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Executive Summary of the Thesis

Hybrid Model for a Tendon-Driven Steerable Catheter for Minimally Invasive Mitral Valve Repair

Laurea Magistrale in Biomedical Engineering - Ingegneria Biomedica

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1. Introduction

Mitral Valve Regurgitation (MVR) is a pathological condition where the Mitral Valve (MV) does not properly work, leading to serious complications such as heart failure or arrhythmias. The worldwide impact of MVR, with a prevalence of over 2 million people only in the USA [2], clearly emphases the critical need for prompt intervention. Nowadays, the recommended surgical approach for treating MV dysfunction is a minimally invasive percutaneous catheter-based procedure. In particular, the most widely used device in such treatment is the MitraClip ® catheter (MC) System, which secures the MV leaflets with a little umbrella-like clip. Despite the achieved superior safety, efficacy and increasing success, the MitraClip procedure is technically demanding, requiring high level of dexterity to precisely maneuver the device and to correctly position the clip on the MV, and thus showing a notoriously steep learning curve. Within this framework, the ARTERY project proposes an innovative solution based on an autonomous robotic catheter system empowered with an Artificial Intelligence, Augmented Reality interface for MV repair. To design the autonomous robotic catheter, a map between the task and the actuation space needs to be defined by means of an Inverse Kinematic (IK) model. The aim of this work is to develop and compare different IK models for the MC system employed in the ARTERY project. In detail, we propose an analytical, a data-driven and a hybrid IK models.

2. State of the Art

The MC, thanks to its flexible and continuous shape, can be characterised as a continuum robot (CR). Continuum Robots (CR) modeling is a subject of much debate in the robotics community, since their flexible structure leads to more complex relationship between the actuators and the end-effector with respect to traditional rigid manipulators. In the recent years, different approaches for modeling CRs have been developed, which can be mainly classified in analytical or data-driven models. Analytical models employ mathematical equations to describe the kinematics of CRs, usually making simplifying assumptions and neglecting real-world effects such as friction, hysteresis, or tendons' deadzones. The Constant Curvature (CC) model is a noteworthy example, as it assumes CR to have a constant curvature along its length. Con-

versely, the Cosserat Rod Theory (CRT) is an analytical model which aims at providing an exact description of the manipulator without making any simplifying assumptions by solving a set of differential equations, but at the cost of high complexity and computational burden [5]. Data-driven models, instead, aim at predicting the CRs' behaviour by learning from data acquired by real-world experiments or simulations, exploiting machine learning techniques. Their main feature is the ability to capture the highly intricate non-linearity of CRs with no computational expense, highlighting their potential for real-time applications. However, they have some drawbacks, such as requiring large amounts of training data, lacking of generalization capability in new situations, and not providing explicit insight into the underlying physical mechanism governing the robot's behavior, thus making the model difficult to interpret [3].
Therefore, we propose a novel approach which combines analytical and data-driven methods to model the IK of tendon-driven surgical-applied continuum robots with the aim of leveraging the advantages of both methods and ultimately improving CR's modeling. To the best of the author's knowledge, little research has been focused on hybrid models in the field of minimally invasive surgery.

3. Materials and Methods

3.1. MitraClip System Description

The MC is a tendon-driven CR externally actuated by pulling or realising tendons, which can be performed manually by an operator, as it happens in the surgical procedure, or automatically by motors, as it is developed in the ARTERY robotic system. In detail, the device in question has 3 tendons displaced around the circular section of the catheter respectively with a distance of 90°. Referring to Figure 1, the cables at 90° and 270° are responsible for bending the catheter in the Antero-Posterior (AP) plane; whereas the cable positioned at 180° for bending the catheter in the Medio-Lateral (ML) plane. Thus, the MC has 3 DoFs:

1. DoF for Linear (LIN) translation;
2. DoF for rotation in ML plane only in the medial direction toward the MV;
3. DoF for rotation in AP plane either in the anterior or posterior direction.

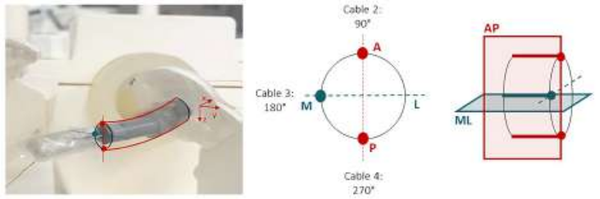

Figure 1: *(A) Lateral view of the MitraClip catheter modelled as a tendon-driven continuum robot, externally actuated by 3 cables routed around the circular section. (B) Frontal view of the catheter's section: the red cables at 90° and 270° are responsible for the bending respectively in the Antero and Posterior direction. The blue cable at 180° is devoted to the bending in the Medial direction. (C) Lateral view of the Antero-Posterior and Medio-Lateral planes in which the system is allowed to move.*

In our robotic setup, each DoF is allowed by a relative motor. Therefore, the IK models take as input the task variables, i.e the pose of the desired target, and return as output the actuation variables, i.e the motors' steps for each of the 3 motors, needed to actuate the system in order to reach the input target.

3.2. Analytical Model

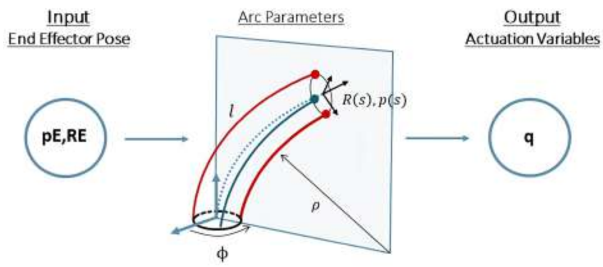

Figure 2: *Analytical Constant Curvature Inverse Kinematic Model Workflow. Given as input the target pose [**pE**, **RE**], the arc's parameters, i.e the beding angle ϕ,the length's backbone l and the constant curvature ρ, describing the simplified-assumed geometry of the robot, are derived. The output actuation variables $\boldsymbol{q}$ are computed as function of the arc's parameters.*

The analytical model developed is the Constant Curvature (CC), according to which the MC is assumed to be a single arc with constant curvature. Under this hypothesis, the shape of the robot is fully described by the so-called arc's parameters, i.e the constant curvature ρ, the length of the backbone l and the bending angle of the plane containing the arc ϕ. The arc's parameters are derived as function of the input end-effector position $\mathbf{p} = [x, y, z]$, as follows [5]:

$$\phi = tan^{-1}\left(\frac{y}{x}\right)$$

$$\rho = \frac{2\sqrt{x^2 + y^2}}{x^2 + y^2 + z^2}$$

$$l = \frac{1}{\rho}cos^{-1}\left(1 - \rho\sqrt{x^2 + y^2}\right)$$

Hence, the i^{th} tendon' displacement is computed as:

$$\Delta l_i = -r\theta cos\left(\frac{\pi}{2}i - \phi\right)$$

where $\theta = \rho l$ and r is the radius between the central backbone and the cable in the cross-sectional plane. The backbone's length l corresponds to how long the MC has to be moved linearly. Therefore it is converted, by an experimentally-derived conversion, into the number of motor steps to be fed to the motor in charge of the linear translation of the system. Analogously, the tendon's displacement Δl_i, indicates how much the tendons have to be pulled or released in the relative direction. Thus, either for the ML and AP bending, they are converted into the number of motor steps with which the relative motors should be actuated. Summarising, as Figure 2 shows, given as input the target pose, the arc's parameters ρ, l,ϕ, which describe the simplified-assumed geometry of the robot, are derived. Then, the tendons' displacement Δl are computed as function of the arc's parameters and, together with the backbone's length l, are finally converted into the number of motor steps, achieving our 3 actuation variables $q = [LIN, ML, AP]\ MotorSteps$.

3.3. Data-Driven Model

The proposed data-driven model is based on Gaussian Regressor Process (GRP). GRP is a probabilistic supervised machine learning algorithm which has been widely used for solving either regression or classification tasks [4].
Being data-driven, the model strongly relies on data to learn and generalize the relationship between the robot's actuation space and task space. Therefore, as first step, we explored the MitraClip's workspace depicted in Figure 3, and we built a representative data-set where known configurations of the motors' state were mapped to the relative pose of the clip, which was measured by using electromagnetic sensors. The data acquired were then sampled, processed and finally fed to the model for learning to predict the robot's behaviour.

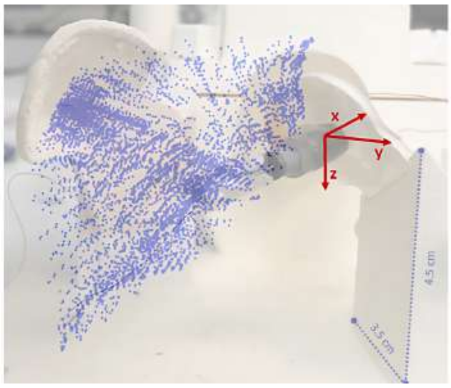

Figure 3: *MitraClip System's workspace, i.e the explored anatomical-simulated environment within the robot can move from the Ventricular Septum to the Mitral Valve.*

GRP aims at finding a function $\boldsymbol{f}$ which best fits the available training data, to be used for predicting new data. Prior observing the input data, GRP assumes a prior distribution of infinite multi-variate normal (MVN) functions. Once data are observed, the prior distribution is iteratively updated and refined, only keeping those functions which fit the data and thus getting the so-called posterior distribution. Therefore, GRP describes the probability distribution over these possible functions which best fit the data-set and defines the function $\boldsymbol{f}$, used for regression predictions, as the mean function of the probability distribution. The probability density function of the function $\boldsymbol{f}$ is defined as follows [4]:

$$P(\boldsymbol{f}, \boldsymbol{X}) = \mathcal{N}(\boldsymbol{f}|\mu, \boldsymbol{K})$$

where
$\boldsymbol{X} = [x_1, .., x_n]$ are the observed data points,
$\boldsymbol{f} = [f(\boldsymbol{x_1}), .., f(\boldsymbol{x_n})]$ is the function's output,
$\boldsymbol{\mu} = [m(\boldsymbol{x_1}), .., m(\boldsymbol{x_n})]$ is the mean function,
$\boldsymbol{K}_{ij} = k(\boldsymbol{x}_i, \boldsymbol{x}_j)$ is a kernel function,
$\mathcal{N}$ is MVN distribution.
GRP also provides, for each predicted output, an uncertainty measure over its prediction given

by the variance of the distribution.
Giving an illustrative explanation of how GRP works in Figure 4, the red points are the data $\boldsymbol{X}$ and the blue line represents the mean function $\boldsymbol{f}$ estimated by GRP after observing the data and the shaded intervals represent the uncertainty range. Having the mean function $\boldsymbol{f}$, the green new data $\boldsymbol{X^*}$ can be predicted as $\boldsymbol{f}(\boldsymbol{X^*})$ with a confidence level σ.

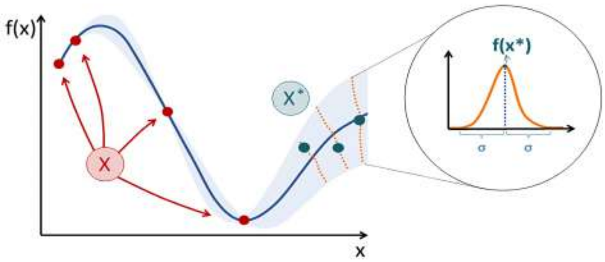

Figure 4: *Illustration of the working principle of Gaussian Regressor Process (GRP). The red points are the training data, the blue line represents the mean function estimated by GRP after observing the data and the shaded intervals represent the uncertainty range. The green points are the new data, whose values are predicted as the mean blue function computed in the relative point and also the confidence level over the prediction is returned.*

In the prior distribution, the infinite functions can be smoothed by using kernel functions, or also known as covariance functions. Kernels allow to embed prior knowledge on the shape of the function we aim to model, thus significantly influencing the properties and the performance of the GRP model. Once the kernel function has been determined, its hyperparameters need to be optimized, since they further modify the function's shape and consequently the ability of GRP to extrapolate the data's behaviour and to predict new data.
For solving the IK, 3 independent GRPs were developed. Each GRP was devoted to learn and predict a specific motor of the system, i.e the linear (LIN) motor, the ML motor and the AP motor, as shown in Figure 5. This hypothesis could be undertaken, since in our setup the motors worked sequentially and independently. The strength of GRP with respect to other data-driven models, lies in the ability of providing a measure of uncertainty over its predictions, indicating how confident the estimated outputs are.

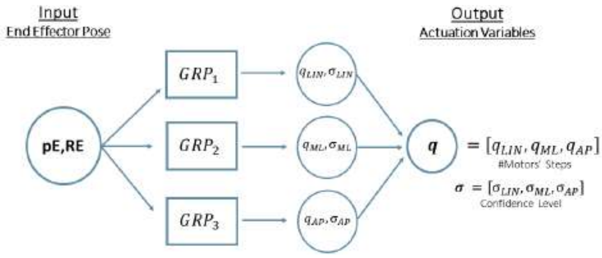

Figure 5: *Data-Driven Inverse Kinematic Model Workflow. 3 independent Gaussian Regressor Process (GRP) based models were developed, each devoted to learn the behaviour of the corresponding motor. Each GRP model returns the predicted number of motor' steps of the relative motor and an uncertainty measure of the output.*

3.4. Hybrid Model

The Hybrid IK Model is given by the combination of the above-explained analytical (CC) and data-driven (GRP) IK models. The output of the Hybrid IK Model can be computed as follows [1]:

$$\boldsymbol{q}(\boldsymbol{\Theta}) = (\boldsymbol{I} - \boldsymbol{W})\boldsymbol{q_d}(\boldsymbol{\Theta}) + \boldsymbol{W}\boldsymbol{q_a}(\boldsymbol{\Theta})$$

where
$\boldsymbol{\Theta} = [\boldsymbol{p}E, \boldsymbol{R}E]$ is the input pose of the IK,
$\boldsymbol{q_d}(\boldsymbol{\Theta})$ is the data-driven (GRP) model's output associated with it confidence level $\boldsymbol{\sigma_d}(\boldsymbol{\Theta})$,
$\boldsymbol{q_a}(\boldsymbol{\Theta})$ is the the analytical (CC) model's output,
$\boldsymbol{I} \in R^{3x3}$ is the eye matrix,
$\boldsymbol{W} \in R^{3x3}$ is the weighting matrix with $W_i \in [0, 1]$

$$W_i = e^{-k_i \frac{(q_{d,i} - q_{a,i})^2}{\sigma^2_{d,i}}}$$

where $k_i = \frac{|q_{d,i} - q_{a,i}|}{t}$ with t is a threshold to set.

The hybrid model differently weights the analytical and data-driven models' outputs on the basis of the confidence level σ returned by the GRP model. Specifically, when the data-driven model is more uncertain about its predictions, showing high variance, the hybrid model will favour the analytical model. Vice-versa, when the data-driven model shows low uncertainty, i.e low variance, the hybrid model will thus prefer the data-driven model over the analytical model. A diagram of the hybrid model's workflow is depicted in Figure 6.

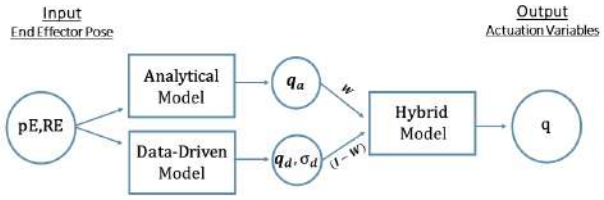

Figure 6: *Hybrid Inverse Kinematic Model Workflow. The final output of the hybrid model is obtained as a weighted sum of the analytical and data-driven models' outputs, where the weights depend on the confidence level returned by the data-driven model.*

4. Experiments

4.1. Experimental Setup

The IK models were tested on the real system in open-loop, assessing and comparing their performances based on the accuracy in following different trajectories. The experimental setup is composed of:

- The robotic MC system,
- A phantom designed to simulate the real anatomical environment within the MC moves,
- Aurora ® electromagnetic tracking system for acquiring in real-time the pose of 3 electromagnetic sensors, respectively located on the stable working platform, on the MC's base and on the MC's end-effector.
- One computer with Ubuntu system installed.

To allow the communication between the different components, ROS network was exploited. The IK model, given as input the target pose, returns the actuation variables which are then communicated to the Micro-Controller Arduino, which in turn actuates the system according to the motor steps received. Once the actuation is accomplished, the end-effector's pose is acquired by means of Aurora ® system. In such a way, we evaluate the position error as the the Euclidean Distance (ED) between the target input position vector $p_t = [x_t, y_t, z_t]$ and the actual reached position vector $p_i = [x_i, y_i, z_i]$, as follows:

$$ED = \sqrt{(x_t - x_i)^2 + (y_t - y_i)^2 + (z_t - z_i)^2}$$

4.2. Experiment Identification

The designed experimental protocol consists into following 9 different trajectories, each repeated for 4 times, and each sampled in 5 points. All the 9 trajectories ended up on the MV, representing plausible target points on which the Clip could have been released in clinical practise. They share the same first part during which the linear insertion takes place, until the catheter reaches the so-called straddle-length, as it is recommended in the guidelines of the clinical procedure. Then, to explore the entire range of the AP bending, 3 trajectories moved toward the maximum limit in the posterior direction, the other 3 trajectories moved toward the maximum limit in the anterior direction, and the remaining 3 trajectories stayed in the middle of the AP motion range. Finally, to analyse the ML bending, the trajectories moved medium-laterally from rest up to the minimum ML bending which allowed to reach the MV or to the maximum ML bending which always ended on the MV. These trajectories were thus chosen in order to analyse how the accuracy varies with the linear translation, the AP and the ML bending respectively changed.

5. Results

As aforementioned, the aim of the tests is to analyse the performance of the catheter in following different trajectories. The average error between the real trajectory and the trajectory accomplished in open loop is 3.68±1.16 mm, 2.14±1.84 mm and 1.84±1.42 mm, respectively for the analytical, data-driven and hybrid model, as reported in Figure 7. A Friedman test was performed and the result shows a statistically significant difference between the performance of the 3 models. A detailed analysis of the results as function of the AP and ML bending, can be appreciated in Figure 8.

Figure 7: *Errors box-plots of the analytical, data-driven and hybrid model in following trajectories.*

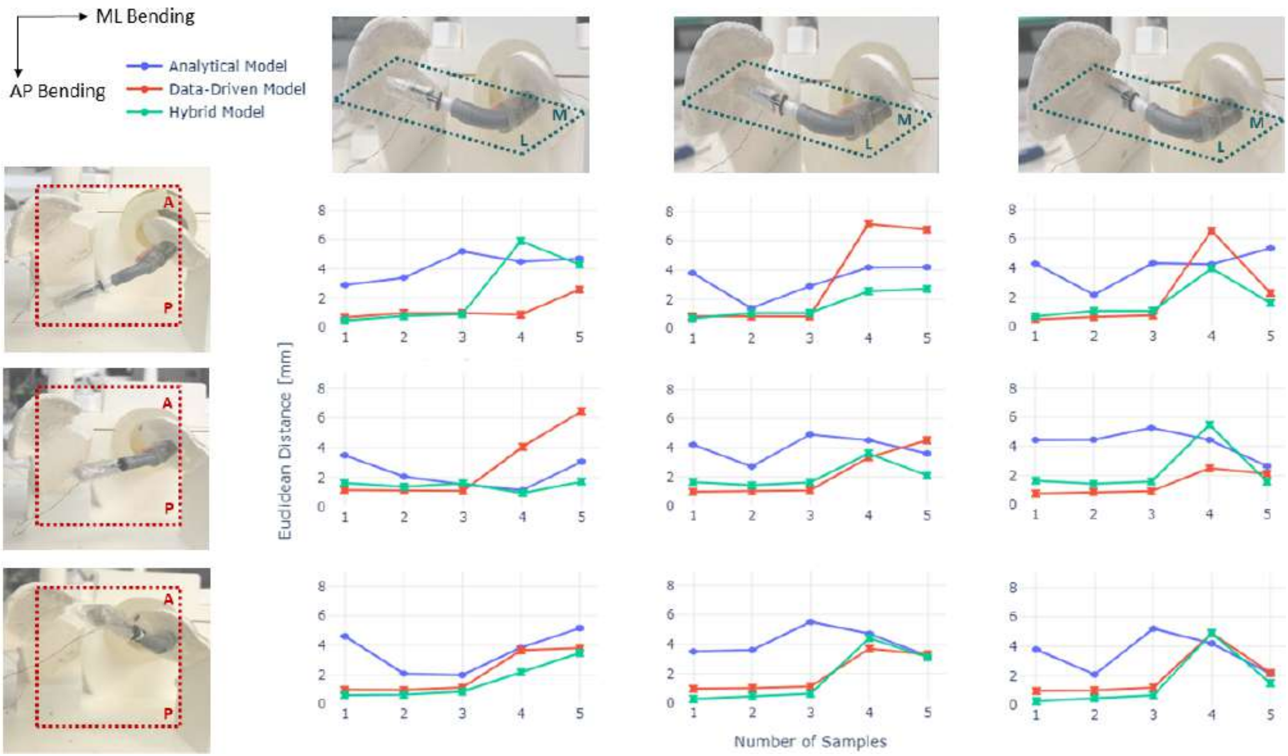

Figure 8: *Euclidean Distance of the analytical, data-driven and hybrid models for each of the 9 trajectories tested. Each row corresponds to a different bending configuration in the Antero-Posterior (AP) plane: from top to bottom, the MitraClip system bends toward the Posterior (P) direction, stays in a rest configuration, and bends toward the Anterior (A) direction. Instead, each column represents a different bending configuration in the Medio-Laterl (ML) plane: from left to right, the MitraClip catheter is lateral with respect to the Mitral Valve, is central with respect to the Mitral Valve, and is medial with respect the Mitral Valve. Thus, each trajectory is characterised by an unique combination of different bending either in the AP or ML planes.*

6. Discussion and Conclusion

In the present work we developed 3 different IK approaches for the automated MC system. The results show that the hybrid model has better performances with respect to the analytical and data-driven models, as reported in Figure 7. Referring to Figure 8, the hybrid model is preferentially closer to the data-driven model, but in regions where the data-driven is uncertain over its prediction, such as in the AP plane, the CC model has influence on the hybrid output, thus improving the final performance. The analytical model does not always behave properly, largely differing from the expected robot's behaviour sometimes, since it relies on too simplifying assumptions. However, under some simpler motions, CC might result satisfactory. At the same time, relying solely on the data-driven model might lead to wrong behaviours as well, due to errors in the collected data from which it learns. The hybrid model promises to be a more reliable solution, allowing accurate performance in real-time automated surgical applications and also providing a more transparent explanation about the model.

7. Future Developments

A possible improvement might be substituting in the hybrid model, the CC model with a more accurate analytical model, e.g CRT. As well, the data-driven model could be improved using data augmentation techniques, to better learn the CR's non-linearity, e.g tendons' dead-zone or hysteresis, and also to avoid over-fitting so as to be able to well perform even in new situations. Furthermore, the performance of the models could be improved using a control-loop and, ultimately, the hybrid approach could be developed for modeling other types of CRs for testing its reliability.

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