Making Soccer Kicks Better: A Study in Particle Swarm Optimization

Namrata Khemka
Department of Computer Science
University of Calgary
Calgary, Canada
khemka@cpsc.ucalgary.ca

Christian Jacob *
Department of Computer Science
University of Calgary
Calgary, Canada
jacob@cpsc.ucalgary.ca

Gerald Cole †
HumanPerformance Lab-Faculty of Kinesiology
University of Calgary
Calgary, Canada
cole@kin.ucalgary.ca

ABSTRACT

Computer simulation is a useful tool for investigating mathematical models of human muscle movement. These, in turn, can be used to help design equipment for sports activities. One biomechanics example is the simulation of a high-speed soccer kick. We used an evolutionary algorithm, based on a particle swarm optimizer, to adjust muscle control parameters for a soccer kick. In this paper we describe our implementation of the soccer kick project, followed by our successful experiments performed with the soccer kick.

Categories and Subject Descriptors

I.6.3 [**Computing Methodologies**]: Simulation and Modeling—*Applications*

General Terms

Algorithms, Experimentation

Keywords

Particle Swarm Optimization, Soccer Kick, Optimization

1. INTRODUCTION

Computer simulation is a useful tool for investigating mathematical models of human muscle movement. These, in turn, can be used to help design equipment for sports activities. One biomechanics example, is the simulation of a high-speed soccer kick. In this project, we investigate the leg and foot movements for kicking a soccer ball [2][3]. The goal is to make the ball travel as far and as fast as possible. Controlling the overall leg and foot movements - which involve 17 muscles - requires a large number of parameters for the simulation. Currently, it is not clear what the 'optimal' settings for these parameters are, within all physical and physiological constraints. In fact, this turns out to be a difficult optimization problem. The biomechanical model was first proposed in [8], which has recently been extended by Cole and Gerritsen [2].

Utilizing numerical optimization algorithms in order to obtain maximum ball velocity and muscle conditions can solve this problem. For example, for different distributions of mass in a soccer shoe, the stimulation patterns of the muscles of the kicking limb can be numerically optimized such that the highest velocity of the ball is obtained. To make things even more challenging, we also ask the question of how to determine global maxima when comparing different shoes. The determination of optimized settings is a prime challenge, as the simulation model consists of 56 parameters (see Section 2 for details). As the fitness evaluation of each parameter vector is time consuming (5-6 seconds for a single run, each over thousands of iterations), we strive to minimize the search time of the optimizer.

The general focus of the study is to compare the performance of three optimization techniques: Particle Swarm Optimization (PSO) [5], Evolution Strategies (ES) [7] and Simulated Annealing (SA) [6]. This entails the visualization, analysis and interpretation of results, which will allow us to determine which of the three algorithms is most fit to find a set of optimized model parameters. To make things even more challenging, we also face the task of tuning the values for the control parameters inherent in the optimizers themselves. So far these parameters have been adjusted manually, which basically leads to a trial and error approach. This is not only time consuming but does not guarantee optimal results at all.

In this paper, we apply PSO to the soccer kick model, describe the experimental setup, and present our first results.

*Supervisor from Computer Science

†Co-Supervisor from Kinesiology

GECCO'05, June 25–29, 2005, Washington, DC, USA.

2. THE *SOCCER KICK* PROJECT

Soccer is one of the most popular sports in the world. A variety of skills are required since the arms and hands can not touch the ball. Kicking is one of the important skills required for playing soccer. A kicking action can be evaluated by the ball speed, ball position and the nature of the kick.

The motion of the leg kicking the ball involves 17 different muscle groups. Some of these muscle groups, as seen in Figure 1, are in the foot and toes, talus, shank, thigh and

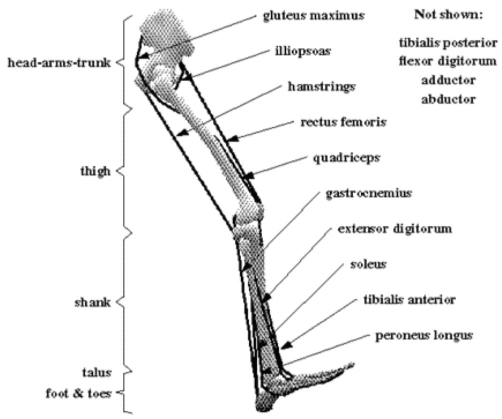

Figure 1: Muscle groups in the human leg [8]

head-arms-trunk sections. Each of the muscles has a start and end time for its stimulation. As seen in Figure 2, for muscle M_k, where k = 1, 2, 3, ..., 17, we define $t_0(M_k)$ to be the start time and $t_{end}(M_k)$ the end time of its stimulation. Each muscle is allowed to change only once during its stimulation at time $t_c(M_k)$, $t_0 \leq t_c \leq t_{end}$, and is denoted by $t_c(M_k)$. In Figure 2, $stim_1(M_k)$ is the initial stimulation level, and the muscle stimulation changes at time $t_c(M_k)$ to $stim_2(M_k)$. Hence, the control parameter vector for muscle M_k is represented as:

$$ctrl_{M_k} = (stim_1(M_k), stim_2(M_k), t_0(M_k), t_c(M_k), t_{end}(M_k)) \tag{1}$$

For all our experiments, we set $t_0(M_k) = 0$, $t_{end}(M_k) = 1$ and k = 1, ..., 9, 11, ..., 17. An exception is muscle M_{10} which changes twice during a simulation and is represented by:

$$\begin{aligned} ctrl_{M_{10}} = \; & (stim_1(M_{10}), stim_2(M_{10}), stim_3(M_{10}), \\ & t_0(M_{10}), t_{c_1}(M_{10}), t_{c_2}(M_{10}), t_{end}(M_{10})) \end{aligned}$$

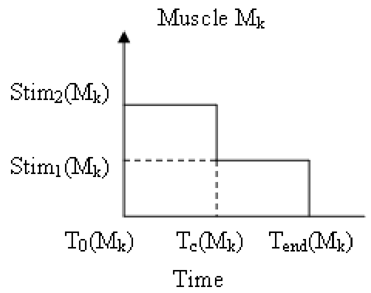

Figure 2: Stimulation profile used for each muscle.

The seventeen muscles with the ball position result in a 56-dimensional search problem.[1] We strive to optimize the leg movement, so that when the foot hits the ball, its obtained velocity is as high as possible. Considering the complexity and non-linearity of this problem, we decided to tackle it by using an evolutionary algorithm. Evolutionary algorithms like Particle Swarm Optimization (PSO) [5][4] are known to be efficient in large and complex search spaces like the Soccer Kick Simulation.

PSO algorithms are especially useful for optimization in continuous, multi-dimensional search spaces. The connection to search and optimization problems is made by assigning direction vectors and velocities to each individual in the search space. Each individual 'flies' through the search space following its velocity vector, which is influenced by the directions and velocities of other points in its neighborhood.

[1]17 muscles * 3 + 2 parameters for M_{10} + 3 ball parameters

3. EXPERIMENT SETUP

In this section we describe our settings for the Soccer Kick using a particle swarm optimizer as described in [4] with the neighborhood radius of 1 on the population vector. We used the following PSO algorithm:

1.Initialize the particle population by stochastically assigning locations and velocities:

$$P = (\overrightarrow{p_1}, \ldots, \overrightarrow{p_i}, \ldots, \overrightarrow{p_\mu}) \; and \; V = (\overrightarrow{v_1}, \ldots, \overrightarrow{v_i}, \ldots, \overrightarrow{v_\mu}) \tag{2}$$

2. Evaluate the fitness of all particles:

$$F(P) = (F(\overrightarrow{p_1}), \ldots, F(\overrightarrow{p_i}), \ldots, F(\overrightarrow{p_\mu})) \tag{3}$$

3. Keep track of the locations where each individual had its highest fitness so far:

$$P = (\overrightarrow{p_1}^{best}, \ldots, \overrightarrow{p_i}^{best}, \ldots, \overrightarrow{p_\mu}^{best}) \tag{4}$$

4. Keep track of the position with the global best fitness:

$$\overrightarrow{p_g}^{best} = max_{\overrightarrow{p} \in P}(F(\overrightarrow{p_i})) \tag{5}$$

5. Modify the particle velocities based on the previous best and global best positions for all $1 \leq$ i $\leq \mu$:

$$\overrightarrow{v_i}^{new} = \overrightarrow{v_i} + \varphi_1(\overrightarrow{p_i}^{best} - \overrightarrow{p_i}) + \varphi_2(\overrightarrow{p_g}^{best} - \overrightarrow{p_i}) \tag{6}$$

6. Update each particle's location:

$$\overrightarrow{p_i}^{new} = \overrightarrow{p_i} + \overrightarrow{v_i}^{new} for 1 \leq i \leq \mu \tag{7}$$

7. Stop if the termination criterion is met else go to step 2.

The population size for our experiment is 10. Each individual is represented by a 56-dimensional vector:

$$ctrl_{sim} = (ctrl_{M_1}, ...ctrl_{M_{17}}, param_{ball}) \tag{8}$$

The parameter settings for PSO are listed in Table 1.[2] We started off with an exploitation rate (local search) $\varphi_1 = 0.2$ and an exploration rate (global search) $\varphi_2 = 0.02$. After the first 5000 iterations the simulation seemed to have reached a fitness plateau (see the vertical line in Figure 4b). At this point we interchanged the exploration and exploitation rates as in Table 1.

The fitness $f(ctrl_{sim})$ is represented by:

$$f(ctrl_{sim}) = max_{ball} - \sum_{i=1}^{3} contact - toeconstraints \tag{9}$$

where max_{ball} is the maximum forward ball speed and *contact* is a vector describing entries for three contact spheres that

[2]The parameter values were initially tested on some test problems (F1 (Sphere), F2 (Rosenbrock), F3 (Step), F4 (Quartic), F5 (Foxholes), F6 (Schwefel), F7 (Rastrigin), F8 (Griewangk)). Although these are low values, they seem to work the best.

PSO Parameters	Iteration 0-5000	Iteration 5001-17,500
velocity range	[-0.1,0.1]	[-0.1,0.1]
location range	[0,1]	[0,1]
exploitation rate, φ_1	0.2	0.02
exploration rate, φ_2	0.02	0.2

Table 1: Parameter settings of the PSO for the Soccer Kick Simulation

approximate the foot. If contact with all spheres occurs, the entry is zero, otherwise it is assigned a large value of 20,000 to ensure a high penalty for not touching the ball. We also determine the lowest point above the surface that the toes are allowed to go to. Otherwise, the toes would either be scrubbing the ground or actually kicking into the ground, none of which is acceptable. The toe constraints compare the end of each toe with the constraint position.

4. RESULTS

The 3-D model used in this simulation was developed using DADS, a software for dynamic motion simulation (Version 9.5, LMS International, Belgium) [1]. The model consists of rigid bodies representing a human right leg. The motion of the model is produced by following the stimulation schedule derived from $ctrl_{sim}$ (Equation 8). Figure 3 shows selected generations of one of the best individuals that we have evolved so far.

The experiment was run for 17,500 iterations.[3] The maximum fitness or ball speed achieved was 93.886 km/hour. The speed reported for an average skilled player is around 84.6 km/hour. We also observed that the foot touches the ball for about 7ms, close to results reported in [2][3]. Both these values have proved to us that the PSO has generated a good solution.

Figure 4 shows the maximum, minimum and average fitnesses at every 100th iteration. The diversity of the population remains high during the whole evolution experiment.

Figure 5 compares the best individual in the first iteration with the individual with the best fitness value (ball speed) of 93.886 after 17,500 iterations.

Each set of muscle parameters is represented by three colored bars. The blue bar (first) is the starting point of the stimulation for a particular muscle k ($t_0(M_k)$), the red bar (second) represents $t_c(M_k)$, the time when a muscle changes its stimulation and the green bar (third) is the end point of the stimulation ($t_{end}(M_k)$).

Figure 5b shows which of these muscles are activated and deactivated at particular points in time during the kicking movement. The human leg is a double pendulum as illustrated in Figure 3; one joint is at the hip and the other is at the knee. The main muscle affecting the movement of the hip is M_3 (Iliopsoas). Initially this muscle is highly activated to produce the hip movement during the early stages of the kick (Figure 3). When the hip has completed its action, the muscle deactivates. Once the hip movement is completed, the movement from the knee contributes mostly to the kick. Muscles affecting the movement of the knee are: M_5 (Vastus Itermedius), M_{15} (Vastus Medialis), M_{16} (Vastus Lateralis) and M_{17} (Castus Medialis Oblique). These four muscles combine to form the quadriceps. Initially, none of these muscles are stimulated. Only after the hip movement is completed, they are strongly activated. Muscles M_6 (Gastrocnemius) and M_7 (Soleus) cause the foot to go back in order to get the foot to contact the ball. These two muscles are highly activated towards the end. M_{10} (Tibialis Anterior) has no muscle stimulation. However M_{12} (Extension Digitorum) deals with the stiffness of the toe.

[3]We have only a few runs to compare our results with. The main reason is that the soccer kick simulation is time-consuming. To run a single-kick simulation, takes around 7 seconds. Given 10 individuals, evaluating a population takes 70 seconds. Running 17,500 iterations takes about 340 hours or 14 days.

5. CONCLUSIONS

In this paper we have described our implementation of the soccer kick project, along with initial successful experiments performed with a particle swarm optimizer, which we used to adjust the muscle control parameters.

The future objectives of this work are to become more familiar with numerical optimization methods (Evolution Strategies, Simulated Annealing and Particle Swarm Optimization) for challenging high-dimensional problems and perform comparison evaluations.

6. REFERENCES

[1] Lms international - www.lmsintl.com.

[2] G. Cole and K. Gerritsen. Influence of mass distribution in the shoe and plate stiffness on ball velocity during a soccer kick. *Adidas-Salomon AG*, 2002.

[3] G. Cole and K. Gerritsen. Influence of medio-lateral mass distribution in a soccer shoe on the deflection of the ankle and subtalar joints during "off-centre" kicks. *Adidas-Salomon AG*, 2003.

[4] C. Jacob and N. Khemka. Particle swarm optimization in mathematica: An exploration kit for evolutionary optimization. In *Proc. Sixth International Mathematica Symposium*, 2004.

[5] J. Kennedy and R. C. Eberhart. *Swarm Intelligence.* Morgan Kaufmann Publishers, San Francisco, 2001.

[6] S. Kirkpatrick, J. Gelatt, C. D., and M. P. Vecchi. Optimization by simulated annealing. *Science*, 220:671–680, 1983.

[7] I. Rechenberg. Evolution strategy. In J. M. Zurada, R. J. Marks II, and C. J. Robinson, editors, *Computational Intelligence Imitating Life*, pages 147–159. IEEE Press, New York, 1994.

[8] I. Wright and K. Neptune. Passive regulation of impact forces in heel to toe running. *Clinical Biomechanics*, 13:521–531, 1998.

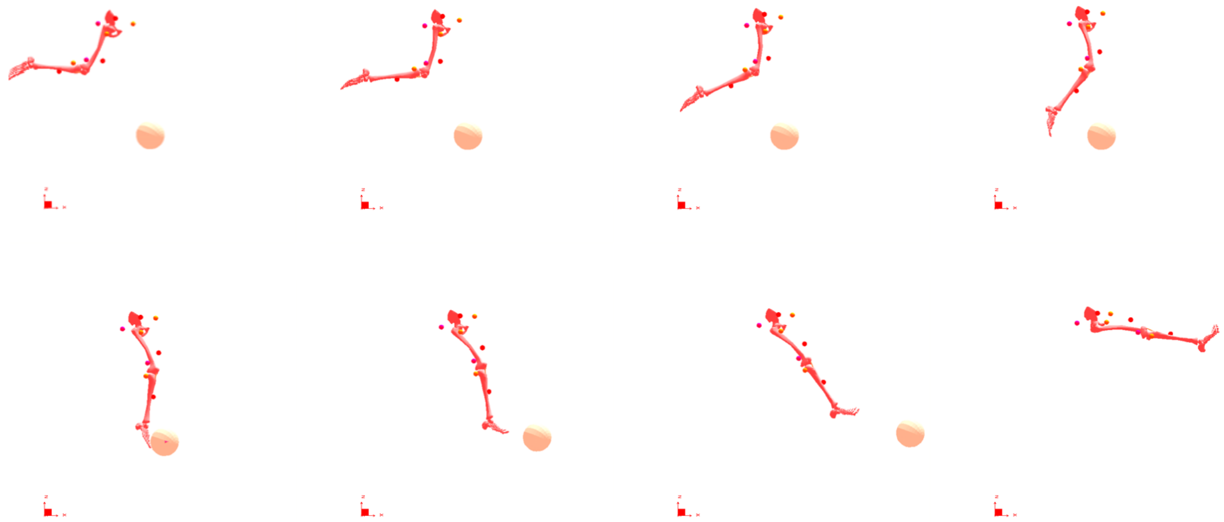

Figure 3: Leg movement resulting from the best solution found in iteration 14,398

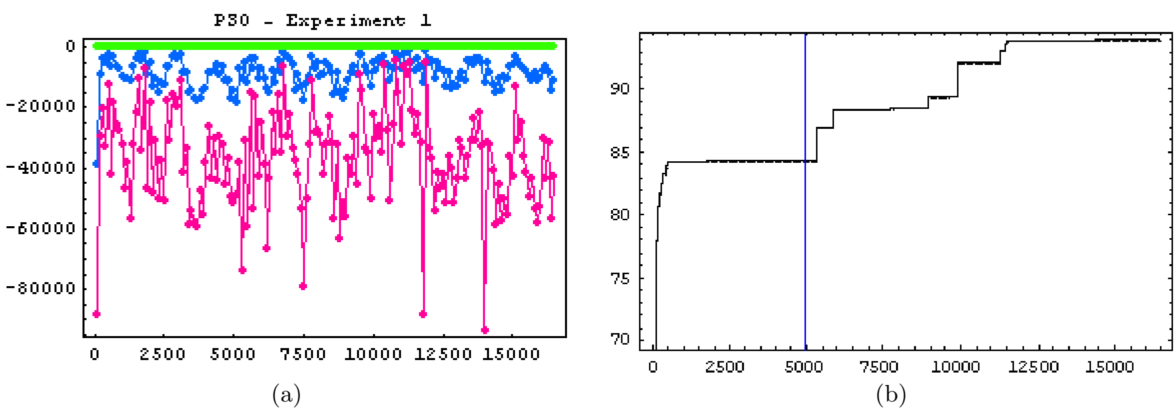

Figure 4: Fitness evolution. (a) Every 100th iteration is plotted for the fitness of the Soccer Kick. Green (top curve) represents the maximum fitness at a particular iteration, blue (middle curve) represents the average fitness and pink (minimum curve) represents the maximum fitness. (b) Best fitness achieved so far. At iteration 5,000 the parameter settings for φ_1 and φ_2 were switched (Table 1).

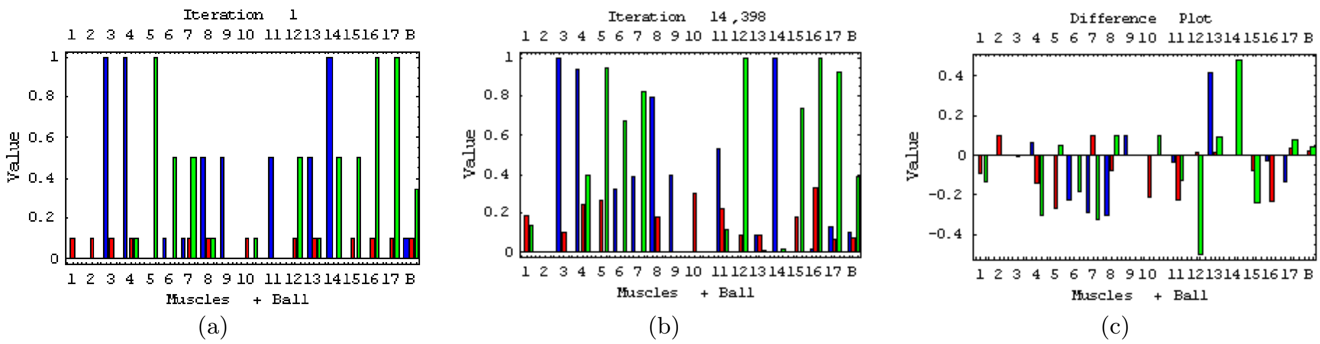

Figure 5: Muscle stimulations and ball parameters. (a) Individual at iteration 1 (b) Overall best individual (c) Difference between (a) and (b)