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Controlling Modern Radars: Challenges and Opportunities

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***Abstract*—There is growing research interest in the problem of closing the radar feedback processing loop at various time scales, down to pulse-to-pulse adaptation. This paper reviews these developments from the point of view of a control systems specialist by examining two examples of waveform adaptation. Closing the loop in the radar context means to change the transmitted waveform depending on the echoes received from potential targets. This is not the classic feedback problem where a plant is to be controlled. Instead, the objective is to manage the uncertainty about significant objects, bringing to the fore the area of sensor management, also examined herein. Finally, the paper provides an illustration of waveform adaptation in nature, namely echolocation in bats.**

I. Introduction

To the layman, radars evoke the image of large rotating parabolic antennas bolted to a stationary structure, managed by human operators. While those radars still exist, modern radars can be rather small, their antennas are non-rotating and are not even parabolic. Modern radars are typically mobile, either flying on aircraft, moving on the ground or aboard ships. The outputs of modern radars are exploited by algorithms as complex as those used to produce the outputs themselves. Below the surface, the changes are equally impressive, mainly brought about by advances in antenna technology and signal processing. Where is control systems theory in all this? The "Radar Handbook", [1] present on the shelf of most radar engineers, counts 26 chapters and over 1000 pages covering all aspects of modern radar technology. Yet, except for a brief mention of mechanical servomechanisms to control the pointing of mechanically steered antennas, control systems are nowhere found in [1]. In addition to the "Hidden Technology" phenomenon discussed in [2], there is an additional reason for this absence: it is only in the past 20 years that radar *transmitters* became fully agile, down to pulse-to-pulse changes in waveforms. Agility in transmission permits feedback of a different type than what is used in control design – compare Figure 1-(a) with Figure 1-(c) – but feedback nevertheless. Under the heading of sensor management or sensor scheduling, radar transmitter feedback is now a subject of steady academic study [3] and making its way into applications [4]. This paper attempts to capture these developments from the point of view of a control systems specialist. The paper is organized as follows. Section II briefly describes radar systems, focusing on what is new from a systems point of view. Section III discusses the general problem of sensor resource management. Section IV describes in some detail one problem in transmitter control where control theoretic developments can bring important breakthroughs. Section V discusses parallels between modern radars and echolocation systems of bats. Section VI closes the paper with our conclusions.

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II. Radars and Modern Radars

A. Pulse-Doppler radars

In this section we discuss the basic elements of pulse-Doppler radars ([5], p. 25) tracking a single target. Pulse-Doppler radars transmit a succession of pulses and recover the range r and the radial velocity (range rate) $\dot{r}$ of the target from the received pulse. Let a narrowband transmitted pulse be represented as:

$$s_T(t) = \sqrt{2}\text{Re}\left[\sqrt{E_T}\tilde{s}(t)\exp(j2\pi f_c t)\right] \tag{1}$$

where f_c is the carrier frequency, E_T is the energy of the transmitted pulse and $\tilde{s}(t)$ is the complex envelope of the pulse. The received signal is:

$$s_R(t) = \sqrt{2}\text{Re}\left[\sqrt{E_R}\tilde{s}(t-\tau)\exp(j2\pi(f_c t + \nu t))\right] + n(t) \tag{2}$$

under the assumption that $2\dot{r} \ll c$. Here $n(t)$ is additive noise, c is the speed of light,

$$\tau = \frac{2r}{c}, \quad \nu = -\frac{2f_c\dot{r}}{c}$$

where τ is the delay of the received signal and ν is the Doppler shift. The problem at hand is to extract r and $\dot{r}$ from the received signal given by equation (2) using an appropriate filter. Due to the small values of $\dot{r}$ in comparison with c, the Doppler shift shows as a small variation in the carrier frequency. For this reason, at least several successive echoes must be received from the target and the first wavefront of each pulse must be separated from the last wavefront in the preceding pulse by an integer number of wavelengths, a property called coherence [5] p. 10.

In very broad terms, the design of a pulse-Doppler radar consists of selecting: (1) E_T, (2) $\tilde{s}(t)$ including its width, (3) the interval between pulses, (4) the number of pulses processed simultaneously (the coherent interval) and (5) a suitable filter, so that estimates of r and $\dot{r}$ are optimal in some sense. We notice that pulse-Doppler refers to a mode of operation, not to a particular structure (mechanically steered or electronically steered).

B. Active Electronically Steered Array (AESA) Antennas

AESA radars represent a substantial advance over mechanically steered structures. In [5] Chapter 37, AESA radars are reviewed in detail. Since no mechanical inertia needs to be overcome in steering the AESA beam, it is far more agile that the beam of a mechanically steered antenna. For purposes of further discussion in this paper, the salient features of AESA radars are:

- The direction of the beam can be changed almost instantaneously.
- The power applied on each dwell (coherent processing interval) can be changed dwell-to-dwell.
- Dwell times can be individually optimized to meet detection and tracking needs.

C. *What is new?*

As noted in [6], the idea of changing the transmitted pulse in response to the receiving echoes of previously transmitted waveforms dates at least to the 1960s. This author performed an extensive literature search and found [7] and [8] as the earliest available references in the area. To the control systems specialist, this feature permits feedback control to be used, where the next sequence of pulses is designed in response to the received signals. The use of feedback control at fast time scales in radar processing is often associated with the term cognitive radar, introduced in [9]. What is new is the formalization and systematic study of pulse-to-pulse transmitter adaptation starting with [10], which we discuss in Section IV.

III. CONTROLLING SENSORS

Before delving into the specifics of controlling modern radars, we recognize that radars are specialized sensors. The past two decades have produced considerable literature on what is called sensor management which is thoroughly surveyed in [6]. In this section, we merely touch the surface of this subject. Our objectives here are threefold: (1) explain what sensor management means and how it relates to traditional feedback control; (2) discuss the role of information theory ideas and (3) illustrate some of the complexities encountered even in simple sensor management problems.

A. *What is Sensor Management?*

Figure 1 contrasts different schemes for processing the output of a dynamical system. Figure 1-(a) depicts the classic feedback loop, where observed signals are used to reconstruct the state. In Figure 1-(b) the feedback loop includes a sensor scheduler which selects appropriate outputs with the objective of improving the control of the dynamical system. Procedures of this second type are usually called measurement adaptive problems or sensor scheduling, and have been studied in [11], [12] and [13]. Controlling the dynamics of the system still occupies central stage, and the choice of outputs is an aid to obtaining better estimates for control. Figure 1-(c) represents a departure from the previous schemes. Here, the objective is to obtain suitable estimates (in a sense described by a performance index) of the state of the dynamical system. No attempt is made to change the dynamic of the system. The main example illustrating this case is multi-target tracking where the dynamical system itself is a collection of distinct targets moving within the observation range of a sensor. The problem is to direct the sensor's attention to events of interest. The sensor has a limited field of view and has to decide at each instant of time where and how to direct its attention. We notice that the nomenclatures "sensor scheduling" and "sensor management" are sometimes used interchangeably in the literature.

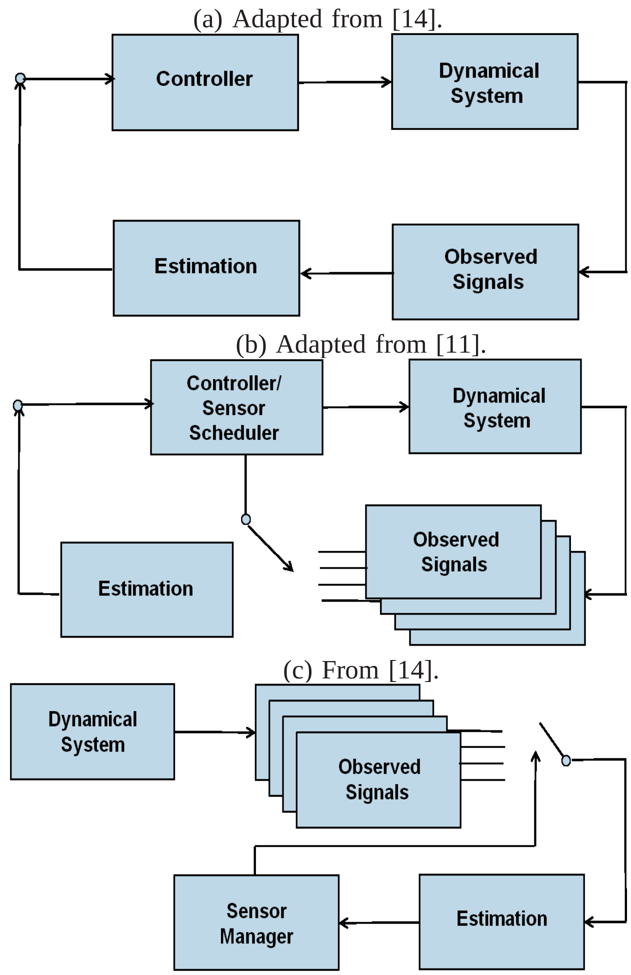

Figure 1. (a) Feedback control. (b) Sensor scheduling. (c) Sensor management.

B. *Information Gain and Sensor Management*

The set-up depicted in Figure 1-(c) points to the fact that what is being controlled is the information state of the system [6], [15]. The idea of maximizing information gain (the Infomax Principle) has appeared with different names in a wide range of fields with multiple definitions of what is meant by information gain [16]. Below we follow an information theoretic approach to define information gain; this is incidental, and information gain can be interpreted and measured in other ways e.g. [17].

Let $x_k \in \mathbb{R}^n$ represent the state of a discrete-time Markov process, and $z_k^s \in \mathbb{R},\ s = 1 : S$ denote S possible sensor selections at time k. Bayes' rule, the Markov property and the law of total probability give:

$$p(x_k|z_{0:k-1}, z_k^s) = \frac{p(z_k^s|x_k)p(x_k|z_{0:k-1})}{p(z_k^s|z_{0:k-1})} \quad (3)$$

$$p(z_k^s|z_{0:k-1}) = \int p(z_k^s|x_k)p(x_k|z_{0:k-1})dx_k \quad (4)$$

Equation (3) gives an expression for the posterior distribution of the state at time k given the prior distribution $p(x_k|z_{0:k-1})$. At time k there are S choices of outputs. We *define* the Information Gain (IG) of measurement s (or sensor s) as the Kullback-Leibler divergence of the prior distribution from the posterior distribution:

$$IG(s) = KL[p(x_k|z_{0:k-1}, z_k^s)||p(x_k|z_{0:k-1})] \quad (5)$$

where the Kullback-Leibler divergence of distribution $g(x)$ from distribution $f(x)$ is defined as [18]:

$$KL[f(x)||g(x)] = \int f(x)\log\frac{f(x)}{g(x)}dx \quad (6)$$

Following [15] our aim is to choose the sensing action before actually receiving the measurement z^k, which will be selected among the $z_k^s,\ s = 1 : S$. We select s to maximize the *expected value* of $IG(s)$, i.e.

$$\widehat{IG}(s) = \mathbb{E}_{z_k^s}\{KL[p(x_k|z_{0:k-1}, z_k^s)||p(x_k|z_{0:k-1})]\}$$
$$\text{and } s^* = \arg\max_{s\in 1:S} \widehat{IG}(s)$$

Using properties of the Kullback-Leibler divergence we have:

$$\widehat{IG}(s) = H[p(x_k|z_{0:k-1})] - H[p(x_k|z_{0:k-1}, z_k^s)] \quad (7)$$

where $H[f(x)]$ denotes the entropy of distribution $f(x)$, defined as $H[f(x)] = -\int f(x)\log f(x)dx$. Since $H[p(x_k|z_{0:k-1})]$ does not depend on s, it follows from equation (7) that

$$s^* = \arg\min_{s\in 1:S} H[p(x_k|z_{0:k-1}, z_k^s)] \quad (8)$$

showing that the application of the Infomax Principle based on the Kullback-Leibler divergence leads to choosing the measurement that minimizes the entropy of the posterior state distribution. Observe that except for the Markov assumption, this result is entirely general.

It is instructive at this point to verify the form these results take for the case of Gauss-Markov systems, which are linear dynamical systems forced by Gaussian noise, and outputs corrupted by Gaussian noise. In this case, the Kalman filter provides the probability density of the state conditioned on the measurements, with covariance Σ_k given by a well known recursion [19]. Hence,

$$p(x_k|z_{0:k-1}, z_k^s) \sim \mathcal{N}(\mu_k, \Sigma_k)$$

where $\mathcal{N}(\mu_k, \Sigma_k)$ denotes the multidimensional Gaussian distribution with mean μ_k and covariance Σ_k. The entropy in this case becomes:

$$H[\mathcal{N}(\mu_k, \Sigma_k)] = \frac{1}{2}\log(\det(2\pi e\Sigma_k)) = \frac{n}{2}\log(2\pi e) + \frac{1}{2}\log(\det(\Sigma_k))$$

and the Infomax Principle reduces to choosing the measurement leading to the smallest $\det(\Sigma_k)$.

C. Greedy policies and multi-step performance indices

As described in the previous subsection, the solution obtained with the Infomax Principle is greedy (or myopic), since the decision is made considering only the performance at the present state. It is well known from Optimal Control Theory that schemes optimizing multi-step performance indices are often advantageous [20]. We now consider a simple problem involving multi-step performance indices. The objective is to show that greedy policies are not necessarily optimal in these cases. Following [21] and [22], consider two identical scalar Gauss-Markov systems of the form:

$$p_{k+1}^{(i)} = fp_k^{(i)} + w_k^{(i)} \quad (9)$$

$$z_k^{(i)} = p_k^{(i)} + v_k^{(i)} \quad (10)$$

where $p_k^{(i)}$ is the state of the i-th system at time k $(i = 1, 2)$, $z_k^{(i)}$ is the corresponding measurement and $\{w_k^{(i)}\}$ and $\{v_k^{(i)}\}$ are sequences of zero mean, independent, identically distributed Gaussian random variables with $\mathbb{E}(w_a^{(i)}w_b^{(i)}) = \Sigma^2\delta_{ab}$ and $\mathbb{E}(v_a^{(i)}v_b^{(i)}) = R^2\delta_{ab}$, where δ_{ab} is the Kronecker delta. Here, $\Sigma^2, R^2 > 0$ and $f \neq 0$. Let the initial probability density of the state $p_0^{(i)}$ be Gaussian with mean $\hat{p}_0^{(i)}$, covariance $\sigma_0^{2(i)}$ and independent of $\{w_k^{(i)}\}$ and $\{v_k^{(i)}\}$. In the formulation in [21], one and only one system is observed at each time slot. A policy is a sequence $\{u_k\}$ of the integers $1, 2$. If $u_k = i$, then the i-th system is observed on the k-th time slot. From the point of view of the estimators, the absence of a measurement can be represented by setting $R^2 \to \infty$. To represent the overall uncertainty of the collection of systems, the following multi-step performance index is suggested:

$$J(\{u_k\}_{k=0}^{k=N-1}) = \sum_{k=1}^{N} \sigma_k^{2(1)} + \sigma_k^{2(2)} \quad (11)$$

where N represents a time horizon over which optimization is performed. The problem at hand is to select a policy $\{u_k^*\} = \mu(\sigma_0^{2(1)}, \sigma_0^{2(2)})$ which minimizes J_N i.e.

$$u_k^* = \arg\min_{u_k\in\{1,2\}, k=0,1,\cdots,N-1} \sum_{k=1}^{N} \sigma_k^{2(1)} + \sigma_k^{2(2)} \quad (12)$$

The greedy policy in this case is given by:

$$u_n^g = \begin{cases} 1, & \text{if } \sigma_n^{2(1)} \geq \sigma_n^{2(2)} \\ 2, & \text{otherwise} \end{cases} \quad (13)$$

In [22] the following is shown:

- When $N = 1$, and arbitrary f, Σ^2, R^2 the greedy policy is optimal.
- When $N = 2$, there exists $f \neq 1$, Σ^2, R^2 and appropriate initial conditions $\sigma_0^{2(1)}$ and $\sigma_0^{2(2)}$ for which the greedy policy is not optimal, i.e. $\{u_n^g\} \neq \{u_n^*\}$. Moreover, given f, Σ^2, R^2 the set of initial conditions for which the greedy policy is not optimal has non-empty interior. An example of this phenomenon is depicted in Figure 2.

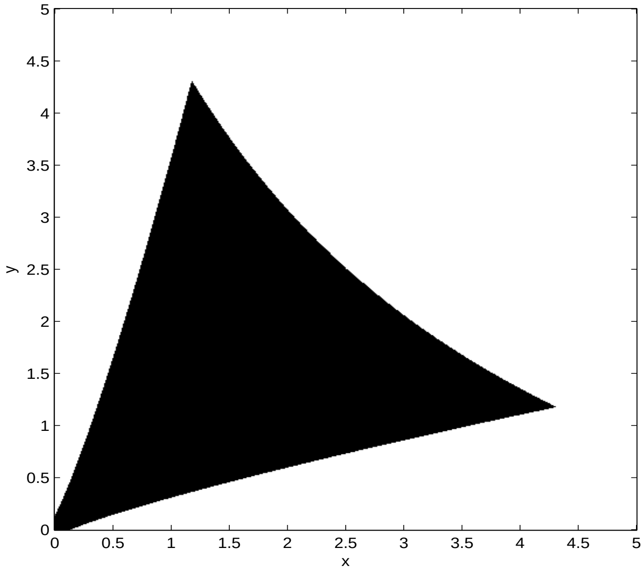

Figure 2. The region where greedy policy is not optimal is marked in black. $f = \sqrt{5}, c = 0.1; x = \sigma_0^{2(1)}; y = \sigma_0^{2(2)}$.

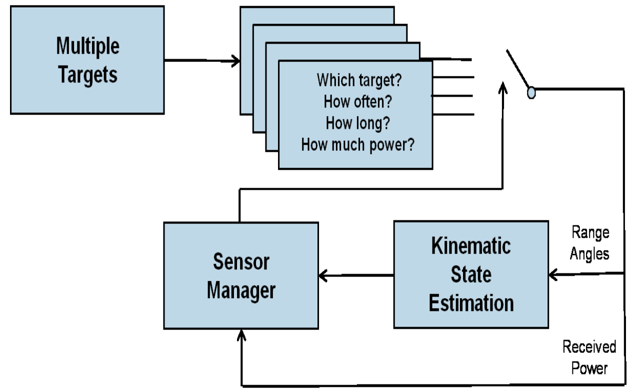

Figure 3. Adaptive power control for multi-target tracking.

IV. Controlling Modern Radars

In this section we describe two examples of feedback adaptation of radar waveforms. These correspond to two time scales of operation.

A. Controlling revisit rate, transmitting power, beam direction

As described in section II-B AESAs can control their direction and transmitted power dwell-to-dwell. This ability was exploited in [23], [24], [25], a line of research we discuss below. All three papers assume tracking of multiple targets which are far apart. The control variables are the revisit rate, the beam direction and the transmitted power per dwell. These three quantities are target dependent. The measurement variables are the received power, the range and the angles (azimuth and elevation) from each target. The control objective is to minimize total energy while maintaining the uncertainty of the tracks within acceptable bounds. This represents adaptation at the dwell time scale. Figure 3 depicts the feedback loop in question.

B. Controlling waveforms pulse-to-pulse

Adapting the transmitted waveform pulse-to-pulse was first studied in [10], a seminal paper which spurred a new direction of research. Several papers followed, with different assumptions concerning the allowed waveforms. For example, in [26] the complex envelope (refer to equations (1) and (2)) $\tilde{s}(t)$ takes the form:

$$\tilde{s}(t) = a(t)\exp(j2\pi b\xi(t))$$

Here,

$$a(t) = \begin{cases} \frac{\alpha}{t_f}\left(\frac{T}{2} + t_f + t\right), & -\frac{T}{2} - t_f \le t < \frac{T}{2} \\ \alpha, & -\frac{T}{2} \le t < \frac{T}{2} \\ \frac{\alpha}{t_f}\left(\frac{T}{2} + t_f - t\right), & \frac{T}{2} \le t < \frac{T}{2} + t_f \end{cases}$$

is a trapezoidal envelope, with rise/fall time $t_f \ll \frac{T}{2}$, α is chosen so that $\tilde{s}(t)$ in equation (1) has unit energy[1]. b is a scalar frequency modulation (FM) parameter and $\xi(t)$ is the phase function. The waveforms considered in [26] are the linear FM, power FM, hyperbolic FM and exponential FM. These are obtained by selecting an appropriate phase function. For linear FM the phase function is given by:

$$\xi(t) = \frac{t}{\gamma} + \frac{(t + \frac{\ell}{2})^2}{2},$$

where γ and ℓ are parameters to be chosen. Notice that $\frac{d\xi(t)}{dt} = b\ell$ which represents a linear increase of instantaneous frequency as we move along the pulse. The collection of waveforms available by changing $a(t)$ and $\xi(t)$ represent the control variables in the problem. Let $\theta_k \in \Theta$ represent all the parameters characterizing $a(t)$ and $\xi(t)$ at time instant t_k. Following [10] assume the target model is described by:

$$x_{k+1} = Fx_k + Gw_k \tag{14}$$

where x_k is the target state vector at time instant t_k while the measurement vector of the target state at t_k is given by:

$$y_k = Hx_k + v_k \tag{15}$$

The noise vectors w_k and v_k are independent identically distributed zero-mean white Gaussian sequences with covariance matrices Q_k and $R(\theta_k)$ respectively. Dependence of the measurement covariance on θ_k is crucial. This allows one to manipulate the state error covariance, which is ultimately the quantity of interest. Refer to Figure 1-(c). The *Observed Signals* block represents the various waveforms that can be chosen in response to the *Estimation* block, which represents a filter with a given structure Γ. For our purposes, the output of the filter is the uncertainty associated with the system's state. Formally, the general problem of waveform adaptation is to select waveforms $\{\theta_1, \theta_2, \cdots, \theta_k\} \in \Theta$ and a filter structure Γ such that

$$P_k = \mathbb{E}\left[||x_k - \hat{x}_k||^2 \mid Y^k\right]$$

[1] This is very important; if the pulse energy would be allowed to vary, we would be back to the problem discussed in subsection IV-A.

is minimum. Here, $Y^k = \{y_1, y_2, \cdots, y_k\}$ and $\hat{x}_k$ is the filter output. Notice that one needs to search over the space of filter structures and waveform selections, which is made very difficult by the fact that the measurement covariance is a nonlinear function of θ_k. A possible approximation is to fix the filter structure, and minimize over the waveforms. In [10] the Kalman filter was utilized. In this case, the Kalman filter update equations (e.g. [19]) allows one to write $P_{k+1} = \Phi\left[P_k, R(\theta_{k+1})\right]$, where P_k is known at time k. When $y_k = [r_k\ \dot{r}_k]^T$ (one-dimensional case) and the waveforms have unit energy, it is possible to obtain $R(\theta_k)$ in closed form [10] p. 1539. This allows one to solve the greedy version of the original problem, i.e. to determine $\hat{\theta}^*_{k+1}$ such that

$$\hat{\theta}^*_{k+1} = \arg \min_{\theta_{k+1} \in \Theta} \mathrm{Tr}\left\{\Phi\left[P_k, R(\theta_{k+1})\right]\right\}$$

In [26] two assumptions in [10] are lifted: (1) a more general class of filters are considered and (2) the target moves in two dimensions. In this case, closed-form solutions are not possible, and one has to resort to numerical approximations. Simulation in [26] demonstrate the benefits of waveform adaptation in comparison to using a fixed waveform.

V. Bats and Modern Radars

Echolocation signals used by bats are brief sounds varying in duration from 0.3 ms to 300 ms, and in frequency from 12 kHz to 200 kHz [27]. In most species the sounds consist of either FM components alone or a combination of a constant frequency (CF) component with FM components. Most species that have been studied to date show changes in the parameters of their sonar signals, for example duration, bandwidth, and repetition rate with foraging conditions, such as their proximity to vegetation, water, and buildings [28]. It is widely believed that sonar signal design reflects the bat's control over acoustic information gathered from the echoes [29]. Interestingly, it is uncertain whether bats are capable of multi-pulse, coherent processing performed by pulse-Doppler radars [30]. However, bats (and dolphins) may produce synthetic aperture sonar images without coherent processing [31].

VI. Conclusions

While echo feedback has been used in radar applications since the 1960s, it is only in the past twenty years that the discipline gained a more precise mathematical formulation. Interestingly, so far it has not caught much attention from the control systems community. This papers attempts to describe recent developments from the point of view of a control systems specialist, and provide a starting point for research in the area. We believe that opportunities for many advances in the field are within reach with increased collaboration between control theorists and radar engineers.

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