Generative design of bionic partition for airplane cabin interiors by reinforcement learning and finite element analysis

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Project GitHub page: https://github.com/gigatskhondia/Reinforcement_Learning_and_FEA
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1. Background and Rationale

Current researches on aircraft design aim to reduce airplanes and components weights, optimizing aircraft performances and contributing to the challenge of reducing fuel consumption and operational costs. From this perspective novel materials and technologies are developed, but also advances in design methods and tools are put forward. Generative design is one of the approaches to automatically optimize component design. It uses evolutionary algorithms and topological optimization to generate novel, unconventional and complex structures like novel bionic partition for Airbus A 320 cabin interiors, [1].

Alternatively, deep reinforcement learning has had great success in artificial intelligence applications. Among them, beating the champion of the game of Go in 2016, mastering many Atari games and optimizing the work of data centers. In my research, I combine deep reinforcement learning and finite element analysis for the purpose of automating structural design of components.

AI in general and deep reinforcement learning in particular are powerful approaches in solving many nowadays problems in information technology, business, healthcare, and engineering. There is a myriad of applications for AI technologies that one can implement to make life easier. Structural engineering design is no exception. Designing a structure or a part of machinery is a very tiring process. One needs to make a lot of manual changes before resulting in the final design that satisfies structural loads. But this iterative process can be automated.

A typical approach to structural engineering design is finite element analysis. A number of authors have tried to combine finite element analysis and machine learning [2-4]. For example, [3] have used deep-autoencoder to approximate the large deformations on a non-linear, muscle actuated beam. In [4], machine learning was used to predict the deformation of the breast tissues during the compression. However, little attention has been paid to using reinforcement leaning in assisting structural engineering design.

In [5], I have tried to combine finite element analysis and deep reinforcement leaning to assist an engineer in her design process. General description on how this combination was implemented as well as a design process for three simple structures had been presented. Structures were: (a) 1D bar, (b) bridge-like 2D truss, and (c) spool-like 2D frame. These structures can be found in most of real-world structural problems. For example, spools are used to connect the subsea pipeline with a fixed riser nearby the offshore platform.

In this work, I have fused RL and FEA for the purpose of generative design of bionic partition like structure.

2. Methodology

a) Finite element model

For the finite element model I have used the Space Frame Element from [6].

b) Reinforcement Learning

Reinforcement learning can be understood by using the concepts of agents, environments, states, observations, actions and rewards. A reinforcement learning agent interacts with its environment in discrete time steps. At each time step, the agent receives an observation, which typically includes the reward. It then chooses an action from the set of available actions, which is subsequently sent to the environment. The environment moves to a new state and the reward associated with transition is determined. The goal of a reinforcement learning agent is to collect as much reward as possible. The advantage of reinforcement learning is that one does not have to provide labeled data for training. Reinforcement learning system learns by maximizing rewards with no supervision. In my current work, a RL agent uses neural network policy gradient algorithm. The algorithm optimizes the parameters of a policy by following the gradients toward higher rewards, [7].

c) Finite Element Environment to Reinforcement Learning Agent Interaction

The finite element model represents an environment to which a RL agent applies actions and from which it gets observations and rewards. The agent uses neural network to decide on its actions. Actions change geometry of the structure or aircraft component, and the resulting geometry is then subjected to FEA. Finite element analysis produces the state, which is then fed to neural network and the process repeats itself. The agent gets rewards if it meets the optimization objective of minimizing (weight of a component) or maximizing (stiffness of the structure) target values. The outcome of the modeling (after inference stage) is an optimized design of the component. The inference stage is a usual predict-function for a neural network where the RL agent makes actions of altering the geometry based on observations only.

3. Model Details

The results in [5] show that deep reinforcement learning in combination with finite element analysis can be used as automatic iterative process of structural engineering design. In the proposed design pipeline, an engineer provides initial geometry of a structure, sets loads and allowed actions to alter the geometry, specifies the optimization objective (e.g. minimize weight, or maximize stiffness of a component), and starts training of the model. After training, in inference stage, the engineer gets her final design. Thus, combination of finite element analysis and reinforcement learning makes structural engineering design automated.

In this work I took a different approach. I made an RL agent move within acceptable bounds and draw a line behind itself. This broken line became an assessable frame of structure at the end of the RL agent’s moves. By an assessable structure I mean that after all the moves of the RL agent the FEA was able to be applied to the drawn structure as to the monolithic frame of nodes.

For the FEA evaluability I incentivized the RL agent move within acceptable bounds as long as possible by punishing it just before the end of the “game” if it left the “board” and rewarding it proportionally to the number of steps the RL agent made (i.e. the bigger the number of step it makes, the bigger the reward). For the same purpose, I encouraged the RL agent visit certain checkpoints on the board by applying huge reward if it had visited them all.

The overall objective of the RL agent was to minimize the structure’s weight while maximizing its strength. To incentivize the agent to do so, I enormously rewarded it if after visiting the last of the checkpoints the weight of the structure went down and the strength improved compared to the previous best.

4. Final Words

In the future, the role of artificial intelligence in assisting engineering design will grow substantially. Today, most companies which develop FE packages already incorporate machine learning in their products in some form or another.

My research should further the development of the automated design tool that will help many engineers to produces sophisticated aircraft designs with characteristics unreachable by conventional manual design.

In the foreseeable future I am thinking of applying a concept of competitive game between two players to help producing an optimal design of the aircraft components.

Codebase for the model can be found at my GitHub page (see the link at the beginning of the paper).

5. Bibliography

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