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SEDPA, an expert system for disease diagnosis in eel rearing systems

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Abstract

The design, development and testing of a prototype interactive expert system (SEDPA) capable of diagnosing eel pathologies is described. The system incorporates a multiple subprogram modular design, although only the inference engine is largely described. Its user interface incorporates a natural language module. Starting from this kind of information, the system obtains its conclusions treating this information with a fuzzy controller and transmitting the uncertainty using the Dempster–Shafer theory (DST). The system's performance was evaluated in a series of tests. The results of a Fisher's exact test of the system's diagnoses versus those of the three fish pathologists for 29 eel pathologies indicated statistical differences in diagnostic performance with the two human experts. On the other hand, the use of different fuzzy associative memory (FAM) or representation of the different human experts's knowledge level indicated the system adaptability to the different work scenarios. The results described in this study have demonstrated the validity of this software for eel pathological diagnosis.

Keywords: Expert system; Decision support system; Aquaculture; Fuzzy control; Dempster–Shafer theory

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1. Introduction

The development of aquaculture and sport fishing have shown the importance of diseases in fish populations. Often these activities are the propagation vector of some diseases (Höglund and Andersson, 1993). The disease is presented in the fish in the form of lesions and symptoms. This causes a decrease in the physical quality of fish and final yield and often the death of the affected fish. This morbid is caused by changes in the physical and chemical parameters of water and the activity of biological aggressors (virus, bacteria, fungus and animal parasites) (Kinkelin et al., 1991). On the other hand, the management confined fish populations requires the introduction of other factors (chemical substances, grading, feeding, transport, etc.) that may further increase the harmful effects of physical, chemical and biological factors present in water (Wickins, 1981). Therefore, a fish health policy has a great economic importance by requiring the control and elimination of pathological problems.

Eel intensive rearing systems are clear examples of the induction of pathological agents. In this kind of system, disease is a consequence of a poor water quality, lack of hygiene, inadequate management (grading and transfer) and nutritional deficiencies, or by the combination of two or more of these factors (Munro and Fijan, 1981). The illnesses may be eliminated by applying an adequate pharmacological treatment which implies a previous diagnosis process. However, the diagnosis process is hindered by the shortage of ictiopathologists or by the abundance, dispersion and lack of the available information. This has a great influence on the time taken for observing the first symptoms until the application of an appropriate treatment. This characteristic justifies the utilisation of the expert systems.

Expert systems arose in the 1970s in the field of artificial intelligence as computer software that employs knowledge captured in a computer program to solve problems that usually require human expertise. Well-designed expert systems imitate the reasoning process of human experts to solve specific problems and can be used by nonexperts to improve their problem-solving capabilities and by experts as knowledgeable assistants.

Most famous expert systems were built as diagnosis assistants and therapy advisors in different medical areas (MYCIN, PIP, CENTAUR, INTERNIST, ONCOCIN, etc.) (Díez et al., 1997) and almost all of them based their reasoning totally or partially on if/then rules which, combined with frames or objects, has constituted until the present the standard method for building expert systems.

However, the use of rules raises serious problems with regard to the knowledge representation and uncertainty management. They apply a formalism developed for classical logic in which every proposition is either true or false and is not suitable to the management of uncertainty through numerical factors (Heckerman and Horvitz, 1988; Díez et al., 1997).

Our goal was to develop an expert system, not based on if/then rules, that incorporates most of the disease which affect eel fishfarms. This system could then be used by the experts and nonexpert users. We tried to lower the risk of obtaining a wrong decision and maximise the possibility of making a right decision by means of a fuzzy controller and the Dempster–Shafer theory. Fuzzy logic technology (Zadeh, 1992) has been recognised recently by the Institute of Electrical and Electronics Engineers (New York) as one of the three key information processing technologies. This fuzzy logic attribute allows the capture of human thought processes in an optimal manner for automation (Lee et al., 2000). Recent results have also shown that fuzzy logic systems are universal approximators for general nonlinear functional relationships to any desired degree of accuracy (Kosko, 1993a,b). This makes fuzzy logic modelling a powerful tool for exploring complex, nonlinear biological problems (Mackinson et al., 1999; Chen, 2001). On the other hand, Dempster–Shafer theory (mathematical theory of evidence) is a numerical method for evidential reasoning. The mathematical theory of evidence begins with the assumptions that a real number between 0 and 1 indicates the degree of support the evidence provides for a proposition and the beliefs are not necessarily additive (Shafer, 1976). Thus, Dempster–Shafer's belief theory can be viewed as an extension of the Bayesian probability theory (Wong and Yao, 1992).

This expert system, called SEDPA, can suggest several diseases with different belief levels, allowing the ultimate decision to be made by the manager of the fishfarm.

2. Materials and methods

The methods discussed here were applied to Hidrorecursos S.A., an intensive eel fishfarm located in the province of Córdoba (southern Spain). The fishfarm has three biological filtration units for water reuse. Globally, the average flow through the system was 3185 ± 1634.2 m^3/day and the exchange rate in the biological filters were 10% per day.

2.1. General structure of the expert system

The expert system consists of several interrelated modules. These relationships together with the data provided by the user allows obtaining a conclusion. This way, the expert system has one or several databases or knowledge bases, an inference engine or kernel of the system, an explicative subsystem (provides information about the inference engine's logic), a proposal engine (help to user in the diagnostic process), a learning subsystem (incorporate knowledge in the system) and an user interface. In this paper, only SEDPA's inference engine is described.

2.2. Domain databases

The domain databases are the permanent memory of the system. They store necessary information that the system uses to obtain its conclusions. These data were obtained from two principle sources: (a) literature and aquacultural journals (Roberts, 1981; Clifton-Hadley et al., 1984; MacConnell et al., 1989; Mellergaard and Dalsgaard, 1989; Kinkelin et al., 1991; Shepherd and Bromage, 1999); and (b) the historic data of physical, chemical, biological and yield parameters obtained from 1997 in the farm. The first kind of data (from literature and aquacultural journals) is stored in the 'Principal Domain Database' (PDD). In PDD, the relationships between syntactic labels and the eel pathologies are established with '1' and '0' (Van Diest et al., 1994). For the organisation of the dictionary used in the syntactic analysis, an adaptation of the lexical approximation is carried out applying a hierarchically structured dictionary (Steffens, 1994). Therefore, only the canonical form of the words are stored in the PDD (Winiwarter, 2000). On the other hand, the historic data of physical, chemical, biological and yield were stored in the 'Secondary Domain Database' (SDD).

2.3. Inference engine

The inference engine is the brain of the expert system. This component provides the methodology for reasoning by using the information from the domain databases to formulate conclusions. In SEDPA, the inference engine has three principle parts: (a) an augmented transition network (ATN); (b) a fuzzy logic controller; and (c) a system of uncertainty transmission based on the Dempster–Shafer theory.

2.3.1. The augmented transition network (ATN)

The ATN is a method of syntactic analysis that allows the inference engine to access the data stored in the domain databases, starting from the information in natural language entered by the user (Woods, 1973; De Carolis et al., 1996). The use of the ATN assures the information introduced to the expert system is coherent. This allows calculating the relative frequencies established between the pathologies associated with the symptoms/lesions observed and the synctactic labels stored in the PDD (Fig. 1). Initially, the system only processed information in Spanish but at the moment an English version of the ATN is being debugged.

2.3.2. The fuzzy logic controller

Fuzzy logic utilises a many valued form of logic. Unlike the 'crisp' logic of a yes–no controller, a fuzzy logic controller has in-between values. That is to say, a fuzzy set is divided by the geometric partitions. This allows us to describe a point as a function of its membership in different sets (Zeldis and Prescott, 2000). In SEDPA, the fuzzy logic controller has two input fuzzy sets (1: the minimum relative frequency (MRF) for each symptom/lesion and 2: the incidence (I) of each one of these pathologies in eel rearing systems) and one output fuzzy set (the categorical belief level that one or more of these pathologies are responsible for the illness in the fishfarm). The explicit relationship between the partitions of the input fuzzy sets and the output fuzzy set is stored in fuzzy associative memory (FAM). A human expert creates a FAM and it is a reflex of his experience. In this paper, SEDPA obtains its conclusions using three different FAMs, each one developed by a different human expert (FAM A [expert A], B [expert B] and C [expert C]). The possible relationships between input and output fuzzy sets for FAM B are shown in Fig. 2.

After the inputs (SL_1 in Fig. 3) to the controller (MRF and I) have been processed by the control algorithm, the result is a fuzzy output $\mu_{out}(y)$ or a categorical belief level (CBEL) for the n pathologies that satisfy all the conditions imposed by the ATN (in Fig. 3, $n = 3$ [Pt_1, Pt_3 and Pt_9] and MRF = 45.3%). For each pathology, selecting a crisp number y^*, representative of $\mu_{out}(y)$, is a process known as defuzzification. In Fig. 3, defuzzification process for Pt_1 is shown. In this case, the MRF for SL_1 implies two rules in the MRF fuzzy input set: rule 1 = normal shared (NS, 0.75) and rule 2 = low shared (LS, 0.30). Over the years, several defuzzification techniques have been suggested (Yager and Filev, 1994;

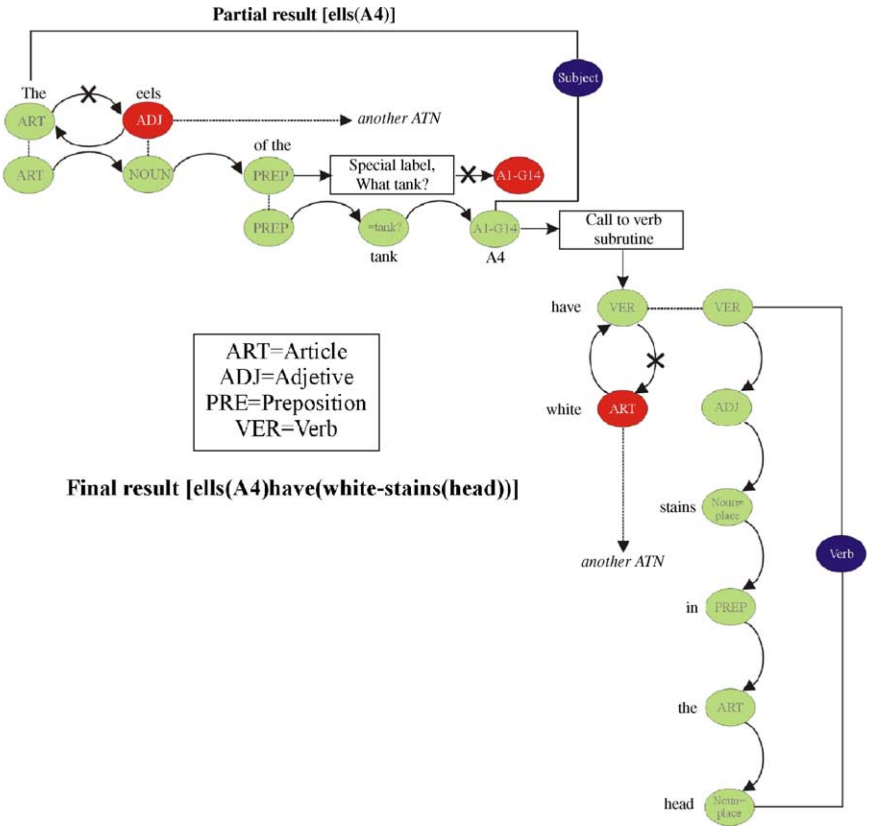

Fig. 1. Augmented transition network (ATN) schematic representation of the symptom/lesion: 'the eels of the tank A4 have white stains in the head'.

Tsoukalas and Uhrig, 1997). In SEDPA, the defuzzification technique is the center of area (COA) or the center of gravity defuzzification:

$$y^* = \frac{\sum_{i=1}^{N} y^{\mathrm{Center}(i)}(\mu_{\mathrm{out}}(y^i))}{\sum_{i=1}^{N}(\mu_{\mathrm{out}}(y^i))} \tag{1}$$

where $y^{\mathrm{Center}(i)}$ is the mass center of the ith fuzzy partition.

In COA defuzzification, the crisp value y^* is taken to be the geometrical center ($y^{\mathrm{Center}(i)}$) of the output fuzzy value $\mu_{\mathrm{out}}(y^i)$, where $\mu_{\mathrm{out}}(y)$ is formed by taking the union of all the contributions of rules whose degree of fulfillment is >0. In the example, the defuzzyficate value for Pt_1 or Pt_1 belief is 38.07 (Fig. 3).

2.3.3. Management of uncertainty: Dempster–Shafer evidence theory

Management of uncertainty is crucial in the design of expert systems. Broadly speaking, three fundamental issues must be considered: the representation, propagation and the combination of uncertain information. A common method for managing uncertainty is the

MRF

I	VLS	LS	NS	ES	VS
VR	VH	H	N	L	VL
R	H	N	L	L	L
C	H	N	N	H	H
VC	VH	N	L	VH	VH

First input: Minimum Relative Frequency (MRF):
VLS=Very Low Shared
LS=Low Shared
NS=Normal Shared
ES=Enough Shared
VS=Very Shared

Second input: Incidence of each pathologies in eel rearing system (I):
VR=Very Rare
R=Rare
C=Common
VC=Very Common

Output: Categorical belief level (CBEL):
VL=Very Low
L=Low
N=Normal
H=High
VH=Very High

Fig. 2. A fuzzy associative memory (FAM) and the meaning of labels. The meaning of ‘shared’ in this context is: with how many pathologies a certain symptom is related to the Principal Domain Database (PDD)?

bayesian network (Liu and Bundy, 1994). Bayesian networks provide a formalism for reasoning about the degrees of belief under the conditions of uncertainty. In this formalism, propositions are given the numerical probability values, signifying the degree of belief accorded them, and the values are combined and manipulated according to the rules of probability theory (Haddawy et al., 1994). However, when the information volume is very low and the use of probability functions is not possible, it is advisable to use other alternative techniques. In this case, a candidate for managing uncertainty in the expert systems is the Dempster–Shafer evidence theory (DST) (Hégarat-Mascle et al., 1997).

DST represents the relevant characteristics of the world as a finite set of mutually exclusive propositions and assumptions called the frame of discernment or space of hypotheses (Θ). In SEDPA, Θ is a set of pathologies that the system may diagnose. DST allows considering any subset of Θ (we denote 2^{Θ}, the set of the subset of Θ). In this case, a

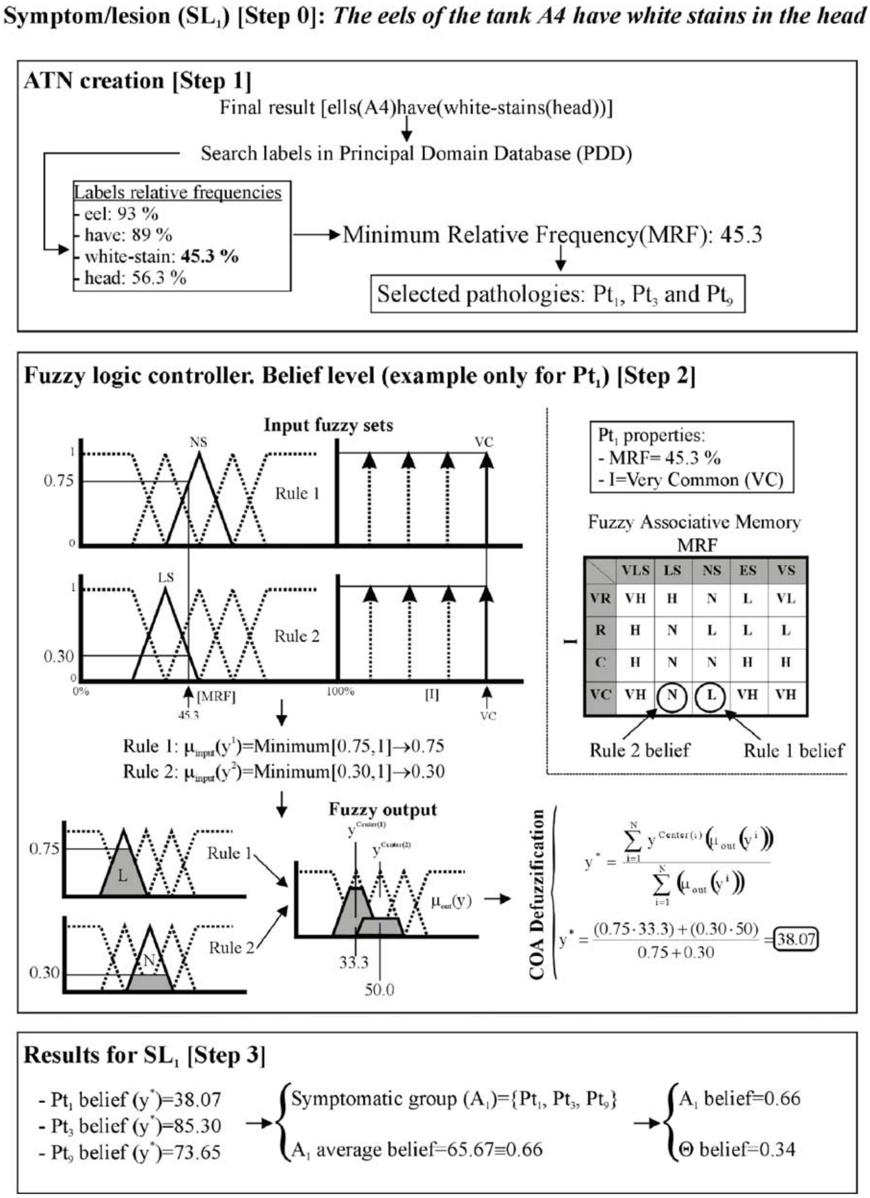

Fig. 3. The example represents the system running (steps 0–3) when the user introduces a first symptom/lesion (SL_1). Step 0 is the introduction of the symptom/lesion in natural language form in SEDPA. Step 1 is the ATN creation and calculus of the minimum relative frequecy (MRF). Step 2 is the assignment of a particular belief level for each pathology that satisfies all the conditions imposed by the ATN (step 1). Step 3 is the calculus of average belief level for the symptomatic group associated to SL_1.

subset of Θ (or symptomatic group) called A_i ($A_i \in 2^{\Theta}$) is formed by n pathologies associated with an event (symptom/lesion) observed by the user. In A_i, each pathology has a belief level (previously assigned through the fuzzy logic controller). This way, the belief level of A_i is the average belief level of its n pathologies (Fig. 3, step 3).

The DST provides a representation of both the imprecision and uncertainty through the definition of two functions, plausibility (PLS) and belief (QBEL) which are both derived from a mass function (m). This m is defined for every subset A_i of 2^{Θ} such that the mass value $m(A_i)$ belongs to the [0, 1] interval and

$$m : \begin{cases} m(\varnothing) = 0 \\ \sum_{\forall i} m(A_i) = 1 \end{cases} \tag{2}$$

where $\varnothing$ is the empty set.

DST provides a method to combine the data from different sources, that is to say, to combine different symptomatic groups from different symptoms/lesions observed by the user. (In Fig. 4, upper square, the results of SL_1 are combined with results of SL_2. The final result is three new symptomatic groups [A_3, A_4 and A_5]. In this case, 93% of the belief is accumulated in the A_3, A_4 and A_5 symptomatic groups.) If m_i is the basic probability assignment provided by a source, the combination: $m = m_1 \oplus \ldots \oplus m_p$, also called orthogonal sum, is defined according to the Dempster's combination rule (Shafer, 1976) by

$$\begin{cases} m(\varnothing) = 0 \\ \text{if } K < 1, \quad m(C) = \dfrac{\sum_{B_1 \cap \ldots \cap B_p = C} \prod_{1 \le i \le q;\, 1 \le j \le p} m_i(B_j)}{1 - K} \\ \text{where } \; K = \sum_{B_1 \cap \ldots \cap B_p = \varnothing} \prod_{1 \le i \le q;\, 1 \le j \le p} m_i(B_j) \end{cases} \tag{3}$$

where C and B_j are sets of symptomatic sets. K represents the mass which would be assigned to the empty set, after combination, in the absence of normalisation (division by $(1 - K)$). Thus, K is often interpreted as a measure of conflict between the different sources and it is introduced in (3) as a normalisation factor (Hégarat-Mascle et al., 1997). In the example (Fig. 4, lower square), the combination of A_3, A_4 and A_5 symptomatic groups with the new symptomatic groups from SL_3 (A_6) generates two empty symptomatic groups (A_7 and A_9). The final belief of no empty groups (A_8, A_{10}, A_{11}, A_{12} and A_{13}) is scaled for $K = 0.50$ (A_7 belief + A_9 belief).

Having computed the mass, plausibility and belief values for each simple and compound hypothesis, we need a criterion, which is called decision rule, to decide which hypothesis is the most realistic (Shafer, 1976). In SEDPA, the decision rule is the maximum of belief. In the example (Fig. 4, lower aquare), A_8 belief is 0.40.

2.3.4. Evaluation of SEDPA

A basic requirement for the acceptability of expert systems for the clinical diagnosis is that, instead of providing unique solutions, they select and submit to the user the whole set of hypotheses which are compatible with the available data. Such a strategy was applied in the present study, assuming that the condition for reliability of the system conclusion was

SL_2

Symptom/lesion (SL_2) [Step 0]

↓

ATN creation [Step 1]

↓

Fuzzy logic controller. Belief level [Step 2]

↓

Results for SL_2 [Step 3]

A_2={Pt_1, Pt_3, Pt_9} belief=0.80 and Θ=0.20

Dempster-Shafer's combination rule

$$m(C)=\sum_{B_1\cap\ldots\cap B_p=C}\ \prod_{\substack{1\le i\le q\\ 1\le j\le p}} m_i(B_j) \qquad K=0$$

SL_1 \ SL_2	{Pt_1, Pt_3, Pt_7} (0.80)	{Θ} (0.20)
{Pt_1, Pt_3, Pt_9} (0.66)	A_3={Pt_1, Pt_3} (0.53)	A_5={Pt_1, Pt_3, Pt_7} (0.13)
{Θ} (0.34)	A_4={Pt_1, Pt_3, Pt_9} (0.27)	{Θ} (0.07)

SL_3

Symptom/lesion (SL_3) [Step 0]

↓

Results for SL_3 [Step 3]

A_6={Pt_5, Pt_8, Pt_9} belief=0.75 and Θ=0.25

Dempster-Shafer's combination rule

$$m(C)=\frac{\sum_{B_1\cap\ldots B_2=C}\prod_{\substack{1\le i\le q\\ 1\le j\le p}} m_i(B_j)}{1-K} \quad where \quad K=\sum_{B_1\cap\ldots B_2=\varnothing}\ \prod_{\substack{1\le i\le q\\ 1\le j\le p}} m_i(B_j) \qquad 0<K<1$$

$SL_1 \cap SL_2$ \ SL_3	{Pt_5, Pt_8, Pt_9} (0.75)	{Θ} (0.25)
{Pt_1, Pt_3} (0.53)	A_7={$\varnothing$} (0.40)	A_{11}={Pt_1, Pt_3} (0.13)
{Pt_1, Pt_3, Pt_9} (0.27)	A_8={Pt_9} (0.20)	A_{12}={Pt_1, Pt_3, Pt_9} (0.07)
{Pt_1, Pt_3, Pt_7} (0.13)	A_9={$\varnothing$} (0.10)	A_{13}={Pt_1, Pt_3, Pt_7} (0.03)
{Θ} (0.07)	A_{10}={Pt_5, Pt_8, Pt_9} (0.05)	{Θ} (0.02)

Scaled belief for K=0.50

$\boxed{A_8=0.40}$
A_{10}=0.10
A_{11}=0.26
A_{12}=0.14
A_{13}=0.06
Θ=0.04
Σ=1

→ Maximum belief after SL_3

Fig. 4. The example represents the system running when the user introduces a second (SL_2) and third (SL_3) symptom/lesion. Upper square represents the combination of SL_1 and SL_2 by Dempster–Shafer' combination rule. The result of this combination is three new symptomatic groups (A_3, A_4 and A_5). Lower square represents the combination of SL_3 and $SL_1 \cap SL_2$. In this case, the Dempster–Shafer' combination rule generates two empty sets (A_7 and A_9). Consequently, the belief level of rest of the symptomatic groups (A_8, A_{10}, A_{11}, A_{12}, A_{13} and Θ) is rescaled for $K = 0.50$ (A_7 belief = 0.40 + A_9 belief = 0.10).

the inclusion of the reference diagnosis among those selected as compatible (Molino et al., 1996).

According to such a strategy, system conclusions were regarded as ‘incorrect’ only when the reference diagnosis was missed. While all the hypotheses selected as compatible were accepted as reliable and classified either as ‘correct’ (when one pathology got the highest belief level) or ‘approximate’ (whenever the right pathology was selected together with other options).

The reference set was compiled using 29 cases detected in Hidrorecursos S.A. The specific data from these 29 cases were not stored into the database domain of the system. The diagnoses of each case (1–29) was judged by three experts in fish pathology (experts RL1, RL2 and RL3) in a reference laboratory. The diagnosis of the reference laboratory experts was taken as the ‘gold standard’ (Van Diest et al., 1994). Later on, these 29 cases were judged by SEDPA and a panel of other three different pathologists (experts D1, D2 and D3) who had varying experience in fish pathology. These pathologists were asked to classify the cases in their usual way, allowing for the consultation of books and/or journals in order to simulate a real situation. Finally, the diagnoses from the SEDPA and D1, D2 and D3 experts were compared with the gold standard.

3. Results

3.1. Human experts versus SEDPA

A comparison of SEDPA diagnoses versus those obtained from experts D1, D2 and D3 are shown in Table 1a and b. The exact relationship between the human experts and SEDPA diagnostics and the reference diagnostic or ‘gold standard’ is presented in the principle diagonal. For example, case 4 (column 4) was correctly judged by the experts D2 and D3 and SEDPA. However, in this case, expert D2 included in his answer possible pathologies of cases 5 and 6. In the same way, expert D3 included in his answer a possible diagnosis of case 5 and SEDPA included in its answers cases 6 and 8. Therefore, in case 4, the answers of experts D2 and D3 and SEDPA were classified as ‘approximate’. On the other hand, the expert D1 included in his answer only one pathology. This pathology was different from ‘gold standard’, therefore; it was classified as ‘incorrect’.

In some cases (6, 15, 17–23, 25 and 27), the human experts included in their answer different pathologies neither of which was the ‘gold standard’. These diagnostics were included in the ‘others’ (O) category.

Globally, in the validation phase, the best result was obtained by SEDPA (20 answers classified as ‘correct’, 8 answers classified as ‘approximate’ and 1 answer classified as ‘incorrect’). Among the human experts, expert D1 obtained the best result (14 answers classified as ‘correct’ and 15 answers classified as ‘incorrect’). The diagnostics of the experts D2 and D3 were similar (expert D2: 6 answers classified as ‘correct’, 7 answers classified as ‘approximate’ and 16 answers classified as ‘incorrect’; expert D3: 7 answers classified as ‘correct’, 3 answers classified as ‘approximate’ and 19 answers classified as ‘incorrect’). Therefore, the success rate of the experts D1, D2 and D3 were 48.3%, 20.7% and 24.1%, respectively. If the answers classified as ‘approximate’ are reclassified as

Table 1
(a and b) Diagnostic of human experts (D1 = 1, D2 = 2, and D3 = 3) and SEDPA (S) vs. the gold standard (GE) for each case

GE	Human experts (D1 = 1, D2 = 2, D3 = 3) and SEDPA (S) diagnostic																											
Case	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29
(a)																													
1	**3, S**																												
2		**1, S**																											
3	2, 3	3	**1, 2, 3, S**		2	2, 3	2	2, 3, S																					
4				**2, 3, S**																									
5	2	2		1, 2, 3	**1, 2, 3, S**	2	2, 3	1, 2	2										S				2				3		
6	1			2, S		**S**	2																						
7							**S**										S					S							
8				S				**S**	3																				
9									**1, S**										S										
10										**1, 2, S**																			
11							1				**1, 2, 3, S**							2											
12												**1, 2, 3, S**																	
13													**1, 2, S**																
14														**2, 3, S**			2			1, 2	3							2, 3	

Table 1 (*Continued*)

GE	Human experts (D1 = 1, D2 = 2, D3 = 3) and SEDPA (S) diagnostic																												
Case	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29
(b)																													
15															**S**	1, 2		2							1				
16																**S**													
17																	**2, S**												
18																		**S**											
19																			**S**										
20																				**S**	S								
21																					**1, 2, S**								
22																						**S**							
23																						S	**S**						
24																								**1, 2, 3, S**	S				
25																									**S**				
26							2	2	2			2		2						2			2			**1**	2		
27																	1, 3										**2, S**		
28														1, 2	2, 3													**1, 2, S**	
29																													**1, 2, 3, S**
O						1									1		2, 3	1	1, 2	2	2	1	1, 3		2		1		

The principle diagonal (bold) indicates the correct diagnosis. Each case results are detailed by the columns. For one case (column), when a number (1, 2 or 3) or S is in more of one file means that human expert or SEDPA generated more of one answer for this case. For example, see case 1 (column 1). The category ‘O’ indicates a diagnosis whose result disagrees with the gold standards judged in the reference laboratory.

Table 2
Fisher's exact test of SEDPA's diagnosis vs. human experts's diagnosis (experts D1, D2 and D3)

	SEDPA's diagnosis	Human expert's diagnosis
Agree	20	14 (Expert D1)
Disagree	8	15 (Expert D1)
	$N = 29$; $p = 0.0910$	
Agree	20	6 (Expert D2)
Disagree	8	23 (Expert D2)
	$N = 29$; $p < 0.001$	
Agree	20	7 (Expert D3)
Disagree	8	22 (Expert D3)
	$N = 29$; $p < 0.001$	

'correct', then the success rates were incremented to 48.3%, 44.8% and 34.5%, respectively. With regard to SEDPA, the success rate with answers strictly correct was 69.9%. When the 'approximate' answers were considered, the success rate was increased to 96.6%.

The results of a Fisher's exact test demonstrated no statistically significant difference in the number of cases agreeing with the 'gold standard' by SEDPA and expert D1 ($p = 0.0910$). On the other hand, the differences were statistically significant when the results obtained by experts D2 and D3 were compared in the same way to the SEDPA results (expert D2 versus SEDPA: $p < 0.001$; expert D3 versus SEDPA: $p < 0.001$) (Table 2). When the approximate answers of the human experts and SEDPA were reclassified to 'correct', the statistical differences were significant in all the cases (experts D1, D2 and D3 versus SEDPA: $p < 0.001$).

4. Discussion

Previous works in the field of expert systems applied to aquaculture have shown that this kind of computer program or software may be useful for a great variety of purposes: financial analysis, yield management, diagnosis and pathology treatment (Schulstad, 1997). These activities are intimately related to the correct management of any aquaculture system. This way, Zeldis and Prescott (2000) developed the FISH-VET system which may process information for different species and may diagnose pathologies associated with fish rearing. The general-purpose systems may provide a correct solution in a multitude of scenarios but their conclusions may be incomplete whenever the available information is scarce. Generally, this is because incorporating of this kind of information complicates the construction of the knowledge base used by the system. The special information is easier to integrate in a system with a limited workspace which makes it easier to obtain useful conclusions to the technician responsible for the health policy in the fish farm. However, the construction of expert systems under special conditions (data absence, fuzzy or redundant information) may imply a high economical and temporal investment that is directly related to the number and kind of rules included by the program designer.

We successfully developed and tested an expert system that can be used as a tool in the diagnosis of eel pathologies. The design of SEDPA permits the entry of data in natural language form, helping the technician to reach a diagnosis. Consequently, SEDPA could potentially improve the technician's efficiency, shorten the time-consuming process of diagnosis, increase the economic efficiency of diagnosis and decrease the cost of mortality.

Computationally, SEDPA combines some advantages of the two kinds of systems previously described. On the one hand, its workspace is reduced to only one species which resulted in success rates close to 70%. On the other hand, the knowledge acquired by SEDPA is not stored in the rule form, so that the system is very versatile and easily adapted to the different work scenarios. This program's nature facilitates the implementation and adaptation of the system to eel fishfarms with different characteristics and permits the inclusion of the knowledge of human experts with different experience levels. Hopefully, the system could serve as the prototype for other species with similar knowledge levels because the binary relations in the PDD are easily replaceable.

Thus, foregoing rules confers both important advantages and high obstacles too. Modelling the knowledge base with if/then rules makes it possible to integrate the heuristics that guide a human expert in the diagnostic decision process. Expert systems based on rules as GOLDFINDER (Hawkes, 1992), MUNIN (Andreassen et al., 1995) and XPHEMO (Nguyen et al., 1996) may provide information to the user about the reasoning process of the inference engine. This retrospective process is not possible in SEDPA.

The results of the evaluation process show that the SEDPA's behaviour was correct because SEDPA's success rate was significantly higher than the human experts success rates. These differences could have several explanations. For example, the human expert process the information in natural language form assuming that this information is compounded by a labels set whose combinations make coherent sentences (Chomsky, 1959).

Usually, in the eel health-policy context, the information obtained from the observation of symptoms and lesions has a 'categorical character'. That is to say, the technician observations are used to define the 'way' or 'route' for the definitive pathology determination (chemical analysis of water, bacterial crop, historical data analysis and antibiogram). This 'categorical character' is enhanced when the action of the different pathological agents produces similar symptoms or lesions. However, SEDPA does not use this information in the same way. In this case, initially the information is statistically treated, calculating for each sentence's label, the appearance frequency and analysing the relationships between the different label sets. Starting from these initial results, the system presents a high level of pathologies discrimination using a fuzzy controller. Lee et al. (2000) designed an expert system to study a denitrification system in a fishfarm using a fuzzy controller. The results showed that the expert system controlled the generated actions in conservative form and the discrimination capacity was better than those obtained when classical techniques were used. Mamdani (1977), Takagi and Sugeno (1985) and Whitsell and Lee (1994) obtained similar results using fuzzy controllers. The discrimination capacity of SEDPA is increased using a method classified as probabilistic technique. Although its use in practical cases has been very rare, Hájek (1994), Hégarat-Mascle et al. (1997) and Murphy (1998) report that the Dempster–Shafer theory is an effective method of uncertainty transmission.

On the other hand, the absence of visual confirmation has a great influence on the human expert conclusions. Although the description of symptoms and lesions in each case was made by the three human experts the more ones systematically possible, one can argue that the information described may be misunderstood by other experts if the pathological effects cannot be personally observed.

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