

Research Article

Linguistic Modeling of Pressure Signal in Compressor and Application in Aerodynamic Instability Prediction

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Using conditional fuzzy clustering, a linguistic model for static pressure signal of compressor outlet in aeroengine was established. The modeling process and the validation result demonstrated unique advances of linguistic modeling in the analysis of complex systems. The linguistic model was used to predict the pressure signal before the engine entered instability. The prediction result showed that the linguistic model could effectively recognize the sudden changes of pressure signal features. The detected change of signal might not necessarily be the commonly considered initial disturbance of compressor instability; however, the pattern recognition ability of linguistic model was still very attractive. At last, it pointed out that setting up a database containing experiment data and historical experience about engine aerodynamic instability and utilizing advanced intelligent computing technology in the database to develop knowledge discovery provide a new idea for the solution to the problem of aerodynamic instability in aeroengine.

1. Introduction

The operating range of aerogas turbine is limited by the stable operating range of compressor. Compression system will enter into aerodynamic instability of surge and control when the flow in compressor keeps on decreasing to the critical point. Surge and rotating stall can reduce the capacity and efficiency of gas turbine and threaten engine safeties like the rise of turbine inlet temperature and extra mechanical vibration. It is one of the main tasks of control system to ensure compressor stable operation under all working conditions.

As a component of an aerogas turbine engine, compressor plays an important role in the efficiency of the whole engine. With higher efficiency of compressor, energy consumption and the emission of greenhouse gases can both be reduced. The main goal of designing a compressor in the future is to increase its aerodynamic loading so as to increase its efficiency. But, meanwhile, its working point will be closer to the surge line. For the moment, to avoid compressor working

in the unstable region, there is a big distance between its working point and the surge line. However, the increase of aerodynamic loading may directly cause the decrease of the safety margin. So, a reliable early warning mechanism for surge line becomes the preconditions of compressor working steadily with high aerodynamic loading. Its main goal is to apply the results of surge detection and prediction into active control of compressor stability. Compressor active stability control can make engine operate in a region nearer to the stability boundary, which has been one of the key technologies of advanced engines [1].

The discovery of initial disturbance phenomenon before compressor instability is one of the major research achievements in active stability control. “Modal wave” and “spike precursor” are generally considered to be the two primary initial disturbance phenomena of compressor aerodynamic instability [2]. It is a requirement for active control to achieve immediate and reliable instability prediction by detecting instability initial disturbance. A lot of researches about instability detection of initial disturbance and detection and

prediction of rotating stall and surge have been proposed [3–7]. To find an appropriate and reliable method, researchers have made a lot of efforts on flow analysis. Because of the complexities of instability mechanism in compression system and the varieties of engine operating conditions, the understanding of instability initial disturbance in compressor is still not enough. It is very difficult to find a universal method which can accurately detect compressor instability signs and precisely model the instability signs as well. As a result, engineering application of active stability control is limited.

System identification is widely used in many areas, especially for modeling and predicting unknown or complex system behavior whose explicit mathematical model cannot be obtained. Compressor instability sign is exactly the output of such complex system whose input and mechanisms are hard to be obtained precisely. Based on the available data, such as all kinds of system input and output parameters, environmental parameters, and engineering experience, it is beneficial for the understanding of complex system and the control of system to work on data mining, obtain system output mode, and recognize the mode by various advanced calculation means of artificial intelligence. All exiting signal processing experience shows that there is a lot of information about engine instability initial disturbance in pressure signals of compressor. Modeling pressure signals of compressor can possibly obtain more useful underlying modes. Using context based fuzzy clustering, a linguistic model for pressure signal difference sequence of compressor outlet is proposed in this paper. It is used to detect signal model exceptions caused by the change of system characteristics before compressor surge.

2. Linguistic Modeling

2.1. Overview. Linguistic modeling is also called granulation modeling, involving complex model which is composed of information granules, especially fuzzy sets. The model is used to reveal the relations between fuzzy sets defined in input and output space [8]. For decades, it has been one of the major goals of intelligence system to develop an accurate, transparent, and user-friendly model. The granularity of information is becoming a basic concept which plays a key role in any modeling efforts. Linguistic modeling is called knowledge based modeling as well. As it conveys acquired knowledge in relevant fields and positions human knowledge at the center in the whole process of modeling by appropriate defining of the semantics of information granule used in system modeling. Among the numerous linguistic models, rule based model occupies an important position. Whatever forms of the rules, they are involved with granules in both conclusions and conditions.

If condition A and condition $B \dots$, then conclusion W . Here, A, B, \dots, W represent information granules defined in their own spaces. Expression of information granule can be classical set, fuzzy set, rough set, and so on. Among them, fuzzy set occupies an important position, which benefits from the fact that the semidetached concept weakens boundary brittleness.

The key of linguistic modeling is the process of transforming data to information granule. Context based fuzzy clustering is one of the major methods among all the granulation tools. Compared with other mathematical modeling methods, linguistic modeling based on fuzzy clustering has many prominent characteristics and advantages [9]. (1) Linguistic model is more elastic at the conceptual level, which is achieved by giving information granule variable granularity. When information granule has smaller granularity, the rule or characteristic described is broader. However, with the granularity of information granule increasing, the detail revealed is more specific and the problem described is more accurate. Appropriate granularity of information granule can not only capture the characteristics useful to users, but also ignore those secondary details. (2) Linguistic modeling puts designer in a more active position, which can be achieved by two approaches. First, specifying granulation degree of information granule can offer the designer a perspective in favor of usage. Secondly, information granule with same information can make the designer focus on some semantics which are considered to be essential for users. (3) Linguistic model can be taken as an example of rapid prototyping. The whole linguistic model is composed of information granule defined by user and information generated by clustering. After completing the clustering, the modeling process will be finished by downloading information granule to the frame of linguistic model, with no need for extra parameter optimization process. (4) Linguistic model produces output in the form of information granule, thus making the model user-friendly. Actually, what user gets are a series of results and their respective subjection degree. It is helpful for users to understand the essence of results and the relations between them by results visualization.

2.2. Context Based Fuzzy Clustering. Clustering is a basic tool for the analysis of detectability characteristics, unsupervised learning, data granulation, and information compression. Clustering algorithms are various, among which the two primary types are level clustering and target-function based clustering. According to the performance indicator of a target function, target-function based clustering can build division of pattern sets. Minimum of a target function can be taken as a optimization approach to obtain class local optimum. It is required for target function to reflect the essence of a problem, thus revealing the meaningful structure of a data set by its minimum. For the N patterns in R^n and assuming the interested question is to form c classes, the prototypes obtained by clustering are v_1, v_2, \dots, v_c , and target functions are usually defined as sum of the deviations from these patterns to prototypes:

$$Q = \sum_{i=1}^c \sum_{k=1}^N u_{ik} \|x_k - v_c\|^2, \quad (1)$$

where $\|\cdot\|$ is the distance between x_k and v_c . An important part of the previous formula is to divide matrix $U = [u_{ik}]$, which is used to determine the pattern in each class. The component of U is binary number. When $u_{ik} = 1$, pattern k is attached to class i , and no longer attached when $u_{ik} = 0$. Matrix division

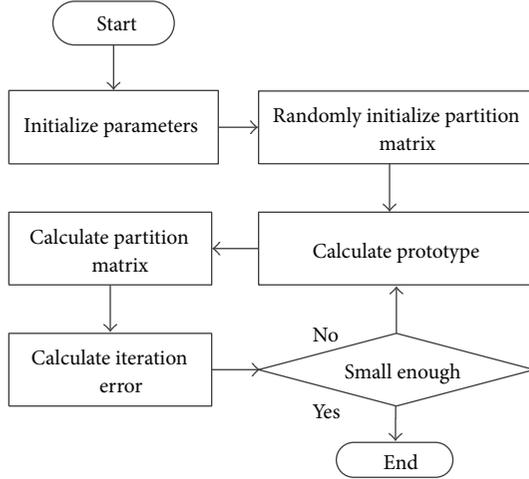


FIGURE 1: Solution process of fuzzy clustering.

must ensure that every class is out of common; namely, it does not contain all patterns and is not blank either. Every pattern can only belong to one class. Marking the set of all satisfying division matrixes as U , clustering process can be expressed as an optimization problem with constraints as follows:

$$\text{Min } Q \quad \text{for } v_1, v_2, \dots, v_c, U \in U. \quad (2)$$

There are several methods to solve the optimization problem. A successful one, which is also the most common one, is called C -means method.

Usually, the boundary of classes division is not clear. And it is not convincing to describe subjection relations by two-value relations. However, fuzzy clustering introduces partial subjection to clustering algorithms and utilizes fuzzy set to express class generated by clustering and prototype of class. Among various fuzzy clustering algorithms, fuzzy C -means (FCM) algorithm is called standard fuzzy clustering algorithm. The performance indicator which leads the clustering process has the following form:

$$Q = \sum_{i=1}^c \sum_{k=1}^N u_{ik}^m \|x_k - v_i\|^2, \quad (3)$$

where m is fuzzification factor. The element of fuzzy partition matrix is no more binary value, but subjection degree of pattern to class partial subjection instead. The set of all satisfying fuzzy partition matrix can be expressed as

$$U = \left\{ U \mid 0 < \sum_{k=1}^N u_{ik} < N, \sum_{i=1}^c u_{ik} = 1 \right\}. \quad (4)$$

The solution of FCM algorithm is an iteration process, which includes the continuous update of prototype and partition matrix. Parameters which need to be set in advance are the number of class (c), clustering function $\|\cdot\|$, fuzzification factor (m), and termination criteria (ϵ). The process of solution can be expressed in Figure 1.

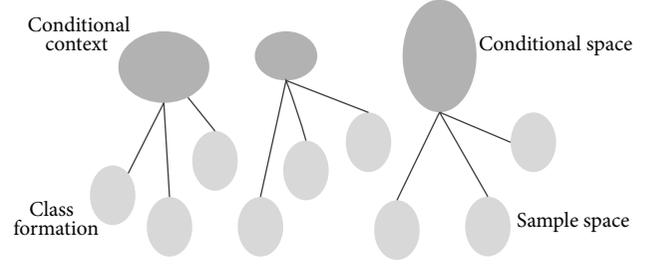


FIGURE 2: Result of conditional fuzzy clustering.

When distance function is chosen as Euclidean distance, update partition matrix and prototype by the following formula:

$$u_{ik} = \frac{1}{\sum_{j=1}^c \left(\|x_k - v_i\| / \|x_k - v_j\| \right)^2}; \quad (5)$$

$$v_i = \frac{\sum_{k=1}^N u_{ik}^m x_k}{\sum_{k=1}^N u_{ik}^m},$$

where $i = 1, 2, \dots, c; k = 1, 2, \dots, N$.

Standard fuzzy clustering is completed without external influence. Sometimes, the structure mined by clustering is not what user needs; meanwhile, more or less experience summaries for specific problems usually have been obtained. Undoubtedly, it is valuable to lead clustering process with experience. Fuzzy clustering under the guidance of given conditions is conditional fuzzy clustering, also called context based fuzzy clustering. Conditional fuzzy clustering can be taken as selecting some samples from sample space for clustering. Conditional context is given in the form of fuzzy set as well. It adjusts partition matrix by pattern to its subjection degree, thus leading the process of clustering. Use f_k to represent the subjection degree of the k th pattern to context, and then the update function of fuzzy partition matrix is

$$u_{ik} = \frac{f_k}{\sum_{j=1}^c \left(\|x_k - v_i\| / \|x_k - v_j\| \right)^{2/(m-1)}}. \quad (6)$$

The result of conditional fuzzy clustering obtains prototype expressions of a series of classes in sample space, conditional context fuzzy sets, and the network between classes and conditions, which is shown in Figure 2.

2.3. Frame of Linguistic Model. Fuzzy class obtained in conditional fuzzy clustering lays a solid foundation for linguistic modeling. The prototypes of these classes can be taken as a “framework” or “blueprint.” Model outputs can be obtained in many ways. The most common one is to obtain the weighted sum in output space. The weights depend on the subjection degree of input pattern to each fuzzy class. Give the subjection degree of an input x , thus the activation degree is $u_1(x), u_2(x), \dots, u_c(x)$. The model output is

$$y = \sum_{i=1}^c v_i u_i(x). \quad (7)$$

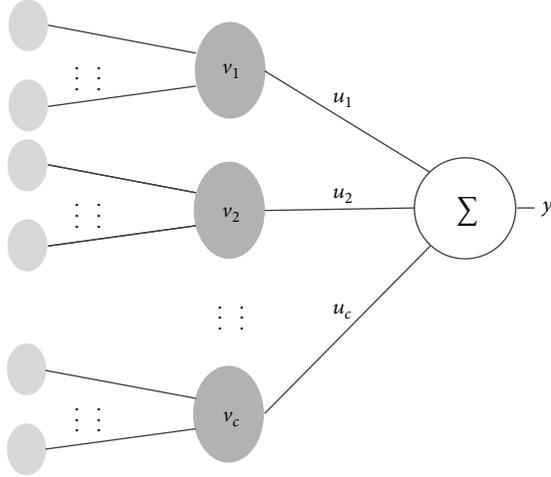


FIGURE 3: Frame of linguistic model based on conditional fuzzy clustering.

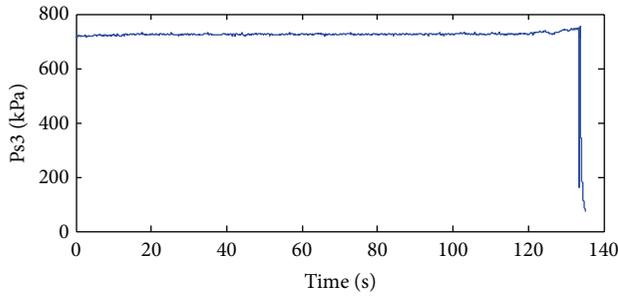


FIGURE 4: Static pressure signal of compressor outlet.

The calculation formula of activation degree is

$$u_i = \frac{1}{\sum_{j=1}^c \left(\frac{\|x - v_i\|}{\|x - v_j\|} \right)^{2/(m-1)}}. \quad (8)$$

Frame of linguistic model based on conditional fuzzy clustering is shown in Figure 3.

3. Instance Analyses

3.1. Data Preparation. Pressure signals measured in compressor reserve abundant information about initial disturbance of compressor aerodynamic instability. Surge experiment of a whole engine is carried out on a turboshaft engine. Static pressure signal measured in compressor outlet is taken as an analysis object. In this experiment, sample rate F_s is 1000 Hz, Figure 4 is the pressure signal after wavelet denoising, and Figure 5 shows partial enlargement of pressure signal of compressor outlet when surge occurs.

The nonstationary flow before engine surge usually shows up as difference sequence of pressure signal [10]. In the real operation of engine, pressure signal often features strong nonstationarity. Numerical difference can eliminate nonstationary trend of signal and keeps local disturbance of

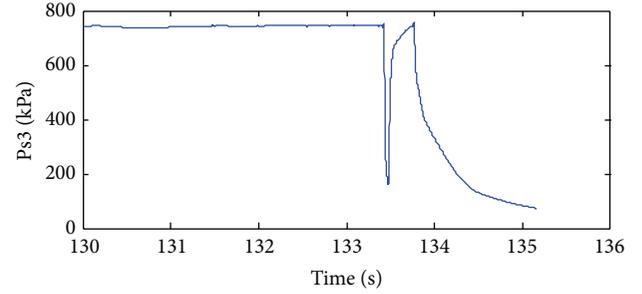


FIGURE 5: Partial enlargement of compressor outlet pressure signal when surge occurs.

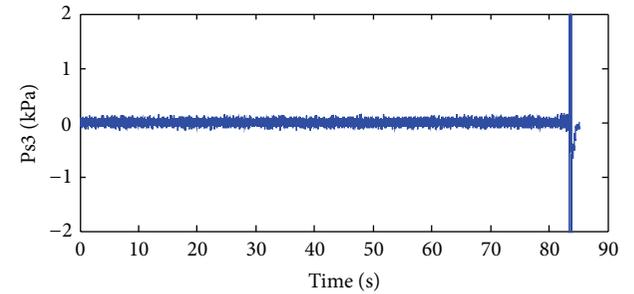


FIGURE 6: Numerical difference sequence of static pressure in compressor outlet.

nonstationarity. Figure 6 is the above-mentioned numerical difference sequence of pressure signal after wavelet denoising.

3.2. Linguistic Model. Selecting numerical difference subsequence of pressure signal in the stable region which is far away from engine surge points as sample space of linguistic modeling and assuming that the current difference value is the nonlinear fuzzy mapping of historical value, then

$$x(k+1) = F_{\text{fuzzy}}(x(k), x(k-1), \dots, x(k-p)), \quad (9)$$

where p is the order of linguistic model and let $p = 4$ tentatively. Take current difference value as output space and construct conditional context on this account. Selecting triangular subjection function, then context can be expressed in the form of upper limit, mode value, and lower limit. Based on the data, the range of pressure difference in the stable region is from -0.2 to 0.2 , and then 7 conditional contexts can be constructed as follows:

$$\begin{aligned} &(-0.20, -0.15, -0.10), \\ &(-0.15, -0.10, -0.05), \\ &(-0.10, -0.05, 0.00), \\ &(-0.05, 0.00, 0.05), \\ &(0.00, 0.05, 0.10), \\ &(0.05, 0.10, 0.15), \\ &(0.10, 0.15, 0.20). \end{aligned} \quad (10)$$

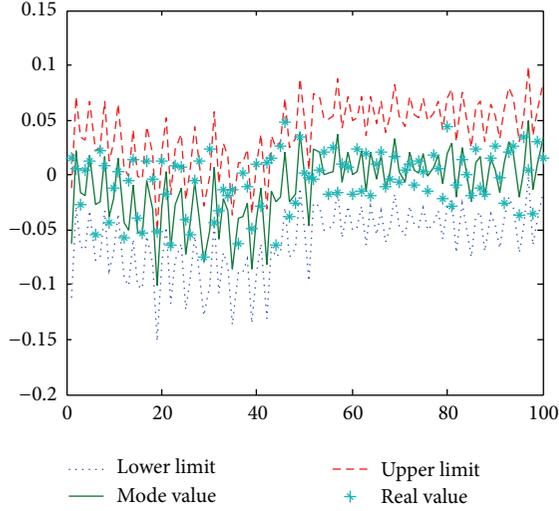


FIGURE 7: Model validation.

Selecting each conditional context and classifying the sample space into 4 categories, prototype expressions of 28 classes are obtained in total. Choose distance function as Euclidean distance, fuzzification factor $m = 2$, and termination criteria $\varepsilon = 0.001$. Prototypes obtained by clustering are listed in Table 1. Every line is a prototype which is the values of the four past moments.

Figure 7 shows model validation results based on the data outside modeling sample. It can be seen that all the actual values are included in the model prediction range and close to the predicted means, showing that the built linguistic model can capture well the characteristics of pressure signal in the stable region.

3.3. Surge Prediction. In order to detect the abnormal pressure signal before engine surge, select data of 30 seconds before surge point and utilize the linguistic model built above for continuous one-step prediction. Select window size of 1000 sample points, slide forward at a rate of 100 points, and calculate the prediction standard deviation in the window. The result is shown in Figure 8.

It can be seen that the prediction error of linguistic model is gradually increasing in the process of approaching surge. The process continues for over 1 second until the engine enters into surge. The result shows that, when approaching surge, system characteristics transformation of engine is reflected in the characteristic space of pressure signal. Moreover, linguistic model is capable of recognizing the sudden change of system characteristics, which can be used for the analysis and detection of initial disturbance of engine aerodynamic instability.

4. Discussions and Conclusions

In this paper, linguistic modeling method based on fuzzy clustering is used in the data analysis of engine surge experiment. The modeling process reveals the advantage and difference of linguistic modeling over normal mathematical

TABLE 1: Prototypes obtained by clustering.

Context 1			
0.0221	-0.0895	-0.0149	0.0235
-0.0410	-0.1156	0.0092	-0.0273
-0.0881	-0.0169	-0.0112	-0.0555
-0.0345	-0.0422	0.0701	-0.0500
Context 2			
-0.0175	-0.0686	-0.0258	0.0243
-0.0734	-0.0139	0.0616	-0.0510
-0.0394	-0.0709	0.0039	-0.0387
-0.0302	-0.0730	-0.0059	-0.0168
Context 3			
0.0150	-0.0329	0.0127	0.0294
-0.0430	-0.0107	0.0183	-0.0322
-0.0225	-0.0395	-0.0128	-0.0167
-0.0029	-0.0305	-0.0284	0.0057
Context 4			
0.0135	0.0000	0.0170	0.0137
-0.0119	0.0037	0.0054	-0.0110
0.0316	0.0027	0.0017	0.0321
-0.0356	-0.0032	-0.0210	-0.0405
Context 5			
0.0421	0.0140	0.0176	0.0352
-0.0053	0.0330	0.0122	-0.0130
-0.0025	0.0348	-0.0135	-0.0154
0.0235	0.0290	0.0196	0.0144
Context 6			
0.0047	0.0573	0.0363	-0.0140
0.0206	0.0917	0.0155	-0.0041
0.0190	0.0363	-0.0222	0.0157
0.0548	0.0345	-0.0183	0.0447
Context 7			
0.0524	0.0309	0.0234	0.0283
0.0365	0.0487	0.0162	0.0275
0.0680	0.0493	0.0065	0.0580
0.0173	0.0786	0.0359	0.0217

modeling. First, there is no need for linguistic model to estimate model structure of system in advance; thus, it is useful for any system theoretically. Secondly, linguistic model is built on the definition of information granule which has a clear meaning for user. It can effectively fuse experience obtained already in related fields, thus improving accuracy and transparency of modeling. Finally, granularity of variable information granule gives linguistic model the ability to focus on different levels of a problem freely. More detail can be revealed when increasing granularity of information granule, whereas unimportant detail can be concealed.

Using the linguistic model built in this paper to predict the data before surge, the result shows that, in a long time before surge in engine (over 1 second), there indeed exists a characteristic different from stable state. It is worth pointing out that the abnormal signal before surge in the experiment

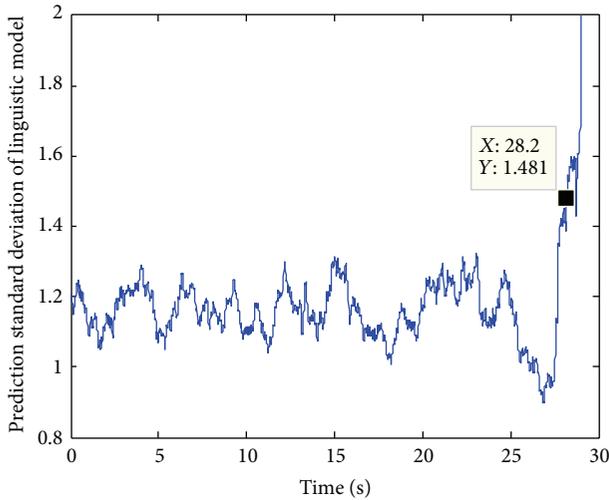


FIGURE 8: Prediction standard deviation of linguistic model.

of this paper is not necessarily the commonly believed instability sign of compressor. However, the pattern recognition ability shown by linguistic model is still attractive, especially for a complex system like aeroengine. Because it is very difficult to obtain an accurate numerical model on one hand and, on the other, data accumulated by long-standing experiment researches is another precious but underutilized treasury. Using advanced intelligent computing to deal with huge database, it is very likely to obtain the revealed precious domain knowledge from it.

The surge signal processing method shown in this paper is just an application example for linguistic modeling. When applied to the actual surge prediction, the work required is far more than this. The work which can be carried out in the future includes (1) analyzing signal of higher sample rate, thus obtaining more detailed signal pattern at higher sample rate; (2) combining several sensor signals for comprehensive fusion analysis; (3) combining parameters like engine operation environment for analysis of linguistic modeling; (4) setting up a database about engine instability which should include inputs and outputs of numerous experiments, various existing conclusion experience, and so on and utilizing advanced intelligent computing method to develop researches of knowledge discovery in the database. It can be imagined that with the development of software and hardware in the field of intelligent computing, intelligent computing technology will provide a new idea for the solution to the problem of engine stability.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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