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Adaptive Active Vibration control for robotic positioning systems using AI

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Abstract

This work addresses the vibration control of positioning movements by different types of industrial robotic systems. The accuracy of positioning systems is affected by the vibrations associated with the structural compliance of the structure, by the excitation of the commanded movements and by the effect of external perturbations. These oscillations can be of different nature depending on the application. On the one hand, machining devices with high structural stiffness normally show high frequency oscillations. On the other hand, the vibration in large robotic manipulators have low frequency components, which can be even lower in the case of tethered manipulators. The vibrations can be handled by passive, semiactive or active vibration controls. The passive ones are normally limited to high frequency content and need to be combined with active methods for assuring the behaviour in the entire frequency range.
Here, we focus on the use of active vibration control techniques, which is a problem that has been largely addressed in the literature. However, it is well-known that many of the current control strategies, while effective, involve a significant complexity in the design and implementation process. In the case of simpler techniques, they tend to be highly sensitive to modelling errors. Therefore, in this contribution, we explore the integration of AI-driven techniques with traditional control approaches to address the trade-offs inherent to these techniques, and to improve the overall system performance. AI-driven techniques are particularly well-suited for this integration due to their adaptability and capacity to handle uncertainties and potential changes in the system.
As a contribution, we develop different control algorithms to tackle the control of active vibration control in industrial robotic systems by merging AI-driven techniques and different control approaches. These results are validated via simulation and compared to more traditional methods, demonstrating the effectiveness of the proposed approach in practical settings.

vibration, artificial intelligence, adaptive control, positioning

1. Introduction

Robots and autonomous systems usually perform accurate positioning and trajectory tracking actuations in order to fulfill a specific task. This movement is highly affected by the oscillations induced in the structure by its inherent compliance, external perturbations and limitations of the control system (sensor noise, accuracy of the actuators, among others). The present work describes an active vibration control capable of reducing the oscillation of an industrial robot following the command of an operator. The analyzed platform is a tower crane, whose tethered load is prone to sway during the displacement therefore reducing the capability of the overall system to accomplish high speed operations. Currently, these systems heavily depend on the operator expertise. However, the proposed method aims to reduce this reliance, making the systems more autonomous.
The control system described below is based on differential flatness, which has already been used in mechanical systems including diverse typologies of cranes, both for trajectory tracking [1, 2, 3, 4, 5] and planning [6]. Differential flatness is a property of dynamic systems which can be fully described by trivial linear representations based on certain trajectories called flat outputs. It can be used in closed loop conditions as it is the case in the previous references, but also with the operator in the loop [7]. In the latter, whose result is patented in [8], the input of the user is directly used as speed command for the trolley of a tower crane and smoothed with a third order filter. The present approach extends that result to be used in all actuators for 3D movements of the load. Instead of the filter from previous approach, the proposed method uses the complete crane diffeomorphism and it can reduce vibrations in all three degrees of freedom.
The complexity of using differential flatness comes from the identification of the linearizing diffeomorphism for projecting the nonlinear system description into a trivial linear representation. Both the identification of the flat outputs and the consequent calculation of the diffeomorphism is not a trivial task. Furthermore, any variation in the system, like the dynamic effects from actuators or attached systems, modify the diffeomorphism. For this reason, an active research line is focused on the identification of the diffeomorphism by means of artificial intelligence (AI). This has been analyzed in [9], where a neural network is used for calculating a feedforward law, or in [10], which also uses differential flatness for identifying an inverse model. The previous approaches rely on open loop solutions and so they lack robustness. To solve this issue, further developments combine the differential flatness with closed loop controllers, like [11] for an electromagnetic actuator. In this case, it uses differential flatness with a sliding control whose response surface in the flat space is adapted using a neural network.
Learning a diffeomorphism has multiple interests, both in modeling and control, and so it represents an active research line by itself [12]. In both cases, the projection of a tangent space into a linear as it is done in flat systems, is also the objective in Koopman and DMD representation [13].

In consequence, although the remaining of the paper focuses on the active vibration control of a tower crane, the proposed approach can be useful for other systems and functionalities.

The paper is organized as follows. Section 2 describes the tower crane system object of the paper. The control structure using flatness with the operator in the loop is presented in section 3 and the performance in a virtual environment appears in section 4. Section 5 shows the potential of using AI for identifying the diffeomorphism of the tower crane. Finally, section 6 summarizes the conclusions of the work.

2. Description of the system

In this work, we address the problem of controlling the load position (x_L, y_L, z_L) in a 3D crane model (Figure 1). The load is moved by three actuators: trolley (s_1), cable length (s_2) and jib angle (ϕ_1). The swing of the load at the end of the cable is described by the angles ϕ_2 and ϕ_3.

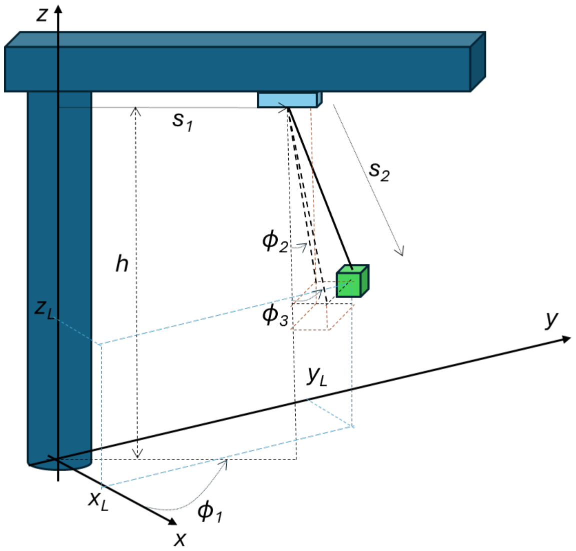

Figure 1: Diagram of the 3D- crane system

The dynamics of the system can be represented by the following set of differential equations [2], where the wire is assumed infinitely rigid in longitudinal direction:

$$\ddot{s}_1 = u_1$$
$$\ddot{s}_2 = u_2$$
$$\ddot{\phi}_1 = u_3$$

$$\ddot{\phi}_2 = \frac{1}{s_2\cos\phi_3}\Big(\big(s_2\dot{\phi}_1{}^2\sin\phi_2 - 2s_2\dot{\phi}_1\dot{\phi}_3\big)\cos\phi_2\cos\phi_3 - 2\dot{s}_2\dot{\phi}_2\cos\phi_3 - g\sin\phi_2 + 2\,s_2\dot{\phi}_2\dot{\phi}_3\sin\phi_3 + \big(u_1 - s_1\dot{\phi}_1{}^2 - (s_2u_3 + 2\dot{s}_2\dot{\phi}_1)\sin\phi_3\big)\cos\phi_2\Big)$$

$$\ddot{\phi}_3 = \frac{1}{s_2}\Big(\big(s_1\dot{\phi}_1{}^2 - u_1\big)\sin\phi_2\sin\phi_3 - 2\dot{s}_2\dot{\phi}_3 + \big(2\,s_2\dot{\phi}_1\dot{\phi}_2\cos^2\phi_3 - g\sin\phi_3\big)\cos\phi_2 + \big(s_2u_3 + 2\dot{s}_2\dot{\phi}_1\big)\sin\phi_2 - \big(s_1u_3 + 2\dot{s}_1\dot{\phi}_1 - (s_2\dot{\phi}_1{}^2\cos^2\phi_2 - s_2\dot{\phi}_2{}^2)\sin\phi_3\big)\cos\phi_3\Big)$$

3. Control structure using differential flatness

In this section, the application of differential flatness for reducing the oscilation (sway) of the load during the movement commanded by the operator is described.

3.1. Differential flatness

A system is said to be differentially flat [14], if there exists a set of variables (flat outputs, ***Y***), which are equal to the number of inputs, such that all states (***x***) and inputs (***u***) are functions of the flat outputs and their derivatives. Conversely, the flat outputs are functions of the states, the inputs and their derivatives. In this case, there exists a diffeomorphism between

$$\boldsymbol{X} = \{\boldsymbol{x}, \boldsymbol{u}, \dot{\boldsymbol{u}}, \dots, \boldsymbol{u}^{(k)}\} \text{ and } \boldsymbol{Y} = \{\boldsymbol{y}, \dot{\boldsymbol{y}}, \dots, \boldsymbol{y}^{(v)}\}$$

Where *k* is the maximum derivative of ***u*** in the expression of ***Y***; and *v* is the maximum derivative of ***y*** appearing in the expression of ***X***.

The tower crane system described in section 2 is flat as there exists a diffeomorphism [5, 7] which linearizes the system using (x_L, y_L, z_L) as flat outputs resulting in the trivial representation:

$$\dddot{x}_L = w_1$$
$$\dddot{y}_L = w_2$$
$$\dddot{z}_L = w_3$$

With w_i as the new inputs (*i=1..3*).

The flat variables can be written in terms of the local variables:

$$x_L = \cos\phi_1\,(s_1 - s_2\sin\phi_2\cos\phi_3) - s_2\sin\phi_1\sin\phi_3$$
$$y_L = \sin\phi_1\,(s_1 - s_2\sin\phi_2\cos\phi_3) + s_2\cos\phi_1\sin\phi_3$$
$$z_L = h - s_2\cos\phi_2\cos\phi_3$$

In order to represent the states of the crane system in terms of the proposed flat outputs and its derivatives, [2] proposes the use of the force equilibrium equations on the load, using the auxiliary variable F_C, which represents the cable tension force. The expression appears below:

$$m_L\ddot{x}_L = F_C(\cos\phi_1\sin\phi_2\cos\phi_3 + \sin\phi_1\sin\phi_3)$$
$$m_L\ddot{y}_L = F_C(\sin\phi_1\sin\phi_2\cos\phi_3 - \cos\phi_1\sin\phi_3)$$
$$m_L(g + \ddot{z}_L) = F_C\cos\phi_2\cos\phi_3$$

By algebraic manipulation of the previous equations, it is possible to obtain the complete diffeomorphism that depends on the flat outputs until ther 4th derivative (Figure 2). The following equations have been derived to relate the local states of the crane system in terms of the flat outputs:

$$\phi_1 = \arctan\left(\frac{(h - z_L)\ddot{y}_L + y_L(g + \ddot{z}_L)}{(h - z_L)\ddot{x}_L + x_L(g + \ddot{z}_L)}\right)$$

$$s_1 = \frac{(h - z_L)\ddot{x}_L + x_L(g + \ddot{z}_L)}{\cos\phi_1\,(g + \ddot{z}_L)}$$

$$\phi_2 = \arctan\left(\frac{(y_L\cos\phi_1 - x_L\sin\phi_1)(\ddot{x}_L\cos\phi_1 + \ddot{y}_L\sin\phi_1)}{(h - z_L)(\ddot{x}_L\sin\phi_1 - \ddot{y}_L\cos\phi_1)}\right)$$

$$\phi_3 = \arctan\left(\frac{\ddot{x}_L\sin\phi_1\sin\phi_2 - \ddot{y}_L\cos\phi_1\sin\phi_2}{\ddot{x}_L\cos\phi_1 + \ddot{y}_L\sin\phi_1}\right)$$

$$s_2 = \frac{y_L\cos\phi_1 - x_L\sin\phi_1}{\sin\phi_3}$$

It is important to notice that even if the right-hand side of s_1 depends on ϕ_1, the latter can be computed from the flat variables. This happens also on the computation of ϕ_2, ϕ_3 and s_2. The equations are described in this manner to present them more concisely, while ensuring that each variable is ultimately computed only in terms of the flat variables.

Only part of the derivation is outlined here due to its complexity and space constraints. The rest of the diffeomorphism can be computed by differentiating the previous equations.

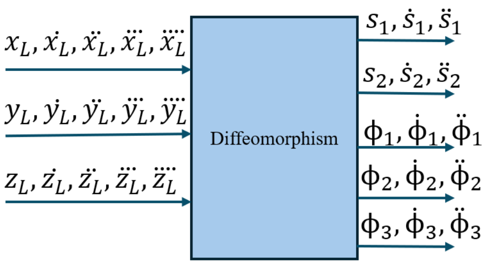

Figure 2. Diffeomorphism relating the state and the flat outputs

3.2. Application of differential flatness for reducing the sway in manual mode

Differential flatness can be used for damping the sway in the load of the tower crane. In normal conditions, the command from the operator is entered with the joystick and directly used as speed command to the actuators. In order to reduce the oscillation, a filter is applied to the signal as it appears in Figure 3. The diagram also presents a differentiation block because the model in section 2 has its input in acceleration. However, the real system is commanded in speed as an input signal to the electric power inverters and so, the differentiator is not present in the physical control unit.

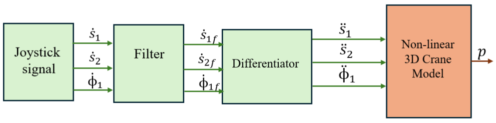

Figure 3: Manual mode diagram

The use of differential flatness is based on reading the joystick input from the operator as a speed command for the load. Given that information and applying robust differentiation the diffeomorphis is used to calculate the speed command for the three crane actuators.

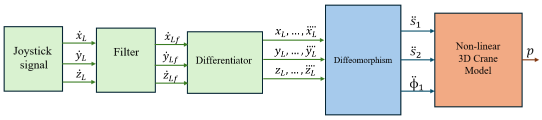

Figure 4: Flatness-based manual mode diagram

4. Virtual validation

In the following, the behaviour of the system is compared in normal and flatness-based manual modes. In both cases, the load has a similar displacement. The actuation commands appear in Figure 5 and Figure 6 respectively.

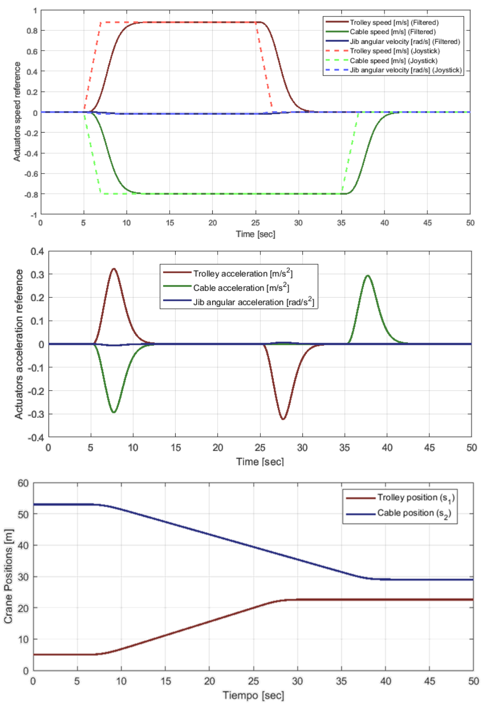

Figure 5. Actuator commands in manual mode (up: actuator speed command entered by the operator; middle: acceleration command in the model; down: displacement of the trolley and the cable)

The **Error! Reference source not found.** compares the oscillation levels in the load with both actuation modes and the effect in the movement of the load. As observed in the figure, the flatness-based approach highly reduces the oscillation and obtains a much smoother trajectory.

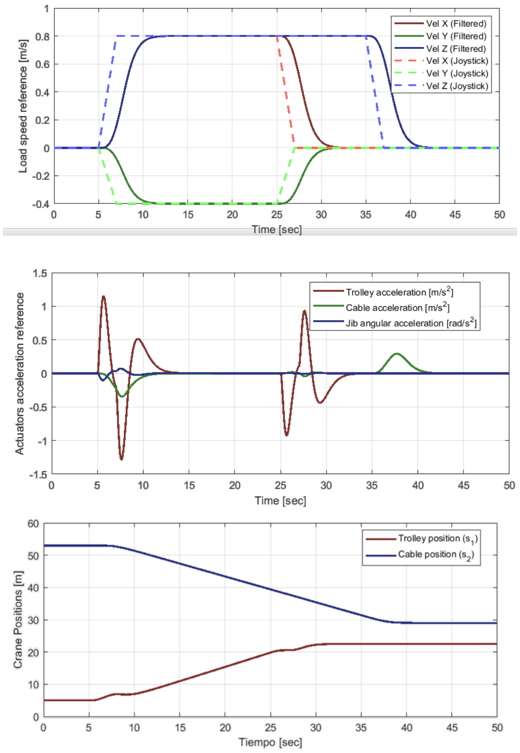

Figure 6. Actuator commands using flatness-based manual mode (up: load speed command entered by the operator; middle: acceleration command in the model; down: displacement of the trolley and the cable)

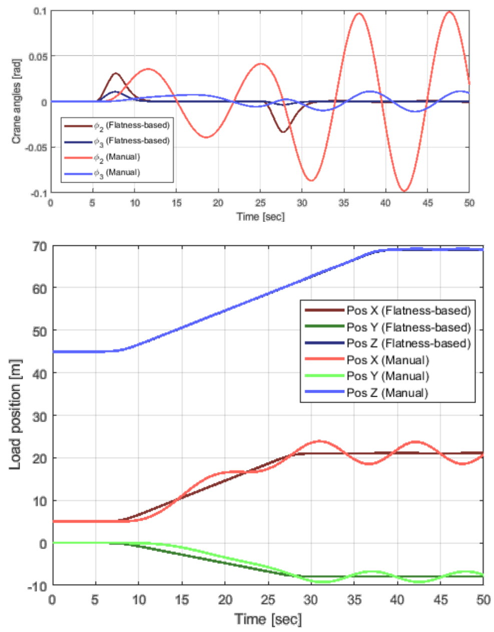

Figure 7. Result of using the approach with flatness-based manual mode (up: sway angles; down: comparison of the load displacement with and without the differential flatness approach).

5. Approximation of Diffeomorphism using AI-driven techniques

As observed in the previous sections, the use of differential flatness highly improves the performance of the system thanks to the relationship of the command with the trajectory of the load itself. However, the calculation of the diffeomorphism is by far the most complex aspect of the proposed approach for its application in different systems. First, it is necessary to prove the fulfillment of the flatness condition. And then, even in theoretically flat systems, the derivation of the flat outputs is not a trivial task. Although there are some theoretical methods for specific types of dynamic systems, the resulting differential equations are not always solvable. This issue gets even more complex when adding more detail to the mathematical description or having variable parameters, which can modify the diffeomorphism. For this reason, its identification by using machine learning techniques is an important issue both in control and system modeling.

In the following, the suitability of using AI models is evaluated by identifying part of the previously described diffeomorphism. To do that, the virtual model has been used for generating the reference data. First, an initial exploratory analysis for characterizing the data distribution, its correlation and quality. After that, three types of models were evaluated: random forest, k-NN and neural network. The later is the one which showed the better predictive capabilities. The selected approach involved two neural networks. The first one (NN1), was designed to predict s_1 and s_2. The second one (NN2), predicted ϕ_1. This approach has been demonstrated to yield better results compared to using a single neural network for all predictions.

The neural networks were implemented using the *TensorFlow* library in *Python*. After an optimization process, the selected architecture consists of layers with [128-64-32] neurons, including a 20% dropout after each layer to enhance the generalization capability of the models. A batch size of 32 was used, and the training dataset comprised 508,128 observations. The validation of the model used the Mean Absolute Error (MAE) metric, yielding the following results:

- s_1 MAE: 3.2 (range: [−95,183] m),
- s_2 MAE: 2.0 (range: [−4,150] m),
- ϕ_1 MAE: 0.1 (range: [−4,4] rad).

The Figure 8 shows the matching obtained. The results prove the feasibility of this NN solution for identifying the diffeomorphism. This opens up important possibilities for the future, like adapting the control law in real time when the system is affected by uncertainties or variations.

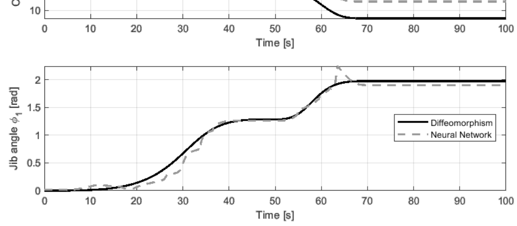

Figure 8: Diffeomorphism vs Neural Network

6. Conclusions

The present work describes the use of differential flatness for reducing the oscilation of a positioning system. Although the description is focused on a tower crane and on a manual actuation, the approach can be extended to different industrial robotic systems and both in manual and in autonomous applications. This approach can be further extended adding a closed loop controller in the flat linear representation for improving the robustness. Compared with previous approaches in tower crane applications, the proposed algorithm is able to reduce the oscilation in actuations involving the three degrees of freedom.

The work also shows the potential of applying AI for learning the linearizing diffeomorphism required for applying the proposed algorithm. Two neural networks have been used for partially idenfying it and they have shown a good prediction capability. The use of a virtual model for generating the training and validating data highly facilitates the initial generation of the model. In this connection, it remains as further work the calculation of the feedforward diffeomorphism for calculating the actuation command using the learned model. This implies filtering and differentiating the generated signals as the model is less smooth that the theoretical function.

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