Faults diagnosis of wind energy conversion chain based on doubly fed induction generator by principal components analysis method

Jacques Fanjason Ramahaleomiarantsoa*
University of Corse
UMR CNRS 6134 SPE
Corse, France
ramahaleojacques@yahoo.fr

Nicolas Héraud
University of Corse
UMR CNRS 6134 SPE
Corse, France
heraud@univ-corse.fr

Eric Jean Roy Sambatra
Institut Supérieur de Technologie
Antsiranana, Madagascar
ericsambatra@yahoo.fr

Jean Marie Razafimahenina
Ecole Supérieure Polytechnique
Antsiranana, Madagascar
razafimaheninajeanmarie@yahoo.fr

Abstract— **This paper deals with the faults diagnosis of wind energy conversion chain based on doubly fed induction generator (DFIG). A complete model of the device is presented. An accurate model of the induction machine is proposed because the considered faults are come from this element. The developed model of the conversion chain allows studying both the cases with and without faults. The principal components analysis (PCA) method is then used for system diagnosis. This approach is based on residues analysis. The complete model has been implemented on the Matlab software to perform the matrix data needed for PCA method. The simulation results of several variables such as stator and rotor currents, shaft rotational speed, electrical power, electromagnetic torque and other variables issued from mathematical transformations of healthy and faulted DFIG are analyzed. Comparisons of simulation results with those of other diagnostic methods are performed to show importance of the PCA method in fault diagnosis of systems. The results show the efficiency of the approach but require a good choice of the number of principal components.**

Keywords- Wind energy; doubly fed induction generator; principal components analysis; residues analysis; modelling; simulation;

I. INTRODUCTION

Nowadays, with technological developments, the progress of power electronics and especially the economic issue of the imminent exhaustion of fossil energy resources and also due to the continuous availability of renewable energy source, the energy production from renewable sources is very coveted. In industrial production of new and renewable energies, the variable speed and pitch control wind turbine are increasingly used due to their robustness and reliability. Despite the research work carried out and improvements, these wind turbines remains the most potential failures of both electrical and electronic or mechanical parts of these elements. Although wind power generation process reaches a technical maturity, the system needs more oversight due to the requirements of industries to produce higher quality at lower cost. Indeed, monitoring and fault diagnosis in a short time become a concern for manufacturers. Therefore, for around ten years, they become a concern of researchers in both academic and industries. Thus, this paper proposes a new methodology of faults diagnosis in wind energy production by the principal component analysis approach (PCA) based on the study of residues. The PCA method, which has shown its effectiveness in the sensor diagnosis, was built recently in system diagnosis. This work is then to show the strength of the PCA method in the system faults diagnosis, using the wind energy conversion chain based on doubly fed induction generator (DFIG) as application device. To do this, we propose firstly an accurate analytical model of doubly fed induction generator (DFIG) because the considered faults come from this element. This model is then inserted into the device complete model. This one allows us to analyze the system without or with fault cases. This model provides the matrix data of several characteristic quantities of the machine. These data will be included as input variables of the PCA method. Special attention is reserved for the choice of the number of principal components to keep. These models are then implemented in the Matlab software. The simulation results of several variables such as stator and rotor currents, shaft rotational speed, electrical power, electromagnetic torque and other variables issued from mathematical transformations of healthy and faulted wind power generation are analyzed. Comparisons of simulation results with those of other diagnostic methods are performed to show the effectiveness and importance of the PCA method in fault diagnosis of systems.

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II. MATERIALS AND METHODS

A. Principal Components Analysis implementation

The PCA method is based on simple linear algebra. It can be used as exploring tool, analyzing data and models design. The PCA method is based on a transformation of the space representation of the simulation data. The new space dimension is smaller than that the original space dimension. It is classified as without models method categories [3] and can be seen as a full-fledged system identification method [4]. Each variable to be monitored for the state of the DFIG are expressed by different units and scales. For that, it is preferable to apply a PCA on a centered and reduced measures matrix X (columns of zero means and units standard deviations) [5]. The orthogonal space defined by PCA is generated by the eigenvalues and eigenvectors of the matrix correlation R of X. These values are sorted in descending order in a diagonal matrix. The eigenvalues analysis of the correlation matrix R provides information on the number of principal components to be retained "l" for the PCA model reconstruction [6]. The PCA allow providing directly the redundancy relations between the variables without identifying the state representation matrix of the system. This task is often difficult to achieve.

1) PCA method formulation

We note by $x_i(j) = [x_1\ x_2\ x_3\ \ldots x_m]$ the measurements vector « i » represents the measurement variables that must be monitored and ranked from 1 to m and « j » the number of the performed measurements for each variable « m », ranked from 1 to N.

The measurements data matrix ($X_d \in R^{N*m}$) can be written:

$$X_d = \begin{pmatrix} x_1(1) & \ldots & x_m(1) \\ \ldots & \ldots & \ldots \\ x_1(N) & \ldots & x_m(N) \end{pmatrix} \tag{1}$$

The data matrix be described with a possible smallest set of new synthetic matrix, that is an orthogonal linear projection of a subspace of m dimension in a less dimension subspace l ($l<m$). The method consists in identifying the PCA model and is based on two steps [7]:

- Determination on the eigenvalues and the eigenvectors of the covariance matrix R.
- Determination of the structure of the model, which consists to calculate the components number « l » to be retained in the PCA model.

2) Eigenvalues and eigenvectors determination

The first step in PCA is the normalization of data. The variables must be centered and reduced to make data matrix independent of variables physical units. Then, the new obtained normalized matrix is:

$$X = [X_1 \ldots X_m] \tag{2}$$

And the covariance matrix R is given by:

$$R = \frac{1}{N-1} XX^T \tag{3}$$

By decomposing R, (2) can be expressed as:

$$R = P\Lambda P^T \tag{4}$$

With

$$PP^T = P^T P = I_m \tag{5}$$

Λ is diagonal matrix of the eigenvectors of R and their eigenvalues are ordered in descending order with respect to magnitude values ($\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_m$).

The orthonormal projection matrix P formed by the m eigenvectors associated with eigenvalues of the correlation matrix R is expressed as:

$$P = [p_1, p_2, \ldots, p_m] \tag{6}$$

p_i is the orthogonal eigenvectors corresponding to λ_i. Then, the principal components matrix can be calculated using:

$$T = XP \tag{7}$$

$T \in \Re^{N*m}$

3) Determination of the model structure

To obtain the structure of the model, the components number "l" to be retained must be determined. This step is very important for PCA construction. The components number to be retained can be determined by utilizing:

$$\left(\frac{\sum_{i=1}^{l} \lambda_i}{\sum_{k=1}^{m} \lambda_k} \right) * 100 \geq t_{hc},\ l<m \tag{8}$$

Where "t_{hc}" is a user defined threshold expressed as percentage. Now, user should retain only the components number "l" which was associated in the first term of (8). By reordering the eigenvalues, it is guaranteed that the minimum numbers of components are retained while still reaching the minimum variance threshold [8]. By taking into account the number of components to be retained and by partitioning the principal components matrix T, the eigenvectors matrix P and the eigenvalues matrix Λ [9] [10], the constructed PCA model is given by:

$$T = \left[T_p^{N*l} T_r^{N*(m-l)} \right] \tag{9}$$

$$P = \left[P_p^{N*l} P_r^{N*(m-l)} \right] \tag{10}$$

$$\Lambda = \begin{bmatrix} \Lambda^{l*l} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \Lambda^{(m-l)(m-l)} \end{bmatrix} \tag{11}$$

T_p and T_r are respectively the principal and residual parts of T, P_p and P_r are respectively the principal and residual parts of P. With this PCA model, the centered and reduced matrix X can be written as:

$$X = P_p T_p^T + P_r T_r^T \quad (12)$$

In considering

$$X_p = P_p T_p^T = \sum_{i=1}^{l} P_i T_i^T \quad (13)$$

$$E = P_r T_r^T = \sum_{i=l+1}^{m} P_i T_i^T \quad (14)$$

The centered and reduced matrix data is given by:

$$X = X_p + E \quad (15)$$

X_p is the principal estimated matrix and E the residues matrix which represent information losses due to the data matrix X reduction. It represents the difference between the exact and the approached representations of X. This matrix is associated with the lowest eigenvalues. $\lambda_{l+1},\ldots,\lambda_m$ Therefore, in this case, data compression preserves all the best the information that it conveys.

4) *Residues generation*

For any measures vector $x(k)$, the equation (15) becomes:

$$x(k) = x_p(k) + e(k) \quad (16)$$

$x_p(k)$ and $e(k)$ vectors represent respectively the estimation vector and the estimation errors vector.

The principal components vector $t(k)$ correspond to $x(k)$ is expressed as:

$$t(k) = P' x(k) \quad (17)$$

$$t(k) = [t_p(k) t_e(k)] \quad (18)$$

$t_p \in \Re^{N*l}$ and $t_e \in \Re^{N*(m-l)}$ are respectively the " *l* " first principal components vector and the " *m-l* " last principal components vector.

With this expression (18), we can see that there is equivalence between the residue vector $e(k)$ and the final components vector $t_e(k)$.

III. DFIG MATHEMATICAL MODELLING

In our previous work [2, 5, 12], the PCA method was used for the faults diagnosis e wound rotor induction machine (WRIM). In this article, the WRIM is integrated into a wind energy conversion chain system and operates as DFIG. The electrical configuration of the considered wind turbine system is given by the following figure:

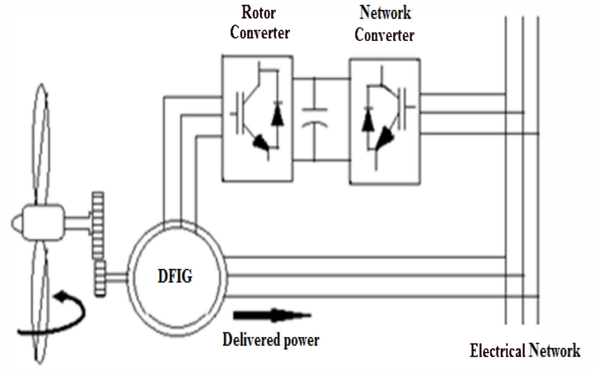

Figure 1. Wind energy conversion chain system based on DFIG

A. *Two axis reference frame*

The electrical quantities of the DFIG are substantially sinusoidal and defined by their module and phase. Then, it can be represented in a two-dimensional reference [11], [13]. The chosen model is projected on stationary stator reference frame. The reference system is illustrated on the figure 2. The Park transform has been used for the passage of electrical quantities in standard referential associated with the three phase's stator and rotor windings, to the two-axis reference.

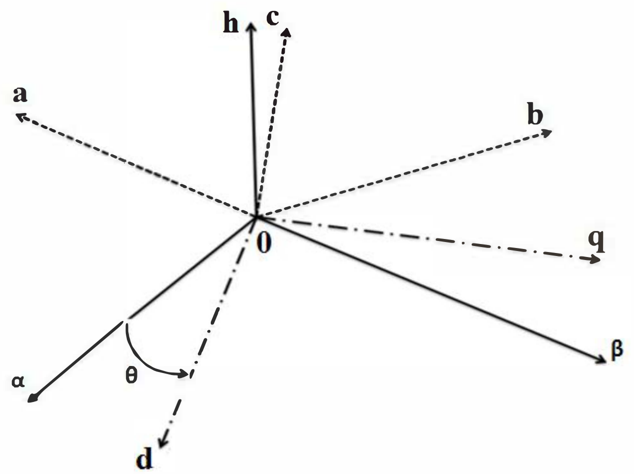

Figure 2. Two-axis (hαβ and hdq frames) and three-axis (abc frame) references representation

All stator and rotor voltages are in the arbitrary three-axis reference frame:

$$\underline{u}_s = R_s \underline{i}_s + \frac{d\underline{\psi}_s}{dt} \quad (19)$$

$$\underline{u}_r = R_r \underline{i}_r + \frac{d\underline{\psi}_r}{dt} - j\omega_m \underline{\psi}_r \quad (20)$$

Where the subscripts "s" and "r" identify respectively the stator and rotor quantities and ω_m is the shaft rotational speed of the rotor.

The equations of flux are written:

$$\underline{\psi_s} = L_s \underline{i_s} + L_h \underline{i_r} \tag{21}$$

$$\underline{\psi_r} = L_r \underline{i_r} + L_h \underline{i_s} \tag{22}$$

Substituting the equations (21) and (22) into the equations of voltages, we obtain:

$$\underline{u_s} = R_s \underline{i_s} + L_s \frac{d\underline{i_s}}{dt} + L_h \frac{d\underline{i_r}}{dt} \tag{23}$$

$$\underline{u_r} = R_r \underline{i_r} + \frac{d\underline{\psi_r}}{dt} + L_h \frac{d\underline{i_s}}{dt} - j\omega_m L_r \underline{i_r} - j\omega_m L_h \underline{i_s} \tag{24}$$

B. Equations in the α and β axes reference frame

We can represent the above equations as a state vector. The currents vector are chosen as state vector in the (α, β) basis. Combining the last two expressions of the voltages, the state equations can be expressed in matrix form [13], [14] and [15]:

$$\frac{d}{dt}\begin{pmatrix} \underline{i}_s \\ \underline{i}_r \end{pmatrix} = \frac{1}{(L_s L_r - L_h^2)}\begin{pmatrix} -R_s L_r - j\omega_m L_h^2 & L_h R_r - j\omega_m L_h L_r \\ L_h R_s + j\omega_m L_s L_h & -R_r L_s + j\omega_m L_s L_r \end{pmatrix}\begin{pmatrix} \underline{i}_s \\ \underline{i}_r \end{pmatrix} + \frac{1}{(L_s L_r - L_h^2)}\begin{pmatrix} L_r & -L_r \\ -L_h & L_s \end{pmatrix}\begin{pmatrix} \underline{u}_s \\ \underline{u}_r \end{pmatrix} \tag{25}$$

The new reference (α, β) is obtained from the Park transformation of the conventional base (a, b, c) and therefore requires the knowledge of the θ, the position of the rotor relative to the stator, and the equation “(25)” becomes:

$$\frac{d}{dt}\begin{pmatrix} i_{\alpha s} \\ i_{\beta s} \\ i_{\alpha r} \\ i_{\beta r} \end{pmatrix} = \frac{1}{(L_s L_r - L_h^2)}\begin{pmatrix} -R_s L_r & \omega_m L_h^2 & L_h R_r & \omega_m L_h L_r \\ -\omega_m L_h^2 & -R_s L_r & -\omega_m L_h L_r & L_h R_r \\ L_h R_s & -\omega_m L_s L_h & -R_r L_s & -\omega_m L_s L_r \\ \omega_m L_s L_h & L_h R_s & \omega_m L_s L_r & -R_r L_s \end{pmatrix}\begin{pmatrix} i_{\alpha s} \\ i_{\beta s} \\ i_{\alpha r} \\ i_{\beta r} \end{pmatrix} + \frac{1}{(L_s L_r - L_h^2)}\begin{pmatrix} L_r & 0 & -L_h & 0 \\ 0 & L_r & 0 & -L_h \\ -L_h & 0 & L_s & 0 \\ 0 & -L_h & 0 & L_s \end{pmatrix}\begin{pmatrix} u_{\alpha s} \\ u_{\beta s} \\ u_{\alpha r} \\ u_{\beta r} \end{pmatrix} \tag{26}$$

$i_{\alpha s}$, $i_{\beta s}$, $i_{\alpha r}$, $i_{\beta r}$ are respectively the stator and rotor phase currents expressed in the (α, β) reference, $u_{\alpha s}$, $u_{\beta s}$, $u_{\alpha r}$, $u_{\beta r}$ the stator and rotor phase voltages, L_s, L_r, L_h the self-inductance and mutual inductance, and R_s, R_r the stator and rotor phase resistances.

With these equations, we can study the dynamic behavior of electrical variables of the machine.
From these equations, the electrical electromagnetic torque of the DFIG is given by:

$$T_{em} = K_t p \,\mathrm{Im}(\underline{\psi_s} * \underline{i_s}) = K_t p L_h \,\mathrm{Im}(\underline{i_r} * \underline{i_s}) = K_t p L_h (i_{\alpha r} i_{\beta s} - i_{\beta r} i_{\alpha s}) \tag{27}$$

K_t is a parameter depending on the Park transformation type (constant power or constant amplitude) and p is the number of pole pairs of the DFIG.

C. Considered faults

The considered faults are resistances values increases of the stator or rotor windings due to a rise of their temperatures. In normal operation, a resistance value variation compared to its nominal value (in ambient temperature, 25°C) is faulted machine due to machine overload or coils fault [5] and [12]. The resistance versus the temperature is expressed as:

$$R = R_0(1 + \alpha \Delta T) \tag{28}$$

R_0 is the resistance value at T_0 = 25°C, α the temperature coefficient of the resistance and ΔT the temperature variation.

IV. SIMULATION RESULTS AND DISCUSSION

In this paper, tests are evaluated on a numerical simulator of a variable speed wind turbine with a pitch regulated based on simple models validated with data from a fixed speed wind turbine. The electrical diagram (Figure 1) translated into the Simulink model is shown in the figure 3. The model developed in Matlab/Simulink software generates data of healthy and faulty wind energy conversion chain system. The data obtained are treated with Principal Component Analysis (PCA) programmed in Matlab to generate the residue of the state variables and visualize the presence or not of failures on the DFIG wind turbine.

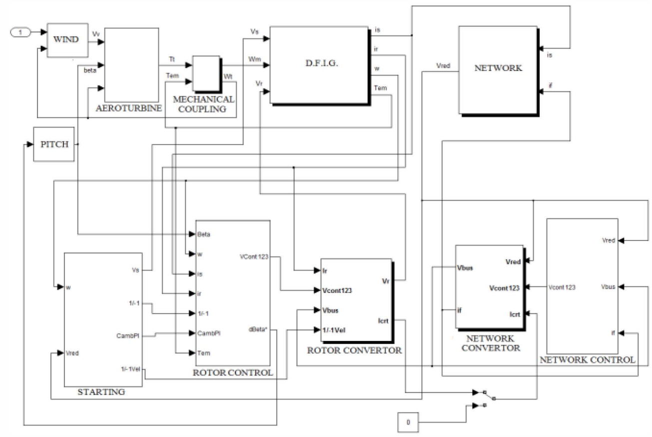

Figure 3. Simulink model of the wind energy conversion chain system based on DFIG

Several types of representations are used in the signals processing domain, in particular for electrical machines diagnosis. We can mention the temporal representation (Figure 4a to 4d) and the signal frequency analysis. Although they have demonstrated their effectiveness, the state variables representations between them also show their advantages (Figure 4e and 4f). They can be performed without mathematical transformation (Figure 4a to 4d) and with mathematical transformation (Figure 4e and 4f). The figure 4 presents the simulation results the wind conversion chain system and shows several characteristic quantities of the healthy DFIG (the stator and rotor phase voltages and currents, the shaft rotational speed, the electromagnetic torque, and the stator voltage and current in the (α, β) reference frame). All sizes are consistent and show a normal operation of the DFIG.

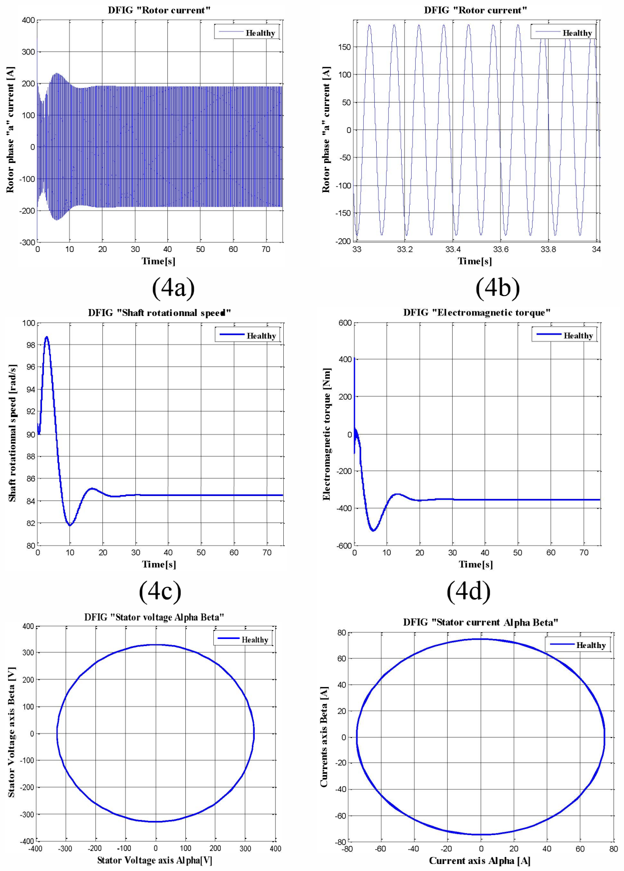

Figure 4. Several representations of characteristic variables of the DFIG

The latter representation type and the temporal representation for healthy and faulty DFIG (Figure 5a to 5c) are confronted with the PCA method application results (Figure 5d to 5f). (5a) and (5d) are respectively the temporal variations of the D-axis current without and with PCA method, (5b) and (5e) are the Q-axis currents versus the D-axis currents without and with PCA method, and (5c) and (5f) are the electromagnetic torques of the DFIG versus the shaft rotational speeds without and with PCA method.

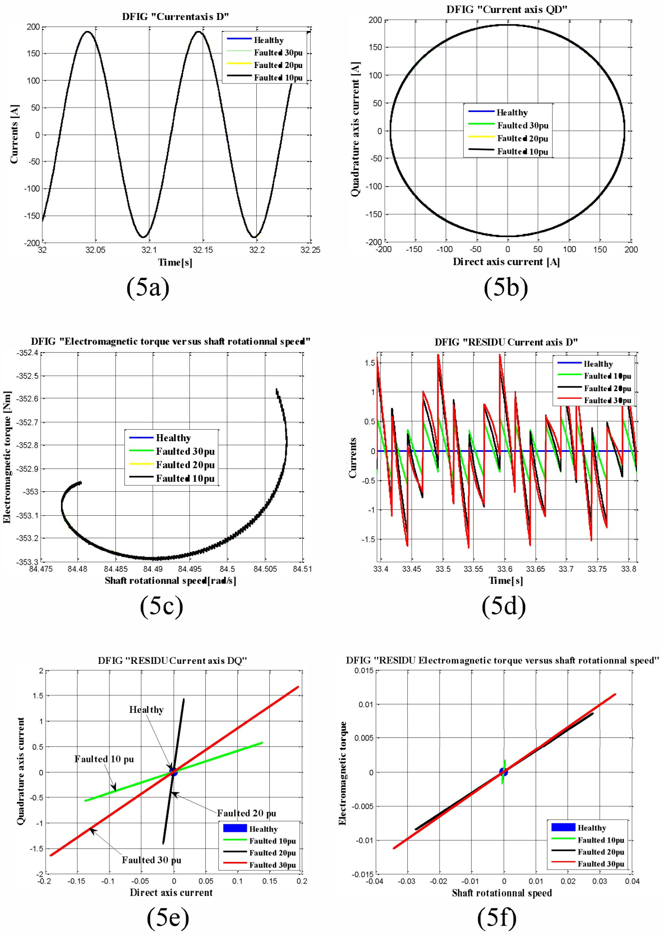

Figure 5. Several representations of characteristic quantities of the DFIG

The considered faults are respectively, increases from 10% to 30% of the resistance value of both the stator and rotor coils. All representations in both cases without (Figure 5c) and with mathematical transformations (Figure 5a and 5b), and without PCA method, do not provide significant information in the presence of faults. Healthy and faulty cases are almost identical regardless of the importance level of the DFIG faults. With PCA method application, all representation types well show the differences between healthy and faulted WRIM (Figure 5d – 5f)). In the healthy case, residues are zero. When faults appear, the residue representations have an effective value with an absolute value greater than zero.

In the figures 5e and 5f, the healthy case is represented by a point placed on the coordinate origins. Also, one can show several right lines corresponding to the faulted cases. This behaviour is due to the proportional characteristic of the considered faults.

PCA method proved so effective in the wind energy conversion system faults detection. This requires a good choice of the number of the principal components to be retained so that information contained in residues is relevant [12].

V. CONCLUSION

PCA method based on residues analysis has been established and applied on wind energy conversion system based on doubly fed induction generator diagnosis.

An accurate analytical model of the machine has been proposed and simulated to perform the healthy and faulted data for PCA approach need.

Several representations of the state variables of the machine have been analyzed. All representations in both cases without and with mathematical transformations, and without PCA method, do not provide significant information in the presence of faults. Indeed, PCA method application shows clearly the presence of faults. This approach is interesting for all type of representation compared to some other signal processing types.

Simulation results show the detection efficiency but require a good choice of the principal components number.

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