System development and improvement within incomplete feedback context: comparative analysis of forests and food systems

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- Inspired by:
  - Events
    - 20th IEEE International Symposium on a World of Wireless, Mobile and Multimedia Networks (WoWMoM)
    - CMEM 2019 is the 19th International Conference in this well-established series on Computational Methods and Experimental Measurements.
  - Marianna Obrist
    - The focal point of my research is to create a rich and systematic understanding on users touch, taste, and smell experiences for interactive technologies. Despite the fact that interactive technologies have permeated our environment (e.g., mobile, ubiquitous, social computing) and have become an essential part of our everyday life (e.g., work, leisure, education, health, etc.), the way we interact with them is still limited. Interactive systems stimulate dominantly our senses of vision and hearing, partly our sense of touch (e.g., vibration in mobile phones), while our senses of taste and smell are widely neglected and under-exploited in Human-Computer Interaction (HCI) research.
    - I have established the Sussex Computer Human Interaction (SCHI) Lab, an interdisciplinary team of researchers and enthusiasts from computer science, psychology, engineering and design. Please find more details on our research and activities at: http://www.multisensory.info
  - Google - https://acm-fca.org/2018/07/01/future-of-computing-food-manifesto/

Research Focus

The aim of the work is to contribute to the development of the theory of systems in the context of an **incomplete feedback**. Analyzing the forest and food information systems, we can conclude that these systems both operate in incomplete feedback context, thus, comparative analysis of systems can make an important contribution to the development of the **theory**. The study, based on the methodology of **ubiquitous computing and human-computer interaction**, is intended to test hypotheses: (1) the feedback system, which significantly improves the system, plays an important role in **system development**; (2) expanding the feedback from the visual message and including other senses can significantly improve **the quality of the feedback**.

Structure of the work

Theory

- Feedback systems
- Dynamic systems
- Food Computing
- Potential link from food computing to 'forest computing'

Data collection

- Existing data sets
- Gaps and opportunities

Feedback system

- Testing of a feedback system
- e.g. food waste at schools/ restaurants/ social media?

Feedback system prototype development

- Improving feedback system elements
- Improving feedback system infrastructure

Improved feedback system

- Testing of a feedback system
- e.g. food waste at schools

Definitions

Feedback
Feedback in engineered systems
System
Dynamical system
Model
Computing and food/forest

Feedback

- A **dynamical system** is a system whose behavior changes over time, often in response to external stimulation or forcing. The term **feedback** refers to a situation in which two (or more) dynamical systems are connected together such that each system influences the other and their **dynamics are thus strongly coupled**.

- **Control/feedback** = the use of algorithms and feedback in **engineered systems**

- **A model** is a mathematical representation of a physical, biological or information system. Models allow us to reason about a system and make predictions about how a system will behave. In this text, we will mainly be interested in models of dynamical systems describing the input/output behavior of systems, and we will often work in "state space" form. Roughly speaking, a dynamical system is one in which the effects of actions do not occur immediately (pp. 27)

https://authors.library.caltech.edu/25062/1/Feedback08.pdf

Model

Models enable us to make decisions. They can help us to visualise, predict, optimise, regulate and control complex systems.

Models should be no more, and no less, complex than they need to be.

The **computational power that people carry around** in their smartphones creates complex webs of cooperation with little central authority, whose consequences are often unclear.

Many of the systems we rely on combine social and technological factors in new ways, such as social networking tools that enable new ways of behaving and cooperating. Access to data, and the range of data available, are spurring efforts to develop new ways to exploit these data for commercial purposes, whose ultimate impact is unknown.

Agent-based simulations — which model each person as a separate interacting entity — have matured to the point that they can be applied to important social, ecological and economic questions.

Ubiquitous sensors will create new areas of application for modelling. Sensors, actuators and processors are becoming more ubiquitous and more intelligent. But extracting reliable information from the systems that use them remains far from straightforward. This is because sensors are noisy; they decalibrate; or they may become misplaced, moved, compromised, and generally degraded over time, both individually and as networks. Yet these systems are growing more autonomous and intelligent, with system lifetimes spanning decades. They are also becoming more important to our everyday lives, underpinning the large-scale engineering of smart cities, autonomous vehicles, and the internet of things.

Models will require more extensively linked data. Models will cover ever-larger segments of reality. Where models require data, these data will need to be drawn from multiple data sets, which requires reliable and traceable data linkage. Some data may be derived not from measurement but from models, requiring additional links to derived data. One of the domains in which this is most needed is healthcare, where targeting of treatments is made more effective by characterising patients according to a variety of features (genotypic, phenotypic, environmental) and building models to relate these.

https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/682579/computational-modelling-blackett-review.pdf

Feedback

- **Feedback is a central feature of life.** The process of feedback governs how we grow, respond to stress and challenge, and regulate factors such as body temperature, blood pressure and cholesterol level. The mechanisms operate at every level, from the interaction of proteins in cells to the interaction of organisms in complex ecologies. M. B. Hoagland and B. Dodson, The Way Life Works, 1995 [99].

- One of the key uses of feedback is to provide robustness to uncertainty (pp. 18)

- Another **use of feedback is to change the dynamics of a system**. Through feedback, we can alter the behavior of a system to meet the needs of an application: systems that are unstable can be stabilized, systems that are sluggish can be made responsive and systems that have drifting operating points can be held constant.

- A major trend in the use of feedback is its application to higher levels of situational awareness and decision making. This includes not only traditional logical branching based on system conditions but also optimization, adaptation, learning and even higher levels of abstract reasoning.

- Control of supply chains was proposed by Forrester in 1961 [75] and is now growing in importance. Considerable economic benefits can be obtained by using models to minimize inventories. Their use accelerated dramatically when information technology was applied to **predict** sales, keep track of products and enable just-in-time manufacturing. Supply chain management has contributed significantly to the growing success of global distributors. Advertising on the Internet is an emerging application of control. With network based advertising it is easy to measure the effect of different marketing strategies quickly. The response of customers can then be modeled, and feedback strategies can be developed. (pp. 15)

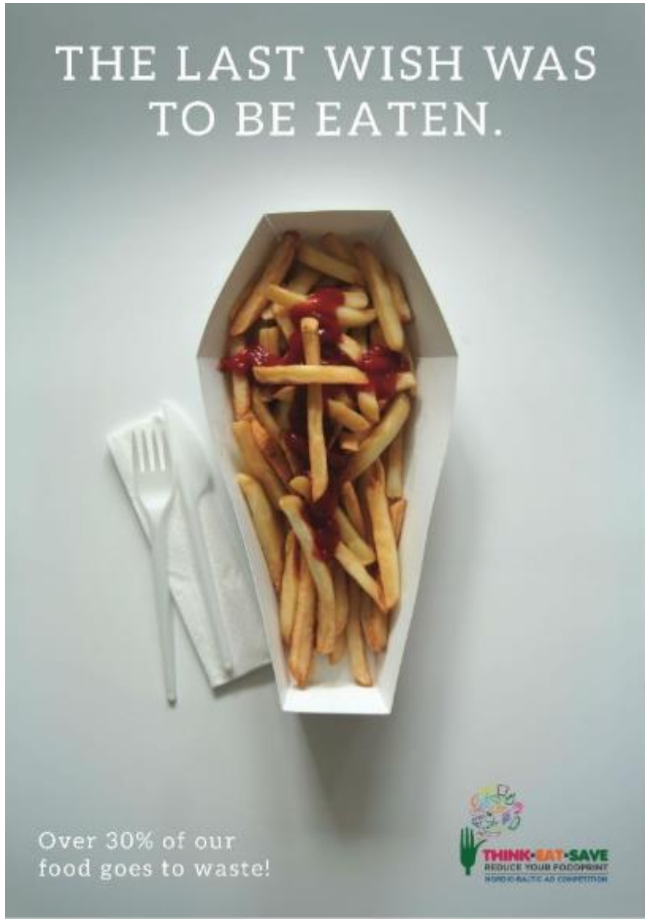
- The **Internet** is probably the **largest feedback control system humans have ever built** (pp. 12)

https://authors.library.caltech.edu/25062/1/Feedback08.pdf

Food Computing

Food intake is a feedback to hunger and/or social activity

Food waste is a feedback to food taste and/or food management. Food management includes such categories as ‘healthy’, ‘resonsible’, ‘optimal’, ‘timely’



Food Computing

With the rapid development of social networks, mobile networks, and Internet of Things (IoT), people commonly upload, share, and record food images, recipes, cooking videos, and food diaries, leading to large-scale food data. Large-scale food data offers rich knowledge about food and can help tackle many central issues of human society. Therefore, it is time to group several disparate issues related to food computing. Food computing acquires and analyzes heterogenous food data from disparate sources for perception, recognition, retrieval, recommendation, and monitoring of food. In food computing, computational approaches are applied to address food related issues in medicine, biology, gastronomy and agronomy. Both large-scale food data and recent breakthroughs in computer science are transforming the way we analyze food data. Therefore, vast amounts of work has been conducted in the food area, targeting different food-oriented tasks and applications.

However, there are very few systematic reviews, which shape this area well and provide a comprehensive and in-depth summary of current efforts or detail open problems in this area

https://arxiv.org/pdf/1808.07202.pdf

Food Computing: Food Related Data

Reference	Dataset Name	Data Type	Num.	Sources	Tasks
[Chen et al. 2009]	PFID	Images with categories	4,545 (101)	Camera	Recognition
[Joutou and Yanai 2010]	Food50	Images with categories	5,000 (50)	Web	Recognition
[Hoashi et al. 2010]	Food85	Images with categories	8,500 (85)	Web	Recognition
[Chen et al. 2012]	-	Images with categories	5,000 (50)	Web+Camera	Quantity Estimation
[Matsuda and Yanai 2012]	UEC Food100[1]	Images with categories	14,361(100)	Web+Manual	Recognition
[Anthimopoulos et al. 2014]	Diabetes	Images with categories	4,868(11)	Web	Recognition
[Kawano and Yanai 2014a]	UEC Food256[2]	Images with categories	25,088(256)	Crowd-sourcing	Recognition
[Bossard et al. 2014]	ETHZ Food-101[3]	Images with categories	10,1000(101)	foodspotting.com	Recognition
[Wang et al. 2015]	UPMC Food-101[4]	Images and text with categories	90,840(101)	Google Image search	Recognition
[Farinella et al. 2014a]	UNICT-FD889[5]	Images with categories	3,583(889)	Smartphone	Retrieval
[Pouladzadeh et al. 2015]	FooDD[6]	Images with categories	3,000(23)	Camera	Detection
[Christodoulidis et al. 2015]	-	Images with categories	(572)	Manual	Recognition
[Meyers et al. 2015]	Food201-Segmented	Images with categories	12,625(201)	Manual	Segmentation
[Bettadapura et al. 2015]	-	Images with categories and location	3,750(75)	Web	Recognition
[Xu et al. 2015]	Dishes[7]	Images with categories and location	117,504(3,832)	Dianping.com	Recognition
[Beijbom et al. 2015]	Menu-Match[8]	Images with categories	646(41)	Social media	Food Logging
[Ciocca et al. 2015]	UNIMIB2015[9]	Images with categories	2000(15)	Smart phone	Recognition
[Ciocca et al. 2016]	UNIMIB2016[9]	Images with categories	1,027(73)	Smart phone	Recognition
[Zhou and Lin 2016]	Food-975	Images with categories	37,785(975)	Camera&yelp	Recognition
[Merler et al. 2016]	Food500	Images with categories	148,408 (508)	Web&Social media	Recognition
[Rich et al. 2016]	Instagram800K[10]	Images with tags	808,964(43)	Instagram	Recognition
[Singla et al. 2016]	Food11	Images with categories	5,000 (50)	Social media	Recognition
[Farinella et al. 2016]	UNICT-FD1200[11]	Images with categories	4,754(1,200)	Mobile camera	Recognition and Retrieval
[Ofli et al. 2017]	-	Images with tags	1.9M	Instagram	Food Perception
[Liang and Li 2017]	ECUSTFD[12]	Images with rich annotation	2978(19)	Smart phone	Calorie Estimation
[Ciocca et al. 2017]	Food524DB[13]	Images with categories	247,636(524)	Existing datasets	Recognition
[Chen et al. 2017e]	ChineseFoodNet[14]	Images with categories	192,000(208)	Web	-
[Thanh and Gatica-Perez 2017]	Instagram 1.7M	Images with comments	1.7M	Instagram	Consumption Patterns Analysis
[Harashima et al. 2017]	Cookpad[15]	Images and recipes	4,748,044	Cookpad	-

https://arxiv.org/pdf/1808.07202.pdf

Food Computing: Food Related Data Sets

Reference	Dataset Name	Data Type	Num.	Sources	Tasks
[Rohrbach et al. 2012]	MPII Cooking 2[16]	Cooking videos	273	Cameras	Cooking Activity Recognition
[Stein and Mckenna 2013]	50 Salads[17]	Cooking videos	50	Cameras	Cooking Activity Recognition
[Kuehne et al. 2014]	Breakfast[18]	Cooking videos	433	Cameras	Cooking Activity Recognition
[Damen et al. 2018]	EPIC-KITCHENS[19]	Cooking videos	432	Head-mounted GoPro	Cooking Activity Recognition
[Kinouchi et al. 2008]	-	Recipes	7,702	-	Culinary Evolution
[Ahn et al. 2011]	Recipes56K[20]	Recipes	56,498	Recipe websites	Ingredient Pattern Discovery
[Teng et al. 2012]	-	Recipes	46,337	allrecipes.com	Recipe Recommendation
[Kim and Chung 2016]	-	Recipes	5,917	Recipesource.com	Recipe Analysis
[Chen and Ngo 2016]	Vireo Food-172[21]	Recipes with images and ingredients	110,241(172)	Web and manual	Recipe Retrieval
[Sajadmanesh et al. 2017]	Recipes157K	Recipes with metadata	157K	Yummly	Cross-region Food Analysis
[Chen et al. 2017b]	Go cooking	Recipes&Images	61,139	xiachufang.com	Cross-modal Recipe Retrieval
[Salvador et al. 2017]	Recipe1M[22]	Recipes&Images	1M	Cooking websites	Cross-modal Recipe Retrieval
[Min et al. 2017a]	Yummly-28K[23]	Recipes&Images	28K	Yummly	Cross-modal Retrieval
[Min et al. 2018a]	Yummly-66K[24]	Recipes&Images	66K	Yummly	Cross-region Food Analysis
[Markus et al. 2018]	Recipes242K[25]	Recipes	242,113	Crowdsourcing	Recipe Healthiness Estimation
[Semih et al. 2018]	RecipeQA[26]	Recipes	20K(22)	instructables.com	Recipe Question Answering

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Food Computing: Food Recognition Using Conventional Visual Features

Reference	Visual Features	Additional Information	Recognition Type
[Bolle et al. 1996]	Texture, Color	-	Food recognition
[Puri et al. 2009]	Color, Textures	-	Mobile food recognition
[Wu and Yang 2009]	SIFT	-	Food recognition
[Hoashi et al. 2010]	SIFT,Color Texture, HoG	-	Food recognition
[Joutou and Yanai 2010]	SIFT,Color, Texture	-	Food recognition
[Yang et al. 2010]	Pairwise Local Features Joint Pairwise Local Features	-	Food recognition
[Zong et al. 2010]	SIFT, Texture	-	Food recognition
[Bosch et al. 2011]	SIFT, Color, Texture	-	Food recognition
[Zhang 2011]	Color, Texture	-	Cuisine classification
[Matsuda and Yanai 2012]	SIFT, Color, HoG, Texture	-	Food recognition
[Matsuda et al. 2012]	SIFT, Color HoG, Texture	-	Food recognition
[Farinella et al. 2014b]	Texture	-	Food recognition
[Nguyen et al. 2014]	SIFT, Texture, Shape	-	Food recognition
[Anthimopoulos et al. 2014]	SIFT, Color	-	Food recognition
[Oliveira et al. 2014]	Color, Texture	-	Mobile food recognition
[Kawano and Yanai 2014c]	HoG, Color	-	Mobile food recognition
[Farinella et al. 2015a]	SIFT, Texture, Color	-	Food recognition
[Martinel et al. 2015]	Color, Shape, Texture	-	Food recognition
[Bettadapura et al. 2015]	SIFT, Color	Location & Menu	Restaurant-specific food recognition
[Farinella et al. 2015b]	SIFT, SPIN	-	Food recognition
[Kawano and Yanai 2015]	SIFT, Color, HoG	-	Mobile food recognition
[Ravl et al. 2015]	HoG, Texture, Color	-	Mobile food recognition
[Martinel et al. 2016]	SIFT, Color, Shape, Texture	-	Food recognition
[He et al. 2017]	Texture	-	Food recognition
[Zheng et al. 2017]	SIFT, Color	-	Food recognition

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Food Computing: Food Recognition Using Deep Visual Features

Reference	Visual Features	Additional Information	Recognition Type
[Kawano and Yanai 2014b]	HoG, Color, CNN	-	Food recognition
[Simonyan and Zisserman 2014]	VGG	-	Food recognition
[Kagaya et al. 2014]	AlexNet	-	Food recognition
[Ao and Ling 2015]	GoogleNet	-	Food recognition
[Yanai and Kawano 2015]	AlexNet	-	Food recognition
[Christodoulidis et al. 2015]	CNN	-	Food recognition
[Wang et al. 2015]	VGG	Text	Recipe recognition
[Xu et al. 2015]	DeCAF	Location	Restaurant-specific food recognition
[Herranz et al. 2015]	DeCAF	Location	Restaurant-specific food recognition
[Herruzo et al. 2016]	GoogleNet	-	Food recognition
[Wang et al. 2016]	CNN	Location	Restaurant-specific food recognition
[Singla et al. 2016]	GoogleNet	-	Food recognition
[Ragusa et al. 2016]	AlexNet, VGG, NIN	-	Food recognition
[Wu et al. 2016]	GoogleNet	-	Food recognition
[Ciocca et al. 2016]	AlexNet	-	Food recognition
[Liu et al. 2016]	Inception	-	Food recognition
[Hassannejad et al. 2016]	Inception	-	Food recognition
[Tanno et al. 2016]	Network In Network	-	Mobile food recognition
[Herranz et al. 2017]	AlexNet	Location & Menu	Restaurant-specific food recognition
[Bolanos and Radeva 2017]	GoogleNet	-	Food recognition
[Pandey et al. 2017]	AlexNet, GoogLeNet ResNet	-	Food recognition
[Chen et al. 2017e]	ResNet-152, DenseNet VGG-19	-	Food recognition
[Termritthikun et al. 2017]	NUInNet	-	Food recognition
[Kaur et al. 2017]	Inception-ResNet	-	Food recognition
[Pan et al. 2017]	AlexNet, CaffeNet RestNet-50	-	Ingredient classification
[Aguilar et al. 2017b]	InceptionV3, GoogLeNet ResNet-50	-	Food recognition
[McAllister et al. 2018]	ResNet-152, GoogleNet	-	Food recognition
[Ming et al. 2018]	ResNet-50	-	Mobile food recognition

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Food Computing: Accuracy in Benchmark Datasets

Table 5. Performance Comparison on the Accuracy in Three Benchmark Datasets (%).

Reference	UECFood100	UECFood256	ETHZ Food-101
[Kawano and Yanai 2014b]	72.26	-	-
[Kawano and Yanai 2014c]	-	50.10	-
[Ravl et al. 2015]	53.35	-	-
[Martinel et al. 2015]	80.33	-	-
[Yanai and Kawano 2015]	78.77	67.57	70.41
[Ao and Ling 2015]	-	-	78.11
[Wu et al. 2016]	-	-	72.11
[Liu et al. 2016]	76.30	54.70	77.40
[Martinel et al. 2016]	84.31	-	55.89
[Hassannejad et al. 2016]	81.45	76.17	88.28
[Zheng et al. 2017]	70.84	-	-
[Bolanos and Radeva 2017]	-	63.16	79.20
[Aguilar et al. 2017b]	-	-	86.71
[Pandey et al. 2017]	-	-	72.12
[McAllister et al. 2018]	-	-	64.98
[Martinel et al. 2018]	**89.58**	**83.15**	**90.27**

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Food Computing: Main Retrieval Methods

Table 6. Summary of Main Retrieval Methods

Reference	Data type		Dataset Name	Task
	Image	Text		
[Wang et al. 2008]	-	Cooking graph	Cooking graph database	Recipe retrieval
[Kitamura et al. 2009]	Food images	-	FoodLog	Food retrieval
[Xie et al. 2011]	-	Cooking graph	-	Recipe retrieval
[Barlacchi et al. 2016]	-	Dish name & Ingredients	Food Taste Knowledge Base (FKB)	Recipe retrieval
[Farinella et al. 2016]	Food images	-	UNICT-FD1200	Food retrieval
[Chen and Ngo 2016]	Food images	Ingredients	VIREO Food-172	Cross-modal retrieval
[Chen et al. 2017b]	Food images	Ingredients	-	Cross-modal retrieval
[Chen et al. 2017a]	Food images	Ingredients	-	Cross-modal retrieval
[Salvador et al. 2017]	Food images	Ingredients & Instructions	Recipe 1M	Cross-modal retrieval
[Min et al. 2017a]	Food images	Ingredients & Attributes	Yummly-28K	Cross-modal retrieval
[Ciocca et al. 2017]	Food images	-	Food524DB	Food retrieval
[Micael et al. 2018]	Food images	Ingredients & Instructions	Recipe 1M	Cross-modal retrieval

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Structure of the work

Theory
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Feedback system
- Testing of a feedback system
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- Improving feedback system elements
- Improving feedback system infrastructure

Improved feedback system
- Testing of a feedback system
- e.g. food waste at schools

Research Questions

In the world where the Internet is developing, there are so many things outside the Internet: e.g. **food waste is less documented on Instagram than food**. How do we deal with those gaps?

- What are the "ubiquitous computing" capabilities and challenges in terms of digitalisation of natural resources and waste?

- What are the most significant factors that determine the accuracy and usability of the system?

Questions related to food computing:

- Does less healthy food means more food waste?
- How food waste is interplayed within cooking at home versus consuming packaged food or dining out of home?
- How does climate change interfere with the food/ food waste habits?
- How does food waste differ in accordance to dishes consumed? (e.g. maybe soup is less wasted?)
- **Will food-log/prediction, IoT decrease food waste?**

Questions

To write dissertation as a narrative or as a collection of articles?

Can the topic still be changed/narrowed down? From food and forest computing to only food computing?

Thank you for your attention!