# Genetic Programming: Biologically Inspired Computation that Exhibits Creativity in Solving Non-Trivial Problems

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**ABSTRACT**

This paper describes a biologically inspired domain-independent technique, called genetic programming, that automatically creates computer programs to solve problems. We argue that the field of design is a useful testbed for determining whether an automated technique can produce results that are competitive with human-produced results. We present several results that are competitive with the products of human creativity and inventiveness. This claim is supported by the fact that each of the results infringe on previously issued patents. This paper presents a candidate set of criteria that identify when a machine-created solution to a problem is competitive with a human-produced result.

## 1. Introduction

One of the central challenges of computer science is to get a computer to solve a problem without explicitly programming it. In particular, the challenge is to create an automatic system whose input is a high-level statement of a problem's requirements and whose output is a working computer program that solves the given problem. Paraphrasing Arthur Samuel (1959), this challenge concerns

> How can computers be made to do what needs to be done, without being told exactly how to do it?

As Samuel (1983) explained,

> “The aim [is] ... to get machines to exhibit behavior, which if done by humans, would be assumed to involve the use of intelligence.”

This paper provides an affirmative answer to the following two questions:

- Can computer programs be automatically created?
- Can automatically created programs be competitive with the products of human creativity and inventiveness?

This paper focuses on a biologically inspired domain-independent technique, called genetic programming, that automatically creates computer programs to solve problems. Starting with a primordial ooze of thousands of randomly created computer programs, genetic programming progressively breeds a population of computer programs over a series of generations using the Darwinian principle of natural selection, recombination (crossover), mutation, gene duplication, gene deletion, and certain mechanisms of developmental biology.

Section 2 states what we mean when we say that an automatically created solution to a problem is competitive with the product of human creativity. Section 3 briefly describes genetic programming. Section 4 presents a problem involving the automatic synthesis (design) of an analog electrical circuit, namely a lowpass filter. Section 5 describes how genetic programming is applied to the problem of analog circuit synthesis. Section 6 shows the results. Section 7 discusses the importance of illogic in creativity and inventiveness. Section 8 shows additional results.

## 2 Inventiveness and Creativity

What do we mean when we say that an automatically created solution to a problem is competitive with the product of human creativity and inventiveness?

We are not referring to the fact that a computer can rapidly print ten thousand payroll checks or that a computer can compute $\pi$ to a million decimal places. As Fogel, Owens, and Walsh (1966) said,

> Artificial intelligence is realized only if an inanimate machine can solve problems ... not because of the machine's sheer speed and accuracy, but because it can discover for itself new techniques for solving the problem at hand.

We think it is fair to say that an automatically created result is competitive with one produced by human engineers, designers, mathematicians, or programmers if it satisfies any of the following eight criteria (or any other similarly stringent criterion):

**(A)** The result was patented as an invention in the past, is an improvement over a patented invention, or would qualify today as a patentable new invention.

**(B)** The result is equal to or better than a result that was accepted as a new scientific result at the time when it was published in a peer-reviewed journal.

**(C)** The result is equal to or better than a result that was placed into a database or archive of results maintained by an internationally recognized panel of scientific experts.

**(D)** The result is publishable in its own right as a new scientific result (independent of the fact that the result was mechanically created).

**(E)** The result is equal to or better than the most recent human-created solution to a long-standing problem for which there has been a succession of increasingly better human-created solutions.

**(F)** The result is equal to or better than a result that was considered an achievement in its field at the time it was first discovered.

**(G)** The result solves a problem of indisputable difficulty in its field.

**(H)** The result holds its own or wins a regulated competition involving human contestants (in the form of either live human players or human-written computer programs).

## 3. Genetic Programming

Genetic programming is an extension of the genetic algorithm described in John Holland's pioneering book *Adaptation in Natural and Artificial Systems* (Holland 1975). Genetic programming applies the genetic algorithm to the space of computer programs.

The biological metaphor underlying genetic programming is very different from the underpinnings of all other techniques that have previously been tried in pursuit of the goal of automatically creating computer programs. Many computer scientists and mathematicians are baffled by the suggestion biology might be relevant to solving important problems in their fields. However, we do not view biology as an unlikely well from which to draw a solution to the challenge of getting a computer to solve a problem without explicitly programming it. Quite the contrary – we view biology as a most likely source. Indeed, genetic programming is based on the only method that has ever produced intelligence – the time-tested method of evolution and natural selection.

Of course, we did not originate the idea that machine intelligence may be realized using a biological approach. Turing made the connection between searches and the challenge of getting a computer to solve a problem without explicitly programming it in his 1948 essay "Intelligent Machines" (Ince 1992).

> Further research into intelligence of machinery will probably be very greatly concerned with "searches" ...

Turing then identified three broad approaches by which search might be used to automatically create an intelligent computer program.

One approach that Turing identified is a search through the space of integers representing candidate computer programs. This approach, of course, uses many of the techniques that Turing used in his own work on the foundations of computation.

Another approach is the "cultural search" which relies on knowledge and expertise acquired over a period of years from others. This approach is akin to present-day knowledge-based systems.

The third approach that Turing specifically identified is "genetical or evolutionary search." Turing said,

> There is the genetical or evolutionary search by which a combination of genes is looked for, the criterion being the survival value. The remarkable success of this search confirms to some extent the idea that intellectual

> activity consists mainly of various kinds of search.

Turing did not specify how to conduct the "genetical or evolutionary search" for a computer program. However, his 1950 paper "Computing Machinery and Intelligence" (Ince 1992) suggested how natural selection and evolution might be incorporated into the search for intelligent machines.

> We cannot expect to find a good child-machine at the first attempt. One must experiment with teaching one such machine and see how well it learns. One can then try another and see if it is better or worse. There is an obvious connection between this process and evolution, by the identifications
>
> Structure of the child machine = Hereditary material
>
> Changes of the child machine = Mutations
>
> Natural selection = Judgment of the experimenter

### 3.1 Implementation of Turing's Third Way to Achieve Machine Intelligence

Genetic programming implements Turing's third way to achieve machine intelligence. Specifically, genetic programming starts with an initial population (generation 0) of randomly generated computer programs composed of the given primitive functions and terminals. The programs in the population are, in general, of different sizes and shapes. The creation of the initial random population is a blind random search of the space of computer programs composed of the problem's available functions and terminals.

On each generation of a run of genetic programming, each individual in the population of programs is evaluated as to its fitness in solving the problem at hand. The programs in generation 0 of a run almost always have exceedingly poor fitness for non-trivial problems of interest. Nonetheless, some individuals in a population will turn out to be somewhat more fit than others. These differences in performance are then exploited so as to direct the remainder of the search into promising areas of the search space. The Darwinian principle of reproduction and survival of the fittest is used to probabilistically select, on the basis of fitness, individuals from the population to participate in various operations. A small percentage (e.g., 9%) of the selected individuals are reproduced (copied) from one generation to the next. A very small percentage (e.g. 1%) of the selected individuals are mutated in a random way. About 90% of the selected individuals participate in the genetic operation of crossover (sexual recombination) to create offspring programs by recombining genetic material from two parents. All operations are performed so as to create offspring that are syntactically valid and executable. After the genetic operations are performed on the current population, the population of offspring (i.e., the new generation) replaces the old population (i.e., the old generation). Then, each individual in the new population of programs is measured for fitness, and this iterative process is repeated over many generations.

Probabilistic steps are pervasive in genetic programming. Probability is involved in the creation the individuals in the initial population, the selection of individuals to participate in the operations of reproduction, crossover, and mutation, and the selection of crossover and mutation points within parental programs.

The dynamic variability of the size and shape of the computer programs that are created during the run is an important feature of genetic programming. It is often difficult and unnatural to try to specify or restrict the size and shape of the eventual solution in advance.

Additional information on current research in genetic programming can be found in *Genetic Programming III: Darwinian Invention and Problem Solving* (Koza, Bennett, Andre, and Keane 1999a) and the accompanying videotape (Koza, Bennett, Andre, Keane, and Brave 1999b) and in Koza 1992; Koza and Rice 1992,; Koza 1994a; Koza 1994b; Banzhaf, Nordin, Keller, and Francone 1998; Langdon 1998; Kinnear 1994; Angeline and Kinnear 1996; Spector, Langdon, O'Reilly, and Angeline 1999; Koza, Goldberg, Fogel, and Riolo 1996; Koza, Deb, Dorigo, Fogel, Garzon, Iba, and Riolo 1997; Koza, Banzhaf, Chellapilla, Deb, Dorigo, Fogel, Garzon, Goldberg, Iba, and Riolo 1998; Banzhaf, Poli, Schoenauer, and Fogarty 1998; and Poli, Nordin, Langdon, and Fogarty 1999.

## 4. Design as a Testbed for Machine Intelligence

Design is a major activity of practicing engineers. The design process entails creation of a complex structure to satisfy user-defined requirements. Since the design process typically entails tradeoffs between competing considerations, the end product of the process is usually a satisfactory and compliant design as opposed to a perfect design. Design is usually viewed as requiring creativity and human intelligence. Consequently, the field of design is a source of challenging problems for automated techniques of machine intelligence. In particular, design problems are useful for determining whether an automated technique can produce results that are competitive with human-produced results.

The design (synthesis) of analog electrical circuits is especially challenging. The design process for analog circuits begins with a high-level description of the circuit's desired behavior and characteristics and entails creation of both the topology and the sizing of a satisfactory circuit. The topology comprises the gross number of components in the circuit, the type of each component (e.g., a capacitor), and a list of all connections between the components. The sizing involves specifying the values (typically numerical) of each of the circuit's components.

Although considerable progress has been made in automating the synthesis of certain categories of purely digital circuits, the synthesis of analog circuits and mixed analog-digital circuits has not proved to be as amenable to automation. There is no previously known general technique for automatically creating an analog circuit from a high-level statement of the design goals of the circuit. As O. Aaserud and I. Ring Nielsen (1995) observe,

> Analog designers are few and far between. In contrast to digital design, most of the analog circuits are still handcrafted by the experts or so-called 'zahs' of analog design. The design process is characterized by a combination of experience and intuition and requires a thorough knowledge of the process characteristics and the detailed specifications of the actual product.
>
> Analog circuit design is known to be a knowledge-intensive, multiphase, iterative task, which usually stretches over a significant period of time and is performed by designers with a large portfolio of skills. It is therefore considered by many to be a form of art rather than a science.

This paper focuses on three particular problems of analog circuit synthesis, namely the design of a lowpass filter circuit, the design of a high-gain, low-distortion, low-bias amplifier, and the design of a cube root computational circuit.

A simple analog *filter* is a one-input, one-output circuit that receives a signal as its input and passes the frequency components of the incoming signal that lie in a specified range (called the *passband*) while suppressing the frequency components that lie in all other frequency ranges (the *stopband*). Specifically, the goal is to design a lowpass filter composed of capacitors and inductors that passes all frequencies below 1,000 Hertz (Hz) and suppresses all frequencies above 2,000 Hz.

An amplifier is a one-input, one-output circuit whose output is a constant multiple of its input. We are seeking a high-gain, low-distortion, low-bias amplifier composed of transistors, diodes, capacitors, resistors, and connections to power sources.

An analog computational circuit is a one-input, one-output circuit whose output is a specified mathematical function. The design of computational circuits is exceedingly difficult even for seemingly mundane mathematical functions. Success often relies on the clever exploitation of some aspect of the underlying device physics of the components that is unique to the particular desired mathematical function. Because of this, the implementation of each different mathematical function typically requires an entirely different clever insight and an entirely different circuit. We are seeking a computational circuit composed of transistors, diodes, capacitors, resistors, and connections to power sources.

It should be noted that the approach described in this paper has also been successfully applied to numerous other problems of analog circuit synthesis, including the design of a temperature-sensing circuit, a voltage reference circuit, a time-optimal robot controller circuit, a difficult-to-design asymmetric bandpass filter, crossover filters, a double passband filter, bandstop filters, highpass filters, frequency discriminator circuits, a frequency-measuring circuit, other amplifiers, and other computational circuits.

# 5. Applying Genetic Programming to Circuit Synthesis

Genetic programming can be applied to the problem of synthesizing circuits if a mapping is established between the program trees (rooted, point-labeled trees with ordered branches) used in genetic programming and the labeled cyclic graphs germane to electrical circuits. The principles of developmental biology provide the motivation for mapping trees into circuits by means of a developmental process that begins with a simple embryo. For circuits, the embryo typically includes fixed wires that connect the inputs and outputs of the particular circuit being designed and certain fixed components (such as source and load resistors). Until these wires are modified, the circuit does not produce interesting output. An electrical circuit is developed by progressively applying the functions in a circuit-constructing program tree to the modifiable wires of the embryo (and, during the developmental process, to new components and modifiable wires).

An electrical circuit is created by executing the functions in a circuit-constructing program tree. The functions are progressively applied in a developmental process to the embryo and its successors until all of the functions in the program tree are executed. That is, the functions in the circuit-constructing program tree progressively side-effect the embryo and its successors until a fully developed circuit eventually emerges. The functions are applied in a breadth-first order.

The functions in the circuit-constructing program trees are divided into five categories: (1) topology-modifying functions that alter the circuit topology, (2) component-creating functions that insert components into the circuit, (3) development-controlling functions that control the development process by which the embryo and its successors is changed into a fully developed circuit, (4) arithmetic-performing functions that appear in subtrees as argument(s) to the component-creating functions and specify the numerical value of the component, and (5) automatically defined functions that appear in the automatically defined functions and potentially enable certain substructures of the circuit to be reused (with parameterization).

Before applying genetic programming to a problem of circuit design, seven major preparatory steps are required: (1) identify the embryonic circuit, (2) determine the architecture of the circuit-constructing program trees, (3) identify the primitive functions of the program trees, (4) identify the terminals of the program trees, (5) create the fitness measure, (6) choose control parameters for the run, and (7) determine the termination criterion and method of result designation.

A detailed discussion concerning how to apply these seven preparatory steps to particular problems is found in Koza, Bennett, Andre, and Keane 1999a (chapter 25).

# 6. Results on Illustrative Problems

## 6. 1 Campbell 1917 Ladder Filter Patent

The best circuit (figure 1) of generation 49 of one run of genetic programming on the problem of synthesizing a lowpass filter is a 100% compliant circuit.

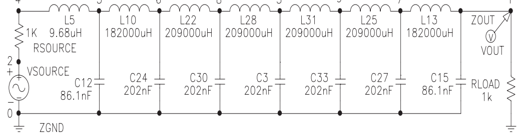


Figure 1 Evolved Campbell filter.

The evolved circuit is what is now called a cascade (ladder) of identical $\pi$ sections and is shown and analyzed in Koza, Bennett, Andre, and Keane 1999a (chapter 25). The evolved circuit has the recognizable topology of the circuit for which George Campbell of American Telephone and Telegraph received U. S. patent 1,227,113 in 1917. Claim 2 of Campbell's patent covered,

> "An electric wave filter consisting of a connecting line of negligible attenuation composed of a plurality of sections, each section including a capacity element and an inductance element, one of said elements of each section being in series with the line and the other in shunt across the line, said capacity and inductance elements having precomputed values dependent upon the upper limiting frequency and the lower limiting frequency of a range of frequencies it is desired to transmit without attenuation, the values of said capacity and inductance elements being so proportioned that the structure transmits with practically negligible attenuation sinusoidal currents of all frequencies lying between said two limiting frequencies, while attenuating and approximately extinguishing currents of neighboring frequencies lying outside of said limiting frequencies."

In addition to possessing the topology of the Campbell filter, the numerical value of all the components in the evolved circuit closely approximate the numerical values specified in Campbell's 1917 patent. But for the fact that this 1917 patent has expired, the evolved circuit would infringe on the Campbell patent.

The legal criteria for obtaining a U. S. patent are that the proposed invention be "new" and "useful" and

> ... the differences between the subject matter sought to be patented and the prior art are such that the subject matter as a whole would [not] have been obvious at the time the invention was made to a person having ordinary skill in the art to which said subject matter pertains. (35 *United States Code* 103a).

The fact that genetic programming rediscovered both the topology and sizing of an electrical circuit that was unobvious "to a person having ordinary skill in the art" establishes that this evolved result satisfies Arthur Samuel's criterion for artificial intelligence and machine learning (quoted in section 1).

Since filing for a patent entails the expenditure of a considerable amount of time and money, patents are generally sought, in the first place, only if an individual or business believes the inventions are likely to be useful in the real world and economically rewarding. Patents are only issued if an arms-length examiner is convinced that the proposed invention is novel, useful, and satisfies the statutory test for unobviousness.

## 6.2 Zobel 1925 "*M*-Derived Half Section" Patent

In another run of this same problem of synthesizing a lowpass filter, a 100%-compliant circuit (figure 2) was evolved in generation 34.

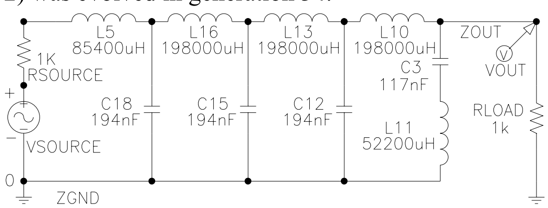


Figure 2 Evolved Zobel filter.

This evolved circuit (presented in Koza, Bennett, Andre, and Keane 1999a, chapter 25) is equivalent to a cascade of three symmetric T-sections and an *M*-derived half section. Otto Zobel of American Telephone and Telegraph Company invented the idea of adding an "*M*-derived half section" to one or more "constant K" sections.

## 6.3 Cauer 1934 – 1936 Elliptic Patents

In yet another run of this same problem of synthesizing a lowpass filter, a 100% compliant circuit (figure 3) emerged in generation 31 (Koza, Bennett, Andre, and Keane 1999a, chapter 27).

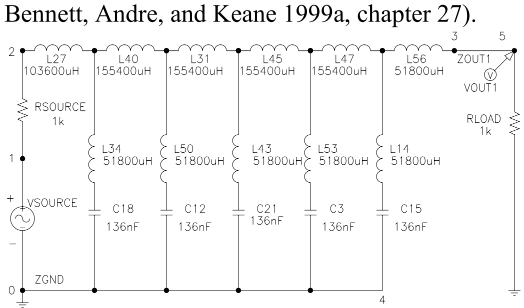


Figure 3 Evolved Cauer (elliptic) filter topology.

This circuit has the recognizable elliptic topology that was invented and patented by Wilhelm Cauer in 1934, 1935, and 1936. The Cauer filter was a significant advance (both theoretically and commercially) over the earlier filter designs of Campbell, Zobel, Johnson, Butterworth, and Chebychev. For example, for one commercially important set of specifications for telephones, a fifth-order elliptic filter matches the behavior of a 17th-order Butterworth filter or an eighth-order Chebychev filter. The fifth-order elliptic filter has one less component than the eighth-order Chebychev filter. As Van Valkenburg (1982) relates in connection with the history of the elliptic filter:

> Cauer first used his new theory in solving a filter problem for the German telephone industry. His new design achieved specifications with one less inductor than had ever been done before. The world first learned of the Cauer method not through scholarly publication but through a patent disclosure, which eventually reached the Bell Laboratories. Legend has it that the entire Mathematics Department of Bell Laboratories spent the next two weeks at the New York Public library studying elliptic functions. Cauer had studied mathematics under Hilbert at Goettingen, and so elliptic functions and their applications were familiar to him.

Genetic programming did not, of course, study mathematics under Hilbert or anybody else. Instead, the elliptic topology emerged from a run of genetic programming as a natural consequence of the problem's fitness measure and natural selection – not because the run was primed with domain knowledge about elliptic functions or filters or electrical circuitry. Genetic programming opportunistically *reinvented* the elliptic topology because necessity (fitness) is the mother of invention.

## 6.4 Darlington 1952 Emitter-Follower Patent

Sidney Darlington of the Bell Telephone Laboratories obtained some 40 patents on numerous fundamental electronic circuits. In particular, he obtained U. S. patent 2,663,806 for what is now called the Darlington emitter-follower section. Darlington emitter-follower sections have been evolved on numerous occasions in the process of solving problems of analog circuit synthesis.

Claim 1 of Darlington's 1952 patent covers

> A signal translating device comprising a pair of transistors of like conductivity type and each including a base, an emitter and a collector, means directly connecting the collectors together, means directly connecting the emitter of one transistor to the base of the other, and individual electrical connections to the other emitter and base.

In a similar vein, claim 3 covers

> A signal translating device comprising a pair of transistors of like conductivity type and each including a base, an emitter and a collector, means directly connecting the emitters together, means directly connecting the collector of one transistor to the base of the other, and individual electrical connections to the other collector and base.

Claim 5 is somewhat more general and covers the case where any two like electrodes of the transistor are connected.

> A signal translating device comprising a pair of transistors of like conductivity type and each including a base, an emitter and a collector, means directly connecting two like electrodes of said transistors together, means directly connecting another electrode of one transistor to an unlike electrode, other than one of said like electrodes, of the other transistor, and individual electrical connections to the other emitter and base.

The Darlington patent also refers to an optional external connection to the connection between the leads of the two transistors. For example, claim 2 is a dependent claim based on claim 1 (where the collectors are connected together) and covers

> A signal translating device in accordance with claim 1 comprising an additional electrical connection to the connected emitter and base.

Similarly, claim 4 is based on claim 3 (where the emitters are connected together) and covers

> A signal translating device in accordance with claim 3 comprising an additional electrical connection to the connected collector and base.

Table 1 shows 12 instances in Koza, Bennett, Andre, and Keane 1999a where genetic programming evolved a circuit containing a canonical Darlington section. The table identifies the particular claims (1, 2, 3, or 4) of U. S. patent 2,663,806 that genetic programming appears to have infringed.

Table 2 Twelve instances where genetic programming appears to have infringed Darlington's emitter-follower patent.

| Problem | Type | Patent claim |
|---|---|---|
| 96 dB amplifier | *npn* | 1 |
| 96 dB amplifier | *npn* | 3 |
| Squaring circuit | *npn* | 1 |
| Squaring circuit | *pnp* | 4 |
| Cubing circuit | *pnp* | 3 |
| Cubing circuit | *pnp* | 3 |
| Cubing circuit | *pnp* | 3 |
| Square root circuit | *pnp* | 2 |
| Cube root circuit | *pnp* | 2 |
| Cube root circuit | *pnp* | 1 |
| Cube root circuit | *pnp* | 2 |
| Logarithmic circuit | *pnp* | 4 |

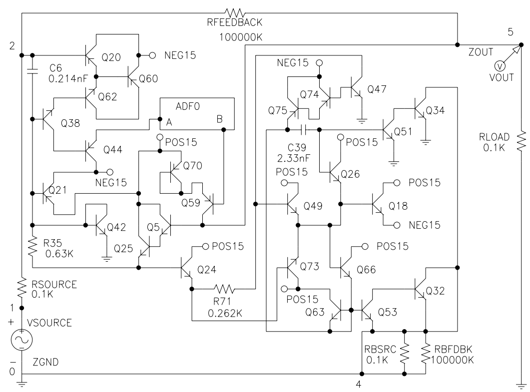


Figure 4 Evolved 96 dB amplifier.

For example, figure 4 shows the best circuit from generation 86 of a run of the problem of evolving a high-gain, low-distortion, low-bias amplifier. The circuit has 25 transistors, no diodes, two capacitors, and two resistors and contains a Darlington emitter-follower section (involving transistors Q25 and Q5).

As another example, figure 5 shows the best-of-run circuit from generation 57 of the problem of synthesizing a cube root computational circuit. The circuit has 38 transistors, seven diodes, and 18 resistors.

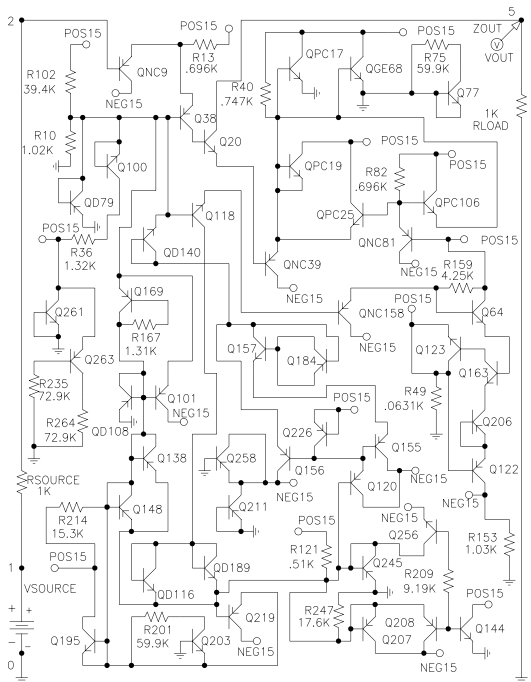


Figure 5 Evolved cube root computational circuit.

## 7. The Illogical Nature of Creativity and Evolution

Many computer scientists and mathematicians unquestioningly assume that every problem-solving technique must be logically sound, deterministic, logically consistent, and parsimonious. Accordingly, most conventional methods of artificial intelligence and machine learning are constructed so as to possess these characteristics. However, in spite of this strong predisposition by computer scientists and mathematicians, the features of logic do not govern two of the most important types of complex problem solving processes, namely the invention process performed by creative humans and the evolutionary process occurring in nature.

A new idea that can be logically deduced from facts that are known in a field, using transformations that are known in a field, is not considered to be an invention. There must be what the patent law refers to as an "illogical step" (i.e., an unjustified step) to distinguish a putative invention from that which is readily deducible from that which is already known. Humans supply the critical ingredient of “illogic” to the invention process. Interestingly, everyday usage parallels the patent law concerning inventiveness: People who mechanically apply existing facts in well-known ways are summarily dismissed as being uncreative. Logical thinking is unquestionably useful for many purposes. It usually plays an important role in setting the stage for an invention. But, at the end of the day, logical thinking is not sufficient in the invention process.

Recalling his invention in 1927 of the negative feedback amplifier, Harold S. Black of Bell Laboratories (1977) said,

> Then came the morning of Tuesday, August 2, 1927, when the concept of the negative feedback amplifier came to me in a flash while I was crossing the Hudson River on the Lackawanna Ferry, on my way to work. For more than 50 years, I have pondered how and why the idea came, and I can't say any more today than I could that morning. All I know is that after several years of hard work on the problem, I suddenly realized that if I fed the amplifier output back to the input, in reverse phase, and kept the device from oscillating (singing, as we called it then), I would have exactly what I wanted: a means of canceling out the distortion of the output. I opened my morning newspaper and on a page of *The New York Times* I sketched a simple canonical diagram of a negative feedback amplifier plus the equations for the amplification with feedback.

Of course, inventors are not oblivious to logic and knowledge. They do not thrash around using blind random search. Black did not try to construct the negative feedback amplifier from neon bulbs or doorbells. Instead, "several years of hard work on the problem" set the stage and brought his thinking into the proximity of a solution. Then, at the critical moment, Black made his “illogical” leap. This unjustified leap constituted the invention.

The design of complex entities by the evolutionary process in nature is another important type of problem-solving that is not governed by logic. In nature, solutions to design problems are discovered by the probabilistic process of evolution and natural selection. There is nothing logical about this process. Indeed, inconsistent and contradictory alternatives abound. In fact, such genetic diversity is necessary for the evolutionary process to succeed. Significantly, the solutions evolved by evolution and natural selection almost always differ from those created by conventional methods of artificial intelligence and machine learning in one very important respect. Evolved solutions are not brittle; they are usually able to grapple with the perpetual novelty of real environments.

Similarly, genetic programming is not guided by the inference methods of formal logic in its search for a computer program to solve a given problem. When the goal is the automatic creation of computer programs, we believe that the non-logical approach used in the invention process and in natural evolution are far more fruitful than the logic-driven and knowledge-based principles of conventional artificial intelligence and machine learning. In short, "logic considered harmful."

# 8 Additional Results

Table 2 shows 14 instances of results where genetic programming has produced results that are competitive with the products of human creativity and inventiveness (Koza, Bennett, Andre, and Keane 1999a). Each claim is accompanied by the particular criterion (from section 2) that establishes the basis for the claim. The instances in the table include classification problems from the field of computational molecular biology, a long-standing problem involving cellular automata, a problem of synthesizing the design of a minimal sorting network, and several problems of synthesizing the design of analog electrical circuits. As can be seen, 10 of the 14 instances in the table involve previously patented inventions.

Table 2 Fourteen instances where genetic programming has produced results that are competitive with human-produced results.

| | Claimed instance | Basis for claim |
|---|---|---|
| 1 | Creation of four different algorithms for the transmembrane segment identification problem for proteins | B, E |
| 2 | Creation of a sorting network for seven items using only 16 steps | A, D |
| 3 | Rediscovery of the Campbell ladder topology for lowpass and highpass filters | A, F |
| 4 | Rediscovery of "*M*-derived half section" and "constant *K*" filter sections | A, F |
| 5 | Rediscovery of the Cauer (elliptic) topology for filters | A, F |
| 6 | Automatic decomposition of the problem of synthesizing a crossover filter | A, F |
| 7 | Rediscovery of a recognizable voltage gain stage and a Darlington emitter-follower section of an amplifier and other circuits | A, F |
| 8 | Synthesis of 60 and 96 decibel amplifiers | A, F |
| 9 | Synthesis of analog computational circuits for squaring, cubing, square root, cube root, logarithm, and Gaussian functions | A, D, G |
| 10 | Synthesis of a real-time analog circuit for time-optimal control of a robot | G |
| 11 | Synthesis of an electronic thermometer | A, G |
| 12 | Synthesis of a voltage reference circuit | A, G |
| 13 | Creation of a cellular automata rule for the majority classification problem that is better than the Gacs-Kurdyumov-Levin (GKL) rule and all other known rules written by humans | D, E |
| 14 | Creation of motifs that detect the D–E–A-D box family of proteins and the manganese superoxide dismutase family | C |

# References


Aaserud, O. and Nielsen, I. Ring. 1995. Trends in current analog design: A panel debate. *Analog Integrated Circuits and Signal Processing*. 7(1) 5-9.

Angeline, Peter J. and Kinnear, Kenneth E. Jr. (editors). 1996. *Advances in Genetic Programming 2*. Cambridge, MA: The MIT Press.

Banzhaf, Wolfgang, Nordin, Peter, Keller, Robert E., and Francone, Frank D. 1998. *Genetic Programming – An Introduction*. San Francisco, CA: Morgan Kaufmann and Heidelberg: dpunkt.

Banzhaf, Wolfgang, Poli, Riccardo, Schoenauer, Marc, and Fogarty, Terence C. 1998. *Genetic Programming: First European Workshop. EuroGP'98. Paris, France, April 1998 Proceedings. Paris, France. April l998*. Lecture Notes in Computer Science. Volume 1391. Berlin, Germany: Springer-Verlag.

Black, Harold S. 1977. Inventing the negative feedback amplifier. *IEEE Spectrum*. December 1977. Pages 55 – 60.

Campbell, George A. 1917. *Electric Wave Filter*. Filed July 15, 1915. U. S. Patent 1,227,113. Issued May 22, 1917.

Cauer, Wilhelm. 1934. *Artificial Network*. U. S. Patent 1,958,742. Filed June 8, 1928 in Germany. Filed December 1, 1930 in United States. Issued May 15, 1934.

Cauer, Wilhelm. 1935. *Electric Wave Filter*. U. S. Patent 1,989,545. Filed June 8, 1928. Filed December 6, 1930 in United States. Issued January 29, 1935.

Cauer, Wilhelm. 1936. *Unsymmetrical Electric Wave Filter*. Filed November 10, 1932 in Germany. Filed November 23, 1933 in United States. Issued July 21, 1936.

Fogel, Lawrence J., Owens, Alvin J., and Walsh, Michael. J. 1966. *Artificial Intelligence through Simulated Evolution*. New York: John Wiley.

Holland, John H. 1975. *Adaptation in Natural and Artificial Systems*. Ann Arbor, MI: University of Michigan Press.

Ince, D. C. (editor). 1992. *Mechanical Intelligence: Collected Works of A. M. Turing*. Amsterdam: North Holland.

Kinnear, Kenneth E. Jr. (editor). 1994. *Advances in Genetic Programming*. Cambridge, MA: The MIT Press.

Koza, John R. 1992. *Genetic Programming: On the Programming of Computers by Means of Natural Selection.* Cambridge, MA: MIT Press.

Koza, John R. 1994a. *Genetic Programming II: Automatic Discovery of Reusable Programs.* Cambridge, MA: MIT Press.

Koza, John R. 1994b. *Genetic Programming II Videotape: The Next Generation*. Cambridge, MA: MIT Press.

Koza, John R., Banzhaf, Wolfgang, Chellapilla, Kumar, Deb, Kalyanmoy, Dorigo, Marco, Fogel, David B., Garzon, Max H., Goldberg, David E., Iba, Hitoshi, and Riolo, Rick. (editors). 1998. *Genetic Programming 1998: Proceedings of the Third Annual Conference*. San Francisco, CA: Morgan Kaufmann.

Koza, John R., Bennett III, Forrest H, Andre, David, and Keane, Martin A. 1999a. *Genetic Programming III: Darwinian Invention and Problem Solving*. San Francisco, CA: Morgan Kaufmann.

Koza, John R., Bennett III, Forrest H, Andre, David, Keane, Martin A., and Brave, Scott. 1999b. *Genetic Programming III Videotape*. San Francisco, CA: Morgan Kaufmann.

Koza, John R., Deb, Kalyanmoy, Dorigo, Marco, Fogel, David B., Garzon, Max, Iba, Hitoshi, and Riolo, Rick L. (editors). 1997. *Genetic Programming 1997: Proceedings of the Second Annual Conference* San Francisco, CA: Morgan Kaufmann.

Koza, John R., Goldberg, David E., Fogel, David B., and Riolo, Rick L. (editors). 1996. *Genetic Programming 1996: Proceedings of the First Annual Conference*. Cambridge, MA: The MIT Press.

Koza, John R., and Rice, James P. 1992. *Genetic Programming: The Movie*. Cambridge, MA: MIT Press.

Langdon, William B. 1998. *Genetic Programming and Data Structures: Genetic Programming + Data Structures = Automatic Programming!* Amsterdam: Kluwer.

Poli, Riccardo, Nordin, Peter, Langdon, William B., and Fogarty, Terence C. 1999. *Genetic Programming: Second European Workshop. EuroGP'99. Goteborg, Sweden, May 1999, Proceedings*. Lecture Notes in Computer Science. Volume 1598. Berlin, Germany: Springer-Verlag.

Samuel, Arthur L. 1959. Some studies in machine learning using the game of checkers. *IBM Journal of Research and Development.* 3(3): 210–229.

Samuel, Arthur L. 1983. AI: Where it has been and where it is going. *Proceedings of the Eighth International Joint Conference on Artificial Intelligence*. Los Altos, CA: Morgan Kaufmann. Pages 1152 – 1157.

Spector, Lee, Langdon, William B., O'Reilly, Una-May, and Angeline, Peter (editors). 1999. *Advances in Genetic Programming 3*. Cambridge, MA: The MIT Press.

Van Valkenburg, M. E. 1982. *Analog Filter Design*. Fort Worth, TX: Harcourt Brace Jovanovich.

Zobel, Otto Julius. 1925. *Wave Filter*. Filed January 15, 1921. U. S. Patent 1,538,964. Issued May 26, 1925.

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