SNATCH TECHNIQUE VALIDATION USING COMPUTATIONAL METHODS: A GENETIC ALGORITHM APPROACH

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An analytical model based on a 6 degrees of freedom robotic manipulator is adopted to represent an individual athlete during weightlifting, snatch technique. The performance of an athlete is observed and the barbell trajectory of the lifter is considered as the lifting clue of our model. The inverse kinematics problem is solved using genetic algorithm. The results could be adopted in enhancing athletic performance through provision of an alternative weightlifting technique for the individual athlete. The performance of the athlete is compared with the generated motion. It is shown that the overall torque applied to the joints can be lessened by having the trunk horizontal angle constant during the first pull. The computational support of the technique is the main focus of the paper.

KEY WORDS: weightlifting, snatch, genetic algorithm, technique, inverse kinematics

INTRODUCTION:

The existing publications on biomechanics of weightlifting tend to concentrate on injury prevention or performance evaluation through various kinetic or kinematics evaluation of the athletes (Garhammer, 1998; Carlock et al., 2004, Gourgoulis et al., 2004; Stone, 1998). In addition, some techniques are introduced in books in order to help the coach and the athlete to perform the lifting with the most proper way. Almost none of these techniques are approved computationally or have been proved to be optimum through out the whole lift (Campillo et al., 1998; Charniga, 2001; Stone et al., 2002).

An analytical model could prove effective in an individualized approach to performance enhancement. The athlete can be represented by a planar 6 degrees of freedom (DOF) robotic manipulator where the barbell trajectory is an input to an inverse kinematics problem. The problem has four degrees of redundancy and the solution includes nonlinearities accompanied by a large number of feasible solutions for most end-effector positions. Closed form approach and many iterative solutions face a major difficulty in avoiding singularities and thus find it difficult, and in some cases impossible, to ensure a smooth and feasible motion of the resulting configurations. The convergence potentials of Genetic Algorithms (GAs) through an efficient search in such large and complex solution spaces are theoretically and empirically exhibited in a number of articles (Goldberg, 1989; Javadi & Mojabi, 2003; Huang et al., 2006). A genetic algorithm approach is therefore adopted to determine a near optimum solution for a highly redundant inverse kinematics problem. Implementation of GA takes place through applying of two categories of constraints, the first of which defines the barbell trajectory, Figure 1(a), and the second contains two sets of physiological and kinesiological constraints. The physiological constraints are defined by joint torques and the kinesiological constraints represent joint angles and velocities.

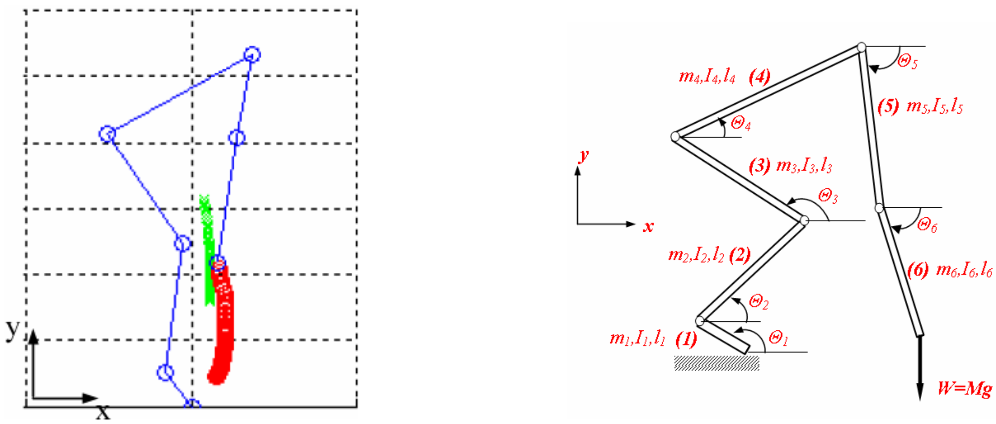
Trunk horizontal angle is considered, and has been shown that keeping the trunk angle constant during the first pull results in less torque on the joints in the whole lifting. Campillo et al. (1998), Charniga et al. (2001) and other researchers have also mentioned this point but no computational model is provided.

METHOD:

Comparative data and the generated model are obtained through motion analysis utilizing WINAnalyze software with a single digital camera placed at right angles to the sagittal plane with the data being recorded at 125fps. The athlete is modeled as a planar 6 degrees of freedom manipulator. The model is fixed on one base (toes). GA is used to solve the trajectory tracking of the barbell during a snatch lift. The generated series of configurations

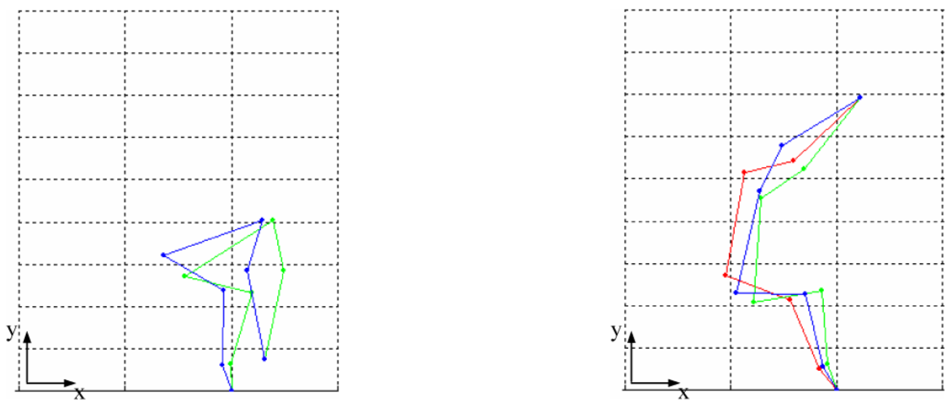
are optimized for minimum total displacement of COM of body-weight system for preserving the maximum stability, and minimum total torque applied to individual joints. Torque is calculated using recursive Newton-Euler method (Shirzad et al., 2006).
The variables of the problem are joint angles as shown in Figure 1(b). Initial joint angles, joint angles for the first frame, are given in vector form as, $\underline{\Theta_s} = \{\Theta_1, \Theta_2, \Theta_3, \Theta_4, \Theta_5, \Theta_6\}$.

GA uses the joint angles variations for its members, as shown below, except for the initial configuration.
$\Delta\underline{\Theta_s} = \{\Delta\Theta_1, \Delta\Theta_2, \Delta\Theta_3, \Delta\Theta_4, \Delta\Theta_5, \Delta\Theta_6\}$ Where $\Delta\Theta_i$ for $i = 1..6$ is less than 5°.



(a) (b)

Figure 1: (a) Body model along with bar trajectory in red circles and COM of the body-weight system in green crosses. (b) Body model, Illustrating a manipulator with 6-DOF.



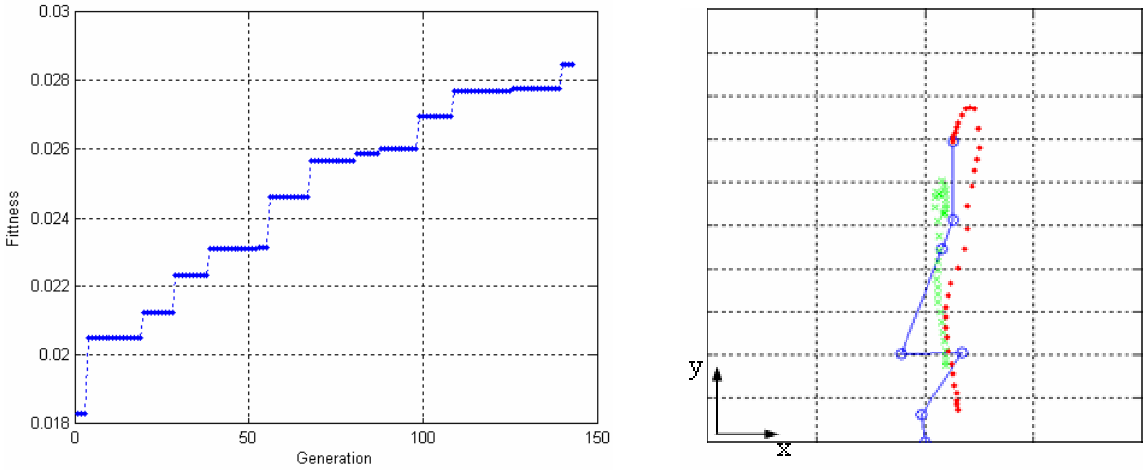
(a) (b)

Figure 2: (a) Two different initial configurations, green and blue. (b) Cross-over operator is applied to the two mentioned configurations in (a) somewhere in the middle of the lifting path and red configuration is generated.

The population size is set to 200. The genetic operators are mutation, 70 members, and uniform crossover, which in each new generation, 30 pairs of members of the current generation are used for crossover and 30 new members are generated. Figure 2(b) shows the resultant configuration (red configuration) of applying crossover operator to two initial configurations (blue and green configurations). Two types of selection methods used are first tournament selection, with tourney-size 15, and selection of the best members. The best first 55 members are survived for the next generation.

RESULTS:

Figure 3(a) shows the fitness of the fittest member of 143 generations. It shows a gradual improvement in generations. The execution of the application for 143 generations took 34 hours of a computer running on 2.8GHz with 2GB RAM using MATLAB.



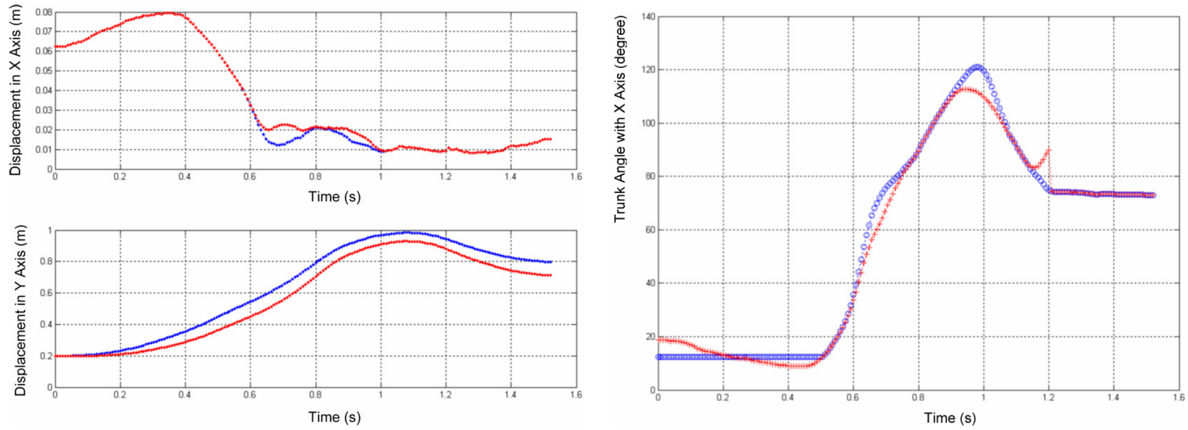
(a) (b)

Figure 3: (a) Fitness of the fittest member is gradually improved through the generations. (b) The resulting configuration of body model using GA.

One configuration generated by GA is shown in Figure 3(b), where the obtained configuration is presented at the end of the second pull phase of snatch. Red points represent the discrete barbell trajectory and green crosses show variations of center of mass of the body-weight system.

DISCUSSION:

The resulting configuration obtained through implementation of genetic algorithm indicates an enhancement in performance by suggesting an alternative technique where joint torques are lower.



(a) (b)

Figure 4: (a) Horizontal, top, and vertical, bottom, displacement of COM of body-weight system. (Blue dots concern the real motion and red dots concern the generated motion) (b) Trunk horizontal angle, Θ_4. (Red crosses concern the real motion and blue circles concern the real motion)

Members in GA are optimized for two criteria. First lower COM of body-weight system displacement and second overall lower torque applied to joints are considered. Figure 4(a) shows the COM of body-weight system, comparing the two real and generated motions. It is shown that the overall displacement of the COM of body-weight system of the generated motion is less than the real motion. Overall torque concerning different joints, also, has been optimized and the resultant overall torque of different joints of the generated motion is less than the real motion.

CONCLUSION:

This paper has aimed at establishing the Genetic Algorithm as a useful tool in formulation of an individualized analytical model towards performance enhancement and injury prevention in weightlifting by providing the athlete and the coach with a more effective alternative weightlifting technique. The most important focus of the project was on technique validation in separate phases of snatch. It is computationally approved that the horizontal trunk angle, Θ_4, during the first pull should be kept constant in order to achieve optimum torques applied to the joints, Figure 4(b). The fittest member in the last generation of GA shows the most effective technique in which the trunk horizontal angle is kept constant during the first pull.

REFERENCES:

Campillo, P. et al (1998). The snatch lift in weightlifting by identification of critical points, *Science and Sports*, 13(2), 90-92.

Carlock, J.M. et al (2004). The relationship between vertical jump power estimates and weightlifting ability: A field-test approach. *Journal of Strength and Conditioning Research,* 18(3), 534-539.

Charniga, A. (2001). *Key Muscles for Weightlifting*, The Russian Weightlifting Library.

Goldberg, D. E. (1989). *Genetic Algorithms in Search, Optimization, and Machine Learning*. Addision-Wesley Publishing.

Garhammer, J. (1998). Weightlifting performance and techniques of men and women. International Conference on Weightlifting and Strength Training. K. Ha¨kkinen, ed. Lahti, Finland: Gummerus Printing, 89-94.

Gourgoulis, V. et al (2004). Snatch lift kinematics and bar energetics in male adolescent and adult weightlifters. *Journal of Sports Medicine and Physical Fitness*, 44(2), 126-131.

Huang, P. et al. (2006). Global Minimum-Jerk Trajectory Planning of Space Manipulator. *International Journal of Control, Automation, and Systems*, 4(4), 405-413.

Javadi, A.H. & Mojabi, P. (2003). Team learning via decentralized conflict resolution through utilizing GA in path planning, In *proc. of 9th European conference of the international society for terrain vehicle systems*, ISTVC03, England.

Shirzad, E. et al. (2006). Mathematical modeling and computer simulation of weightlifting sport, phase 1: pull phases in snatch technique. *International Journal of Scientific Research*, 6, 323-327.

Stone, M. et al (1998). Analysis of bar paths during the snatch in elite male weightlifters. *Strength Conditioning Journal,* 20(4), 56-64.

Stone, M. et al (2002). *The Use of Weightlifting Pulling Movements in Sport: Introduction/ Snatch Versus the Clean*, Published by the Faculty of Education, The university of Edinburgh, Old Moray House.