

# A Novel Aircraft Fault Diagnosis and Prognosis System based on Gaussian Mixture Models

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**Abstract—** The goal of this work is to build an effective and practical system to diagnose and prognose faults of complex systems, like aircraft, satellite and so on. In this paper, a machine-learning method Gaussian Mixture Models (GMMs) is used to automatically detect, isolate, and even forecast the faults, while keeping the reliability and safety of complex system. Each dysfunctional model is completed by GMMs during machine learning, which constitutes the diagnosis system to distinguish and troubleshooting the faults. On the other side, principal component analysis (PCA) is combined with the system to improve the efficiency of GMMs, which can effectively compress the high dimensional data. Except for that, GMMs helps the system to achieve the visualization of dysfunctional models. With this visualization, the prognosis system can surveil the evolution of data and estimate their tendency, which is important to forecast the next condition of the complex system. The diagnosis and prognosis system proposed in this paper has been fully tested by using actual experimental data of aircraft X, which is supplied by Dassault Aviation.

## I. INTRODUCTION

As a complex system, aircraft becomes more and more complex with the development of aerotechnics which requires the increase of sub-component systems monitoring and maintenance [1]. Traditionally, the diagnosis and the troubleshooting are performed by experts, by observing how the system works, generally through unit tests on each component of the complex system. But for modern aircraft, this "planned maintenance" becomes nearly impossible, in terms of the complexity and the economic cost [2]. Especially for combat aircraft, the traditional examination and repair period has a great impact on the attendance rate of aircraft. Consequently, aircraft needs to embed intelligent systems dedicated to their self-diagnosis [3]. In addition, a prognosis system is required to monitor and forecast the health condition of aircraft, which can be used to prevent the faults and optimize the planning of overhaul.

Different from classical diagnostic and prognostic system, like Condition-Based Maintenance / Prognostic Health Management [4], the system proposed in this paper can be used not only in the off-line case for maintenance, but also can be mounted on aircraft and work in the on-line case during its mission. In fact, the whole system consists of three principal parties: one center and two monitoring terminals. Machine learning will be done with a powerful computer at Aircraft

Ground Center (AGC), the system will learn and cognize every type of faults with database. Then the complete dysfunction model is accomplished by GMMs and it is sent to monitoring terminals, so as to isolate, distinguish or forecast the faults. According to the different situations requirement and equipment conditions, two monitoring terminals are set at the different areas: one is on operation at the aircraft for the on-line condition, which only needs to make three judgments of the health of aircraft and show them to pilot: 1) normal; 2) mild dangerous (- there are faults, but tolerant system can resolve them); 3) dangerous (- the aircraft must go back to airport). Another monitoring terminal is off-line for the maintenance office, which needs detailed diagnosis and prognosis results to repair or evaluate aircrafts.

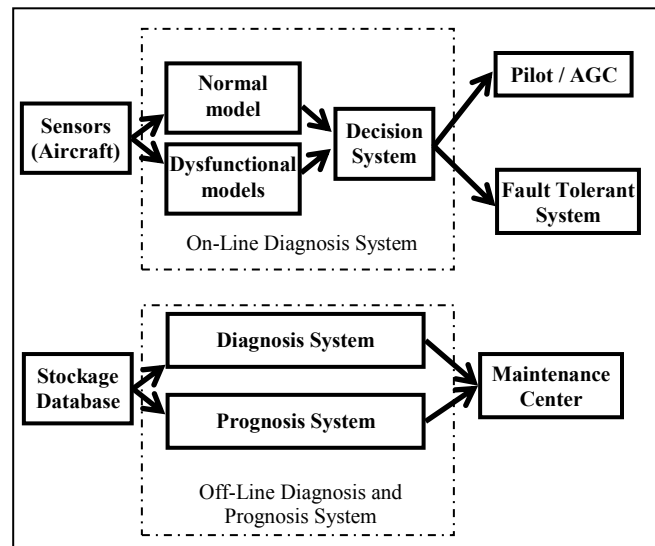


Figure 1. Schema of Overall Fault Diagnosis and Prognosis System

In the aircraft system, although there are tens or hundreds of sensors, they can be regrouped into four classes: sensors of temperature (T), sensors of pressure (P), sensor of air flow (D) and sensor of system variables (S) (for example to indicate the position of the valve, etc.). All of them are defined as the inputs of the diagnosis and prognosis system, while the

outputs are delivered to the decision system which can come to a conclusion (see Fig. 1).

In this paper, GMMs is proposed to build this diagnosis and prognosis system. It is a classical method of pattern recognition, but it can be improved by combining with PCA to achieve the visualization of data and the dysfunctional models, which is relatively new concept for forecasting the tendency of evolution of data. In comparison with some other methods of diagnosis and prognosis, GMMs is more convenient and stable. At first, it can easily add new faults or new dysfunctional models into database, unlike expert system [5] which always needs to resolve conflict of new rules and old rules; secondly, the speed of machine learning of GMMs is more rapid than Neural Networks and other complex advanced methods [6]; thirdly, it can be combined with method Discriminant Analysis [7] or Principal component analysis to make a visualization of high dimensional data; at last, the evolution of aircraft data can be supervised by the dysfunctional models. On basis of evolution of distances from cloud of data and the models, the system can estimate the tendency of the evolution of data and forecast the probable faults in the future. Obviously, besides a short term prognosis of faults, the system can also be used to do a long term evaluation of aircraft. This method of prognosis is more convincing and efficacious than regression methods and statistical methods which always have problems of precision of a long term regression and needs more time to analysis the data.

In addition to that, this system should not be a black box. On the one hand, the system and its dysfunction models of aircraft faults can be designed to illuminate engineering consulting service, who needs to keep watching on the condition of aircrafts to ensure the safety of clients; on the other hand, this system can also accumulate the knowledge for re-engineering purposes (including diagnosis operational rules) and perfect the design of new aircrafts. The system proposed in this paper has been fully tested by using actual experimental data of aircraft X from Dassault Aviation.

The rest of this paper is organized as follows. The fault diagnosis system based on PCA and GMMs are depicted in Section II; Section III demonstrates fault prognosis system and the working of dysfunctional models; Section IV shows a test of the system on the anti-icing system of an aircraft X from Dassault Aviation, which consists of three engines and a complex tubes system; finally, the last section is devoted to the conclusion and future works.

## II. FAULT DIAGNOSIS SYSTEM BASED ON PCA AND GMMs

### A. Pretreatment of data by PCA

Principal Components Analysis is a method that reduces data dimensionality by performing a covariance analysis between factors [8]. As such, it is suitable for data sets in multiple dimensions, such as a large experiment in aircraft expression. For a given data matrix X which represents m columns of measured variables (sensors) at n rows of sampling points during normal operation condition, the covariance matrix of X is:

$$\text{cov}(X) = X^T X / (n - 1) \quad (1)$$

The data X has been normalized before using PCA, whose mean of each column is zero, and the data of each column are

divided by its standard deviation. Therefore, the covariance matrix is the correlation matrix [9]. The loading vector of PCA decomposition  $\mathbf{p}_i$  is the  $i^{\text{th}}$  eigenvector of the covariance matrix and  $\lambda_i$  is the eigenvalue corresponding to the eigenvector  $\mathbf{p}_i$ .

$$\text{cov}(X)P_i = \lambda_i P_i \quad (2)$$

PCA decomposes the data matrix X as:

$$X = \mathbf{t}_1 \mathbf{P}_1^T + \mathbf{t}_2 \mathbf{P}_2^T + \dots + \mathbf{t}_k \mathbf{P}_k^T + \mathbf{E} \quad (3)$$

where  $\mathbf{t}_i$  is a scores vector,  $\mathbf{p}_i$  is a loading vector,  $k$  is the number of principal components (PCs) retained in PC model, and  $\mathbf{E}$  is a residual matrix. Obviously, PCA is a linear transformation. It is not appropriate to perform PCA decomposition in original input space with strong nonlinear data structure, so sometimes kernel method is combined with PCA (KPCA) [10] to resolve the non-linear problem. But the system must deal with problems in the light of specific conditions. In the case of aircraft, the measurement by main sensors, as temperature, pressures etc. are linear; PCA is enough to complete this task.

### B. Classification by GMMs

GMM is a parametric probability density function represented as a weighted sum of Gaussian component densities [11]. Its parameters are estimated from training data using the iterative Expectation-Maximization (EM) algorithm or Maximum a posteriori (MAP) [12] estimation from a well-trained prior model. In the Gaussian case, a Gaussian MM (GMM) is a simple linear superposition of Gaussian components, which aims at providing a richer class of density models than a single Gaussian. For a model of M Gaussian states, a GMM density function of a variable  $\mathbf{X}_n$  can be defined as

$$p(X|\lambda) = \sum_{i=1}^M p_i b_i(x_n) \quad (4)$$

where  $\mathbf{p}_i$  is the probability of being in the state  $i$  and  $\mathbf{b}_i$  the Gaussian density function of mean  $\mu_i$  and covariance  $\Sigma_i$ .  $\lambda$  can be written as

$$\lambda = \{p_i, \mu_i, \Sigma_i, i = \{1, \dots, M\}\} \quad (5)$$

and represents the set of weights  $\mathbf{p}_i$ , mean vectors  $\mu_i$  and covariance matrices  $\Sigma_i$  of the GMM.

In the faults diagnosis task, an M state GMM is associated to each situation (S) of aircraft: the normal condition and each type of faults. On the basis, the aim is to determine which model of situation  $\hat{S}$  has the biggest a posteriori probability over a set  $X = \{x_1, x_2, \dots, x_N\}$  of the values transformed by PCA, which are from the measures of sensors. So, according to Bayes rules,  $\hat{S}$  is

$$\hat{S} = \text{Arg max } p(\lambda_k | X) = \text{Arg max } \frac{p(X|\lambda_k)p(\lambda_k)}{p(X)} \quad (6)$$

In this case,  $\lambda^k = \{p_i^{(k)}, \mu_i^{(k)}, \Sigma_i^{(k)}\}$ ,  $i = \{1, \dots, M\}$ , represents the mixture parameterization of the M-state GMM associated to the  $k^{\text{th}}$  situation of aircraft. Assuming that the a priori probability  $p(\lambda_k)$  is the same in all situations and for one set of measured data X, equation (6) can then be simplified as

$$\hat{S} = \text{Arg max } p(X|\lambda_k) \quad (7)$$

Now, the next step is to determine the  $3 \times M$  parameters included in  $\lambda_k$  describing the GMM related to the  $k^{th}$  situation. This is achieved through the classical iterative Expectation – Maximization (EM) algorithm [13]. Such a method exhibits a fast convergence of the parameters and it is based on two successive steps: expectation (E) and maximization (M). These two steps are iterated until convergence of the set  $\lambda_k$ ; the convergence of the algorithm is evaluated through the log-likelihood  $\log(p_l(X|\lambda_k))$ , with  $l$  denoting the  $l^{th}$  iteration of the algorithm. The learning is initialized with a first clustering of the data obtained with a K-means algorithm. Note that during this learning step, no interaction occurs between the GMMs of different situations.

Once the  $3 \times M \times S$  GMM parameters of the  $S$  situations are known, these Gaussian models are exploited to perform the recognition as follows. As soon as a set of new features  $X$  is available, the situation of aircraft is selected as being the situation having the GMM with the highest a posteriori probability  $p(X|\lambda_k)$ , see Equation (7).

### C. Monitoring of sensors

It is already clear that the system of fault diagnosis and prognosis completely depend on the measurement of sensors. They are the inputs of system. Therefore, conditions of sensors are necessary to be considered. Whether they are normal or abnormal, the system needs to check them at first. Especially for combat aircraft, losing sensors information and breakdown of sensors are common problems during its mission.

As regards the faults of sensors, three problems are summarized: sensors seized (8), sensors gain change (9) and sensors constant deviation failure (10).

$$y_{out}^i(t) = a_i, i = 1, 2, \dots, n \quad (8)$$

$$y_{out}^i(t) = \beta * y_{normal}^i(t) \quad (9)$$

$$y_{out}^i(t) = y_{normal}^i(t) + \Delta \quad (10)$$

where  $y_{out}^i(t)$  is the real measurement of  $i^{th}$  sensor at the moment (t),  $a$  and  $\Delta$  are constants,  $y_{normal}^i(t)$  is the theoretical normal measure of  $i^{th}$  sensor at the moment (t),  $\beta$  is a constant coefficient [14]. As these equations shown, sensors seized means that the measure of sensor is always changeless. Maybe the value is equal to zero or constant value. It signifies that the sensor is either mute or losing completely the measure from a moment. Sensors gain change means that the measurement has a proportional increment or decrement in comparison with normal sensor. Perhaps the inner amplifier has a problem. Generally, sensors constant deviation failure signifies problem of calibration.

Hence, in order to resolve these problems, the system monitors and filters the measurement at the first step. If some sensor's measure becomes changeless, the system will take a note of this sensor and give this information to pilot and AGC. Otherwise, during the machine learning, the system records some indicators in a database, likes maximum and minimum of measure for each sensor, including all the situations. After the takeoff of aircraft, the system compares these indicators between the real measure for a period of time and the records in the database to check whether there is gain change or not.

Certainly, before the takeoff, the system needs to check the calibration of sensors.

### D. Fault Diagnosis System

Depending on the precedent parties, the whole fault diagnosis system consists of four sub-systems, as shown in the Fig. 2. At first, sensors are checked by sub-system 1; if there isn't any problem of sensors' measures, all the measures are pretreated in sub-system 2 by engine-normalization and PCA; and then GMM models calculate the posteriori probability of each set of example data from PCA; at last the sub-system 4, decision system concludes the results of diagnosis and give the report to the pilot, AGC and Maintenance Center.

In fact, all the measures of aircraft  $X$  sensors are recorded per second during its mission. Although GMM analyze the example of each second and give out the model which has the highest a posteriori probability, the decision system makes a conclusion of these diagnosis results for a period of time, for example 5 seconds and 15 seconds, not only for one second. In this way, some noise can be avoided, and the missed detection ratio and false alarm ratio can be reduced.

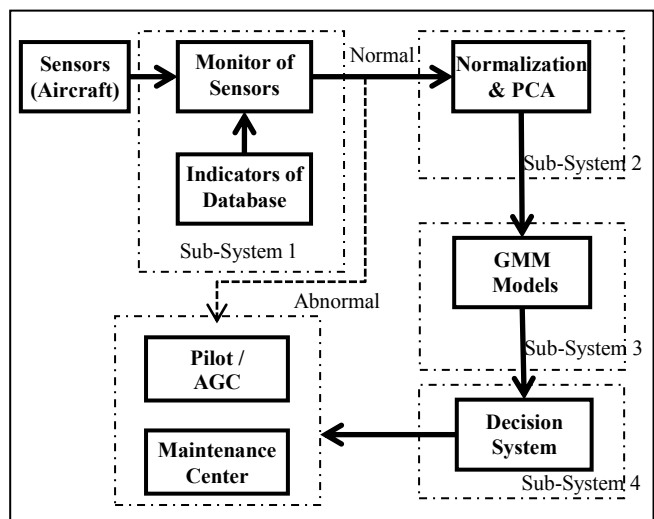


Figure 2. Schema of Faults Diagnosis sub-Systems

## III. FAULT PROGNOSIS SYSTEM

With the help of GMMs, the system finds a set of Gaussian models for each situation of aircraft. Except for the weight, each model presents the mean  $\mu_i$  and variance  $\Sigma_i$ . With these two parameters, the system can define the zone influence of each model. Fig. 3 illustrates two different classes – 'Normal situation' and 'Fault'. Each of them has three models and every model has a power zone influence. The zone influence can have a high dimension, but for the sake of visualization, it is shown on 3D here. As shown in Fig. 3, the zone influence is in form of ellipse. From the center to around, the a priori probability decreases step by step. The frontier of ellipse presented in the figure is determined by the a posteriori probability equals 50%.

Therefore, with the map of these models, it is easy to observe evolution of data. If system finds that the cloud of data moves to the ellipse (model) of fault, it means the fault is more and more possibly occurred in a future time. So, the fault

prognosis system sends a report about this tendency to the pilot/AGC and maintenance center, so as to prevent it.

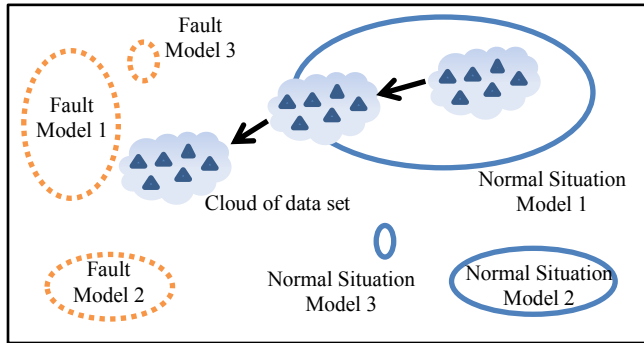


Figure 3. Schema of Theory of Faults Prognosis System

#### IV. RESULTS OF EXPERIMENTS OF AIRCRAFT

##### A. Experiment Drawing

In this work, the fault diagnosis and prognosis system is built for an anti-icing system of an aircraft X, which uses the hot air from engines to warm wings and fuselage. As Fig. 4 shown, it mainly consists of engine bleed systems, bleed air systems and valves system. The database of the anti-icing system consists of 230000 samples (230000 records, with 1 sample per second) of 33 sensors. In others words, the size of the database is 230000 multiplying by 33. Among these data, 75% of data are chosen randomly for machine learning and the remaining is used to test the system.

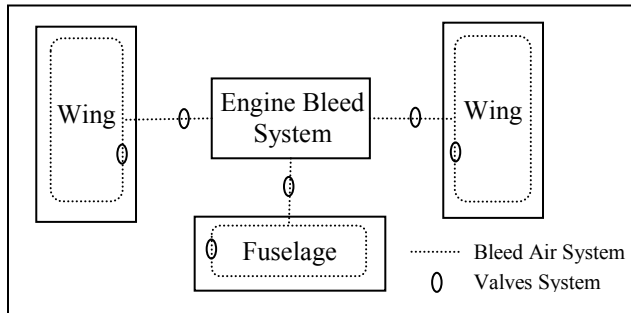


Figure 4. Schemat of Anti-icing System's Structure

In fact, the mechanical engineer introduces three types of faults (Fault 1, Fault 2 and Fault 3). So, including the normal situation, there are 4 situations in total to diagnosis and prognosis.

##### B. Application of PCA of the Test Data

As explained in section II - A, the data are pretreated by PCA before using GMMs so as to reduce the high dimension. Fig. 5 shows that the first principal component's variance constitutes more than 50% of the total sum of all variances over all components. The variance decreases as the order of the corresponding component increases. Finally, six principal components are found to add up to 95% of the total sum of the variances explained. Note that these principal components are computed based on the 33 used anti-icing system sensors and thus a big dimension reduction is performed, while keeping most of the beneficial information.

In addition to this, there is another reason to explain why PCA is so efficient for reducing the data dimension in this case. For the sake of safety, many redundant sensors are installed in the aircraft. Multiple sensors can do the same role; if one sensor is broken, there is another one which can substitute of it. But for the diagnosis and prognosis system, the redundant sensors are burden. These redundant sensors are easily to be reduced by PCA. It is also true that the system can cut out these useless sensors at first, but it is not sensible. Because engineer needs to offer another database of redundant sensors to the system, it is not very necessary. PCA can resolve them by itself.

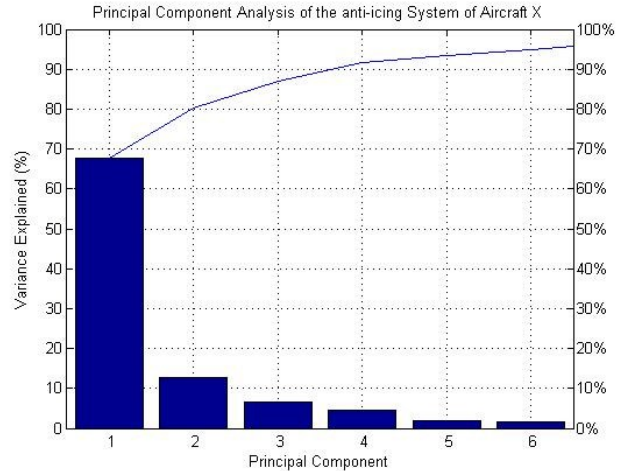


Figure 5. PCA of the anti-icing system of the aircraft X

The data of 33 dimensions are well visualized on 2D by PCA, as in Fig. 6. The points of normal situation and faults are clearly shown, which is necessary for engineers to study the distribution of faults' data.

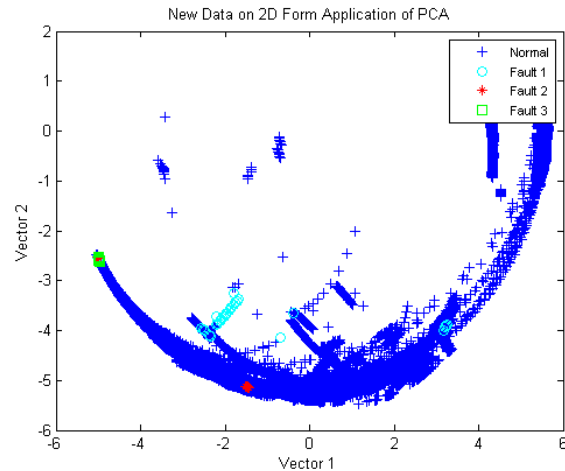


Figure 6. New data corresponding to principal component on 2D

In general, PCA is employed, as being a tool that effectively reduces the input data dimension and improves the computational loads of the fault diagnosis and prognosis process, and thus of the overall system.

### C. Fault Diagnosis Test by GMM

According to the results of PCA, six principal vectors are chosen as the inputs of sub-system GMMs. GMMs builds special Gaussian models for each set of situation data. But for next, there is an optimization of number K to be determined: How many Gaussian models are needed to do the best classification? As shown in Fig. 7, the score of classification (recognition rate) depends on the number of models (K). It is clear that the score is not proportionate to K. It will be saturated during the increase K. Moreover, the score might be fall down a little after the saturation, because of too many models which reacts on each other.

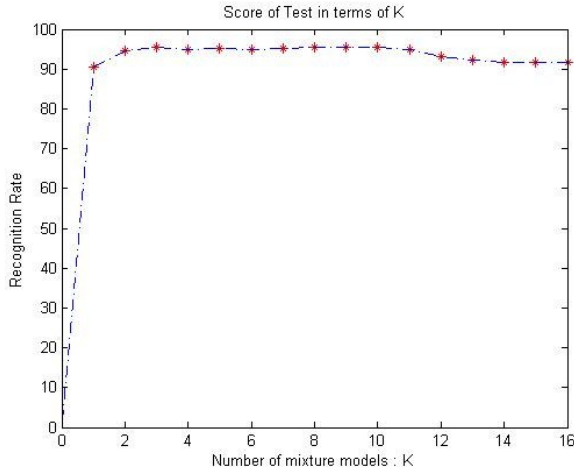


Figure 7. The recognition rate corresponding to quantity of models K

In this test, three models (K=3) for each type of situation are enough to distinguish them. Table I shows the result of test in form of confusion matrix. From this table, a big surprise is found: the system can absolutely distinguish these faults while there are only faults. It is said that the system impossibly confuses the faults, only if the classification is between normal situation and some faults. Another good discovery from this table is, there isn't false alarm of Fault 3 (see the last column of table). If the system says there is Fault 3, there is indeed Fault 3. In general, the score of test is 95.51%, and the cost time of machine learning is about ten minutes (with a computer – Intel Pentium Dual-Core T4400 and 2G memory). In order to show the advantage of GMMs, the same data is tested by method neural network (training algorithm: back propagation) to do this fault diagnosis, which needs about one hour of machine learning and its score is 90.12%. Therefore, it is clear that GMMs can offer a result more effective and more accurate.

TABLE I. CONFUSION MATRIX OF TEST (PER ONE SECOND), PCA = 95% (WITH 6 PRINCIPAL VECTORS), SCORE = 95.51%

Target/Output	REF	Fault 1	Fault 2	Fault 3
REF	93.50%	0.50%	6.00%	0.00%
Fault 1	3.23%	96.77%	0.00%	0.00%
Fault 2	2.70%	0.00%	97.30%	0.00%
Fault 3	1.69%	0.00%	0.00%	98.31%

TABLE II. CONFUSION MATRIX (15SEONCDS), PCA = 95% (WITH 6 PRINCIPAL VECTORS). SCORE = 100.00%

Target/Output	REF	Fault 1	Fault 2	Fault 3
REF	100.00%	0.00%	0.00%	0.00%
Fault 1	0.00%	100.00%	0.00%	0.00%
Fault 2	0.00%	0.00%	100.00%	0.00%
Fault 3	0.00%	0.00%	0.00%	100.00%

If the decision system concludes the results of test for a period of 15 seconds, the score of test becomes 100%, as shown in Table II. So the noises are avoided by the rules of decision.

### D. Fault Prognosis Test

The fault prognosis is realized by monitoring the evolution of data and estimating the distance between data cloud and the centers of models. As shown in Fig. 8, every model is presented on 3D in the above figure. The biggest ellipse is a model of normal situation, and the frame with dotted line consists of three models of fault 3 as shown in the figure below. In each model, there are two numbers. The upper number is the number of model, and the number at the bottom is the weight of model. Even if some models are superposed, the system can differentiate them by a high dimension. For example, 5 vectors are used in this test. It means that the system estimates the evolution of data on 5D.

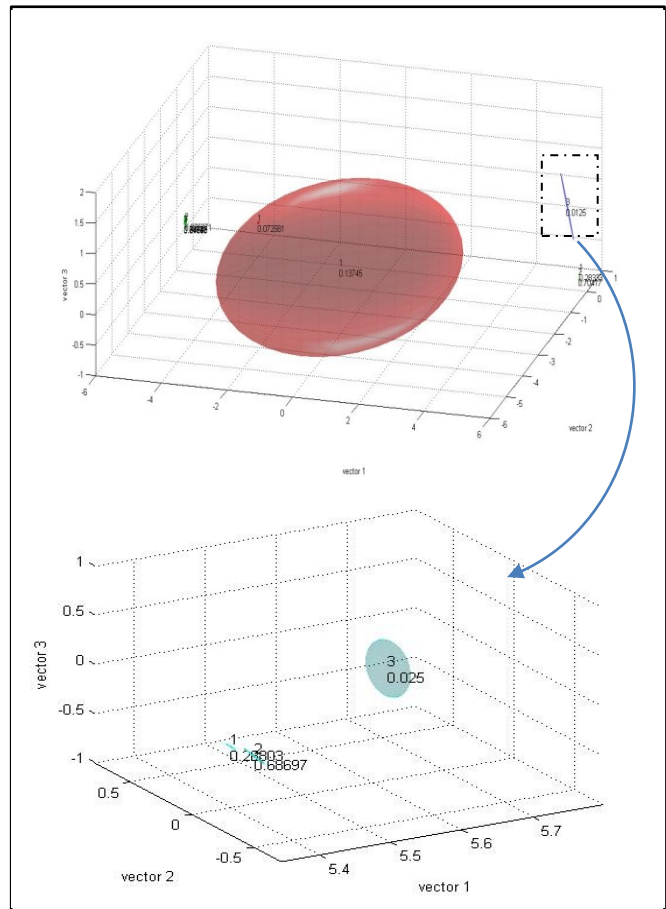


Figure 8. Visualization of three models of each situation on 3D

Fig. 9 shows an example of evolution of data. At the beginning, the cloud of data is nearby the model of normal situation. Thirty minutes later, the system rechecks the cloud of data and finds that the cloud of data is moving in direction of models of fault 3. So this dangerous tendency (arrow in Fig. 9) of evolution is reported to pilot / AGC and maintenance center. Certainly the system can estimate the tendency by high dimension of data, not only on 3D.

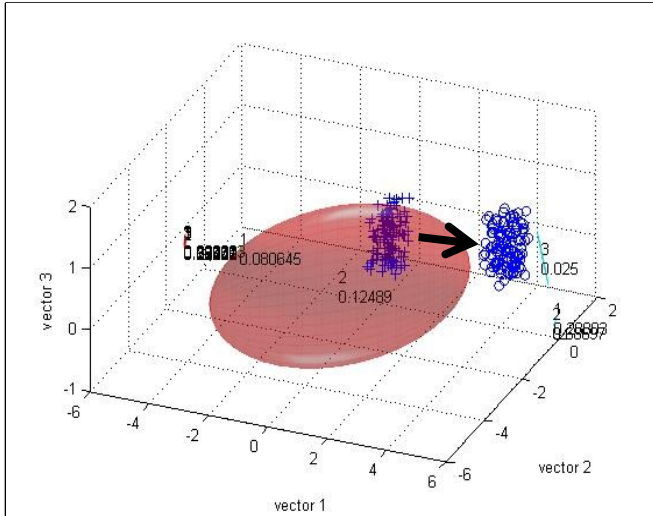


Figure 9. Visualization of evolution of data on 3D

## V. CONCLUSION

In this paper, a faults diagnosis and prognosis system of aircrafts based on PCA and GMM is presented. At first, the system checks whether there is already some problems from sensor or not. These good measures of sensors are used as inputs of the system. If there is any problem from sensor, the system sends an alarm. PCA pretreats the inputs at the next step, so as to reduce the dimension of data and ameliorates the efficiency of machine learning. Then GMMs builds models for each situation of aircraft. These Gaussian models constitute the fault diagnosis system to distinguish different situations. In addition to this, the prognosis system checks the evolution of data cloud at regular time and forecasts its tendency. The report of diagnosis and prognosis results is sent to pilot / AGC and maintenance center. In comparison with other methods, the machine learning speed of this intelligent system is faster than others, like neural networks or SVMs. In addition, the recognition rate reached 100% with a decision rule of 15 seconds in the test. Some words about the prospect, in the future, the same system will be built for other complex systems, for example train and ship. According to different condition of complex system, kernel method is prepared for PCA and GMMs, if it is needed.

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