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Dynamic Data Mining of Sensor Data

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ABSTRACT The research of data mining has aroused widespread concern in academia and industry. However, an important mark of the Internet of Things era is that sensor data replaces artificially compiled data. How to extract valuable knowledge and patterns from a large amount of data generated by sensors is a meaningful research topic. This paper proposes a dynamic data mining framework for processing sensor data. A sensor data mining model which can be used in the process of dynamic change is constructed. In this model, different sensor network environments are considered as different physical systems. The physical system and its parameters are trained by collecting and mining historical changes in sensor data; the associations between different sensor network environments are discovered by mining the associations between the parameters of different physical systems. In our limited experimental environment, the physical quantities considered included transmission distance, transmission delay, sensor data, data changes, and so on. Experiments were carried out on the designated experimental platform, and the results showed that the model could mine the dynamic data and find stable patterns. Through the analysis of the experimental results, it was found that the model had reference value for the dynamic mining of sensor data, and was expected to construct new methods for industrial big data analysis.

INDEX TERMS Clustering, dynamic characteristics, dynamic data mining, IoT, sensors.

I. INTRODUCTION

Data mining is a hot research area. It explores knowledge and patterns in data through mathematical statistics and machine learning. Data mining has been widely used in supermarket shopping, e-commerce, search engines, customer behavior analysis and other fields. The characteristics of these data are collected under the supervision of people, that is, the collected data is data of people in a loop. However, with the advent and popularity of the Internet of Things (IoT), more and more sensors are continuously collecting data autonomously. This data is stored in GB, TB and even YB and ZB sizes. How to use data mining technology to mine the data collected by sensors autonomously is a worthwhile and worthwhile topic.

In addition, the data collected by sensors (called sensing data) reflects the characteristics of various physical systems. It is an interesting research topic to explore the existence and interrelationship of physical systems through data mining methods. However, this research method of exploring and mining the interrelationships between physical systems is rarely involved in academia at present.

Traditional data mining locates associations between commodities [1]–[3], so it is impossible to mine associations between one physical system and another physical system. Therefore, directly copying traditional data mining methods cannot mine the relationship between physical systems and different physical systems.

In order to mine sensor data, we need to extend the concept of traditional data mining [4]. We need to combine the dynamic characteristics, time variability, and stability of physical systems with data mining methods to build a new sensor data mining model.

According to the promotion of the development of the data mining field, we divide the related research into four categories, namely, information dynamics research, e-commerce data mining, clustering-based research, and network data stability research. (*i*) Information dynamics research: Golan proposed the idea of information dynamics [7], which proved that dynamic theory and information technology can be combined [5], [6]; Lai *et al.* put forward the hypothesis of dynamic information flow and provided the information of nonlinear

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dynamic model Solution [8]; Rosenauer *et al.* studied the information limit equation [9]. Information dynamics also needs to study the distributed deployment of data, because the dynamics and variability of data can have a serious impact on the load on the system. Ahlin *et al.* Studied the problem of dynamic data deployment in a distributed environment [10]; Yin *et al.* established a distributed computing platform and tested the dynamic transfer of information [11]. Belikov and Levron proposed a dynamic information transfer model to capture the relationship between game features [12]. *(ii)* Cluster-based research: Based on the specific application scenarios of the Internet of Things, clustering analysis of the collected data is a common research method. Hutchinson *et al.* studied the collection and storage model of drug treatment data and performed cluster analysis [13]. Chen *et al.* also proposed a clustering-based data mining model by analyzing the sensing data [14]. *(iii)* E-commerce data mining: Jamison and Snow studied online data and further proposed a structural equation model [15]; Yang studied the data stability model using the mobile industry as an example [16]; Thomas *et al.* proposed an evaluation model to mine the e-commerce environment stable mode [17]. *(iv)* Research on network data stability: For the suddenness, randomness and ambiguity of data, Iova *et al.* studied the stability of the network in a big data environment and proposed a verification model for network stability [18]; Zhang *et al.* summarized methods to improve the stability of the network [19]; Chen *et al.* studied the global exponential stability based on Hopfield neural networks and used it for optimization calculations [20]; Bouhamed *et al.* studied the network structure and analyzed the network instability [21].

These studies will be an effective attempt to mine sensor data.

In this context, it is of great significance to combine dynamic theory with data mining methods, so this paper aims to build a data mining model based on dynamic theory. Table 1 is a comparison between this study and related studies, where DM stands for data mining and IoT stands for Internet of Things.

In our method, dynamic mining can discover the relationship between physical systems, for example, dynamic mining can help us find the dynamic relationship between several classes. Since dynamic theory can be applied to data mining, the target system is not only a control problem, but also a hybrid system. Therefore, many techniques about control science and computer science can be used in such model. Yin *et al.* described the feedback control model in data mining and introduced the PID control application [22]. Al-Daraiseh *et al.* proposed a framework using the intelligent control technique to data analysis [23]. Sleptchenko and Johnson investigated the distributed control technique and constructed the model to handle data in parallel [24]. Zhang *et al.* took the distributed network as dynamics system and studied the issue of absolute exponential stability [25]. Shah and Adhyaru discussed the problem of relative stability on dynamical hybrid system with time delay [26].

TABLE 1. Related research comparison.

Related Researches	Descriptions	Basic research	New DM methods
Information dynamics	Find hidden dynamic relationships through data analysis in the field of information technology	Y	N
Cluster-based research	Improve the data mining methods such as clustering based on the IoT application scenarios.	Y	Y
E-commerce dat: mining	According to the characteristics of the target data, different data mining methods are selected.	N	N
Network data stability	Mining the impact of changes in network data on the stability of the network environment.	Y	N
Research of this article	Modeling the IoT environment and mining associations between physical systems	Y	Y

The motivation of this paper is to build a dynamic data mining framework based on simple dynamics systems, and to build a new dynamics system through the mining and correlation analysis of dynamic attributes. In this article, we discuss a simple application example, that is, we try to correlate the maximum amplitude of a single pendulum with the maximum transmission distance of the sensor, damped vibration and signal attenuation, the initial state of the pendulum motion, and the initial state of the sensor network.

The rest of the paper is organized as follows: Section 2 introduces the dynamics system and stability theory; Section 3 introduces the dynamic mining framework of sensor data; and further discusses the dynamic mining model of sensor data based on stability theory; Section 4 provides the algorithm and carries out relevant experiments. Finally, the fifth part summarizes the research.

II. PHYSICAL SYSTEM AND STABILITY

The dynamics system describes the evolution of a point in geometric space with time, and the sensing data also evolves with time. There is a close relationship between the two.

A. BASIC CONCEPT

Definition 1 (Stability): After perturbed by the outside, the system movement can be kept in a limited boundary or can return to the initial equilibrium state.

Stability can be formulated as the following:

$$p \to 0 \Rightarrow S' \to S_0 \tag{1}$$

where, p denotes the perturbation, and $p \to 0$ denotes the perturbation is close to 0; S' denotes the state of movement perturbed by the outside, and S_0 denotes the equilibrium state; $S' \to S_0$ denotes the movement is close to the equilibrium state.

For different physical system, there exist different responses for the external perturbation. For some systems, if there is a small perturbation, it can cause a large change to them; however, for other systems, the same perturbation can only cause a minor impact. Therefore, for the former systems, there is considerable difference between the movement being perturbed and not being perturbed; for the latter system, there is little difference between the movement being perturbed and not being perturbed.

The system belonging to the former is unstable; whereas the system belonging to the latter is stable.

For certain system, to achieve the desired state, stability is a necessary condition. In the actual system, there always exists energy storage element, so there is inertia for the system. If the input of the system is given, the output may fluctuate around the expected valued. The system absorbs energy from outside, thus the oscillation damps for the stable systems, while divergent for the unstable system. Finally, the stable systems can be kept at certain state, while the unstable systems may continue to grow until the system is damaged.

Definition 2 (Dynamics): Dynamics studies the relationship between the force and the motion.

The research object of dynamics is the macro-object whose speed is far less than the speed of light.

Dynamics takes Newton second law as the core, and constructs the model among force, acceleration and mass. The basic contents of dynamics include particle dynamics, rigid body dynamics, d'Alembert principle, and so force.

The dynamics of the social field is a hot research, e.g., the dynamical behavioral mining [27], [28]. The Appendix details the dynamics model used in sensing data dynamics system mining.

Definition 3 (IoT): The Internet of Things refers to the interconnection of items through sensor devices for intelligent identification and management.

Definition 4 (Interval-Valued): Interval-valued refers to the possible range of a variable as a "value" or field, and use it to participate in the calculation and limit the change of the variable. One-dimensional interval values are commonly used.

B. PREMISES AND ASSUMPTION

Taking the sensing data for example, the premises and assumptions of dynamics system mining is as follows:

(1) The amplitude of single pendulum corresponds to the transmission distance of sensors.

(2) The oscillation damping corresponds to the influence of communication, e.g., communication delay.

(3) The maximal amplitude of single pendulum corresponds to the maximal distance in each communication.

(4) Initial point of single pendulum motion corresponds to the initial states of the sensor network.

III. DYNAMIC MINING FRAMEWORK FOR SENSOR DATA

A. PROCESS FLOW

The processing flow of the dynamic data mining framework is shown in Fig. 1.

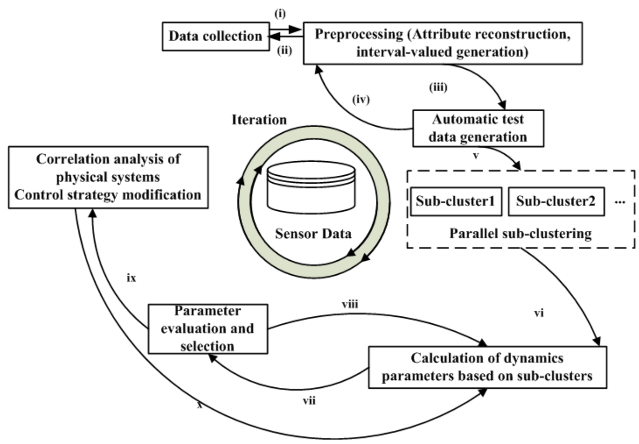

FIGURE 1. Process of dynamic data mining framework. Treat different sensor network environments as different physical systems, and mine the associations between different physical system parameters to discover the associations between different sensor network environments.

In Fig. 1, data set collection is the first step of the entire method, and the sensor data after data collection is sent to a preprocessing module for processing. The work performed by the preprocessing module includes attribute reconstruction, interval-valued generation, etc. Among them, attribute reconstruction refers to combining multiple attributes according to dependencies or splitting one attribute into multiple attributes; interval-valued generation refers to associating attributes are combined into a single interval-valued attribute. Automatic test data generation refers to dividing the test data set into several sub-data sets. Then, parallel clustering is performed for each sub-data set. Then, according to the results of the sub-clustering, the dynamic parameter training and calculation are performed. Each sub-cluster is equivalent to a physical system. The generated dynamics parameters need to be evaluated and selected, and the modified parameters are used to iteratively calculate the dynamics parameters. Finally, the association relationship of the physical system is analyzed, and the dynamic parameters are trained and calculated iteratively. Among them, (i) indicates that the collected data is transmitted to the preprocessing module; (ii) indicates that the data collection method is suggested and modified based on the results of attribute reconstruction and interval-valued generation; (iii) indicates the preprocessed data transfer to the test data automatic generation module; (iv) indicates that the preprocessing method is modified according to the generated test data; (v) indicates that each test data set is transmitted to the sub-clustering module; (vi) indicates that each sub-cluster results are transmitted to the dynamic parameter calculation module; (vii) indicates that the calculated parameters are transmitted to the parameter evaluation and selection module; (viii) indicates that the training and calculation process of the dynamic parameters is modified; (ix) indicates that the estimated parameters are transmitted to the correlation analysis module of the physical system; (x) indicates that the control strategy is modified, and dynamic parameters are trained and calculated iteratively.

B. PRINCIPLE

Let $S = (l, \mu, m, \theta)$ be a model of dynamics system, where l, μ, m, θ denotes:

m: expected amount of information transmitted (bytes);

l : transmission distance;

μ: communication delay or packet loss rate (communication barrier);

θ: packing and unpacking changes of transmitted data.

As discussed in Appendix, the single pendulum dynamics equation is:

$$\theta''(t) + 2\zeta\theta'(t) + \omega^2\theta(t) = H\sin(pt) \tag{2}$$

Let $\theta' = \Phi$, then $\theta'' = \phi'$, the Eq. (2) can be changed into the state-space model:

$$\begin{cases} \dfrac{d\theta}{dt} = \phi \\ \dfrac{d\phi}{dt} = -2\zeta\phi - \omega^2\theta + H\sin(pt) \end{cases} \tag{3}$$

And, the solution of Eq. (3) is as follows:

$$y = E\,cos(pt) + F\,sin(pt). \tag{4}$$

where,

$$E = \frac{2p\zeta H}{\left(\omega^2 - p^2\right)^2 + 4\zeta^2 p^2}, \quad F = \frac{\left(\omega^2 - p^2\right)H}{\left(\omega^2 - p^2\right)^2 + 4\zeta^2 p^2}.$$

According to Eq. (2) and (4), the convenient state space model is formulated:

$$\begin{cases} \phi' = -2\zeta\phi - \omega^2\theta + H\sin(pt) \\ y = E\cos(pt) + F\sin(pt) \end{cases} \tag{5}$$

For lightly damped vibration, commonly, θ is less than 5° and $\omega^2\theta$ can be neglected.

Let $A = -2\zeta$, $B = sin(pt)$, $D = \frac{2p\zeta}{(\omega^2-p^2)^2+4\zeta^2p^2}\cos(pt) + \frac{\omega^2-p^2}{(\omega^2-p^2)+4\zeta^2p^2}\sin(pt)$, so a simplified state space model with lightly damped vibration is as follows:

$$\begin{cases} \phi' = A\phi + BH \\ y = DH \end{cases} \tag{6}$$

In Eq. (6), y is the swing angle of single pendulum, viz. θ; θ' is the differential of θ; and ϕ' is the differential of θ', viz. $\phi' = \theta''$.

If A, B, D are given and a group of data $\tilde{\phi}$ are observed, how to work out the maximal amplitude H^* of the dynamics system? Obviously, this is a meaningful and worth studying problem, because A, B, D, H^*, etc. have the corresponding physical meaning.

Sensing data can be classified into different dynamics systems by clustering, so different dynamics system has different $(A, B, D, \tilde{\phi})$.Different dynamics system also corresponds to different sub-cluster.

In Fig. 2, the sensing data are classified into n sub-clusters, and for each sub-cluster, there is a sub-dynamics system, and denotes a knowledge discovery process. All the results are combined into an integrated pattern, viz. $w_1{}^*S_1 + w_2{}^*S_2 + \ldots + w_n{}^*S_n$, where $w_1, w_2, \ldots, w_n$ are weights related to each sub-cluster.

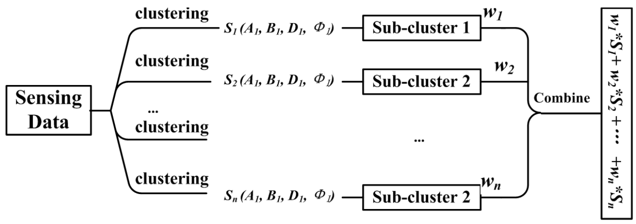

FIGURE 2. Sub-clusters and combination.

Based on the ''sub-clusters and combined pattern'', experimental platform can be constructed in distributed network, where a specific sub-cluster processing corresponds to a client node. Firstly, the sensing data are classified into n classes allocated to the corresponding client nodes, where communication technique is used to exchange data. And then, different dynamics system conducts an iterative calculation. Thirdly, a synchronous management mechanism is applied to collaborate to achieve the total goals. Finally, the results generated are integrated.

C. CASE STUDY

How to mine the physical system data is the key to dynamic mining of sensing data. The following example illustrates the idea of dynamic data mining based on dynamics systems.

Suppose $S = \{cI, cII, cIII, bI, bII, bIII, fI, fII, fIII\}$, cI,cII, and CIII represents carpenter I, II and III, repectively; bI, bII and bIII represents blacksmith I, II and III; fI, fII and fIII represents farmer I, II and III.

Corresponding domain knowledge is as follows:

Rule 1: denoted by *r1 that means carpenter needs wood;*

Rule 2: denoted by *r2 that means blacksmith needs steels;*

Rule 3: denoted by *r3 that means farmer needs fine seeds.*

According to Definition 1 and 2, a dynamic data mining based on dynamics systems can be conducted as follows:

Firstly, for domain S, different sets are classified and each set is regarded as a dynamics system. So, *S1 = {cI, cII, cIII}, S2 = {bI, bII, bIII}, S3 = {fI, fII, fIII}* are three sets.

Based on the dynamics models (see also Appendix and Eq. 6), three state space models are designed with different $(A, B, D, \tilde{\phi})$:

$$\begin{cases}\phi' = A_1\phi + B_1H_1 \\ y = D_1H_1,\end{cases} \qquad \begin{cases}\phi' = A_2\phi + B_2H_2 \\ y = D_2H_2\end{cases}$$

and

$$\begin{cases}\phi' = A_3\phi + B_3H_3 \\ y = D_3H_3\end{cases}$$

where, A_i, B_i, and D_i can be worked out from different (l, μ, m, θ).

Next, according to domain knowledge, different connotations are given based on $H_i (i = 1, 2, 3)$:

For the carpenters, let $H_1 = F1$;

For the blacksmith, let $H_2 = F2$;

For the farmers, let $H_3 = F3$.

Finally, the optimal values of H_i ($i = 1, 2, 3$) can be obtained.

Therefore, a dynamics system mining is completed based on {*S1/F1, S2/F2, S3/F3*}.

In this case, if over damped vibration system is encountered or critical damped vibration system is encountered, then let H_i take as large as possible.

D. DESIGN OF MODEL

1) SUB-CLUSTER

Sub-cluster is a class used to encapsulate a dynamics system. It consists of a name, attributes, and operations.

In order to obtain the attributes and operations of the sub-cluster, clustering is required, and then high-level abstraction is performed according to multiple attributes in the same class, for example, gray, black, and blue are abstracted into dark colors. After clustering and high-level abstraction, sub-clusters with names, attributes, operations, and related data will be generated.

Generally, the state diagram is used to describe the behavior of the sub-cluster, where "state" is the property of the system at a specific time, and "state transfer" is the response of the sub-cluster in the state diagram to external forces.

The six sub-clusters consist of slightly damped vibrations (without neglecting very little resistance), critically damped vibrations, over-damped vibrations, and large-damped vibrations. Each cluster includes "attribute description", "external performance" and "operation logic", where "external performance" refers to the external interface provided by this cluster, and "operation logic" refers to external force execution logic used to maintain a stable state.

2) DYNAMIC DATA MINING BASED ON PHYSICAL SYSTEM

Given the parameter (l, μ, m, θ), dynamic data mining is constructed as follows:

$$\begin{cases}\phi' = A\phi + BH \\ y = DH\end{cases} \tag{6}$$

where,

$$A = -2\zeta, \quad B = sin(pt), D = \frac{2p\zeta}{\left(\omega^2 - p^2\right)^2 + 4\zeta^2p^2}\cos(pt) + \frac{\omega^2 - p^2}{(\omega^2 - p^2) + 4\zeta^2p^2}\sin(pt),$$
$$\zeta = \frac{u}{m}, \quad \text{and } \omega^2 = \frac{g}{l}.$$

According to (l, μ, m, θ), A, B, and D can be calculated. A is a matrix coefficient, B is a sine function, and D is a complex trigonometric function, where P is set by the user.

The dynamic data mining is shown in Table 2 that related with the sub-clusters.

In Table 2, m, l, μ, p, ω, and ζ can be computed based on the equations (1) to (6). Among them, in Table 2, the parameter value range only represents the specific setting in our experiment, because the setting of each parameter is different in different experimental environments.

IV. ALGORITHM DESIGN AND EXPERIMENT

In this section, we first introduce the main algorithms involved in a dynamic mining framework based on physical systems, then perform experiments, and finally discuss them.

A. ALGORITHMS

Four algorithms to describe the dynamic data mining based on physical system is designed; one is classification algorithm of dynamics systems; the second is clustering algorithm of dynamics systems; the third is algorithm of stability mining; and the fourth is synthesizing algorithm.

1) CLASSIFICATION OF DYNAMICS SYSTEMS

Through the classification algorithm of the dynamics systems, the dynamics systems is divided into different groups to find the correlation between the dynamics systems and the parameters of the dynamics systems. As described in Section 3, the characteristics of the dynamics systems can be characterized as vectors (l, μ, m, θ), and classification based on these vectors.

Different from traditional classification algorithms, the classification algorithms of dynamics systems not only compare data sets of dynamics systems, but also compare dynamic parameters.

In Algorithm of *DynClassification*, firstly, the dynamics classification system is set up by the threshold (m_0^k, l_0^k, μ_0^k, θ_0^k); and then, for every item in the database *db*, the comparisons are conducted between the items and the relatives in θ_0^k; if items are in the ranges of the relative items in θ_0^k, a comparison will be followed by $m \subseteq l \subseteq l_0^k \&\& \, m_0^k \&\& \, \mu \subseteq \mu_0^k$; finally, if the conditions are true, the class of sub-cluster k is returned, or else false is returned.

2) CLUSTERING OF DYNAMICS SYSTEMS

Since $(m_0, l_0, \mu_0, \theta_0)$ may be intervals-valued, and the dataset also includes intervals-valued, the clustering algorithm of interval-valued is introduced [25]–[27].

TABLE 2. Sub-clusters and dynamic data mining.

Sub-Cluster	(*l*, *μ*, *m*, *θ*)	A	B	D
1	$m\geq 100$; $0<l\leq 1;\mu\geq 0.5$	$-2\frac{u}{m}$	*Sin(pt)*	$\frac{2p\zeta}{(\omega^2-p^2)^2+4\zeta^2p^2}\cos(pt)+\frac{\omega^2-p^2}{(\omega^2-p^2)+4\zeta^2p^2}\sin(pt)$
2	$m\geq 30$; $0.5<l\leq 1;\mu\geq 0.3$	$-2\frac{u}{m}$	*Sin(pt)*	$\frac{2p\zeta}{(\omega^2-p^2)^2+4\zeta^2p^2}\cos(pt)+\frac{\omega^2-p^2}{(\omega^2-p^2)+4\zeta^2p^2}\sin(pt)$
3	$\frac{u}{m}=\sqrt{\frac{g}{l}}$	$-2\frac{u}{m}$	*Sin(pt)*	$\frac{2p\omega}{(\omega^2+p^2)^2}\cos(pt)+\frac{\omega^2-p^2}{(\omega^2+p^2)}\sin(pt)$
4	$m\leq 10$; $l\geq 30;\mu\geq 0.6$	$-2\frac{u}{m}$	$d_2exp\{pt\}$	$d_1exp\{pt\}$, d_1 *and p are specified by user.*
5	$m\leq 4$; $l\geq 50;\mu\geq 0.8$	$-2\frac{u}{m}$	$d_2exp\{pt\}$	$d_1exp\{pt\}$, d_1 *and p are specified by user.*
6	Otherwise	*specified values*	*User specified*	*User specified functions*

Algorithm 1 DynClassification (double l, double m, double μ, Table *db*)

Input: ($m_0{}^k$, $l_0{}^k$, $\mu_0{}^k$, $\theta_0{}^k$), interval-valued thresholds; *m, l,* and μ are parameters related to *db* that is database, and $k = 1, 2, \ldots, N$;
Output: class of sub-cluster of *db*;
Method:

1) *classification system of dynamics* ← ($m_0{}^i$, $l_0{}^i$, $\mu_0{}^i$, $\theta_0{}^i$);
2) *for (i = 1; i<=N; i++) {*
3) *for each transaction* $t_k \in db$*, and k from* 1 *to* $|db|$ *{*
4) *for each item* $I_{kj} \in t_k$*, and j from* 1 *to* $|t_j|$
5) *If* ($I_{kj} \not\subset (r_{kj} \in \theta_0{}^i)$)//$r_{kj}$ *is the record of* $\theta_0{}^i$; I_{kj} *and* r_{kj} *are interval-valued;*
6) *return false;*
7) *}*
8) *If* ($l \subseteq l_0^i$ && $m \subseteq m_0^i$ && $\mu \subseteq \mu_0^i$)
9) *return k;*
10) *else*
11) *return false;*
12) *}*

Algorithm 2 *IntervalCluster* (double λ_0, double α_0, Table *db*)

Input: *db*, database to be clustered; λ_0, similarity threshold; α_0, confidence threshold;
Output: C, class of sub-clusters;
Method:

1) *(m, n) = size(db);* *// m: rows, n: columns*
2) *for (k = 0; k<n; k++)*
3) *for (j = k+1; j<n; j++) {*
4) $t^- = \frac{1}{\max\{|t_k-t_j|; t_k\in x_k, t_j\in x_j\}}$, $t^+ = \frac{1}{\min\{|t_k-t_j|; t_k\in x_k, t_j\in x_j\}}$; //$x_k$, $x_j \in_{db}$
5) $r(x_k, x_j) = [t^-, t^+]$;
6) $R(r_{kj}) += r(x_k, x_j)$; *//* $R(r_{kj})$*: similarity matrix*
7) *}*
8) *for any element* $r_{kj} \in R$*, and* $k, j = 1, 2, \ldots, n$
9) *if* ($t_{kj}{}^- > \lambda_0$)
10) $[t_{kj}{}^-, t_{kj}{}^+] \leftarrow$ "×";
11) *else if* ($t_{kj}{}^+ < \lambda_0$)
12) $[t_{kj}^-, t_{kj}{}^+] \leftarrow$ " ";
13) *else*
14) $[t_{kj}{}^-, t_{kj}{}^+] \leftarrow$ "#";
15) *C={rec(R)};* *// rec(R) is relatively explicit classification of R*
16) *C+ = {sfc(R)};* *// sfc(R) is similarly fuzzy classification of R*
17) *for each element in* C, $\alpha_k = [t_k{}^-, t_k{}^+]$ *in C {*
18) $\alpha = min\{\frac{t_1^+-\lambda_0}{t_1^+-t_1^-}, \frac{t_2^+-\lambda_0}{t_2^+-t_2^-}, \ldots, \frac{t_n^+-\lambda_0}{t_n^+-t_n^-}\}$;
19) *if* ($\alpha > \alpha_0$ && $\alpha_i = max\{\alpha_1, \alpha_2, \ldots, \alpha_n\} \geq 0.5$) // $1 \leq i \leq n$
20) i^{th} *sub-cluster* ← *uncertain object;*
21) *}*

In the algorithm of *IntervalCluster*, the similarity matrix R is worked out firstly, and then, the process of "netting" is conducted from *step (8) to (14)*. In addition, two clustering processes are used to generate an initial class set being relatively explicit classification & similarly fuzzy classification. In order to generate explicit clusters, the attribution of uncertain objects needs to be determined. Finally, in the sensing data dynamic mining process, classes of sub-clusters are returned.

3) ALGORITHM OF DYNAMIC MINING

As discussed in Section 3, dynamic mining is also one of the models of data mining based on dynamics systems which is formulated as follows:

$$\begin{cases} \phi' = A\phi + BH \\ y = DH \end{cases}$$

where, y denotes θ that describes the pendulum angle, which represents the dataset of the changing pendulum angles. The differential of θ is Φ. In discrete system or hybrid system, if the dataset with time stamp $\theta(t)$ is given, we can describe as follows:

$$\begin{cases} \phi = \theta(t) - \theta(t-1) \\ y = \theta(t) \\ \phi' = \theta(t) - 2\theta(t-1) + \theta(t-2) \end{cases} \tag{7}$$

The H^*(relatively maximum) related to H can be obtained that indicates the maximum external force that can be applied to the dynamics system.

Algorithm 3 *S-Mining* (Φ, A, B, D)

Input: $\Phi(t)$, differential of θ; A, real-value; B, the coefficient of H, viz. B(t); D, the coefficient of H in $y = DH$, viz. D(t); *p, d1, d2*, parameters specified by users; n, number of steps; h, length of step;
Output: H^*, maximum of H;
Method:

1) $H = y/D$;
2) $\phi' = B^*y/D + A^*\phi$;
3) $y\_s = y[0] + n^*h$; // y_s: the maximum of y
4) for(j = 0; j<n; j++) {
5) $\Phi s = \Phi$; //Φs: used to save Φ
6) $d\phi = B^*y/D + A^*\phi$; // iterative process, Φ is changing
7) $\Phi[i+1] = h^*\, d\,\Phi/6 + \Phi$;
8) $yp = h/2 + y$; // yp: minimum increment for y
9) $\Phi p = h^* d\Phi/2 + \Phi s$; // Φp: increment for Φ
10) $d\phi = B^*yp/D + A^*\phi p$; // iterative process
11) $\Phi[i+1] = \Phi[i+1] + h^*\, d\Phi/3$;
12) $\Phi p = h^*\, d\Phi/2 + \Phi s$;
13) $d\phi = B^*yp/D + A^*\phi p$; // iterative process
14) $\Phi[i+1] = \Phi[i+1] + h^*\, d\Phi/3$;
15) $yp = yp + h/2$;
16) $\Phi p = h^* d\Phi + \Phi s$;
17) $d\phi = B^*yp/D + A^*\phi p$; // iterative process
18) $\Phi[i+1] = \Phi[i+1] + h^*\, d\Phi/6$;
19) $y[i+1] = yp$;
20) if($ys <= y[i+1]$)
21) break;
22) }
23) return ($H^* = y/D$);

In the algorithm of *S-Mining* (Φ, A, B, D), the initial value H is obtained by solving the 4th order differential equation according to Eq. (6). Then, the approximate process of numerical solution about the differential-equation $\phi' = B^*y/D + A^*\phi$ is conducted in *step (3)* to *step (21)*. After optimizing y and D, $H^* = y/D$ can be computed. Finally, H^* is obtained and returned.

Through the results of y, Φ, H^*, and so forth, the dynamics system can be analyzed.

4) WEIGHT-BASED SYNTHESIS ALGORITHM

After each separated computing task is conducted, synthesizing process is necessary for the local results. The synthesizing algorithm of dynamic data mining is designed as follows:

Algorithm 4 *Synthesizing* (Int k, Clusters C)

Input: C: class of sub-cluster; k: number of sub-clusters;
Output: $V =< v_i, v_2, \ldots >$: synthesized dynamics system vector;
Method:

1) for each $c_j \in C$ and $j = 1, 2, \ldots k$ {
2) $v_j.A = w_j * c_j.A$; //w_j: weight related to c_i
3) $v_j.B = w_j * c_j.B$;
4) $v_j.D = w_j * c_j.D$;
5) }
6) $H^* = w_1 * c_1.H_1^* + w_2 * c_2.H_2^* + \ldots + w_k^* c_k.H_k^*$;
7) $V =< v_1, v_2, \ldots, v_k >$;

In *Synthesizing* (int$k$, clusters C), the model that synthesizes the local computation results is shown. For different dynamics systems, the synthetic approach is to assign them different importance. In addition, $w_1, w_2, \ldots$ are weights to $c_1, c_2, ..$ that are the sub-cluster of C. In the algorithm, H^* is used to calculate the theoretical maximum.

B. EXPERIMENTS

1) EXPERIMENTAL SETUP

In this section, we test the effectiveness of the proposed method through experiments on two experimental datasets.

The algorithms were implemented in C++, and the distributed experimental platform can carry out large-scale distributed parallel computing. The service program ran on the HP workstation with 3.8 GHz Intel Xeon CPU and 64 GB of RAM; RadHat Enterprise Version was the operating system. The distributed experimental network consisted of 6 Lenovo computers with 3.08 GHz CPU and 4GB of RAM. Through NI's data acquisition card, sensors collect environmental information, such as fire smoke information.

2) EXPERIMENT 1: DATA OF DEVELOPMENT PROCESS OF FIRE SMOKE

The collected data include heat release rate (HRR), temperature (divided into upper temperature and lower temperature), flue gas layer height, air pressure, etc. The sensor data collected has 12,000,000 records. In order to facilitate the experiment, some attributes are reduced and reconstructed, in which reconstruction refers to combining two related attributes into interval value attributes, and their values will also be merged into interval value.

In order to speed up the test and compare, the data set is divided into six sections: 1 – 2,000,000, 2,000,000 – 4,000,000, 4,000,000 – 6,000,000, 6,000,000 – 8,000,000, 8,000,000 – 10,000,000, 10,000,000 – 12,000,000. Different segments may find different attributes.

Firstly, the sub-cluster method is used for each dataset, where $\lambda_0 = 0.94$, $\alpha_0 = 0.5$. Table 2 shows the result of sub-cluster.

Seven experiments were conducted that includes 6 partitions. In Table 3, "Sub-clusters" denotes the numbers of data clustering.

TABLE 3. Result of sub-clusters.

No.	Scales	Items	Sub-clusters
1	1 – 2,000,000	14	8
2	2,000,000 – 4,000,000	13	6
3	4,000,000 – 6,000,000	14	9
4	6,000,000 – 8,000,000	14	11
5	8,000,000 – 10,000,000	14	8
6	10,000,000 – 12,000,000	13	8
7	1 – 12,000,000	14	11

Then, the dynamics systems are classified based on sub-clusters. And different sub-cluster was regarded to be different dynamics system and assigned different parameters. The standard dynamics systems in the experiments was set to type 1, type 2,..., and type 7; therefore, it is interesting evaluation to compare between the standard and the generated dynamics systems. Through the comparisons, the dynamics systems generated will be evaluated, as shown in Table 4.

TABLE 4. Impactful sub-clusters.

No.	Scales	Sub-clusters	Impact. Sub-clusters	Selected Ratio
Part 1	1 – 2,000,000	8	6	75%
Part 2	2,000,000 – 4,000,000	6	5	83%
Part 3	4,000,000 – 6,000,000	9	7	78%
Part 4	6,000,000 – 8,000,000	11	7	64%
Part 5	8,000,000 – 10,000,000	8	7	88%
Part 6	10,000,000 – 12,000,000	8	6	75%
Part 7	1 – 12,000,000	11	7	64%

"Impactful sub-clusters" indicates the number of eligible sub-clusters compared to the standard dynamics systems. "Selected ratio" refers to the ratio of selected sub-clusters to all sub-clusters. As described, the second part and the fifth part are over 80% selected ratio that means there are stronger features of dynamics. For the complete data set, all 7 standard dynamics systems are selected, that is, there are 7 standard models of dynamic systems in total.

Figure 3 shows the trend on the sub-clusters generated and the impactful ones.

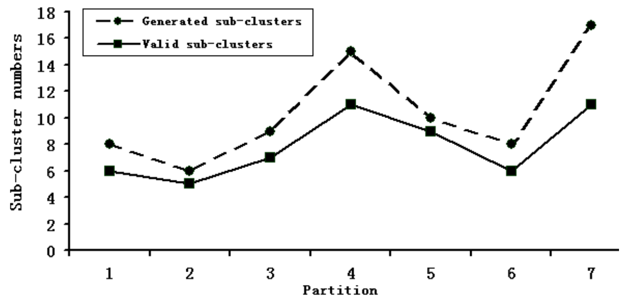

FIGURE 3. Sub-clusters and impactful ones.

The trends on the sub-clusters generated and the impactful ones are basically same, that means the dataset complies with the dynamics features; in addition, there are relatively concentrated distributions in type 3, 4, and 5.

Thirdly, sub-cluster type 3, 4 and 5 are selected for dynamic data mining. In the experiments, the parameters p, $d1$, $d2$ were set by 3.2, 7, and 25, respectively.

The dynamics parameters A, B, and D, and the computational result H^* are listed in Table 5. As shown, c1 related with sub-cluster 3 and c2 related with sub-cluster 5 are damped vibrations, and c3 related with sub-cluster 4 is critical damped vibration. The experiments indicate that the stronger dynamics system features exist in the dataset, and therefore, by a periodical outer-force, the sensing system can be in a stable state.

TABLE 5. Dynamic data mining for experiment 1.

Cluster	Parameter A	Parameter B	Parameter D	H^*
C1	-0.00495	*Sin(3.19t)*	*0.912cos(3.19t)+ 0.119sin(3.19t)*	52.19
C2	-0.0749	*Sin(3.19t)*	*36.38cost(3.19t)+ 0.82sin(3.19t)*	93.38
C3	-0.0196	*Sin(3.19t)*	*34.66cos(3.19t)+ 0.48sin(3.19t)*	28.49

After giving weight -1000 to A, the trends between A (-1000) and H^* are similar. To keep the dynamics system in stable, H^* should be given. Therefore, give decision to H^* according to different A.

Finally, in the distributed network, a weighting method was used to synthesize the results of local dynamics systems mining, as shown in Table 6.

TABLE 6. Mined patterns for experiment 1.

Para.	Pattern of Dynamics Systems Mining
A	<-0.00495*w_1, -0.0749*w_2, -0.0196*w_3>
B	<Sin(3.19t)*w_1, Sin(3.19t)*w_2, Sin(3.19t)*w_3>
D	<*0.912cos(3.19t)*w_1+ *0.119sin(3.19t)*w_1,
	36.38cost(3.19t)w_2+ *0.82sin(3.19t)*w_2,
	34.66cos(3.19t)w_3+ *0.48sin(3.19t)*w_3>
H^*	<52.19*w_1, 93.382*w_2, 28.498*w_3>

In Table 6, w_1, w_2, w_3 corresponds with sub-cluster 3, 4, 5 that are weights, and the final pattern of stability data mining is formed by the synthesizing method.

3) EXPERIMENT 2: UAV FLIGHT CONTROL DATA

The sensor data set used in Experiment 2 is related to the RMAX UAV experimental platform, which is used to test the coordination control quality of UAVs cluster. In the experiments, the attributes, including sback, sright, throttleStick, rudderStick, sleft, kdelay, timedelay, time, delm[0], delm[1], delm[2], pos[0], pos[1], pos[2] and so force were used. The dataset of the experiments has 7,000,000 records and 48 attributes, as shown in Fig. 4.

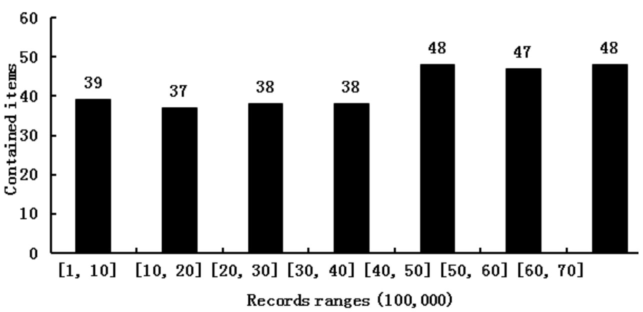

FIGURE 4. UAV experimental dataset.

The dataset was divided into 1 – 1,000,000, 1,000,000 – 2,000,000, 2,000,000 – 3,000,000, 3,000,000 – 4,000,000, 4,000,000 – 5,000,000, 5,000,000 – 6,000,000, and 6,000,000 – 7,000,000.

Firstly, the clustering method of sub-clusters is used to handle this data, where $\alpha_0 = 0.6$, $\lambda_0 = 0.8$. Table 7 is the result of the experiments.

In Table 7, 8 experiments are conducted, where "Sub-clusters" denotes the number of clustering of each partition. Obviously, sub-cluster number is different, although the length of the partitions is identical, for the hidden dynamic system in dataset is different in different stages and different parameter settings.

Next, a classification of dynamics system was conducted for the sub-clusters generated. Different sub-cluster

TABLE 7. Sub-clusters.

No.	Scales	Items	Sub-clusters
1	1 – 1,000,000	38	5
2	1,000,000 – 2,000,000	36	7
3	2,000,000 – 3,000,000	37	17
4	3,000,000 – 4,000,000	37	6
5	4,000,000 – 5,000,000	47	3
6	5,000,000 – 6,000,000	46	11
7	6,000,000 – 7,000,000	47	6
8	1 – 7,000,000	41	18

TABLE 8. Selected sub-clusters.

Part No.	Sub-clusters	Impactful Sub-clusters	Selected Ratio
1	5	4	80%
2	7	5	42.9%
3	17	6	35.3%
4	6	5	83.3%
5	3	2	66.7%
6	11	6	54.5%
7	6	5	83%
8	18	6	33.3%

corresponds with different dynamics systems and assigned different parameters. The standard dynamics systems were set 8 in this experiment, viz. type 1, 2,..., and 8. Compare the standard system with the generation system to determine whether the generation system is standard.

The sub-clusters that comply with the standard dynamics systems are impactful sub-clusters. The selected ratio is the ratio of the number of impactful sub-clusters to the total number of sub-clusters. Part 1, 4 and 7 have over 80% selected ratio, so they have the features of stronger dynamics. Figure 5 shows the trend on the sub-clusters generated and the impactful ones.

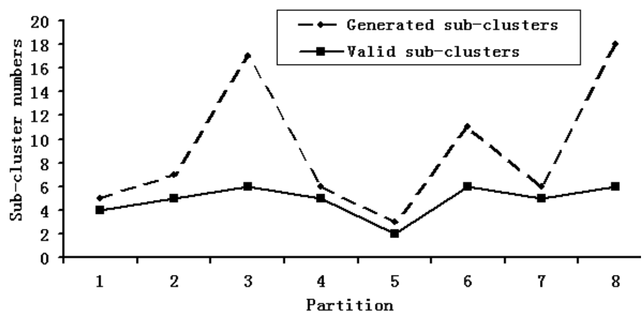

FIGURE 5. Sub-clusters and impactful clusters.

The trends of selected ratio and total sub-clusters are basically same, and therefore, the sub-cluster 1, 2,... and 6 are selected.

Thirdly, based on the impactful sub-clusters, dynamic data mining is conducted. In the experiments, *p*, *d1* and *d2* were *9.5, 10,* and *39*, respectively. Table 8 is the results of experiments.

The experimentally obtained kinetic parameters A, B and D and H* can be seen in Table 9. The cluster *1* and *2* are damped vibrations, *3* is critical damped vibration and *4*, *5*, *6* are over damped vibration. Experiments show that the UAV data have stronger dynamic characteristics.

TABLE 9. Dynamic data mining for experiment 2.

Cluster	Parameter A	Parameter B	Parameter D	H^*
1	-0.019	*Sin(9.49t)*	*0.42cos(9.49t)+ 0.018sin(9.49t)*	15.91
2	-0.067	*Sin(9.49t)*	*9.83cost(9.49t)+ 0.55sin(9.49t)*	28.52
3	-0.049	*Sin(9.49t)*	*22.46cos(9.5t)+ 0.37sin(9.5t)*	15.52
4	-0.139	$39e^{9.49t}$	$10e^{9.49t}$	57.94
5	-1.79	$39e^{9.49t}$	$10e^{9.49t}$	2048.29
6	7	$-60.39e^{-19.2t}$	$-12.59e^{-19.2t}$	1942

The relationship between A and H^* is similar on cluster *1, 2, …* and *6* after giving a weight 100 to A.

Finally, the dynamics systems mining results were synthesized by the weighting method, as shown in Table 10.

TABLE 10. Patterns mining for experiment 2.

Para.	Pattern of Dynamics Systems Mining
A	<-0.019*w_1, -0.067*w_2, -0.049*w_3, -0.139*w_4, -1.79*w_5, 7*w_6>
B	<Sin(9.49t)*w_1, Sin(9.49t)*w_2, Sin(9.49t)*w_3, $39e^{1.2t}$*w_4, $39e^{1.2t}$*w_5, $-60.39e^{-2.5t}$*w_6>
D	<0.42cos(9.49t)*w_1+ 0.018sin(9.49t)*w_1, 9.83cost(9.49t)*w_2+ 0.55sin(9.49t)*w_2, 22.46cos(9.49t)*w_3+ 0.37sin(9.49t)*w_3, $10e^{9.49t}$*w_4, $10e^{9.49t}$*w_5, $-12.59e^{-19.2t}$*w_6>
H^*	<15.91*w_1, 28.52*w_2, 15.52*w_3, 57.94*w_4, 2048.29*w_5, 1942*w_6>

By the synthesizing method, the final pattern of dynamics system mining is generated, where w_1, w_2 and w_3 are weights corresponding to Cluster *1, 2,...* and *6*.

V. CONCLUSION

Dynamic data mining of sensor data is a meaningful research topic. In order to construct a new data mining framework, we first introduced the dynamics theory, including stability, pendulum dynamics model, sub-clustering and so on. To build the relationship between sensing data and dynamics systems, four basic assumptions was listed. And then, the technique of classification was used to conduct differentiated processing for different partitions of the dataset; the distribution technique was used to construct the dynamic data mining in network environment; interval value clustering was used to cluster data distributed within a certain range, and the generated classes were named after sub-cluster; principle of dynamic data mining of sensor data was discussed by the case study to illustrate its main idea; the design of dynamics system data mining was discussed including the design of sub-clusters, stability data mining and so forth. The experimental results showed that the dynamic data mining of sensor data had potential application prospects in enterprise data mining and analysis, and it was an extension of existing data mining.

In order to make dynamic mining of sensor data more complete and practical, more in-depth research and practice are needed, such as mining with damage automatic detection data [29] and dynamic judgment with Belief function based decision fusion [30], which will be the future research direction of this paper.

Statement of Limitations: This paper aims to mine the dynamics system from the sensor data, but the structure and initial value of the parameter values of the dynamics system need to be set according to different environments. The current research work only targets a limited area of the Internet of Things, and more in-depth and extensive research requires the participation of many researchers.

APPENDIX

Dynamics Model:

The model of dynamicsis a four-element vector as follows:

$$S = (l, \mu, m, \theta) \tag{A1}$$

The dynamics model is denoted by S, where θ is the swing angle of the single pendulum, m is the mass of the single pendulum, μ is the damping coefficient, and L is the length of the single pendulum.

As a typical dynamic model, the simple pendulum fully demonstrates the stability of the system, as shown in Fig. 6.

In Fig. 6, the small ball with mass m and a thin line with length l are suspended at O. The ball will be periodic oscillating under gravity. The mass of the thin line and the diameter of the ball can be ignored. θ is swing angle.

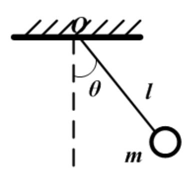

FIGURE 6. Dynamics model based on single pendulum.

Suppose: t is independent variable and θ is unknown function that denoted by $\theta(t)$; μ is damping coefficient; g is acceleration of gravity; and the counter-clockwise direction is the positive.

According to the above conditions, the motion equation of the single pendulum can be worked out as followings:

$$\theta''(t) + \frac{u}{m}\theta'(t) + \frac{g}{l}\sin\theta(t) = 0 \tag{A2}$$

The motion equation can be given as follows:

Let $\theta' = \Phi$, and then $\theta' = \phi'$, so change Eq. (A2) into:

$$\begin{cases} \dfrac{d\theta}{dt} = \phi \\ \dfrac{d\phi}{dt} = -\dfrac{u}{m}\phi - \dfrac{g}{l}\sin(\theta) \end{cases} \tag{A3}$$

Let $z = \begin{pmatrix} \theta \\ \phi \end{pmatrix}$, $f_1 = \phi$, $f_2 = -\frac{u}{m}\phi - \frac{g}{l}\sin\theta$, and then:

$$A = \begin{bmatrix} \dfrac{\partial f_1}{\partial\theta} & \dfrac{\partial f_1}{\partial\phi} \\ \dfrac{\partial f_2}{\partial\theta} & \dfrac{\partial f_2}{\partial\phi} \end{bmatrix}_{(\theta,\phi)=(0,0)} = \begin{bmatrix} 0 & 1 \\ -\dfrac{g}{l} & -\dfrac{u}{m} \end{bmatrix} \tag{A4}$$

$$det(A - \lambda E) = \begin{vmatrix} -\lambda & 1 \\ -\dfrac{g}{l} & -\dfrac{u}{m} - \lambda \end{vmatrix} = \lambda^2 + \frac{u}{m}\lambda + \frac{g}{l} \tag{A5}$$

Let $det(A - \lambda E) = 0$, and then

$$\lambda_{1,2} = \frac{-\frac{u}{m} \pm \sqrt{\frac{u^2}{m^2} - \frac{4g}{l}}}{2} \tag{A6}$$

Obviously, $\lambda_{1,2}$ has a negative real part.

Therefore, for the solutions θ(t) of Eq. (A2), there exists the relationship $\lim\limits_{t\to\infty} |\theta(t)| = 0$. Viz., the zero solutions of Eq. (A2) are asymptotically stable. Figure 7 shows the cases.

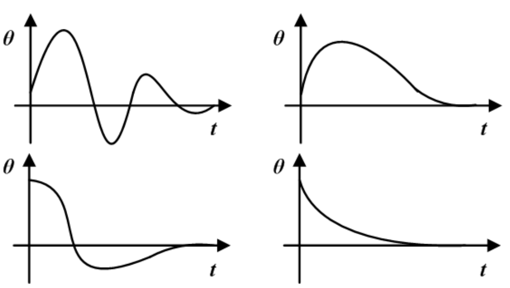

FIGURE 7. Solutions of dynamics model.

However, the vibration will be reduced step by step, viz., $\lim\limits_{t\to\infty} |\theta(t)| = 0$, since the damp and energy conversion.

How to keep the system in stable state is a problem worthy of study.

Commonly, outer-force is needed to keep a system stable. Therefore, the motion of the single pendulum is changed:

$$\theta''(t) + 2\zeta\theta'(t) + \omega^2\theta(t) = H\sin(pt) \tag{A7}$$

In Eq. (A7), $H^*\ sin(pt)$ is a periodic outer-force.

Let $\zeta = \frac{u}{m}$, $\omega^2 = \frac{g}{l}$, and then, the solutions of Eq. (A7) are as followings.

(1) Damped vibration system ($\zeta < \omega$)

The solutions of Eq. (A7):

$$y = E\cos(pt) + F\sin(pt) \tag{A8}$$

where,

$$E = \frac{2p\zeta H}{\left(\omega^2 - p^2\right)^2 + 4\zeta^2 p^2}, \quad F = \frac{\left(\omega^2 - p^2\right)H}{\left(\omega^2 - p^2\right)^2 + 4\zeta^2 p^2}.$$

For convenience:

$$y = H^*\sin\left(pt + \theta^*\right) \tag{A9}$$

where,

$$H^* = \sqrt{E^2 + F^2} = \frac{H}{\sqrt{\left(\omega^2 - p^2\right)^2 + 4\zeta^2 p^2}}, \theta^* = arctan\frac{-2\zeta p}{\omega^2 - p^2}.$$

In practice, p is an important factor to H^*; p is the frequency of the outer-force making H^* to the maximum.

Let $G(p) = (\omega^2 - p^2)^2 + 4\zeta^2 p^2$, and then, $G(p) = 4p(\omega^2 - p^2) + 8\zeta^2 p^2 = 0$.

Take $\zeta < \frac{\sqrt{2}}{2}\omega$, and then, $p = \sqrt{\omega^2 - 2\zeta^2}$.

So, $G''(p) = G''(\sqrt{\omega^2 - 2\zeta^2}) = 8p^2 > 0$.

If $p = \sqrt{\omega^2 - 2\zeta^2}$, $G(p)$ takes the minimum, and H^* takes the maximum, viz., the maximal amplitude: $H^* = \frac{H}{2\zeta\sqrt{\omega^2 - \zeta^2}}$.

(2) Over damped vibration system ($\zeta > \omega$)

In this case, the vibration is a typical non-periodic damping motion, and no way can keep it periodical vibration. Therefore, to make the system produce the maximal amplitude, imposing a force as large as possible to make the system reach maximal oscillation is necessary.

(3) Critical damped vibration system ($\zeta = \omega$)

Similarly, in this case, the vibration is also a non-periodic damping motion, and there is no way to keep the system periodical vibration. To make the system produce the maximal amplitude, applying a possibly largest force to make the system obtain its maximal oscillation is considered.

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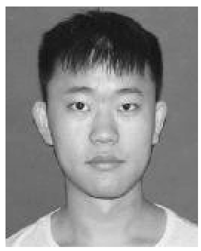

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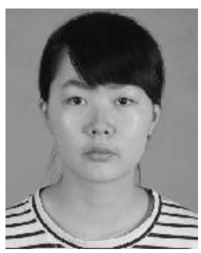

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