Use of Sensor Systems with Spectral Pattern Recognition for Food Authentication

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Outline

- Overview of food authentication
  - Methods
  - Challenge
- Research problems and aims
- Spectral pattern recognition
  - Classification
  - Model interpretation
- Sensor systems
  - Near-infrared spectroscopy
  - Diffraction grating
  - Computer vision (video based)
- Conclusion
- Future work

1. Overview

- Food adulteration and fraudulent labelling
  - Damage public health
  - Reduce consumer confidence
  - Ruin brand reputation
  - Examples:
    - *"Foreign beef 'is sold as British," BBC News, 2008.*
    - *"Germany investigates possible organic egg fraud," Reuters, 2013.*
    - *"Meat testing: A fifth of samples reveal unspecified animals' DNA," BBC News, 2018.*

1. Overview

- Food authentication is a process which verifies the food compliance with its label description.
    - Origin (species, geographical or genetic)
    - Production method (conventional, organic, traditional procedures, free range)
    - Processing technologies (irradiation, freezing, microwave heating).
- Conventional authentication methods
    - Sensory analysis → five organs perception → expensive, subjective and inconsistent
    - Laboratory-based instrumentation → wet chemistry and chromatography → time-consuming, require complex sample preparation and technical knowledge

1. Overview

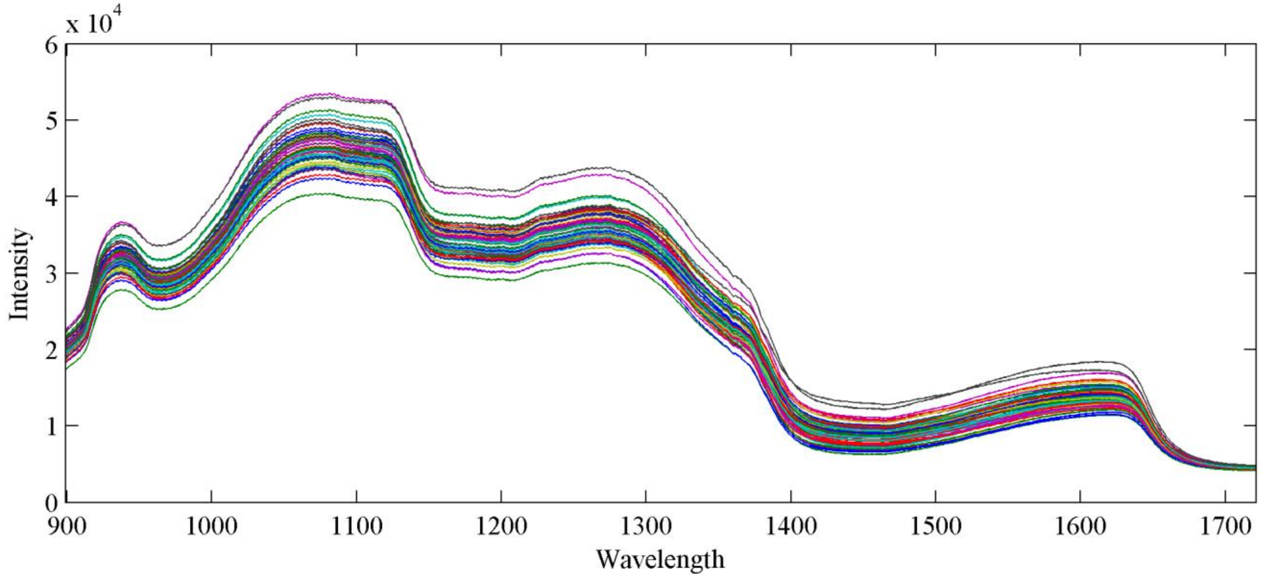
- Challenge: seek and develop efficient and low-cost methods for food authentication
  - Accurate determination
  - Fast and non-destructive
  - Minimal or no sample preparation and reagent consumption
- Novel methods for real-time food authentication methods
  - Optical measuring technologies, such as NIR spectroscopy, hyperspectral imaging and computer vision
  - Pattern recognition algorithms

2. Research problems and aims

- Problems:
  - Low-cost and portable sensors
    - Variable sampling conditions and instrumental limitations
    - Lower fingerprint data quality
    - Pose a serious challenge to pattern recognition methods
  - Nonlinear conditions
    - Caused by instrumental and experimental artefacts
    - Classical methods (PLS) often degrade in performance
- Aims:
  - Extract useful fingerprint data from noisy field data
  - Assist low-cost spectral-based sensors in obtaining the required level of performance compared to high-resolution spectrometers
  - Develop efficient and low-cost sensor systems

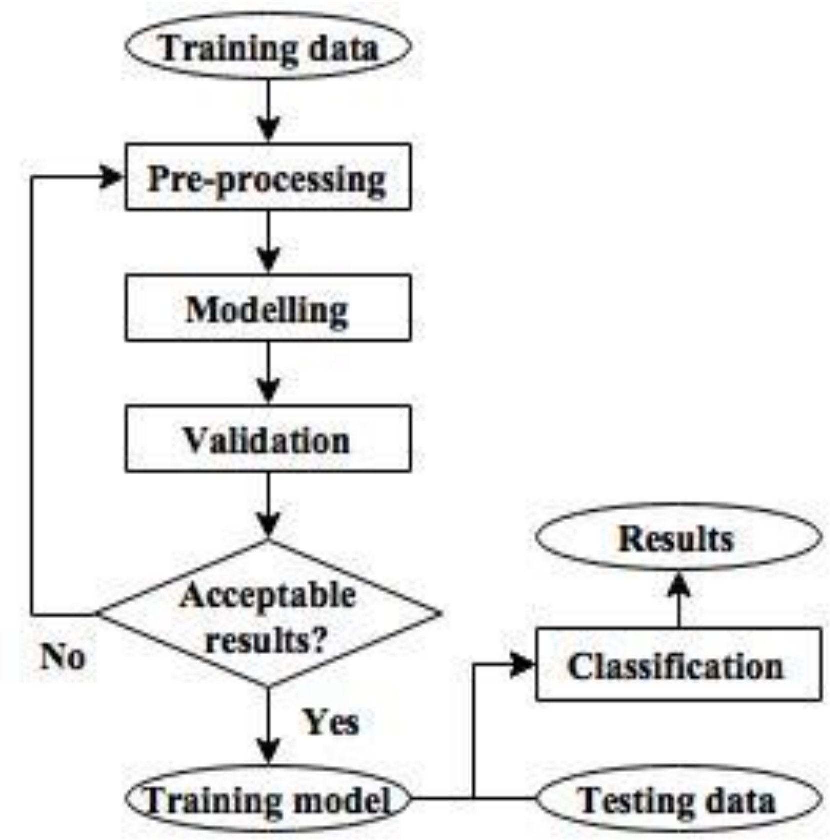
3. Spectral pattern recognition

- An interdisciplinary science of using mathematical, statistical and machine learning methods to identify regularities in spectral data
  - Regularities → chemical compositions and physical properties
  - Data presentation → radiation intensity versus wavelengths or frequencies
- Essential characteristics
  - High-dimensionality
  - High-collinearity
  - Non-linearity



3. Spectral pattern recognition: framework

- Pre-processing removes physical artefacts in spectra and improves the performance and robustness of classification model
- Modelling discovers the relationship between spectral data and qualitative/quantitative information
- Parameter optimization
- New input data prediction



3. Spectral pattern recognition: partial least squares (PLS)

- PLS is standard chemometric method for processing a wide spectrum of chemical data problems.
- Basic assumption: the investigated system or process is driven by a set of underlying latent variables (LVs).
- PLS searches for linear combinations of independent variables that maximize the covariance between the LV and the response:

$$\max \boldsymbol{w}^T \boldsymbol{X}^T \boldsymbol{Y} \boldsymbol{c},$$

$$s.t.\ \boldsymbol{w}^T \boldsymbol{w} = \boldsymbol{c}^T \boldsymbol{c} = 1.$$

where ***X*** is the matrix of independent variables, ***Y*** is the matrix of response, ***w*** and ***c*** is the weight vector of ***X*** and ***Y***, respectively.

3. Spectral pattern recognition: partial least squares (PLS)

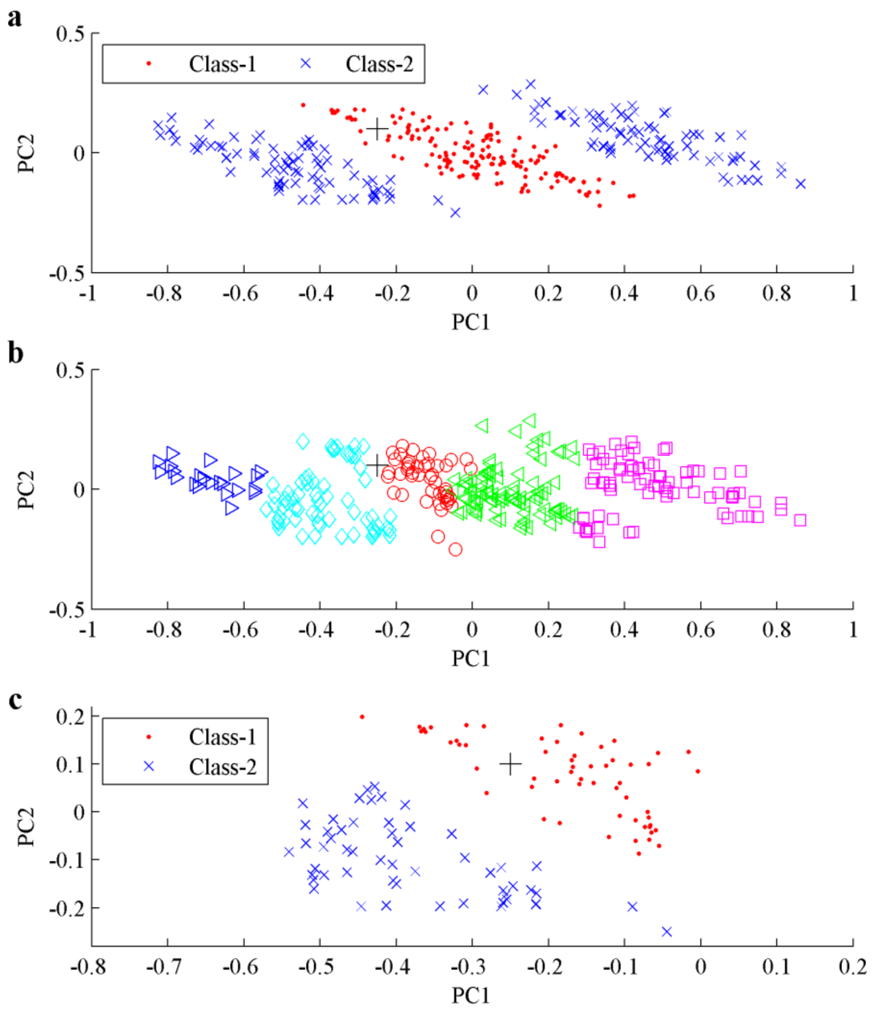
- PLS classification: dummy matrix coding transforms category information into numerical responses.
- Advantages
  - Stably estimate regression coefficients from low-dimensional LVs
  - Efficiently handle some ill-conditioned problems
    - Small sample size
    - High-dimensionality
    - High-collinearity
  - Model interpretation: PLS is good at showing significant variables via loadings or weights compared to SVM and LDA.
- Performance degradation in nonlinear, class imbalance and multiclass conditions

3. Spectral pattern recognition: some proposed methods

- Motivations
  - PLS is practically suitable for high-dimensionality and multicollinearity
  - Local models reduce global nonlinearity
  - Use weighting schemes based on the distance between query and training samples
- The proposed methods
  - Local PLS for classification
    - Nearest neighbors
    - Nearest clusters
    - Locally weighted
  - Representation classification with PLS regression
    - Model interpretation

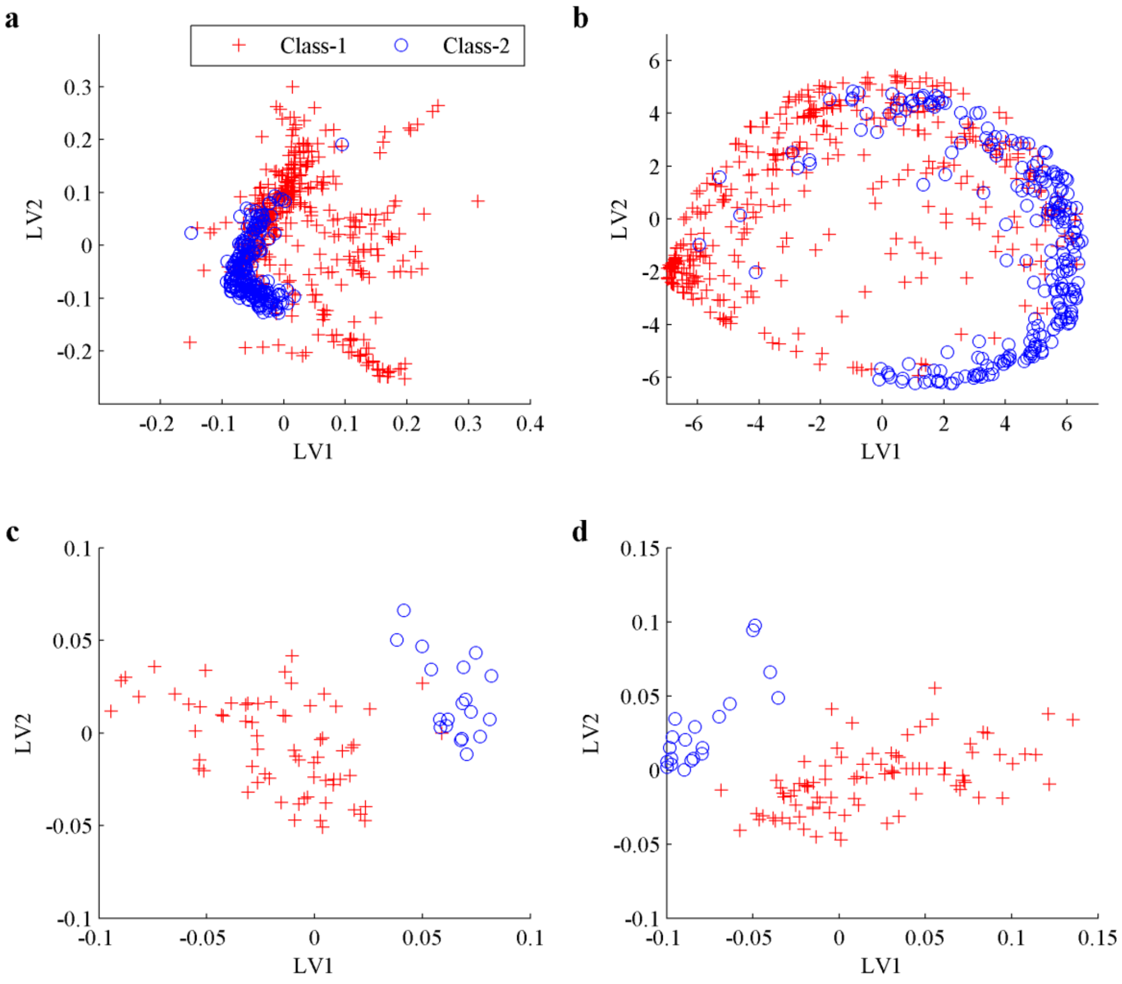
3. Spectral pattern recognition: some proposed methods

- Example 1: nearest clusters PLS-DA
  - Generate multimodal PCA scores
  - Simulate orthogonal combination of Gaussian peaks and reference spectrum can produce simulated data
- The black-cross (+) sample is wrongly classified by PLS-DA
- Local PLS approaches shows simplified and distinctive structure which is approximately linear separable.



3. Spectral pattern recognition: some proposed methods

- Training sample (a real-world spectral data) projections in the latent variable space of the PLS-DA and kernel PLS-DA model (a & b). Local training sample projections in the latent variable space of the local PLS-DA models (c & d).



3. Spectral pattern recognition: some proposed methods

- Example 2: LW-PLS classification
- Weighting scheme ω_n

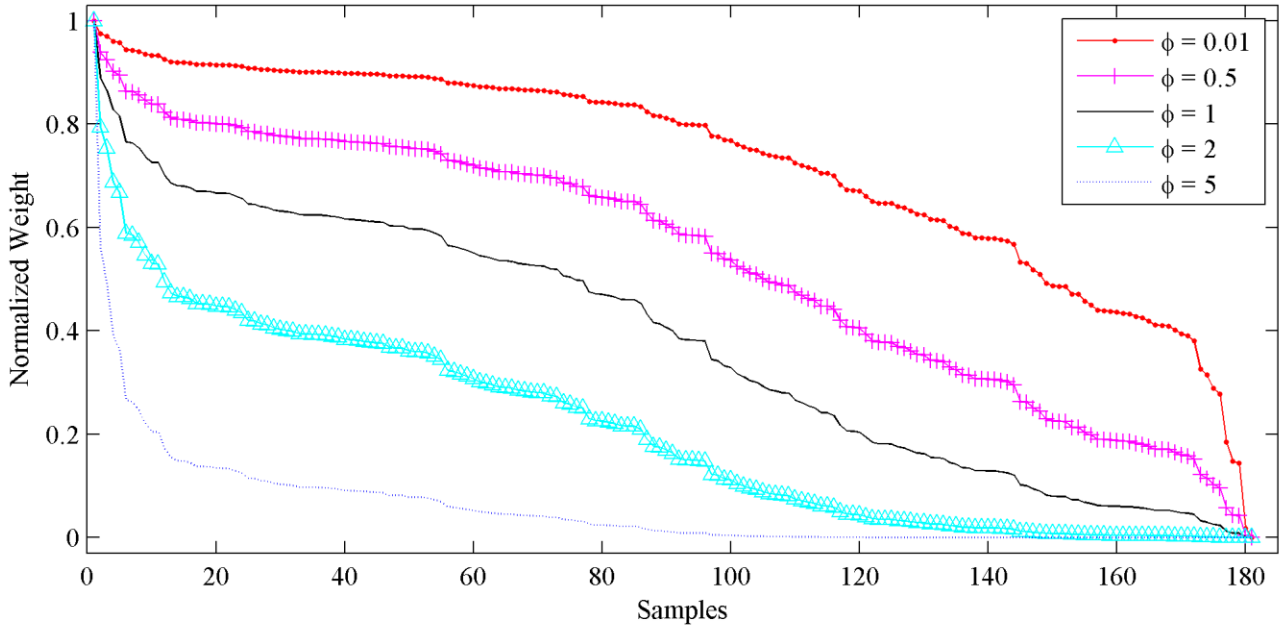
$$\omega_n = \exp\left(-\frac{\varphi d_n}{\sigma_d}\right)$$

where φ is localization parameter, d_n is Euclidean distance between query and training samples, σ_d is a standard deviation of $\{d_n\}$.

- For a given query, the weighting scheme respectively enlarges and lessens the influence of neighboring and remote samples towards a PLS-DA model.
- Two parameters localization parameter φ and LVs controls sample weights and model complexity, respectively.

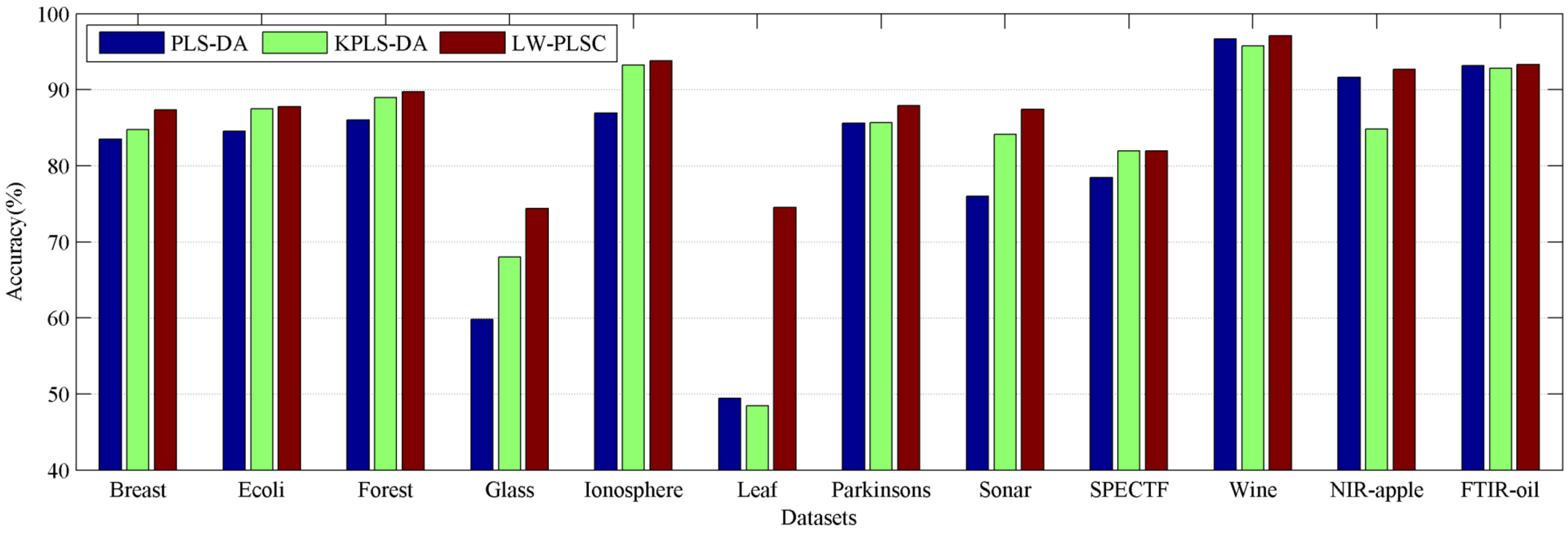
3. Spectral pattern recognition: some proposed methods

- Graphical representation of different φ values with respect to sample weights for a query sample
  - Small φ value: LW-PLSC becomes to PLS-DA
  - Large φ value: enlarged influence of neighboring samples



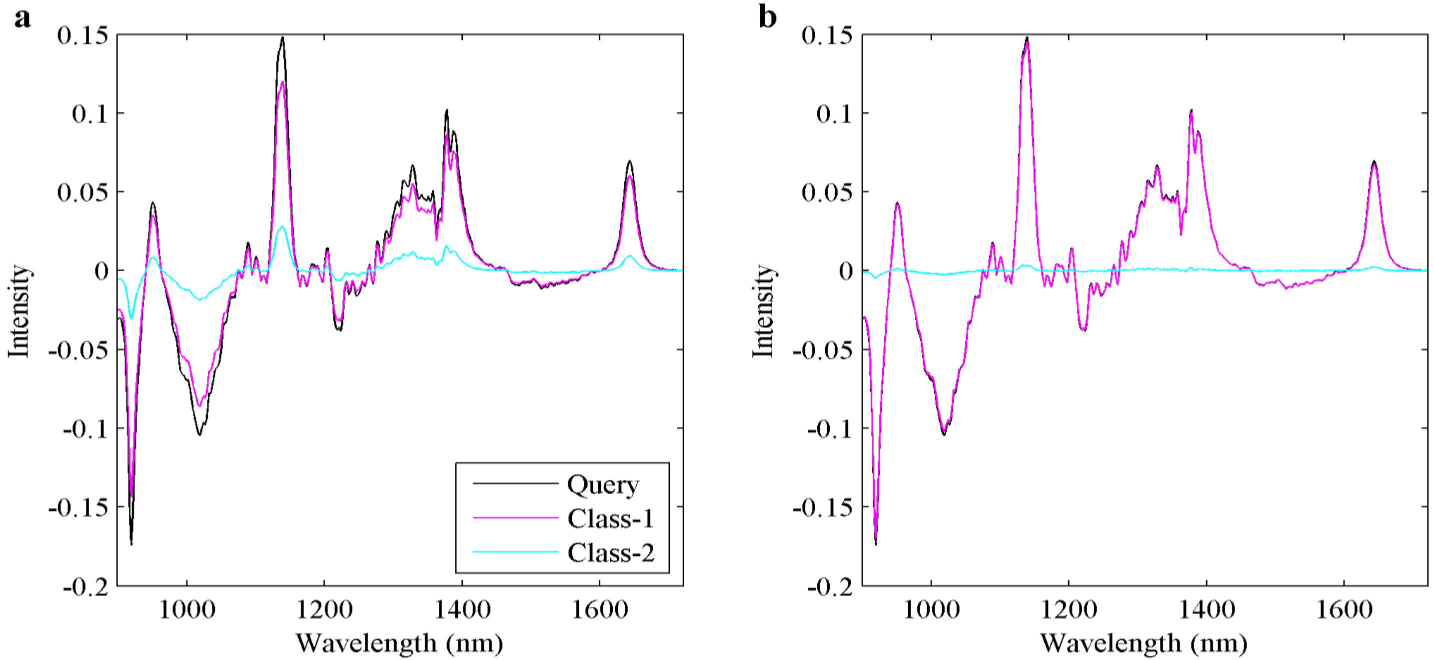
3. Spectral pattern recognition: some proposed methods

- Classification accuracy of PLS-based methods on UCI and spectral datasets.
- LW-PLSC > Kernel PLS-DA (RBF) > PLS-DA



3. Spectral pattern recognition: some proposed methods

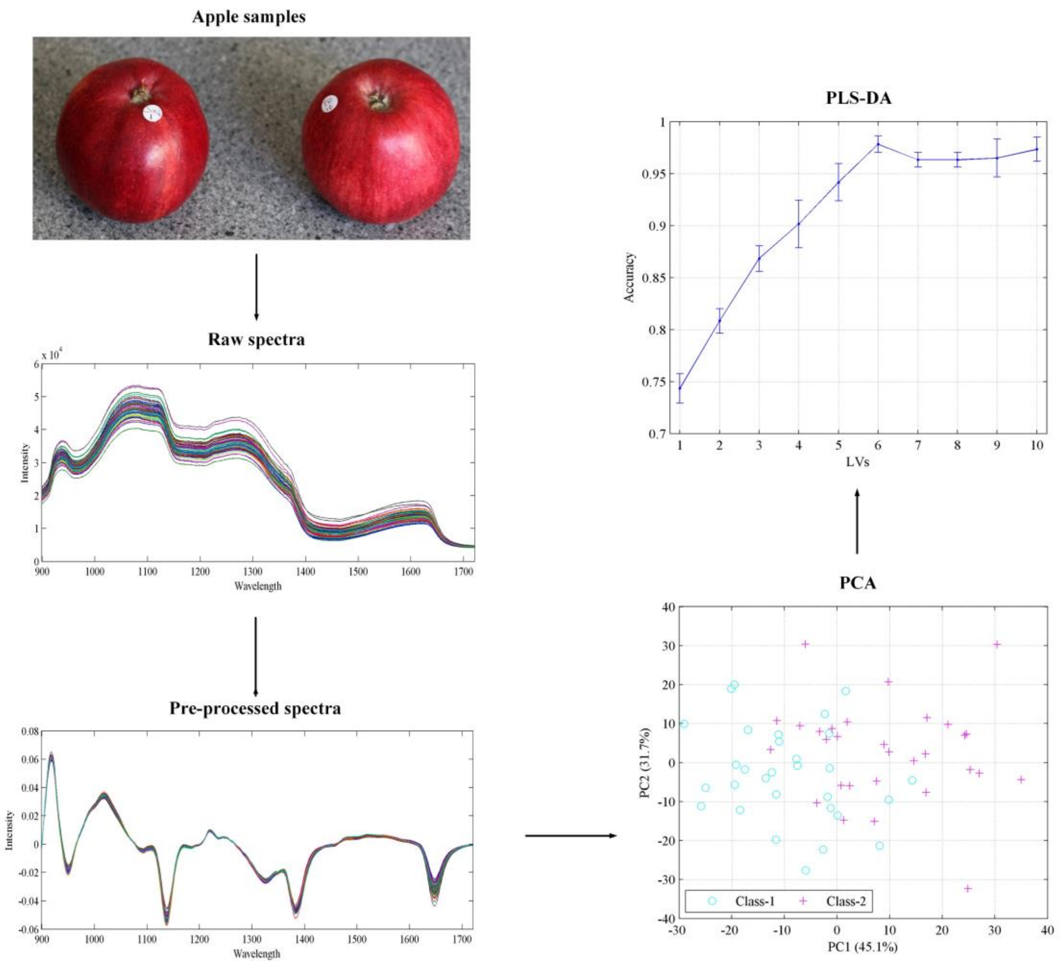
- Example 3: representation classification with weighted PLS regression
  - Use a weighted linear combination of training samples to represent a query
  - Attribute the query to the class which yields the least PLS approximation error
- Classification model interpretation (comparison)



4. Sensor systems

- Near-infrared spectroscopy (NIRS)
  - Organic and conventional apples
- Diffraction grating
  - Apple varieties
  - Organic and conventional apples
- Computer vision system (CVS)
  - Olive oil adulteration
  - Milk fat content (whole, skimmed and semi-skimmed)
  - Milk powder

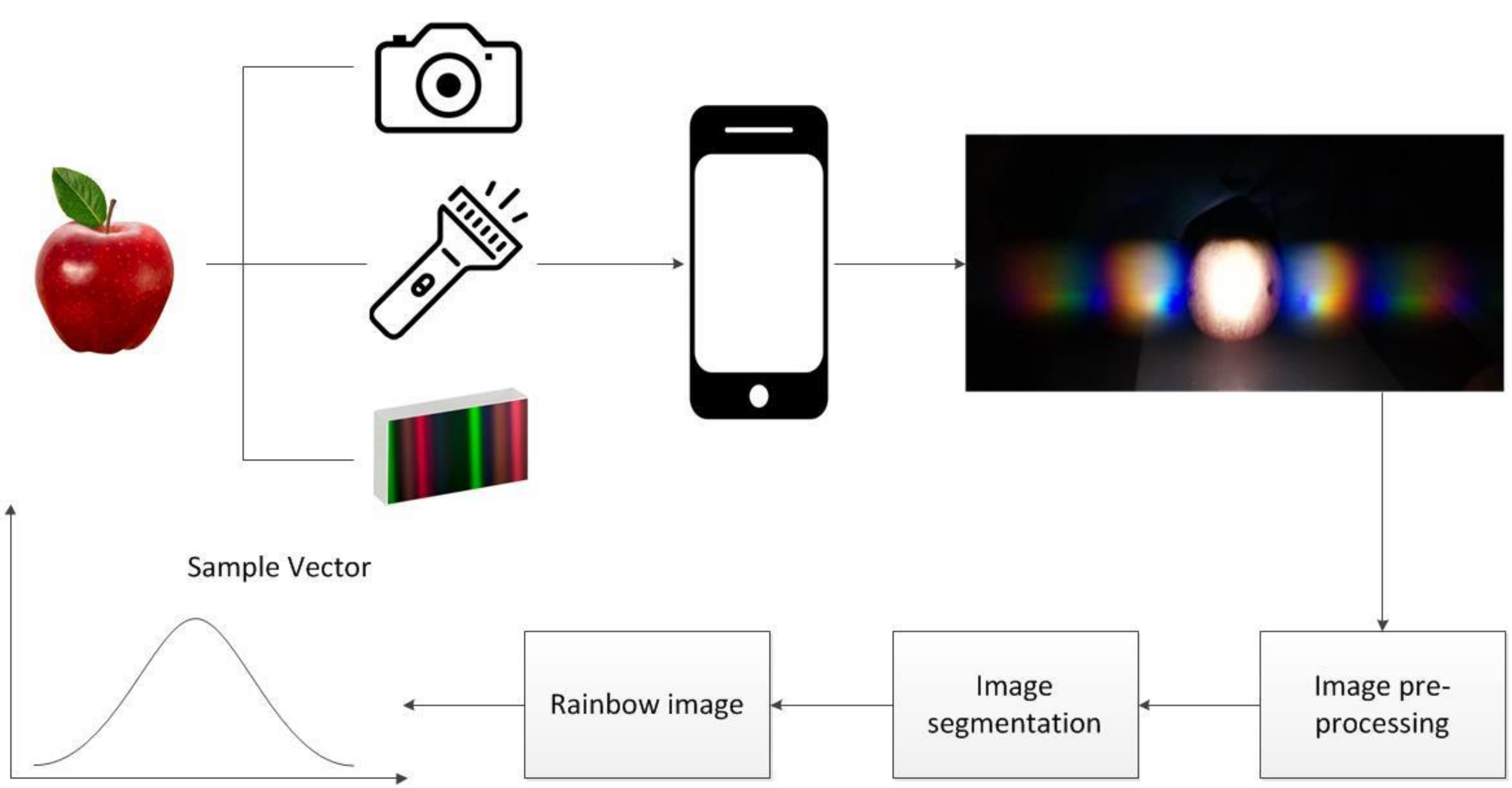
4. Sensor systems: NIRS



- Differentiation of organic and conventional apples
- Accuracy:
  - LOOCV: 95% (LW-PLSC)
  - Classification: 93% (LW-PLSC)

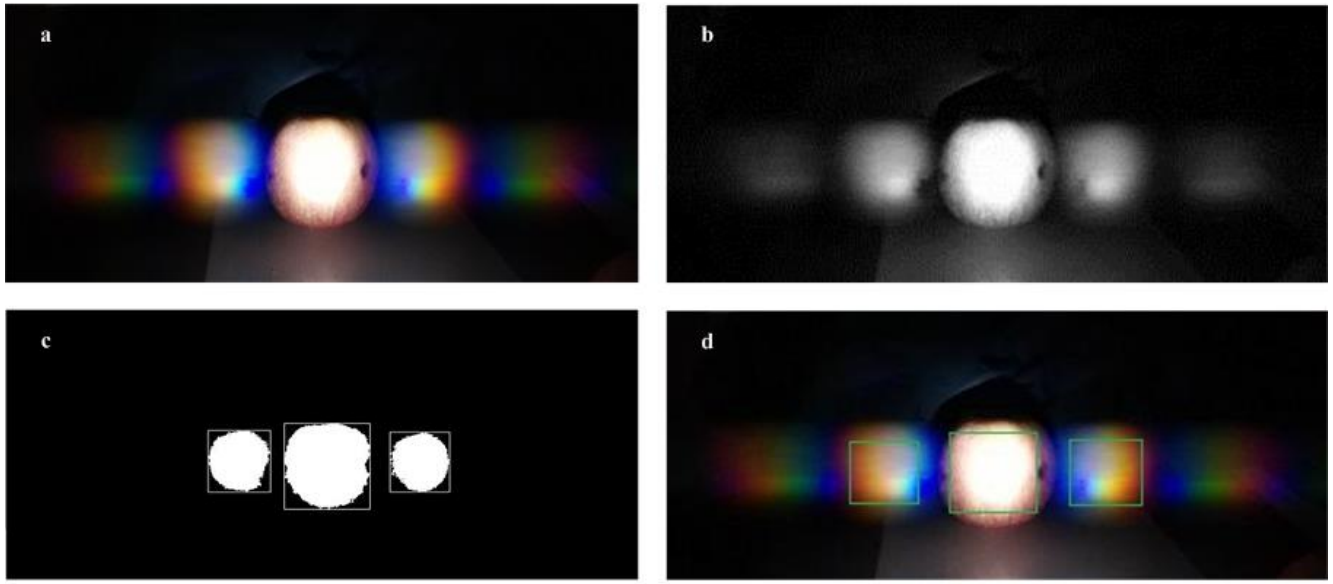
4. Sensor systems: diffraction grating

- Framework



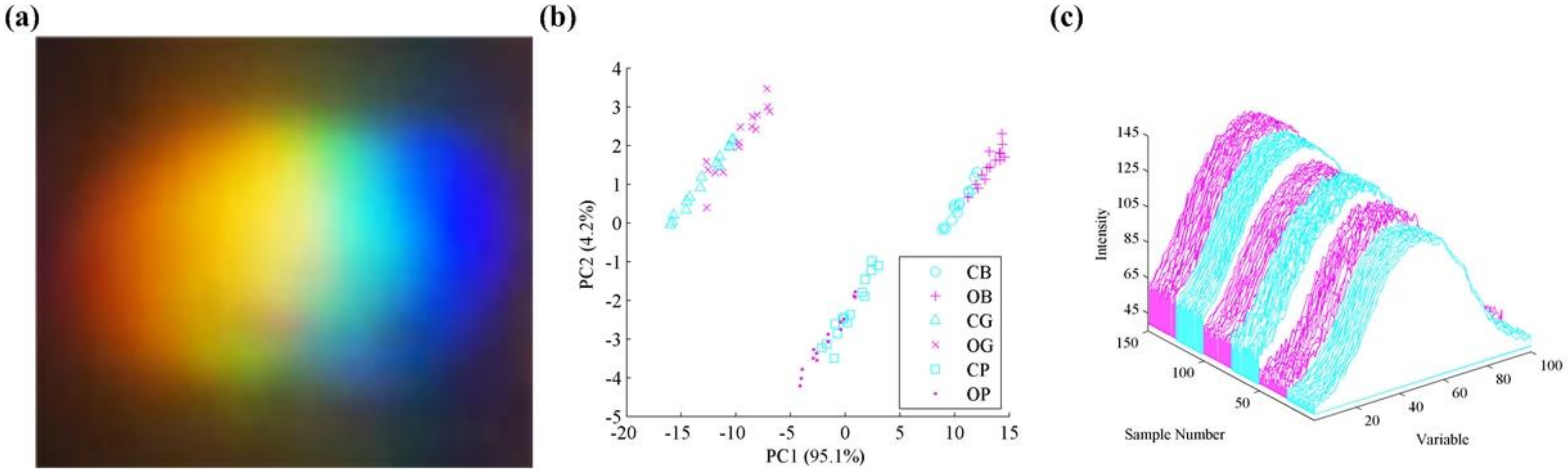
4. Sensor systems: diffraction grating

a) Rainbow images
b) Grayscale processing
c) Mathematical morphology
d) OSTU for image extraction



4. Sensor systems: diffraction grating

- Rainbow image (a) → numerical values (c) → PCA scores (b)
- Results
  - Over 93% accuracy
  - LW-PLSC, SVM and LS-SVM outperforms other 9 baseline classifiers
  - Comparable to portable NIR spectrometers



4. Sensor systems: computer vision system

- CVS aims to replace human visual system by artificial sensor and automatically gain high-level understanding from digital images.
- It extracts useful food external information, such as colour, size and shape.
- Procedures: image acquisition, processing and analysis
- Hardware: illumination, camera and computer
- Common applications:
    - content estimation
    - freshness assessment
    - defect detection

4. Sensor systems: computer vision system

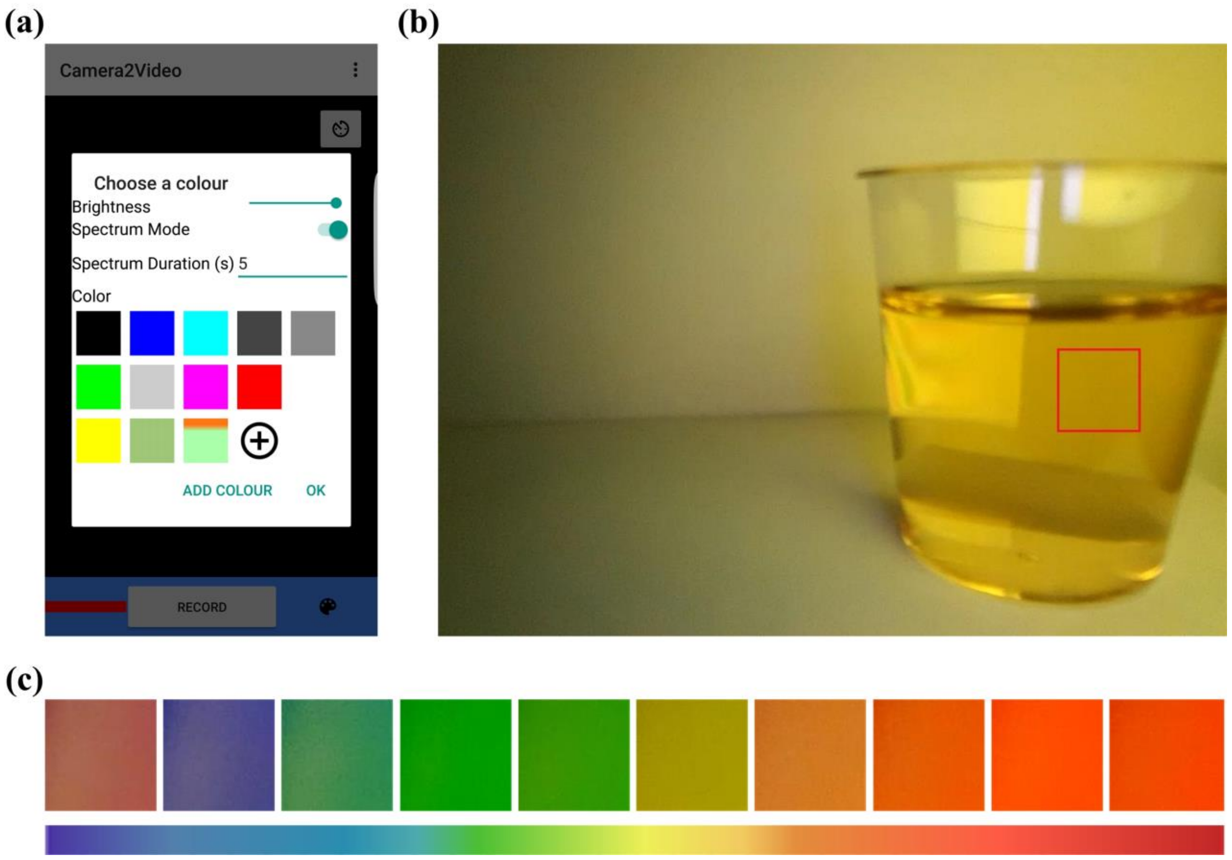
- Limitations of conventional CVS
  - Less practical for consumers
  - Properly designed illumination
  - Careful setting of camera
  - Varying sampling conditions
  - External camera and computer software
- Motivations
  - A feasible alternative to external camera: smartphone
  - Use CVS to capture spectral information (video)

4. Sensor systems: smartphone video

a) The user interface of Camera2Video app;

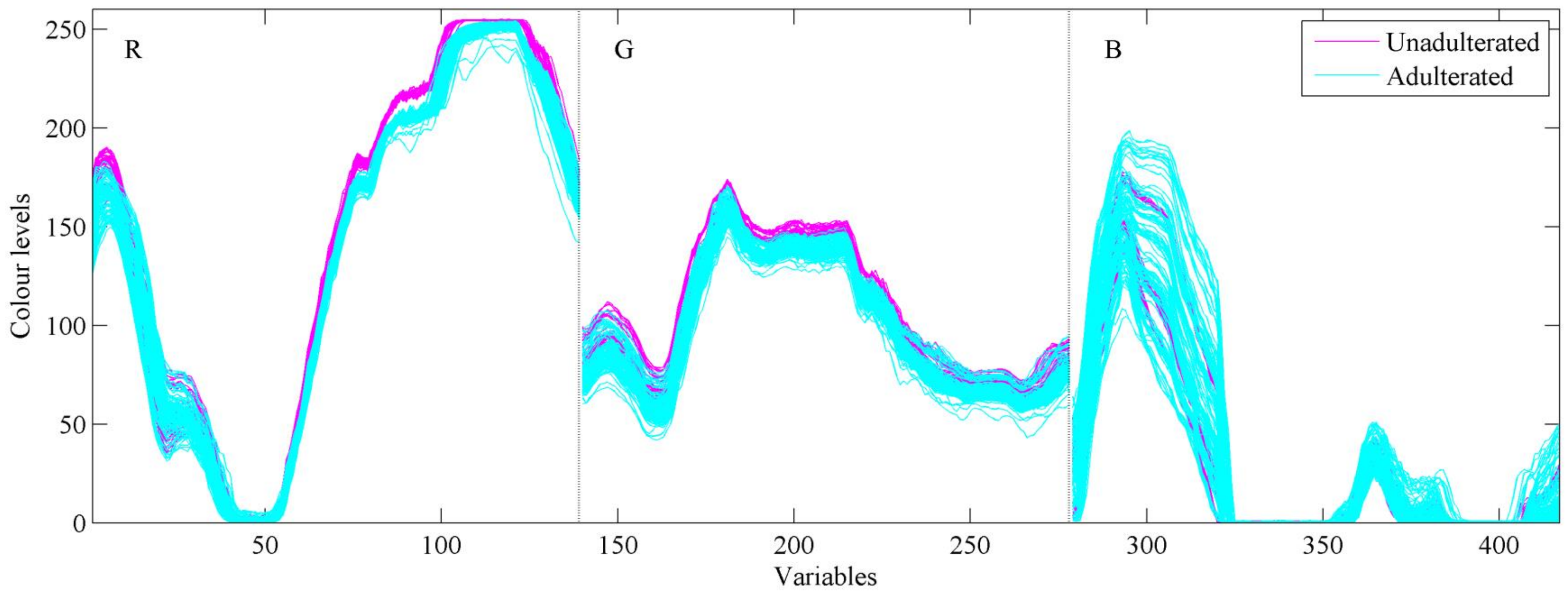
b) Image (960 × 720 pixels) of oil sample illuminated by yellow light. The selected ROI is marked by a red box with 100× 100 pixels;

c) Images of ROI illuminated by lights with a sequence of spectral colours.



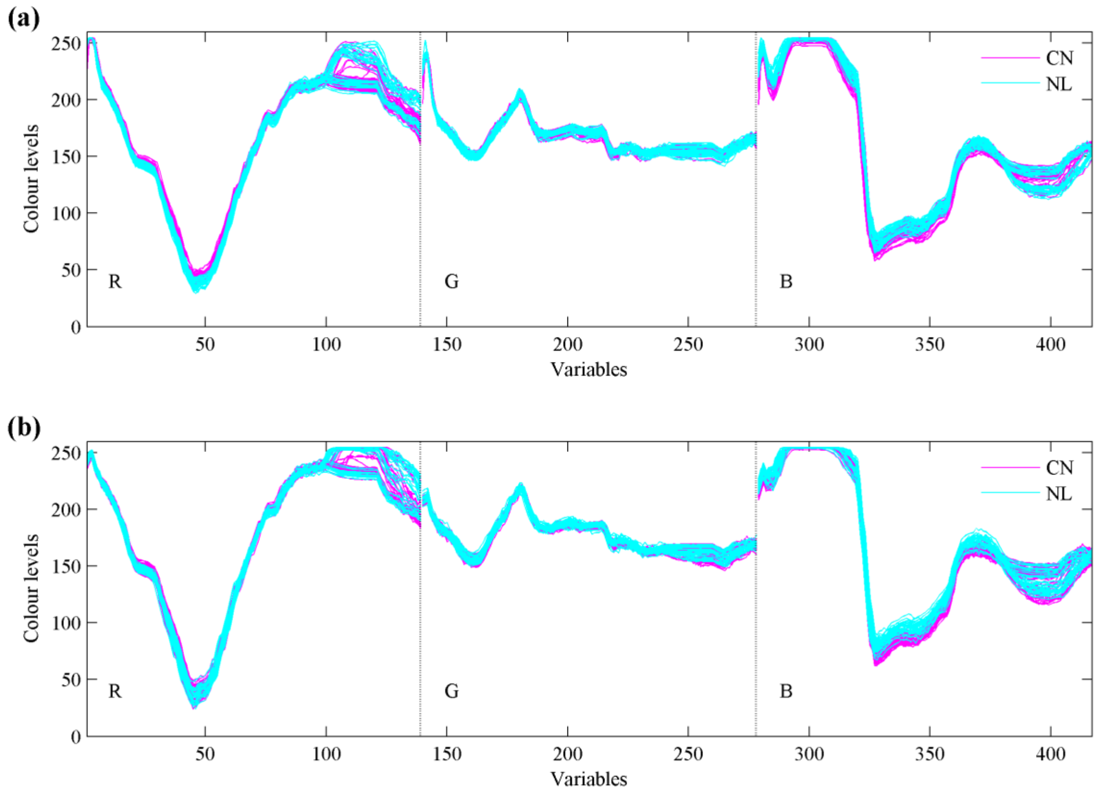
4. Sensor systems: smartphone video

- Video data of unadulterated and adulterated olive oil.
- Distinction of unadulterated and adulterated 80 samples in red colour channel variables 85-125.



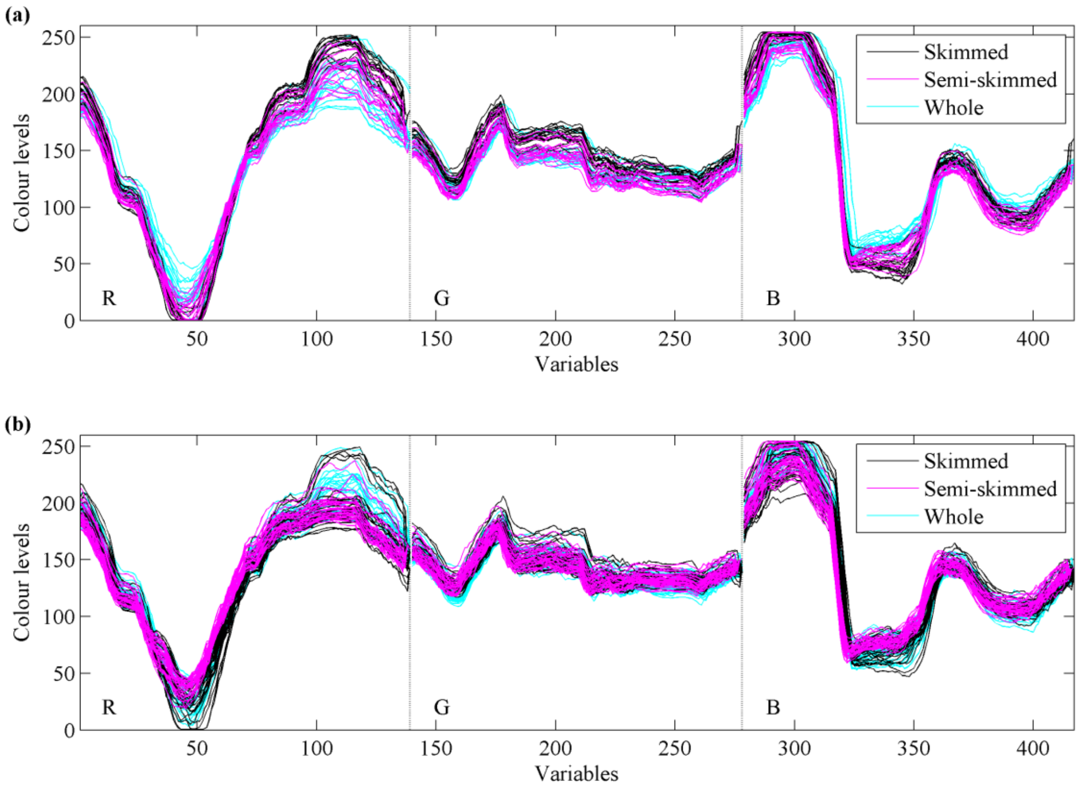
4. Sensor systems: smartphone video

- Identification of milk powder origin (CN and NL)
- Two sampling sessions, 168 samples
- Results
  - LOOCV: 86.6% (LW-PLSC)
  - Classification: 89.3% (SVM)



4. Sensor systems: smartphone video

- Classification of skimmed, semi-skimmed and whole milk
- Two sampling sessions, 138 samples
- Results
  - LOOCV: 97.8% (PLS-DA and LW-PLSC)
  - Classification: 100% (PLS-DA and LW-PLSC)



5. Conclusion

- The proposed methods improve the modelling performance and simplicity in classifying nonlinear spectral data.
- They outperform baseline methods in most of the time.
- Low-cost sensor yields comparable results to commercial spectrometer with the aid of state of the art methods, such as LW-PLSC.
- The use of phone videos coupled with pattern recognition has great potential for efficient and low-cost food authentication.

6. Future work

- Model interpretation
  - A comparison between machine learning and chemometrics variable selection.
- Data representation
  - Small sample size
  - ‘Variable’ weighted regression
  - Between class regularization
- Big data and deep learning
  - Sampling
  - Modelling
  - App development

Publications

- W. Song, H. Wang, P. Maguire, O. Nibouche, Differentiation of organic and non-organic apples using near infrared reflectance spectroscopy — A pattern recognition approach, in: SENSORS, 2016 IEEE, IEEE, 2016.
- W. Song, H. Wang, P. Maguire, O. Nibouche, Local Partial Least Squares classifier in high dimensionality classification, Neurocomputing. 234 (2017) 126–136.
- W. Song, H. Wang, P. Maguire, O. Nibouche, Nearest clusters based partial least squares discriminant analysis for the classification of spectral data, Anal. Chim. Acta. 1009 (2018) 27–38.
- W. Song, H. Wang, P. Maguire, O. Nibouche, Collaborative representation based classifier with partial least squares regression for the classification of spectral data, Chemom. Intell. Lab. Syst. 182 (2018) 79-86.
- W. Song, H. Wang, P. Maguire, O. Nibouche, Spectral data classification using locally weighted partial least squares classifier, Data Science and Knowledge Engineering for Sensing Decision Support – Proceedings of the 13th International FLINS Conference (2018) 700-707.
- N. Jiang, W. Song, H. Wang, G. Guo, Y. Liu, Differentiation between organic and non-organic apples using diffraction grating and image processing—A cost-effective approach, Sensors (Switzerland). 18 (2018) 1667.