Methodology of Virtual Wood Piece Quality Evaluation

Jeremy Jover, Vincent Bombardier and Andre Thomas

Abstract This paper presents a way to evaluate the quality of virtual wood products according to their tomographic image. The main objective is to anticipate a sawmill divergent process in order to enhance the production plan. From a virtual representation of the product, singularity features are extracted and their impact on the product virtual quality is assessed thanks to the Choquet integrals. Next, the visual quality is evaluated by merging singularity impacts and singularity number criterion using suitable operators. Three operators are compared to the mean operator which is the commonly used one when there is little knowledge on the decision process. Finally the measure is express in the Sawmill expert language using linguistic variables which give the possibility degree that the product belongs to each quality. This degree could be understood as the risk to attribute the concerned quality. It is finally used to determine which quality is to attribute to product in order to satisfy customer needs and maximize sawyers benefit by a linear programming algorithm.

Keywords Virtual product · Quality · RX computed tomography · Information fusion · Divergent bill of material

1 Introduction

Divergent processes have always presented a difficulty for the traceability implementation. The raw material cutting leads two problems:

- The link between material and production information is difficult to establish and to maintain all along the product cycle life.

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- Foresee the finish products features, which are very useful for traceability and production management, is full of uncertainty.

Some solutions are proposed to overcome this problem especially in the food industry. These solutions are based on marking and documenting batches [7]. However a part of the root information is lost and a unique identification is not still possible (what is ideally expected).

The wood industry is also concerned by these divergent process problems. From a tree, products satisfying the end customer's needs must be produced. Moreover the product origin traces have to be conserved for traceability reasons [13]. The wood, being a heterogeneous material, increases complexity. Structurally, the wood is composed of aligned fibers following a longitudinal axe. It not reacts in the same way following the different axes (longitudinal, radial, and tangential). The wood color is not homogeneous too: the growing rings alternation, the singularity presence or the fungal attacks (blue stain) create heterogeneity on visual and mechanical points of view.

In sawmills, the optimization, in order to have the right products, is an important and complicated task. Sawyers have to saw products which have characteristics needed by customers, from a raw material which internal characteristics are unknown. Dimensionally, it is easy to foresee and have the right product dimension (apply the cutting pattern), but other features as the color or the mechanical resistance are more complicated to estimate and to characterize before the log is sawed due to their subjectivity character and the wood heterogeneity.

Our researches are concerned by the information loss reduction in the wood industry. We have proposed a solution to mark and maintain the origin information of the trees [11]. In this study, we propose a way to determine the wood product characteristics before sawing operation in order to satisfy the customer needs and the optimal determination of the production element (net requirement for each product quality class). The proposed approach aims to automate the product qualification process (quality product estimation) usually done by an operator. The global process is described Fig. 1.

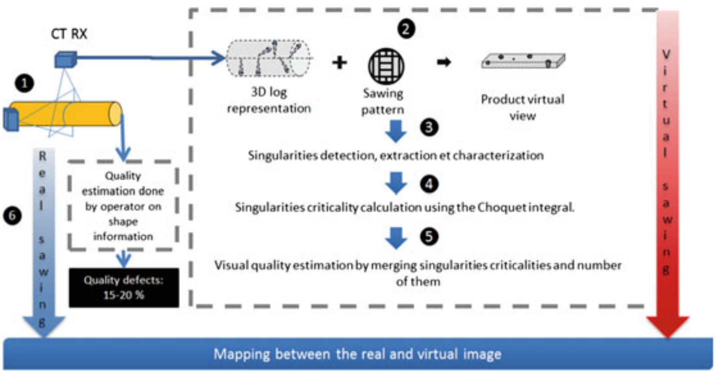

Fig. 1 Extraction and exploitation process of virtual products

In this article, we shortly present the wood quality notion, the sawing optimization process and the virtual sawing concept allowing to extract the virtual product. Then we explain how we characterize singularities and calculate their impact on product with the Choquet integral. Impact calculation is improved by using learning process to calculate the Choquet capacities. To finish, we describe a way to estimate the wood products quality by using the impact singularities. We demonstrate the feasibility with distinguish wood pieces.

2 Production Foresee in Sawmill

2.1 The Visual Quality of Wood Products

Concerning the needs of the first transformation customers, there are three kinds of quality: the dimensional quality, the mechanical quality and the visual (aesthetic) quality. The dimensional quality is easy to characterize (dimension piece precision). The mechanical quality is more skillful to evaluate. The clear wood has a mechanical resistance which can be reduced by the singularities presence (knots, crack, rot . . .). Techniques based on the vibrations give results as explained in [10].

The last one is the visual quality. It is the most complicated to evaluate because the visual quality is a subjective decision. The visual quality is defined in the standard NF EN 1611. This standard defines different classes (five) of qualities based on the singularity feature measurements (size, numbers, type . . .). But the evaluation is done by a Human Expert which has to estimate the quality within a short time (according to sawmill high production rate). In this short time the expert cannot evaluate singularity features as precisely as the standard defines them. So the standard definition is not adapted to the evaluation. More over the wood is “intrinsically fuzzy” [3]. Boundaries between clear wood and singularities are not so easy to determine and impact the characteristic measures. A big part of the price is based on this quality, so its determination is important for customer and sawyers.

2.2 Raw Material Optimization

Sawyers optimize wood by estimating which cutting plan allows to have the best material yield and the customer requirement. That is why it is essential to foresee product features which would be cut in the log.

The Expert (present at the optimization post) estimates product features (dimension, mechanical resistance, and visual quality) according to the external log features and his experiment. He is able to determine approximately which defects are present in the wood (according to the external log features) and decides which cutting plan is the most appropriate to obtain the customer requirement. So final product aspect and

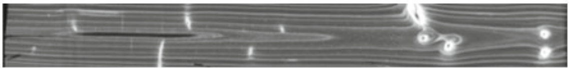

Fig. 2 Example of a virtual sawing extracted side

quality are more or less well determined. We easily understand that all singularities are not visible on the surface and singularities which are visible give only incomplete information on their shapes in wood. Lot of researches have proposed solutions taking into account the external shapes of logs [15]. But these optimizations are only based on the log dimensional features and do not take into account the visual and mechanical characteristics. This paper proposed a way (virtual sawing) to address this issue.

2.3 Virtual Sawing

The use of non-destructive control techniques [4], in particular X ray computed tomography, allows to have a 3D representation of the log (internal and external) to be cut. [1] use volumetric information to improve part log quality determination and their sorting. In our proposition, we investigate this step and the global process is described in the Fig. 1.

The log representation is virtually sawed with ad-hoc software according to a cutting plan. This leads to obtain a numerical view of all product faces which should be obtained. The Fig. 2 shows one face for one product. The obtained image represents the face of a product according to the density data. Some information cannot be obtained (the color) and the distinction between detected object is not so easy. All of these add imperfection, imprecision and uncertainty and make the quality determination harder.

2.4 Problematic

Our aim is to propose a process to estimate the wood product quality according to the face picture extracted by the virtual sawing stage. We consider that the singularity features are computed in a similar way as [3]. So we propose a way to determine quality products from these measurements. As obtained information is uncertain, incomplete and imprecise, we use methods allowing taking into account this imperfection especially the Choquet Integral and fuzzy fusion operators. In this paper, we decide to estimate the singularity impact on the product and then to determine the piece quality.

3 Singularity Impact Evaluation on Virtual Product

3.1 Singularity Criterion Measurement

In our study, we evaluate the visual quality of the wood. So the criteria have to reflect singularity impact on the visual quality. [1] defines forty criteria to evaluate quality. From these forty criteria, only around twenty concern the final product and only a dozen the visual quality. To evaluate singularity impact on density data, we only use the four of them which are measurable on a grey scale image.

The first criterion μ_t, described by the Eq. 1, reflects the singularity size. Bigger a singularity is, more the visual quality is down grading. Moreover the expert judgment stipulates a singularity higher than 50 mm is considered as highly critical.

$$\begin{cases} \mathit{If}\ l \le 50\,\text{mm}, \quad U_t = 1 - T_s/l \\ \mathit{If}\ l > 50\,\text{mm}\ \mathit{and}\ T_s \le 50\,\text{mm}, \quad U_t = 1 - T_s/50 \\ \mathit{If}\ l > 50\,\text{mm}\ \mathit{and}\ T_s > 50\,\text{mm}, \quad U_t = 0 \end{cases} \tag{1}$$

The second criterion u_x, described by the Eq. 2, reflects the position of the singularity on the product length. More a singularity is close to the product end, more this singularity lost importance and the quality becomes higher.

$$u_x = \frac{|L/2 - X_s|}{L/2} \tag{2}$$

The third criterion μ_y, given by the Eq. 3, reflects the position of the singularity on the product width. More a singularity is close to the product edge, more this singularity lost important and the quality becomes higher.

$$u_y = \frac{|l/2 - Y_s|}{l/2} \tag{3}$$

The last criterion μ_c, (Eq. 4), reflect contrast between the singularity and the product background. More the contrast is weak, less this singularity is visible and more the quality increases.

$$u_c = 1 - \frac{|I_s - I_p|}{I/p} \tag{4}$$

In the following part, we proposed a method using Choquet integral according to the fact that the singularity characteristic measurements are full of imperfection and imprecision (see Sect. 2).

3.2 Impact Calculation Using the Choquet Integrals

The Choquet integrals were proposed by Gustave Choquet in 1954 [5]. Their use in the multi criteria decision making domain appears in the nineties in different context (car industry, strategical placement …) and similar classification problems are usually process with the Choquet integrals [8]. They allow taking into consideration importance of each criterion and the interactions existing between each of them.

Let {X}:{x1,…,xn} be a set of normalized criteria, consider a capacity μ:P(X)→ [0,1] on this set, verifying Eq. 5:

$$\begin{cases} \mu(\emptyset) = 0 \\ \mu(X) = 1 \\ \mu(A) < \mu(B),\ \forall A \in B\, and\, B \in X \end{cases} \tag{5}$$

The capacity defines all weights and interactions. Then Choquet integral is defined by Eq. 6:

$$C_\mu(u_1, \ldots u_n) = \sum\nolimits_{i=1}^{n} (u_{\sigma k} - u_{\sigma k-1})\mu(A_{\sigma k}) \tag{6}$$

where σ is the index permutation satisfying Eq. 7:

$$\begin{aligned} &0 = \mu_{\sigma 0} \leq \mu_{\sigma 1} \leq \cdots \leq \mu_{\sigma n-1} \leq \mu_{\sigma n} \\ &\mu_{\sigma 1} = Min(u_i)\, and\, \mu_{\sigma n} = Max(u_i) \end{aligned} \tag{7}$$

and $A\sigma k = \{g\sigma k, \ldots, g\sigma n\}$ the features non used in previous step.

In our case, the $C\mu(u)$ corresponds to the measure of the singularity impact on the product when the Choquet integral is apply on the criteria μi. More the value tends to 1, less the singularity is important (our own standards). The Choquet integral is useful when the knowledge and the learning batches are low. The greatest challenge is the definition of the capacities [8]. To do so, some approaches were developed to learn the capacities.

3.3 Learning Process of the Capacities

In order to have a better definition of the capacities used in the Choquet integral, we decide to use a learning process. Different approaches can be used to identify capacities [8]:

- The Least Square approach (LS): based on the expert knowledge on each element. The expert attributes a target impact value to each element (expected value) in the learning lot and system searches capacities values that minimize the difference square between the computed value and the expected value (Eq. 8).

$$Min\ F_{LS}(\mu) := \sum\nolimits_{x \in O} [C_\mu(u(x)) - y(x)]^2 \tag{8}$$

- The Linear Programming approach (LP): proposed by Marichal and Roubens in [12], it is based on the expert knowledge on the global ranking of the batch elements (Eq. 9). The approach looks for the value which satisfy as closely as possible the ranking establish by the expert.

$$Max\ F_{LP}(\varepsilon) := \varepsilon$$
$$subj.\,to \begin{cases} \Sigma_{T \subseteq S} m_v(T \cup i) \geq \forall i, \forall S \\ \quad \Sigma_{T \subseteq N} m_v(T) = 1 \\ C_v(u(A)) - C_v(u(B)) \geq \delta_c \\ \qquad \vdots \end{cases} \tag{9}$$

In [8], authors explain that the least square approach is appropriate when it is possible to attribute precisely the desired value. They explain too that the linear programming is better for cases which it is easy to give a pre-order between the learning lot elements. This is our case for the evaluation of the singularity impact because it is hard for the expert to give a score for each singularity (due to number and variation of the cases). The expert decides of a pre-order between elements composing the learning batch (with a δ_C corresponding to the minimum margin to respect the ranking). This constraint, noted E, can be translate by equation (10):

$$\begin{gathered} C_\mu(a) > C_\mu(b) > \cdots > C_\mu(k) \\ with\, C_\mu(u(i)) \leq C_\mu(u(i+1)) + \delta_c \end{gathered} \tag{10}$$

Some conditions can be imposed, over the element pre-order, on the criterion importance and/or interaction. The expert can express the criterion importance against one another. By the used of the Shapley indexes ϕ (which indicates the global importance of each criterion), the expert expresses the equality between two criteria. The value δ_ϕ is the maximal distance between two Shapley values to consider two criteria are equal. This constraint, noted S, can express for a couple of criteria A and B as:

$$-\delta_\phi \leq \phi_v(\mu_A) - \phi_v(\mu_B) \leq \delta_\phi \tag{11}$$

More over the Expert can express constraints on the interaction between the criteria. The interaction between two criteria can be easily expressed by the expert because the phenomenon is understandable. But the interaction between more than two criteria is harder to understand and express. The last condition (apply on the interaction indices) is only expressed on interaction between a pair of criteria. This constraint, noted I, can be:

- negative (redundancy): $I_v(\{A, B\}) < 0 - \delta_I$
- positive (synergies): $I_v(\{A, B\}) > 0 + \delta_I$
- null (no interaction): $I_v(\{A, B\}) = 0 \pm \delta_I$

δ I is the minimum threshold value in absolute value to consider the interaction as significant.

Using the software R and the Kappalab R package, we compute the LP approach in order to determine the capacities and influence of the calculated values on the Choquet integral results.

3.4 Result of the Learning Process LP

The learning batch described in the Table 1 is composed of singularities which are commonly found in the wood.

Expert constraints are described below:

- About the elements' batch (E): The singularities are ranked as they are stored in the Table 1 from the best to the worst with $\delta_C = 0.05$.
- About the importance criterion (S): criteria $[\mu_t, \mu_c]$ have the same importance, criteria $[\mu_x, \mu_y]$ too and criteria $[\mu_t, \mu_c]$ are more important than $[\mu_x, \mu_y]$ ($\delta_\mu = 0.1$):

$$\phi_v(\mu_T) = \phi_v(\mu_C) > \phi_v(\mu_X) = \phi_v(\mu_Y) \tag{12}$$

- About the influence among criterion (I): criteria $[\mu_t, \mu_c]$ are in synergy and $[\mu_x, \mu_y]$ too ($\delta_I = 0.05$):

$$I_v(\{T, C\}) > 0 \; and \; I_v(\{X, Y\}) > 0 \tag{13}$$

The results of the Choquet value, the Shapley values and the interaction indices are respectively presented in the Tables 2, 3 and 4. In Table 2, the second column

Table 1 Learning batch

Singularity	a	b	c	d	e	f
T	0.75	0.41	0.39	0.69	0.42	0.75
X	0.72	0.09	0.27	0.36	0.75	0.81
Y	0.2	0	0.24	0.8	0.32	0.52
C	0.93	0.98	0.9	0.37	0.3	0.09

Table 2 Results for the LP approach for the different constraints

Singularity	a	b	c	d	e	f
Ø	0.65	0.37	0.45	0.55	0.46	0.49
E	0.878	0.815	0.753	0.45	0.387	0.325
E+S	0.878	0.815	0.753	0.569	0.422	0.359
E+S+I	0.873	0.799	0.738	0.593	0.532	0.471

Table 3 Shapley indices for the different constraints

Shapley value	T	X	Y	C
E	0.152	0.117	0.069	0.662
E+S	0.397	0.074	0.045	0.484
E+S+I	0.322	0.169	0.098	0.411

Table 4 Interaction indices for the different constraints (symmetric matrix)

Constraints E

Criteria	T	X	Y	C
T	NA	0.006	−0.138	−0.119
X		NA	0.131	0.137
Y			NA	0.007

Constraints E + S

Criteria	T	X	Y	C
T	NA	−0.133	−0.090	0.113
X		NA	0.179	−0.133
Y			NA	−0.090

Constraints E + S + I

Criteria	T	X	Y	C
T	NA	−0.219	0.032	0.050
X		NA	0.050	−0.285
Y			NA	−0.226

corresponds to values obtained without any importance (singleton capacity equal to 0.25) and constraints (other capacity equal to the sum of the singleton capacities) between criteria.

Imposed Constraints are respected at each step (E, E + S, E + S + I). We can see in the Table 2 that the order of the singularity is the same as the expert ranking.

The first constraint (based on the elements ranking) accords lot of importance to the contrast (Shapley value $\phi_{\nu}(\mu_{c} = 0.762)$) and few on the other criteria. Moreover interaction between the criteria [T C] is negative (that is not corresponding to the expert choice). The Fig. 2 shows the variation of the Choquet integrals value function of [X Y]. The criterion Y has little influence except up to 0.75. This translates an

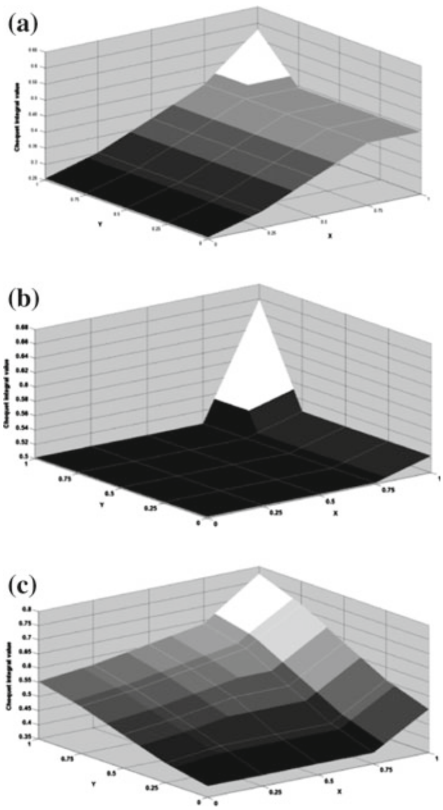

Fig. 3 Influence of the X and Y criteria modification on the Choquet value with the weights obtained under the three different constrain and no variation of the T and C criteria (u = (0.75, Δ(X), Δ(Y), 0.09)). **a** Under E constrains, **b** under E + S constrains, **c** under E + S + I constrains

expert view: the singularity position on the width upgrade the singularity only when it is very close to the side.

The addition of the constraint S (on Shapley indices) offers a positive interaction between [T, C] but does not with [X, Y]. Moreover, the importance of the criteria [X,Y] is so small that they have few influences on the Choquet value. The Fig. 3b shows the Choquet value variation function of X and Y variation for a singularity (u = (0.75, Δ(X), Δ(Y), 0.09)). The criteria have no action when theirs values are below 0.75. This comportment means that singularity position is only important when a singularity is close to the end and the side of the product.

The addition of the last constraint gives capacities which allow the respect of the constraints given by the expert. Moreover all criteria have impact on the calculation result. The Fig. 3c translates the [X, Y] impact. Thereafter we use this weight for the product quality estimation.

4 Virtual Product Quality Evaluation

Once singularity impacts are determined, an estimation of the quality of a virtual product is evaluated by merging these impacts and the criterion related with the singularity number. In this part, we describe this criterion and the fusion operation.

4.1 Singularity Number Criterion

In the quality evaluation, the number of singularities is important. A product with a lot of singularities is more down grading because the clear wood homogeneity is broken.

To evaluate the number, we used the criterion R_{nb} defined by (12). This criterion represents the expert vision: more there are singularities, more the product is down grading. Moreover when the number reaches towards a particular value, the criterion reaches towards 0. We choose to use an exponential function. Following the particular number of singularities fixed by the expert, the k coefficient can be changed. In our case, we determine that up to 20 singularities, the value starts to become constant ($k = 1.1$).

$$u_{nb} = k^{-NB_s} \, with \, k = 1.1 \tag{14}$$

4.2 Quality Determination by Data Fusion

In order to determine the quality product, we merge singularity impacts and the singularity number criterion. There are three kinds of merging operators [2]: Severe, Indulgent and compromise operators.

In the quality evaluation, Expert never evaluates products on the best singularities. So, indulgent operators cannot be used. The two other kinds of operators translate different visions from the expert in quality evaluation. We propose to compare different operators which appear to be well adapted to our use and Expert quality evaluation.

The first operator which can be used is the operator defined by Perez-Orama in [14] and describe by 15. This operator (PO) is a compromise operator when the minimum value is under 0.5; otherwise it is an indulgent operator. This characteristic can be interesting to isolate product with few singularities and evaluate the worst product.

$$F(a, b) = \min(1, \frac{\min(a, b)}{1 - \min(a, b)}) \tag{15}$$

The Hamacher operator, described in 16, is a severe operator. That means this operator gives result under the worst singularity. This can be useful to evaluate quality for product where visual quality is very important (joinery, cabinet . . .) because only products with high quality are highlighted.

$$F(a,b) = \frac{ab}{a+b-ab} \tag{16}$$

The Ordered Weight Average (OWA) adapted to our situation too, described in 17, is a compromised operator. Usually the product quality is based on a part of the worst singularities (represented by α which represent the percent of product fusion). The OWA allows to attribute weight only on this part of the singularities impact C_i.

$$\begin{gathered} \mathrm{F}(u_1,\ldots,u_n) = \sum\nolimits_{i=1}^{n} w_i C_i \\ and\; C_1 \geq C_2 \geq \cdots \geq C_{n-1} \geq C_n \\ with \begin{cases} w_i = 0, \forall i \in [1, \lfloor \alpha n \rfloor] \\ w_i = \frac{1}{\alpha * NB_s}, \forall i \in [\lceil \alpha n \rceil, n] \end{cases} \end{gathered} \tag{17}$$

The results provided by these three operators will be compared to the arithmetic mean (used as a benchmark) which is a classical operator when the aggregation comportment is unknown.

4.3 Sample Set Presentation

We will consider the batch described in the Table 5 taken into sawmill. The first column indicates the piece number, the second the criterion R_{nb} (function of the number of singularities), the third, the impact of all the singularities present on the product and the last corresponds to the product aesthetics class given by the sawmill Expert. The aim is to compare some fusion operators with the expert vision so as to find the closest.

Table 5 List of the piece used to compare fusion operators

Product	R_{nb}	Cu							
1	0.91	0.888							
2	0.91	0.439							
3	0.42	0.888	0.866	0.826	0.776	0.748	0.746	0.674	0.601	0.520
4	0.75	0.814	0.740	0.259						
5	0.75	0.888	0.372	0.332						
6	0.51	0.814	0.740	0.694	0.601	0.565	0.432	0.312		
7	0.51	0.725	0.667	0.587	0.479	0.423	0.372	0.332		

- Piece 1: only one singularity with few impact (impact value close to 1), used for cabinet work.
- Piece 2: only one singularity with high impact, used for joinery work.
- Piece 3: lot of singularity with little impact, function of the use, the quality can be high or not depending on the singularities number. In our case expert classes the product for joinery.
- Pieces 4 and 5: the same number of singularities but one with more singularities with few impact (4) used for joinery work and the other (5) used in industrial carpentry.
- Pieces 6 and 7: more singularities than pieces 4 and 5. Used respectively in industrial carpentry and traditional carpentry.

To compare the operators, two features are studied: the products ranking (cf. Table 6) and the distance between them (cf. Fig. 4). Operators have to be compared on the distance and the groups of products they make. If the ranking is good but groups are totally different from the Expert choice (two products by in the same aesthetic class on the Expert judgment have to be close one to the other) the operator is less efficient than an operator which wrong ranks but keeps the right groups of products.

The Hamacher operator, as it is the only pessimist operator, gives the lowest results. This operator is very efficient to highlight product which have good features. When there are a lot of singularities, this operator reaches towards highly downgrade product (up to 2 singularities, maximum value is 0.5). Three groups of product are made: (a, b) on the top as the expert, (e, d) and (c, f, g) on the low. These seconds' two groups mix quality product express by the Expert. So this operator is useful to evaluate high quality products.

The Perez-Orama operator gives high importance to product with all singularity impacts up to 0.5 and downgrades the others. It assumes that products with less than 8 singularities with an impact up to 0.5, have a quality equal to 1. This operator is particularly useful for a first ranking and extracts products previously described (less than 8 singularities with impact up to 0.5). The operator places on opposite ends *a* and *d* and mades two groups, (b, c) and (e, f, g). This classification is close

Table 6 Piece ranking for each fusion operator

Rang	CE	QE	Hama	PO	OWA ($\alpha = 0.2$)	OWA ($\alpha = 0.8$)	Means
1	a	0	a (0.82)	a (1)	a (0.89)	a (0.90)	a (0.90)
2	b	1	b (0.42)	b (0.43)	c (0.47)	b (0.67)	c (0.71)
3	c		d (0.05)	c (0.43)	b (0.44)	c (0.66)	b (0.67)
4	d		e (0.04)	e (0.31)	g (0.37)	d (0.64)	d (0.64)
5	e	2	c (0.00)	g (0.31)	f (0.35)	e (0.59)	e (0.59)
6	f		f (0.00)	e (0.33)	f (0.55)	f (0.29)	f (0.58)
7	g	3	g (0.00)	d (0.26)	g (0.48)	d (0.23)	g (0.51)

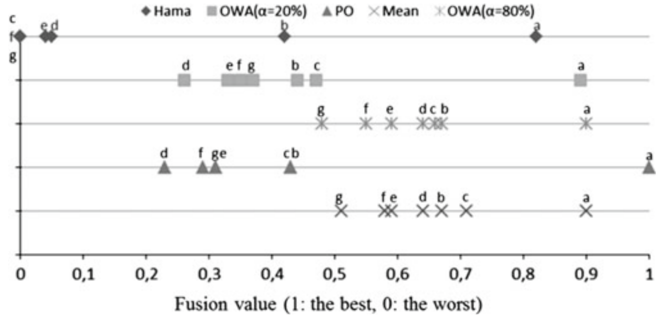

Fig. 4 Result of the fusion operation for each piece

to the expert choice (except for *d*). This operator is efficient to classifie low quality products.

α factor in the OWA operator may change value function of the singularity numbers to be evaluated. We propose to compare $\alpha = 0.2$ and $\alpha = 0.8$. In the $\alpha = 0.2$ case, the ranking gives, as the PO operator, four classes ((a), (c, b),(e, f, g) and (d)) and the same observation as the previous operator. In $\alpha = 0.8$ case, the ranking is the same as the expert. Moreover, product groups do by this operator is the same as the expert classification ((a), (b, c, d), (e, f), (g)). Classes are close to each other but allowed to classify product as the Expert estimation. The Expert who chooses this ranking should have a decision process following this view.

The last is the mean operator. It gives ranking different to the expert ranking but the product groups are respected. This operator may be used to group products with the same features without respecting the ranking. This behavior is interesting for carpentry products for which the ranking is not important.

In the following sections, we use OWA ($\alpha = 0.8$) results which are the closest results to the Expert view.

5 Quality Class Determination

The aim of this section is to propose a way to determine the best quality to be attributed to virtual products in relation with the production data (storage, needs . . .). There are two last steps in our methodology, the first to express the subjectivity and the hesitation which are present in the quality determination and the second one which determines the profitable quality to be attributed to virtual product so as to foresee production and generate product BOM.

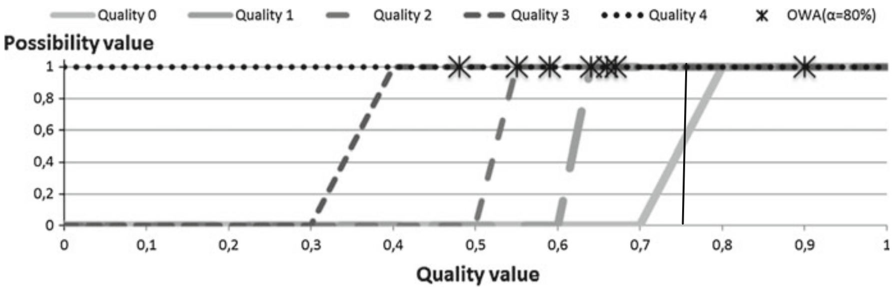

Fig. 5 Membership functions of the visual quality classes based on OWA($\alpha = 0.8$) values

5.1 Quality Measure Expression in the Expert Vocabulary

In order to express the quality measure in the expert vocabulary, we propose to use fuzzy linguistic variables. Its definition is based on constraints coming from the expert definition of the aesthetic quality:

- There are five classes of quality from 0 (the best) to 4 (the worst)
- Lower qualities are included in the best qualities; this means that a product with quality 1 can satisfy needs for the same product with lower quality (2, 3 or 4) but not 0 quality needs.
- Each membership function has core, which means for each quality that there is at least one singularity
- All products have a quality, which means for each quality measure, there is a non-null quality possibility measure.
- We consider that distributions are empirically trapezoidal.

All these constraints allow to determine membership functions for quality classes as describes in the Fig. 5. To define the membership function cores we, use the OWA ($\alpha = 0.8$) value by considering the Expert ranking.

This definition of these linguistic variables gives the possibility degree for each virtual quality. For example, a product with an aesthetic quality value equal to 0.75 (black vertical line) has a vector of possibilities $Q_v = \{0.5\ 1\ 1\ 1\ 1\}$. This measure could be understood by different ways [6], in our case these values correspond to the membership possibility to a quality classes or to the risk taken by the sawyer to attribute a quality class to a product (with the example: 0.75 to quality 0 (a little part of risk), 1 to quality 1, 2, 3, 4 (no risk).

5.2 Most Profitable Quality Determination Using Linear Programming

The previously expressed quality is very interesting for the sawyer because it maintains hesitation and subjectivity in the decision. However as the product sell price is based on its quality, clients need products that match with their needs without any hesitation. So it is essential to determine which quality must be attributed to products in order to satisfy all customer needs while generating the best profit.

To perform this choice, we propose to use a linear program whose variables, constraints and goal are described below, to know if sawyer has to sell product:

- In the best quality with the upper possibility degree, taking no risk of product return
- In the best quality non-null (upgrade the product) and taking the risk of a possible product returns but avoiding storage and maximizing sell price.
- In lower quality (downgrade product) avoiding a too longer storage period and lost link to it.

The risk is evaluated in the goal function by taking directly the possibility degree for a quality.

Variables et constraints
Indices
i : *Sawed product index*
j : *Quality index ($j \in [1, 5]$).*

Variable
x_{ij} : *Function variable {0, 1};*

Sales constants
Qij : *Quality possibility (same as the risk take to attribute the quality)*
Cpij: *Sale cost for product i in quality j*
P_{ij} : *Matrix of the needs for each product reference (1 when needs is present ,0 then*

Storage constants
Cs_{ij} : *Storage cost for the product i*
T_i : *Storage time*

Log constant
Cg : *Log cost*

Constraints

$x_{ij} = [0, 1]$; $P_{ij} = [0, 1]$; $Q_{ij} = [0,1]$; $j \in \{0,1\}$

$\forall i, \sum_i x_{ij} = 1$

Goal function

Table 7 Result of the optimization to determine the profitable quality

Product	Section	F	$Q_{i,0}$	$Q_{i,1}$	$Q_{i,2}$	$Q_{i,3}$	$Q_{i,4}$	Q
2	0.25/0.25	0.7033	0.03	1	1	1	1	1
7	0.25/0.25	0.6331	0	0.66	1	1	1	1
5	0.25/0.25	0.269	0	0.54	1	1	1	3

Table 8 Production data used to determine the profitable quality

Section	Quality	Product need	Cell price	Storage cost	Delay (days)
0.25/0.25	0	6	100	20	12
	1	4	75	20	3
	2	0	60	20	90
	3	10	50	20	7

$$Pour\ i = 1 \ldots n,\ Max(\textstyle\sum_i \left((C_{p_{ij}} * P_{ij} * Q_{ij} - C_{s_{ij}} * T_{ij}) * x_{ij}\right) - C_g = GD$$

We implement this linear programing on a product batch (Table 7 is an extract) whose qualities have to be determined in relation with the production data presented in the Table 8. As we can see, there are three cases to attribute the product quality. The first one is to attribute the best quality with a possibility degree ($Q_{i,j}$) equal to 1 (see product 2). In this case, we insure to satisfy the client need without risk of product come back and a high cell price. The second cases is to attribute the high quality possible with a possibility degree included in]0,1[(see product 7). In this case, we take the risk that the customer can be unsatisfied and to have a product return but to sell it with the higher price. The last case is to attribute a lower quality than the quality used in the first case. In this case, the product is downgrading, the sawyer takes no risk and sells it with a lower price, but avoids a too high storage imposed by a log storage period (see product 5).

6 Conclusion

In this article, we present a way to determine the product quality in the wood industry. We decided to base the product quality evaluation on the singularities impact. As the information used to determine the singularity impact and the quality product are uncertain, imprecise, imperfect, we have to use operators which take into account of them.

The singularity impact is evaluated on criteria (size, position and contrast) which are linked by interaction. Moreover, the poorness of the sample and the knowledge on the process decision, lead us to use the Choquet integral to determine impact. By the use of learning process, we have determined the capacities in order to satisfy the Expert vision.

The quality measure is done by merging the singularity impact and the number of singularities. The use of different operators allows us to cover the majority of cases concerning the product quality determination. The comparison with the expert ranking and classification allows to conclude OWA operator with $\alpha = 0.8$ reflects as close as his choice.

Then quality measures are express in the expert vocabulary by the use of a linguistic variable which transcribes expert decision subjectivity. Finally the uncertainty is removed by determining the most profitable quality function of production data like the storage cost and the sell price.

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