An Interval Fuzzy Logic-Based System to Predict Pests in Agriculture

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Abstract. *Precision Agriculture is a relatively new area of study in Brazil, with its expansion in the mid 90s. In this period, there were government incentives in credit lines for rural producers, making possible the use of new technologies in rural areas for maximizing production and reducing costs. In this sense, this work proposes to apply environmental sensing technologies to assist farmers to detect the possibility of pests occurrence (or proliferation) in their culture. For that, the Arduino platform is being used in combination with adequate sensors to capture meteorological conditions in a given region. We apply an approach based on Interval Fuzzy Logic for the assessment of the sensing data to report if the weather conditions are favorable for the emergence of pests, especially fungi, which depend on factors such as temperature, humidity and leaf wetness. Besides, a discussion about an experiment performed to test the developed system is presented. The experiment is based on a common disease encountered, mainly, in the southern region of the state of Rio Grande do Sul, in Brazil. The disease, called Brown Rot, is caused by a fungus known as* Monilinia fructicola.

1. Introduction

Agriculture, as an important economy sector, aims to improve methods and processes to achieve better results and increase its productivity. Sensors are being used in several areas, including agriculture. However, it is necessary to consider some constraints in their use, such as energy restriction, reduced storage capacity (when available) and data security. Such problems serve as a source of investigation for many researchers [Ceken 2008, Huang 2009, Akyildiz et al. 2002].

Precision Agriculture is the production system used in advanced technology countries. The aim is to perform the application of supplies in a fair way in every area of a culture, minimizing extra spending in regions that do not require its application and increasing the productivity in underserved areas of those components.

In order to reduce the use of pesticides is necessary to have knowledge about the specific diseases (pests) that can attack a plant. *Phytopathology* is the science that studies plant diseases, covering all aspects: diagnosis, symptoms, etiology, epidemiology and control. Thus, Phytopathology presents itself as an important tool to support the development of agricultural production, seeking to solve the problems regarding the emergence of diseases that reduce the quantity and quality of the produced food [Fernandes 2005].

The successful in cultures development is not only a producer concern, but rather of a whole equipment and services supply chain, which is related to the production growth, distribution and marketing. E.g., many workers employed in support industries, whose livelihood depends on machinery and products used in processing of vegetable raw material such as the textile machines, food packaging, processed agricultural products and so on. Furthermore, good health of plants should interest mainly the consumer, since several products derived from plants (fruit, vegetables, grains) are consumed.

Three basic conditions are necessary for the development of plants: water availability, soil nutrients and meteorological conditions (temperature, light, humidity) within suitable limits. Another important factor is the protection from damage caused by pests, which directly influences their growth and yield. Thus, it is important to study the organisms and environmental conditions, which cause diseases in plants, and also methods for preventing diseases (or to minimize the damage that they cause) [Agrios 1996].

Some authors have worked with wireless sensor networks in order to minimize attacks caused by fungi in certain cultures. E.g., in [Baggio 2005], the author uses sensors to prevent attacks by the fungus (*Phytophthora*) on a potato culture. In her work, it is emphasized that the weather conditions in the region are determinants in the strength of the fungus attack, especially when there is moisture. Similarly, in [Tamayo et al. 2010], the authors developed a prototype that includes tools to provide real-time information about the state of the harvest, region conditions and potential risks to the pests appearance. The data received by the sensors, data mining algorithms and neural networks helped to detect fungi in tomato and pumpkin crops.

In this paper, we present the development of an application to assist the prediction of the appearance (or proliferation) of pests in crops, considering meteorological conditions observed in the region. For that we use the Arduino Platform [Arduino Team 2012a] in combination with adequate sensors to capture meteorological data in a given region. We apply an approach based on Interval Fuzzy Logic [Bedregal and Takahashi 2006, Bedregal et al. 2010, Cavalheiro et al. 2011, Dimuro et al. 2011] for the assessment of the sensing data to report if the weather conditions are favorable for the emergence of pests, especially fungi, which depend on factors such as temperature, humidity and leaf wetness. In this way, the chances of production losses can be reduced, since whenever any pest appears the producer will be able to act in time so that he/she can avoid major damage to his/her crop. Furthermore, unnecessary expenses with pesticides can be avoided when there is no real need for their application.

We also present a discussion about an experiment performed to test the developed system, considering the disease called Brown Rot (a common disease encountered, mainly, in the southern region of the state of Rio Grande do Sul, in Brazil), which is caused by a fungus known as *Monilinia fructicola*.

The paper is organized as described in the following. In Section 2, we discuss how the Arduino Platform captures the meteorological data of the environment where a particular crop is located. Section 3 describes the approach based on interval fuzzy logic, which is employed to deal with the uncertainty on the imprecise sensing and/or measure data, and also with the opinion of different experts, in order to assist in decision making. Section 4 discusses issues related to the experiment conducted in this project, as well as the definitions used by the system. Section 5 presents the results obtained until now, and Section 6 is the Conclusion.

2. Sensing the Environment

Arduino is an open-source platform. It can sense the environment by receiving data from a variety of sensors and act on their environment by controlling lights, motors or any other type of actuator [Arduino Team 2012a].

An Arduino board consists of a 8-bit AVR Atmel microcontroller with complementary components, facilitating its programming and incorporation into other circuits. The way the connectors are arranged allows the CPU to be connected to a variety of modules (known as *shields*). Generally, an Arduino board uses chips from megaAVR series, e.g.: ATmega8, ATmega168, ATmega328, ATmega1280 and ATmega2560.

Arduino Uno is a board with a microcontroller based on ATmega328. There are 14 digital I/O pins (6 can be used as PWM outputs) and 6 analog inputs. It also has a 16 MHz crystal oscillator, a USB connection, power connector and a reset button. The board contains all components necessary to support the microcontroller. The connection with computer is via USB cable, power adapter or battery.

Through all available connections, a variety of sensors can be connected. In this project, we used the following sensors/modules: 1 module with temperature and humidity sensors, 1 Global Positioning System (GPS) module, 1 luminosity (light) sensor, 1 leaf wetness sensor, 1 *shield* with MicroSD memory card slot and WiFi communication integration possibility (feature not used in this project), and 1 rain sensor. To control some of the modules, extra libraries were used. A library is a collection of code that make easy the process of using external hardware, such as a sensor, a display module, or a shield. Thus, the following libraries were used: *SD.h* [Arduino Team 2013], *Timer.h* [Monk 2012], *SoftwareSerial.h* [Arduino Team 2012b] and *TinyGPS.h* [Hart 2012].

All captured data by the sensors are saved in a text file and stored in the memory card. The file name is set according to the date of the day that the data is captured. The information saved in the text file is: temperature, relative humidity, luminosity, level of leaf wetness, amount of overturning of the rain gauge seesaw, date, time, latitude and longitude. The output of the system is as shown in Code 1.

```
// 12-08-04.txt
22,69,0287,0008,0000,12-08-04,17:52:54,-32.0745811,-52.1679801
22,69,0273,0009,0000,12-08-04,17:54:33,-32.0745811,-52.1679801
22,69,0186,0008,0000,12-08-04,17:56:29,-32.0745811,-52.1679801
22,69,0070,0006,0000,12-08-04,17:58:33,-32.0745811,-52.1679801
21,71,0037,0007,0000,12-08-04,18:00:05,-32.0745811,-52.1679801
21,71,0031,0008,0000,12-08-04,18:02:21,-32.0745811,-52.1679801
21,71,0026,0008,0000,12-08-04,18:04:37,-32.0745811,-52.1679801
```

Code 1. Arduino system output.

Importantly, not all the information collected is crucial for the emergence of a particular pest. E.g., some types of fungi depend only on temperature and humidity to proliferate, however, other types require suitable temperature and optimum light periods. This work is not intended to employ optimization methods nor reduction in power consumption of the developed hardware.

3. Interval Fuzzy Logic Approach for the Analysis of the Sensing Data

Fuzzy Systems [Zadeh 1965, Zadeh 2008] have been used over the years in order to solve problems involving uncertainty and ambiguity. However, this approach does not always offer a good solution for some particular problems, such as the one presented in this paper. When we faced the creation of the fuzzy system, we got opinions from several experts, considering slight divergences between the information provided by different sources. This leads to different ideas, e.g., related to the membership function for the fuzzification process. To solve such problems, we adopt an extension of fuzzy logic, namely, interval fuzzy logic. In the following, we briefly present the basic concepts of the Interval Fuzzy Set (Logic) approach adopted in this work.[1]

The interval fuzzy sets are a particular case of type-n fuzzy set [Zadeh 1975, Grattan-Guiness 1976, Mendel 2007], whose structural properties are related to Interval Mathematics [Moore 1979, Moore et al. 2009]. Interval fuzzy sets allow to deal with both imprecision (classes with unprecise limits) and uncertainty (lack of information) [Lodwick 2004]. Then, interval membership grades may be used to represent either the numerical uncertainty related to a membership grade or a range of values concerned with different opinions about the membership grade to be adopted.

Interval Mathematics has been used for deal with the numerical uncertainty and to the error analysis in scientific computing [Moore 1979, Moore et al. 2009]. A *real interval* X is a nonempty set $X = [x_1; x_2] = \{x \in \mathbb{R} \mid x_1 \leq x \leq x_2\}$, where x_1 and x_2 are X's left and right endpoints, denoted by $\underline{X}$ and $\overline{X}$, respectively. An interval X with $\underline{X} = \overline{X}$ is known as *degenerated interval*. The set of all real intervals is denoted by $\mathbb{IR}$. Arithmetic operations, parcial orders, set operations and different other important concepts were defined on $\mathbb{IR}$, so that several applications become possible[2].

Let $U = [0, 1]$ be the so-called unit interval and consider the set $\mathbb{U} = \{X \in \mathbb{IR} \mid X \subseteq U\} = \{[a, b] \in \mathbb{IR} \mid 0 \leq a \leq b \leq 1\}$.

Definition 1 *An interval fuzzy subset A of a universe $\mathbb{X}$ is defined as the set of the ordered pairs $A = \{(x, \varphi_A(x)) \mid x \in \mathbb{X}\}$, where $\varphi_A : \mathbb{X} \rightarrow \mathbb{U}$ is the interval-valued membership function of A.*

If the interval-valued membership function φ_A is Moore-continuous[3], there exist continuous functions $\varphi_{A_l}, \varphi_{A_u} : \mathbb{X} \rightarrow U$, called, respectively, *lower membership function* (LMF) and *upper membership function* (UMF), such that, for all $x \in \mathbb{X}$, it holds that:

$$\varphi_A(x) = [\varphi_{A_l}(x); \varphi_{A_u}(x)], \tag{1}$$

with $\varphi_{A_l}(x) \leq \varphi_{A_u}(x)$. Figure 1 shows an example of an interval fuzzy set, representing the LMF and UMF.

[1] See [Bedregal and Takahashi 2006, Bedregal et al. 2010, Cavalheiro et al. 2011, Dimuro et al. 2011] for details on the adopted Interval Fuzzy Set (Logic) approach, and [Zadeh 1975, Grattan-Guiness 1976, Mendel 2007] for the more general type-n fuzzy sets.

[2] See [Moore 1979, Moore et al. 2009] for more details about Interval Mathematics.

[3] The continuity of interval functions was defined by Moore [Moore 1979] as an extension to the continuity of real functions.

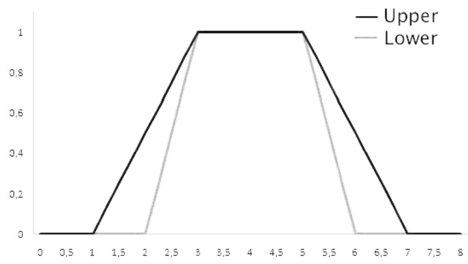

Figure 1. Interval fuzzy set.

The basic arithmetic and set operations in interval fuzzy set theory and logic are defined as extensions of the respective concepts defined for the fuzzy set theory and logic, considering interval operations. T-norms, T-conorms, negations, implications and other fuzzy operators were extended to the interval fuzzy approach [Bedregal and Takahashi 2006, Bedregal et al. 2010, Cavalheiro et al. 2011, Dimuro et al. 2011].

For our Interval Fuzzy Rule Based System, we developed an interval fuzzy logic rule base, which is composed by a combination of two fuzzy logic rule bases, namely LRB and URB, related to both LMF and UMF, respectively. The adopted inference method is Mamdani[4] [Nguyen and Walker 2006], which works with the two rule bases separately, with multiple inputs (the meteorological conditions, e.g., temperature and humidity) and a single output (risk of pest ocurrence) for each rule base, which are combined to produce a single interval output. The defuzzification process is the centroid method [Nguyen and Walker 2006], generating two crisp outputs, which are the endpoints of an interval representing the minimum and the maximum values of the risk of occurring pests in a given culture. For the implementation, we used the *Fuzzy Logic Toolkit*, a software tool available for GNU Octave [Octave Forge 2013].

4. Case Study: Fungus *Monilinia fructicola*

The Brown Rot is one of the diseases that cause more damage in the lump fruits culture (peach, nectarine, plum) and, if not handled properly, it brings huge losses for the producer. This disease is caused by *Monilinia fructicola* and it is considered the most important fungal disease of peach (Fig. 2 (a)), especially in warm humid areas, such as the production area in Southern Brazil [Santos et al. 2012].

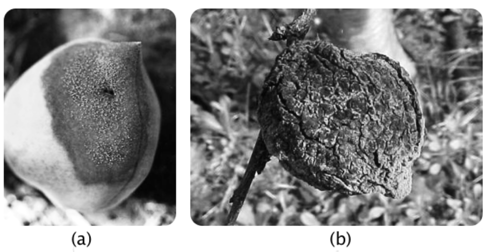

Figure 2. (a) A diseased fruit and (b) a mummified fruit.

[4]We use *minimum* T-norm and the *maximum* T-conorm [Nguyen and Walker 2006].

To control this disease, chemical applications are required during the vegetative cycle, hampering production by less capitalized producers. Thus, it becomes necessary a disease monitoring system that engages environment-friendly measures, in this case, using control methods more efficient and less harmful to the environment. The damage caused by brown rot are common, but becomes more pronounced when there are weather conditions of high humidity and heat at the same time [Fachinello et al. 2003]. Therefore, one must know very well the interactions between the pathogen and the environment [Monteiro et al. 2004].

The fungus can survive from one crop to another in several ways: through the mummified fruits (Fig. 2 (b)), stems, twigs and wilted flowers in the cankers. Spores are spread by wind and rain and germinate quickly when exposed to favorable weather conditions. With the rainy weather, the orchard can suffer with epidemics. The optimum temperature for the fungus proliferation is $25°C$ and the ideal relative humidity is above 80%. The detection of the infection allows to estimate beforehand the incidence of the disease even in the period before the harvest, assisting the establishment of appropriate control strategies, as well as storage and marketing of fruits.

4.1. Interval Fuzzy System Definitions

This section describes the interval fuzzy system using the Fuzzy Logic Toolkit and the values used are consistent with Brown Rot development characteristics. In order to show how the system is implemented, we show a simplified example, where just two inputs are considered, namely, *temperature* and *humidity*.

Each linguistic variable is qualified by four linguistic terms, defined, respectively by four interval fuzzy sets, predefined in two different files with ".fis" extension, one for the LMFs and the other for UMFs. The *temperature* presents the following linguistic terms: **Low**, **Medium**, **Good**[5] and **High**. The *humidity* presents the same linguistic terms, however, with different meanings. Code 2 shows, respectively, the definitions of the LMFs and UMFs for those linguistic terms.

```
// '(a) Lower'                                  | '(b) Upper'
[Input1]                                        | [Input1]
Name='Temperature(Lower)'                       | Name='Temperature(Upper)'
Range=[-8 41]                                   | Range=[-8 41]
NumMFs=4                                        | NumMFs=4
MF1='Low':'pimf',[-9 -8 8 14]                   | MF1='Low':'pimf',[-9 -8 8 16]
MF2='Medium':'pimf',[9 15 17 23]                | MF2='Medium':'pimf',[7 15 17 25]
MF3='Good':'pimf',[18 24 26 32]                 | MF3='Good':'pimf',[16 24 26 34]
MF4='High':'pimf',[27 33 41 42]                 | MF4='High':'pimf',[25 33 41 42]
                                                |
[Input2]                                        | [Input2]
Name='Humidity(Lower)'                          | Name='Humidity(Upper)'
Range=[1 100]                                   | Range=[0 100]
NumMFs=4                                        | NumMFs=4
MF1='Low':'pimf',[-1 1 5 21]                    | MF1='Low':'pimf',[-1 0 5 30]
MF2='Medium':'pimf',[9 25 35 51]                | MF2='Medium':'pimf',[0 25 35 60]
MF3='High':'pimf',[39 55 65 81]                 | MF3='High':'pimf',[30 55 65 90]
MF4='Good':'pimf',[69 85 100 101]               | MF4='Good':'pimf',[60 85 100 101]
```

Code 2. (a) LMFs and (b) UMFs for the variables *temperature* and *humidity*.

Since the ideal temperature for the growth of the Brown Rot disease is around $25°C$, we consider the ideal temperature range around this value. At the same time, the

[5] The word "Good" represents the ideal situation to the brow rot development

fungus needs high humidity values for its proper growth. So, we set the ideal relative humidity range from 85% to 100%. The other subsets values are defined according to those parameters (ideal temperature and humidity). The system outputs indicates the minimum and maximum percentage of the risk of the development of the disease in the environment in which the sensors are operating. The output variable, called "WarningLevel", presents four linguistic terms, representing risk levels: **Weak**, **Low**, **High** and **Danger**, whose fuzzy sets are defined as shown in Code 3.

```
// '(a) Lower'                                    | '(b) Upper'
[Output1]                                         | [Output1]
Name='WarningLevel'                               | Name='WarningLevel'
Range=[1 100]                                     | Range=[1 100]
NumMFs=4                                          | NumMFs=4
MF1='Weak':'pimf',[-1 1 20 28]                    | MF1='Weak':'pimf',[-1 1 20 32]
MF2='Low':'pimf',[22 30 50 58]                    | MF2='Low':'pimf',[18 30 50 62]
MF3='High':'pimf',[52 60 80 88]                   | MF3='High':'pimf',[48 60 80 92]
MF4='Danger':'pimf',[82 90 100 101]               | MF4='Danger':'pimf',[78 90 100 101]
```

Code 3. (a) LMFs and (b) UMFs for the system output variable.

Since the inputs present four fuzzy sets each, it is achieved a total of 16 inference rules. All the rules have the same weight, regardless of the possibility of occurring or not. That depends on the degree of certainty that the expert has in relation to such rule. Code 4 shows the definition of the rules, where **T** is the temperature, **H** is the humidity and **W** is the warning level.

```
[Rules]
1 1, 1 (1) : 1 %01 T=LOW    & H=LOW,    W=WEAK   | 3 1, 1 (1) : 1 %09 T=GOOD & H=LOW,    W=WEAK
1 2, 1 (1) : 1 %02 T=LOW    & H=MEDIUM, W=WEAK   | 3 2, 2 (1) : 1 %10 T=GOOD & H=MEDIUM, W=LOW
1 3, 2 (1) : 1 %03 T=LOW    & H=HIGH,   W=LOW    | 3 3, 3 (1) : 1 %11 T=GOOD & H=HIGH,   W=HIGH
1 4, 2 (1) : 1 %04 T=LOW    & H=GOOD,   W=LOW    | 3 4, 4 (1) : 1 %12 T=GOOD & H=GOOD,   W=DANGER
2 1, 1 (1) : 1 %05 T=MEDIUM & H=LOW,    W=WEAK   | 4 1, 1 (1) : 1 %13 T=HIGH & H=LOW,    W=WEAK
2 2, 2 (1) : 1 %06 T=MEDIUM & H=MEDIUM, W=LOW    | 4 2, 1 (1) : 1 %14 T=HIGH & H=MEDIUM, W=WEAK
2 3, 2 (1) : 1 %07 T=MEDIUM & H=HIGH,   W=LOW    | 4 3, 2 (1) : 1 %15 T=HIGH & H=HIGH,   W=LOW
2 4, 3 (1) : 1 %08 T=MEDIUM & H=GOOD,   W=HIGH   | 4 4, 3 (1) : 1 %16 T=HIGH & H=GOOD,   W=HIGH
```

Code 4. Inference rules.

The numbers used in the Code 4 represent the membership functions (MF1, MF2, MF3 or MF4) of each set. E.g., by analyzing rule 12, we come to the following condition:

IF *Temperature*=GOOD (MF3) **AND** *Humidity*=GOOD (MF4) **THEN** *WarningLevel*=DANGER (MF4).

After the defuzzification process, the output is an interval within the range of [1,100], indicating the risk of fungal growth. Figure 3 shows an example of output when the inputs are *temperature* = $23.19°C$ and the *humidity* = 69.56%. Vertical lines indicate the location (x axis) of the centroid of each (lower and upper) membership function.

5. Results

An experiment was performed to test the developed system. We analyzed the emergence/proliferation of the *Monilinia fructicola* fungus in a crop of peaches at Pelotas city, Brazil. In Table 1, I_x, with $x \in \{1, 2, 3, ..., n\}$, represents the notation of interval output. To perform the analyzes, we selected five plants separated by a distance of approximately four meters each. During the observation period, in samples of each plant, we counted the number of healthy, diseased and mummified fruits. Therefore, it was possible to check if the plants suffered increased incidence of the fungus when meteorological parameters were analyzed in the period in which occurred the observations.

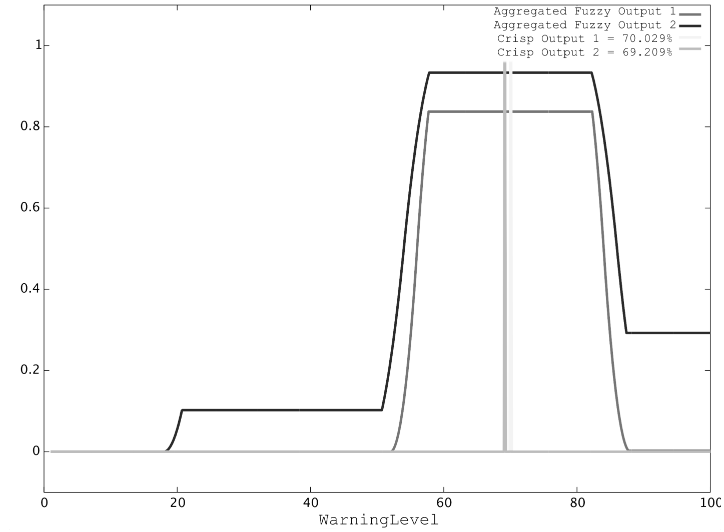

Figure 3. Example of the crisp output, which is [69.209,70.029].

Table 1. Captured data and the outputs obtained.

Date	T_A (°**C**)	RH_A (%)	**Output** (%)
06/12/2012	30.30	67.78	$I_1 = [46.65, 53.11]$
07/12/2012	25.72	66.61	$I_2 = [70.00, 70.53]$
08/12/2012	24.17	56.54	$I_3 = [68.75, 70.00]$
09/12/2012	26.00	53.59	$I_4 = [65.27, 70.00]$
10/12/2012	27.72	53.52	$I_5 = [60.08, 68.88]$
11/12/2012[1]	23.19	69.56	$I_6 = [69.21, 70.03]$
12/12/2012	24.22	70.05	$I_6 = [70.11, 71.97]$
13/12/2012	26.10	62.20	$I_7 = [68.88, 70.00]$
14/12/2012	22.23	61.41	$I_8 = [63.37, 68.72]$
15/12/2012	24.07	78.70	$I_9 = [78.78, 89.86]$
16/12/2012	28.22	76.09	$I_{10} = [67.46, 73.45]$
17/12/2012	26.14	62.04	$I_{11} = [68.78, 70.00]$
18/12/2012[2]	23.36	69.79	$I_{12} = [69.84, 70.06]$

For the lack of space, in this paper we present the partial results of the experiment observed in two visits to the orchard of peaches. For simplicity, the five plants were named as follows: 9A, 12A, 15A, 18A and 21A. Only two parameters were analyzed: the temperature and humidity. In each day of the observation period we calculated the average temperature (T_A) and humidity (RH_A), submitting such values as inputs in the fuzzy system. Table 1 shows the captured data, the days when the observations occurred, and the outputs for each case.

The proliferation of the fungus in a given day is a consequence of the events in the days before it. For this reason, we considered the weighted average across five days prior to each observation, both for the lower bound and for the upper bound of output reported by the system. The day prior to the first observation received weight 5, the second day received weight 4, and so on until the fifth day prior to observation, which received weight

[1]First observation at the orchard.
[2]Second observation at the orchard.

1. The intervals P_1 and P_2 of the warning level for each day observed are calculated as:

$$
\begin{aligned}
\underline{P}_1 &= \frac{60.08 \times 5 + 65.27 \times 4 + 68.75 \times 3 + 70 \times 2 + 46.65 \times 1}{5+4+3+2+1} \\
\overline{P}_1 &= \frac{68.88 \times 5 + 70 \times 4 + 70 \times 3 + 70.53 \times 2 + 53.11 \times 1}{5+4+3+2+1} \\
P_1 &= [\underline{P}_1, \overline{P}_1] = [63.62, 68.57] \\
\\
\underline{P}_2 &= \frac{68.78 \times 5 + 67.46 \times 4 + 78.78 \times 3 + 63.37 \times 2 + 68.88 \times 1}{5+4+3+2+1} \\
\overline{P}_2 &= \frac{70 \times 5 + 73.45 \times 4 + 89.86 \times 3 + 68.72 \times 2 + 70 \times 1}{5+4+3+2+1} \\
P_2 &= [\underline{P}_2, \overline{P}_2] = [69.71, 74.72]
\end{aligned}
$$

At the first observation, we noticed that all plants had mummified fruits, *indicating that the disease was present in the orchard*. However, among the five plants observed, only two (18A and 21A) were not suffering with the disease. Thus, $\frac{3}{5}$ (or 60%) of the plants showed the disease spread among their fruits. In the second observation, in spite of all plants presenting fruits still mummified, only one (18A) showed low levels percentage of diseased fruits about 14%. In plants 21A and 15A approximately 25% of fruits were diseased. The plant 9A reached a rate of 35% of diseased fruits. The plant 12A reached a rate of approximately 42% of diseased fruits. In this case, we can consider that $\frac{4}{5}$ (or 80%) of the plants showed high levels of diseased fruits.

It is important to observe the behavior of the fruits when the system increases or decreases the possibility of developing the disease, checking if the number of diseased fruits follows the pattern of increasing or decreasing specified by the system. Comparing the results from the first to the second observation, the system showed an increased warning level for the development of the disease, from [63.62, 68.57] (Eq. 2) to [69.71, 74.72] (Eq. 2). Likewise, as indicated by the system, the amount of plants with significant levels of disease also increased from 60% to 80%.

6. Conclusion

The study of diseases in agriculture is a subject that deserves special attention. The use of technology in agriculture is growing in Brazil and it is an investment that offers a guaranteed return [Rural BR Agricultura 2009]. This work is important in this context and aims to improve production efficiency, reducing spending on supplies. In this case, the system was employed for a fungal disease caused in peach orchard.

The developed system used hardware components to collect weather information of a given region, as well as Interval Fuzzy Logic processes the collected data and provides an indication of the disease development conditions. Fuzzy interval approach increases the confidence level of the analysis by evaluating inputs (temperature and humidity) performed by the sensors, as well as by the intertwining of different opinions of experts. Both situations represent diffuse information that can be used as interval concepts to improve the evaluation of the output values of the system.

The experiment presented here, although simplified due to the lack of space, showed the satisfactory results we have obtained with the system tests period. However, we are still performing more complex experiments in order to ensure that the system works satisfactorily in any conditions.

Furthermore, the developed system can be used in other experiments, by combining the set of sensors accordingly with the process in analysis. There are several possible applications for the developed system, some of them even unknown.

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