Calibration of a Fully-Constrained Parallel Cable-Driven Robot

Julien Alexandre dit Sandretto[*†], David Daney[†] and Marc Gouttefarde[§]
[*†]COPRIN INRIA, [§]LIRMM
INRIA, 2004 route des Lucioles, B.P. 93, 06902 Sophia Antipolis, France
{David.Daney, Julien.Alexandre_dit_Sandretto}@inria.fr

Abstract An identification of the model parameters for a parallel cable-driven robot (8 cables for 6 degrees of freedom) is performed by using both a calibration and a self-calibration approach. Additionally, advanced tools and algorithmic improvements are presented to perform the parameter identification. A complete experimentation validates the robot accuracy improvement.

1 Introduction

Because of tolerances in manufacturing or assembly, the geometry of the actual manipulator does not correspond to the desired design and its theoretical kinematic model. Consequently, the performances of the manipulator are reduced if not lost. Calibration consists in identifying model parameters through redundant information on the state of the robot generally provided by internal/external measurements. The more simple and common approach to calibrate a parallel robot is the implicit method as presented in Wampler et al. (1995). In the self-calibration case, the necessary data are provided by additional internal sensor(s). Many solutions have been proposed for parallel manipulators, and some of them Patel and Ehmann (2000); Takeda et al. (2004) may be easily adapted to the case dealt with in the present paper.

Cable-driven robots have several interesting properties like reduced mass of moving parts (for cables of negligible mass), ease of reconfiguration and, especially, a potentially very large workspace. They are notably used for a flying camera system sky (2007), and have been proposed for heavy loads transportation, for orienting heavy devices and for contour crafting Bosscher and al. (2007). In our case, the robot is actuated by eight cables for six DOF. Several studies have been run on cable-driven robot kinematics, but few concerning their calibration. However specific procedure are presented in Tadokoro et al. (1999) and in Varziri and Notash (2007) respectively.

The basic identification method is the non linear least squares approach, which computes the parameters so as to match model estimations with measures. Similar methods are orthogonal distance regression (ODR) Boggs et al. (1987) and χ^2 used in Patel and Ehmann (2000). Different approaches have been proposed like filtering adapted in Wampler et al. (1995), or an original interval approach proposed in Daney et al. (2006).

2 Cable-driven robot

This study is part of a project named CoGiRo (Control of Giant Robot) which notably aims at designing a parallel cable robot having $n = 6$ degrees of freedom and a very large workspace. It uses $m = 8$ cables controlling the 6 DOF motion of its mobile platform and its geometry has been chosen so that the platform is fully constrained by the cables. The moving platform or end-

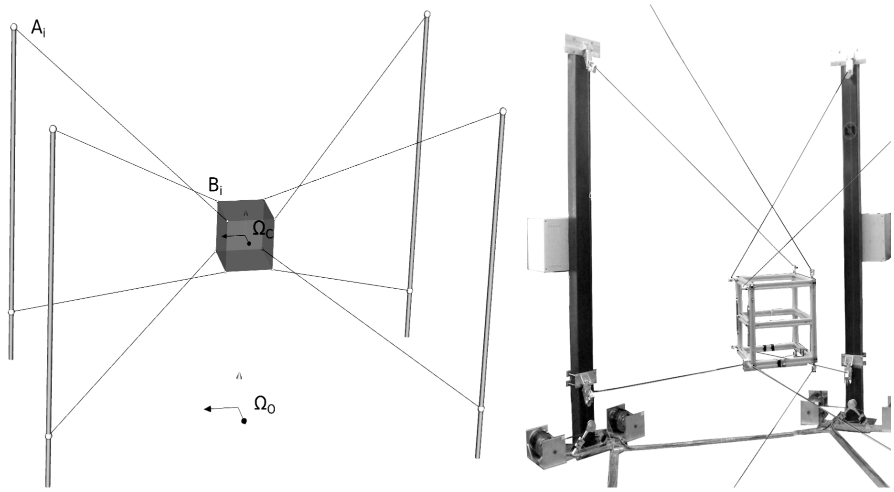

Figure 1. A cable-driven robot sketch and ReelAx8 picture

effector (mobile reference frame Ω_C) is connected to the base (fixed reference frame Ω_O). The i^{th} cable connects the point A_i of the base (coordinate a_i in Ω_O) to the point B_i on the mobile platform (coordinate b_i in Ω_C). The pose of the mobile (defined by the position P and the orientation R of Ω_C expressed in Ω_O) is directly controlled by the length and the tension of each cable. The implicit kinematic system of equations is given by

$$||P + Rb_i - a_i||^2 - L_i^2 = 0, \quad i = [1...m] \tag{1}$$

where L_i is the distance A_iB_i.

3 Calibration

The calibration goal is to enhance the robot performances by improvement of model knowledge.

We will see that calibration can be considered as a generic process Wampler et al. (1995). We will make a difference between the case where we have additional external measures on the state of the robot and the case where the proprioceptive sensor data of the robot are sufficient for calibration (also called self-calibration).

The robots studied, $m > n$, are redundant in terms of measurement if we make the hypothesis of non elastic and mass-less cables.

3.1 Generic view

Based on Wampler et al. (1995), for each of the N_C measure configuration the calibration equations links three types of variables:
The measurements M_k ($k = 1..N_C$), the parameters ξ we want to identify (geometrical parameters) and unknowns variables Υ required to model our equations. These variables $\Upsilon = [\hat{\Upsilon}, \check{\Upsilon}_{1..N_C}]$ should be

- Constant $\hat{\Upsilon}$: their values do not change during the calibration process;
- Variable as a function of the robot configurations $\check{\Upsilon}_{k=1..N_C}$.

We consider a system of equations linking a set of measures M and the unknowns $V = [\xi, \Upsilon]$ in the calibration equations:

$$f_k(M_k, V) \simeq 0, \quad k = [1...N_C] \qquad (2)$$

A solution of the system (2) could be computed by different methods, most of them give a non linear least squares solution which minimizes the criteria $F^T.F$ with $F = [f_1, \dots, f_{N_c}]^T$. This could be obtained with a classical Levenberg-Marquart algorithm but some improvement on criterion definition are possible.

Weighted Least Squares technique introduces the ability to prioritize a measure by considering the criterion $F^T \Sigma_F F$. The weight matrix Σ_F is built as a function of knowledge on some uncertainties linked with the measurement modeled through a covariance matrix Σ_M. A linear approximation of Σ_F is obtained as $\Sigma_F = J_M^T \Sigma_M J_M$ with $J_M = \frac{\partial F}{\partial M}$.

Orthogonal Distance Regression takes into account the possible errors in measurements Boggs et al. (1987) and considers the criteria $F^T \Sigma_F F + \tilde{M}^T \Sigma_M \tilde{M}$. We put $\tilde{M}$ as the difference between the current M and the initial M.

χ^2 permits a control of deviation in identification of the unknowns Patel and Ehmann (2000). The considered criteria is now $F^T \Sigma_F F + \tilde{M}^T \Sigma_M \tilde{M} + \tilde{V}^T \Sigma_V \tilde{V}$. We put $\tilde{V}$ as the difference between the current V and the initial V.

For the parallel cable robot calibration, the equations used are directly the kinematic relationships (1) provided that the hypothesis of negligible cable elasticity and mass is acceptable:

$$f_{k,i}(M_k, V) = ||P_k + R_k b_i - a_i||^2 - (\rho_{k,i} + \Delta l_i)^2 = 0$$

for $k = 1...N_C$ and $i = 1...m$.

Now let's discuss two different calibration approaches, with and without external measurements.

Calibration with external measures In addition to the articular coordinates given by the proprioceptive sensors, the measurement of the robot pose (position and orientation) provided by an external device like a camera or a laser tracker is assumed to be available. The calibration system to be solved is made of the functions $f_{k,i}(M_k, V)$ with the following data: $M_k = [\rho_{i,k}, P_k, R_k]$, $\xi = [a_i, b_i, \Delta l_i]$ and $V = [\Upsilon, \xi] = [\emptyset, \xi] = \xi$.

Self-calibration without external measures If we don't have any external measurement, we can calibrate the robot with the proprioceptive sensors only. The calibration system to be solved is still made of the functions $f_{k,i}(M_k, V)$ but with the following data: $M_k = [\rho_{i,k}]$, $\xi = [a_i, b_i, \Delta l_i]$ and $V = [\Upsilon, \xi] = [P_k, R_k, \xi]$.

With these data, the Jacobian $J_V = \frac{\partial f}{\partial V}$ is composed of the Jacobian of kinematics parameters (as in a calibration case) J_ξ and of the inverse kinematics Jacobian J_Υ.

One difficulty of calibration is to eliminate the $\check{\Upsilon}_k = [P_k, R_k]$ variables Daney (2000) in the identification vector $V = [\check{\Upsilon}_k, \xi]$. In Patel and Ehmann (2000), it is done indirectly with an iterative Forward Kinematics (FK) in order to determine Υ in each iteration of the identification algorithm.

We propose a complete identification which looks for Υ together with ξ. This allows us to avoid the problem of the FK convergence.

4 Experiments

ReelAx8, shown in Fig. 1, is a reconfigurable cable driven robot. Eight cables, wound round winches, are each attached to the eight corners of a cube shaped platform of about 40 centimeters, by means of spherical joints. The winches are fixed 2 by 2 on four posts up to three meters arranged at the four corners of a three by four meters rectangle.

4.1 Measurement

The measurements were made by means of a laser tracker system and a portable 3D measuring arm.

The acquisition of the measurements were made in 2 different steps. First, we found the estimation of geometrical parameters. We measured the eyelet positions on the frame with the laser tracker and the attachment points on the mobile platform with a portable 3D measuring arm. The pose measurement step could then start. We placed the mobile platform in 44 different poses and took measures of three types:

- Proprioceptive sensors gave cables lengths ;
- The robot force sensors gave us the tension in the cables (we don't use these data in this paper) ;
- Positions of three points measured with the laser gave us the position and orientation of the mobile platform.

A measure is useful if its precision is known. Having this in mind, we estimated the expected error for each device. This error was used in the verification step and in the computation of the weights of the identification process. In our case we considered a mix between the precision of measurement device and the way the acquisition was done(maximized on purpose): $\sigma_{poses} = 5mm$, $\sigma_{length} = 5mm$, $\sigma_A = 20mm$, $\sigma_B = 10mm$, $\sigma_{\Delta l} = 100mm$.

4.2 Experimental results

From the 44 measures done, we used 30 measures for the identification and 10 for validation (4 outliers were eliminated). For the self-calibration, 30 poses are sufficient and reduce the measurement noise effect. In our calibration study and with the goal of adapting it on a giant robot, we made an important work investment to obtain well-estimated kinematic parameters (by laser and CMM measurements) in order to check the robustness of the algorithms used.

Initially, we identified the 56 parameters $[a_i, b_i, \Delta l_i]_{i=1..8}$ but we found a strong dependence between the a_i and the b_i. This came from the small rotations allowed by the prototype. The parameters a_i and b_i are linked by the relation $R_k b_i - a_i$ in the identification equations with $R_k \simeq I_{3*3}, k = 1..N_C$. It's not an important problem, indeed, the parameters of the platform are well known, easy to measure and don't change unlike Δl_i and a_i, which changes at each new configuration, restarting of motors, etc. In the particular case of self-calibration, it's necessary to choose the reference frame of the robot as follows Besnard and Khalil (2001) : $a_{1x} = a_{1y} = a_{1z} = a_{2y} = a_{2z} = a_{3z} = 0$.

The results of the **calibration** which consists in the identification of the 32 parameters $[a_i, \Delta l_i]_{i=1..8}$ with external measures (expressed with the

	WLS		ODR	
Identification (30 configurations)				
Initial err	**mean(std)**		**mean(std)**	
	20mm (20mm)		20mm (20mm)	
Final err	3mm (6mm)		1mm (4mm)	
Validation (10 configurations)				
Err on calib eq	**initial** 40mm	**final** 6mm	**initial** 40mm	**final** 9mm
Err positioning	37%	9%	37%	10%
Error orienting	40.2%	25%	40.2%	21%

Table 1. Results for the calibration

	WLS		χ^2	
Identification (30 configurations)				
Initial err	**mean(std)**		**mean(std)**	
	20mm (30mm)		20mm (30mm)	
Final err	0.5mm (0.5mm)		2mm (4mm)	
Validation (10 configurations)				
Error on calib eq	**initial** 40mm	**final** 1mm	**initial** 40mm	**final** 0.7mm
Err positioning	37%	1.2%	37%	0.3%
Error orienting	40.2%	12%	40.2%	1.9%

Table 2. Results for the self-calibration

residual error on the cable lengths between measures and inverse model), are collected in the first part of table 1.

The results of the **self-calibration** which consists in the identification of the 26 parameters $[a_{2x}, a_{3x}, a_{3y}, a_i]_{i=4..8}$ and $[\Delta l_i]_{i=1..8}$ simultaneously to the N_C pose estimation, without external measures (residual error on the cable lengths), are collected in the first part of table 2.

For the both method, after 4 iterations we reach a correct minimum (with a medium error at 0.5mm for WLS and 2mm for χ^2) and after about 10 iterations the solver stops at the expected precision ($\Delta F < 10^{-8}$).

First, a simple validation is done by the checking of model improvement on the 10 validation measures. The results (residual error on the cable lengths) are then presented in the second part of table 1 for calibration and table 2 for self-calibration.

Second, we validate the manipulator accuracy by computing the improvement of general positioning. We measure a moving (difference) between two validation configurations, on position ΔP_{meas}, and on orientation

ΔR_{meas} (in Euler angles). We compute the theoretical moving ΔP_λ and the rotation ΔR_λ with a FK process, where λ means the kind of kinematic parameters used in the FK (i.e initial, post WLS calibration, post ODR, post WLS self-calibration, or post χ^2 identification). The results are given as relative error in percentages and defined by $100 * (\frac{\Delta P_\lambda - \Delta P_{meas}}{\Delta P_{meas}})$.

A graphical result for one displacement is shown in detail for the positioning and for the orienting in Fig. 2 .

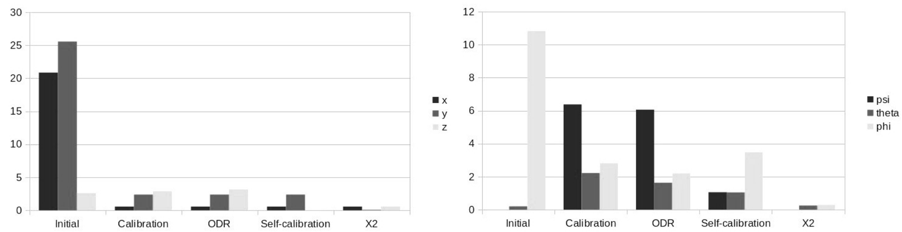

Figure 2. Error on positioning and orienting % (for initial parameters and after 4 different identification methods)

The complete results are expressed with a maximal error on P and R given in percentages. They are shown in the lower part of table 1 for calibration and table 2 for self-calibration.

We see that the orienting is not perfectly corrected (except for the χ^2 method), this is due to the fact that we could not obtain measurements in a wide workspace at different orientations larger than 5 degrees.

5 Conclusions and future works

In this paper, we have verified experimentally the hypothesis of self-calibration capacity for a particular parallel cable-driven robot. Now those allow us to test a simple new approach for the elimination of pose variables in the self-calibration process. We try three different methods derived from the least squares approach for the parameter identification, and make some proposals on their use. To conclude, our robot can be either calibrated if we don't have accurate kinematics parameter estimation, or self-calibrate, both with robust algorithms.

The robot under construction for the CoGiRo project will have a different geometry and different cables to handle heavy loads; for that, a new model is in progress with mass and elasticity consideration. Future works will include certification of the identification results. In the project, we plan to use camera for 3D pose sensing, and we are developing a calibration method based on the vision result.

Acknowledgments

This work was supported for one part by the French National Research Agency (ANR) under grant 2009-SEGI-018 (CoGiRo ANR project) and for the other part by the Région Languedoc-Roussillon under grant 115217. Thanks to Gilles Trombettoni for fruitful discussions.

Bibliography

Skycam, 2007. URL `www.skycam.tv`.

Sebastian Besnard and Wisama Khalil. Identifiable parameters for parallel robots kinematic calibration. In *International Conference on Robotics and Automation*, volume 3, pages 2859–4729, Seoul, Korea, may 2001.

Paul T. Boggs, Richard H. Byrd, and Robert B. Schnabel. A stable and efficient algorithm for nonlinear orthogonal distance regression. *SIAM Journal on Scientific and Statistical Computing*, 8(6):1052–1078, 1987.

Paul Bosscher and al. Cable-suspended robotic contour crafting system. *Automation in Construction*, 17(1):45 – 55, 2007.

David Daney. *Etalonnage geometrique des robots paralleles.* PhD thesis, Nice - Sophia Antipolis, 2000.

David Daney, Nicolas Andreff, Gilles Chabert, and Yves Papegay. Interval method for calibration of parallel robots : Vision based experiments. *Mechanism and Machine Theory*, 41:929–944, 2006.

Amit J. Patel and Kornel F. Ehmann. Calibration of a hexapod machine tool using a redundant leg. *International Journal of Machine Tools and Manufacture*, 40(4):489–512, mar 2000.

S. Tadokoro, R. Verhoeven, M. Hiller, and T. Takamori. A portable parallel manipulator for search and rescue at large-scale urban earthquakes and an identification algorithm for the installation in unstructured environments. In *Intelligent Robots and Systems, IROS '99.*, volume 2, pages 1222 –1227 vol.2, 1999.

Yukio Takeda, Gang Shen, and Hiroaki Funabashi. A DBB-Based kinematic calibration method for In-Parallel actuated mechanisms using a fourier series. *Journal of Mechanical Design*, 126(5):856–865, 2004. doi: 10.1115/1.1767822.

M. Saeed Varziri and Leila Notash. Kinematic calibration of a wire-actuated parallel robot. *Mechanism and Machine Theory*, 42(8):960 – 976, 2007.

Charles W. Wampler, John M. Hollerbach, and Tatsuo Arai. An implicit loop method for kinematic calibration and its application to Closed-Chain mechanisms. *IEEE Transactions on Robotics and Automation*, 11 (5):710–724, oct 1995.