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A Review Study on Neuro Evolution

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***Abstract*-With the steady improvement in the field of artificial intelligence and information technology, the part of evolutionary algorithms is likewise booming. There is a need to raise these ideas in-order to broaden the sky-lines amongst newbies. Neuro Evolution is an integral part of artificial intelligence and machine learning wherein it centers around evolutionary algorithms in order to create artificial neural networks. This is a procedure that utilizes the entire parcel of biology and assists with developing and constructing artificial intelligence-based evolutionary algorithms. It is a branch which takes motivation from the evolution of the biological nervous system and attempts to incorporate it with the innovation ace "artificial intelligence". This paper focuses on the fundamental understanding of what neuro evolution is and what is it doing here, how can it work and get implemented, how are neuro evolution and artificial intelligence working inseparably and furthermore it attempts to raise the algorithmic working alongside the significant applications that neuro evolution presents.**

***Keywords*- Neuro evolution, Neural network, Human, Learning, Artificial Intelligence, ANN.**

I.INTRODUCTION

Oh, how brilliant is the origin of earth and its species! It is as wonderful and astute as one could consider it. We should not fail to remember the fact that this is the same earth and environment where once stone-age man with very little brain power survived. Also, today what we see is that human mind has developed and turned out to be so smart to the point that now it is making what we call artificial neural networks considering the neurons as the basis of it.

Neuro evolution is a branch of artificial intelligence that utilizes the evolutionary algorithms to produce artificial neural networks i.e. ANN. This method tries to train the neural networks with the help of evolutionary algorithms. We may believe it to be something related to deep learning yet neuro evolution is somewhat not the same as what essentially deep learning is. As stated, Neuro evolution is a machine learning technique that applies evolutionary algorithms to develop artificial neural networks, taking motivation from the advancement of biological nervous systems in nature [1]. Just as the natural selection process that happens in nature to select the best of the best species for existence i.e. survival of the fittest, neuro evolution is also guided by some proportion of performance selection criterion and that it happens inside the machines.

Generally, neural networks are prepared by utilizing the backpropagation algorithm. Back propagation is restricted in its application particularly in situations where a training set of adequate size is inaccessible as in artificial life or evolutionary robotics. Backpropagation additionally puts a great deal of constraints on the topology of the network. Thenumber of hidden layers as well as the number of neurons per layer should be known ahead of time, the activation function must be differentiable, the network must be completely associated and recurrent connections are not permitted. Neuro evolution thus gives an elective methodology which produces nets that don't experience the ill effects of these restrictions and can evolve to any topology [7].

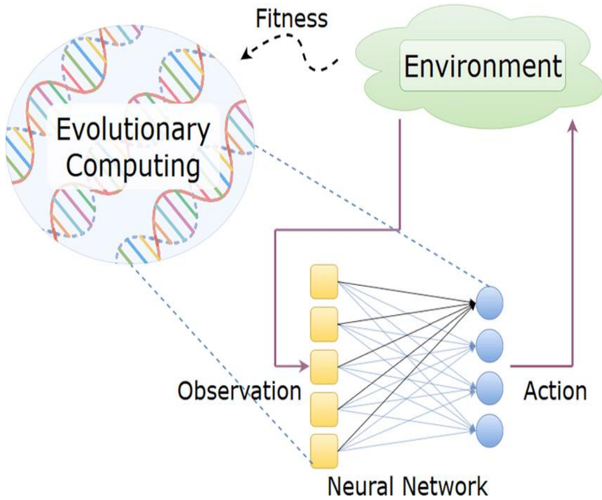

Fig 1.Evolving neural networks by evolutionary computing methods.
Figure Reproduced from [15]

Contrasted with the other neural network learning methods, neuro evolution is profoundly general which means that it permits learning without explicit goals, with just meagre feedback, and with arbitrary neural models and network structures. Therefore, we can say that it is a viable way to deal with taking care of solving reinforcement learning problems, and is most commonly applied in evolutionary robotics technology and the artificial life. First methods using neuro evolution can be traced back to the 1980s and 1990s, where direct genetic algorithms were used to evolve the weights of fixed ANNs [5].A principle advantage of neuro evolution is that it permits learning even when a corpus of input output set is unavailable and can work based only on sparse feedback also. For example, in game playing, vehicle control, and robotics, the ideal actions at each point in time are not generally known; it is only conceivable to see how well a sequence of activities worked, e.g. bringing about success or misfortune in the game[1].

Neuro evolution generalizes to a wide range of network architectures and neural models; applying neuro evolution requires only that the performance of networks can be evaluated over time, and that the behavior of the networks can be modified through evolution. Broadly speaking, the 100 trillion neuron based architecture of human brain evolved through a theory named "Darwinism" over many millions of years. The goal of neuro evolution thus is to trigger a similar evolutionary process inside a computer machine. In this way, neuro evolution is the only branch of AI with an actual proof of concept: brains did evolve, so we know that's one way to produce intelligence.[6]

II. NEUROEVOLUTION AND ARTIFICIAL INTELLIGENCE

The real advantage of neuro evolution is the thing that it brings to the improvement of Artificial Intelligence. Before, computer scientists dealing with AI would plan an algorithm that would show intelligent behavior, and at a point change that algorithm's parameters until it displayed "ideal" intelligent behavior. The artificial intelligence framework they designed was either functioning well or it did not work out, and intermittently their outcomes didn't instruct us much about how human brains work. Now, in neuro evolution, researchers can begin to pose questions about the development of human-level intelligence like as follows : "What difficulties or group of challenges were confronted by the earlier researchers that led them to develop intelligence and forwarded to succeed?" or "What were the main 'building blocks' of making a well-defined human-level intelligence model?" and many more.

Without a doubts, neuro evolution vows to be an insightful field of study, since scientists can endeavor to create an artificial intelligence, yet at the same time also hypothesize about how knowledge was created in the first place, how it was brought into action and that is the reason numerous neuroscientists and biology scholars are also interested and are engaging in this of artificial intelligence and neuro evolution. Since neuro evolution targets at evolving ANNs, what is the connection between neuro evolution, artificial intelligence (AI) and machine/deep learning? AI research targets at computing intelligence, for example creating machines that can exhibit human as well as animal-like intelligence by seeing its current circumstances of sustainence and taking actions in order to achieve its objectives. Machine learning (ML), similarly to deep learning, is a field that takes statistical methods in order to get familiar with a particular undertaking. In this way, these artificial neural networks are viewed as one of the numerous ways to deal with machine learning. Moreover, neuro evolution estimates performance in terms of a fitness metric and hence works with sparse feedback as opposed to conventional machine/deep learning techniques which regularly rely on gradient descent to guide optimization. Neuro evolution, in this manner, can be applied more broadly because it does not require a large set of correct input-output pairs. Instead, it only requires that the performance can some way or the other be estimated after sometime and the conduct of the networks can be changed through evolution.

III. HOW IT WORKS

The first neuro evolution algorithms showed up during the 1980s. At the point, its small gathering of experts figured it very well may be an option in contrast to the more conventionalANN training algorithm called backpropagation. In these early frameworks, neuro evolution researchers would decide on the neural architecture themselves which neurons connect to which and essentially permit evolution to choose the weights as opposed to using stochastic gradient descent. But since the design couldn't be changed by evolution, this methodology came to be known as fixed-topology neuro evolution.

These frameworks are somewhat not the same as nature in that the genes of the evolving ANNs in fixed-topology neuro evolution in reality encode their weights, which are frozen from birth. Thus, the ANNs are conceived knowing everything they will ever know and can't learn anything further during their lifetime. This situation might be a bit of confounding on the grounds that we for the most part consider picking up something we do during our lifetime, however all things being equal, the reproducing occurring in these frameworks as a result is the learning. That is, when parents produce children better adjusted to a task, a sort of "learning" over ages is constantly going on.

How do you develop an artificial brain to solve a problem? Indeed, it's a ton like animal breeding. Assume that you need to advance a neural network to control a robot to walk. Now in such a task, we would ordinarily have on hand a simulator as neuro evolution takes a great amount

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of preliminaries, which are lot quicker and safer to run in simulation. So, we'll start with a robot body in a physics simulator.Presently we need some ANNs to kick everything off. Towards the start, we don't know how to solve the task, so we simply prepare a population of random ANNs. On account of fixed-topology ANNs, the weights of the predetermined design would be randomized in every one of the 100 people in the population. Again, we simply need to perform selection, which means rearing the better candidates to produce next generation of off-springs. To assess our present population, we first take an ANN from the population and, basically, hand over to it control of the simulated robot's body. We let the ANN tell the body how to move, which is called the output of the organized network. The ANN may likewise get contribution from the body and then at this point the computer just watches what the ANN does when it's in charge. Every ANN in the population is tried and given a score called its fitness, based on the quality of its performance [3].

Now, it is entirely certain that the arbitrarily created networks in the initial population are not going to work precisely. They're bound to thrash around than anything else. But that is alright, on the grounds that the key is not that one ANN is particularly good, but instead that some are superior to other people, even if just by a little bit. The algorithm will construct their offspring by slightly altering their ANNs. While some offspring are worse than their parents, some will function slightly better, and those will then become parents of the next generation, and so on. Along these lines, the general methodology is to constantly continue selecting increasingly fit individuals as parents. Essentially, the cycle of neuro evolution is a sort of automated breeding farm for ANNs, where the PC chooses the parents to breed based on their wellness [3].

Throughout the very long time since the first fixed-topology neuro evolution algorithms started to show up, specialists have constantly run into the frustrating reality that even as the algorithms make additional possibilities, the brains they can evolve stay a long way from what evolved in nature. There are numerous reasons for this hole, however an entrancing part of the field is that every so often a surprising new knowledge gain into the workings of natural evolution emerges, bringing about a jump in the ability of neuro evolution algorithms. Regularly, these bits of knowledge are counter-intuitive, overturning previous assumptions and highlighting the mysteriousness of nature [3].

IV. NEAT ALGORITHM

NEAT–Neuro Evolution Augmenting Topologies is a population based algorithmic concept of self-learning machines inspired by evolutionary algorithm that creates artificial neural networks in the process of AI and evolution. It implements the idea that it is most effective to start evolution with small, simple networks and allow them to become increasingly complex over the coming generations.

That way, just as organisms in nature increased in complexity since the first cell, so do neural networks in NEAT.This process of continual elaboration allows finding highly sophisticated and complex neural networks [12].

This approach focuses on the following concepts:

1. Encoding:NEAT's genetic encoding scheme is designed to allow corresponding genes to be easily lined up when two genomes cross over during mating [11]. The NEAT algorithm chooses a direct encoding methodology wherein it represents a neural network that each gene will directly be linked to some node, connection, or property of the network representation is a little more complex than a simple graph or binary encoding, however, it is still straightforward to understand. It simply has two lists of genes, a series of nodes and a series of connections. The point is that there will always be a direct connection between genotype and phenotype that is very obvious and readable [8].

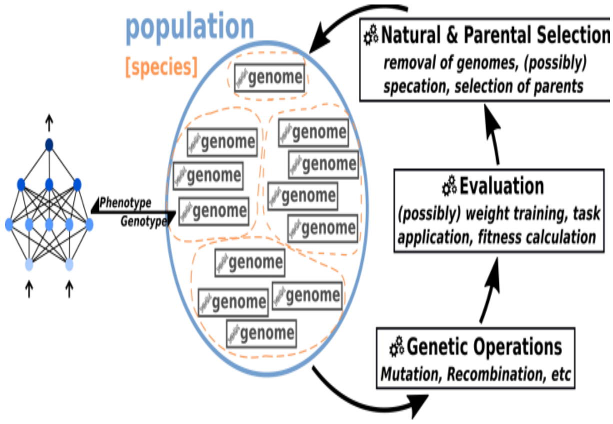

Fig 2. Basic concepts covered in Neuro Evolution. FigureReproduced from [14]

2. Mutation: In NEAT, mutation can either mutate existing connections or can add new structure to a network. If a new connection is added between a start and end node, it is randomly assigned a weight. If a new node is added, it is placed between two nodes that are already connected. The previous connection is disabled. The previous start node is linked to the new node with the weight of the old connection and the new node is linked to the previous end node with a weight of 1. This was found to help mitigate issues with new structural additions [8].

3. Historical Markings: The historical markings give NEAT a powerful new capability. The system now knows exactly which genes match up with which. When crossing over, the genes in both genomes with the same innovation numbers are lined up. These genes are called matching genes. This way, historical markings allow NEAT to perform crossover using linear genomes. By adding new genes to the population and sensibly mating genomes representing different structures, the system can form a population of diverse topologies [11].

4. Speciation: Speciating the population allows organisms to compete primarily within their own niches instead of with the population at large [11]. A very interesting idea put forth in NEAT was that most new evolutions are not good ones. In fact, adding a new connection or node before any optimization of weights have occurred often leads to a lower performing individual. Since NEAT uses historical markings in its encoding, this becomes much easier to measure. A function for deciding how to speciate is given in the paper, but the important part to note is that individuals in a population only have to compete with other individuals within that species. This allows for new structure to be created and optimized without fear that it will be eliminated before it can be truly explored [8].

5. Minimal Structure:
A large goal of the NEAT paper was to create a framework for evolving networks that allowed for minimal networks to be evolved. NEAT sets up the algorithm to evolve minimal networks by starting all networks with no hidden nodes [8]. Each individual in the initial population is simply input nodes, output nodes, and a series of connection genes between them. Since the population starts minimally, the dimensionality of the search space is minimized, and NEAT is always searching through fewer dimensions. Minimizing dimensionality gives NEAT a performance advantage compared to other approaches [11].

V. APPLICATIONS

Neuro evolution methods are powerful especially in continuous domains of reinforcement learning, and those that have partially observable states. These domains include many real-world applications of reinforcement learning. Evolution is typically strongest as an off-line learning method where it is free to explore potential solutions in parallel. Neuro evolution has proved useful in designing players for board games such as checkers, chess, and Othello. Interestingly, the same approach works in constructing characters in artificial environments, such as games and virtual reality. Neuro evolution can help facilitate new kinds of video games, such as games where players train a team of AI agents. Evolution of neural networks is a natural tool for problems in artificial life, and is increasingly being applied to explore issues that are difficult to probe through more traditional techniques in evolutionary biology. Neuro evolution can be applied in controlled experiments to investigate what conditions are necessary for certain behaviors to evolve [1].

CPPNs– a kind of networks developed by the neuro evolution's NEAT have been used in a wide range of applications that benefit from their tendency towards regular structure, from generating pictures to creating three- dimensional objects, including the forms of soft robots. Even though these ideas originated in the 1990s, it was not until the computation was available to scale them up to tens of millions of parameters and train them at length on large datasets that they started to work well enough to make a difference in real-world applications such as speech recognition, language understanding and language translation [6].Some applications of neuro evolution might also include detection or generation of time sequences,speechrecognition,language understanding and language translation. As the evolution of the networks will constantly keep on increasing and broadening, more and more advancements will be seen in neural networks and their advancements.

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