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Accuracy of Fuzzy Logic-based Contamination Grading System on Abaca Tissue Culture

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Abstract

This study aimed to support the coalition for abaca rehabilitation program of the different cooperating agencies of Southern Leyte with the use of intelligent systems in the grading of abaca tissue culture contamination. As the Southern Leyte State University Tissue Culture Laboratory has since used manual grading of contaminated specimen, the use of image acquisition technology can lessen the human effort involved in this activity. Fuzzy logic was used in the grading of the contamination. There were five inputs for the inference engine, namely red, green, blue, whitish and brownish. There were 62 rules identified covering the different combinations, and the triangular-shaped membership function was used for all the membership types of the inputs. Based on the result of the testing, it had an accuracy rate of 82.00% for the binary contamination in 50 sample specimens, and an over-all accuracy of 80.33% in multiclass contamination grading. The system could not match the precision of the human expert, but the model is comparable to that of the expected actual result, while minimizing human intervention in grading the contamination of tissue cultured abaca.

Keywords: *Algorithm; Automated grading; Expert system; Fuzzy logic*

Introduction

The Philippines supplied 84% of the global production of abaca which is equivalent to an average fiber production of 68,982 tons per year from from 1999 to 2008. The Eastern Visayas region (composed of the islands of Leyte, Biliran, Samar, and Pana-on) was the major abaca producer that supplied the bulk of the product contributing an annual average of 25,517 tons or 38.5% of the total production (FIDA, 2010). The average annual yield in Eastern Visayas is 913 kg fiber per hectare, which is above the national average of 610 kg per hectare (PCARRD, 2003) but far behind the 2,000 kg of fiber per hectare (Armecin, Cosico & Badayos, 2011).

The abaca fiber is used as a raw material for pulp and paper, fiber craft, cordage (Cobrado, & Fernandez, 2016) and even garment accessories. Moreover, for farmers who rely on abaca as the source of their income, it is a must to plant healthy abaca specimen for a better harvest.

However, challenges in the cultivation of abaca are inevitable. Plant diseases in agriculture are a normal phenomenon in the case of the province of Southern Leyte in 2003, where 80% of the province's abaca plantation was widely affected and was estimated to suffer about 30% in damages because of abaca disease (Gorne, 2006). With the help of technology, earlier detection might have prevented or at least minimized the effects

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brought about by the infection.

One of the aims of research in agriculture is the development of the disease resistant variants of seed using gene technology, that can help increase productivity and food quality at reduced expenditure (Sato et al., 2008). Plant tissue culture technology is widely utilized for large-scale plant multiplication. Even though it is possible to produce a large number of plants by micro-propagation, the problem in this technique is contamination (Leifert & Cassells, 20001). Tissue culture can become contaminated at any stage. Hence, this study was conducted to grade the severity of contaminants for tissue culture using fuzzy logic.

The manual and naked eye observation of experts is the primary approach adopted in practice for the detection and identification of plant diseases (Dhaygude & Kumbhar, 2013). The conduct of manual visual inspection on tissue cultures of abaca is the observation method generally used to decide the severity in the production practice but results are subjective, and it is not possible to measure the disease extent precisely (Patil & Bodhe, 2011).

The use of information and communications technology (ICT) in agriculture, and the application of image processing in agriculture is increasing day by day (Fakhri et al., 2012). IT equipment and software have also become cheaper with technological advancement. Kulkarni et al. (2013) proposed a novel framework for recognizing and identifying plants using shape, vein, color, texture features with Zernike movements. Sannakki et al., (2011) also propose an image processing methodology to address one of the core issues of plant pathology, i.e. disease identification and its grading. The system is an efficient module that identifies various diseases of the pomegranate plant and also determines its stage by grading.

Fuzzy logic, one of the decision-making techniques of artificial intelligence, has been proven to be applicable in almost all scientific fields. The aim of the application of fuzzy logic in image processing is based on an identification of objects or the achievement of healthy perception and more realistic results in image clarity (Mahesh Prasamma & Shantharam Rai, 2015).

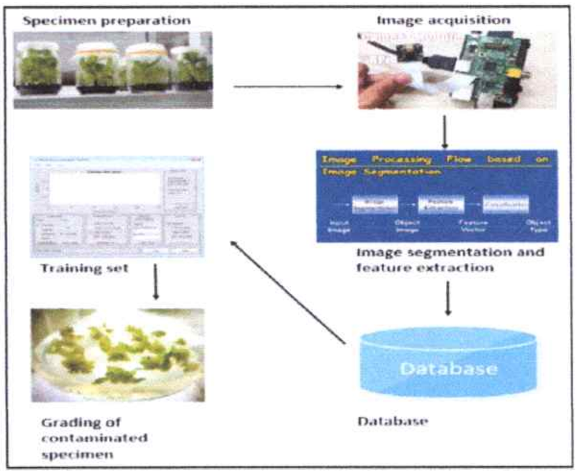

Figure 1. System architecture of the automated contamination grading of tissue cultured abaca

In a study of apple grading using fuzzy logic (FL), the author applied FL as a decision making support to grade apples. The same set of apples were graded by both a human expert and an FL-designed system. In the study, FL-designed system obtained results that were consistent with the results from the human expert. The outcome also provided good flexibility in reflecting the expert's expectations and grading standards. The author suggested to fully automate the system by using machine vision in the decision making using fuzzy logic (Kavdir & Guyer, 2004).

Materials and Methods

Specimen Preparation

The laboratory technician prepared the specimen in the laboratory room.

Image Acquisition

With the use of a 12-megapixel camera, raspberry pi microcontroller, OpenV, and Xbee wireless data transmission, images of both

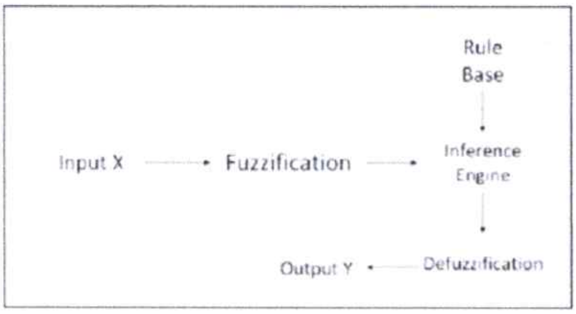

Figure 2. Fuzzy rule-based scheme

healthy and contaminated specimens were captured.

Image Segmentation and Feature Extraction

The region of interest (ROI), which is the plant image, was separated from the background. Images were converted from video streams into binary thus indicating the segmentation of the specimens after segmentation, color, morphological and texture features were extracted. Masking was applied onto the image to obtain useful segment. The red, green and blue component of the pixel was assigned to a value of zero by the mapping of RGB components. These values were stored in the database for use in the next step.

Fuzzy Logic Classification

Lotfi Zadeh conceived and introduced the concept of fuzzy logic. It is described as a problem-solving control system methodology that lends itself to the implementation of different systems, in hardware, software, or a combination of both. FL's approach to problem control imitates how a person would make decisions, only much faster. Fuzzy logic requires fuzzy rules and inference to transform fuzzy input sets to crisp outputs. The transformation process incorporates a simple, rule-based 'if x and y then z' approach to problem solving rather than attempting to model a system mathematically.

Fuzzy logic deals with propositions that can be true to a certain degree, somewhere from 0 to 1. Therefore, a proposition's value indicates the degree of certainty about which is true (Rao, 1995). It is suitable to handle ill-defined and complex problems due to the partial and imprecise information for decision making. The process of fuzzy logic can be defined as a rule-based systems, in which the input is first fuzzified (i.e., converted from a crisp number to a fuzzy set) and subsequently processed by an inference engine. This engine retrieves the knowledge in the form of fuzzy rules contained in a rule-base. The fuzzy sets computed by the fuzzy inference as the output of each rule are then composed and defuzzified (i.e., converted from a fuzzy set to a crisp number) (Sharma & Goyal, 2015). Fig. 2 shows the fuzzy rule-based system scheme (Hanafiah et al., 2015).

A Component of a Inference System (FIS)

Fuzzification. In this stage, each piece of input data is converted to degrees of membership by a lookup in one or more several membership functions.

Fuzzy Rule Base. Fuzzy rule base includes rules that have all possible fuzzy relation between inputs and outputs. The rules are expressed in the IF–THEN format. There are primarily two type of rule base: (1) Sugeno type and (2) Mamdani type. Mamdani's fuzzy inference method is the most commonly seen fuzzy methodology. It was proposed in 1975 by Ebrahim Mamdani as an attempt to control a steam engine and boiler combination by synthesizing a set of linguistic control rules obtained from experienced human operators.

Fuzzy Output Engine. It takes into consideration all the fuzzy rules in the fuzzy rule base and learns how to transform a set of inputs to the corresponding outputs. There are two kinds of inference operators: minimization (min) and product (prod).

Defuzzification. Defuzzification is the method that converts the resulting fuzzy outputs from the fuzzy inference engine to a number. There are many defuzzification methods such as weighted average (wtaver) or weighted sum (wtsum). In the present study, the fuzzy model used is the Mamdani fuzzy rule type, and the prod method is employed because of its more precise methodology. The centroid (also called center of the area, a center of gravity) returns the center of an area under the curve, and it is the point along the x-axis which this shape would balance.

Training and Testing The specimens were prepared in the Southern Leyte State University Tissue Culture Laboratory by a technician. Averages of 500 specimens were prepared daily. Plant tissue culture technology is being widely used for a large-scale plant multiplication. Even though it is possible to produce a large number of plants by micro propagation, the problem in this technique is contamination. A wide range of microorganisms (filamentous fungi, yeast, bacteria, viruses, and viroids) and micro-arthropods (mites and thrips) have been identified as contaminants in plant tissue cultures (Cobrado, & Fernandez, 2016). In this phase, the decision of the laboratory technician was evaluated in actual contamination grading. Table 1 shows the principal microbial contaminants frequently reported in in-vitro cultures.

The execution of the simulation was done using the MATLAB Simulink tool box. The goal was to design a fuzzy logic-based grading of abaca tissue culture contamination. The figure shows the fuzzy inference system (FIS) model for the contamination grading of the tissue cultured abaca.

The inputs of the inference system are Red, Green, Blue, Whitish, and Brownish. Linguistic values for all the inputs are Level 1, Level 2, Level 3, Level 4, Level 5, Level 6, and Level 7. Table 3 shows the linguistic values, MF types , and universe of discourse of the Red input. The values are the binary of the color Red during the image processing.

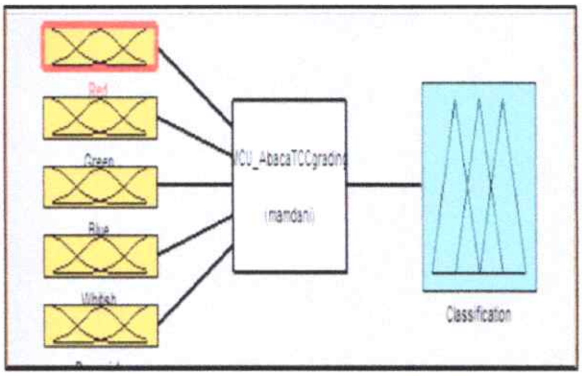

Figure 3. Inference system model for abaca tissue culture contamination grading

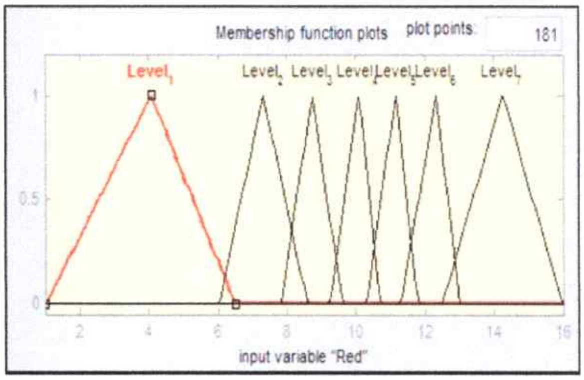

Figure 4. The membership function of the input variable Red

Figures 4,5,6,7 and 8 show the membership function of the input variables.

Each membership function can be equivalently described by a family of its α-cuts $S\alpha$ def = x :$\mu(x) \geq \alpha$ corresponding to different degrees $\alpha \in [0, 1]$.

Figure 4 shows the membership function of the input variable Red. The overlapping values of the universe of discourse and the triangular membership functions of fuzzy logic can also be seen. To fully describe a function $\mu(x)$, there is a need to know its values for all real numbers x. However, there are infinitely many real numbers, from which we can only ask finite questions to each expert. Thus, some values can be elicited and then interpolated. This elicitation and interpolation in often performed in terms of α-cuts. For example, elicit the intervals S0 = [X, X] and

Table 1. Characterization and identification of fungal contaminants of tissue-cultures abaca (*Musa textiles nee*) (Miravillas & Malangsa, 2017)

Contaminants	Cultural Characteristics	Morphological Characteristics
Aspergillus sp.	Colonies are flat, circle, filamentous, velvety, woolly or cottony texture. Colony color is gray to green at center with a white border. The reverse is yellow to pale yellow	Conidiophores bears heads, long and hyaline that terminates in bulbous heads while conidia are globose to sub globose and usually yellowish green and dark brown
Chrysosporium sp.	Colonies are semi-elevated, circle, fairly rapid grower, smooth. Colony color is white to off white color.	Produced septate, hyaline hypae. Conidia often appeared to be minimally differentiated from the hypae and may appear to form directly on the hyphae. Conidia more often formed at the ends of simple or branched conidiophores of varying lengths. Conidiophores were ramifies, forming tree-like structure.

Table 2. Linguistic values, membership function types and universe of discourse for the fuzzy logic input Red

Input	Linguistic Values	MF Type	Universe of Discourse
	Level 1	trimf	[0.1 4.0 6.5]
	Level 2	trimf	[6.0 7.10 8.40]
	Level 3	trimf	[7.90 8.60 9.80]
Red	Level 4	trimf	[9.70 10.4 11.2]
	Level 5	trimf	[10.2 11.10 11.90]
	Level 6	trimf	[11.30 12.20 13..00]
	Level 7	trimf	[12.25 14.00 16.00]

S1 = [x, x], and then interpolate it to arbitrary α.

Figure 5 shows the membership functions of the input variable Green. It also shows the use of the triangular membership function for ease of modification of the parameters (modal values) of membership functions on the basis of measured values of the input to output of a system; and the possibility of obtaining input to output mapping of a model which is a hypersurface consisting of linear segments.

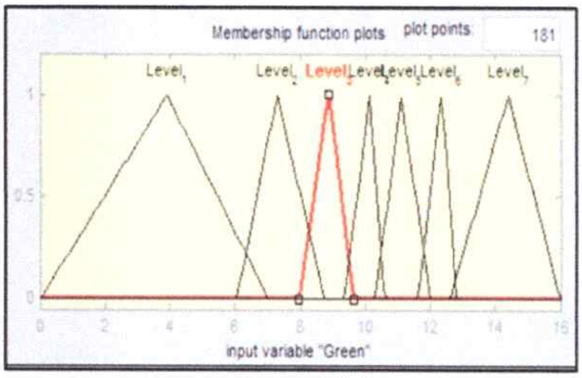

Figure 5. The membership function of the input variable Green

In Fig. 6, the use of the triangular and trapezoidal membership function for the easy calculations with triangular and trapezoidal

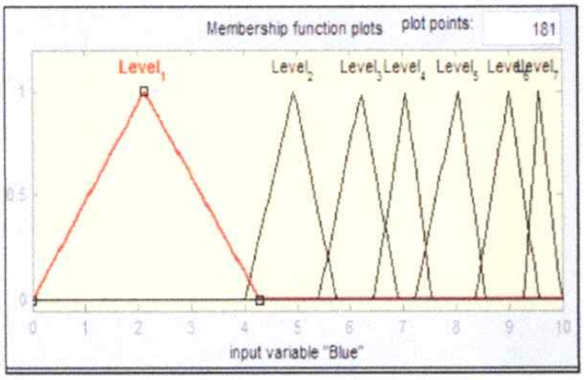

Figure 6. The membership function of the input variable Blue

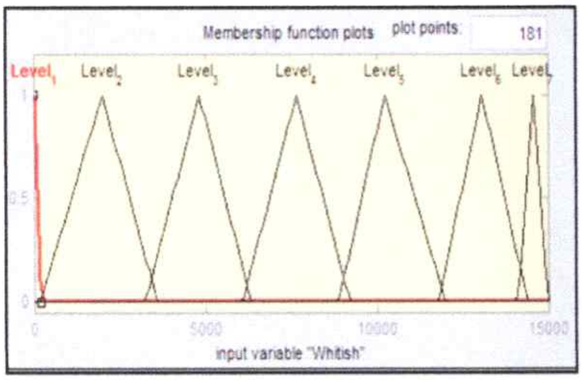

Figure 7. The membership function of the input variable Whitish

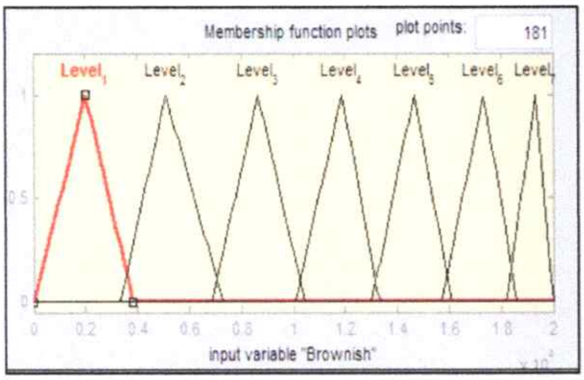

Figure 8. The membership function of the input variable Brownish

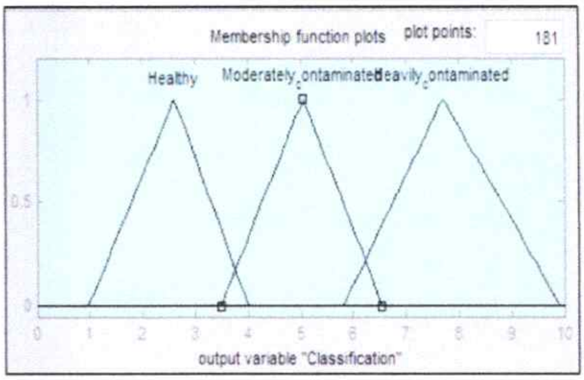

Figure 9. Membership function for the output variable classification

membership are shown.

Membership functions are the building blocks of the fuzzy set theory. In Fig. 7 the membership functions for each input and output data are shown depending on range and variability.

Figure 8 gives the surface diagrams between various parameters. As a diagnostic, it can show which rules are active, or how individual membership function shapes are influencing the results to predict the model.

A total of 62 rules were identified for the grading of the specimens as healthy, moderately contaminated and heavily contaminated. Figure 9 shows the membership function of the variable output classification.

Results and Discussion

The 200 samples of tissue cultured abaca which were used as training data obtained different training values (Miravillas & Malangsa, 2017). The training parameters are Red, Green, Blue, White , and Brown. These parameters are inputs to the Fuzzy Inference System. Figure 10 shows the top ten rules in the FIS.

Table 3 shows the data for the testing. Fifty specimens tested were composed of 15 healthy or contamination-free specimens and 35 contaminated specimens.

The accuracy is computed using the formula

1. If (Red is Level_6) and (Green is Level_6) and (Blue is Level_6) and (Whitish is Level_5) and (Brownish is Level_2) then (Classification is Healthy) (1)
2. If (Red is Level_6) and (Green is Level_6) and (Blue is Level_6) and (Whitish is Level_4) and (Brownish is Level_5) then (Classification is Healthy) (1)
3. If (Red is Level_7) and (Green is Level_6) and (Blue is Level_6) and (Whitish is Level_4) and (Brownish is Level_5) then (Classification is Healthy) (1)
4. If (Red is Level_6) and (Green is Level_5) and (Blue is Level_5) and (Whitish is Level_1) and (Brownish is Level_6) then (Classification is Healthy) (1)
5. If (Red is Level_6) and (Green is Level_6) and (Blue is Level_5) and (Whitish is Level_2) and (Brownish is Level_7) then (Classification is Healthy) (1)
6. If (Red is Level_5) and (Green is Level_5) and (Blue is Level_5) and (Whitish is Level_2) and (Brownish is Level_5) then (Classification is Healthy) (1)
7. If (Red is Level_7) and (Green is Level_7) and (Blue is Level_7) and (Whitish is Level_4) and (Brownish is Level_6) then (Classification is Healthy) (1)
8. If (Red is Level_7) and (Green is Level_7) and (Blue is Level_7) and (Whitish is Level_4) and (Brownish is Level_5) then (Classification is Healthy) (1)
9. If (Red is Level_4) and (Green is Level_4) and (Blue is Level_4) and (Whitish is Level_2) and (Brownish is Level_4) then (Classification is Healthy) (1)

Figure 10. Top 10 rules of the Fuzzy Inference System

Table 3. Binary contamination grading

Class	Specimen for Testing	Identified by FIS	Accuracy
Healthy	15	11	73.33%
Contaminated	35	30	81.71%
Total accuracy			82.00%

$$\text{accuracy}= \frac{\text{True Positive}}{\text{Total Samples}} \times 100 \quad \text{(Equation 1)}$$

Where true positive = number of samples whose variety is correctly identified.

shown in equation 1.

accuracy= (True Positive)/(Total Samples)×100

It has also been noticed during that testing that the results of the grading contamination for fuzzy logic is comparable to the result of the testing using KNN where K=7 based on another study (Miravillas & Malangsa, 2017).

Table 4 shows the data for testing. Of the 100 specimens tested, 40 were composed healthy specimens, 40 were moderately contaminated, and 20 were heavily contaminated specimens.

Figure 11 shows a moderately contaminated and heavily contaminated specimen of tissue cultured abaca during the testing.

a.) healthy b.) moderate c.) critical d.) critical

Figure 11. The different samples of contamination specimens

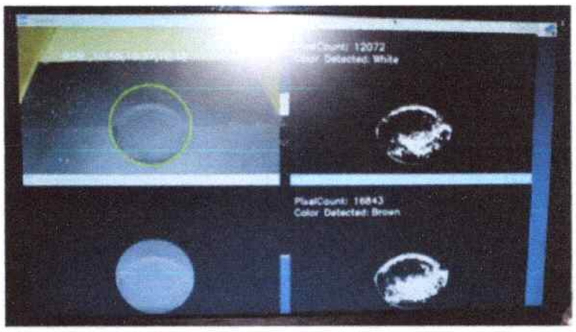

Figure 12. The monitor showing the feature extraction during the training phase

Conclusion

Contamination grading of abaca tissue culture using fuzzy logic was able to grade the

Table 4. Multiclass contamination grading

Class	Specimen for Testing	Identified by FIS	Accuracy
Healthy	40	35	87.5%
Moderately	40	30	75%
Heavily	20	16	80%
Total accuracy			80.33%

Figure 13. Preparation of abaca tissue culture specimen (in vitro)

contamination classification based on the simulation of 62 rules covering possible combinations of the different levels of the parameters. Although the system could not match the precision of a human expert, the simulations yielded an accuracy result of 82.00% in binary contamination grading and 80.33% in multiclass contamination grading of the model. This is comparable to the expected actual result, while minimizing the human intervention in the grading of the abaca tissue culture contamination.

Future Work

The model of this study was limited only to testing in a controlled environment. It would be a good area of research to continue the testing on the open field of an abaca plantation to do automated grading of abaca diseases to help in minimizing contamination.

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