Journal of Food Engineering 197 (2017) 87–97

Contents lists available at ScienceDirect

Journal of Food Engineering

journal homepage: www.elsevier.com/locate/jfoodeng

Smart sensor to predict retail fresh fish quality under ice storage

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ARTICLE INFO

Article history:
Received 9 September 2016
Received in revised form
28 October 2016
Accepted 5 November 2016
Available online 9 November 2016

Keywords:
Smart sensor
Retail fish quality
Quality index method
Predictive microbiology
Core predictions
Fish-to-fish variability

ABSTRACT

Fish wastage and market prices highly depend on accurate and reliable predictions of product shelf life and quality. The Quality Index Method (QIM) and EU grading criteria for whitefish (Council Regulation(EC) No 2406/96, 1996) are established sensory methods used in the market to monitor fish quality. Each assessment requires the consultation of a panel of trained experts. The indexes refer exclusively to the current state of the fish without any predictions about its evolution in the following days.

This work proposes the development of a smart quality sensor which enables to measure quality and to predict its progress through time. The sensor combines information of biochemical and microbial spoilage indexes with dynamic models to predict quality in terms of the QIM and EU grading criteria. Besides, the sensor can account for the variability inside the batch if spoilage indexes are measured in more than one fish sample.

The sensor is designed and tested to measure quality in fresh cod (*Gadus morhua*) under commercial ice storage conditions. Only two spoilage indexes, psychrotrophic counts and total volatile base-nitrogen content, were required to get accurate estimations of the two usual established sensory methods. The sensor is able to account for biological variability as shown with the validation and demonstration data sets. Moreover, new research and technologies are in course to make these measurements faster and non-destructive. This would allow having at hand a smart non-intrusive fish quality sensor.

1. Introduction

Freshness is one of the most important attributes to define the market value of fish. Fresh fish are highly perishable, with shelf-lives ranging from some days to a few weeks. Immediately after fishing, a series of autolytic processes start to occur. These processes lead first to rigor mortis, and afterwards, to autolysis of proteins and fats, creating favorable conditions for bacteria to growth. The loss of quality becomes increasingly evident with time.

In the industry, quality is commonly assessed by sensory analyses relying on the visual inspection of fish by a panel of trained experts (Cheng et al., 2015). The method consists of evaluating a list of sensory attribute separately and select the most repeated score. In the European Union, sensory assessment of fresh fish is defined by Council Regulation(EC) No 2406/96 (1996), which classifies fish quality into four categories (Extra, A, B and unfit or NA). The EU Standard Quality Method (from now on, SQM) is based on the state of skin, skin mucus, eyes, gills, and flesh. However, the regulation has been -and still is- a subject of considerable controversy, what has encouraged the emergence of the quality index method (QIM, Luten and Martinsdottir (1997)) as an alternative. The QIM scores depend on the fish species and are defined attending to several properties such as skin color, odor, texture; eyes pupils and form; gills color, mucus, and odor; flesh color and viscera. The QIM defines 3 to 4 scores per quality parameter thus enabling a more refined characterization as compared to SQM.

Sensory indexes, however, refer exclusively to the current state of the fish without predicting shelf life or the loss of quality in the following days. Despite some attempts to estimating shelf life using sensory indexes (Bonilla et al., 2007; Heising et al., 2012) or spectroscopy (Sivertsen et al., 2011), most works (Dalgaard, 1995; Jørgensen et al., 1988; Koutsoumanis and Nychas, 2000; McMeekin et al., 1992; Taoukis et al., 1999) propose to correlate shelf life with a particular microbial load using the concept of predictive microbiology. These authors suggest the use of microbial growth models to predict when this bacterial load is achieved and thus predict shelf life.

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http://dx.doi.org/10.1016/j.jfoodeng.2016.11.006
0260-8774/

Whereas shelf life allows to plan ahead to avoid fish wastage, quality models are preferable as they can also estimate differences on sensory quality and can be used to fix market prices. However, the nonlinear nature of fish quality characteristics hinders the modeling and prediction of fish quality as characterized by the established sensory indexes. First attempts to estimate quality proposed the use of non-established sensory indexes (Nuin et al., 2008; Tsironi et al., 2009). García et al. (2015) proposed a model that is able to correlate *Pseudomonas* and *Shewanella* growth with the SQM. However, these indexes were insufficient to predict QIM. Giuffrida et al. (2013), on the other hand, were able to predict the QIM, but at the expense of measuring six different microbiological indexes (skin, gills and flesh sulphide producers and non-producers).

The majority of quality and shelf life models in the literature focus on the most probable prediction. However, these indexes may vary significantly due to, for example, the use of different fishing gear or variations in season or ground. Even within the same batch variability may be substantial due to intrinsic fish-to-fish variability and differences in handling. It is, therefore, desirable to accompany most probable quality dynamics with the associated variability. García et al. (2015) and Koutsoumanis et al. (2002) explored that variability in the SQM and shelf life respectively.

Nevertheless, and for practical purposes, it is of the highest interest to design a strategy to assess and predict fish quality together with its variability from a limited number of measurements. In this context, we propose the development of a smart fish quality sensor. Smart, here, refers to the capability of the sensor to assess the quality and, in addition, to predict its evolution through time and variability. The first step to develop the smart sensor is to define the minimum measurements that allow characterizing quality indexes. The second, is to define and calibrate the mathematical relationship (predictive model) that correlates those measurements with quality. The third step, is to validate the smart sensor.

In this work, the sensor was designed, calibrated and validated to assess quality of fresh cod (*Gadus morhua*) under commercial ice storage conditions exploring the relationship between psychrotrophic counts and total volatile base-nitrogen (TVB-N) content with established sensory indexes.

2. Materials and methods

The design of the smart sensor includes the definition of the purpose (output) based on the available measurements (inputs) as depicted in Fig. 1.

This is a complex problem that requires the design of the three main parts:

- **Sensor observations or outputs** In this work we aim to take a step forward and to predict, not only shelf life, but the usual established quality indexes used nowadays in the market (QIM and QSM). The sensor output estimates those indexes at current time and predicts their evolution through time. Moreover, fish-to-fish variability inside the same fishing batch are studied to provide its impact on quality variability.
- **Sensor inputs or necessary measurements** The smart sensor will combine a number of “hardware” sensors and a mathematical model which is able to characterize the relationship between measurements, quality indexes and time. In this work we tested the possibility of using a minimum number of measurements as the inputs for the model. Psychrotrophic counts and TVB-N were finally selected based on previous findings, the most important of these are described in the following:

Psychrotrophic counts Fish spoilage under cold storage has been correlated with the growth of some particular gram-negative psychrotrophic bacteria. Specifically, *Shewanella* spp. has been reported as the specific spoilage organism (SSO) of fresh air-stored chilled fish from cold marine waters. However, different SSOs were found when fish was caught in warmer waters or stored under a CO_2-enriched atmosphere (Gram and Dalgaard, 2002). Recently, Chaillou et al. (2015) found that spoilage bacteria mainly originated from the environment (water reservoirs) and that storage conditions exert strong selective pressure on the initial bacteria. Also, that seafood spoilage involves the growth of various bacterial communities, with specific groups of psychrotrophic bacterias key components.

TVB-N Spoilage also occurs because of action of microbial metabolites of psychrotrophic bacteria responsible for off-flavors and off-odors (Cheng et al., 2015; Gram and Dalgaard, 2002; Vogel et al., 2005). Among those metabolites, trimethylamine, ammonia and, to a lower extent, dimethylamine are the most abundant. The total volatile base-nitrogen (TVB-N) index combines these amines into a unique indicator used to assess spoilage of fresh fish. In fact, the content of TVB-N is the only biochemical index presently included in EU regulations to discriminate fit from unfit fish in commerce or official inspection. Neither TVB-N nor trimethylamine (TMA) content can be used as indexes of quality in the early stages of storage (Dalgaard, 2000; Howgate et al., 2010). However, some studies have found significant correlations between TVB-N and TMA and storage time (Baixas-Nogueras et al., 2001; Oehlenschläger, 1998; Ruiz-Capillas and Moral, 2001). Therefore indicating that the modeling of TVB-N or TMA dynamics could be used to predict shelf life.

- **Sensor engineering, input-output relationship or model** Finding the appropriate, usually non-linear, relationship between the inputs and the sensor outputs is a typically rather complex task (Saguy, 2016). We will follow an iterative procedure which combines experimental, statistical and numerical methods as illustrated in Fig. 2. This procedure consists of iterating between theory and data to select the best mathematical structure (model selection) and the set of unknown parameters (model calibration). Each pair of model structure and set of parameters are tested until the predictive capabilities of the sensor are considered satisfactory (sensor validation). Details are described in the sequel.

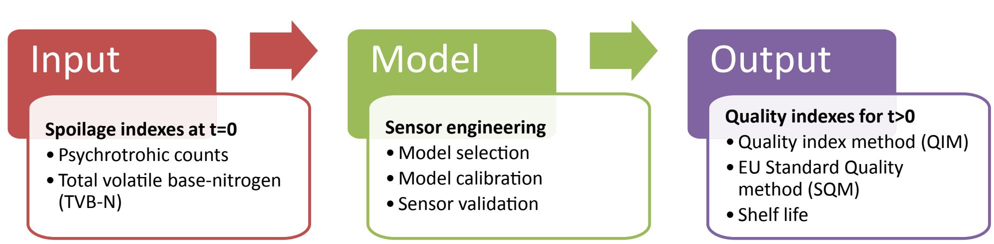

Fig. 1. Smart sensor design.