Software Sensor for a Harvested Fish Population Model

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Summary

This paper deals with the problem of software sensor (state estimation) to study the uncertain continuous age-structured model of a harvested fish population, in order to get an estimation of the biomass of fishes by age class. In our case the fishing effort is considered as a control term, the age classes as a states and the quantity of captured fish as a measured output. We formulate the observer corresponding to this system and show its asymptotic convergence. With the Lie derivative transformation, we show that the model can be transformed to a canonical observable form; then we give the explicit gain of the estimation. The considered model is nonlinear and contains an unknown function, which is supposed to be bounded. The proposed observer do not assume or require any model for this function and is very successful for accurately estimating it. The simulation results demonstrate the effectiveness of the proposed method.

Key words:
uncertain stage structured model, Fishery system, Software sensor, High gain observer.

1. Introduction

Fish population dynamics models are essential to provide assessment of the fish biomass and fishing pressure. Their use forms the basis of scientific advice for fisheries management. Continuous and discrete age-structured models are most of the time used for fisheries stock assessments [5]. Indeed, ecologists, mathematicians and population biologists have observed that the age structure provides more realistic results at reasonable computational expense for a widevariety of biological populations. They permit a qualitative description of the system since they take into account both the fish size and the time mechanism of reproduction of the exploited stock. Theirs complexities and their control that are associated withbiological and ecological phenomena offer many challenge for thecontrol engineer. As it is well known, measurements of the ageclasses biomass are of great importance for monitoring and controlof the fish stock, in order to find a reasonable

strategy whichguarantees a lasting supply of the resource. Although, there exist some hardware sensors (acoustiques methods), they often present many drawbacks: they are very expensive, and they are not generalized yet.

Therefore, it is very interesting to use software sensors (or state observer) which are able to estimate on-line the biomass of fish. Software sensor is the association of a sensor (hardware), which allow on-line measurements of some process variables, with an estimation algorithm (software) in order to provide on-line estimates of the unmeasurable variables, model parameters or to overcome measurement delays.

When solving control engineering problems, it is often necessary to know the state of a dynamical system. Most of the modern control design methods, especially for nonlinear systems, usea state feedback as the controller. Knowing the system state is also important for the monitoring of a technical system, either manually or automatically. But in most applications, it is very difficult or even impossible to measure the entire state of the system: either because applying sensors for all states would require too much effort, or because there are no methods to measure a state variable in real time. Thus the problem of observer design is how toget an estimate for the state of a dynamical system from theknowledge of its input and output signals. In this sense, several techniques have been introduced to estimate state variables from the available measurements, usually related to meaningful variables. From the obtainable information about the process, there exist many possible kinds of estimators to be used depending on the mathematical structure of the process model [15,20,28,29].

The high gain software sensor which is the aim of this work is an appropriate technique for several class of

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nonlinear systems. Its origin can be traced back to Gauthier [16]. The basic idea of this approach is to dominate the nonlinear behavior of the system by applying high gains to a slightly modified Luenberger observer. Convergence is then usually proven by giving aquadratic Lyapunov function, as normally used for linear systems. Anextension of this observer synthesis to the multi out-put case is given in [11, 12, 13].

In fishery systems the states variables can\'t be measured, and the resources cannot be counted directly except with acoustic method which is not generalized yet. This difficulty leads some authors to estimate the biomass through available data. Ouahbi [21] construct an observer that gives an estimate of the state of the discrete time model and which is independent of the choice of stock recruitment function. Iggidr et al [19] formulate of an exponential observer for the discret age-structured model of an exploited fish population in order to get an estimation of the number of fishes by age class.

They consider a nonlinear model taking into consideration a stock-recruitment function which is not well known. The observer that they construct is independent of this function. Gouzé et al [14] present a technique for the dynamic estimation of bounds and no-measured variables of an uncertain dynamical systems. They show the applicability of this method to the three stages structured population model; one of the disadvantages of this method is formulated under the assumption that only the oldest stage is subject to be captured.

In the previous paper [6] proposed the high gain observer technique for the continuous age-structured fish population model without uncertainties in order to get an estimation of the biomass of fishes by age class. Our main goal here is to show that similar technique can be exploited for the uncertain continuous age-structured model.

In this contribution, we deal with an uncertain continuous age-structured model of population dynamics of exploited fish. The model is structured in age classes and we assume that at each time we can measure the quantity of caught fishes. we show that it is possible to construct an observer which gives an estimation of the biomass of fishes by age class. The high gain observer technic is used relying on to the work of [13,16]. The asymptotic observer is explicitly formulated in an invariant domain. Numerical example is given and simulation results are shown.

2. Problem formulation and assumptions

To evaluate the fisheries resources, two groups of models were made: global models that gives a general vision of the stock, which is represented with a single variable [3,23] and structured models that distinguish between several stages (classes of ages, of size...) of the stock, the evolution of each one is described separately [7, 8, 9, 18, 21, 22, 25, 26]. The principle of the stage structured stock is represented in the figure 1.

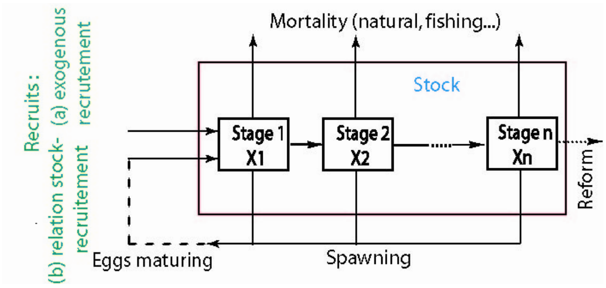

Figure 1: Representation of a stage structured stock.

$$\begin{cases} \dot{X}_0 & = & -\alpha_0 X_0 + \sum_{i=1}^{n} f_i l_i X_i - \sum_{i=0}^{n} p_i X_i X_0 + r \\ \dot{X}_1 & = & \alpha X_0 - (\alpha_1 + q_1 E) X_1 \\ \vdots & & \vdots \\ \dot{X}_n & = & \alpha X_{n-1} - (\alpha_n + q_n E) X_n \\ \dot{r} & = & \epsilon(t) \\ Y & = & q_1 X_1 + q_2 X_2 + \ldots + q_n X_n \end{cases} \quad \textbf{(1)}$$

Where

$\alpha_i = \alpha + M_i$:

M_i : is the natural mortality of the individuals of the i th age class;

α : is the linear aging coefficient;

p_0 : is the juvenile competition parameter;

p_i : is the predation parameter of class i on class 0;

f_i : is the fecundity rate of class i;

l_i : is the reproduction efficiency of class i;

q_i : is the catchability of the individuals of the ith age class;

X_i : is the biomass of class i;

E : is the fishing effort at time t and is regarded as an input;
Y : is the total catch per unit of effort and is regarded as output;
r : can be viewed as an unknown signal composed of model
uncertainties, non-linearities and disturbances, etc.;
which affects the other states of the system ϵ: stands for any unknown bounded function.

Let us note that all the parameters of the model are positive. The recruitment from one class to another can be represented by a strictly positive coefficient of passage. The passage rate α from the juvenile class to the adult stages is supposed to be constant with respect to time and stages. This means that the time of residence is equal to $\frac{1}{\alpha}$. The laying eggs is considered continuous with respect to time. The total number of eggs introduced in the juvenile stage is given by $\sum_1^n f_i l_i X_i$. The cannibalism term $\sum_1^n p_i X_0 X_i$ is based on the Lotka-Volterra predating term between class i and class 0. The intra-stage competition for food and space is expressed as $p_0 X_0^2$. The mortality of each stage i is caused by the fishing and natural mortality which is supposed linear [26].

In [6] we have studied the state estimation of the nominal model [1] (model with known parameters and without uncertainties). But, in the realistic situations, several uncertainties may appear:

- The recruitment function is not well known. For instance, the parameters are uncertain (it is often the case in fisheries that the stock-recruitment function is hard to obtain [26].
- The harvesting effort E(t) is unknown, because of lack of official data; or there is an uncontrolled harvesting or poaching.

One supposes that the system [1] satisfies the following assumptions :

Assumption 1
One non linearity at least must be considered.

$$\sum_{i=0}^{n} p_i \neq 0$$

Assumption 2
he spawning coefficient must be big enough so as to avoid extinction.

$$\sum_{i=1}^{n} f_i l_i \pi_i > \alpha_0 \text{ where: } \pi_i = \frac{\alpha^i}{\prod_{j=1}^{i}(\alpha_j + q_j \bar{E})} \text{ and } \bar{E}$$

is a constant fishing effort.

Assumption 3
All age classes are subject to catch and the oldest one yields eggs.

$$\forall i = 1 \dots n \quad q_i > 0 \text{ and } f_n l_n \neq 0$$

Assumption 4
Each predator lays more eggs than it consumes.

$$X_0^* < \mu = \min_{i=1\dots n}\left(\frac{f_i l_i}{p_i}\right) \text{ for } f_i l_i p_i \neq 0$$

Assumption 5
We assume that he fishing effort is subject to the constraint.

$$0 < E_{min} \leq E \leq E_{max}$$

Assumption 6
The unknown functions r(t) and ϵ are bounded . So there exist two positives numbers δ_1 and δ_2 such that:

$$\|r(t)\| \leq \delta_1 \text{ and } \|\epsilon(t)\| \leq \delta_2$$

Under the assumptions 1and 2 the nominal system of [1] (r=0) has two equilibrium points [26]: The first one is the origin X=0 which corresponds to the extinction of population and is therefore not very interesting. The secondone is the nontrivial equilibrium X^* defined as:

$$X_i^* = \pi_i X_0^* \text{ and } X_0^* = \frac{\sum_1^n f_i l_i \pi_i - \alpha_0}{p_0 + \sum_1^n p_i \pi_i},$$

where

$$\pi_i = \frac{\alpha^i}{\prod_{j=1}^{i}(\alpha_j + q_j \bar{E})} \text{ and } \bar{E} \text{ is a constant fishing effort.}$$

2. Software sensor design

In [7,8,9] we construct a state feedback law that allows to stabilize the system around the nontrivial steady state X*. However in fish population science one evolves in dubious world were the observation and the direct experimentation are practically impossible and it is very difficult to measure the entire state of the system. So the state feedback control law is not realizable. There are tow ways to solve this problem the first one consists on the synthesis of the output feedback [10], the second one consist on the design of a software sensor to estimate the biomass of stock through available data, captured quantity and fishing effort which is the aim of this work.

A software sensor is the association of a sensor (hardware) that measures on-line some process variable, with an estimation algorithm (software) that infers on-line some hidden meaningful information from the data provided by the sensor. A critical element in the synthesis of a ‘‘software sensor’’ is the available knowledge of the process. An accurate process model generally expresses this knowledge. However, it is normally impossible to obtain an exact process model, so that the estimation algorithm must be robust enough to deal with model errors. A schematic diagram of a software sensor is shown in figure 2.

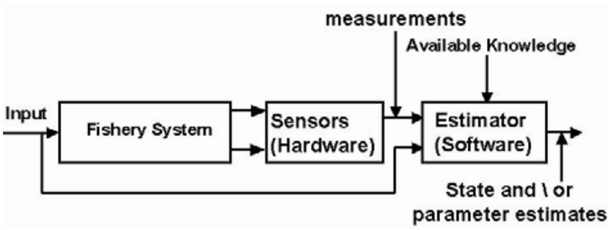

Figure 2: Principle of a software sensor

The problem addressed here is how to use the measurable information the input E and the output Y in order to construct an observer. This state estimation problem consists of recursively computing an estimate $\widehat{X_i}(t)$ of $X_i(t)$ for which the error decays to zero as $t \to +\infty$. That is, to design a system of differential equation whose state $\widehat{X_i}(t)$ are such that: $\lim_{t\to+\infty}(\widehat{X_i}(t) - X_i(t)) = 0$

The system [1] can be written in the following general form.

$$\begin{cases} \dot{X} &= A_1X + B_1Xu + A_2X + F(X) + \overline{\epsilon} \\ Y &= C_1X \end{cases} \quad (2)$$

Where: $X = (X_0, X_1, ..., X_n, r)$

$$\delta_1 \leq max(\dot{X}_i(a_0, a_1, ..., a_n), -\frac{Q}{2})$$

$$Q = \dot{X}_0(\mu, \mu\pi_1, \mu\pi_2, ..., \mu\pi_n)$$

2.1 Tables and Figures

To facilitate the design of the nonlinear observer, we consider the following change of coordinates:

$$\phi_1 : X \to Z = (h(X), L_f h(X), \ldots, L_f^n h(X), q_n\alpha^n r)$$

Where: $f(X)=A_1X$ and $h(X)=C_1X$

L denotes the Lie derivative operator defined as:

$$L_f h(X) = \frac{\partial h(X)}{\partial X} f(X)$$

and $$L_f^n h(X) = L_f(L_f^{n-1}h(X))$$

Z can be expressed as:

$$\begin{aligned} Z &= (C_1X, C_1A_1X, ..., C_1A_1^nX) \\ &= MX \end{aligned}$$

where

$$M = \begin{pmatrix} 0 & q_1 & q_2 & \cdots & q_n & 0 \\ q_1\alpha & q_2\alpha & \cdots & q_n\alpha & 0 & 0 \\ q_2\alpha^2 & \cdots & q_n\alpha^2 & 0 & 0 & 0 \\ \vdots & . & 0 & 0 & 0 & 0 \\ q_n\alpha^n & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & q_n\alpha^n \end{pmatrix}$$

It is easy to see that: $\det M = (-1)^n q_n^{n+2} \alpha^{\frac{n(n+3)}{2}}$

Thus $\forall q_n \neq 0$ we have $\det M \neq 0$ $(q_n \neq 0)$ means that the last stage-class is subject to catch.

Consequently ϕ is a diffeomorphism in D.

So it transform [1] to:

$$\begin{cases} \dot{Z} &= AZ + MBM^{-1}Zu + MA2M^{-1}Z \\ &+ MF(M^{-1}Z) + M\overline{\epsilon(t)} \\ Y &= CZ \end{cases} \quad (3)$$

Where:

$$A = \begin{bmatrix} 0 & 1 & \dots & \dots & 0 \\ 0 & 0 & 1 & \dots & 0 \\ 0 & 0 & 0 & \ddots & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} C = [1,0,0,\dots,0]$$

Proposition 1

For any initial condition $X(0)$ and $\hat{X}(0)$ such that:

$$(X_0(0), X_1(0), ..., X_n(0)) \in D$$

and $$(\hat{X}_0(0), \hat{X}_1(0), ..., \hat{X}_n(0)) \in D,$$

for θ large enough, the system [2] satisfying the assumptions [1], [2], [3], [4], [5] and [6] can be estimated by the following dynamical system:

$$\begin{aligned} \dot{\hat{X}} &= A_1\hat{X} + B_1\hat{X}u + A_2\hat{X} + F(\hat{X}) \\ &- \theta M^{-1} d_\theta^{-1} S_1^{-1} C'(C_1\hat{X} - Y) \end{aligned} \quad (4)$$

Where: S_1 is the symmetric positive definite solution of the Sylvestre algebraic equation:

$$\theta S_\theta + A'S_\theta + S_\theta A - C'C = 0 \quad (5)$$

and it can be expressed as:

$$S_1(i,j) = (-1)^{i+j} C_{i+j-2}^{j-1}$$

d_θ is a diagonal matrix defined by:

$$d_\theta = diag(1, \frac{1}{\theta}, \dots, \frac{1}{\theta^{n+1}})$$

Lemma 1

For θ large enough the system below is an observer for the system [3]:

$$\begin{aligned} \dot{\hat{Z}} &= A\hat{Z} + MBM^{-1}\hat{Z}u + MA2M^{-1}\hat{Z} \\ &+ MF(M^{-1}\hat{Z}) - \theta d_\theta^{-1} S_1^{-1} C'(C\hat{Z} - Y) \end{aligned} \quad (6)$$

Proof

Let: $e = \hat{Z} - Z$

Then on can check that:

$$\dot{e} = (A - \theta d_\theta^{-1} S_1^{-1} C'C)e + M(A_2 + Bu)M^{-1}e + M\Delta(F)$$

Where: $\Delta(F) = MF(M^{-1}\hat{Z}) - MF(M^{-1}Z)$

F is lipschitz with the constant:

$$L = 2p_0b_0 + \sum_1^n p_ib_i + \sum_1^n f_il_i + (\alpha_0^2 + \alpha_1^2 \dots + \alpha_n^2)^{\frac{1}{2}}$$

So $\|\Delta(F)\| \le \|L_1 e\|$ where $L_1 = L\|M\|\|M^{-1}\|$

Let $V_\theta = \frac{1}{\theta} e'd_\theta S_1 d_\theta e$ the candidate Lyapunov function.

Then the time derivative of V_θ is given by:

$$\dot{V}_\theta = \frac{1}{\theta}(e'(A'd_\theta S_1 - \theta C'C)d_\theta e$$
$$+ \frac{1}{\theta} e'd_\theta S_1 d_\theta M(A_2 + Bu)M^{-1}e + e'd_\theta(S_1 d_\theta A - \theta C'C)e$$
$$+2\frac{1}{\theta} M^{-1}(F(M^{-1}\hat{Z}) - F(M^{-1}Z))d_\theta S_1 d_\theta e)$$
$$-\frac{2}{\theta}\bar{\epsilon}' M' d_\theta S_1 d_\theta e$$
$$= \frac{1}{\theta} e'd_\theta(d_\theta^{-1}A'd_\theta S_1 - \theta d_\theta^{-1}C'C - \theta C'Cd_\theta^{-1})d_\theta e$$
$$+ \frac{1}{\theta} e'd_\theta S_1 d_\theta M(A_2 + Bu)M^{-1}e$$
$$+2\frac{1}{\theta} M(F(M^{-1}\hat{Z}) - F(M^{-1}Z))d_\theta S_1 d_\theta e - \frac{2}{\theta}\bar{\epsilon}' M' d_\theta S_1 d_\theta e$$

Taking into account the algebraic equation (5) and

$$(d_\theta A d_\theta^{-1} = \theta A, C'Cd_\theta^{-1} = C'C)$$

It follows:

$$\dot{V} = \frac{1}{\theta} e'd_\theta(-\theta S_1 - \theta C'C)d_\theta e$$
$$+2\frac{1}{\theta} e'd_\theta S_1 d_\theta M(A_2 + Bu)M^{-1}d_\theta^{-1}d_\theta e$$
$$+2\frac{1}{\theta} M(F(M^{-1}\hat{Z}) - F(M^{-1}Z))d_\theta S_1 d_\theta e$$
$$-\frac{2}{\theta}\bar{\epsilon}' M' d_\theta S_1 d_\theta e$$

We indeed get:

$$\begin{aligned} \dot{V} &\le -\theta V + \frac{2}{\theta}\lambda_{max}(S_1)(\|A_2\| \\ &+ \|B\|umax + L_1)\|d_\theta e\|^2 \\ &+ \frac{2}{\theta}\lambda_{max}(S_1)\frac{q_n\alpha^n\delta_2}{\theta^{n+1}}\|d_\theta e\| \end{aligned}$$

Using the above Rayleigh inequality :

$$\lambda_{min}(S_1)\|d_\theta e\|^2 \le e'd_\theta S_1 d_\theta e \le \lambda_{max}(S_1)\|d_\theta e\|^2$$

where $\lambda_{min}(S_1)$ and $\lambda_{max}(S_1)$ are respectively the minimal and the maximal eigenvalues of S_1

Then:

$$\dot{V} \leq -(\theta-\theta_1)V + \frac{\theta_{2\sqrt{\theta}}}{\theta^{n+1}}\sqrt{V}$$

it Follows:

$$\sqrt{V} \leq \exp[-(\frac{\theta-\theta_1}{2})t]\sqrt{V(0)} + \frac{\theta_2\sqrt{\theta}}{\theta^{n+1}}(1-\exp[-(\frac{\theta-\theta_1}{2})t])$$

Where $\theta_1 = 2\lambda_{max}(S_1)(\|B\|E_{max}+L)$

and $\theta_2 = 2\lambda_{max}(S_1)q_n\alpha^n\delta_2\frac{1}{\sqrt{\lambda_{min}(S_1)}}$

Consequently for $\theta > \theta_1$ we have

$$\|d_\theta e\| \leq \sqrt{\frac{\lambda_{max}(S_1)}{\lambda_{min}(S_1)}}\exp[-(\frac{\theta-\theta_1}{2})t]\|d_\theta e(0)\| + \frac{\theta_2}{\sqrt{\theta}\theta^{n+1}(\theta-\theta_1)\sqrt{\lambda_{min}(S_1)}}$$

From the Rayleigh inequality:

$$\frac{1}{\theta^{n+1}}\|e\| \leq \|d_\theta e\| \leq \|e\|$$

we get:

$$\|e\| \leq \theta^{n+1}\sqrt{\frac{\lambda_{max}(S_1)}{\lambda_{min}(S_1)}}\exp[-(\frac{\theta-\theta_1}{2})]\|e(0)\| + \frac{\theta_{2\sqrt{\theta}}}{(\theta-\theta_1)\sqrt{\lambda_{min}(S_1)}}$$

Consequently for θ large enough $\|e\|$ converge to zero

Proof of the Proposition

We have $\hat{X} = M^{-1}\hat{Z}$
Then

$$\begin{aligned}
\dot{\hat{X}} &= M^{-1}\dot{\hat{Z}} \\
&= M^{-1}(A\hat{Z} + MBM^{-1}\hat{Z}u + MA_2M^{-1}\hat{Z}) \\
&+ M^{-1}(MF(M^{-1}\hat{Z}) - \theta d_\theta^{-1}S_1^{-1}C'(C\hat{Z}-Y)) \\
&= M^{-1}A\hat{Z} + BM^{-1}\hat{Z}u + A_2M^{-1}\hat{Z}) + (F(M^{-1}\hat{Z}) \\
&- \theta M^{-1}d_\theta^{-1}S_1^{-1}C'(C\hat{Z}-Y)) \\
&= M^{-1}AM\hat{X} + A2\hat{X} + B\hat{X}u + F(\hat{X}) \\
&- \theta M^{-1}d_\theta^{-1}S_1^{-1}C'(C_1\hat{X}-Y) \\
&= A_1\hat{X} + A_2\hat{X} + B\hat{X}u + F(\hat{X}) \\
&- \theta M^{-1}d_\theta^{-1}S_1^{-1}C'(C_1\hat{X}-Y)
\end{aligned}$$

Which end the proof of the proposition.

4. Results and discution.

fisheries were recognized as a key sector of the Moroccan economy. The sardine of the Moroccan Atlantic coast is the dominant species in the small pelagic which, represents approximately 70% of the total pelagic catches. It is, from this fact, a socio-economical resource of key importance. So we are interested to give a simulation example for this species.

To visualize the observer obtained from the algorithm one considers here a population with seven stages age (n=6): Stage 0 represents the biomass of juvenile; stage 1 represents the young adults biomass without reproduction and cannibalism; the stages 2, 3, 4, 5 and 6 are the biomass of adults with the same term of predation and the same proportion on the female mature but have different reproduction rate. The results obtained from the observer are illustrated by the example characterized by the parameter value inspired from literature data [26]. given in table1. Here we have employed for the simulation a constant fishing effort $E(t) = \overline{E}$ and arbitrary initial states

$$X(0) = (0,8,4,10,10,1,10); \hat{X}(0) = (8,4,0,1,4,4,4)$$

In order to show the effect of high gain, we simulate the proposed system with the high gain $\theta = 20$ and $\theta = 40$ the results are presented in figures (3,4,5,6,7,8,9, and 10) which give time evolution of the stage age X_i and theirs estimates $\widehat{X_i}$ respectively for i=0 to 6 and the time evolution of the unknown function r and its estimate $\hat{r}$. Both the two values of θ guarantees asymptotic convergence, and the second one shows good tracking performances than the first. For simulation the unknown function r is chosen as :

$$r(t) = 0.5sin(-\pi t)exp(-t).$$

The numerical ageing coefficient is $\alpha = 1$ and the fishing effort $\overline{E} = 1$.
the other parameters are presented in the table 1

stage i	0	1	2	3	4	5	6
p_i	0.2	0	0.2	0.1	0.1	0.1	0.1
f_i			0.5	0.5	0.5	0.5	0.2
l_i		7.6	1.2	0.2	0.2	0.2	0.2
m_i	0.5	0.2	0.2	0.2	0.2	0.2	0.2
q_i	0	0.12	0.12	0.12	0.12	0.12	0.12
α_i	1.4	1.2	1	1	1	1	1
X_{ini}	0	8	4	10	10	1	10
$\hat{X}_{ini}$	8	4	0	1	4	4	4

Table 1: Fishery system parameters

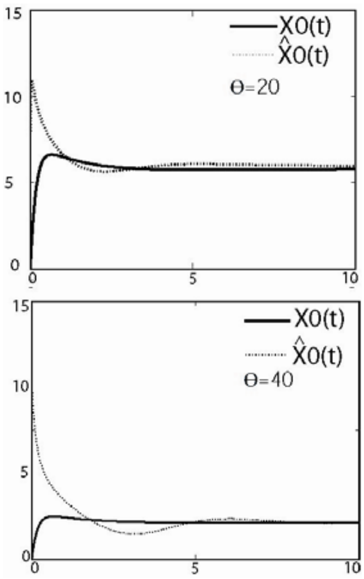

Figure 3 $X_0(t)$ and $\hat{X}_0(t)$ for $\theta = 20$ and $\theta = 40$

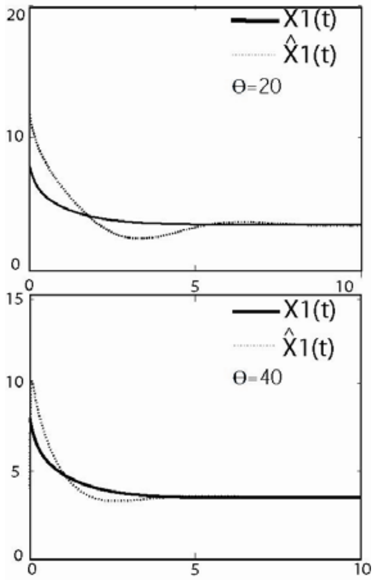

Figure 4 $X_1(t)$ and $\hat{X}_1(t)$ for $\theta = 20$ and $\theta = 40$

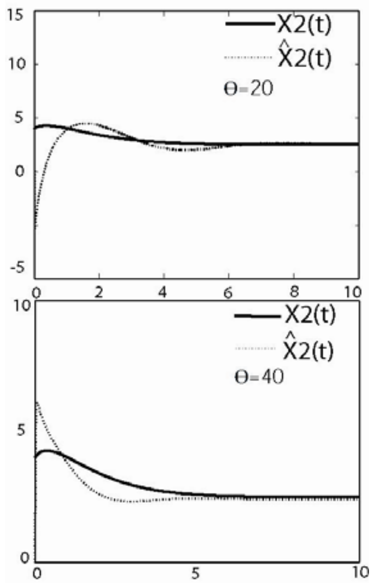

Figure 5 $X_2(t)$ and $\hat{X}_2(t)$ for $\theta = 20$ and $\theta = 40$

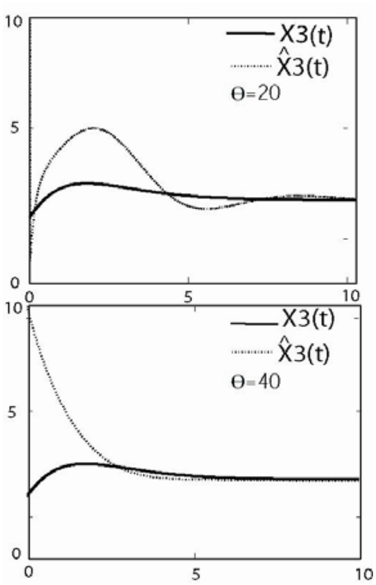

Figure 6 $X_3(t)$ and $\hat{X}_3(t)$ for $\theta = 20$ and $\theta = 40$

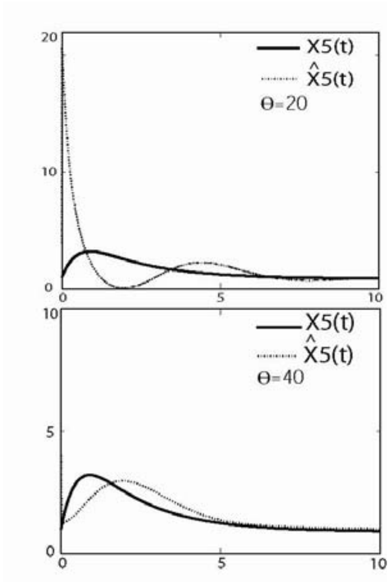

Figure 8 $X_5(t)$ and $\hat{X}_5(t)$ for $\theta = 20$ and $\theta = 40$

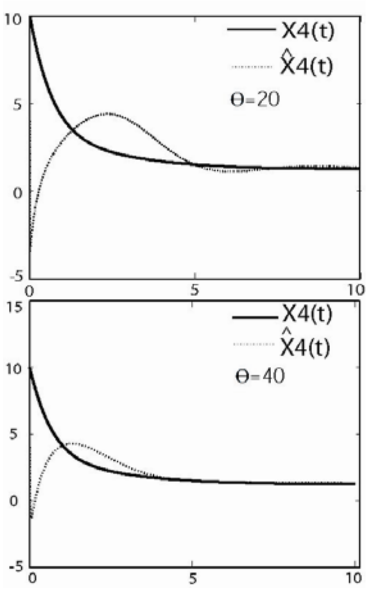

Figure 7 $X_4(t)$ and $\hat{X}_4(t)$ for $\theta = 20$ and $\theta = 40$

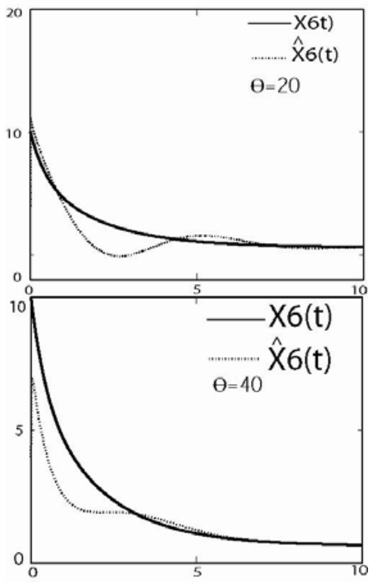

Figure 9 $X_6(t)$ and $\hat{X}_6(t)$ for $\theta = 20$ and $\theta = 40$

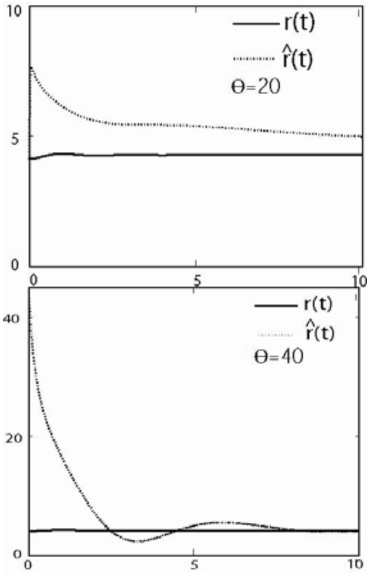

Figure 10 r and $\hat{r}(t)$ for $\theta = 20$ and $\theta = 40$

5. Conclusion

Software sensors, which provide on-line estimates of unmeasurable process variables from available sensors, are very useful tools in fishery systems monitoring and control. Their performances depend on both the measurement quality delivered by the sensor and on the associated estimation algorithm (software). In this work, we have studied the software sensor design problem for an uncertain structured fishing model which describes the evolution of the biomass by age classes. The considered model takes into consideration the competition between the juvenile and the predation of the adults on the small, and contains an unknown function composed of model uncertainties, non-linearities and disturbances, which is supposed to be bounded. The high gain observer technique is applied. The asymptotic convergence of the estimation error is proved under certain conditions and the gain of the observer is
explicitly formulated. In the future work, it wold be necessary to see what will happen for all the positive orthant $\Omega = \{X \in \mathbf{R}^n / X_i > 0, i = 0, \ldots, n+1\}$ with other states estimations techniques.

References

[1] R.J.H. Beverton and R.J.H. Holt, Recruitement and egg-Production in on the dynamics of exploited fish population, Chapman-hall , 6, pp. 44-67, 11, 1993.

[2] O.Bernard G.Sallet and A.Sciendra, Nonlinear observer for a class of nonlinear systems : Application to validation of phitoplanktonic growth model, IEEE Trans. Automat. Contr, 43, pp. 1056-1065, 1998.

[3] C. Clark; The optimal management of renewable ressourecs, Mathematical Bioeconomics, vol 2, 1990.

[4] M. .Della Mora, A. Germani and C. Mans, Design of state observer from a drift observability property, IEEE Trans Automat. Contr. vol 45, pp. 1536-1540, 2000.

[5] B. Megrey, Review and comparison of age-structured stock assessment models from theoritical and applied points of view, in: E. Edwards, B. Megrey (Eds.), Mathematical Analysis of Fish Stocks Dynamics, vol. 6, American Fishery Society Symposium, 1989, pp. 8–48.

[6] E.H. EL Mazoudi, N. Elalami, M. Mrabti, Observer design for a fish population model. Procceding du Journal Arima du colloque africain pour la recherche en informatique CARI06, Coutonou, Bénin 4-6 novembre 2006.

[7] E.H. EL Mazoudi, N. Elalami, M. Mrabti, On the stabilisation of a system describing the dynamics of a fishery. Procceding du Journal Arima du colloque africain pour la recherche en informatique CARI06, Coutonou, Bénin 4-6 novembre 2006

[8] E.H. EL Mazoudi, N. Elalami, M. Mrabti, Stabilization of a harvested fish population. Multi conférences Computational Engineering in system Applications CESA06, Beijing Chine, 4-6 octobre 2006.

[9] E.H. EL Mazoudi, N. Elalami, M. Mrabti, Output feedback control for an exploited structured model of a fishing problem. Submitted to International journal of applied mathematics and computer science.

[10] E.H. EL Mazoudi, N. Elalami, M. Mrabti, Stabilization of a harvested fish population. Multi conférences Computational Engineering in system Applications CESA06, Beijing Chine, 4-6 octobre 2006.

[11] M.Farza, K.Busawon and H.Hammouri Simple nonlinear observers for on-line estimation of kinetic rates in bioreactors, Automatica , vol 34, pp 301–318; 1998.

[12] M.Farza, H.Hammouri, C.Jallut and J.Lieto, State observation of nonlinear systems: Application to (bio)chemical AICHE, vol 45, pp 93-106, 1999.

[13] M..Farza, M..M'Saad and L.Rossignol, Observer design for a class of MIMO nonlinear systems IEEE Trans. Automat.Contr., vol 40. 1, pp. 135-143, 2004.

[14] J.L Gouzé, A. Rapaport and M.Z.Hadj-Sadok, Interval observers for uncertain biological systems. Ecological Modelling, vol 133, pp.45-56, 2000.

[15] J.P. Gauthier G. Bornard, A Simple Observer for nonlinear systems Application to Bioreactors. IEEE Trans. Automat. Contr. 26, pp.922-926 , 1981.

[16] J.P. Gauthier H. Hammouri S. Othman, Observability for any u(t) of a class of bilinear systems. IEEE Trans. Automat.Contr. vol. 37, pp.875-880. 6, 1992.

[17] A. Iggidr, M. Oumoum and M.Vivalda, State Estimation for Fish Population Via a Nonlinear Observer, Proceeding of the American Control Conference; Chicago, 2000.

[18] A.Iggidr A.Ouahbi and M. El Bagdouri, Stabilization of an Exploited Fish Population., Systems Analysis Modelling Simulation, vol 43, pp.513-524 , 2003.

[19] D.G. Luenberger Observing the State of a Linear System. IEEE Trans. On Military Electronics, vol 8, pp. 74-80, 1964.

[20] A. Ouahbi. Observation et contrôle de modèles non linéaires de populations marines Exploitées. Thèse, Université Cadi Ayyad Faculté Des Sciences Semlalia Marrakech, 2002.
[21] W.E. Ricker. Stock and Recruitement. J. Fish. Res. Board Can. Vol 11, pp. 559-623, 1954.
[22] M.B. Schaefer, Some Aspects of the Dynamics of Populations Important to the Management of the Commercial Marine Fisheries, Bull.Inter-American Tropical Tuna Comm. , vol 1 1954.
[23] R. Stengel, Stochastic Optimal Control Wiley, vol 1986. S. Touzeau Modèles de Contrôle en Gestion des Pêches, Thèse, Université de Nice-Sophia Antipolis, 1997.
[24] S. Touzeau Modèles de Contrôle en Gestion des Pêches, Thèse, Université de Nice-Sophia Antipolis, 1997.
[25] S. Touzeau J.L Gouzé, On the stock-recruitment relationships in fish population models, Environmental modeling and Assessment. Vol 3, pp. 87-93, 1998.
[26] H.Zak, On the Stabilization and Observation of Nonlinear/Uncertain Dynamic Systems. IEEE Transaction on Automatic Control., vol35, 5, pp.604-607, 1990.
[27] M. Zeitz, Extended Luenberger Observer for Nonlinear Systems, System Control Letters , vol 9, pp. 149-156, 1987