

# Red-green Alarming Method To Determine Adulterated Skimmed Milk Powder

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#### Background

Milk powders are a common target for food adulteration. Two approaches to adulteration are:

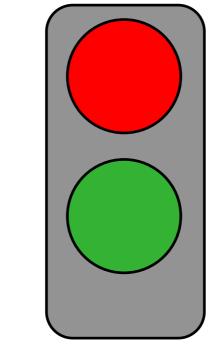
#### **Results and discussion**

- To 'dilute' the product or increase the dry matter content with a cheap bulk ingredient, e.g. starch or maltodextrin
- To increase the nitrogen content readings, e.g. with plant protein isolates or chemical compounds

Although the reason for adulteration is economically driven, it may result in serious public health consequences when the adulterant is toxic, allergenic or leads to malnutrition.

# **Objective**

Current detection methods are usually targeted, timeconsuming and expensive. Therefore, there is a need for non-destructive and preferably in-line methods to screen for any type of adulterant.

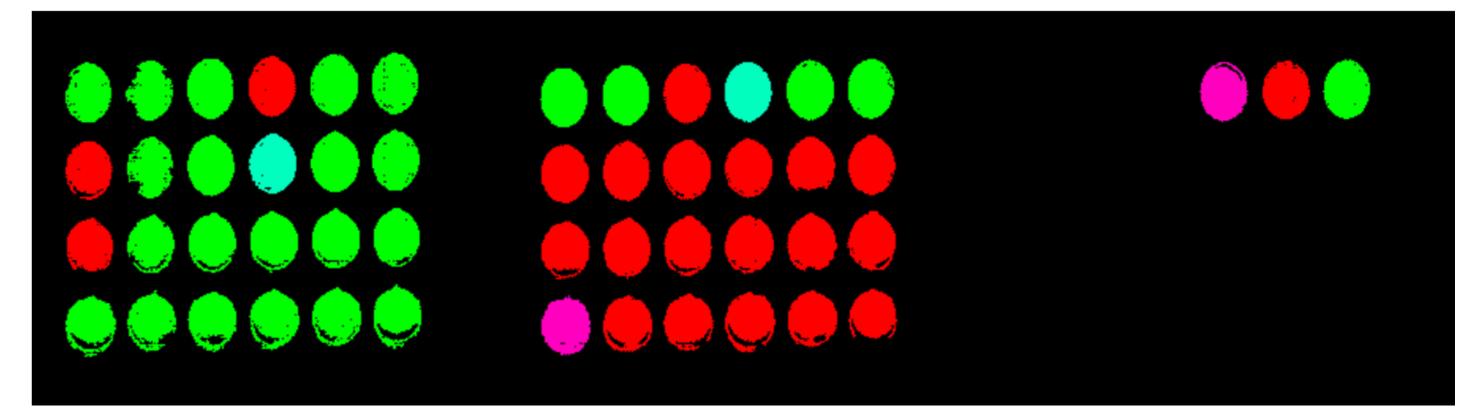


# Hyperspectral imaging is an interesting technique, which was evaluated in this study for broad anomaly testing of skimmed milk powders (SMP).

# **Materials and methods**

#### Hyperspectral imaging

Hyperspectral imaging is an imaging technique, combining imaging with spectroscopy, which provides a high resolution spectrum at every pixel. The analysis was performed at 400-1000 nm (VIS/NIR) using an ImSpector type V10E (Spectral Imaging Ltd, Oulo, Finland).



**Figure 2.** RGB picture based on the first three principal components of the spectral features. Green indicates a sample being classified as genuine SMP, red indicates classification as an adulterated sample. Blue and purple indicate that there is doubt on the classification, but the sample tends to be genuine or adulterated, respectively.

Figure 2 shows the RGB picture after calculations of the analysed samples. Out of the 21 adulterated SMP tested, only one was not classified correctly and two were uncertain. All three samples were adulterated with wheat protein isolate. The adulterated sample that was classified as genuine contained the lowest concentration (2%wt) wheat protein isolate. Adulteration with maltodextrin, starch, acid whey, buttermilk powder, pea and soy protein isolate were classified successful.

Out of the 30 genuine SMP tested, four samples were incorrectly classified as adulterated and two were uncertain. One of the incorrectly classified samples contained lumps, which might have been

### Skimmed milk powders

Commercial SMP (n=30) were used and adulterated with different levels (2, 5 and 7.5%wt) of plant protein isolates, maltodextrin, starch, acid whey and buttermilk powder (in total: n=21). Samples were prepared on a plate with 24 wells (Figure 1).



Figure 1. Skimmed milk powder samples prepared for analysis.

## **Chemometrics**

The dimension of the hyperspectral data cube was reduced to the first three scores of a principal component analysis of the first derivative of the cause. Classification is summarized in table 1. The PLS-DA model has been cross-validated (50x a random stratified selection was take from 80% of the data as training set and 20% as testset).

Predict.	Genuine	Adulterated
Actual		
Genuine	26	4
Adulterated	1	20

Table 1. Classification of genuine and adulterated milk powders based on a PLS-DA model.

## Conclusions

- With the help of a PLS-DA model, 87% of the genuine and 95% of the adulterated SMP were correctly classified (Table 1).
- Adulteration with wheat protein isolate was difficult to detect.
- Adulteration with maltodextrin, starch, acid whey, buttermilk powder, pea and soy protein isolate was successfully discerned.
- In this study, hyperspectral imaging has shown to be a promising red-green alarming method. However, more samples are required to strengthen the model and a wider range of adulteration will need to be tested in the future.

each spectrum. The automatically recognised sample images were subjected to spectral features calculation (Pau et al., 2010). Spectral features used for sample classification were sample mean, sum average and sum of variance, according to Haralick et al. (1973). The features were modelled by Partial Least Squares – Discriminant Analysis (PLS-DA), with prior autoscaling, and an RGB-picture (Figure 2) was composed based on the first three principal components of these three features. Both image analysis and classification has been performed using R (R Core Team, 2013).

#### References

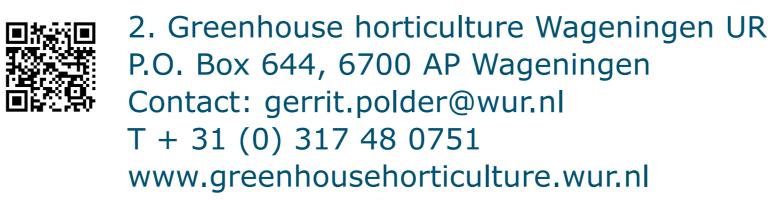
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