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Neural Network based Pulley Friction Compensation for Tension Control of a Cable-Driven Parallel Robot

Jae-Hyun Park, Jinlong Piao, Eui-Sun Kim, Eunpyo Choi, Jong-Oh Park*, *Member, IEEE*, and Chang-Sei Kim*, *Member, IEEE*

Abstract— **Cable driven parallel robots (CDPRs) have several advantages compared to conventional parallel robots such as large workspace, high dynamics, and high payload by virtue of elastic lightweight cable links instead of existing rigid links. However, the CDPRs have a force and position control problem caused by nonlinearity and uncertainty in pulleys and elastic cable. Notably, the friction between pulley and cable brought significant force differences between winch-motor and end- effector. In this paper, we present the pulley friction compensation method to obtain direct tension at the end-effector without utilizing additional force sensor by using an Artificial Neural Network (ANN). The proposed control algorithm which is composed of a PID-controller to track the desired tension and an ANN to estimate unmodeled force differences between winch-motor tension and the end-effector tension. The ANN could estimate the friction in the pulley used for the CDPRs based on the measured datasets of the elastic cable for the given experimental condition. The experimental results showed that pulley friction could be remarkably compensated during single cable tension control.**

I. INTRODUCTION

Cable-driven parallel robots (CDPRs) have lots of advantages such as large workspace, high dynamic response, and high payload compared to conventional robots, because elastic lightweight cable links are used for robot actuators instead of rigid links. The CDPRs are mainly composed of cables, winches, motors, end-effector, and pulleys [1][2][3]. The CDPR has attracted high attention from the industrial field where high dynamic features and accurate position control performances are required in a wide workspace, e.g., construction [4][5], large robotic camera [6], high-speed cable robot [7]. Moreover, these CDPRs have been utilized to achieve several specific purposes as surgical robot [8], haptic interaction related to the medical field [9][10]. For the particular applications mentioned above, the cable force control to prevent cable damages or inaccurate control performance from an excessive input tension to an end-effector is an important issue. And thus, actual cable tension measurement is essential for the force control of the CDPRs [8][9][10].

However, it is crucial to measure actual cable tensions because of CDPR's structural component designed to guide the cable from winch-motor to the end-effector. In general, force sensors to measure the cable tension are primarily connected to winch-motor which can allow measuring the force directly from a winch for moving cables [11], where the cable tension discrepancy between the actual force acting on the end effector and measured tension arises. The main differences come from unexpected friction effects at the CDPRs pulleys in addition to the winches for operating the motor, the motor, and the gearbox [12]. Among them, the pulley plays an important role for the CDPRs where changing a direction of the cables to necessary locations without an inconvenient movement of components such as heavy motors and winches. For common CDPRs, the multiple pulleys are directly connected with the respective cables. According to some research papers about the pulley friction indicated that variable has a substantial impact on the force measurement [12][13][14].

Because of the considerable pulley friction effect, there have been many types of research about friction compensating methods. Miyasaka et al. developed a model of cable-pulley interaction based on Coulomb and viscous friction theory by experimental verification for RAVEN II surgical robot. The result indicates that the friction effect of the pulley exclusively affects to the measured cable tension [8]. Kraus et al. also measured the cable tension from the winch-integrated cable force sensor and developed a pulley friction model based on Coulomb model and Dahl model for 6-DOF Mini-IPAnema cable robot. They also developed an algorithm and verified their performance by compensating approximately 70% of the existing pulley friction effect [13]. Although many researchers had tried to compensate the pulley frictions based on the conventional friction modeling, the proposed models were still complicated to represent the unpredictable non-linear behavior of the cable. They need complicated equations and lots of parameters for establishing applicable models. Besides, there were slight vibration because of the limitation of modeling non-linear system when they control the end-effector [8][13][14].

In order to avoid complicated friction models, we suggest ANN approach to compensate frictions in the pulleys of CDPRs. By using the ANN, if inputs and desired outputs are given, the relationship between the inputs and the desired outputs is estimated by adjusting the weights by itself through the back-propagation process without establishing complicated friction modeling. Recently, ANN has been applied to solve complicated forward and inverse kinematics as well as speech recognition, language understanding, nonlinear behavior modeling [15][16][17]. In this paper, we proposed a novel approach of compensating pulley friction effect using the ANN that can consider non-linear behavior of the cable. In the designed ANN, a cable length, a linear velocity, a linear acceleration, and the cable tension near to the pulley are used as the inputs and the cable tensions of the end-effector edge point are set as the desired

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output. Eventually, through the ANN, we could obtain the end-effector side cable tension form the winch-motor side cable tension by compensating the mechanical frictions at the pulleys.

This paper is organized as follows; Inverse kinematics and force equilibrium of the CDPRs are shown in Section 2. The effects of the pulley friction with system description are explained in Section 3. The proposed algorithms based on the ANN will be described in section 4. Experimental setup, results, and analyses of experimental data will be presented in Section 5. Discussions with future work and concluding remark will be made in Section 6.

II. Kinematics and Force Equilibrium

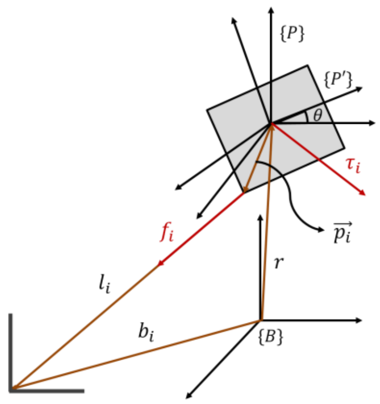


Fig. 1. A kinematic geometry of a single cable driven robot : The vectors for explaining inverse kinematics and force equilibrium are depicted.

A schematic of the geometry of the CDPRs to derive kinematic equations and force equilibrium is shown in Fig. 1. Inverse kinematics which can calculate each cable length from the given end-effector position is shown as follows:

$$l_i = \|\vec{b}_i - \vec{r} - R\vec{p_i}\|_2 \qquad (1)$$

where $\vec{l_i}$ is a cable length vector, $\vec{b_i}$ is a robot frame vector, $\vec{p_i}$ is an End-effector position vector, R is a rotation matrix, and $\vec{r}$ is a vector of connecting a middle point of the end-effector in a global coordinate system. The cable length vector $\vec{l_i}$ can be calculated from the vectors as illustrated in Fig. 1. And the force equilibrium to derive cable force distribution of the CDPRs is given as follows. m is the number of the cables.

$$\sum_{i=1}^{m} \vec{f_i} + \vec{f_p} = 0 \ \text{, and} \quad \sum_{i=1}^{m} \vec{p_i} \times \vec{\tau_p} = 0 \qquad (2)$$

where $\vec{f_i}$ is a cable tension vector, $\vec{f_p}$ is an external force vector including a gravitational force, $\vec{\tau_p}$ is a torque vector caused by an external force, and $\vec{p_i}$ is the edge point vectors of the end-effector. Then, the cable tension vector $\vec{f_i}$ can also be obtained by,

$$\vec{f_i} = f_i \cdot \frac{\vec{l_i}}{\|l_i\|_2} = f_i \cdot \vec{v_i} \qquad (3)$$

By combining the equation (1), (2), and (3), force distribution equations with the structure matrix A^T can be derived as follows.

$$\begin{bmatrix} \vec{v_i} & \cdots & \vec{v_m} \\ \vec{p_i} \times \vec{v_i} & \cdots & \vec{p_m} \times \vec{v_m} \end{bmatrix} \begin{bmatrix} f_1 \\ \vdots \\ f_m \end{bmatrix} + \begin{bmatrix} \vec{f_p} \\ \vec{\tau_p} \end{bmatrix} = 0, \text{and } \ A^T f + w = 0 \qquad (4)$$

From equation (4), we can compute the desired cable forces for the given wrench space forces.

III. Pulley Frictions

A. Location of the loadcell

CDPRs are mainly composed of cables, winches, motors, end-effector, and pulleys. The pulley plays an important role in the CDPRs where the pulleys change the direction of the cables to the necessary locations without an inconvenient movement of its heavy components. Typically, the loadcell is primarily connected to a pulley to measure the cable tension from near to the winch as shown in Fig. 2 (a)-(b). Hence, the tension measurements are commonly different with the measured cable tension at the end-effector significantly, mainly because of frictions between cable and pulleys. These frictions have been compensated by modeling technique regarding the behavior of the cable.

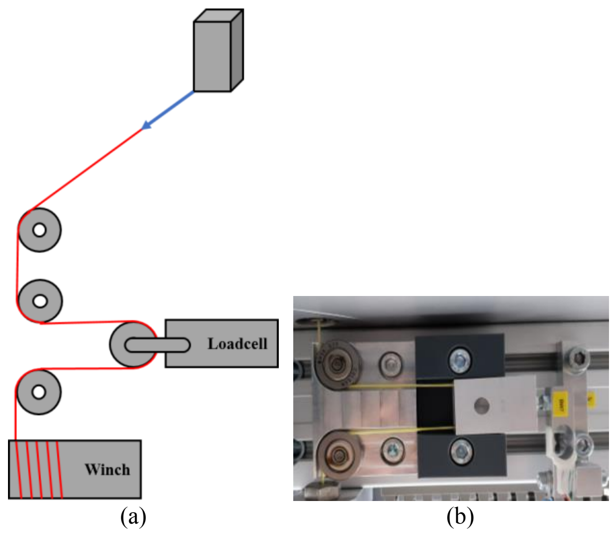


Fig. 2. The location of loadcell for measuring cable tension: The loadcell is typically connected with the pulley. (a) Schematic diagram, (b) Actual photo.

B. Conventional friction modeling methods

Previously, to compensate the friction effects on the force control of the CDPRs, several basic mechanical friction models were utilized. In Fig. 3, The normal friction force can be derived from both friction forces which are directly applied to pulley using a cosine law, α_j is a wrapping angle of between the cable and the pulley.

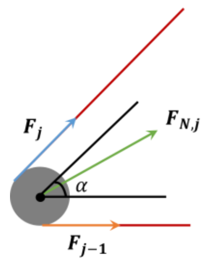


Fig. 3. A schematic diagram of applied friction force to the pulley for calculating a normal vector of the friction vectors : There are two friction force vectors applied onto the pulley.

$$F_{N,j} = \sqrt{F_{j-1}^2 - 2F_{j-1}F_j\cos(\alpha_j) + F_j^2} \tag{5}$$

To simplify the complexity in equation (5), the normal vector was approximated to the equation below by dividing summation of both friction forces.

$$F_{N,j} \approx \frac{F_{j-1}+F_j}{2}\sqrt{2(1-\cos(\alpha_j)} \tag{6}$$

One of the famous friction models is a coulomb friction model which can be used in a static case, μ_j is the coulomb coefficient of friction as following.

$$F_{c,j} = \mu_j F_{N,j} \tag{7}$$

Another famous friction model for a dynamic motion is Dahl friction model that can be used for compensating a hysteresis effect by,

$$\frac{df}{dx} = \sigma\left[1 - \frac{f}{f_c}\mathrm{sgn}(v)\right]^{\alpha} \tag{8}$$

This equation mainly describes a hysteresis area. α defines the shape of the hysteresis area and σ is a design parameter of a stiffness. The final equation for the Dahl model is given below.

$$F_d = F_f\mathrm{sgn}(v_k) + \left(F_0 + F_f\mathrm{sgn}(v_i)\right)e^{-\frac{\sigma}{F_f}|l-l_0|} \tag{9}$$

where F_0 is a friction force of the Dahl model, l_0 is an actual cable length, and v is the linear velocity of the cable.

According to the existing pulley friction modeling methods (5)-(9), complicated equations with parameters to be estimated were exist. In order to be free of models and uncertainties in parameters, we use the ANN which can simply estimate the output tension for the given inputs provided by available sensor measurements.

IV. Artificial Neural Network

The Artificial Neural Network (ANN) theory is motivated by a neuron in the human brain. In this study, to derive a simple method for the friction compensation of the CDPRs, we designed the ANN circuits in 3 layers (input layer, hidden layer, output layer). We set the output layer as individual cable tension and the input layer as a measured status signal of the CDPRs from the available sensors equipped in.

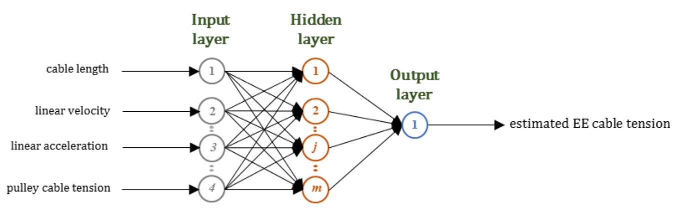


Fig. 4. Structure of the proposed ANN

As shown in Fig. 4, The given inputs in the input layer are the cable length, the linear velocity of cable, the linear acceleration of cable, and the cable tension near to the pulley. And, the output from the output layer is the cable tension near to the end-effector.

A. Influence factors to pulley friction

Fig. 5 shows the experimental setup to identify the influence factors to the pulley friction. We utilized loadcells to measure cable tensions through a force to tension converting mechanism, so called T-configuration as shown in Fig. 5. For training sets for the ANN, we incorporated an additional loadcell to the end of the cable that is directly connected to the end-effector. Since the actual control force required for the force control is the end-effector connected force, the added on loadcell measurements can be gold standard measurements to be compared with our estimated force via the ANN algorithm.

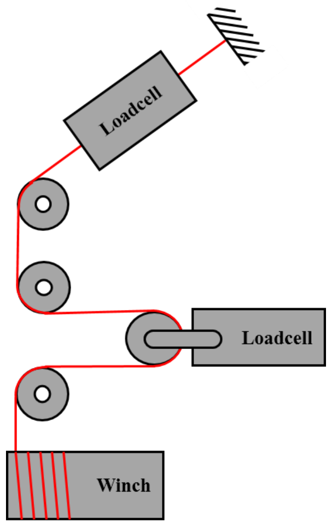
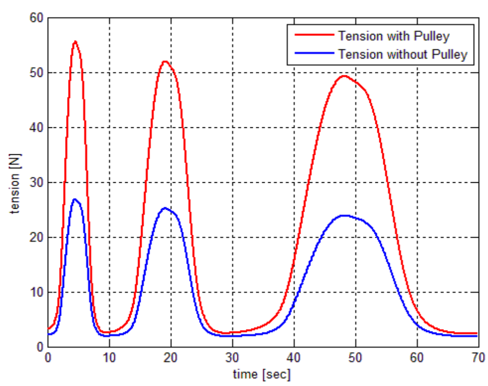
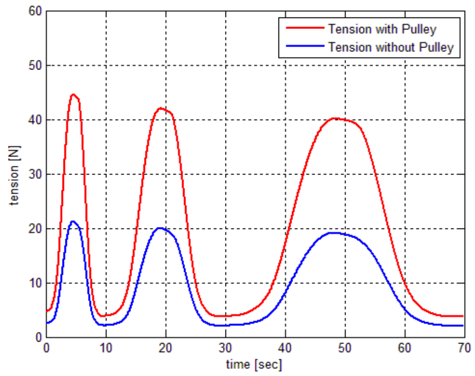


Fig. 5. Schematic diagram of an experimental setup for finding the factors which can affect the pulley friction of a single cable : The single cable was fixed with a frame instead of the End-effector.

Fig. 6 depicts the experimental results of the measured tension while winding and unwinding the cable to a certain displacement. The graphs are drawn with the measured cable tension near to the pulley (red line) and the frame (blue line). The same experiment was performed three times with the different velocities, and accelerations. The cables were wounded and unwounded while 10sec, 20sec, and 40sec.



(a)



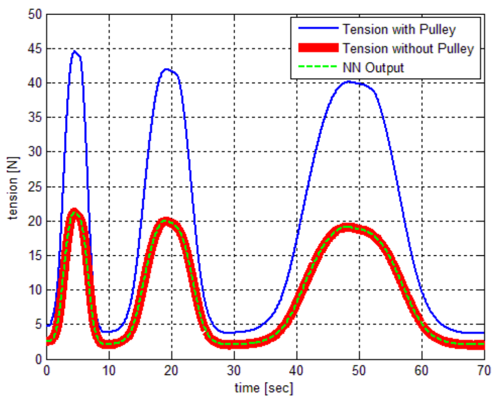
(b)

Fig. 6. Experimental results to find the variables which can affect the pulley friction : (a) cable 1 and (b) cable 2. The cables were wounded and unwounded to a certain displacement. The graphs are drawn with the measured cable tension near to the pulley (red line) and the frame (blue line).

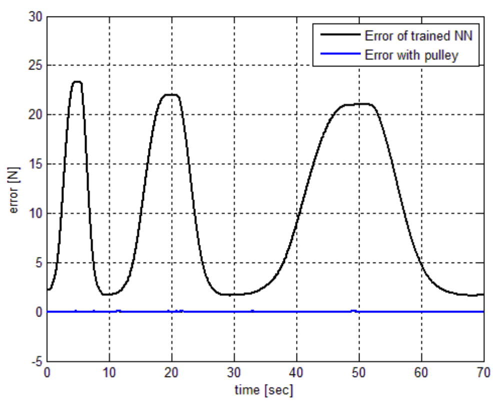
The initial cable length of Fig. 6(a) was shorter than that of Fig. 6(b). By comparing Fig. 6(a) and Fig. 6(b), the measured cable tension of the cable 1 is higher than the cable 2. This result means that the cable tension is being differed with its own length. Also, by seeing both graphs, the measured cable tension is being differed according to its linear velocity and linear acceleration even if the displacements are same. These results mean that the linear velocity, the linear acceleration, and the cable length affect the pulley friction.

B. Proof of the factors

In Fig. 7, An experimental result for proving the identified influence factors which may affect the pulley friction using the trained ANN is shown. The trained data is same as Fig. 6, (a)-(b). Almost 8000 samples were used for training.



(a)



(b)

Fig. 7. An experimental result for proving the founded factors which may affect to the pulley friction using the trained ANN : An experimental setup for training data was thoroughly same with Fig. 5. (a) Evaluation of the accuracy of the trained ANN, (b) Comparison of pulley friction and error between the desired output and estimated output.

The training was performed while winding and unwinding the cable to a certain displacement with different velocity and acceleration. The above graph (Fig. 7(a)) shows that the ANN mostly estimates the cable tension which is near to the frame because desired cable tension (Tension without pulley) and estimated cable tension from the ANN (NN output) is almost same. By following the graph drawn below (Fig. 7(b)) for comparing the size of pulley friction and calculated error between desired cable tension and estimated cable tension, it shows that the most of pulley friction remarkably decreased because the calculated error is very small.

V. Experimental Results and Limitations

A. Block diagram of the cable tension controller

To verify the control performance improved, we designed a force controller as shown in Fig. 8. In our proposed ANN structure, inputs are the measured pulley cable tension, the linear velocity of cable, the linear acceleration of cable, and the cable length. The output is the estimated frame cable tension.

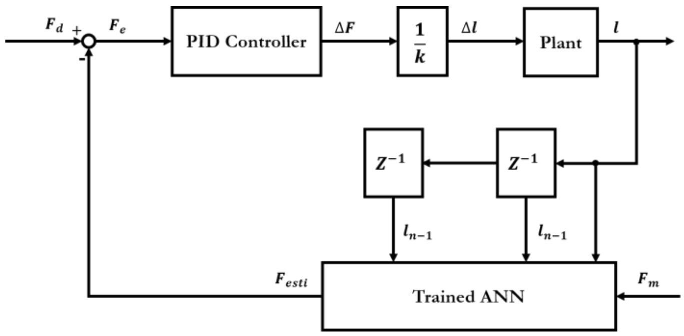


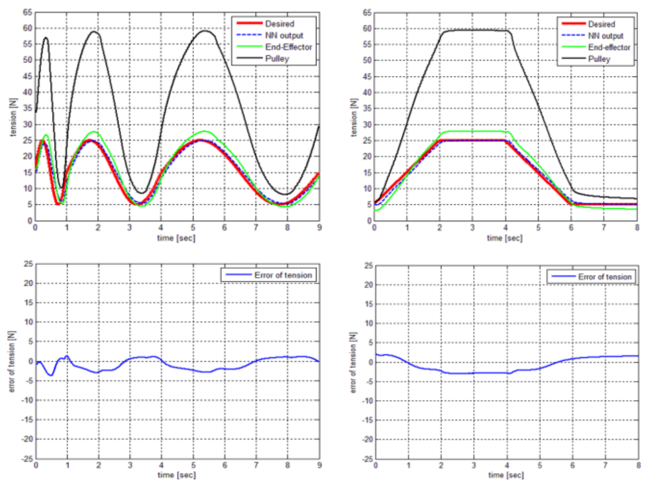
Fig. 8. Block diagram of a cable tension controller

According to our proposed algorithm, if the desired frame cable tension is given, the error between the desired frame cable tension and the estimated frame cable tension from the ANN is derived. And then, the calculated Δl from the PID-controller and the stiffness model is given as input to the system to perform tension control of the frame. The controller is realized with a Beckhoff PC, TwinCAT 3.1 CNC. Its sampling time is 10 [ms].

B. Result

Fig. 9 shows the result of the control experiment from the proposed control algorithm in Fig. 8. The desired force trajectory were a sine input and a trapezoidal input. The experiments were performed only with given pulley cable tension as the input for controlling the tension of a single cable.

Fig. 9(a) shows the experimental result with the sine input, and Fig. 9(b) shows the experimental result with the trapezoidal input. In the graphs above, the desired output (red line), the estimated output from the ANN (blue dotted line), cable tension near to the frame (green line), the measured pulley cable tension (black line) are shown. Also, In the graphs below, the error of tension between estimated cable tension and measured cable tension (blue line) is drawn. For the sine input, the three different frequencies are used. The frequencies were 1 [Hz], 1/3 [Hz], 1/5 [Hz]. For the trapezoidal input, the duration of the ramp input was 2 [sec]. After rising the force input, the force input is sustained while 2 [sec], and finally decreases to initial force input size at 0 [sec].



(a) (b)

Fig. 9. An experimental result of a tension of the cable : (a) a sine input and (b) a trapezoidal input.

According to those results, Firstly, there was a significant error between cable tension near to the pulley and the frame. Secondly, after compensating pulley friction through the trained ANN, the error considerably decreased shown as Fig. 9(a)-(b). According to the drawn error graphs after performing the tension control of the single cable as below between estimated output and measured output, the mean error is 0.82 [N], and the original mean error before compensating the pulley friction is 18.3 [N]. Hence, the error was compensated by nearly 95%. These analyses show that the ANN approach is a suitable solution for compensating pulley friction as we assumed.

VI. CONCLUSION

In this work, we analyzed the effect of our proposed Artificial Neural Network (ANN) approach for compensating the pulley friction. The Cable-Driven Parallel Robots (CDPRs) are mainly composed of the cables, the winches, the motors, the end-effector, and the pulleys. In case of the pulley plays an important role for the CDPRs where a changing direction of the cables to necessary locations without an inconvenient movement of heavy components. But, this pulley commonly affects dominantly measured End-effector cable tension. Therefore, many researchers had tried to compensate this significant error, but they need complicated equations, lots of parameters for modeling the non-linear behavior of the cable. For this reason, we utilized the ANN approach which can easily estimate the relationship with desired output and inputs by adjusting weights itself called as the back-propagation process without the complicated equations and lots of parameters.

For realizing our proposed ANN approach, Firstly, we had found the factors which can affect the pulley friction such as the cable length, linear velocity, and linear acceleration of the cable with the experiment by winding and unwinding the single cable to the certain displacement. By following this experiment, we choose the cable length, the linear velocity, the linear acceleration, and the pulley cable tension for inputs for the ANN. Secondly, for proving the effect of the proposed ANN approach, we evaluated the accuracy of the trained ANN while performing a similar experiment with the previous one by winding and unwinding the single cable to a certain displacement. The experimental results showed that the pulley friction remarkably decreased by showing significantly small error between desired cable tension and estimated cable tension. Finally, we tested the proposed control algorithm for performing tension control of the single cable by using the sine input and the trapezoidal input. By analyzing the results, the pulley friction was 95% compensated, and there was a slight mean error of 0.82 [N] between estimated cable tension and measured cable tension while following desired force input.

One of the reasons could be the untrained data such as sine input and trapezoidal input was given because the trained data into the ANN was just different velocity and acceleration. Another reason could be the inertia of the motors while changing the direction of the force input to the system. Hence, one of the future works is to come up with ideas for making the suitable trajectories to get extensive and quality data by using a variety of force inputs. Another future work is to make the smooth velocity profile for preventing the occurrence of inertia of the motors. The other future work is to extend the single cable system to the CDPRs which have 8 cables for accomplishing an admittance control.

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