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The Dynamic Coupling Identification between the Artificial Robot Hand and the Actuators using Genetic Algorithm

André Ribeiro Lins de Albuquerque [1], Cláudio Adriano Policastro [2], Leonardo Marquez Pedro[1] and Glauco Augusto de Paula Caurin[1]

[1] University of São Paulo, School of Engineering of São Carlos, Mechanical Engineering Department. Av. Trabalhador São Carlense, 400, CEP 13566-590, São Carlos, SP, Brazil

[2] Atenatec Technological Solutions Ltd.. Av. Santos Dumont, 800, CEP 13566-445, São Carlos, SP, Brazil

Abstract: This paper presents an approach for determining the dynamic coupling between the joints of an artificial robot hand and their actuators using genetic algorithms optimization method. The dynamic coupling is verified by the model parameters identification. Based on the experimental data, we estimated the equivalent stiffness and damping parameters in the coupling. The cost function is generated through the analytic model response combined with the experimental data, which are torques applied by the actuators, the difference of angular displacements and velocities between the actuators and joints. The optimization process results can be easily compared with the a-priori knowledge the transmission system. Designing a high quality controller depends on the model parameters knowledge.

Keywords: model parameters identification, genetic algorithms, robot hand, optimization method, dynamic model.

NOMENCLATURE

σ_m = motor torque
σ_c = torque due to the load
D_m = motor inertia
D_c = load inertia
B_m = motor viscous friction
B_c = load viscous friction
θ_m= motor angular displacement
θ_c= load angular displacement
K_c = stiffness of the coupling between the motor and the load

η = gear system ratio
Fitness = the mean of the torque difference for n sparks of the system
NewValue = average of each gene of the parents, weighted by the fitness value of the chromosome

Subscripts

c relative to motor
m relative to load

INTRODUCTION

The development of new dexterous robot hands that is closer to the human hand continues to make progress on the research community. On the other hand, high rejection levels of commercial hand prosthesis (Caurin, 2004) reveal that hand prosthesis require more than proper functionality. Better esthetics, greater functionality and a more human friendly behavior might hold possible answers for both fields.

Within this context recent works, for example Albuquerque (2005), have been dedicated to observe and accurately reproduce in detail the human hand regarding geometrical and also dynamical characteristics. The project of the Brazilian Anthropomorphic Hand, Fig. 1, should serve as a basis for analysis of future strategies for friendly interaction between man and machine. The robot hand is intended to be, in first place, thought of as an open and useful environment for executing manipulation tasks that approximate the abilities of human hands. In the project, the artificial hand, as a whole as well as the individual mechanical links are joints that have a total of 22 degrees of freedom (d.o.f.), 4 in each of the 5 fingers and 2 additional ones at the wrist. The coupling between the actuators and the joints is done by cables and is modeled as an equivalent springs and dampers.

Although the whole has already been modeled and analyzed in detail (Albuquerque, 2005), the physical coupling identification between the artificial robot hand and its actuators still was a point to be further developed. In this paper the physical parameters of that coupling are identified using the genetic algorithms optimization method.

a) **b)**

Figure 1 – a) The Brazilian Anthropomorphic hand structure using polyurethane based on ricinus oil; b) its cable transmission system.

This work is organized as follows: in section “Coupling Identification Strategy” the problem is presented and the experimental setup strategy is proposed. The technique used to identify the coupling parameters is presented in section “The Genetic Algorithm”. Moreover in this section a description of the genetic algorithms optimization method development is made. The section “Results” shows the algorithm convergence and the evaluation tests. Additionally, section “Results” presents a critical analyzes for the approach proposed in this paper.

COUPLING IDENTIFICATION STRATEGY

The artificial hand joints are driven by DC servomotors through a cable transmission system. This way, the dynamic model for each set (servomotors, coupling and joint) can be represented as the Fig. 2.

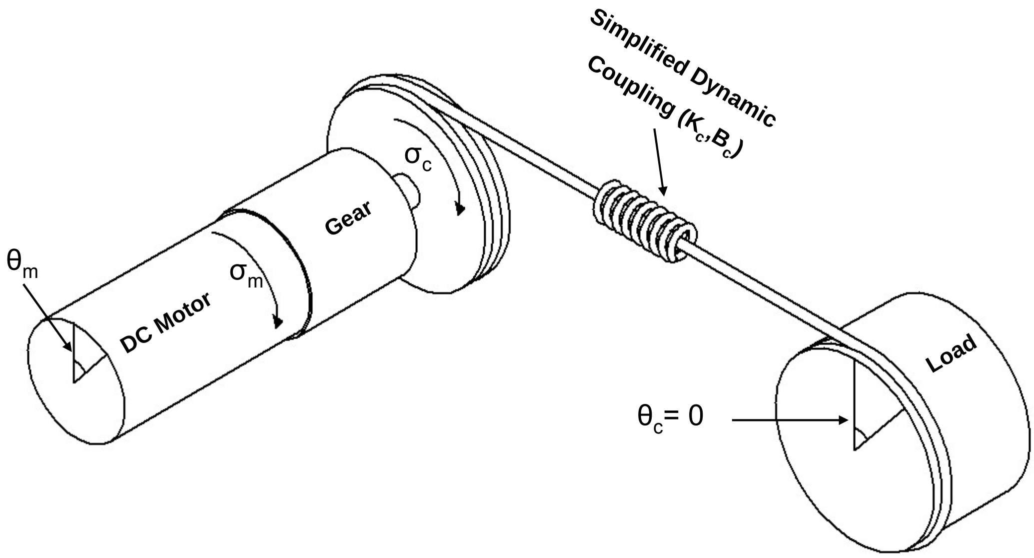

Figure 2 – Transmission system– servomotor, coupling and load

By analyzing the servomotor axes input we can write that:

$$\sigma_m = D_m.\ddot{\theta}_m + B_m.\dot{\theta}_m + \frac{\sigma_c}{\eta} \tag{1}$$

where D_m is the motor inertia and B_m the viscous friction in the motor. The torque due to the load can be representing in a simple form such as:

$$\sigma_c = D_c.\ddot{\theta}_c + K_c.\left(\frac{\theta_m}{\eta} - \theta_c\right) + B_c.\left(\frac{\dot{\theta}_m}{\eta} - \dot{\theta}_c\right) \tag{2}$$

where θ_c is the load angular displacement, D_c is the load inertia, K_c is the stiffness of the coupling between the motor and the load and B_c is the damping of the coupling between the motor and the load.

In the experimental setup the load is always fixed while the motor follows a certain input. Using this strategy the load inertia effect is override, decoupling in this case the load dynamic.

By representing the system in block diagram form Fig. 3 each dynamic element of the system can be observed. In this paper, the goal is identify the coupling physical parameters (K_c, B_c) using the genetic algorithms optimization method.

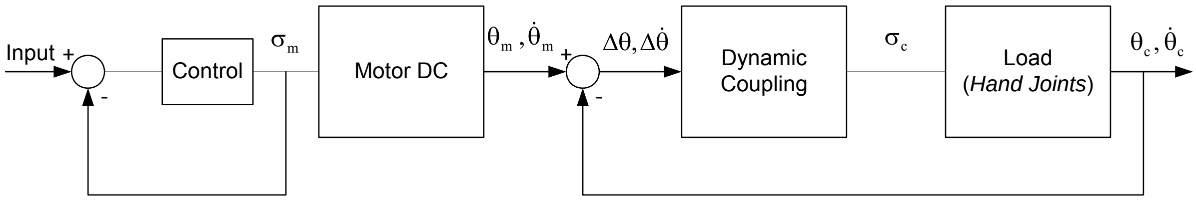

Figure 3 – Block diagram system representation

THE GENETIC ALGORITHM

Genetic Algorithms are methods for optimization and search inspired in the mechanisms of evolution and natural selection. They were introduced by John Holland (Holland, 1975) and popularized by one of his students, David Goldberg (Goldberg, 1989). These algorithms follow the beginning of the natural selection and survival of the most capable, declared in 1859 by the naturalist and English physiologist Charles Darwin (Darwing, 2003).

In a typical Genetic Algorithm, the first step is the generation of an initial population of chromosomes. This population is formed by a random group of chromosomes that represents possible solutions of the problem to be solved. During the evolutionary process, this population is evaluated and each chromosome receives a note (fitness) that indicates the quality of the solution encoded by the chromosome. In general, the most capable chromosomes are selected and the least capable ones are discarded. The selected members can suffer modifications in their fundamental characteristics through crossover and mutation operators, generating new chromosomes for the next generation. This process is repeated until a satisfactory solution is found. For the proposed algorithm, it repeats this process until a predefined number of generations is not reached. The Algorithm 1 illustrates the Genetic Algorithm for system, proposed in this paper. The structure and operation of this algorithm are discussed next.

Algorithm 1 The Genetic Algorithm Employed for System Identification.

Let $P(t)$ be the population of chromosomes c in time t

$t \leftarrow 0$

Generate and evaluate the Initial Population $S(t)$

while number of generation is not reached **do**

  Select two chromosomes, c_1 and c_2 from $S(t)$

  Apply *crossover* over c_1 and c_2 to create one new chromosome c_3.

  Apply mutation over c_3, with rate of 10%

  Evaluate c_3

  Insert c_3 in $S(t)$

  $t \leftarrow t+1$

End

Problem Encoding

In a Genetic Algorithm, a chromosome is a structure of data, usually vector or chain of bits (chain of bits is the most traditional structure, however not always the best), that represents a possible solution of the problem to be optimized. For the algorithm proposed for the identification of the dynamic system, a chromosome is formed by two genes, each one representing the parameters of the function objective (parameters K_c and B_c) that should be identified for the algorithm. The K_c and B_c parameter has real type representation, K_c varying from 0.5 to 200 and B_c varying from 0.01 to 10. This encoding allows fast operations over the genes and evaluation of the chromosomes. Figure 4 illustrates the structure of the chromosome.

B_c	K_c
0.54	105

Figure 4 – Structure of the chromosome.

Fitness Function

A fitness function is a particular type of objective function that quantifies the optimality of a chromosome. In the genetic algorithm, optimal chromosomes - chromosomes with larger fitness - have higher probabilities of selection to generate child chromosomes for next generations. The proposed algorithm employs a fitness function that captures several sparks of the dynamic of the system to be identified, in time i, i = 0..n. For each spike, the fitness function takes the difference of angles of the actuators of the real dynamic system and the rate of these angles difference ($\Delta\theta$ i and $\Delta\dot{\theta}$ i) and calculates the value of the output σ_c i. Then the function compares this result with the real torque taken from the dynamic system, extracting the absolute value of the difference, given by the Equations (3 and 4).

$$\sigma_{c\mathrm{i}} = \Delta\theta_{\mathrm{i}} \times K_c + \Delta\dot{\theta}_{\mathrm{i}} \times B_c \tag{3}$$

$$\textit{Fitness Value}_i = abs\ (Real\ \sigma_{c\mathrm{i}} - \sigma_{c\mathrm{i}}) \tag{4}$$

where: $\Delta\theta$ i and $\Delta\dot{\theta}$ i are the inputs taken from the real system, K_c and B_c are physical parameters taken from the chromosome being evaluated, and Real $\sigma_{c\mathrm{i}}$ is taken from the real system. Then the fitness function calculates the mean of the torque difference for n sparks of the system, where n is a predefined number, given by the Equation (5).

$$\text{Fitness} = \frac{1}{\text{n}} \sum_{i=1}^{n} \textit{FitnessValue}_i \tag{5}$$

The objective of this algorithm is to minimize the fitness. Therefore, a chromosome with fitness near to zero is supposed to contain the expected identification of the parameters of the real dynamic system. Figure 5 shows the application of the fitness function over a chromosome.

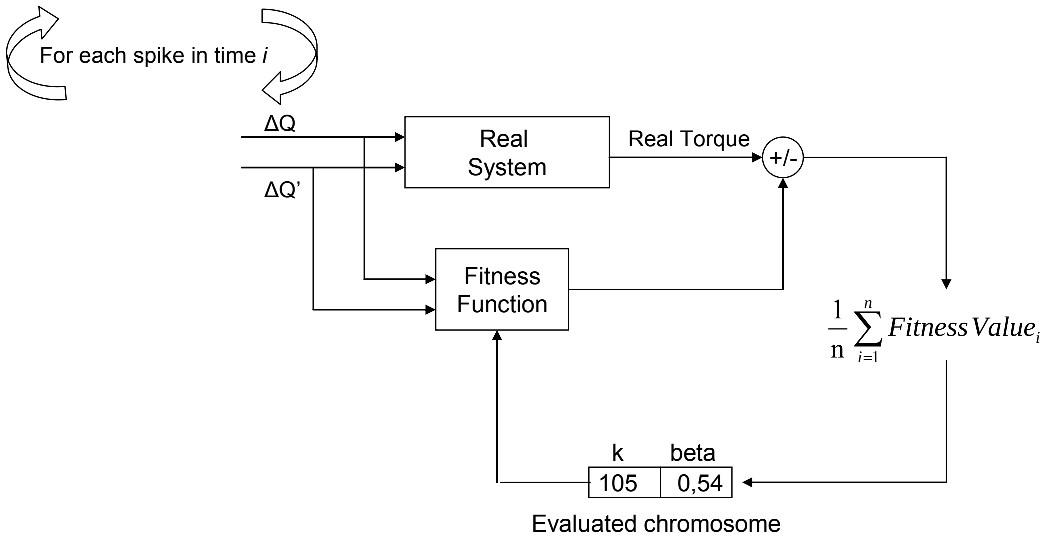

Figure 5 – Evaluation of the fitness of a chromosome.

Initial Population

As stated above, the first step in a Genetic Algorithm is the generation of an initial population of chromosomes. The proposed creates the initial population by setting random values for K_c and B_c for each chromosome of the initial population, restricted to the data types and ranges stated in Section 3.1. Additionally, each created chromosome is evaluated by employing the adopted fitness function.

Selection

Inspired in the process of natural selection, the Genetic Algorithm selects the best chromosomes of the population (those of high fitness) to generate children chromosomes through the crossover and mutation operator. This selection process can be accomplished by several methods. For the algorithm proposed for the identification of the dynamic system, the selection process implemented is denominated Tournament Selection. In this process, three chromosomes of the current population are chosen randomly (with same probabilities), and the chromosome with larger fitness is selected for reproduction (application of the genetic operators). In the proposed algorithm, this process is repeated until the selection of 2 chromosomes that will generate one child chromosome through the application of the genetic operators.

Crossover

The crossover operator is one of the mechanisms of search of Genetic Algorithms to explore unknown areas of the space of the search. The crossover operator is generally applied to a pair of chromosomes, generating one or two children chromosomes. Each one of the parent chromosomes contributes with a piece of genetic material to produce the children chromosomes. In the proposed algorithm, the crossover operator is applied to generate each new individual (100% of probability). The crossover operator developed is an arithmetic operator that combines two parent chromosomes to produce one children chromosome. This operator calculates the average of each gene of the parents, weighted by the fitness value of the chromosome, given by the Equation (6).

$$NewValue = \frac{(g_1 \times f_1) + (g_2 \times f_2)}{(f_1 + f_2)} \tag{6}$$

where g_1 and g_2 are the values of the genes of the parent chromosomes, and f_1 and f_2 are the values of fitness of the parent chromosomes. Figure 6 shows the application of the crossover operator over two selected chromosomes.

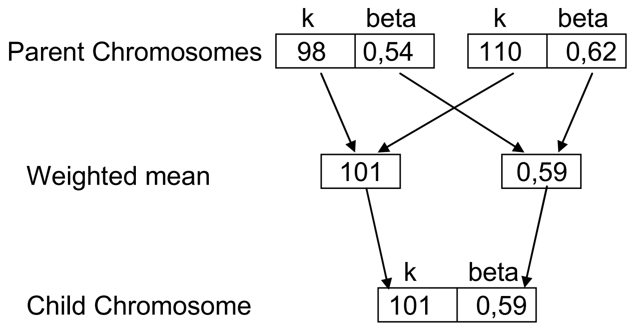

Figure 6 – Crossover operation over two selected chromosomes.

Mutation

After the application of the crossover operator, the mutation operator is applied on the children chromosomes, with a given probability, in order to randomly modify the value of one or more genes. In the proposed algorithm, the mutation operator is applied to a each new individual with probability of 10%. The mutation operator developed randomly chooses a gene of the chromosome and change it value to a new value randomly chosen, restricted to the data types and ranges stated in Section 3.1. Figure 7 shows the application of the mutation operator over one selected chromosome.

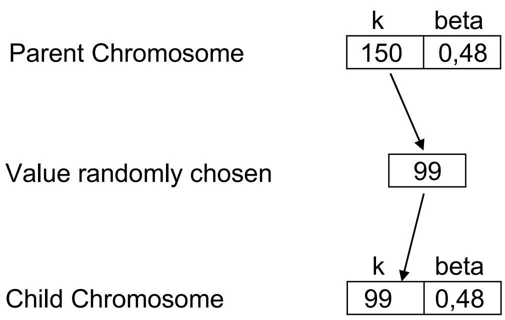

Figure 7 – Mutation operation over one selected chromosomes.

RESULTS

This Section presents an evaluation of the Genetic Algorithm in the identification of the dynamic system stated above. The algorithm was tested in off-line mode, that is, the data from the dynamic system was acquired and stored and then used by the Genetic Algorithm. For the experiments, 2,500 spikes of data from the dynamic system were taken, as stated in the Section Coupling Identification Strategy.

For the experiments, the Genetic Algorithm ran thirty times, in order to obtain a result distribution near to the normal. The algorithm was tested with using mutation rate equal 60%. The crossover operation was applied to all new individual created during the experiments. The population size was set to 10 and the algorithm runs with 200.000.000 fitness evaluations (200.000.000 generations). The authors have found empirically that these settings produce better results, given the convergence characteristic of the algorithm, that is, the convergence of the best fitness in the population per generation, shown in Fig. 8.

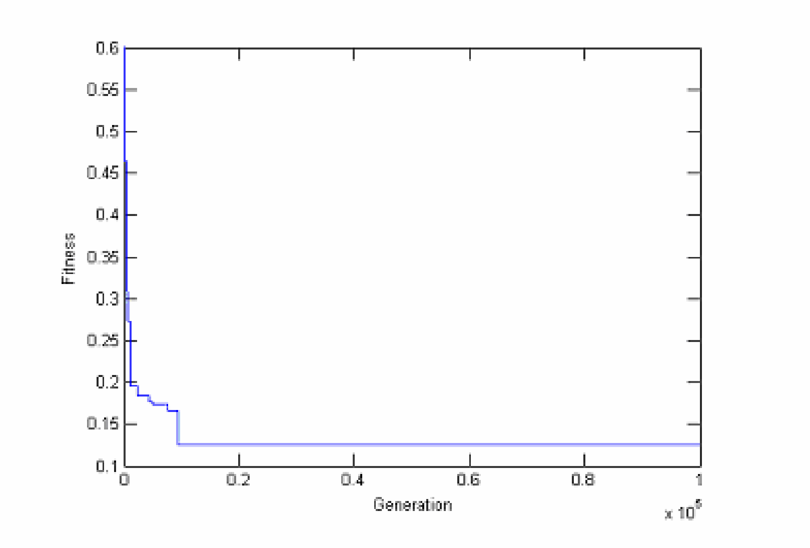

Figure 8 – Algorithm Convergence.

Table 1 shows the results found in the experiments of identification of the parameters K_c and B_c, where Real Parameters are the known parameter values on the real dynamic system, Best Parameters is the best individual found in thirty trials of the algorithm, and Avg and Std are the mean and standard deviation found for the thirty trials.

Table 1 – Results of the evaluation tests.

	K_c [mNm]	B_c [mNms]
Real Parameters	17.75	?
Parameters Distribution (Avg and Std)	17.52±6.62	0.19±0.075

The results suggest that the proposed algorithm may deal with identification of parameter in dynamic systems and may be useful. This methodology also seems proper to work with several parameters setting and different dynamic systems. Moreover, the proposed algorithm has shown to be able to find good values to the parameters of the dynamic system, even though new experimental tests still have to be done to improve the results, specially the standard deviation of K_c.

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