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Iso-m Based Adaptive Fractional Order Control With Application to a Soft Robotic Neck

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ABSTRACT This article proposes an adaptive fractional feedback control using recursive least squares algorithm for plant identification and a recent real-time method (iso-m) for fractional controller tuning. The combination of both methods allows keeping the same original performance specifications invariant, combining adaptability and robustness in a single scheme. Thanks to the robust controller, the system performance is maintained around a specified operating point, and due to the adaptive scheme, this operating point is adjusted depending on plant changes. Extensive experimentation of the proposal is carried out in a real platform with non-linear time varying properties, a soft robotic neck made of 3D printer soft materials. The experiments proposed consist in the neck inclination control using tilt sensors installed on the tip. According to expectations, an invariant performance despite plant parameter changes was observed throughout the experiments. The good results obtained in the proposed test platform suggest that the benefits of this control scheme are suitable for other nonlinear time varying applications.

INDEX TERMS Adaptive control, fractional robust control, bio-inspired neck, soft robotics.

I. INTRODUCTION

Feedback control of nonlinear or time varying systems has been a challenging problem since the early works in the beginning of the last century (see [1]). Many control approaches have been proposed to deal with nonlinearity. Among them, robust and adaptive control have been extensively used for that purpose, having each method its own limitations.

Robust controllers can deal with small deviations in real-time, but their performance decreases once out of operation range limits. On the other hand, adaptive schemes are able to cope with any range of plant variations through controller re-tuning, but the time needed for system identification is much higher.

The robust control strategy aims to achieve constant system performance despite potential plant changes. Although this is a simple idea, a wide range of solutions are possible, from proportional integral derivative (PID) control as in [2] or [3], to more advanced works such as the sliding mode control shown in [4]. A very interesting approach to the robust control problem is found using fractional calculus. Fractional controllers (FCs), based on non-integer order derivative/integral operators, show a greater flexibility compared to their integer order alternatives. Although many fractional controller definitions have been proposed since the first works in [5], usually the non-integer order generalization of the classic PID is used. See, for example, the works in [6], [7], or [8], to name a few.

Fractional controllers are good for linear time invariant (LTI) systems, but they have limitations when applied to linear time variant (LTV) or nonlinear (NLTI) systems. The main issue is that the fractional control is designed for a specific static plant, and then the robustness range is limited to that static specification. Once the plant parameters change beyond a certain value, the system falls outside the design range, weakening the robust performance.

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Adaptive control is a well known method addressing the plant variation problem. Using system inputs and outputs analysis, it updates the plant model for controller re-calibration, so that the final performance of the system remains unchanged. The ways this goal can be achieved are very diverse, leading to a wide variety of adaptive control strategies.

During modern adaptive control inception around the 1950s (see [9]), many adaptive schemes using different approaches were described, including some relevant works such as [10] by Rudolf Emil Kálmán. Since then, this field has attracted the interest of many researchers all over the world, resulting in a huge number of contributions.

Modern adaptive control systems may be classified in the following groups:

- Open-Loop: Perhaps a more descriptive name for this group would be out-of-the-loop adaptive control. Here, the values of some environment variables are used for controller tuning regardless of current system performance. An example of this group is the gain scheduling control, where the controller parameters are recovered from a table schedule) based on environment measurable variables. Some examples of recent applications are [11] and [12].
- Direct: In this case, a target model is used and the controller is adjusted so that the actual system performance is as close as possible to the target model. The flagship of this method would be the Model Reference Adaptive Control (MRAC), first developed by Whitaker in [13]. It was soon followed by [14] with an approach based on least squares and pole placement, and many other works like [15] or [16], to name a few.
- Indirect: The concept behind this form of adaptive control is simple. With an online identification method and a controller tuning algorithm, it is possible to use the identified plant model for online controller tuning. Since identification provides an updated plat model, the tuning algorithm can keep performance specifications always met despite plant changes. This idea was originally introduced by Kálmán in [10], and since then, important contributions have been done, such as those in [17], [18] and [19]. This concept is also followed in some recent works, such as in [6], [20] and [21].
- Multiple Model Switching: The main idea in this methodology is the selection of previously identified models based on the current system response. An additional block, often called supervisor, selects the previously identified model that best fits the system response and tunes the controller accordingly. Like the open-loop adaptive control, computations can also be done offline, resulting a gain scheduling method based on system response rather than an environment variable. This technique was used in [22] and [23]. In the late 1980s, the development of artificial intelligence provided new supervisor possibilities, resulting in proposals such as in [24], where fuzzy logic is used, or in [25], which is based on neural networks. Those kinds of supervisors were also used in recent works such as [26]–[28] and [29].

The previous list is a summary of current adaptive methods. See [30] for a more detailed description of the above classification. See also [31] for an overview of adaptive control development from the initial works to current contributions, and [32] for a detailed survey of different modern adaptive control applications.

The main drawback of adaptive systems is the long time it takes to stabilize the model parameters, which makes adaptive systems unable to track rapid variations. Fortunately, robust control performance is not affected by rapid system variations as long as they are within the operating range.

Therefore, on the one hand, the main problem of adaptive systems can be addressed with a robust controller, and on the other hand, the drawbacks of robust systems can be addressed with an adaptive scheme. The combination of both methods, which is usually called ''adaptive robust control'' in the literature, intends to get the best of each. It keeps robust performance for model uncertainties and small variations, while the adaptive scheme addresses larger differences in plant parameters and always keeps the controller within its operating range.

For instance, combining a fractional controller with an adaptive control method allows improving robustness properties by extending its operation to LTV or NLTI systems. The result is a system whose performance is stable despite rapid plant variations while is also able to cope with plant variability in the long run. This field is known in the literature as Adaptive fractional control.

Although it is a very recent field, the large number of contributions suggests significant interest of the control community in that kind of systems.

In this article, the performance-based fractional tuning method (iso-m) described in [33] is extended to a broader set of systems, including LTV and NLTI systems, using an adaptive scheme. This is not based on a reference model but on parameter specifications, falling within the classification of indirect adaptive methods. There is no similar approach in the literature to our knowledge.

Different authors addressed the problem of fractional controller adaptation in many different ways. For instance, in [15], a fractional pole is used in a Model Reference Adaptive Control (MRAC), improving the set of candidates to be used as a model, therefore increasing specification options. In a similar approach, but using a different transfer function, Ladaci proposed a fractional order model reference adaptive control (FOMRAC) in [34].

In these approaches, the controller exponent is not part of the adaptation, resulting in a system that adapts the parameters of an integer order controller to meet a fractional model specification.

A similar approach is used in [35], where an Internal Mode Control (IMC) scheme with a fractional parameter is applied. This approach shows a non integer exponent inside the loop, but it is still different from a fractional adaptive system, as no controller tuning is performed.

A different approach using an actual fractional controller tuning method is described in [6]. First, a relay identification is applied to the system, obtaining the current plant parameters, and then Monje's method [36] is used to tune the fractional controller. After tuning, the system enters the normal operation state where no further identification or tuning is done.

This adaptation approach falls in the category of Self Tuning Regulators (STR). First, system identification techniques are used in an LTI plant, and then, controller tuning is performed based on that plant parameters and user specifications. The system identification runs only during initial calibration. After the adaptation period, all the parameters of the controller must converge, so the self-tuning ends and the system enters the production state. Note that plant must be invariant for the controller to be effective.

STR is useful for time invariant plants, but it has the same drawbacks stated for robust controllers regarding LTV or NLTI systems (plant changes deteriorate the controller performance). In those systems, identification must be done continuously during system operation (online identification) so that the adaptation may be valid.

The scheme that combines some controller tuning method with an online identification is known in the literature as continuous adaptation (CA). This approach is similar to STR, but adaptation is also used during system operation. Therefore, any changes detected in the plant will update the controller parameters according to the initial specifications.

Classic fractional tuning processes are too slow for that, several times longer than plant time constants, and this is the reason why the continuous adaptation approach is impossible. Only a fractional controller tuning algorithm fast enough to be run online within one (or a few) control loop(s) can be used. This method, which is able to find new tuning parameters for each loop iteration, may turn the STR into a CA adaptive system, extending the suitable plants from invariant to time variant.

As shown in [33], very competitive controller performances can be achieved with low computation efforts, thus allowing the application of the tuning method in real time. Therefore, the adaptation of the controller based on control specifications could be done during plant operation, avoiding the constant constraint of plant parameters in a self tuning regulator.

This proposed fractional adaptive control scheme basically consists of:

- Identification algorithm.
- Iso-m tuning method.
- Fractional controller Implementation.

If all items in the list can run in real time, then a continuous adaptation is possible, resulting in the new approach described here. The obvious benefit of CA is the power to cope with time variant plants, obtaining a robust and adaptable system, capable of dealing with plant changes and uncertainties at the same time. There is no similar approach in the literature, to our knowledge. Current proposals for adaptive fractional control are limited to model-based or self-tuning regulators.

The model-based strategy relies on adaptive techniques that make the output of the system resemble a target model, as, for example, in the proposals by [15] (MRAC) or [35] (IMC). These approaches do not allow robust specifications in the controller design, which is a significant drawback, and the fractional exponent only provides more flexibility in the selection of the reference model. Their adaptability allows LTV plant control to some extent, but does not provide a robust response to sudden changes in plant parameters that could occur in non-linear plants.

The approach based on self-tuning regulators using a fractional controller with robust specification constraints, as in [36], solves the robustness problem discussed above. Although this approach is useful in many situations, the controller tuning can only be done during operation start-up. Therefore, any plant change after the initial calibration will compromise the performance of the system, which is a major drawback.

The advantage of the proposed method is the combination of the previous methods strengths. The fractional controller provides robustness to the system, ensuring that performance is not affected by sudden changes in plant parameters. At the same time, any major plant variation will cause a controller readjustment through the indirect adaptive scheme, always keeping the robust controller working under optimal conditions.

Next section (II) describes the adaptive iso-m scheme, including system identification (II.A), iso-m controller tuning (II.B) and system stability (II.C). Section III describes the plant used for experiments, and section IV focuses on the description of the experiment and comments on the results. Finally, the conclusions of this article are discussed in section V.

II. ADAPTIVE iso-m CONTROL

Since the plant information required by iso-m algorithm is minimal, any system identification method could be used. For example, it is possible to use an empirical transfer function estimation, and avoid the need for any previous knowledge of the system. However, the adaptive scheme requires the plant information to be updated in real time while operating in closed loop, which rules out this method.

Model accuracy is important, but algorithm speed is also significant; the more updated the system information, the better the controller adaptation. Given the real-time constraint, a low computation plant estimation effort will be considered. Also, as an online identification algorithm, the loop frequency could limit the responsiveness of the system, reducing the specification possibilities.

To build a continuous adaptation, the estimation of the plant parameters must be done during the system operation in closed loop. According to the excellent description shown in [37], the options are Recursive least squares (RLS) and Closed loop error output (CLOE) adaptive scheme families. As it will be shown in the following sections, given the tuning method used, the best option to check the stability condition is RLS.

The recursive least squares method has a fast algorithm with low computational complexity, which is accurate enough for our tuning method. It consists of several steps recursively repeated, that improve the plant estimation in each loop. We implemented this method to get a good balance between plant parameter stability and tracking, in a very similar way to the approach described in [38], but with one additional condition obtained from [39] that ensures the stability conditions of the system.

A. RLS SYSTEM IDENTIFICATION

Consider a discrete system model defined by a transfer function as follows:

$$\frac{Y(z)}{U(z)} = G(z) = \frac{b_1 z^{-1} + \cdots + b_{nb} z^{-nb}}{1 + a_1 z^{-1} + \cdots + a_{na} z^{-na}} = \frac{B}{A}, \tag{1}$$

where A and B are the polynomials in z variable, for denominator and numerator, respectively. Rearranging the equation

$$Y(z) + a_1 z^{-1} Y(z) + \cdots + a_{na} z^{-na} Y(z) \tag{2}$$
$$= b_1 z^{-1} U(z) + \cdots + b_{nb} z^{-nb} U(z), \tag{3}$$

and solving the inverse transform through time shift property, results in:

$$y(t) + a_1 y(t-1) + \cdots + a_{na} y(t-na) = b_1 u(t-1) + \cdots + b_{nb} u(t-nb), \tag{4}$$

being $y(t)$ the output and $u(t)$ the input for time point t.

Now, the output value at current time ($y(t)$) can be expressed in terms of previous inputs and outputs

$$y(t) = -a_1 y(t-1) - \cdots - a_{na} y(t-na) + b_1 u(t-1) + \cdots + b_{nb} u(t-nb), \tag{5}$$

that can be packed in the matrix form:

$$y(t) = \theta \phi'(t-1), \tag{6}$$

for $\phi(t-1) = [-y(t-1), \ldots, -y(t-na), u(t-1), \ldots, u(t-nb)]$ and $\theta = [a_1, \ldots, a_{na}, b_1, \ldots, b_{nb}]$.

Equation (6) represents the model output prediction based on past inputs and outputs $\phi(t-1)$, and model parameters θ ($\theta(t)$ if the system is time variant).

Recursive identification methods use Eq. (6) as an estimator for the next system output only by advancing the index one position:

$$\hat{y}(t+1) = \hat{\theta}(t)\phi'(t), \tag{7}$$

being $\hat{y}(t+1)$ the system output estimation for a known set of past inputs and outputs, based on current system estimate $\hat{\theta}(t)$. Note hat notation used to differentiate the estimated variables from the measurements.

The difference between predicted ($\hat{y}$) and measured (y) system output is the prediction error (ϵ), as shown in Fig. 1 and Eq. (8).

$$\epsilon(t) = y(t) - \hat{y}(t) \rightarrow \epsilon(t+1) = y(t+1) - \hat{y}(t+1). \tag{8}$$

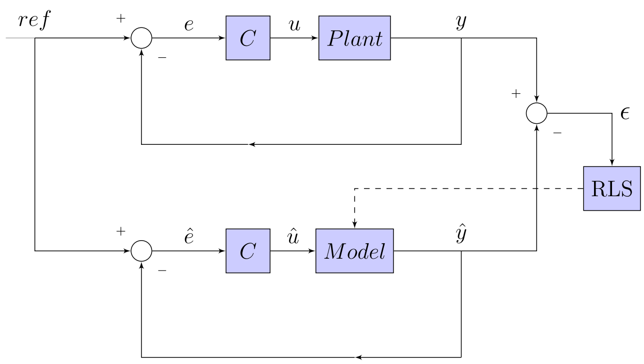

FIGURE 1. Closed loop RLS system identification block diagram.

When the next output $y(t+1)$ is known, this error will be used to compute an improved plant estimate $\hat{\theta}(t+1)$. Plant estimation $\hat{\theta}$ changes with each iteration based on the error gradient, resulting in a family of system identification methods. There are many approaches depending on how that error is computed.

Recursive least squares method uses the squared error of all the previous data for identification. At this point, it is only applicable to LTI systems, since all previous identification data are considered, which makes the resulting model a mixture of all previous systems.

Considering a time variant parameter model similar to (1) but with time dependent parameters, the best approach is time variable forgetting factor algorithm. As described in [39], one parameter is introduced, shaping the algorithm to change the impact of past identification data. Variable forgetting factor RLS is summarized in the following equations:

$$\hat{\theta}(t+1) = \hat{\theta}(t) + F(t+1)\phi(t)\epsilon(t+1), \tag{9}$$

$$\lambda_1(t)F(t+1) = F(t) - \frac{F(t)\phi'(t)\phi(t)F(t)}{\lambda_1(t) + \phi(t)F(t)\phi'(t)}, \tag{10}$$

$$\epsilon(t+1) = y(t+1) - \hat{\theta}(t)\phi'(t), \tag{11}$$

where $\lambda_1(t)$ is the forgetting factor and F is the gain matrix.

For $\lambda_1(t) = 1$ the basic RLS method is obtained, considering all the past values. The forgetting factor requires $\lambda_1(t) < 1$, where the smaller $\lambda_1(t)$, the greater preference for current values (stronger forgetting factor). When $\lambda_1(t) = 0$, $1/\lambda_1(t) = \infty$ and $F(t+1)$ cannot be computed, so the method requires $0 < \lambda_1(t) < 1$.

Using this factor, the adaptation speed can be changed based on different approaches, from basic filters to specific functions, depending on how $\lambda_1(t)$ is computed. See [39] for a summary of frequently used forgetting factors.

For continuous adaptation systems, a convenient approach is to modify the forgetting factor according to the Persistent

Excitation (PE) content of the input signal. In the function shown in (12), λ_1 decreases for uncorrelated $\phi(t)$ values, making new data more relevant when the input signal is PE. Otherwise, when $\phi(t)$ values are correlated, λ_1 increases, reducing impact of the new data in the identification.

$$\lambda_1(t) = 1 - \epsilon(t+1)\frac{\phi(t)F(t)\phi'(t)}{1+\phi(t)F(t)\phi'(t)}. \tag{12}$$

In addition, the modeling error from (8) is considered to stop adaptation when low errors are obtained, improving system stability.

With this method, we can ensure that system identification is only updated when necessary if a wide spectrum of input signals is available. This feature ensures that the estimates converge asymptotically (see [40] and [39]) while preventing corruption of plant estimates in a sustained steady state. This is also critical for stability analysis.

The RLS identification method described is based on the assumption of open loop configuration for inputs and outputs. However, further analysis is required when the adaptive system is used in a feedback configuration.

The control scheme for RLS applied in a feedback system is shown in Fig. 1.

Again, the modeling error is obtained from the difference of current system (y) and model ($\hat{y}$) outputs.

$$\epsilon_{cl}(t) = y(t) - \hat{y}(t) \rightarrow \epsilon_{cl}(t+1) = y(t+1) - \hat{y}(t+1). \tag{13}$$

The error prediction is similar to RLS, and Eq. (8) can be used with a remark, one new equation relating u and y arise from the feedback loop ($u(t) = ref(t) - y(t)$). Therefore, during closed loop operation, system inputs are correlated with outputs, resulting in a poor system identification.

Åström showed in [41] how the correlation problem is solved by filtering both signals (u,y) by a filter that includes the estimation of the closed loop system poles and the controller inverse as shown in Eq. (14).

$$L = \frac{C^{-1}}{(C^{-1}\hat{A} + \hat{B})} = \frac{1}{(\hat{A} + C\hat{B})}. \tag{14}$$

Note that $\hat{A}$ and $\hat{B}$ are the plant estimate parameters, and C is the actual controller. Since the expression above matches feedback model poles, and will tend to be the design poles when the error tends to zero, it is common practice to use the design poles. In our case, closed loop poles are not defined, but we can find a filter based on the target open loop system response.

As shown in the next section, our target open loop system is an ideal Bode's transfer function defined by crossover frequency and phase margin specifications, $CG = \left(\omega_{gc}/s\right)^{\mu}$. The closed loop function results in:

$$\frac{CG}{1+CG} = \left(\frac{\omega_{gc}^{\mu}}{s^{\mu} + \omega_{gc}^{\mu}}\right), \tag{15}$$

where $\mu = (\phi_m/90) - 2$, and phase margin is given in *deg*.

Note that the closed loop poles are also fractional, as well as the filter L. Several approaches for defining L are valid here. An invariant filter approach roughly similar to closed loop poles is possible. Updating L with every new C, $\hat{A}$ and $\hat{B}$ obtained in tuning and plant identification is also valid. During the stability analysis it will be shown that the first option is more suitable here, but the tuning method will be described first.

B. REAL TIME CONTROLLER iso-m TUNING

Once the plant model is obtained, its parameters will be used for controller tuning using the iso-m method. Following the guidelines outlined in [33], the frequency specifications used for fractional controller tuning are:

- ϕ_m: Phase Margin relative stability.
- ω_{gc}: Crossover frequency system dynamics.
- Flat phase specification defined in Eq. (18).

The first (ϕ_m) is related to stability (overshoot and settling time) while the second (ω_{gc}) specifies the responsiveness of the system (rise time). To apply these specifications, Eqs. (16) and (17) are used in [33] to solve the controller parameters for a known plant.

$$\arg\left(C(j\omega_{gc})G(j\omega_{gc})\right) = -\pi + \phi_m, \tag{16}$$

$$|C(j\omega_{gc})G(j\omega_{gc})|_{dB} = 0\,\mathrm{dB}, \tag{17}$$

where $C(j\omega_{gc})$ is the frequency response of the controller at ω_{gc}, $G(j\omega_{gc})$ is the plant frequency response at ω_{gc}, and ϕ_m and ω_{gc} are the desired open loop phase margin and crossover frequency.

Robustness specifications are also included in the iso-m method. Similar to works like [2], [7], [36], [42], [43], open loop flat phase around ω_{gc} frequency is considered as a robustness constraint. It is defined by the following equation:

$$\left(\frac{d(\arg\left(C(j\omega_{gc})G(j\omega_{gc})\right))}{d\log_{10}\omega}\right)_{\omega=\omega_{gc}} = 0. \tag{18}$$

Flat phase specification ensures that plant changes will not change the open loop phase for frequencies close to ω_{gc}. Since for different ω_{gc} the plant will have similar open loop phases, the feedback response will show a constant overshoot despite small plant variations. This property, today called iso-damping, was first described in [44] by Hendrik Bode. That is why the fractional transfer function model $\left(\frac{\omega_{gc}}{s}\right)^{\mu}$ is called Bode's ideal.

The controller definition used throughout this article is shown in Eq. (19) as described in [33].

$$C(s) = k_p + k_a s^{\alpha} = k(1 + \tau_a s^{\alpha}), \tag{19}$$

with three adjustable parameters, k_p, k_a, and α, which using the zero-pole-gain notation, are $k = k_p$, $\tau_a = k_a/k_p$, and α. These parameters should be defined using a tuning method in order to fulfill all the previously discussed constraints.

Finding the controller parameters that meet all the constraints defined in Eqs. (16), (17), and (18), is the problem to solve for all fractional robust controller tuning methods. Searching for these parameters usually involves solving a non-linear equation. In [33], similar results were obtained avoiding the numerical solver, with a significant reduction in the computing load and, hence, in the controller tuning speed.

That iso-m method feature leads to the approach discussed in this article. We propose a continuous adaptation fractional controller based on performance specifications such as ϕ_m and ω_{gc}, but also based on plant parameters. Therefore, online system identification is required.

In the previous section, we defined RLS with a forgetting factor that depends on signal frequency content. This ensures that the plant identification converges into a reliable solution if the conditions are met. Therefore, an updated plant model ($\hat{G}$) is always available for use in controller tuning.

According to [33], the required information from the system model is phase and slope at the specified gain crossover frequency. Since the plant estimate is a discrete transfer function, with $z = e^{Ts}$, these terms can be computed as follows:

$$\hat{\phi}_G = tan\left(\frac{\Im(\hat{G}(e^{Tj\omega_{gc}}))}{\Re(\hat{G}(e^{Tj\omega_{gc}}))}\right), \tag{20}$$

$$\hat{m}_G = \frac{d(G(e^{Tj\omega_{gc}}))}{d\log_{10}\omega}. \tag{21}$$

Once the phase and slope of the plant are obtained and control specifications are defined, the controller can be tuned according to iso-m method. First, the required phase and slope of the controller are obtained through Eqs. (22) and (23).

$$\phi_C = \phi_m - \hat{\phi}_G - 180, \tag{22}$$

$$m_C = -\hat{m}_G. \tag{23}$$

Note that ϕ_m is known from controller specifications.

Then, α exponent is found from them. The equation that relates these two computed values to the exponent (α) is:

$$m_C = \frac{\log(10)}{\sin(\phi_C)}\alpha\left(1 - \frac{\tan(\phi_C)}{\tan(\alpha\pi/2)}\right), \tag{24}$$

that cannot be solved directly for α. Several options are proposed in [33] as a solution, including the plot shown in figure 2, a lookup table, and the fit function.

Since the controller tuning has to be done in real time, the lookup table or the fit function are the best options to calculate the exponents. Both could be used here, but we chose the lookup table for simplicity and accuracy.

With the α exponent and the crossover frequency (ω_{gc}), τ_a can be calculated using Eq. (25).

$$\tau_a = \frac{1}{\tau_x {\omega_{gc}}^{\alpha}}; \quad \tau_x = \frac{\sin(\alpha\pi/2)}{\tan(\phi_C)} - \cos(\alpha\pi/2). \tag{25}$$

Finally, the controller gain is calculated using (26), based on Eq. (16), which meets the crossover frequency specification.

$$k = \frac{1}{|\bar{C}(j\omega_{cg})G(j\omega_{cg})|}, \tag{26}$$

where $C(j\omega_{cg}) = k\bar{C}(j\omega_{cg})$ (see [33]).

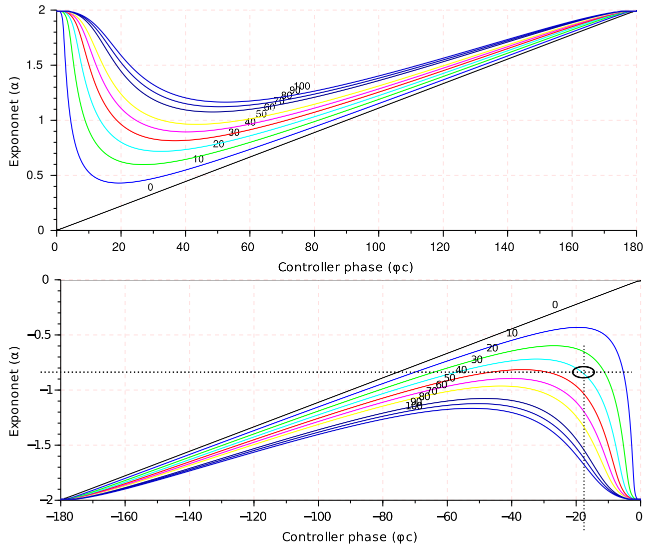

FIGURE 2. Iso-m method. Fractional order α exponent in ordinates and controller phase ϕ_C [deg] in abscissas. Iso-m curves in [deg/decade].

Once all three parameters are found and the controller is tuned according to the specifications, it can be used in our adaptive scheme after the identification step. These two steps will be repeated alternatively during the continuous adaptation operation.

To have a functional adaptive system, stability must be provided, which is discussed in the next section.

C. STABILITY ANALYSIS

The most important part of adaptive control applied to LTV plants is stability analysis. Although the tuning method is static, re-tuning can result in an unstable system, since controller tune depends on identification, which is uncertain because of the time varying nature of the plant.

The immediate solution to this problem is to verify that every possible controller tuning result falls within a stability range. To assure this, the following conditions should be confirmed:

- Identification error decreases asymptotically.
- Plant parameter estimates ($\hat{\theta}$) are bounded and converge to a value.
- Controller tuning method results are bounded and stabilize the system.

For the first condition of asymptotic error decrease, Landau proved in [19] the following theorem.

If the a posteriori error can be written as a filtered function of the measured error:

$$\epsilon(t+1) = H[y(t+1) - \hat{\theta}(t)\phi'(t)], \tag{27}$$

the sufficient condition is that the function $H'(z)$ is strictly positive real. For the RLS algorithm described in Eqs. (9) to (11), this function is computed as $H'(z) = H(z) - 1/2$.

Filtering the observation vector ϕ through the L filter, as described in the previous section, is equivalent to the filter in Eq. (27), then, $L = H$. This renders the filter update option unfeasible for L. Since all the above conditions are met, a static filter that satisfies the positive definition condition of $L'(z) = L(z) - 1/2$ will be used.

For the second stability condition, there is an additional requirement. The gain matrix F must also be strictly positive, which is provided here by the method selected for λ_1 calculation. This algorithm prevents the gain matrix (F) updates when the input does not have enough PE data by increasing λ_1 values.

First and second stability conditions are granted if the filter L is chosen correctly, resulting in a plant identification that converges to reliable phase and slope data. Note that both are bounded if the first two conditions are met.

Regarding the third condition, we must check the tuning output range and verify the final stability of the system. Figure 2 shows how, for any possible value of phase and slope, the exponent α is bounded in the interval $(-2, 2)$. In addition, the phase and slope of the plant model, used as iso-m tuning inputs are bounded due to previous considerations.

As all parameters are computed from those values with bounded functions as described in [33], we can be sure that all controller parameters are proper numbers.

Furthermore, given the way we defined the specifications, stability is implicitly granted if the controller is properly tuned. Note that, since the phase margin is among the initial specifications, we can accurately know or even change the stability through this parameter. In short, by using the iso-m method for controller tuning, stability is not only assured, but specified.

III. PLANT DESCRIPTION

With our fully defined adaptive scheme, it is time to validate the results on a real platform. The soft robotic neck prototype shown in Fig. 3 was used for this purpose. A brief description of the system is shown below, and the experimental results will be presented and discussed after that description.

As described in [45], the neck is made of a central soft link, which acts as a spine, and a cable-driven parallel mechanism (CDPM), which acts as a muscular system. Three tendons are used to bend the central link, so that the upper platform reaches different inclinations and orientations within a range.

The following components are shown in Fig 3:

1) Base.
2) Moving platform.
3) Soft link.
4) Tendons.
5) Actuators.
6) Tilt sensor.

The three actuators located at the base consist of four elements each:

- Driver: Technosoft iPOS4808 MX-CAN; 400 W, 12-50 Volt, 8 Amp (intelligent motor driver).
- Motor: Maxon RE 16, 16 mm, Graphite Brushes, 4.5 Watt.

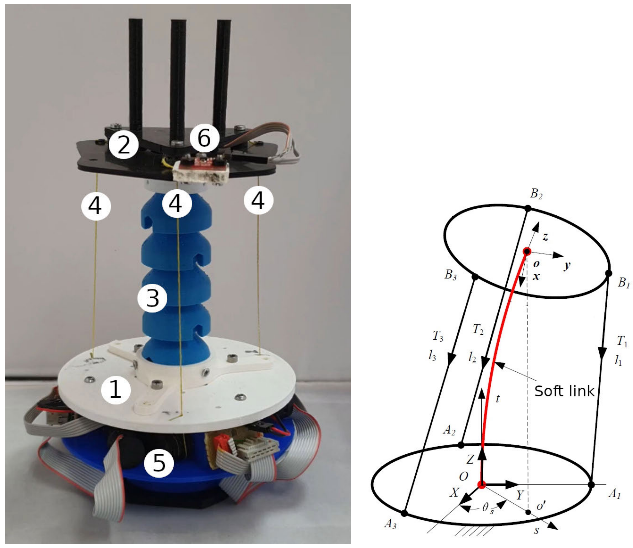

FIGURE 3. Robotic soft neck prototype (left) and kinematics model (right). See [45] for details on kinematics.

- Gear: Maxon planetary gear head GP16A (24 : 1).
- Encoder: Maxon MR Type M, 128–512 CPT (2048 positions).

The prototype was assembled from 3D printed parts, including the elastic link in the middle, with a 125 g weight. It was designed to support a total mass of 1000 g, with a payload equivalent to 800% of its mass. It is equipped with a MPU-9250 sensor to measure neck tilt and target orientation.

The first control approach of this neck, as described in [45], was done through the inverse kinematics solution. This operation results in a set of tendon lengths configuration to achieve the specified tilt and orientation targets. Through the winch mechanism, each cable length takes a specific motor angular position. Therefore, control of the motor angle positions was required to reach the desired platform inclination and orientation.

Later, in [46] it was shown that the open loop kinematics is prone to error, probably due to the nonlinear and time variant properties of the neck. A closed loop configuration was proposed as future work to cancel those errors.

The described system is non-linear and time variant from various perspectives. First, the different neck inclinations place a changing load on the motor, which means that the gain depends on the neck inclination, resulting in the uncertainty of the plant parameters and time variation. Furthermore, the central link material is a polymer with unknown viscoelastic behavior, which adds non-linearity and more uncertainty. Therefore, we are faced with a system that varies over time with uncertainty and nonlinearity.

Therefore, a control scheme with certain features such as stability and robust performance is required, leading to the application of the adaptive fractional control described above. Some previous works have addressed the same problem using robust control approaches.

In [47], a control approach using inclination sensors and torque actuation was proposed for this kind of plant. A robust fractional controller was used in the feedback control configuration, achieving the desired inclinations by means of a force action applied on the neck tendons. Another approach based on tilt sensors and tendon lengths was proposed in [46], where a fractional order controller was used to reach and hold the desired motor positions, bending the central soft link to a desired inclination and orientation.

Given that the precision of our neck torque actuator is quite rough, the control approach is better based on position or velocity inputs. Accordingly, the experimental setup presented in this work follows the approach in [46], and proposes a feedback control scheme based on inclination readings from the tilt sensor on the platform.

The control scheme is based on inclination sensor readings. Considering factors such as identification feasibility, precision and modeling complexity, the best input variable option is the actuator velocity. After a series of initial experiments, it was found that a second order model can be used to capture the behavior of our plant with the actuator speed as input and the neck inclination as output. Knowing that the input response of the central soft link changes for different positions, a second order model with variable parameters was considered. To address these variations, the new adaptive control scheme was used. The results are discussed in the next section.

IV. EXPERIMENTAL SETUP AND RESULTS

The objective of this experiment is to assess the performance of the proposed method and to compare the results with other control schemes. For this purpose, in addition to the adaptive iso-m, we consider one fractional order proportional integral (FOPI) controller and one integer order proportional integral (IOPI) control.

Adaptive iso-m performance specifications are set through phase margin and gain crossover frequency. The following values were considered for all the experiments described in this section:

- Phase Margin: $\phi_m = 50$ deg.
- Gain crossover frequency: $\omega_{gc} = 3$ rad/s.

The other FOPI and IOPI controller parameters were obtained as an average of the adaptive iso-m results. Given the plant characteristics, this is similar to using an average of the system identifications and then tuning the controllers for that average plant.

The main cause of neck uncertainty and non-linearity is the bending angle of the central soft link, which depends on the tilt. Neck orientation does not influence the plant parameters, so we will focus on the tilt movement of the neck. Since the experiment only involves inclinations, the neck can be actuated using a single tendon, simplifying the model input to the motor velocity. Therefore, plant identification is based on velocity inputs and neck inclinations outputs.

One integrator is expected from this configuration, due to the integral relationship between tendon velocity and platform inclination. Therefore, one pole located at $z = 1$ should be found during identification. Additionally, since the plant is considered as a velocity target input with an inclination output, DC motor dynamics, soft link behavior and sensor measurements are included in the system. This leads to the introduction of an additional pole to capture this dynamics, resulting in a second order plant model estimate.

Note that due to the soft link, this second pole would be necessary, even considering ideal motor and sensor conditions. Any additional behavior of the plant is neglected, as it is expected to be many orders of magnitude lower than those considered.

Figure 4 shows the evolution in time of both poles and the gain for 0 g (no payload) experiment. Note that the convergence of system parameters is correct in this plot, while identification is also capable of tracking plant changes. Note how the pole located at $z = 1$ converges very quickly, and how the other pole and the gain evolve through the experiment. As expected, higher gains and faster system responses are obtained for small inclinations.

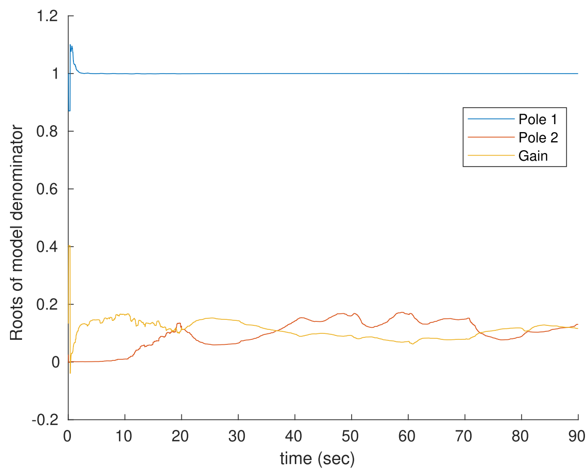

FIGURE 4. Convergence of poles and gain of the model during system identification for 0 g payload.

An important issue in adaptive systems is parameter convergence. Therefore, as the identification converges, we can consider the order of the chosen system enough for the purposes of adaptive control.

The experiment consists of a series of inclination targets in the range of 10 deg to 30 deg after an initialization period. This initial phase is intended to populate the identification system matrices and vectors, for providing a proper and stable model estimate when the continuous adaptation begins. The input signal at this stage is a frequency rich sinusoidal linear combination, designed to have sufficient persistent excitation (PE) to ensure good initial identification.

After this 20 s stage, the system enters continuous adaptation mode. During this second stage, a sequence of step inputs are programmed to bring the plant to different working conditions. These target inclinations are repeated twice to validate the experiment, verifying that similar results are obtained from the same input conditions.

Using this trajectory, three experiments were be performed. First, the adaptive iso-m scheme was applied to the soft neck. Then, two constant controllers, one fractional order (FOPI) and one integer order (IOPI) were used for comparison. All experiments were repeated for different masses from 0 g to 600 g, to analyze the effect of mass variation on the identified system and the resulting performance.

The results of the adaptive iso-m controller are shown in figure 5. It can be seen how the system response remains unchanged despite the different payloads and inclinations.

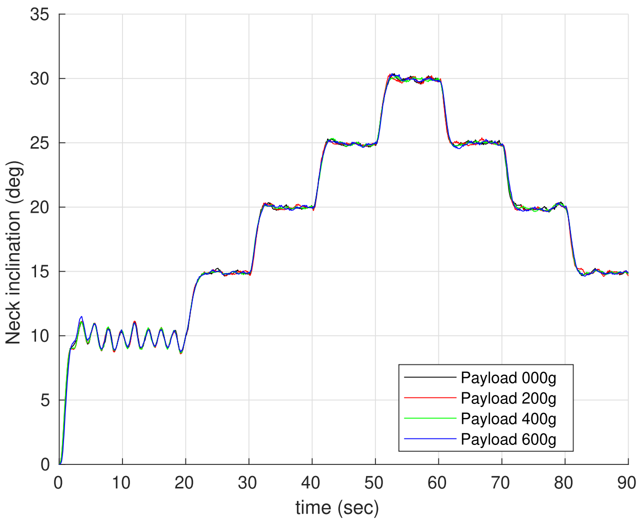

FIGURE 5. Time response of neck inclination for different payload configurations using the adaptive iso-m method with FOPI controller.

The control signals during the experiment are shown in Fig. 6, where correct values are observed and no signs of saturation are found, since all values are under 14 rad/s.

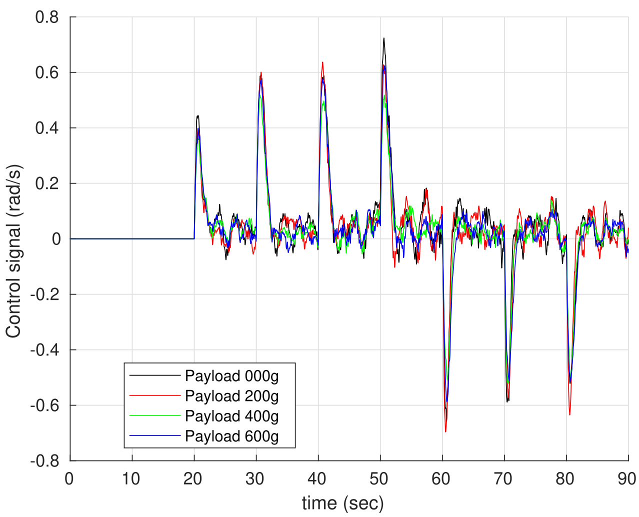

FIGURE 6. Control signals during the adaptive iso-m method with FOPI controller experiment.

Figure 7 presents the values of the estimated plant parameters during the experiment, showing the correct parameter

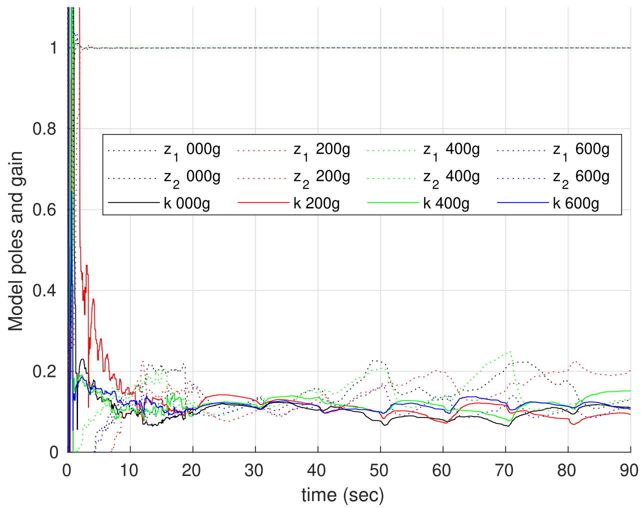

FIGURE 7. Plant parameter estimation during the adaptive iso-m method with FOPI controller experiment as a zero-pole-gain model.

convergence for all mass configurations. Minor deviations can be seen for high payloads, which are consistent with the decreasing inclination situations.

The information found in the plot of phase and magnitude in Fig. 8 shows the values obtained from the system identification parameters and Eq. (21).

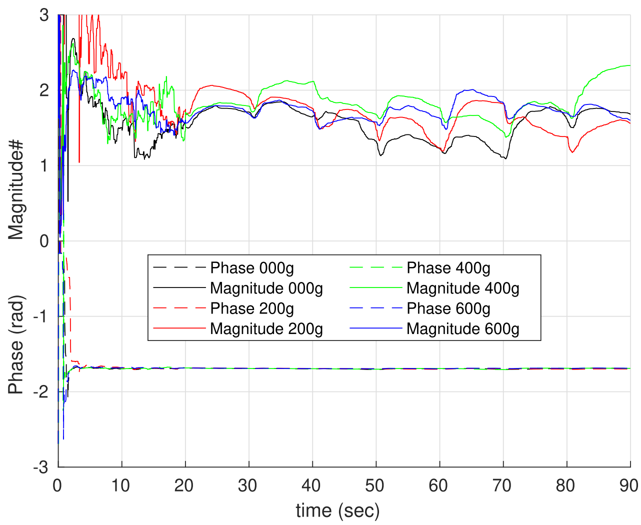

FIGURE 8. Computed phase and magnitude obtained using Eq. (21) and RLS online identification plant estimates for the adaptive FOPI controller experiment.

Note how the phase rapidly converges and remains constant through the experiment, while the magnitude changes with the inclination as expected. Considering the inclinations shown in Fig. 5, a clear link between low inclination and large magnitude can be deduced from the plot for lower payload cases.

Since controller tuning is based on the plant phase margin and magnitude, the controller parameters are related to the previous phase and margin values. This correspondence can be seen in Fig. 9 where a direct relationship between high controller gains and low plant gains can be seen. As a result of this correspondence, the time response of the adaptive system is invariant, as Fig. 5 shows, which was the goal of the proposed controller.

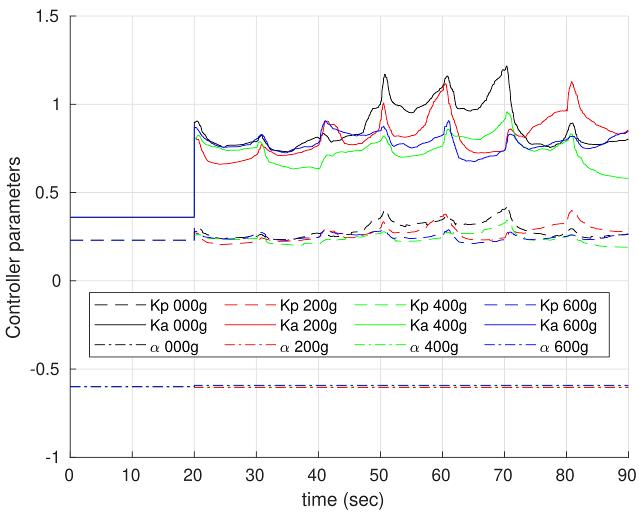

FIGURE 9. Controller parameters obtained through iso-m method based on estimated system phase and magnitude during the adaptive FOPI controller experiment.

In addition, a disturbance experiment was performed on the adaptive iso-m control scheme. The recording, available at https://vimeo.com/438681435 https://vimeo.com/438681435., shows an initialization period of 30 s as in the other experiments, followed by a 20 deg step input. Once the set point is reached, a payload variation of 600 g is first included and then the tendon is moved to provide an output disturbance. Correct tracking and robust performance in the presence of disturbances can be observed in the system.

Besides, a fractional order proportional integral (FOPI) controller with constant parameters was used in the same plant for comparison. The FOPI parameters were obtained by the average of the controller parameters shown in Fig. 9, resulting in the following values:

- $k_p = 0.2342$
- $k_a = 0.7370$
- $\alpha = -0.59$

This constant FOPD time response result is shown in Fig. 10. As expected, the robust controller shows similar performances for the different mass configurations, but a noticeable difference can be seen for different inclinations. As discussed above, the robust controller is designed for an operation range, which in our case can be considered centered at 20 deg inclination, since the average of the controller parameters has been used. Note how the overshot and the oscillations increase with the inclination angle, with a large difference for 0 g and 20 deg.

The control signals in Fig. 11 seem correct, but although the velocity values are always below 14 rad/s, there are some signs of saturation in the motor torque. During the step from

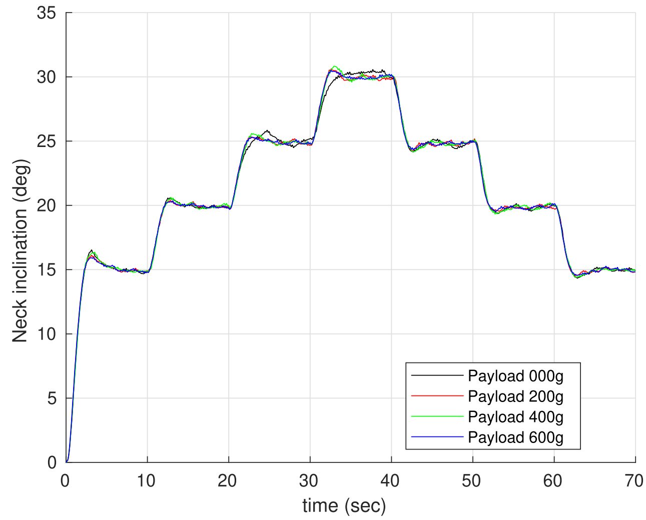

FIGURE 10. Time response of neck inclination for different payload configurations using the robust FOPI controller.

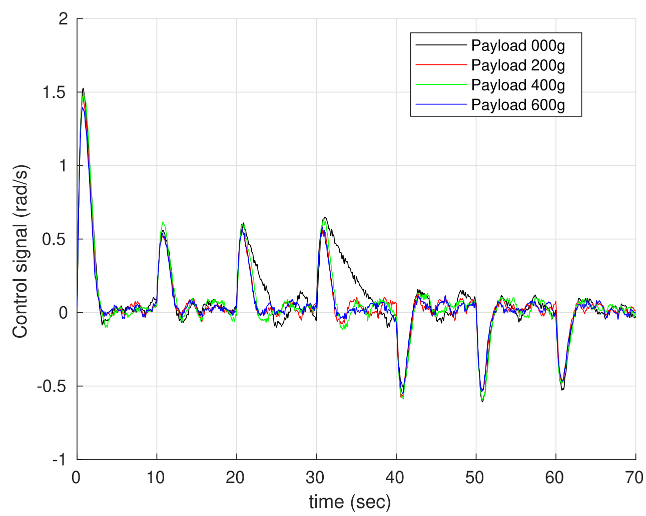

FIGURE 11. Control signals during the robust FOPI controller experiment.

25 deg to 30 deg, starting at 30 s, the deviation of the control signal shows that the system is having trouble developing the required velocity. This is due to the low value of the control signal, which explains the performance problem shown in Fig. 10 for this same payload. Since the FOPI robust controller is designed to operate in a range, robustness is compromised when the system falls out of this design range.

In addition, an integer order proportional integral (IOPI) controller with constant parameters was used in the same plant for further comparison. The same FOPI parameters were used, except the exponent order, which was considered as integer (-1), resulting in:

- $k_p = 0.2342$
- $k_a = 0.7370$
- $\alpha = -1$

The results of the IOPI controller are shown in Fig. 12, where a great variability in mass configuration and different

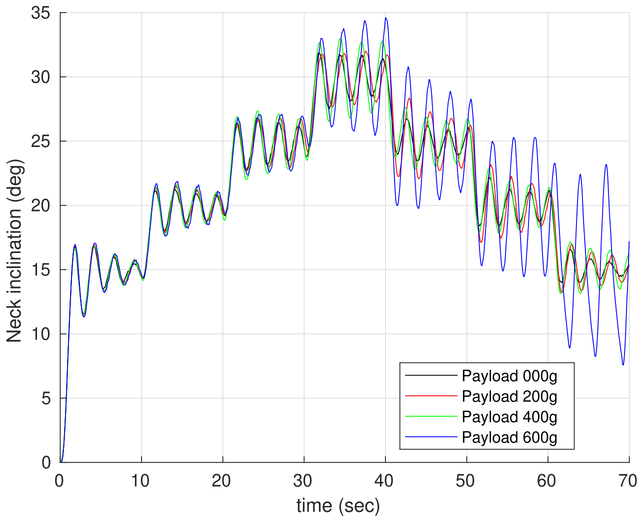

FIGURE 12. Time response of neck inclination for different payload configurations using the IOPI controller.

inclinations can be noticed, even reaching instability in the case of 0 g at the 20 deg to 15 deg transition.

The control signals in Fig. 13 are correct values, except in cases of instability, and there is no saturation.

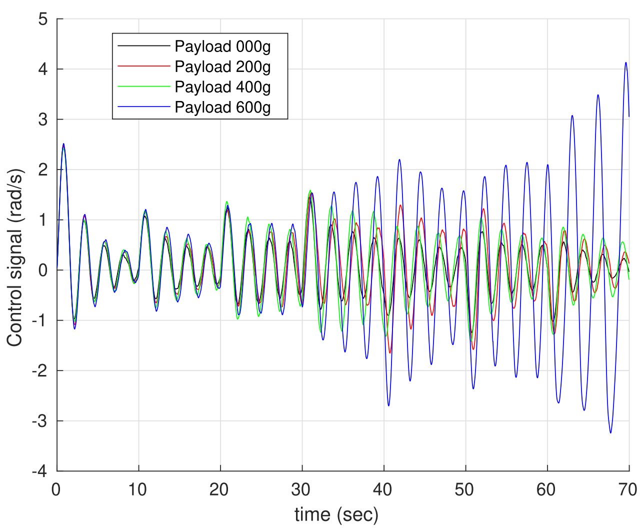

FIGURE 13. Control signals during the IOPI controller experiment.

Since the IOPI controller is not robust, the system performance changes for different inclinations and payloads.

Note that the intent here is not to compare performance of the FOPI and IOPI controllers, but to see their variability depending on different payloads and inclinations. Better performances can be found for both controllers, but these issues are out of scope now, and have been extensively addressed in other works such as [36], [48], [49] and [50].

Finally, Fig. 14 shows the plant phase and magnitude plots for the FOPI and IOPI experiments.

Again, phase is maintained throughout the experiment, while the magnitude changes with the inclination as expected, relating low inclinations and high magnitudes. System identification was similar in all the experiments, which can be considered as a validation of the results found through the experiments performed.

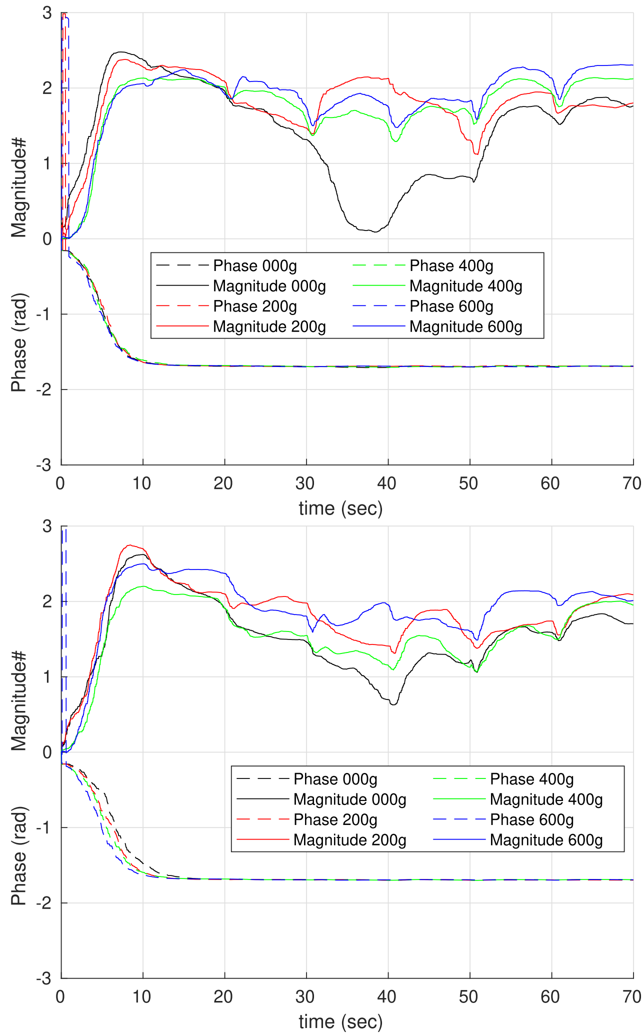

FIGURE 14. Computed phase and magnitude obtained using Eq. (21) and RLS online identification plant estimates for the robust FOPI (top) and IOPI (bottom) controller experiments.

V. CONCLUSION

Control requirements for nonlinear time varying systems can be difficult to meet. Plant parameters may change depending on configuration or time, and control performance will change accordingly, no longer meeting specifications.

The proposed adaptive fractional control uses real-time plant parameters obtained through the RLS identification algorithm as described in [39]. Combined with a fast controller tuning method such as iso-m, (see [33]) it provides adaptability and robustness in a single control scheme.

Due to the robustness of the system, the performance does not change for the operating point, and due to the adaptability of the system, plant changes will update the controller tuning to obtain the same original operating point specifications.

The proposed scheme has been validated through its application to a non-linear time varying system. The soft robotics neck described in [45] and later improved with sensors and feedback control in [46] was used. This soft neck is a good test bench due to the described plant properties, highlighting the benefits of the proposed method in nonlinear time varying applications compared to other control methods.

The experimental section shows how the resulting system can cope with variations in plant parameters while maintaining performance settings in the short and long run. Although a more extensive set of tests in different plants is needed, the results are very promising compared to current solutions of similar problems, such as [46] or [47]. Both proposals show good results, however, some performance variations were observed around the nominal working point. Compared to them, the new approach provides unchanged performance despite target inclination changes. This feature, which is a major contribution of the present paper, is achieved by combining a robust fractional controller with an indirect adaptive scheme.

Further developments derived from the proposed approach are expected to follow in the future.

More advanced methods of system identification like CLOE (see [37]), may be implemented to improve modeling accuracy, which would lead to higher precision in terms of system performance.

Another approach that is currently under research is the method implementation in lightweight computers. It is a very promising application of this method, and may improve the performance and robustness of currently available embedded control systems like [51].

Since the control scheme has been tested on a single soft neck tendon, it will be interesting to check the outcome for the entire range of motion. A kinematic model, for instance, the one in [45], will be required, resulting in different plant models. Furthermore, a wide variety of non-linear systems are suitable to use this method, among them, robot manipulators, especially soft robots, artificial muscle actuators, and many others.

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