A Knowledge-Based Interference Rejection Scheme for Direct Sequence Spread-Spectrum Systems *

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Abstract

A knowledge-based interference rejection scheme for removal of Narrow Band Interference (NBI) in Direct Sequence Spread-Spectrum Systems (DSSS) is presented. The interference rejection system monitors the environment and identifies the types of interference embedded in the DSSS signal. An accurate estimate of the characteristics of the NBI is obtained and is used to direct the subsequent interference rejection schemes. The system performance is illustrated by means of simulation results.

Index Terms - Spread-spectrum systems, Interference rejection, Knowledge-based signal processing.

1 Introduction

In modern spread-spectrum cellular communication systems, a large number of users share the same channel. In addition there may be other communication systems occupying the same bandwidth. In such situations, the likelihood of users interfering with one another is high . The capacity of a cellular system is directly related to the amount of interference it can withstand while meeting desired performance goals. Thus, interference rejection has a direct impact on spread-spectrum system performance and is an important design issue. We concentrate on rejection of Narrow Band Interference(NBI) in Direct Sequence Spread-Spectrum (DSSS) systems. Spread-spectrum systems display an inherent interference immunity by virtue of their design. However, we encounter many situations where the interference immunity provided by the system processing gain is not sufficient in meeting the desired performance goals. Thus, additional interference rejection schemes are required to enhance the receiver performance.

Various schemes, including adaptive notch filtering, estimation/prediction type filters, transform domain processing schemes, decision feedback filters, and nonlinear techniques have been presented in the literature for rejection of NBI [?, ?, ?, ?]. The spread-spectrum signal is represented in the frequency domain by a wide, flat spectrum. The narrowband interferers are represented in the spectrum by narrow spikes. Therefore, such narrowband interferers can be removed by adaptively placing a notch filter at the location of the spikes in the received signal spectrum [?]. The problem of interference suppression now becomes one of trying to accurately determine the time-frequency locations of each inidividual narrowband interference tone in the signal.

The class of estimation/prediction type filters attempt to achieve interference suppression by estimating the narrowband interferers and subtracting the estimated interferering components from the received signal [?, ?, ?]. The The spread-spectrum signal and AWGN, being wideband processes, display no correlation between future and

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past sample values. Interference, being a narrowband process, displays correlation between past and future sample values. The interference can therefore, be predicted from the past values of the received signal samples and subtracted from the current input signal. The wideband spread-spectrum signal would then appear at the error output of the filter.

The prediction type cancelation schemes suffer from the drawback that they do not perform well in the presence of multiple narrowband interferers and in situations where the interference has significant amounts of frequency modulation. Although these drawbacks may be partially overcome by increasing the order of the filter employed, this imposes additional problems in the form of filter transient times and receiver design complexity. Alternative approaches [?] to narrowband interference involving time-frequency analysis performed using filterbanks have been proposed to handle scenarios with narrowband interference with significant frequency modulation rates. While these solutions are suitable for suppressing a few interference tones, they generally fail when applied to signals with multiple interference notes. The primary cause for failure is the fixed tradeoff between time and frequency resolution at any given point in the time-frequency plane.

A remedy for the drawbacks of fixed resolution time-frequency analysis techniques is to adapt the analysis filters at each point in the time-frequency plane in a data-dependent manner. One such adaptation strategy developed by Parks and Jones [?] involves choosing at each time-frequency point a filter that maximizes a kurtosis-like local energy concentration measure. This strategy suffers from the drawback that it is computationally very expensive due to the exhaustive search over $\mathcal{O}(10^2)$ candidate filters performed at each time-frequency point. It should be noted that for each candidate filter a short-time Fourier transform has to be computed over a time-frequency subregion of the time-frequency point under consideration. Another major drawback in using the concentration measure is that it does not utilize any knowledge about the time-frequency behaviors of spread-spectrum jammers that may possibly exist in the environment.

We have developed an alternative knowledge-based strategy for choosing appropriate analysis filters at each time-frequency point. This strategy, relies on an iterative procedure based upon the Integrated Processing and Understanding of Signals (IPUS) paradigm [?] for adapting the filters at each time-frequency point. We begin in Section 2 with an overall description of our interference suppression framework that encompasses our knowledge-based filter adaptation strategy. In Section 3, we provide a description of how this strategy achieves the isolation of individual narrowband interference tones. Finally in Section 4, we describe the filtering schemes utilized to suppress the isolated interference tones. Furthermore, we also present simulation results that demonstrate the efficacy of our interference suppression framework and its superiority over conventional interference suppression approaches.

2 Interference Suppression Framework

The problem of interference cancelation may be formally described by considering spread spectrum signals of the form:

$$x(t) = s(t) + \sum_{k=0}^{k=N} y_k(t) \tag{1}$$

where $s(t)$ is the information-bearing spread spectrum signal and each $y_k(t)$ is a narrowband interferer of the form $y_k(t) = cos\left[\omega_k(t) + \phi_k\right]$.

Our objective is to cancel all the interference tones $y_k(t)$ and recover the original spread-spectrum signal $s(t)$. In our research we have have assumed that interferers are restricted to be of the types listed below.

(1) Multiple tone interferers operating in continuous wave (CW) mode,

(2) Linear-FM (or chirp) interfering tones,

(3) Multiple CW tones operating in on-off mode.

This assumption was made on the basis that the cancelation problem is fairly complex even in scenarios limited to have combinations of these interferer types and offers ample scope for demonstrating the benefits of our knowledge-based approach. CW tones are the most common type of interference occuring in a spread-spectrum communication environment. Chirp interferers pose a significant challenge to interference rejection schemes. Their instantaneous BW is narrow, but their effective bandwidth can cover the entire spread spectrum bandwidth. Chirp interferers require some form of adaptive filtering by the receiver.

3 Knowledge-Based Interference Isolation

Our knowledge-based strategy for adapting the analysis filters follows the IPUS blackboard paradigm. For processing any particular signal interval, our IPUS-based strategy relies on an iterative procedure guided by local and global constraints on the time-frequency characteristics of the narrowband interference signals. This procedure, which is outlined in Figure 1, begins by *predicting* the time-frequency evolution of narrowband interference tones from the previous processing block to the current one. The bandwidths of the analysis filters in a uniform filterbank are then adjusted on the basis of the predicted narrowband interference.

An iteration in our procedure commences with the processing of the signal data in the current analysis interval using the adjusted filterbank. Spectral peaks are picked from the output and fed to a Kalman tracker [?] that hypothesizes time-frequency trajectories corresponding to partials. We refer to these trajectories as "tracks." *Discrepancy detection* is carried out in order to search for "distortions" that cause mismatches between the predictions and the tracks. Examples of such distortions include the absence of a track where one has been predicted and mismatch in frequency modulation rates between a prediction and a corresponding track. Following discrepancy detection, the identified distortions are explained through a process of *discrepancy diagnosis*. The diagnostic process is aided by knowledge regarding the possible time-frequency interactions between narrowband interference tones. We were able to determine these interactions by means of a thorough analysis of all possible scenarios with the types of jammers considered in our research. Time-frequency information extracted from the data, such as the frequency modulation rate and the on-time of on-off jammers, are utilized within diagnosis to identify the relevant interactions within the current signal context. The identified interactions form the basis for attributing causes such as low frequency resolution and low time resolution to the distortions in the processed data. A set of *reprocessing plans* are then retrieved for removing each distortion by erasing its causes. Execution of the reprocessing plans result in an adaptation of the analysis filters and also (if necessary) a refinement of predictions in the current processing interval. This leads to the end of an iteration in our knowledge-based strategy. Reprocessing of the data followed by the formation of fresh tracks marks the start of a new iteration. The iterative procedure involving discrepancy detection, discrepancy diagnosis, reprocessing planning, and reprocessing is repeated until all distortions are either eliminated or an iteration limit is reached.

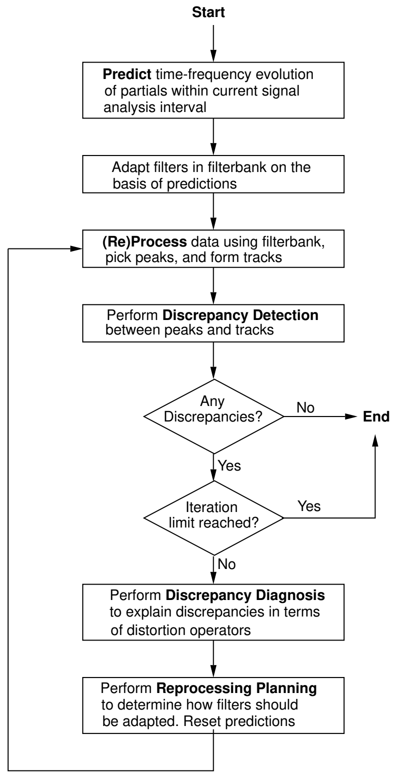

Figure 1: IPUS-based strategy for adapting the filters used in the time-frequency analysis of multicomponent music signals.