Applying CS and WSN methods for improving efficiency of frozen and chilled aquatic products monitoring system in cold chain logistics

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Abstract: Wireless Sensor Network (WSN) is applied widely in food cold chain logistics. However, traditional monitoring systems require significant real-time sensor data transmission which will result in heavy data traffic and communication systems overloading, and thus reduce the data collection and transmission efficiency. This research aims to develop a temperature Monitoring System for Frozen and Chilled Aquatic Products (MS-FCAP) based on WSN integrated with Compressed Sending (CS) to improve the efficiency of MS-FCAP. Through understanding the temperature and related information requirements of frozen and chilled aquatic products cold chain logistics, this paper illustrates the design of the CS model which consists of sparse sampling and data reconstruction, and shelf-life prediction. The system was implemented and evaluated in cold chain logistics between Hainan and Beijing in China. The evaluation result suggests that MS-FCAP has a high accuracy in reconstructing temperature data under variable temperature condition as well as under constant temperature condition. The result shows that MS-FCAP is capable of recovering the sampled sensor data accurately and efficiently, reflecting the real-time temperature change in the refrigerated truck during cold chain logistics, and providing effective decision support traceability for quality and safety assurance of frozen and chilled aquatic products.

Keywords: Food safety and traceability; Cold chain logistics; Monitoring system; Wireless Sensor Network; Compressed Sensing

1. Introduction

Wireless Sensor Network (WSN) has been adopted in many sectors, such as food cold chain logistics and agriculture (e.g., Coates et al., 2013; Qi et al., 2014; Myo & Yoon, 2014), environmental monitoring (e.g., Weimer et al., 2012; Guobao et al.,2014), and heavy industry (e.g., Wei et al., 2013; Xiao et al., 2014). WSN is a new technology that combines sensor technology, embedded computing, networking, and wireless communication, and distributed processing. It senses and collects information of monitoring objects and sends information to the end-user via wireless and multi-hop network. Wireless transmission has many advantages over traditional wire transmission in terms of low maintenance cost, higher mobility, better flexibility, and fast deployment in special occasions (Qi et al., 2011; Alayev et al., 2014; Suryadevara et al., 2015). However, a significant amount of real-time sensor data transmission will result in heavy data traffic and overload the communication bandwidth in WSN, and thus reduce the data collection and transmission efficiency (Qi et al., 2011; Li et al., 2012).

Compressed Sensing (CS) is a new signal acquisition method which recovers a sparse signal efficiently, accurately with a relative small number of samples and overcomes some of the limitations of the classical compression schemes (Candes and Tao, 2006; Donoho, 2006; Tsaig and Donoho, 2006; Haupt et al., 2008; Baraniuk et al., 2010). The traditional signal processing maintains that a signal must be sampled at a Nyquist rate at least twice its bandwidth in order to be represented without error. CS provides a low complexity approximation to the signal reconstruction, which benefits storage, transmission and processing of natural signals, without restricting the Nyquist sampling criterion. It also brings the benefits of simple compression in WSN without introducing excessive control overheads, which meets the limited resource constraint of WSN (Chen et al., 2012; Xiao et al., 2013; Yunhe et al., 2013; Caione et al., 2014).

Quality and safety of fresh food have attracted increasing attention from around the world, especially in emerging economies, such as China thanks to the quickly rising living standards (Jiehong et al, 2013; Chuan-Heng et al., 2014). For example, fish consumption per head in China is now 36.4 kg, which is twice the international average for fish consumption. However, the official data show that the inspection pass rate of aquatic products in China is less than 95% (China Catfish Institute, 2012), putting serious threat to the health of consumers.

Fresh foods, such as aquatic products, are typically perishable, with the rate of deterioration accelerating when temperature increases owing to a number of factors, such as microbial metabolism, oxidative reaction, and enzymatic activity (Raven et al., 2014; Kotta et al., 2014; Pack et al., 2014). Unless appropriately packaged, transported and stored, aquatic products will spoil in very short time. Therefore, an important aspect of aquatic products distribution management is the effective monitoring of time-temperature conditions and effective temperature management, which affect both safety and quality of aquatic products (Bytnerowicz et al., 2014).

Typical aquatic products cold chain logistics utilizes artificial refrigeration technology to meet low-temperature requirements through temperature control. Traditional temperature measurement and monitoring system, such as temperature chart recording system, is the most popular, reliable and accurate method to control and document temperature condition in the cold chain storage and transportation (Chen et al., 2014). However, such systems have high management costs while the data collection is time consuming. Moreover, each recorder of those systems needs to be connected physically to a PC and the data collection is manually processed, thus resulting in highly complicated system structure and high rate of inaccurate data monitoring (Trebar et al., 2013; Asadi et al., 2014). Therefore, automated and efficient monitoring system and effective information management system are needed for effective cold chain logistics.

In consideration of the benefits of WSN and CS, this research aim to adopt WSN integrated with CS as the network infrastructure, and develops a temperature Monitoring System for Frozen and Chilled Aquatic Products (MS-FCAP) in cold chain logistics. The system was designed to monitor the real-time temperature fluctuation and the quality of frozen and chilled aquatic products by integrating the aquatic shelf-life prediction model. Moreover, the system was implemented and evaluated in cold chain logistics between Hainan and Beijing in China.

This research contributes to the field of study in the following ways. First, the implementation of the MS-FCAP helps to improve the transparency and traceability of the cold chain logistics and enables more effective control of the quality and safety of the frozen and chilled aquatic products. Second, the MS-FCAP pilots the seamless integration of WSN and CS for more effective temperature monitoring in cold chain logistics. Third, the successful implementation of the MS-FCAP proves the feasibility of adopting WSN integrated with CS and paves the way for much wider application in the areas of cold chain logistics monitoring.

The next section discusses the system analysis and architecture. This is followed by the system models discussion and design. The paper then discusses the system implementation and evaluation. Finally, the discussion and conclusion about this research as well as implications for future work are presented.

2. System analysis and architecture design

Multiple methods proposed Cortes et al. (2014) and Xiao et al. (2014) were followed to make sure that temperature monitoring system would be designed to meet the need of potential users: a) Field observation for frozen and chilled aquatic products in cold chain logistics; b) Field survey and interviews.

2.1. Field observation for frozen and chilled aquatic products in cold chain logistics

A field observation for frozen and chilled aquatic products in cold chain logistics was conducted in 2013, in Hainan province, China. The purpose is to understand the actual process of cold chain logistics, including any factors that may affect the safety and quality of aquatic products. As illustrated in Figure1, the typical cold chain logistics process consists of the following basic steps:

Step 1: Catching the fresh fish from the farm.

Step 2: After the catching, fresh aquatic products are transported immediately via live or refrigerated transportation to processing plants for further processing.

Step 3: Aquatic products processing and storage. Aquatic products are normally divided into two categories for processing, either segmentation (with fish scales, cheek and viscera cast off) or whole fish. Processed aquatic products are stored in cold storage or freezer maintained in -18℃ or lower.

Step 4: Transporting the frozen and chilled aquatic products from processing plants to retail stores. In this process, temperature fluctuations, such as the variation from ambient temperature of about 20℃ to -18℃ or lower, may cause safety and quality problems during the cold chain logistics process.

Step 5: Display and sale of frozen and chilled aquatic products by wholesalers and retailers. A large number of refrigerated and frozen shelves are used to keep the appropriate temperature on -10℃ or lower.

Throughout the cold chain logistics, the chilled or refrigerated transportation has significantly impacted on products safety. Pathogens, such as Listeria monocytogenes, can grow as low as -0.4°C (Fallah et al., 2013). Clostridium botulinum type E and non-proteolytic type B and F can grow at temperatures as low as 3.3°C (Smelt et al., 2013). Therefore, the ideal storage temperature of the frozen and chilled aquatic products should be maintained in -18℃ or lower to ensure the products quality and safety.

Fig.1. Process of frozen and chilled aquatic products in cold chain logistics

2.2. Field survey and interview

To find out more about the needs of potential users, an interview based semi-structured survey was conducted to explore and identify the potential users' functional and information requirements. 6 senior managers and 20 first-line managers working in the cold-chain logistics were involved in the survey. The interviewees were asked to describe their routine work process, *how they normally record the temperature information in the cold chain, how they get the shelf-life information of the frozen and chilled aquatic products, and whether they knew about wireless monitoring or if they have ever used it, what kind of information requirements are the most concerned or expected of such systems*. The interview survey lasted for one week. The results of the survey also helped the researcher to identify functional and information requirements and system module divisions of MS-FCAP, which is discussed in the system architecture below.

2.3. System architecture

In consideration of the functional and information requirements identified from the field observation and field survey, the MS-FCAP architecture is developed consisting of three basic layers, namely wireless temperature sensor nodes, the aggregation node, and the Aquatic Cold-chain Management System (ACMS) (see Figure 2).

- A sensor node is a ZigBee wireless temperature sensor node. It is deployed at the refrigerated truck or storage to sense the real-time temperature data and then send them to the network coordinator via ZigBee network during cold chain logistics. A number of sensor nodes and a network coordinator will make up of a WSN. The sensor nodes acquire and send the temperature data after the successful network synchronization and fall into sleep after the successful data sending at regular intervals.

- The aggregation node consists of a network coordinator and an Advanced RISC Machines (ARM) controller. The network coordinator not only creates and controls the entire network, but also aggregates the sensor data from the sensor nodes and sends them to the ARM controller to sparse sampling. The sparse sampling aims to sample the sensor data and represents the original sensor data by a relative small number of samples. The sampled data will be sent to the ACMS via General Packet Radio Service (GPRS) module for reconstruction and generating predictions of the product shelf-life.

- The ACMS is responsible for data receiving, reconstruction, and processing at the remote terminals. It includes two layers: one is the server layer, which is responsible for data receiving/storage, sampled data reconstruction, aquatic products shelf-life prediction via the data warehouse. The server layer serves as the pipeline to connect the users and the sensor nodes, and also serves as the knowledge base and the model base. The other one is the client layer, which provides not only the real-time and shelf-life information for the users, but also the user-friendly operation and configuration interface for system managers.

Fig.2. Architecture diagram of the MS-FCAP

The temperature data is transmitted to the remote monitoring center via WSN integrated with CS, which includes data sparse sampling and data reconstruction. The aquatic products shelf-life was then predicted via the shelf-life prediction model (see Figure 3). The next section discusses in more detail about the system models of the MS-FCAP.

3. System models of MS-FCAP

3.1. Compressed sensing

Compressed Sensing (CS) ensures that the temperature signals can be acquired the global measurements with a low sampling rate and reconstructed with a much smaller number of samples than those required by the Nysquist theorem. This is possible only if the signals can be sparse represented under certain appropriate orthogonal basis (Candes et al., 2006; Candes and Wakin, 2008; Chen and Wassell, 2012).

The sensor data $\mathbf{x}=[x(1),x(2),\cdots,x(N)]^T \in R^N$ are sparse transformed by the equation (1) as follows:

$$\mathbf{x}=\sum_{i}^{N} s_i\psi_i \quad \text{or} \quad \mathbf{x}=\mathbf{\Psi s} \tag{1}$$

where $\mathbf{\Psi}=\left[\psi_1,\psi_2,\cdots,\psi_N\right]$, $\psi_i \in R^N$ is the $N\times N$ sparse matrix which is built according to the signal characteristic, and $\mathbf{s}=[s_1,s_2,\cdots s_N]^T$, $s_i \in R^N$, where s is the sparse representation of original signal $\mathbf{x}$ under the basis of $\mathbf{\Psi}$.

Vector $\mathbf{y}$ denotes the sampled data by calculating the inner product $\{\phi_j\}_{j=1}^{M}$ as in equation (2).

$$\mathbf{y} = \mathbf{\Phi x} = \mathbf{\Phi \Psi s} = \mathbf{\Theta s} \tag{2}$$

where $\mathbf{\Phi} = [\phi_1, \phi_2, \cdots \phi_M]^T$ is the $M \times N$ observation matrix.

The sensor nodes are deployed at the refrigerated truck or storage to acquire the temperature data. The biorthogonal wavelet transform matrix is built as the sparse matrix $\mathbf{\Psi}$, and the Gaussian random matrix $\mathbf{\Phi}$ is built as the signal observation matrix according to the temperature signal's space-time characteristic to realize the sparse sampling of the sensor data (see Figure 3). The sparse sampled data are sent via the GPRS module to the ACMS for data reconstruction, data storage and processing, and for aquatic products shelf-life prediction.

The sparse sampled data $\mathbf{y}$ are reconstructed by choosing the Orthogonal Matching Pursuit (OMP) algorithm model (Tropp and Gilbert, 2007; Donoho et al., 2012; Zhao et al., 2015) as described in equation (3) and (4):

$$\hat{\mathbf{s}} = \arg\min_{s} \|\mathbf{x}\|_2^2 \qquad s.t. \qquad \mathbf{y} = \mathbf{\Phi x} \tag{3}$$

$$\hat{\mathbf{x}} = \mathbf{\Psi}^{-1}\hat{\mathbf{s}} \tag{4}$$

where $\hat{\mathbf{x}}$ is the accuracy or approximation value reconstructed by the 2-norm optimization method. Vector $\hat{\mathbf{s}}$ is an optimization sparse representation after the signal reconstruction.

The OMP is an efficient method to solve the data reconstruction problem. It is considered to be faster and easier to implement for signal recovery problems (Tropp and Gilbert, 2007; Donoho et al., 2012; Zhao et al., 2015). The OMP follows 5 steps as below:

- *Step 1*: Initializing the model parameters. Setting I to be a null set and matrix $\mathbf{q}$ to be null to store the suffix and the basis vectors of the recovery matrix respectively. Setting the initial residual $\mathbf{r} = \mathbf{y}$, the sparse coefficient $\mathbf{s} = \mathbf{0}$, the recovery matrix $\mathbf{T} = \mathbf{\Phi \Psi}$ and iterations $n = 0$.
- *Step 2*: Choosing the basis vectors. To choose the maximum inner product value within the residual $\mathbf{r}$ from the recovery matrix $\mathbf{T}$ as the basis vectors. Setting i to be the suffix of basis vectors, then it can get the suffix value via the equation (5) as follows:

$$\hat{i} = \max_{i} |\langle r_i, t_i \rangle| \tag{5}$$

  After the calculating, updating the set $I = \{I, \hat{i}\}$, the matrix $\mathbf{q} = [\mathbf{q}, t_i]$ and the basis vectors to be zero.
- *Step 3*: Finding the sparse representation coefficient $\hat{\mathbf{s}} = \arg\min_{s} \|\mathbf{y} - \mathbf{q s}\|_2^2$ by the chosen basis vectors.
- *Step 4*: Updating the residual $\mathbf{r} = \mathbf{y} - \mathbf{q}\hat{\mathbf{s}}$.
- *Step 5*: Stopping the iteration when the iterations get the maximum sparse value or the sparse coefficient equal or less than reconstruction error. If not, then return to the step 2 to continue the iteration.

Fig.3. Flow chart of the system data transmission

3.2. Shelf-life prediction model

The frozen and chilled aquatic products shelf-life is the length of time aquatic products may be stored without becoming unsuitable for use or consumption. Accurate shelf-life prediction can provide aid for the managers to improve cold chain logistics processes and ensure aquatic products quality and safety. However, since temperature fluctuations in the environment occur very frequently, it is impossible to use simple mathematical expressions directly to describe the time-temperature change. In this study, the time-temperature change is divided into multiple shorter time intervals which are assumed to be constant. As shown in equation (6) to (7), the Gompertz equation is used to describe the microbial growth kinetics under different temperature and to calculate the predicted product shelf-life (Mosqueda et al., 2012).

$$\log N(t) = \log N_0 + \frac{\log N_{\max}}{\log N_0} \times \exp\left\{-\exp\left[\frac{\mu_{\max} \times 2.718}{\log N_{\max}} \times (Lag - t) + 1\right]\right\} \tag{6}$$

$$SL = Lag - \frac{\log \frac{N_{\max}}{N_0}}{2.718 \times \mu_{\max}} \times \left[\ln\left(-\ln \frac{\log \frac{N_s}{N_0}}{\log \frac{N_{\max}}{N_0}}\right) - 1\right] \tag{7}$$

where $N(t)$ is the number of bacteria at time t, $N_{\max}$ is the maximum number of bacteria, N_s is the minimum number of bacteria, N_0 is the initial number of bacteria at $t = 0$, $u_{\max}$ is the maximum bacteria growth rate, Lag is the bacteria growth delay time, and SL is the predicted product shelf-life when the number of bacteria proliferate from N_0 to N_s. The effect of temperature on microbial growth could be described using the Belehradek equation as shown in equation (8) and (9) (Xing et al., 2013; Pang et al., 2015).

$$\sqrt{\mu_{\max}} = \mathrm{b}_{u\max} \times (T - T_{\min}) \tag{8}$$

$$\sqrt{Lag} = \mathrm{b}_{Lag} \times (T - T_{\min}) \tag{9}$$

where T is the monitoring temperature, $T_{\min}$ is the minimum temperature when the microbial growth rate is zero, $b_{\mu\max}$ and b_{Lag} are the constant coefficient of the equations.

3.3. Data analysis

The Normalized Mean Square Error (NMSE) is adopted to analyze the data reconstruction error. The NMSE is defined in equation (10) (Candes and Wakin, 2008).

$$NMSE = \frac{\left\| \hat{x}_j(n) - x_j(n) \right\|_p}{\left\| x_j(n) \right\|_p} \tag{10}$$

where $x_j(n)$ and $\hat{x}_j(n)$ are the j-th value before and after the data reconstruction, p is the norm. Set p =2 to solve the mean square value of each element in vectors according to the data reconstruction model.

In addition, the data compression ratio is used to analyze the data compression efficiency. The data compression ratio ρ is defined in equation (11) (Cho, et al., 2015).

$$\rho = \frac{N - M}{N} \times 100\% \tag{11}$$

where N is the number of original data, and M is the number of sampled data. The Mean Absolute Error (MAE) and Mean Relative Error (MRE) are adopted to measure the accuracy of the recovered data by comparing with the original sensor data.

4. System design and implementation

This section discusses in more detailed in the system design and implementation of the MS-FCAP, which includes the ACMS and the system hardware.

4.1. Hardware design and implementation

As shown in Figure 4, the system hardware mainly consists of the hardware of the sensor nodes and the aggregation node. A sensor node is an integration of a microcontroller, a temperature sensor, and a battery power supply. The aggregation node consists of the network coordinator, the ARM controller, and the GPRS remote transmission module. The sensor node and the network coordinator adopt the CC2530 wireless sensor system on a chip, which integrates a radio frequency transceiver with an enhanced 8051 microcontroller to improve the integration and optimization of the hardware design. The sensor node and the network coordinator apply the CC2591 as the radio frequency front end to increase the transmission distance.

A sensor node adopts the DS18B20 as the temperature sensor, of which the temperature range is between -55°C and +125°C and the temperature accuracy is ±0.5°C. The aggregation node adopts the S3C2440 as the ARM controller to process the sparse sampling of data and to send the sampled data to the GPRS module. The network coordinator and the GPRS module are all communicated with the ARM controller via the RS232 bus. The physical implementation of the system hardware is illustrated in Figure 5. Each sensor node with an external antenna is integrated in a plastic case.

Fig.4. Block diagram of the system hardware

Fig.5. Physical implementation of the sensor node hardware

4.2. ACMS design and implementation

ACMS serves as the management system for end-users. It is also responsible for maintaining the database of the data received from the WSN, the reconstructed data of the sampled data, and data of aquatic products shelf-life prediction during the cold chain logistics. The ACMS provides the function to add or edit the raw data from daily operation and to search or review monitoring records.

ACMS adopts a 3-tier architecture, which includes the User Interface tier, the Functional Logic tier and the Database tier (see Figure 6).

(1) User Interface tier provides a user interface for checking input data integrity and displaying information. For example, cold chain managers can inquire the real-time temperature and the remaining products shelf-life in the cold chain. Inquiry results can be displayed in the form of numerical temperature data or graphs and charts. The User Interface tier also performs the data transmission between users and business logics.

(2) Business Logic tier consists of two components, is responsible for a variety of processing logics:

- *System management logic component* consists of 5 modules of authorization management, communication management, data management, model management and knowledge management. The authorization management and communication management modules exchange data with the basic database in the database tier. The data management module, the model management module, and the knowledge management module exchange data with the data warehouse, the model base, and the knowledge base respectively.
- *Data processing logic component* is the system core to realize the system real-time monitoring, data reconstruction, and shelf-life prediction. The real-time temperature information is exchanged between the

temperature monitoring module and data management module within the system management component. Data processing component reconstructs the sampled data and predicts the aquatic products shelf-life based on the model management module and knowledge management module in the system management component. After data reconstruction and shelf-life prediction, the data processing component sends the real-time temperature monitoring and products shelf-life information based on model determined to user interface tier.

Fig.6. Architecture of the ACMS

(3) Database tier consists of the following 4 independent databases, which communicate with each other and are driven by the corresponding database management modules in the Business Logic tier:

- *The basic base* is responsible for storing the authority and communication configuration information.
- *The data warehouse* is responsible for storing the real-time temperature data which include the sampled and reconstructed temperature data.
- *The knowledge base* is responsible for storing knowledge models used for data analysis and decision making.
- *The model base* is responsible for storing the parameters and equations of system models.

SQL Server 2008 database management system is applied to manage all the databases. ACMS is developed using C# in Microsoft Visual Studio 2008 which is integrated with the real-time monitoring chart and shelf-life prediction model powered by the Matlab M-language dynamic link library.

5. System test and evaluation

The MS-FCAP system is designed to improve the transparency of the cold chain logistics by better understanding the temperature characteristics of cold chain process, and hence to ensure the quality and safety of the frozen and chilled aquatic products. To evaluate the performance of the MS-FCAP system, system test and evaluation was carried out, which is discussed in this section. The evaluation results were analyzed using Origin 8.1 software (OriginLab Corporation, Northampton, MA) and SPSS 20.0 software (IBM Corporation, New York, NY, USA).

5.1. Experiment scenario

The MS-FCAP system was implemented in a Chinese aquatic products company to monitor the cold chain logistics of frozen tilapia. The frozen products were kept in a refrigerated truck in 15-day transportation from Hainan, China to Beijing, China. The transportation distance is around 2760 km. The length, width and height of the refrigerated truck container are 3.0m×2.5m×2.4m. 27 sensor nodes were installed in the truck. Figure 7 indicates the sensor nodes deployment in the refrigerated truck. Each sensor node was put into a box containing frozen and chilled tilapia before loading. One aggregation node was installed in the driver's cabin and the ACMS was installed in a remote control center located in the company's office.

To satisfy the low temperature storage requirements, the frozen tilapia transported should be kept in the container at -18°C during the transportation and cold chain logistics (Qi et al., 2012; Calil et al., 2013). Real-time monitor and control of the temperature in the refrigerated truck was carried out. The sensor nodes were calibrated using the Resistance Temperature Detector calibrator (Fluke, Washington, USA) before deployed.

The temperature sample interval of the sensor nodes was set to 1 second, and the data sending interval of the aggregation node was set to 1 minute. The length of data sending packet was 9 Bytes, which included the sensor ID (1 Byte), the temperature data (4 Bytes) and the battery voltage (4 Bytes). The aggregation node aggregates and sparse sampling the temperature data acquired from the 27 sensor nodes for every sample interval (1 second), and transmits the sampled data to the ACMS for data reconstruction, and products shelf-life prediction via the GPRS module for every data sending interval (1 minute). The aggregation node also stores the original temperature data to test and evaluate the data reconstruction error while the sparse sampling of temperature data is being carried out.

Fig.7. Wireless temperature sensor nodes deployment in the refrigerated truck

The temperature distribution acquired from the MS-FCAP was analyzed to improve the transparency of the temperature in the cold chain logistics and the aquatic products shelf-life predictions were also analyzed according to the experiment scenario.

5.2. Data reconstruction error analysis

The cold chain for the frozen and chilled tilapia needs the pre-cooling step after loading to cool the temperature down to -18°C from the ambient temperature, which takes around 2 hours. After pre-cooling, the temperature stays constant at -18°C, which is referred to as the constant temperature condition, and then unloading (Wang et al., 2011). The pre-cooling and unloading steps are referred to as the variable temperature condition. The data reconstruction model was run at the ACMS to recover the sampled data. One of the sensor nodes, located nearby the door to reflect the worst case temperature condition in refrigerated truck, was dedicated to analyze the temperature reconstruction error in the cold chain. The absolute error with fitting surface between reconstructed and original temperature is shown as Figure 8.

Fig.8. The absolute error between reconstructed and original temperature data in the cold chain

During the experiment, N is about 1620 and M is 256 (see also equation (1) and (2)). The NMSE, Mean Absolute Error (MAE), Mean Relative Error (MRE) of reconstructed temperature data, and data compression ratio under variable and constant temperature conditions are described in Table 1.

Table 1

Errors of the reconstructed temperature data under variable and constant temperature conditions

Conditions	NMSE (%)	MAE (°C)	MRE (%)	Data compression ratio (%)
Variable temperature	8.42	0.56	7.03	84.19
Constant temperature	0.76	0.12	0.66	84.19

The NMSE, MAE and MRE of reconstructed temperature data are 8.42%, 0.56°C and 7.03%, respectively under variable temperature condition, while they are 0.76%, 0.12°C and 0.66% respectively under constant temperature condition. The data compression ratios under both conditions are 84.19%. Therefore, the accuracy of data reconstruction under variable temperature condition is lower than that under constant temperature condition. The reason is that the temperature is in continuous fluctuation under variable temperature condition, such that the system is unable to sparse sampling as well because of the temperature variation. However, the result of the data reconstruction error analysis still satisfies the real application in cold chain (Qi et al., 2011; Xiao et al., 2014).

The results show that the data reconstructed model could recover the sampled temperature accurately and efficiently, which reflected the real-time temperature variation in refrigerated truck and thus satisfied the monitoring requirements of cold chain logistics.

5.3. Temperature distribution analysis

The monitoring data results show that WSN and ACMS worked well at the sample interval and the data sending intervals set previously. The temperature distribution in refrigerated truck could be real-time monitored via the sensor nodes installed. The lateral view and the top view of the temperature field in truck container under constant temperature condition are illustrated in Figure 9.

Fig.9. The lateral view (a) and top view (b) of the temperature field in refrigerated truck

Specifically, the temperature near the container door is about -16.4°C and inside the container is about -18.5°C. After evaluating the truck container, it was found that the temperature near the door being higher than that on the inside because the refrigerator is installed inside of the container, and the cold winds are unevenly distributed, and thus result in spatial differences in the temperature distribution (Cruz et al., 2009; Tarrega et al., 2011; Liu et al., 2014). The results show that the MS-FCAP could provide complete and accurate temperature monitoring information in cold chain, so that to provide the more effective safety and quality assurance for the frozen and chilled aquatic products in the cold chain.

5.4. Shelf-life prediction

The shelf-life of aquatic products was predicted according the determination of spoilage organism and the results of fitting curve. The Total Viable Count (TVC) and Pseudomonas spp. spoilage organism for tilapia were determined at the laboratory in Beijing between the year of 2012 and 2013 according to the literatures (Gram & Huss, 1996; Boari et al, 2008; Xing et al., 2013).

Tilapias, which were almost the same size about 300-400g, were put into constant temperature incubators (DPJ-100, Shanghai, China) with 0℃, 5℃, 10℃, 15℃, 20℃ and the variable temperature respectively for about 25 days. The Total Viable Count (TVC) and Pseudomonas spp. were determined from the samples every 48 hours. The determination was composed of the following steps:

Step 1: Weighing tilapias for about 25g from each incubator by aseptic operation every time.

Step 2: Mincing by the meat grinder (TS-22, Beijing, China) with sterilization.

Step 3: Putting minced tilapia into 225mL conical flask within sterile physiological saline and several glass pearls.

Step 4: Shaking fully on the shaker (VS-10, Beijing, China).

Step 5: Diluting with 10 times volume.

Step 6: Determining the TVC using the pour method on plate count agar (Oxoid CM463, Hampshire, UK).

Step 7: Determining Pseudomonas counts using the spread plate method on agar base (Oxoid CM733, Hampshire, UK) with CFC (cetrimide fucidin cephalosporin) selective supplement (Oxoid SR103, Hampshire, UK).

The TVC growth kinetics at various temperatures is shown as Figure 10. The fitting coefficients of determination are about 0.996, 0.974, 0.994, 0.996 and 0.993 under 0℃, 5℃, 10℃, 15℃ and 20℃ temperature respectively. The initial bacteria number is 5.12 log CFU/g and the maximum number is 20.12 log CFU/g. It can be seen that the number of TVC increases with the storage time generally. However, the maximum growth rate is larger and the lag phase is shorter when the temperature is higher (Xing et al., 2013). The initial TVC number under various temperature conditions are almost identical because that's the same amount of samples were weighed. The effect of temperature on $u_{\max}$ and Lag at various temperatures is shown as Figure 11. The temperature has a good linear relation with the maximum Pseudomonas growth rate $u_{\max}$ and growth delay time Lag, whose coefficient of determination is about 0.973.

The TVC growth kinetics at variable temperature is shown as Figure 12. The variable temperature was controlled according to the actual aquatic products cold chain, and the TVC and Pseudomonas counts were determined as the same steps mentioned above. The coefficient of determination is about 0.956. It can be seen that the number of TVC also increases with the storage time, but slower than that above 0℃. The calculated minimum Pseudomonas growth temperature T_{min} is about -0.112℃ according to the equation (8) and (9). This is may affect of the psychrophilic bacteria. The psychrophilic bacteria will increase activity at below 0℃, but be inhibited at the normal temperature. However, it has little impact on the quality of aquatic products because of the slower psychrophilic bacteria growth rate compared with the Pseudomonas spp. (Farag et al. 2009).

The shelf-life prediction model, integrated the determined kinetic parameters, was performed by ACMS. The calculated results interface is shown in Figure 13.The evaluation results show that the aquatic products shelf-life prediction model built on the MS-FACP could be used to predict the remaining shelf-life of the aquatic products during cold chain logistics and provide the effective decision support for the frozen and chilled aquatic products managers in cold chain.

Fig.10. The TVC growth curve at various temperatures

Fig.11. The effect curve of temperature on u_{max} and Lag at various temperatures

Fig.12. The TVC growth curve at variable temperature

Fig.13. The calculated results interface of aquatic products shelf-life prediction

5.5. System evaluation

System evaluation measures the current performance and provides the basis for the improvements of cold chain management for frozen and chilled aquatic products on technological capacity, performance and system utilization which brought by the MS-FCAP as well as the defects of this system prototype.

Managers and workers from the enterprise were invited to take part in a committee to evaluate the system and discuss the system performance and form a consistent view on how this system should be perfected to improve management efficiency of frozen and chilled aquatic products.

Table 2 shows the efficiency and performance analysis before and after the MS-FCAP implementation; table 3 shows the suggestions for the MS-FCAP improvement and perfection.

Table 2

Performance analysis before and after the MS-FCAP implementation

ID	Content	Before implementation	After implementation
1	Cold chain logistics temperature monitoring	Null	Real-time
2	Number of the data transmission	Large	Decrease
3	Data compressed sensing transmission	Null	Real-time
4	Efficiency of WSN-based monitoring system	Low	High
5	Cold chain logistic traceability	Null	Real-time
6	Shelf-life prediction for the aquatic products	Null	Real-time

Table 3

Suggestions for the improvement and perfection of MS-FCAP

ID	Suggestion	Suggestion type
1	Increase the WSN immunity and stability on-site	Functional
2	Reduce the economic cost and size of WSN hardware	Non-functional
3	Reduce the sample data number in further	Non-functional
4	Increase the data reconstruct accuracy and efficiency in further	Non-functional
5	Improve certain system operation to be easier	Non-functional

According to the data reconstruction error, temperature distribution and system evaluation analysis, CS method enables the sensor data being transmitted with a relatively small number of samples and reconstructs the sparse sampled data with high accuracy and efficiency, which improves the efficiency of WSN-based monitoring system for frozen and chilled aquatic products in cold chain logistics.

6. Conclusions

This paper presents the design of the MS-FCAP system based on WSN and CS, which was implemented and evaluated in cold chain logistics from Hainan to Beijing. The WSN technology enables a real-time sensor data acquisition without complicated network infrastructure**.** The CS method enables the sensor data being transmitted to the ACMS with a relatively small number of samples and reconstructs the sparse sampled data with high accuracy and efficiency. The aquatic product shelf-life prediction function can help the cold chain managers to carry out real-time monitoring of the products shelf-life, so that to more effectively control the safety and quality of the aquatic products in the cold chain logistics.

The data reconstruction error analysis and the temperature distribution analysis suggest that the MS-FCAP could recover the sampled sensor data accurately and efficiently with reasonable error terms. It is also shown that the reconstructed temperature data can reflect the real-time temperature variation and spatial temperature differentiations in the refrigerated truck during the cold chain logistics, and thus satisfies the cold chain logistics monitoring requirements in practice. Moreover, the aquatic products shelf-life prediction results indicate that the aquatic products shelf-life prediction model built in the MS-FCAP can be used to predict the microbial growth and the remaining shelf-life of the aquatic products during the cold chain logistics.

The system implementation and evaluation suggest that the MS-FCAP is an effective quality management tool that enables real-time temperature monitoring and shelf-life prediction of the aquatic products in the cold chain logistics. Compared with traditional monitoring systems, the MS-FCAP can be used to provide more effective decision support for managers and traceability of the frozen and chilled aquatic products in the cold chain.

Although the MS-FCAP is developed to monitor aquatic products cold chain logistics, the system architecture and system models can be exploited by future researchers or practitioners in developing monitoring systems to perform wider cold chain monitoring tasks. The successful integration of CS with WSN in MS-FCAP, also paves the way for CS to be applied to other areas of application that need huge amounts of data collection from the sensor nodes. Furthermore, building on MS-FCAP system architecture and system models, future researcher could also explore the possibility of combining multiple kinds of sensors in the system, such as sulfur-dioxide and oxygen sensors, to examine and implement integrated multi-sensors models in the cold chain logistics.

Acknowledgment

This research is funded by the 'Special Fund for Agro-scientific Research in the Public Interest' (201203017) from the Ministry of Agriculture of China and the 'China Spark Program' (2013GA610002).

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