Proceedings of the 7th RSI
International Conference on Robotics and Mechatronics (ICRoM 2019)
November 20-21, 2019, Tehran, Iran

A Calibration Framework for Deployable Cable Driven Parallel Robots with Flexible Cables

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***Abstract*—Due to their simple and inexpensive structures, suspended cable driven parallel robots are suitable choices for many real-world applications. However, only when the accurate kinematic parameters are available, can we control the robot to the best of its abilities. This is specially a stringent requirement for fast deployable cable driven robots. With the aim of addressing these needs, in this paper we propose an effective framework for calibrating the kinematic parameters of suspended cable driven parallel robots with no requirements for expensive tools and measurement devices. Moreover, the proposed algorithm utilizes the existing force sensors in the cable robot to nominate the best set of data for calibration. The integrity and effectiveness of this framework is reported through simulation and practical experiments, which verifies promising horizons for deployable real-world applications.**

***Index Terms*—Calibration, Optimization, Cable Robots, Sensor Fusion, Identification**

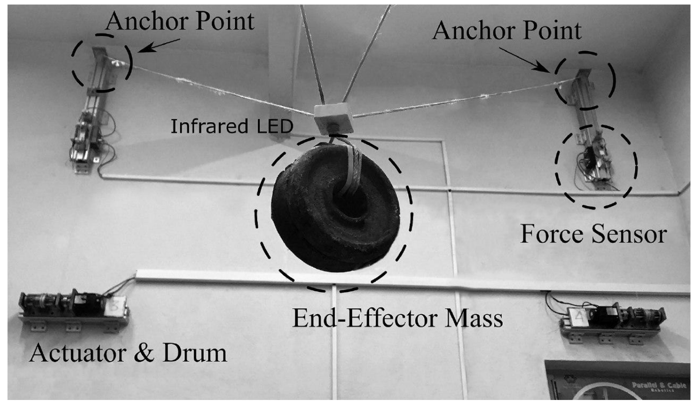

Figure 1: ARAS-CAM robot developed by Advanced Robotics and Automated System (ARAS) research group.

I. Introduction

Owing to their simple structures and low costs, cable driven parallel manipulators are strong candidates for many industrial and civil applications. Being in the category of parallel robots, these manipulators inherit distinct properties such as high acceleration, strength and accuracy [1]. Moreover, cable robots can cover a much larger work-space compared to other types of robotic manipulators. The combination of these features has made them a solution of choice for applications such as rescue missions [2], radio telescopes [3] and movie industries [4]. These manipulators can be classified into two classes of fully constrained and suspended types. Due to lower cable interference with environment and less expensive structures, Suspended Cable Driven Parallel Robots (SCDPR) are attractive choices for real-world applications.

One of the most important factors for achieving a suitable performance in controlling these robots is the accuracy of the kinematic parameters. Furthermore, in many applications the robot is required to be quickly installable at a new site. This often implies that the kinematic parameters will be contaminated with high amounts of uncertainties.

Therefore, the subject of dealing with uncertainties and performing calibration has been of great interest to researchers. This has been dealt with through two main approaches. The first category tries to cope with it through applying robust controller schemes [5], [6]. Even though this methods requires no meticulously accurate installation procedure, their performance and accuracy are bounded and the impact of uncertainty can not be completely eliminated. On the other hand, the second category tries to eliminate the sources of uncertainty all at once through performing calibration routines on the robot [7]–[11].

The calibration itself can be categorized into two classes. The first category tries to augment the models by adding previously unmodeled behaviors. For example, [12] provides an accurate model for the pulley structures. However, in this work cable lengths are the only modality exploited for performing calibration and the phenomena of loosened cables and their elongations due to flexibility are not considered. Furthermore, it is assumed that the cable's absolute length is measurable which is not true for most applications where incremental encoders are used.

The other methods focus on exploiting new types of sensors for performing calibration. For instance, the authors in [13] present a single dimensional length measurement tool for calibrating a cable robot. However, the working constraints of this sensor curbs the feasibility of this method in real-world scenarios.

The gap in all of these researches is that sensors in a cable driven robot do not provide reliable measurements globally. For example, in near singular configurations cables get loosened which leads to inaccurate length measurements by the encoders. To address this, we propose using force modalities to detect these situations and weight the measurements accordingly.

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The contributions of our work are as follows. First, we present a calibration algorithm that exploits the data from multiple modalities to achieve a more robust and accurate calibration system for suspended cable-driven robots. Second, we offer a novel initialization procedure that yields proper initial values to be used by the calibration algorithm, which leads to higher computational efficiency and robustness. And third, we present an affordable IR-tracker system to be used as a calibrator tool within our framework. To the best of our knowledge, this approach of multi-sensor calibration and initial point estimation for a cable-driven parallel robot has not been addressed before in the literature.

This paper is organized as follows. In section 2 we briefly present the kinematic model of our robot and propose our calibration methodology. Following on that, we introduce our initialization algorithm in section 3. Next in section 4, we present our experimental results. Finally, we provide the concluding remarks and future works in section 5.

II. Methodology

Basically, the goal of calibration is to exploit the difference between responses coming from the real-world system and its corresponding model to achieve a more accurate estimate for the parameters. In the case of ARAS-CAM robot, the dynamics may be reduced to a free mass in 3D space under the influence of Cartesian forces applied to it by the cables. Since the end-effector's mass as the major dynamic parameters is easy to measure, the focus of this paper is on kinematic calibration. In what follows we first introduce the inverse kinematic formulation of ARAS-CAM robot and then we propose the calibration algorithm.

A. ARAS-CAM Kinematic Model

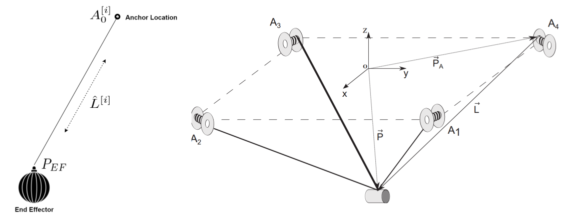
As presented in detail in [14], the forward and inverse kinematic equations of ARAS-CAM can be easily obtained trough kinematic loop closure. Here, we need the inverse kinematic equations to construct the calibration algorithm. Based on the schematic illustrated in Figure 2b, the inverse kinematic can be expressed using the following equation:

$$L^{[i]} = \|P - A^{[i]}\| \tag{1}$$

Where $L^{[i]}$ is the cable length between the end-effector and anchor point i. Often in a real robot, this quantity is measured using incremental encoders installed on the drums. Thus, Equation (1) should be augmented as follows:

$$L^{[i]} = \|P - A^{[i]}\| + L_0^{[i]} \tag{2}$$

Where $L_0^{[i]}$ is the initial length ambiguity due to the incremental encoders. Identifying the kinematic parameters is of paramount importance since any mismatch between them and their real values causes wrong mappings between work and joint space variables which eventually leads to non-vanishing errors during robot's operation.



(a) Single Cable. (b) Robot structure.

Figure 2: The schematic diagram of the ARAS-CAM SCDPR.

B. Calibration Framework

Calibration is often formulated as a nonlinear optimization problem where the goal is to minimize the residue between what the model predicts for the output of a sensor and the real corresponding measurement. The sensor measurement can be modeled using a state dependent nonlinear function $f(X)$ where X is vector comprised of the kinematic parameters to be estimated. Thus, the calibration algorithm may be formulated as follows:

$$X^\star = \underset{X}{\operatorname{argmin}} \|f(X) - q\|_\Sigma^2$$

In the above equation, X is the vector of kinematic parameters and q is the real sensor measurements. Furthermore, Σ is the measurement covariance through which the influence of the corresponding loss terms are normalized.

Given that this problem is generally nonlinear, providing a closed form solution is often infeasible. Hence, iterative nonlinear least square algorithms such as Levenberg-Marquadt (LM), Gauss Newton, and steepest descent [15] are adopted. The procedure is as follows. First, the Taylor expansion for f is written:

$$f(X_0 + \Delta X) \approx f(X_0) + H(X_0)\Delta X \tag{3}$$

where matrix H is known as identification Jacobean matrix which is the Jacobian of f at the linearization point. Substituting this back into the equation (3) yields:

$$\begin{aligned} \Delta X^\star &= \underset{X}{\operatorname{argmin}} \|H(X_0)\Delta X - (q - f(X))\|_\Sigma^2 \\ &= \underset{X}{\operatorname{argmin}} \|H(X_0)\Delta X - z)\|_\Sigma^2 \end{aligned} \tag{4}$$

In the above equation $z_i = (q - f(X))$ is the prediction error which is the difference between sensor's value and its corresponding prediction using the current estimate. This is in fact a conventional Linear least Square (LS) problem for which a closed form solution exists:

$$\Delta X_{LM} = (A^T A + \lambda diag(A^T A))^{-1} A^T b \tag{5}$$

where A and b respectively represent the normalized Jacobian and predictions errors [15]. Furthermore, LM algorithm adds the term $\lambda diag(A^T A)$ to improving the numerical stability where λ is a tuning parameter. At each iteration, the ΔX_{LM} is calculated and used to update the solution as follows:

$$X_{i+1} = X_i + \Delta X_{LM} \tag{6}$$

It is important to note that the data through which the calibration is performed should be persistently-excited for the algorithm to converge. This has been addressed in the literature as a trajectory optimization problem to maximize an observability index (which is usually defined using the singular values of the identification Jacobean matrix). The reader can refer to [16] for a survey on this matter.

C. ARAS-CAM Kinematic Calibration

In the ARAS-CAM robot, cable lengths are measured using motor encoders. Furthermore, for tracking the end-effector we use our own open source IR-Tracker system [1]. First we assume cables are ideally tensioned and formulate a basic calibration algorithm. Next we augment this algorithm by taking the cable's flexibility into consideration. Given the diagram illustrated in Figure 2a and Equation (2) the observation model can be expressed as follows:

$$f(x) = \|P_{EF} - A_0^{[j]}\| + L_0^{[j]} \tag{7}$$

Where P_{EF}, $A_0^{[j]}$ and $L_0^{[j]}$ respectively represent the end-effector's position , j'th anchor point location and initial cable length. Here, the parameters to be estimated are $X = [A_x^{[j]} A_y^{[j]} A_z^{[j]} L_0^{[j]}]^T$ where the first three elements are the components for anchor point locations. As we mentioned before, we need the Jacobian of $f(x)$ to formulate the optimization algorithm. This Jacobian is calculated as follows:

$$H(X) = \left[h_1 h_2 \dots h_m\right]^T \tag{8}$$

$$\begin{aligned} h_i(X) &= \left[\frac{\partial f_i}{\partial A_x^{[i]}}, \frac{\partial f_i}{\partial A_y^{[j]}}, \frac{\partial f_i}{\partial A_z^{[j]}}, \frac{\partial f_i}{\partial L_0^{[j]}}\right] \\ &= \left[\frac{(P_{ix} - A_x^{[i]})}{l^{[i]}}, \frac{(P_{iy} - A^{[j]} i_y)}{l^{[j]}} \frac{(P_{iz} - A_z^{[j]})}{l^{[j]}}, 1\right], \\ l^{[j]} &= \|P_i - A^{[j]}\| \end{aligned} \tag{9}$$

In which m is the number of data points and $(.)^{[j]}$ denotes the parameter related to the j'th cable. Now, given the Jacobian matrix and using the optimization algorithm discussed in the previous section, we can solve for the kinematic parameters. Nevertheless, in reality we know that in a large-scale cable driven robot, non-ideal effects such as cable flexibility deteriorate the quality of length measurements using encoders. When cables are under high loads, their flexibility leads to elongations that are unobservable by the encoders. Similarly this happens when cables are loosened. Hence in this paper, we propose to take into account these real-world problems by assigning importance to the cable length measurements based on their tensions which are measured by the force sensors. To do this, we consider the mathematical model of a cable. Elastic cables can be modeled using the following equation:

$$\Delta L = K^{-1} T \tag{10}$$

[1]https://github.com/aras-cdrpm-projects

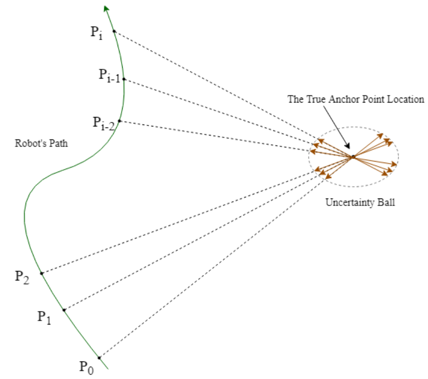


Figure 3: Geometric illustration of anchor point identification sensitivity to cable length measurement errors.

In this equation, $K = \frac{EA}{L}$ represents the cable's stiffness where E is the Young's elasticity modulus, A is the cable's cross section area and L is the cable's length. Based on this model, encoders gradually lose their reliability as the cable force T and cable length L become larger. Therefore, we can design weighting functions based on the product of these two parameters.

The final question to be addressed is that how the anchor locations and cable length errors are mapped. To address this, we perform a geometrical sensitivity analysis. When we optimized the Equation (7), we were basically trying to localize an unknown location (The anchor point) given its distance from the end-effector's position measurements. Assuming a rigid cable, the true anchor location as illustrated in the Figure 3 can be found. However if we add the cable length uncertainties, we can create an uncertainty ball around the true anchor location as illustrated in Figure 3. Obviously the radios of this ball is equal to the cable length error interval. Hence, the length measurement errors should not exceed the tolerable anchor point's error.

III. The Initialization Algorithm

For an optimization algorithm to converge, suitable initialization is of utmost importance. In this section, we propose a simple and effective method for finding the anchor point's locations purely based on end-effector's position. To do so we leverage the specific geometry of our robot. Without losing generality, we propose the algorithm for a 3-cable robot. For robots with more than three cables, we can easily apply the algorithm to each set of three cables and then average their results. Our method is based on an experiment comprised of three phases. At each phase, two cables are fixed while the other is pulled. As a result of that, the end-effector will follow a circular trajectory created by the intersection of two spheres with centers located at the other two actuator locations and with radii equal to the length of fixed cables. The center of this circle will be on the line intersecting the two anchor points. After performing the experiment, we identify the centers, radii and the plane at which these circles are located. Using these identified parameters, we can formulate three lines that intersect at the anchor locations. Finally, having the anchor points and the end-effector's position, the initial cable lengths are also available.

One important point to be mentioned is that our purposed calibration framework finds the anchor locations expressed in the IR-tracker's coordinate system. Hence, we can place the tracker wherever we wish for our global coordinate to be. This way, we can perform fast and simple calibration routines when installing the robot at a new location.

IV. Experimental Results

In this section, the proposed calibration and initialization algorithms are implemented on ARAS-CAM robot. Designed and built by Advanced Robotics and Automated System (ARAS) research group[2], ARAS-CAM is an easy deployable suspended cable driven manipulator with three degrees of transnational freedom. This robot has been illustrated in Figure 1. Our robot covers an area of $7m \times 3.5m \times 4m$ and is equipped with length measurement encoders, cable force sensors and a portable IR-Tracker system. The robot's mechanical structure has been presented in more detail at [6].

Moreover, as part of our proposed calibration framework we introduce our low cost and portable embedded IR-tracker system. This system can accurately measure the 3D position of an IR LED attached to the end-effector. We have employed two global shutter IR sensitive image sensors with a resolution of 752×480 pixels to create a stereo rack. We have implemented the required image processing and visual geometry algorithms on a Xilinx Zynq SOC[3] device which has a dual core ARM Cortex-A9 and a powerful FPGA all in a single chip. Our system is potable, power efficient and affordable which provides accurate measurements with a maximum error of $0.5cm$ within its FOV[4]. This device has been illustrated in Figure 4.

Since we did not have access to an accurate laser tracking system for measuring the true anchor locations, we verify the calibration results through investigating the discrepancy between cable length measurements obtained from the encoders and their calculate values using the anchor locations and end-effector's position. If the calibration is successful, these two values would become identical throughout the robot's maneuver (co-reiteration between sensor measurements).

In the following sections, first we will evaluated our initialization algorithm using the ARAS-CAM robot. Next, we use the initial guess form the previous step to run our calibration algorithm with and without incorporating force sensors.

A. Initialization Algorithm

The initialization algorithm was executed on the data captured using the IR-tracker system installed on the lab's ceiling. We performed the described three phase experiment on the robot. To do that, each servo motor was configured into its position-control mode. Next, at each phase we pulled one cable while the two others were fixed. Finally, the captured data where exported to the Matlab software to be used by the initialization algorithm. The followed path during this experiment is illustrated in Figure 6 where the paths corresponding to each phases is depicted with a distinct color. In this figure, the identified circle centers and anchor locations are respectively illustrated with red and blue markers. It is important to note that the forth anchor position has been inferred from other ones.

The first notable point in this figure is that the resulting estimations are in correspondence with the general configuration of the robot. However, in order to verify the results more rigorously, we used a simple length measurement tool to roughly measure the distance between anchors points. the result is reported in TableI. As it can be seen, the errors are around $50cm$ which is quite acceptable considering the robot's dimension.

[2]aras.kntu.ac.ir
[3]System On a Chip
[4]Field Of View

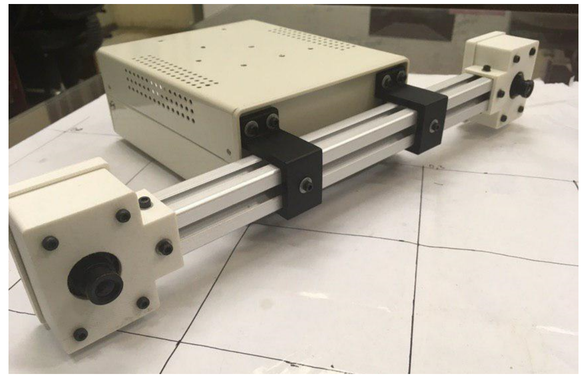


Figure 4: The embedded IR-tracker system used as a calibrator tool in this paper.

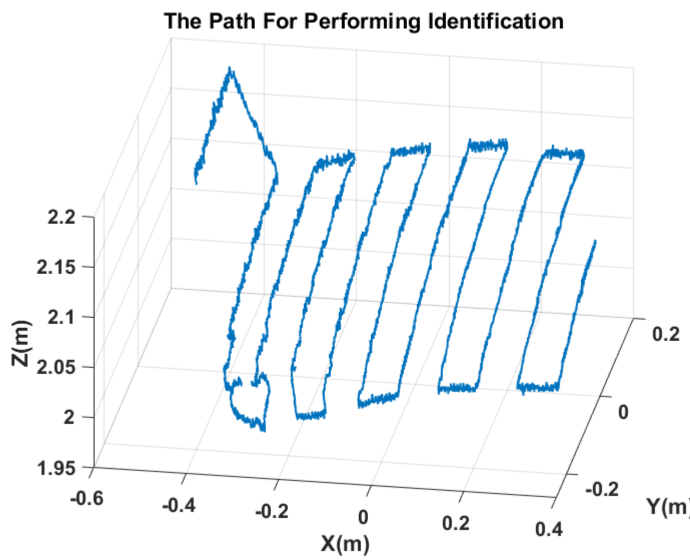


Figure 5: The path followed by ARAS-CAM robot for performing force aware calibration.

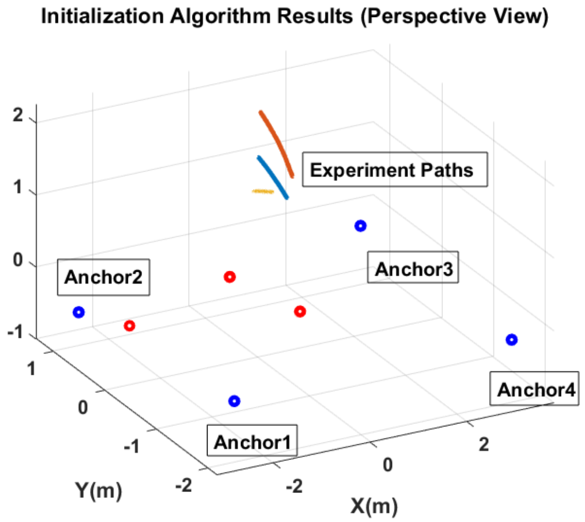


Figure 6: The path followed by ARAS-CAM robot to collect data for initialization algorithm. Red and blue markers respectively represent the identified circle centers and anchor locations.

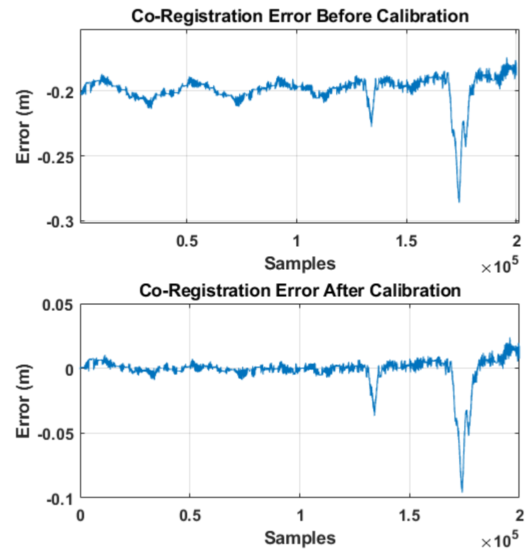


Figure 7: Encoder measurements compared to calculated values before and after calibration.

Table I: Experimental result of the initialization algorithm.

	work-space width m	work-space height m
Predicted value	6.4495	3.036
Roughly measured value	∼6.5	∼3.5

B. Calibration Algorithm

Given the initial estimates from the previous step, we use our proposed force aware calibration algorithm to refine the results. To measure the calibration's quality, we take the co-registration errors as a metric.

In order to see the impact of incorporating force into the calibration procedure , we conducted an experiment where the robot was commanded to move relatively fast while it was allowed to approach near singular positions. The 3D path followed by the robot has been illustrated in Figure 5. As we can see, the robot could not follow the desired trajectory at the vicinity of $X = -0.3m, Y = 0m, Z = 2m$ where the cables had become loose.

Given these acquired data and the initial anchor point locations from the previous step, we ran the calibration algorithm. The results have been illustrated in Figures 7 - 9. First, from Figure 7 we can see that through calibration procedure the error has been reduced significantly. Before calibration, the average error was around $20cm$ while after this, the error value has dropped to $1cm$. The reason for this large reduction is that the new anchor locations after calibration are closer to their true values. Similarly, correction of the initial cable lengths during calibration plays a pivotal role in reducing the errors. It is important to note that the significant variations in the error of Figure 7 are due to loosened cables during the experiment. At these locations, the measured length for the cables did not coincide with the assumption of Euclidean distance between end-effector and anchor points as cable lengths. However, the error's amplitude between samples 0-10000, where the cables are in tension, is reduced due to a more accurate estimate for the anchor location.

Next, the effect of force incorporation in calibration has been illustrated in Figure 8. The red crosses in the figure indicate cable length measurements with forces lower than $3N$. As we expect, when cables are loosened, their measured length by the encoders are highly inaccurate and lead to large co-registration errors which has been marked on the graphs accordingly. As we can see, when these inaccurate measurements are removed from calibration, errors reduce to less than half.

It is important to mention that loosened and too much stretched cables impose similar effects on the calibration accuracy. However, the former is less evident in the case of ARAS-CAM robot due to its moderate size.

Furthermore, to compare the co-registration errors more accurately, we plotted their histograms for both scenarios as presented in Figure 9. As it can be seen, when force weighting is enabled, the errors are mostly focused withing the interval of $\pm 0.5cm$. On the other hand, when we do not exploit force sensors, the errors expand more than twice which is visible in the graph from the distribution's width.

V. Conclusions and Future Works

In this paper we have proposed a simple and affordable calibration framework which employs data form force sensors, an affordable IR-Tracker and the encoders within the ARAS-CAM robot to solve for the kinematic parameters. We showed that when cables are loosened or under too much tension, their corresponding length measurements are not as accurate as we need. To address this we proposed a weighing mechanism

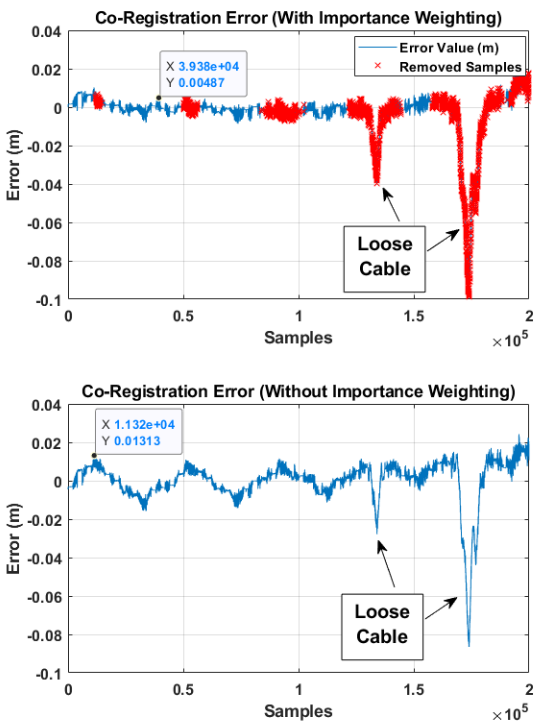


Figure 8: Encoder measurements compared to calculated values. In the first figure, the force sensors are incorporated in the calibration algorithm. Peak error after incorporating the force sensors has reduced to 0.00487m compared to 0.01313m without force sensors, which indicates a 270% error reduction.

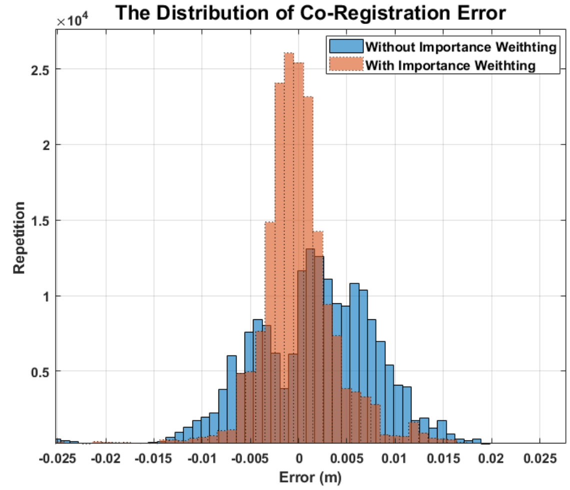


Figure 9: The histogram of the error plots presented in Figure 8. As it can be seen, by enabling the force withing module, the error has reduced to less then half.

that incorporates the cable's model to attenuate the effects of low accuracy data samples on the calibration framework. We verified the effectiveness of this approach both through simulation and experimental results.

Furthermore, since calibration is formulated as a nonlinear optimization problem, it is sensitive to initial conditions. To address this, we proposed a simple and effective initialization method purely based on end-effector's position and robot's geometry.

The combination of these modules together morph our calibration framework which is applicable in real-world deployable applications. In the future, we aim to incorporate other kinds of sensors such as IMUs and auxiliary load-cells to augment our calibration system. We are also working on other optimization tools such as GTSAM instead of Matlab since using them we will be able to integrate the sensor fusion and calibration systems into a unified framework.

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