SOCIETY FOR SCIENCE AND EDUCATION
UNITED KINGDOM

JBEMi JOURNAL OF BIOMEDICAL ENGINEERING AND MEDICAL IMAGING

ISSN: 2055-1266
VOLUME 1, ISSUE 6

A Fuzzy Set Approach to Bacterial Wilt Recognition

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ABSTRACT

Bacterial wilt (Ralstonia Solanacearum) is a bacterial which attack most plant species in different plant families resulting in numerous financial implications to farmers. The predominant symptoms includes: yellowish leaves, permanent wilted leaves, permanent upright leaves, brownish vascular tissues, dark brownish cortex and thin thread of ooze infected structure. Bacterial wilt can be readily spread through the movement of contaminated soil and infected vegetative propagated plants, in contaminated irrigation water, and on the surfaces of tools (cutting knives) and equipment used to work with the plants, and on soiled clothing. It often attacks many floricultural and vegetable bedding plant crops. Some of the other known hosts of bacterial wilt include Pelargonium, tomato, peppers, eggplant, bean, and beet. Most of the approaches for bacterial wilt recognition are quite time consuming and subjective in nature. Therefore we proposed an objective approach, capable of initiating fuzzy rules with the aim of quick and objective recognition of bacterial wilt attack.

Keywords: Bacterial wilt, Fuzzy classifier, Fuzzy logic, Inference Rules, Set theory

1 Introduction

Bacteria called Ralstonia Solanacearum (bacterial wilt) attack almost 200 plant species in 33 different plant families (Gary, 2014). This constitutes one of the largest known host ranges for any plant pathogenic bacterium. In tobacco, it is called bacterial wilt, Granville wilt, Moko disease, southern wilt or southern bacterial wilt (Jones, 1993). This bacterium is noted for diseases caused outdoors in land areas bounded by 45N and 45S latitudes where rainfall averages above 100 cm/year (39 in/year), the average growing season exceeds 6 months, the average winter temperatures are not below 10°C (50°F), the average summer temperatures are not below 21°C (70°F) and the average yearly temperature does not exceed 23°C (72°F) (Kim et al., 2003). It can be moved from such areas into the greenhouse industry in and on plants propagated in those regions and then sold to growers throughout the world. Although the primary location of survival in the environment is in crop and weed hosts, it can also survive in soil. It can be readily spread through the movement of contaminated soil and infected vegetative propagated plants, in contaminated irrigation water, and on the surfaces of tools (cutting knives) and equipment used to work with the plants, and on soiled clothing (Gary, 2014).

The bacteria were first named Bacillus solanacearum. After several revisions, it was called for many years Pseudomonas solanacearum (Kim et al, 2003). The latest revision has settled on the name

DOI: 10.14738/jbemi.16.761
Publication Date: 1st January 2015
URL: http://dx.doi.org/10.14738/jbemi.16.761

Ralstonia solanacearum (Jones, 1993; Kim et al., 2003). It is described as a non-spore forming, gram negative staining, nitrate-reducing, ammonia-forming, aerobic, rod-shaped (0.5-1.5 µm) bacteria with one polar flagellum. Populations within this genus and species can be further divided into races and biovars based on differing host ranges, biochemical properties, susceptibility to bacteria-infecting viruses (phages), and serological reactions. It attacks many floricultural and vegetable bedding plant crops including geraniums (all Pelargonium), Catharanthus, Impatiens, Ageratum, Chrysanthemum, Gerbera, Tagetes, Zinnia, Salvia, Capsicum, Lycopersicon, Nicotiana, Petunia, Solanum melongena (eggplant), Tropaeolum (nasturtium) and Verbena (Jones, 1993; Kim et al., 2003). Some of the other known hosts include Pelargonium, tomato, peppers, eggplant, bean, and beet. Weed hosts include black nightshade, climbing nightshade, horsenettle, Jimson weed, purslane, mustards, lambs-quarters, and bitter-gourd. The bacteria can infect through roots and through any fresh wounds. The bacterium can be difficult to work with in the laboratory because it quickly loses pathogenicity and viability in artificial. The symptoms of bacterial wilt includes; yellowish leaves, permanent wilted leaves, permanent upright leaves, brownish vascular tissues, dark brownish cortex and thin thread of ooze infected structure.

The focal point of this paper centres on recognizing bacterial wilt utilizing an objective fuzzy set theory (union) approach. Fuzzy Logic provides a means of representing and manipulating data that are not precise, but rather fuzzy. The theory of fuzzy logic utilizes mathematical strength to capture the uncertainties associated with human cognitive processes. Existing methods (traditional or conventional) for analysing (test data) of bacterial wilt uses approaches (techniques) that are unable to handle uncertain or vague data. In this paper, the rich facilities of fuzzy classifier is utilize for dealing with such uncertainties.

2 Material and Method

A Fuzzy classifier is an algorithm that assigns a class label to an object, based on the object description. It is also said that the classifier predicts the class label (Angelov and Zhou, 2008). The object description comes in the form of a vector containing values of the features (attributes) deemed to be relevant for the classification task (Ishibuchi et al., 1995). Typically, the classifier learns to predict class labels using a training algorithm and a training data set. When a training data set is not available, a classifier can be designed from prior knowledge and expertise. Once trained, the classifier is ready for operation on unseen objects (Cordon et al., 1999). Classification belongs to the general area of pattern recognition and machine learning (Babuska, 1998). The attributes includes:

a. Soft labelling. The standard assumption in pattern recognition is that the classes are mutually exclusive. This may not always be the case. A standard classifier will assign a single crisp label. A fuzzy classifier can assign degrees of membership (soft labels). A standard classifier can output posterior probabilities, and offer soft labeling too. A fuzzy classifier, D, producing soft labels can be perceived as a function approximator $D:F \rightarrow [0,1]c$, where F is the feature space where the object descriptions live, and c is the number of classes. While tuning such a function approximator outside the classification scenario would be very difficult, fuzzy classifiers may provide a solution that is both intuitive and useful (Kuncheva, 2000 and Mamdani, 1977).

b. Interpretability. Automatic classification in most challenging applications such as agricultural problems has been sidelined mostly due to the black box philosophy underpinning classical pattern recognition. Fuzzy classifiers are often designed to be transparent, i.e., steps and logic statements leading to the class prediction are traceable and comprehensible (Kuncheva, 2003).

c. Limited data, available expertise. Examples include predicting and classification of rare diseases, oil depositions, terrorist activities, natural disasters. Fuzzy classifiers can be built using expert opinion, data or both.

2.1 Fuzzy rule-based classifiers

The simplest fuzzy rule-based classifier is a fuzzy if-then system, similar to that used in fuzzy control. Consider a 2D example with 3 classes. A fuzzy classifier can be constructed by specifying classification rules, e.g.

IF X1 is medium and X2 is small Then Class is 1

IF X1 is Medium and X2 is large Then Class is 2

IF X1 is large and X2 is small Then Class is 2

IF X1 is large and X2 is Large Then Class is 2

IF X1 is Large and X2 is small Then class is 3

If X1 is small and X2 is large Then Class is 3

The two features x1 and x2 are numerical but the rules use linguistic values. If there are M possible linguistic values for each feature, and n features in the problem, the number of possible different if-then rules of this conjunction type (AND) is Mn. If the fuzzy classifier comprises of all such rules, then it turns into a simple look-up table. Unlike look-up tables, however, fuzzy classifiers can provide outputs for combinations of linguistic values that are not included as one of the rules. Each linguistic value is represented by a membership function.

2.2 Methodology

The methodology of our work is geared toward specifying fuzzy rules utilizing fuzzy set theory application. We utilize several symptoms (S) of bacterial wilt (yellowish leaves, permanent wilted leaves, permanent upright leaves, brownish vascular tissues, dark brownish cortex and thin thread of ooze infected structure). Each of these symptoms fall into a rule (R1 - R6) and Label (High, moderate and low). The fuzzy rules Specifies

a. IF a plant exhibit $S < 2$ THEN Not Bacterial Wilt Recognized

b. IF a plant exhibits $2 \leqslant S \leqslant 4$ THEN Moderately Bacterial Wilt Recognized

c. If a Plant exhibits $S \geqslant 5$ THEN Bacterial Wilt Recognized

In set theory, the union (denoted by $\cup$) of a collection of sets is the set of all distinct elements in the collection. It is one of the fundamental operations through which sets can be combined and related to each other. The initial $\cup$ is initialized as $R \cup \emptyset = R$, for the set R. Therefore the fuzzy set rules are thus:

R0: $R \cup \emptyset$

R1: $\{\emptyset \cup$ yellowish leaves$\}$ = Not Bacterial Wilt Recognized

R2: {Ø ∪ yellowish leaves} ∪ permanent wilted = Not Bacterial Wilt Recognized

R3: {Ø ∪ yellowish leaves ∪ permanent wilted} ∪ permanent upright leaves = Moderately Bacterial Wilt Recognized.

R4: {Ø ∪ yellowish leaves ∪ permanent wilted ∪ permanent upright} ∪ brownish vascular tissues = Moderately Bacterial Wilt Recognized.

R5: {Ø ∪ yellowish leaves ∪ permanent wilted ∪ permanent upright ∪ brownish vascular tissues} ∪ dark brownish cortex = Bacterial Wilt Recognized.

R6: {Ø ∪ yellowish leaves ∪ permanent wilted ∪ permanent upright ∪ brownish vascular tissues} ∪ dark brownish cortex} ∪ thin thread of ooze infected structure = Bacterial Wilt Recognized.

3 Results

The dataset stipulated on table 3.1 was derive from a research survey utilizing questionnaires as the research tools which was further analyzed utilizing line graph.

Table 3.1: Dataset Showing the Degree of Membership of Bacterial Wilt

PARAMETERS OR FUZZY SETS	CODES	DEGREE OF INTENSITY OF BACTERIAL WILT		
		Cluster 1 (C_1)	Cluster 2 (C_2)	Cluster 3 (C_3)
Yellowish Leaves	P01	0.50	0.00	0.50
Permanent Wilted Leaves	P02	0.20	0.50	0.60
Permanent Upright Leaves	P03	0.00	0.50	0.50
Brownish Vascular Tissues	P04	0.20	0.10	0.70
Dark Brownish Cortex	P05	0.30	0.60	0.10
Thin Thread Of Ooze Infected Structure	P06	0.05	0.05	0.90
RESULTS		**NOT BACTERIAL WILT RECOGNIZED**	**MODERATELY BACTERIAL WILT RECOGNIZED**	**BACTERIAL WILT RECOGNIZED**

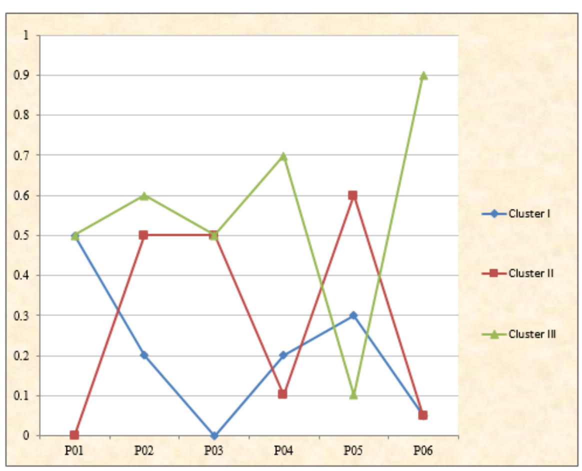

Figure 3.1: Graphical representation of Membership function for Bacterial Wilt

The graphical representation in Figure 3.1, is a representation of Table 3.1 and clearly show one criterion with high degree membership function of "Not Bacterial Wilt Recognized" in cluster 1, three criteria's with degree membership function of Moderately Bacterial Wilt Recognized" in cluster 2 and five criteria's with degree membership function of "Bacterial Wilt Recognized" in Cluster 3.

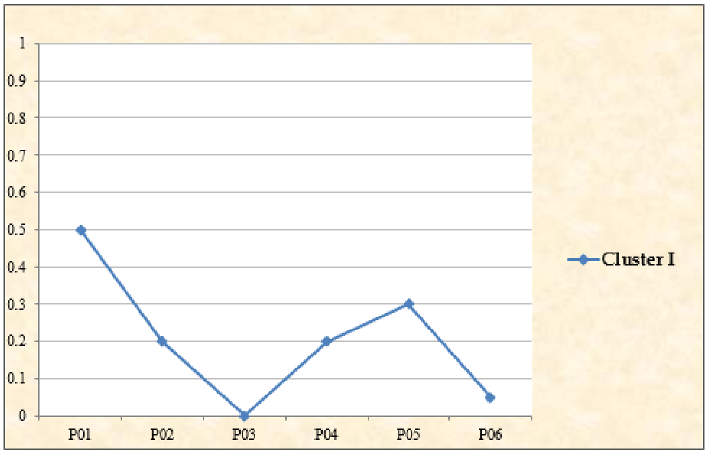

Figure 3.2: Graphical representation highlighting the degree of membership function for Cluster I of Bacterial Wilt

Figure 3.2 clearly shows one criterion with high degree of membership function in P01, and five criteria with Low degree of membership function in P02- P06.

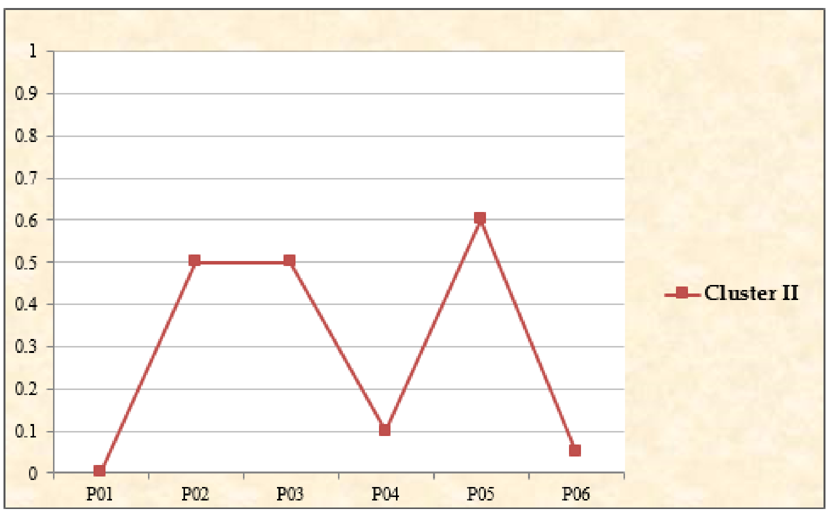

Figure 3.3: Graphical representation highlighting the degree of membership function for cluster II of Bacterial Wilt

Figure 3.3 clearly shows three criteria with high degree of membership function in P02, P03 and P05, and three criteria with low degree of membership function in P01, P02 and P06.

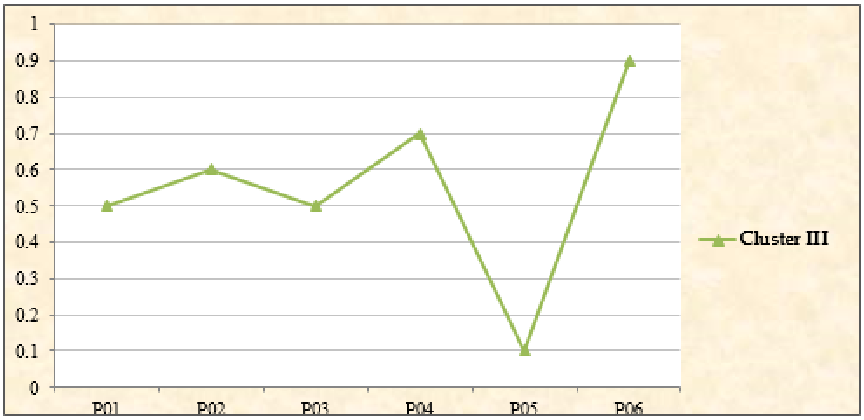

Figure 3.4: Graphical representation highlighting the degree of membership function for cluster III of Bacterial Wilt

Figure 3.4 clearly shows four criteria with high degree of membership function in P01- P04, and P06 and one criterion with low degree of membership function in P05.

4 Discussion

The main focus of our approach is geared toward recognizing bacterial wilt utilizing the rich facilities of fuzzy set theory application which is more pivotal in nature, flexible and robust. Unlike previous approaches which are times consuming and quite expensive because of repeated unnecessary test, this is just a simple based approach with interaction in merging plant symptoms exhibited.

5 Conclusion

Fuzzy logic with the aid of fuzzy-rules has been applied objectively to the recognition of bacterial wilt utilizing the symptoms sponsored and exhibited by each plant and the occurrence level at the point of exhibition. This approach has help us to objectively sub-divide plant symptoms occurrence into varied classes which is more precisely than the previous approaches.

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