

Proposal for Evolutionary Computation in Muscle Action Simulations

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1 Project Summary

In biomechanics, there are many interactions between the body and brain. Some interactions can be quantified as electrical signals to motor nerves of muscles. The result is a particular muscular reaction due to an electrical signal. The input is an electrical nerve signal, and the output is a measured velocity at a joint. The overall result to this system of inputs and output is actions like walking.

In the proposed project, the focus will be on how to relate these inputs to the outputs. Each muscular system adapts to what each input signal should mean, so predicting the output for each system becomes a difficult challenge. The project will focus on optimizing solutions that will explain test data. These solutions could then be used for predicting outputs for inputs that have not yet been measured. This would result in a better understanding of treatment of muscle problems, and better simulations for fixes of muscle irregularities.

1.1 Background

Walking requires a lot of complex tasks to make locomotion possible [1]. The inputs to muscle motor nerves and the outputs of joint motion are one way of measuring all these complex tasks. The data collected as inputs and outputs fits nicely into Evolutionary Computation (EC). EC uses many measured inputs and expected outputs, and evolves a system that will produce those expected outputs on its own.

The EC program will do this with some margin of error, of course, but the error of the solution should be small. The EC solution will then be useful when there are a set of inputs that the output is not already known, like in a simulation. The proposed project, two kinds of EC will be considered: Genetic Algorithms and Genetic Programming. Each has its strength and drawbacks, at least one approach will be used to optimize a model for simulation.

1.2 Problem Statement

For Dr. Craig McGowan's research, a framework already exists. It has been a collaboration between many researchers for many years. There are two problems that the research faces, that the project will focus on: optimizing models for the current evaluation function, and creating a better evaluation function. A solution for the first problem will be attempted, and a solution for the second will be attempted if time remains.

McGowan's research has produced their own evaluation function for how well a simulated biomechanical model is walking. The function is very large and abstract, although supported by research. It has many parameters itself that are educated guesses. McGowan then produces many semi-random models, and uses Simulated Annealing optimization to find the best model per the evaluation function.

1.3 Objectives

The project will use a Genetic Algorithm (GA) for the first problem, and could use a Genetic Program (GP) for the second. GAs are good for producing models for an evaluation function, while GPs are good at actually finding out what that evaluation function should be. The models from

the GA would show a representation of the actual inputs and outputs in a human biomechanical system, while a GP would show what actual algorithm represents the system.

Although McGowan does not talk about optimization methods in his paper, the research uses Simulated Annealing. This is a method used for steady convergence to an optimal solution. This is most likely a local solution in the full domain of potential models. What all optimizations want is to find better global solutions, instead of getting stuck on good local solutions. GAs are better at this than methods like Simulated Annealing, if they are set up correctly.

Other researchers also use Simulated Annealing, but a paper by WHO? [?] tries to parallelize the Simulated Annealing method. Parallelization is a method of programming that finds tasks that can be done simultaneously, and does them all at once on many CPUs / GPUs. The proposed project will use GAs that behave similarly to Simulated Annealing at first, and then more variance will be tried. Through the proposed project, an eye for parallelizable areas will also be active. If any areas are parallelizable, the gains will be analyzed and produced. If there is time, parallelization may even be implemented.

2 Project Description

2.1 Agenda

2.1.1 Algorithms / Programming

In doing some of our own research, it seems like Simulated Annealing is a common approach or suggestion for optimizing biomechanical models [1] [2] [3], so the project will choose **generational** methods of GAs. Generational methods tend to get rid of variability in potential models, similar to how Simulated Annealing simply never sees them. If the Generational method doesn't work well, a **steady state** approach will be tried. Each can be tried with combinations of mutation rates, crossover rates, and selection values.

The generational approach has another similarity to Simulated Annealing, in that it tends to find local optimums faster. Hopefully the project will be able to use the benefits of this, without getting stuck at local optimums. The generational approach can be enhanced by using Age Layered Populations (ALPs), or an age limit for every model. This would be an interesting feature to experiment with, and would be a minor addition to our current GA code base.

Both approaches will use a **population size** starting with $P = 500$. **Crossover** methods will be picked from two point and uniform. For crossover, the best individuals will be selected using a rank based / tournament **selection function**. A random sample of k individuals will be selected, starting with 10. k will be increased if solutions are not converging quickly enough (restricts population variability), and k will be decreased if population solutions seem to get stuck in local optimums. This was the best approach in previous projects, for similar search spaces.

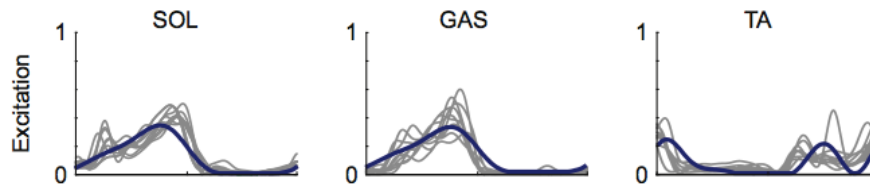


Figure 1: Sample muscle excitations and optimizations [1]

The output curves (see samples in Figure 1) seems to be relatively smooth, but perhaps less predictable than the typical GA benchmarks. This means we may have to keep the value of k low to avoid local optimums. But it is our first priority to come up with really good solutions in reasonable time. The current results look inaccurate compared to the results in previous projects using GA's, so we're anticipating some hidden complexities and lots of local optimums to overcome in optimization. These have probably foiled Simulated Annealing a bit.

2.2 Methodology

The development for the project will start with replacing the current Simulated Annealing function in Dr. McGowan's code base with our own GA interface. Simulated Annealing will probably be run side by side with the GA until it is determined that the GA performs better. If the GA outperforms Simulated Annealing, then Simulated Annealing will be left out. Generational and steady state

approaches will both be tried. Once a better method is found, performance improvements will sought, including candidate tasks for parallelism.

If parallelism proves to be theoretically beneficial, it will be documented, and may be implemented. Simulations will be run at first on a few multicore machines, and if speed-ups warrant, may be run on small to medium size compute clusters. It is our experience that model evaluation / fitness functions are where parallelism becomes possible and beneficial. But our experience is that large speed-ups are not common.

If the GA and performance evaluation portions of the project are successful, then the project will attempt to enhance the fitness / evaluation function (called the 'objective' function in Dr. McGowan's research). Dr. McGowan will often change parameters very slightly for the evaluation function, in an attempt to represent the real world biomechanical model with this evaluation function. A GP would probably be a good approach. Time may not permit this much work, but would be a good future task for future research.

2.2.1 Existing Software

Dr. McGowan has made available to our project a code base that is currently running his optimizations. This code is written in C++ using Microsoft's Visual Studio, and interfaces with the 3d simulation software and MatLab to show optimization results. MatLab may be a challenge to our project, so some open source language like R might be our option to compare optimization results. The Simulated Annealing optimization will be replaced with our EC interface, and this will hopefully be the only other alteration.

2.2.2 Project Software

Our software will probably be written in C++. Our current GA code base is written in R, and will have to be adapted to C++. Our current GP code base is in C++, so it won't require much adaptation. The proposed project code will work in Dr. McGowan's current development environment without any changes.

3 Workplan

3.1 Schedule

November 11th - 15th	Project proposal
November 16th - 18th	Current code base experimentation
November 19th - 23rd	GA implementation
November 24th - 25th	Performance analysis
November 26th - 30th	Performance enhancement and GP analysis

4 Statement of Qualifications

This project is an application of 1 semester of Evolutionary Computation study. Further experience of evolving systems is taken from another semester of Artificial Intelligence. The biological software development and performance analysis experience comes from 2+ years working in the University of Idaho IBEST Computing Core, as well as from experience from NCMGRP, a research project

lead by Ph. D. student Adam Wells at the University of Idaho College of Natural Resources. This research project focuses on spatial analysis of animal movement throughout the northwest.

5 Conclusion

In conclusion, Dr. McGowan's research is important because it helps us understand the mechanics of motion in the body. Results from his research good apply to anything from CGI in video games to adaptive prosthetics for humans. Getting usable results from the research could come down to having a good optimization. It is therefore important to develop better optimization over Simulated Annealing, as Simulated Annealing has left a lot of room for improvement. It may or may not make sense to GA's or GP's over other methods (like Artificial Neural Networks), considering what the actual biomechanical system does. But an evolutionary optimizations like GAs or GPs almost certainly should offer improvements over more static optimizations, like Simulated Annealing.

6 Bibliography

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