Application of Blind Source Separation Techniques for Generation of PHM Useful Information

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ABSTRACT

One of the most important issues when dealing with PHM developments is the availability of adequate sensors to provide measures that indicate the health state of a component or system. Installation of additional sensors for such purpose usually implies increments in costs and weight and reduction of reliability and availability. Sometimes equivalent information can be inferred from other available sources, allowing the design of PHM solutions with no need for additional sensors. The power consumed by a set of components may provide information concerning their health states. These components may be all fed by the same power supply. This paper proposes a novel application of blind source separation techniques to infer the power consumed by the components using only the measurement of the power supply output. The usefulness of such techniques is demonstrated in a real application.[*†]

1. INTRODUCTION

Prognostics and Health Management (PHM) has been rapidly evolving in the latest years and many different applications of this technology are being pursued for industrial and vehicle components and systems. Many benefits can potentially be provided by such kind of technologies, such as the reduction of maintenance costs and increase in safety. On the other hand, the application of advanced PHM techniques to real systems still faces many challenges. The availability of adequate measurements of the variables of interest is maybe the most difficult challenge that must be overcome on the development of real world PHM solutions. Usually, this is not a technical challenge, since dedicated sensors could be added to measure such variables. However, additional sensors may represent additional cost, weight, and even reduced system reliability and availability, since the additional sensor failures may increase the overall system failure rate. All these factors may lead to an unfavorable cost-benefit analysis for PHM solutions that require dedicated sensors. Therefore, in order to provide affordable PHM solutions, it is interesting to take advantage of the already available measurements as much as possible.

The work described in this paper is aimed at improving the use of available measurements by extracting useful PHM information that would otherwise require dedicated sensors to be acquired. This is accomplished by the use of blind source separation (BSS) techniques. These signal processing techniques have the goal of recovering unobserved signals, also called sources, from the observation of a limited number of different mixtures of them. This is accomplished with little or no *a priori* knowledge about the original signals, therefore the use of the term "blind". Independent component analysis (ICA) is probably the most popular BSS technique. It assumes that the original signals are statistically independent from each other and the measured mixed signals are linear combinations of the original ones. A brief explanation of the method is provided in the following sections. Hyvärinen (1999a) provides a complete survey on the ICA technique.

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[†] This work is partially funded by Financiadora de Estudos e Projetos (FINEP), Brazil.

Many applications of ICA for BSS can be found on the literature. Hyvärinen and Oja (2000) present practical applications in analysis of medical and financial data, image processing and telecommunications. Examples of applications of such techniques for health monitoring are also available in the literature. Most previous works in this area are related to the application of ICA and other BSS techniques for processing vibration and acoustic signals with the purposes of diagnostics and condition monitoring of rotating machines (Gelle et al., 2003; Li and Qu, 2002; Chen et al., 2003; Ma and Hao, 2004; Tian et al., 2003). Other applications of ICA related to health monitoring which use this technique with the diverse purpose of data dimension reduction are also found in the literature. Schimert (2008) uses principal component analysis (PCA) and ICA for data dimension reduction with the purpose of monitoring aircraft sub-systems. Banard and Aldrich (2003) describe the application of this methodology for monitoring internal combustion engines.

The present work proposes a novel application of ICA which may be useful when the signals of interest for PHM influence a set of different measurements and each of these measurements are affected by disturbances in an unknown deterministic manner. This is illustrated for the monitoring of electro-mechanical systems using electrical current measurements. ICA is used for inferring the electrical loads consumed by aircraft flaps and slats systems using only the measurements of the total electrical loads of the aircraft electrical generators. The architecture of such systems usually comprises electro-mechanical actuation with closed loop position and speed control. Since they are closed loop electro-mechanical systems, the power consumed is a good indicator of the health of the system for certain failure modes. This is valid, for instance, for monitoring failure modes related to mechanical performance degradation that may result in friction increase and surface jam.

The next section describes the independent component analysis theory used for the development of this work.

2. INDEPENDENT COMPONENT ANALYSIS

Blind signal separation, also known as blind source separation, is the separation of a set of signals from a set of mixed signals, without the aid of information (or with very little information) about the source signals or the mixing process.

There are different methods of blind signal separation, but the one that is most commonly found in the literature is independent component analysis. ICA is a statistical technique whose classical model formulation can be expressed as

$$\mathbf{x} = A\,\mathbf{s} \tag{1}$$

where $\mathbf{x} = [x_1\ x_2\ ...\ x_n]^T$ is a matrix containing the vectors of observed random variables x_i. The matrix containing the vectors of the independent latent variables s_i is denoted by $\mathbf{s} = [s_1\ s_2\ ...\ s_n]^T$ and A is an unknown constant matrix, called the mixing matrix.

The main purpose of ICA is to learn the decomposition presented in Eq. (1), that is, estimate both $\mathbf{s}$ and A based only on the observed values $\mathbf{x}$. It is worth noting that covariance-based decomposition techniques, such as PCA could be used for such a purpose (Jolliffe, 1986). However, those techniques yield latent variables associated to directions of maximum variance in the data space, which may not necessarily be related to the actual sources under consideration. The starting point for ICA is the assumption that the sources are statistically independent. The importance of this assumption is explained by the central limit theorem.

The central limit theorem, a classical result in probability theory, tells that the distribution of a sum of independent random variables tends toward a gaussian distribution, under certain conditions. Thus, a sum of independent random variables usually presents a distribution that is closer to gaussian than any of the original random variables (Hyvärinen and Oja, 2000).

As a consequence of the theorem, assuming that the latent variables are not gaussian, the problem of estimating A and $\mathbf{s}$ is turned into a problem of minimizing the similarity between a gaussian distribution and the distribution resulted from the combination of the elements of $\mathbf{x}$.

Many quantitative measures of nongaussianity were proposed such as kurtosis, negentropy, negentropy approximations and others (Hyvärinen and Oja, 2000). All of them have particular advantages and disadvantages that may be analyzed according to a particular application. The present work employs the FastICA algorithm (Hyvärinen, 1999b), which is based on a measure of nongaussianity associated to negentropy.

3. SYSTEM UNDER CONSIDERATION

The present work has been developed using real data measured from aircraft systems. The following sub-sections describe the considered systems, as well as the motivation for using ICA.

3.1 Flaps and Slats Systems

Flaps and slats are control surfaces used for fixed wing aircraft to provide additional lift during takeoff and landing. Flaps are located on the trailing edge and slats are located on the leading edge of the wings. These surfaces usually present few possible predetermined positions which are associated with takeoff and landing configurations for different conditions. The transition between each position is commanded by the flight crew. Surface position and speed are usually controlled in closed loop to guarantee that the extension and retraction of flaps and slats will follow a predefined pattern. The controller also comprises logics responsible for coordinating the surfaces motion. One of these logics guarantees that the slats finish their extension before the flaps start extending. The contrary is valid for surface retraction.

Flaps and slats systems architectures considered here provide electro-mechanical actuation of the surfaces. Figure 1 presents a schematic of part of an illustrative architecture for a flap system. The pilot/copilot moves the flap handle to one of its discrete positions. This handle provides the indication to the electronic controller, which in turn commands system electric motors and verifies position and speed feedback signals from system sensors. The torque is transmitted from the motors to the actuators through a gearbox and mechanical linkages (usually torque tubes or flexible shafts). Actuators are purely mechanical components which transform the rotary movement from the mechanical linkages to a linear movement of extension or retraction of the surfaces.

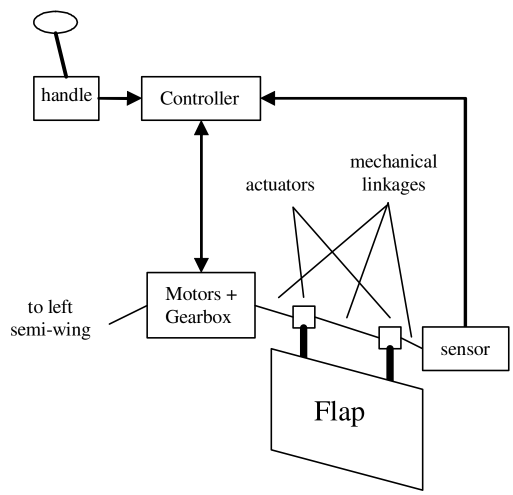

Figure 1. Sample flap system architecture.

One of the most relevant failure modes of flaps and slats electro-mechanical systems is surface jamming. This jamming may present operational and safety adverse consequences. Various failure mechanisms may lead to a surface jam. Some failure mechanisms may be abrupt such as water freezing, but many times this failure mode is a consequence of gradual degradation of the mechanical components, which leads to a corresponding increment of total system friction. Monitoring this gradual degradation and performing diagnostics and prognostics can be accomplished through measurements of the power delivered to the motors. This occurs because the closed loop controller tries to compensate the friction increment by a corresponding increase in the command current. Leão et al. (2009) describes a methodology for monitoring this failure mode using current measurements. These measurements can also provide information for performing PHM for other failure modes, such as those related to the health of the electrical components of the system.

Ideally, the current measurements would be obtained directly from the controller or using a current sensor directly at the power input of each motor. However, this information is usually not available and it is typically not cost-effective adding this kind of measurements to existent and even new aircraft designs. Therefore, in order to monitor the condition of such systems, it is necessary to consider alternative means of gathering this information.

3.2 Electrical Power Supply

Figure 2 presents a simplified schematic of a fictitious aircraft electrical architecture. Since a high reliability must be attained in order to guarantee aircraft safety, redundancy is a recurrent characteristic of such systems. This fictitious architecture comprises two three phase electrical generators (EG1 and EG2) which are mechanically coupled to the aircraft engines to produce the electrical energy consumed by the aircraft. Each generator feeds one or more electrical buses (EB1, EB2 and EB3). All the aircraft loads (e.g. L1 and Lz) are fed through these buses. The loads are distributed among the buses in order to provide adequate reliability for each electrical load according to its criticality for the airworthiness.

The flaps and slats architectures considered comprise two electrical motors for each system (two for the flaps and two for the slats), for redundancy purposes. Both motors are simultaneously actuated (active-active configuration) to provide the surfaces extension or retraction. Each motor is independently connected to an electrical bus. For the considered architecture, one slat motor is connected to a bus fed by EG1 (e.g. L1) and the other three motors (both flap motors and the other slat motor) are connected to buses fed by EG2 (e.g. L2, L3 and L4).

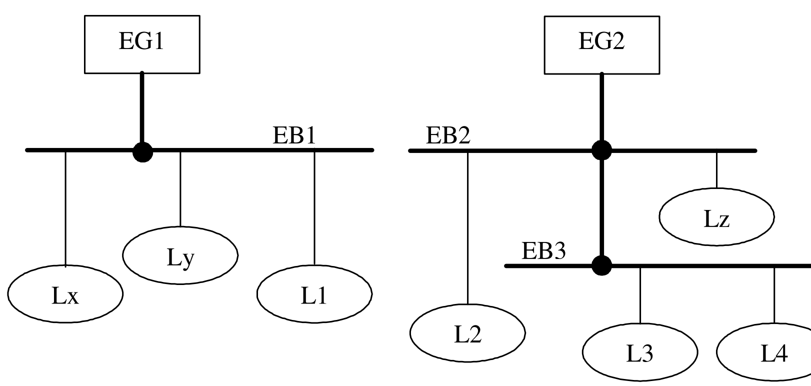

Figure 2. Sample electrical system architecture.

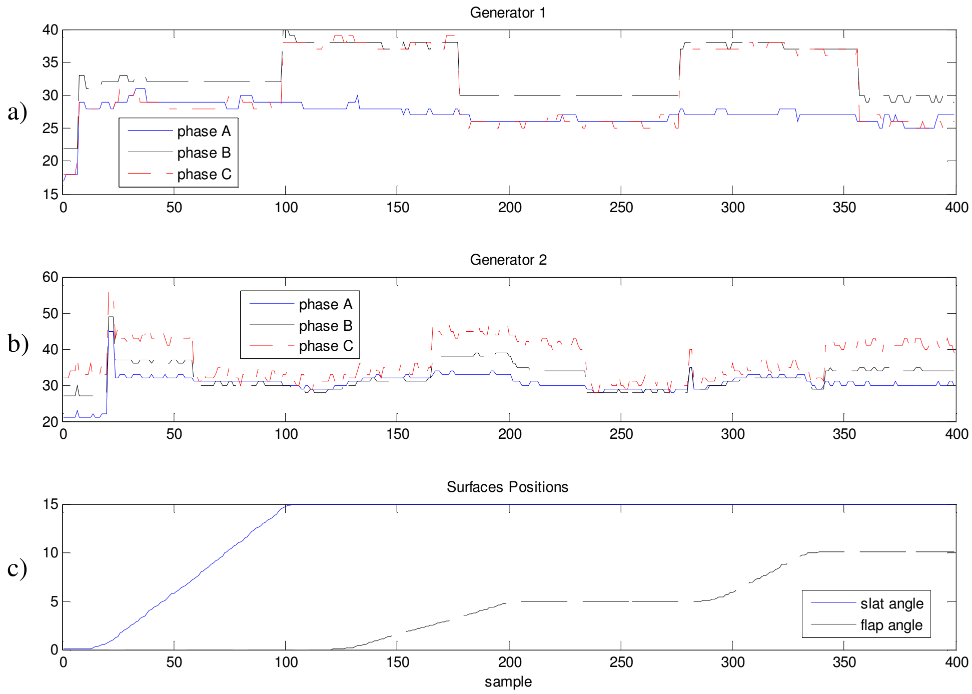

Figure 3. Sample recorded data window: generators currents and surfaces positions.

Therefore, the information of the electrical loads consumed by the motors should be contained in the measurements of the electrical power delivered by the generators. The generators currents and voltages are readily available in this architecture and can be recorded for monitoring purposes. However, all the other electrical loads of the aircraft are also fed by the same generators and it is usually not straightforward to isolate the influence of a load of interest in the total electrical power produced by the generators. The next section presents how ICA was used to solve this issue.

4. DEVELOPMENT AND RESULTS

Flaps and slats are usually actuated following a well defined operational procedure during flight. Before approach, these surfaces are fully retracted. During the approach procedure, they are subsequently extended in discrete steps until reaching the desired landing configuration. Therefore, it is not difficult to define a standard data window to be used for comparing different flights in order to assess the evolution of the degradation of such systems. The analysis described herein was based on real data windows with 40 seconds length and 10Hz sample rate acquired from aircraft during flight. The voltages and currents for each of the three phases for both generators were recorded on each data window together with other useful variables. A set of data windows was recorded (one per flight) triggered by the first command for flaps and slats extension during approach. Figure 3 presents the plots of generators currents and surfaces positions from one of the recorded data windows. Figure 3a and 3b present the RMS values of the current measurements for each of the generators phases. Figure 3c presents the corresponding slat and flap surfaces positions for reference. It can be noticed that it is not straightforward to relate the raw measurements of the currents to the surfaces actuation.

One may assume that the three currents are affected by the same loads in different ways, i.e. there is a certain level of unbalance among the three phases. As a consequence, the three current signals are different mixings of the same signals generated by the loads fed by the generator. Moreover, the load profiles may be assumed to be independent and non-gaussian. Such an assumption is reasonable, as the activation of loads occurs independently and in a deterministic pattern for each load. Therefore, the currents can be processed using ICA in order to separate the different sources of loads that were being fed by the generators. For this purpose, the FastICA algorithm described in Hyvärinen (1999b) was adopted. This algorithm has already been successfully used for various applications such as those described in Hyvärinen and Oja (2000) and the condition monitoring of rotating machines (Li and Qu, 2002; Ma and Hao, 2004).

One hypothesis that must be fulfilled in order for the BSS techniques to be applicable is that the number of independent sources must be lower than or equal to the number of measurements. Since in this case the measurements of three phases in electrical generators are being used, no more than three independent sources can be identified. Therefore, it is important to choose data windows that have a good chance of providing adequate information. If data windows that presents more independent sources than measurements are used, the separation may yield inadequate results.

In order to identify what each independent component (IC) resulting from ICA represents, i.e. to differentiate useful information from disturbances, it is necessary to use some domain specific knowledge. The technique is classified as a BSS in terms that the original signals and the way they are mixed are not known *a priori*. However, one must know what to expect when processing the measurements. This is not a limitation of this specific application, but rather a characteristic of the BSS methodologies. Depending on the application, post-processing techniques may be required to automatically distinguish the ICs associated to the disturbance from those that represent useful information. Preliminary analysis of the collected set of measurements for the specific application considered in this work showed that the main disturbance affecting the current profile was a square wave signal generated by a switching load. This square wave varied in frequency, amplitude and duty cycle for each different data window. Therefore, for this particular problem, the main purpose of the application of the ICA was to remove this square wave disturbance in order to allow subsequent analysis of flaps and slats systems based on the generator current signals.

The data processing sequence adopted in this work comprises four steps, as shown in Figure 4. The first step is to obtain the ICs. They are calculated using the currents from the three phases of each generator as inputs for the ICA algorithm. Figure 5 shows the results obtained after the ICA processing for the generator 2 current signals presented in Figure 3. The square wave load can be visually associated to IC1 and slat and flap loads to IC2.

Steps 2 and 3 in Figure 4 are aimed at identifying the IC corresponding to the disturbance signal in an automatic manner, since the order of the ICs is random for each time the algorithm is processed. This automatic identification cannot make use of any frequency, amplitude or duty cycle information for the square wave, since those characteristics are different for each data set.

In step 2, each of the three ICs is processed using the k-means clustering algorithm (Duda et al., 2001) in order to find two centroids. The main reason for that is that a square wave presents two well separated groups of samples, as illustrated in Figure 6.

In step 3, the two-sample z-test (Vachtsevanos et al., 2006) is used to quantify the distance between the two sets of data points. Based on the fact that the square wave samples values should be more separated than the other ICs samples, the two-sample z-test is expected to yield a higher value for the square wave IC than for the other ones. The two-sample z-test is defined in Eq. (2):

$$z = \frac{m_1 - m_2}{\sqrt{\dfrac{s_1^2}{n_1} + \dfrac{s_2^2}{n_2}}} \qquad (2)$$

where m_1 and m_2 are the means of the two sets, s_1 and s_2 are the standard deviations and n_1 and n_2 are the number of element in each set. A greater value of z indicates a greater separation between the two groups.

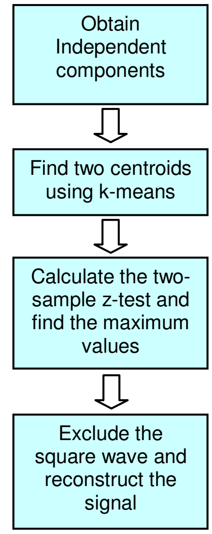

Figure 4. Data processing steps.

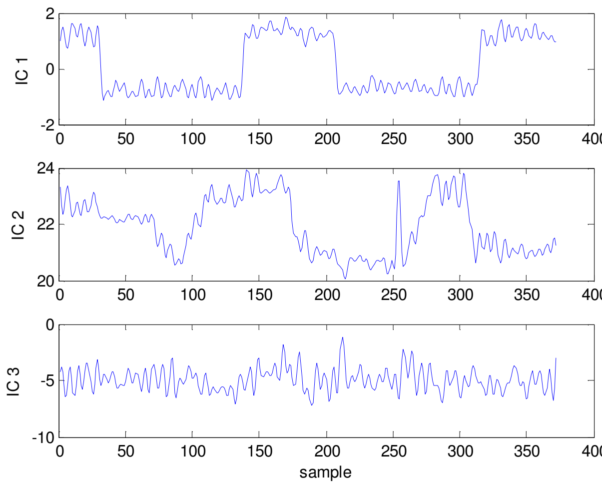

Figure 5. Independent Components

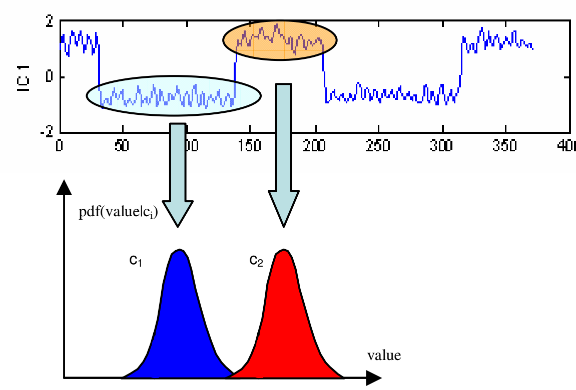

Figure 6. Square wave samples distribution

After the identification of the square wave, it is possible to reconstruct the original signal just by eliminating the IC corresponding to the undesired signal and performing the reconstruction of the original signals (step 4 in Figure 4). The reconstruction may be performed according to Eq. (1) through the inversion of the A matrix. Figure 7 presents the final results after automatic identification and extraction of the square wave and reconstruction of the original signals. Figure 7a and 7b present the resulting phases of the generators after reconstruction of the signal. These results were obtained from the same signals of Figure 3. Figure 7c presents the corresponding slat and flap surfaces positions for reference. By visual inspection of these figures it is straightforward to associate surface positions to the currents in the generators. Recalling that generator 1 only provides power to the slats and generator 2 provides power to both surfaces, it can be noticed that current values increase accordingly to surface movements. This power consumption information is useful for monitoring the health of such systems. For instance, it could provide early indications concerning the surface jam failure mode described earlier. For a complete description of a method for monitoring the health of this kind of system using the power input measurements, refer to Leão et al. (2009).

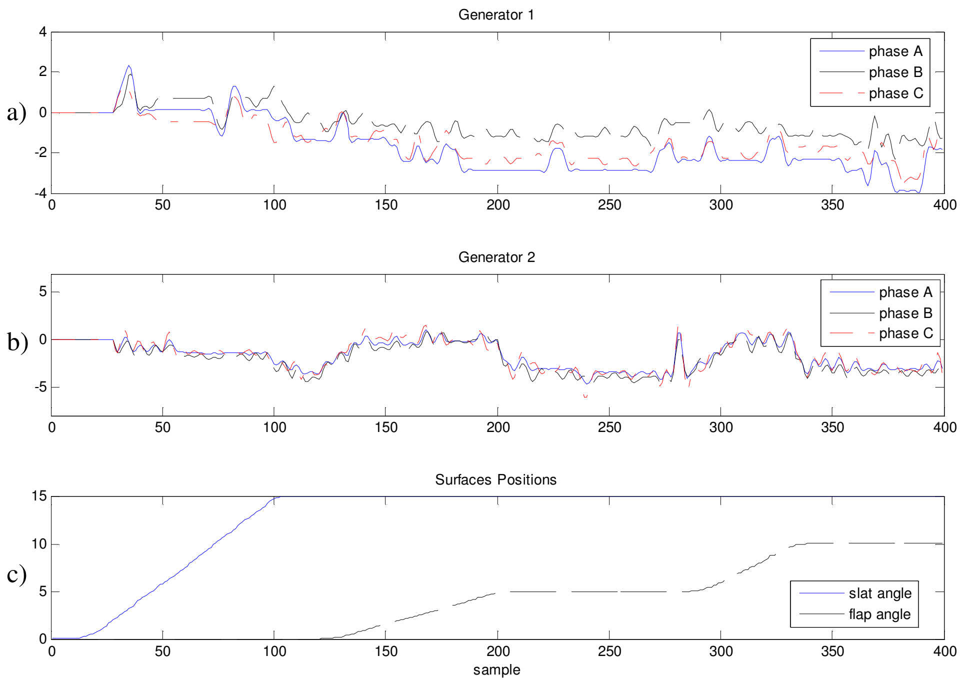

Figure 7. Currents reconstructed after removal of disturbances

5. CONCLUSION

This work presented a novel application of blind source separation techniques based on ICA to extract useful PHM information from measured signals. This methodology may be of value when the signals of interest for PHM influence a set of different measurements and each of these measurements are affected by disturbances in a deterministic (albeit unknown) manner. The use of ICA could then be a cost-effective alternative to the deployment of additional sensors. The method was tested using real data extracted from electro-mechanical flight control systems. More specifically, the raw data consisted of current measurements, which exhibited significant load disturbances with periodic switching behavior. Such disturbances were successfully removed by the proposed ICA-based methodology, thus facilitating the health monitoring of the systems from their input current profile. Such a monitoring may be useful to guide condition-based maintenance actions and prevent jamming problems caused by friction increase in the mechanical parts of the system. Although the methodology was illustrated and validated for the removal of a square wave disturbance in the signal, similar ICA-based methodologies could be used to extract other kinds of PHM useful information from power supply loads measurements or other kinds of measurements resulting from the mixing of different sources.

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