

Applying the Fuzzy Ant-Miner Algorithm to Extract the Success Indicators of Balloon Dilation in PA-IVS

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Abstract: Several studies have sought to identify the parameters that determine the outcome of balloon dilation in pulmonary atresia with ventricular septum. However, none of these studies was based on the ant colony algorithm. In this paper we focus on the implementation of an algorithm based on ant colonies: Fuzzy Ant-Miner. This method uses the concepts of fuzzy logic to extract rules from the training data. These rules are exploited using a Mamdani fuzzy inference system for classification and prediction. The results obtained by this method in the form of fuzzy rules are easy to interpret, and close to human reasoning.

Keywords: Atresia with Intact Ventricular Septum, Balloon Dilation, Fuzzy Ant-Miner, Fuzzy Partitions, Fuzzy Rules

1. Introduction

The decision tree algorithms present the disadvantage of using sequential variables (non-simultaneous). On the other hand, the passage from a tree node to another, divides the attribute into two separate partitions in a sudden manner: noise superimposed on the discretization value can generate errors.

To overcome these drawbacks, we used a method based on ant colonies algorithms: Fuzzy Ant-Miner [8]. This is an extension of the cAnt-Miner [9] algorithm that extracts fuzzy rules from training data. It can handle both nominal and continuous data, which is an interesting improvement compared to other methods based on ant colonies like Ant-Miner [2].

The rest of the paper is organized in three sections:

The first is devoted to the explanation of the Fuzzy Ant-Miner method. The subsequent analysis will focus on the results achieved by decision trees and those obtained by the Fuzzy Ant-Miner method. In the third section, we analyze the classification of new instances using a fuzzy inference system.

2. Fuzzy Ant-Miner

A. Fuzzy discretization

In order to avoid the crisp discretization used by cAnt-Miner, our method discretizes the values of a continuous

attribute into fuzzy partitions [3]. First a threshold x is determined in the same way as cAnt-Miner (the one that leads to the minimum entropy). We assume that the threshold is a fuzzy number around x . Then the values of the continuous attribute are transformed into membership degrees to the fuzzy values:

$A_i \ll x$ (low), $A_i \approx x$ (average) and $A_i \gg x$ (high).

The membership function of the continuous attribute A_i to a fuzzy value $A_i \ll x$ is calculated using Equation (1) with reference to FIG. 1.

$$\mu_{A_i \ll x}(v) = \begin{cases} 1 & \text{if } v \leq a \\ \frac{b-v}{b-a} & \text{if } a < v < b \\ 0 & \text{if } v \geq b \end{cases} \quad (1)$$

And the membership functions of the continuous attribute A_i to a fuzzy value $A_i \approx x$ are calculated by the equation (2):

$$\mu_{A_i \approx x}(v) = \begin{cases} 1 & \text{if } b \leq v \leq c \\ \frac{v-b}{b-a} & \text{if } a < v < b \\ \frac{d-v}{d-c} & \text{if } c \leq v \leq d \\ 0 & \text{if } v \leq a \text{ or } v \geq d \end{cases} \quad (2)$$

Similarly, the membership functions of the continuous attribute A_i to a fuzzy value $A_i \gg x$ are calculated by:

$$\mu_{A_i \gg x}(v) = \begin{cases} 1 & \text{if } v \geq d \\ \frac{v-d}{d-c} & \text{if } c < v < d \\ 0 & \text{if } v \leq c \end{cases} \quad (3)$$

Where parameters (a, b, c and d) determine the boundaries of the fuzzy area and so the degree of fuzziness. These parameters are determined in the same way as the threshold x (value that gives the minimum entropy in a given partition). Note that other ways of generating the fuzzy partitions can be used in our method.

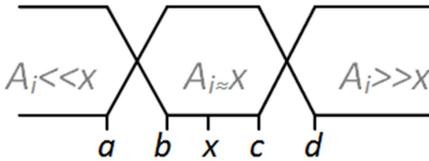


Fig. 1. Fuzzy discretization of a continuous attribute.

```

BEGIN
  Training Set = all training examples;
  Induced Rule Set = O;
  WHILE (No. of uncovered examples in
    the Training Set >
    Max Uncov Examples)
    Fuzzy discretization depending
    on the value  $\alpha$ ;
    i = 0;
    REPEAT
      i = i + 1;
      Ant (i) constructs a fuzzy rule Ri;
      Ant (i) constructs a fuzzy rule class of Ri
      depending on  $\beta$ ;
      Prune the fuzzy rule;
      Update fuzzy pheromone of attribute
      terms;
    UNTIL (i >= NoAnt) OR (the same rule Ri
    has been constructed;
    Select the best fuzzy rule;
    Add the best fuzzy rule to
    Induced Rule Set;
    Remove training examples covered by
    the best fuzzy rule from the
    Training Set;
  END WHILE
  Create default fuzzy rule;
  Output Induced Rule Set;
END

```

Fig. 2. Pseudo-code of Fuzzy Ant-Miner algorithm.

B. Fuzzy Ant-Miner Algorithm

The In order to deal with fuzzy concepts we have extended the algorithm Ant-miner to treat these concepts. The pseudo code of Fuzzy Ant-Miner method is presented in the Figure 2.

The method begins with all learning examples and an empty list of rules. Fuzzy discretization is performed on the fly [10] in the outer loop (While). The inner loop (Repeat. .. Until) finds a fuzzy rule, simplifies and updates the pheromone levels in different terms. This rule will be elected (stored in the list of rules) if its quality is the highest, in this case all the examples covered by this rule will be removed from the training set. A sample is removed from the training set if the rule covers this example with a number greater than a certain degree β . The rule extraction process stops when the training set contains only a number of examples less than a number entered by the user. The number of iterations of the inner loop is equal to the number of ants if there's no convergence (the same rule found several times).

C. Rule pruning

After obtaining the complete rule, the method proceeds to pruning it [7]. The pruning process is based on the quality of the fuzzy rule. Indeed the quality is computed with TP^* (fuzzy true positive), FP^* (fuzzy false positive), FN^* (fuzzy false negative) and TN^* (fuzzy true negative) that are determined by calculating the membership degree of each term in the rule.

The e^{th} example O_e of the training set is defined by:

$$O_e = \langle (x_i^e)_{i=1..n}, c_e \rangle$$

Where:

- $(x_i^e)_{i=1..n}$ represents the attribute values of the example.
- c_e : Class of the example.

Each rule r_m obtained by our method is defined by

$$r_m = \langle (A_i = v_j)_{i=1..n_r}, c_{r_m} \rangle$$

Where:

- v_j is the fuzzy value
- n_r is the number of terms in the rule.
- c_{r_m} : Class predicted by the best rule obtained.

To determine the quality of the fuzzy rule, the examples are injected into the rule:

The filter $f_{O_e r_m}$ of the example O_e in the rule is defined by the membership degree of a term x_i^e to a fuzzy value v_j and the membership degree of a class example to a class rule:

$$f_{O_e r_m} = \langle (\mu_{A_i=v_j}(x_i^e))_{i=1..n_r}, \mu_{C_{r_m}}(c_e) \rangle$$

A fuzzy true positive value of example O_e is calculated by:

$$TP^*_{O_e} = \min_{i=1..l} [\mu_{A_i=v_j}(x_i^e)] * \mu_{C_{r_m}}(c_e) \quad (4)$$

A TP^* value of a training set is:

$$TP^* = \sum_{e=1}^l TP^*_{o_e} \quad (5)$$

Similarly we calculate FP^* , TN^* and FN^* :

$$FP^*_{o_e} = \min_{i=1..l} [\mu_{A_i=v_j}(x_i^e)] * \mu_{\bar{C}_m}(c_e) \quad (6)$$

Where $\mu_{\bar{C}_m}(c_e) = 1 - \mu_{C_m}(c_e)$

$$FP^* = \sum_{e=1}^l FP^*_{o_e} \quad (7)$$

$$FN^*_{o_e} = \max_{i=1..l} [\mu_{\bar{A}_i=v_j}(x_i^e)] * \mu_{C_m}(c_e) \quad (8)$$

Where $\mu_{\bar{A}_i=v_j}(x_i^e) = 1 - \mu_{A_i=v_j}(x_i^e)$

$$FN^* = \sum_{e=1}^l FN^*_{o_e} \quad (9)$$

$$TN^*_{o_e} = \max_{i=1..l} [\mu_{A_i=v_j}(x_i^e)] * \mu_{\bar{C}_m}(c_e) \quad (10)$$

$$TN^* = \sum_{e=1}^l TN^*_{o_e} \quad (11)$$

The fuzzy quality Q^* is then calculated by:

$$Q^* = \frac{TP^*}{TP^* + FN^*} * \frac{TN^*}{FP^* + TN^*} \quad (12)$$

Before pruning the rule, the class is determined by the most frequent class among the examples covered by the rule in the training set: The rule covers the example O_e if $TP^*_{o_e}$ Eq. 4 is higher than a parameter β . This parameter (between 0 and 1) is adjusted for better performance. It filters the examples covered by the rule. If $\beta = 0$ then all examples of which an attribute has a value within the fuzzy area are covered by the rule. If $\beta = 1$ then all examples of which an attribute has a value within the fuzzy area are not covered by the rule. The user sets this parameter for the best accuracy. In each rule pruning iteration, every term is temporarily removed from the rule (note that a change in a rule antecedent may result in a change of the rule consequent), and the quality of the rule is re-evaluated. At the end of the iteration, only the term removal of which leads to an improvement of the rule quality is actually removed. The process of rule pruning stops when there is only one term left, or each term removal no longer leads to an improvement of rule quality. Once the rule pruning has been performed, the artificial ant increases the level of pheromone of the terms still present in the rule antecedent according to the fuzzy quality of the rule:

$$\tau_{ij}^*(t+1) = \tau_{ij}^*(t) + \tau_{ij}^*(t) * Q^* \quad (13)$$

The results obtained with Fuzzy Ant-Miner showed an obvious improvement compared to those of Ant-Miner and cAnt-Miner.

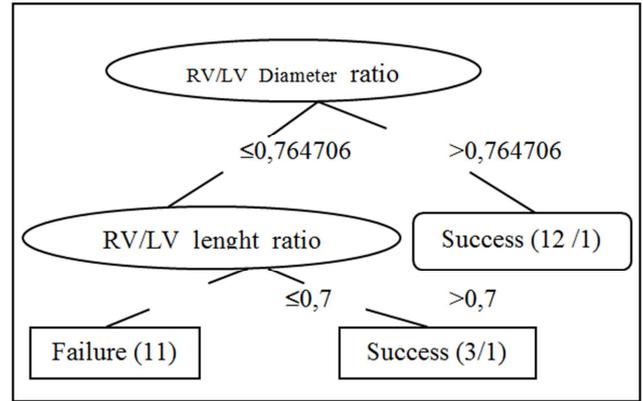


Fig. 3. Decision tree generated by J48 algorithm using the Weka software.

D. Results

This data set is composed of 26 echocardiograms [1] done on patients diagnosed with PA-IVS who underwent balloon dilatation. Each instance consists of 32 numeric attributes, two nominal attributes and a nominal class that indicates the success or failure of the intervention. The small number of cases of all the data that was provided to us, is the consequence of the fact that congenital heart disease is rare.

The tree generated by the J48 algorithm [1] is shown in Figure 3. This tree has the disadvantage of using sequential variables (non-simultaneous: we must first test attribute: RV / LV_diameter_ratio), and if a variable changes in the tree, then all the tree changes. On the other hand, the passage from a tree node to another, divides the attribute into two separate partitions in a sudden manner: noise superimposed on the value of discretization can generate errors (eg partitions: RV / LV_diameter_ratio > 0.764706 and RV / LV_diameter_ratio ≤ 0.764706).

Results of Fuzzy Ant-Miner method

The Fuzzy Ant-Miner algorithm uses a fuzzy discretization of continuous attributes and extract rules that will be exploited by using the fuzzy inference systems for classification and prediction [4]. The results obtained by this method in the form of fuzzy rules are easy to interpret, and close to human reasoning. The average predictive accuracy obtained is 0.7862. The results obtained by this method as three fuzzy rules are noted below:

- IF ratiolen is Low (a=0.620500 || b=0.755176) && IF ratiodia is Low (a=0.652807 || b=0.861898), the result is: failure
- IF ratiodia is High (a=0.700000 || b=0.900000), the result is: success
- IF ratiolen is High (a=0.710024 || b=0.761486) && IF ratiotm is Low (a=0.825595 || b=0.882738), the result is: success

The fuzzy rules 1 and 2 justify the tree generated by the J48 algorithm, while overcoming the disadvantages of decision trees already mentioned. Our approach has generated rule 3 which uses a new term (ratiotm). The attributes contained in the rules are: ratiodiam, ratiolen and ratiotm. The learning examples involving these attributes and their coverage by the rules are given in Table 1.

Table 1. Class'S predictions of six examples by the three fuzzy rules obtained.

Sample	Ratio lengt	Ratio diam	Ratio tm	Class	Rule 1	Rule 2	Rule 3	Class predicted
1	0.8	0.94	0.9	s	0	1	0	1*s
				f	0	0	0	
2	0.58	0.62	0.808	s	0	0	0	1*f
				f	1	0	0	
3	0.864	0.68	0.75	s	0	0	1	1*s
				f	0	0	0	
4	0.62	0.8	0.722	s	0	0.5	0	0,5*s
				f	0,3	0	0	
5	0.72	0.64	0.70	s	0	0	0.2	0,26*f
				f	0,26	0	0	
6	0.72	0,8	0,8	s	0	0.5	0.2	0,5*s
				f	0,26	0	0	

s:success, f:failure

3. Fuzzy Inference

The fuzzy rules generalized by Fuzzy Ant-Miner algorithm from the training set are used to classify new examples [5]. This classification is based on the principle of fuzzy inference system. Indeed each rule obtained, that involves a fuzzy term from the continuous attribute, has a degree of validity [6]. This degree depends on the fuzzy probabilities. An example filtered by this rule will have the class of this rule with a degree of uncertainty calculated using the principle of generalized modus ponens. The fuzzy inference system used is the SIF Mamdani.

The output class is constructed by aggregating the classes obtained by each rule. We deem that the rules are linked by a logical "OR", and therefore we calculate the maximum of the resulting membership functions for each rule. Since the output is categorical, we affect the class of the rule, with the highest output value, to the injected example.

Table 1 presents six examples injected into our method and whose class is predicted with a degree of uncertainty.

In our case, Example 6 will be assigned to the class of rule 2 (success) with a level of 50%:

$$MAX(MIN_1, MIN_2, MIN_3) = MIN_2 = 0,5$$

4. Conclusion

Fuzzy Ant-Miner is an extension to the learning algorithms based on ant colonies in order to process continuous valued attributes. These parameters are discretized on the fly according to the concepts of fuzzy logic.

We got three fuzzy rules by applying the algorithm Fuzzy Ant-Miner on these medical data.

The domain expert has confirmed that the rules obtained by Fuzzy Ant-Miner reflect their way of thinking in the face of confusing situations: that is to say, when the attribute value is exactly equal to the decision threshold.

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