Prediction of warmed-over flavour development in cooked chicken by colorimetric sensor array

Su-Yeon Kim a,1, Jinglei Li a,c,1, Na-Ri Lim a, Bo-Sik Kang b,s,1, Hyun-Jin Park a,s,1

a Department of Biotechnology, College of Life Sciences and Biotechnology, Korea University, Anam-dong, Seongbuk-gu, Seoul 02841, Republic of Korea
b HiBiO Co., Ltd., 903, Jungang Induspius 2, 144-5, Sangdaewon-dong, Seongnam, Gyeonggi 13201, Republic of Korea
c College of Biotechnology and Food Engineering, Hefei University of Technology, Hefei 230009, China

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1. Introduction

Pre-cooked and reheated meat after short-term refrigerated storage rapidly develops a distinctive off-flavour referred to as warmed-over flavour (WOF) (Byrne, Bredie, Mottram, & Martens, 2002). WOF development results not only in the increase of ‘rancid’ flavour but also in the disappearance of ‘meatiness’ and ‘sweetness’ of freshly cooked meat concurrently (Byrne et al., 2002). These sensory defects in meat flavour are not desirable for consumer preference, and do not lead to repeated purchases. In addition, WOF development causes nutritional losses, shortens shelf life, and is accompanied by production of toxic compounds such as free radicals, hydroperoxides, and malonaldehyde by lipid oxidation (Choe et al., 2011). Many efforts to minimise WOF in meat products have been reported (Jayathilakan, Sharma, Radhakrishna, & Bawa, 2007; Lepper-Billie et al., 2014). The global market for meat products and ready meals had shown a steady growth between 2009 and 2013 (KHIDI & Korean Health Industry Statistics System, 2014). The meat industry has to be aware of the WOF problem with the increasing demand for meat-based convenience products and thus needs to monitor WOF development.

WOF development is attributed to the result of the oxidation of membrane phospholipids, a process catalysed by active iron from iron-containing proteins during thermal treatment of meats (Tikk, Haugen, Andersen, & Aaslyng, 2008). The reactions produce many lipid oxidation related off-flavours, such as aldehydes, ketones, alcohols, acids, and hydrocarbons called secondary lipid oxidation products (Ross & Smith, 2006). Thiobarbituric acid reactive substances (TBARS) have also been used as an indicator for evaluation of WOF development in cooked meats. It has been reported that TBARS is correlated with hexanal and negative sensory attributes in cooked meats (Beltran, Pla, Yuste, & Mor-Mur, 2003; Campo et al., 2006).

Traditionally, most of the chemicals causing WOF have been analysed by two methods: determination of TBARS by a colorimetric method using spectrophotometry, and determination of volatile compounds such as aldehydes by liquid chromatography (LC), gas chromatography (GC) or electrochemical techniques (Li et al., 2014; Yang et al., 2002). It is obvious that these are valid methods to evaluate WOF. However, they have unavoidable drawbacks, such as expensive and cumbersome operations and time-consuming procedures (Li et al., 2014). Hence, it is important to
develop and test new methodologies, which are faster, low cost, and reliable alternatives to these expensive and time-consuming determinations.

Fortunately, the recently established colorimetric sensor array (CSA) combined with pattern-recognition methods enables such a task (Janzen, Ponder, Bailey, Ingison, & Suslick, 2006). This technology has emerged as a potentially powerful approach towards the detection and recognition of chemically diverse analytes. On the basis of cross-responsive sensing elements rather than specific receptors, the sensor array produces composite responses unique to an analyte in a fashion similar to the mammalian olfactory system (Askim, Mahmoudi, & Suslick, 2013).

The basic principle of the CSA technique to detect and differentiate chemical vapour is that it utilises colour changes induced by reactions between volatile compounds and chemically responsive dyes of an array, as a result of ligand binding (Rakow & Suslick, 2000). In the process, CSA utilises chemically cross-responsive dyes, which are sensitive to the analytes, to generate a composite and olfactory-like response unique to a given odorant that can be quantified by digital imaging. The colours of such dyes are affected by a wide range of intermolecular interactions between analytes and dyes, including Brønsted and Lewis acid-base, hydrogen bonding, dipolar and π–π interactions (Suslick, Rakow, & Sen, 2004).

A CSA comprises multiple sensor elements consisting of dye spots coated on a supporting material. A single sensor element in the array does not need to possess perfect specificity or selectivity for target analytes. Some sensor elements respond differently not only to the target analytes but also to others (Hou et al., 2011). Various analytes can be distinguished via the difference of the overall response in the sensor array.

The cross-reactive array has shown great potential for classifying complex mixtures such as beers (Zhang, Bailey, & Suslick, 2006), soft drinks (Zhang & Suslick, 2007) and coffees (Suslick, Feng, & Suslick, 2010), as well as successfully differentiating volatile organic compounds (Janzen et al., 2006), toxic industrial chemicals (Feng, Musto, & Suslick, 2010; Lin & Suslick, 2010), and bacteria (Nopwinyuwong, Trevanich, & Suppakul, 2010; Zaragozá et al., 2015).

The aim of the present study was to develop a simple and rapid method based on CSA technique for evaluation of WOF in cooked chicken. The array responds to the aldehydes associated with WOF based on the specific reaction between aldehyde and DNPH used to detect carbonyl groups of aldehydes and ketones. From the specific reaction, hydrazone derivatives and H₂O are produced, and these lead to colour changes in each sensing spot of the array. To the best of our knowledge, this is a first attempt to monitor WOF development by CSA. We investigated the relationship between the CSA data and the results of TBARS and GC and assessed the potential of CSA.

2. Materials and methods

2.1. Preparation of cooked chicken samples

Five Cobb broiler chickens (30 days old) packed individually in low-density polyethylene (LDPE) bags were purchased at a local supermarket in Seoul, Korea. A whole chicken (approximately 800 g) was washed in tap water and boiled in 1 L of mineral water for 60 min, in an automatic electric cooker (Model WHA-VF1060G, Lihom-Cuchen Co., Ltd, Republic of Korea). The boiled sample was immediately transferred to a 2-L laminated bag (PET/Al/nylon/CPR), sealed with a film sealer, cooled in cold water, and stored in a refrigerator at 4 °C for 6 days.

2.2. Reheating of cooked chicken samples

Each sample bag (stored for either one, two, four, or six days, respectively) was reheated in a water bath at 100 °C for 20 min, and then the reheated sample was immediately cooled in cold water. The sample was taken out of the bag, deboned, and minced using a blender. The minced chicken meat was then used for analysis. The samples were analysed in quintuplet trials.

2.3. Determination of TBARS

Secondary lipid oxidation products in samples were measured by TBARS method (Peiretti, Medana, Visentin, Bello, & Meineri, 2012). Approximately 10 g of the sample were mixed with 20 mL of 10% (w/v) trichloroacetic acid (TCA). The mixture was centrifuged at 2000 rpm for 10 min, and the supernatant was filtered through a filter paper (No. 2, Advantec). Two millilitres of the filtrate were mixed with 2 mL of 0.02 M 2-thiobarbituric acid (TBA). The mixture was heated at 95 °C for 25 min. After cooling in cold water, the absorbance was measured at 532 nm by a UV–vis spectrophotometer, and the results were expressed as malonaldehyde (mg/kg) using a standard calibration curve of 1,1,3,3-tetramethoxy propane (0.14–0.86 μg/mL).

2.4. Determination of aldehydes by gas chromatography

Approximately 1.50 g of each sample and 10 μL of 2-methyl-3-heptanone (1000 μg/mL) used as an internal standard were transferred to a 20-mL glass vial capped with a silicon septum. The vial was left for 1 h at room temperature (approximately 23 °C) to equilibrate the headspace. Volatile compounds in the headspace were extracted using a solid-phase microextraction (SPME) fibre (Supelco, Bellefonte, PA) coated with 50/30 μm divinylbenzene/Carboxen/polydimethylsiloxane (DVB/CAR/PDMS). The fibre was then exposed to the headspace of the vial for 30 min at the same temperature. To desorb the absorbed compounds, the fibre was inserted into the injection port of a model 7890 GC (Agilent Technologies) for 4 min at 250 °C with a split ratio of 10:1 and helium flow of 10 mL/min. The aldehydes were separated on an HP-5MS column (30 m × 0.25 mm × 0.25 μm, Agilent Technologies). The oven temperature was maintained at 40 °C for 4 min, then raised at 5 °C/min to 160 °C, and finally held for 5 min. The temperature of the injector and the flame ionisation detector (FID) were set at 250 °C and 280 °C, respectively. Each of the three dominant aliphatic aldehydes (pentanal, 0–1000 μg/mL; hexanal, 0–1000 μg/mL; and heptanal, 0–100 μg/mL) was identified by comparing their retention time with an authentic standard and quantified by internal standardisation based on the relative response factor as described by Cachet (2011). The absolute response factors for an analyte in a standard solution (Rₐ) and internal standard (Rₛₐ) were obtained by Eqs. (1) and (2), respectively. The relative response factors (RRF) and concentrations of each aldehyde (mₐ, mg/kg) were obtained by Eqs. (3) and (4), respectively.

\[ Rₐ = \frac{Aₐ}{mₐ} \]  \hspace{1cm} (1)

\[ Rₛₐ = \frac{Aₛₐ}{mₛₐ} \]  \hspace{1cm} (2)

\[ \text{RRF} = \frac{Rₐ}{Rₛₐ} = \frac{Aₐ \times mₛₐ}{Aₛₐ \times mₐ} \]  \hspace{1cm} (3)

\[ mₐ = \frac{Aₐ \times mₛₐ}{\text{RRF}} \]  \hspace{1cm} (4)

where:
$m_a$ is the known amount of analyte (a) in a standard solution, $m_{is}$ is the known amount of internal standard (is) introduced into the standard solution, $A_a$ is the peak area of analyte (a) in a standard solution, $A_{is}$ is the peak area of internal standard (is) introduced into the standard solution, $m_b$ is the concentration of analyte in the sample, $A_b$ is the peak area of analyte in the sample.

2.5. Fabrication of CSA and data acquisition

2.5.1. Fabrication of CSA

In order to fabricate a sensor array to detect aldehydes as marker compounds of WOF, a 3 × 3 colorimetric sensor array based on the method of Li, Chen, Zhao, and Ouyang (2014) was developed. Each of nine sensing materials was prepared by mixing 2,4-dinitrophenylhydrazine (DNPH) and a different pH indicator. For pH indicator solutions, each indicator was dissolved in ethanol as follows: bromothymol blue (100 mg/10 mL), bromocresol green (100 mg/10 mL), bromocresol purple (100 mg/10 mL), neutral red (5 mg/10 mL), bromoxynoline blue (20 mg/10 mL), malachite green chloride (5 mg/10 mL), methyl violet (5 mg/10 mL), bromophenol blue (100 mg/10 mL), and chlorophenol red (20 mg/10 mL). For DNPH solution, 0.4 g DNPH were added to a mixture of 3 mL water and 10 mL ethanol, and 2 mL concentrated sulfuric acid were then added dropwise. To increase the stability of the sensing materials, 10% (w/v) PEG-400 ethanol solution was added. The final pH indicator/DNPH/PEG-400 ratios were 1:3:3. A CSA was fabricated by printing the nine sensing materials on a polyvinylidene fluoride (PVDF) membrane. The array was next dried in a fume hood and stored in a desiccator filled with nitrogen gas for over 12 h before use. Eventually, the CSA was more selective to the target analytes and less affected by the interference from non-target species although the pH indicators also respond to other volatile compounds.

2.5.2. Data acquisition

An online monitoring system coupled with Colour Analysis software was developed. It consisted of a nitrogen gas bottle, sample and reaction chambers, CCD camera, and a computer with the software program (Fig. 1). Briefly, before the analysis, CSA reaction time was considered on the basis of two equilibria for CSA responses to the analytes in samples (Chen et al., 2013). The equilibration time in headspace was determined by preliminary experiments to equal 5 min.

![Fig. 1. Schematic diagram (a) and photograph (b) of the colorimetric sensor array system.](image)
For the experiments, CSA was placed in the reaction chamber. To stabilise the array, nitrogen gas at 300 mL/min was passed towards A for 5 min after the two three-way valves have been turned. Subsequently, after turning the two three-way valves towards B, CSA images were captured by the digital camera at 2-min intervals for 18 min. All gas lines were purged with nitrogen gas before the next sample was analysed. After monitoring, average colour values (R, G, and B) were extracted from the centre of each sensing spot in the captured array image. Colour change values (ΔR, ΔG, and ΔB) were obtained by respectively subtracting R, G, and B values of the initial image from the R, G, and B values of the final image.

To find the appropriate reaction time for CSA analysis, the changes in the squared Euclidean distance (the sum of the squares of each ΔRGB value of the nine sensing materials) were then calculated (Fig. S1a). Based on these results, the reaction time was set to 14 min as the time-point when the total squared Euclidean distances stabilised. Ultimately, CSA analysis time was shorter than that for either the TBARS or GC method.

For visualisation only, a colour difference image of the array was obtained from colour change values expanded from 5–30 to 0–255 using Power point version 2013.

2.6. Statistical analysis

For data processing, IBM SPSS Version 22 was used. One-way analysis of variance (ANOVA) was performed on TBARS values and individual volatile compounds, such as pentanal, hexanal, and heptanal. The data were further analysed using Duncan’s multiple range test when ANOVA revealed \( p < 0.05 \). Principal component analysis (PCA) (Li et al., 2014) and hierarchical cluster analysis (HCA) (Qin et al., 2012) were performed with the CSA data to classify the samples with different storage times. Each CSA provides 27 colour difference values (3 colour components × 9 sensing materials). From the full dataset, only 23 colour difference values were used for PCA and HCA because the remaining 4 colour difference values were equal to zero and were not suitable for the analysis. In HCA, squared Euclidean distance was used to calculate similarities between the samples and a between-group linkage method was applied to define clusters. Partial least squares regression (PLSR) (Wold, Sjöström, & Eriksson, 2001) was used to assess relationships between independent variables (e.g., CSA data) and dependent variables (e.g., TBARS, pentanal, hexanal, or heptanal). In order to create robust prediction models, all 20 samples were divided into 2 subsets. One was a calibration set, where all the samples were used for modelling. The other was a prediction set, where all the samples were used to test the performance of the final model. Three out of five samples for each storage day were assigned to the calibration set, and the other two samples were assigned to the prediction set. Consequently, the calibration set contained 12 samples, and the prediction set contained 8 samples. Coefficient of determination \( (r^2) \), root mean square error of calibration (RMSEC), and root mean square error of prediction (RMSEP) were evaluated for each prediction model. Independent-sample \( t \)-test was used to evaluate a significant difference between RMSEC and RMSEP in a prediction model.

3. Results and discussion

3.1. Evaluation of WOF development by TBARS assay

As shown in Fig. 2a, TBARS values of the chicken samples significantly increased until Day 4 \( (p < 0.05) \). This indicates that WOF development occurred in the samples at this stage by lipid oxidation. However, TBARS values decreased at Day 6. This tendency

![Fig. 2. Changes in TBARS (a), pentanal (b), hexanal (c), and heptanal (d) of the samples during refrigerated storage. Means on each day with different letters above the bar are significantly different at \( p < 0.05 \) by Duncan’s multiple range test.](image-url)
was also observed in a study by Liu, Tsau, Lin, Jan, and Tan (2009). Kuo, Wang, Huang, and Ockerman (1987) explained that TBA values in chicken sausages increased and then decreased during storage because various intermediates, including MDA, probably decomposed into further oxidized compounds that did not react with the TBA. We concluded that the WOF-related compounds in the chicken samples increased up to a maximal point and then decreased, due to continued oxidation during refrigerated storage.

### 3.2. Evaluation of WOF development by SPME/GC-FID

The concentrations of three dominant aliphatic aldehydes in chicken samples during refrigerated storage are shown in Fig. 2b–d. Hexanal concentrations were remarkably higher than those of pentanal and heptanal during refrigerated storage. Aldehydes are directly associated with WOF development in cooked meats during storage and subsequent reheating. Hexanal has been proposed by many researchers as the most important indicator of meat oxidation (Ross & Smith, 2006).

All aldehyde concentrations increased in the first 2 days in the samples. The concentrations of pentanal, hexanal, and heptanal at Day 2 were 2.07 ± 0.16 mg/kg, 11.05 ± 0.86 mg/kg, and 0.16 ± 0.01 mg/kg, respectively. After 2 days, the concentrations of hexanal and heptanal decreased, while the concentration of pentanal did not significantly change. The decrease in aldehyde concentrations indicates that the aldehydes had decomposed into other products rather than had been formed during this stage. These tendencies were also observed in a previous study by Price, Díaz, Bañón, and Garrido (2013), who reported that the concentrations of pentanal, hexanal, and heptanal in each sample was highest on Day 2. The decrease in aldehyde concentrations indicates that the aldehydes had decomposed into products other than those that had been formed during this stage. These tendencies were also observed in a previous study by Price, Díaz, Bañón, and Garrido (2013), who reported that the concentrations of hexanal and heptanal in cooked meatballs stored at retail display conditions increased during 8 days of storage and then decreased during a further storage of 8 days.

Several researchers have reported a positive correlation between TBARS and aldehyde concentrations in cooked meat samples during refrigerated storage (Brunton, Cronin, Monahan, & Durcan, 2000; Teets, Sundararaman, & Were, 2008). Meanwhile, in a study by Ahn, Olson, Jo, Love, and Jin (1999) of lipid oxidation in irradiated cooked pork sausages during refrigerated storage, TBARS correlated with specific volatile compounds in aerobic packed samples, but there was little relationship between TBARS and volatiles in vacuum-packed samples. On the other hand, in a study by Mielnik, Olsen, Vogt, Adeline, and Skrede (2006), TBARS correlated with specific volatile compounds in aerobic packed samples, but there was little relationship between TBARS and volatiles in vacuum-packed samples. We found that concentrations of the aldehydes and TBARS in our samples decreased after reaching a maximum within 6 days of refrigerated storage. The oxygen-impermeable bag used in the present study appeared to limit the development of WOF. We thus analysed the samples only until 6 days because further analysis may not be meaningful. TBARS was highest at Day 4, while the concentration of each of the aldehydes was highest at Day 2. The reason for the discrepancies might be that TBARS measurement is relatively non-specific and does not detect all the volatile compounds specifically associated with WOF.

### 3.3. Evaluation of WOF development by CSA

Fig. S1b shows the initial and final images of an array captured by a digital camera before and after exposure to the sample for 14 min of reaction time. Colour difference values were obtained from these digital images by digital subtraction of the initial image from the final image (i.e., \( R_{\text{final}} - R_{\text{initial}} \), \( G_{\text{final}} - G_{\text{initial}} \), \( B_{\text{final}} - B_{\text{initial}} \)). To avoid non-uniformity at the edge of the spots, the centre of each sensing spot, covering 50% of the total spot area, was averaged using Colour Analysis software. Each sensing spot provides three dimensional vectors; all the nine sensing spots provide a total of 27 dimensional vectors. The data set can be used for multivariate statistical analysis.

The difference image from the RGB colour difference values was generated for visualisation only. The image was composed of the combinations of absolute RGB colour difference values for each sensing spot. Moreover, in order to enhance the visualisation, the range of the absolute RGB difference values was expanded from 5–30 to 0–255 (Fig. S1b). The difference image showed a unique colour pattern for each sample. Generally, a difference image with an expanded RGB value scale has been used for visual representation in many CSA studies (Qin et al., 2012; Zhang et al., 2006). The difference image provides a colour change profile as well as a fingerprint for each sample. This is a remarkable feature unlike traditional methods.

### 3.4. Verification of CSA method by PCA and HCA

PCA is an unsupervised linear pattern recognition method and is commonly used to classify different samples. The PCA transforms...
original variables into fewer new variables known as principal components (PCs) by reducing the dimensionality of numerical datasets. Each PC is a linear combination of the original variables within which the PCs account for the maximal possible variability contained (Li et al., 2014). A PC score plot constructed from the top two or three PCs can be used for classifications or groupings of observations through clustering based on their similarity.

As shown in Fig. 3a, the first 6 dimensions of 23 total dimensions explained 87.0% of the total variance. In general, many studies reported that CSA has the highest dimensionality (Qin et al., 2012; Zhang & Suslick, 2007). In accordance with these, our results demonstrate that CSA possesses high ability to discriminate chemicals. A 2-dimensional score plot using the first two PCs was obtained from PCA (Fig. 3b). Although the first two PCs explained only 54.42% of the total variance (PC 1 = 37.74%, PC 2 = 16.68%), most samples remarkably clustered according to refrigerated storage time and separated from each other. The results suggest that CSA could successfully classify samples according to refrigerated storage time.

The CSA data were also analysed by HCA using only 23 colour difference values of the full dataset in the same manner as PCA. HCA is a well-known unsupervised method of classifying samples by measuring either the distance or similarity between the samples to be clustered (Qin et al., 2012). In contrast to classical classification methods such as PCA, HCA has the advantage of using the complete dimensionality of data and providing a graphic output in the form of a dendrogram (Salinas et al., 2014). The samples were sequentially clustered in order of their similarities in the 23-dimensional vector space. As shown in Fig. 4, the samples were correctly clustered according to refrigerated storage time without misclassifications. There were three main clusters, namely, Group 1 (Day 1), Group 2 (Day 2 and Day 4), and Group 3 (Day 6). These results revealed that the CSA is able to identify samples depending on increasing storage time. In other words, the CSA can recognise complex changes in concentration of volatile compounds for each sample according to storage time, including significant changes \((p < 0.05)\) in TBARS values and aldehyde concentrations. The CSA technique is considered as a powerful method for rapid detection and classification of WOF development in chicken samples when used in combination with PCA or HCA.

3.5. Correlation between the results obtained with CSA and traditional methods

PLSR analysis is a multivariate projection method that models a relationship between dependent variables \((Y)\) and independent variables \((X)\). The principle of PLSR relies on finding components in the input matrix \((X)\) that closely delineate the relevant variations in the input variables and that, at the same time, have the highest correlation with the target value in \(Y\), giving the lowest weight to the variations that are irrelevant or associated with noise (Berrueta, Alonso-Salces, & Héberger, 2007).

PLSR prediction models for TBARS values and each of the aldehyde concentrations were created with 23 colour difference values in the same manner as PCA and HCA. The results of the PLSR models using the results of TBARS and each of aldehydes are shown in Table 1. As observed, the ranges of each of the four variables \((Y)\) in the prediction sets were closely included in the ranges in the calibration set. In addition, no significant differences between the

<table>
<thead>
<tr>
<th>Variables</th>
<th>Calibration set ((n = 12))</th>
<th>Prediction set ((n = 8))</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Range ((\text{mg/kg}))</td>
<td>(r_c^2)</td>
</tr>
<tr>
<td>TBARS</td>
<td>0.27–0.69</td>
<td>0.9986</td>
</tr>
<tr>
<td>Aldehydes</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pentanal</td>
<td>0.33–2.24</td>
<td>0.9609</td>
</tr>
<tr>
<td>Hexanal</td>
<td>5.40–11.54</td>
<td>0.9710</td>
</tr>
<tr>
<td>Heptanal</td>
<td>0.07–0.17</td>
<td>0.9643</td>
</tr>
</tbody>
</table>

Fig. 4. HCA dendrogram of the CSA results.
calibration and prediction sets were observed. Thus, we confirmed that the samples of the calibration set can be used for testing the robustness of the final model. Furthermore, we evaluated the result of the calibration by root mean square error of calibration (RMSEC), root mean square error of prediction (RMSEP), and coefficient of determination ($r^2$). As shown in Table 1, there was no significant difference between RMSEC and RMSEP in each model. The models had very low RMSEC and RMSEP values, indicating that all the prediction models have a high precision (Zaragozá et al., 2013). All our models had very high coefficients of determination. For the prediction model with TBARS, coefficients of determination were 0.9986 and 0.9997 in the calibration set and the prediction set, respectively. Each aldehyde concentration also showed good coefficients of determination, which were higher than 0.960 in both the calibration set and the prediction set. The PLSR results are represented on the PLSR plots for each variable in Fig. 5a–d. The measured and predicted values represent the experimental and calculated values, respectively, determined by PLSR algorithm. Prediction models for indices of food quality using CSA data with a high degree of precision and accuracy are also observed in previous studies (Zaragozá et al., 2013, 2015). The PLSR results demonstrate that CSA was able to predict changes in volatile compounds responsible for WOF even when the concentrations of these compounds are low. In the present study, we suggested that the good predictions were attributed to the specific reaction between sensing materials on the array and the analytes in the samples.

4. Conclusions

We used the CSA technique to develop a simple and rapid method for evaluation of WOF development in cooked chicken. The CSA coupled with PCA or HCA showed a high ability to classify samples with different storage times. The PLSR results demonstrated that the CSA was able to predict compounds responsible for WOF, including TBARS, pentanal, hexanal, and heptanal. The CSA achieved WOF detection without laborious and time-consuming procedures, unlike traditional methods such as TBARS and GC methods. The present investigation is worthy of notice in that it is a first attempt to evaluate WOF development by CSA. We found that CSA could be readily utilised as a new method for evaluation of WOF.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.foodchem.2016.05.084.

References


Fig. 5. Measured versus predicted values of TBARS (a), pentanal (b), hexanal (c), and heptanal (d) by PLSR.


Choe, J. H., Jang, A., Lee, E. S., Choi, J. H., Choi, Y. S., Han, D. J., ... Kim, C. J. (2011). Oxidative and color stability of cooked ground pork containing lotus leaf (Nelumbo nucifera) and barley leaf (Hordeum vulgare) powder during refrigerated storage. Meat Science, 87(1), 12–18.


