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A SELF-ADAPTIVE GENERIC IMM DATA FUSION ALGORITHM

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САМОРЕГУЛЬОВАНИЙ ТИПОВИЙ АЛГОРИТМ СПІЛЬНОЇ ОБРОБКИ ДАНИХ ВЗАЄМОДІЮЧИХ БАГАТОРІВНЕВИХ МОДЕЛЕЙ

Purpose. For the problem of hybrid estimation, this paper proposes the self-adaptive generic interacting multiple-model (IMM) data fusion algorithm for solving the model selection problem of IMM. To find the optimal solution of the hybrid estimation problem, the history information of all the models was considered.

Methodology. According to the prior knowledge, the parameter space describing the model is mapped to the model set. According to the similarity of the parameter variations, the parameter space is divided into several sub-spaces. Then, each subspace is mapped to a sub-model set. The model transition of each sub-model obeys the Markov Chain.

Findings. The center model of every sub-space was calculated out self-adaptively. The center models were organized as the model set of the IMM algorithm.

Originality. The final output of the algorithm is the data fusion of the model set estimations using IMM algorithm. At last, the simulation experiments showed that the proposed algorithm is superior to the traditional IMM algorithms under the condition of equivalent computation quantity.

Practical value. The experimental results show that the performance of the algorithm proposed was improved notably under the condition of equivalent computation.

Keywords: *hybrid estimation, Markov Chain, IMM, estimation fusion, adaptive generalized, model set*

Introduction. The hybrid estimation problem is sourced from the maneuvering target tracking. But for now, apart from maneuvering target tracking, it is also used for fault diagnosis [1], target tracking [2], target location [3], online noise identification, sectional linear filtering for a nonlinear stochastic system and so on. Generally, the kinetic model of the hybrid estimation system is constructed using the stochastic hybrid system. As to the estimation of the system with an unknown structure or with stochastically mutated structure, it is hard to build a model with the time-varied parameters. That is because it is required to identify the motion mode (or the system structure) of the system at this moment when estimating the system states, to build an effective filtering model. However, when the motion mode of the system is uncertain or undergoes stochastic mutations, the conventional algorithms will delay or misreport the identification of the system motion mode, resulting in severe deviations on the estimations. This deviation will cause further misreport of the identification of the system motion mode thus significantly affecting the accuracy and stability of filtering. This is the so described hybrid estimation problem [4].

To find the optimal solution of the hybrid estimation problem, it is necessary to consider the history information of all the models, which makes the complexity of the algorithm grow exponentially [5]. Therefore, multi-model was developed out as a suboptimal solution in response to this kind of problem. Currently, the multi-model estimation is the mainstream for the research of hybrid estimation. Multi-model estimation, as the robust method for self-adaptive estimation, can handle the situations of unknown structures, unknown parameters or parameter variations and break down the complex problem into several simple sub-problems. The basic idea of the multi-model estimation is: the parameter space (or mode space) is mapped to model set; the filters based on the models work in parallel; the system state estimation is just the data fusion of the estimations of all the model filters. Among the multi-model algorithms, the interacting multi-model algorithm [6] by Blom and Bar-shalom is considered as superior. The main idea of IMM is to design a series of models to demonstrate the possible behaviors of the system. The filters of the models work in parallel. The transition of the models is based on Markov probabilistic matrix. The interaction of the model filters is realized via the combinations of the estimation states. By the weighted combination of the model filter estimations, the final filtering state estimation is obtained. For getting better performance in the use of IMM algorithm, a model set containing more models and covering more aspects is required. However, the addition of the model count of the model set not only increases the complexity of the computation but also lowers the performance of the algorithm. This is because the overly detailed mode space may destroy the completeness of the Bayesian interference and the independence among the models. Excessive models will cause unnecessary competitiveness, which makes the algorithm performance drops. This makes the problem fall into an awkward situation: on one hand, more models are necessary in order to get better algorithm performance; on the other hand, excessive models will lower the performance of the algorithm. For these reasons, researchers started to consider the method to break the limitations of IMM algorithm. They have attempted many modified methods. For now, there are two effective methods for solving this problem: one is the multiple-model estimation with variable structure [7] and the other is model-set adaptive IMM algorithm [8]. By the analysis of the above two algorithms, it can be known that these two algorithms refine the IMM algorithm by using different model sets. The multiple-model estimation with variable structure divides the whole model and forms the sub-model sets. At each sampling moment, the sub-models are transitioned based on different transitioning rules (including the hard transitioning rule and the soft transitioning rule). At each sampling moment, a specified sub-model set of the sub-model sets is used [9]. The model-set adaptive IMM algorithm self-adapts the model set according to the target variation at each sampling moment and it uses a self-adaptive model set.

Based on the ideas of the multiple-model estimation with variable structure and model-set adaptive IMM algorithm, this paper proposes a self-adaptive generic interacting multi-model algorithm. According to the prior knowledge, the parameter space describing the model is mapped into the model set. Based on the similarity of the parameter variations, the parameter space is divided into several sub-spaces. Each sub-space is mapped to a sub-model set. The model transition of each sub-model obeys the Markov Chain. According to the self-adaptive method, the center model of each sub-model is calculated out and the center models of the sub-model sets are organized as the model set of the IMM algorithm. The model transition of this model set also obeys to the Markov Chain. The final output of the algorithm is data fusion of the model-set estimations using IMM algorithm.

Self-adaptive generic IMM algorithm. The hypotheses of the self-adaptive generic IMM algorithm are:

Hypothesis 1. In the self-adaptive generic IMM algorithm, the model transition of the model set obeys the Markov Chain and the transition is irrelevant to the history measurements.

Hypothesis 2. In the self-adaptive generic IMM algorithm, the model set and the selection of the model meet the independence and completeness of Bayesian Inference.

Assuming the model at time $k-1$ of the self-adaptive IMM algorithm is $m_1, m_2, \cdots m_n$, the corresponding model probabili-ty is $u'_1(k-1), u'_2(k-1), \cdots, u'_n(k-1)$. The model transition ob-eys the priori Markov Chain. The transitioning probabilistic matrix is $[P'_{ij}]$, where P'_{ij} denotes the probability for model m_i transferring to m_j. And the transition is irrelevant to the history measurements.

The self-adaptive generic IMM algorithm employs the layered processing structure:

First Layer of the algorithm: according to the similarity of the models, the model $m_1, m_2, \cdots m_n$ is divided to $m_1 \cdots m_k, m_{k+1} \cdots m_l, \cdots, m_{p+1} \cdots m_n$. The $m_1 \cdots m_k, m_{k+1} \cdots m_l, \cdots, m_{p+1} \cdots m_n$ forms the sub-model sets $A_1, A_2, \cdots A_q$. The predictive probability of each model at time k is calculated as

$$\bar{c}'_j = \sum_i^n P'_{ij} u'_i(k-1) \quad j = 1, 2, \cdots, n.$$

According to the idea of the self-adaptive model set, the center model of each sub-model ($A_1, A_2, \cdots A_q$) at time k is calculated by

$$m_{Ai} = \bar{c}'_1 m_1 + \bar{c}'_2 m_2 + \cdots + \bar{c}'_{li} m_{li} \quad i = 1, 2, \cdots, q.$$

In the above formula, l denotes the corresponding model count of each model set ($A_1, A_2, \cdots A_q$).

Second Layer of the algorithm: the center models of the sub-model sets $A_1, A_2, \cdots A_q$ construct the model set *M*. The probabilities of models in model set *M* at time *k-1* are $u_{A1}(k-1), u_{A2}(k-1), \cdots, u_{Aq}(k-1)$, respectively. The model transition of model set *M* obeys the priori Markov Chain. The transition probabilistic matrix is $[P_{ij}]$, where P_{ij} denotes the transition probability from m_{Ai} to m_{Aj}. And the transition is irrelevant to the history measurements.

The feature of the self-adaptive IMM algorithm is the sub-model set and the center model will vary self adaptively according to the system structure and characteristics. This improves the generalization ability of the model set. From time $k-1$ to k the implementation steps of the generic IMM algorithm are as follows:

Step 1: Input interaction

For model $m_{Aj}\ (j = 1, 2, \cdots q) \quad \forall m_{Aj} \in M$.

Model predictive probability

$$\bar{c}_{Aj} = \sum_i^q P_{ij} u_{Ai}(k-1). \tag{1}$$

Model transition probability

$$u_{Ai/Aj}(k-1/k-1) = P(m_{Ai}(k-1)/m_{Aj}\ (k), z^{k-1}) = \\ = \frac{1}{\bar{c}_{Aj}} P_{ij} u_{Ai}(k-1).$$

Hybrid input

$$\hat{x}^{0j}(k-1/k-1) = \sum_i^q \hat{x}^i(k-1/k-1) u_{Ai/Aj}(k-1/k-1);$$

$$P^{0j}(k-1/k-1) = \sum_i^q u_{Ai/Aj}(k-1/k-1)\{P^i(k-1/k-1) + \\ + [\hat{x}^i(k-1/k-1) - \hat{x}^{0j}(k-1/k-1)] \\ [\hat{x}^i(k-1/k-1) - \hat{x}^{0j}(k-1/k-1)]^T\}.$$

Step 2: Model conditional filtering

For model $m_{Aj}\ (j = 1, 2, \cdots q) \quad \forall m_{Aj} \in M$, taken $\hat{x}^{0j}(k-1/ /k-1)$, $P^{0j}(k-1/k-1)$ as the input, substitute it to the filter based on model m_{Aj} and obtain the state estimation $\hat{x}^j(k/k)$ and the covariance $P^j(k/k)$.

Step 3: Model probability update

The likelihood function of model $m_{Aj}(j = = 1, 2, \cdots q) \quad \forall m_{Aj} \in M$ at time k is calculated as

$$\Lambda_{Aj}(k) = P(z(k)/m_{Aj}(k), z^{k-1}) = \\ = P(z(k)/m_{Aj}(k), \hat{x}^{0j}(k-1/k-1); \\ P^{0j}(k-1/k-1)) = \\ = N((z^j(k) - z^j(k/k-1)) \,|\, 0, S^{Aj}(k)).$$

Where $\Lambda_{Aj}(k)$ follows the normal distribution with mean 0 and covariance $S^{Aj}(k)$. $S^{Aj}(k)$ is the innovative information covariance matrix.

The calibration probability of model $m_{Aj}(j = 1,2,\cdots q)$ $\forall m_{Aj} \in M$ is

$$u_{Aj}(k) = P(m_{Aj}(k)/z^k) = \\ = \frac{1}{c}P(z(k)/m_{Aj}(k), z^{k-1})P(m_{Aj} \times \\ \times (k)/z^{k-1}) = \frac{1}{c}\Lambda_{Aj}(k)\bar{c}_{Aj}.$$

Where $\bar{c}_{Aj}$ is given by formula (1). c is calculated by the following formula.

$$c = \sum_j^q P(z(k)/m_{Aj}(k), z^{k-1})P(m_{Aj}(k)/z^{k-1}) = \\ = \sum_j^q \Lambda_{Aj}(k)\bar{c}_{Aj}.$$

Step 4: Output interaction

$$\hat{x}(k/k) = \sum_j^q \hat{x}^j(k/k)u_{Aj}(k);$$

$$P(k/k) = \sum_j^q u_{Aj}(k/k)\{P^j(k/k) + \\ + [\hat{x}^j(k/k) - \hat{x}(k/k)][\hat{x}^j \times \\ \times (k/k) - \hat{x}(k/k)]^T\}.$$

The self-adaptive generic IMM algorithm utilizes the idea of the multi-model estimation with variable structure, which effectively reduces the model count of the model set and avoids unnecessary model competitiveness affecting the algorithm performance. The model set of the IMM algorithm is obtained using the idea of the self-adaptive model set algorithm. Therefore, the proposed algorithm has a certain degree of self-adaptive ability.

The structure of the self-adaptive generic IMM algorithm is shown as Fig.1.

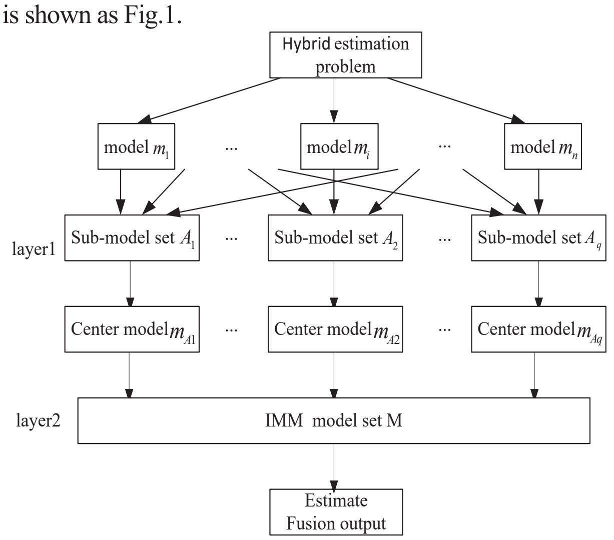

Fig. 1. Structure of the self-adaptive generic IMM algorithm

Experiments and analysis. In order to validate the effectiveness of the method, the experiments take the maneuvering target tracking as an example.

The simulation track of the target is: the target is in motion on a two-dimensional plane; from time 0 to 140s, it is in uniformly accelerated motion (the accelerated velocity is $18 m/s^2$); from time 141 to 320s, it is in uniform motion (the velocity is $300 m/s$); from time 321 to 420s, it is in left-turn motion ($\omega = 4\ deg/s$); from time 421 to 500s, it is in right-turn motion ($\omega = 4\ deg/s$). The initial state value is $[30000\ 300\ 20\ 30000\ 0\ 0]'$. The sampling period $T = 1s$. The observation noise variance $R = 10^4 m^2$. Three tracking experiments are performed on the target. The first time uses the standard IMM algorithm. The used model set contains 9 models, which is expressed as $M_1 = \{-8\ -6\ -4\ -2\ 0\ 2\ 4\ 6\ 8\ deg/s\}$. The initial model probability is $[1/9\ 1/9\ 1/9\ 1/9\ 1/9\ 1/9\ 1/9\ 1/9\ 1/9]$. The model transition probabilistic matrix is

$$P = \begin{bmatrix} 0.92 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 \\ 0.01 & 0.92 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 \\ 0.01 & 0.01 & 0.92 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 \\ 0.01 & 0.01 & 0.01 & 0.92 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 \\ 0.01 & 0.01 & 0.01 & 0.01 & 0.92 & 0.01 & 0.01 & 0.01 & 0.01 \\ 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.92 & 0.01 & 0.01 & 0.01 \\ 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.92 & 0.01 & 0.01 \\ 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.92 & 0.01 \\ 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.92 \end{bmatrix}.$$

The second time uses the self-adaptive generic IMM algorithm. In order to compare with the standard IMM algorithm, the used model set also contains 9 models, which is expressed as $M_2 = \{-8\ -6\ -4\ -2\ 0\ 2\ 4\ 6\ 8\ deg/s\}$. The initial model probability is $[1/9\ 1/9\ 1/9\ 1/9\ 1/9\ 1/9\ 1/9\ 1/9\ 1/9]$.

The model transition probabilistic matrix is

$$P = \begin{bmatrix} 0.92 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 \\ 0.01 & 0.92 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 \\ 0.01 & 0.01 & 0.92 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 \\ 0.01 & 0.01 & 0.01 & 0.92 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 \\ 0.01 & 0.01 & 0.01 & 0.01 & 0.92 & 0.01 & 0.01 & 0.01 & 0.01 \\ 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.92 & 0.01 & 0.01 & 0.01 \\ 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.92 & 0.01 & 0.01 \\ 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.92 & 0.01 \\ 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.92 \end{bmatrix}.$$

The third time used the two-stage IMM algorithm. In order to compare with the standard IMM algorithm and the proposed algorithm, the used model set also contains 9 models, which is described as $M_3 = \{-8\ -6\ -4\ -2\ 0\ 2\ 4\ 6\ 8\ deg/s\}$. The 9 models are divided into 3 sub models. Model 1, 2, 3 belong to sub-model set A_1; Model 4, 5, 6 belong to sub-model set A_2; Model 7, 8, 9 belong to sub-model set A_3. Then the center models A_1, A_2, A_3 of are calculated out. And the center models construct the model set $M_c = \{m_1\ m_2\ m_3\}$. The initial model probability is $[1/3\ \ 1/3\ \ 1/3]$. The model transition probabilistic matrix is

$$P = \begin{bmatrix} 0.98 & 0.01 & 0.01 \\ 0.01 & 0.98 & 0.01 \\ 0.01 & 0.01 & 0.98 \end{bmatrix}.$$

The evaluation indices of the experimental results lie in the state estimation quality and the computation complexity [10]. The state estimation quality is decided by the root mean square error (RMSE), which is defined as $\tilde{x}(k) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(x(k) - \hat{x}^i(k/k)\right)^2}$. Where, N denotes the times of the Monte Carlo simulation. i denotes the i th time of simulation. x denotes the position, velocity or accelerated velocity of the motion state vector of the target. The computation complexity is decided by the consuming of the CPU time. In the experiment, the times of Monte Carlo simulation is 10. The total step number of the simulation is 500. Fig. 1–3 respectively show RMSEs of the position, velocity and accelerated speed velocity estimations. Table 1 shows the mean error of the motion process of the target. Table 2 shows the computation time.

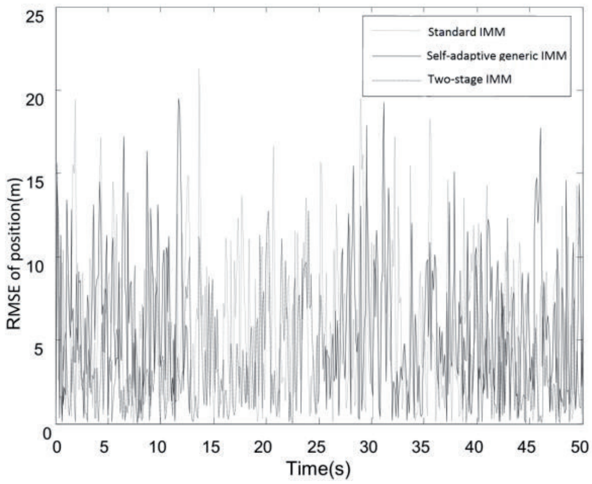

Fig. 2. RMSE of position

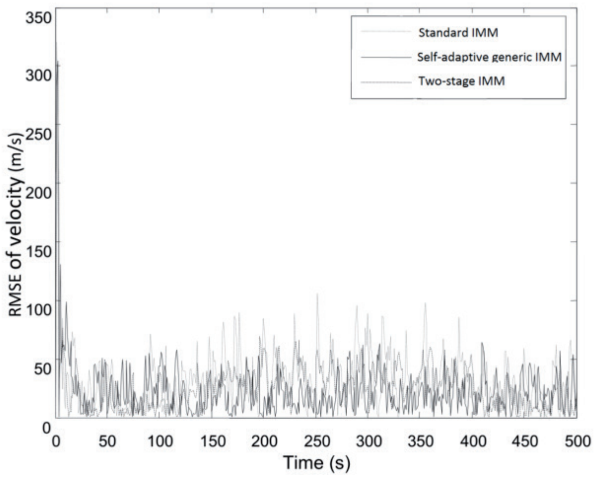

Fig. 3. RMSE of velocity

From Fig. 2–4 and Tables 1, 2, we can see the performance of the self-adaptive IMM algorithm is superior to the standard IMM algorithm and the two-stage IMM algorithm.

Conclusion. This paper proposed a self-adaptive generic IMM data fusion algorithm for solving the model selection problem of IMM. According to the prior knowledge, the parameter space describing the model is mapped to the model set. Based on the similarity of the parameter variations, the parameter space is divided into several sub-spaces. Then the center models of the sub-model set are calculated out. The final output is the data fusion of the model set estimations of the IMM algorithm. The experimental results show that the performance of the algorithm proposed in this paper is improved notably under the condition of equivalent computation.

Table 1

The mean errors in the movement process

	Standard IMM	Self-adaptive generic IMM	Two-stage IMM
Position (m)	57.1753	55.1530	36.8845
Velocity (m / s)	32.2231	22.2074	25.4256
Accelerated velocity (m/s^2)	6.6826	5.2968	6.6861

Table 2

The computation complexity of the algorithm

	Standard IMM	Self-adaptive generic IMM	Two-stage IMM
Computation time (s)	22.058	22.831	23.062

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Мета. Для вирішення завдань змішаної оцінки в роботі запропонований саморегульований типовий алгоритм спільної обробки даних взаємодіючих багаторівневих моделей (IMM) з метою вирішення проблеми вибору моделі в IMM. Проаналізована хронологічна інформація по всім моделям з метою визначення оптимального рішення задачі змішаної оцінки.

Методика. Згідно з попередніми даними, параметричний простір, що описує модель, зводиться до модельної безлічі. Параметричний простір розділяється на декілька частин за схожістю характеру зміни параметрів. Потім кожен підпростір зводиться до підмодельної безлічі. Перехід підмоделей з одного стану до іншого відбувається за моделлю ланцюга Маркова.

Результати. З урахуванням саморегуляції розрахована центральна модель кожного підпростору. Центральні моделі склали модельну множину IMM-алгоритму.

Наукова новизна. Кінцевим результатом запропонованого алгоритму є спільна обробка даних оцінки модельної безлічі з використанням IMM-алгоритму. Моделюючі експерименти довели перевагу запропонованого алгоритму над традиційним IMM-алгоритмом за умови рівної кількості обчислень.

Практична значимість. Результати експериментів показали, що робочі характеристики алгоритму були значно покращені за однакових умов обчислення.

Ключові слова: *змішана оцінка, ланцюг Маркова, взаємодіючі багаторівневі моделі (IMM), узагальнена модельна безліч*

Цель. Для решения задач смешанной оценки в работе предложен саморегулирующийся типовой алгоритм совместной обработки данных взаимодействующих многоуровневых моделей (IMM) с целью решения проблемы выбора модели в IMM. Проанализирована хронологическая информация по всем моделям в целях определения оптимального решения задачи смешанной оценки.

Методика. Согласно предварительным данным, параметрическое пространство, описывающее модель, сводится к модельному множеству. Параметрическое пространство разделяется на несколько частей по схожести характера изменения параметров. Затем каждое подпространство сводится к подмодельному множеству. Переход подмоделей из одного состояния в другое происходит по модели цепи Маркова.

Результаты. С учетом саморегуляции рассчитана центральная модель каждого подпространства. Центральные модели составили модельное множество IMM-алгоритма.

Научная новизна. Конечным результатом предложенного алгоритма является совместная обработка данных оценки модельного множества с использованием IMM-алгоритма. Моделирующие эксперименты доказали превосходство предложенного алгоритма над традиционным IMM-алгоритмом при условии равного количества вычислений.

Практическая значимость. Результаты экспериментов показали, что рабочие характеристики алгоритма были значительно улучшены при одинаковых условиях вычисления.

Ключевые слова: *смешанная оценка, цепь Маркова, взаимодействующие многоуровневые модели (IMM), адаптивный, обобщенное модельное множество*

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