Color recognition enhancement by fuzzy merging

Vincent Bombardier, Emmanuel Schmitt, Patrick Charpentier

Color Recognition Enhancement by Fuzzy Merging.

Vincent Bombardier, Emmanuel Schmitt and Patrick Charpentier,

Centre de Recherche en Automatique de Nancy (CRAN), CNRS UMR n°7039
Faculté des Sciences, Bd des Aiguillettes – BP 239
54506 Vandoeuvre-lès-Nancy Cedex, France
{vincent.bombardier, emmanuel.schmitt, patrick.charpentier}@cran.uhp-nancy.fr

Abstract. This paper deals with color matching in a wood quality control problem. The main difficulty consists in the recognition of gradual color in an industrial context. The wood, which is a natural material, implies a subjective processing to make the controls. The current methods do not take into account the human aspect of the process. An improvement consists in integrating the imprecision of this subjectivity by using the concept of Fuzzy Sensor. Such a sensor has been developed and done with a Fuzzy Rule Classifier which is quite efficient with imprecise data. Then, in multi-face color matching case, the color recognition is enhanced by merging the outputs of the sensors used together. A specific fuzzy merging operator is proposed to use and compared with more classical merging methods. The obtained results show the efficiency of the proposed enhancement.

Keywords: Image processing, Color matching, Pattern recognition, Fuzzy sensor, Fuzzy merging.

1 Introduction

The problem of matching wood pieces is an important issue. It affects many activities of the timber industry (veneer, paneling, manufacture of squares, etc ...). Since we try to get a product, a result of the assembly of several component pieces, with a visual consistency, this problem is found.

In this paper, a new method is proposed for the matching of red oak pieces to produce squares which will be assembled to become stair handrails (fig.1). The wood pieces have to be assembled according to their color of appearance. The aim is mainly to provide a wood piece that seems to be homogeneous and massive.

The colors which must be identified are intrinsically fuzzy (impact of the wooden fiber in the wooden color notion). Thus the colour descriptors calculated on the images are uncertain and imprecise. Moreover, the user of the system expresses his needs under the guise of linguistic terms. The output classes are subjective and non-disjointed. The perception of colors is then gradual. For example, there are no strict bounds between a “red” wood and a “light red” wood. In this case, the difference is given by the wood expert and not by the vision expert. Even if the contrast is not very good in this picture, the real hue of the wood board is not evident for a non-specialist In this way, the fuzzy logic concept stands out as the most flexible technique [1].

Another difficulty takes place in small number of samples that it can be obtained for learning step. Thus, the industrialist cannot provide a consequent and homogeneous data set because of the rarity of particular wood color. So, we proposed to use for the color recognition step a Fuzzy Rule Classifier, which is well-adapted in this industrial context [2].

In the following sections, the color identification vision system is first detailed. Then some backgrounds on the Fuzzy Linguistic Rule Classifier are introduced. Finally the merging method and its application in an industrial context are presented.

2 Proposed Matching Process

This study concerns the development of a matching system for wooden boards according to their colorimetric aspect [3]. This recognition is carried out in real time on the industrial production line. These lines may reach speeds up to 400 meters of board length per minute. After the color identification step, done by the vision system, color information is sent to an optimization step. Then each board is sent to a sorting line or to a cutting line. The cutting line aims to split the boards into uniformly colored piece of wood. The sorting line aims to group pieces of wood into specific classes, whose number and definition are given by the final customer. The boundary classes are very subjective in both cases.

The originality of the process concerns the color sorting which is realized only on the wooden board edges (board thickness). Indeed, the machining of handrails requires a uniform color in a large thickness (Fig. 1). To obtain this large thickness, three boards are glued by their face. So, the final product makes illusion of a product carved in an uncut wood piece. However, operators use the two wide faces to take their single and global decision and it is necessary to make the same classification only by taking into account the edge decisions.

Fig. 1: Schematic representation of the final products considered in the study.

The used acquisition system is made up of one type of linear sensors: CCD color cameras. This CCD sensor provides the red, green and blue components of the signal. The signals are sampled at the rate of 1500 lines per second. Each line is composed of 900 pixels. Fig. 2 illustrates the acquisition system with the processing parts in the case of two color cameras.

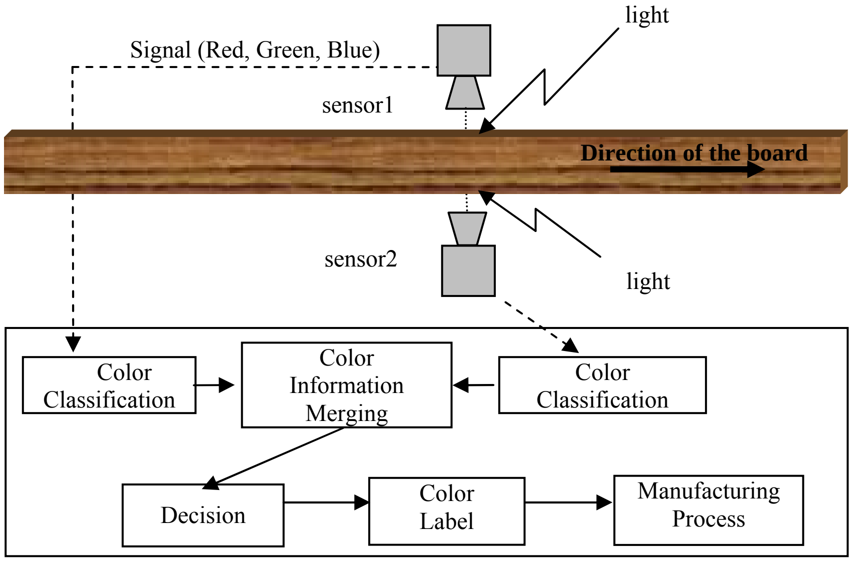

Fig.2: Acquisition system and processing parts.

Several factors can have an impact on the measurements provided by these sensors. Among these parameters, it can be listed the ageing of the acquisition system, the ambient temperature of use, and the precision of the wooden board convoying, i.e. the precision on the distance sensor/board. By integrating correction models concerning the evoked parameters, the imprecision in the measurements will be reduced [2]. That is why we decide to develop our system under the form of an appearance fuzzy sensor [4].

Two aspects are essential to characterizing color: the reference color space and the characteristic vector.

One of the most common color spaces denoted RGB, organizes the color information of an image into its red, green, and blue components. However, the International Commission on Illumination (CIE) does not recommend its use because the color components are not independent of one another [5]. Other popular color spaces include the Lab and HSV (Hue, Saturation, Value (intensity)) spaces. Many studies on color space selection have been conducted elsewhere, i.e. [6] [7]. After conducting several internal tests on various sets of wood samples, we decided to work in the Lab space because it provides the best color discrimination in term of recognition rates. We have also done this choice in relation with an objective criterion funded on Δ_{cielab} recommended distance [8]. This could perhaps be explained because this colorimetric reference space represents colors in the same order than humans do and the color class definitions are given by customers.

In the same way, it is necessary to characterize a color with a set of parameters which are extracted from the image. This set, called "characteristic vector" characterizes color in a simpler way. We choose one of the simplest attribute responding to the calculation time criterion: the average of L, a, b values in the

Region Of Interest (ROI). The size of 300 lines was selected after a study of ROI size impact in processing time between 50 lines and 450 lines [8].

It must be noticed that colors we have to recognize are closed and are supposed to be homogeneous in the ROI, so the average gives a good characterization of the R.O.I. CIELab space has metric color difference sensitivity and is very convenient to measure small color difference, while the RGB space does not [30].

The second part of the vision system is the color identification step which uses for input the characteristic vector and provides for output the label of processed ROI's board.

3 Fuzzy Linguistic Rule Classifier

For the color identification in wood context, the used methods are often based on k nearest neighbor algorithm [9] [10] or on distance minimization algorithms [11] [12].

However, these methods are not really well-adapted to the applicative context as described in section 1 (color subjectivity in human classification, gradual output classes …).

The Fuzzy Rule Classifier (FRC) [13], based on a fuzzy linguistic rule mechanism, is more convenient for our industrial context. Indeed, it has got a good generalisation capacity as it is shown in several comparisons done with other classifiers such as bayesian classifier, K-Nearest Neighbour, Neural Network or Support Vector Machine [14]. It is able to take into account the graduality of the output classes.

This fuzzy recognition method is a supervised mechanism divided into three parts as shown in Fig. 3: Input fuzzification, Fuzzy rule generation and Model adjustment.

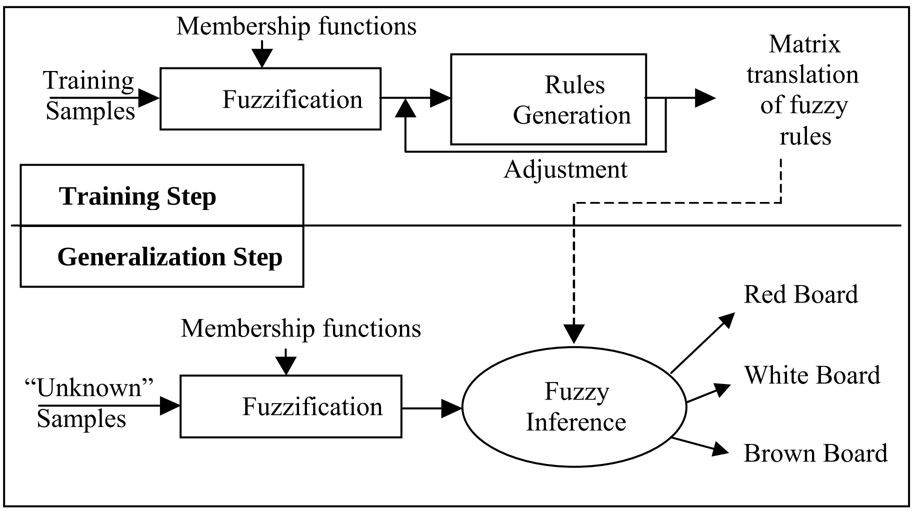

Fig. 3: Overall description of the Fuzzy Rule Classifier

3.1. Input Fuzzification

The fuzzification step aims to translate numerical variables into linguistic variables. A linguistic variable [15] is defined by a triple value (V, X, Tv) where:

- V is a variable (area, size, etc.) defined on a set of reference X
- X is the universe of discourse (field of variation of V)
- Tv is the chosen vocabulary to describe in a symbolic way the values of V (small, big, etc.).

The set Tv = {A1, A2, ...}, finite or infinite, contains normalized fuzzy subsets of X which are usable to characterize V. Each fuzzy subset, Ai, is defined by the membership degree µAi(x). This fuzzification step defines the decomposition number of the considered variable to provide the fuzzy rule premises.

For example the L color composant could have a Weak, Medium or High value. The symbolic vocabulary associated with this variable is then Tv = {Weak, Medium, High}. So, this variable will be split into three terms and characterized by a vector composed of three membership degrees: $[\mu Weak(x), \mu Medium(x), \mu High(x)]^T$.

The different terms are chosen in relation to the expert vocabulary. The number of terms used to qualify a linguistic variable is, generally, empirically defined. But, the industrial user, who is not an expert in pattern recognition, often chooses a regular distribution of terms, generally having more terms than are needed. Whenever the number of terms increases, so does the number of rules and, thus, the overall complexity of the entire system. Classical automatic methods are based on Genetic Algorithm [16] or Clustering [17]. The main drawback of these methods is that they need lots of samples to be efficient.

The chosen fuzzification method is based on the study of the output class typicality [18]. From the Typicality measure T(V), the correlation (Corr) and the cross-correlation (Xcorr), coefficients are computed for each output class. Then, from the ratio Corr/Xcorr, which characterizes inter-class similarities, the number of fuzzification terms is determined. Their positions are obtained by calculating the mean value of the samples belonging to the considered output classes [14].

3.2. Fuzzy Rule Generation

This second step allows the defining of "If… Then…" fuzzy rules. For instance:

« IF L is (High) AND a is (Big) AND b is (Medium) THEN the Color IS (Light Red) »

Each rule describes the perceived delay, related to the system. Such rules can be classified into two categories: conjunctive rules and implicative rules. These two categories are regrouped respectively. On the one hand, there are the possibility rules and the anti-gradual rules and, on the other hand, the certitude rules and the gradual rules. The conjunctive rules are derived from the data analysis field where reasoning mechanisms are led by the data whereas implicative rules are most utilized in the cognitive sciences field where reasoning is led by knowledge [19].

For this application, conjunctive reasoning mechanisms have logically been selected. Each rule is activated in parallel and a disjunction operator combines the intermediate results. Moreover, this inference mechanism assures the consistency of the rule base [20]. If no information is processed, that is, the input space is not covered by the rule set; the output gives an "unknown defect" class. The two main models using these rules are the Larsen's model and the Mamdani's model. The Sugeno's model is not suitable in this case because the aim is not to achieve numerical output values.

The chosen classifier is based on Ishibuchi's algorithm which provides an automatic rule generation step [21]. There are many methods, which automatically obtain fuzzy rules according to data sets such as a genetic algorithm [22], but the Ishibushi's algorithm is quite simple and gives better results [14]. Moreover, its inference mechanism follows the Larsen's model, which is better than the Mamdani's model, because the Product is more adapted than the Minimum for the manipulation of several premises [23]. In fact, it allows non-linear splitting of variable input space. The iterative version of the Ishibushi's algorithm [24] is used here. It allows to adjust the input space splitting by supporting the rule of having the maximum response.

3.3. Model Adjustment

The adjustment represents the iterative part of the algorithm. The following mechanism allows for the adjustment of the decomposition of representative space according to the achieved results. From the training patterns, the algorithm generates the first model and a CF confident coefficient is calculated from the truth degree of each rule.

If the classification rate is below ą threshold, defined by the user, the iterative part is performed to adjust this rate by modifying the CF value. This coefficient is increased if the sample confirms the rule and decreased in the contrary case

The output of the fuzzy classifier is a fuzzy vector whose components indicate the possibility that such board belongs to such color class. It can be noticed that these possibility degrees are not complementary.

Usually, the final decision is taken at this level by using a disjunction operator as max. The board is allocated to the color class corresponding of the maximal possibility degree. However, in this industrial context, two color sensors are used to give the board final color. So, it will be better not to take the decision sensor by sensor but to keep the possibility degree and to decide by merging both fuzzy information provided by each sensor. The next section details this merging step.

4. Multi-Face Matching by Fuzzy Merging

4.1. Fuzzy Merging Operator Used

Then, at this level, both delivered information must be merged to provide a single decision to classify the board. To define the final color thanks to the collected information, it is currently used a Symbolic Merging performed only from the symbolic terms provided by each colorimetric fuzzy sensor [25] [26]. The *AND* operator is applied to merge the data. Thus, a color class is allocated to a final product, only if the two sides have been recognized as the same color (*IF* Red on side 1 *AND IF* Red on side 2 *THEN* color is RED). All the other cases are considered as a rejection class. This Symbolic Merging is very restrictive.

In this case, the fuzzy outputs of the system are not used. By using the possibility degree provided by the each sensor, the uncertainty of the results can be taken into account. For instance, the results of two fuzzy sensors can be considered. The first sensor S_1 gives the color class Red with a membership degree value equal to 0.8 and the class Brown with a membership degree value equal to 0.3. The second sensor S_2 gives the color class Red with a membership degree value equal to 0.5 and the class Brown with a membership degree value equal to 0.6. If the maximum value for each sensor is considered, the merging result allocates the rejection class. However, the output of sensor S2 seems not to bet sure because the difference between the two possibility degrees is reduced. Thus, if the fuzzy output is considered by using a merging operator, these possibility degrees can be taken into account.

In order to totally exploit the fuzzy outputs through their possibility degrees, it will be better to use a suitable merging operator [27]. In our application case, a wise operator is proposed to be used [28].The presented operator has been developed in CRAN research team and have been soon applied in similar industrial vision context.

It is defined from two linguistic variables x and y.

$$F\left(x, y\right) = \min\left[1, \frac{\min\left(x, y\right)}{1 - \min\left(x, y\right)}\right] \tag{1}$$

where F(x,y) is the wise operator
x and y are the linguistic variables.

From the calculation of the expression (1) for all possibility degrees of each color classes, the merging results are obtained for the color class, which allows to check these relations (2).

$$\begin{cases} \text{if } x \leq y \text{ then } x \leq F\left(x, y\right) \leq y \\ \text{if } y \leq x \text{ then } y \leq F\left(x, y\right) \leq x \end{cases} \tag{2}$$

In the case where possibility degrees of both linguistic variables are superior to 0.5, the relation (3) is checked.

$$F\left(x, y\right) \geq \max\left(x, y\right) \tag{3}$$

In this way, by using a fuzzy merging of both single-face fuzzy results, the sorting rates in the rejection class can be reduced as it can be seen in the following section. A numerical example of using this fuzzy merging operator is given in [2].

4.2. Results

The whole tests have been made on “red oak “ boards. This wood specie is divided for this application case into 6 “customer” color classes: Dark Brown, Brown, Light Brown, Dark Red, Red and Light Red.

In order to check the choice of the merging operator, the final recognition rates obtained after merging are then compared. Two databases used have been provided by the industrialist, one corresponding to the acquisition data of the Left Sensor, and the second relating to the Right Sensor. The learning database, used for generating the rule model is composed with 316 data samples. The database used in the generalization step hold 627 samples.

The recognition rates provided by the Fuzzy Rule Classifier for both Left and Light sensors are respectively 85.65% and 86.12% with generalization data set. A comparison with other classifiers on this study case can be found in [2]. These recognition rates are satisfactory but using a Symbolic Merging has defined in section 4.1, the final recognition rate decreases to 79,9% as shown in Fig 4. Others comparisons are given in this figure, with usual fuzzy merging operators [27].

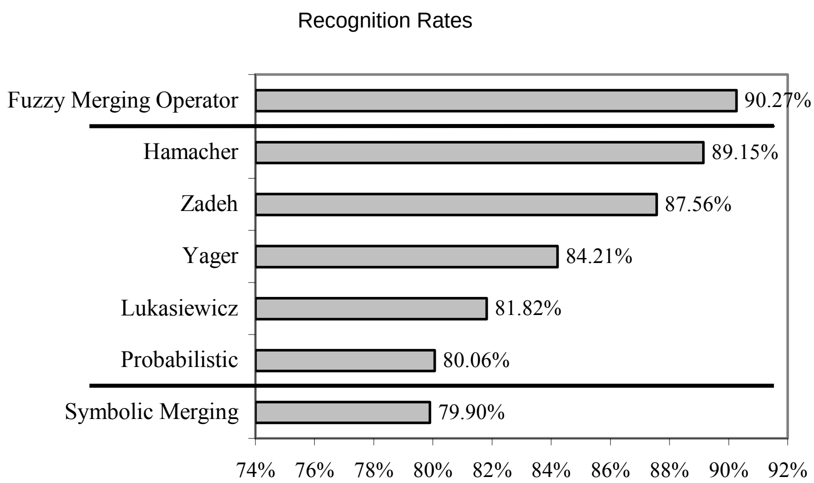

Fig. 4: Comparison of the recognition rates provided by merging both right and left sensors.

To do this comparison, the intermediate results provided by each T-norm are aggregated using Max operator. Thus, the outputs delivered by probabilistic and Zadeh T-norm respectively correspond to the implementation of Larsen and Mamdani models whose rules are the ones used in the Symbolic Merging.

The results show that using a fuzzy merging operator really increases the final recognition rate and then the global classification. Moreover, the proposed F operator gives an even better result. Indeed, the final recognition rate reaches 90%.

In a specific case, where the customer tolerates the matching of similar faces in terms of luminance (ie matching a Red face with a Light Red face), the final classification rate increases to 95%.

5. Concluding Remarks

In this paper, a wood color classification has been presented. The color perception is a very subjective notion and it is strongly linked to the wood species or to its final use. This industrial application supports the development of an original Colorimetric Fuzzy Sensor [2]. However, the classification can even more be enhanced in the specific application matching case. So, we have proposed to do this matching with a fuzzy merging operator rather than using a Symbolic Merging. These results show the good behaviour of the proposed method and especially of the presented fuzzy merging method (F operator).

The main evolution of the proposed system concerns the expansion to other notions than color. The wooden board appearance is not due to the only concept of hue. Texture and wood grain are also to be taken into account. That is why we would like to develop an appearance fuzzy sensor putting together several wood appearance attributes.

Then, further investigations aim to reduce the number of generated rules in order to improve the interpretability of the rule set given by the Fuzzy Rule Classifier. For that, it could be consider the use a tree version of it [29] where the configuration of each fuzzy Inference System is led by expertise and expert knowledge integration.

Another investigation way concerns the integration of Fuzzy Information delivered by such a sensor in the global Information System of the plant.

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