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MULTI-COMPONENT MACHINE MONITORING AND FAULT DIAGNOSIS USING BLIND SOURCE SEPARATION AND ADVANCED VIBRATION ANALYSIS

ALI MAHVASH MOHAMMADI

DÉPARTEMENT DE GÉNIE MÉCANIQUE

ÉCOLE POLYTECHNIQUE DE MONTRÉAL

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présentée par : MAHVASH MOHAMMADI Ali

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a été dûment accepté par le jury d'examen constitué de :

M. BALAZINSKI Marek, Ph.D., président

M. LAKIS Aouni A., Ph.D., membre et directeur de recherche

M. HOJJATI Mehdi, Ph.D., membre

M. KAUSHAL Ashok, Ph.D., membre

To my sister Batoul

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RÉSUMÉ

Dans le diagnostic des machines rotatives, l'analyse des vibrations est largement connue pour être l'une des techniques les plus efficaces. Les vibrations sont une caractéristique inhérente des machines rotatives et les différentes composantes de ce type de machines telles que les arbres, les roulements et les engrenages produisent de l'énergie vibratoire avec différentes caractéristiques. N'importe quelle détérioration de l'état de telles composantes peut affecter leurs propriétés vibratoires et se manifester par conséquent dans la signature de vibration. Ceci est valable pour le diagnostic des défauts en analysant la signature des vibrations du système.

Pour faire un excellent diagnostic des défauts utilisant les techniques d'analyse de vibration, il faut que les signaux acquis atteignent un certain niveau de propretés de telle sorte que le plus petit changement des attributs du signal dû à un défaut imminent dans n'importe quelle composante peut être détecté. Néanmoins, ce n'est pas le cas dans la pratique, car les signaux de vibration sont souvent encombrés par le bruit. Dans le cas des machines complexes à plusieurs éléments ce problème est aggravé encore plus car les différentes composantes produisent de l'énergie vibratoire. En effet à toutes les fois qu'il est nécessaire de surveiller n'importe quelle composante d'intérêt, les vibrations produites par les autres affectent le signal. Parmi les moyens pour contourner ce problème est de placer des capteurs aussi proches que possible des composantes données. Mais, certaines restrictions telles que la complexité, la politique de garantie du fabricant et l'inaccessibilité empêchent de tel emplacement, de ce fait, dans la majorité des cas les capteurs sont placés sur la surface extérieure de la structure. Par conséquent les capteurs collectent non seulement des signaux de vibrations d'une composante spécifique mais des autres composantes aussi, de ce fait, les signaux de chaque capteur est en effet, la combinaison de l'énergie vibratoire des différentes composantes, plus le bruit. La dissipation de l'énergie des vibrations complique la situation encore plus.

Pour surpasser ce problème, principalement deux approches peuvent être adoptées. La première consiste à considérer ces cas comme un problème de séparation aveugle de sources et en tirer profit des méthodes statistiques et mathématiques développées à cet effet, surtout l'analyse en composantes indépendante (ACI), qui sépare les signaux provenant de sources différentes. La deuxième approche, et sans passer par la "séparation" des signaux et de les relier aux différentes composantes (sources) consiste à utiliser comme base, les spécifications et les caractéristiques

des signaux produites par les différentes composantes dans des conditions normales et défectueuses. Dans cette étude, ces deux approches sont étudiées, pour le cas de détection des défauts dans les roulements.

Dans la première approche, une complexité commune avec l'application soit des techniques de séparation aveugle de sources soit des méthodes mathématiques propres à la séparation des sources c'est qu'en général aucune mesure métrique ou standard n'existe pour évaluer la qualité de la séparation afin de valider les résultats. En effet pour une évaluation idéale, il faut que les vrais signaux originaux produits par chaque composante soient disponible et cela comme une condition fondamentale. Cela nécessite que les signaux de chaque composante soient collectés en strict isolement pendant leur fonctionnement dans un laboratoire. Une telle tâche est parfois très couteuse et difficile, sinon impossible. Afin de surpasser ces difficultés, une nouvelle méthode est développée, elle consiste à la distribution d'énergie de vibration à l'égard de l'emplacement des sources de vibration et de capteurs et est basée sur le comportement mécanique de la structure. Cette méthode adopte certains concepts clés de l'analyse statistique d'énergie (ASE) pour soutenir le fait que chaque capteur recueille une version différente des vibrations produites dans le système par rapport à son emplacement dans la structure. Par la suite, en comparant le spectre de la signature vibratoire du signal et en utilisant une connaissance a priori de la distribution spatiale des capteurs et des composantes, une représentation graphique de la signature spectrale des sources de vibration est obtenues. Cette méthode proposée est vérifiée avec des données artificielles et expérimentales. Avec une évaluation métrique disponible, une analyse plus rigoureuse des techniques de séparation aveugle de source peut être atteinte. La première formulation mathématique existante pour la séparation aveugle de sources est l'analyse en composantes indépendantes (ACI). Dans l'analyse en composantes indépendantes, on suppose que les signaux sources sont statistiquement indépendants les uns des autres et peuvent être récupéré par la formulation de l'indépendance. Néanmoins, il existe toujours deux ambigüités et indéterminations dominantes liées à l'analyse en composantes indépendantes. Premièrement, l'index original des sources est inconnu. La seconde ambigüité est que l'échelle réelle des sources ne peut être déterminée.

L'analyse en composantes indépendantes peut être appliquée soit dans le domaine temporel ou fréquentiel. Quel domaine choisir dépend principalement du mécanisme du signale mélangé. Si le mécanisme du mélange est instantané, (c'est à dire, les signaux sont mélangés de façon linéaire) les méthodes dans le domaine temporel sont les plus efficaces. Si le mécanisme du mélange est convolutif, (c'est à dire, les signaux sont convoluée) alors les méthodes dans le domaine fréquentiel sont plus appropriées. Dans la plupart des cas réels, y compris les vibrations dans les systèmes mécaniques, le mécanisme du signal mélangé est souvent convolutif, alors dans ce cas-ci, l'analyse en composantes indépendantes dans le domaine fréquentiel doit être utilisée. Dans un tel cas, la construction de signaux temporels à partir des résultats de séparation des bandes de fréquences pose problème. Cette difficulté est causée par l'indétermination de permutation locale par opposer aux ambiguïtés de l'indétermination globale confrontée lors de l'analyse des résultats globaux. Les contournements existants à ce problème sont soit des calculs numériquement couteux, soit des hypothèses qui ne sont prises en compte par les systèmes mécaniques. Dans cette thèse, une nouvelle techniques est proposée et est basée principalement sur les attributs mécaniques du système plutôt que sur des hypothèses mathématiques ou statistiques irréaliste. Cette technique repose sur la supposition que le mécanisme du mélange pour des bandes de fréquences voisines serait légèrement varié d'une bande à autre. Ainsi, en liant et en attachant numériquement les matrices mélangées des bandes de fréquences contiguës, les problèmes de permutation locale et l'indétermination de l'échelle seront résolus. Cette méthode est vérifiée en utilisant une série de tests expérimentaux sur des signaux synthétiques et des signaux de laboratoires et les résultats sont comparés avec l'évaluation métrique présentée précédemment. L'excellente concordance entre les résultats confirme l'efficacité de la méthode.

Quant à la deuxième approche, l'efficacité de l'analyse spectrale cyclique est évaluée pour détecter les défauts de roulements dans les machines complexes. Ces défauts sont connus pour produire des vibrations avec impulsivité périodique dans l'énergie, connus en termes techniques pour être cyclostationnaire. L'analyse spectrale cyclique est un outil qui permet de mesurer la cyclo-stationnarité du signal à différentes gammes de fréquence. A cet effet, pour que l'analyse spectrale cyclique soit efficace dans des applications liées aux machines complexes, deux exigences sont jugées indispensables. La première est qu'elle soit capable de détecter les défauts d'un signal faible, la deuxième exigence est qu'il est essentiel que cette méthode permette une tendance robuste, réalisable et cohérente. En plus, ces caractéristiques étant repérés doivent être cohérentes dans le sens que leurs valeurs portent une certaine correspondance à la sévérité des défauts.

Dans cette thèse, la cyclostationnarité est examinée selon ces exigences est cela à travers deux séries de tests expérimentaux. Les résultats expérimentaux ont démontré que l'analyse spectrale cyclique est en effet capable de détecter des défauts de roulement à partir des signaux faible. En plus, cette méthode peut être utilisée comme un outil très fiable de surveillances et de diagnostic, même si, la correspondance entre les valeurs de propriétés et la sévérité des défauts de roulements ne peut être établie.

ABSTRACT

In diagnosis of rotating machinery, vibration analysis is widely known to be one of the most effective techniques. This stems from the fact that oscillation is an inherent characteristic of rotating machines and different components of these types of machinery such as shafts, bearings and gears produce vibration energy with different characteristics. Any deterioration in the condition of such components can affect their vibratory attributes and manifest itself in the vibration signature. This allows diagnosis of machine faults by analyzing the vibration signature of the system.

For improved and authentic fault diagnosis using vibration analysis techniques it is necessary that the acquired vibration signals be 'clean' enough that small changes in signal attributes due to an impending fault in any component can be detected. Unfortunately, this is not the case in common practice and vibration signals received from operating machinery are almost always cluttered with noise. In complex multi-component machines this problem is aggravated because vibration energy is generated by each individual component. Whenever it is necessary to monitor a specific component, vibration produced by other components affect the signal. One solution for this problem is to mount the vibration sensors as close as possible to the targeted components. Some restrictions such as complexity, manufacturer's warranty policy and inaccessibility constrain this approach and in a majority of cases sensors are placed on the innermost surface possible (i.e., casing) of the structure. As a consequence, the sensors collect vibration signals which are not uniquely generated from the targeted component, but also include contributions from many other components. The vibration signals collected by each sensor are in effect the combination of vibration energy produced by different components in addition to the noise. Dissipation of vibration energy through transmission path complicates the situation even further.

To tackle this problem, one of two alternative approaches can be adopted. One approach is to regard this case as a blind source separation (cocktail party) problem and take advantage of statistical and mathematical methods developed for this purpose, primarily *independent component analysis* (ICA), to separate signals coming from different sources. The other approach is to avoid making the effort to 'separate' the signals and relate them to different components (sources) and instead make use of the specification and characteristics of vibration signals

produced by the different components in normal and faulty conditions. In this dissertation, these two approaches are studied for the case of bearing anomaly detection.

In the first approach, a common difficulty with applying blind source separation techniques (or, in general any mathematical methods) to separation of vibration sources is that no standard measure exists to assess the quality of separation and validate the results. In fact, for an ideal assessment the true original signals produced by each component must be available as a prerequisite. This requires gathering signals from each component in strict isolation during operation in a lab environment which, if not impossible, is very costly and difficult. To alleviate this difficulty, a novel method is developed that presents the distribution of vibration energy with regard to the respective locations of vibration sources and sensors, and takes into consideration the mechanical attributes of the structure. This method uses some key concepts from statistical energy analysis (SEA) to support the fact that each sensor collects a different version of the oscillations produced in the system with respect to its location in the system. Therefore, by comparing the spectral signature of the vibration signals and making use of a priori knowledge of the spatial distribution of sensors and components, a schematic representation of the spectral signature of the vibration sources are obtained. This method is verified using a series of experiments with synthetic and real data.

If a standard evaluation metric is available, more rigorous evaluation of blind source separation techniques can be achieved. The foremost existing solution to blind source separation is Independent Component Analysis (ICA). In ICA it is assumed that the source signals are statistically independent from one another and can therefore be recovered by formulating the independence. There are, however, two dominant ambiguities and indeterminacies associated with ICA results. One ambiguity is that the original index or permutation of the recovered source signals is unknown. The other ambiguity is that the actual scale of the source signals cannot be determined. ICA can be applied in both time and frequency domains. The choice between these two domains depends mainly on the mixing mechanism. If the mixing mechanism is *instantaneous,* (i.e., the signals are linearly mixed) time-domain methods are the most effective and efficient. If the mixing mechanism is *convolutive*, (i.e., the signals are convolved) then frequency methods are more appropriate whilst time-domain methods are limited. In most real cases including vibration in mechanical systems, the mixing mechanism is known to be convolutive and frequency-based ICA should be used. In such cases reconstruction of time signals from separation results of individual frequency bins poses a difficulty. This problem has been referred to as local permutation indeterminacy as opposed to global ambiguities indeterminacy and is confronted while analyzing the overall results. Existing solutions to this problem are either computationally demanding or based on assumptions that normally do not hold in mechanical systems. In this dissertation, a new technique is proposed based mainly on the mechanical attributes of the system rather than unrealistic mathematical or statistical assumptions. This technique is developed based on the presumption that the mixing mechanism for neighboring frequency bins varies only slightly from one bin to another. Therefore, by numerically tying and relating the mixing matrices of contiguous frequency bins, local permutation and scale indeterminacy problems are resolved. This method is studied experimentally using laboratory data and the results are also compared with the evaluation metric presented in the previous study. Accordance between the results confirmed the efficacy of the proposed method.

In the second approach, the effectiveness of cyclic spectral analysis is assessed for detecting bearing faults in complex machinery. Bearing faults are known to produce vibration with recurring impulsiveness in the energy which is referred to as cyclostationarity. Cyclic spectral analysis is a powerful tool to measure the cyclostationarity of a signal in different frequency ranges. For this tool to be effective in applications related to complex machinery, two requirements are identified. One requirement is that the tool must be capable of detecting defects from a weak signal as it passes and attenuates through its transmission path. The other requirement is that it must allow robust, attainable and consistent trending. Also the feature being tracked must be consistent in the sense that its value bears some correspondence to the severity of the faults. In this thesis, cyclostationarity is examined for these requirements through two sets of experimental tests. The experimental results show that cyclic spectral analysis is indeed capable of detecting bearing faults from faint signals. Also, it can be utilized as a reliable monitoring tool, even though the correspondence between the feature value and the severity of the bearing faults may not be robustly established.

CONDENSÉ EN FRANÇAIS

Introduction

Lors du diagnostic des machines tournantes, l'analyse des vibrations est l'un des moyens le plus important pour l'acquisition des données. En effet, les vibrations sont une caractéristique inévitable des machines tournantes. Différentes composantes de ce type de machines telles que les arbres, les roulements et les engrenages produisent de l'énergie vibratoire avec différentes propriétés. Toutefois la détérioration de l'état de ces composantes peut affecter le comportement vibratoire de ces machines et par la suite se manifester dans les signaux vibratoires acquis. De ce fait, cela permet le diagnostic des défauts par le traitement de signature vibratoire de tout le système. Ce type d'analyse a gagné de popularité ces dernières années et est devenu indispensable pour la détection des défauts dans les machines tournantes.

Pour avoir un diagnostic précis des défauts à l'aide d'une analyse de vibrations, il faut que les signaux acquis aillent un certains niveaux de «pureté» de telle sorte que la plus petite variation dans le signal en raison d'un défaut imminent dans n'importe quel composante peut être détecté. Malheureusement, dans la pratique ce n'est pas le cas et les signaux de vibration sont toujours encombrés de bruit. Le problème s’aggrave encore lorsqu'il s'agit de machines complexes à plusieurs composantes où ces dernières produisent de l'énergie vibratoire, et qu’à chaque fois qu'il est nécessaire de surveiller une de ces composantes, les vibrations produites par les autres brouillent le signal. Une façon d'atténuer ces effets est de placer des capteurs aussi près que possible des composantes d'intérêt. Toutefois, ce n’est pas toujours possible en raison de certaines restrictions et délimitations telles que la complexité, la politique de garantie du fabricant, l'inaccessibilité, etc. Le seul choix sera de placer des capteurs sur la surface extérieure de la structure (par exemple, le revêtement). Dans ce cas, les capteurs recueillent des signaux non pas d'une composante spécifique, mais un mélange avec les signatures des autres composantes. De cette façon, les signaux de chaque capteur sont en effet la combinaison de l'énergie des vibrations produites par les différentes composantes, plus le bruit. La dissipation de l'énergie des vibrations complique la situation encore plus. Suite à ces difficultés majeures, dans la pratique il est difficile d'obtenir la signature vibratoire réelle de chaque composante.

Pour surpasser ce problème, principalement deux approches peuvent être adoptées. La première consiste à considérer ces cas comme un problème de séparation aveugle de sources et en tirer profit des méthodes statistiques et mathématiques développées à cet effet, surtout l'analyse en composantes indépendante (ACI), qui sépare les signaux provenant de sources différentes. Cette approche et les sujets connexes sont expliqués dans les paragraphes suivant est développés dans les chapitres 2 et 3.

La deuxième approche, et sans passer par la "séparation" des signaux et de les relier aux différentes composantes (sources) consiste à utiliser comme base, les spécifications et les caractéristiques des signaux produites par les différentes composantes dans des conditions normales et défectueuses. Cette approche est développée dans le chapitre 4 et est présenté en ce qui suit comme une troisième étude de cas.

Première étude de cas

Avant-propos

Une complexité commune avec l'application soit des techniques de séparation aveugle de sources soit des méthodes mathématiques propres à la séparation des sources c'est qu'en général aucune mesure métrique ou standard n'existe pour évaluer la qualité de la séparation afin de valider les résultats. Pour une évaluation idéale, il faut que les vrais signaux originaux produits par chaque composante soient disponible et cela comme une condition fondamentale. Cela nécessite que les signaux de chaque composante soient collectés en strict isolement pendant leur fonctionnement dans un laboratoire. Une telle tâche est parfois très couteuse et difficile, sinon impossible.

Dans cette étude, une nouvelle méthode est développée, elle consiste à la distribution d'énergie de vibration à l'égard de l'emplacement des sources de vibration et de capteurs et est basée sur le comportement mécanique de la structure. Cette méthode adopte certains concepts clés de l'analyse statistique d'énergie (ASE) pour soutenir le fait que chaque capteur recueille une version différente des vibrations produites dans le système par rapport à son emplacement dans la structure. En appliquant la transformée de Fourier sur les signaux et en utilisant une connaissance a priori de la distribution spatiale des capteurs et des composantes, les signaux de vibration d'origine peuvent être récupéré grâce à la comparaison entre les représentations de fréquence (transformée de Fourier) des signaux reçus par chaque capteur. Cette méthode proposée est vérifiée avec des données artificielles et expérimentales.

Concept

Lors de la collecte des signaux d'un système complexe à l'aide de multiples capteurs, chaque capteur, en fonction de son emplacement par rapport aux sources de vibrations va enregistrer une version différente d'énergie de vibration. En comparant ces différentes versions d'enregistrements, on peut identifier la source de la composante correspondante des signaux vibratoires. Pour ce faire, la compréhension de la façon dont l'énergie des vibrations se propage de la source aux capteurs est inévitablement nécessaire. Afin de cerner l'effet de propagation sur l'énergie de vibration, l'ASE a été utilisé pour qu'elle ne nécessite aucune charge élevée de calculs afin de donner une estimation de la distribution spatiale de l'énergie des vibrations et des niveaux de réponse dans le système. La première étape pour effectuer une analyse basée sur le concept ASE est de déterminer les sous-systèmes. Une façon raisonnable pour déterminer les sous-systèmes et d'identifier les couplages entre eux. Un couplage peut s'étendre d'un joint boulonné à une discontinuité, tel qu'un changement d'épaisseur d'une paroi.

Procédure

La procédure pour la méthode proposée est la suivante: *N* donné comme le nombre de capteurs;$X_i(f)$la transformée de Fourier des signaux $x_i(t)$ (où i = 1, ..., N) est obtenu pour une période donnée. Pour chaque bande de fréquence notée *f*, les intensités sont mis à zéro, sauf pour l'intensité maximale (c.-à-d.$argmax_i X_i(f)$) parmi tous les signaux provenant des différents capteurs. En utilisant cette approche, à chaque fréquence, les intensités des *N* spectres sont soient nulles soient au maximum. Finalement, en utilisant la diversité spatiale de l'endroit du capteur par rapport aux sous-systèmes et aux composantes, chaque capteur avec sa représentation en fréquence modifiée est associé à une composante. Afin de diminuer l'effet des fluctuations aléatoires et transitoires la transformée de Fourier à fenêtre réduite (*Short Time Fourier Transforms* (*STFT*)) peut être utilisée de telle sorte que la procédure précitée est appliquée à chaque fenêtre et ensuite la moyenne des résultats de toutes les fenêtres est établie. Utilisant cette approche l'effet des perturbations aléatoires (et dans une certaine mesure du bruit) disparait.

Expérimentation

Afin de vérifier la faisabilité de la méthode proposée, deux études de cas utilisant des signaux de vibration cueillis à partir de deux différents bancs d'essai ont été effectuées.

Dans le premier cas, les signaux de vibration ont été recueillis à partir d'un banc d'essai à l'École Polytechnique de Montréal qui est constitué d'un moteur de 2 CV couplé à un arbre supporté par deux roulements différents. Un des roulements est un roulement à rouleaux de Pratt & Whitney (PWC15) avec un défaut de la bague externe et l'autre est un nouveau roulement à billes SKF (1217 K). Quatre accéléromètres ont été utilisés, l'un monté sur chaque boîtier et deux posés sur la base principale. En utilisant cette méthode, le défaut de la bague extérieure du palier PWC15 a été détecté avec succès. Dans le second cas, un ensemble de données fourni par le « *Center for Intelligent Maintenance Systems* » (IMS) de l'Université de Cincinnatià traversla « *NASA Ames Prognostics Data Repository* » a été utilisé, où, quatre roulements à doubles rangées« *Rexnord ZA-2115* » ont été montés sur un arbre entrainé par un moteur AC. Les données ont été recueillies en utilisant quatre accéléromètres, un sur chaque palier, à un taux d'échantillonnage de 20 KHz. Un mécanisme à ressort exerce une charge radiale de 6000 livres sur l'arbre tournant et le roulement. Des extraits de données d'environ 1 seconde en durée ont été recueillis à des intervalles de 10 minutes à travers un test dit « exploitation jusqu'à défaillance ». Dans cette étude, l'un des extraits a été sélectionné pour lequel un défaut de la bague externe sur le troisième palier est clairement distingué. Afin de démontrer comment cette méthode va être appliquée, les résultats ont été comparés avec les résultats d'une méthode statistique. Dans ce cas, la méthode de l'analyse en composantes indépendantes « ACI »a été utilisée pour séparer les signaux de vibration et une très bonne concordance entre les résultats des deux méthodes a été établie. Dans l'ensemble, les résultats expérimentaux ont confirmé l'efficacité de la méthode. Certaines lacunes associées à cette méthode sont brièvement discutées: cette méthode ne peut pas être très efficace et précises dans les systèmes avec un comportement transitoire. En plus, dans les systèmes avec des composantes très densément montés, la détermination des sous-systèmes et donc le meilleur emplacement pour les capteurs peuvent être très difficiles. En guise de recommandation pour les travaux futurs, l'efficacité de cette méthode peut être encore étudiée avec des signaux obtenus à partir d’autres cas expérimentaux ou industriels.

Deuxième étude de cas

Avant-propos

La première formulation mathématique existante pour la séparation aveugle de sources est l'analyse en composantes indépendantes (ACI). Dans l'analyse en composantes indépendantes, on suppose que les signaux sources sont statistiquement indépendants les uns des autres et peuvent être récupéré par la formulation de l'indépendance. Néanmoins, il existe toujours deux ambigüités et indéterminations dominantes liées à l'analyse en composantes indépendantes. Premièrement, l'index original des sources est inconnu. C'est-à-dire, la méthode ACI ne fournit pas d'étiquetage ou de permutation des signaux récupérés à l'égard de leurs sources réelles. Il vient du fait que l'indépendance mathématique est insensible à la permutation des sources. La seconde ambigüité est que l'échelle réelle des sources ne peut être déterminée. Cela signifie que les signaux récupérés peuvent être une version amplifiée ou atténuée des signaux originaux. Ceci est également dû à l'insensibilité de l'indépendance mathématique du facteur de l’échelle. Il ya un certain nombre d'algorithmes et de méthodes pour effectuer la séparation de signaux basée sur le concept de l'ACI. Ces méthodes peuvent être appliquées soit dans le domaine temporel ou fréquentiel. Quel domaine choisir dépend principalement du mécanisme du signale mélangé. Si le mécanisme du mélange est instantané, (c'est à dire, les signaux sont mélangés de façon linéaire) les méthodes dans le domaine temporel sont les plus efficaces. Si le mécanisme du mélange est convolutif, (c'est à dire, les signaux sont convoluée) alors les méthodes dans le domaine fréquentiel sont plus appropriées. Dans la plupart des cas réels, y compris les vibrations dans les systèmes mécaniques, le mécanisme du signal mélangé est souvent convolutif.

Le problème avec le choix de la méthode de fréquence basée sur l’ACI est que, la séparation résultante de l'ensemble des bandes de fréquence n’est pas nécessairement englober par la même échelle et permutation. D'une bande de fréquence à l'autre, il est probable que la permutation des sources soit différente. Ainsi, lors de la transformation des résultats de la séparation du domaine de fréquence au domaine temporel des signaux qui en résulte ne peuvent pas être composé de fréquence d'une source unique. Dans cette étude, nous avons cherché à employer l'analyse en composantes indépendante (ACI) dans le domaine fréquentiel pour récupérer les signaux produits par les composantes d’un système complexe. Une nouvelle approche est proposée et testée pour surmonter le problème de la permutation «locale» indéterminée. Afin de démontrer l'applicabilité de la nouvelle approche, des expériences ont été effectuées sur un banc d'essai avec un arbre entrainé par un moteur électrique et supporté par deux paliers différents.

Concept

L'indétermination locale est initialement due à l'indétermination inhérente de la méthode d'ACI. Plus précisément, elle provient du fait que l'ACI est généralement mise en œuvre sur chaque bande de fréquence de façon indépendante, et par conséquent les résultats de séparation à différentes bandes peuvent avoir une permutation et une échelle différentes. Une façon de régler ce problème est de relier l'exécution de l'ACI à différentes bandes de fréquences. Dans ce cas-ci une compréhension du mécanisme des signaux mélangés ainsi que le comportement du système à différentes fréquences est indispensable. Une analyse approfondie du mécanisme du mélange permet de définir la fonction de transformation entre les sources et les capteurs. Cette analyse est toutefois assez difficile en raison de la complexité et la diversité des systèmes mécaniques. Néanmoins, si le chemin de la transmission d'énergie des vibrations entre un capteur et une source est simplement considéré comme un système de 1 degré de liberté (DDL), un changement lisse et progressif dans la transmissibilité entre différentes valeurs de l'amortissement à fréquences différentes est présent, c'est à dire, aucune brusquerie n'est visible. Cet évènement reste plus ou moins similaire dans les systèmes complexes avec plus de degrés de liberté, à l'exception des fréquences naturelles des systèmes non amorties. On peut donc supposer qu'il ya une légère différence dans le mécanisme du signal mélangé pour les bandes de fréquences voisines. Cela se reflète aussi sur la matrice du mélange tel que les matrices de deux bandes de fréquences adjacentes contenant des valeurs très proches. Pour utiliser ce concept, au cours des calculs, une fois la convergence des itérations et la matrice de mélange pour une bande de fréquence est calculé, la matrice obtenue du mélange sera définie comme une valeur initiale pour le calcul de la bande de fréquence suivante. De cette façon, puisque les valeurs des matrices du mélange de deux bandes de fréquences adjacentes sont proches les uns des autres, la convergence est atteinte très rapidement. De plus, la permutation de la matrice du mélange est maintenue équivalente d'une bande de fréquence à autre. En restreignant les conditions de convergence, la sur-itération est donc évitée et les matrices du mélange ne serait pas distante les unes des autres.

Expérimentation

Afin de vérifier la faisabilité de la technique proposée, les signaux de vibration ont été recueillis du banc d’essai de l'École Polytechnique de Montréal tel que décrit dans l'étude précédente. Les résultats ont été également comparés à la méthode présentée avant (i.e., la proximité spatiale). L'intéressante concordance entre les résultats de l'ACI, la méthode de proximité spatiale et la méthode d'analyse du pic a confirmé l'efficacité et le potentiel de l'ACI dans le domaine fréquentiel ainsi que dans l'approche introduite pour résoudre le problème de permutation locale.

Troisième étude de cas

Avant-propos

Dans la troisième étude, une approche alternative sur l'utilisation de la technique de séparation aveugle de source est présentée. Cette approche consiste à mettre l'accent sur chaque composante, sur ses défauts et les variations spécifiques qu'ils induisent sur les caractéristiques des signaux acquis loin de la composante réelle. Étant donné qu'un outil puissant pour détecter de telles caractéristiques est disponible ainsi que des caractéristiques obtenues le long du chemin de la transmission, cette approche pourrait être très efficace dans le diagnostic des défauts dans les machines complexes. Comme pour d'autres cas tout au long de cette thèse, les défauts dans les roulements ont été choisis pour cette étude. De tels défauts sont connus pour produire des vibrations avec impulsivité périodique dans l'énergie. Des signaux avec un tel comportement sont connus en termes techniques pour être cyclostationnaire. L’analyse spectrale Cyclique est un outil qui permet de mesurer la cyclo-stationnarité du signal à différentes gammes de fréquence. Par conséquent, on peut affirmer que dans ce cas-ci, le diagnostic consisterait à utiliser cet outil afin de détecter la cyclo-stationnarité des signaux de vibration et vérifier toute liaison avec les défauts du roulement. Dans cette étude, l'application de cette technique est évaluée pour la détection des défauts des roulements dans les machines complexes.

Concept et expérimentation

Pour que l'analyse spectrale cyclique soit efficace dans des applications liées aux machines complexes, deux exigences sont jugées indispensables. La première est qu'elle soit capable de détecter les défauts d'un signal faible, car en principe, le chemin de transmission dissipe généralement l'énergie du signal, mais il ne devrait pas affecter certaines caractéristiques du signal telles que son cyclo-stationnarité. Par conséquent, il est raisonnable de s'attendre à ce que le comportement du signal cyclo-stationnarité soit préservé. Ceci est expérimenté à partir d'un essai similaire sur le banc d'essai de l'École Polytechnique, où les signaux ont été recueillis à partir d'un roulement défectueux à l'aide d'un accéléromètre placé loin de ce roulement. L'analyse spectrale cyclique a été comparée aux méthodes traditionnelles d'analyse spectrale et les résultats ont démontré sa supériorité par rapport aux autres techniques. La deuxième exigence est que, dans la surveillance automatique de l'état d'une composante ainsi que le diagnostic des défauts, il est essentiel pour une méthode de permettre une tendance robuste, réalisable et cohérente. Également ces caractéristiques étant repérés doivent être cohérentes dans le sens que leurs valeurs portent une certaine correspondance à la sévérité des défauts. Dans la deuxième étude de cas, la cyclo-stationnarité est examiné selon ces exigences grâce à l'expérience « exploitation jusqu'à défaillance » décrite dans la première étude. Les résultats expérimentaux ont démontré que l'analyse spectrale cyclique qui permet la détection précoce des défauts de roulement ne peut être utilisée comme un outil de mesure de la gravité de ces défauts d'une part, mais d'autre part, utilisée comme un outil de surveillance fiable et cela tant que sa valeur est toujours plus élevée pour un roulement défectueux que pour un normal. En conclusion, les résultats expérimentaux ont été satisfaisants. En guise de recommandation pour les travaux futurs, l'efficacité de cette méthode peut encore être étudiée avec des signaux obtenus à partir d'autres cas industriels.

Conclusion

Dans cette thèse, trois études concernant le diagnostic des défauts mécanique dans les machines complexes en utilisant l'analyse des vibrations sont présentés.

Dans la première étude, une nouvelle méthode de séparation basée sur les signatures de fréquence obtenue à partir des signaux recueillis auprès de plusieurs capteurs placés à différents endroits du système est présentée. Cette méthode à une base théorique simple et solide adopté par l'analyse statistique énergétique. Une série de tests expérimentaux sur des signaux synthétiques et des signaux de laboratoires recueillis auprès de différents roulements sont fournis pour la vérification. Les résultats confirment l'efficacité de la méthode. Certaines lacunes associées à cette méthode sont également discutées telles que l'inexactitude et l'inefficacité dans les systèmes avec comportement transitoire et les systèmes avec des composantes complexement montée où la détermination des sous-systèmes peut être très difficile.

Dans la seconde étude une méthode basée sur la fréquence d'analyse en composantes indépendantes est appliquée dans le cas de séparation de sources de vibrations. Une nouvelle technique est présentée pour la construction de signaux dans le domaine temporel à partir des résultats de séparation des bandes de fréquences individuelles. En conséquence, des modifications sont apportées à l'algorithme de séparation adapté pour le cas de la séparation de sources de vibrations. La performance de la méthode est vérifiée à l'aide d'une série de tests expérimentaux sur des signaux réels recueillis auprès de différents bancs d'essais. Les résultats sont comparés et vérifiés à l'aide de la méthode de séparation métrique présentée dans la première étude. La concordance entre les résultats de la technique présentée, la méthode de la proximité spatiale et la méthode d'analyse de pic confirme sa grande efficacité.

Dans la troisième étude, l'application de la densité spectrale cyclique dans la détection des faibles signaux de roulements est considérée. Il a été démontré que, pour que cette technique soit efficace dans la détection de défauts dans les systèmes complexes deux conditions préalables doivent être remplies. De telles Conditions sont identifiés d’avoir la capacité de détecter des défauts de roulements à partir d'un signal faible. À cet effet, les insuffisances des traditionnelles approches sont discutées. Deux séries d'expériences sont présentées afin d'évaluer et soutenir les résultats expérimentaux des idées proposées.

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LISTE OF ACRONYMS AND ABREVIATIONS

AC	Alternative current
ACI	Analyse en composantes indépendantes
Amcor	Amplitude modulation correlation
ASE	Analyse statistique d’énergie
BCS	Blind component separation
BSS	Blind source separation
CBM	Condition-based maintenance
CV	Cheval-vapeur
DC	Direct current
DDL	Degré de liberté
DOF	Degree of freedom
EVT	Extreme value theory
FEM	Finite element method
FFT	Fast Fourier transforms
FT	Fourier transforms
HP	Horse power
Hz	Hertz
ICA	Independent component analysis
IMS	Intelligent maintenance systems
JADE	Joint approximate diagonalization of eigenmatrices
LLH	Log-likelihood
MA	Moving average
MSE	Mean square error

NASA	National aeronautics and space administration
NRC	Natural research council of Canada
NSERC	Natural sciences and engineering research council of Canada
PCA	Principal component analysis
PWC	Pratt & Whitney Canada
RCTE	Residual cross-talking error
SEA	Statistical energy analysis
STFT	Short time Fourier transforms
VQM	Vestigial quadratic mismatch

INTRODUCTION

1.1 Preamble

Failure of machinery and relevant components has always been a major concern in industry due to costliness of reparation and other costs associated with interruption of the production line or the required functions. Maintenance of machinery has consequently been an important field of research and development in both industry and academia. Different approaches for performing maintenance have evolved. They can be listed under three categories; breakdown or run-to-failure maintenance, preventive or time-based maintenance and predictive or *condition-based maintenance* (CBM) [1].

Breakdown or run-to-failure maintenance consists in reparation of the problematic parts of the system as they fail. This intrinsic reaction to failure is the simplest approach. One obvious disadvantage is that an unexpected breakdown is usually very costly and frustrating. It can also be very time consuming, as the necessary arrangements for reparation must be made at the time of failure.

Preventive or time-based maintenance, which is the most common approach, consists in performing maintenance based on a predetermined schedule. For different sections of the system a service schedule is elaborated based on experience and life cycle analysis. This schedule is determined such that cost and halt time are minimized. This approach in comparison with the run-to-failure approach is a mature way of preventing catastrophic failures. Yet, its major drawback is that it often leads to redundant and unnecessary servicing and hence a waste of resources.

A resolution to the shortcomings of the previous approach is to perform maintenance whenever and wherever needed; based on the condition of the system rather than on a strict or prescheduled agenda. A component, machine, etc. is repaired when a failure is likely to occur. This approach is known as predictive or condition-based maintenance. In this approach, it is necessary to constantly monitor the condition of the system by acquiring some appropriate parameters. Then, based on such parameters, the condition or even the remaining lifetime of the system is estimated. In a more state-of-the-art scenario, the process of estimating the condition of the system is carried out in an automated way with minimal human interference. This is usually where artificial intelligence methods come into play. These artificial intelligence methods aim at predicting an impending fault or failure in a system's part by extracting 'information' from acquired data. Many methods have been used in this case; some of the best known are the neural networks method, fuzzy logic and hidden Markov models.

In diagnosis of rotating machinery, vibration acquisition is one of the most prevalent ways of acquiring data. In fact, oscillation is an inherent characteristic of rotating machines. Different components of these types of machinery such as shafts, bearings and gears produce vibration energy with different characteristics. Any deterioration in the condition of such components can affect their vibratory behaviour and manifest itself in the vibration signals acquired. This allows for diagnosis of faults by analyzing the vibration signature of the system. As a result, vibration analysis has gained popularity in recent years and vibration sensors have become indispensible for rotating machinery of critical importance.

A prerequisite to accurate fault diagnosis using vibration analysis is that the acquired vibration signals be 'clean' enough that very small changes in the signal due to an impending fault in any component can be detected. Unfortunately, this is not the case in common practice and vibration signals are almost always cluttered with noise. This problem is aggravated in the case of complex multi-component machines. The different components all contribute to produce vibration energy and it is difficult to monitor a specific component because vibration produced by other components jumble the signal. One way to alleviate this effect is to mount the vibration sensors as close as possible to the components of interest. However, this is often not possible due to restrictions such as complexity, manufacturer's warranty policy and inaccessibility. The only alternative is to place the sensors on the innermost surface possible of the structure (i.e., the casing). As a consequence, the signal collected by the sensors is not only from the specific targeted component, but from many components. The signals collected by each sensor are in effect the combination of vibration energy produced by different components in addition to noise. Dissipation of vibration energy through transmission path complicates the situation even further. The above factors make it difficult to obtain the actual vibration signature for each component.

To tackle this problem, one of two alternative approaches can be adopted. One approach is to regard this case as a blind source separation (cocktail party) problem and take advantage of statistical and mathematical methods developed for this purpose, primarily *independent* *component analysis* (ICA), to separate signals coming from different sources. The blind source separation together with its mathematical definition and description are further detailed in the following sections of this introduction. Some limitations and difficulties of this approach are mentioned. Proposed solutions to such limitations and difficulties are then spelled out in Chapters 2 and 3.

The other alternative is to avoid the effort to 'separate' the signals and relate them to different components (sources) and instead make use of the specification and characteristics of the signals produced by different components in normal and faulty conditions. This approach is elaborated in Chapter 4.

The experimental results presented in this thesis are all related to the case of bearing fault detection.

1.2 Blind Source Separation (BSS)

In the context of acquiring information from a multi-component system, it is generally desired to have information about each component in isolation. However, this is not always possible and normally the acquired data is at best a mixture of signals produced by different components or sources in the system. Therefore, in order to consider the components individually mixed signals must be decomposed into elements pertaining to the system components. This is the subject of a subfield in signal processing entitled 'source separation'. Cases abound where either there is not enough available a priori information about the system or the mechanism of mixing is very complex. In such cases, the system can be considered a black box and the problem of separating sources is called *blind source separation*. BSS has been usefully applied in many fields and areas such as radio-communication, speech and audio processing and biomedical applications [2]. It has also been used to separate vibration signals in mechanical systems for the purpose of fault diagnosis.

In the following sections the general model and a brief mathematical background of BSS are introduced followed by a concise review of the literature in the field of BSS as applied to mechanical systems fault diagnosis.

1.2.1 General model

Blind source separation is a method to recover the signals produced by different individual sources from a number of observations of mixed source signals. In mathematical terms the general model for blind source separation can be described as follows:

If there are p zero-mean source signals at time *t*, $S(n) = [s_1(t), \ldots, s_p(t)]$ that are assumed to be statistically independent, and $X(t) = [x_1(t), \ldots, x_m(t)]$ denote the mixed signals received by m sensors, the data model for an instantaneous mixture can be written as:

$$X(t) = AS(t) + N = \sum_{i=1}^{m} a_{ki}(t)s_k(t) + N \qquad \text{Eq. 1.1}$$

where A is the $m \times p$ mixing matrix consisting of unknown mixture coefficients. It is always assumed that the sources are independent and the number of sensors is at least equal to the number of sources (i.e., $p \leq m$).

The primary technique for finding the unknown mixture coefficients (*A*) is ICA. A prerequisite for ICA to be applicable is that no more than one source can have a Gaussian distribution. This stems from the fact that it is impossible to separate several Gaussian sources using ICA technique [3].

1.2.2 Independent component analysis

Independent component analysis consists in finding an estimation of the sources:

$$\hat{S}(t) = BX(t) = Y(t) \qquad \text{Eq. 1.2}$$

by determining matrix B such that a given objective function defined for components of Y becomes minimum. Several objective functions based on different estimation criteria exist for ICA. Some of the most important criteria include: maximization of non-Gaussianity[3], minimization of mutual information [3] and maximum likelihood estimation [4]. A brief description of these criteria is provided later.

Regardless of what criterion is used, there are always two dominant ambiguities and indeterminacies associated with independent component analysis. First, the original labeling of the sources is unknown. This means that, because both S and A are unknown, the order of the terms can be freely permutated. It is a result of the fact that the mathematical independency is insensitive to permutation of the sources. The second ambiguity is that the actual scale of the sources cannot be determined. The reason for this is that any scalar multiplier in one of the sources s_i can always be canceled by dividing the corresponding column a_i of *A* by the same scalar. This is also due to insensitivity of mathematical independency to the scaling factor.

1.2.2.1 Maximization of non-Gaussianity and minimization of mutual information[3]

Random variables are known to be Gaussian or normally distributed. There is a general consensus that a mixture of two or more independent variables tends towards randomness or Gaussianity. Consequently, by distancing from Gaussianity or by maximizing 'non-Gaussianity', one may approach independency. One of the main measures of non-Gaussianity is 'negentropy'. Negentropy is derived from 'entropy' and serves as its converse. In the same manner, it is known that the more variables are unstructured and mixed, the higher is the entropy or the 'mutual information'. Therefore, it can be stated that negentropy ties the two criteria of maximization of non-Gaussianity and minimization of mutual information together and provides a measure for evaluating independency. The formulation for deriving negentropy is described below.

If the probability density function of a random variable *s* is denoted by $f_s(u)$, then, according to probability theorems, in order for vector *S* with *N* elements to have mutually independent components the following equation holds:

$$f_s(u) = \prod_{i=1}^{N} f_{s_i}(u_i) \qquad \text{Eq. 1.3}$$

In this case a standard approach for verifying the independency between the components of vector *S* is to measure the distance between both sides of the above equation. There are several different measures to evaluate such a distance; one of these is Kullback divergence [5]. Based on Kullback divergence, the average mutual information of *S* can be written as:

$$I(f_s) = \int f_s(u) \log \frac{f_s(u)}{\prod f_{s_i}(u)} du \qquad \text{Eq. 1.4}$$

The average mutual information of *S* vanishes if and only if the variables s_i are mutually independent; otherwise it is a positive value. Therefore, this feature makes the average mutual information an appropriate measure for independency.

Moreover, if the differential entropy of *S* is defined as:

$$DE(f_s) = -\int (u) \log f_s(u) du \qquad \text{Eq. 1.5}$$

and the negentropy as:

$$J(f_s) = DE(\phi_s) - DE(f_s) \quad \text{Eq. 1.6}$$

where ϕ_s is the Gaussian density with the same mean and variance as f_s , then the average mutual information defined beforehand with respect to negentropy can be written as (proof is given in [3]):

$$I(f_s) = J(f_s) - \sum J(f_{s_i}) + \frac{1}{2}\log\frac{\prod cov_{ii}(s)}{|cov(s)|} \quad \text{Eq. 1.7}$$

The above equation is an approximation of the mutual information while taking the non-Guassianity into account.

1.2.2.2 Maximum likelihood estimation[4]

In this method, it is first assumed that the sources are independent and identically distributed at different times. This is not an essential assumption and is referred to as a working assumption. In order to derive a likelihood function, the probability density functions of the sources are needed while they are unknown. In this case, they are assumed to be known up to a scaling factor. Then the density of the sources with respect to independency can be written as:

$$f\big(S(t)\big) = \prod_{i=1}^{N} f_i\left[\frac{s_i(t)}{\sigma_i}\right]/\sigma_i \quad \text{Eq. 1.8}$$

where *f* denotes the probability density function, *S* and s_i are the source vector and an individual source respectively and σ_i is the scaling factor. Then, given that $X(t) = AS(t)$ and assuming that *A* is invertible, the *log-likelihood function* (*LLH)* which is the logarithm of the density of the data can be written as:

$$LLH = T\left\{\sum_{i=1}^{p} E\ln\left[\frac{n}{\sigma_i} f\left(\frac{e_i^T A^{-1} X}{\sigma_i}\right)\right] - \ln|\det A|\right\} \quad \text{Eq. 1.9}$$

where *E* denotes the average operator over time, e_i is the *i*th column of the unit matrix of order *p* and *T* denotes the transpose operator. In order to have the maximum likelihood, the differential of the above equation with respect to unknown matrix *A* must be zero. This enables calculation of the estimators $\hat{A}$ and $\hat{\sigma}$ as follows:

$$\hat{\sigma}_i = E\left[\psi_i\left(\frac{e_i^T \hat{A}^{-1} X}{\hat{\sigma}_i}\right) e_j^T \hat{A}^{-1} X\right] = 0 \text{ for } i \neq j = 1, \dots, p \quad \text{Eq. 1.10}$$

where $\psi_i = -(\ln f_i)'$ and prime($'$) denotes derivative. Pham and Garat introduced this method and presented a way of finding an optimal choice for ψ_i based on linear space of functions.

1.2.3 Convolutive mixtures and frequency domain analysis

The data model presented above pertains to the case where the mixing mechanism is assumed to be linear and instantaneous. This assumption is too simplistic for the majority of real applications. The mixing model in most cases is more consistent with a convolutive mixture. In the case of convolutive mixtures the data model can be rewritten as follows:

$$X(t) = A * S(t) + N = \sum_{i=1}^{m} a_{ki}(t) * s_k(t) + N \qquad \text{Eq. 1.11}$$

where A is the $m \times p$ mixing matrix consisting of unknown mixture coefficients. In this case, solving the inverse problem is not as straightforward as it was for the instantaneous data model. Certain methods have been suggested to solve the convolutive mixture model in its general form. However, such methods are very limited [1].

Fortunately, a convolutive mixing model in the time domain becomes an instantaneous model when brought into the frequency domain. To be more precise, when data is represented using the joint time-frequency domain, at each frequency bin the mixing model is instantaneous and existing methods for instantaneous mixtures can be employed with minor modifications. Since data in the frequency domain are complex valued, instantaneous ICA methods must be modified for consistency with complex data. This can be simply done by taking a conjugate transpose wherever matrix transposition is needed throughout computations. After performing separation at each frequency bin, the resulting separated signals are transformed back from frequency domain to time domain and the source signals are recovered.

1.2.4 A review on the application of BSS in fault diagnosis

A comprehensive review of the literature on the subject of BSS and ICA is well beyond the scope of this thesis. Here, the focus is on previous studies on the application of BSS in separation of vibration signals as applied to fault diagnosis in rotating machinery. A short description is given for each study where its relevancy to works presented in this thesis is given in the corresponding chapters.

Capdevielle et al (1996) [6] seem to be the first to apply BSS to separate “rotating machine signals”. However, it is not clear from their paper if the signals were vibration or other types of signals. Also, no information was provided about their test setup. In any case, they used a Kurtosis-based non-Gaussianity method to separate “rotating machine noise”, which they argue to be convolutive mixtures of wide-band sources in the frequency domain. In order to reconstruct the source spectra from signals identified at each frequency bin they proposed a method based on relating the *moving average* (MA) filtering of the estimated sources.

Gelle et al (2000) [7] used the assumption that the propagation medium is linear (even though they argue that this is not the case) and applied BSS to rotating machine monitoring. They employed a method based on the Nguyen-Jutten algorithm on the time-domain signals collected by accelerometers and microphones from a test bench consisting of two low-powered DC motors independently running at two different rotation speeds. In their setup, an accelerometer was mounted on each motor and two microphones were placed in front of each motor and the entire setup was isolated from surroundings. They performed their analysis on vibration signals and acoustic signals using three sets of; artificial signals, artificial mixtures of real signals and real signals. For the case of artificial signals and artificially mixed real signals, in order to check the performance of their method, they used two performance criteria. One criterion was *vestigial quadratic mismatch* (VQM) between the original source signals and estimated ones. The other was the *mean square error* (MSE) between transformation matrix parameters. In the case of real vibration signals, they used spectral analysis of the estimated signals to evaluate their method and the results were satisfactory to some extent, but only up to a certain frequency.

Gelle et al (2001) [8] considered the mixing mechanism for vibration in mechanical structures to be convolutive and made a comparison between temporal and frequency based methods for separation. This study can be considered as an extension to the abovementioned study. A similar approach was used to evaluate these methods using synthetic signals and real signals. To assess the quality of separation for the case of synthetic signals, *residual cross-talking error* (RCTE) and MSE were used. For acquiring real signals, a test bed with two DC motors running independently at different speeds was used. Each motor was coupled to a shaft lying on two roller bearings. Their main focus was to simulate a case of two rotating machines operating simultaneously in a factory and to separate the signals gathered by two accelerometers into signals produced by each machine. To assess real signals, characteristic frequencies of the system were utilized. Overall, they argued that the frequency-based method performed better even though it is more costly due to the required computations.

Ympa et al (2001) [9] discussed the mixing mechanism in acoustical and vibratory structures. They introduced bilinear form functions for several types of signal characteristics for the case of instantaneous mixing. They applied time-based instantaneous (bilinear form) and convolutive methods to separate vibration signals obtained from two water pumps running simultaneously. To assess the quality of separation they used as reference the signals gathered from each pump while the other one was stopped. Finally, they concluded that bilinear forms would be a more robust method for separation of acoustical signals. For the case of vibration signals a convolutive mixture model would be better.

Servière and Fabry (2004) [10] developed a new preprocessing technique to apply to signals before feeding them into ICA. They made the assumption that, unlike noise, the source signals are periodic and the autocorrelation length of the source signals is greater than that of noise. Their preprocessing technique was based on *principal component analysis* (PCA) adapted to use spectral matrices of delayed observations to remove noise from periodic source signals. For separation, they used (in the frequency domain) the JADE algorithm that seeks to maximize non-Gaussianity using spectral Kurtosis. They applied their method to artificial signals where they used 2-norm distance to assess the quality. Their test structure comprised two independent test beds, each consisting of a synchronous alternator, a motor and a pump. A total of six accelerometers were used for recording vibration signals. The separation results for only a few specific frequency bands were presented and they were satisfactory. The fact that the two test beds were running at different speeds made it possible for them to validate their results by comparing with the characteristic frequencies of the two systems. They finally concluded that their method was efficient for low signal-to-noise ratios. Later, as an extension to their previous work, Servière and Fabry (2005) [11] improved their method to be applicable to the cases of modulated sources where no assumption is made on the statistical properties of the noise.

Antoni (2005) [12] listed a number of difficulties in applying blind source separation for separating vibration sources. He discussed that, in vibration source separation, separating vibration signals into signal components that share the same characteristic is more realistic than separating signals with respect to the sources. He called his concept *blind component separation*

(BCS). His technique decomposes the vibration signals into their constituting periodic, non-stationary random and stationary random components using short time Fourier transforms and spectral Kurtosis. He applied his method to fault diagnosis of rolling bearings in a few real cases. In all of the experiments, the faults were evident in the non-stationary random signals as the masking effect of periodic and stationary random signals were removed. The author presented only the diagrams of the resultant time signals showing the fault-related impulses in non-stationary random components. No further detail was given on the results.

The above studies are more or less the fundamental works done in this field. Other studies are to a great extent in line with the above studies. One common point among these studies is that no real metric or measure is presented for evaluating and validating real case experiments. Another issue is that, in the frequency-based approach, in order to solve the permutation ambiguity as one tries to reconstruct the time signals from resulting frequency signals, methods based on the statistical relation between different frequency bins have been used. Such methods, as declared by many authors are very voluminous and involve high computation load. These two drawbacks are revisited in this thesis.

The rest of this thesis is structured as follows:

In Chapter 2 a method is presented based on system mechanics and by adopting some key concepts from *statistical energy analysis* (SEA) to provide a measure or metric for validating other separation methods. This method seeks to extract the energy distribution of vibration signals produced by different components with respect to spatial distribution of the vibration sensors.

In Chapter 3 the application of ICA for the case of vibration source separation is discussed. A new method is presented to overcome permutation indeterminacy between different frequency bins to allow faster and computationally lighter reconstruction of estimated time signals from resulting frequency signals.

Chapter 4 presents an alternative approach to applying BSS and ICA to the problem of fault detection in complex machinery. Such an approach focuses on processing signals in such a way that specific characteristics imposed on the vibration signals due to specific faults in components are accentuated.

As mentioned earlier, experimental results related to the case of bearing fault detection are given in each chapter to support and validate the proposed concepts.

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CHAPTER 2 A NOVEL APPROACH TO EVALUATION OF VIBRATION SOURCE SEPARATION BASED ON SPATIAL DISTRIBUTION OF SENSORS AND FOURIER TRANSFORMS

Ali Mahvash and Aouni A. Lakis

Section of Applied Mechanics, Department of Mechanical Engineering, École Polytechnique de Montréal, Montréal H3T 1J4, Canada

2.1 Abstract

An obstacle in diagnosis of multi-component machinery using multiple sensors to acquire vibration data is firstly found in the data acquisition itself. This is due to the fact that vibration signals collected by each sensor are a mixture of vibration produced by different components and noise; it is not evident what signals are produced by each component. A number of research studies have been carried out in which this problem was considered a Blind Source Separation (BSS) problem and different mathematical methods were used to separate the signals. One complexity with applying such mathematical methods to separate vibration sources is that no metric or standard measure exists to evaluate the quality of the separation. In this study a method based on Statistical Energy Analysis (SEA) is proposed using Fourier transforms and the spatial distance between sensors and components. The principle of this method is based on the fact that each sensor, with respect to its location in the system, collects a different version of the vibration produced in the system. By applying a Short Time Fourier transform to the signals collected by multiple sensors and making use of a priori knowledge of the spatial distribution of sensor locations with respect to the components, the source of the peaks on the frequency spectra of the signals can be identified and attributed to the components. The performance of the method was verified using a series of experimental tests on synthetic signals and real laboratory signals collected from different bearings and the results confirmed the efficacy of the method.

Keywords: Source separation quality measure, Statistical Energy Analysis, Fourier transform, Multi-sensor vibration acquisition.

2.2 Introduction

A difficulty in diagnosis of faults in components of rotating machinery using vibration signals is that these signals are always a cluttered mixture of ambient noise and vibration produced by different parts. This problem is encountered in its most severe form when diagnosis of certain components in a compact complex system such as an engine is desired. In this case, in order to lessen the effect of vibration from neighbour components, it is necessary to place the sensors as close as possible to the components of interest. However, due to restrictions such as the manufacturer's warranty policy and inaccessibility, it is not always practical to place the sensors as such. The only choice is therefore to place the sensors on the innermost possible surface of the structure. As a result, even if the sensors are positioned very close to the components, they collect signals not just from one specific component but from other components as well. That is to say, signals collected by each sensor are a combination of the vibration produced by different components in addition to ambient noise. This makes it difficult to determine which component dominates the collected signals.

The first challenge in diagnosis of faults in a complex system is therefore to decompose the signals into components corresponding to the system's individual components. In other words, determining what signals come from which components. This concept is referred to in the literature as 'source separation' and in the case where components of the system are not well identified it is called 'blind source separation'. A number of mathematical methods exist to solve this blind source separation problem, among which the Independent Component Analysis (ICA) [1] method is the most dominant. The performance of blind source separation methods in mechanical systems and fault diagnosis has already been trialled by a number of researchers [2-9]. A common complexity with applying blind source separation techniques or any mathematical methods, in general, to separation of vibration sources is that no metric or standard measure exists to assess the quality of separation and validate the results. For an ideal assessment, the true original signals produced by each component must be available as a prerequisite. This requires gathering signals from each component in strict isolation during operation in a lab environment. Such a task, if not impossible, is very costly and difficult. In previous works, a number of authors [3-6] performed experiments on systems consisting of two separate sub-systems running on a structure where reference signals from each sub-system could be recorded by halting the other sub-system. Others [7,8] considered the signals recorded from sensors located very close to the components as a reference. Using a priori knowledge about the component's signature was also one of the metrics.

In this study, we sought to develop a method that presents the distribution of vibration energy with regard to location of vibration sources and sensors and based on the mechanical behaviour of the structure. This method adopts some key concepts from statistical energy analysis (SEA) to support the fact that each sensor collects a different version of the oscillations produced in the system with respect to its location in the system. Applying a Fourier transform to the signals and making use of a priori knowledge of the spatial distribution of sensors and components, the original vibration signals can be recovered through comparison between the frequency representations (Fourier transform) of signals received by each sensor. The proposed method was verified with synthetic and experimental data.

2.3 Concept

The vibration recorded by a sensor is never exactly similar to the actual fluctuating motion produced. This is due to the fact that between the sensor and the vibration source there is always a propagation medium that dissipates the energy of vibration. This dissipation of energy is the effect of a combination of different factors; the most significant of these is damping. For this reason, in order to reduce such effects during measurements it is always considered necessary to mount the sensors as close as possible to the sources of interest. This is also the case when more than one sensor is used to record the data. Each sensor, depending on its location with respect to vibration sources, will record a different version in terms of vibration energy. By comparing these different versions of recordings one may be able to identify the source of harmonic components of the vibration signals. This is the purpose of this study. To do so, an understanding of how the propagation medium influences the vibration energy as it propagates from a source to the sensors is deemed necessary.

In order to pin down the effect of propagation medium on the energy of vibration, mainly three approaches can be adopted: modal analysis, finite element methods (FEM) and SEA. In this study, a concept similar to SEA was used for it does not require a high load of detailed calculations to provide an estimate of the spatial distribution of vibration energy and response levels in the system. SEA originated in the early 1960s by Lyon [10] who later in the mid-1970s wrote an entire book [11] on the subject. Its main use has been in the field of structural engineering and in areas related to aerospace industries.

A good way of understanding the concept of SEA is through a thermal analogy. In its simplest case we can consider a system wherein two subsystems are connected to each other through a conductive link. One subsystem is given thermal energy (heat) and as a result thermal energy flows from the heated subsystem to the colder subsystem. Because of energy losses through heat radiation and in the conductive link, the heated subsystem retains a higher temperature. Vibration energy flow quite interestingly abides by a similar behaviour. For the same simple case, vibration energy is analogous to heat energy, vibration levels to heat levels, damping losses to radiation losses and coupling loss factors to conductive link losses [12].

The main intention for developing SEA was to create a method for analysis of the vibratory behaviour of complex structures and to estimate their dynamic characteristics including vibration response levels and noise radiation. For SEA to hold true there are some assumptions whose discussions are beyond the scope of this article. Notwithstanding that SEA has been considered to be valid for any range of frequency [13], there are some considerations regarding its accuracy in different frequency ranges. Care must be taken when using SEA at low frequencies where the accuracy of estimations is low. Also, at high frequencies response of the system at any single frequency comprises contributions from a high number of excited modes so that some frequency averaging may be needed.

On the other hand, in this study SEA was not employed to obtain any "quantities". SEA was rather brought in only to support the hypothesis that sensors located in subsystems farther from a subsystem containing a vibration source would pick up attenuated versions of the vibration signals compared to the ones located on nearer subsystems. Also it served to establish a "feel" [13] of how different subsystems in a structure interact with each other to attain a rough estimation of the distribution of vibration energy throughout the structure. This will allow determination of the right subsystems where the sensors should be placed.

The initial step to perform an analysis based on the above concept is to determine subsystems. The rational way to determine subsystems is by identifying the couplings between them. A coupling may range from a bolted joint to a discontinuity such as a step change in wall thickness [14].

For illustration, consider a system composed of three subsystems (Figure 2.1). Subsystems 1 and 3 both contain a vibration source. Vibration signals are measured using three accelerometers located in each subsystem. Assume that each source produces vibration signals with different signatures; i.e., frequency bands of any two sources do not overlap or at least this is not the case for frequency ranges of interest. In such case the vibrations produced, for example, by source 1 manifest themselves in the signals collected by sensor 1 with higher amplitudes compared to the signals of the other two sensors. This is due to internal losses and losses in the couplings. If the frequency representations of the signals collected by sensors 1 and 2 are compared, the frequency bins at which the amplitude is higher for signals of sensor 1 can be concluded to be produced by a source in subsystem 1. This stems from the fact that vibration energy in subsystem 2 has respectively lower amplitude and therefore sensor 2 collects an attenuated version of the energy collected by sensors 1 and 3. This is the basis for the proposed separation method in which emphasis is put on identifying vibration peaks in the frequency representation as is the case when diagnosing faults using vibration [15].

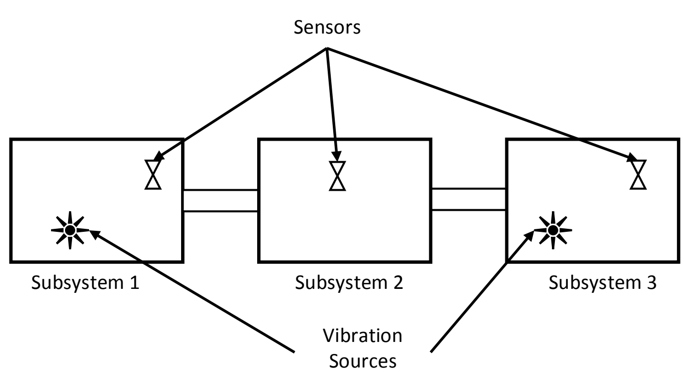

Figure 2.1: A schematic depiction of a system with three subsystems

Further, for disambiguation, a counter example is considered here. One might think of a case in which a clamped-free beam is excited by a force near the clamped end. It is then obvious that a sensor near the excitation point will record lower vibration energy than a remote sensor located near the free end in spite of energy dissipation. On the surface, this appears to be inconsistent with what is presented in this study. However, by bearing in mind the concept of subsystems in

SEA, a clamped-free beam will be recognized as a single subsystem. SEA can only be applied to the case when interactions between subsystems are in question. It loses its applicability when the distribution of the energy inside a single subsystem is at issue. Therefore this case is irrelevant.

2.4 Development

2.4.1 Multi-sensor data acquisition

Using multiple sensors to collect signals is a requirement for almost any separation method. In blind source separation it is usually necessary to have at least as many sensors as the number of components in the system. In some applications, determining the number of components is obscure due to the definition of a component [9]. For example, a ball bearing can be considered a single component, which is usually the case, or as a number of parts (i.e., balls, outer race and inner race). Which concept to adopt depends on the motivation behind performing source separation. For fault diagnosis the following definition may be implemented based on a practical point of view: a component is a part of a structure, machine, etc. that is either repairable or replaceable during maintenance. Although the number of components may be approximated based on the above definition, it does not necessarily follow that a 'component' will act as though it is a single source. A replaceable part can consist of different elements, each of which can produce statistically independent vibration signals. Fortunately, this problem is less likely to arise in the proposed method. In fact, this method is based on the concept of subsystems where recordings from different subsystems are compared to one another. Therefore, as long as a component and its element are considered to be in a subsystem and the sensors used for comparison are mounted in other subsystems the abovementioned problem will not affect the results. In other words, all the elements of the component will have the same characteristics as far as the proposed method is concerned. To determine the number of sensors for this method, the same criterion applies i.e., the number of sensors must be at least equal to the number of 'components'.

2.4.2 Methodology

The procedure for the proposed method is as follows: given N as the number of sensors; $X_i(f)$, the Fourier transform of the signals $x_i(t)$ (where $i = 1, \dots, N$), is obtained for a given period. For each frequency bin denoted by f, the intensities are set to zero except for the maximum intensity (i.e., $argmax_i\ X_i(f)$) among all the signals from different sensors. Using this approach, at each frequency the intensities of N spectra are either zero or the maximum. Finally, using the spatial diversity of sensor locations with respect to the subsystems and the components, each sensor together with its modified frequency representation is associated with a component.

One problem with the above approach is that spectral density does not contain any temporal information about the signal. Therefore certain random and transient fluctuations can cause misinterpretation. One way to get around this problem is to utilize Short Time Fourier Transforms (STFT), apply the aforementioned procedure to each short window and then average the results of all windows. Using this approach the effect of random disturbances (and to some extent noise) subsides. On the other hand, averaging the results of all windows can jeopardize the effectiveness of this method in the event of transient behaviours.

2.5 Experiments using artificial signals

2.5.1 Signal generation

In an attempt to test the proposed method, four different types of signals (Figure 2.2) with a sampling frequency of 1000 Hz for a duration of 2 seconds were generated and multiplied by the mixing matrix:

$$\begin{bmatrix} 1 & 0.4 & 0.8 & 0.4 \\ 0.5 & 1 & 0.7 & 0.6 \\ 0.6 & 0.3 & 1 & 0.28 \\ 0.4 & 0.5 & 0.7 & 1 \end{bmatrix}$$

This enables construction of four signal mixtures (Figure 2.3) using LabVIEW software. The elements of the mixing matrix are chosen such that in each row the diagonal elements hold the maximum since they simulate the case in which each sensor is in the same subsystem as a given vibration source.

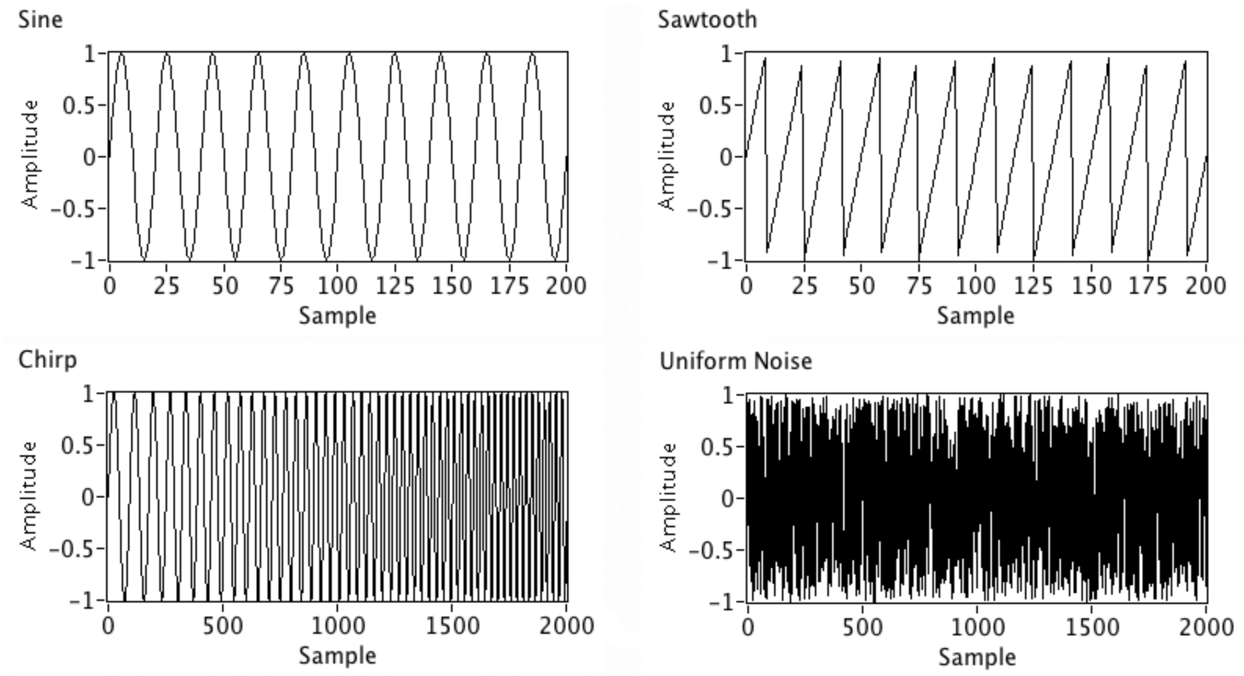

Figure 2.2: Generated signals: Sine (50 Hz), Saw-tooth (60 Hz), Chirp (10-40 Hz) and Uniform Noise

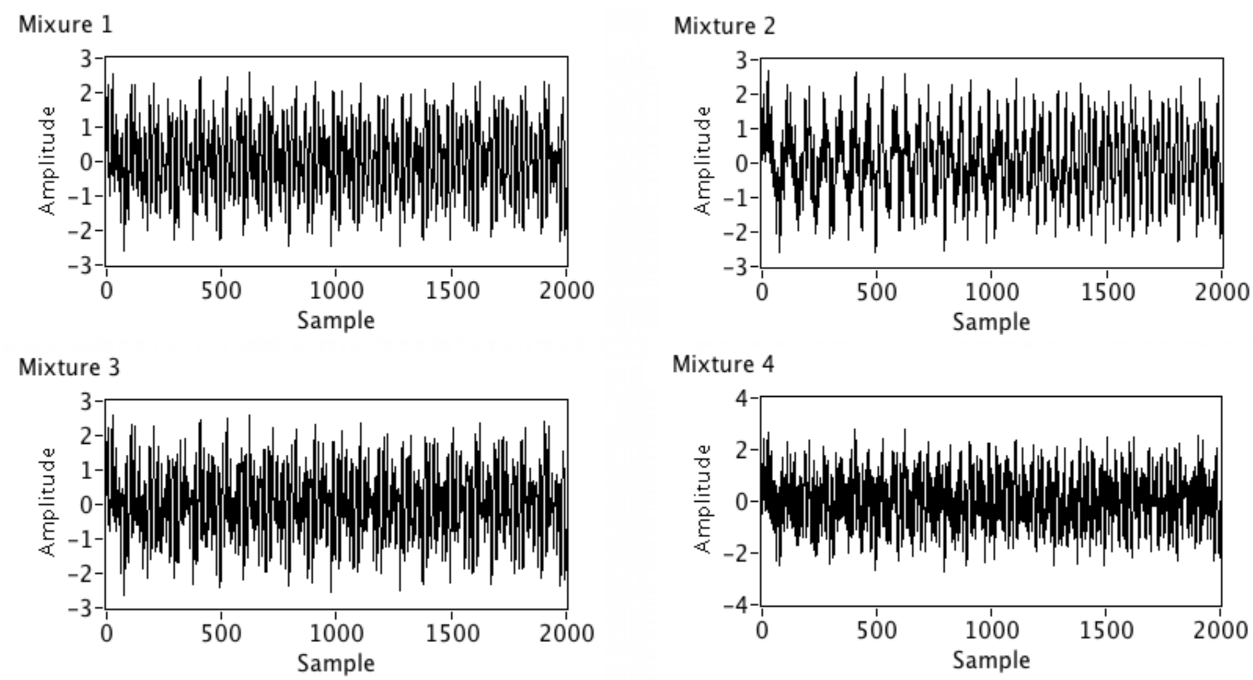

Figure 2.3: Signal mixtures obtained by multiplying the signals by a mixing matrix

2.5.2 Separation results

Separation was performed on the mixture signals by taking short time Fourier transforms of the signals with window length and time steps of respectively 512 and 32 points. The separation results for four generated signals are given in Figure 2.4. For comparison the STFT of the generated signals are given in Figure 2.5.

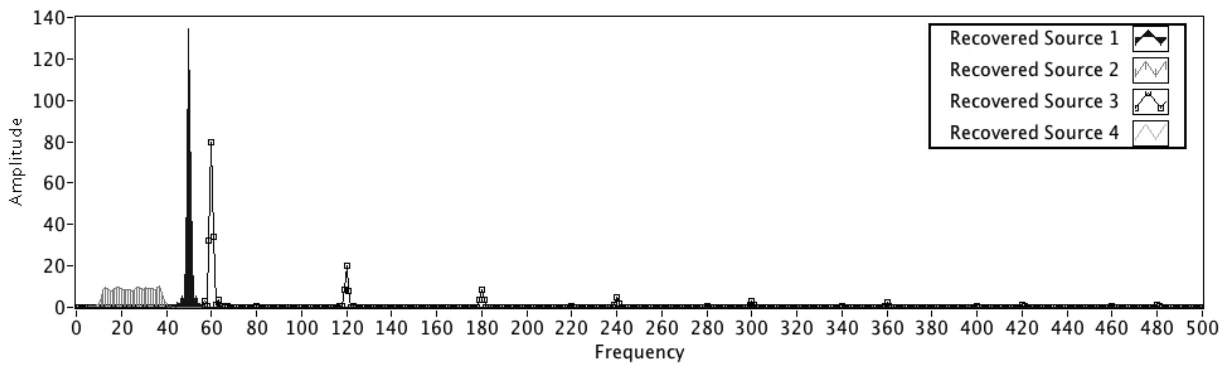

Figure 2.4: Separation results in the frequency domain

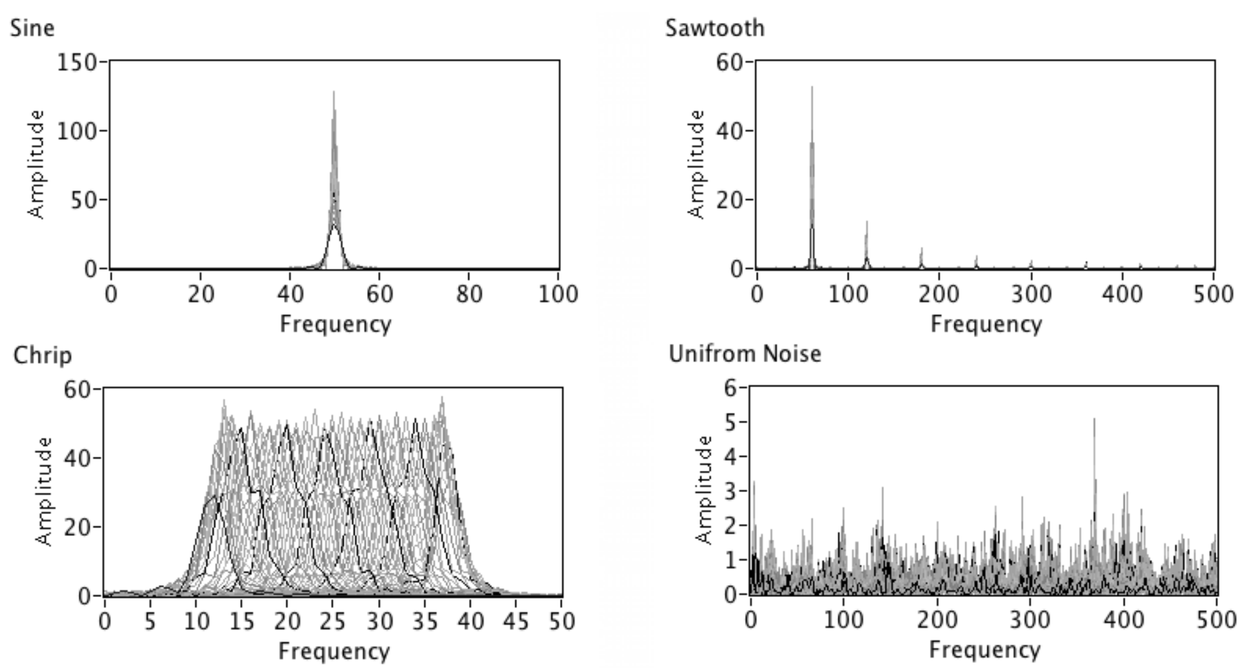

Figure 2.5: STFTs of the source signals

As shown, peaks pertaining to sine (50 Hz) and rectangular (60 Hz and its harmonics) signals are easily distinguishable. Uniform noise is attenuated to a great extent i.e. there are not any noticeable random peaks. The chirp signal appears as a signal covering a range of frequencies from 10 to 40 Hz. In fact, due to the transient nature of the chirp signal the instantaneous figures of the signal were lost during averaging. This however, does not reduce the effectiveness of the proposed method since chirp-like signals are very rare in rotating machinery and seldom exist unless non-stationary states of the machines are considered.

2.6 Experiments using real signals

In order to verify the practicability of the proposed method, two case studies using vibration signals from two different test facilities were carried out. The description of each test facility and the discussion of the results for each case are represented in the following sections.

2.6.1 First case study

2.6.1.1 Experimental setup and data acquisition

In the first case, vibration signals were collected from a test setup at École Polytechnique de Montréal consisting of a 2 HP motor coupled to a shaft supported by two different bearings. One bearing was an overhauled roller bearing (PWC15) provided by Pratt & Whitney Canada from one of their engines. The other bearing was an SKF ball bearing (1217K). Each bearing was encompassed by a housing that was bolted to an adjustment base. The adjustment base was also bolted to the main base. This way each housing together with the bearing inside can be considered a subsystem that is connected through another subsystem (adjustment base) to the main base. Four accelerometers were used, one mounted on each bearing housing and two on the

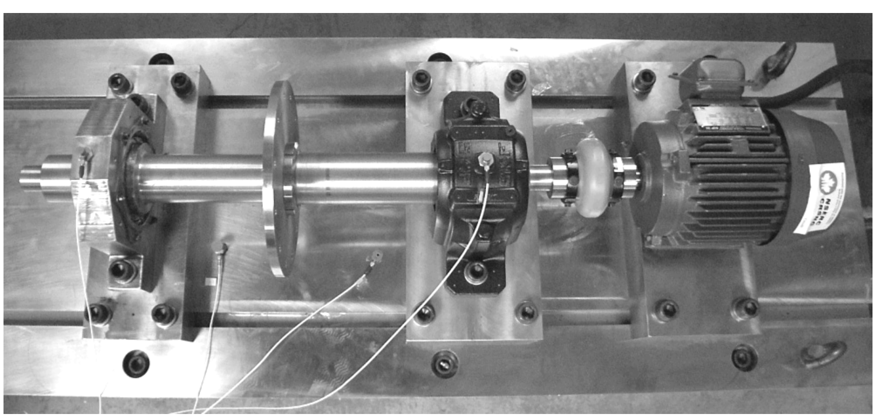

Figure 2.6: Test setup with a PWC15 bearing mounted on the left end of the shaft

main base (Figure 2.6). Signals were gathered at a sampling frequency of 2 kHz for a period of 10 seconds while the shaft was running at a speed of 900 RPM (15 Hz).

2.6.1.2 Separation results and discussion

Similar to the case using synthetic signals, short time Fourier transforms of the signals with window length and time steps of respectively 512 and 32 points were obtained. The Fourier transforms of signals gathered by each accelerometer are shown in Figure 2.7. The four frequency representations show certain distinguishable peaks at different frequencies. However, it is not clear if the peaks are noise or actual oscillations caused by a component. Also, it is not possible to determine the source of each peak. The separation results up to 150 Hz are shown in Figure 2.8. The results are plotted in different styles. Each style represents the signals pertaining to an accelerometer. For the profile pertaining to accelerometer 1 (located on the PWC15 roller bearing housing) two dominant peaks, one at around 69 Hz and another at around 138 Hz can be singled out. Further, for accelerometer 2 (located on the 1217K SKF bearing) except for one peak at 30 Hz there is another dominant peak at 59 Hz. For other accelerometers on the base there are a number of peaks, mostly occurring in the range from 100 to 150 Hz.

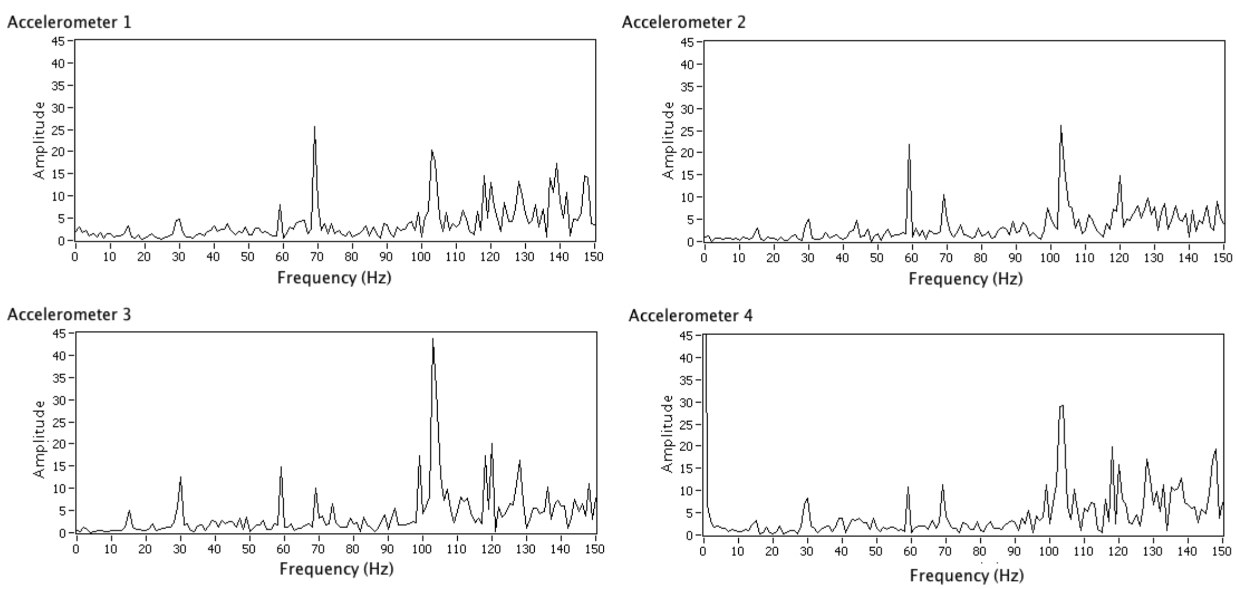

Figure 2.7: Frequency representations of signals collected by four accelerometers

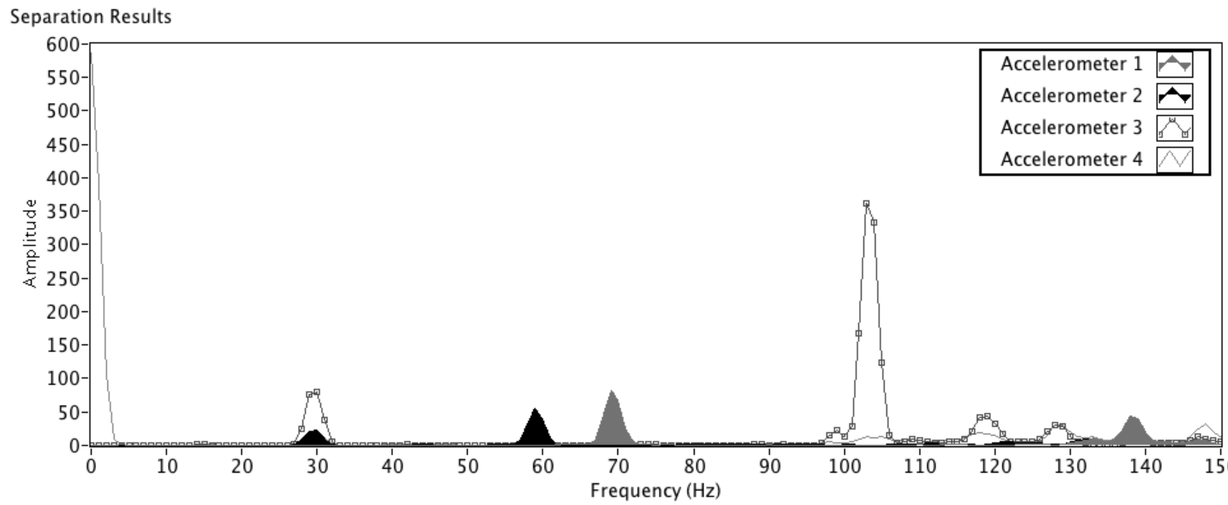

Figure 2.8: Separation results for case of PWC15 and 1217K SKF bearings

As discussed in the introduction, verifying the performance of separation methods used for vibration sources is very complicated and is the main purpose of this study. The question arises; how to verify the separation quality of the results obtained using the proposed method? Fortunately in this case there are not many components and also the bearings are of different types. Under these conditions the characteristic frequencies of the bearings can be used to verify the results. It must be noted that this method of evaluation loses its effectiveness in complex systems wherein different components may produce vibration in near frequency bands.

Table 2.1: Characteristic frequencies of the bearings used in the experiments

Bearing		**PWC**	**SKF 1217K**	**SKF 1216K**	**Rexnord**
Rotational frequency of rolling element assembly [Hz]	f_c	5.77	6.6	6.65	14.8
Rotational frequency of a rolling element [Hz]	f_r	30.7	61.2	65	140
Over-rolling frequency of one point on inner ring [Hz]	f_{ip}	111	176	184	297
Over-rolling frequency of one point on outer ring [Hz]	f_{ep}	69.2	139	146	236
Over-rolling frequency of one point on rolling element [Hz]	f_{rp}	61.5	122	130	280

The characteristic frequencies of the bearings (Table 2.1) were calculated using following equations [16]:

Rotation frequency of rolling element assembly:

$$f_c = \frac{f_s}{2}\left(1 - \frac{D_B}{D_P}\cos\theta\right) \qquad \text{Eq. 2.1}$$

Rotational frequency of a rolling element:

$$f_r = \frac{f_s}{2}\frac{D_P}{D_B}\left(1 - \frac{D_B^2}{D_P^2}\cos^2\theta\right) \qquad \text{Eq. 2.2}$$

Over-rolling frequency of one point on the inner ring

$$f_{ip} = \frac{f_s}{2}N_B\left(1 + \frac{D_B}{D_P}\cos\theta\right) \qquad \text{Eq. 2.3}$$

Over-rolling frequency of one point on the outer ring

$$f_{ep} = \frac{f_s}{2}N_B\left(1 - \frac{D_B}{D_P}\cos\theta\right) \qquad \text{Eq. 2.4}$$

Over-rolling frequency of one point on a rolling element

$$f_{rp} = \frac{f_s D_P}{D_B}\left(1 - \frac{D_B^2}{D_P^2}\cos^2\theta\right) \qquad \text{Eq. 2.5}$$

where f_s is the shaft rotation speed in Hz, D_B is the diameter of the ball, D_P is the distance between the center of two opposing balls (pitch), $N_B$is the number of balls and θ is the contact angle of the ball. In comparison with the separation results it can be noticed that the peak at 69 Hz relating to the closest component to accelerometer 1 (i.e., PWC15 bearing) equals the over-rolling frequency of one point on the outer ring of the PWC15 bearing. The existence of such a fault on the outer ring of the PWC15 bearing was confirmed by visually analysing the bearing after the tests. Further, at around 60 Hz, which is very close to the rotational frequency of a rolling element of the SKF bearing, there is a peak related to a component in the vicinity of accelerometer 2. Contrary to the abovementioned concurrences, there is a peak at around 139 Hz related to accelerometer 1 and supposedly to the PWC15 bearing that matches with the 1217K SKF bearing's frequency of one point on the outer ring. This might be considered as a misconstrue but, as mentioned before, the SKF 1217K bearing was a new bearing and an outer race fault is very unlikely. Moreover, this peak occurs at 139 Hz which is, not accidentally, twice the frequency of the outer ring fault of PWC15. In order to further investigate from which bearing this peak emanated, a separate test session was carried out in which the PWC15 bearing was replaced with a 1216K SKF bearing. The separation results are demonstrated in Figure 2.9. The two peaks at 69 Hz and 139 Hz no longer exist, showing that they most probably emanated from PWC15 in the previous test. Another significant difference with the previous test is that the high amplitude peaks ranging from 100 to 150 Hz disappeared. Instead there are peaks at frequencies equal to the rotation frequency and its harmonics. These frequencies are mostly related to wellness of the shaft mount and bearings, the imbalance disk, etc. Even with further adjustments in the shaft mount it is possible that the frequency peak at 59 Hz might have been provoked in the bearing by shaft misalignment.

It must be pointed out here that the probable sources of the peaks that are dominant for accelerometers 3 and 4 are neither evident nor of main concern for the authors. Nevertheless, motor, resonance frequencies of the base or other external sources can be blamed for such occurrences.

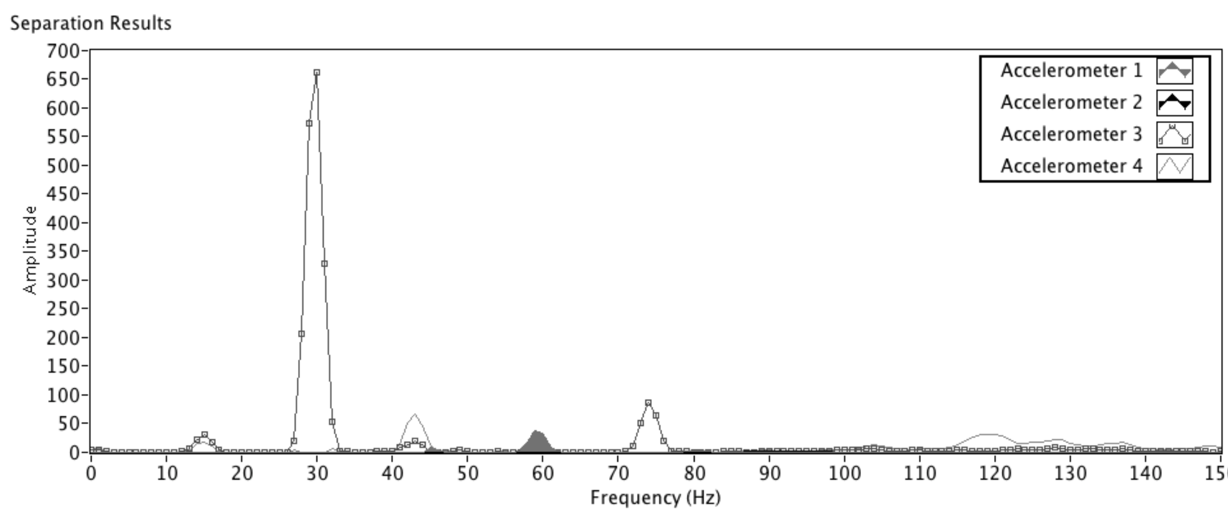

Figure 2.9: Separation results for case of 1216K SKF and 1217K SKF bearings

2.6.2 Second case study

In order to further validate the proposed method, a bearing data set provided by the Center for Intelligent Maintenance Systems (IMS) of University of Cincinnati through NASA Ames Prognostics Data Repository [17] was used.

2.6.2.1 Experimental setup and data acquisition

In this test four double row Rexnord ZA-2115 bearings were mounted on a shaft driven by an AC motor (Figure 2.10). Vibration data was gathered using four accelerometers, one on each bearing housing, at a sampling rate of 20 kHz. A spring mechanism exerted a radial load of 6000 lbs on the rotating shaft and the bearing. Data snippets of approximately 1 second in duration were gathered at 10 minute intervals throughout a run-to-failure test. In this study, one of the snippets was selected in which an outer race fault on the third bearing was clearly discernible.

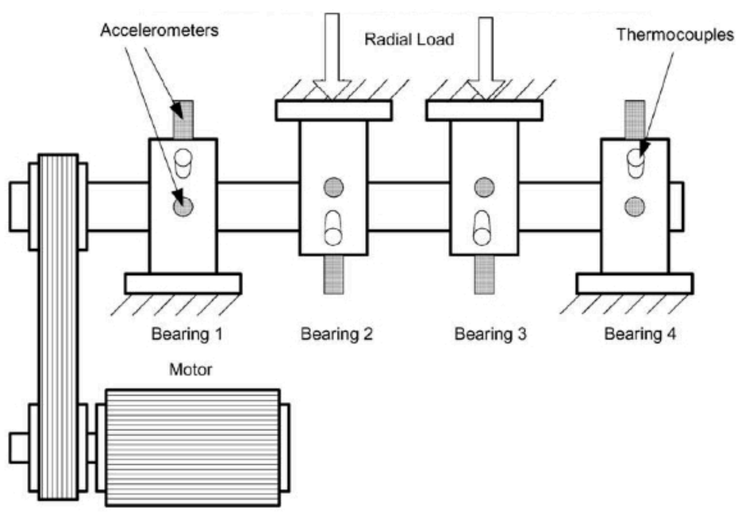

Figure 2.10: Schema of the test rig at IMS, of University of Cincinnati (by courtesy of [18])

2.6.2.2 Separation results and discussion

Separation results for this case are shown in Figure 2.11. The same window length and time steps were used with a higher number of frequency bins to attain better frequency resolution. According to Table 2.1, due to a fault on the outer race of the third bearing, a peak at 236 Hz is expected in the resulting profile corresponding to accelerometer 3. In Figure 2.11 this peak occurs on the right profile but with a slightly lower frequency. This error has also been reported in [18]. To briefly summarize; results are consistent with the proposed method for this case as well.

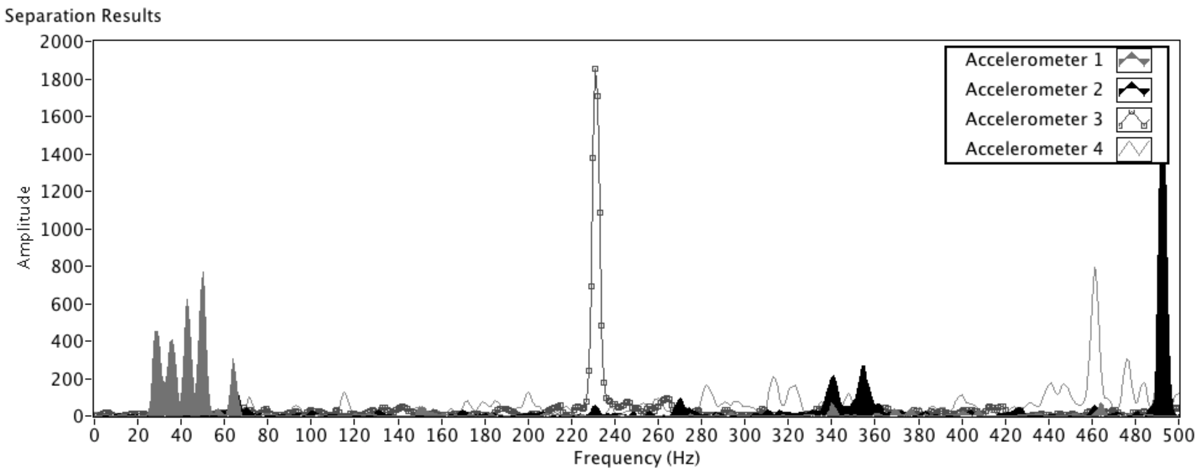

Figure 2.11: Separation results for case of Rexnord bearings

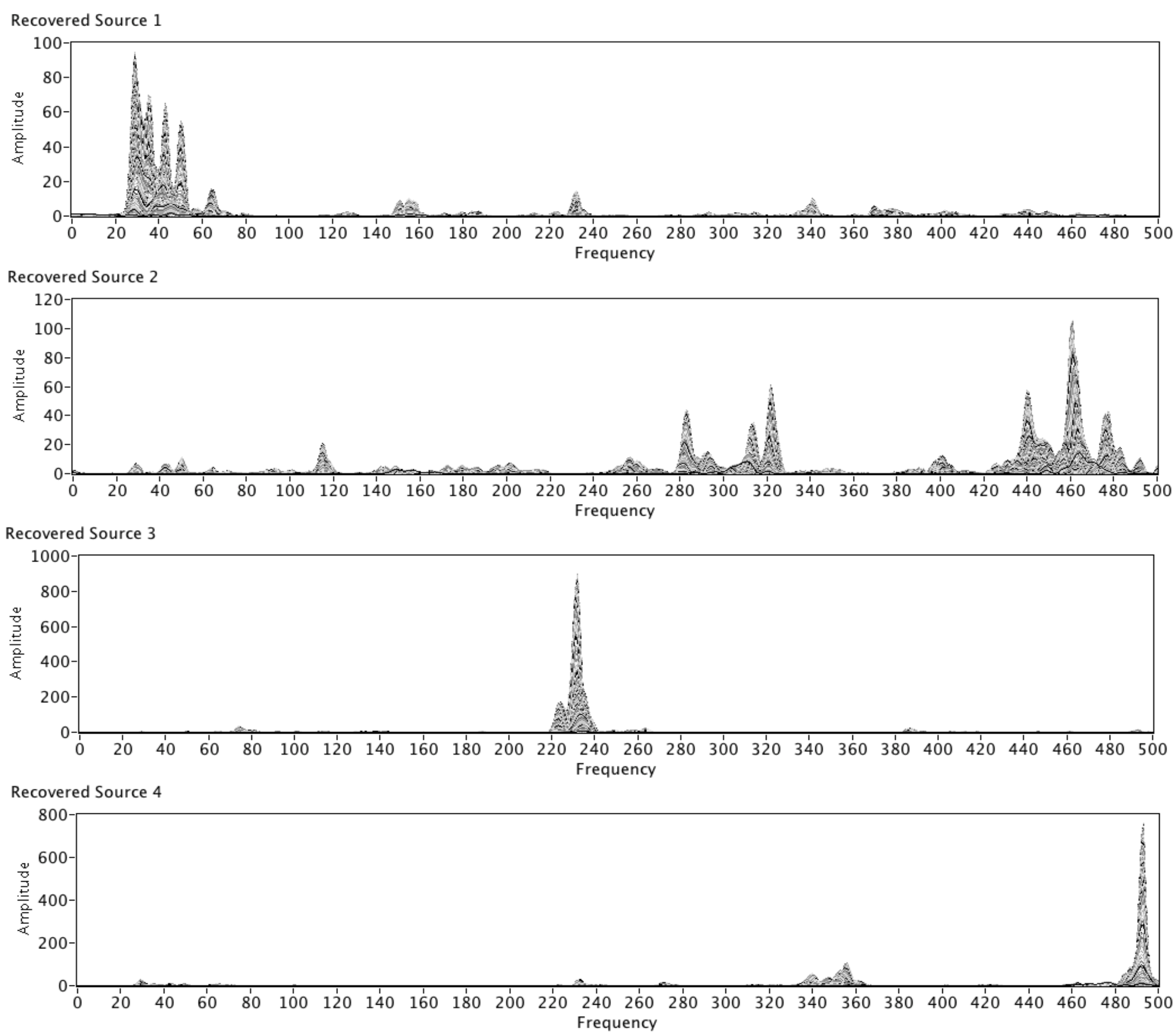

Figure 2.12: Separation results for the case of Rexnord bearings using an ICA technique

For the purposes of demonstrating how this method would be applied, the results are compared with the outputs of a statistical method. In this case, an ICA technique developed by Cichocki and Unbehaunen [19] was used to separate the vibration signals and the results are presented in Figure 2.12. Unfortunately, due to permutation ambiguity inherent to ICA [1], the results may not be in the same order as the other method. Nonetheless, a very good correspondence between the results of the two methods can be established. That is, the four recovered sources (i.e., 1, 2, 3 and 4) using the ICA technique of Figure 2.12 closely resemble the profiles obtained for accelerometers 1, 4, 3 and 2 respectively. It can be concluded that the results from different methods are in very good complimentary agreement.

Overall, the experimental results support the proposed method very well. One shortcoming of this method however, is that the vibration produced or provoked by shaft itself might be misinterpreted as signals from the bearings as in the first case. The cause for this lies in the fact that the bearings are usually the only connection between the shaft and the base, casing or whichever surface can be used to attach a sensor.

2.7 Conclusion

A separation method based on frequency signatures obtained from signals gathered from multiple sensors positioned in different locations of the system was presented. This method has a simple yet solid theoretical basis driven by the concept of statistical energy analysis. The performance of the method was verified using a series of experimental tests on synthetic signals and real laboratory signals collected from different bearings. Despite its simplicity, the results confirmed the efficacy of the method. Some shortcomings associated with this method were also discussed. To summarize: this method may not be very effective or accurate in systems with transitory behaviour. Also, in systems with very densely mounted components, determining the subsystems and therefore the best location for the sensors can be very challenging. As a recommendation for future work, the effectiveness of this method can be further investigated with signals obtained from other test cases as well as a real industrial case.

2.8 Acknowledgement

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CHAPTER 3 INDEPENDENT COMPONENT ANALYSIS AS APPLIED TO VIBRATION SOURCE SEPARATION AND FAULT DIAGNOSIS

Ali Mahvash and Aouni A. Lakis

Section of Applied Mechanics, Department of Mechanical Engineering, École Polytechnique of Montréal, Montreal H3T 1J4, Canada.

3.1 Abstract

In health monitoring of complex mechanical systems such as aircraft engines there are many components the diagnosis of which is of great interest for the industry. A conventional way to monitor these components is to collect vibration signals using accelerometers placed in their closest vicinity. However, due to some restrictions such as inaccessibility, it is not always practical to place the accelerometers as such. In many cases, the pre-installed instrumentations are used which are usually inadequate and placed on the carcass of the structure. Nevertheless, even if the accelerometers are positioned very close to the components, they would collect signals not just from one specific component but from other components as well. In this study, we sought to employ frequency-based Independent Component Analysis (ICA) to recover the signals produced by components within a single complex system. In such a case, differences between 'blind source separation' and vibration source separation are discussed. A new workaround for the permutation ambiguity encountered in the implementation of ICA is proposed. Finally, in order to demonstrate the applicability of the new proposed approach, experimental results carried out on a test bed are presented.

Keywords: Vibration Source Separation, Independent Component Analysis, Blind Source Separation, Multi-sensor vibration acquisition.

3.2 Introduction

Complex mechanical systems such as aircraft engines are composed of many components that must be included in a health monitoring system. Diagnosis of the condition of these components is of great interest for the industry. A conventional way to monitor these components is to collect vibration signals using accelerometers placed in their closest vicinity. However, due to some restrictions such as the manufacturer's warranty policy and inaccessibility, it is not always practical to place the accelerometers in these locations. In many cases, the only options are to use pre-installed instrumentation (usually inadequate) or to place a number of accelerometers on the innermost possible surface of the structure. In either case, even if the accelerometers are positioned very close to the components, they collect signals from not just one specific component but from other components as well. Hence, signals collected by a sensor are a complex combination of the vibration energy produced by different components entangled with ambient noise. This makes it difficult to determine which component dominates the collected signals.

The first attempt in diagnosis of faults in a complex system is therefore to decompose the signals into components corresponding to the system's components or, simply put; determining what signals come from which component. This concept in the literature is referred to as 'source separation' and if the components of the system are not well identified it is called 'blind source separation'. The foremost existing mathematical solution to blind source separation is Independent Component Analysis (ICA).

In Independent Component Analysis it is assumed that the source signals are statistically independent from one another and can be recovered by formulating the independence [1,2]. However, as will be further discussed, there are always two dominant ambiguities and indeterminacies associated with independent component analysis. First, the original index of the sources is unknown. That is to say, ICA does not provide labeling or permutation of the recovered signals with respect to their actual sources. It comes from the fact that the mathematical independency is insensitive to the permutation of the sources. The second ambiguity is that the actual scale of the sources cannot be determined. This means that the recovered signals might be an amplified or otherwise attenuated version of the original signals. This is also due to insensitivity of the mathematical independency to the scaling factor.

There are a number of algorithms and approaches to carry out signal separation based on the concept of ICA [2]. These methods can be applied in both time- and frequency-domains. Which domain to choose depends mostly on the mixing mechanism. If the mixing mechanism is *instantaneous,* (i.e., the signals are linearly mixed) time-domain methods are the most effective and efficient. If the mixing mechanism is *convolutive*, (i.e., the signals are nonlinearly and convolutedly mixed) then frequency methods are more appropriate whilst time-domain methods are limited. In most real cases including vibration in mechanical systems the mixing mechanism is known to be convolutive [3].

A number of researchers [3-11] have assessed the practicability of ICA in mechanical systems and fault diagnosis. Most previous works have focused on separating environmental noise from relevant signals produced by components or setups [4-7]. They perform their experiments on systems consisting of two separate sub-systems running on a structure and use both frequency- and time-domain methods to recover the signals emanating from each sub-system. Some authors employed only time-domain ICA methods to either reduce the noise [8] or extract relevant features [9] from signals. There does not seem to be any study with the direct focus of recovering source signals in a complex compact system [10,11].

In this study, we sought to employ frequency-based ICA to recover the signals produced by components within a single complex system. A new approach is proposed and tested to tackle “local” permutation indeterminacy. In order to demonstrate the applicability of the new approach, experiments were carried out on a test bed with a shaft driven by an electric motor and supported by two different bearings. This paper is structured as follows: first a concise description of blind source separation prepares the way to the basic theory of ICA. Then some considerations regarding source separation as applied to vibration source recovery are discussed followed by a presentation of a proposed approach of treating the convolutive signals in the frequency domain. This paper is finally concluded with a discussion and presentation of experimental results.

3.3 Blind source separation

3.3.1 Preamble

In the context of diagnosis of faults in a multi-component mechanical system, it is desired to have isolated data from every individual component in the system. This however cannot be attained using conventional measurement methods including vibration acquisition. Due to the mechanics of vibration propagation, signals gathered from one point on the system are at best a combination of the vibration energy produced by different components and sources. Treatment of this situation is the subject of a sub-domain in signal processing known as blind source separation. In blind source separation, it is assumed that adequate a priori information about the system components (i.e., sources) and mixing mechanism is not available and hence the system is considered a black box. The only requirement is that it be fitted with at least as many sensors as the number of components in the system. As will be discussed, considering a mechanical system as a black box is not realistic or necessary when dealing with fault diagnosis. This however, does not diminish the potential use of blind source separation techniques for this application.

Blind source separation consists in recovering the signals produced by different sources from a number of observations of mixed source signals. In mathematical terms the general model for blind source separation can be described as follows:

If there are p zero-mean source signals at time *t*, $S(t) = [s_1(t), \dots, s_p(t)]$, that are assumed to be statistically independent, and $X(t) = [x_1(t), \dots, x_m(t)]$ denote the mixture signals received by m sensors, the data model for an instantaneous mixture can be written as:

$$X(t) = AS(t) + N = \sum_{i=1}^{m} a_{ki}(t) s_k(t) + N \qquad \text{Eq. 3.1}$$

where A is the $m \times p$ mixing matrix consisting of unknown mixture coefficients. Figure 3.1 shows the block diagram of the above equation. It is always assumed that the sources are independent and the number of sensors is at least equal to the number of sources (i.e., $p \leq m$).

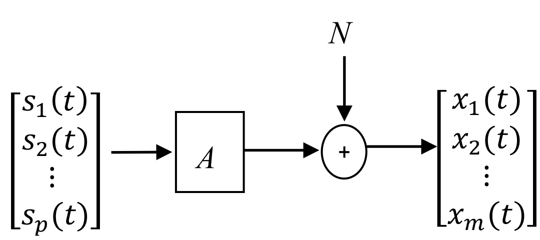

Figure 3.1: General data model for blind source separation

The most significant technique for finding the unknown mixture coefficients (A) that can be used in the model to recover the original sources (S) is Independent Component Analysis (ICA). A prerequisite for ICA to be applicable is that at most one source retains a Gaussian distribution.

This stems from the fact that ICA, if built on high-order statistics cannot separate Gaussian sources [1,2,12]. This is a downside of ICA as the vibration energy produced by different components can usually be distributed as though it were a Gaussian distribution. On the other hand, real events rarely, if ever, represent a perfect Gaussian distribution and therefore ICA can still be considered effective. In the following section the principle of ICA is presented.

3.3.2 Independent component analysis

Independent component analysis consists in finding an estimation of the sources:

$$\hat{S} = Y(t) = BX(t) \qquad \text{Eq. 3.2}$$

by determining matrix B such that the elements of Y become statistically independent. In other words, the value of one element does not provide any information on the value of the other elements of Y [13]. The procedure of applying independent component analysis is as follows: An independency measure is constructed to rank the independency between the elements of Y. The values of the elements of matrix B are iteratively estimated until the extremum independency for Y is reached. Among the most popular independency measures are maximization of non-Gaussianity [1], minimization of mutual information [1], maximum likelihood estimation [14] and (in earlier studies) nonlinear decorrelation [15]. Although these measures are different in principle, in some cases their algorithms are quite similar.

Regardless of the independency measure adopted, there are always two indeterminacies associated with independent component analysis. First, the original labeling of the sources is unknown. Since both S and A are unknown, the order of the terms can be freely changed. This is due to the fact that mathematical independency is insensitive to permutation of the sources. The second ambiguity is that the actual scale of the sources cannot be determined. Since both S and A are unknown, any scalar multiplier in one of the sources s_i can always be canceled by dividing the corresponding column a_i of A by the same scalar. This is also due to the insensitivity of mathematical independency to the scaling factor.

There are many algorithms to choose from, and for this study an algorithm presented by Cichoki and Unbehaunen [16] was used in the separation procedure due to its simplicity. This algorithm was driven using the nonlinear decorrelation measure. It is to be noted that the relationship between correlation and independence is that independent random variables are always uncorrelated while the contrary is not necessarily true. Nevertheless, independence can be to a great extent approached if some nonlinear functions of the random variables are uncorrelated. This is the basis for application of nonlinear decorrelation algorithms. The learning algorithm proposed by Cichocki and Unbehaunen is as follows:

$$\Delta B = \mu[I - f(y)g(y^T)]B \quad \text{Eq. 3.3}$$

where μ is a learning rate, B is the mixing matrix, I is the identity matrix, f and g are some nonlinear functions and T denotes transpose and in case of complex values conjugate transpose. This algorithm can be considered as a special case of the Amari et al. [17] method which is based on maximum likelihood estimation.

3.3.3 Convolutive mixtures and frequency domain analysis

The data model presented above pertains to the case where the mixing mechanism is assumed to be linear and instantaneous. This assumption is too simplistic for the majority of real applications. The mixing model in such cases is more consistent with a convolutive mixture. In the case of convolutive mixtures the data model can be rewritten as follows:

$$X(t) = A * S(t) + N = \sum_{i=1}^{m} a_{ki}(t) * s_k(t) + N \qquad \text{Eq. 3.4}$$

where A is the $m{\times}p$ mixing matrix consisting of unknown mixture coefficients. In this case, solving the inverse problem is not as straightforward as it was for the instantaneous data model. Certain methods have been suggested to solve the convolutive mixture model in its general form. However, such methods are very limited [13].

Fortunately, a convolutive mixing model in time domain becomes an instantaneous model when brought into the frequency domain. To be more precise, when data is represented using the joint time-frequency domain, at each frequency bin the mixing model is instantaneous and existing methods for instantaneous mixtures can be employed with minor modifications. Since data in the frequency domain are complex valued, instantaneous ICA methods must be modified for consistency with complex data. This can be simply done by taking a conjugate transpose wherever a matrix transposition is needed throughout computations. After performing separation at each frequency bin, the resulting separated signals are transformed back from frequency domain to time domain and the source signals are recovered. A problem with adopting this approach is indeterminacies associated with ICA. Due to this problem, separation results for all of the frequency bins may not necessarily encompass the same scale and permutation. From one frequency bin to another it is likely that the permutation of the sources is different. Thus, when transforming the separation results from frequency domain back to time domain the resulting time signals may not be comprised of the frequency components of a single source. This problem is sometimes referred to local permutation and scale determinacy compared to global ambiguities discussed earlier. A number of authors have suggested techniques to overcome this problem. For example, Anemuller and Kollmeier [18] introduced a method called AMCor based on the principle of amplitude modulation correlation. They argue that their method is applicable in cases where "the signal amplitude in different frequency bands undergoes interrelated changes" (i.e., speech signals). Capdevielle et al. [19] derived a criterion using second order moments based on the fact that from one frequency bin to another the moving average (MA) filtering of signals pertaining to the same source are equal. Servière and Fabri [7,11] used maximal cross correlation to relate the separation results of different frequency bins.

In this study a new approach is presented to overcome this difficulty. This approach is very fast and more computationally efficient than other existing methods. The approach will be detailed later on in this paper. First, the problems of scale and permutation indeterminacies for the case of vibration sources are discussed in more detail.

3.4 Blind source separation versus vibration source separation

As previously mentioned, in blind source separation the mixing medium is considered a black box. That is, no information is available about the components or the mixing mechanism. The only requirements are that the sources be statistically independent and the number of sensors be no less than the number of components. In this section these two requirements are discussed.

Concerning the number of the components or vibration sources, obscurity in the definition of component makes it difficult to come to a determination of the exact number of components [3]. For example, a ball bearing can be at the same time considered as a single component (which is usually the case) or as a number of parts (i.e., balls, outer race and inner race) each of which produce independent signals. In fault diagnosis, based on a practical point of view, a component can be considered as a part of a structure, machine, etc. that is either repairable or replaceable during maintenance. This way, the number of components can be approximated. However, it does not necessarily follow that a 'component' will act as though it is a single source. A replaceable part can consist of different elements, each of which produces statistically independent vibration signals. Hence, this remains an open question. In this study we apply ICA to vibration source separation by considering a component as a replaceable or a repairable part based on common sense.

Our first step in facilitating interpretation of the results of our analysis (i.e., use the separation results for fault diagnosis purposes) is to reconsider the definition of the system as a black box. This definition is not reasonable because the actual source of each signal component and its characteristics must be known as a prerequisite to any analysis. If, for example, the basic peak based spectrum analysis [20] is used for specifying possible faults in a bearing, one must have the characteristic frequencies of that bearing. In such cases, limiting our knowledge to consider only that an unknown source inside system is producing such a signal (the black box approach), is not necessary or efficient. In our approach, the components (sources) in the system are required to be known and also the global permutation indeterminacy must be resolved. Otherwise applying ICA is not effective for fault diagnosis in mechanical systems.

3.5 Permutation and scale indeterminacies

As mentioned earlier, there are two indeterminacies associated with ICA. These two indeterminacies are present in two stages while solving the convolutive mixtures problem using frequency methods. The first stage is when we link the separation results of all the frequency bins to construct time domain signals (local ambiguities). The second stage is when we associate the overall results to the sources (Global ambiguities). In this section, solutions for resolving these problems are proposed.

3.5.1 Local indeterminacies

Local indeterminacy is initially due to the inherent indeterminacy in ICA. To be more precise, it can be stated that it stems from the fact that ICA is usually implemented on each frequency bin independently. Thus the separation results at different bins may have different permutation and scaling. One way to tackle this problem is to tie or relate the implementation of ICA for different frequency bins. In this case, an insight of the mixing mechanism and system behaviour at different frequencies in the mechanical structure is helpful. A thorough analysis of the mixing mechanism allows one to define the transform function between the sources and the sensors. This analysis is, however, rather challenging due to the complexity and diversity of the mechanical systems. Yet, if the transmission route of the vibration energy between a sensor and a source is simplistically considered as a 1 degree of freedom (DOF) system, the in-between transmissibility for different values of damping and at different frequencies is as shown in Figure 3.2. As seen, there is a smooth and gradual change in the transmissibility as the frequency increases or decreases, i.e., no abruptness is present. This occurrence remains more or less similar in complex systems with more degrees of freedom, with the exception of natural frequencies of undamped systems. It can be therefore assumed that there is only a slight difference in the mixing mechanism for neighbouring frequency bins. This reflects also on the mixing matrix such that the mixing matrices of two adjacent frequency bins contain very close values.

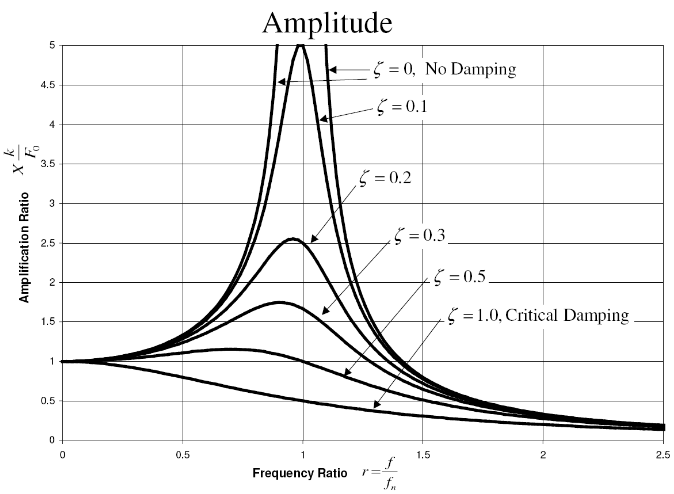

Figure 3.2: Transmissibility in a 1 DOF system

In the current algorithm (Eq. 3), matrix B is initialized as iterations are carried out at each frequency bin. The common initial value is identity matrix. To employ the abovementioned concept, once the iterations converge and the mixing matrix for one frequency bin is calculated, the obtained mixing matrix is set as an initial value for the next frequency bin calculation. This way, since the values of the mixing matrices for two adjacent frequency bins are close to one another, convergence is reached very fast leading to a fast overall convergence. Moreover, permutation of the mixing matrix is kept equivalent from one frequency bin to another. The only problem that may arise is that the new mixing matrix becomes too distant from the initial mixing matrix due to over-iteration. This problem can be corrected to some extent by restricting the convergence conditions such that over-iteration is avoided.

3.5.2 Global indeterminacies

Once the separation results are obtained and the original source signals are recovered, the next challenge is to relate these separation results to the system components. One possible approach to do this is by analyzing the spectrum of the signals based on the characteristic frequencies of each component. Although this method is beneficial, it is limited in the sense that the characteristic frequencies of all the components are not always available. Further, the characteristic frequencies of a component may or may not be present based on the component's health condition.

Another approach is to utilize the information about spatial distribution of the sensors and the components. That is, due to the difference between the propagation medium between any source and sensor, each sensor will record a different version of vibration produced in terms of vibration energy. This difference comes from the fact that dissipation of the energy of the vibration is not the same for different media. By comparing these different versions of recordings, one may be able to identify the source of harmonic components of the vibration signals. In fact, if the system is considered as a number of proper subsystems that are coupled to one another, according to the concept of Statistical Energy Analysis [21] sensors located in the subsystems farther from a subsystem enclosing a vibration source should pick up attenuated versions of the vibration signals compared to the ones located in the nearer subsystems due to internal and coupling losses. The only prerequisite is to correctly determine the subsystems and place the sensors in the right subsystems. A subsystem can be distinguished by first identifying the couplings. These take many forms, and may range from a bolted joint to a discontinuity such as a step change in wall thickness [22]. This approach is used in this study to solve the global permutation indeterminacy.

The procedure to employ this approach, hereinafter referred to as the *spatial proximity* approach is as follows:

The total number of sensors is (*N*). $X_i(f,t)$ the Short Time Fourier Transform of the signals $x_i(t)$ (where $i = 1, \ldots, N$) is obtained for a given period. For each short window and at each frequency bin *f* the intensities are set to zero except for the maximum signal intensity from each sensor (i.e. $argmax_i\, X_i(f,t)$). This way at each frequency the intensities of *N* spectra are either zero or maximum. Then, using the spatial diversity of sensors' location with respect to the components, each sensor together with its modified frequency representations is associated with a component. Finally, the results for all windows are averaged. This process leads to a sketch-like frequency representation of how the separation results may look in the frequency domain. By correlating this representation to the separation results obtained using ICA, it is possible to not only estimate the true source for each independent component, but also examine the quality of the separation.

3.6 Experiments

3.6.1 Data acquisition

In order to verify the practicability of the proposed method, vibration signals were collected from a test setup at École Polytechnique de Montréal consisting of a 2 HP motor coupled to a shaft supported by two different bearings. One bearing was an overhauled roller bearing (PWC15) provided by Pratt & Whitney Canada from one of their aircraft engines. The other bearing was an SKF ball bearing (1217K). Four accelerometers were used, one mounted on each bearing housing and two on the test base (Figure 3.3). Signals were gathered at a sampling frequency of 2 kHz for a period of 10 seconds while the shaft ran at a speed of 900 RPM (15 Hz).

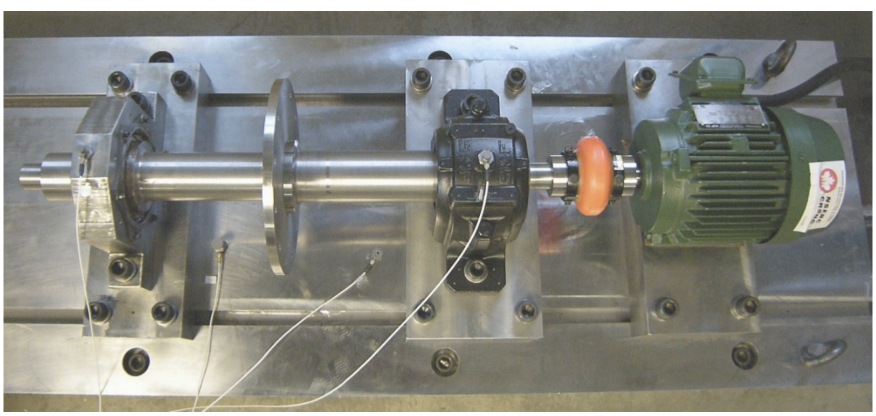

Figure 3.3: Test setup with PWC15 bearing mounted on the left end of the shaft

3.6.2 Separation results and discussion

Original time-domain vibration signals measured over a 10-second time interval were transformed into the time-frequency domain using short time Fourier transforms (STFT) with a window length and time step of respectively 512 and 32 points. The Cichocki and Unbehaunen algorithm [16] was used by setting $g(y) = \tanh(y)$ and $f(y) = 1 - \tanh^2(y)$. These functions were applied to real and imaginary parts of the random variable y separately so that the complex data could be handled more efficiently, as suggested by Smaragdis [23]. The outputs were brought together to shape complex data in order to retain consistency.

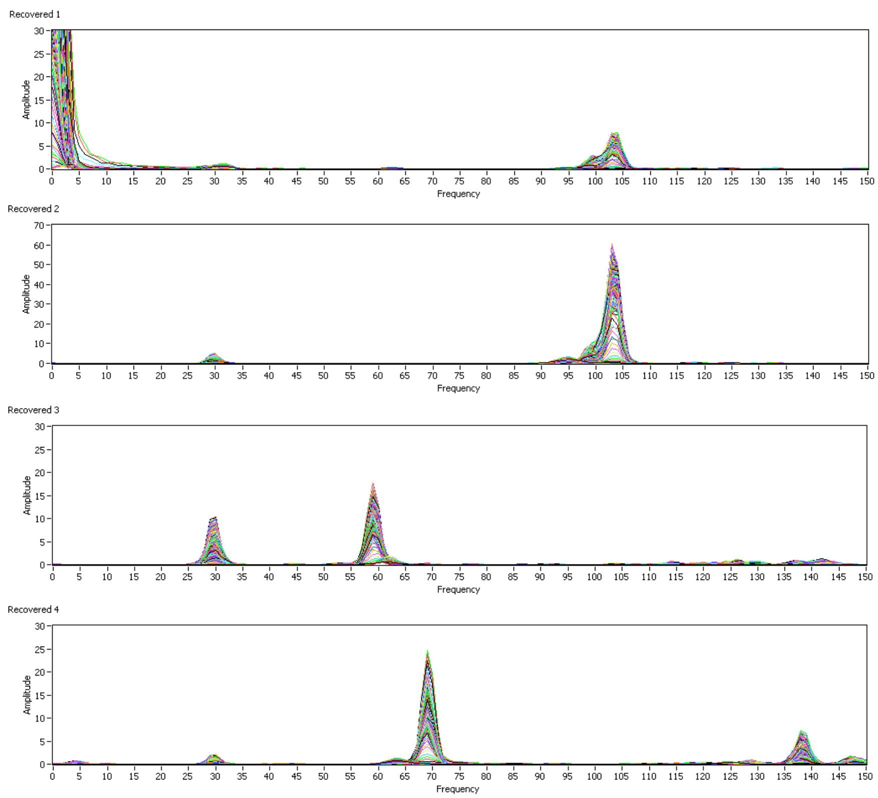

Figure 3.4: Separation results using ICA for the case of PWC15 and 1217K SKF bearings

The separation results up to 150 Hz (which is 10 times the rotation speed) are shown in Figure 3.4. For comparison and to estimate the correct permutation of recovered signals, the results obtained using the sensor spatial diversity method with STFTs of signals with the same window length and time step as above are shown in Figure 3.5. In this figure separation results are plotted in different styles where each style represents the signals pertaining to a given accelerometer.

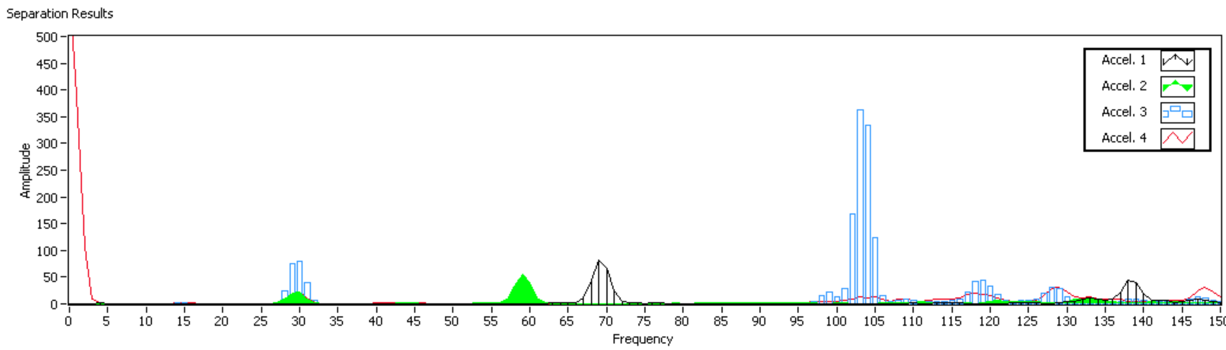

Figure 3.5: Separation results using the spatial proximity method

As shown in Figure 3.4, apart from vibration peaks occurring at 30 Hz (that is, twice as high as the shaft's rotation speed and present in all the plots) recovered signals 1 and 2 both contain high peak vibration ranging from around 95 Hz to 105 Hz. According to the spatial proximity plot (Figure 3.4), these signals are coming from a source close to the setup base. By further comparing the two figures it can be seen that a vibration peak at around 59 Hz appears in both recovered signal 3 (Figure 3.4) and the signals thought to be coming from a source closer to accelerometer 2 (Figure 3.4). For recovered signal 4 there are two vibration peaks; one at around 69 Hz and another at around 138 Hz that are interestingly also distinguishable on the other plot for accelerometer 1. It can be concluded that recovered signals 1 and 2 pertain to sources close to accelerometers 3 and 4 and recovered signals 3 and 4 to accelerometers 2 and 1. Therefore, recovered signals 1 and 2 are assumed to be from unknown sources on the setup base or perhaps the base itself. This is not a main concern for this study. We are more concerned about recovered signals 3 and 4, which emanate from the 1217K SKF bearing and PWC15 roller bearing respectively.

Table 3.1: Characteristic frequencies of the bearings used in the experiments

Bearing	***PWC15***	***SKF 1217K***
f_c	5.77	6.6
f_r	30.7	61.2
f_{ip}	111	176
f_{ep}	69.2	139
f_{rp}	61.5	122

Verifying the performance of the separation methods used for vibration sources is quite complicated. So far, the results obtained using two different methods; the ICA and spatial proximity method, are shown to be in close agreement. In order to further investigate the wellness of the obtained results they were analyzed and compared to the characteristic frequencies of the bearings. The characteristic frequencies of the bearings (Table 3.1) were calculated using following equations [24]:

Rotation frequency of a rolling element assembly:

$$f_c = \frac{f_s}{2}\left(1 - \frac{D_B}{D_P}\cos\theta\right) \qquad \text{Eq. 3.5}$$

Rotational frequency of a rolling element:

$$f_r = \frac{f_s}{2}\frac{D_P}{D_B}\left(1 - \frac{D_B^2}{D_P^2}\cos^2\theta\right) \qquad \text{Eq. 3.6}$$

Over-rolling frequency of one point on the inner ring

$$f_{ip} = \frac{f_s}{2}N_B\left(1 + \frac{D_B}{D_P}\cos\theta\right) \qquad \text{Eq. 3.7}$$

Over-rolling frequency of one point on the outer ring

$$f_{ep} = \frac{f_s}{2}N_B\left(1 - \frac{D_B}{D_P}\cos\theta\right) \qquad \text{Eq. 3.8}$$

Over-rolling frequency of one point on a rolling element

$$f_r = \frac{f_s D_P}{D_B}\left(1 - \frac{D_B^2}{D_P^2}\cos^2\theta\right) \qquad \text{Eq. 3.9}$$

where f_s is the shaft rotation speed in Hz, D_B is the diameter of the ball, D_P is the distance between the center of two opposing balls (pitch), $N_B$is the number of balls and θ is the contact angle of the ball.

By comparing the separation results, it can be observed that the vibration peak at 69 Hz in the resultant PWC15 bearing signature equals the over-rolling frequency of one point on the outer ring of that bearing. The existence of this fault was confirmed by visually analyzing the bearing after the tests. Further, at around 60 Hz, which is very close to the rotational frequency of a rolling element of the 1217K SKF bearing, there is a peak related to a component in the vicinity of accelerometer 2. Contrary to the abovementioned concurrences, there is a peak at around 139

Hz related to accelerometer 1 and supposedly to the PWC15 bearing that matches the 1217K SKF bearing's frequency of one point on the outer ring. This might be considered as a misconstrue but, as mentioned before, the 1217K SKF bearing was a new bearing and an outer race fault is very unlikely. Moreover, this peak occurs at 139 Hz which is, not accidentally, twice as big as the frequency of the outer ring fault of PWC15.

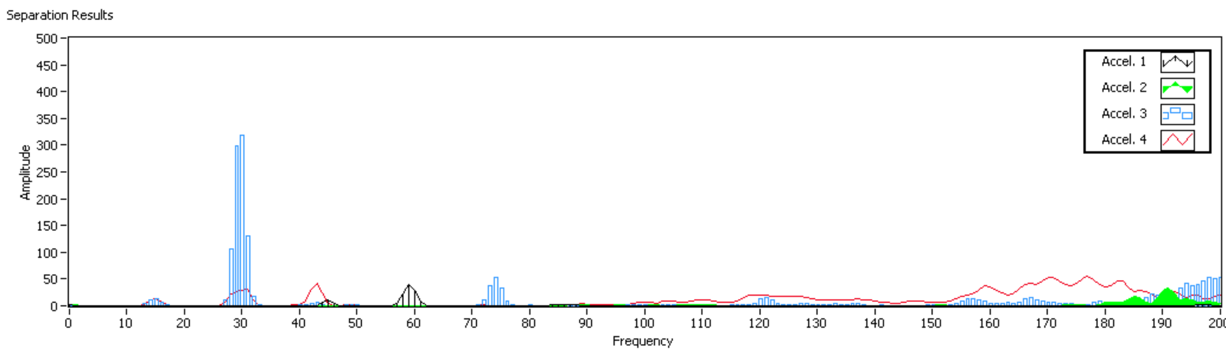

Figure 3.6: Results using spatial proximity for the test with two SKF bearings

In order to further verify the accuracy of the method, a separate test session was carried out in which the PWC15 bearing was replaced with a 1216K SKF bearing. Figure 3.6 shows the results obtained using the spatial proximity method over a range of 1 to 200 Hz. As seen, by replacing the PWC15 bearing, the two peaks at 69 Hz and 139 Hz disappeared, showing that they most probably emanated from PWC15 in the previous test. Another significant difference with the previous test is that the high amplitude peaks ranging from 100 to 150 Hz disappeared. Instead there are peaks at frequencies equal to the rotation frequency and its harmonics. These frequencies are mostly related to wellness of the shaft mount and bearings, the imbalance disk and such. It is also possible that the vibration peak at 59 Hz might have been provoked by shaft misalignment in the shaft mount. Moreover, except for some vibration peaks occurring between 180 and 200 Hz, there are no signals produced by the 1216K SKF bearing at lower frequencies with high enough amplitude to stand out in the results of proximity method.

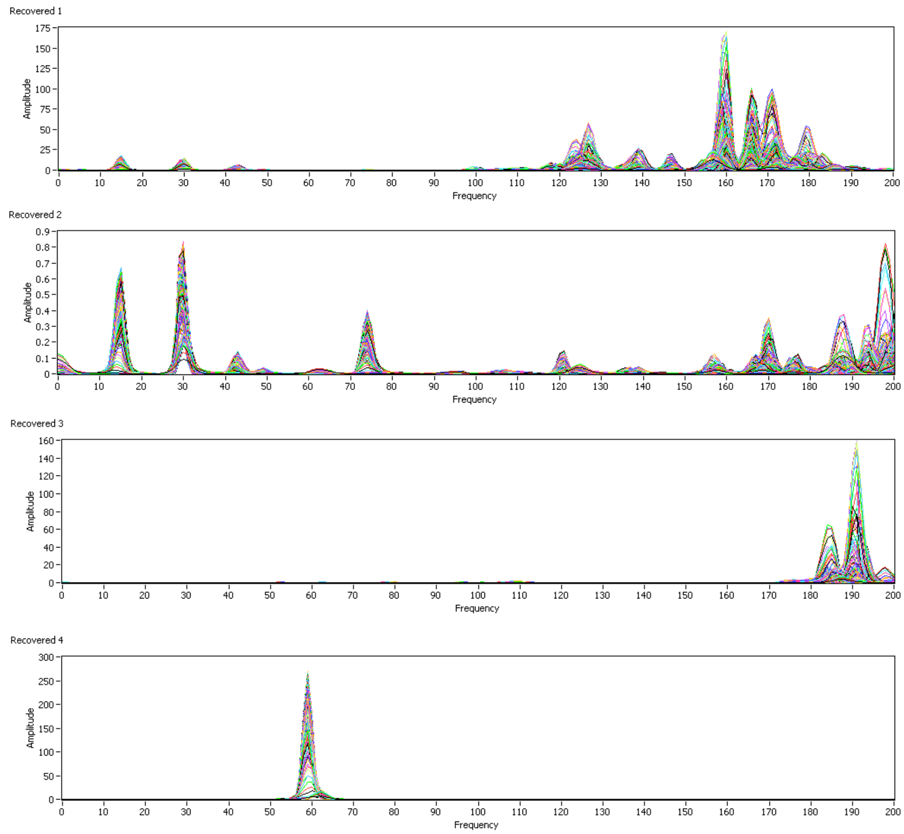

Figure 3.7: Separation results using the ICA method for the case of two SKF bearings

The separation results using ICA method for the case of two SKF bearings are given in Figure 3.7. These results are in good agreement with the results of the spatial proximity method. However, since the bearings were both in new condition and hence no bearing-related vibration peaks appeared in the results, it is very hard to draw conclusions from the observations. Most of the vibration peaks are harmonics of the rotational speed produced by shaft itself. In this case, the proximity method is unreliable since no distinction can be made in terms of shaft's distance to the accelerometers.

3.7 Conclusion

Independent Component Analysis was applied to the case of vibration source separation with modifications to the learning algorithm to adapt it for the case of vibration separation. The performance of the method was verified using a series of experimental tests on real laboratory signals collected from different bearings. Results were compared with another method based on frequency signatures obtained from signals gathered from multiple sensors positioned in different locations in the system. The interesting accordance between results from ICA, the spatial proximity method and the peak analysis method confirmed the efficacy and potential of the ICA frequency-domain method and approach introduced for tackling the local permutation problem. As a recommendation for future work, the effectiveness of this method can be further investigated with signals obtained from a real industrial case. Additionally, the separated signals can be fed into an automatic fault diagnosis method to verify its competence in such cases. Moreover, this method can be tried on a system with limited instrumentation.

3.8 Acknowledgement

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CHAPTER 4 APPLICATION OF CYCLIC SPECTRAL ANALYSIS IN DIAGNOSIS OF BEARING FAULTS IN COMPLEX MACHINERY

Ali Mahvash and Aouni A. Lakis

Section of Applied Mechanics, Department of Mechanical Engineering, École Polytechnique of Montréal, Montreal H3T 1J4, Canada.

4.1 Abstract

Bearing failure can lead to major damage to rotating components and its diagnosis and prognosis are therefore of paramount importance. Techniques and approaches for detecting bearing faults abound. However, application of these methods is limited for complex systems such as aircraft engines. This stems from the fact that the complex configuration of the system and inaccessibility make it difficult to place the vibration transducers close to the bearings. In most cases, available instrumentation is limited to a few vibration transducers on the casing of the machine. In such cases, the vibration due to bearing faults are barely detectable using traditional methods, as they normally make only a small contribution to the overall energy and this is to some extent dissipated by the transmission path. For bearing fault detection to be effective in such applications, the methodology must be capable of detecting faint bearing signals and also allow consistent trending and tracking. This study examines these requirements in detail and presents an experimental assessment of newly emerging cyclic spectral analysis in this field for such requirements.

Keywords: cyclic spectral analysis, cyclostationary, bearing fault detection, complex machinery, condition monitoring.

4.2 Introduction

Bearings are one of the key components found in almost any rotating machinery and have notably drawn attention from the health monitoring research community. As bearing failure can lead to catastrophic damage to other rotating components, its diagnosis and prognosis are of paramount importance. Fortunately the mechanics of bearing deterioration are well-known. The development of the very familiar bearing characteristic frequencies (tones) dates back to a few decades ago [1]. These characteristic patterns have enabled monitoring of bearings through vibration data acquired using pertinent transducers. For any fault on the bearing, its corresponding tone is expected to appear on the frequency domain (spectral) representation of vibration signals. Fourier transforms (FT) and their derivatives, namely, Fast Fourier transforms (FFT) and Short Time Fourier Transforms (STFT) are extensively used to obtain such spectral representations. One difficulty with this approach is that the vibration transducers are usually required to be mounted close to the bearings. This is due to the fact that the energy of vibration signals attenuates as one goes farther away from the bearings and the likelihood of detecting bearing tones decreases. Also, in complex systems, interfering noise from other components can further complicate the situation.

In highly sophisticated and complex systems such as gas turbine engines, complexity of the system and inaccessibility make it difficult to place the vibration transducers close to bearings. In most cases, available instrumentation is very limited and only a few accelerometers are available that collect the vibration signal from the casing of the engine. With many components producing vibration, the bearing tones are very hard to distinguish in the spectral representation of the vibration signals. Moreover, they normally generate minimal energy in the early stages of failure and this energy is further dissipated by the complex transmission path.

To tackle the problem of making the faint bearing signal more distinctive among the signals from other components, different signal processing approaches can be adopted. One approach is to regard this case as a blind source separation (cocktail party) problem and turn to developed statistical and mathematical methods for this purpose, mainly Independent Component Analysis (ICA) [2], to separate bearing tones from interfering signals. Apart from statistical independence, no other specific assumption is made on the type of signal produced by the bearings. The main focus usually is put on the mixing mechanisms which may be considered either instantaneous (linear) or convolutive. This approach has been experimentally tested by a number of researchers [2-9] and despite promising preliminary results, it seems to be far from the level of robustness and reliability required for use in common practice. One reason is due to strict ICA requirements such as equality or superiority of the number of sensors to the number of sources. Another reason is the inherent ambiguity in the scale and permutation of the results obtained from ICA. Furthermore, inconsistency between ICA assumptions and the true characteristics of vibration sources can be listed as one of the pitfalls (see [10]).

An alternative approach is to avoid the effort of "separating" the actual bearing signals from the background noise. In this approach, a threshold for the noise level in different regions of the spectral representation of the vibration signal is established and the signal is monitored for any levels which exceed this threshold. Recently, Clifton et al. [11] introduced a probabilistic method called the probabilistic novel tracked order. In this method, the spectrogram of the vibration signal gathered from an accelerometer on the casing of a jet engine (gas turbine engine) is divided into speed and frequency bins. Then for each bin, by adopting Extreme Value Theory (EVT) concepts, a dynamic threshold is established for the noise floor. It is demonstrated using real engine data that this technique is actually capable of detecting bearing tones as they protrude above the established noise floor. A drawback with this technique, though, is that no distinction between the characteristics of the noise and the actual bearing tone is made. As long as a bearing tone does not exceed the noise threshold, it is considered noise and therefore ignored. Bearing tones must be strong enough to be detected by this technique. Further, should the overall noise level increase for any reason it can mask a bearing tone which could be otherwise detected.

An alternative to above approaches is to use the specifications and characteristics of signals produced due to bearing faults as a basis for distinction. A monitoring scheme can be established that probes the signals acquired to recognize such specifications. Bearing defects are now known to produce vibration with recurring impulsiveness in the energy. Signals with such a behaviour are known in technical terms to be cyclostationary. Briefly, this approach consists in detecting any cyclostationary behaviour in the vibration signals and checking for any association with bearing defects. Very recently, Jérôme Antoni published a number of articles ([12-14] and references therein) on this subject. Also, for a more detailed review on bearing fault diagnosis in general, interested readers may consult [15].

In this study, different aspects of applying cyclostationarity-based methods to the case of bearing fault detection in complex machinery are investigated. For a bearing fault detection technique to be effective in such applications, it must retain two features. One is the ability to detect faint bearing tones as they pass through the transmission path. The other is to allow consistent trending. This paper is structured as follows: first a short description of the mechanics of bearing failures is given. Then, concepts and formulations for cyclostationarity are briefly introduced. Finally, two sets of relevant experiments are provided, followed by a discussion on the results.

4.3 Bearing faults and cyclostationarity

4.3.1 Bearing faults

As mentioned earlier the mechanics of bearing faults are to a great extent known and characteristic frequencies have been formulated. These frequencies for the common case where only the inner race of the bearing is rotating are listed in Table 4.1.

Table 4.1: Characteristic frequencies of bearing faults [16]

Rotation frequency of a rolling element assembly	$f_c = \frac{f_s}{2}\left(1 - \frac{D_B}{D_P}\cos\theta\right)$
Rotational frequency of a rolling element	$f_r = \frac{f_s}{2}\frac{D_P}{D_B}\left(1 - \frac{D_B^2}{D_P^2}\cos^2\theta\right)$
Over-rolling frequency of one point on the inner ring	$f_{ip} = \frac{f_s}{2} N_B \left(1 + \frac{D_B}{D_P}\cos\theta\right)$
Over-rolling frequency of one point on the outer ring	$f_{ep} = \frac{f_s}{2} N_B \left(1 - \frac{D_B}{D_P}\cos\theta\right)$
Over-rolling frequency of one point on a rolling element	$f_r = \frac{f_s D_P}{D_B}\left(1 - \frac{D_B^2}{D_P^2}\cos^2\theta\right)$
f_s: rotation speed, D_B: roller diameter, D_P: pitch diameter, N_B: the number of balls and θ: the contact angle of the ball.	

One misconception regarding the above formulas is that they are often misinterpreted to represent the bearing's natural frequencies. A closer look at the procedure of obtaining these formulas can provide a better understanding of the concept. The procedure for obtaining each one of these formulas is briefly: if any defective point is considered on any of the main bearing components (i.e., rolling element, outer and inner races), then based on the geometry of the bearing components and kinematic concepts the frequency of any possible contact between that point and other components is calculated. For example, if there is a defective point on the inner race of bearing, the rate at which such point comes into contact with the rolling element determines the over-rolling frequency of one point on the inner ring (f_{ir}). Depending on the case, the introduction into and out of the bearing load zone can be of importance, which necessitates calculation of the rolling assembly frequency. Overall, the basis for calculating these formulas is solely kinematics; the bearing's natural frequencies are dependent on the design, geometry and material among many other factors and it is not possible to establish a general formulation for all bearings.

Another misconception related to bearing characteristic frequencies is that bearings are sometimes thought to produce harmonic sinusoidal components at such rates. This may stem from the fact that conventional bearing diagnosis systems are largely based on spectral analysis and consequently Fourier Transforms (FT) which represent signals with harmonic sinusoidal components. It should be clear from the previous paragraph that bearing frequencies are produced by striking of a defective point of a bearing component on other component. Such striking results in excitation (ringing) of the bearing assembly at its natural frequencies. The striking itself occurs at rates equal to the characteristic frequencies (easily computable) and creates impulses in the signal and not harmonic sinusoidals. The ringing effect, on the other hand, occurs at natural frequencies of the bearing components in the shape of a random stationary signal at normally higher frequencies (usually unknown). The combination of these two phenomena creates vibration with repetitive bursts of energy. To be more accurate, vibration signals produced by a bearing defect are modulated signals; vibration energy at natural frequencies of the bearing (carrier frequency) is modulated with characteristic frequencies of the bearing (modulation frequency). Such signals in signal processing terminology are entitled cyclostationary.

According to above discussion, typical spectral (FFT) analysis is not a strong tool for detecting bearing anomalies as it gives the averaged spectral representation (spectrum) based on stationarity assumptions. In fact, spectral analysis is only capable of detecting bearing defects when they are greatly developed and in presence of little noise. In such cases the modulation frequency and its harmonics are visible on the spectrum. An alternative for typical spectral analysis is to use spectrogram (STFT) or any other joint time-frequency representation. In this case, the repetitive bursts of energy occurring at higher frequencies (ringing frequencies of the bearing component) are observable throughout the spectrogram. The duration between successive bursts is equal to the inverse of any one of the characteristic frequencies depending on the case. These methods are very representative and appropriate for analysis purposes. On the other hand, they are not suitable for an automated diagnosis system since it is difficult to establish a robust trending and alarming scheme.

Envelope analysis [16] is also one of the methods widely used for bearing fault detection. It consists in spectral analysis of the envelope of the time-domain signal. For envelope analysis to be effective it is usually necessary that sensors be located very close to the bearing so that the repetitive bursts of energy due to bearing faults are discernible in the time-domain signal. This limits its use for applications where the sensors are not mounted as such or where the vibration produced by other components mask the recurring pulses in the signals. One solution to this limitation is to band-pass filter the signal around some appropriate frequency band and then perform envelope analysis on the filtered signal. Again, selecting the appropriate band entails knowing the natural frequency of the bearing assembly a priori.

One might think of performing envelope analysis on the signal narrow-band filtered around all frequencies of interest. This bears a similarity to taking STFT of the signal and then performing envelope analysis on each frequency bin over the range of interest. This concept sets the stage for what is covered in the following section under cyclic spectral analysis.

4.3.2 Cyclic spectral analysis

Given $x(t)$ the signal in time, cyclic spectral analysis uses FT to scrutinize the alternation of the spectral contents of the signal at each frequency f throughout signal duration T. More accurately, if the narrow-band filtered constituent of the signal $x(t)$ around frequency f is denoted as $x_f(t)$ then the FT of the square of this signal reads:

$$\lim_{T\to\infty} \frac{1}{T} \int_T \left|x_f(t)\right|^2 e^{-j2\pi\alpha t} dt \qquad \text{Eq. 4.1}$$

where α is cyclic frequency (carrier frequency) as opposed to f the spectral frequency (modulation frequency). Since the representation obtained using this equation will actually reveal the modulation of the signal in terms of cyclic frequency, it is also called the cyclic modulation spectrum. The above formulation is straightforward and apt for understanding the concept. Nonetheless, deriving the discrete version of this formulation suitable for implementation is not as straightforward. An alternative approach to formulate the same concept is to use correlation approach, which leads to a more straightforward discrete formulation, yet harder to grasp. This approach is described as follows [17]:

According to the definition of cyclostationarity, the mean and the autocorrelation for a cyclostationary signal (or process in general) $x(t)$ are periodic and the following equations hold:

$$m_X(t+T) = m_X(t) \qquad \text{Eq. 4.2}$$

$$R_{XX}(t_1+T, t_2+T) = R_{XX}(t_1, t_2) \qquad \text{Eq. 4.3}$$

for any possible t, t_1 and t_2 and where T denotes the period. For notational simplicity Eq. 1 can be reformulated as:

$$R_{XX}\left(t+T+\frac{\tau}{2}, t+T-\frac{\tau}{2}\right) = R_{XX}\left(t+\frac{\tau}{2}, t-\frac{\tau}{2}\right) \qquad \text{Eq. 4.4}$$

Now if the Fourier coefficients of the autocorrelation function for a range of frequencies (α) equal to integer multiples of the fundamental frequency $(\frac{1}{T})$ are written as:

$$R_{XX}^{\alpha}(\tau) = \frac{1}{T}\int_{-\frac{T}{2}}^{\frac{T}{2}} R_{XX}\left(t+\frac{\tau}{2}, t-\frac{\tau}{2}\right) e^{-i2\pi\alpha t} dt \qquad \text{Eq. 4.5}$$

then the Fourier expansion of the autocorrelation function reads:

$$R_{XX}\left(t+\frac{\tau}{2}, t-\frac{\tau}{2}\right) = \sum_{\alpha} R_{XX}^{\alpha}(\tau) e^{i2\pi\alpha t} \qquad \text{Eq. 4.6}$$

To generalize this notation, Eq. 5 must be revised so that it covers the whole range of possible frequencies. By letting T be any possible periodicity in the signal, an extension to Eq. 5 can be expressed as:

$$R_{XX}^{\alpha}(\tau) = \lim_{T\to\infty} \frac{1}{T}\int_{-\frac{T}{2}}^{\frac{T}{2}} R_{XX}\left(t+\frac{\tau}{2}, t-\frac{\tau}{2}\right) e^{-i2\pi\alpha t} dt \qquad \text{Eq. 4.7}$$

According to above notation, the cyclostationarity of a signal $x(t)$ will manifest itself as a non-zero Fourier coefficient. Similarly, a non-zero coefficient at any frequency α conveys that the signal exhibits cyclostationarity at that frequency. In its standard terminology frequency α is referred to as cyclic (or cycle) frequency and $R_{XX}^{\alpha}(\tau)$ as a cyclic autocorrelation function. The set of cyclic frequencies for which the cyclic autocorrelation function is non-zero is called the cyclic spectrum.

In an analogy to spectral analysis where the spectral density is defined as the Fourier transform of the autocorrelation function, the cyclic spectral density is defined as:

$$S_{XX}^{\alpha} = \int_{-\infty}^{\infty} R_{XX}^{\alpha}(\tau) e^{-i2\pi f\tau} d\tau \qquad \text{Eq. 4.8}$$

Finally, from Eq. 8 the discrete cyclic spectrum for a discrete signal $x(k\Delta t)$ (for $k = 0, 1, 2, ...$) is adapted as:

$$S_{XX}^{\alpha}[f] = \sum_{n=0}^{\infty} R_{XX}^{\alpha}[n\Delta t] e^{-i2\pi n\Delta t f} \qquad \text{Eq. 4.9}$$

where Δt and K denote the sampling interval and number of samples respectively and the discrete autocorrelation function is obtained as:

$$R_{XX}^{\alpha}[n\Delta t] = \lim_{K\to\infty} \frac{1}{2K+1} \sum_{k=0}^{K} R_{XX}(k\Delta t + n\Delta t, k\Delta t) e^{-i2\pi\alpha\left(k+\frac{n}{2}\right)\Delta t} \qquad \text{Eq. 4.10}$$

4.4 Experiments

As mentioned earlier, for a bearing detection method to be effective in applications related to complex machinery it must allow consistent trending and be able to detect defects from a weak signal. In this section cyclic spectral analysis is examined for these features using two sets of experiments.

In principle, the transmission path mainly dissipates the energy of the signal but generally should not affect certain characteristics of the signal such as its cyclostationarity. For the transmission path to diminish the signal's cyclostationarity it must operate as a rather complicated filter that evens out the repetitive bursts of energy that occur in a specific frequency range. Therefore, it is reasonable to expect that the cyclostationarity behaviour of the signal is preserved through the transmission path. In our first case study, this premise is tested experimentally by collecting the signals from a faulty bearing using an accelerometer positioned far from the bearing.

In automated health monitoring and fault diagnosis, it is essential for a method to allow robust, attainable and consistent trending. As an example, cyclostationarity due to bearing anomalies can be detected with most time-frequency methods as long as the ringing frequencies or the natural frequencies of the bearing assembly are known to some extent. However, in the majority of cases the natural frequencies of the bearing assembly are not readily available. This limits the application of such methods in automated health monitoring. Another important point is that the feature being tracked must be consistent in the sense that its value bears some correspondence to severity of faults. In our second case study, cyclostationarity is examined for these requirements through a run-to-failure experiment.

The description of these two case studies followed by discussion and the results for each case are represented in the following sections.

4.4.1 First case study

4.4.1.1 Experimental setup and data acquisition

In the first case, vibration signals were collected from a test setup at École Polytechnique de Montréal consisting of a 2 HP motor driving a shaft supported by two different bearings. One bearing was an overhauled roller bearing (PWC15) from an aircraft engine provided by Pratt & Whitney Canada. The other bearing was a new SKF ball bearing. Each bearing was contained in a housing and bolted to an adjustment base. The adjustment base was also bolted to a main stiff base which was fixed to the concrete floor. An accelerometer was mounted on each bearing housing along with two more on the main base (Figure 4.1). Signals were gathered at a sampling frequency of 50 kHz during operation of a shaft running at 1200 RPM (20 Hz). One of the accelerometers on the base was positioned about 4 ft. away from the shaft assembly. Signals from this accelerometer were used for analyzing the effect of the transmission path on the cyclostationarity of the signals.

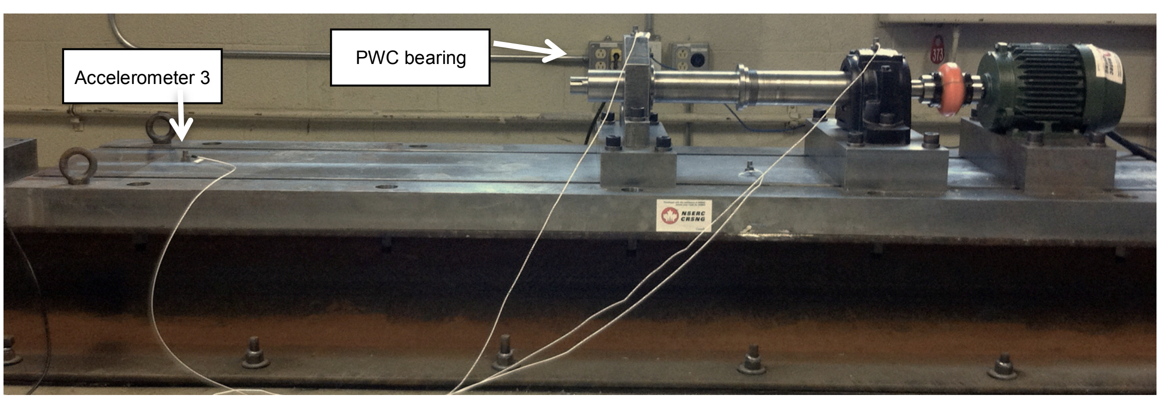

Figure 4.1: Test setup at École Polytechnique de Montreal

4.4.1.2 Results and discussion

Visual inspection of PWC15 bearing indicated an outer race fault. The SKF bearing, on the other hand, was a new bearing. Figure 4.2 shows the cyclic spectrum or cyclic spectral density of the signals gathered by accelerometer no.3. This was obtained from a 1 sec portion of the signal. Two dominant peaks are clearly discernible at cyclic frequencies of 90 Hz and 180 Hz and for a range of spectral frequencies centred around 4 kHz. This indicates that the vibration energy around 4 kHz (the natural frequencies of the bearing assembly) is modulated with a modulation frequency of 90 Hz. This modulation frequency coincides well with the over-rolling frequency of one point of the outer race of the PWC15 bearing given in Table 4.2.

Table 4.2: Characteristic frequencies of the bearings used in the experiments

Description		PWC15	Rexnord
Rotational frequency of rolling element assembly [Hz]	f_c	7.73	14.8
Rotational frequency of a rolling element [Hz]	f_r	41.7	140
Over-rolling frequency of one point on inner ring [Hz]	f_{ip}	147	297
Over-rolling frequency of one point on outer ring [Hz]	f_{ep}	92.7	236
Over-rolling frequency of one point on rolling element [Hz]	f_{rp}	83.5	280

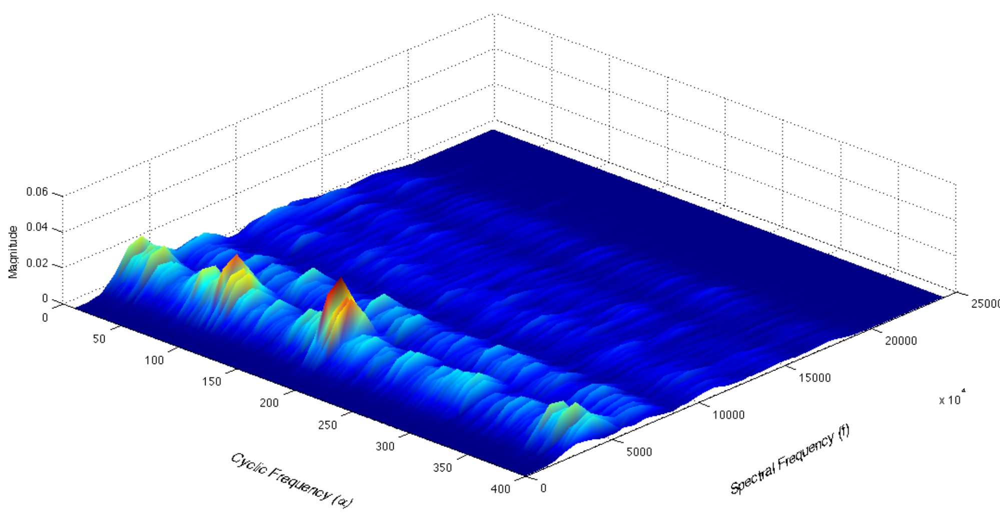

Figure 4.2: Cyclic spectral density of the faulty PWC15 bearing

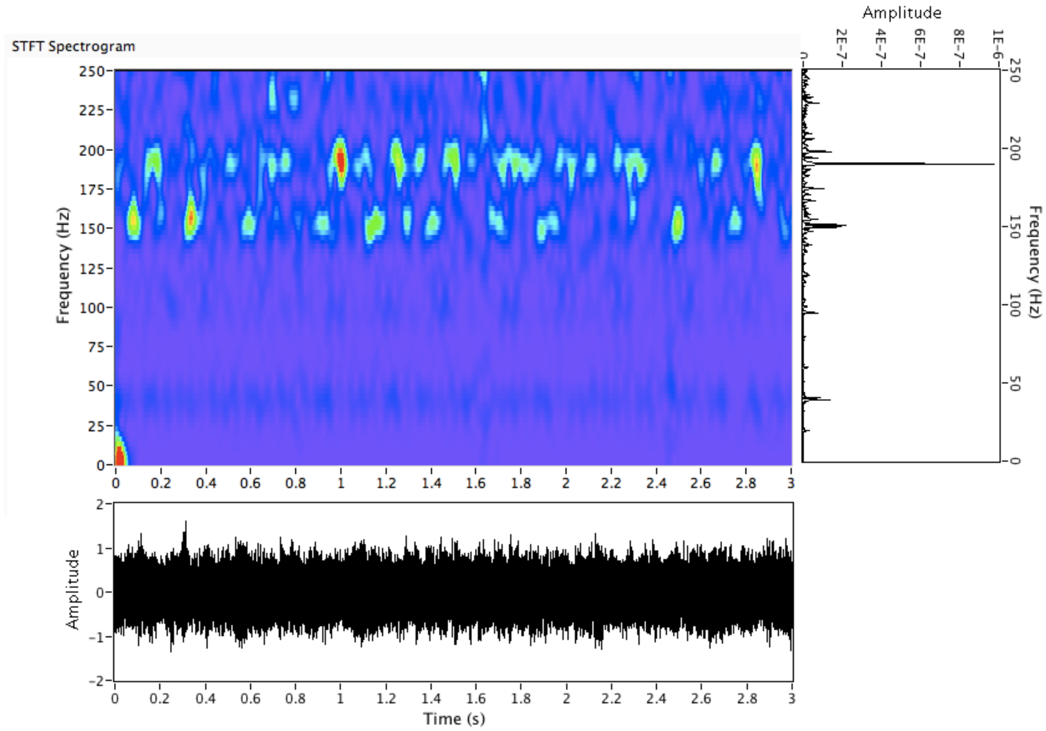

Figure 4.3: Low frequency range spectrogram and spectrum of the faulty PWC15 bearing

To compare this method over typical methods, the spectrum and spectrogram of the signals up to 250 Hz are shown in Figure 4.3 along with the corresponding time-domain signal. As is typical with spectral analysis for the purpose of bearing fault detection, it is expected to have a peak at around 92 Hz on both diagrams. The spectrum in this case shows a minuscule peak around 95 Hz. Slightly higher spectral energy can also be observed from the spectrogram around the same frequency. Such low amplitude indications would be completely masked in presence of noise. Moreover, as mentioned earlier the bearing used in this experiment was an overhauled bearing with a predominantly developed outer race fault.

According to the discussion in Section 4.2, in order for the vibration produced by faulty bearings to be clearly discernible on the spectrogram one needs to look at a broader frequency range. Figure 4.4 shows the spectrogram and spectrum of signal up to 12.5 kHz. On the spectrogram, the outer race fault manifests itself as a series of bursts taking place at around 3.5 kHz (the natural frequencies of bearing assembly or carrier frequencies) with an interval equal to the inverse of the outer race fault characteristic frequency (modulation frequency). These results suggest that for this approach to be effective in automated monitoring, prior knowledge of the natural frequencies of bearing assembly is required. Moreover, it is necessary that other machine components do not produce vibration within the same frequency band and jumble the signal. This is definitely not the case for complex systems with many components producing vibration.

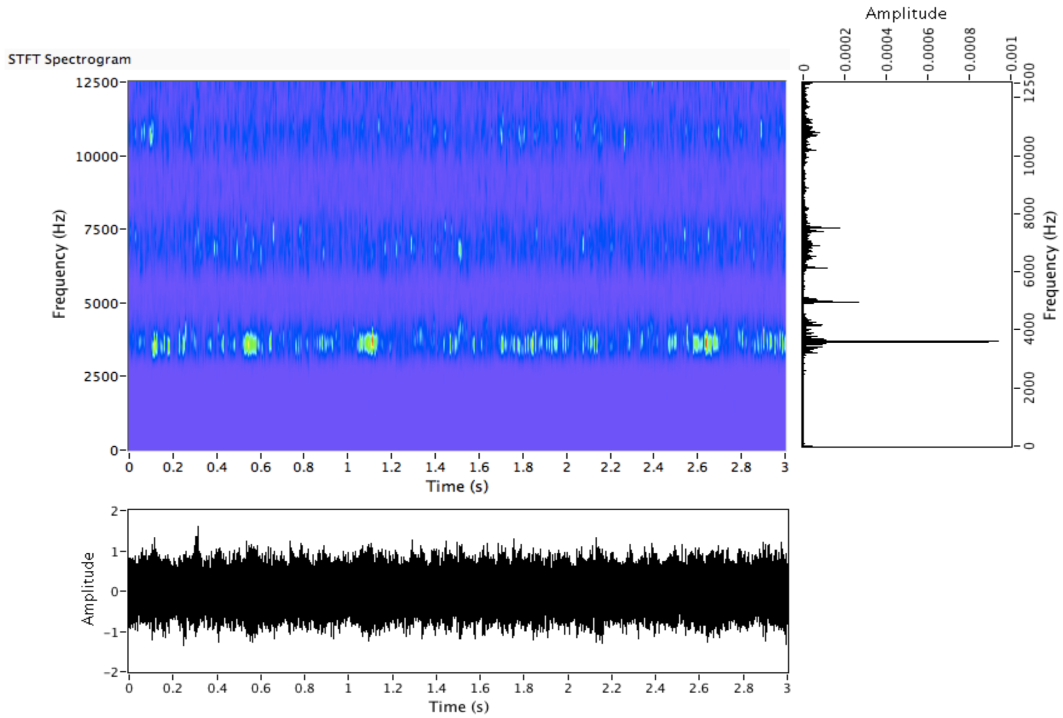

Figure 4.4: Wide range frequency spectrogram and spectrum of the faulty PWC15 bearing

4.4.2 Second case study

In order to investigate if the cyclic spectral density enables consistent trending, a bearing data set from a run-to-failure test provided by the Center for Intelligent Maintenance Systems (IMS) of University of Cincinnati through NASA Ames Prognostics Data Repository [18] was used.

4.4.2.1 Experimental setup and data acquisition

In this test four double row Rexnord ZA-2115 bearings were mounted on a shaft driven by an AC motor (Figure 4.5). Vibration data was gathered using four accelerometers, one on each bearing housing, at a sampling rate of 20 KHz. A spring mechanism exerted a radial load of 6000 lbs on the rotating shaft and the bearing. Data snippets of approximately 1 second in duration were gathered at 10-minute intervals throughout a run-to-failure test. In this study, around 50 snippets were selected over a 190 min interval covering the progress of bearing from healthy to faulty. At the end of this test, an outer race fault on the third bearing was observed.

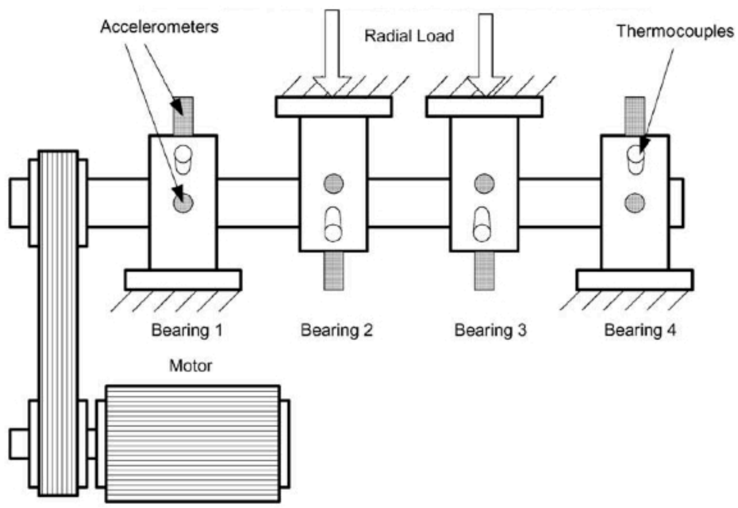

Figure 4.5: Schema of the test rig at IMS, of University of Cincinnati (by courtesy of [18])

4.4.2.2 Results and discussion

According to Table 2.1, due to a fault on the outer race of the third bearing, it is expected that the signal exhibit degrees of cyclostationarity at a cyclic frequency of 236 Hz as the fault progresses. Figure 4.6 shows the cyclic spectrum of the signals gathered by accelerometer 3 on the third bearing when the outer race fault is developed. As shown, the vibration energy distributed around 4.5 kHz is modulated with a frequency of about 230 Hz which slightly deviates from the calculated characteristic frequency for an outer race. This deviation has been reported in [19] as well.

In order to analyse the correspondence between the cyclic spectral energy and the progress of the bearing defect, the overall narrow-band (5 Hz) cyclic spectral energy around the bearing's outer race frequency (231 Hz) is studied. Figure 4.7 shows the variation of the magnitude of vibration energy values with respect to operation time. According to this graph, first indications of bearing fault appear after 92 hours of operation. Comparing this to the bearing's total service life in number of hours (i.e., 165 hours) this can indeed be considered an early indication. After this early indication, the value of the cyclic energy goes through a number of significant fluctuations, which can be due to healing phenomenon [20]. This indicates that strict connections cannot be established between cyclic energy and the severity of fault. Nevertheless, it remains a significant distance from the initial value observed for normal conditions during early hours of operation.

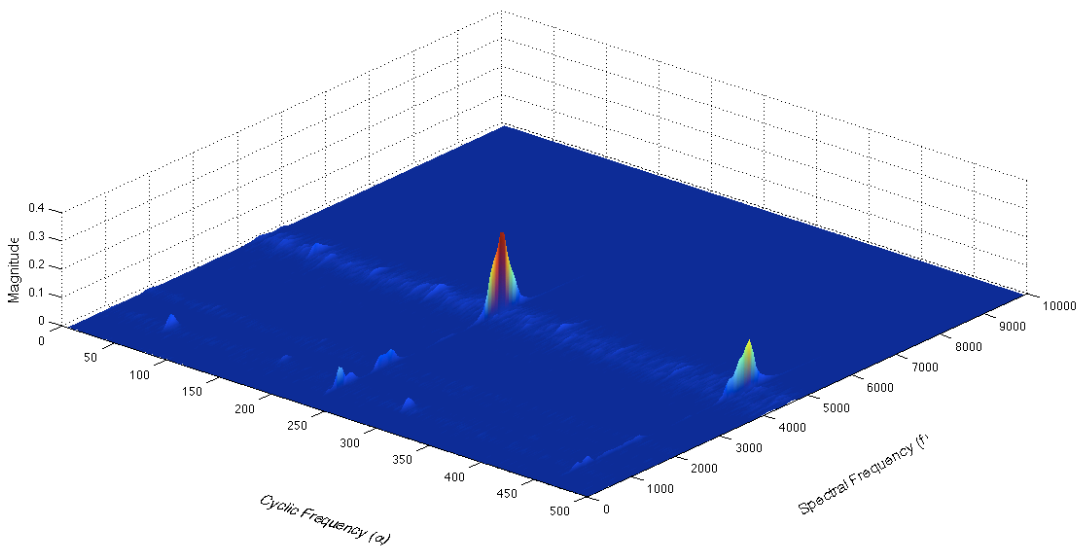

Figure 4.6: Cyclic spectral density of faulty Rexnord bearing

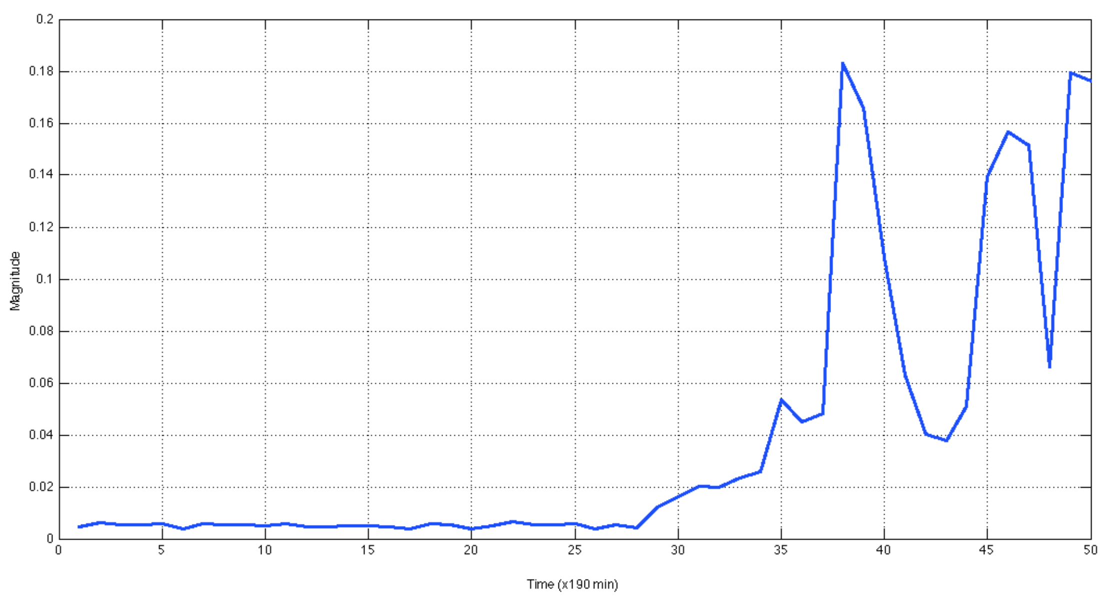

Figure 4.7: Progress of banded cyclic spectral density

This experiment demonstrates that cyclic spectral analysis should not be used as a tool to measure the severity of bearing faults. On the other hand, it can be utilized as a reliable monitoring tool because its value always reads higher for a faulty bearing than for a normal one; and also it enables early detection of bearing faults.

4.5 Conclusion

In this study the problem of bearing fault detection in complex machinery was revisited. Two prerequisites for a method to be effective in detecting bearing faults in complex systems were identified to be the capability of detecting bearing faults from a faint signal; and a consistent trending feature. Relevant shortcomings of traditional approaches were discussed. Cyclic spectral density was then argued to be an appropriate candidate that could overcome difficulties with traditional approaches and meet the prerequisites. This was examined through two sets of experiments. In conclusion, the experimental results were satisfactory. As a recommendation for future work, the effectiveness of this method can be further investigated with signals obtained from other test cases as well as a real industrial case.

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CHAPTER 5 GENERAL DISCUSSION

The concept of vibration analysis for the purpose of fault diagnosis in complex multi-component machinery such as gas turbine engines was revisited. The principal difficulty in this case was identified to be the fact that many components functioning at the same time produce a very complicated overall vibration signature. A blind source separation concept was introduced to address this difficulty and separate signals with respect to components. Due to the non-existence of a practical way to obtain vibration signatures of the individual components of machinery in isolation, verification and validation of results obtained using blind source separation techniques were itself an obstacle. To tackle this obstacle a new method was developed. This method is based on the spatial distribution of sensors with respect to the components. By adopting key concepts from statistical energy analysis, schematic vibration signatures for different components are obtained. The major advantage of this method is that it is based on the system's mechanical attributes rather than any mathematical assumptions.

With an evaluation metric at hand, more rigorous evaluation of blind source separation techniques could be achieved. Among such techniques, frequency-based independent component analysis was chosen to be appropriate. However, it turned out that the reconstruction of time signals from separation results of individual frequency bins associated with the frequency-based technique posed a difficulty as existing solutions were either computationally demanding or based on assumptions that normally do not hold in mechanical systems. Again, as one of the main intentions of this thesis, a new technique was proposed based mainly on the mechanical attributes of the system rather than any unrealistic mathematical or statistical assumption. This technique was developed based on the presumption that the mixing mechanism for neighbouring frequency bins would vary only slightly from one bin to another. Experimental results for this case were, to a great extent, satisfactory.

Despite encouraging preliminary results, independent component analysis techniques at this current stage seem to be far below the level of robustness and reliability required for use in practice. One reason is due to strict requirements such as equality or superiority of the number of sensors to the number of sources. Another reason is the inherent ambiguity in the scale and permutation of the results obtained using this technique. In addition, the inconsistency between independent component analysis assumptions and the true characteristics of vibration sources is a further drawback.

An alternative to above approaches was discussed and consists of putting the focus for each component on its faults and the specific variation they induce on the characteristics of the signals acquired far from the actual component. Given that a powerful tool for detecting such specific signal characteristics was available and these characteristics get through the transmission path, this approach could be very effective in diagnosis of faults in complex machinery. As was the case for other studies throughout this thesis, faults in bearings were chosen for this study. Such faults are known to produce vibration with recurring impulsiveness in the energy. Signals with such behaviour are known in technical terms to be cyclostationary. Cyclic spectral analysis is a tool to measure the cyclostationarity of a signal at different ranges of frequency. Therefore, it can be stated that, in this case diagnosis would consist in using cyclic spectral analysis to detect cyclostationary effects in the vibration signals and checking for any association with bearing defects. It is uncertain whether cyclostationary properties would be retained through the transmission path; and if cyclic spectral analysis would be a powerful tool allowing consistent trending. These two questions were addressed using two sets of relevant experiments. In general, our experimental results corroborated the effectiveness of this approach.

CONCLUSION

In this dissertation, three studies concerning mechanical fault diagnosis in complex machinery using vibration analysis were presented.

In the first study, a novel separation method based on frequency signatures obtained from signals gathered from multiple sensors positioned at different locations on the system was presented. This method had a simple and solid theoretical basis adopted from statistical energy analysis. A series of experimental tests on synthetic signals and real laboratory signals collected from different bearings were provided for verification. The results confirmed the efficacy of the method. Some shortcomings associated with this method were also discussed including inaccuracy and degraded effectiveness in systems with transitory behaviour and in systems with very densely mounted components where determining the subsystems could be very challenging.

In the second study, frequency-based independent component analysis was applied to the case of vibration source separation. A new technique was presented for constructing time-domain signals from separation results of the individual frequency bins. Accordingly, modifications were made to the separation algorithm to adapt it for the case of vibration source separation. The performance of the method was verified using a series of experimental tests on real laboratory signals collected from different bearings. Results were compared and verified using the separation metric presented in the first study. The accordance between results from the presented technique, the spatial proximity method and the peak analysis method confirmed its effectiveness.

In the third study, the application of cyclic spectral density in detection of faint bearing signals was considered. It was argued that for this technique to be effective in detecting bearing faults in complex systems two prerequisites must be met. Such prerequisites were identified to be the capability of detecting bearing faults from a faint signal and aptness for consistent trending feature. In this regard, the shortcomings of traditional approaches were discussed. Two sets of experiments were presented for evaluation and the experimental results supported the proposed ideas.

As recommendations for future work, the following research works may be conducted:

- In the abovementioned studies, verification of the methods and the techniques were all performed using data acquired from test setups. The effectiveness of these methods can be further investigated with data obtained from other test cases as well as a real industrial case.
- In the second study, among blind source separation techniques, independent component analysis was used. As blind source separation is an ongoing area of research, new techniques may emerge that perform better than independent component analysis. At the time of writing methods such as factor analysis and empirical mode decomposition exist in which some of the restricting requirements of independent component analysis are relaxed. These methods may also be experimentally tested.
- In this study, the experiments and analyses were performed only for the case of bearing faults. Similar analyses may be carried out using data from other machine components such as gears.
- The separation results obtained using methods presented in this study may be fed into an automatic fault diagnosis scheme to verify their competence in such cases.

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