Determining the joints most strained in an underactuated robotic finger by adaptive neuro-fuzzy methodology

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Abstract

The main purpose of this paper is to determine what joints are most strained in the proposed underactuated finger by adaptive neuro-fuzzy methodology. For this, kinetostatic analysis of the finger structure is established with added torsional springs in every single joint. Since the finger’s grasping forces depend on torsional spring stiffness in the joints, it is preferable to determine which joints have the most influence on grasping forces. Hence, the finger joints experiencing the most strain during the grasping process should be determined. It is desirable to select and analyze a subset of joints that are truly relevant or the most influential to finger grasping forces in order to build a finger model with optimal grasping features. This procedure is called variable selection. In this study, variable selection is modeled using the adaptive neuro-fuzzy inference system (ANFIS). Variable selection using the ANFIS network is performed to determine how the springs implemented in the finger joints affect the output grasping forces. This intelligent algorithm is applied using the Matlab environment and the performance is analyzed. The simulation results presented in this paper show the effectiveness of the developed method.

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1. Introduction

To overcome the limited success of the early robotic finger designs due to the cost of the control, a special emphasis has been placed on the reduction of the number of degrees of freedom, thereby decreasing the number of actuators [1]. The strategy for reducing the number of actuators while keeping the hand capability to adapt its shape to the grasped object is referred to as underactuation [2]. Paper [3] shows that underactuation allows reproducing most of the grasping behaviors of the human hand, without augmenting the mechanical and control complexity.

The main goal of this paper was in selection of the most strained joints of the proposed underactuated finger by adaptive neuro-fuzzy methodology. To perform it, kinetostatic analyzing of the finger structure was established with added torsional springs in every single joint. The kinetostatic analysis is based on screw theory [4]. Screw theory [5] can be used to do contact analysis of the underactuated robotic finger. Screw theory uses a matrix representation to describe the degrees of freedom of parts (twist-matrix) and the directions along which the contact forces react (wrench-matrix) [6]. From these screw-matrices it is possible to individuate the exact contact conditions of parts into the assembly.

The proposed finger structure was optimized in article [7] as compliant structure. To perform kynetostatic analysis the compliant finger was converted to the rigid-body counterpart mechanism. The rigid-body finger mechanism was composed of two four bar crank mechanisms, one for each of the two finger phalanges. Since the rigid-body finger mechanism has more degree of freedom than the number of inputs (one), torsional springs were added in each of the finger joint. The stiffness of the implemented springs has different effect on each of two grasping contact forces. To build a finger model with the best features, it is desirable to select and analyze a subset of joints that are truly relevant or the most influential to the finger grasping forces. Hence it should be selected the most strained finger joints during grasping process. This procedure is typically called variable selection [8]. A solution to the variable selection problem could be the utilization of prior...
knowledge in order to screen out the irrelevant variables [9]. However, in most cases, the large number of variables and the complexity of the process dictate the application of more sophisticated methods [10]. In this study, the variable selection procedure was modeled by using adaptive neuro-fuzzy inference system (ANFIS).

Variable searching using the ANFIS network was performed to determine how the finger joints affect the output grasping forces. The kinetostatic model of the finger was used to extract training and checking data for the ANFIS network. ANFIS [11], as a hybrid intelligent system that enhances the ability to automatically learn and adapt, was used by researchers for modeling [12–15], predictions [16–18] and control [19–23] in various engineering systems. The basic idea behind these neuro-adaptive learning techniques is to provide a method for the fuzzy modeling procedure to learn information about data [24,25]. The ANFIS is one of the methods to organize the fuzzy inference system with given input/output data pairs [26,27]. This technique gives fuzzy logic the capability to adapt the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data [28].

2. Materials and methods

2.1. Finger structure topology

Fig. 1 shows the target functions for optimization process of the finger structure. These functions represent two grasping shapes of object, convex (a) and concave (b). The design domain for the unknown mechanism is shown, as well.

Topology optimization of compliant mechanisms can be performed based on continuum, as well as truss and frame, discretization. Here, the continuum discretization was used. The goal of the topology optimization problem is to design a structure that converts an input displacement on a prescribed output displacement. To be able to transfer work from the input port to the output port, the displacement must be performed in a structurally efficient way. Here, the finger contact points with object were assumed fixed. The optimal finger structure topology obtained by optimality criteria method [7] is shown in Fig. 2. The finger behavior verification is shown in Fig. 3 for both grasping shapes, convex (a) and concave (b).

Afterwards FEM simulations were performed in order to make additional improvements of the finger structure. According to the performed FEM simulations, the final structure of the finger mechanism is presented in Fig. 4(a). According to the obtained compliant finger topology the rigid-body counterpart mechanism was designed (Fig. 4(b)). The rigid-body finger mechanism was composed of two four bar compliant mechanisms, one for each of the two finger phalanges. Since the rigid-body finger mechanism has more degree of freedom than the number of inputs (one), torsional springs were added in each of the finger joint [29].

2.2. Kinetostatic analysis of the underactuated finger mechanism

Underactuated fingers generally use elastic elements in the design of their unactuated joints. In underactuated fingers, the actuation wrench $T_a$ is applied to the input of the finger and is transmitted to the phalanges through suitable mechanical elements, e.g. four-bar linkages. Passive elements are used to kinematically constrain the finger and ensure the shape-adaptation of the finger to the object grasped. The type of underactuated two-phalanx finger considered in this paper and all important parameters are illustrated in Fig. 5. The actuation torque $T_a$ is applied to the first link which transmits the effort to both phalanges.

A simple kinetostatic model for the fully adaptive finger with compliant joints can be obtained by adding springs to every joints of the finger. A grasp state is defined as the set of the geometric configuration of the finger and the contact locations on the phalanges necessary to characterize the behavior of the finger. Static model of the finger is built to obtain generic grasping forces exerted by the phalanges where some notations are used:

- $A_h$: the length of the proximal phalanx.
- $B_h$: the length of the distal phalanx.
- $A_t$: the length of the first driving bar.
- $B_t$: the length of the second driving bar.
- $A_t$: the length of the underactuation bar.
- $F_1$: the grasping force on the proximal phalanx.
- $F_2$: the grasping force on the distal phalanx.
- $s_1$: the force arm of $F_1$ with respect to $A_h$.
- $s_2$: the force arm of $F_2$ with respect to $B_h$.
- $\theta_1$: the rotating angle of the first driving bar with respect to the base.
- $\phi_1$: the rotating angle of the proximal phalanx with respect to the base.
- $\phi_2$: the rotating angle of the distal phalanx with respect to the proximal phalanx.
- $k_t$: the stiffness of the torsional spring associated with $\theta$.
- $T_a$: the torque of actuator.
- $T_i$: the torque produced by the decoupling spring $T_i = -k_t \cdot \Delta \theta_i$, $i = 1, 2, 3, 4, 5, 6$
- $\Delta \theta_i$: the $i$th joint coordinate relative to the rest configuration $\theta_{i-1} = 0$.

To determine the contact forces in depend of contact point location and the joint torques inserted by springs the friction must be ignored and grasping object has to be fixed. Equating the input and the output virtual powers of the finger

$$T_a \cdot \omega = F^T \cdot V_c$$

where
\[
T^T = \begin{bmatrix}
T_0 \\
T_1 \\
T_2 \\
T_3 \\
T_4 \\
T_5 \\
\end{bmatrix} \rightarrow \text{input torque vector exerted by the actuator and the springs}
\]

(1)

\[
\omega = \begin{bmatrix}
\dot{\theta}_0 \\
\dot{\theta}_1 \\
\dot{\theta}_2 \\
\dot{\theta}_3 \\
\dot{\theta}_4 \\
\dot{\theta}_5 \\
\end{bmatrix} \rightarrow \text{corresponding velocity vector}
\]

(2)

\[
F^T = \begin{bmatrix}
F_1 \\
F_2 \\
\end{bmatrix} \rightarrow \text{vector of contact forces for two finger phalanges}
\]

(3)

\[
V_c = \begin{bmatrix}
V_1 \\
V_2 \\
\end{bmatrix} \rightarrow \text{vector of the projected velocities of the contact points}
\]

(4)

Fig. 3. Deflections of the optimal finger mechanism for convex (a) and concave grasping shapes (b).

Fig. 4. Compliant finger structure (a) and rigid-body counterpart finger (b).

Fig. 5. Underactuated finger with all parameters for kinetostatic analysis.
Contact point velocities for both phalanges $V_c$ can be expressed as the product of a Jacobian matrix $J$ and the derivatives of the phalanx joint coordinates, i.e.

$$V_c = \begin{bmatrix} V_1 \\ V_2 \end{bmatrix} = J \cdot \begin{bmatrix} \dot{\theta}_1 \\ \dot{\theta}_2 \\ \dot{\theta}_3 \\ \dot{\theta}_4 \\ \dot{\theta}_5 \end{bmatrix}$$

(5)

where

$$J = \begin{bmatrix} s_1 & s_2 & s_3 & s_4 & s_5 \\ s_2 - B_0B_3 \cos(\theta_2 + s_2) & s_2 - B_0B_3 \cos(\theta_3 + s_2) & s_2 - B_0B_3 \cos(\theta_4 + s_2) & s_2 - B_0B_3 \cos(\theta_5 + s_2) & s_2 \end{bmatrix}$$

The first row in the matrix $J_F$ represents the finger mechanism without compliance i.e. only with added spring in one joint to ensure coherent motion. Expressions in the other rows represent added compliance in the other finger joints. For non-compliant mechanism there are expressions only in the first row. Matrix $J_F$ relates vector $\omega$ to the time derivatives of the phalanx joint coordinates as

$$\omega = \begin{bmatrix} \dot{\theta}_a \\ \dot{\theta}_b \\ \dot{\theta}_c \\ \dot{\theta}_d \\ \dot{\theta}_e \end{bmatrix} \rightarrow J_F \cdot \begin{bmatrix} \dot{\theta}_a \\ \dot{\theta}_b \\ \dot{\theta}_c \\ \dot{\theta}_d \\ \dot{\theta}_e \end{bmatrix} = \begin{bmatrix} 1 & B_{12} & 0 & 0 & 0 \\ 0 & 1 & B_{23} & B_{24} & 0 \\ 0 & 0 & 1 & 0 & B_{35} \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

where

$$B_{12} = \frac{P_{31}B_0}{P_{31}B_0 + B_2B_3}$$

$$B_{16} = \frac{P_{31}B_0B_6}{P_{31}B_0B_6 + B_2B_3B_6}$$

$$B_{23} = \frac{P_{32}A_0}{P_{31}B_0}$$

$$B_{24} = \frac{P_{32}B_0 + B_3B_4}{P_{31}B_0B_4}$$

$$B_{35} = \frac{P_{35}B_0}{P_{31}B_0 + B_5B_6}$$

$$B_{36} = \frac{P_{31}B_0B_6 + B_2B_3B_6}{P_{31}B_0B_6 + B_2B_3B_6 + B_3B_4B_5B_6}$$

Using previous equation one can obtain

$$F' = T' \cdot \omega \cdot V_c^{-1}$$

(12)

After some transformations the final expression of the contact forces becomes

$$F' = [C_{11} \ C_{12} \ C_{13} \ C_{14} \ C_{15} \ C_{16}] \cdot J^{-1}$$

(13)

where

$$C_{11} = T_0$$

$$C_{12} = T_1 + \frac{T_0}{P_{31}B_0 + B_2B_3}$$

$$C_{13} = T_2 + \frac{T_0}{P_{31}B_0 + B_2B_3}$$

$$C_{14} = T_3 + \frac{T_0}{P_{31}B_0 + B_2B_3}$$

$$C_{15} = T_4 + \frac{T_0}{P_{31}B_0 + B_2B_3}$$

$$C_{16} = T_5 + \frac{T_0}{P_{31}B_0 + B_2B_3}$$

(13)

By some trigonometric manipulations with the instantaneous centers of rotation for the four-bar linkages, the following relationships can be obtained:

$$\theta_a = \frac{P_{31}B_0}{P_{31}B_0 + B_2B_3} \cdot \theta_1$$

$$\theta_b = \frac{P_{31}B_0}{P_{31}B_0 + B_2B_3} \cdot \theta_2$$

$$\theta_c = \frac{P_{31}B_0}{P_{31}B_0 + B_2B_3} \cdot \theta_3$$

$$\theta_d = \frac{P_{31}B_0}{P_{31}B_0 + B_2B_3} \cdot \theta_4$$

$$\theta_e = \frac{P_{31}B_0}{P_{31}B_0 + B_2B_3} \cdot \theta_5$$

In matrix representation it becomes

$$J_F = \begin{bmatrix} 1 & B_{12} & 0 & 0 & 0 & B_{16} \\ 0 & 1 & B_{23} & B_{24} & 0 & 0 \\ 0 & 0 & 1 & 0 & B_{35} & B_{36} \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$
Finally, the grasping forces on the phalanges are expressed as function of all angles, inserted spring torques in every joint and phalanx contact distances.

\[
F^i = \left[ F_1(\theta_0, \theta_1, \theta_2, \theta_3, \theta_4, T_0, T_1, T_2, T_3, T_4, T_5, s_1, s_2) \right] \\
\left[ F_2(\theta_0, \theta_1, \theta_2, \theta_3, \theta_4, \theta_5, T_0, T_1, T_2, T_3, T_4, T_5, s_1, s_2) \right]
\]

(14)

2.3. Variable selection using adaptive neuro fuzzy inference system

ANFIS can serve as a basis for constructing a set of fuzzy ‘IF-THEN’ rules with appropriate membership function to generate the stipulated input–output pairs. The membership functions are tuned to the input–output data. ANFIS is about taking an initial fuzzy inference (FIS) system and tuning it with a back propagation algorithm based on the collection of input–output data. The basic structure of a fuzzy inference system consists of three conceptual components: a rule base, which contains a selection of fuzzy rules; a database, which defines the membership functions used in the fuzzy rules; and a reasoning mechanism, which performs the inference procedure upon the rules and the given facts to derive a reasonable output or conclusion. These intelligent systems combine knowledge, technique and methodologies from various sources. They possess human-like expertise within a specific domain – adapt themselves and learn to do better in changing environments. In ANFIS, neural networks recognize patterns, and help adaptation to environments. Fuzzy inference systems incorporate human knowledge and perform interfacing and decision-making.

Fuzzy logic toolbox in MATLAB was used for the entire process of training and evaluation of fuzzy inference system. Fig. 6 shows an ANFIS structure for two inputs, the most strained joint of the robotic finger, estimated contact force magnitude on the first or the second phalange. Here, the analysis was constrained on the selection of two of the most influential joint springs on the grasping forces.

In this work, the first-order Sugeno model with two inputs and fuzzy IF-THEN rules of Takagi and Sugeno’s type is used:

If \( x \) is \( A \) and \( y \) is \( C \) then \( f_1 = p_1 x + q_1 y + r_1 \)  

(15)

The first layer consists of input variables membership functions (MFs), input 1 and input 2. This layer just supplies the input values to the next layer. In the first layer every node is an adaptive node with a node function \( O = \mu_{AHD}(x) \) and \( O = \mu_{CD}(x) \) where \( \mu_{AHD}(x) \) and \( \mu_{CD}(x) \) are MFs. In this study, bell-shaped MFs with maximum equal to 1 and minimum equal to 0 is chosen, such as

\[
\mu(x) = bell(x; a_i, b_i, c_i, d_i) = \frac{1}{1 + \left(\frac{x - c_i}{a_i} \right)^{b_i}}
\]

(16)

where \( \{a_i, b_i, c_i, d_i\} \) is the set of parameters set that in this layer are referred to as premise parameters. In this layer \( x \) and \( y \) are the inputs to nodes and they represented the stiffness of the most influential torsional springs.

The second layer (membership layer) checks for the weights of each MFs. It receives the input values from the 1st layer and acts as MFs to represent the fuzzy sets of the respective input variables. Every node in the second layer is non-adaptive and this layer multiplies the incoming signals and sends the product out like

\[ w_i = \frac{\mu_{AHD}(x) \times \mu_{CD}(y)}{\sum_{i=1}^{3} \mu_{AHD}(x) \times \mu_{CD}(y)} \]

Each node output represents the firing strength of a rule.

The third layer is called the rule layer. Each node (each neuron) in this layer performs the pre-condition matching of the fuzzy rules, i.e. they compute the activation level of each rule, the number of layers being equal to the number of fuzzy rules. Each node of these layers calculates the weights which are normalized. The third layer is also non-adaptive and every node calculates the ratio of the rule’s firing strength to the sum of all rules’ firing strengths like

\[ w_i^0 = \frac{w_i}{\sum_{i=1}^{3} w_i} \]

The outputs of this layer are called normalized firing strengths.

The fourth layer is called the defuzzification layer and it provides the output values resulting from the inference of rules. Every node in the fourth layer is an adaptive node with node function \( O_i^f = w_i^0 \times f_i(p, x + q_i y + r_i) \) where \( \{p_i, q_i, r_i\} \) is the parameter set and in this layer is referred to as consequent parameters.

The fifth layer is called the output layer which sums up all the inputs coming from the fourth layer and transforms the fuzzy classification results into a crisp (binary). The single node in the fifth layer is not adaptive and this node computes the overall output as the summation of all incoming signals

\[ O_i^f = \sum_{i=1}^{3} w_i^0 \times f_i = \frac{\sum_{i=1}^{3} w_i \times f_i}{\sum_{i=1}^{3} w_i} \]

(17)

The hybrid learning algorithms were applied to identify the parameters in the ANFIS architectures.

3. Results

A comprehensive search was performed within the available inputs to select the set of inputs (most strained finger joints) that most influence the output parameters (grasping forces). Essentially, the functions build an ANFIS model for each combination and trains it for one epoch and reports the performance achieved. In the beginning, the one most influential input in predicting the output was determined (Figs. 7 and 8). It can be seen that on the both grasping forces joint spring torque 2 has the most influence. This indicates that the input variable joint 2 is the most influential for grasping force 1 prediction and also for grasping force 2 prediction. The left-most input variable in Figs. 7 and 8 has the least error or the most relevance with respect to the output. The plot and results from the function clearly indicates that the input attribute that the input variable joint 2 is the most influential for grasping force 1 prediction and also for grasping force 2 prediction. The training and checking errors are comparable, which indirectly suggests that there is no overfitting. This means it can be increased and explored to select more than one input parameter to build the ANFIS model. It can be simply selected joint 2 and torque 5 (J-2 and J-5) for grasping force 1 and spring torque 2 and torque 3 (J-2 and J-3) for grasping force 2 since they have the least errors as shown in the plots. However, this will not necessarily be the optimal combination of two inputs that result in the minimal training error. To verify this, it can be performed search for the optimal combination of 2 input parameters. The results in Tables 1 and 2 indicate that J-2/J-5 form the optimal combination of two inputs attributes for grasping force 1 prediction and J-2/J-3 for grasping force 2 predictions. It may not be appropriate to use more than two inputs for building the ANFIS model. However in Tables 1
and 2 is shown results of selecting three inputs, in which combination J-2/J-4/J-5 are selected as the best combination of three input variables for contact force 1 prediction and J-1/J-2/J-3 for contact force 2 prediction. Although the minimal training error was much minimized for better generalization, a model with a simple structure was always preferred. Therefore emphasis will be focused to the two-input ANFIS for further examination. The selected input parameters from the original training and checking datasets were then extracted.

Fig. 9 shows the locations of the two most strained finger joints for the both grasping forces. The contact locations were fixed during the variable selection procedure and it was in the middle of the both finger phalanges.

The ANFIS predictions can be compared against a linear regression model by comparing their respective root mean square values against checking data. For contact force 1, ANFIS regression error was 0.000 and the linear regression error was 0.001 and for contact force 2 it was 0.005 and 0.109, respectively. It can be noticed that the ANFIS model outperforms the linear regression model.

Table 1
ANFIS regression errors for contact force 1.

<table>
<thead>
<tr>
<th></th>
<th>Contact force 1 training error</th>
<th>Contact force 1 checking error</th>
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<tbody>
<tr>
<td>J-2</td>
<td>0.2977</td>
<td>0.2914</td>
</tr>
<tr>
<td>J-2/J-5</td>
<td>0.2017</td>
<td>0.2348</td>
</tr>
<tr>
<td>J-2/J-4/J-5</td>
<td>0.0957</td>
<td>0.0806</td>
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</table>

Table 2
ANFIS regression errors for contact force 2.

<table>
<thead>
<tr>
<th></th>
<th>Contact force 2 training error</th>
<th>Contact force 2 checking error</th>
</tr>
</thead>
<tbody>
<tr>
<td>J-2</td>
<td>0.1793</td>
<td>0.1763</td>
</tr>
<tr>
<td>J-2/J-3</td>
<td>0.1573</td>
<td>0.1629</td>
</tr>
<tr>
<td>J-1/J-2/J-3</td>
<td>0.1349</td>
<td>0.1516</td>
</tr>
</tbody>
</table>

Fig. 7. Every input parameter’s influence on contact force 1.

Fig. 8. Every input parameter’s influence on contact force 2.

Fig. 9. Two most influential joint springs on the both grasping forces separately.

Fig. 10. ANFIS predicted relationship between the most strained finger joints and contact force 1.

Fig. 11. ANFIS predicted relationship between the most strained finger joints and contact force 2.
The ANFIS input–output (decision) surface of the model for contact force 1 is shown in Fig. 10. The input–output surface shown is a nonlinear and monotonic surface and illustrates how the ANFIS model will respond to varying the joint springs 2 and 5 torques or how the torques affect the both contact forces. Fig. 11 shows the ANFIS decision surface for the contact force 2 predictions.

4. Conclusion

Kinetostatic analysis of an underactuated finger was established on a two-phalanx linkage-driven underactuated rigid finger with concentrated compliance inserted in all its joints. The method of obtaining the analytical expressions of the contact forces generated by this type of finger was emphasized. What is evident from the results presented in the paper is the significant increase in analysis complexity: the kinetostatic expressions become rapidly cumbersome. The thorough analysis of underactuated fingers without compliance is already challenging and adding compliance only amplifies the challenge. Both finger phalanges were designed as a four-bar linkage mechanism.

Several parameters (input variables) define grasping contact forces, such as contact locations and joint spring torque. The inclusion of many input variables, however, has a number of drawbacks: explaining the model is difficult, irrelevant variables act as noise, the generalization capability of the model deteriorates, and data collection can be much more costly. It would therefore be useful to conceive methods that allow reducing the number of input variables, thus reducing the model complexity and possibly gaining better predictive performance and insight into the relevance of the variables for the problem.

Therefore, in this study a variable selection method using the ANFIS network was performed to determine how the implemented joint spring torques affect the grasping contact forces. In other words, the main goal was to locate which gripper joints become strained the most during the grasping process. Two selected parameters served as inputs to the ANFIS network in order to build a regression procedure for joint spring torque and grasping contact forces separately.

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