# Dairy Foods: Chemistry-Protein

**797 Ability of Smart Nose to discriminate *tina* biofilms contributing to produce unique volatile compounds in inoculated milk.** S. Carpino*[1], I. Stampelou[2], G. Belvedere[1], C. Pediliggieri[1], and G. Licitra[3,1], [1]*CoRFiLaC, Regione Siciliana*, *Ragusa, Italy*, [2]*Wageningen University*, *the Netherlands*, [3]*DACPA, University of Catania*, *Catania, Italy*.

Wooden equipment is used in the traditional cheese making process of PDO Ragusano cheese and no starters are added in the cow raw milk. A source of aromatic components in milk might be the biofilm microflora released from the traditional wooden vat called *tina*, used during cheese making, as well as the flora naturally present in raw milk. Thus, the objectives of this work were to investigate the potential role of the *tina* biofilm to generate aroma compounds when inoculated into milk and to assess the ability of a Smart Nose to discriminate them by analyzing the aroma profiles of the inoculated milks. Pasteurized milk was used to avoid the interference of aroma compounds generated by the natural microflora present in raw milk. In this study, *tina* biofilms isolated from 3 different farms were inoculated in milk and incubated at conditions simulating the ones of the real cheese making of Ragusano before brining. The inoculated milk samples were analyzed through Smart Nose and the data were statistically treated by Principal Component Analysis (PCA). The PCA results showed first of all a good separation of the inoculated milks from the blank one (non-inoculated milk), highlighting a significant influence of *tina* biofilm on the developed milk aroma profile. In addition, all inoculated milk samples showed a clear separation among them, thus showing that each *tina* biofilm had a different behavior regarding aroma releasing when inoculated into milk under certain conditions. Certain volatile compounds were detected by GC-MS analysis in all 3 inoculated samples while these were totally absent in the blank, showing that were produced by the biofilm. Moreover, it was observed that the microbiological composition of each *tina* biofilm gave respectively a different aroma contribution. In conclusion, it was shown that Smart Nose is able to discriminate quite well aromatic profiles attributed exclusively to the biofilm bacteria during the first steps of cheese making.

**Key Words:** *Tina* biofilm, aroma profile, Smart Nose

**798 Segmentation of scanning electron microscopy images using incremental learning.** G. Impoco[1], L. Tuminello[1], M. Caccamo*[1], and G. Licitra[1,2], [1]*CoRFiLaC, Regione Siciliana*, *Ragusa, Italy*, [2]*DACPA, University of Catania*, *Catania, Italy*.

This study tested a method for automatic quantification of digital micrographs based on statistical classification of pixels and incremental learning. Ten scanning electron microscope (SEM) images of Ragusano cheese were used as training set and the main microstructural features were gathered in 3 morphologically meaningful classes: fat globules, whey pockets, and protein matrix. A series of 10 numerical values (descriptor) was associated to each pixel. Images were partitioned into significant regions (segmentation) by clustering pixel descriptors using the k-means algorithm. According to the resulting clusters, an initial automatic classification associated each region to a specific microstructural feature. The classified images, used as reference labelings, were used to automatically learn a Bayesian statistical model which associates to each pixel its probability to belong to a certain feature class. This model was used to classify again input images. Output classifications were presented in color to a SEM specialized operator, who could select misclassified regions and associate them with a different, more appropriated label (re-labeling). New statistics obtained from the re-labeled regions were integrated into the model. The updated model was used to re-classify input images. This process of supervised re-labeling and automatic pixel classification was iterated until satisfactory results were obtained. We compared incremental learning to off-line image labeling, where the input images are manually labeled only for the initial training of the model, from a single reference data set. Experimental data showed that incremental learning gives better results than off-line learning. The training phase is less burdensome and time consuming for the user, and it can be adapted to new image samples without executing from scratch the long and tedious initial training.

**Key Words:** image analysis, SEM, cheese microstructure

**799 Improvements and validation of mid-infrared predictions of milk fatty acid.** H. Soyeurt*[1,2], S. McParland[3], D. Berry[3], E. Wall[4], N. Gengler[1,2], F. Dehareng[5], and P. Dardenne[5], [1]*University of Liege, Gembloux Agro-Bio Tech, Animal Science Unit*, *Gembloux, Namur, Belgium*, [2]*National Fund for Scientific Research*, *Brussels, Brussels, Belgium*, [3]*Teagasc Moorepark Dairy Production Research Centre*, *Fermoy, Cork, Ireland*, [4]*Sustainable Livestock Systems Group, Scottish Agricultural College*, *Penicuik, Midlothian, United Kingdom*, [5]*Agricultural Walloon Research Centre, Quality Department*, *Gembloux, Namur, Belgium*.

The development of mid-infrared equations to predict the milk fatty acid (FA) content of milk allows prompt analysis of large numbers of samples. The first aim was to improve these predictions by comparing 6 statistical approaches. The second one was to validate the new equations using an independent sample set. The calibration set contained 239 spectrally different Belgian milk samples collected for over 2 years from several cows and breeds. FA were quantified by gas chromatography (GC). Statistical approaches tested were 1) partial least squares regression (PLS), 2) PLS and first derivative, 3) PLS and repeatability file (RF), 4) PLS, first derivative and RF, 5) PLS, second derivative, and 6) PLS, second derivative and RF. This last file contained spectra obtained from the same samples using 5 spectrometers. Cross-validation (CV) used 20 groups from the calibration set. Methods were compared using the ratio of the standard deviation of GC values to the standard error of CV (RPD). An external validation permitted a second comparison and was done using 362 samples collected for one year from multiple breeds and cows in Belgium, Ireland, and Scotland. Different RPD values were obtained by the 6 methods. Generally the equations developed using method 4 gave better results suggesting the adaptation of the methodology to the studied FA. It confirms by the obtained validation coefficients of determination. Highest values were observed for the equations with the highest RPD values except for C18:0. The ability to predict FA using method 4 gave superior results to those shown in previous publications.

**Key Words:** mid-infrared, milk, fatty acid

**800 Evaluation of a faster extraction and purification procedure for the analysis of vitamin D in fortified milk.** T. C. Schoenfuss*[1] and O. Shimelis[2], [1]*University of Minnesota*, *St. Paul,* [2]*Sigma-Aldrich*, *Bellefonte, PA.*

Current methods to analyze vitamin D in milk require lengthy sample preparation steps to extract vitamin D before analysis by chromatographic methods like HPLC. The approved method from Standard Methods for the Examination of Dairy Products requires multiple days to accomplish and includes over-night saponification, liquid-liquid