Topic: Evaluation of Methods for Error Compensation in Mechatronic Products

Radiation therapy is a cornerstone in the treatment of cancer, relying on the precise delivery of radiation doses to target tissues while sparing surrounding healthy organs. This level of precision places stringent demands on the mechanical accuracy of the radiation delivery system, particularly the treatment couch, which serves as the reference platform for patient positioning. Deviations in mechanical behavior - such as deflection due to the self-weight of the system and patient load - can lead to pose-dependent positioning errors that compromise treatment quality and safety by shifting the actual dose delivery away from the planned target.

This work focuses specifically on the compensation of non-geometric system errors, which arise during operation, in contrast to fixed geometric deviations such as those caused by manufacturing or assembly inaccuracies. In this context, error compensation refers to the use of predictive models that estimate and correct such deviations - typically caused by elastic deformation - by adjusting control signals during system operation. These corrections aim to preserve sub-millimetric positioning accuracy under varying load and pose conditions.

Historically, efforts have focused on designing systems as stiff as possible to minimize deformation under load and maintain positional accuracy. State-of-the-art treatment couches provide motion capabilities across three to six degrees of freedom, enabling flexible patient positioning. However, this level of mechanical complexity is already pushing the limits of what can be achieved through structural design alone. At the same time, the precision requirements in radiation therapy remain exceptionally high - typically demanding positioning accuracy within 0.5 mm across a treatment volume of 1200 mm x 400 mm x 400 mm. Meeting these requirements in a cost-effective manner poses a significant challenge and calls for alternative strategies for error compensation beyond purely mechanical improvements.

Our current baseline approach uses linear least squares polynomial fitting to compensate for pose-dependent system deviations and is implemented in a real-time control context using live sensor feedback. While easy to interpret, the current polynomial fitting approach lacks embedded physical insight and offers limited adaptability to varying conditions. To overcome these limitations, we investigate advanced surrogate modeling strategies including data-driven [2, 4, 9], reduced-order [1, 3, 7], and physics-informed methods [5, 6, 8] that offer greater flexibility and predictive accuracy.

The goal of this work is to characterize methodologies for generating models capable of compensating for system-related errors during the operation of mechatronic products.

The study is based on an experimental dataset gathered from twelve different six-axis radiation therapy couches. Each couch is planned to be measured at 225 discrete poses under varying load conditions, resulting in a total of 6525 configurations. For each pose, calibrated 6-D position data of a point on the table top will be obtained using a high-precision laser tracker system. Additionally, sensor data from all couch axes, information on the applied load, and a corresponding kinematic model - including both ideal and non-ideal forward and inverse kinematics - will be available. This experimental dataset will be complemented by a validated elastic multi-body simulation model, which provides comparable data. Unlike the experimental dataset, the simulation model excludes real-world errors such as those introduced during manufacturing and assembly. This distinction will allow for a systematic analysis of discrepancies between simulated and real-world data, highlighting the influence of these errors.

Building upon the current baseline approach - based on linear least squares polynomial fitting - this work will systematically explore three additional modeling strategies. First, a Gaussian Process Regression with an RBF kernel, will be implemented following the methodology outlined by Blumberg et al. [2]. Second, given the availability of both simulation and experimental data, a transfer learning strategy using domain-adversarial neural networks, as proposed by Ye et al. [9], will be applied to leverage synthetic data for improved real-world generalization. Third, both approaches will be extended through the incorporation of physics-related constraints to improve physical consistency and robustness. While these three modeling strategies form the core of the planned investigation, the methodology remains open to refinement or extension should further promising approaches emerge in the course of the thesis. All developed models will be evaluated with respect to accuracy and computational efficiency. Furthermore, their data requirements, and their suitability for real-time error compensation will be discussed in relation to the use case of handling patients in radiation therapy.

To ensure the practical applicability of the developed models, experimental validation will be (optionally) conducted on the six-axis radiation therapy couch, provided that both the machine and the test equipment are available. This step will involve deploying the models on the machine under realistic operating conditions, assessing their performance in compensating for system-related errors.

Finally, a generic workflow will be developed to guide the end-to-end modeling process, from input data selection to model deployment, ensuring transparency and reusability for other mechatronic systems.

The proposed work consists of the following parts:

- Literature Review: Analyze existing methods for error compensation, focusing on data-driven, reduced-order, and physics-informed approaches.
- Data Preparation: Preprocess experimental and simulation data from a six-axis radiation therapy couch to enable model development.
- Model Development: In addition to the existing baseline approach based on polynomial least squares fitting, implement three further modeling strategies:
  - Gaussian Process Regression with RBF kernel, following Blumberg et al. [2].
  - Transfer learning using Domain-Adversarial Neural Networks, based on Ye et al. [9], to leverage simulation and experimental data.
  - Physics-informed modeling by embedding physical constraints into the previous approaches.
- Model Evaluation: Assess the models based on accuracy, computational efficiency, and suitability for real-time applications.
- Experimental Validation: Test the models on the radiation therapy couch under realistic operating conditions (optional).
- Workflow Design: Develop a generic process for input data preparation, model creation, and validation for future applications.

The thesis must contain a detailed description of all developed and used algorithms as well as a profound result evaluation and discussion. The implemented code has to be documented and provided. An extended research on literature, existing patents and related work in the corresponding areas has to be performed.

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