Localization of a Compliant Cable Robot

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I. Background

In cable robotics, powered cable winches replace the actuators found in conventional robots, enabling a larger workspace [1–3]. As cables can only act in one direction, capable of pull but not push, the unidirectional nature of cables requires the implementation of redundancy in the robotic system. Information about the end effector viable workspace is necessary to achieve system level performance, for example path planning and wire actuation configuration [1].

Cable robots afford a low inertia while also using large motors [1,4–7]. This is possible due to actuator attachment to the robot’s base, enabling enhanced acceleration and high velocities [4,5]. In certain cases, parallel manipulators have also proven to have greater stiffness and accuracy than serial manipulators. This may be attributed to a serial manipulator’s cantilevered rigid link architecture which must support its own load as well as the load of the following attached rigid links, thus causing a decrease in positioning accuracy. Alternatively stated, independent link deformation and joint uncertainties stack up towards the end effector, decreasing system accuracy [5]. Through cable robots multiple points of contact with the end effector, increased payload capacity may be achieved when compared to conventional servo driven rigid body robots [5–8], while greater modularity compared to conventional robots may be achieved through the use of flexible cables rather than rigid links [1,5,7].

Parallel robots are making their way into the applications of machine tools and healthcare. Resulting from parallel robots enhanced accuracy and increased load bearing capabilities, they have been used in applications requiring precise positioning, motion generation and high speed pick and placement [9]. In the past, conventional robots have shown favor towards stiff actuation for achievement of high speed and position accuracy. However, as robotic presence increases outside factories and controlled environments, increasing interaction with humans, safety becomes increasingly significant, leading to an increase in soft robot popularity [3].

Applications of cable robot may be found in: agriculture [10], manufacturing & assembly [11–13], cameras and actuated sensing [14–17], construction [18–22], dredging [23], haptics [24,25], high speed manipulation [26], painting & sandblasting [27], rehabilitation [28–35], rescue operations [36,37], simulation [38–42], and warehouse stocking [43–45].

II. Exigence

Cable robots have been stated to be well suited for “portable reconfigurable systems that can be rapidly installed and operated”. To enable this, calibration is critical. Self-calibrating cable drive parallel manipulators (CDPMs) have therefore been put forth in the literature [2]. However, further challenges arise in the design and deployment of cable robots such as control of cable lengths, cable nonlinearity modeling, and pose determination of the end effector [2]. While control approaches for cable robots have been researched with respect to redundant cables as seen in [46–
these do not address the pose issues affecting positioning control. Moreover, these studies continue to experience cable oscillation [1].

Dexterity limitations also exist in today’s robot manipulators, negatively influencing robot adoption. Further research is needed into sensor integration, materials, and methods for planning and control [50]. While navigation processes have demonstrated robot autonomy. Sustained autonomy with little or no human intervention remains a challenge. Professional systems still require skilled operators and have interfaces which may be improved. A need exists for greater robot situational awareness, adaptability, and renderable services [50].

Cooperative localization techniques are therefore required to enable autonomous robot operation in unknown environments, and have been used in areas such as automated vehicle tracking, metrology, and robot navigation. Referencing the positioning challenge inherent to many robotic applications, localization aids in data synthesis, velocity approximation, and environmental awareness. Through the process of localization, robots may greater perform the assigned task with incomplete positioning knowledge [51] and is therefore the subject of this document’s research.

III. Project Description

Cable robots may be classified as fully [6,8], over [6], or under constrained cable robot systems [6,8]. In fully constrained cable robots the end effector pose may be fully known as a function of the length of the cables. In under constrained cable robots, the end effector pose may not be fully known as a function of the length of the cables. Instead, under constrained cable robots depend on the presence of gravity [8]. Fully and over constrained cable robot systems may fully determine the pose (position and orientation) of the end effector given the lengths of the cables and achievement of force closure. While determination of the workspace may remain a challenge, as it is a function of cable length, base location, and end effector attachment points, it should be noted that not all poses may be achievable [6]. For over and fully constrained cable manipulators, the end effector pose may be known from the cable lengths, therefore achieving force closure. However, for under constrained cable manipulators, the end effector pose may not be fully known via the cable lengths alone [3]. The authors therefore sought to answer the research questions:

*To what accuracy may a cable robot end effector position be obtained through localization methods in virtual environment?*

and

*What are the quantitative effects of sensor location in localization methods?*

To answer these questions, the student researchers created a three dimensional virtual MATLAB® environment to simulate possible scenarios which may occur, for example sensor occlusion due to obstacles, via motion and sensitivity studies. Ultrasonic sensors were varied in quantity and location throughout the virtual environment and analyzed under the influence of process noise within the system. Such noise may be found in physical cable robot systems and sensors via cable oscillation, sensor uncertainty, and cable elasticity. Results and discussion from this study are be found in Section 0, with computational methods first described in Section IV.
IV. Computational Methods

Using the multilateration method, localization of the cable robot end effector was performed. To do this, \( n \) ultra-sonic receivers and transmitters were used with the receivers being statically placed within the 3D environment and transmitters placed on the mobile cable robot end effector. The distances between the receivers and transmitters were then measured and assigned values \( D_1, D_2, \ldots, D_n \). Global coordinate positions were then assigned to the receivers in the 3D frame as \((x_1, y_1, z_1), (x_2, y_2, z_2), \ldots, (x_n, y_n, z_n)\). The distance between the estimated robot end effector and the receiver locations \((x_1, y_1, z_1), (x_2, y_2, z_2), \ldots, (x_n, y_n, z_n)\) could then be written as

\[
D_1 = \sqrt{(x_1 - x_m)^2 + (y_1 - y_m)^2 + (z_1 - z_m)^2} \\
D_2 = \sqrt{(x_2 - x_m)^2 + (y_2 - y_m)^2 + (z_2 - z_m)^2} \\
D_n = \sqrt{(x_n - x_m)^2 + (y_n - y_m)^2 + (z_n - z_m)^2}
\]

Equation 1

Where \((x_m, y_m, z_m)\) is the estimated end effector position coordinates. By squaring both sizes of Equation 1 we can obtain

\[
x_1^2 - x_n^2 - 2(x_1 - x_n)x_m + y_1^2 - y_n^2 - 2(y_1 - y_n)y_m + z_1^2 - z_n^2 - 2(z_1 - z_n)z_m = D_1^2 - D_n^2 \\
x_2^2 - x_n^2 - 2(x_2 - x_n)x_m + y_2^2 - y_n^2 - 2(y_2 - y_n)y_m + z_2^2 - z_n^2 - 2(z_2 - z_n)z_m = D_2^2 - D_n^2 \\
x_{n-1}^2 - x_n^2 - 2(x_{n-1} - x_n)x_m + y_{n-1}^2 - y_n^2 - 2(y_{n-1} - y_n)y_m + z_{n-1}^2 - z_n^2 - 2(z_{n-1} - z_n)z_m = D_{n-1}^2 - D_n^2
\]

Equation 2

Substituting Equation 1 into Equation 2 we may achieve the matrix form \(Ax=b\)

\[
A = \begin{pmatrix}
2(x_1 - x_m) & 2(y_1 - y_m) & 2(z_1 - z_m) \\
2(x_2 - x_m) & 2(y_2 - y_m) & 2(z_2 - z_m) \\
\vdots & \vdots & \vdots \\
2(x_{n-1} - x_m) & 2(y_{n-1} - y_m) & 2(z_{n-1} - z_m)
\end{pmatrix}
\]

\[
b = \begin{pmatrix}
x_1^2 - x_n^2 + y_1^2 - y_n^2 + z_1^2 - z_n^2 + D_1^2 - D_n^2 \\
x_2^2 - x_n^2 + y_2^2 - y_n^2 + z_2^2 - z_n^2 + D_2^2 - D_n^2 \\
\vdots \\
x_{n-1}^2 - x_n^2 + y_{n-1}^2 - y_n^2 + z_{n-1}^2 - z_n^2 + D_{n-1}^2 - D_n^2
\end{pmatrix}
\]

\[
x = \begin{pmatrix}
x_m \\
y_m \\
z_m
\end{pmatrix}
\]
Where \((x_m, y_m, z_m)\) are the estimated coordinates in the global coordinate frame. However, approximations exist within the multilateral measurement localization method. Therefore, we implement the Newton-Raphson equation, solve the systems of nonlinear equations using the Taylor series expansion, and compute the Jacobian. Through using this process within the discrete space, we are able to avoid singularities and obtain new, “real”, coordinates \((x_r, y_r, z_r)\) which closer describe the physical position of the cable robot end effector in the presence of system noise.

V. Results & Discussion
Matlab based simulations were conducted in order to evaluate the accuracy, precision, and robustness of the end-effector localization method. In the simulations three ultrasonic receiver grid configurations were used, labeled configurations A, B, and C. This is illustrated in Figure V.1 where each configuration displayed and labeled in a global 3D coordinate frame.

Distance data estimated by each receiver was simulate using the true end-effector position and added error. The error was obtained through the MATLAB rand function and was only permitted to at most added 0.5 m in error. Two sets of experiments were conducted: one to analyze the localization method’s performance according to the grid configuration and the other to analyze effects of occlusions. The effects of occlusions were studied using configuration A and B.

Figure V.1: Cable Robot Simulation Environment
Grid Configuration Effects

The virtual end-effector was localized multiple times at eight positions along a diagonal trajectory within the workspace using the proposed localization method. At each position a sample of the distance measurements were collected and the localization algorithm was run one hundred times. These results are shown below in their corresponding simulation environment. The same trajectory was evaluated using A, B, and C acoustic receiver configurations. The results are shown in Figure V.2. From Figure V.2a one may observe the variance of end-effector location results increasing as the distance between the grid plane and end effector increase. Locations near the enclosed volume of the grid have decreased variation in localization results.

![Figure V.2: Grid Configuration Localization Effects.](a) effects of configuration A, b.) effects of configuration B, c.) effects of configuration C)

Histograms of standard deviations and percent error were formed for each configuration. Figure V.3 shows standard deviations and percent error histograms along the x, y, and z axes using configuration A. The largest standard deviations can be observed the further away from the enclosed volume of the grid space. The percent errors of the end-effector location along each axes also increase as the distance of the end-effector from the enclosed receiver grid increases. Figure
V.4 displays the standard deviation and percent error histograms results for configuration C. From the figure the standard deviations and percent errors in localization at the center of the trajectory are shown to be lower compared to the started and ending points.

**Figure V.3**: Standard Deviation and Percent Error Histograms for Configuration A
Figure V.4: Standard Deviation and Percent Error Histograms for Configuration C

Occlusion Effects
Simulations were conducted to study the effect occlusions on the localization algorithm. The effects of obstacles were considered as blocking the acoustic signal from the receivers. The effects of obstructions were studied using configuration A and B. Figure V.5 shows occlusion simulation using configuration A and configuration B. Red is used to indicate receivers that are not able to observe the end effector due to the occlusions.
Figure V.5: Occlusion Effects on Localization. a.) Configuration A and b.) Configuration B.

Figure V.5a suggests that signal loss from a positional plane negatively effects the methods ability to localize the object along the x axis. There is 61.35% error difference along the x axis between the estimated end-effector location and the true location. Figure V.5b reveals that once objects are observed by a sensor on another plane the end effector may be localized. The end-effector in Figure V.5b is localized with a total error of 1.92% from the true location.

VI. Conclusion and Future Work

Answering the research questions stated in Section III, the student researchers found a 61.3% error along the x axis in the event of an occlusion prohibiting sensor reading from a plane with a 1.92% error reading being found when two plane are able to perform readings. This study was conducted using a Matlab based simulation of a static cable robot. Research suggests enhanced measurement capability when two planes are used to acquire localization estimates in the event of system occlusions. Additionally, research suggest the sensor positions should be staggered, compared to lying in the same plane. This has shown to enable better estimates of the end-effector location even amidst heavy occlusions. Finally, results suggest the grid should encapsulate the expected work area allowing the location estimations to be more accurate and robust to erroneous measurement.

Future work includes path planning of the end effector through the use of the grid based potential field method. This analysis will aid in obstacle avoidance and may be carried out in Matlab. Collision free path-planning remains a challenge in the topic of cable robotics. While collision avoidance with path-planning has been studied in depth with respect to serial and conventional robots, it has not been well established for cable robots. Predominately work within cable robotics has surrounded singularity avoidance. However, little works exists for both singularity and collision avoidance [8].

Two types of methods exist for cable robot collision avoidance, global and local [8]. Global methods generally perform in two phases. The first phase spatially represents the robot’s available space. This may be done via grid sampling or random sampling. Once a model of the available space has been compiled, the second phase may begin. Wherein, using artificial intelligence, a path within the compiled model may be identified. While a disadvantage of the global method is
the increased time for computation, it should be noted that this method guarantees a solution, provided one exists [8].

Local methods are fit for real time path planning. Using this method, the robot, previously unaware of its surroundings, realizes obstacles as it traverses the workspace. Local methods implement potential fields. However, implementation of potential fields may introduce local minima. As such, researchers have presented alternative methods to circumvent local minima [8].

The Clemson Automation, Robotics, Mechatronics (ARM) Lab is currently looking into the use of such a cable robot system for implementation during vehicle assembly as shown in the figure below.

![Figure VI.1: Cable Continuum Vehicle Assembly](image-url)