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Adaptive Control of a Flexible-Link Robotic Manipulator with Unknown Payload Dynamics

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Abstract

For many applications, flexible-link robot arms may handle payloads that are not simple rigid bodies. In space applications, the RMS (remote manipulator system) will be manipulating satellites that may contain fuel or have flexible appendages. High-performance control schemes for flexible-link manipulators require end-point feedback. If the payload dynamics are not accounted for in the control design, degraded performance or instability are possible [1]. This paper presents technology that extends the concept of end-point control to handle payloads with unknown internal dynamics.

High-performance control is merged with an innovative identification algorithm in a self-tuning regulator approach. The identification of the payload is done using recently developed subspace-fitting techniques. These techniques allow real-time determination of the order of the payload dynamics. Sufficient excitation problems are addressed by performing the identification closed loop. Experimental results are presented.

1 Introduction

Space-based robots such as the shuttle Remote Manipulator System (RMS) and the proposed Space Station Remote Manipulator System (SSRMS) have been and will be essential elements of future space exploration. These manipulators are long, light-weight, and are required to manipulate massive payloads. As a consequence, structural flexibility in the links is significant. Further, the payloads manipulated by these large, flexible-link robots may themselves include unknown internal dynamics: for example sloshing fuel or flexible appendages (e.g., vibrating solar panels on a small satellite).

The goal of this research is to develop control techniques that provide precise high-bandwidth end-point control of flexible-link manipulators, while simultaneously damping any internal oscillations of the payload. The internal dynamics of the payload will not be known apriori. Furthermore, it is assumed that it will not be practical to outfit the payload with sensors that measure the internal state of the payload. The sensory input for controlling the robot-payload system will be based on the robot system sensors only[1].

The control approach that is developed and demonstrated experimentally in this paper is based on extensions to the self-tuning regulator solution of adaptive control. The approach is unique in that (1) it exploits the closed-loop dynamic characteristics of the class of systems being investigated in order to solve the persistent excitation problem and (2) it incorporates the first experimental, on-line demonstration of a new eigenvalue identification technique. The result is a feasible, real-time control that potentially can be implemented in future space robotic systems.

2 Experimental Apparatus

Figure 1 shows a schematic diagram of the hardware. The experiment represents a large spaced-based manipulator holding a payload that has internal vibrating dynamics. The robot arm is a flexible beam which moves in the horizontal plane. At one end of the beam, there is a motor, and on the other end there is the payload which is a pad that floats on an airbearing. The pad and air bearing prevent out of plane vibrations. Floating the pad on a smooth granite table simulates the zero-g environment of space in the horizontal plane. The pad has a pendulum on it that represents the dynamics of the payload. The pendulum can be locked in place resulting in a rigid-body payload, or it be left free to oscillate producing a dynamic payload. Additionally, the pendulum length can be manually adjusted; hence, the natural frequency of the pendulum is an unknown property of the payload.

The sensed signals available for feedback are the hub angle, the inertial position of the payload, and inertial orientation of the payload. The pendulum angle is also sensed but is not used for feedback or identification, since it would not be available on deployed systems. The pendulum has a time constant of 30 seconds corresponding to a natural damping ratio of less than 0.3%: the open-loop response of the pendulum is shown in Figure 2. See

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[1]This includes vision sensing.

references [2] and [3] for a more detailed description of the hardware.

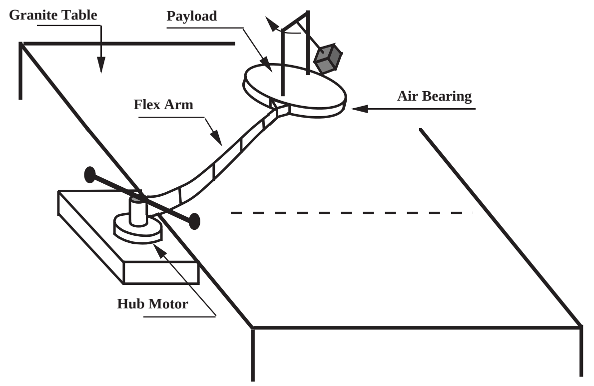

Figure 1: **Experimental System**

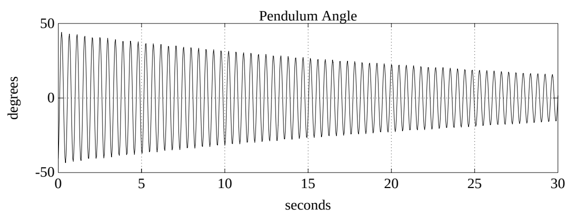

Figure 2: **Pendulum Open-Loop Response**

3 Adaptive Algorithm

Schmitz [4] surveyed control design approaches applicable to high-order, lightly-damped structures typical of the class of systems dealt with here. Two conclusions are drawn from that work. First, the use of end-point feedback is critical for high-performance end-point control of a flexible arm. The second conclusion is that linear quadratic gaussian (LQG) synthesis tools are effective in generating control systems that exploit end-point feedback.

Extending the techniques of Schmitz to account for dynamic payloads, it is possible to accurately position the payload while simultaneously damping internal vibrations of the payload [3]. The results show that high-performance control is possible, but *only* if an accurate model of the total system is available.

In this paper, an adaptive control algorithm will be presented that merges the LQG controllers with a identification procedure that is able to provide the model fidelity that is required. The approach presented is based on extensions to the self-tuning-regulator (STR) class of adaptive control. The concept of a self-tuning regulator is presented in Figure 3. It demonstrates the combination of two functions. First, an identification algorithm is used to update the equations of motion of the plant. Second, a control design algorithm (either gain calculation or scheduling) is used to modify the control law.

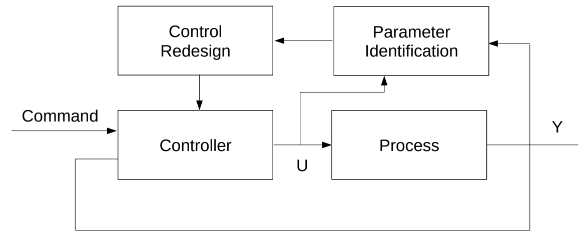

Figure 3: **Self-Tuning Regulator**

This paper focuses on the identification aspects of the self-tuning regulator. It is assumed that once the plant has been identified correctly an appropriate controller can be designed.

Identification Approach

In the general case, nothing about the payload is known apriori; however, for this research the structure of the payload model is assumed known. Specifically, in the experiment the payload can either be a rigid body, or it can include a single pendulum of unknown length. A consequence of this is that the unknown properties of the payload can be constructed from the exact open-loop eigenvalues of the system (payload plus arm). Thus, the payload dynamics can be determined from identification of eigenvalues only.

To pursue this solution, an algorithm was developed that is capable of identifying lightly damped eigenvalues of a system (all of the open-loop eigenvalues of the experimental system are lightly damped). The algorithm is described in Appendix A and does not require knowledge of the system order.

A shortcoming of this approach to identifying the payload is that *all* of the open-loop system modes must be identified, which requires all of the modes to be excited. If all of the modes are not identified, then it may not be possible to distinguish a flexible mode of the arm from that of the payload oscillations. Since the payload may be delicate, injecting excitation to guarantee that all modes of the arm are excited is unacceptable. To solve this problem, a *nominal* controller is used, and the identification is performed closed loop. The task of the *nominal* controller is to damp the structural flexibility of the arm so that the arm dynamics are not mistaken for the lightly damped oscillatory dynamics of the payload.

For the experimental system, a *nominal* controller is designed using LQG synthesis techniques assuming that the payload is a rigid body. Figure 4 shows how the *nominal* controller performs when the payload is dynamic. The *nominal* controller yields a set of well-damped closed-loop system modes that have eigenvalues that are relatively insensitive to the presence of payload dynamics. Further, if the payload is dynamic, a lightly damped or slightly unstable mode appears that has an eigenvalue that is highly sensitive to the length of the pendulum. Since the eigenvalue of the lightly damped mode appears in a region of the s-plane that is *remote* from the eigenvalues of the nominal set of controlled modes, the existence of payload dynamics can be detected by determining the presence or absence of modal content of the closed-loop system in a "critical region" of the s-plane only. When a lightly damped or slightly unstable closed-loop mode is detected, it must be associated with payload dynamics. Thus, only natural excitation is required to detect and identify the payload dynamics.

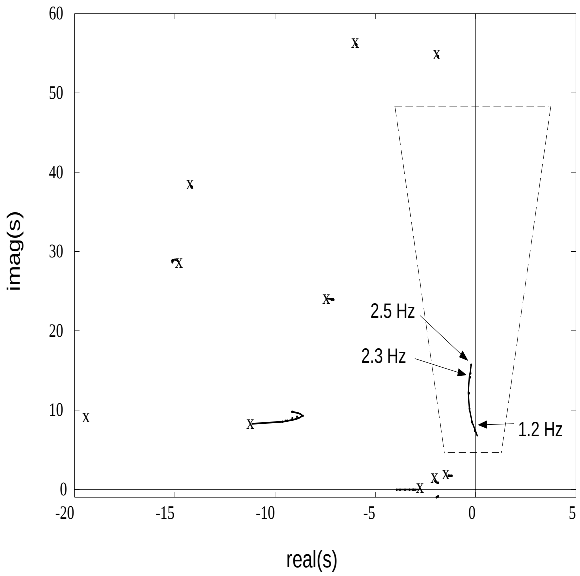

Figure 4: **Critical Region of S-Plane**

This figure shows the locus of closed-loop roots of the system versus the open-loop frequency of the payload. The controller is designed assuming the payload is a rigid body. The x's are the location of the closed-loop roots when the payload is rigid. The lines show how the closed-loop roots move as the open-loop frequency of the payload is varied from 2.5 to 1.2 Hz. The open-loop frequency of the payload is the frequency of the pendulum when the payload is detached from the arm and floating on the air-bearing. The dotted region in the s-plane is the critical region. Once a pole is detected in the critical region, the pendulum is known to exist, and its frequency can be determined.

The identification procedure that is applied to the experimental system is summarized in Figure 5. The procedure is split into detection and identification phases. The detection is accomplished by evaluating the modal content (e.g., the eigenvalues) of the system while under normal operation (closed-loop). The controller that is running during the detection phase is the *nominal* controller—no identification-specific inputs are required. When evaluating the modal content, all of the closed-loop eigenvalues might be found, but only the lightly damped poles within the critical region of the s-plane are of interest (see Figure 4). If a pole appears within the critical region, the payload is assumed to have internal dynamics. If a pole is not detected in the critical region, then either the pendulum is locked or it is not excited; in either case, it does not need to be controlled. If the pendulum becomes excited, the pole will be detected in the critical region of the s-plane.

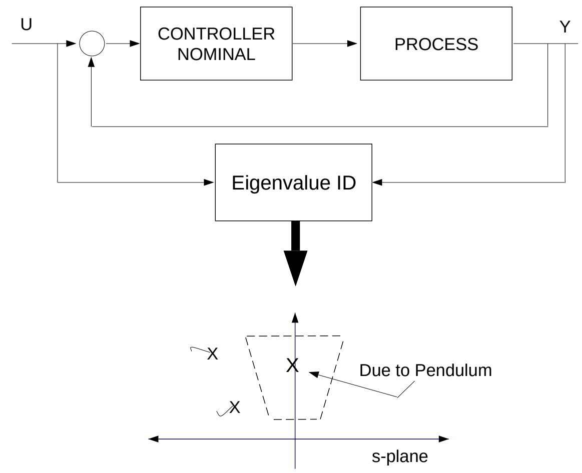

Figure 5: **Closed-Loop Identification**

The figure shows the eigenvalue identification routine reporting the closed-loop eigenvalues of the system. Performing the identification closed-loop allows the poles that are sensitive to the payload dynamics to be isolated. A mode in the critical region (dotted trapezoid) signals the presence of payload dynamics.

Once a pole is located in the critical region, its exact location can be used to identify the unknown parameter (in this case, the length of the pendulum). For the experimental system under *nominal* control, the location of the lightly damped mode is directly related to the length of the pendulum. The relation between the critical eigenvalue and the pendulum length can be plotted (see Figure 4) and inverted graphically. Thus, once the location of the pole is determined, the identification of the pendulum length is accomplished using a straightforward table look-up. Then, an appropriate controller is designed based on the identification of the payload. The new controller is then swapped into the control loop and damps the oscillations of the payload.

Since no identification of the pendulum length is performed until a pole is detected in the critical region, the payload is only identified when sufficient excitation exists naturally. There is no need to provide identification-specific excitation.

The performance of the adaptive logic depends heavily on the ability of an identification algorithm to provide accurate estimates of the eigenvalues of the system. The approach for accomplishing this utilizes a linear identification algorithm called ESPRIT which is described in Appendix A.

4 Experimental Results

The result of two experimental tests are presented: the disturbance response test, and the drop and slew test. The payload natural frequency is different for each test.

The disturbance response test, shown in Figure 6, demonstrates the response of the adaptive algorithm to large unmodelled disturbances for both rigid and dynamic payloads. The pendulum is initially locked hanging straight down. An impulsive disturbance is applied to the tip of the manipulator, and the controller rejects the disturbance. As expected, no adaptation takes place. This is in contrast to other adaptive algorithms that respond unfavorably to unmodelled disturbances. The pendulum is then released; however, since the pendulum is not oscillating, there is no need to identify or control it. A second impulsive disturbance is then applied to the tip of the manipulator. This disturbance excites the pendulum enabling the adaptive algorithm to identify the payload dynamics (natural frequency), select the proper controller, swap it in, and then damp the pendulum while simultaneously regulating the payload position. Note that neither the identification nor control algorithm is able to sense the pendulum angle directly even though it is plotted.

The drop and slew test, shown in Figure 7, demonstrates adaptation during a slew. It starts with the pendulum mechanically held at a 45 degree initial condition so that the payload is initially a rigid body. For the first two seconds, the controller is regulating the payload. The pendulum is then dropped just as the robot is commanded to slew the payload to a new position on the table. The adaptive algorithm detects and controls the pendulum oscillations while simultaneously tracking the slew command.

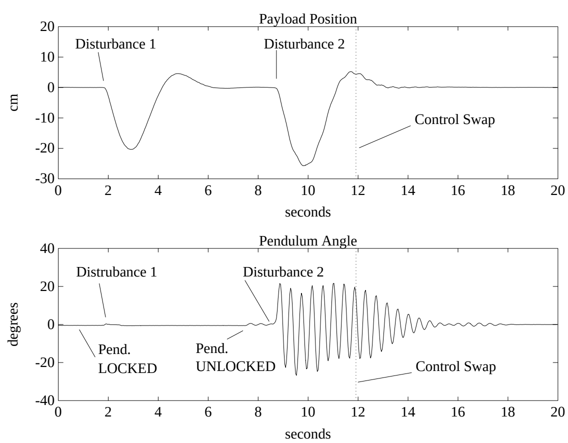

Figure 6: **Disturbance Response**

5 Conclusions

In this research, a new approach to identification is developed that utilizes a *nominal* controller in order to isolate the dynamic effects related to the uncertain parameters from the other known system dynamics. For the class of systems presented here, the identification is reduced to determining the eigenvalues of the system under *nominal* control. An eigenvalue identification routine based on ESPRIT is used to identify accurately any lightly damped modes that are indicative of the payload dynamics. Externally supplied excitation is not necessary for payload identification: the approach does not identify the payload dynamics unless they are excited naturally.

Experiments show the response of the system in disturbance rejection and slew. In all cases, the adaptation only occurs when there is natural excitation of the payload dynamics. If the pendulum is not excited, the controller does not need to account for it. Once the pendulum is excited, the algorithm first detects it and then controls it. This adaptive approach has proven successful in experimentally demonstrating precise high-bandwidth end-point control while simultaneously damping internal oscillations of a payload with unknown internal dynamics.

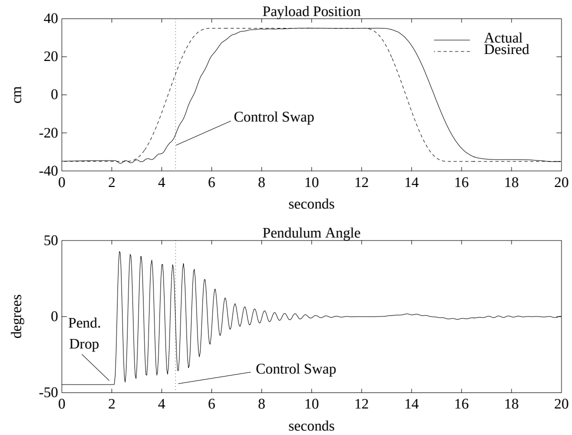

Figure 7: **Drop and Slew**

A Eigenvalue Identification

This appendix describes the subspace-fitting technique called ESPRIT. Reference [5] presents the algorithm in the context of direction of arrival determination for signal processing. The algorithm is presented here in the context of linear system identification.

The subspace-fitting technique is inherently digital. Suppose that the system is linear time-invariant and is described in state-space form by

$$\mathbf{x}_{k+1} = \mathbf{A}\mathbf{x}_k + \mathbf{B}\mathbf{u}_k \quad (1)$$

$$\mathbf{y}_k = \mathbf{C}\mathbf{x}_k + \mathbf{D}\mathbf{u}_k \quad (2)$$

where $\mathbf{x}_k$ is the state of the linear system at time k, $\mathbf{u}_k$ is the input to the linear system, and $\mathbf{y}_k$ is the observed output ($\mathbf{x}_k \in \mathbb{R}^{n\times 1}$, $\mathbf{u}_k \in \mathbb{R}^{q\times 1}$, and $\mathbf{y}_k \in \mathbb{R}^{m\times 1}$). Since the states are not measured, the system matrices are identifiable only to within an arbitrary non-singular state (similarity) transformation. The identifiability of the system matrices is also limited by the excitation of the system from the inputs or initial conditions.

The algorithm requires a window of data. The length of the data, N, must be selected. A sliding window length size M $\ll$ N/2 must also be chosen.

The first step in the procedure is to take the input and output data and form the Hankel matrices

$$\mathbf{Y} = \begin{bmatrix} \mathbf{y}_1 & \mathbf{y}_2 & \cdots & \mathbf{y}_{N-M+1} \\ \mathbf{y}_2 & \mathbf{y}_3 & \cdots & \mathbf{y}_{N-M+2} \\ \cdots & \cdots & \cdots & \cdots \\ \mathbf{y}_M & \mathbf{y}_{M+1} & \cdots & \mathbf{y}_N \end{bmatrix} \quad (3)$$

$$\mathbf{U} = \begin{bmatrix} \mathbf{u}_1 & \mathbf{u}_2 & \cdots & \mathbf{u}_{N-M+1} \\ \mathbf{u}_2 & \mathbf{u}_3 & \cdots & \mathbf{u}_{N-M+2} \\ \cdots & \cdots & \cdots & \cdots \\ \mathbf{u}_M & \mathbf{u}_{M+1} & \cdots & \mathbf{u}_N \end{bmatrix} . \quad (4)$$

Thus,

$$\mathbf{Y} = \mathbf{\Gamma X} + \mathbf{HU} \quad (5)$$

where

$$\mathbf{\Gamma}^{\mathrm{T}} = [\ \mathbf{C}^{\mathrm{T}} \quad (\mathbf{CA})^{\mathrm{T}} \quad \cdots \quad (\mathbf{CA}^{M-1})^{\mathrm{T}}\ ] \quad (6)$$

$$\mathbf{X} = [\mathbf{x}_1\ \mathbf{x}_2\ \cdots\ \mathbf{x}_{N-M+1}] \quad (7)$$

$$\mathbf{H} = \begin{bmatrix} \mathbf{D} & 0 & \cdots & 0 \\ \mathbf{CB} & \mathbf{D} & \cdots & 0 \\ \mathbf{CAB} & \mathbf{CB} & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots \\ \mathbf{CA}^{M-2}\mathbf{B} & \mathbf{CA}^{M-3}\mathbf{B} & \cdots & \mathbf{D} \end{bmatrix} . \quad (8)$$

Thus $\mathbf{Y} \in \mathrm{I\!R}^{mM \times (N-M+1)}$ and $\mathbf{U} \in \mathrm{I\!R}^{qM \times (N-M+1)}$, $\mathbf{\Gamma} \in \mathrm{I\!R}^{mM \times n}$, $\mathbf{X} \in \mathrm{I\!R}^{n \times (N-M+1)}$, and $\mathbf{H} \in \mathrm{I\!R}^{mM \times Mq}$. Note that $\mathbf{U}$ and $\mathbf{Y}$ are the only matrices that are formed from measured data.

The second step of the procedure is to find a matrix $\mathbf{U}^\perp$ such that $\mathbf{UU}^\perp = 0$. The matrix $\mathbf{U}^\perp$ can be found from the singular value decomposition of $\mathbf{U}$. Once $\mathbf{U}^\perp$ has been calculated, $\mathbf{YU}^\perp$ can be formed from Equation 5. Thus,

$$\mathbf{YU}^\perp = \mathbf{\Gamma X U}^\perp . \quad (9)$$

Note that the column space of $\mathbf{YU}^\perp$ is contained in the column space of $\mathbf{\Gamma}$. The matrix $\mathbf{\Gamma}$ has n columns. Thus, performing a singular value decomposition of $\mathbf{YU}^\perp$ should yield n or less non-zero singular values. However, since the data has noise, the last $mM - n$ singular values will not be exactly zero but will be significantly smaller than the first n. The large drop in the singular values of $\mathbf{YU}^\perp$ determines the number of excited poles of the system, n.

Once the order of the system has been determined, the next step is to find the $\mathbf{A}$ matrix that is of the proper order that best fits the data. To find $\mathbf{A}$, note that the observability matrix $\mathbf{\Gamma}$ possess a shift invariant structure. This means that the second row of $\mathbf{\Gamma}$ can be found by multiplying the first row by $\mathbf{A}$, and the third row can be found by multiplying the second row by $\mathbf{A}$, and so on. However, $\mathbf{\Gamma}$ is unknown. Fortunately, $\mathbf{\Gamma}$ can be computed in a different coordinate system maintaining the shift invariant property. Compute the singular value decomposition of $\mathbf{YU}^\perp$:

$$\mathbf{YU}^\perp = \mathbf{P \Sigma Q}^T . \quad (10)$$

Let $\mathbf{P}_s$ be the matrix containing the first n left singular vectors of $\mathbf{YU}^\perp$. It can be shown from Equation 9 and 10 that there exists a full rank $n \times n$ matrix $\mathbf{T}$ such that

$$\mathbf{P}_s = \mathbf{\Gamma}\,\mathbf{T} . \quad (11)$$

Expanding the rows of this equation yields

$$\mathbf{P}_s = \begin{bmatrix} \mathbf{P}_0 \\ \mathbf{P}_1 \\ \mathbf{P}_2 \\ \vdots \\ \mathbf{P}_{M-1} \end{bmatrix} = \begin{bmatrix} \mathbf{C} \\ \mathbf{CA} \\ \mathbf{CA}^2 \\ \vdots \\ \mathbf{CA}^{M-1} \end{bmatrix} \mathbf{T} = \begin{bmatrix} \bar{\mathbf{C}} \\ \bar{\mathbf{C}}\bar{\mathbf{A}} \\ \bar{\mathbf{C}}\bar{\mathbf{A}}^2 \\ \vdots \\ \bar{\mathbf{C}}\bar{\mathbf{A}}^{M-1} \end{bmatrix} . \quad (12)$$

Hence, there is a matrix $\bar{\mathbf{A}}$ that is the state-transition matrix of the system in some coordinate frame such that the second row of $\mathbf{P}_s$ can be found by multiplying the first row by $\bar{\mathbf{A}}$, etc. $\mathbf{P}_s$ is $\mathbf{\Gamma}$ in some new coordinate system.

To find $\bar{\mathbf{A}}$, form

$$\mathbf{P}_{s1} \equiv \mathbf{P}_s \ \textit{with last row deleted} \quad (13)$$

$$\mathbf{P}_{s2} \equiv \mathbf{P}_s \ \textit{with first row deleted} \quad (14)$$

and observe that

$$\mathbf{P}_{s1}\bar{\mathbf{A}} \approx \mathbf{P}_{s2} . \quad (15)$$

The approximation is due to the fact $\mathbf{P}_{s1}$ and $\mathbf{P}_{s2}$ are created from noisy data. $\bar{\mathbf{A}}$ is computed by solving the least squares problem or more accurately the total least squares problem (see [5]) that is posed by Equation 15. From $\bar{\mathbf{A}}$ the eigenvalues of the system can be found.

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