The “Intelligent Container”—A Cognitive Sensor Network for Transport Management

Walter Lang, Reiner Jedermann, Damian Mrugala, Amir Jabbari, Bernd Krieg-Brückner, and Kerstin Schill

***Abstract*—The “Intelligent Container” is a sensor network used for the management of logistic processes, especially for perishable goods such as fruit and vegetables. The system measures relevant parameters such as temperature and humidity. The concept of “cognitive systems” provides an adequate description of the complex supervision tasks and sensor data handling. The cognitive system can make use of several algorithms in order to estimate temperature related quality losses, detect malfunctioning sensors, and to control the sensor density and measurement intervals. Based on sensor data, knowledge about the goods, their history and the context, decentralized decision making is realized by decision support tools. The amount of communication between the container and the headquarters of the logistic company is reduced, while at the same time the quality of the process control is enhanced. The system is also capable of self-evaluation using plausibility checking of the sensor data.**

***Index Terms*—Cognitive systems, cool-chain telemetric, intelligent container.**

I. Introduction

THE “Intelligent Container” project [1] is developing a sensor network used in logistics, especially for the management and control of the transport of perishable goods such as fruit and vegetables. The idea can be explained by looking at fruit transport. Today when bananas are transported by ship, say from Middle America to Europe, their temperature is recorded by data loggers. If a certain threshold is not superseded, the transport is classified as OK. In general, a container has 2–3 temperature measurement points. More advanced systems are equipped with telemetric which sends the temperature data to a remote server. The temperature value is communicated to the headquarters of the company, where the temperature values of all transport units are evaluated. This standard telemetric approach has two disadvantages: First, the costs for a permanent transfer of temperature data over satellite links are high. Second, if the remote headquarter uncovers a problem during the transport, it has very limited options to influence the container directly.

The vision of the “Intelligent Container” project is not just to measure, but to evaluate data in the sensor network and to make decisions locally. From the temperature history of the bananas, with information on their quality when the container was loaded, the system estimates the quality they have at the present time, which is essentially the status of their ripening process. Furthermore, it makes a prediction of the future development, estimating how long the fruit will be OK for further processing in a banana ripening plant, and when the fruit will have to be disposed of since their quality has fallen below a given threshold. This estimation of their shelf life is performed by software agents in the sensor network.

By making decisions locally using decision support tools, the amount of data transferred is drastically reduced: from hundreds of temperature data, to just “temperature is OK” and “remaining shelf life is five days” [2].

For logistics, this development implies a change of paradigm. Currently, the logistic paradigm is first in first out (FIFO): the goods coming in first are the first to be moved onward. The decay of goods is described by a date of expiry, which is defined at production time and remains unchanged. For perishable goods, it is much more effective to change the logistic process according to the remaining time of shelf life. Goods that are close to decay have to be transported or sold with preference [2]. The key idea of the new paradigm is first expire first out (FEFO): temperature sensing motes with shelf life estimators allow estimating the expiry date according to the circumstances the goods are being exposed to. As an example, red tomatoes are to be stored at 12 °C; when stored at $10,5$ °C, the loss of shelf life will be two days per day, the shelf life is cut in half [2]. When the expiry date is changed during the logistic process dynamically, the term dynamic FEFO is used. A large number of research groups are working world wide on sensor motes and processes to push the FEFO paradigm [3]. As a further step, we will use direct information about the fruit themselves: their present state of ripening, given the emission of ethylene gas, which is an indicator for fruit ripening and also a ripening hormone that triggers the ripening process of many kinds of fruit [4].

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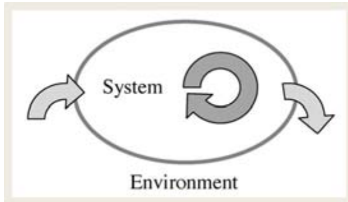

Fig. 1. A general view of a cognitive system.

In order to perform the tasks described above, the sensor network has to do much more than measuring the temperature and sending data; this type of advanced sensor is referred to as "intelligent sensor." We adopted this terminology when we called our project "Intelligent Container." However, it remains rather unclear what this "intelligence" really means. The term "intelligent sensor" may just refer to a pressure sensor with a linear compensation of the cross correlation to temperature, or it may call for complex data evaluation and decision support tools. Upon closer inspection, we realize that the features we are implementing in the container network are much better described as cognitive features.

Cognition science investigates the mechanisms that intelligent actions are based on [5]. A very general view of a cognitive system is shown in Fig. 1. The system is embedded in the environment. The internal states of the system are established from two sources: the data received from the outside, on the one hand, and the internal processes, on the other; such processes may be calculating representations, performing internal communication, and self-evaluation. The system is open to signals from outside, but the system behavior is not determined by that external information alone. The external information is assimilated in the system, of course, but it is not any longer defining the internal states in a deterministic way. Thus, a new perspective, looking at sensor systems primarily as data processing systems assimilating information from the physical world would be much closer to reality. Being nondeterministic and "operationally closed" are considered to be key features of cognitive systems [6].

After these general considerations, we will present the specific research results. This paper is organized in the following way. In Section II we describe our own work performed in the Intelligent Container Project. Since the topic is very wide, we cannot go into detail for all important aspects. The key features of the decision support tools and the most recent experimental results are presented. In Section III, we are looking at our R&D work from the new perspective of cognition. The approach of cognitive science led us to a new understanding of our system. As shown in Fig. 12, a circular process provides a better description of the high level data processing capabilities than the feedforward only approach (Fig. 11) we used until now. The feedforward approach can be used for systems with strict deterministic behavior. The decision support tools that we have been developing consider the data in the history of the transported goods. Furthermore, they use strong nonlinear functions for the ripening processes. For these two reasons, we cannot predict what the decision in a specific case will be. This aspect of indeterminism can be understood using our new model including circular processes.

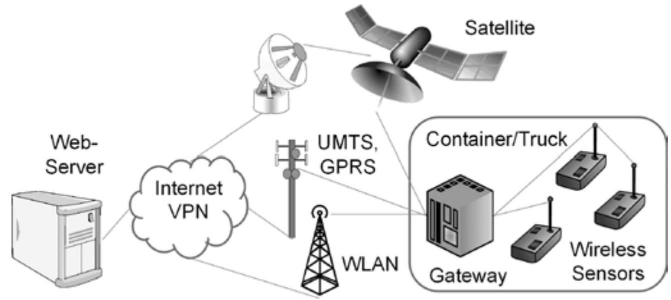

Fig. 2. Communication infrastructure.

II. The Intelligent Container

The intelligent container provides remote supervision of the spatial distribution of transport parameters. This section starts with an overview of the required hardware and communication infrastructure.

Although we combine commercially available hardware components, there is still no ready-to-use solution on the market. The general methods for the processing of sensor data are well known, but they have not been applied to the use-case of monitoring of cool-chain transports. The main part of Sections II-C–II-E summarizes the efforts and results of our work group to adapt and tailor these methods to the intelligent container. The cognitive features of the intelligent container are not related to a single method, but rather to the container's ability to apply and select different approaches depending on the situation. The different methods are combined to a decision-support-tool (DST), which is executed on an embedded processor platform inside the container, or even on single sensor nodes. A software framework is introduced, which allows to integrate and dynamically update the different elements of the cognitive sensor system.

Finally, some selected experimental results are presented (Section II-F) in order to illustrate the need for spatial temperature supervision, the performance of the internal wireless network, and the system's capability to detect disorders by an ANN. It has to be stated that the supervision system on its own, without a DST, brings only little benefit: communication channels would be overloaded due to lack of data filtering and sensor batteries would discharge quickly due to unnecessarily high measurement frequencies.

A. Communication Infrastructure

The intelligent container system consists of the following elements: a wireless sensor network that measures spatial deviations of environmental parameters inside a container; a communication gateway which operates as a bridge between the internal wireless sensor nodes and external networks. A web server gives access to the data by means of a graphical user interface. The system can also be applied inside trucks, or even warehouses, with slight modifications. All these hardware platforms can be made 'intelligent' by using their microprocessors to execute part of the DST. Fig. 2 gives an overview of the communication infrastructure.

Our wireless sensor nodes are based on the TmoteSky/TelosB platform [7]; a combined temperature and humidity sensor is mounted outside the water protected housing. A micromachined, low-power flow sensor [8] is planned for the future. The TinyOS operating system provides access to the functions of 802.15.4 radio protocol, which uses 2.4 GHz frequency range. Because of the high signal attenuation of water-containing food products, the sensor nodes have to forward messages over multiple hops to the gateway. The main challenge for the development of a protocol for battery powered sensor nodes is to keep the radio-up-time as low as possible. The ZigBee protocol, which is based on the 802.15.4 standard, provides only marginal flexibility. Sensors nodes can either operate as a forwarder in a multiple hop network, or implement a power down mode. Specialized protocols that directly access 802.125.4 layer provide much better performance.

In total, 16 sensor nodes per container were packed inside the goods. Four additional nodes were placed on top of the pallets or mounted on the container wall in order to improve the network connectivity.

Each container (truck, ship, etc.) is equipped with a communication gateway that collects data from the internal sensor network and provides a platform for the major part of the DST. A networks manager detects which external networks are available and selects one according to its cost and reliability [9]. Communication is secured by a VPN-Tunnel (Virtual Private Network). GPRS or UMTS are normally used during road transportation for external communication. However, during sea transportation, the ship's existing satellite system is used. The gateway is powered by the truck engine or uses the same power supply as the cooling aggregate. Because of the higher energy consumption, gas sensors are typically applied at the gateway level. Currently, the power supply of the gateway is buffered by a large capacitor to ward off the disturbances on the power line, but the capacitor should be replaced by a rechargeable battery in order to bridge phases with disconnected power during transshipment of the container.

Because of the high price of sensor nodes at the present time, it is not viable to equip every pallet or box with such a device. Passive RFID labels provide a much cheaper solution for tagging single items. An RFID gate at the container doors, connected to the communication gateway, supervises the loading process. The RFID tags provide information about the kind of good, allowed temperature range, and the required type of supervision. The gateway has to assign items, which are equipped only with a passive RFID tag, to an active sensor in its neighborhood. The required localization is based on radio-signal-strength information (RSSI) of the RFID reader and the sequence of loading.

Fig. 3 shows the reduced scale prototype of the intelligent container with its RFID reader on the right side, sensor nodes in the middle, processing platform on the back wall, and the communication gateway on the left wall.

Although the system is still in the state of research and pilot tests, the finial system costs can be estimated as follows: 20 sensor nodes at a price of 30 Euros each, a gateway at 800 Euros, software, and general costs sum up to a total cost of 2000 Euros per container at present. It is expected for the price to drop to below 1400 Euros if the number of sold units increases. If we assume eight transports per year over a lifetime of seven years and maintenance costs of 200 Euros per year, the cost of ownership is estimated at about 50 Euros per transport. The usual sea-freight rate for the transcontinental shipment of 15 tons of goods inside a refrigerated container is about 4000 Euros. The value of the load is typically between 10.000 and 40.000 Euros for fruits, but can increase to several million Euros for pharmaceutical products. Compared to these costs, there is a clear business case for an investment of 50 Euros per transport, if thereby the risk of losses by undiscovered temperature deviations is reduced. Furthermore, the traceability is improved. It can also be assumed that the companies that apply a concise transport supervision system may get a discount on their insurance premiums.

Fig. 3. Reduced scale prototype of the intelligent container.

B. State of the Art

Several studies [e.g., [10] and [11]] of local temperature deviations inside the cargo hold have been carried out recently with data loggers, which provide only "offline" access the recorded data after the end of the transport. However, these studies clearly substantiate the necessity for spatial monitoring. Local temperature deviations in the range of 2 °C and 12 °C were found inside trucks and containers.

Standard telemetric systems do not provide the functionalities for the detection of these local deviations. They provide only remote "online" access to the supply and the return air temperature or a maximum of four sensors, which is far too low to put the concept of the intelligent container into practice. Several new projects for remote container supervision were triggered by the Container Security Initiative of the American of Homeland Security after September 11, 2001, but their main focus lays on the detection of unauthorized opening of the doors and intrusion detection by motion sensors, not the online supervision of perishable goods. Commercial products like the SeCureSystem by EADS Astrium [12] and the Container Security Box [13] provide interfaces for external sensors, but have not been tested for spatial temperature monitoring so far. The secure trade lade project by IBM [14] for transport monitoring with ZigBee sensors was stopped after initial tests. Ruiz-Garcia [15] reports of a further test with ZigBee-based sensor nodes, but only one of the four installed sensors could successfully deliver its data to the gateway.

The development of multihop protocols based on the 802.15.4 standard is an active research area. Boano [16], for example, lists and compares five different protocols. Since most of these protocols were not available at the start of the intelligent container project, we developed our own that provides more flexibility for reading out performance and signal strength data. Further research has been carried out on the localization inside sensor networks. Zanca [17] experimentally compares four different methods to calculate the position of a sensor node by the received radio signal strength from a number of anchor nodes with known positions. For less than ten static anchor nodes the average error of the estimated position is greater than 3 meters for all methods. However, correct assignment of pallets to available storing positions inside a container requires an accuracy better than 1 meter.

The intelligent container is much more than a new technical system for wireless supervision; it is rather an application platform for up-to-date methods for sensor data evaluation.

Several mathematical models have been developed by food science research to predict quality changes as a function of the temperature. The speed of chemical reactions, as decay progresses, depends on the current temperature and their specific activation energies as described by the law of Arrhenius. A generic model by Tijskens [18] calculates the loss of shelf life for agricultural products by a combination of two Arrhenius functions. Quality loss of meat products is approximated by calculating the exponential growth rate of spoil microorganisms [19]. However, only a few of these models have been integrated into a sensor system so far. Beyond the application in our project there are only few types of data loggers [20] which implement a simple Arrhenius model.

The situation for the analysis of spatial temperature data is similar to the state of implementation of the shelf life algorithms. There are several methods available, especially, from the fields of geologic statistics and artificial neural networks (ANNs), but they have not been applied to detect local temperature variations in cool chain transports.

The problem that the number of probe points is insufficient for the calculation of the spatial distribution of an environmental parameter is well known in geological research. However, there are only very few examples for application of the related geostatistical methods for spatial interpolation of temperature data in wireless monitoring, e.g., [21]. A simple approach for interpolation is to multiply the measured values of neighboring sensors by a weighting factor that is proportional to the inverse-squared geometrical distance between the sensor and the test point. The Kriging method [22] provides a more accurate way: it estimates the weighting factors as a function of the Variogram that describes the statistical dependency of expected temperature difference between pairs of points as a function of their geometrical distance. As the first step in Kriging, the Variogram function has to be estimated by calculating the variance between pairs of probe points with the same distance. In the second step a linear matrix equation has to be solved to determine the weighting factors.

An ANN is a massive parallel computing structure, based on information encoding and processing, which functions like biological neurons [23]. The ANN is able to learn a continuous process in order to approximate the future events based on relationships within the training data. Number of input sets, accuracy of the training, and parameters of the network greatly influence the accuracy of the approximation. There are two main ANN approaches for parameter approximation: "radial basis function" (RBF) approach and "multilayer perceptron" (MLP) that incorporates the backpropagation technique. Considering flexibility and nonlinear mapping features, ANN is applicable for data approximation and classification in transportation systems. An automated food inspection system is an example to use neural networks in intelligent food transportation industries [24]. Moreover, when wireless sensor networks are utilized, neural networks could be implemented for data fusion [25], [26].

The multitude of available methods for sensor data evaluation requires an appropriate software platform. The DST may conclude that it is necessary to upload and install an additional method, depending on the current situation. For example, if a sensor fault is detected, the measurement at this point has to be replaced by a spatial interpolation. Therefore, the platform has to support dynamic loading of updated software as a fundamental requirement. This feature is one of the main ideas of the Java programming language. Furthermore, Java supports the coexistence of different processing hardware by its platform independence. The use of an existing software framework simplifies the programming of new DST functions. The DST for shelf life evaluation can be programmed as a mobile software agent [27]. The Java-based JADE Agent framework provides mechanisms for agent migration and communication. The Open Source Gateway initiative (OSGi) framework [28] provides similar features, but its implementation uses the processing recourses more efficiently. OSGi allows installing software bundles on a remote embedded system.

The following subsections describe how we have adapted and implemented the above methods as elements of a DST in order to form a cognitive system for transport supervision.

C. *Adjusting the Focus of the Sensor System*

A cognitive sensor system can adjust its focus on critical spots, prolong the measurement interval of sensors, which do not provide crucial information, or put them temporarily into sleep mode.

As a prerequisite for these decisions, the sensor system has to be aware of the location of the sensor nodes inside the container. Inside a packed container it is almost unfeasible to carry out a localization by comparison of radio signal strengths. The standard localization methods do not provide satisfactory accuracy, and the signal attenuation is unpredictable and too high due to its dependence on the loaded cargo. But, because the position of the pallets do not change during transport, it is sufficient to estimate them during the loading process. Four RFID antennas are mounted on the container door to scan for newly loaded pallets. By comparing the signal strengths of the four antennas the pallet is assigned to one of four cells (left, right, up, down). This information is combined with a record of the sequence of loading to determine the final position of the pallet [29].

The sensor system has to supervise itself to determine whether a sufficient number of sensors for crucial environmental parameters are activated with a sufficient measurement interval at the necessary spatial positions. The system can decide to turn on sensors that are currently in sleeping mode or to send a request to the transport operator to place additional sensors in the cargo hold.

The temperature of items not presently equipped with an own sensor can be estimated by spatial interpolation. The Kriging method was applied to a set of 40 sensors that were installed inside one compartment of a loaded delivery truck [30]. The estimated Variogram shows that a temperature deviation has an influence on its neighborhood with a radius of 2.8 meter. The type and the radius of the Variogram changes only very little between different tours of the same vehicle. For subsequent transports with a similar loading scheme the application of the Kriging method can be simplified. The weighting factors can be applied to the new measurements without modification because they depend only on the Variogram.

In order to evaluate whether the sensor density is sufficient to provide an accurate interpolation, the system can compare the actual measurement of one sensor with the interpolated prediction for its position. A high value for this residual indicates that the number of active sensors has to be increased. If for example the number of sensors is reduced to 20, the average residual rises to 1.1 °C.

However, Kriging provides a more advanced way to estimate the interpolation error. The so-called Kriging-Variance gives a prediction for the expected interpolation error for any point in space inside the container. The sensor system can scan for points with high Kriging-Variance and decide whether the tolerance is acceptable.

A sensor could give a wrong measurement caused by low battery voltage or sensor damage due to the tough conditions of food transports with mechanical stress and air humidity of almost 100%. The above described residual between measurement and interpolation can also be applied to detect faulty sensors by plausibility checking. A high residual value could mean one of the following: a) the spatial sensor density is too low; b) the sensor is faulty or has a high tolerance; or c) there is a local physical cause for the deviation, e.g., a "warm" pallet was loaded into the container or an unwanted ripening process started inside a fruit pallet and creates a large amount of heat by conversion of starch to sugar.

The probability for case a) is low if the residual is much higher than the expected deviation according to the Kriging-Variance. Further classification and comparison with typical fault situations from previous transports is necessary in order to discern between cases b) and c).

Alternatively, the plausibility of the records could be evaluated by knowledge-based algorithms, as shown in Fig. 4, to evaluate the sensor records inside a container including two main zones (A and B) [35].

The plausibility-checking algorithm could be applied either locally to evaluate neighboring sensor nodes in each cluster, or globally to process the neighboring clusters to detect any abnormality in the sensor network. The required intelligence of each sensor node to evaluate the collected records varies depending on the desired data processing level.

The local plausibility-checking was implemented by a two-stage artificial neural network (ANN) algorithm. The first ANN implements the approximation mechanism, the second a classification algorithm [31] as shown in Fig. 5. At first, a multi-

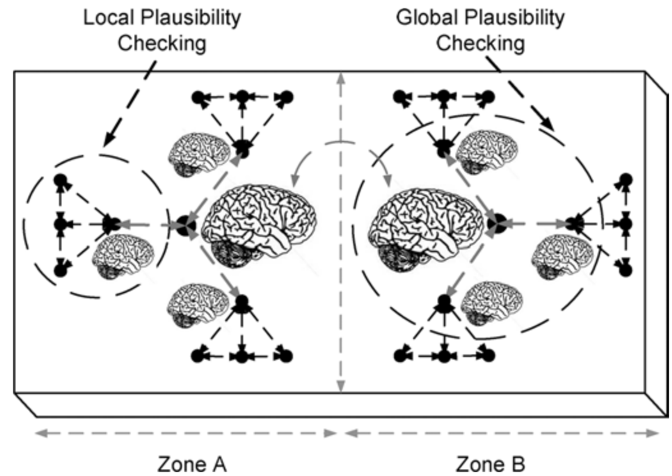

Fig. 4. Knowledge-based plausibility checking in the intelligent container.

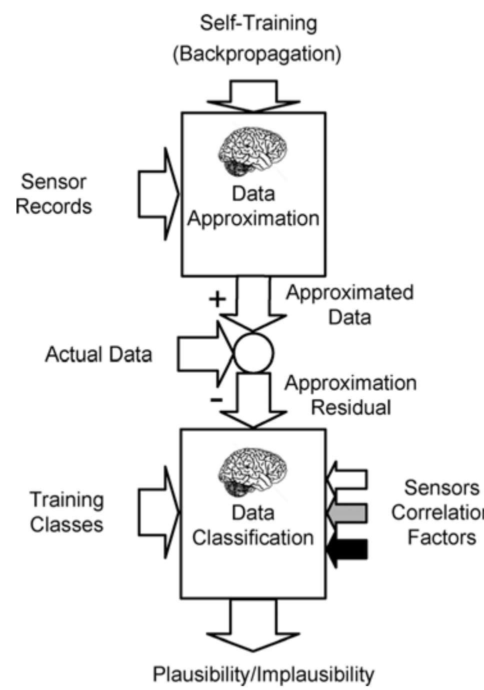

Fig. 5. Data approximation and classification in a wireless sensor network using ANN.

layer-perceptron neural network calculates a prediction based on the current measurement of the three closest neighbors; a dynamic sliding back-propagation is used to train the approximation network, which depends highly upon the last few records of the sensor nodes. Due to nonlinear mapping features, the proposed network led to more accurate results compared to the classical data approximation approaches like least squares [31]. The approximation residual is given by the difference between ANN prediction and the actual measurement.

To design the approximation network, two hidden layers are taken into consideration, while an output layer merely sums the weighted data. Various network architectures and parameters were tested to optimize the network to approximate the records. The number of first hidden layer units varied between 2 and 9; and the number of second hidden layer units varied between 2 and 5. The results showed that in the majority of cases, it is

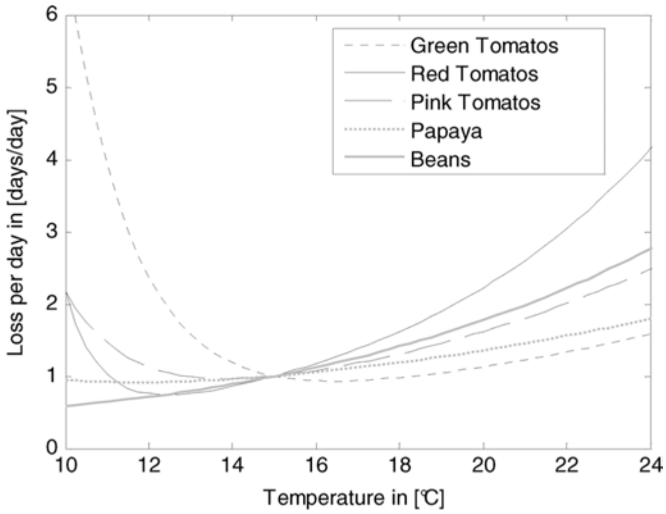

Fig. 6. Loss per day of shelf life for typical food products.

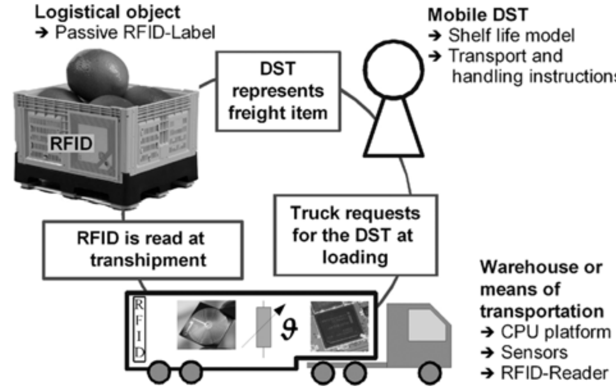

Fig. 7. Transfer of the mobile DST.

preferable to use four neurons in both hidden layers to approximate the data of each sensor using three neighboring sensors [31]. However, by using fewer neurons, the mapping is less precise, and using more neurons is unfeasible due to increased saturation in data mapping, calculation time, and power demands. Furthermore, using two hidden layers increases the nonlinear mapping feature between input pattern and target [31].

The second neural network uses a radial basis function structure to classify the approximation residual (as plausible or implausible) considering the correlation factors between sensor nodes. The probabilistic neural network estimates the "probability density function" for each class based on the given training samples.

For example, a simultaneous rise of relative humidity and temperature indicates that warm air with high absolute humidity penetrates through an open door, whereas falling relative humidity indicates a local warming without air exchange. A cognitive sensor system should also adapt its measurement intervals, if necessary. An intelligent sensor predicts the slew rate for the change of an environmental parameter by an ANN with the four last recent samples as input parameters [32]. The interval to the next measurement is set in a way that the expected change of the parameter during the interval is lower than a tolerance threshold.

D. Evaluation of Sensor Data

Apart from adjusting the focus, the main task of the decision support tool is to evaluate the effects of environmental parameter deviations on the product quality. The shelf life algorithm from Tijskens [18] was taken as an example. The algorithm was transferred into a form, which allows updating the shelf life value on-the-fly with only few mathematical operations after each temperature measurement. The loss of shelf life per day is calculated as a function of temperature. Fig. 6 shows the loss-per-day curve for some typical fruits and vegetables. The current loss per day is subtracted from the initial shelf life.

This algorithm can run as a software bundle or an agent as part of the DST on the gateway unit inside the container or directly on individual sensor nodes. The typical hardware of wireless sensor nodes provides only little processing power. Mathematical calculations are restricted to integer operations. Therefore, further optimization of the shelf life algorithm had to be carried out [2]. The algorithm has already been implemented on a commercial sensor node from Ambient Systems [33]. The DST decides on the bases of prediction for the remaining shelf life, whether the goods are in proper condition or the logistic planning has to be adjusted in order to prevent losses by decay.

E. Implementation of the Decision Support Tool

Simple functions of the DST can be implemented at the sensor level, but more complex decisions have to be performed on the gateway level. A part of the DST is permanently implemented, but special functions can be installed upon request as in the following examples. a) The system detects one faulty sensor and requests for a Kriging tool to interpolate temperature and humidity at the missing position. b) The RFID reader informs the system that a new kind of good was loaded. The systems download a specific shelf life model.

The latter example leads to the idea of a mobile DST, which accompanies a freight item along its course through the logistic chain. The DST contains specific instructions, how temperature and quality deviations should be handled. Furthermore, it contains the temperature history and transport information as part of an electronic way-bill. Fig. 7 illustrates process of transferring the mobile DST. New freight items are detected by an RFID reader. The truck or container sends a request for the DST that represents the loaded freight item. The request is answered by the last processing platform, which executed the DST software, and transfers it to the new means of transportation.

So far, the above described cognitive features are implemented and tested in separate software frameworks, but our aim is to provide them on a fully integrated OSGi platform.

F. Experimental Results

The remote supervision of spatial temperature deviations and the newly developed BananaHop protocol for communication inside the sensor network were tested during the transport of two containers, loaded with Bananas, from Costa Rica to Germany [34]. This experiment provides another proof for the existence of spatial temperature in almost all transport situations. Especially the duration of the "cooling-down process" varied tremendously for different positions inside one container and

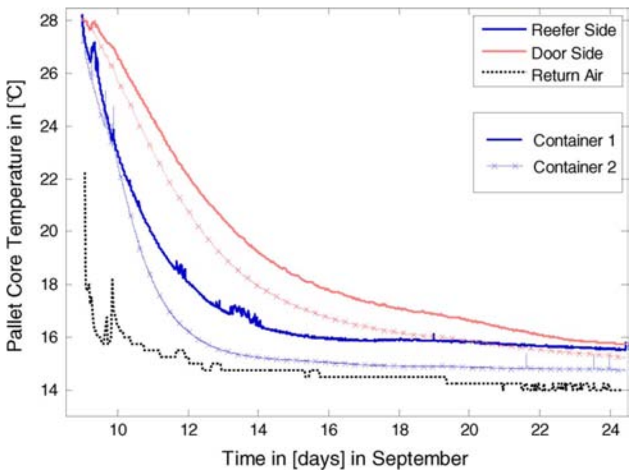

Fig. 8. Comparison of core temperatures for different positions and containers.

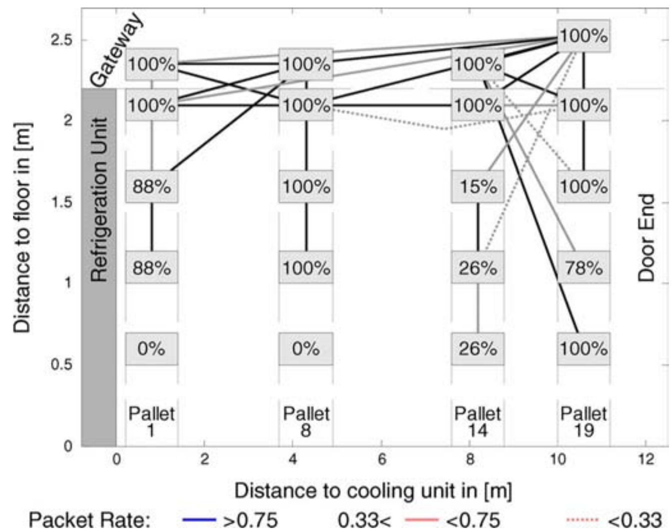

Fig. 9. Protocol performance and links between sensors.

also between the two supervised containers. Fig. 8 shows the decline of the core temperature over time for pallets close to the door and those at the opposite end of the container. Pallets, which stood close to the refrigeration unit, required 58% less time for cooling-down than those at the door end. The average temperature differences over the length of the container were 1.85 °C and 2.03 °C, respectively. The maximum temperature difference of 4.98 °C was observed in the second container, 2.1 days after leaving Costa Rica. Although both containers were of the same type and used identical refrigeration units, the cooling-down was 38 % faster in container 2.

The experiment also showed that concise temperature supervision is impossible without additional sensors inside the freight. The built-in sensors of a standard refrigeration unit measure only the supply and the return air temperature, but not the freight temperature. The supply air temperature stayed almost constant at 13.75 °C. The state of the cooling process can be verified by the difference between the return and the supply air temperatures, but it is impossible to conclude the pallet core temperature if the only available measurements are the latter two.

During the two weeks of transport the battery voltage of the sensor nodes dropped from 3 to 2.77 Volts, which is still above the minimal required supply voltage of 2.4 Volt. The power consumption mainly depends on the interval between radio transmissions. If the interval is extended from the current 2 to 15 min, the sensors could operate for several months without maintenance.

In order to evaluate the signal attenuation inside the container due to water-containing food products, a supplementary feature was added to the sensor node software. For each sampling interval, the nodes kept a record of all neighbors from whom a transmission was received. After the end of transport, the records were combined for an analysis of possible routes within the network. Fig. 9 indicates the existing links between pairs of sensors and their packet rate (lines between boxes), as well as the percentage of messages that were actually delivered by the BananaHop protocol [34] to the gateway from each sensor (numbers inside boxes). Although the vertical distance between sensors inside one pallet was only 0.5 meters, two sensors were completely disconnected from the network due to the high signal attenuation. The maximum transmission power of the TelosB platform is only 1 mW. Future experiments should make use of a platform with higher radio power, such as the ZigBitAmp from Meshnetics.

In total 76% of all the sent messages arrived at the gateway. Part of the losses was due to inappropriate routing. However, an analysis of the combined link data showed that the route to the gateway was physically interrupted for certain number of intervals and no alternate route existed. The probability for the latter case was calculated to 20%. This implies that the BananaHop protocol lost 4% of all messages during this experiment due to inappropriate routing.

The BananaHop protocol uses a simplified method to estimate the quality of links to the neighbor sensor nodes. The link quality is calculated as a function of the signal strength (RSSI) of the last received beacon. Routing losses are mainly caused by wrong link estimation. One option to improve the link estimation would be to send additional ping-messages to the neighbors. But, by adding cognitive features to the routing mechanism, the performance could be improved without increasing the number of control messages and thereby reducing the energy consumption. Such a cognitive sensor node could detect inappropriate routing by the fact that it does not receive acknowledgement messages for its transmitted sensor data. The sensor can then try to adjust its model for estimation of the neighbor link quality, e.g., by modifying the thresholds to discern between "good" and "weak" links.

The performance of the ANN-plausibility check was tested with the data of an experiment inside a refrigerated truck at the premises of the University of Bremen. Two faults were simulated including: a) battery failure of a sensor by removing its power supply and b) a temperature disturbance by opening the door. Fig. 10 shows the experimental results of a two phase test inside a real truck [35]. First phase models the internal faults

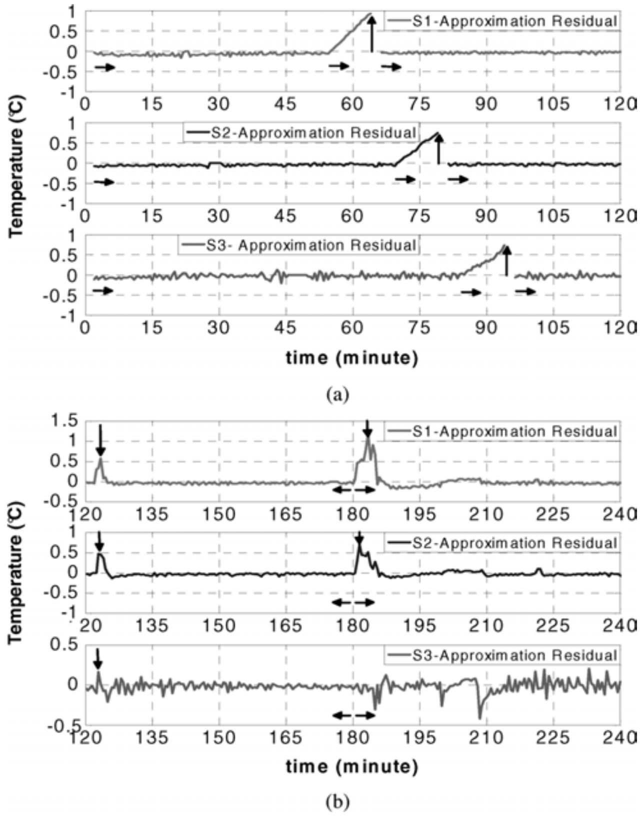

Fig. 10. Approximation residuals during the test. (a) First phase. (b) Second phase [35].

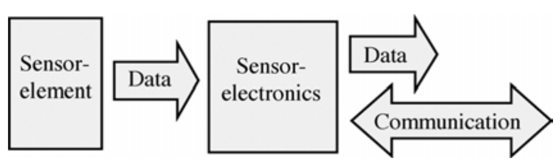

Fig. 11. A classical sensor system.

such as battery discharge and disconnection of the communication link. They occur at 55th, 70th, and 85th min within 10 min for the first, second, and third sensor nodes, respectively.

The second phase begins at 120th min and lasts until 240th min. The doors of the truck are opened once at the 120th min for 2 min. Thereafter, the doors remain closed until the 178th min, after which they are reopened for 4 min until 182nd min and then reclosed [35]. As shown in Fig. 10, the approximation of faulty sensor nodes shows large deviations from the actual values, which could be detected by classification mechanism.

The next section discusses these cognitive features from a more general perspective.

III. Cognitive Features in the Sensor Network

A classical sensor system works, as shown in Fig. 11. There is a direct path from the physical phenomenon such as temperature to the electrical sensor output. The characteristics of the sensor should be strongly deterministic.

An advanced sensor system is shown in Fig. 12. There is a second layer of data evaluation, and there are circular processes or feedback loops between the layers.

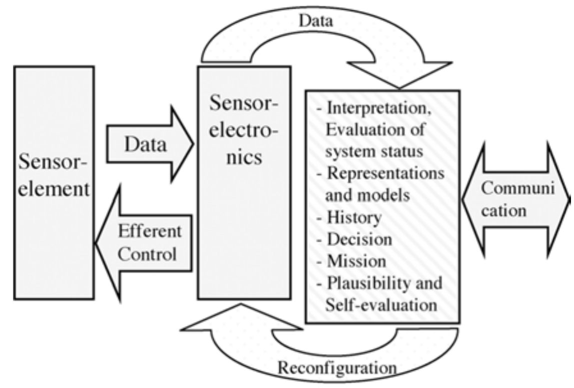

Fig. 12. The new approach to a sensor system applying cognitive features.

One feedback loop may be used for efferent control, when the sensitivity of the sensor element is changed according to the signal strength. Efferent control is known from biology: the human eye adapts to light, the ear adapts to noise. It is possible to reduce the voltage of a capacitive microphone when the sound levels are too high. This reduces the sensitivity, but it does not prevent mechanical stress on the microphone membrane. In biological systems, the change of sensitivity is done on the hardware side. If light is too strong, the iris of the eye closes. The sensitivity is reduced and the retina is protected simultaneously. This type of control acting on the physical part of the transduction mechanism is very rarely used for technical sensor systems so far.

The most important new feature is the new level for higher functions of data evaluation. The data are synthesized to generate a view of the status ("theses apples will be ripe in two days, temperature and humidity are in range"). Specific knowledge (specific shelf life models for each kin of fruit) and historic information (quality of the fruit at the time of loading) are considered. If the sensor network does not have this specific information available, it may retrieve it from an external source. Based on this, the system can make decisions. Estimating a remaining shelf life is a decision, also approving a situation as OK versus triggering an alarm. Plausibility checking is used for self-evaluation. Can I believe the sensor elements? Do I have enough sensors and the sensors appropriate to control the situation?

Under certain circumstances, the system has to change the mission of the sensor network. If a dangerous situation is detected, e.g., gas sensors report that they detect traces of gases emitted by mildew, then more information about the humidity situation is needed. A reconfiguration has to be performed. Particular sorts of reconfiguration are being investigated or implemented for the intelligent container:

— When measured values change faster than expected, the measurement interval can be dynamically adapted [32].
— Sensors in energy saving sleeping mode can be aroused.
— Sensors identified as possibly unreliable may be replaced.
— During loading, the system can ask for more or other sensors to be supplied before the transport is started. This way, it dynamically adapts to the goods and the situation.
— Hazards for safety and security may cause the exclusion of compromised motes.

These features are similar to the active perception in biological systems as described by Schill [36]. Active perception enables biological systems to exploit their limited resources of recognition capabilities in an efficient way in order to make conclusions about a current state.

The circular sensing model illustrated in Fig. 12 shows a number of analogies to the above-described properties of active multimodal recognition in humans. As in human cognition the recognition of the current state of the intelligent container is determined not only by bottom-up sensor information, but also by top-down knowledge and task-related information. Top-down information is used in the form of the interpretation of the system status together with the history, conclusions drawn, and decisions made. This top down information together with the bottom-up sensor data determines the evaluation of the current state. Moreover the sensor network used is not static, but can be reconfigured based on the current state. Similar to multimodal biological systems that direct the limited recognition capabilities towards informative features and use the combination of information from different modalities, an advanced intelligent container might react on a trace of gas which could be the metabolite product of a fungus or mildew by waking up some humidity detectors presently down in sleep mode for energy saving.

The project of the intelligent container is part of a larger initiative at the University of Bremen that is concerned with autonomous processes in logistics [36]. A logistic item such as a parcel shall have the information and the decision power to organize itself and to choose its own way through transport or production processes [37]. Autonomy in logistics is expected to improve performance and robustness for very large tasks which cannot be controlled by a central unit due to their complexity. Three important criteria for autonomy in logistics are given in [38]:

1) Decentralized decision making in heterarchical structures.
2) Interaction of the elements.
3) Nondeterministic behavior and positive emergence.

In the case of the sensor network, these criteria are closely linked with cognitive structures. The internal processes for calculating representations and for self-evaluation not only render the system nondeterministic, they also are the basis for decentralized decision making. The application of cognitive structures to the sensor network is thus a necessary prerequisite for it to act as an enabler for autonomously operating logistic processes.

IV. Summary and Outlook

The intelligent container is a complex sensor network applicable in logistics, especially, if perishable goods such as fruits are transported. To begin with, the sensor network measures the important transport parameters such as temperature and humidity with a special resolution superior to the one implemented today. Next, it documents transport parameters such as acceleration. Then, it looks at the status of the goods. For fruits this is done by measuring the amount of ethylene gas emitted, which gives information on the status of the ripeness.

These measurements are the input for data evaluation on a higher level. The status of the fruits is estimated with fruit ripening models. They use the temperature history measured by the container, and also the data about the history before the fruits have been loaded, which is stored in an electronic way-bill. Based on these data, the remaining shelf life time is estimated and continuously updated. A second class of high level processes concerns the self evaluation of the system. Using plausibility checking, faults in measurements are found and corrected. This way the sensor network may change its configuration autonomously during the operation.

Due to the observance of the history of the goods, the high degree of nonlinearity of the ripening models, the complexity of the decision support tools, and possible reconfiguration there is no way to predict the decisions the container will come to during transport. This aspect of indeterminism is known to logistic science, and it is considered to be one of the main features of autonomous or self-monitoring systems. It is also well known in cognition science. Cognitive systems perform large amounts of data processing and transfer within the system (Fig. 1). External information influences the system, but does not determine it. This model is proposed as a new approach for the understanding of complex sensor systems (Fig. 12).

Why do we apply this much of local evaluation and complexity? First, in this specific application, autonomy is a must. In general, a container in the sea cannot be controlled from a central station since communication cannot be guaranteed. Second, even if there is a communication path, bandwidth is too small to send all the data, making local data reduction and on-site evaluation unavoidable.

For an outlook, where does this research aim at? The intelligent container will be an enabling tool for the new logistic paradigm of FEFO. Taking into account the remaining shelf life, we expect better quality of the goods for the customer, less loss during transport, and thus a reduced CO_2 footprint.

At the moment, the system has been developed and tests are being performed. The Intelligent Container Project is now leaving the research phase and moving in to transfer and application. Results of the first field test performed with fruits on a ship en route from Middle America to Europe will be reported soon.

References

[1] R. Jedermann, C. Behrens, R. Laur, and W. Lang, “Intelligent containers and sensor networks, approaches to apply autonomous cooperation on systems with limited resources,” in *Understanding Autonomous Cooperation and Control in Logistics—The Impact on Management, Information and Communication and Material Flow*. Berlin, Germany: Springer-Verlag, 2007, pp. 365–392.

[2] R. Jedermann, J. P. Edmond, and W. Lang, “Shelf life prediction by intelligent RFID,” in *Proc. 1st Int. Conf. LDIC 2007*, 2008, pp. 231–238.

[3] T. E. Tsironi, P. Gogou, and P. S. Taoukis, “Chill chain management and shelf life optimization of MAP seabream fillets: A TTI based alternative to FIFO,” in *Proc. 3rd Int. Workshop of Cold Chain Management*, Bonn, Germany, Jun. 2–3, 2008, pp. 83–89.

[4] A. Sklorz, A. B. Alamin Dow, D. Mrugala, R. Jedermann, W. Benecke, and W. Lang, “In-situ ethylen-konzentrationsmesssysteme für die qualitätsüberwachung in der fruchtlogistik,” *DFMRS-Fachtagung*, Feb. 27–28, 2008, Forschungsbericht Nr. 2008-1.

[5] M. Urchs, *Maschine, Körper, Geist: Eine Einführung in Die Kognitionswissenschaft*. Frankfurt am Main, Germany: Klostermann, 2002.

[6] F. J. Varela, “Cognitive Science. A Cartography of Current Ideas,” 1988.

[7] MoteIV Corporation, “Tmote Sky—Ultra Low Power IEEE 802.15.4 Compliant Wireless Module Datasheet,” Jun. 2, 2006 [Online]. Available: http://www.sentilla.com/pdf/eol/tmote-sky-datasheet.pdf, MoteIV Corporation

[8] R. Buchner, K. Froehner, C. Sosna, W. Benecke, and W. Lang, “Forward flexible thermoelectric flow sensors: A new technological approach,” *J. Microelectromech. Syst.*, vol. 15, no. 5, pp. 1114–1119, 2008.
[9] M. Becker *et al.*, “Challenges of applying wireless sensor networks in logistics,” in *Proc. CEWIT 2009. Wireless and IT Driving Healthcare, Energy and Infrastructure Transformation*, 2009.
[10] J. Moureh and D. Flick, “Airflow pattern and temperature distribution in a typical refrigerated truck configuration loaded with pallets,” *Int. J. Refrigeration*, vol. 27, no. 5, pp. 464–474, 2004.
[11] D. J. Tanner and N. D. Amos, “Heat and mass transfer—Temperature variability during shipment of fresh produce,” *Acta Horticulturae*, vol. 599, pp. 193–204, 2003.
[12] “SeCureSystem—We keep you save,” 2010. [Online]. Available: http://www.securesystem.net/, Astrium GmbH
[13] CSB Technologies GmbH, “Container security box CSB—A patented plug & play solution.” [Online]. Available: http://www.csb-technologies.com/
[14] S. Schaefer, “Secure trade lane: A sensor network solution for more predictable and more secure container shipments,” in *Proc. Companion to the 21st ACM SIGPLAN Symp. Object-Oriented Program. Syst., Languages, and Appl.*, Portland, OR, 2006, pp. 839–845.
[15] L. Ruiz-Garcia *et al.*, “Testing zigbee motes for monitoring refrigerated vegetable transportation under real conditions,” *Sensors*, vol. 10, no. 5, pp. 4968–4982, 2010.
[16] C. A. Boano *et al.*, “Making sensornet MAC protocols robust against interference,” in *Proc. 7th Eur. Conf. Wireless Sensor Networks, EWSN 2010*, Coimbra, Portugal, 2010, pp. 272–288.
[17] G. Zanca, F. Zorzi, and A. Zanella, “Experimental comparison of RSSI-based localization algorithms for indoor wireless sensor networks,” in *Proc. Workshop on Real-World Wireless Sensor Networks Eur. Conf. Comput. Syst.* , Glasgow, Scotland, 2008, pp. 1–5.
[18] L. M. M. Tijskens and J. J. Polderdijk, “A generic model for keeping quality of vegetable produce during storage and distribution,” *Agricultural Syst.*, vol. 51, no. 4, pp. 431–452, 1996.
[19] J. Kreyenschmidt *et al.*, “Determination of the shelf life of sliced cooked ham based on the growth of lactic acid bacteria in different steps of the chain,” *J. Appl. Microbiol.*, vol. 108, no. 2, pp. 510–520, Feb. 2010.
[20] S. E. Zweig, “LifeTrack technology for smart active-label visual and RFID product lifetime monitoring,” in *Proc. 3rd Int. Workshop Coldchain Management*, , Bonn, Germany, 2008, pp. 29–36.
[21] A. Camilli *et al.*, “From wireless sensors to field mapping: Anatomy of an application for precision agriculture,” *Comput. Electron. Agriculture*, vol. 58, no. 1, pp. 25–36, 2007.
[22] R. Webster and M. A. Oliver, *Geostatistics for Environmental Scientists, Chichester*. New York: Wiley, 2007.
[23] S. Haykin, *Neural Networks: A Comprehensive Foundation*. Englewood Cliffs, NJ: Prentice-Hall, 1999, p. 73.
[24] G. J. Hueter, “Neural network automate inspections,” *Quality*, vol. 32, pp. 41–44, 1993.
[25] G. Betta and A. Pietrosanto, “Instrument fault detection and isolation: State of the art and new research trends,” *IEEE Trans. Instrument. Measure.*, vol. 49, pp. 100–107, 2000.
[26] P. Auer, H. Burgsteiner, and W. Maass, “A learning rule for very simple universal approximators consisting of a single layer of perceptrons,” *Neural Netw.*, vol. 21, pp. 786–795, 2008.
[27] F. F. Bellifemine *et al.*, “Jade—A white paper, EXP in search of innovation—Special issue on JADE,” *TILAB J.*, vol. 3, Sep. 2003.
[28] G. Wütherich *et al.*, *Die OSGi-Service-Platform: eine Einführung mit Eclipse Equinox*. Heidelberg, Germany: verlag.dpunkt, 2008.
[29] A. Wessels, R. Jederman, and W. Lang, “Embedded context aware objects for the transport supervision of perishable goods,” in *Proc. 9th WSEAS Int. Conf. Electron., Hardware, Wireless and Opt. Commun. (EHAC’10)*, 2010, pp. 119–125.
[30] R. Jedermann and W. Lang, “The minimum number of sensors—Interpolation of spatial temperature profiles,” in *Proc. 6th Eur. Conf. Wireless Sensor Networks, EWSN*, 2009, Lecture Notes in Computer Science (LNCS), pp. 232–246, .
[31] A. Jabbari *et al.*, “Application of neurocomputing for data approximation and classification in wireless sensor networks,” *Sensors J.*, vol. 9, pp. 3056–3077, 2009.
[32] X. Wang *et al.*, “Dynamic control of data measurement intervals in a networked sensing system using neurocomputing,” in *Proc. Int. Conf. Networked Sensing Systems (INSS 2010)*, Kassel, 2010.
[33] R. Jedermann *et al.*, “Wireless quality monitoring in the food chain,” in *Proc. 6th Eur. Conf. Wireless Sensor Networks—Poster/Demos Session*, Cork, Ireland, 2009, pp. 1–2.
[34] R. Jedermann *et al.*, “Field test of the intelligent container,” in *Proc. 7th Eur. Con. Wireless Sensor Networks EWSN2010, Posters and Demos*, Coimbra, Portugal, 2010, pp. 11–12.
[35] A. Jabbari, “Application of autonomous fault detection and isolation in wireless sensor network,” Ph.D. dissertation, University of Bremen, Bremen, Germany, 2009.
[36] K. Schill, C. Zetzsche, and J. Hois, “A belief-based architecture for scene analysis: From features to knowledge and ontology,” *Fuzzy Sets Syst.*, vol. 160, pp. 1507–1516, 2008.
[37] Collaborative Research Centre 637 (CRC 637), “Autonomous cooperating logistic processes—A paradigm shift and its limitations,” May 2010. [Online]. Available: http://www.sfb637.uni-bremen.de/
[38] B. Scholz-Reiter, J. Kolditz, and T. Hildebrandt, “Engineering autonomously controlled logistic systems,” *Int. J. Prod. Res.*, vol. 47, pp. 1449–1468, 2009.
[39] F. Böse and K. Windt, “Catalogue of criteria for autonomous control in logistics,” in *Understanding Autonomous Cooperation and Control—The Impact of Autonomy on Management, Information, Communication, and Material Flow*, M. Hülsmann and K. Windt, Eds. Berlin, Germany: Springer-Verlag, 2007, pp. 57–72.

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