i-RM: An intelligent risk management framework for context-aware ubiquitous cold chain logistics

Kwanho Kim, Hyunjin Kim, Sang-Kuk Kim, Jae-Yoon Jung

1. Introduction

Maintaining the freshness of goods in food or pharmaceutical logistics is of great importance since the decreased freshness of items directly causes significantly adverse effects on consumer prices or human health (Olafsdottir et al., 2010). It is strongly desired that a greater amount of attention is paid to environmentally sensitive (perishable) food such as fruit, fish, and meat to guarantee that such goods are held under proper environmental conditions during their distribution (Heising, Dekker, Bartels, & van Boekel, 2013). For instance, the quality of an apple can easily be damaged when the temperature and humidity for the item are outside of range. Moreover, providing customers with information as to how the distribution channel is controlled to maintain the freshness of items is beneficial to strengthen customers’ confidence in the items’ quality, as it is difficult for consumers to identify whether items were really held under proper environmental conditions during their distribution processes.

Recently, to meet requirements, there has been an increasing interest in cold chain logistics (CCL). The objective of CCL is to maximize the freshness of goods over the entire distribution process through monitoring and controlling environmental conditions directly related to the items’ freshness (Xu, Zhang, & Zheng, 2012). In particular, CCLs that adopt the advancement of ubiquitous technologies such as radio frequency identification (RFID) and sensors are called ubiquitous cold chain logistics (UCCL). Here, RFID tags are installed on entities (such as a delivery item, worker, or container) during distribution processes and they are used for automatically identifying the entities based on the unique identifiers assigned to the tags. On the other hand, a sensor refers to a device that measures environmental conditions in terms of particular environmental features, such as temperature and humidity. Information from a sensor contains a pair of environmental features and their measured values. By combining the information transmitted from RFID and sensors, one can figure out which entity is under which environmental condition.

Since the information on entities and environmental conditions is periodically transmitted to other systems via wireless sensor networks (WSNs), the environmental conditions of delivery items across the entire distribution process are traceable without latency in UCCL.

Owing to the increasing interest in food quality in terms of freshness, a special type of logistics, called ubiquitous cold chain logistics (UCCL), has become an essential part of the distribution of environmentally sensitive items. UCCL aims to guarantee that delivery items are held under proper environmental conditions.

By incorporating ubiquitous technologies such as radio frequency identification (RFID) tags and various types of sensors, monitoring and tracking environmental conditions for delivery items in UCCL have been easily achievable without latency. Nevertheless, addressing the complex nature of risk management rules caused by a large number of possible risk cases in UCCL has not yet been fully developed. Therefore, in this research, we suggest an intelligent risk management framework for UCCL, namely i-RM, which is designed to accommodate various types of risk situations by introducing the notion of context-aware real-time risk management. More specifically, i-RM takes a divide-and-combine approach where rules for risk management functions, context identification, risk detection, and response action judgment are defined in semantic ontologies. While rules for the risk management functions are defined independently of the others, they are dynamically linked for handling risks during run time. Moreover, i-RM is fully responsible for all of the risk management tasks required in UCCL, from information acquisition to responses in real time, by adopting event-based processing techniques. The effectiveness of the risk management ability of i-RM is demonstrated based on a real-world UCCL scenario.

Keywords:
Risk management
Real-time context-awareness
Complex event processing
Ontology
Ubiquitous cold chain logistics

© 2015 Published by Elsevier Ltd.
Although UCCL is entirely concerned with temperature conditions, other environmental conditions that greatly affect an item’s freshness are also a concern. To achieve the maximum freshness of delivery items, managing risks caused by the unexpected changes in environmental conditions for delivery items during distribution processes is incredibly important, as such risks can directly or indirectly lead to negative effects on item freshness, unless proper responses to eliminate risks are immediately taken during the distribution processes. That is, the effectiveness of a distribution process in UCCL is mainly determined by not only the automatic detection of possible risks based on the information collected through WSNs, but also the immediate responses against risks.

Fig. 1 illustrates the importance of risk management in UCCL by means of changes in item freshness when accidental situations, which lead to an increase in temperature, occur on the way from warehouse A to warehouse B, both without and with risk management in UCCL. It is assumed that the freshness of delivery items in a case is directly affected by temperature conditions, and their freshness is significantly damaged if the average temperature of the delivery items is out of the suggested range for 10 min. Without risk management, it is highly unlikely for accidental situations to be found within 10 min after the problems occur. The freshness of the items cannot be revitalized when they arrive in warehouse B, resulting in a loss of productivity. In contrast, the freshness of the delivery items with risk management is able to be maintained without a loss in item quality by conducting proper treatments, which is achieved by notifying the person in charge of the risks.

Compared to conventional logistics, risk management for UCCL is considered to be a challenging issue for the following reasons: first, whenever a risk occurs, all of the involved tasks for risk management should be done in a real-time manner since slower responses imply a lower quality of items. Let us assume a situation where the refrigerator in a freezer container with fruits inside is suddenly turned down, and the fruits’ quality becomes seriously damaged if the average temperature in the freezer container is greater than 5°C, for a time period of 10 min. In this case, the key to the fruits’ freshness largely depends on whether a risk management system is able to immediately notify this accidental situation to a person in charge rather than just tracking the temperature conditions for the delivery items.

Second, for each individual risk case, the defining rules, which map entities and environmental conditions into risks and responses, are very complex due to the fact that the number of rules to be defined significantly increases as more entities and environmental conditions come under consideration. This indicates that building rules for individual risk cases is a labor-intensive task requiring a large amount of time and costs. In addition, much more effort is needed to update such rules according to the changes in distribution policies. As an example, the proper temperature ranges differ according to the specific types of fruit. In addition, the proper humidity range for long-term storage is different from that for short-term storage.

Finally, to effectively control UCCL in terms of risk management without human intervention, an integrated framework which accounts for all of the risk management steps, from receiving information to taking responses, is necessary. An automated risk management framework is essential to minimize subsequent problems caused by human error and late responses. In the meantime, an integrated framework capable of providing a unified view of food freshness is used to understand the weak points and frequently found accidents during the distribution processes.

Therefore, we suggest an intelligent risk management framework for UCCL, namely i-RM. It is designed to automatically handle risks, resulting in maximum flexibility and minimum manual effort by combining the notions of context awareness based on ontology and real-time risk management. The real-world situation in UCCL is modeled by means of entities, states of entities, and responses which are contained in the ontology for i-RM, and three risk management functions (context identification, risk detection, and response judgment) are incorporated for managing risks. Based on the information collected by the WSNs reflecting the real-world situation, i-RM attempts to identify the underlying context of the current situation that initially represents which entities are under which states by using a context identification function. Then, by incorporating risk detection and response judgment functions, contexts are changed to additionally represent the risks and proper responses for contexts.

For the purpose of improving flexibility by reducing the complexity during the rule definition period, all while automating risk management tasks during this run time, we adopt a divide-and-combine approach. This approach allows i-RM to not only independently define rules according to risk management functions but to also be dynamically combined for handling risks based on contexts. In detail, during the rule definition period, unlike the previously proposed frameworks that intensively rely on constructing rules according to possible risk cases without understanding contexts, i-RM has the ability to significantly reduce the complexity of rule definitions by dividing risk management tasks into sub tasks, each of which is preceded in a function that works independently of the others. That is, whenever a particular rule is updated or added, the remaining rules are not necessarily changed, resulting in a minimum amount of changes to the system when delivery policies are changed.

Subsequently, i-RM dynamically links rules for risk management functions during run time to handle a particular risk. Whenever the information for entities and environmental features arrives, i-RM first identifies the context of the received information. Then, the meaning of a context is successively changed by resolving the risk level and proper responses for the context by utilizing risk and response rules. That is, i-RM performs risk management tasks not by relying on a single rule for each specific risk case, but by linking multiple rules to be suitable for the risk case.

Our approach is characterized compared to recently reported studies related to this research as follows. Some of the previous researches mainly focus on developing real-time decision systems such as Nechifor et al. (2014) and Olafsdottir et al. (2010), while others attempt to maintain delivery process by using context-aware models such as Cao, Shao, Yu, and Chen (2014); and Engel and Supangkat (2014). Their approaches deal with a specific setting considered rather than for understanding various contexts compared to the proposed approach in this research. Our approach that utilizes an ontology base for dynamically combining three decision tasks such as context identification, risk evaluation, and response detection is able to make systems flexible enough to accommodate various contexts by simply adjusting ontology rules. In addition, such advantages of the proposed approach are helpful for accessing flexible maintenance and its wide adoption in real-world environments.

The rest of this paper is organized as follows: in Section 2, the previous studies and their limitations are discussed. In Section 3, we suggest the concept of i-RM, and its components and their relationships are explained. Next, we demonstrate how risk management tasks in UCCL are achieved by utilizing i-RM based on a real-world scenario in Section 4. Finally, we conclude this research in Section 5.

2. Literature review

In this section, the previous studies related to the problem we are considering, along with their limitations, are explained. The previous research falls into five categories, as summarized in Table 1: real-time item state change detection, food quality evaluation and risk avoidance, process discovery and traceability, context-aware monitoring, and risk management.

First, in the studies related to real-time item state change detection, they concentrated on how the state changes of environmental conditions for delivery items can be detected during distribution processes. Abad et al. (2009); Olafsdottir et al. (2010); and
Yan and Lee (2009) showed in detail the potential of RFID tags for real-time traceability and temperature monitoring in UCCL. By focusing on the temperature conditions and variations, Kreyenschmidt (2003) suggested a generic model to predict the remaining life of the delivery items. Recently, Nechifor et al. (2014) introduced an automatic monitoring approach for real-time monitoring of transportation based on machine learning techniques.

Second, there is a line of research that focuses on the estimation and monitoring of food quality based on ubiquitous technologies such as RFID tags and sensors. Cao et al. (2014) attempted to monitor temperature obtained from RFID tags during transportation by incorporating information processing techniques. Oh et al. (2011) proposed a food quality monitoring system for UCCL which enables problems to be tracked in terms of the delivery process by means of storing historical lots of distributions. Wang and Li (2012) demonstrated a food quality evaluation method to reduce food spoilage waste and to maximize food retailers’ profits through a pricing approach based on the dynamically-identified food shelf life.
Third, Engel and Supangkat (2014) reported the possible combination of context-aware approaches for UCCL environments ranging from learning to ontology based models. In addition, to discover the processes and traceability of items, Kelepouri, Pramataris, and Doukidis (2007) developed information data models and a system architecture that aim to discover end-to-end traceability across supply chains. Kim, Oh, Rosales, Kim, and Jung (2010) presented an architecture that aims to manage UCCL from the viewpoint of distribution processes. Premkumar (2000) suggested a concept for understanding distribution processes in terms of the flow of information and the strategies for realizing this concept by integrating heterogeneous information systems for supply chain management.

Next, Ngaia et al. (2011) studied context-aware decision support for real-time monitoring in container terminal operations by employing ZigBee based on WSNs. Moreover, Verdouw, Robbemond, Verwaart, Wolfert, and Beulens (2015) proposed a reference architecture models for implementing UCCL information systems. Xu, Wijesooriya, Wang, and Beydoun (2011) attempted to address exceptional cases in logistics based on multi-perspective ontologies that include static, social, and dynamic sub-ontologies to effectively reflect situational dependencies among logistics exceptions.

Finally, Cucchiella and Gastaldi (2006) addressed the uncertainty problem in logistics used for risk reduction of businesses by showing the possible options for risk management in accordance to the risk sources. Similarly, Yang, Jung, Kim, and Kim (2011) suggested factors that affect risks in global supply chains, and Son, Wenning, Timm-Giel, and Gorg (2009) proposed a model that aims to distinguish important information from noise, based on contexts for logistics applications.

Although the previous research has successfully coped with the problems in UCCL in terms of monitoring status and suggesting risk policies, these limitations still remain not only for dealing with the flexible and complex nature of UCCL, but also for the proper responses to risks according to their underlying contexts in a real-time fashion.

3. i-RM: intelligent risk management

3.1. Framework

In this section, we first introduce the framework of i-RM and then explain the main components of the framework in detail. As shown in Fig. 2, i-RM is composed of an ontology base and a risk management system. The ontology base contains three ontologies which support the corresponding stages of the risk management system: (i) entities involved in logistics processes and their relationships; (ii) states that define environmental changes of interest; and (iii) responses that take the actions to be done for each risk level. The three ontologies represent which entities are under which environmental conditions and the resulting responses that should be taken when the entities are considered to be out of proper environmental conditions.

Meanwhile, the risk management system takes charge of the three stages for manipulating risk situations: real-time context identification, risk detection, and response action judgment. First, the real-time context identification is used to gather, filter and aggregate the significant input events from logistics systems. The real-time inputs of i-RM are mainly stream-like information related to entities and environmental conditions, which are periodically transmitted from RFID tags and sensors to i-RM. Once the information arrives from the WSN, the information on the environmental conditions is used to determine the states of the entities in a distribution process. In addition, the entities and their states are combined as a context. To obtain the states from the stream-like information, an event processing language (EPL) is adopted to capture the states of interest (Zappia, Paganelli, & Parlanti, 2012). In the risk detection step, their risk is evaluated by using the risk rules defined based on the entities and states in the ontology; this risk evaluation is based on the contexts identified in the previous step. After determining the risk level of a context, i-RM searches for the appropriate responses corresponding to the context by using response rules that map risk levels to responses. Finally, i-RM controls the distribution process for the context by providing the judged response actions to the legacy systems, such as supply chain management systems, or directly interfacing with a person in charge.

The dynamic combination of rules becomes feasible since all of the parameters and entities shown in the EPL statements for capturing states and rules for risk evaluation and response judgment are presented by referring to the elements in the ontology in i-RM, regardless of the other rules. For a particular risk, the rule to be applied in a component is dynamically determined according to the result of the previous component rather than specific rules being defined for the risk in advance. The response decision component is incorporated into risk management tasks in i-RM as needed, according to the existence of risks, while the context identification and risk detection components are always involved.

3.2. Ontology for i-RM

Ontology is widely used for structurally and formally representing domain knowledge as conceptualized elements and their relationships for a specific domain. Moreover, it is beneficial to reuse domain knowledge by reconfiguring its structure (Gruber, 1991).

In this research, ontology is employed in i-RM for defining three elements which reflect the logistics situations and required actions: entities, states, and responses. These three elements are described by means of the ontology web language (OWL). Table 2 shows the hierarchical structure of the ontology, divided into three levels. In the third level, additional elements can be considered in order to fit the ontology into different logistics settings.

By implementing the elements for risk management, the ontologies are able to be shared across the components in i-RM in a standard way, thus improving the interoperability of its components. Furthermore, by using the hierarchical structure and inheritance concept provided by the ontology, the elements in the ontology are able to be specified or broadened based on other elements in the ontology. For example, if a special type of container needs to be newly inserted into the ontology, the new element for the container type can be added under an existing generic container element by narrowing its meaning.

3.3. Real-time context identification

To understand contexts based on the information of entities and environmental conditions, we adopt the notion of context-aware event processing that allows for flexible event processing through dynamic generation of EPL statements based on ontology. In detail, it maintains EPL templates that are represented by using parameters referring to the elements in the ontology. When an executable version of an EPL statement is based on an EPL template, the parameters in the EPL statement are dynamically substituted for the values defined in the elements in the ontology that are referred to by the parameters. We note that the concept of the dynamic parameter substitution based on the EPL templates was originally proposed by Tejada and Jung (2013) to capture higher level events (contexts) from stream data that simply capture the current snapshot of a system.

Whenever information is transmitted from the RFID tags and sensors to i-RM, an EPL template, in which the entities and sensors related to the information are associated, is selected for the context identification against the information. Based on the selected EPL template, an executable EPL statement is dynamically generated by replacing the notations that refer to elements in the ontology. Fig. 3 depicts the relationships between the elements in the ontology and

Please cite this article as: K. Kim et al., i-RM: An intelligent risk management framework for context-aware ubiquitous cold chain logistics, Expert Systems With Applications (2015), http://dx.doi.org/10.1016/j.eswa.2015.11.005
an EPL template that concerns the delivery item “apple” and two environmental features “temperature” and “humidity”; the maximum values of the environmental features are also depicted. In addition, Fig. 4 shows the generated EPL statement for capturing a context of interest.

3.4. Risk detection and response action judgment based on contexts

Based on identified contexts, their risks and responses are determined by using risk and response rules, respectively, which are presented as a form of the Semantic Web Rule Language (SWRL; Horrocks, Patel-Schneider, Boley, & Tabet, 2004). SWRL is capable of encoding the relationships between causes and results; it is a special type of rule language based on the ontology web language (OWL) (McGuinness & Van Harmelen, 2004).

There exist two reasons why risk and response rules are represented by means of SWRL. First, SWRL is suitable for representing high level concepts that connect causes to results in a standard way. This implies that the risk rules are interoperable in any SWRL engine without modifications. Second, SWRL enables rules to be built based on ontology since objects in the rules presented by SWRL can be defined by referencing any of the elements in the ontology. As a result, when values defined in the ontology are modified, the risk rules are not necessarily changed.

Fig. 5 shows two examples, R1 and R2, of detection rules that aim to detect risks based on temperature and door status, respectively. In R1, the presented rule is activated whenever two entities, “freezer container” and “apple”, and one environmental condition, “temperature”, are found in a context. If the average value of the “temperature” of an “apple” in the “freezer container” is higher than the value...
Context of interest

When apples are out for delivery on a freezer truck, the average temperature and humidity for the past five minutes of the delivered items is calculated; this calculation occurs every ten minutes.

Event processing language (EPL) statement

SET ctx:int = 5 min;
SELECT ent:item, ent:container, ctx:avg(stat:temperature, ctx:int), ctx:avg(stat:humidity, ctx:int)
FROM STREAM [EVERY timer:interval(10 min) →
(ent:item = “Apple” AND ent:container = “Freezer truck”)]

Fig. 3. Dynamic EPL generation based on entities and environmental features.

Fig. 4. Example of EPL statements for context identification.

As mentioned in Section 3, the inputs of the system are the information collected from RFID tags and sensors, whereas the outputs of the system are messages to legacy systems and/or logistics components. For the inputs of the system, after the RFID tags and sensors are periodically scanned, information is transmitted and processed by a middleware for WSNs. The middleware converts multiple raw pieces of data into a single structured data item that represents entities and environmental conditions for the inputs of our system. The details of the four major modules are presented as follows:

- **Ontology engine**: the ontology engine provides reasoning functions which are used to search for elements and their relationships. That is, other modules are able to easily access particular values of the elements regardless of the structure of the ontology.

- **EPL engine**: the aim of the EPL engine is to execute EPL statements generated based on EPL templates for context identification. Whenever it receives information on entities and their environmental conditions from the middleware, it generates an executable EPL statement by substituting the parameters with
Rule identifier | Risk detection rule
---|---
**Context**

**Entities**: item is “apple”, container is “freezer container”, and measured environmental condition is “temperature”.

**States**: the average temperature for 10 minutes is higher than 5 degrees.

**Risk level**: Critical

**Risk detection rule**

\[
\text{hadLoaded}(rc, "apple") \land \text{container}(rc, "freezer truck") \land \text{swrlb:higherThan}(\text{average}(rc, 5, ?temp), 10) \land \text{swrlb:lowerThan}(\text{average}(rc, 5, ?hum), 30) \rightarrow \text{hasRiskLevel}(rc, "Serious")
\]

**Context**

**Entities**: container is “freezer container”.

**States**: door is open for more than 5 minutes.

**Risk level**: Serious

**Risk detection rule**

\[
\text{hadLoaded}(rc, "apple") \land \text{container}(rc, "freezer truck") \land \text{swrlb:higherThan}(\text{average}(rc, 5, ?temp), 10) \land \text{swrlb:lowerThan}(\text{average}(rc, 5, ?hum), 30) \rightarrow \text{hasRiskLevel}(rc, "Serious")
\]

Fig. 5. Examples of risk detection rules.

---

the appropriate real values, which is achieved by using the ontology engine.

- **Risk rule matcher**: the risk rule matcher evaluates the level of a context provided by the EPL engine. Since risk rules are defined as a form of SWRL, and the risk rule matcher is in charge of the execution of risk rules, this module is regarded as a special type of SWRL engine.

- **Response rule matcher**: the response rule matcher maps the risk levels evaluated by the risk rule matcher to the corresponding responses. Similar to the risk rule matcher, it performs the matches between risk rules and responses by interpreting SWRL.

Along with the components described above, there also exist four tools in the implemented system for the purpose of editing the ontology and rules, as follows:

- **Ontology editor**: the ontology editor allows system managers to add, remove, and modify the elements and their relationships. We employed an open source ontology editor, called Protégé, which provides a variety of functionalities for rapid prototyping and application development. The details of the ontology editor are shown by Noy et al., 2001. Fig. 6 describes a part of the ontology used for i-RM by using Protégé.

- **EPL statement manager**: the EPL statement manager visualizes which information is currently being received from the middleware and which EPL statements are generated for the information. Fig. 7 depicts the user interface of the EPL statement manager. Among the six parts of the user interface, the two on the left are for monitoring stream data from the middleware, and the one on the bottom left is for showing the results of the context identification from the received stream data. The three parts on the right present EPL templates and the final version of the EPL statement after substituting its parameters into the values in the ontology.

- **Risk rule manager**: by using the risk rule manager, the risk rules in our system are handled, and the contexts to be evaluated and their risk evaluation results are shown. Fig. 8a shows the risk detection monitor that presents the list of risk rules, currently evaluated contexts, and the risks for the contexts. Upon clicking a particular risk rule in the list of risk rules (shown in the upper part of the user interface), the risk rule editor appears. We used the SWRL editor of Protégé as the
The proposed framework, i-RM, is a prototype and open reference model developed by the authors for the purpose of realizing and validating the concept of context-aware management based on ontology in real-world settings. Although we implemented the entire system that operates with ontology bases and information captured from RFID tags, unfortunately, we could not adopt the proposed framework in actual transportation tasks due to the limitation of time and cost. Therefore, we demonstrate how the proposed system works to manage risks based on a real-world scenario designed by experts on UCCL instead of presenting the results obtained by using actual datasets.

The objective of the distribution process presented in the scenario is to maintain the delivery items, “apples”, at their proper temperature during the delivery process. In addition, it is assumed that (i) a risk rule editor, as shown in Fig. 8b. On the bottom, two parts show which contexts are currently evaluated along with their corresponding risk levels.

- **Response rule manager**: similar to the risk rule manager, the response rule manager maps risk levels onto their corresponding responses in a form of SWRL. To edit response rules, we employed the Protégé editor.

Table 3

<table>
<thead>
<tr>
<th>Date time</th>
<th>Entity identifier (set of RFID tag identifiers)</th>
<th>Sensor identifier and temperature (feature code and temperature value)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2015/07/01 02:01:22</td>
<td>(E001001, E002002)</td>
<td>(T011001, 8)</td>
</tr>
<tr>
<td>2015/07/01 02:01:22</td>
<td>(E001001, E002002)</td>
<td>(T011001, 8)</td>
</tr>
<tr>
<td>2015/07/01 02:01:22</td>
<td>(E001001, E002002)</td>
<td>(T011001, 8)</td>
</tr>
<tr>
<td>2015/07/01 02:01:22</td>
<td>(E001001, E002002)</td>
<td>(T011001, 8)</td>
</tr>
</tbody>
</table>
Fig. 9. System installation for a UCCL scenario.

(a) RFID reader  (b) RFID tag and temperature sensor

Fig. 10. Risk management tasks based on i-RM for accidental situations during "apple" delivery using a freezer truck.

(a) Real-time risk detection and response based on contexts.

(b) Changes in the risk levels according to the time period.

Please cite this article as: K. Kim et al., i-RM: An intelligent risk management framework for context-aware ubiquitous cold chain logistics, Expert Systems With Applications (2015), http://dx.doi.org/10.1016/j.eswa.2015.11.005
freezer truck delivers apples from a distribution center to retailers by
way of two warehouses, (ii) the apples are in the freezer container
in a truck, (iii) the freezer truck and apples are recognizable by us-
ing RFID tags as shown in Fig. 9, (iv) the temperature in the freezer
container is transmitted to our system along with the entity informa-
tion based on the RFID tags, and (v) the quality of the apples in terms
of freshness significantly decreases when the average temperature is
out of the proper temperature range for 5 min.

Table 3 shows an example of information collected from the RFID
tags installed on a “freezer container” and “apple” and a sensor that
measures the temperature in the “freezer container”. The middleware
was set to collect information from the RFID tags and sensors after
every 1 min. Two entity identifiers, “E001001” and “E002002”, cor-
respond to the “freezer container” and “apple” entities, respectively
(Fig. 9a), while sensor the identifier “T011001” corresponds to the
“temperature sensor” (Fig. 9b).

To demonstrate the way in which our system identifies risks and
makes decisions to eliminate the risks, we consider two possible
accidental situations, door open and refrigerator turnoff, which
cause the temperature to increase in the container. Fig. 10a illustrates
the risk detection and response tasks by utilizing i-RM under such
accidental situations. The logistics process can be divided into four
parts according to the time period: (t0, t1), (t1, t2), (t2, t3), and (t3, t4).
First, at (t0, t1), based on the information of entities and environ-
mental conditions collected from RFID tags and temperature sensors,
a context whose entities are “freezer truck” and “apple” is identified,
and the state that represents the average temperature for 10 min is
over 5 °C by using the EPL engine according to the state definition for
“apple” in the ontology. Since there is no risk rule defined for the con-
text, “no risk” is assigned to the risk level of the context.

Second, at (t1, t2), due to the accidental situation occurring in
this time period, it is expected that the temperature might in-
crease rapidly. Thus, the state of the context at (t1, t2) is identi-
fied as “the average temperature for 10 min is 15”, and its risk
level is determined to be “critical” according to the risk rule for
the context. Unlike the context at (t1, t2), the context at (t2, t3)
is considered to be a risk situation: our system operates the re-
sponse rule matcher to find the proper response to the detected
risks. By informing the delivery driver in charge of the logistics
process of the current risk levels and states in accordance to the
corresponding response rule for the risk level, they are able to
take effective actions such as closing doors and turning on the
refrigerator.

Next, at the next time period, (t2, t3), if the temperature in the
freezer container is still too high, the system detects the risk and at-
ttempts to push the delivery driver to take another action. Since the
average temperature at this time period is less than that observed at
(t1, t2), the risk level is judged to be “minor”.

Finally, at (t3, t4), after eliminating risks, no risk is identified by
the system, as was the case at (t0, t1), and therefore no response is
determined.

Fig. 10b shows the changes in the risk levels according to the
time period. This implies that the accidental situation that
occurred at (t1, t2) is detected and handled immediately. More-
over, if additional actions are required at the next time period,
(t2, t3), our system is able to respond to such unresolved risks in
a real-time manner due to the ongoing risk management abil-
ity of the proposed framework, rather than forgetting reported
risks.

5. Conclusions

In this research, we first introduce the notion of real-time,
context-aware risk management by combining real-time event pro-
cessing technologies and semantic ontology. The proposed frame-
work, i-RM, is able not only to understand the underlying contexts
during delivery processes but also to detect risks based on semantic
contexts. This indicates that i-RM is suitable for recognizing semanti-
cally complex risk situations and for choosing proper responses with-
out latency. In particular, when frequent updates occur in contexts,
risk detection, and response judgment according to the changes in
logistics policies, i-RM provides a better way to handle such flexibil-
ity as compared to the frameworks previously developed.

The proposed framework demonstrates the possibility of appli-
cation to real-time event processing, context-aware monitoring, and
semantic description. It also shows the feasibility of the ePL
engine to carry out the risk response by using context information.
In particular, we make it possible to handle an accidental situation
in a real-time manner due to the ongoing risk management abil-
ity of the proposed framework, rather than forgetting reported
risks.

Acknowledgment

This research was supported by the Basic Science Research Pro-
gram through the National Research Foundation of Korea (NRF)
funded by the Ministry of Science, ICT & Future Planning (No.
2012R1A1B4003055).

References

Abad, E., Palacio, F., Núñez, M., González de Zárate, A., Juarros, A., Gómez, J. M., &
Marco, S. (2009). RFID smart tag for traceability and cold chain monitoring of
foods: demonstration in an intercontinental fresh fish logistic chain. Journal of Food
Engineering, 93(4), 394–399.

tuna cold chain logistics system. In Proceedings of the 11th World Congress on Intel-
ligent Control and Automation (pp. 4638–4641).


logistics monitoring. In Proceedings of International Conference on ICT for Smart
Society (ICISS) (pp. 192–196).


Heising, J. K., Dekker, M., Bartels, P. V., & van Boekel, M. A. J. S. (2013). Monitoring the
quality of perishable foods: opportunities for intelligent packaging. Critical Reviews

rule language combining OWL and RuleML. http://www.w3.org/Submission/2004/
SWB-SWRL-20040521.


