A FUSION OF BAYESIAN AND FUZZY ANALYSIS FOR PRINT FAULTS DIAGNOSIS

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Abstract

This paper is part of a larger study of remote print defect diagnosis. The goals of the integrated print defect diagnosis system are to reduce diagnosis time, streamline communication between customers and call center personnel, increase print defect handling efficiency and boost customer satisfaction through improved service. In this paper, we aggregate the information stemming from two diagnostic tools – Bayesian belief networks and fuzzy logic – to arrive at a more robust diagnostic result than possible from either tool alone.

1. Introduction

The problem with most complex diagnostic problems, in general, is that there are usually several symptoms and each of these symptoms can result from several failures. The mapping from printer failure to associated print defects is fairly well understood. However, the mapping from a set of print defects to a specific printer failure is not as well understood and the available solutions have a variety of shortcomings. Probabilistic methods can be used to link symptoms to failures if the necessary failure probabilities can be obtained. Bayesian belief networks have been effective in modeling probabilistic relationships in complex diagnostic situations and in providing a framework to identify critical probabilistic mappings. These probabilities can be obtained from operating data, if available for all prior probabilities and fault mappings over a sufficient period of time, or through the solicitation of subjective probabilities from experts. The modeling and probabilistic assignments can become complicated when symptoms are interdependent or multiple failures occur simultaneously. Fuzzy logic has been found useful when prior operating data are lean, particularly when prior probabilities are not available. Some experts find it easier to map their knowledge onto fuzzy relationships than onto probabilistic relationships between crisply defined variables.

Data fusion of disparate information can be tackled by several different methods, such as generalized evidence processing theory (Thomopoulos, 1990), Bayesian methods (Agogino 1988, Kim. 1992, Alag, 2001), Dempster-Shafer methods (Blackman 1990) and linear estimators (Ayache and Faugeras 1988). A methodology to fuse Bayesian belief networks and fuzzy logic is presented in this paper. Fusing these two techniques results in more accurate and robust results than using either tool alone.

2. Print defect

There are many print defects, however the most common problems are few in number and contribute to the majority of all printing problems. Figure 2.1 shows the typical print defects that were used in our analysis.

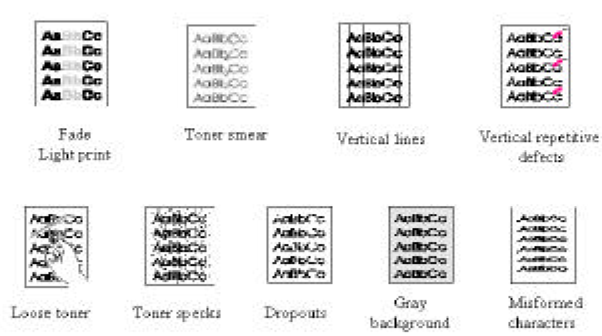

Fig. 2.1 Samples of print quality problem

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The samples of print defects shown above are symptoms of printer faults. The definition of symptoms and faults are shown in table 2.1. Three classes of faults and nine fault events are identified. Three classes of symptoms and ten specific symptom events are also listed.

Fault		Description	Symptom		Description
FA	FA1	Cartridge clogged	SA	SA1	Fade
	FA2	Excessive ink flow		SA2	Specked
	FA3	Misalign		SA3	Dropouts
	FA4	Protective tape	SB	SB1	Vertical repetitive defects
FB	FB1	Wrong font chosen		SB2	Smear
	FB2	Debris build-up		SB3	Gray background
FC	FC1	Wrong colorsmart setting	SC	SC1	Vertical line
	FC2	Grayscale selected		SC2	Loose toner
	FC3	Econo-fast print quality selected		SC3	Misformed character

Table 2.1 Definition of fault states and symptoms

3. Bayesian network analysis

The Bayesian Network for Print Defect Diagnosis was shown in fig. 3.1. The refinement of the Bayesian network was done based on the Minimum Description Length (MDL) principle via machine learning approach (Wai Lam, 1998). In the period that the network is been used, new data about the domain can be accumulated. It is advantageous to be able to improve or refine the network using this new data. Besides improving accuracy of this network, refinement can also provide an adaptive ability. Particularly if the probabilistic process underlying the relationship between the domain variables changes over time, the network can be adapted to these changes and its accuracy maintained through a process of refinement. The description length for a particular network is:

$$\sum_{X_i \in X_N} \left[k_i \log_2(N) + d(s_i - 1) \prod_{j \in Y_{X_i}} s_j \right] \qquad (2.1)$$

where there are N nodes; for node i, k, is the number of its parent nodes, s_i is the number of values it can take on, and Y_{X_i} is the set of its parents; and d represents the number of bits required to store a numerical value. For a particular problem domain, we simplified the formula for the refinement of the network as follows:

$$\sum_{X_i \in X_N} [k_i \log_2(N)] \qquad (2.2)$$

For the refinement of the network, further discussion for the issues revealed that there was a hidden hypothesis, namely that there actually was 'Print Defect', so that, an additional node maybe required to fix the problem.

The prior probabilities of print fault could be obtained from data mining gathered from both repair log and consulted with experts. After all the conditional and prior conditions were entered, we compiled the entire Bayesian network. We tried out several typical cases to test the network. In our classification some states that are in different symptom nodes might occur concurrently. The Bayesian network has been successfully modeled as a first pass and is made to work and show results. The network has been tested with many possible cases and the results have been analyzed for meaning and accuracy.

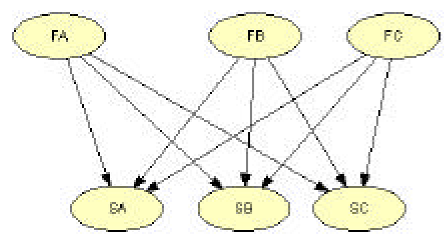

Fig. 3.1 Bayesian Network of Symptom and fault

4. Fuzzy Logic analysis

Fuzzy set theory offers a convenient way for modeling inexactness and uncertainties in fault diagnosis, especially for printing quality problems in which subjective judgments of print quality are communicated in such terms as 'light', 'dark', 'fade' or 'blur'. Fuzzy set theory is used in this project to determine the most likely print failure. The membership function of a possible failure is used to describe the extent to which the available information and the system knowledge match this failure. Membership functions provide a convenient means of ranking the candidate faults. Membership functions are manipulated during inference based on rules concerning printing failures. The degree of membership of general fuzzy variables is shown in fig. 4.1 and special ones for print failures is shown in fig. 4.2.

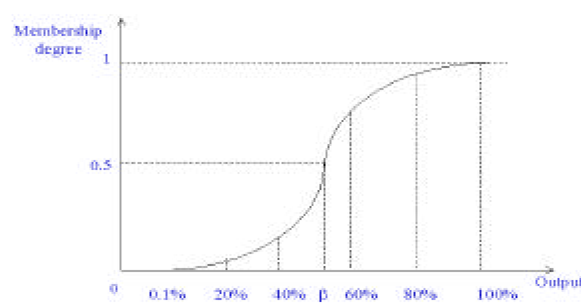

Fig. 4.1 Membership for output

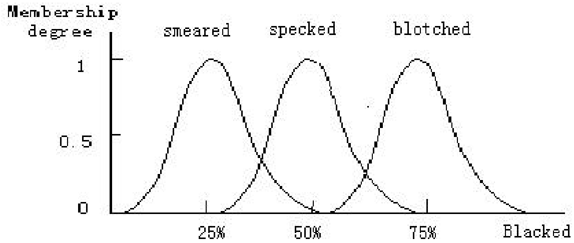

Fig. 4.2 The membership grade of specked

Diagnostic systems are modeled in a cause-effect relation according to an understanding of which causal antecedent produces an outcome. Fault possibility distributions can be shown as below:

$$m_F(f) = \min\{m_{Fs1}(f), m_{Fs2}(f), .. m_{Fsn}(f)\} \qquad (4.1)$$

And it can be obtained by aggregating local fault possibilities associated with each symptom through

$$F_i = S_i * R_{S_i \times F} \qquad (\text{i}=1,2 \ldots \text{n}) \qquad (4.2)$$

To achieve this, a degree of similarity with each possible failure has been assigned. We build on the notion on abduction using a fuzzy causal diagrams (Goebel 2000). The scheme makes use of fuzzy causal diagrams. The failure-symptom relationships are expressed in fuzzy causal diagrams as displayed in fig.5.2-5.4 (here we only take several faults as example).

The fuzzy connection between fault and symptom can be encoded in a fault-symptom matrix. Each fault causes a number of symptoms to some degree. With the assumption that several faults will cause the maximum value of both individual symptoms, modeling of multiple concurrent faults can be achieved.

5. The fusion of Bayesian network and fuzzy logic

In our fusion methodology we use two approaches: Bayesian and fuzzy, to diagnoses print faults. Both of the original diagnoses have a degree of uncertainty associated with them. In the fusion block, the fused values were calculated by taking a weighted average of all the valid diagnosis results using their confidence values as the weights. For the Bayesian networks, we used the probabilities as weights. For the fuzzy logic approach, the weight was calculated by the grade of membership for both diagnosis fault and the symptom of fault

$$U_f = \frac{\sum_{i=1}^{n} u_i s(u_i) + \frac{aU_e}{c}}{\sum_{i=1}^{n} s(u_i) + \frac{a}{c}} \qquad (5.2)$$

Where U_f is fused value, u_i is measurement, s is confidence value, a is adaptive parameter, U_e is expected value, c is constant scaling factor.

Note that the weighted average should also include the predicted value (therefore it needs a confidence value as well), so that if none of the diagnosis results are valid, the predicted value can be taken as the current fused value.

The architecture for the print defect diagnosis fusion system is shown in fig. 5.1. The customer service unit provides print defects information from the customer, which are sent to the database for the data mining and fault diagnosis modules. Failure identification is completed through use of natural language processing and statistical data mining methods. The print defect dictionary information is then used to structure the knowledge base and provide the framework to elicit fuzzy relationships from experts. In the diagnosis module, both Bayesian networks and fuzzy logic were used to diagnose print faults. The confidence values for diagnosis results from both the Bayesian network and the fuzzy logic system were calculated for the fusion calculation in order to get more accurate and robust diagnosis results for print defect diagnostics. The results are returned to the customer service and knowledge base.

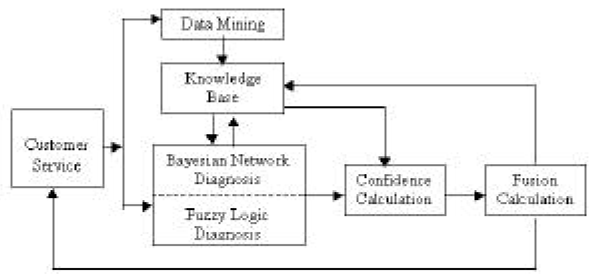

Fig. 5.1 Print defect diagnosis Fusion system

According to this system we take several typical print defect samples as examples to calculate the diagnosis fusion values.

• Symptom SA1

Fault / Symptom	FA1	FA2	FA3	FA4	FB1	FB2	FC1	FC2	FC3
Fuzzy	Very likely			unlikely			likely		
Bayesian	0.592			0.083			0.325		
Fusion	[illegible]			[illegible]			[illegible]		

Table 5.1 The diagnosis fusion for symptom SA1

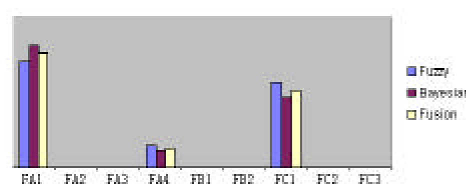

Fig. 5.2 The diagnosis fusion for symptom SA1

• Symptom SB1

Fault / Symptom	FA1	FA2	FA3	FA4	FB1	FB2	FC1	FC2	FC3
Fuzzy		likely		Very likely		un-likely			
Bayesian		0.221		0.622		0.159			
Fusion									

Table 5.2 The diagnosis fusion for symptom SB1

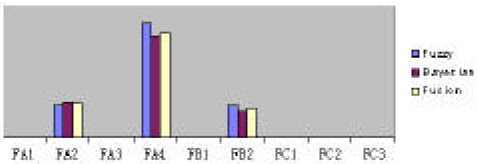

Fig. 5.3 The diagnosis fusion for symptom SB1

Symptom SC1

Fault / Symptom	FA1	FA2	FA3	FA4	FB1	FB2	FC1	FC2	FC3
Fuzzy		likely							Very likely
Bayesian		0.284							0.736
Fusion									

Table 5.3 The diagnosis fusion for symptom SC1

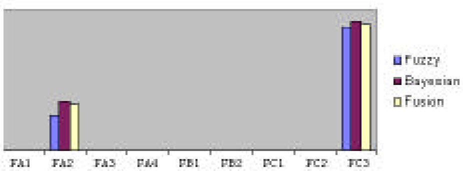

Fig 5.4 The diagnosis fusion for symptom SC1

Discussion and conclusion

A methodology for diagnostic information fusion was described. We aggregated the information stemming from two diagnostic tools to arrive at a more robust result than possible from either tool alone. We dealt with conflict resolution, specifically that dealing with disparate information from multiple sources. The results shown in the previous section were surprisingly accurate and robust after fusion.

There exist many issues involved with the fusion of Bayesian belief networks and fuzzy logic for print defect diagnosis. One issue is the trade-off between the amounts of information a user is willing to provide versus the accuracy of the diagnosis. Another issue is the uncertainty and fuziness associated with the user definition of the problem and symptoms. Yet another issue is how information should be requested and provided to the user. All of these issues will be important for quality implementation of such a system.

A successful implementation of a print defect diagnosis system will streamline communication between customers and call center personnel and reduce diagnosis time. By using the customer as a diagnosis tool, and by better leveraging the existing product knowledge base a more efficient technical support program can be created. Ultimately this will increase prints defect handling efficiency and boost customer satisfaction through improved service.

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