UNCLASSIFIED

2

AD-A205 054 DOCUMENTATION PAGE

Form Approved OMB No. 0704-0188

DTIC ELECTE MAR 0 3 1989 D

DTIC FILE COPY

1b. RESTRICTIVE MARKINGS			
2a. SECURITY CLASSIFICATION AUTHORITY		3. DISTRIBUTION/AVAILABILITY OF REPORT Approved for public release; distribution unlimited	
2b. DECLASSIFICATION/DOWNGRADING SCHEDULE			
4. PERFORMING ORGANIZATION REPORT NUMBER(S)		5. MONITORING ORGANIZATION REPORT NUMBER(S)	
6a. NAME OF PERFORMING ORGANIZATION Research Laboratory of Electronics Massachusetts Institute of Technology	6b. OFFICE SYMBOL (If applicable)	7a. NAME OF MONITORING ORGANIZATION Office of Naval Research Mathematical & Information Sci. Division	
6c. ADDRESS (City, State, and ZIP Code) 77 Massachusetts Avenue Cambridge, MA 02139		7b. ADDRESS (City, State, and ZIP Code) 800 North Quincy Street Arlington, VA 22217	
8a. NAME OF FUNDING/SPONSORING ORGANIZATION Advanced Research Proj. Agency	8b. OFFICE SYMBOL (If applicable)	9. PROCUREMENT INSTRUMENT IDENTIFICATION NUMBER N00014-81-K-0742	
8c. ADDRESS (City, State, and ZIP Code) 1400 Wilson Blvd. Arlington, VA 22217		10. SOURCE OF FUNDING NUMBERS	

PROGRAM ELEMENT NO.	PROJECT NO.	TASK NO.	WORK UNIT ACCESSION NO.
		NR 049-506	

11. TITLE (Include Security Classification)
The Role of Interpretation & Diagnosis in Signal Processing

12. PERSONAL AUTHOR(S) E.E. Milios and S.H. Nawab

13a. TYPE OF REPORT	13b. TIME COVERED	14. DATE OF REPORT (Year, Month, Day)	15. PAGE COUNT
Paper	FROM 6/6/88 TO 6/9/88	1988	4 pages

16. SUPPLEMENTARY NOTATION
Presented at 1988 IEEE International Symposium on Circuits and Systems, June 6-9, 1988, Espoo FINLAND

17. COSATI CODES			18. SUBJECT TERMS (Continue on reverse if necessary and identify by block number)
FIELD	GROUP	SUB-GROUP	

19. ABSTRACT (Continue on reverse if necessary and identify by block number)

ABSTRACT

A framework is proposed for adaptive signal processing that combines classical signal processing with adaptation criteria involving interpretation of the output signal and qualitative information about the classical signal processing itself. Interpretation of the output signal is achieved by expressing the signal at multiple levels of abstraction, capturing different levels of signal detail. A key aspect of the proposed framework is the computation of rich error descriptions by matching signal abstractions, as opposed to correlating numeric signals. Another key aspect is the encoding of qualitative information about the behavior of the classical signal processing component as processes that act upon reference signal abstractions and produce output signal abstractions. A search is then conducted for the most plausible processes that explain the differences between the reference output and the actual output of the system.

20. DISTRIBUTION/AVAILABILITY OF ABSTRACT ☒ UNCLASSIFIED/UNLIMITED ☐ SAME AS RPT. ☐ DTIC USERS	21. ABSTRACT SECURITY CLASSIFICATION UNCLASSIFIED
22a. NAME OF RESPONSIBLE INDIVIDUAL Elisabeth Colford - RLE Contract Reports	22b. TELEPHONE (Include Area Code) (617)258-5871 / 22c. OFFICE SYMBOL

DD Form 1473, JUN 86 Previous editions are obsolete. SECURITY CLASSIFICATION OF THIS PAGE

UNCLASSIFIED

THE ROLE OF INTERPRETATION AND DIAGNOSIS IN SIGNAL PROCESSING

Evangelos E. Milios
Department of Computer Science, University of Toronto,
Toronto, Canada, M5S 1A4

S. Hamid Nawab
Department of Electrical, Computer and Systems Engineering,
Boston University, Boston, MA 02215, USA

ABSTRACT

A framework is proposed for adaptive signal processing that combines classical signal processing with adaptation criteria involving interpretation of the output signal and qualitative information about the classical signal processing itself. Interpretation of the output signal is achieved by expressing the signal at multiple levels of abstraction, capturing different levels of signal detail. A key aspect of the proposed framework is the computation of rich error descriptions by matching signal abstractions, as opposed to correlating numeric signals. Another key aspect is the encoding of qualitative information about the behavior of the classical signal processing component as processes that act upon reference signal abstractions and produce output signal abstractions. A search is then conducted for the most plausible processes that explain the differences between the reference output and the actual output of the system.

1. INTRODUCTION

A major component of real-world signal processing is adaptation of signal processing parameters according to the situation at hand. A single setting of the parameters of a signal processing system is often inadequate, and will cause the system to fail, if the input signal violates too drastically the assumptions behind the design of the system. Adaptation of a single stage signal processing system can be achieved by adjusting its parameters according to the deviation of the output from an ideal output. In the case of a multistage system, parameter adjustment must be preceded by identification of the stages responsible for the system failure. In this paper we propose a novel framework for adaptive multistage signal processing that combines classical signal processing with interpretation and diagnosis [12]. Signal abstraction [8,9] is the backbone of both the interpretation and the diagnosis components.

Signal interpretation in our context analyzes the output signal to determine whether the result is satisfactory for the problem at hand. For example, if we analyze periodic signals and the output is a spectrum, a satisfactory result is a line spectrum. A related question is that of optimality: is the result the best that can be obtained? For example in the periodic signal case, we want to obtain the sharpest spectral peaks possible. We purposefully distinguish between a satisfactory and an optimal result, because we feel that optimality may be very difficult to define, unless in restricted cases, whereas criteria for a satisfactory but not necessarily optimal result may be easier to obtain.

Diagnosis in adaptive signal processing is reduced to search for the causes of any deviation of the output signal from the criteria that determine what is a satisfactory result. For example, if the spectrum of a presumably periodic signal is not a line spectrum, the goal of diagnosis is to track the cause of this discrepancy either to a parameter misadjustment of the spectrum estimation algorithm or to a violation of the periodic signal assumption. In the case of a single stage system, such as a spectral estimation algorithm, the diagnosis problem may be fairly straightforward, in that there are very few parameters that can be misadjusted. Diagnosis becomes more challenging in the case of multistage systems, such as the one described in [12], which have several sets of parameters associated with interacting stages, and therefore deciding which parameters are misadjusted and why becomes a search problem [5].

In section 2 we review adaptive signal processing and we place subsequent discussion in the context of generalizing the classical adaptive signal processing paradigm. In section 3 we define diagnosis as a search problem. The question of how to obtain the initial and goal states associated with the resulting search problem is addressed by signal interpretation, the role of which is examined in section 4. Finally, section 5 is a conceptual design of an adaptive signal processing framework that integrates diagnosis and signal interpretation.

2. ADAPTIVE SIGNAL PROCESSING

Adaptive Signal Processing has been extensively investigated, primarily in the context of adaptive filtering [4,2,3]. The block structure of an adaptive signal processing system is shown in Figure 1. The Signal Processing System is commonly a linear filter specified by a number of weights, the filter parameters. Examples of programmable filters are tapped-delay lines (transversal filters) or state-space matrices (Kalman filters). The Error Estimate is usually a numeric measure of the distance between the output signal and the reference signal. The Adaptation Algorithm specifies an incremental change to the system parameters as a function of the error estimate. The large number of adaptive signal processing techniques found in the literature is mainly due to the large number of possible adaptation algorithms. A common characteristic of most adaptation algorithms is that the new set of parameters is obtained from the old set of parameters multiplied by an "innovations" matrix. In this paper, we retain the basic structure shown in Figure 1, but we propose a more general view of the signal processing system, error estimation and adaptation algorithm.

1988 IEEE Int. Symp on Circuits and Systems
June 6-9, 1988, Espoo, Finland

Concerning the signal processing system, we include any kind of signal processing, not only linear filter structures. Furthermore, we include both single stage and multistage systems. Signal Processing systems in real applications are usually Multistage systems, namely they are built out of a sequence of stages, each of which has a concise mathematical description. The classical adaptation scheme mentioned above has been applied primarily to *single-stage systems*, which give *rise* to mathematically amenable optimization problems, solved by mathematical optimization techniques [7]. In multistage signal processing systems, the connection between the parameters of a particular stage and the output signal becomes less direct, and therefore the adaptation process becomes much more difficult, because it involves identifying the stage or stages that need to be adapted, in addition to parameter adaptation itself.

Concerning the error estimate, we view it as the bottleneck in current adaptive filters: all the information about the difference between the output signal and the reference signal (or criteria) must be expressed in terms of a single numeric error measure. We propose that the error estimate be a symbolic description of the differences between the actual and the desired filter output. Computation of the error estimate is thus viewed as *signal matching*, which can be conveniently approached via *signal abstractions* [8,9], i.e. condensed descriptions of signal features and their groupings at multiple levels of detail. Other relevant approaches include waveform matching by tree correlation [1], by feature correlation [13], or using a scale-space representation [14].

In many cases, a reference input is lacking, but criteria are available related to the acceptability of the filter output. For example, we filter a noisy image in order to enhance it. It is usually not easy to measure the amount of noise present in an image, so that we can tell whether filtering offers any improvement or not. Usually, some aspects of the image improve (e.g. background noise gets smoothed) and other aspects worsen (e.g. edges become blurred). Although it is difficult to define a quantitative measure of the amount of noise in the image, we can describe the characteristics of a "good" image, for example sharp edges and clean background. Given these criteria, we can compare enhanced images obtained with different filter parameter settings, order them according to our criterion and select the parameter setting that gives a satisfactorily enhanced image. In this case, denoted by "reference criteria" in Figure 1, the error estimate is a description of whether adaptation so far has brought us closer to the satisfaction of the reference criteria. A similar approach was used in [8,9] for adjusting spectral estimation parameters.

3. DIAGNOSIS

A diagnostic problem starts with the observation of some behavior that is recognized as a deviation from the expected. Diagnosis is the process of determining the cause of such deviation [11]. As a component of adaptive signal processing, diagnosis is the process of determining why the output of a signal processing system deviates from our expectations. In the case of classical adaptive signal processing, the deviation of the output signal from the reference signal is attributed to inappropriate values of the elements of a vector quantity, such as the filter coefficient vector. No finer grain explanation is sought, and the adjustment of system parameters is performed using an mathematical optimization approach. Therefore the diagnosis problem is not addressed explicitly, because the causes of system misbehavior cannot be traced to individual system parameters. However, in the case of multistage signal processing systems, the number of parameters is large. Furthermore, different parameters are associated with different aspects of the signal processing system, and therefore parameters cannot be grouped together and treated as a vector quantity. The task of diagnosis then becomes to associate system misbehavior to specific parameters of individual *stages, so that the adaptation problem is simplified by* being reduced to adjustment of a small number of misadjusted parameters.

The mathematical theory underlying multistage signal processing systems can be used to facilitate the diagnostic task. Unlike other diagnostic tasks, e.g. medical diagnosis, signal processing systems generate enormous amounts of intermediate data, and therefore production rules that map symptoms of system misbehavior to possible faults would be overwhelmed. The underlying mathematical theory can be used to define processes that transform the reference or ideal output into the actual output signal. Each process is specified in terms of how it transforms its input, and it is fully characterized by a set of parameters, that are directly associated with actual system parameters.

In the case of no fault, the reference output is identical to the system output, and therefore each process acts as an identity transformation. In the case of faulty behavior, one or more of the processes are *non-identity transformations*, and diagnosis becomes search for the non-identity processes. This formulation has been used as the basis of an implemented framework for diagnosis as search [12]. In formulating a problem as search, we must first define the problem space, which consists of a set of states of the problem, and a set of operators that change the state of the problem, or, equivalently, are mappings between states [5]. An operator may have preconditions associated with it that determine which states it can be applied to. A problem instance includes a problem space, and an initial and goal state, and the task is to find a sequence of operators that change the initial to the goal state. The goal state does not have to be explicitly specified. Instead, it can be specified as a set of conditions (goal conditions). In [12], the states of the problem are signals at multiple levels of abstraction, and operators correspond to processes defined on the basis of the underlying mathematical theory.

The search strategy used in the above framework is means-ends analysis at multiple levels of abstraction. Means-ends analysis consists of matching the initial with the goal state and selecting a process that can explain some of the differences. In general, the selected process is not quite applicable to the initial state, therefore a subproblem is created, how to transform the initial state into another state that satisfies the preconditions of the process. Furthermore, the output of the process is not exactly the same as the goal state, therefore another subproblem is present, namely transforming the output of process into the goal state. If the process is selected properly, the resulting subproblems are easier to solve than the original problem. The two subproblems are also attacked by means-ends analysis.

In the diagnosis associated with adaptive signal processing, intermediate signal data is usually enormous and often unavailable. Therefore, it is not easy to verify the intermediate signal states generated by the means-ends analysis strategy. To remedy this problem, means-ends analysis is augmented by a verification stage, which takes place at the lowest level of abstraction. If the sequence of processes computed by means-ends analysis at the highest level of abstraction fails to be verified at the lowest level of abstraction, then means-ends analysis is repeated at an intermediate level of abstraction. The verification stage is an important characteristic of the diagnostic framework, and it is made possible by the existence of a mathematical theory describing the associated signal processing system. Full details of the framework and its application to diagnosis of an acoustic signal processing system are presented in [12].

To apply the above framework to the diagnosis of other multistage signal processing systems, we need to identify the nature of our expectations about the output of the signal processing system, their representation, and how they are obtained. In [12] expectations about the output of the signal processing system have the form of an abstract representation of the "correct" or reference signal interpretation. How such a representation is obtained can vary. In test situations, a reference signal interpretation is available because information about the underlying physical event is available a priori. In operational use of a system, the reference signal can be the result of less accurate but more robust signal processing, that is capable of producing abstract signal interpretations, but lacks the accuracy that the complex system can provide, if properly adapted. As in the case of general search, the reference signal may not be explicitly available, but described as a set of criteria or properties that the output signal must satisfy.

4. SIGNAL INTERPRETATION AND MATCHING

An important input to the diagnosis engine is a reference signal interpretation and the actual output signal interpretation of the signal processing system. In a real application, these are not available, as it was assumed in [12], but they have to be extracted as signal abstractions from low-level signals. Deriving signal interpretations from low-level numeric signals is therefore a major component of adaptive signal processing based on diagnosis. In classical adaptive signal processing, the need for signal interpretation is obviated by a direct computation of the error as a numeric correlation between the system output and the reference signal. In adaptive signal processing based on diagnosis, the error computation is performed in two steps. The first is computation of signal abstractions of the system output and the reference signal, and the second is their matching and computation of an abstract description of their differences. The latter is also a component of the diagnostic framework that uses means-ends analysis.

Computation of signal abstractions was addressed in [8,9]. In the context of diagnosis, signal abstractions correspond to search states and therefore we can draw a parallel between a general theory of abstractions [5] and the formulation proposed in [8,9]. In [5], two models of abstraction in search are proposed. In the first, the set of abstract states is a subset of the states in the original problem space. In the second, each state of the abstract space corresponds to a subset of the states in the base space. The formulation of signal abstraction in [8,9] is equivalent to the second, more general model.

The problem of deriving the abstract states given the base states, which correspond to the numeric signal, has also been addressed [8,9]. It involves a grouping process, the ingredients of which are formally defined. An implementation is also provided in the context of a specific application, tracking of harmonic signals over time. The grouping framework proposed is quite general, but the choice of specific abstractions depends on the signal processing problem under consideration. So far, we have defined abstractions for three distinct problems [12, 9, 6] and we have implemented computationally the two of them [9, 6].

Computing signal abstractions is the first step towards obtaining a description of the error between the reference signal and the output signal. In diagnosis based on means-ends analysis, the error should be a rich enough description of the differences between the reference and output signal to enable selection of the appropriate process or operator. A single numeric error measure, as the one produced by numeric correlation of two signals, is usually not rich enough to permit operator selection. In the example presented in [12], differences between signals are computed from their abstract descriptions and they are related to several of their aspects, such as high-power spatial frequencies or and the associated bandwidths. In matching harmonic acoustic signals [9], the differences between two spectra refer to the different numbers of harmonic present and the relative sharpness of the respective spectral peaks.

Matching a signal against criteria can also arise in adaptive signal processing, when the reference signal is not given explicitly, but is described as a set of conditions. For example, in the computation of harmonic spectra, the goal condition is a spectrum with maximally sharp harmonic peaks. A goal state specified by conditions may occur in subproblems arising during means-ends analysis. In this case, we need to find the differences between the initial state and the preconditions of the operator. In [12], such differences are computed within the same framework as matching two explicit abstract signal descriptions.

5. CLOSED-LOOP OPERATION

Diagnosis and interpretation are two of the three components of a closed-loop framework for adaptive signal processing. The third component is adaptation of system parameters based on the diagnosis outcome. The framework shown in Figure 2 can be viewed as a generalization of classical adaptive signal processing. Classical adaptive signal processing mostly applies to single stage systems and therefore its diagnosis component is very simple. Furthermore, the process of finding the differences between the actual output signal and the reference signal takes place at the lowest level of abstraction, the numeric signal, with the resulting difference being an numeric error measure. Therefore, the proposed framework includes two generalizations of the classical adaptive approach. The first is along the signal representation dimension and introduces signal abstraction as a means of using conceptual clusters of signal points in the difference/error finding process. The second is along the complexity of the underlying signal processing system, and introduces diagnosis as search for its misadjusted parameters, which is applicable to multistage signal processing systems.

6. DISCUSSION

In this paper we reviewed the formulation of adaptive signal processing as a problem that involves diagnosis, signal interpretation and qualitative reasoning about signal processing systems. Parts of the proposed framework have already been explored in the context of specific problems with promising results. Although a lot of work remains to be done in terms of validation of the proposed framework and its formalization, we believe that there is enough evidence at this point to suggest that diagnosis and signal interpretation can play an important role in extending the spectrum of available adaptive signal processing techniques and methodologies.

Acknowledgements: This research was sponsored at the MIT Lincoln Laboratory by the Defense Advanced Research Projects Agency under contract F19628-85-C-0002, at the MIT Research Laboratory of Electronics by the Advanced Research Projects Agency monitored by ONR under contract N00014-81-K-0742 and at the University of Toronto by a strategic grant from the National Sciences and Engineering Research Council of Canada. The views expressed are those of the authors and do not reflect the official policy or position of the U.S. government.

References

[1] Y-C. Cheng and S-Y. Lu. Waveform correlation by tree matching. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 7:299–305, May 1985.

[2] C. Cowan and P. Grant, editors. *Adaptive Filters*. Prentice Hall, Englewood Cliffs, NJ, 1985.

[3] T. Durrani. Adaptive signal processing. In J-L. Lacoume, T. Durrani, and R. Stora, editors, *Signal Processing, Session XLV, NATO Advanced Study Institute*, pages 486–513, North Holland, 1987.

[4] S. Haykin. *Adaptive Filter Theory*. Prentice Hall, Englewood Cliffs, NJ, 1986.

[5] R. Korf. Planning as search: a quantitative approach. *Artificial Intelligence*, 33:65–88, 1987.

[6] S. Lee, E. Milios, R. Greiner, and J. Rossiter. Signal abstractions in the machine analysis of radar signals for ice profiling. In *International Conference on Acoustics, Speech and Signal Processing*, page , 1988.

[7] D. Luenberger. *Introduction to Linear and Nonlinear Programming*. Addison-Wesley, 1973.

[8] E. Milios and H. Nawab. Adaptive signal processing using signal abstractions. In J. Kowalic and T. Kitzmiller, editors, *Coupling Numeric and Symbolic Processing in Knowledge-Based Systems*, Elsevier Publishing Co. (North Holland), 1988 (in press).

[9] E. Milios and H. Nawab. Signal abstractions in signal processing software. *IEEE Transactions on Acoustics, Speech and Signal Processing*, Submitted, May 27 1987.

[10] E. Milios and H. Nawab. Signal abstractions in signal processing software. In *International Conference on Acoustics, Speech and Signal Processing*, 1987.

[11] R. Milne. Strategies for diagnosis. *IEEE Transactions on Systems, Man and Cybernetics*, 17(3):333–339, May/June 1987.

[12] H. Nawab, V. Lesser, and E. Milios. Diagnosis using the formal theory of a signal processing system. *IEEE Transactions on Systems, Man and Cybernetics*, 17(3):369–379, May/June 1987.

[13] Ph. Vincent, J.E. Gartner, and G.Attali. An approach to detailed dip determination using correlation by pattern recognition. *Journal of Petroleum Technology*, 232–210, February 1979.

[14] A. Witkin, D. Terzopoulos, and M. Kass. Signal matching through scale space. In *Proceedings of the American Association for Artificial Intelligence Conference*, pages 714–719, 1986.

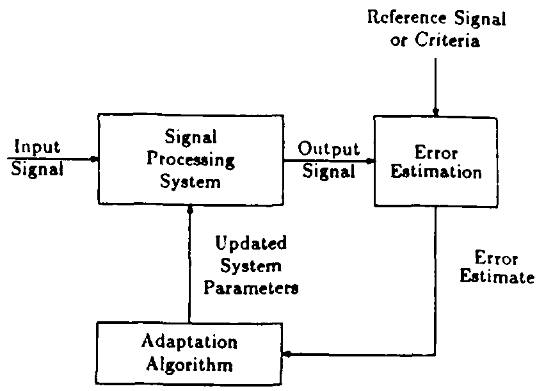

Figure 1: Classical Adaptive Signal Processing.

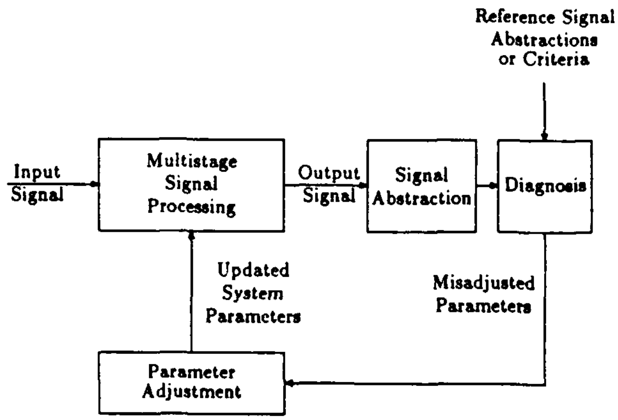

Figure 2: Adaptive Signal Processing using Interpretation and Diagnosis

DISTRIBUTION LIST

	DODAAD Code	
Director Defense Advanced Research Project Agency 1400 Wilson Boulevard Arlington, Virginia 22209 Attn: Program Management	HX1241	(1)
Head Mathematical Sciences Division Office of Naval Research 800 North Quincy Street Arlington, Virginia 22217	N00014	(1)
Administrative Contracting Officer E19-628 Massachusetts Institute of Technology Cambridge, Massachusetts 02139	N66017	(1)
Director Naval Research Laboratory Attn: Code 2627 Washington, D.C. 20375	N00173	(6)
Defense Technical Information Center Bldg 5, Cameron Station Alexandria, Virginia 22314	S47031	(2)
Dr. Judith Daly DARPA / TTO 1400 Wilson Boulevard Arlington, Virginia 22209		(1)