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2pMU1. Modeling of the subjective quality of saxophone reeds

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The subjective quality of cane reeds used on saxophones or clarinets may be very different from one reed to another even though the reeds have the same shape and strength. The aim of this work is to understand the differences in the subjective quality of reeds and to explain them with objective measurements. A subjective study, involving a panel of 10 musicians, was first conducted on a set of 20 reeds of the same strength. Second, signal recordings during saxophone playing (in vivo measurements) were made of the pressures in the player's mouth, in the mouthpiece and at the bell of the instrument. These measurements enable us to deduce specific parameters, such as the threshold pressure or the spectral centroid of the notes. After an analysis of the subjective and objective data (assessment of the agreement between the assessors and the main consensual differences between the reeds), correlations between the subjective and objective data were performed. To propose a model of the subjective quality, a machine learning approach was proposed using partial least-squares (PLS) regression and PLS discriminant analysis. Results show interesting performance of the model in cross validation and open the potential for an objectification of the perceived quality.

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INTRODUCTION

For a saxophone player, the quality of a reed (piece of cane that the player places against the mouthpiece) is fundamental and has big consequences on the quality of the sound produced by the instrument. The experience of saxophone players roughly shows that in a box of reeds, 30% are of good quality, 40% are of medium quality and 30% are of bad quality. Usually, the only indicator a musician can see on a box of reeds is the strength, which is usually measured by submitting a static force on a particular location from the tip. The reeds are then classified according to the strength measured. But the strength is not representative of the quality of the reed. Even for the stiffness of the reed (which should be linked to the strength), there are many differences among the reeds in a box. So the strength is not able to explain the differences among the reeds in a box.

The study of the perceived quality of reeds is important for makers to improve the quality of their production. It is nevertheless a difficult problem because of the important variability of this natural material and of the huge number of influencing factors. In [1], optical measurements were used to assess the vibrational modes of clarinet reeds, which have been correlated with the quality of the reeds as judged by musicians. The authors suggest different patterns of vibrations that should be representative of good reeds. A chemical analysis of the reed material was made in [2], but no significant differences could be identified between good and poor reeds. In [3], B. Gazengel and J.P. Dalmont proposed two categories of measurement to explain the behavior of a tenor saxophone reed. On the one hand, they performed “in vitro” measurements using a mechanical bench to characterize the mechanical response of the reed. The results showed that the repeatability of the measurements was low, and that the mechanical properties of the material may change a great deal over time. Furthermore, except for the stiffness, no variable extracted from the frequency response was able to explain the perceived differences among the reeds. On the other hand, they performed “in vivo” measurements during saxophone playing, by measuring the acoustic pressure at the bell of the saxophone and in the mouthpiece, and the pressure in the player's mouth. These studies, [4], [5], showed that the perceived strength can be explained by the estimated threshold pressure in the musician’s mouth, and that the perceived brightness correlates with the high-frequency content of the sounds. These results were based on a small set of reeds (12) and were limited to simple correlations between subjective variables and objective measurements. To define a predictive model of the subjective quality, more reeds and specific modeling techniques, coming from machine learning theory, are needed.

This article proposes to carry out subjective and objective studies on a set of tenor saxophone reeds in order to define a predictive model of subjective quality. We conducted a thorough subjective study with several assessors in order to evaluate the inter-individual differences and to be confident in the results of this subjective part. Two musicians were used for the objective ‘in vivo” measurements, and their variability was estimated. The modeling of the subjective quality went further than the simple correlation. Partial least-squares regression and Partial least-squares discriminant analysis [6] were used to model the data.

The paper is organized as follows. Section 2 presents the details of the experiment carried out with a set of reeds and a panel of musicians for the subjective study. The objective “in vivo” measurements, made by 2 musicians, are described in detail. Section 3 is dedicated to the presentation of the results of the subjective and objective studies, and the relations between them. After an analysis of the agreement between the different assessments, a predictive model of the subjective quality of reeds is proposed with the partial least-squares method. The last section draws the general conclusions and discusses the contribution of this study.

MATERIAL AND METHODS

Reed Samples – Panel of Musicians

The product space was composed of 20 reeds for tenor saxophone of the same cut, strength and brand (Classic Vandoren, Strength 2.5). There was no preliminary selection of the reeds; they all came from 4 commercial boxes of 5 reeds each. The objective here is to estimate the perceived differences in the 20 reeds.

Ten musicians participated in the subjective tests. They were all skilled saxophonists (students or professionals, with more than 10 years of practice). For the sake of consistency, all subjects used the same mouthpiece during the study (Vandoren V16 T7 Ebonite), however they were asked to play on their own tenor saxophone. These subjective tests took place at CIRMMT (Center for Interdisciplinary Research in Music Media and Technology) in Montreal, Canada. Two skilled saxophonists participated in the objective measurements, labeled as PK and GS in the following. PK and GS performed two sessions of measurements spaced two months apart. They used the same mouthpiece employed for the subjective tests and the same saxophone, a "Conn New Wonder" tenor saxophone.

Subjective Evaluation of the Reeds

In subjective tests, different semantic dimensions are generally defined to assess the differences between products [7]. For saxophone reeds, interviews of saxophonists have shown that the most frequent dimensions relate to "ease of emission", "quality of sound", or "homogeneity". We proposed three subjective descriptors to assess the reeds:

- The *brightness* of the sound produced with the reed,
- The *softness* of the reed, which corresponds to the ease of producing a sound,
- The global perceived *quality* of the reed.

The test was divided into 3 phases: a training phase, an evaluation phase, and the filling out of a questionnaire concerning the mouthpiece, reed, saxophone and musical style the musicians usually play, as well as their past experience.

The training phase was proposed to help the subjects understand the meaning of the two descriptors *Softness* and *Brightness* and to verify their use of the scale. "Anchor reeds", located at the extremes of the "softness" scale, were proposed, and recorded sounds with different *brightness* were proposed. The method is inspired from the training phase described in [8]. Finally, subjects were asked to rate 3 quite different reeds on the interface, to train them in the use of the scales and to verify their discrimination.

The evaluation phase used a graphical interface to assess the reeds. The musician was asked to play each reed and to assess each descriptor on an unstructured continuous scale. The reeds were presented to the subject in an order following a Williams Latin square in order to control the order and carry over effects. Given that we have 20 reeds and 10 subjects, the presentation plan was perfectly balanced. The assessments were repeated two times in two independent blocks. For each of the 10 subjects, the subjective data consist of 2 arrays of quantitative values (one per repetition). The arrays have 20 rows (one per reed) and 3 columns (one per descriptor).

Objective Evaluation of the Reeds

Experimental Set-up

The principle of in vivo measurements is to record objective variables when the musician is playing the reed. The advantage is that we have a real playing situation, but this method has the disadvantage of introducing variability, particularly because of the way the musician plays. We chose to measure the acoustic pressure $\boldsymbol{p_a(t)}$ at the bell of the saxophone and the pressure in the musician's mouth $\boldsymbol{p_m(t)}$. The mouth pressure was measured using a differential pressure sensor Endevco 8507-C1 attached to the front of the mouthpiece in such a way that it was inside the mouth during normal playing. The pressure in the mouthpiece was measured by another Endevco 8507-C1 inserted into a hole drilled in the mouthpiece. The acoustic pressure was measured by a B&K 4190-L-001 microphone placed in front of the saxophone bell. The sampling frequency used was 44100 Hz.

The saxophonists (PK, GS) made the measurements for the 20 reeds with the same material as the subjective test concerning the mouthpiece and the reeds. PK and GS performed two sessions of measurements two months apart. The pattern played by the saxophonists was a descending arpeggio of 7 notes (C4, G3, Eb3, C3, G2, Eb2, and C2-concert key). The playing of the seventh note (the lowest note: C2) was often risky, so we chose to keep the data for only the first six notes. This pattern was repeated 5 times for each reed and each saxophonist.

Playing Variable Estimation (in Vivo)

From the signals, we extracted several variables that are characteristic of the interaction between the musician, the reed, and the saxophone. These variables, defined in [9], are estimated as described in [3]. All of these variables are computed for each note, each reed, and each of the 5 repetitions of the pattern.

A first category of variables concerns the acoustics of the sound, computed from the harmonics of the spectral representation of the stationary part of the signal, defined from the acoustic pressure $\boldsymbol{p_a(t)}$. These variables are:

- The Spectral Centroid (*SC*)
- The Odd-harmonic Spectral Centroid (*OSC*)
- The Even-harmonic Spectral Centroid (*ESC*)

- The ratio between Odd and Even harmonics (*OER*)
- The amplitude of the harmonic signal (*Lv*)
- The 3 tristimuli (*TR1, TR2, TR3*) and an additional stimulus *TR4*

One variable concerns the transient part of the acoustic signal:

- The Attack Time, time to establish the permanent regime (*AtT*)

Finally, 3 additional variables are defined with the pressure in the mouth $\boldsymbol{p_m(t)}$

- The mean Static Pressure, mean of the pressure in the mouth during the stationary part of the signal (*StP*)
- The Pressure Threshold, corresponding to the pressure in the mouth at the beginning of the note (*Pth*)
- The efficiency, defined by the ratio between the amplitude of the harmonic pressure signal to the mean static pressure *StP*, (*Eff*).

The reader may refer to [9] and [3] for a clear description of these variables. In conclusion, each reed is defined by 13 objective variables × 6 notes × 5 repetitions × 4 musicians/sessions. For each of the 2 musicians, the objective data consist of 5 arrays of quantitative values (one per repetition) with 20 rows (one per reed) and 13×6 columns (one per variable and note).

RESULTS AND DISCUSSION

Subjective Results

Agreements Between the Assessors

The sensory panel consisted of J=10 assessors who judged I=20 reeds during K=2 sessions using M=3 attributes. Let Y_k^m denote the $(I{*}J)$ matrix describing the assessments made during session k on descriptor m by all the assessors. The agreement between the assessors in their evaluation of the reeds can be estimated by consonance analysis, a method based on a principal component analysis (PCA) of the assessments. A description of this method can be found in [10]. To study the agreement for each descriptor (independent of the sessions), the repetitions are merged vertically (repetitions are considered as different products). A standardized PCA is performed on the matrix $Y^m(2\,I \text{ x } J)$:

$$Y^m = \begin{bmatrix} Y_1^m \\ Y_2^m \end{bmatrix} \quad (1)$$

A perfectly consensual panel would consist of assessors who rate the reeds in the same way. In this case, the first component of PCA would account for a very large variance. The more the panel is consensual, the more the arrows of the assessors point in the same direction. The percentage of the variance explained by the first principal component is considered as an indicator of the consonance of the panel. The results of the PCA of the matrices Y^m are given in figure 1 for each descriptor. In this PCA, the variables are the assessors (S1 to S10) and the individuals are the reeds.

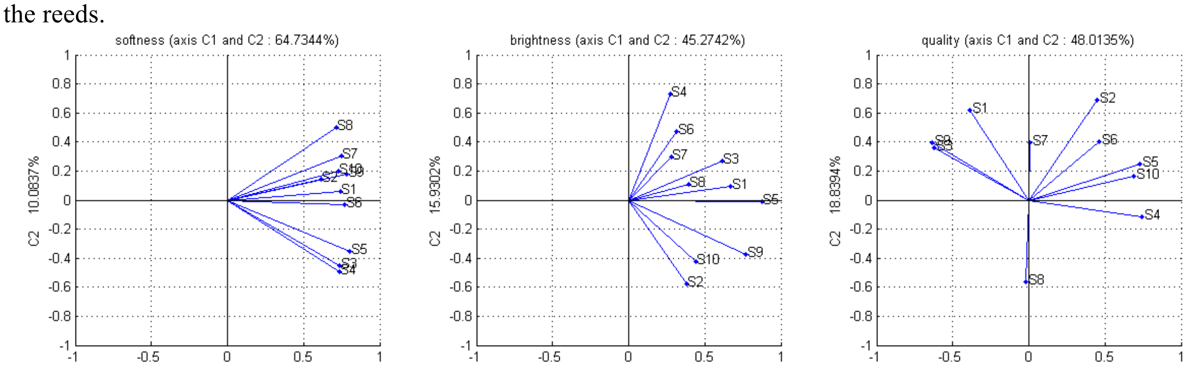

FIGURE 1. Consonance analysis for each descriptor: plot of the first two factors of the PCA (plane of the variables)

The highest agreement is obtained for the descriptor "Softness" (54.6% of variance on the first component). The ratings of the assessors are convergent, and the agreement is the highest. For "Brightness" (29.3%), the agreement is weaker, even though no assessor is very discordant. For "Quality" (29.2%), the agreement is the weakest. This is rather normal, given that this descriptor expresses the preferences of the saxophonist, which are in essence subjective and a function of the tastes of the musician. Subjects S1, S3, S9 are rather opposite to the rest of the panel, and subject S8 is discordant with respect to the general trend of the group.

For the descriptors *Softness* and *Brightness*, no particularly discordant assessor was identified and the descriptors were considered as consensual enough. For the descriptor *quality*, a partitioning of the group and subgroups of homogeneous subjects were defined (not reported in this paper). Additional analyses, not reported here, using the eggshell plot [11] and the GRAPES method [12] led to convergent conclusions concerning the agreement between the assessors.

Global Performance of the Panel

A general method to estimate the discriminatory ability and reproducibility of a panel of assessors is the Analysis of Variance (ANOVA). It is used in sensory analysis to study the differences between products and, more generally, to test the statistical significance of levels of qualitative factors [13].

The assessment of the product i by assessor j during session k is denoted y_{ijk} (i=1 to I, number of products, j=1 to J, number of assessors, k=1 to 2, number of sessions). A model for the whole panel (equation 2) can be created, taking into account the reed effect α_i, the session effect γ_k, and the session*reed $\alpha\gamma_{ik}$ interaction:

$$y_{ijk} = \mu + \alpha_i + \gamma_k + (\alpha\gamma)_{ik} + \epsilon_{ijk} \tag{2}$$

In this model, we don't introduce the subject effect because we consider that we don't have enough degrees of freedom to estimate correctly the contribution of the subject effect, the reed effect, the session effect and the associated interactions in the same model. As a matter of fact, the reed effect determines the discriminant power of the panel, and the reed*session interaction determines the repeatability of the panel. Consequently, the subject becomes a random variable in the model and gives us more analysis power. A least-squares procedure is used to estimate the coefficients of the model. An ANOVA model is fitted for each descriptor. The results of the ANOVA model for the whole panel are given in TABLE **1**.

TABLE 1. ANOVA table for the three descriptors

Softness					
Source	**Sum of Square**	**df**	**Mean Square**	**F**	**P-value**
Reed	1273.18	19	67.01	16.83	<0.001
Session	83.74	1	83.74	21.03	<0.001
Reed/Session	95.23	19	5.01	1.26	0.21
Error	1433.58	360	3.98		
Total	2885.75	399			
Brightness					
Source	**Sum of Square**	**df**	**Mean Square**	**F**	**P-value**
Reed	523.01	19	27.52	5.46	<0.001
Session	39.75	1	39.74	7.88	0.005
Reed/Session	60.35	19	3.18	0.62	0.88
Error	1816.45	360	5.046		
Total	2439.56	399			
Quality					
Source	**Sum of Square**	**df**	**Mean Square**	**F**	**P-value**
Reed	184.71	19	9.72	1.74	0.028
Session	5.00	1	5.00	0.90	0.34
Reed/Session	53.18	19	2.80	0.50	0.96
Error	2010.02	360	5.58		
Total	2252.91	399			

The reed effect is significant for all the descriptors ($p<0.05$), which signifies that the panel discriminated the reeds well. The reed*session interaction is not significant for all the descriptors ($p>0.05$), which means that there is no disagreement in the panel from one session to another. Given that the reed effect is significant, we consider that the panel of assessors is discriminant/repeatable enough to aggregate the data in a consensual evaluation, representative of the reeds.

Subjective characterization of the reeds

Several methods are proposed in sensory analysis to transform individual evaluations in an average multivariate description of products. The first method is to compute the average values of the reeds according to the 2 descriptors *Softness* and *Brightness*, for the 10 subjects, denoted $y_{i..}$. The position of the reeds (R1 to R20) is given in Figure **2**.

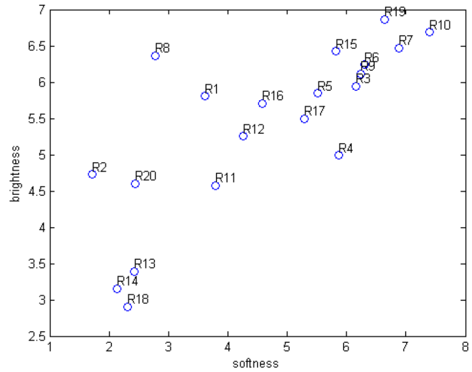

FIGURE 2. Position of the reeds according to "softness" and "brightness" (average configuration)

R10 , R7, R19 are the most soft and bright reeds, R14, R18, R13 are the least soft and bright reeds. There is also a correlation between the two descriptors *Brightness* and *Softness*: a bright reed is also generally soft. To get a group average configuration, we used different methods of multivariate analysis that differ in the way consensus is defined, like the GAMMA method [14] and the Generalized Procrustes Analysis [15]. Given than the agreement between the musicians was good, in the end these methods gave very similar results to the simple average configuration. So we decided to use the scores of the average configuration $y_{i..}$ to characterize the reeds.

Objective Results

Individual Results of Each Musician

For both musicians PK and GS, the intra-reed variance was generally low, since particular reeds sometimes had high variance due to experimental conditions (reproducibility error of the musician, change in the positioning of the reed, change in the positioning of the instrument/microphone…). These conclusions were confirmed by an individual one-way ANOVA, performed for each musician on each descriptor, according to the factor "reed". The results showed that for PK and GS, the effect of the reed was significant for almost all the descriptors ($p<0.05$).

Definition of Consensual Measurements

To define consensual measurements for each objective variable named with the generic notation z_{ijk}, we built an ANOVA model (equation 3) taking into account the reed effect α_i, the musician effect β_j, the session effect γ_k and the reed*musician $\alpha\beta_{ij}$ and musician*session $\beta\gamma_{jk}$ interactions. We didn't take into account the reed*session and reed*session*musician interactions because they were not significant.

$$z_{ijk} = \mu + \alpha_i + \beta_j + \gamma_k + (\alpha\beta)_{ij} + (\beta\gamma)_{jk} + \epsilon_{ijk} \qquad (3)$$

The results of the ANOVA showed that the reed effect was significant ($p<0.01$) for all the descriptors, except OER. These α_i coefficients are used to characterize the reeds according to the objective measurements. Another method, the GAMMA method, was also used to define consensual objective measurements of the reeds and gave similar results (not reported in this paper).

Predictive Model of the Subjective Assessments

One to One Correlation

A simple way to study the relations between subjective and objective variables is to compute the linear Pearson coefficient of correlation. In TABLE **2** are presented the correlation coefficients between the coefficients of reed effect α_i of the global model with interaction (equation 3) for the 13 objective variables on the one hand, and the average values of the subjective assessments of the reeds $y_{i..}$ according to *Softness* and *Brightness* on the other hand. Absolute values greater than 0.8 are indicated by grey cells.

TABLE 2. Correlation coefficients between the subjective descriptors and the objective variables

	Variables												
	AtT	*SC*	*OSC*	*ESC*	*OER*	*Lv*	*TR1*	*TR2*	*TR3*	*TR4*	*PTh*	*StP*	*Eff*
Softness	-0.57	0.64	0.62	0.70	-0.19	-0.38	-0.24	-0.01	0.59	0.37	-0.82	-0.67	0.23
Brightness	-0.33	0.84	0.83	0.84	0.04	-0.39	-0.42	0.10	0.80	0.45	-0.81	-0.80	0.33

The variable that is most correlated with *Softness* is the Pressure Threshold *PTh* (–0.82). This negative correlation makes sense from a physical point of view: a "soft" reed necessitates a low pressure and a "hard" reed a high pressure. *Brightness* has a strong correlation with the Pressure Threshold *PTh* (–0.81), the mean Static Pressure *StP* (–0.80), the Tristimulus 3 *TR3* (0.80), the Odd Spectral Centroid *OSC* (0.83), the Even Spectral Centroid *ESC* (0.84), and finally with the Spectral Centroid *SC* (0.84), which is in agreement with the literature [16]. These correlations also make sense from a physical point of view: a "bright" reed will produce a sound with a high Spectral Centroid and a "dark" reed will produce a sound with a low Spectral Centroid.

Partial Least-Squares Regression Model

The PLS regression is an interesting alternative to multiple regression when the explanatory variables X are numerous and correlated, which is the case with our data [17]. We defined a PLS1 model for each descriptor *Softness* and *Brightness*, using the coefficients of reed effect α_i of the global model with interaction (equation 3) as explanatory variables. The number of PLS components was determined by optimizing the PRESS (PREdiction Sum of Squares with a leave-one-out cross-validation). The prediction error of the model is given by the PRESS RMSE (equation 4), with $E^{(i)}$ the error of the model for reed (i) and n the number of reeds.

$$PRESS\ RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} E^{(i)^2}} \tag{4}$$

The results of the models are given in TABLE **3**. They are compared with the results of a simple linear regression (**LR**) using the objective variable with the highest correlation with the descriptor, i.e., the Pressure Threshold *PTh* for the descriptor *softness*, and the Spectral Centroid *SC* for the descriptor *Brightness*.

TABLE 3. Results of the two predictive models, PLS1 and LR, for each descriptor

	Softness				*Brightness*			
	Nb comp	R^2	RMSE	PRESS RMSE	Nb comp	R^2	RMSE	PRESS RMSE
PLS1	2	0.85	0.76	0.88	1	0.75	0.61	0.66
LR	1 (*PTh*)	0.66	1.10	1.17	1 (*SC*)	0.69	0.67	0.74

The PLS1 models give better predictions than a simple regression model (the PRESS RMSE is always lower with the PLS1 model). The PRESS is interesting for comparing among models, but it is not easy to give indications of the quality of these models in terms of prediction. To interpret the quality of the prediction more easily, a model based on a qualitative variable for the independent variable Y can be fit to the data. The PLS approach, used for classification in the case of a qualitative variable, is in this case called the Partial least-squares Discriminant Analysis (PLS-DA) [18]. First, we have to divide the reeds into classes according to the descriptors Softness and Brightness. To achieve this, we applied a Hierarchical Ascendant Clustering on the subjective ratings $y_{i..}$ of Softness and Brightness, using the Euclidian distance and the Ward criterion. Three classes of reeds were considered on the dendrogram (soft, medium, hard). The classifier is next trained on the data to built discriminant functions, based on PLS components that are linear combinations of the objective variables. A standard evaluation of the quality of a classifier is the Correct Classification Rate (CCR), the rate of items (here reeds) assigned in the correct class by the classifier. Of course, this indicator is not relevant if all the data have been used to build the model. A more relevant indicator is the CCR obtained by a Leave-One-Out Cross validation (the classifier is trained on all the samples except one; then the model predicts the class of the withdrawn sample; this operation is made N times, for each sample, and the CCR-LOOCV is computed). The results of the PLS-DA applied to the 3 classes of reeds are given in TABLE **4**.

TABLE 4. Results of the PLS-DA predictive models (Correct Classification Rate)

Nb comp	**CCR**	**CCR random**	**CCR (LOOCV)**	**CCR random (LOOCV)**
4	85%	41%	80%	40%

The results show that the CCR-LOOCV is 80%, which signifies that the model has 4 chances out of 5 to predict correctly the perceived quality of the reeds from the objective measurements. For comparison, we also made a random assignment of the reeds into 3 classes to verify that the CCR random LOOCV remains very weak (40%).

CONCLUSIONS

This paper presented a combined subjective and objective study of a set of 20 saxophone reeds. Three descriptors were assessed during the subjective study by 10 musicians: *Softness*, *Brightness* and *Global Quality*. Objective "in vivo" measurements were performed on the reeds during saxophone playing and 13 objective variables were extracted from these measurements. Finally, a predictive model of the softness and the brightness was built using the PLS regression and PLS-DA classification. The results show that the model has interesting prediction qualities and achieves a Correct Classification rate of 80% in cross validation. The objective variables were chosen from previous studies performed on the saxophone reeds, and we studied the variability of the measurement before extracting the relevant information on the reeds using an ANOVA model. Future work could consist in finding other objective variables that have less variability, for example by the use of an artificial mouth.

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