Automatic Classification of Crispiness: Integration of Mechanical and Acoustical Sensor Data

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Uhrenturm der TVM

MATLAB Expo

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Bourne 2002; Saeleaw & Schleining 2011; Van Vliet & Primo-Martín 2011 soberingthoughts.info; thenounproject.com; www.clipartbest.com; www.iconfinder.com

Overview

ТШ

1) Instrumental sounds \rightarrow crisps freshness distinction by humans?

2) Multimodal texture characterization \rightarrow improved accuracy of crisps freshness classification? 3) Spectral features vs. traditional temporal features \rightarrow impact on classification?



Multimodal data aquisition





Light microscopy [500µm bar]



Compression test + sound recording



٦Π

Automatic classification strategy





Temporal vs. Spectral analysis



→ No reproducible & reliable prediction of crispiness using single texture parameters

- → STFT, CWT & HHT suitable for irregular multi-fracture phenomena
- → Fourier spectrum in octaves suitable for classification

Classification Learner App

Algorithms screening:

- Decision trees
- Discriminant analysis
- Nearest neighbor
- Ensemble classifiers
- Support vector machines (SVM)
- Artificial neural networks (ANN)



Classification results



Non-linear relationships between food physics and freshness

- → mimics psychophysics of sensory integration
- Best predictions using
 - selected temporal
 - third-octave spectral features
 - from mechanics & acoustics

91.8% overall accuracy



Quadratic SVM: 5-fold cross-validation, 20% test data, measured at 10 mm/s crushing

Learning Curve





Conclusion





Thanks





- Horst-Chrisitan Langowski (institute access)
- Raffael Osen (TA access + extruder)

TUM Diversity Laura Bassi-award

- Hubert Kollmannsberger (sensory)
- Carlotta Ziegltrum, Simone Maurer, Katja Jontes
- Many colleagues (advice, discussion, sensory panel)



Let's ride food science waves!

MMMM

Externals

- Henri Braun (EMD)
- Lisa Drobny (Winopal, TA-help)
- Michael Mudra, Uwe Beis (acoustics)

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- Crispy project timeline
- Sensory freshness classes
- PCA representation
- Automatic classification strategy
- SVM results
- ANN results

Crispy project

Timeline

2017

2014 Prework on mechanical & spectral analyses ✓ Food Oral Processing Conference: Dynamic alternatives to fractal and Fourier methods for analysis of crispy / crunchy food products

2015 ✓ Journal of Texture Studies, 46, 171-185: Dynamic spectral analysis of jagged mechanical signatures of a brittle puffed snack

Mechanical, acoustical and sensory data collection

- 2016 ✓ Modelling & Poster at MATLAB Expo: Strategies to classify sounds and mechanics using dynamic spectral information
 - ✓ Submitted paper





Strategies to classify crispy sounds and mechanics using dynamic spectral information

Motivation

Crispy food textures = stimulating, fresh, pleasant & have → highest impact on consumer preference and quality evaluation ^[1]	 Optimizing crispy products = appropriately stiff and brittle during chewing & release pleasant rhythmic sounds of particular pitch and loudness avoiding use of sensory panels
Food industry and research requirements for quality control and development	 Improvement of available texture measurements and data analysis methods
• Crispiness evaluation = essential but causes persistent difficulties in practice, in particular for differentiating low-humidity crispness levels (10 to 20 % RH) ^[1]	 Freshness levels classification from instrumental data corresponding to sensory crispiness grades, mimicking multisensory & temporal integration during oral breakdown

Goals



Conclusion

Classification needs more than simple mechanical features
 Instrumental crushing sounds → perception of food freshness
 Dynamic spectral analysis → mathematical analytic description & display of whole complexity of foods' signature
 Multimodal classification → multitude of modern methods & optimum not straightforward, but improved accuracy

Further Improvements

 Synchronized denoising & bone-conducted sounds using transfer function models of isolation box and human head
 Sanahuja, S. and Briesen, H. 2015. Dynamic spectral analysis of jagged mechanical

signatures of a brittle puffed snack. Journal of Texture Studies, 46, 171-186. Technische Universität München, Process Systems Engineering, Gregor-Mendel-Straße 4, 85354 Freising, http://wzw.tum.de/svt Contact: solange.sanahuja@gmx.de Humans perceive & evaluate freshness of chips only based on instrumental texture analysis sound records



- Significant differences (Friedman-Test, $\alpha = 0.01$) & ranking (Page-Test, $\alpha < 0.05$)
- 2 groups (LSD "Least Significant Difference")

Full PCA



Linear relationships not sufficient for modelling psychophysics phenomenon of crispiness sensation



Automatic classification strategy





Classification models & results

Modeling & evaluation

- 10 x 5-fold cross-validation: suited for small datasets
 → average accuracy & variability estimation
- Training/validation with 80%, test with 20% random samples for each sub-model

Model selection

- Psychophysics models: non-linear relationships between food physics and sensory sensation
- → Best models: Quadratic SVM & ANN with disabled PCA preselection (linear)

Results

- Best predictions using selected temporal + third-octave spectral features from mechanics & acoustics
- Crushing velocity: better overall accuracy at 10 mm/s but better distinction between 11 & 23% RH at 0.33 mm/s



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ANN results

Confusion matrices

- one of the best ANN models
- 1 layer of 10 hidden neurons
- high-velocity selected temporal combined with third-octave spectral . mechanical and acoustical features

Overall accuracies [%] on the test sets:

- (a) 1 layer of 10 hidden neurons;
- (b) 3 layers of 20 hidden neurons;
- (c) 1 layer of 250 hidden neurons.

Domain	Features	Octave	Number of	Test velocity	ANN model			
Domain		bands	features	Test velocity	(a)	(b)	(c)	
Time &	Combined	1/3	68	10 mm/s	85 8+3 8	85 1+4 0	80.0+5.8	
Frequency	selected	1/5	00	10 1111/5	00.010.0	05.1±4.9	00.9±3.0	

				rraining confusion matrix										
	A: Fresh	96 22.9%	1 0.2%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	99.0% 1.0%						
True class	B: 11 %RH	0 0.0%	71 16.9%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%						
	C: 23 %RH	0 0.0%	0 0.0%	63 15.0%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%						
	D: 33 %RH	0 0.0%	0 0.0%	1 0.2%	65 15.5%	0 0.0%	0 0.0%	98.5% 1.5%						
	E: 44 %RH	0 0.0%	0 0.0%	0 0.0%	0 0.0%	61 14.6%	0 0.0%	100% 0.0%						
	F: 53 %RH	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	61 14.6%	100% 0.0%						
		100% 0.0%	98.6% 1.4%	98.4% 1.6%	100% 0.0%	100% 0.0%	100% 0.0%	99.5% 0.5%						
		Predicted class												
			T	Predi	Predicted class									
			-		ntusio	n Matr	IX							
	A. Frank	27	0	2	ntusio 0	n Matr 0	0	93.1%						
	A: Fresh	27 20.9%	0 0.0%	2 1.6%	0.0%	0.0%	0 0.0%	93.1% 6.9%						
	A: Fresh B: 11 %RH	27 20.9% 1 0.8%	0 0.0% 16 12.4%	2 1.6% 0 0.0%	0.0%	0.0%	0 0.0% 0.0%	93.1% 6.9% 94.1% 5.9%						
SS	A: Fresh B: 11 %RH C: 23 %RH	27 20.9% 1 0.8% 1 0.8%	0 0.0% 16 12.4% 3 2.3%	2 1.6% 0 0.0% 17 13.2%	0 0.0% 0 0.0% 0 0.0%	0 0.0% 0 0.0% 0 0.0%	0 0.0% 0 0.0% 0 0.0%	93.1% 6.9% 94.1% 5.9% 81.0% 19.0%						
ue class	A: Fresh B: 11 %RH C: 23 %RH D: 33 %RH	27 20.9% 1 0.8% 1 0.8% 0,0%	0 0.0% 16 12.4% 3 2.3% 0 0.0%	2 1.6% 0 0.0% 17 13.2% 3 2.3%	0.0% 0.0% 0.0% 0.0% 16 12.4%	n Watr 0.0% 0.0% 0.0% 0.0% 2. 1.6%	0 0.0% 0 0.0% 0 0.0% 0 0.0%	93.1% 6.9% 94.1% 5.9% 81.0% 19.0% 76.2% 23.8%						
True class	A: Fresh B: 11 %RH C: 23 %RH D: 33 %RH E: 44 %RH	27 20.9% 1 0.8% 0.8% 0.0%	0 0.0% 16 12.4% 3 2.3% 0 0.0%	2 1.6% 0 0.0% 17 13.2% 3 2.3% 0 0.0%	0 0.0% 0 0.0% 0 0.0% 16 12.4% 1 0.8%	n Matri 0.0% 0.0% 0.0% 2 1.6% 18 14.0%	0 0.0% 0 0.0% 0 0.0% 0 0.0% 1 0.8%	93.1% 6.9% 94.1% 5.9% 81.0% 19.0% 76.2% 23.8% 90.0% 10.0%						
True class	A: Fresh B: 11 %RH C: 23 %RH D: 33 %RH E: 44 %RH F: 53 %RH	27 20.9% 1 0.8% 0 0.0% 0 0.0% 0 0.0%	0 0.0% 16 12.4% 3 2.3% 0 0.0% 0.0% 0.0%	2 1.6% 0.0% 17 13.2% 3 2.3% 0.0% 0.0%	0 0.0% 0 0.0% 0 0.0% 16 12.4% 1 0.8% 0 0.0%	n Matri 0 0.0% 0 0.0% 2 1.6% 18 14.0% 0 0.0%	0 0.0% 0 0.0% 0 0.0% 0 0.0% 1 0.8% 21 16.3%	93.1% 6.9% 94.1% 5.9% 19.0% 76.2% 23.8% 90.0% 10.0%						
True class	A: Fresh B: 11 %RH C: 23 %RH D: 33 %RH E: 44 %RH F: 53 %RH	27 20.9% 1 0.8% 0 0.0% 0 0.0% 0 0.0% 93.1%	0 0.0% 16 12.4% 3 2.3% 0 0.0% 0 0.0% 84.2%	2 1.6% 0.0% 17 13.2% 3 2.3% 0.0% 0.0% 777.3%	0 0.0% 0 0.0% 0 0.0% 16 12.4% 1 0.8% 0 0.0% 94.1%	0 0.0% 0 0.0% 0 0.0% 2 1.6% 18 14.0% 0 0.0% 90.0%	0 0.0% 0 0.0% 0 0.0% 1 0.8% 21 16.3% 95.5%	93.1% 6.9% 94.1% 5.9% 19.0% 76.2% 23.8% 90.0% 10.0% 100% 0.0% 89.1%						

volution Confusion Matul



		All Confusion Matrix									
True class	A: Fresh	142 22.0%	1 0.2%	3 0.5%	0 0.0%	0 0.0%	0 0.0%	97.3% 2.7%			
	B: 11 %RH	2 0.3%	96 14.9%	1 0.2%	0 0.0%	0 0.0%	0 0.0%	97.0% 3.0%			
	C: 23 %RH	1 0.2%	3 0.5%	94 14.6%	0 0.0%	0 0.0%	0 0.0%	95.9% 4.1%			
	D: 33 %RH	0 0.0%	0 0.0%	4 0.6%	97 15.0%	3 0.5%	0 0.0%	93.3% 6.7%			
	E: 44 %RH	0 0.0%	0 0.0%	0 0.0%	2 0.3%	94 14.6%	2 0.3%	95.9% 4.1%			
	F: 53 %RH	0 0.0%	0 0.0%	0 0.0%	0 0.0%	1 0.2%	99 15.3%	99.0% 1.0%			
		97.9% 2.1%	96.0% 4.0%	92.2% 7.8%	98.0% 2.0%	95.9% 4.1%	98.0% 2.0%	96.4% 3.6%			
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		Predicted class									

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Predicted class