CEAI, Vol. 8, No. 2, pp. 54-60, 2006 Printed in Romania

THE INTELLIGENCE OF A HYBRID SYSTEM: DIAMED

Sabina Munteanu, Ioan Dumitrache

T.A., Department of Computer Science and Applied Informatics,
"Dunarea de Jos" University of Galati,
Prof., Department of Automatics and Systems' Engineering
Politehnica University of Bucharest

Abstract: *GFS (Group, Filter, Search) are the three basic computational procedures that underlie intelligence. We reveal their implication in some intelligent approaches to reasoning in Artificial Intelligence, and also use them to develop a new perspective over an original approach to nonmonotonic reasoning (the DiaMed system).*

Keywords: *hybrid systems, fuzzy decision, direct argumentation systems, medical diagnosis.*

1. INTRODUCTION

Reasearch has made clear that the three basics operations that underlie intelligence are [2]: grouping, filtering (focusing attention) and combinatorial search (GFS: Group, Filter, Serach). So, GFS is the elementary unit of intelligence made up of a triple of computational procedures whose purpose is the "transformation of large volumes of information into a manageable form which ensures success of functioning" [2]. The search procedure implies the formation of multiple combinations of elements, grouping comprises rules and conditions for transforming these elements into entities (it is a paradigm of conceptual abstraction), and focusing attention takes care that in the real world we can only work inside a bounded space.

Section 2 discusses broadly the importance and meaning of the three procedures mentioned above in relation with some intelligent techniques, and Section 3 proposes a new point of view, GFS-related, of an original two-leveled hybrid system which was used for medical diagnosis in previous papers [3, 4].

2. THE INTELLIGENCE OF INTELLIGENT TECHNIQUES

2.1. *Main features of intelligent techniques*

Intelligent techniques are supposed to compensate the incompleteness of a model by approximating a domain through shallow knowledge. This allows an efficient approach to complex, non-linear, time-varying problems.

Neural networks are non-structured models for non-linear regression. They are especially known for their generalization, robustness and learning abilities, being a representative example of inductive inference. Their usefulness is mainly revealed by those problems for which neither a good model, nor a clear algorithm exist. A main drawback resides in the lack of good explanation abilities for the decisions made. Genetic algorithms are adequate for the search of an optimal solution in a continuous space, when the possible solutions represent a significant part of the total search space. They work with populations of solutions simultaneously, encoding these solutions under the form of genetic chromosomes. Mutation and crossover are translated from a genetic theory to each specific problem, to provide the "evolution" of solutions, through fitness-based selection. These operators can be considered the weak point of this intelligent techniques: very often it is difficult to find natural and useful definitions for them.

Fuzzy inference systems are a formalism suited to use human expertise under the form of un uncertain symbolic model. Different concepts from a domain's ontology are encoded as fuzzy variables that may have fuzzy linguistic values (modeled as fuzzy sets). They are universal approximators, effective for non-linear, complex systems. Rule-based systems model shallow expert knowledge under the form of IF-THEN rules. Inference is quick, as they rely on shallow associations from causes to effects, but the drawback is they cannot offer a detailed explanation for such a decision.

There exist two main paradigms for search: heuristic search and combinatorial search. Heuristic search uses different types of heuristics in order to avoid the test of all the possible combinations that build the search space. An evaluation function is usually used to guide the searching process; it tries to estimate how far from an optimum a point might be. For instance, genetic algorithms are well known for their use of such evaluators in ranking the fitness of solutions, but other approaches with different types of evaluation functions are also largely used. A distinctive characteristic of heuristic search is that it is incomplete: its heuristics are used exactly to avoid exhaustivity and therefore improve efficiency.

As already mentioned, genetic algorithms are an intelligent approach to heuristic search. Their strength is given by the populations of solutions that actually perform search simultaneously in different parts of the space of possible solutions, as opposed to traditional search algorithms like greedy or backtracking that considered a single point at a time. Combinatorial search, on the other hand, is closer to a kind of "brute force" method that systematically addresses each point of the space of possible solutions. Yet improvements can be made here too, in order to avoid reaching useless points: backtracking is a standard technique that drops partial assignments as soon as they appear faulty from a solution's point of view. CSPs (Constraint Satisfaction Problems) improve backtracking with different heuristics; for example, some of the CSP algorithms preprocess the constraint graph such that backtrack will be less frequent.Focusing attention during search is essential to avoid the curse of dimensionality. Its purpose is to restrict the search to "interesting" parts of the space only. For instance, the rules of an expert or fuzzy system represent means of drawing attention to the variables activated by evidence and restrict inference operations at them only. Neural networks used for pattern recognition (matching) are also a means of selecting relevant aspects from a multitude of possibilities. The operation of grouping is closely related to the notion of knowledge engineering: it is somehow a creation of concepts and classes. Mainly, the field of data mining addresses different techniques for drawing higher-level entities (notions) from primitive data. Fuzzy clustering or SOMs (Self Organizing Maps) represent typical examples for organizing knowledge into classes. Causal networks are an interesting and particular way of structuring together elements that are already known to be related before processing (from a model).

3.HYBRID INTELLIGENT SYSTEMS FOR MEDICAL DIAGNOSIS

3.1.Introduction

Hybridization of intelligent techniques is meant to combine advantages and to compensate for the drawbacks. Four main types of hybrid architectures developed throughout the years:

- Fusion systems: they melt the representation and computation of two different techniques (for instance, adaptive neural networks to represent fuzzy inference systems);
- Transforming systems: they transform a technique into another (for instance, neural networks for symbolic rules' extraction);
- Combinative systems: they keep the identity of the methodologies and aggregate their results;
- Associative systems: they combine two or more of the types above.

The complexity of the medical field makes it necessary to distribute tasks among different techniques. We mainly have two steps to approach: selection and refinement of hypotheses. Each step could benefit from a technique that is especially suitable for it. The techniques could maintain their identity when working for the separate tasks, but could bring together their results in the end, leading to combinative hybrid architecture. For instance, it would be appropriate to choose an efficient method to select relevant hypotheses out of a multitude of possibilities, but quite adequate to switch to a transparent technique when dealing with the refinement step: even if this latter one is computationally expensive, we have already narrowed down the space.

3.2.The DiaMed System

DiaMed is an intelligent hybrid system we've designed to deal with the particular difficulties of medical diagnosis (discontinuity, variability, dynamism, non-monotonicity [4]). It comprises two levels: a level for diagnostic hypotheses' selection, modeled in terms of fuzzy decision, and a level for refining, discriminating and explaining results, modeled by means of arguments and implemented with a modified version of dynamic backtracking for DCSP (Dynamic Constraint Satisfaction Problems) [7]. We briefly describe the two levels below.

a) Selection of hypotheses with fuzzy decision

The key of this representation is to define the diagnostics $\Delta = \{d_1,...,d_N\}$ by means of fuzzy weighted decision functions ($D_1^{w_1},...,D_N^{w_N}$) [3]:

$D_i^{w_i} = h_i(M_{i_1}(o),...,M_{in_i}(o))$ (2.1.1) , where:

- $Symptoms(d_i) = \{m_{i_1},...,m_{in_i}\}$, and $i_1,...i_{n_i} \in \{1,...,K\}$ represent the indices of the symptoms relevant for disease d_i;
- $M_j : dom_j \to [0,1]$, is a fuzzy function that defines symptom m_j (dom_j represents the domain of the M_j function),
- w_i is the weight vector of symptoms within definition of disorder d_i;
- h_i is an aggregation function defined by means of fuzzy operators which model a human expert's way of reasoning; and
- $o = (M_1(o),...,M_K(o))$ is a K-dimensional point that represents observations for a given patient.

Definition [6] Let *C={c₁,…,cₘ}* be a set of decision criteria. Let *P(C)* denote the power set of *C*, i.e. the set of all subsets of *C*. A *fuzzy measure* on *C* is a function *g:P(C)? [0,1]* that satisfies:

1. *g(0)=0, g(C)=1;*
2. *A⊂ B⊂C Þ g(A) ≤g(B).* _

Definition[6] Given a fuzzy measure *g* on *C*, the *Sugeno* fuzzy *integral* of a function *p:C? [0,1]* with respect to *g* is defined by:

(3.1)

In equation (3.1) "$_{(i)}$" indicates that the indices have been permuted such that

, and

 _

Definition Let d_iÎ*D*, *p* be a patient under observation. The *score of the disease* d_i at a given patient *p* is defined as:

$Score(p, d_i)=S_g(M_{i_1}(o),\ldots,M_{in_i}(o))$

where *g* is defined using w_i, the fuzzy measure of a set of symptoms being the normalized sum of their weights, *o* is the observation vector associated with *p* and S_g is the Sugeno integral defined above). _

•

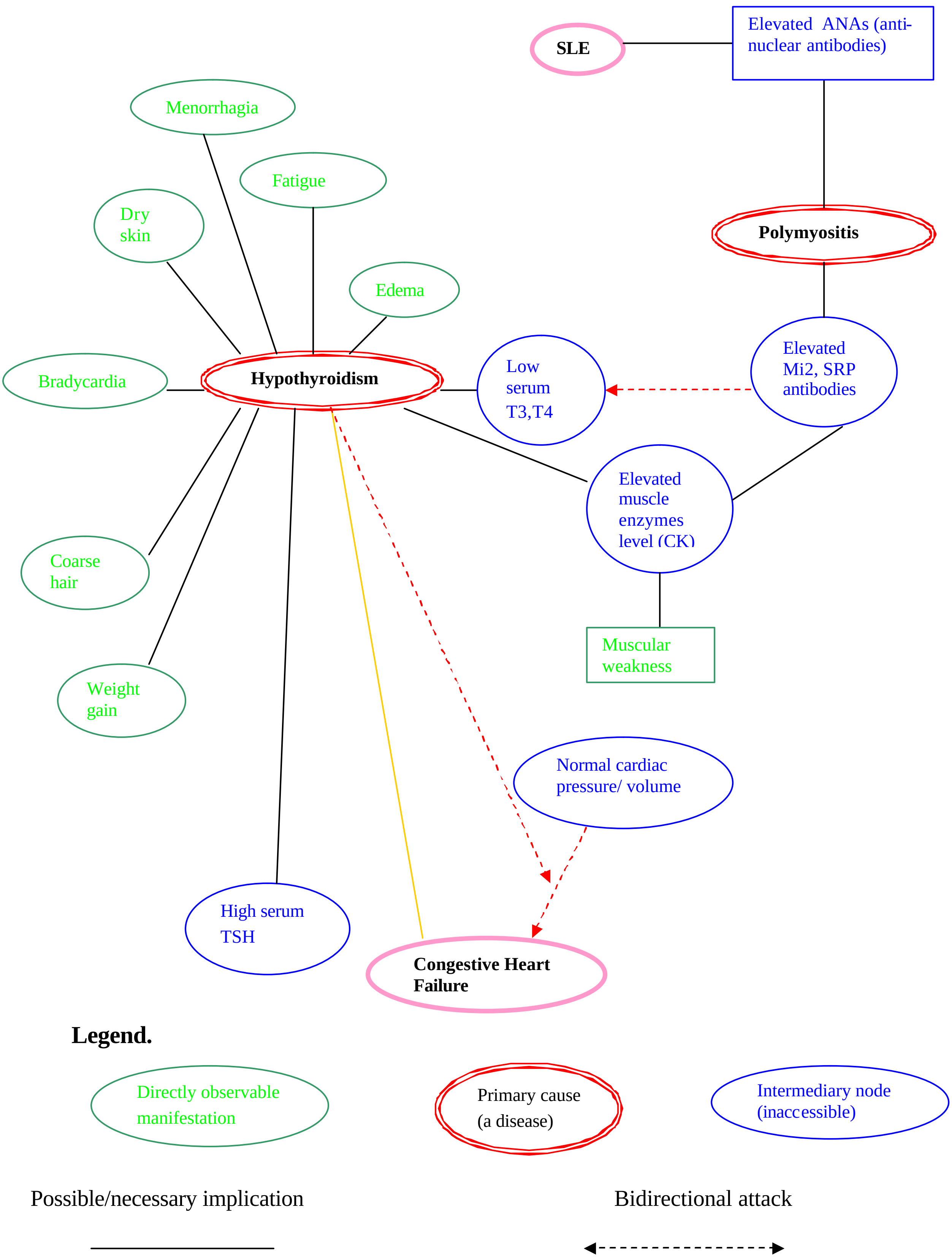

Fig. 1. Example of causal dependencies

The idea is to compute the indices $D_i^{w_i}(o)$ that measure the degree of match between the observations vector and the complex criterion which defines diagnostic d_i and to use these indices for a hierarchyzation of diagnostic hypotheses, based on the particular evidences of a given case. The selection step compares the indices with a given threshold (e.g. 0.2). This level quickly focuses the search towards relevant directions, by means of simple and efficient computation; it naturally corresponds to the "filtration" procedure. The first level of the hybrid system deliberately ignores possible interactions among hypotheses for efficiency reasons, and it also lacks explanation facilities. These drawbacks shall be dealt with by the second level, described following.

b)Refinement and explanation of the diagnostic decision

This step makes use of deep causal models associated to each disorder (see Fig. 1. for an example). These nets comprise the "grouping" operation of the GFS paradigm.

Definition.[1]

1. An *argumentation framework* AF ("Argumentation Framework") is a pair AF=<AR, *attacks*>,

where AR is a set of arguments, and *attacks* is a binary relation over AR: $attacks \subseteq AR \times AR$;

2. A set S of arguments is *conflict-free* if there are no arguments A, B in S such that A attacks B.

Definition([1]). An argument A is *acceptable* with respect to a set S of arguments iff any argument that defeats A is defeated by an argument in S.

Definition([1]). A conflict-free set of arguments S is *admissible* iff any argument in S is acceptable with respect to S.

Definition[5].A *state assignment* for a set X of arguments ordered by a binary defeat relation represents the assignment of either the state "in" or the state "out" to each and every argument, such that the following conditions are satisfied:

1. An argument is "in" if all the arguments that defeat it are "out";
2. An argument is "out" if it is defeated by an argument "in".

Definition 3.1 [4]. A *multiple diagnosis* (i.e. a non-empty set of possible diseases at a given patient) is an admissible hypotheses set that covers all observations and is minimal with this property.

Definition 3.2 [4]. An *argument* attached to a certain class is an instance of the causal net defining the class. An *instance* of a causal net is given by a specific subset of its nodes, that contains at least one observed manifestation (all the rest are assumed true). It corresponds to the specific configuration of symptoms present in at a given patient, through which the class (disorder) manifests itself, and which can vary from patient to patient.

Definition 3.3[4]. A *solution* to a diagnostic problem is a complete and consistent (admissible) assignment of truth values for each active variable (i.e. activated through the selection of certain hypotheses), which covers all confirmed manifestations. A solution is *minimal* if it has the minimum number of nodes, while still respecting the previous conditions.

The diagnostic hypotheses selected by the first level of DiaMed form a set of active variables (*ActiveVar*) over which the algorithm of [7] is applied in a modified form. Its steps are basically the ones following [4]:

1. Try to determine an admissible state assignment for variables selected in *ActiveVar*, mainly solving the CSP problem defined by the set of constraints in which variables of *ActiveVar* take part.

2. Print solutions (Definition 3.3.); record inadmissible assignments.

3. If we do not have solutions, or simply if the user wishes to clarify things further, extend previous inadmissible assignments with "defenses", following the steps below:

- perform new tests, apply selection step again on the new set of evidences, and adjust *ActiveVar* accordingly; also correct the set of new applicable constraints;
- for each inadmissible assignment, keep its variables (V) fixed (with the value already assigned) and apply CSP over the newly added variables from *ActiveVar*.

4. Repeat from step 1 until no more tests are possible, or simply until the user stops the algorithm.

The algorithm above represents an efficient and dynamic scheme of dealing with nonmonotonic reasoning, with explanations for decisions embedded in the structure of the arguments. Dynamic backtracking for DCSP naturally represents the operation of combinatorial search within our intelligent system.

4.CONCLUSIONS

The present work develops a new perspective of an original hybrid system (DiaMed), from the GFS paradigm's point of view. The purpose was to give insight of the mechanism by which our model mimics intelligence, and of the relation of each part of the system with the three basic operations which form the foundation of intelligent behavior: Grouping, Filtering, Search.

REFERENCES

[1] Dung.P.M. (1995): "On the acceptability of arguments and its fundamental role in nonmonotonic reasoning, logic programming, and n-persons games", *Artificial Intelligence* 77:321-357;

[2]A.Meystel, J.Albus (2002): "Intelligent Systems: Architecture, Design, Control", Wiley;

[3] Munteanu, S.(2005), "A Hybrid Model for Diagnosing Multiple Disorders", *International Journal of Hybrid Intelligent Systems*, Vol 2. No.1 IOSPress;

[4] (2006): "A DCSP-based framework for nonmonotonic reasoning applied to medical diagnosis", *Technical Report*;

[5] H.Prakken,G.Vreeswijk: "Logics for Defeasible Argumentation", Gabbay D., Guenther F., eds. "*Handbook of philosophical logic*", vol. 4, Kluwer Academic Publishers (2002), :218-319;

[6] Sousa, J., Kaymak, U. (2002) :*"Fuzzy Decision Making in Modeling and Control"*, World Scientific Pub Co;

[7] Verfaillie G., Schiex T., "Dynamic Backtracking for Dynamic Constraint Satisfaction Problems", *Proceedings of the ECAI '94 Workshop on Constraint Satisfaction Issues Raised by Practical Applications*, Amsterdam, the Netherlands, 1994.