An integrated framework for clinical problem solving in agriculture

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Abstract

The goal of this paper is to give an overview of a general problem-solving framework for diagnosis, investigation and treatment tasks, that incorporates concepts of abductive inference, fuzzy set logic and decision theory. In this work we focus on the use of this framework in agriculture, with an illustration in corn plantations. The general framework models time durations and intensity of manifestations as fuzzy sets, and, in the particular case of agriculture, it takes into account the favorable conditions for the development of a given disorder and the severity of its manifestations to recommend a treatment, together with other important factors such as risk and cost.

Key words: abductive inference, fuzzy sets, diagnosis, investigation, treatment.

1 Introduction

Clinical problem solving has been the subject of intense interest by researchers who intend to model human reasoning. Research in cognitive science, decision theory and computer science has supplied a large view of the cognitive process that is the foundation of the clinical decision-making process. The main segments of a clinical problem are diagnosis, investigation and treatment. The success of clinical problem-solving depends on 2 main factors: diagnosis correctness and treatment effectiveness. Furthermore, when the investigation task is well done, better diagnoses and treatments are obtained, with a reduction of risks and costs.

Diagnosis is a traditional focus of attention in Artificial Intelligence. Diagnostic reasoning is a complex cognitive process that involves knowledge about a particular domain, general and domain specific heuristics about the diagnostic reasoning itself, and constraints imposed by cognitive limitations of human diagnosticians. Systems have been designed for medical diagnosis and treatment, e.g. Mycin (Shortlife,1976), as well as "earth diagnosis" in view of mineral prospection, e.g. Prospector (Henrion et. al., 1992). Most reasoning frameworks have been based on inference from the consequences to the causes, as the ones employed in the systems cited above. More recent approaches base the inference from the causes to the consequences, in an abductive manner, such as Parsimonious Covering Theory (PCT) (Peng and Reggia, 1990).

PCT is an attempt to formalize abductive reasoning of the diagnostic process. Several extensions for PCT have been proposed for that purpose, involving possibility theory (Dubois and Prade, 1995a); intervals to model duration of manifestations (Wainer and Rezende, 1997), and fuzzy intervals to treat duration and intensity of manifestations (Wainer and Sandri, 1998).

Also decision-making is usually employed in the process of diagnosis. An agricultural engineer, for instance, may have to decide which laboratory analysis is more helpful and cost-effective, in order to confirm or rule out a possible disease in a given crop. Also, once a diagnosis has been reached, he/she has to decide which of the possible treatments has a better chance of controlling the culture, taking into account prognosis, financial limitations and possible side effects.

The tasks of diagnosis and treatment involve decision-making under uncertainty. Even though strongly related, diagnosis and treatments are not often focused together. Moreover, other aspects relevant to these two subjects are usually not given the necessary consideration. Recent works integrate decision-theory concepts with techniques from knowledge-based expert systems and artificial intelligence, notably in applications of influence diagrams and Bayesian Belief networks (Henrion et. al., 1992). Several publications have been proposed for qualitative decision-making where uncertainty is described by possibility theory (Dubois and Prade, 1995b).

The goal of this paper is discuss a new integrated framework for diagnosis, investigation and treatment, called Fuzzy Covering Theory (FCT), that incorporates concepts of fuzzy logic, abductive inference and qualitative decision theory (Massruhá, 2003; Massruhá et al, 2004). An application of this framework in agriculture is presented in Massruhá (2003) and Massruhá et al. (2003). This work is organized as follows. Section 2 presents the decision-making process in diagnosis, investigation and treatment. Section 3 brings an example of this decision-making process in phytopatology. Section 4 presents a quick description of FCT and, finally, section 5 brings the conclusions.

2 Problem Definition

Fig. 1 shows an overview of the clinical problem-solving process. The clinical problem-solving tasks are depicted as rectangles and decision-making tasks are depicted by diamonds. On the left-hand side of Fig.1 the four main stages of this process are described: pre-diagnosis, diagnosis, investigation and treatment.

The pre-diagnosis stage includes the initial tasks of the clinical problem-solving process. Given a subject (e.g. patient, plantation or computer), the diagnostician tries to acquire information about the case, such as present or absent symptoms, through interviews, inspection or anamnesis. Each hypothesis obtained in this stage is compared with a disorder model and new data can be acquired, as the initial hypotheses set is refined. The investigation stage begins from this problem synthesis.

New hypotheses can be generated from the investigation process and new strategies can be elaborated to solve a clinical problem. When a new piece of information is obtained, be it positive or negative, it must be added for the problem synthesis. In a cyclical reasoning process, the addition of new manifestations or symptoms transform the plausible hypotheses set.

After that the problem synthesis is established, the diagnosis stage starts. The expertise decides what hypotheses are more plausible to explain a clinical problem. For such, the expertise evaluates if the problem synthesis corresponds to active hypothesis, comparing the positive and negative findings of the particular case with the expected findings of a diagnostic hypothesis. Once the several hypotheses are evaluated, the most plausible ones are taken and the most appropriate treatment for them are generated (the final stage of Fig. 1). The choice of treatment can involve several factors, such as effectiveness, cost, risks, etc. In the case of medicine, in addition the therapeutic decision-making, patient monitoring may also be necessary, as described in Réa-Neto (1998), and the results of the patient monitoring process during treatment can modify the problem synthesis in a cyclical and dynamical process.

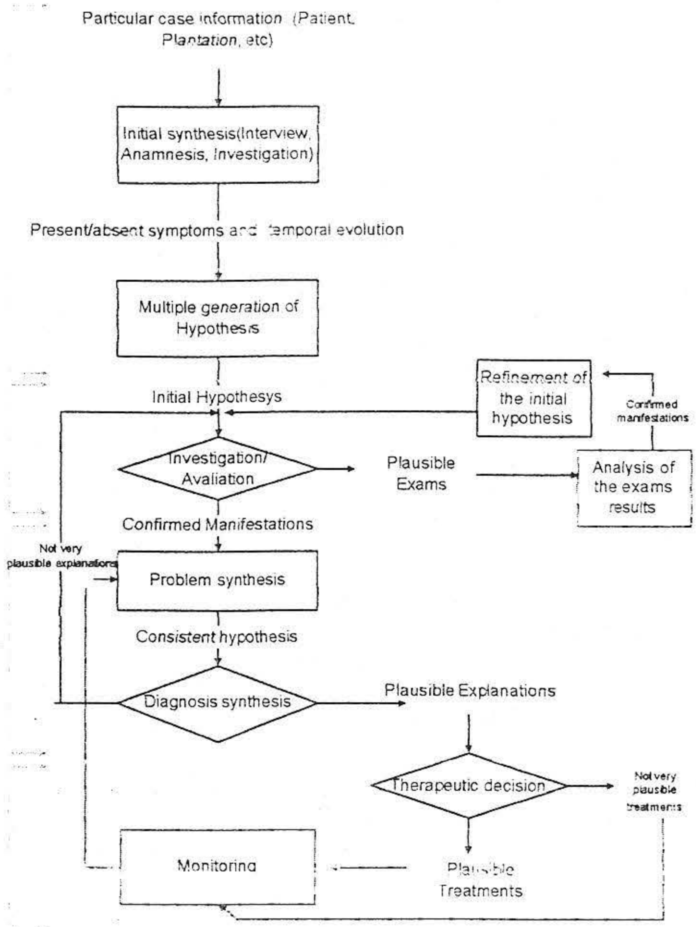

Fig. 1: An overview of the clinical problem-solving process.

3 A Clinical Problem-Solving in phytopatology

An example of the decision-making process in diagnosis, investigation and treatment in phytopatology is represented in the Fig. 2. Each node m_j denotes a manifestation possibly caused by a disorder d_i. Fig. 3 brings a simplified graph that represents the model of Cercospora (d_{10}), a disorder that affects corn plantations; the degrees on the arcs represent the frequency with which d_{10} causes each m_i considering that no other cause can be deemed possible.

An arc between a node A_c and a disorder d_i in Fig.2 indicates that A_c is a causal agent of disorder d_i. An arc between a treatment t_k and a disorder d_i indicates that treatment t_k is adequate to treat disorder d_i. (For example, the causal organism for Cercospora disorder (d_{10}) is the fungus "Cercospora zeae-maydis", that can be treated by some fungicides.) The treatment and test decision variables are depicted as rectangles. If a hypothesis is confirmed, a treatment is chosen considering not only the set of manifestations present (M^{+}) but also the value of some other observation variables, such as severity (SEV^{+}), development stage (DS^{+}), favorable conditions (FC^{+}), and cost (not indicated in the figure). A decision-making measure to evalutate outcomes is depicted by a diamond node.

The uncertain causal relations presented in Fig. 2 can be expressed by probability models. However, it is rather difficult to obtain quantitative and statistical information from experts. In this work, we use possibility theory (Dubois and Prade, 1988) as an alternative means to represent uncertain information. The FCT model involves some characteristics to support the decision-making process illustrated above:

– an abductive inference model to represent expert knowledge;

– a model to represent the uncertain and incomplete information of a clinical problem solving process;

– a model to order the generated hypothesis from diagnostic through a generalization of the temporal/categorical PCT proposed in Wainer and Sandri (1998) combining the consistency indexes to use them in a diagnostic-problem solving;

– functions associated with decision theory concepts to help in the choice and classification of the manifestations for investigation;

– a model to identify incomplete associations between disorders and manifestations;

– a mecanism to identify favorable conditions for the development of a disorder aiming decision making in treatments.

In following, a fuzzy abductive framework to support the characteristics above is presented.

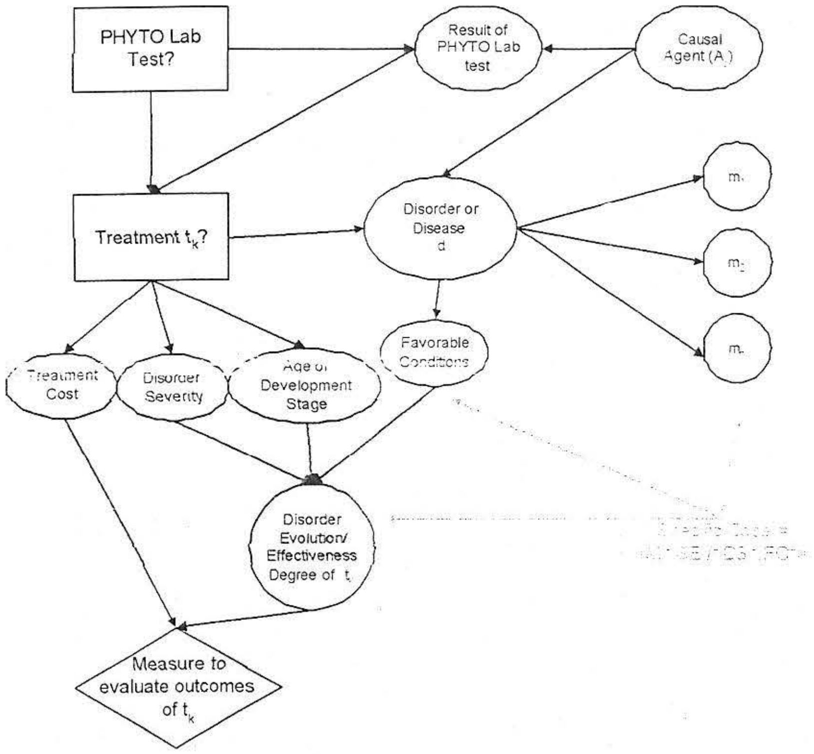

Fig. 2: An example of the decision-making process in phytopatology.

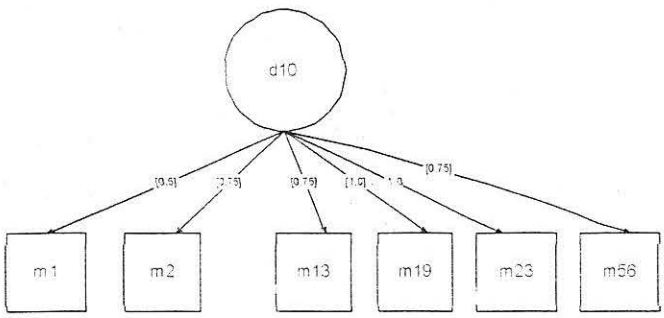

Fig. 3: An example of causal relation of cercospora disorder $R(d_i,m_j)$.

4 An Integrated Approach for Diagnosis, Investigation and Treatment

FCT puts together concepts of Parsimonious Covering Theory (PCT), fuzzy sets logic and decision theory, in order to address the various inherent aspects involved in clinical reasoning, such as the possibility of several disorders to conjunctively cause a series of manifestations, the manipulation of temporal information, the influence of favorable conditions in the development of a disorder, the difficulty of an expert to yield generalized knowledge devoid of uncertainty/imprecision, the manipulation of crucial factors in decision making in investigation and treatment tasks like cost and risk, etc. We use the Parsimonious Covering Theory (PCT) as the foundation for our approach (Peng and Reggia, 1990), in which knowledge is represented by associative (or semantic) networks of binary relations, and which uses parsimony criteria to order hypotheses.

The basic version of PCT uses two finite sets to define the scope of diagnostic problems: set D, representing all possible disorders d_i that can occur, and set M, representing all possible manifestations m_j that may occur when one or more disorders are present. An association $< d_i,m_j >$ means that d_i may directly cause mj. A knowledge base KB is defined as a triple KB $=< D,M,C >$, where C is the causal relation between the disorders in D and the manifestations in M. The goal of the system is to order the possible diagnoses (hypotheses) for a particular case, based on the models built for the set of disorders D. Given a subset M^- of the manifestations present in a case as evidence, a subset of disorders that can explain M^- is called a cover. A set is an explanation of M^- for a diagnostic problem, if E covers M^-, and satisfies a given parsimony criterion. In this work we use the irredundancy parsimony criterium, (see aproach Peng and Reggia (1990) for other parsimony criteria). A cover C for a case CA is said to be irredundant if none of its proper subsets is also a cover of CA; it is redundant otherwise.

Like in PCT, the knowledge in FCT (Fig. 4) is represented by associative (or semantic) networks of binary relations. In the diagnosis phase, knowledge is modeled by associations of the type *disorders to manifestations*. Given a set of observations of a particular case, an abductive inference mechanism is used to model the more plausible explanations for this case. In the investigation and treatment phases knowledge is modeled, respectively, by associations of the type *exams to manifestations* and *treatments to disorders*. Then, as in the diagnostic case, the abductive mechanism is used to infer, accordingly, sets of exams and sets of treatments adequate for the ongoing diagnostic hypothesis. The formal definition of a clinical problem-solving is described as follows. Given a clinical problem-solving P (definition 1), we can define the solution of the problem (definition 6).

Definition 1: *A clinical problem-solving for diagnosis, investigation and treatment is defined as a quadruple* $P =< KB_d,KB_e,KB_t,CA >$ *where:*

- KB_d *represents disorders information and their effects;*
- KB_e *represents exams or laboratory tests information and the disorders that they verify;*
- KB_t *represents treatments information and the disorders controlled by them;*
- *CA represents the case information (symptoms of a sickness, malfunction signs, etc).*

The associative knowledge of the diagnosis, investigation and treatment are very complex. In this work, the clinical-problem solving is divided in three subproblems: diagnosis, investigation and treatment. Each subproblem is represented for an abductive framework that has two set of entities and a binary relation between them.

Definition 2: *A diagnostic problem is defined as a 6-tuple* $KB_d =< D,M,R,G,CC,\theta >$ *where:*

- *D is a set of disorders;*
- *M is a set of manifestations and symptoms;*
- *R relates each disorder* d_i *to its manifestations. An expert assigns a value for each* $R(d_i,m_j)$, *taken from a set of predefined word values which are associated to a scale. Here, we suppose that the following pairs (terms, numerical values) are used: (d_i* ***always*** *causes* m_j, *1), (d_i* ***typically*** *causes* m_j, *0.75), (d_i* ***may*** *cause* m_j, *0.5), (d_i* ***seldom*** *causes* m_j, *0.25) and (d_i* ***doesn't*** *cause* m_j, *0).*
- *G(V,T) is the temporal graph of events of a disorder;*

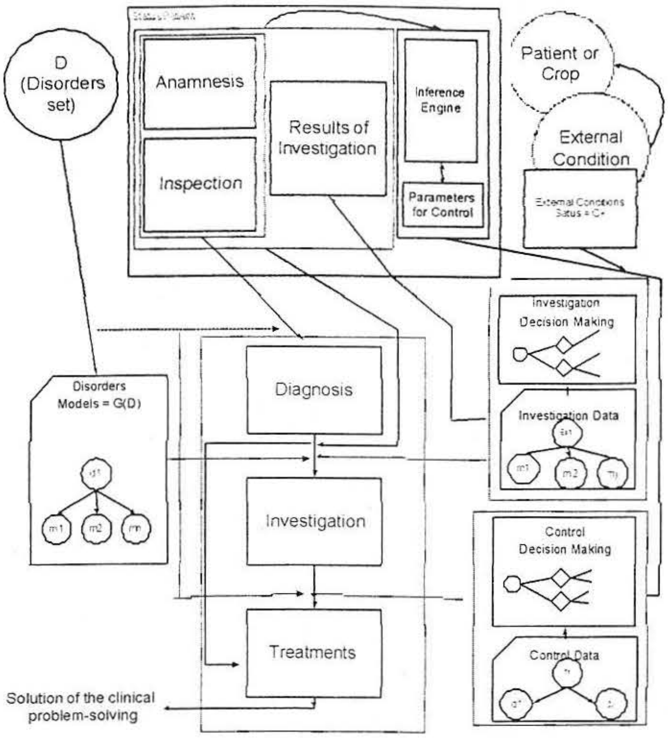

Fig. 4: An integrated framework for diagnosis, investigation and treatment.

- *CC is a set of control conditions that are taken into account in the specification of the disorders control. In our case CC is formed by: FC, which are the favorable environmental conditions for the evolution of a disorder; SEV, the severity scale of the disorder (in the patient or plantation), and DS, the development stages of the culture or age of the patient.*
- *θ is a time scale.*

***Definition 3**: A investigation problem is defined as a 5-tuple $KB_e =< E,M,D,I,R>$ where:*

- *E is a set of exams or laboratory tests;*
- *M is a set of manifestations and symptoms observed;*
- *D is a set of disorders;*
- *I relates each exam e_j to the manisfestations (or disorders) whose existance it can verify;*
- *R relates each disorder d_i to its manifestations.*

Definition 4: *A therapeutic problem is defined as a 5-tuple $KB_t =< T,D,Z,CC,V>$ where:*

- *T is a set of treatments;*
- *D is a set of disorders;*
- *Z relates each treatment t_k to the disorders (or manifestations) that it can treat or control;*
- *CC is a set of control conditions that have to be consistent with the case to guarantee that a given treatment tk is effective to control a given disorder d_i;*
- *V is a set that helps the expertise in the decision making in treatment for a disorder.*

Each variable in sets CC and V are modeled by fuzzy intervals. The context of CC and V depend on the application domain. Given a knowledge base KB_t=<T,D,Z,CC,V>, in phytopathology, the control conditions (CC) associated to each pair <t_k,d_i> is represented by a set CC={FC,SEV,DS} where the set FC depends largely on the kind of subject, for each treatment sought. In the context of plant pathologies we may have, for instance, FC=(TEMP, HUMID) where TEMP and HUMID are fuzzy intervals respectively representing the temperature and humidity that are favorable for t_k to control d_i; SEV, the severity scale of the disorder evolution, and DS, the development stage of the culture.

The information about a particular case and an abductive solution for the case CA are defined as follows.

***Definition 5**: The information about a particular case is modeled by 5-tuple $CA = <M^{+}, M^{-}, EV^{+}, TIME^{+}, CC^{+}>$ where:*

- *M^{+} is the of manifestations known to be, or to have been, present in the case.*
- *M^{-} is the set of manifestations known to be absent from the case.*
- *EV^{+} is a set of events for which one has temporal information. Among the events in EV^{+} are the ones that represen t the beginning and end of each manifestation in M^{+}.*
- *$TIME^{+}$ is a function that associates to each event $e \in EV^{+}$ a fuzzy temporal interval that represents the possible moments in which that event happened.*
- *$CC^{+} = \{CF^{+}, SEV^{+}, DS^{+}\}$ where: CF^{+} is the function that associates to each case the temperature and humidity conditions ($TEMP^{+}$ and $HUMID^{+}$) in the moment of the diagnosis; SEV^{+} and DS^{+} are the functions that associate the severity for each $mi \in M^{+}$ and the phase of the culture in the moment of diagnosis, respectively.*

***Definition 6**: Given a set of knowledge bases $\theta = \{KB_d, KB_e, KB_t\}$ for a clinical problem-solving P and a particular case CA, $SOL(P) = \{SOL_d, SOL_e, SOL_t\}$ is an abductive solution for the case CA iff $\theta \cup SOL(P)$ covers CA according to some given parsimony criteria and $\theta \cup SOL(P)$ is consistent.*

From the particular case, we can infer the most plausible causes of observed problems (for example, diseases or machine faults) given a set of evidences (symptoms, patient characteristics or test results). Then, we have to verify the consistency of the case in relation to a disorder model and the consistency of the disorder (plausible hypothesis) in relation to exams and treatments to control them. To do so, we use the degrees of consistency proposed in Massruhá (2003) (see also Massruhá et al (2003) and Massruhá et al (2004) for details on the framework).

5 Conclusions

In this paper, we present an overview of an integrated framework for clinical problem-solving process involving the tasks of diagnosis, investigation, and treatment. This framework was developed under a new approach for diagnosis, investigation and treatment that allows the organization of various pieces of information generated in these tasks during a clinical problem-solving process. In this new approach, called Fuzzy Covering Theory (FCT), the knowledge is basically modeled through causal associations and inference is abductive (see Massruhá 2003).

The framework proposed models the knowledge of the diagnosis, investigation and treatment tasks in a clinical problem, respectively from disorders to manifestations, exams to manifestations and treatments to disorders, in counterpart to the expert systems, in which the knowledge is structured from the manifestations to disorders and disorders to treatments. Also, the framework uses fuzzy sets instead of intervals to model variable values, adding flexibility to the tool. The framework uses a fuzzy decision-making in the treatment phase instead of the traditional methods of representing problems in decision theory. The cost decision variable is incorporated in the treatments knowledge base and we use a new consistency index to calculate it.

The literature brings several works in the area of decision-making in treatments (Tunez et al. 1998; Taboada et al. 1999). However, the abductive approach integrated to fuzzy sets provide a powerful alternative method in IA for treatments problem-solving. This method makes the clinical problem-solving process better because it uses directly the results of the diagnostic framework aiming to minimize the complexity of picking a choice of treatment.

To validate our approach, we worked with a knowledge base with 42 disorders of the corn plantation and 15 kinds of fungicides. The obtained results were compatibles in each phase (diagnosis, investigation and treatment). In the diagnosis and investigation phases, we obtained an 86% reduction of the hypotheses set in the simulation of Cercospora disorder data using FCT compared with the original PCT. Considering the symptoms evolution of Cercospora, we obtained a 67% reduction using FCT. In the treatment phase, we observed that the results generated about the best fungicides to control Cercospora using FCT, corresponded the results obtained in the field (Morandi and Menezes, 2002).

Our studies show that our approach attends the main requirements of clinical reasoning, uncertainty and decision-making to support the clinical problem-solving process in plants diseases. It is also expected that the theoretical developments obtained therefrom can be successfully applied for another problems of dynamic diagnosis.

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