A FUZZY REASONING RULE-BASED SYSTEM FOR LACE PATTERN DETECTION

Nasser Sherkat, Chi-Hsien V. Shih, Peter Thomas
The Nottingham Trent University, Department of Computing

Burton Street, Nottingham NG1 4BU, United Kingdom
Tel: +44 602 486538 Fax: +44 602 486518

ABSTRACT

Lace is liable to stretch as it is passed through the feed mechanism, in which a vision system is engaged to detect the changes of the motif and find the cutting path (river) across the lace pattern. The vision system has to work with many different lace patterns, sizes and tolerate misalignment, stretch and other distortions. A *Fuzzy Reasoning Rule-based technique* is employed in order to overcome the problems of flexibility. Several experiments have been carried out using lace patterns of varying complexity. All cutting paths across the patterns were successfully found. Experimental results indicate that this method can correctly detect the river path in different lace patterns.

I. INTRODUCTION

Handling lace in terms of cutting it along the designed paths is usually carried out manually. Skilled operators use high speed rotating blades or hot wire to cut the lace along the designated path. In order to satisfy industrial requirements two main conditions must be satisfied [4]. Firstly, to achieve a sufficient degree of automation the river must be found without prior knowledge of the lace pattern. Secondly, the process of river location must be carried out in real-time. To achieve this, the extracted knowledge can be used to speed up the search for the river in subsequent frames. The resolution required for image analysis is considerably lower than that provided by general purpose Charge Coupled Device camera (Figure 1). A bi-level image merely consisting of bright and dark areas would suffice (Figure 2) [4].

In white or near white lace, after the thresholding operation, a river shows up as a dark area (pixel group) within the edges that crosses from one side of the image to other in a nearly unbroken sequence (Figure 2). There are *thick white threads* that cross the river at intervals that are indistinguishable from the material surrounding the river (marked by circles in Figure 2). Allowance must be made for small breaks in continuity of the river due to these cross threads.

Lace comprises a fine and intricate pattern, with various densities of knit and holes. On most designs the mirrored pattern repeats many times, but in practice the repeats are never absolutely identical. Furthermore, lace is flexible, extensible and easily distorts, effectively changing the pattern. Norton-Wayne [1] experienced this problem and states this characteristic of lace making it impossible to cut in a consistent position. Russell [3] *et al.* approached this problem by trying to locate a reference feature in the lace motif so they can keep track of the change in the pattern due to stretch. Moreover, the vision system has to work with many different lace patterns and sizes and tolerate misalignment, stretch and other distortions [4]. To overcome the flexibility problem, we employ an inexact decision making theory - fuzzy rule-based inference technique.

In classical normative decision theory the components of the basic model of decision making under certainty are taken to be crisp sets or functions. By *crisp* we mean dichotomous - that is, of the yes-or-no type rather than of the more-or-less type" [8]. The set of actions is as precisely defined as the set of possible states and the utility function is also assumed to be precise. In descriptive decision theory this precision is no longer assumed; but ambiguity and vagueness are very often modeled verbally, which usually does not permit the use of powerful mathematical methods for purposes of analysis and computation. The presented approach draws on this characteristic to cope with the flexibility problems described above.

II. PATTERN RECOGNITION

The scheme for applying fuzzy inference techniques to find the first river across the lace pattern with no previous

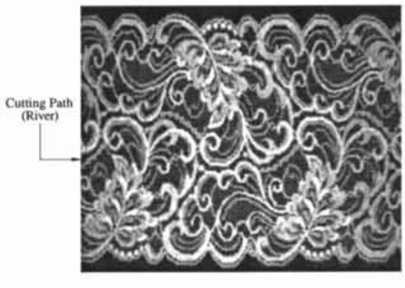

Figure 1: Lace image received from the CCD camera

Figure 2: Bi-level lace bitmap image

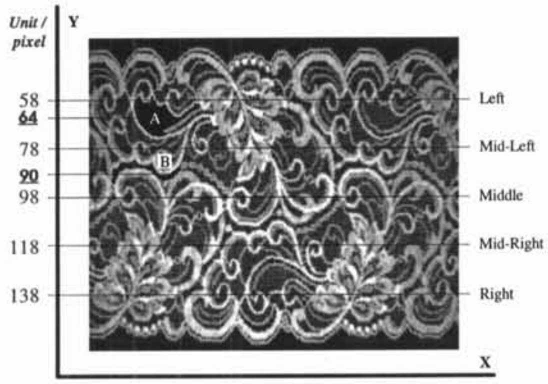

Figure 3: Corresponding positions for black pixel group A and B

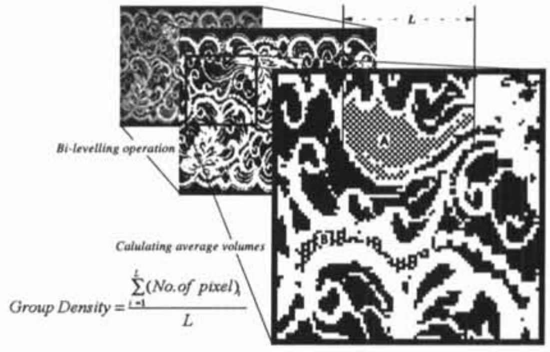

Figure 4: A example for calculating the group densities for group A and B

knowledge can be broken down into the following tasks:

- Defining system input and output membership functions;
- Fuzzification process;
- Inference and composition;
- Defuzzification process;
- Verification.

The system reads two input variables (position and density) after each black pixel group has been processed. The fuzzification process then assigns a value to represent an input's degree of membership in one or more fuzzy sets. During inference and composition process, strengths are computed based on antecedent values and then assigned to the rules' fuzzy output. Finally, the defuzzification process employs compromising techniques to calculate the average weight for system output. These steps are described in detail as follows.

2.1 Defining system input and output membership functions

The degree of membership is decided from overlapping sets of a membership function, which is defined normally based on intuition or experience. The pre-defined membership functions cover the entire range of values for system input and output, and will define a degree of truth for every point in the universe of discourse. The shapes and number of fuzzy-set membership functions we chose depend on parameters such as the required exactitude, steadiness and responsiveness of the system. Different shapes such as triangles and trapezoids are often employed to define fuzzy-set membership functions [7][8].

The objective here is to find the river along a lace pattern, by using linguistic variables to represent the common feature of the river shape in various lace patterns. These common features may be described as:

i) that the *position* of the river is around the *centre* of a lace pattern;
ii) the river pixel group density is not large.

From these linguistic descriptions, two system inputs, *group position* and *group density*, can be defined. By monitoring the position and density of the black pixel groups (Figure 2) across a lace pattern, a fuzzy decision making system can determine whether the pixel group is a possible segment of the river. Figure 3 and Figure 4 illustrate the two system inputs corresponding to an example lace pattern together with two candidate groups A and B.

Two initial experiments were carried out to define the system input and output membership functions. Frequency histograms were used on the sample data to define input membership functions [2][5]. From these experimental results we can obtain a set of data from the *River group* part to define the membership functions. The triangular membership function is most common and has proved to be a good compromise between effectiveness and efficiency. Overlapping between fuzzy-set boundaries is desirable and the key to smooth operation of the system. To simplify the procedure of defining fuzzy membership functions, an overlap of 50 percent between adjacent fuzzy sets is used in this experiment. Besides, each fuzzy set is chosen according to the central value and the slope on either side (Figure 5).

2.2 Fuzzification process

Fuzzification is the procedure of calculating an input value to represent a degree of membership in one or more fuzzy sets. This process uses two basic steps which are repeated for each system input. First, a crisp input has to be read and scaled to a value between 0 and 100. Second, the input must be translated to a degree of membership function. Figure 5 shows two system inputs, *position* and *density.*

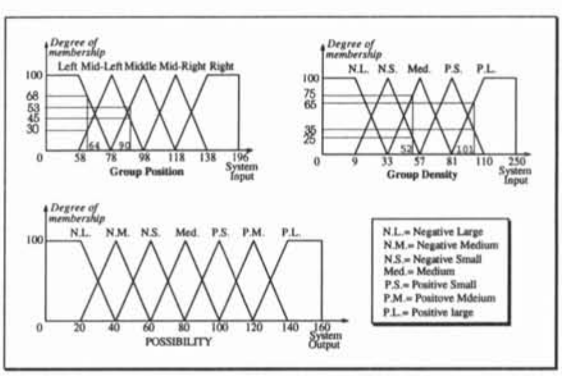

Figure 5: System input and output membership functions

Rule 1:	IF position is Left	AND density is N.L.	THEN possibility is N.M.
Rule 2:	IF position is Left	AND density is N.S.	THEN possibility is P.S.
Rule 3:	IF position is Left	AND density is Med.	THEN possibility is P.S.
Rule 4:	IF position is Left	AND density is P.S.	THEN possibility is N.M.
Rule 5:	IF position is Left	AND density is P.L.	THEN possibility is N.L.
Rule 6:	IF position is Mid-Left	AND density is N.L.	THEN possibility is P.S.
Rule 7:	IF position is Mid-Left	AND density is N.S.	THEN possibility is P.M.
Rule 8:	IF position is Mid-Left	AND density is Med.	THEN possibility is P.L.
Rule 9:	IF position is Mid-Left	AND density is P.S.	THEN possibility is Med.
Rule 10:	IF position is Mid-Left	AND density is P.L.	THEN possibility is N.L.
Rule 11:	IF position is Middle	AND density is N.L.	THEN possibility is P.S.
Rule 12:	IF position is Middle	AND density is N.S.	THEN possibility is P.M.
Rule 13:	IF position is Middle	AND density is Med.	THEN possibility is P.L.
Rule 14:	IF position is Middle	AND density is P.S.	THEN possibility is P.S.
Rule 15:	IF position is Middle	AND density is P.L.	THEN possibility is N.L.
Rule 16:	IF position is Mid-Right	AND density is N.L.	THEN possibility is P.S.
Rule 17:	IF position is Mid-Right	AND density is N.S.	THEN possibility is P.M.
Rule 18:	IF position is Mid-Right	AND density is Med.	THEN possibility is P.L.
Rule 19:	IF position is Mid-Right	AND density is P.S.	THEN possibility is Med.
Rule 20:	IF position is Mid-Right	AND density is P.L.	THEN possibility is N.L.
Rule 21:	IF position is Right	AND density is N.L.	THEN possibility is N.M.
Rule 22:	IF position is Right	AND density is N.S.	THEN possibility is P.S.
Rule 23:	IF position is Right	AND density is Med.	THEN possibility is P.S.
Rule 24:	IF position is Right	AND density is P.S.	THEN possibility is N.M.
Rule 25:	IF position is Right	AND density is P.L.	THEN possibility is N.L.

***Figure 6:** System rule base*

Each value of system input has a degree of membership in each of these sets. Once the degrees of memberships are assigned, the values are used to evaluate the rules.

2.3 Inference and composition

Fuzzified inputs are processed through a pre-defined set of rules using min-max evaluation to form fuzzified outputs. The author developed a set of rules that have the form of

IF [*antecedent_1*] AND [*antecedent_2*]
THEN [*consequence*]

which are listed in Figure 6. The antecedents of rules correspond directly to degrees of membership calculated during the fuzzification process. Each antecedent has a degree of truth assigned to it as a result of fuzzification.

In inference and composition processes, strengths are enumerated based on antecedent values and then assigned to the rules' output strengths. Figure 7 illustrates the actual fuzzy outputs calculated during rule evaluation process for pixel group A. The strength of a rule is assigned the value of the weakest (*minimum*) antecedent. As more than one rule applies to the same specific action, the strongest (*maximum*) value of rules is used :

i) from Rule 4:

$N.M.^{rule\ strength}$

$= \min(antecedent\_1, antecedent\_2)$

$= \min(68, 35) = \underline{35}$

ii) Rule 5:

$N.L.^{\text{rule strength1}} = \min(68, 65) = 65$,

from Rule 10 also

Rule1:	IF position is 68	AND	density is 0	THEN possibility is N.M.
Rule2:	IF position is 68	AND	density is 0	THEN possibility is P.S.
Rule3:	IF position is 68	AND	density is 0	THEN possibility is P.S.
Rule4:	IF *position is 68*	AND	*density is 35*	THEN possibility is *N.M.*
Rule5:	IF *position is 68*	AND	*density is 65*	THEN possibility is *N.L.*
Rule6:	IF position is 30	AND	density is 0	THEN possibility is P.S.
Rule7:	IF position is 30	AND	density is 0	THEN possibility is P.M.
Rule8:	IF position is 30	AND	density is 0	THEN possibility is P.L.
Rule9:	IF *position is 30*	AND	*density is 35*	THEN possibility is *Med.*
Rule10:	IF *position is 30*	AND	*density is 65*	THEN possibility is *N.L.*
Rule11:	IF position is 0	AND	density is 0	THEN possibility is P.S.
Rule N:	*IF position is A*	*AND*	*density is B*	*THEN possibility is C......*

***Figure 7:** Inference and composition for pixel group A*

$N.L.^{\text{rule strength2}}$

$= \min(30, 65) = 30$

then the maximum rule strength on fuzzy set N.L. is

$N.L.^{rule\ strength}$

$= \max(65, 30) = \underline{65}$

iii) Rule 9:

$Med.^{rule\ strength}$

$= \min(30, 35) = \underline{30}$

2.4 Defuzzification process

Defuzzification process is to convert its fuzzy outputs into a signal raw or crisp output. There are many defuzzification methods. In these experiments, we chose the *"centre-of-gravity method"* which is a common and accurate defuzzification technique for resolving both the vagueness and conflict [6][7]. Figure 8 illustrates defuzzification of the output using the centre of gravity method. The weighted average is calculated as follows:

$$Weighted\ average = \frac{\sum(shaded\ area \times centroid\ point)}{\sum(shaded\ area)}$$

By relying on the use of fuzzy inference technique, each black pixel group is calculated and assigned an average weight (*possibility*). For instance, in Figure 4, the output value for group A is 39.37 (*16.14 %*) (see Figure 8), also group B is 134.64 (*95.53 %*). Since the average weight of group A is only 16.14% (less than 50%), the pixel group only has a 16 percent *possibility* of being a segment of the river. Therefore group A is not a part of the river.

2.5 Verification

Once *all* the black pixel groups have been assigned a *possibility value* (average weight), pixel groups whose

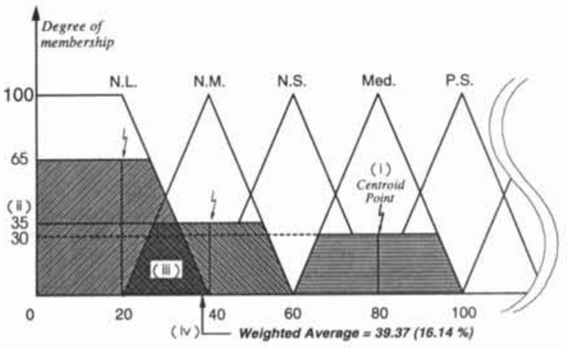

***Figure 8:** Defuzzification process for pixel group A*

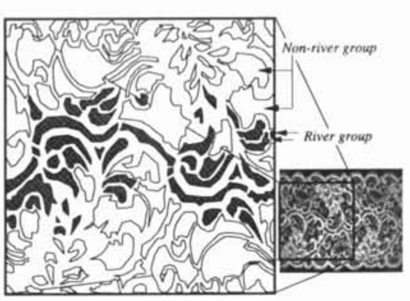

***Figure 9:** Each possible river segments whose weights are bigger than 80 (50%)*

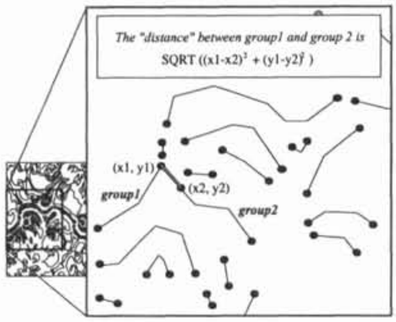

Figure 10 : An example for calculating the distance between pixel groups

possibility values are less than 80 (50%) are abandoned (Figure 9). The verification process can then be broken down into the following tasks:

i) Calculate the distance between two adjacent groups;
ii) If the distance is shorter than a specified value (set to six pixels long in these experiments) a network is built to record this path;
iii) Continuously trace the distances between pixel groups while recording all the correct paths until a new pixel group reaches the border of the image (right hand edge of the frame);
iv) Calculate the total possibility values and divide by the number of the group in this path (*average possibility*);
v) If the *average possibility* is bigger than a specified value, (110 or 75% was used in the experiments) then the correct river has been found; if the average possibility is less than this value, repeat step (iii) to (v) until the correct river is located.

Figure 10 illustrates the computation of the distance between two adjacent pixel groups. By calculating the distances and tracing the average possibilities in all these segments, the river location, highlighted in Figure 11, can be pin-pointed.

III. EXPERIMENTAL RESULTS

A number of experiments were carried out to evaluate the effectiveness of this method. Various kinds of lace patterns were employed for detecting the river location. All cutting paths across the patterns were successfully found. The time taken to isolate the river and produce cutting path depends on complexity of the pattern. Time taken for most kinds of motif is typically about 0.3 second using an Intel 80486 processor running at 66 MHz. However, in the case of a very few intricate lace patterns (e.g. Figure 1), up to 1.5 seconds is required. Once the river path on the first frame is found, this knowledge can be utilised to speed up the detection for the river in subsequent frames to meet the real-time requirements of the system. Some sample laces

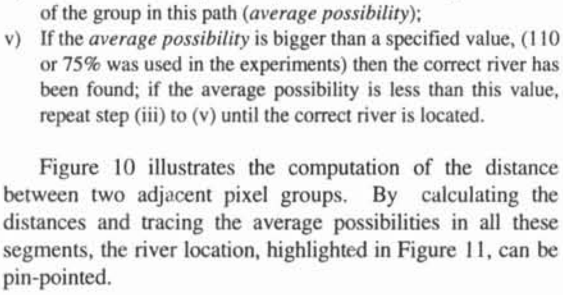

Figure 11: Interconnection between each possible river segments

together with the resulting river path are shown in Figure 12 and Figure 13.

IV. CONCLUSION

We have described attempts to develop a fuzzy reasoning rule-based system for detecting various kinds of lace patterns. Experimental results indicate that the objectives have mostly been fulfilled. The system requires no prior knowledge of any particular lace pattern or training. According to the results this method can precisely detect the proper river path within diversified lace patterns. Comparing with the previously reported methods [3][4], it is not only relatively easy to design and implement the system by means of using the fuzzy reasoning techniques, but also more maintainable.

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Figure 12: Example A of river extraction

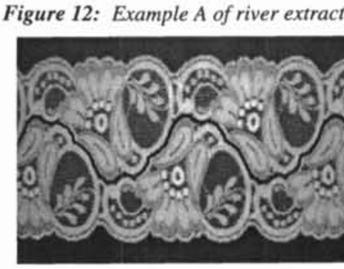

Figure 13: Example D of river extraction