Risk Analysis for Weed Occurrence

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Abstract: This talk presents a fuzzy system for the analysis of the risk of infestation by weeds in agricultural zones considering the weeds' variability. The inputs of the system are attributes of the infestation extracted from estimated maps by Kriging for the weed seed production and weed coverage, and from the competitiveness, inferred from narrow and broad-leaved weeds. Results for the risk inference in a corn-crop field are presented and evaluated by the estimated yield loss.

Keywords: Kriging, fuzzy rules, Bayes rules, risk inference.

INTRODUCTION

Usually, herbicides are spread uniformly over the whole field aiming the control of the weeds. However, the weed infestation does not occur all over the field and the amount of herbicide can be reduced by spraying only on the weed patches (Wallinga, et al., 1998). The prediction of the dispersion of weeds can efficiently be used in the prevention of infestations with the application of herbicides only in specific regions (Jurado-Expósito et al., 2003). There are a few modeling formalisms that can be used for the classification of the risk of weed infestation in a crop field (Primot et al., 2006). Fuzzy rule based inference systems which assigns non fuzzy input vectors to one of a given set of classes have often been used because boundaries among classes are not always clearly defined (Yang et al., 2003). In the literature, Bayesian based methods have already been used for modeling a few similar problems (Hughes and Madden, 2003; Banerjee et al., 2005). The main goal of this talk is to present a methodology to classify the risk of weed infestation in agricultural zones considering the variability of weeds using both fuzzy and Bayesian inferences. The risk of weed infestation of regions of the crop, is analyzed from the combination of weed coverage, weed seed production, weed seed patches, obtained from estimated maps by Kriging, and weed-crop competitiveness. Results for the classification of the risk of infestation of a corn-crop are given.

MATERIAL AND METHODS

Map Objects

Let $\Re(x,y)$ represent the entire map region with (x,y) the spatial coordinate of the intensities in the map. The clusters detected in $\Re(x,y)$ associated to the weed maps provide the attributes to infer the weed infestation risk. Aiming at a better division of the intensities levels, the clusters in $\Re(x,y)$ are described by connected objects obtained as follows. First, to obtain encoded objects 0, 1, 2 and 3, the intensities $f(x,y)$ of $\Re(x,y)$ are quantized into four levels L_0, L_1, L_2, L_3 associated to ranges equally apart of $f(x,y)$ by an encoder. Then, a map $I(x,y)$ with pixels given by coded intensities 0, 1, 2 or 3 is formed. The pixels in $I(x,y)$ may represent the same intensity range but may belong to different clusters within the image. Connected objects are thus obtained by image analysis using a 4-connected model. In this model, two pixels in the 4-neighbors are connected if they have the same value. The 4-connected model is implemented by generating a binary matrix .Finally, connected objects are labeled and organized in a matrix. The pixels labeled 0 form the first connected object, the pixels labeled 1 form the second connected object, and so on.

Modeling of the Fuzzy System

A classification fuzzy system contains rules characterized as follows:

$$\text{If feature } v_j \text{ is condition } A_{ij} \text{ then class } c_i \tag{1}$$

where $v_j \in \{v_1, \cdots, v_m\}$, $A_{ij} \in \{A_{i1}, \cdots, A_{im}\}$ and $c_i \in \{c_1, \cdots, c_C\}$, $i = 1, \cdots, C\}$ with C the number of classes and $j = 1, \cdots, m\}$, with m the number of attributes (Pedrycz and Gomide, 1998).

Attributes of the infestation were evaluated per regions of size not exceeding the spatial dependence of the data sets. Let $R_i, i = 1, \cdots, n_R$ denote sub region $\Re_i$ of $\Re$, $S_i(x,y)$ be the pixels of $I(x,y)$ in $\Re_i$, $J_\ell(x,y)$ the pixels with label ℓ in $J(x,y)$, n_ℓ the number of cells occupied by the connected object $J_\ell(x,y)$ and n_i the number of connected objects in a region $\Re_i$. The attributes per region were established as follows (Bressan et al. 2008).

v_1: W*eed coverage attribute*. Indicates the percentage of surface infested by emergent weeds in each region. It is obtained as follows:

$$v_1 = \sum_{x,y \in J_\ell} \frac{S_i(x,y) J_\ell(x,y)}{n_\ell}. \tag{2}$$

v_2: W*eed seed production attribute*. Characterizes the locations of seeds which can germinate and is associated with the weed seed production. It is obtained in the same way as attribute v_1.

ν_3: *Weed seed patches attribute at life-cycle t*. Represents how the seeds contribute to weed proliferation in the surroundings of each region. It is obtained as follows:

$$\nu_3 = \sum_{x,y \in J_\ell} \frac{S_i(x,y) J_\ell(x,y)}{n_i}. \qquad (3)$$

ν_4: *Competitiveness attribute*. Reflects the high level of competitiveness of certain species of weeds and their proliferation.

The attributes $\nu_1;\nu_2;\nu_3$ are derived from estimated maps and image analysis and are obtained per region. The attribute ν_4 can not be directly inferred and it is obtained from a neurofuzzy system. The neurofuzzy inputs are chosen as the total density of weeds per parcel, that is, the number of weeds per m^2, and the corresponding proportions of narrow and broad-leaved weeds. The output is the weed biomass, which is defined as the amount of dry material per m^2 of the aerial part of the weeds. To evaluate the attributes by region, the crop is divided into n_R regions of *p* x *p* cells not exceeding the data sets spatial dependence.

Modeling of the Bayesian Networks

A Bayesian network can be viewed as a form of probabilistic graphical model used for knowledge representation and reasoning about data domains. Instead of encoding a joint probability distribution over a set of random variables, as done by a Bayesian network, a Bayesian classifier aims to correctly predict the value of a discrete class variable given the value of a vector of attributes (predictors). Since Bayesian classifiers are a particular type of Bayesian networks the concepts and results described in this section are valid for both.

As formally stated in Cheng, et al. (2002), a Bayesian network is represented by $\mathrm{BN} = < \mathrm{N}, \mathrm{A}, \theta >$, where $< \mathrm{N}, \mathrm{A} >$ is a directed acyclic graph - each node $x_i \in N, i = 1, \cdots, n$ represents a domain variable (corresponding perhaps to a database feature) and each $\mathrm{arc}\, a \in A$ between nodes represents a probabilistic dependency between the associated nodes. Associated with each node $x_i \in N$ there is a conditional probability distribution (CPtable), collectively represented by $\theta = \{\theta_i\}$, which quantifies how much a node depends on its parents. The conditional independence assumption (Markov condition) allows the calculation of the joint probability distribution function over the variables $x_1, \cdots, x_n$ based on the background knowledge (BK), as

$$P(x_1, \cdots, x_n \middle| BK = \prod_{i=1}^{n} P(x_i \mid \pi_{x_i}, BK) = \prod_{i=1}^{n} P(\theta_{x_i} \mid \pi_{x_i}, BK) \qquad (4)$$

where $n = |N|$, x_i is the i-th node or variable, and π_{x_i} is the set of parents of x_i. The learning of a Bayesian network can be divided into two steps: the network structure learning and the conditional probability tables learning. The learning of these tables can be carried out using empirical conditional frequencies from data (Cheng, et al., 2002). When building a Bayesian network based on human expert knowledge, the major problem is the conditional distribution probability definition. To avoid this difficulty it is possible to use expert knowledge to build only the Bayesian network structure and then use learning algorithms to induce θ from data.

In a Bayesian network structure, with λ_A as the set of children of node A and π_A as the set of parents of node A, the subset of nodes containing π_A, λ_A and the parents of λ_A is called the Markov blanket of A. In a Bayesian network the only nodes that have influence on the conditional probability distribution of a given node A are the nodes that belong to the Markov blanket of A. Thus, after learning a Bayesian network classifier from data, the Markov blanket of the node that represents the class can be used as a attribute subset selection method, in order to identify, from all the nodes that define the network, those that influence the class node. The knowledge represented by a Bayesian classifier is not as comprehensible as some other forms of knowledge representation, as for instance, classification rules. However, the method named BayesRule (Hruschka, et al. 2007), after inducing the Bayesian classifier yields a set of if-then rules probabilistically qualified of the form

$$\text{If} < condition > v_j \text{ then } class \text{ with certainty } F \tag{5}$$

where the *condition* is called antecedent and *F* is a percentage value. Let $V_1, \cdots, V_n, C$ be the sets of linguistic variables values for $v_1, \cdots, v_n$ and c, respectively. Also, let $|V_i| = j_i, i = 1, \cdots, n$ and $|C| = j$. A linguistic probabilistic if-then rule can be characterized as:

$$\text{If } v_1 \text{ is } V_{1,J_1} \text{ and} \cdots \text{and } v_n \text{ is } V_{n,J_n} \text{ then } c \text{ is } C_J \text{ with certainty } F \tag{6}$$

where $J_i \in \{1, \cdots, j_i\}$, $i = 1, \cdots, n$ and $J \in \{1, \cdots, j\}$. Considering a particular situation where the Markov blanket of the class variable c is the set $v_1, \cdots, v_k$, the a posteriori probability of class $c = C_J$ given the values of the variables in the Markov blanket of class c for a particular instantiation of indexes $J_i, i = 1, \cdots, k$ is

$$P(c = C_J \mid V_{1,J_1}, \cdots, V_{k,J_k}) = \max_{J \in \{1,\cdots,j\}} \{P(c = C_J \mid V_{1,J_1}, \cdots, V_{k,J_k}\} \tag{7}$$

with $P(c = C_J \mid V_{1,J_1}, \cdots, V_{k,J_k}) = P(c = C_J) \prod_{i=1}^{k} \dfrac{P(c = C_J) V_{1,J_1}, \cdots, V_{k,J_k})}{P(C_J \mid V_{1,J_1}, \cdots, V_{i-1,J_{i-1}}}\}$.

The a posteriori probability can be translated into a linguistic probabilistic if-then rule as:

$$R_r : \text{If } v_1 \text{ is } V_{1,J_1} \text{ and} \cdots \text{and } v_n \text{ is } V_{n,J_n} \text{ then } c \text{ is } C_J \text{ with certainty } F \text{ given by } (9)$$

where index $r = 1, \cdots, R$ with R the number of rules given by the BayesRule method.

DISCUSSIONS AND CONCLUSIONS

A classification fuzzy system to analyze infestations by weed in regions of a field was presented. Important attributes including weed seed production, weed coverage, weed seed patches and competitiveness were used. For comparison purposes, a hybrid approach, which articulates Bayes and linguistic rules, was used to improve the model understandability by extracting classification rules from the Bayesian network. Further work includes the use of extensive simulations and experiments to analyze the sensibility of the solution to the membership function intervals and attributes.

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