USE OF INTELLIGENT AGENTS TO INCLUDE SIGNAL ANALYSIS DATA

Donna L. Hudson[1], Maurice E. Cohen[1,2]
[1]University of California, San Francisco, Fresno, CA 93703 USA
[2]California State University, Fresno, CA 93740, USA
hudson@ucsfresno.edu

Abstract – **Signal analysis data, especially electrocardiogram (ECG) and electroencephalogram (EEG) data, provide important information for clinical decision-making. In order to arrive at a diagnosis, it is often necessary to combine these results with other clinical parameters. Problems remain in the automation of this process for the development of computer-assisted diagnosis tools. A promising approach includes the use of intelligent agents, a procedure that involves the development of a central mechanism to provide communications among differing methodologies and different information types to provide a comprehensive solution to the problem. This methodology is illustrated in a decision model for diagnosis of dementia emphasizing the inclusion of summary measures for EEG data.**

Keywords – **Signal analysis, intelligent agents, EEG analysis, hybrid systems**

I. INTRODUCTION

Intelligent agents had their origins in distributed artificial intelligence and have been used successfully in a number of business applications [1]. Each agent is an independent methodology with reasoning capabilities working on a prescribed task. The goal of the overall system is to provide a cooperative environment in which two or more agents can be combined to solve a problem through the use of a mediator or facilitator [2]. A major role of the facilitator is to provide a common means of communication. The intelligent agent approach is a natural extension of hybrid systems for combining various methodologies without altering the independent agents or algorithms. The use of intelligent agents in biomedical systems has been limited, with the major focus on health care delivery [3,4]. Some complex medical decision making problems have been addressed [5,6].

In many disease processes, results from signal analysis provide vital information for clinical decision-making. In many cases, however, these results must be combined with other clinical and historical information to provide a comprehensive conclusion. While physicians often perform this process manually, computer-assisted decision support systems have not completely addressed the use of multiple models in arriving at one overall decision. While traditional hybrid systems have dealt with this problem, often modifications are needed in the individual algorithms to permit combination of results [7]. The intelligent agent approach allows free interaction among agents by providing an external facilitator to deal with communications issues and with combination of results. This approach is especially useful for the incorporation of signal analysis data that is often supplied in the form of lists of abnormalities or as summary data that is not easily combined with traditional clinical parameters.

This methodology is illustrated in the diagnosis of dementia using data from the following sources: cognitive evaluation, family history, genetic testing, functional imaging, and EEG analysis. The goal of the system is to differentiate between types of dementia so that appropriate treatment can begin at an early stage.

II. METHODOLOGY

The overall structure of the system is shown in Fig. 1. The three components are the collection of agents, the task manager, and the communicator.

A. Agents

The agents represent the independent decision entities, including the client. The client in the case of a medical decision support system is the human decision maker. The other agents may be any of a variety of methodologies possessing some form of decision-making capabilities. Possibilities include knowledge-based systems, neural network models, Bayesian systems, risk analysis, statistical results, and signal processing algorithms. Each agent utilizes it own sources of information, which may be shared with other agents. Table I shows examples of agents along with domain knowledge information sources. For a patient analysis problem, these sources are used in conjunction with patient-specific information.

B. Task Manager

The principal components of the control structure are the task manager and the communications interface. The task manager breaks the problem into subtasks that are then directed toward the appropriate agents. It also combines results from agents, including the client, for the overall response to the problem.

C. Communicator

The communicator must present input to each agent in a form that it can understand and interpret output from each agent so that other relevant agents can understand it. This process is illustrated in Fig. 2. The three main components

Report Documentation Page

Report Date	Report Type	Dates Covered (from... to)
25 Oct 2001	N/A	-

Title and Subtitle Use of Intelligent Agents to Include Signal Analysis Data	**Contract Number**
	Grant Number
	Program Element Number
Author(s)	**Project Number**
	Task Number
	Work Unit Number
Performing Organization Name(s) and Address(es) University of California San Francisco, CA 93703	**Performing Organization Report Number**
Sponsoring/Monitoring Agency Name(s) and Address(es) US Army Research, Development & Standardization Group (UK) PSC 802 Box 15 FPO AE 09499-1500	**Sponsor/Monitor's Acronym(s)**
	Sponsor/Monitor's Report Number(s)
Distribution/Availability Statement Approved for public release, distribution unlimited	
Supplementary Notes Papers from 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, October 25-28, 2001, held in Istanbul, Turkey. See also ADM001351 for entire conference on cd-rom.	
Abstract	
Subject Terms	
Report Classification unclassified	**Classification of this page** unclassified
Classification of Abstract unclassified	**Limitation of Abstract** UU
Number of Pages 4	

are the symbolic to numeric converter, the numeric to symbolic converter, and the common language generator that interprets output in a form that can be communicated to each agent. The objective is to overlay the conversion similarly to a human user interface so no agent modification is required.

TABLE I
EXAMPLES OF AGENTS

Type of System	**Information Source**
Knowledge-Based Systems	Domain rules
Neural Network Models	Decision Equation
Signal Analysis	Time Series Evaluation
Imaging	PACS
Patient Analysis	Medical records

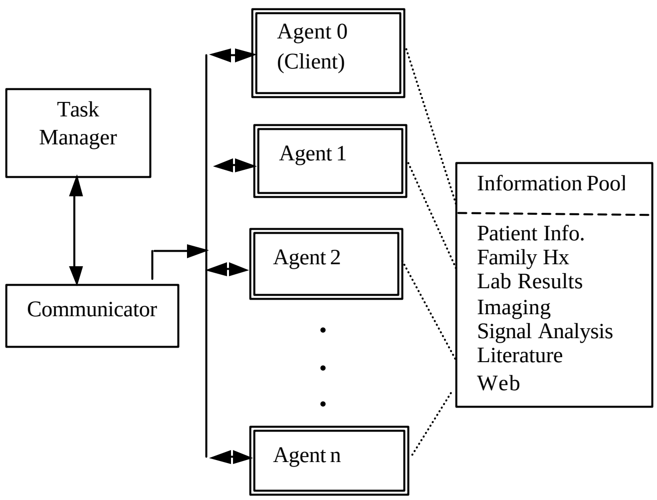

Fig. 1: Computational architecture for decision support

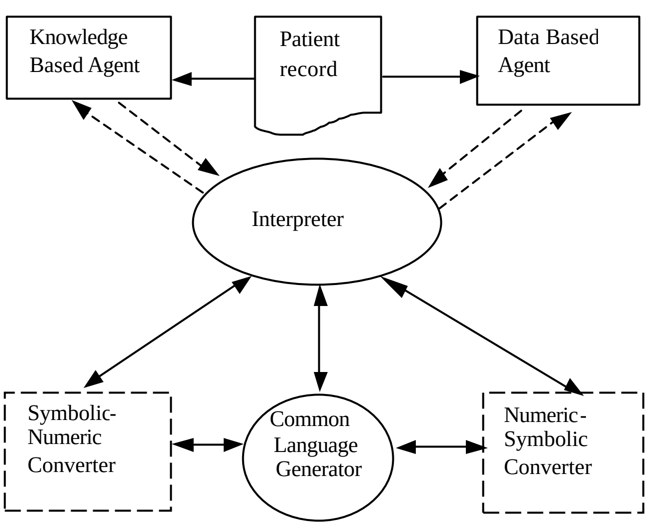

Fig. 2: Communicator

III. RESULTS

The methodology described above has been applied to diagnosis, treatment, and management problems associated with dementia. Alzheimer's disease (AD) is a devastating illness with a relentless progressive course. Patients suffering from AD gradually lose memory, visio-spatial ability, judgment, and even personality. Assessment tools for cerebral cortical dysfunction secondary to Alzheimer's disease (AD) or stroke are urgently needed. With our increasingly aging population, cortical dysfunction due to AD and stroke is becoming increasingly common. Nationwide, these are the top two causes for cognitive impairment and loss of the ability for independent living. The cost to patients, family members, and society is staggering. The need to provide accurate diagnostic classification and staging to assess prognostic indicators, and to have tools for reliable evaluation of the efficacy of intervention, becomes critical. Evidence exists that early intervention can lead to more successful treatment and improvement of quality of life.

A. Problem Definition

The overall goals for the project are:

1. Development of a package for quantitative EEG analysis based on the combination of new approaches to wavelet and chaotic analysis;
2. Implementation of a classification model using EEG, imaging, clinical and cognitive data, including algorithms for learning patterns in data, expert input, imaging results, and EEG analysis through the use of intelligent agents;
3. Evaluation of the effectiveness of the model in classifying patients by disease category;
4. Evaluation of the ability of the model to track disease progression.

The structure of the intelligent agent configuration for dementia evaluation is shown in Fig. 3.

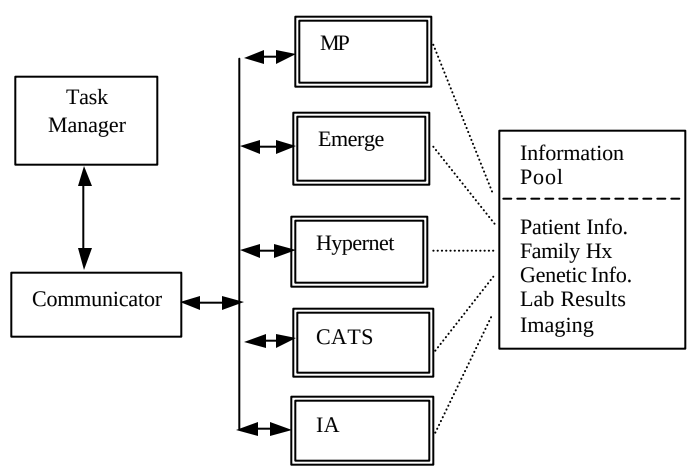

Fig. 3: Computational Architecture for Dementia

B. Relevant Agents

Agent 0: Medical Professional (MP)

The human decision maker functions as agent 0 and interacts with the communicator using natural language. In the current design, agent 0 can also perform as one of the other agents, as discussed below.

Agent 1: Knowledge-Based System (Emerge)

A system previously developed by the authors, Emerge, is used as the knowledge-based component [8]. The original application was analysis of chest pain in the emergency room. The method has subsequently been used on numerous applications through the derivation of new knowledge bases. The inference engine uses approximate reasoning techniques to include weighted antecedents, partial presence of findings, and partial substantiation of rules. The general rule structure is shown in Table II. The truth of proposition P, represented by this structure, is determined by assuming there exists some subset C of V such that 1) the number of elements in C satisfies Q; or 2) each element in C satisfies the property A. The degree S to which C satisfies P is:

$$S = \max_{C\,\varepsilon A} \{V_P(c)\} \tag{1}$$

where

$$V_P(c) = \max[(Q \sum_{i=1}^{n} c_i \wedge a_i) \wedge \min_{i=1,\ldots,n} (w_i^{\,c_i \wedge a_i})] \tag{2}$$

where ^ indicates minimum, w_i and a_i are the weighting factor and degree of substantiation, respectively, of the i^{th} antecedent, $c_i \varepsilon \{0,1\}$, and n is the number of antecedents. The sources of information that are relevant for rule base development for dementia evaluation are listed in Table III.

Agent 2: Neural Network Model (Hypernet)

The neural network model is based on the authors' Hypernet system [9]. Hypernet uses an expanded potential function approach in a supervised learning algorithm resulting in a nonlinear network structure with three or more layers. Input parameters can be any type of ordered data. In this application, the neural network is used to assess treatment strategies. Output is in the form of a decision function:

$$D(x) = \sum_{i=1}^{n} w_i x_i + \sum_{i=1}^{n} \sum_{j=1\,(i\neq j)}^{n} w_{ij} x_i x_j \tag{3}$$

TABLE II
RULE STRUCTURE

	Antecedent	Weighting Factor	Degree of Substantiation
IF	1	w_1	a_1
	2	w_2	a_2
	.		
	.		
	.		
	n	w_n	a_n
THEN	Conclusion if S > Threshold		

TABLE III
CLINICAL PARAMETERS

Cognitive Factors
Mini-Mental State Examination (MMSE)
Clinician evaluation of level of function
Caregiver evaluation of level of function
Family History
Number of first - or second-degree relatives with dementia
Number of first - or second-degree relatives with AD
Number of first - or second-degree relatives with early onset dementia
Number of first - or second-degree relatives with early onset AD
Genetic Testing
Presence of E4 isoform of apoE

Agent 3: Chaotic Analyzer (CATS)

The EEG is evaluated in terms of both amplitude and frequency of wave occurrence using a method previously developed by the authors for ECG analysis [10]. The EEG presents a much more complex problem in that is has recognizable patterns that do not repeat at definable intervals. In addition to this problem, EEGs typically record up to 22 channels of data resulting in very large numbers of points that require analysis. A convenient method of viewing this data graphically is to plot dT_{n+1}/dt versus dT_n/dt where T_n is the value of the series at time n. The degree of variability in a time series is better represented by the second-order difference A_n, or acceleration, given by

$$A_n = dT_{n+1}/dt - dT_n/dt = (T_{n+1} - T_n) - (T_n - T_{n-1}) \tag{4}$$

The second-order difference plot is generated by plotting A_{n+1} vs. A_n. The degree of variability is determined for each channel through the use of the Central Tendency Measure (CTM) computed by selecting a circular region around the origin of radius r, counting the number of points that fall within the radius, and dividing by the total number of points. Let t = total number of points, and r = radius of central area:

$$CTM = [\sum_{i=1}^{t-2} \delta(d_i)]/(t-2) \tag{5}$$

where $\delta(d_i) = 1$ if $[(T_{i+2}-T_{i+1})^2+(T_{i+1}-T_i)^2]^{.5} < r$, and 0 otherwise. Preliminary results for EEG analysis of Alzheimer's patients and normal controls are given in Table IV. Peaks are determined using an algorithm developed by the authors [11]. For amplitude computation T_n represents the nth point in the series, while for frequency computation T_n represents the nth peak in the series.

TABLE IV
EEG AMPLITUDE AND FREQUENCY RESULTS

ID #	Amplitude (r=0.1)	Frequency (r=.05)
N_1	0.54	0.29
N_2	0.71	0.57
A_1	0.81	0.52
A_2	0.40	0.62
A_3	0.67	0.28
A_4	0.60	0.44
A_5	0.68	0.40
A_6	0.58	0.18

N_i: Normal controls; A_i: Alzheimer's Patients

Agent 4: Image Analysis (IA)

In general, imaging of all types are accessible using picture archiving and computer storage (PACS) systems. While many pattern recognition algorithms have been developed for automated interpretation of images, these are in general supplemental to radiologist interpretation. For this implementation, natural language descriptions of abnormalities are used, along with functional imaging comparisons of activities in each lobe of the brain. In this situation, the radiologist can also be considered an agent.

C. Task Manager

The task manager breaks the problem down into subtasks that are assigned to the appropriate agent. These assignments are given in Table V. Note that the EEG information is generated by Agent 3 but is used as input by many other agents.

D. Communicator

The role of the communicator here is to provide a common language for agent communication. The communicator uses linguistic quantifiers for conversion for numeric-symbolic translation, as well as meta rules for interpretation.

IV. DISCUSSION

The dementia model is designed as a starting point for dealing with a complex medical problem. The expectation is that the model will expand as more domain information becomes available and new methodologies are developed. The usefulness of the EEG analysis in dementia is yet to be well-established. It will be investigated in this study in two ways: as an independent entity and as part of a more complex decision model. Two decision models are currently being used. The knowledge-based component uses EEG results in the form of rules and the neural network model uses the CTM result as a node in the network along with clinical, historical, and genetic parameters.

V. CONCLUSION

Effective early diagnosis of the basis for dementia will become increasingly important as the population ages. The use of intelligent agents provides a means for dealing with rapid developments both in terms of knowledge as well as new methodologies. The inclusion of EEG analysis as a major factor in differentiation of types of dementia remains to be demonstrated, partially due problems with traditional time series analysis when applied to non-stationery signals. The use of chaotic analysis in conjunction with the hybrid approach will help to determine the utility of the EEG in this setting. The general structure proposed by the intelligent agent method can be adapted to address other related decision topics that involve signal analysis, such as differential diagnosis in cardiology.

TABLE V
AGENT TASKS

Agent	Task	Input from	Output to
0	Diagnosis	Emerge(1)	Final decision
	Staging	Emerge (1)	Final decision
	Treatment	Hypernet (2)	Final decision
	Image interp.	PACS	IA (4)
1	Diagnosis	Patient record CATS (3) IA (4)	MP (0)
2	Treatment	Patient record Database	MP (0)
3	EEG analysis	EEG	MP (0) Emerge (1) Hypernet (2)
4	Image analysis	PACS MP (0)	MP (0)

(*) Indicates agent number

ACKNOWLEDGMENT

This work was supported by NIH Grant MBRS-SCORE ISO6GM61223-01.

REFERENCES

[1] O. Hofmann, F. Bodendorf, A framework for agent mediated electronic business, *ISCA CATA*, pp. 120-123, 2000.
[2] K.M. Swigger, L. Ducksworth, Supporting computer-mediated collaboration through user-defined agents, *ISCA CAINE*, pp. 43-46, 2000.
[3] S. Mack, J. Holstein, K. Kleber, D.H. Grönemeyer, New aspects of image distribution and workflow in radiology, *J. Digital Imaging*, **13(2)**, pp. 17-21, 2000.
[4] C. Hsu, H.S. Goldberg, Knowledge-mediated retrieval of laboratory observations, *Proc., AMIA*, pp. 809-813, 1999.
[5] G. Lanzola, L. Gatti, S. Falasconi, M. Stefanelli, A framework for building cooperative software agents in medical applications, *Artificial Intelligence in Medicine*, **16**, pp. 223-249, 1999.
[6] B.G. Silverman, The role of Web agents in medical knowledge management, *MD Computing*, **15(4),** pp. 221-31, 1998.
[7] D.L. Hudson, M.E. Cohen, *Neural Networks and Artificial Intelligence for Biomedical Engineering*, IEEE Press, 1999.
[8] D.L. Hudson, M.E. Cohen, An approach to management of uncertainty in an expert system, *International Journal of Intelligent Systems*, **3(1)**, pp. 45-5, 1988.
[9] D.L. Hudson, M.E. Cohen, *Neural Networks and Artificial Intelligence for Biomedical Engineering*, IEEE Press, 1999.
[10] M. E. Cohen, D.L. Hudson, M.F. Anderson, P.C. Deedwania, A conjecture to the solution of the continuous logistic equation, *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems*, **2(4)**, pp.445-461, 1994.
[11] Cohen, M.E., Hudson, D. L. New Chaotic Methods for Biomedical Signal Analysis, *IEEE EMBS Information Technology Applications in Biomedicine*, pp. 117-122, 2000.