A General-Purpose Fuzzy Engine For Crop Control

Moataz Ahmed[1], Ernesto Damiani[2], and Andrea G. B. Tettamanzi[2]

[1] King Fahd University of Petroleum & Minerals, Dhahran, Saudi Arabia
moataz@kfupm.edu.sa
[2] University of Milan – Polo di Crema,
Via Bramante 65, 26013 Crema (CR), Ita\ly
edamiani@crema.unimi.edu, tettaman@dsi.unimi.it

Abstract In this position paper we outline an architecture of a general-purpose *indirect fuzzy-based* crop control. Some ways of exploiting previous work on a control system for single-plant hydroponics nurseries are also discussed.

1 Introduction

Recording physical Earth phenomenon from remote locations is a time-honored technique, as first attempts at using aerial photography for environmental monitoring date back to the early 1900's, while satellite remote sensing was first introduced in the 1960's [1]. More recently, the huge amount of high-quality environmental data available from remote sensing devices has boosted the interest for applying remote sensing to critical applications such as crop control and agricultural resources optimization, increasingly perceived to be crucial for the development of agriculture in many countries.

In fact, today's remote sensors are capable of presenting data both in analog form, such as photographs that must be later digitized and line plotted, and in high resolution digital form. In the latter case, images are typically available as $N \times M \times B$ matrices, where $N \times M$ is the sensor's spatial resolution and B is the number of bands (spectral resolution). In such images, each pixel is stored with fixed number of bits (typically 8-12) called *pixel depth* or *quantization*. For example, the NASA Landsat Thematic Mapper (TM) offers a spectral resolution of 7 bands in the range 0.45 to 12.5 mm (visible blue through thermal infrared) with a spatial resolution of 30×30 meters at 8 bits per pixel quantization. Besides imaging, remote sensing can now seamlessly provide all sorts of crop related biophysical measurements, such as surface temperature, geographic location, vegetation - chlorophyll, biomass, foliar water content, and soil moisture [2].

For instance, the *ARTEMIS (Africa Real Time Environmental Monitoring Using Imaging Satellites*) system, that became operational at the FAO Remote Sensing Center in Rome in August 1988, provides real and near-real time precipitation and vegetation assessment for Africa, the Near East and South West Asia. ARTEMIS data are now, more and more, provided to users involved in early warning for food security and desert locust control at the regional and national levels in Africa [3]. The ARTEMIS products are currently distributed to its users on color hard copies, IBM-PC compatible diskettes, tapes, and as point-listing using mail, pouch and courier services.

In addition, FAO and the European Space Agency (ESA) are collaborating to develop a dedicated satellite communications system, *DIANA* (*Data and Information Available Now in Africa*), which will enable high speed digital dissemination of ARTEMIS products, and other information, to remote stations in Africa. A distinct through related approach was followed in systems such as the first European Remote Sensing Satellite [4], which was launched in July 1991 by the European Space Agency. ERS-1 uses advanced microwave techniques to acquire measurements and images regardless of clouds and sunlight conditions. In comparison to other satellite systems, the ERS-1 (and, now, ERS-2) is unique in the simultaneous measurement of many parameters, including sea state, sea surface winds, sea surface temperature, ocean circulation and sea and ice level, as well as all-weather imaging of ocean, ice and land. ERS-1 satellite is both an experimental and pre-operational system. The nature of its orbit and its complement of sensors enable a global mission providing a worldwide geographical and repetitive coverage, primarily oriented towards ocean and ice monitoring, but with an all-weather high resolution microwave imaging capability over land and coastal zones for environmental monitoring and crop control.

However, the systems described above only aim at detecting exceptional stress situations of crops, so that emergency actions can be taken. In this paper, we propose an approach we believe to be novel, relying on feeding remote sensing data, together with an evolvable model of crop behavior, to an intelligent decision support system based on a backward-chaining-based fuzzy reasoning engine. Decisions suggested by our system could be later translated into control actions to be performed by humans and/or by on-site actuators, and disseminated using techniques not unlike those used in the ARTEMIS approach. As an experimental test bed for our approach, we set up a greenhouse cell equipped with local sensors, including a video camera, and actuators.

2 Fuzzy Control Systems

It is clear that many control theorists have successfully dealt with a large class of control problems (complex, large-scale, nonlinear, non-stationary and stochastic control problems) by mathematically modeling the process and solving these analytical models to generate control. However, the analytical models tend to become complex, especially in large, intricate systems. The non-linear behavior of many practical systems and the unavailability of quantitative data regarding the input-output relations make this analytical approach even more difficult. On the other hand, it is well known that for most engineering systems, there are two important information sources:

1. Sensors which provide numerical measurements of variables and
2. Human experts who provide linguistic instructions and descriptions about the system.

The information from sensors is called numerical information and the information from human experts is called linguistic information. Numerical information is represented by numbers whereas linguistic information is represented by words such as *small*, *large*, *very large*, and so forth. Conventional engineering approaches can only make use of numerical information. Because so much human knowledge is represented in linguistic terms, incorporating it into an engineering system in a systematic and efficient manner is very important. However, linguistic information can be represented in fuzzy terms [5]. A fuzzy-logic system representation has the ability to incorporate the human knowledge, represented in linguistic terms, into the engineering system very efficiently. Fuzzy-logic systems are constructed from fuzzy *IF-THEN* rules. Representing the process to be controlled as a fuzzy logic system makes it much easier to understand its behavior, and complex requirements may be implemented in amazing simple, easily maintained, and inexpensive controllers.

Fuzzy controllers have found particular applications in industrial systems that are very complex and cannot be modeled precisely even under various assumptions and approximations. Crop control systems fall into this class of systems.

Using fuzzy logic, a crop and its surrounding environment may be described by fuzzy predicates [6]. Fuzzy predicates are predicates with associated values in a form of fuzzy sets (as opposed to the *TRUE* and *FALSE* crisp values). Each predicate describes some properties of the process and/or its surrounding environment in its present state. Each predicate may or may not have arguments. The crop surrounding environment might be represented by fuzzy predicates such as: *WIND(LOC)*, *LIGHT(LOC)*, *HUMIDITY(LOC)*, *RAIN(LOC)*, etc. Where *WIND(LOC)*, with one argument *LOC*, gives the speed of the wind at location *LOC* as a fuzzy set, and *LIGHT(LOC)* gives the level of lightening at location *LOC* as a fuzzy set. *COLOR(LEAF)* is an example of using a fuzzy predicate to represent a property, that is the color, of a given leaf, *LEAF*. The state of the crop and its surrounding environment, at any point in time, is represented by a set of fuzzy predicates.

The use of fuzzy control and classification systems for environmental monitoring is a well established subject in soft computing research [7]

In this position paper we discuss the feasibility of a complete fuzzy-based solution for crop control problems, focusing on some factors like temperature, humidity and light.

2.2 Direct Fuzzy Control vs. Indirect Fuzzy Control

Linguistic information from human experts can be classified into two categories:

1. Fuzzy control rules, which propose a suitable control action for each possible situation. For example, the following fuzzy IF-THEN rule may be used to control the level of lightening in a crop nursery:

   IF

   the growth rate is low

   THEN

   apply more lightening,

   where *low* and *more* are labels of fuzzy sets. This type of control rule is called *direct fuzzy control*.

2. Fuzzy IF-THEN rules, which describe the behavior of the plant (i.e., the crop). For example, the behavior of the crop can be described as:

   IF

   you apply more lightening

   THEN

   the growth rate will increase,

   where *more* and *increase* are labels of fuzzy sets. This type of control rules is called *indirect fuzzy control*.

3 The Approach

We propose an *indirect fuzzy control approach* for crop control; that is using fuzzy rules to describe the behavior of the crop rather than using them to specify control actions. The justification for this approach is threefold. (1) Taking an indirect control approach, a *crop model* is produced as a by-product of the control process; this crop model can then be reused for several other applications. (2) The evolvement of the crop model during the control process may be done through training with historical data only, and without a need for a real-time data; thus saving the effort and risks of experimental-based training. (3) This approach accommodates for easy change of the controller objectives (e.g., for simulation purposes).

Since, in this approach, the crop behavior is represented by *indirect* IF-THEN rules, the fuzzy controller, that is to control the crop to achieve a certain state, can be seen as a *planning* system. Planning systems are concerned with the problem of generating a sequence of actions to accomplish a goal. Normally, each action has a set of *pre-conditions* which must be satisfied before the action can be applied, and a set of *post-conditions* which will be true after the action execution. A *planning problem* is characterized by an initial state and a goal statement. A *state* is a collection of characteristics of an object that is sufficiently detailed to uniquely determine the new characteristics of the object that will result after an action. The initial state description tells the planning system the way the *world* is "right now". The *goal statement* tells the planning system the conditions which must be satisfied when the plan has been executed. The world in which the planning takes place is often called the *application domain*. We will sometimes refer to the goal statement as simply *the goal*. A plan is said to be a solution to a given problem if it is applicable in the problem's initial state, and if after plan execution, the goal is true. A plan is applicable if all the preconditions of any action, within the plan, are satisfied before applying that action.

The *indirect fuzzy control problem* as a planning problem can be described as follows. Given an initial state of a crop and its surrounding environment, a set of indirect fuzzy rules, and a desired crop goal state, find the sequence of actions which can change the state of the crop from its initial state to its desired goal state. The produced sequence of actions is a *plan*. We propose to use a backward chaining inference to generate such a plan.

4 Indirect Fuzzy Crop Control

The indirect fuzzy crop control process involves two main stages (Figure 1):

1. *Training Stage*: Off-line model identification via evolutionary computation and fine tuning, and

2. *Control Stage*: On-line control that generate control actions on the basis of the model identified during the Training Stage, as well as actual input data.

The Training Stage is concerned with building a fuzzy rule base that represents a linguistic description of the crop behavior. This rule base is to be used later during the on-line control stage in order to generate control actions.

During the Training Stage, the crop model is identified through training using data from two sources: historical data, that is readings of the environmental variables and their outcomes and supplement data generated through experiments on a small-scale crop in a laboratory setting. The objective of the supplement data is to consider extreme or unusual conditions that are not well represented in the historical data. A small-scale lab crop can be used to conduct collect such supplement data. The experiments on that small-scale lab crop are guided and constrained by expert meta-knowledge that describes feasible ranges for control variables.

Developing the crop model involves two phases: exploration, and fine tuning. *Exploration* involves searching the whole space of models to find a set of models that well represent the crop under discussion. This exploration phase can be achieved by means of suitable heuristics such as evolutionary algorithms. Such evolutionary algorithms ought to be guided and constrained by expert *meta-knowledge* in order to avoid unrealistic models. The initial population of such evolutionary algorithms can be seeded with handcrafted models based on experts' interviews.

Once the exploration phase is complete, the fine tuning phase starts. The objective of the fine tuning phase is to conservatively adapt the set of models, that are provided as a result of the exploration phase, in order to obtain a satisfactory level of performance. The model that gives such a satisfactory level of performance is used during the on-line control stage.

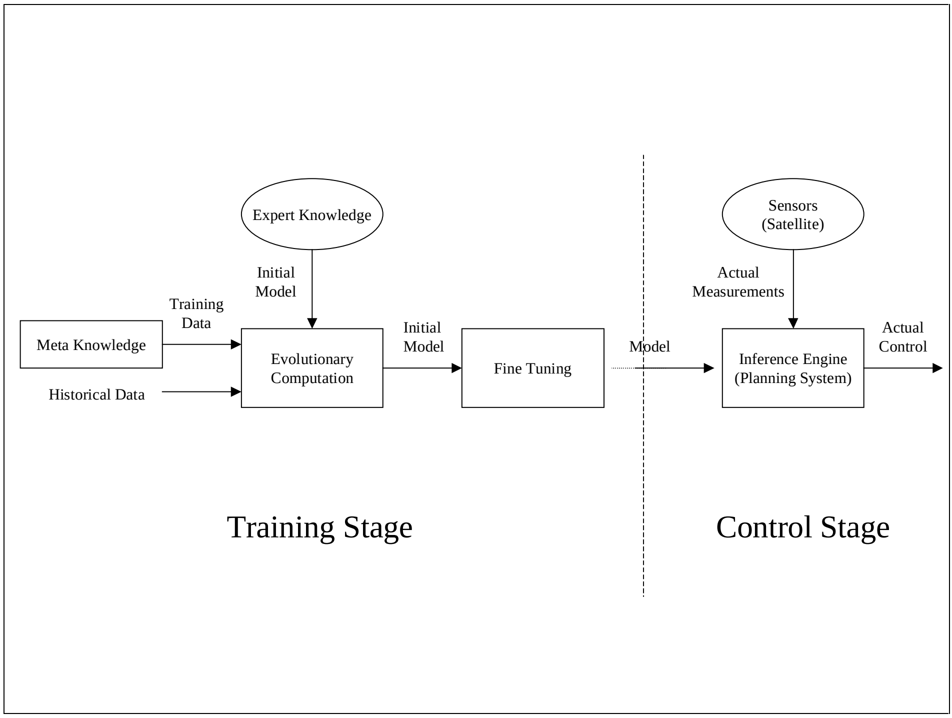

Fig. 1. The two stages of the proposed system

At the control stage, actual measurements are read from the sensors located in the field, and the model of the system is used to generate the control action through fuzzy backward chaining.

5 Overall System Architecture

A possible architecture for implementing and deploying the above described control system consists of four blocks:

1. *Data acquisition*, involving image and sensor measurements,
2. *Data transmission* to the fuzzy engine, possibly involving long-range satellite links,
3. *On-line control* involving the generation of the control action starting from the fuzzy model of the crop behavior, and
4. *Application of control actions* that can be either automated or carried out manually following the system advice.

5.1 Using A Nursery Control System As Experimental Test-Bed

An experimental cell, that is a nursery environment, has been realized at the University of Milan – Polo di Crema [8]. This cell could be used as a test-bed for validating the control system described in the previous sections.

The cell consists of a double-chamber alveolate polycarbon box divided into two sections. One section contains a small water tank for hydroponic cultivation and a number of sensors; the other section, which is isolated from the former, contains a video camera. Attached to the outside of the box are all electronic devices and actuators that are used to control environmental variables such as light, temperature and humidity.

Lightening is provided by three 400W metallic iodide lamps. These lamps provide light with a spectrum very similar to natural light from the sun.

The cell can maintain a very broad gamut of micro-climates, with temperatures ranging from 16°C to 42°C and humidity ranging from 32% to 96%. While the currently installed refrigerating and heating machines can only support this range of temperature, in principle any temperature could be attained given more powerful equipment.

It is interesting to notice that the microclimate is not maintained by an on/off control, but by proportional actuators like proportional electro-valves.

The sensors in the cell provide measurements for the following quantities:

- *pH*, *temperature*, *conductivity*, and *oxygen* in the solution;
- Global *radiation* (via a photo diode), relative *humidity*, *temperature* and CO_2 of the environment.

All solution sensors are thermally compensated.

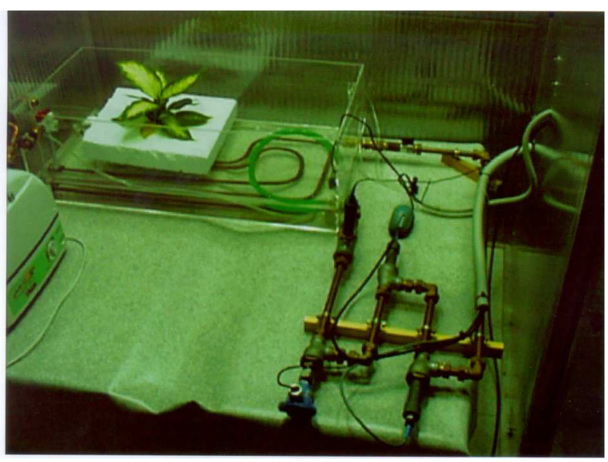

Fig. 2. The experimental cell (inside)

The video camera points to the plant. At programmable intervals, it takes snapshots, from which the values of a number of significant parameters are extracted using fuzzy techniques. These include:

- Average color of the leaves;
- Image area of the plant;
- Height and width of the plant.

All these values can serve as input to a fuzzy inference engine located on a control station, which can adjust the set points of most control variables.

Figure 2 and Figure 3 show respectively the inside and the outside of our experimental cell.

Fig. 3. The experimental cell (outside)

Possible validation of the proposed approach includes:

- Comparison between "close" and "remote" image data processing, in order to simulate satellite image acquisition and assess the controller performance when only remote sensor data are available. The objective of this comparison is to assess the sensitivity of the controller to the accuracy of the available data.
- Use of nursery control variables (such as humidity and temperature) to simulate various microclimates in order to assess the flexibility of the tuning mechanism.
- Comparisons between *coarse-grained* and *fine-grained* control actions in order to evaluate possible differences in performance caused by the use of the controller as a decision support system rather than automatically control actuators. In the latter case, precise control actions are possible while in the former, control actions are to be executed by humans who always combine their own perception of the situation while applying the control action.

An experimental protocol is being designed in order to allow unbiased evaluation of results.

6 Potential Benefits

Once implemented, the system described above could greatly help rationalizing crop cultivation, especially in developing countries, where scarcity of resources is one of the major obstacles to matching agricultural production to demand.

The system is conceived to work at different scales, allowing crop control applications to wide areas of land by means of remote image and sensor data acquisition as well as small to medium intensive or high-quality cultivation by means of fixed or mobile image and data acquisition devices.

In addition to the potential benefits in the area of crop control, the crop model that is the product of the training stage is expected to be very useful for researchers that are interested in studying crop behavior. These researchers could use the model as accurate simulators during their studies.

References

1. Sabins, F.F. Jr. "Remote Sensing: Principles and Interpretation", W.H. Freeman, 1987.
2. Jensen, J.R. "Introductory Digital Image Processing: A Remote Sensing Perspective", 2nd Edition, Prentice-Hall 1996.
3. http://www.neonet.nl/ceos-idn/campaigns/ARTEMIS.html
4. http://www.asi.it/00HTL/eng/asicgs/remotesens/ers_m1.html
5. Wang, L. *Adaptive Fuzzy Systems And Control*. Prentice-Hall, Inc., 1994.
6. Ahmed, M., Damiani, E., and Rine D. Fast Recall of Reusable Fuzzy Plans Using Acyclic Directed Graph Memory, *1998 ACM Symposium on Applied Computing (ACM SAC'98), Fuzzy Applications Track,* February 27-March 1, 1998.
7. Binaghi, E., Madella, P., Montesano, M.G., and Rampini, A. "Identification of glacier snow equilibrium line using a fuzzy rule-based classifier". Proc. of International Geoscience and Remote Sensing Symposium, pp. 1768-1780, 1995.
8. Tarzia, G. *Sistema di Controllo e Ricerca per Colture Idroponiche in Serra.* Master's Thesis, University of Milan, 1998 (In Italian).
9. Chen, J., and Rine, D. Training Fuzzy Logic Based Software Components by Combining Adaptation Algorithms, Soft Computing, vol. 2, no.2, pp.48-50, 1998.
10. Mamdani, E.H. "Twenty years of fuzzy control: experiences gained and lessons learnt." In *1993 IEEE International Conference on Fuzzy Systems* (San Francisco, CA, March 28-April 1). IEEE, Piscataway, N.J., pp.339-344.