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APPLICATION OF INDEPENDENT COMPONENT ANALYSIS FOR SOUND SOURCE SEPARATION

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ABSTRACT

In this paper, experiments on the application of the independent component analysis (ICA) technique to separate unknown source signals are reported. ICA is one of the fastest growing fields in signal processing with applications to speech recognition systems, telecommunications, and biomedical signal processing. It is a data-transformation technique that finds independent sources of activity from linear mixtures of unknown independent sources. The statistical method to measure independence is to find a linear representation of the non-Gaussian data so that the components are as independent as possible and the mutual information between them is minimum. Although extensive simulations have been performed to demonstrate the power of the learning algorithm for the problems of instantaneous mixing and un-mixing of sources, its application to the noise diagnosis and separation in an industrial setting has not been considered. Noise separation in machinery has a strong basis in the “cocktail problem” in which it is difficult to separate/isolate the voice of a person in a room filled with competing voices and noises. The experiments conducted consist of separating several artificially generated sources of noise. Our results demonstrate that ICA can be effectively employed for such kinds of applications. The underdetermined problem in which there are fewer sensors than sources in the ICA formulation is also examined by applying a time-invariant linear transformation of the acquired signals to identify a single source.

1 INTRODUCTION

Independent Component Analysis (ICA) separates a set of signal mixtures into a corresponding set of statistically independent component signals or source signals. It is based on simple, generic and physically realistic assumptions that if different signals are from different physical processes (e.g. different people speaking) then those signals are statistically independent. ICA takes advantage of the fact that the implication of this assumption can be reversed, leading to a new assumption which is logically unwarranted but which works in practice, namely: if statistically independent signals can be extracted from signal mixtures then these extracted signals must be from different physical processes. Accordingly, ICA separates signal mixtures into statistically independent signals. If the assumption of statistical independence is valid then each of the signals extracted by independent component analysis will have been generated by a different physical process, and will therefore be a desired signal. The independence assumption is correct in most cases so the blind ICA separation of a mixed signal gives very good results.

To identify the independent components successfully, we need a rule for evaluating the independency of the identified components. According to the Central Limit Theorem, the distribution of the sum of a large number of independent random variables tends to be a Gaussian distribution. Since the collected signals are weighted sums of the independent sources, the sources to be isolated must have less Gaussianity than the collected signals. Thus, non-Gaussianity can be used for separating independent components. This non Gaussianity can be evaluated using negentropy of the separated components so as to evaluate separation performance. With this concept, we can seek the separation that provides the least Gaussian ness of the separated components [3].

2 HISTORICAL BACKGROUND AND OVERVIEW:

The sound recognition and separation effect was first described (and named) by Colin Cherry in 1953 as part of psychoacoustics [17]. Much of the early work in this area can be traced to problems faced by air traffic controllers in the early 1950's. At that time, controllers received messages from pilots over loudspeakers in the control tower. Hearing the intermixed voices of many pilots over a single loudspeaker made the controller's task very difficult.

Cherry (1953) conducted perception experiments in which subjects were asked to listen to two different messages from a single loudspeaker at the same time and try to separate them.

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His work reveals that our ability to separate sounds from background noise is based on the characteristics of the sounds, such as the gender of the speaker, the direction from which the sound is coming, the pitch, or the speaking speed.

In the 1950's, Broadbent conducted dichotic listening experiments where subjects were asked to hear and separate different speech signals presented to each ear simultaneously (using headphones). He concluded that human hearing is basically like a spectrum analyzer, that is, the ear resolves the spectral content of the pressure wave without respect to the phase of the signal. In practice, though, some phase information can be perceived. Inter-aural phase difference, that is the difference in sound between the ears, is a notable exception by providing a significant part of the directional sensation of sound.

The ability to focus one's listening attention on a single talker among a cacophony of conversations and background noise—has been recognized for some time as the *cocktail party* effect**.** This specialized listening ability may be because of characteristics of the human speech production system, the auditory system, or high-level perceptual and language processing.

In many engineering problems, empirical measurements are obtained without much knowledge of the sources or even the physical model of the system. This may be the case for complex systems comprising of many subsystems which are often found in aerospace, civil, and mechanical engineering, and in emerging problems in biomedical engineering, controls, economics, and others, which are inherently difficult to model. An example is the automotive engine system, which consists of ducts, compressor, intercooler, intake manifold, engine cylinders, exhaust manifold, catalytic converter, muffler, and other related components. Unwanted engine noise can thus be caused by several or all of these subsystems simultaneously, and the contribution to the noise problem from each subsystem will likely vary with time. An ability to identify these noise sources would help engineers to design effective noise suppression strategies. This ability to *learn* from the empirical data, which in most cases are assumed to be obtainable, will enhance our understanding of the underlying physical principles and will help us to arrive at models for sound source separation, identification and system characterization?

The ability to model and synthesize a physical system and its sources, and to predict its response based on measurement data is extremely useful for engineers in optimal designs and control considerations. However, when a priori insight of the system is not available (or given) and the goal is to learn about the nature of the system, the problem becomes more complex and challenging.

3 APPLICATIONS OF SOUND SOURCE SEPARATION

The study of engine noise has been carried out since the early stages of engine development [20]. Although there are a number of engine noise sources, one of the most fundamentals is the combustion-induced noise The rapid pressure change due to the combustion transmits through engine structures and forms a part of the airborne noise. This pressure change also causes the vibration of the engine components such as the cylinder head, pistons, connecting rods and engine body. The vibration of these components then provides another part of the overall engine noise. Other noise sources are due to engine functions such as the injection of fuel and the operation of inlet and exhaust valves. All of these sources usually produce low level noise and make up a good fraction of the overall noise.

Although the above engine noise sources have distinctive time instances, it is still difficult to resolve them accurately based on only noise measurement.. A variety of signal processing methods including statistical analysis, spectral analysis, time frequency analysis and wavelet transform have been used to analyze this engine noise. These methods are applied to investigate the noise-generation mechanisms and to reveal the individual features of the noise sources. Each method is based upon component energy contributions to retrieve information about engine noise. The general steps followed are firstly, the noise signals are represented by using either the time domain, frequency domain or the joint time frequency domain. The noise sources are then identified by the energy variations of the represented signals. As these methods are based on energy conservation; they are useful for finding predominant information such as combustion peaks etc. but, the other low-level noise sources cannot be identified successfully,. This is because these methods retain the signal energy information from one domain to another. The low-energy noise sources are either buried by the combustion events or too small to be recognized. Hence, these signal energy conservation based methods are unable to recognize such noises induced by fuel injections or valve movements, which contain relatively small energy. Thus, it becomes a challenge to separate these noises from the overall engine noise.

The frequency analysis has been widely used on the vibration data to detect gear faults [15]. The traditional methods such as spectrum analysis, cepstrum analysis, and matching filtering, were developed for the application on the stationary data. However, many physical phenomena from acoustics and structural dynamics are time-varying events with transients, complex harmonic interaction and frequency changing with time. The vibrational frequencies measured by the accelerometers can change rapidly in time, especially when the fault occurs. Many types of gear faults produce localized changes in the vibration signal so that the signal is no longer stationary on the time-scale of the gear tooth meshing. These vibration signals are often heavily contaminated by large background noise. Great challenge is encountered when the conventional signal processing is applied to extract subtle fault-related changes from the measured vibration signals. Since most gear faults will produce localized changes in the signal, there is no way for standard Fourier analysis to determine at what point in time the changes have occurred. There are signal processing methods such as time-frequency methods, which give local information in both time and frequency. But, the time-frequency methods expand the dimensionality of the representation of the data. The other undesirable effect of the time-frequency architecture is that the feature fusion may not be as accurate as the one with raw data because a significant portion of the raw information would be lost in feature extraction [18]. The fundamental objective in vibration analysis of gear systems is to obtain accurate representation of the data dynamics. Optimal and relevant representations are desired for efficiency and consistency between the data decomposition and the gear system.

Diagnosing the vibrational characteristics of the heavy sizing-press drops [25]is a big challenge because the mechanism is very complex, as it includes motions of closed rotating parts (motor, gearbox) and open reciprocating frame, and has low work frequency that hampers the classical vibration analysis. So the sound diagnosis becomes an effective way in practice. However the heavy strike and industrial environment always disrupts the acoustic signals recorded. So, it is necessary to develop new methods to deal with the problem.

Biomedical signals from many sources including hearts [14], brains and endocrine systems pose a challenge to researchers who may have to separate weak signals arriving from multiple sources contaminated with artifacts and noise [26]. The analysis of these signals is important both for research and for medical diagnosis and treatment. The separation of these biomedical signals is a rapidly expanding area of research and many groups are now actively engaged in exploring the potential of statistical methods for revealing new information about the brain and body.

Recently a statistical method for signal processing, called Independent component analysis (ICA), is becoming a promising tool for machine diagnosis, detecting gear faults [16], processing of biomedical signals etc. Its goal is to find different physical sources independently from observations recorded by sensors without any a priori knowledge of the sources. Of course, the lack of knowledge must he compensated by certain assumptions on source signal like statistical independence and linear mixture of sources. Until now ICA has been successfully used in some fields include medicine, telecommunication and audio processing. The applications of the ICA to the analysis of mechanical signals such as vibration and sound have been little investigated. So the goal of this paper is mainly on the study of the acoustic signals generated from mechanical sources like a diesel engine, gear noise data etc and using the ICA in an effort to identify the various noise sources.

Not only the noise measurement but some dominant and important features embedded in the data are also extracted to provide automated information like for gear system diagnosis; data could be retrieved with features. Methods for such feature extraction process are often based on entropy or other statistical measures. For computational and conceptual simplicity, such a feature extraction is often sought as a linear transformation of the original data. Well-known linear transformation methods include principal component analysis, projection pursuit etc. An accurate data fusion scheme can be designed where independent component analysis method can be used for the feature extraction. The accelerometer measurements are assumed to consist of gear meshing components and non-harmonic additive noise. The dominant gear meshing components are considered as features and can only be estimated by independent component analysis. Then, the estimated dominant gear meshing components can be filtered through time-frequency methods for gear fault detection and identification.

4 INDEPENDENT COMPONENT ANALYSIS

The independent component analysis (ICA) brings a different strategy in dealing with the problems of blind source separation (BSS). In the ICA it is assumed that the measured data is a linear combination of the indirectly observed latent sources. As long as the latent signals are statistically independent, the ICA should be able to decompose them into independent components (ICs) successfully. It has been reported recently that the ICA is an elective approach for analyzing brain electroencephalogram (EEG) data, image processing, feature extraction, telecommunications and financial applications.

Imagine that you are in a room where two people are speaking simultaneously. You have two microphones, which you hold in different locations. The microphones give you two recorded time signals, which we could denote by $x_1(t)$ and $x_2(t)$, with x_1 and x_2 the amplitudes, and t the time index. Each of these recorded signals is a weighted sum of the speech signals emitted by the two speakers, which we denote by $s_1(t)$ and $s_2(t)$. We could express this as a linear equation:

$$x_1(t) = a_{11}s_1 + a_{12}s_2$$
$$x_2(t) = a_{21}s_1 + a_{22}s_2$$

where a_{11}, a_{12}, a_{21}, and a_{22} are some parameters that depend on the distances of the microphones from the speakers. It would be very useful if we could now estimate the two original speech signals $s_1(t)$ and $s_2(t)$, using only the recorded signals $x_1(t)$ and $x_2(t)$ without any information about their source. This is called the *cocktail-party problem*.

In matrix form, the above equations can be written as

$$x = \mathrm{A}\, s$$

where A is called the mixing matrix.
We need to find the demixing matrix such that

$$\mathrm{w}.x = y$$

where y is as close as possible to the source signals.

We find the demixing matrix iteratively using the criteria of maximizing the independency of the mixed signals x called the concept of *independent component analysis*. [1]-[12] Almost all the real world problems are analogous to the cocktail party effect which needs to be solved and shall be demonstrated experimentally in this paper

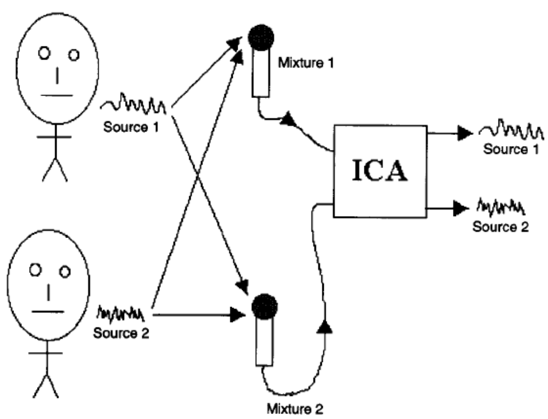
5 OTHER METHODS

ICA is not the only method that can be used for sound separation. Other statistical method for sound separation includes Principal Component Analysis. In statistics, principal components analysis (PCA) is a technique for simplifying a dataset, by reducing multidimensional datasets to lower dimensions for analysis. Technically speaking, PCA is a linear transformation that transforms the data to a new coordinate system such that the greatest variance by any projection of the data comes to lie on the first coordinate (called the first principal component), the second greatest variance on the second coordinate, and so on. PCA can be used for dimensionality reduction in a dataset while retaining those characteristics of the dataset that contribute most to its variance, by keeping lower-order principal components and ignoring higher-order ones. Such low-order components often contain the "most important" aspects of the data. But this is not necessarily the case, depending on the application.

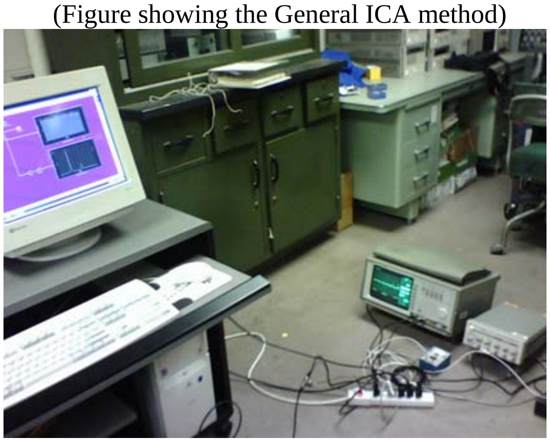
Historically, Principal Component Analysis (PCA) and Factor Analysis (FA) have been widely used for the same types of problems currently being investigated using ICA. The main difference between ICA and PCA/FA is that ICA finds non Gaussian and independent source signals whereas PCA/FA finds source signals which are merely Gaussian and uncorrelated i.e. PCA decomposes a set of signal mixtures into a set of uncorrelated signals and ICA decomposes a set of signal mixtures into a set of independent signals. PCA is like a version of ICA in which the source signals are assumed to be Gaussian. Factor Analysis (FA) is also a form of PCA with the addition of extra terms for modeling the sensor noise associated with each signal mixture. Normally, both ICA and PCA are based on the assumption that such noise is zero.

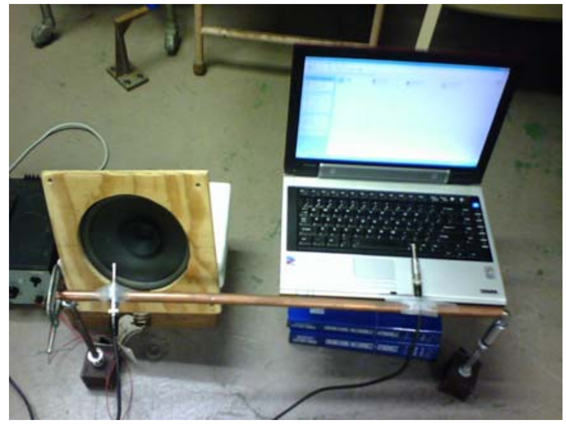
6 METHODOLOGY AND EXPERIMENT

Our experiment to demonstrate the ICA is similar to solving the cocktail party problem where we have two independent sound sources with two receivers. Figure shows the schematic diagram of our experiment



(Figure showing the General ICA method)




(Figure showing the experimental setup and hardware for ICA)

Before we start with the measurement, there are several conditions that need to be considered.

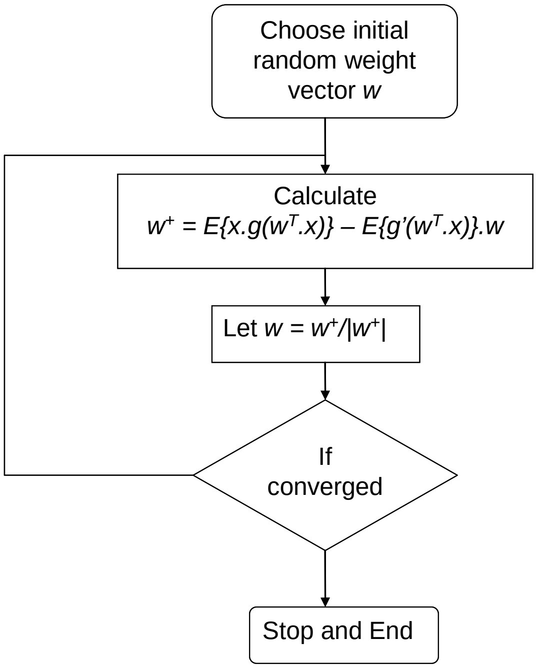
1. Two microphone probes are needed to record the sound from two different sound sources.
2. The position of the probes is such that the mixing matrix obtained is not a singular matrix.
3. Extra care should be taken so that the background noise is minimum or the effect of the background noises is not taken under consideration.

In order to meet the above considerations, we used two sensitive microphones made by PCB with an inbuilt pre amplifier having a sensitivity of 48.5mV/Pa. The frequency response of the microphone is from 10 to 20,000 Hz. The first microphone was placed at an area close to the speaker being driven by the power amplifier run through a function generator and the second was placed close to the computer where the song was being played. A pure sine wave was passed to the speaker through the function generator. The microphones have BNC output, which were connected to the PCB signal conditioner 483A having a 12 channel input output AC or DC function and then to the data acquisition card manufactured by Data Translation Inc., Model DT 2801A, into the computer. This data acquisition card converts the analog output of both terminals and stores it in a digital format. Located inside the computer, it has 16 channels and uses 12-bit precision for conversions. The software provided with the converter determines all the parameters needed for the converter to function. A Gateway computer was used to record the data using the Hypersignal digital signal processing software.

7 RESULTS AND DISCUSSION

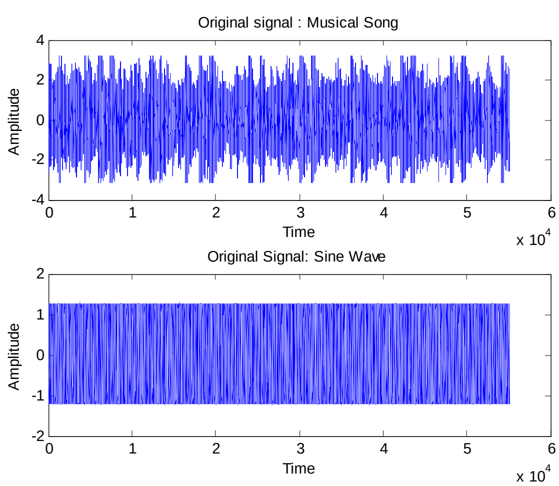
The FastICA algorithm proposed by Hyvarinen and Oja [12] that is used in our study basically consists of two steps, the preprocessing step and the FastICA algorithm itself. The preprocessing process consists further of centering and whitening steps. The centering step is done by subtracting the mean of the observed data $\boldsymbol{x}$. Therefore, the result of this step is a zero mean data. A whitening step is used to remove the correlation between the observed data. A common method to do whitening is by doing the eigen value decomposition of the covariance matrix of the mixed signal. The final step is the FastICA algorithm which is briefly summarized as follow:

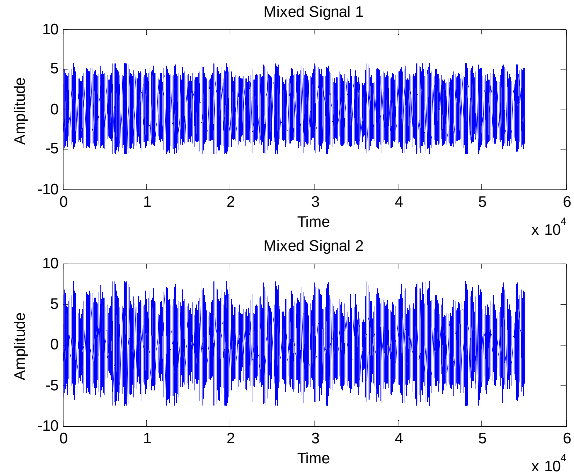
General flowchart of Fast ICA algorithm

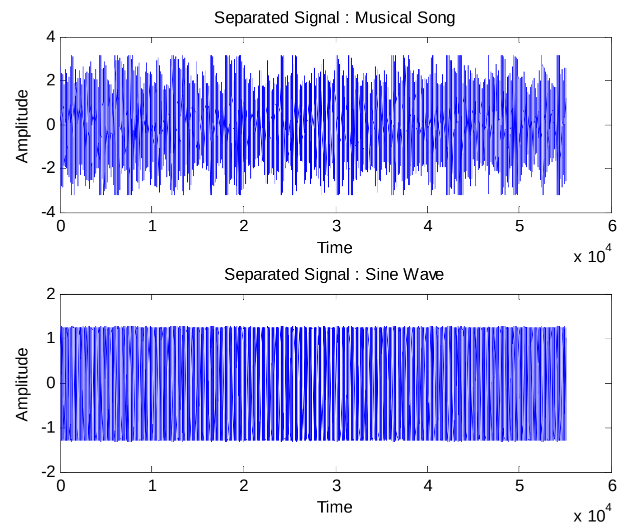


Here E denotes the expectation and g is any non linearity function. We used the power function of order 3 non linearity for the calculation of our results.

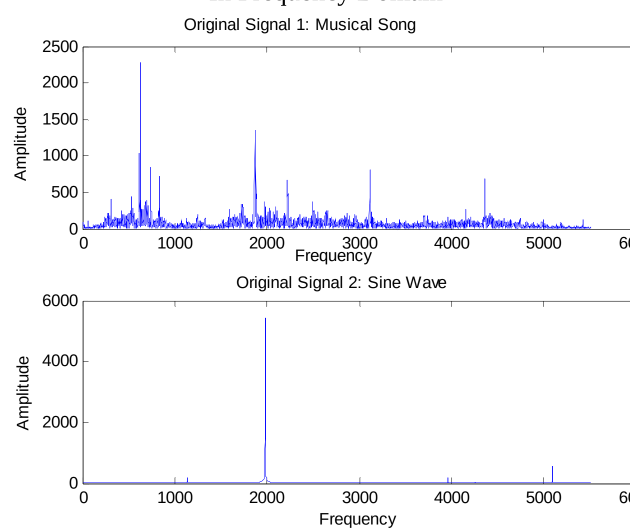
The following figure shows the original signal, the mixed signal and the separated signal in both the time domain and the frequency domain.

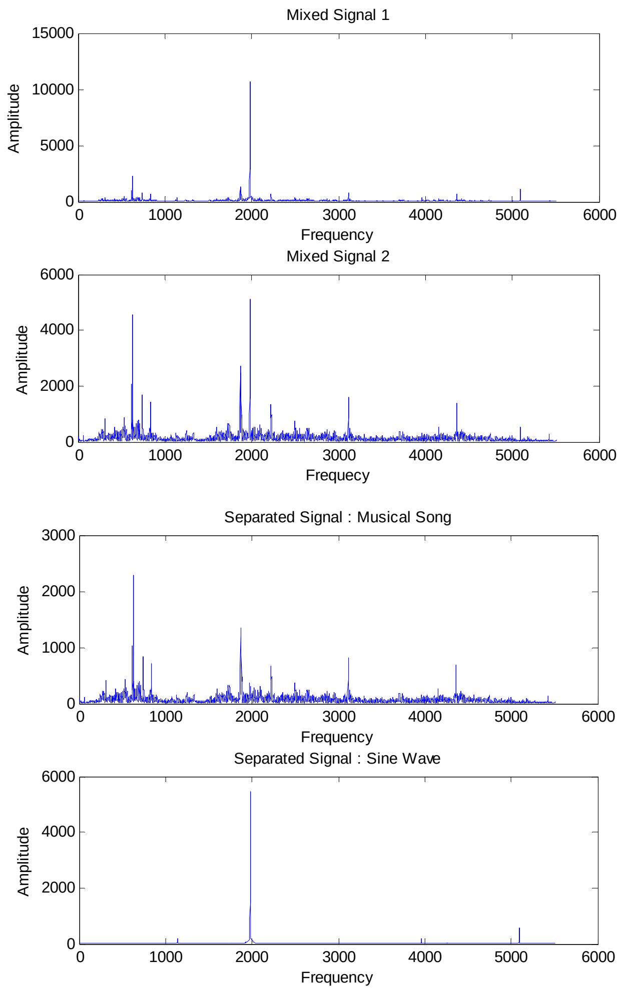






In Frequency Domain





The underdetermined problem in which there are fewer sensors than sources in the ICA formulation is also examined by applying a time-invariant linear transformation of the acquired signals to identify a single source like a single sensor was being taken and was made to collect the mixed signal at different locations to transform the underdetermined data to over determined data and the problem was then solved using the standard ICA formulation.

8 CONCLUDING REMARKS

The independent component analysis is presented in this paper as a novel method for real world signals like the engine acoustic source identification. The ICA is different from the conventionally used acoustic signal processing methods in that it separates individual sources based on their statistical independence. Like engine noise signals are a combination of a number of possible sources and background noise, the ICA can be a useful tool to identify these sources individually and to study them in detail.

The ICA is a unique and efficient blind signal separation strategy by emphasizing the statistical independence among the sources. This is very helpful in identifying embedded low-level events such as transients which are very common in sources like diesel engines. The numerical example by the ICA demonstrated that the unknown mixed sources could be successfully recovered. The example also provided some guidance in justifying its separation efficiency.

Before applying the proposed ICA method, the acoustic signal needs to be tested with the normalized kurtosis. It is known that a majority of the acoustic signals had sub-Gaussian distributions to which the ICA could be applied. The results obtained by applying the ICA demonstrate that the ICA can become powerful in the retrieval of engine noise sources such as combustion and valve operations

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