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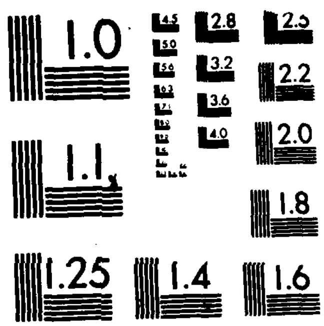

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ARTIFICIAL INTELLIGENCE APPLIED TO SPECTRUM ESTIMATION*

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ABSTRACT

Many techniques are available for the estimation of the power spectrum of a stationary random process. While power spectrum estimation is a problem which falls within the domain of signal processing, the problem of inferring information falls within the domain of artificial intelligence (AI). With a wide variety of different types of power spectrum estimation techniques to choose from, an equally wide range of differing spectral estimates may be produced. Each estimate, however, may be used to infer information about the time series. By defining an appropriate knowledge base, a system is being developed to infer information from power spectrum estimates. This system combines the estimates produced by a variety of current spectrum estimation techniques in order to formulate a composite spectral estimate.

INTRODUCTION

The integration of signal processing with artificial intelligence (AI) is not a new idea. In fact, the merger of both of these disciplines is proving useful in applications where the goal is the symbolic description of a signal or the extraction and recognition of signal features. Systems which presently apply artificial intelligence to signal processing include HEARSAY-II [1], SIAP [2], and the dipmeter advisor [3]. In this paper, we describe some preliminary work on the development of a system which applies AI techniques to the problem of estimating the power spectrum of a stationary random process. In particular, the general philosophy and structure of a Knowledge-Based Spectral Estimation (K-BASE) program is overviewed.

Although many signal processing techniques have been developed for estimating the power spectrum of a stationary random process, each produces a different estimate of the power spectrum [4]. While these estimates may be quite different, each sheds light on the underlying characteristics of the random process and provides useful information about the true power spectrum. The goal of our K-BASE program is to extract the relevant pieces of information from each of these estimates to form a composite description of the power spectrum. Thus, for any given spectrum estimation technique, the underlying assumptions concerning the signal generation process, the inherent strengths and limitations of the technique, and the signal features or model parameters produced by the technique are viewed as the knowledge. Collecting these pieces of knowledge together, a knowledge base is produced which forms the foundation for the K-BASE program. A control strategy is used to guide the search through the space of possible solutions. The information in the knowledge base is used to make inferences and deductions about the true power spectrum. Such a system, therefore, is able to draw upon the strengths of each of the power spectrum estimation techniques to derive a spectral estimate in a data-adaptive and "intelligent" manner. With this knowledge base and control structure it is also possible to make inferences and apply various signal processing techniques to test the validity of these inferences.

In the following sections, we overview the structure of the K-BASE program. First, we describe the contents of the knowledge base which is divided into four knowledge domains and provides the "intelligence" of the K-BASE system. Then we describe the control strategy which draws upon the knowledge base to direct the search through the problem space to reach the desired goal of the program, i.e., the description of the power spectrum. Finally, we describe a prototype system being developed which focuses on a problem of limited scope by restricting the size of the knowledge base.

K-BASE PROGRAM

We are currently in the preliminary stages of developing a Knowledge-Based Spectral Estimation (K-BASE) system. The purpose of this program is to develop a prototype system to find the power spectrum by using information gained from a set of spectral estimation techniques.

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The key components of the K-BASE program are the knowledge domains required for spectral estimation, the control strategies for reaching the final goal and the methods used to determine when the final goal is reached, and a representation of the knowledge. Due to the large amount of information available on power spectrum estimation, the prototype program is being developed using a subset of the available spectral estimation techniques. As with other knowledge-base systems (primarily expert systems) performance deteriorates when the signal analysed falls outside the scope of the knowledge-base [5]. Therefore, the development of the K-BASE system will be a continual process with the knowledge base being expanded with each version of the program.

Knowledge Domains

The first step in the development of the K-BASE program is the specification of the knowledge base. Preliminary studies indicate that there are four general knowledge domains to be considered in the development of the knowledge base. These domains include:

- The knowledge domain associated with the spectrum estimation techniques,

- The data models and the a priori information associated with the generation of the time series,

- The signal-to-symbol transformation, and

- Signal processing and signal manipulation techniques

The knowledge domain of the spectrum estimation techniques includes a variety of different types of information. At the highest level within this domain is a list of the various power spectrum estimation techniques, i.e., the estimation tools used in deriving information for making inferences and deductions about the time series structure. For each of these techniques there is a catalogue of information which specifies the *characteristics, behavior, and* limitations about the estimate produced by the technique. For example, it will be important to specify the ways in which a spectrum estimate is affected by variations of such parameters as the order of an AR or ARMA model, the time series record length, the number of autocorrelation lags, and the type of spectral or data record window. Another important piece of knowledge includes the strengths and limitations of the spectral estimation technique. Included in this area would be information concerning the data types for which the technique is best suited. The maximum entropy method (MEM), for example, performs very well for time series which may be accurately modelled as an AR process. Pisarenko's method, on the other hand, works very well for pure tones (sinusoids) in white noise. Equally important is information concerning the performance of the technique when it operates on data which does not fit the assumed model as well as lists of potential problems associated with a given technique operating a certain classes of signal. For example, it will be important to know for what types of signals and with what types of spectral estimation techniques line splitting is likely to occur. As another example, it will be important to know when a spectrum estimation procedure produces biased estimates of spectral peaks. In other words, the knowledge domain associated with the power spectrum estimation techniques should be an exhaustive catalogue of information and facts about each estimation procedure.

The second domain of knowledge concerns information about the signal which is being analysed. Within this domain falls such information as the data model and a priori information associated with the generation of the time series. The physics of wave propagation within geological formations, for example, provides information about seismic time series records. The theory of speech production, on the other hand, provides useful models which may be used in describing the time series representing speech waveforms.

The third knowledge domain, which traditionally is not usually considered to be a part of a knowledge base, is a signal-to-symbol transformation [3]. This signal-to-symbol transformation provides a convenient means for storing and manipulating conceptually inferred information about *a signal or its estimated spectrum.* Signal-to-symbol transformations are accomplished by a grammar which parses the time series [6] and can lead to representations of the form:

INTERVAL	SYMBOLIC REPRESENTATION
10kHz to 20kHz	*FLOOR->CUSP->RISE->CAP->RAMP*

This symbolic representation may have a quantitative description associated with each symbol such as the level of the floor, the slope of a rise or a ramp, the minimum value of a cusp, or the area under a cap [7]. The primary reason for including this signal grammar in the knowledge base is to allow for the possibility of incorporating knowledge about how the grammar is structured, how it is designed, and what its characteristics and features are.

The last knowledge domain contains the signal processing and the signal manipulation techniques. These techniques include such operations as filtering, windowing, and the removal of sinusoids. They are intended to be used as additional tools to further enhance a signal or its spectrum estimate to test various hypotheses. More specifically, after an initial analysis is performed, a set of hypotheses are made. Following this analysis, other techniques may be invoked in order to help confirm or disprove these hypotheses, thus increasing the confidence of inferences. For example, it has been recently observed that for the case in which two closely spaced spectral peaks are not resolved by a high resolution spectral estimation technique such as MEM, the peaks may often be resolved by placing zeros in the spectrum (usually in an adaptive fashion) [8]. Zero insertion, therefore, is viewed as a potentially useful tool for confirming the existence of multiple smeared peaks or for checking for the possibility of spectral line splitting. For each signal processing technique considered, knowledge about its properties, limitations, and desired goals needs to be identified.

The development of a total system to handle all types of specturm estimation techniques, various types of signals, many signal parsing grammars, and general signal processing techniques is a formidable task. Thus, the knowledge base to be initially developed will be limited in scope. Concentration is being focussed on a small number of spectral estimation techniques and attention is being directed towards a specific class of signals. However, as the knowledge base evolves, other information in the form of additional power spectrum estimation techniques and signal classes will be incorporated.

<u>Control Strategy</u>

The control strategy provides the mechanism to progress form the initial state (unknown signal) to the goal state (signal description). It directs the search through the problem space. The initial state is the sequence of samples, and the goal state might be:

> Two sinusoids in white noise at frequencies 10kHz and 20kHz with equal power; signal-to-noise ratio 4dB.

Since the desired output of a spectrum estimation program is typically answers to questions such as "are there one or two sinusoids," the control structure uses a goal-directed or forward chaining control strategy to generate a set of initial hypotheses [9]. Based on this initial set of hypotheses, additional signal processing and signal analysis is performed to evaluate the probability of each hypothesis. For example, if the initial pass deduces that either one or two sinusoids are present in the time series, then the controller analyzes the data record in the context of this hypothesis. The second pass uses a mixed strategy (e.g. means-ends analysis) to determine the characteristics of the sinusoids and the confidence level of the analysis.

<u>Knowledge Representation</u>

In the K-BASE system, different types of knowledge are used in the knowledge base. There is the signal-to-symbol transformer, the relational information associated with the spectral estimation techniques and their properties, and the rules for how, when, and what to extract from each power spectrum estimate generated. There are a number of different ways of representing knowledge. Two common methods are the use of production rules and the use of semantic frames. In K-BASE, both of these forms are used in knowledge representation. For example, since the knowledge about how to use the set of spectral estimation techniques is in the form of rules, production rules are used. Knowledge about the properties and limitations of a given power spectrum estimation technique, on the other hand, is easier to represent in terms of relations. Semantic frames provide a convenient mechanism for representing this relational knowledge. The symbolic representation of the power spectrum estimate is also in a relational (sequential) form and is therefore also easily represented in the form of semantic frames.

<u>Subset of Knowledge</u>

The development of a knowledge-based power spectrum estimation system which includes all estimation techniques is impractical as an initial attempt. The first prototype system, therefore, concentrates on a selected number of spectral estimation techniques. In the K-BASE program, the spectral estimation techniques chosen are the periodiogram, the maximum entropy method (MEM), and Pisarenko's method. These methods were selected since they produce very different spectrum estimates.

In addition to constraining the spectrum estimation methods used in the K-BASE program, the types of signals are also constrained. Specifically, the program focusses its attention on relatively low order ($N \leq 4$) AR processes to which sinusoids have been added.

A promising technique, zero insertion [8], will also be included as a technique to analyze signals. This technique is not a spectrum estimation technique, but a method to process the signal to resolve ambiguity. It relies on an initial hypothesis of the characteristics of the attempts to do. These type of signal manipulation techniques should be of great use in an AR system to accomplish spectral estimation.

The development of the K-BASE program on a subset of the spectral estimation knowledge-base will not be as powerful as using all spectral estimation techniques, for all signal types, with all signal modification procedures. It is hoped that the subset knowledge-base will demonstrate the feasibility and prove useful for the class of problems for which its knowledge covers. The development of a knowledge-base system is an on going process of development-test-upgrade. It is antipicated that other areas of knowledge may be included in later versions.

CONCLUSIONS

The K-BASE program's goal is to automate the analysis of the power spectrum based on estimates generated by a variety of techniques. To infer information about the true power spectrum from a variety of PSE techniques requires the use of knowledge. An artificial intelligence approach appears to be suited to this problem.

The knowledge base is composed of four major parts: the signal-to-symbol transformer, the spectral estimation techniques, the type of signals, and the signal manipulation techniques. A control strategy directs the search for the desired goal state (description of the true power spectrum). The strategy is to reason forward to a set of hypothesis, then use a mixed strategy to determine a more detailed analysis with confidence factors. The initial knowledge base is limited in scope to a few spectral estimation techniques and for a specific signal generation model. This will form the foundation for further extensions of the knowledge base.

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7