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Rapid evaluation of craft beer quality during fermentation process by vis/NIR spectroscopy

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ABSTRACT

The present work aimed to carry out a preliminary study to verify the possibility of employing an optical, portable and inexpensive non-destructive device, based on vis/NIR, spectroscopy, directly on the production line of craft beer.

Three types of craft beer were analyzed. For each type of craft beer, transflectance spectra were acquired in the wavelength range of 450–980 nm and at different stages of fermentation. Spectral sampling for each craft beer was conducted on filtered and non-filtered samples.

The vis/NIR device was tested for the quick evaluation of soluble solid content (SSC) and pH. Spectra were elaborated in order to perform principal component analysis (PCA) and to build partial least square (PLS) regression models.

The PCA results show that vis/NIR spectroscopy could be effective in discriminating between non-filtered (condition in the process line) and filtered samples. PLS models are promising for both the prediction of SSC and pH.

1. Introduction

A quality beer is produced using malt, hops, water and yeast, which are dosed during an extended production process. Craft beer is a non-filtered and unpasteurized product that maintains unaltered sensorial characteristics. When compared to industrial beers, craft beer is more subject to microbial contamination that may cause spoilage (turbidity, acidification and the production of undesired aromatic compounds). In particular, fermentation is one of the most delicate phases of the beer production process. In this step, the conversion of sugar into alcohol takes place, thanks to the yeast, along with the development of many secondary fermentation compounds, which determine the flavor profile of the product (esters, higher alcohols, sulfur compounds, organic acids, aldehydes and ketones).

Moreover, due to the absence of pasteurization and microfiltration in craft beer brewing, the yeast remains in the product; for this reason, craft beer remains "alive" and evolves over time. These justify the need for quality measurements during the entire process and not only on finished beer. Monitoring must be performed on raw materials and at individual process stages.

In the industrial process, brewers install measuring systems (hydrometers, oxygen sensors, gas chromatographs, hazemeters and spectrophotometers) which enable them to make their measurements automatically, with an associated control system responding to the measured values that adjust relevant parameters to control the process (Bamforth, 2003). For instance, temperature is easily measured remotely during fermentation and, if it increases, may be automatically lowered by triggering the circulation of coolant through the jacket of the fermenter. Small-scale breweries have a lower investment capacity than industry, despite maintaining at least the same requirements for process control. In the literature, the parameters usually monitored in microbreweries during fermentation are the pH (Almonacid et al., 2012; Lachenmeier, 2007) and soluble solids content (SSC) or optical density (OD) (Almonacid et al., 2012; Lachenmeier, 2007; Liu et al. 2009; McLeod et al. 2009). Another often controlled parameter is the number of cells in suspension (dry cell weight, DCW) (Almonacid et al., 2012; McLeod et al. 2009) that increase while the yeast grows, but thereafter, the yeast count falls, because cells flocculate and leave the body of the beer. During fermentation, SSC decreases due to the transformation of sugars into ethanol. This phenomenon should be monitored through specific gravity; sugar has a much higher specific gravity than water, and ethanol has a lower specific gravity than water. The pH level also falls during fermentation. Bitterness units, ethanol content, EBC (European Brewing Convention) color and lactic acid are other factors used to control beer production, as described by Lachenmeier (2007). Ethanol content was also analyzed by McLeod et al. (2009) and

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Almonacid et al. (2012) to monitor beer fermentation and by Engelhard et al. (2004) using interpretive near-infrared spectroscopy.

Beers may be divided into ales, lagers and stouts, and differentiated according to the type of fermentation, i.e. high fermentation (using *Saccharomyces cerevisiae*, temperature range of 18–22 °C) or low fermentation (using *Saccharomyces carlsbergensis*, temperature range of 6–15 °C) (Bamforth, 2003).

The recent rediscovery of original and genuine products deeply linked to the region has led to an increase in the consumption of craft beer in Italy. This is reflected in a considerable increase in production (from 290,000 hl/year in 2008 to 450,000 hl/year in 2012) and of the number of small scale breweries. Microbreweries increased from 175 in 2007 to 653 in 2013 (Assobirra, 2012; microbirrifici.org, 2013).

Currently, problems related to the small quantity available and the high price of craft beers have resulted in difficulty selling craft beers. Moreover, variability in the quality level of craft beer prevents the possibility of it replacing industrial beer in terms of consumer use. However, passion and effectiveness has been shown by many microbreweries, which has attracted a growing number of people who have become keen on craft beer and has contributed to its spread. Standardizing the quality of craft beer at a high level is also a requirement for small companies, such as microbreweries. To do this, however, cheap and easy-to-use instrumentation is desired by producers. Optical non-destructive analyses and, in particular, NIR and vis/NIR spectroscopy, therefore, may be considered valid methods for the qualitative and quantitative analysis of many food products (Guidetti et al., 2012) and, among them, craft beer. This optical technique has been proposed as a viable alternative to classical analytical methods. Traditional methods require destructive analysis performed in the laboratory, which requires time, skilled operators and the use of reagents. In addition, vis/NIR spectroscopy is a cheap technology, rapid and effective in reducing the waste of material for laboratory analysis. Finally, optical technology may be applied directly online, providing data in real time during the fermentation process. In particular over the last years a lot of applications of vis/NIR spectroscopy in the food sector are described, among others, concerning the evaluation of grape ripening (Guidetti et al., 2010) and monitoring the nutraceutical properties of apples (Beghi et al., 2013). Liu et al. (2009) and Ghasemi-Varnamkhasti et al. (2012) have proposed the application of optical techniques in the beer industry. The first study performed a screening analysis of beer ageing using near infrared spectroscopy; the second one carried out correlation modeling between the SSC and visible/near infrared spectra. Kirsanov et al. (2010) studied some different beer types like dark, alcohol-free, strong, yeast-containing and filtered white beer. All the samples were analyzed with a number of different spectroscopic techniques (ATR-IR, NIR, Vis and UV). The analysis covered the standard characterization of beer quality attributes (exctractivity, alcohol content, color, pH, foam resistance, turbidity, concentration of bitter-forming components). Madsen and Esbensen (2010) presented the results from a comparison study using FT-NIR, FT-MIR and Raman laser spectroscopy applied to the same set of samples obtained from a pilot-scale beer brewing process. Quantitative PLS1 models were elaborated for the most interesting parameters: ethanol, maltose and total sugar.

This work aimed to evaluate the feasibility of using an optical non-destructive, portable and inexpensive device, based on spectroscopy of visible and near infrared light (450–980 nm), for quick evaluation of qualitative parameters (pH and soluble solid content, SSC) in three types of craft beer (straw, amber and copper). Qualitative analysis was performed to discriminate craft beer samples according to their optical properties. Additionally, quantitative analysis was performed to predict SSC and pH values, the principal parameters used in microbreweries to evaluate the processes at the end of fermentation. The system studied in this work is a simpler and more versatile device compared to bench-top NIR instruments. These are interesting features, especially for small-scale breweries with low potential for investment but with a strong need for process control, because they work with highly variable and non-standardized processes compared to industrial breweries. The possibility of an on-line application of similar optical instrumentation for real time monitoring of trends in craft beer fermentation, for qualitative and quantitative analysis is therefore desirable.

2. Materials and methods

2.1. Sampling

Sampling of craft beers occurred over nine months, from November 2010 to July 2011, and was done in collaboration with *Birrificio Lambrate,* the biggest craft microbrewery in Milan, Italy. The three types of craft beer analyzed are: *Montestella* (straw, Helles style), *Sant'Ambroeus* (amber, Belgian Strong Golden Ale style) and *Lambrate* (copper, Bock style).

Table 1 shows the main characteristics of the studied craft beers.

For each craft beer, a different number of samples was analyzed, since the fermentation process time changes as a function of craft beer type. The samples were taken at different times during fermentation (maximum fermentation process time is 12 days). Analyses were conducted on wort with the addition of yeast (necessary for beer fermentation), then on filtered and non-filtered samples (filtration is necessary for qualitative analysis in the laboratory). At the same time, samples "as is", i.e. non-filtered, designated NF, and samples that were filtered before spectral acquisition, designated F, were analyzed.

A total of 205 craft beer samples were evaluated (three types of craft beer, F and NF samples); 615 spectra were acquired, including three repetitions for each sample (sampling times in the fermentation process were variable, due to the different needs of different kinds of craft beer). For each sample, three spectra were acquired in transflectance at different fermentation stages. In transflectance mode, radiation from the optical fiber passes through the sample, hits the reference (100%) and returns to the probe. Spectral measurements were taken in the laboratory on samples in quartz cuvettes (1 ml) (Fig. 1). The possible influence of temperature changes was limited by freezing craft beer samples taken from the line process and thawing at 4 °C. In fact, each craft beer has different optimal conditions of brewing, including temperature.

For each sampling date, the chemical analysis of qualitative parameters was carried out at the microbrewery. The concentration of sugar is usually measured by specific gravity (°Plato) or in a refractometric way evaluating the SSC. This parameter was measured using a portable digital refractometer (model PR-32, Atago, Tokyo, Japan) and reported in °Plato. pH was measured with a pH meter (model HI 2211-02, Hanna Instruments, Milan, Italy).

Chemical analyses were performed only on filtered material (as the standard protocol), so the value of the chemical parameters used for spectral correlation was the same for NF and F samples (100 samples).

2.2. Portable vis/NIR device

For spectral acquisitions, a portable system based on vis/NIR technology was used. In this system, samples were hit by radiation produced by a lighting system, and the back-scattered component of the spectrum was measured by a spectrophotometer (Fig. 1).

Table 1
Main characteristics of the three craft beers.

Craft beer	Type	Fermentation	Alcoholic strength (% by vol.)	Specific gravity[a] (°Plato)	Color	Style
Montestella	Lager	Low	4.9	12	Straw/gold	Helles
Sant'Ambroeus	Ale	High	7.1	16	Amber	Belgian Strong Golden Ale
Lambrate	Lager	Low	6.8	16	Copper	Bock

[a] Specific gravity is a measure of sugar concentration.

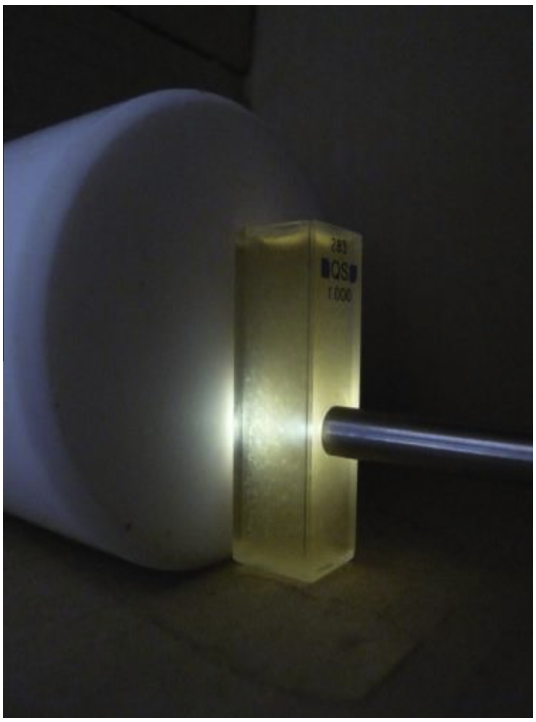

Fig. 1. Detail of spectral acquisition on *Montestella* craft beer sample. Transflectance technique was used.

The system was composed of five elements (Guidetti et al., 2010): a lighting system, a fiber optic probe, a portable spectrophotometer, a PC for instrument control, and a battery as the power supply.

The light source was a 50 W halogen lamp (Decostar Coolblue, Osram, Munich, Germany) with a peak in the emission spectrum at 500 nm. The light source was embedded in a metal holder fitting the optical fiber to a SMA connector, specifically designed to have the halogen spotlight focused on the illuminating optical fiber.

Light radiation was shone on the craft beer sample through a Y-shaped, bidirectional fiber optic probe (FCR-19IR200-2-ME-S1, Avantes, the Netherlands). The probe consists of a tight bundle of 19 optical fibers in a stainless steel ferrule (17 illumination fibers around 2 read fiber, each one with a diameter of 200 μm). The tip of the optical probe was equipped with a soft plastic cap to ensure contact with the sample during measurements while avoiding environmental light interference.

The fiber optic probe was connected to a portable spectrophotometer (AvaSpec-2048, Avantes, the Netherlands). The spectrophotometer was equipped with diffractive grating for spectral measurements optimized in the range 450–980 nm and a CCD sensor with a 2048 pixel matrix, corresponding to a nominal resolution of 0.3 nm.

The system was controlled by a portable PC with a custom software, realized with LabVIEW software package (National Instruments, Austin, USA), for data acquisition, pre-processing and logging, as well as for automatic control of the instrument and illumination.

The system was powered by a 12 V battery, and all components were housed in a backpack.

Since spectral measurements can be affected by the possible influence of environmental conditions, especially those related to diurnal changes in sunlight, spectral acquisitions were performed in a darkened zone to standardize the lighting conditions as much as possible. Tests conducted at different times of the day confirmed the repeatability of measurements allowed by the artificial lighting, which was sufficient to minimize the possible influence of ambient illumination on samples.

2.3. Data processing

Chemometric analysis was performed using The Unscrambler software package (version 9.8, CAMO ASA, Oslo, Norway). Moving average smoothing and second derivative treatments were applied to vis/NIR spectra, aimed at reducing noise before building the calibration models. Second derivatives were performed using the Norris Gap transformation. Principal component analysis (PCA) was performed on vis/NIR spectra to examine samples grouping and to identify outliers. PCA allows to figure out the spectral difference between F and NF samples and consequently to define the sample sets to be used for the PLS analysis.

The vis/NIR spectra were correlated with quality parameters (SSC and pH) using the partial least square (PLS) regression algorithm. To evaluate model accuracy, the coefficient of determination in calibration (R^2_{cal}), the root mean standard error of calibration (RMSEC), the coefficient of determination in cross-validation (R^2_{cv}), the root mean standard error of cross-validation (RMSECV) and the Ratio Performance Deviation (RPD) were applied. RPD is defined as the ratio between the standard deviation of the response variable. This ratio is desired to be larger than 2 for a good calibration (Sinnaeve et al., 2001). RPD ratio less than 1.5 indicates incorrect predictions and the model cannot be used for further prediction. RPD between 1.5 and 2 means that the model can discriminate low from high values of the response variable; a value between 2 and 2.5 indicates that coarse quantitative predictions are possible, and a value between 2.5 and 3 or above corresponds to good and excellent prediction accuracy, respectively.

Cross-validation is an internal validation method, usually used in cases with a small number of samples available for regression. With cross-validation, some samples are kept out of the calibration and used for prediction. This is repeated until all samples have been kept out once. In this case, leave-one-out cross-validation was used, so only one sample at a time was kept out of the calibration. The optimum calibrations were selected based on minimizing the RMSECV. PLS models were calibrated for each craft beer separately.

To investigate the feasibility of a low-cost device based on few selected wavelengths, Martens' Uncertainty Test was applied. This is a significance testing method to assess the stability of regression results and the significance of selected X-variables (Chudnovsky and Ben-Dor, 2008; Esbensen, 2002). The wavelength selection takes into account the top of the peaks of the X regression coefficients plot deriving from the PLS regression (Bjørsvik and Martens, 2001).

3. Results and discussion

The three beers have different fermentation times, depending on type (*Montestella*, *Sant'Ambroeus* and *Lambrate*). Table 2 shows the descriptive statistics applied to chemical analysis. For each craft beer analyzed, SSC and pH were evaluated, on the basis of at least three repetitions, for each analysis time. Since the craft beer process is less standardized than industry beer brewing, fermentation time can change (by a few hours) for the same type of craft beer. Considering the natural variability of craft beer brewing, good repeatability of SSC and pH values was observed during fermentation. *Sant'Ambroeus* was the most variable craft beer both in terms of SSC and pH values.

Comparing the SSC parameter of the three craft beers, it was possible to see changes, already after 18 h (*Montestella*, 10.4 °Plato; *Sant'Ambroeus* 13.9 °Plato and *Lambrate* 15.23 °Plato). Each craft beer decreased by 7%, 12% and 4% of °Plato, respectively, from before fermentation (t0) to 18 h after the process started.

Fig. 2 shows results of spectral pretreatments. In panel **a**, the noisy raw spectra of the craft beer samples are shown. In panel **b**, the same spectra are shown after smoothing treatment; peaks are noise-free for better instrument performance. In panel **c**, spectra are presented after smoothing and second derivative treatments.

Evaluating the spectra of the three craft beer samples (Fig. 3), changes in the visible region spectra between 500 and 600 nm were observable. This was due to the variable pigmentation of each beer. The transflectance pattern of *Lambrate* craft beer (L) was characterized by a generally lower transflectance throughout the spectrum. This occurred since this beer had the darkest color, and so the greatest capacity for absorption in this part of the visible region compared to the other craft beers.

The water content of beer is around 93% (INRAN, 2013) and is noticeable as a small in-depth peak at 760 nm (Fig. 3), caused by the third overtone of OH stretching (Clement et al., 2008; Bertrand, 2000). This absorption band is more evident in Fig. 2(a and c). In fact, by using the derivative spectra, it is possible to remove overlapping peaks and correct the baseline. The derivative brings the overlapping peaks apart and the linear background becomes to a constant level in the first derivative spectrum and zero in the second derivative spectrum (Osborne et al., 1993).

PCA discriminated craft beer samples according to their optical properties. In particular, samples spectra of F and NF were clearly distinguished. Fig. 4 shows a good separation along the first component (PC1). For this reason different PLS models were separately elaborated for F and NF craft beers.

The performance of the vis/NIR technology in monitoring the beer fermentation process was evaluated using PLS analysis. Table 3 shows the statistics used to assess the accuracy of the regression models of the studied craft beer in filtered and non-filtered samples, respectively. Regarding SSC models, in validation, R^2_{cv} ranged 0.61–0.82 and RPD 1.5–2.3. For pH models, R^2_{cv} ranged 0.73–0.89 and RPD 1.3–3. According to the rules, the models could be overall classified from inadequate to excellent. Differences in models prediction performances depends on different inherent characteristics of the three craft beers, on the quality parameters to be estimated and on the physic conditions of the matrix utilized for the spectral acquisitions (F or NF). In fact, color and turbidity evolutions during fermentation are different for each kind of beer and this could affect models calibration. Models with RPD > 2 are useful for quantitative predictions of quality parameters and for the identification of the time to stop the fermentation, considering the accuracy requirements of craft beer brewers. Models for SSC prediction on *Sant'Ambroeus* and *Lambrate* F samples and for the pH prediction of *Montestella* F samples, gave coarse quantitative estimations; excellent predicted pH values were obtained for *Sant'Ambroeus* NF and *Lambrate* F. The other models with RPD < 2 cannot be used at the moment and require further investigations (e.g. increasing the number of the samples, optimizing the measurement conditions with reduction of spectral noise).

Concerning SSC, the best model was elaborated for *Lambrate* F with $R^2_{cv} = 0.82$ and RMSECV = 1.9. Liu et al. in 2009 used a handheld device (325–1075 nm) to calculate PLS models for SSC evaluation using the full spectrum for data processing. The optimal performance of the PLS model was $r = 0.98$ in validation while the less robust proposed PLS model gave $r = 0.92$ in validation.

Regarding regression models for the prediction of pH, the *Lambrate* type provided the most satisfactory results. Good coefficients of determination and low prediction errors were obtained (R^2_{cv}: 0.73–0.89, RMSECV: 0.10–0.14). Lachenmeier (2007) used the PLS elaboration method to correlate Fourier transform infrared (FT-IR) spectra and pH. The accuracy of the FT-IR-PLS model was in validation $R^2 = 0.97$ if carried out using selected wavelength ranges, or 0.71 (test-set validation) using the full spectrum. Guidetti et al. (2010) tested, with good results, the same optical, portable vis/NIR experimental system used in this work on homogenized samples of grapes with a similar experimental setting.

More accurate PLS models were obtained for filtered samples. However, the statistics regarding the models calculated for NF samples (beer matrix usable in the case of application on-line) were fairly good, namely the NF models can discriminate low from high values of the response variable. In fact, concerning SSC

Table 2
Descriptive statistics applied to chemical analyses (SSC and pH) of the three craft beers at different fermentation times.

Kind of beer	Fermentation time (h)	N	SSC (°Plato)			pH		
			Mean	SD	Range	Mean	SD	Range
Montestella (straw, Helles type)	0	6	11.2	0.2	10.9–11.6	5.23	0.04	5.16–5.30
	18	6	10.4	0.3	9.9–10.7	4.98	0.12	4.86–5.18
	48	4	5.8	0.7	5.2–6.9	4.37	0.05	4.32–4.45
	72	3	3.2	0.3	3.0–3.5	4.28	0.01	4.27–4.28
Sant'Ambroeus (amber, Belgian Strong Golden Ale type)	0	9	15.8	0.3	15.3–16.3	5.22	0.03	5.18–5.28
	18	8	13.9	1.8	11.0–15.9	4.83	0.22	4.48–5.08
	48	5	8.6	4.0	4.2–14.3	4.48	0.21	4.27–4.80
	72	4	4.8	1.3	3.2–6.3	4.28	0.02	4.25–4.30
	144	3	4.9	2.4	3.2–8	4.35	0.06	4.28–4.40
Lambrate (copper, Bock type)	0	4	15.8	0.3	15.4–16.2	5.23	0.04	5.18–5.30
	18	4	15.2	0.2	14.9–15.5	5.11	0.05	5.06–5.18
	120	3	10.8	1.1	10.1–12.2	4.69	0.03	4.66–4.72
	144	3	9.2	0.5	8.8–9.8	4.58	0.04	4.54–4.62
	288	3	3.5	0.1	3.4–3.5	4.46	0.12	4.36–4.56

N = number of samples; SSC = Soluble solid content.

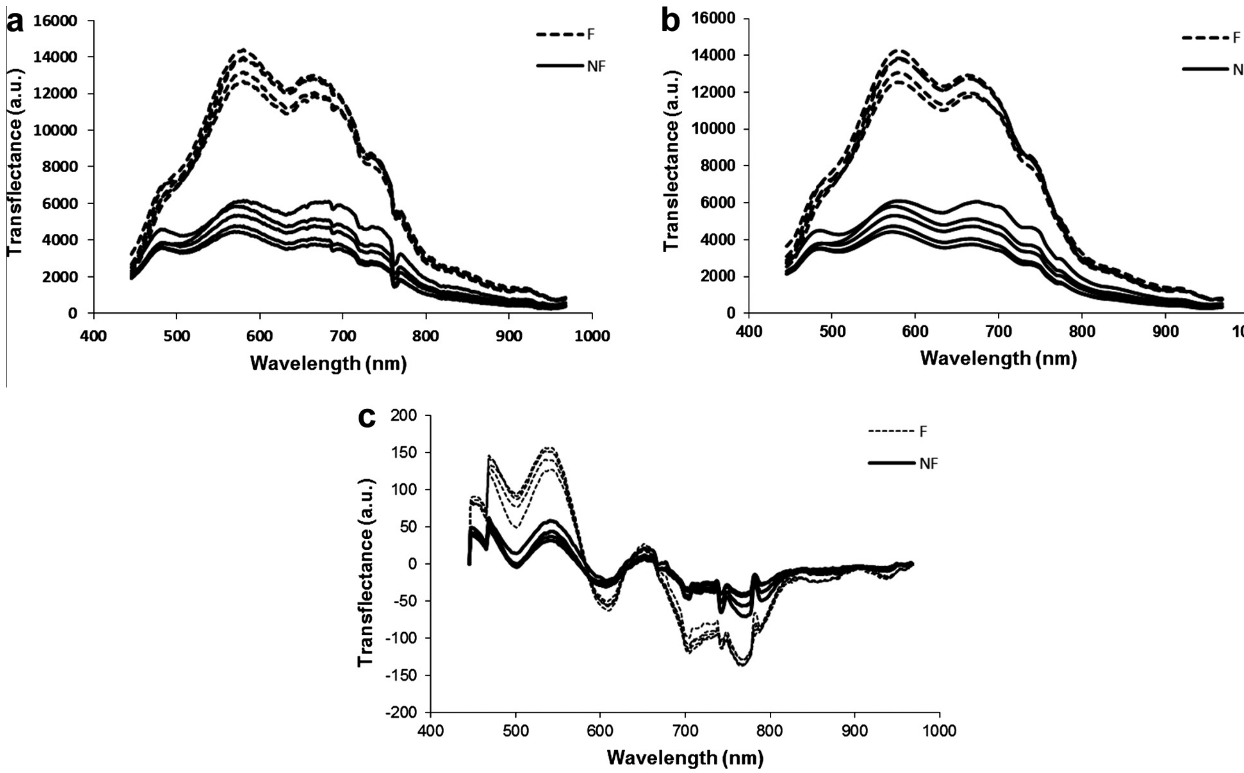

Fig. 2. Examples of spectra of the *Sant'Ambroeus* samples. (a) Raw spectra; (b) smoothed spectra; and (c) spectra after smoothing and second derivative treatments. F = filtered samples, NF = non-filtered samples.

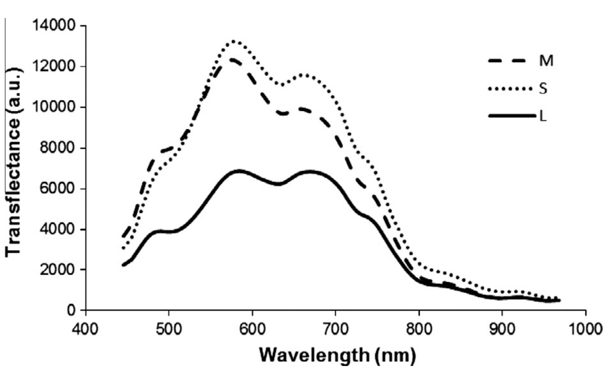

Fig. 3. Averaged spectra of the filtered *Montestella* (M), *Sant'Ambroeus* (S), and *Lambrate* (L) samples. All spectra are referred to the fermentation time equal to zero (t0).

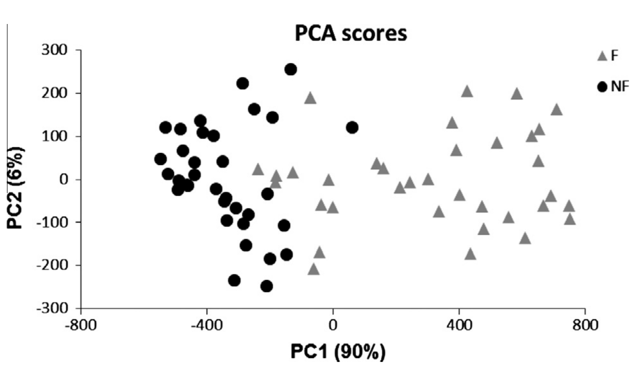

Fig. 4. The PCA of the *Sant'Ambroeus* spectra. F = filtered samples, NF = non-filtered samples.

models, RPD ranged from 1.8 to 2.3 and from to 1.5 to 1.8 for F and NF samples, respectively. Similar performances were obtained for pH models except for *Sant'Ambroeus* craft beer which showed, instead, an unexpected behavior. The reason for the lower prediction performance using NF spectra might be due to the presence of more noise in data arising from a variable matrix such as non-filtered beer during fermentation (caused by small particles in suspension). In fact, the filtration process makes samples more homogeneous and less subject to noise during vis/NIR acquisition. Moreover, models could be further improved by selecting only some variables to reduce the spectral noise (Ghasemi-Varnamkhasti et al., 2012; Liu et al., 2009). These results encourage the use of an on-line application of vis/NIR technology to control the craft beer fermentation process. On this topic, McLeod et al. (2009) evaluated the performance of predicting beer biomass and composition using an online probe during fermentation with a desktop FT-NIR system (1000–2500 nm). The best results achieved by the PLS-FT-NIR model, in validation, were $r = 0.99$, 0.99, 0.98 and 0.98 for ethanol concentration, specific gravity, optical density and dry cell weight, respectively.

The more informative wavebands were selected by Martens' Uncertainty Test and used for models calibration. Fig. 5 shows, as an example, the loadings plot with highlighted the selected variables by Martens' Uncertainty Test for SSC prediction of *Sant'Ambroeus* F craft beer samples.

In recent years, there has been a growing interest towards the development of simplified systems that could be used directly on the production line (Temma et al., 2002; Zude et al., 2006). The identification of the most significant bands can be used as starting point for the selection of a few highly informative wavelengths. These individual fingerprint wavelengths could be used for the design of a simplified handheld device which would allow real-time assessment of fermentation process. Liu et al. in 2009 proposed a method to select the effective wavelengths for the estimation of beer quality using vis/NIR spectroscopy.

Table 3
Statistics of the PLS models elaborated on vis/NIR spectra for the three kind of craft beer (for the two samples F and NF) and respective wavebands selected. Spectral pretreatments were smoothing and second derivative for all samples. LV = latent variables.

Sample	F/NF	*n*	LVs	Calibration models		Validation models			Vis/NIR regions (nm)
				R^2_{cal}	RMSEC	R^2_{cv}	RMSECV	RPD	
SSC (°Plato)									
Montestella	F	26	6	0.88	1.1	0.68	1.8	1.8	468; 484–503; 574–580; 613–616; 626–628; 644–648; 730–737; 762–766; 773–782; 839–845; 850; 865; 905; 910–916; 946; 954–960
	NF	23	10	0.96	0.6	0.61	2.1	1.5	509–512; 645–655; 737–751; 757–769; 785–807
Sant'Ambroeus	F	32	7	0.87	1.8	0.78	2.5	2	498–502; 516–517; 537–540; 558–559; 629; 665–668; 936–939; 947–948
	NF	27	4	0.77	2.3	0.69	2.8	1.8	461–479; 648–649; 653–659; 679–680; 683–691; 718–726; 755–757; 776; 779–780; 802–808; 884–888; 935–937
Lambrate	F	23	4	0.87	1.6	0.82	1.9	2.3	481–482; 485–505; 548; 561–581; 626–628; 671–675; 677; 684; 688; 726–729; 787; 793; 795; 829–831; 833; 869; 875–876
	NF	21	5	0.78	1.8	0.68	2.4	1.7	488–498; 562–621; 665–721; 789–930
pH									
Montestella	F	21	6	0.91	0.1	0.84	0.15	2.4	486–506; 574–579; 624; 626–628; 644; 753–765; 774–778; 837–844; 849–850; 946; 955–960
	NF	20	3	0.76	0.2	0.72	0.19	1.8	462–478; 492–496; 540; 547; 598; 641–647; 672–673; 683–684; 752–757; 789
Sant'Ambroeus	F	29	5	0.69	0.2	0.38	0.29	1.3	454–462; 485–505; 555–559; 680–681; 692; 766–768; 773–774; 778
	NF	26	9	0.97	0.06	0.87	0.13	2.9	488; 543; 555; 601; 697
Lambrate	F	21	5	0.92	0.1	0.89	0.1	3	454–459; 482–491; 549–588; 664; 667; 696–700; 718; 788–802; 828–829; 832; 854; 877; 891; 920–935
	NF	19	3	0.8	0.1	0.73	0.14	1.9	454–458; 464–485; 516; 520–523; 533–552; 559–563; 583–603; 609–620; 629–641; 652–712; 717–753; 771; 783–813; 829–833; 842–844; 853–858; 862–865; 869–882; 888–905; 920–936; 959–960

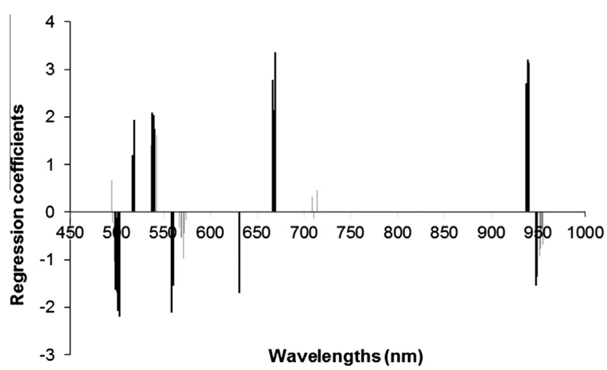

Fig. 5. Loadings plot with highlighted the selected variables by Martens' Uncertainty Test for SSC prediction of *Sant'Ambroeus* F craft beer samples.

4. Conclusions

An optical, portable and inexpensive non-destructive device, based on visible and near infrared spectroscopy (vis/NIR), operating in the range of 450–980 nm, was tested for quick quality evaluation of craft beers. The application of PCA on craft beer spectra, when appropriately treated, allowed a qualitative assessment of the predictive ability of the device. A good separation of filtered craft beer samples was obtained. Elaboration of regression models using the PLS technique was done by correlating vis/NIR spectra with the classical chemical data required for the control of the fermentation process.

The results show differences in models prediction performances for both the chemical parameters related to craft beer quality (SSC and pH), depending on different inherent characteristics of the three craft beers. Particularly, for both qualitative indices, good prediction ability was obtained with filtered craft beers, while fairly good performance in the estimation of non-filtered samples was shown.

This trend was similar for each type of the three craft beers analyzed. The online analysis must necessarily predict the measurement of non-filtered samples. Therefore, models (except for prediction of pH in *Sant'Ambroeus* beer) obtained on non-filtered wort might create problems in the performance estimation during fermentation. The robustness of the prediction models could be improved increasing the number of samples of the data set and optimizing the measurement conditions with reduction of spectral noise.

The system proved to be suitable not only for the evaluation of craft beer quality parameters, but also to identify the time to stop the fermentation of craft beer. In fact, the possibility of a real time estimation of qualitative characteristics of the wort, and beer arising from it, would be of fundamental importance in order to obtain beers which fully meet the specifications required, but with a certain degree of variability typical of craft productions. The application of this technique on-line could be a further evolution for the research in the future that will require engineering and automation. The investigation of wavelengths in order to highlight and select a small number of high informative bands could improve the prediction capabilities of the models not taking into account the useless variables in the considered wavelengths range.

The possibility to adjust light sources with specific wavelengths with high-power LEDs (light emitting diodes), which may be optically filtered to select emission at chosen wavelengths, could allow the realization of compact devices that could be reasonably transferred to the on-line process. This type of LED based simplified optical tool, avoiding specific chemometric analyses and trained personnel, could support the conventional techniques in the online process.

In conclusion, the replacement of traditional laboratory analysis with vis/NIR spectroscopy would provide some advantages, such as avoiding the need for a specialized workforce, as well as saving time and beer. Furthermore, the instrument is easy to use and inexpensive. These are interesting features, especially for small-scale breweries with low potential for investment but with a strong need for process control, because they work with a highly variable and non-standardized process compared with industrial breweries.

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