A Model for an Intelligent Support Decision System in Aquaculture

Cornelia / C Novac Ududec

Dunarea de Jos University, Galati, Romania, Faculty of Economics

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Cornelia Novac-Ududec
„Dunarea de Jos" University of Galati, Romania

cornelia.novac@ugal.ro

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Abstract:

The paper purpose an intelligent software system agents–based to support decision in aquculture and the approach of fish diagnosis with informatics methods, techniques and solutions. A major purpose is to develop new methods and techniques for quick fish diagnosis, treatment and prophyilaxis at infectious and parasite-based known disorders, that may occur at fishes raised in high density in intensive raising systems. But, the goal of this paper is to presents a model of an intelligent agents-based diagnosis method will be developed for a support decision system.

1. Introduction

Fish diseases generally develop as a result of nutritional deficiencies or because of the waters' quality. As a result, infections of different types occur (caused by viruses, bacteria, fungus, parasites). If an efficient treatment, based on a correct diagnosis is not found, the infected fishes will dye very soon. Both diagnosis and treatment sholud be established by a veterinary physician or by an ichtiopatology expert, but in practice it is almost impossible to consult a human expert in time, when an emergency arrives, because fish farms are located in the countryside, far away from veterinary centres or research insitutions. Aquaculture is an agricultural branch with the mission to satisfy the increasing consumer's request for fish and other aquatic organisms. FAO estimations for 2030 foresee that aquaculture will assure 50 % of the necessary aquatic organisms for the global consume. Algae, moluscs, crustaceus and fish can be raised in different habitats: ponds, floating viviers, tubes, aquariums etc. These raising systems can be extensive, intensive or super-intensive; through appropiate technologies may be obtained productions varying from a few hundreds kilos per ha to over a hundred thousands kilos per ha. The higher the density is, the higher the intensivity will be, but also the risk of diseases for the biologic material increases. In such situations, the specialist/ farmer/ manager should quickly and efficiently intervene in order to avoid huge losses. The problem of fish disorders has become very serious not only from the economical point of view but also because some parasites and disorders can be transmitted from fishes to humans.
The first step of the development of a support decision system is the knowledge acquisition. Multiple approaches to **knowledge acquisition** exist, generated by the need to build knowledge based informatic systems. The difficulties encountered during the knowledge acquisition process led to numerous automatisation tentatives. Academic approaches try to support the system's builders all through the acquisition process. Among software academic systems which help the knowledge acquisition activity, we mention: ROGET, realised by Bennet in 1983, ETS -Boose 1985, KEATS- Motta 1991. There is a general and methodic approach to the acquisition process that describes the organisation and planning of the process, while the practical implementation follows the particular characteristics of each

concrete application. The general approach is called CANVAS and it is a research result of the STARS program (Software Technology for Adaptable, Reliable Systems) sponsored by DARPA (U.S. Defense Advanced Research Projects Agency) and published by Lockhead in 1996. The most important forms of knowledge extraction are:

- Interaction between an investigator and an informer. Most often, as a result of this interaction, both the investigator and the informer gain new knowledge, given the common effort to express in terms, concepts and relations the practical knowledge of the informer.
- Investigator's analysis of the activity results from a community workspace (for instance, reports, articles, handbooks, etc., called *artifacts*). Observation is still another form of knowledge acquisition, being used to check results obtained through other methods. According to literature, knowledge acquisition should come from domain's experts, (ichtiopatologists in our case), through specialist investigators and at should be understandable by the target communiyt. Any action with only an individual result is not considered knowledge acquisition [Acho01]. There are many ways to perform knowledge acquisition, inclusively in human medicine [Mara01]. We shalll mention only two of them: knowledge acquisition sessions and knowledge acquisition campaigns. A knowledge acquisition session is an event or a set of events in which an investigator consults a knowledge source, extracts a knowledge quantity and codes a part of it into an acquisition result. A knowledge acquisition campaign consists of a project-level planning that integrates the acquisition process in a wider context, like the development of diagnosis models ichtiopatology. A campaign may include multiple subjects which shall be explored in different frameworks. A knowledge acquisition campaign shall be subsumed to the discovery of that specific knowledge which is necessary to model fish diseases for diagnosis, and to create an ontology for aquaculture.

2. The decision and the knowledge based systems

A very important factor to prepare a good support for a decision is to evaluate the state of the context, to diagnose the aquatic system. Diagnosis is an important challenge of the real world. It represents the identification of a disease, based on a set of symptoms (in the medical case). Starting from a set of diagnosis criteria, a disorder is identified and an adequate treatment is recommended. An important problem that often arises in practice is wrong diagnosis, with a frequency ranging between 8% and 40%. The errors' causes can occur from three main directions: (according to www.wrongdiagnosis.com): patient's errors (which is not the case in ichtiopatology), laboratory tests' errors and the physician's errors. Diagnosis can be basically treated as a classification process, which builds a set of discriminant functions for each class, and ranks diagnostic hypotheses by means of these functions. We subsequently review some major directions in this field, and place fish diagnosis inside the general context, suggesting new possible approaches to follow. An informatic system for diagnosis should be able to solve various problems, starting from the diagnosis techniques and following with domain – specific problems. Two major approaches exist: a classical software application and artificial intelligence systems, among which the most numerous are knowledge based systems. Expert systems are an illustrative example of knowledge based systems (expert systems with or without neural netrworks, *case-based* expert systems, rule-based expert systems, systems with fuzzy logic, etc.) Any software package should start from the purpose to facilitate diagnosis. Some important problems with fish diagnosis are:

- Disorders do not develop all symptoms described in literature. Each disorder has a certain evolution, and usually, the acute phase and the cronic phase of the same disorder significatively differ. Therefore, the system should be able to diagnose correctly even in the presence of partial information.
- Inputs received from human users raise the need for a standard and unitary terminology. International organizations have tried to accomplish this aim for veterinary terms [CAP98], which were unanimously accepted in SNOMED. Nevertheless, cultural differences still determine terminology for the same notion.

- Very often, problems become evident only when a second agent is implicated (virus + bacteria, fungus + bacteria, etc.). Therefore, the observed symptoms can belong to different diseases from the system's base.

Bayesian and causal networks can completely describe a diagnosis process, but usually shortcuts through the model are created, to achieve computational efficiency. The inference is statistically focused, but unfortunately probabilistic inference remains NP-difficult in the general case (with the notable exception of noisy-OR architectures).

One classic example of a medical diagnosis tool using causal nets is CASNET. If the medical field is very well-understood and allows a clear and detailed description of the physiological mechanisms that lye behind the symptoms, one has no reason to restrict himself to a shallow disease-symptoms association (like in PIP or INTERNIST, for instance). Besides using NP-difficult probabilistic inference, a major drawback of CASNET comes from the way contradictions are handled. Adding and substracting quantities to compute the score for each node in the net can often lead to ambiguous, difficult to intepret or even completely errounous results. (For instance, when we get score 0 for a node, by repeated additions/ substractions, a contradiction is reported to the user, because the system cannot handle it). The main conclusion here is that probabilistic reasoning is not suitable to handle contradictions, and therefore a categorical approach is needed for them. CASNET is also not able to represent those frequent situations in medical diagnosis when hypothesis is supported only by the conjugated presence of "several" symptoms (vague criteria).A remarkable improvement of CASNET is realized by the hybrid CHECK system, and also by the DiaMed system [Mun05].

Symbolic approaches to medical diagnosis. The most used symbolic structures are decision trees and expert systems. They are built around a knowledge base and inference mechanism and use heuristics that resume a human expert's knowledge (usually shallow knowledge).

MYCIN is an expert system, built around the model of belief factors of Shortliffe, and used to diagnose hematological infections. The main purpose of this new model was to overcome the problems of bayesianism for medicine (i.e. a limited number of accessible tests; results obtained sequentially, on a step by step basis; too many conditional probabilities to be known apriori). Therefore, Shortliffe defines a new measure which combines beliefs and disbeliefs (conditioned by the presence of certain evidences) in a hypothesis in a single number (the belief factor). The belief factors are used to rank diagnostic hypotheses. One of the greatest drawbacks of MYCIN' evidence combination is that unexpected and incorrect interactions often occur between the rules from the knowledge-base, if this is not carefully constructed. It has been shown that the theory of belief factors is but an approximation of probabilistic reasoning and the apparent success of MYCIN is due to the simplicity of the domain's theory (short inferential paths and simple hypotheses), but theoretically do exist problems with its model. Still, rules can be of great help when integrated in a hybrid system. For instance, **Fish-vet** [Zeld00] is a fish diagnosis hybrid system which uses rules only to cut down the problem space. The same idea is used in CHECK, and also in DiaMed: an efficient technique narrows the field for a rigorous but inefficient approach.

3. Combinative hybridization in medical diagnosis

Torasso and Console have described a causal diagnosis theory and implemented it inside the CHECK system. CHECK is a combinative hybridization between shallow and deep reasoning. The reason for shallow reasoning inside the first level of the system is to focus the search and overcome the difficulties of medical model-based diagnosis (NP-completeness). Search space pruning in model-based diagnosis can also be achieved numerically, through probabilistic/ possibilistic measures. In CHECK, formal logic (for the deep causal model) is assisted by a symbolic intelligent technique, the whole architecture being an improved alternative to CASNET. Knowledge, represented by means of frames with specific slots, is distributed over 3 levels: data description level (1), heuristic level (2) (shallow knowledge – based inference), deep causal knowledge level (3), used for generating explanations). The system was successfully used in diagnosing hepatic disorders (human medicine).

Each diagnosis hypothesis is assigned a plausibility degree, by matching evidences against prototypical definitions of disorders, in a given context. The matching mechanism is controlled by special activation rules that select possible disorders into an active list. Validation rules are then used to confirm/ exclude the generated instantiations of frames, and diagnosis is performed through breadth-first search. The deep-knowledge causal level is used to confirm/ exclude hypotheses generated at the heuristic level, to generate alternative hypotheses or to analyze unexpected data (it can be queried). Basically, a causal network with specialized nodes is transformed into a set of logical formula, upon which qualitative reasoning can be performed (non-monotonic-based logic). Extended resolution principle is used to determine the source of an inconsistency (that is, if a manifestation caused by a state is missing, indirect abduction tries to find an explanation for this inconsistent observation).
Problems with fish diagnosis has, in particular, supplementary difficulties. Firstly, there are not enough cases to study, and one has to deal with a huge problem space because all the diseases have to be considered at the same time. Moreover, there still exist differences in terminology (although a start for unifying veterinary terms was made in SNOMED) [CAP98]. Secondly, input data (composed of symptoms) is often affected by human errors, diseases exhibit only a part of the symptoms described in literature, and these symptoms evolve with time, as the disease progresses. To make things even more confusing for a human expert, multiple disorders can be present at the same individual.
The most recent and numerous tacklings of computer-assisted fish diagnosis come from chinese researchers [Yuan06], [Daol06], [Nan06], [Xiao04], *Fish-Expert* [Daol02] . Advanced researches in fish diagnosis can also be found in [Ross05] and we also notice the Fish-Vet system [Zeld00].

4. Multiagent systems in diagnosis

After 2000, software agents developed very quickly and a new branchy of Artificial Intelligence emerged - DAI (Distributed Artificial Intelligence). A traditional diagnosis tool can be viewed as a single diagnosis agent, with a whole view of the system under observation. This can lead to several inconveniences. Firstly, if the system is physically very large and distributed in space, it just might not be enough time for the informatic system to perform diagnosis in a centralized manner and to comunicate all the observations. Secondly, if the system has a dynamic structure, it might change too quickly to have an accurate global model.
Multiagent systems for model-based diagnosis often fail when dealing with large and dynamic systems for which one can hardly maintain a global model. Nevertheless, one can use different incomplete models of the system in order to establish a diagnostic (possible defects). These models can be also physically distributed. The solution is given by a multiagent system with diagnosis agents which can collaborate to establish a global diagnosis. When different agents for each incomplete model of the system are used, finding a global diagnosis reduces to a negotiation-collaboration problem among these agents. This raises the question if a set of diagnosis agents, (each restricted to a sub-model) can perform global diagnosis, with the same efficiency as compared to a single agent that uses the overall model [Roos01]. Worldwide interest has been shown lately [Khal04] to solving complex problems through experts' collaboration. Different types of agents, with various behaviours, can co-exist in such a system, working together to meet the same purpose. A multiagent system for medical diagnosis is presented in [Khal04], with two types of agents: diagnosis agents and treatment agents. Each agent is an independent expert-system, and data is collected through an interface-agent.
A similar approach is taken in our system and presented in this paper, regarding that expert systems in aquaculture-ichtiopatology became agents like the ones described above.

5. The model of the diagnosis agent in the AcvaSD multi agent system

AquaSDS (**Aqua**culture **S**upport **D**ecision **S**ystem) is an original hybrid-combinative system with two levels. Combinative hybridization of the type chosen here was favored over other approaches not only for the reasons resumed above, but also because it was a good option when compared to, for instance, neuro-fuzzy or neuro-symbolic hybrids, with their curse of dimensionality and difficulties related to modeling interactive, dynamic problems (like medical diagnosis is).

In AquaSDS, uncertainty is modeled logically, by nonmonotonic reasoning. The problem of complex interactions is approached in a generative manner: composite hypotheses are built based upon *admissible* solutions to a dynamic constraint satisfaction problem (instead of an explicit codification of all possible composite hypotheses and their effects). Admissibility is a theoretic-argumentative view of consistency, appropriate for a diagnosis problem. This generative approach needs a causal model, in order to better understand possible interactions among different elements of the medical model.

Therefore, composite hypotheses (i.e. multiple disorders at the same patient) are defined as covering admissible sets. Admissibility is defined through individual attack relationships, and allows us to dynamically compose hypotheses, dependently on a given context of manifest symptoms. Like in CASNET, CHECK or Abel, AquaSDS is built around causal knowledge representation. Complete causal models are not necessary, but only the nodes relevant for the decision process.

Although the architecture of AquaSDS resembles CHECK, implementation differs. The first level implements hypotheses' selection with an efficient associative method (it uses fuzzy decision functions to rank disorders [Mun05]) The main advantage of these decision functions, compared to the law of evidence combination in CHECK resides in the fact they can accurately express a great variety of vague criteria (for instance, *the majority, at least x out of n, a significant part of*, etc.)

The second level uses a deep causal model, restricted to the context of hypotheses selected at the first level, in order to discriminate and refine the final diagnostic, and to solve the conflicts generated – if any. A DCSP algorithm controls which constraints are active at a given moment, having the role to focus on interesting sub-parts of the model, like triggering rules do in CHECK, -and this is an advantage over CASNET. Moreover, this phase considers a complete and precise model (to the maximum possible extent), which represents exceptions in a natural and efficient way, and the reasoning scheme suits the nonmonotonicity of diagnosis. To this purpose, the second level uses the logical and symbolic methods of direct argumentation systems and CSP algorithms in order to refine and explain diagnostic results. The main advantage of this nonmonotonical approach to hypotheses'refinement (over CHECK's approach) resides in its efficiency, in opposition to the use of indirect abduction to determine the source of inconsistencies (used by CHECK).

Knowledge representation in AquaSDS. The knowledge model of AquaSDS contains causal associations between classes and their characteristics. Its components are described following.

The *diagnostic classes* (i.e. the diseases) are modeled by a special type of *causal nets*, with different kinds of nodes and arcs, which describe the deep causal model. There exist three types of nodes:

- root-nodes corresponding to classes (diagnostic hypotheses); they are primary deep causes of observed manifestations;
- nodes related to deep manifestations (inaccessible or accessible only through expensive/ time-consuming/ invasive tests);
- nodes related to shallow manifestations (easy to access or direct observations).

The nodes of the net (either deep or shallow) can be of two kinds: **necessary** or **supplemental**. If a necessary node is infirmed by tests, the diagnostic hypothesis which contains it is eliminated.

Arcs linking the nodes can also be of various types:

- <u>Necessary implications:</u> the cause always determines the effect;
- <u>Possible implications:</u> the cause *may* determine the occurrence of the consequence,

but it is not compulsory; (this uncertainty comes from the model's incompleteness: there exist certain elements/ conditions that influence the validity of the implication but which were not explicitly modeled);

- Attacks (either bi- or unidirectional): these relations connect elements that cannot be simultaneously assumed "in" (i.e. *true*) in the case of one and the same system (i.e. patient, in the medical field).

Each diagnostic class is defined by such a causal net that contains all possible elements related to the class, and these elements are organized in progressive shallow (i.e. accessible to direct observation) levels. Intermediary nodes between the root and the leaves are usually inaccessible or difficult to access (only through expensive, invasive, time-consuming tests).

Definition 1. An *argument* associated to a class is an instantiation of the causal net that defines the class. An instantiation of a causal net is a subset of its nodes that contains at least an observed manifestation (the rest of the nodes being assumed true).

Definition 2. A *multiple diagnosis* (i.e. a non-empty set of possible diseases for a given patient) is an admissible hypotheses[1] set that covers all observations and is minimal with this property.

Definition 3. A *solution* to a diagnostic problem is a complete and consistent (admissible) assignment of truth values to all the active variables (i.e. activated through the selection of some particular hypotheses), which covers all confirmed manifestations. A solution is *minimal* if it has a minimum number of nodes, while still respecting the previous conditions. This definition corresponds to the definition of multiple diagnosis above.

Fuzzy decision –based selection of hypotheses in AquaSDS

The phase of selection of relevant hypotheses from a large context should use efficient techniques (rather than precise and transparent ones), in order to quickly reduce the search space. The majority of these efficient methods model human expertise on basis of input-output pairs, the statistical correlation being the key concept behind them.

The selection of hypotheses in AquaSDS uses an original model, based upon fuzzy decision functions [Mun05]. Each symptom relevant to a specific disorder is modeled as a fuzzy criterion and all criteria which are relevant to a given disorder are aggregated by fuzzy (compensatory) operators, forming a fuzzy decision function to which the disease is assimilated. The degree of match between a given set of observations (for a patient under consideration) and a fuzzy decision function represents the score of the associated disease, and scores induce a ranking among diagnostic hypotheses. The ranking is effectively used for selection through comparison with a significance threshold (experimentally settled).

Fish-Vet [Zeld00] so uses the idea of fuzzy logic, if not the technique itself: it defines membership functions for signs, and this allows to obtain the same diagnostic even when sampling at different stages of the disease (a symptom may evolve from light to severe).

6. Conclusions and future work

The problem of complex interactions occurs when multiple disorders are present in one and the same patient, and their symptoms unexpectedly interact. Even CASNET, with all its causal representation, has serious problems with interacting or overlapping symptoms, and therefore resumes its utility at single-disorders cases, because of the difficulties with the probabilistic treatment of uncertainty and inference.

The probabilistic approach to uncertainty is to blame for the unappropriate tackling of contradictions. When two rules are in conflict, this is treated –likewise concordance-, by adjusting the trust in some related hypotheses. But in real world reasoning, human experts have a much deeper and complex reaction at the detection of a contradiction: they reconsider previously accepted data, and/or add new possible hypotheses to the active set (i.e. those currently taken into consideration). The conclusion is that a probabilistic model is inherently inadequate to deal with contradictions, and a categorical approach is needed.

[1] A hypothesis is any active disease, which can be, in particular, associated to the argument that sustains it.

And yet, the medical field is far too complex to completely give up probabilities. As structural and probabilistic measures complement each other, they should both be used in diagnosis. Moreover, general strategies are needed to initially pre-process extended medical contexts. Probabilistic / associative efficient types of reasoning would be useful exactly during this phase of pre-processing, in order to focus search. The AquaSDS system combines probabilistic/ categorical reasoning, taking advantage of the qualities of both of them, and leading to a combinative hybridization.

The DCSP-based approach from AquaSDS represents an efficient translation of the dynamic re-modeling of the working context, which is directed by the evidences resulted from tests. This re-modeling focuses reasoning on limited sections of the medical domain. The activity constraints add or delete variables to/from the problem according to the context of selected hypotheses, which is dynamically tuned through testing and through the application of domain-dependent rules. These activity constraints are implicitly defined by the fuzzy decision functions that perform the selection and by the arguments (i.e. active instances of causal nets).

Multiple diagnosis is originally defined in terms of arguments (using the admissible semantics), and arguments are adapted to match the medical field, by structuring information and grouping disorders according to possible interactions. Because arguments were especially created to model human reasoning confronted with uncertainty and incremental evidence gathering, they are appropriate for iterative belief revision which is a main characteristic of medical diagnostic reasoning, and they can handle the interactivity of sequential testing which interleaves with hypotheses' generation.

The nonmonotonic mechanism of belief generation and cancellation is reflected in the addition and deletion of constraints within DCSP. The main advantage of this method over CHECK, for instance, resides in its tractability, as compared to the computational approaches of indirect abduction.

The original approach of AquaSDS uses argumentative non-formal logic and DCSP algorithms, can be very useful during the phase of discriminating among alternative diagnoses. "Further research in nonmonotonic reasoning should focus on computational aspects, because it is only so that nonmonotonicity can have an impact on Artificial Intelligence and an utility for real-world problems" [BreDix97].

The system has to be further improved. A great part of the decisions associated to testing are still delegated to the user (which maybe is not a drawback after all). Also, the medical model needs to be completed by a team of human experts, in order to test the system on a significant amount of real data. It would also be worth to study the impact intelligent techniques can have on propositional inference in general.

Besides adjustments to AquaSDS, there is still a lot that can be done in general, and we intend to do it within our project in fish diagnosis. Firstly, we intend to explore possible hybrid architectures for difficult, complex diagnosis problems (with huge search space, incomplete/ erroneous input data, concomitant multiple disorders, and which undergo various types of changes with time) and secondly, to exploit in different ways the advantages of dynamic constraint satisfaction algorithms for time-varying problems. Also, the development of an ontology-based knowledge representation for fish diagnosis is necessary, starting from the available information in SNOMED [Cap98]. The perfection of a database of cases, in a field where no legal constraints hold (unlike in the case of human diagnosis) could lead to innovative systems, which can later be adapted for human diagnosis.

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