                    | 0.0 (0.0)    | 1.0         | str, str     | str                | ✓                    |
| Even Squares                          | 0.0 (1.0)    | 15.0        | int          | int[]              | ✓                    |
| Wallis Pi                             | 0.0 (0.0)    | 0.0         | int          | float              | ✓                    |
| String Lengths Backwards              | 35.0 (57.0)  | 100.0       | str[]        | int[]              | ✓                    |
| Last Index of Zero                    | 30.0 (40.0)  | 96.0        | int[]        | int                | ✓                    |
| Vector Average                        | 32.5 (72.25) | 100.0       | float[]      | float              | ✓                    |
| Count Odds                            | 5.0 (10.0)   | 22.0        | int[]        | int                | ✓                    |
| Mirror Image                          | 71.5 (75.0)  | 100.0       | int[], int[] | bool               | ✓                    |
| Super Anagrams                        | 2.0 (25.0)   | 82.0        | str, str     | bool               | ✓                    |
| Sum of Squares                        | 7.0 (12.25)  | 41.0        | int          | int                | ✓                    |
| Vectors Summed                        | 7.5 (18.5)   | 93.0        | int[], int[] | int[]              | ✓                    |
| X-Word Lines                          | 6.0 (56.75)  | 98.0        | int, str     | str                | ✓                    |
| Pig Latin                             | 0.0 (0.0)    | 5.0         | str          | str                | ✓                    |
| Negative To Zero                      | 58.0 (60.0)  | 98.0        | int[]        | int[]              | ✓                    |
| Scrabble Score                        | 4.0 (17.0)   | 90.0        | str          | int                | ✓                    |
| Word Stats                            | 0.0 (0.0)    | 0.0         | str          | int[], int, float  | ✓                    |
| Checksum                              | 0.0 (1.0)    | 56.0        | str          | str/char           | ✓                    |
| Digits                                | 10.0 (28.0)  | 100.0       | int          | int[]              | ✓                    |
| Grade                                 | 23.2 (67.5)  | 100.0       | int, int, int, int | str/char | x                    |
| Median                                | 62.0 (39.5)  | 100.0       | int, int    | int                | x                    |
| Smallest                              | 78.0 (50.0)  | 100.0       | int, int, int| int                | x                    |
| Syllables                             | 12.5 (19.5)  | 76.0        | str          | int                | ✓                    |

It is notable, that for none of the three easiest problems (Number IO, Smallest, and Median) iteration or recursion is required for a correct solution. Additionally, an explanation for the high success rates of Number IO is certainly that the source code of a correct solution is very short since only two numbers must be added [16]. A driving factor for the high success rates observed for the Smallest and the Median problem, where a program should be found that returns the smallest/median value for some given integers [16], is that the correct output is already a part of the given input values. Therefore, the input can be mapped directly to the output without any interference and including any new input value (into the program’s output) is rewarded with a positive fitness signal. Therefore, such problems are simple for guided search methods like evolutionary algorithms as a solution can be build step by step [60]. An example is given in Figs. 5 and 9 which show a straightforward solution for the Smallest problem where a min() function accepting two inputs is nested multiple times such that four inputs can be processed. Whenever a min() function is added in a correct way, the fitness (or the correct cases if lexicase selection is used) improves and guides the search to a working solution.

In contrast, for the more difficult problems, a direct mapping from the inputs to the outputs is not possible as iterative or recursive structures are required and/or the input types differ from the output types which requires several intermediary steps in the source code to transform the given input values. These intermediary steps, like loops (or recursion), several function calls, or type conversions, are necessary for a correct solution but they interfere the mapping from the inputs to the outputs. Such complex structures make problems difficult for most current evolutionary program synthesis approaches as only the output is used to assess a program and to guide the


search while the program itself is treated like a black box. A first step to lighten up this black box was made by introducing lexicase selection, as it considers the individual training cases instead of only a compressed fitness value that leads to a heavy loss of information [44], [43].

In the next step, research must go beyond the naïve evaluation of the training cases to assess a program. We need to know what is going on inside a program to enable proper guided search methods for general program synthesis. This idea is not new, as already Cramer [3] (in the very first GP paper) considers the semantics of a program for calculating the fitness value. For example, it is checked whether initial values have changed or if there are working loops in the program. However, such simple approaches will not be sufficient to achieve the goal of general program synthesis, but it illustrates in which direction researchers must think of in the future when designing novel methods for program synthesis based on evolutionary algorithms.

In addition to the varying performance achieved for different benchmark problems, Table IIII often shows also a high variance in the success rates reported for the same benchmark problems. E.g., for some of the problems the IQR is even larger than 50. To study this further, we analyze the distribution of the reported success rates separated by the used approach for the two benchmark problems with the largest variance, which are Mirror Image and Vector Average with an IQR of 75 and 72.25, respectively. For the Mirror Image problem, a synthesizer should find a program that returns true for two given integer lists if one list is the inverted form of the other one, and for the Vector Average problem a program should be found that returns the average of a given list of numbers rounded to four decimal places [16]. Figure 10 shows boxplots comparing the success rates for the Mirror Image (left) and the Vector Average problem (right) for stack-based GP and grammar-guided GP.

For these two benchmark problems, we see a huge difference in performance between the stack-based and the grammar-guided GP approaches which influences the high variance in the results. For the Mirror Image problem, stack-based GP achieves a median success rate of nearly 100 while the grammar-guided GP approaches fail most of the time. The results are similar for Vector Average, where stack-based GP has a median success rate of around 70 and grammar-guided GP achieves only a median success rate lower than 10. Certainly we cannot conclude from these two results that stack-based GP generally performs better than grammar-guided GP, as grammar-guided GP, e.g., performs best on the Pig Latin problem (see Table I). Nevertheless, it shows that a comparison of different methods is still challenging despite all the efforts made in the benchmark suite as small differences in program synthesis approaches may lead to huge differences in performance. For example, program synthesis approaches often considerably differ with regard to the supported functions and structures which is problematic as the choice of the right functions has a huge impact on the problem solving performance. Forstenlechner et al. [12] already made the point that by adding specialized functions, a benchmark problem may become quite easy. For example, adding Python’s reverse(), round(), and sum() functions to a grammar would turn Mirror Image and Vector Average into simple problems. However, the quality of a program synthesis approach that finds working solutions without such specialized functions should be rated higher, as such an approach must be able to construct complex structures such as loops and conditionals which is more valuable in practice. For future research, we recommend not only to provide the used grammar (or function set), but also making sure that the range of the used functions is similar when comparing different methods. In addition, we recommend not to search explicitly for specialized functions which make a solution for the benchmark problems simple, but to strive for more general program synthesis methods. The recently published expansion of the benchmark suite [92] may also help to achieve this goal, as we expect that a larger number of benchmark problems will direct the focus of program synthesis research towards generalizing approaches that work on many different problem types.

C. In-Depth Analysis of a Complex Benchmark Problem

To illustrate the main challenges in program synthesis with evolutionary algorithms in detail, we consider a complex problem from the benchmark suite as example. Figure 11 shows an exemplary hand-written Python function implementing a solution for the Checksum problem where the majority of the studied approaches fail to find a successful solution (see Table IIII). The given example code consumes more LOC than necessary but this allows us to analyze the code line by line. The Checksum problem consists of several steps. For
TABLE III: Program trace showing all variable states of the implementation for the Checksum problem for the input 'ProgSys'.

| Step | Line | input0 | result0 | str0 | list0 |
|------|------|--------|---------|------|-------|
| 1    | 2    | 'ProgSys' | 0 | '' | [] |
| 2    | 4    | 'ProgSys' | 0 | 'P' | [80] |
| 3    | 4    | 'ProgSys' | 0 | 'Y' | [80, 114] |
| 4    | 4    | 'ProgSys' | 0 | 'O' | [80, 114, 111] |
| 5    | 4    | 'ProgSys' | 0 | 'G' | [80, 114, 111, 103] |
| 6    | 4    | 'ProgSys' | 0 | 'S' | [80, 114, 111, 103, 83] |
| 7    | 4    | 'ProgSys' | 0 | 'Y' | [80, 114, 111, 103, 83, 121] |
| 8    | 4    | 'ProgSys' | 0 | 'S' | [80, 114, 111, 103, 121, 115] |
| 9    | 5    | 'ProgSys' | 727 | 'S' | [80, 114, 111, 103, 121, 115] |
| 10   | 6    | 'ProgSys' | 23  | 'S' | [80, 114, 111, 103, 121, 115] |
| 11   | 7    | 'ProgSys' | 55  | 'S' | [80, 114, 111, 103, 121, 115] |
| 12   | 8    | 'ProgSys' | 77  | 'S' | [80, 114, 111, 103, 121, 115] |

a successful solution, a given input string (input0, line 1) is converted to a list containing the ASCII value for every character of the input string (line 3-4). Then, the list is summed (line 5) and the resulting sum is taken modulo 64 (line 6). Finally, the ASCII value of the space character is added (line 7) and then the temporary value is converted back to a character (line 8) before the result is returned (result0, line 9) [16].

```python
1  def checksum(input0):
2      result0, str0, list0 = 0, '', []
3      for str0 in input0:
4          list0.append(ord(str0))
5      result0 = sum(list0)
6      result0 %= 64
7      result0 += ord(' ')  
8      result0 = chr(result0)
9      return result0
```

Fig. 11: Reference implementation in Python for the Checksum problem.

It is not surprising that this program synthesis problem is quite challenging for evolutionary algorithms as it consists of many individual sub-problems. For a given set of input/output examples, we would not even expect to get a correct solution from an experienced human programmer as without additional information it is nearly impossible to identify the process required to map the input to a correct output.

In order to illustrate the program flow for a specific example input, Table III presents a program trace showing all variable states of the reference implementation for the Checksum problem (Fig. 11) for the input 'ProgSys'. We see that several differently typed variables have to match exactly such that a correct result can be returned. Additionally, it is noticeable that it is not possible to assess the quality of the program based on the variable states in the first eleven execution steps. In the first eight execution steps the variable result0 = 0 which gives us no information about already correctly solved sub-problems. Also the integer values in steps 9-11 for input0 give us no information as we only have input/output examples (where the known output is a character) for training and during the evolutionary search we cannot see what happens inside the program. This is problematic as sub-problems that have already been solved correctly may be lost again during a continued search.

However, with the current evolutionary search strategies a guided search for solutions to problems like the Checksum problem is not possible as they belong to the class of needle-in-a-haystack problems where finding a correct solution is strongly influenced by chance [60]. Consequently, we recommend to focus research on uncovering these hidden sub-problems such that solutions can be generated step by step during evolution. A software development method that may be suitable for a combination with evolutionary algorithms is test-driven development [93], where the software tests and the functional code are developed in parallel and large problems are regularly divided into several smaller sub-problems. Using this approach, program synthesis could be a real support for programmers in practice, since only the tests for the sub-problems have to be provided.

VI. CONCLUSIONS

The automatic generation of computer programs is one of the applications with practical relevance in evolutionary computation and especially in the field of GP. With program synthesis techniques programmers could be supported in everyday software development and also users without any knowledge in programming could easily automate their repetitive tasks.

To ensure comparability while studying the performance of novel evolutionary program synthesis approaches, in recent years usually the general program synthesis benchmark suite by Helmuth and Spector [16] is used. The benchmark suite consists of 29 curated introductory programming problems of different complexity and also defines the structure of the training and test data.

Using the program synthesis benchmark suite as starting point, we identified in this work the relevant approaches for program synthesis with evolutionary algorithms and provided an in-depth analysis of the performance of the recent approaches on the benchmark problems.
As most relevant evolutionary approaches for program synthesis, we identified and described stack-based GP, grammar-guided GP as well as linear GP. Mainly, these three approaches differ in their way of representing the solutions, which results in individually different challenges and opportunities like, e.g., genotype-phenotype mapping or novel variation operators, respectively. However, for all three approaches, we see that in future research it will be necessary to generate programs that are structurally similar to programs written by human programmers such that the resulting programs can be used in real-world software.

Further, we analyzed the performance of the recent program synthesis approaches on the individual benchmark problems reported in the literature. We found, that the approaches perform well on problems where a correct solution is small or if a program’s input maps directly to its output. Problems are difficult for the recent program synthesis approaches if they consist of several sub-problems, need type changes, or require iterative/recursive structures which interfere the mapping process from the inputs to the outputs. In such cases, there exists no strong fitness signal that guides the evolutionary search towards a correct solution. To overcome these problems, we encourage researchers to study methods that consider and search towards a correct solution. To overcome these problems, we encourage researchers to study methods that consider and assess also what happens inside a program such that useful solutions for sub-problems or working loops and conditionals are also rewarded instead of only evaluating a program’s output.

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