RFID-based Supply Chain Process Mining for Imported Beef

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Abstract

Through the development of efficient data collecting technologies like RFID, and inter-enterprise collaboration platforms such as web services, companies which participate in supply chains can acquire visibility over the whole supply chain, and can make decisions to optimize the overall supply chain networks and processes, based on the extracted knowledge from historical data collected by the visibility system. Although not currently active, the MeatWatch system has been developed, and is used in part for this purpose, in the imported beef distribution network in Korea. However, the imported beef distribution network is too complicated to analyze its various aspects using ordinary process analysis approaches. In this paper, we suggest a novel approach, called *RFID-based supply chain process mining*, to automatically discover and analyze the overall supply chain processes from the distributed RFID event data, without any prior knowledge. The proposed approach was implemented and validated, by using a case study of the imported beef distribution network in Korea. Specifically we demonstrated that the proposed approach can be successfully applied to discover supply chain networks from the distributed event data, to simplify the supply chain networks, and to analyze anomaly of the distribution networks. Such novel process mining functionalities can reinforce the capability of traceability services like MeatWatch in the future.

Key words: imported beef, supply chain, process mining, traceability system

Introduction

The Ministry for Food, Agriculture, Forestry and Fisheries (MFAFF) of Korea has established an imported beef traceability system (called MeatWatch), by which imported beef traders and sellers are forced to report the transactions at each distribution step, from the point of import, all the way to retail sales. MFAFF wanted to provide customers with the traceability information of imported beef, thereby establishing a transparent and safe imported beef distribution system. MeatWatch, funded by the MFAFF, was developed in 2009, and starting from April 2010, has been operated by the Animal, Plant and Fisheries Quarantine and Inspection Agency (QIA). The core functionality and goal of MeatWatch is to track imported meat on a real-time basis, using a twelve digit number called 'the Import Distribution Identifier' (IDI), and to quickly pinpoint the location of any beef package that must be called

back due to problems such as mad cow disease.

According to a BAI (The Board of Audit and Inspection of Korea) report, however, the system was not very successful. It turned out that a significant portion of the transaction data stored in MeatWatch is incorrect, mismatched (with each other), and even missed. For many traders and distributors, MeatWatch could not even determine if a specific meat package had been sold, or was still in a warehouse. Such unsuccessful deployment of MeatWatch mainly arises from the fact that it is not mandatory for the distributors to tag IDIs on their commodities. The government might have to make IDI tagging mandatory in the end in order to secure the public health and food safety.

Besides such policy issues, MeatWatch should also be able to give more benefits to participants for the successful deployment of the system. One of the most important benefits for users is the ability to analyze and improve the imported beef supply chain network. However, it is very difficult to analyze the beef distribution network due to the severely complicated and unstructured nature of the distribution network. This research is focused on the information system viewpoint of MeatWatch, by suggesting

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a method to automatically identify and analyze problematic distribution steps (e.g., with long-term inventory, delayed delivery, and/or shrinkage) for the supply chain network improvement. Our approach utilizes *process mining* techniques, which are well established in business process management areas. Regarding the traceability system model, in the consideration of generality, extensibility and compatibility, we used the *EPCglobal network* model, which is a *de facto* standard for RFID-based track-and-trace.

The remaining part of this paper is organized as follows. From Section 2 to Section 4, we review the MeatWatch systems overview, process mining techniques, and EPCglobal-based traceability framework. In Section 5, we suggest a process mining framework for imported beef distribution-process analysis, based on the EPCglobal track-and-trace model. In Section 6, we demonstrate how the suggested process mining approach can be applied to real practice, by using simulation data. Finally, we conclude our research results, along with discussing future work, in Section 7.

MeatWatch System

MeatWatch system consists of the trader system, government officer system, and customer system, according to the classification of users, as shown in Fig. 1, and as explained below (Animal, Plant and Fisheries Quarantine and Inspection Agency, 2010).

- **Trader's system:** the system by which beef import traders, meat packers, and meat sellers manage the detailed information on importing, packaging, and other business transactions, along with hazardous meat sales prohibition information.

- **Government officer's system:** the system which pro-

vides traceability and inventory information to the people in charge of sanitation monitoring and call-back operations, so that they can effectively cope with hazardous situations, such as the immediate call-back of spoiled meat.

- **Customer's system:** the system by which imported-beef customers can inquire of the traceability information of imported beef via the Internet (www.meatwatch.go.kr), or cell phone.

After import declaration, import traders are given unique IDI numbers for each meat package from MIFAFF, and attach the IDI-printed tags to the meat. When a meat package is sold, the transaction is to be reported to the MeatWatch system. Meat packers in turn, when they buy and sell the IDI-attached meat, have to report the transaction details (including packaging records), to the system. Finally, meat sellers and by-product traders also report the transactions, when they buy or sell the meat packages.

Standard Framework of RFID Track and Trace

RFID data must be handled by different participants in a supply chain network, meaning that a standard way (or at least ways that are in common to all the participants) of data sharing (or exchanging) is necessary. Auto-ID Labs (originated from MIT) have been working on such a platform, and have suggested an EPC (Electronic Product Code; a standard RFID code)-based model for this purpose. The model, which is now under the control of EPCglobal Inc., is now accepted as a *de facto* standard in the industry (Thiesse *et al.*, 2009). An implemented data sharing network based on the EPCglobal standards is called an *EPCglobal network* or *EPC network*. In order for trading partners to exchange the RFID data in an EPCglobal network, three core information services are necessary.

Fig. 1. Conceptual view of the MeatWatch system.

The core services of the EPCglobal network include:

- **EPCIS:** EPC Information Services (EPCIS) enables trading partners to exchange EPC-related data, which are stored in their local repository (called EPCIS repository). EPCIS mainly deals with event data, which hold information of the historical events that have occurred in the consequence of carrying out business processes (EPCglobal Inc., 2007).

- **DS:** Discovery Service (DS) enables complete lifecycle-information gathering from multiple information providers, across an object's supply chain or lifecycle. The role of DS is to provide links, to enable a client to locate the sources of information providers, like an EPCIS that may have information of an EPC in question. The standardization is currently under progress, based on the final requirement analysis results from the BRIDGE project (Cambridge Univ. *et al.*, 2007).

- **ONS:** Object Naming Services (ONS) is to provide a lookup service, similar to DNS, which converts the domain address to the IP address. Users query the ONS with a particular EPC, and the ONS returns the address information of the servers that contain information associated with the target EPC (EPCglobal, 2005).

Fig. 2 depicts the track and trace mechanism of an EPCglobal network, based on the core services - EPCIS, DS, and ONS. A company (e.g., a product manufacturer) stores event data in its EPCIS ('Manufacturer EPCIS' in the figure) every time the RFIDs attached on their products are read at the reading points (e.g., at the end of production, packaging, palletizing, or shipping), within their site. When

the products are shipped, the manufacturer needs to report the shipment to the DS. In the same way, a trading partner who received the products in their site, for example a DC (distribution center), reports the receiving event to the DS, and stores the following internal events in its own EPCIS, just like the manufacturer did. The essential information reported to the DS includes EPCIS address, EPC, and the event time. In this way, all the historical information about a product is stored in an EPCIS and a DS, in a distributed manner. A user can inquire of the address of a DS from ONS first, and then ask the DS for the addresses of EPCISs. The users can access the EPCISs based on the addresses, and collect the event data about the product of interest, finally reconstructing the entire track and trace information (Cantero *et al.*, 2008; Muller *et al.*, 2010; VeriSign Inc., 2004).

Process Mining

Process mining (or workflow mining, originally) is a relatively new research field, which emerged in the mid 90's. The goal of process mining is to extract (meaningful) business process-related information from event logs (Aalst and Weijters, 2004; Aalst *et al.*, 2007). The concept of process mining was first introduced by Cook and Wolf (1995), who carried out research on extracting process models from event logs in the software development environment. They called it 'process discovery.' Later in 1998, Agrawal *et al.* (1998) introduced this concept in the business context, and called it 'workflow mining'. Accord-

Fig. 2. Track and trace mechanism of the EPCglobal network.

Fig. 3. The three main types of process mining: discovery, conformance and enhancement.

ding to Aalst (2011), process mining research can be classified into three types - *discovery*, *conformance*, and *enhancement*, depending on the purpose of the process mining, as shown in Fig. 3.

The discovery type of process mining is to build up a process model from an event log, without any preliminary information (Aalst, 2011), and is currently the most actively researched area. The event log L1 in Fig. 4 depicts the process event log information, which is recorded chronologically as a process proceeds. By analyzing the execution sequences of individual process instances from such an event log, a process model, M1 in Fig. 4, can be derived.

The main focus of discovery-type research is on the development of efficient algorithms for extracting process models from fragmentary event data. Cook and Wolf (1995) suggested process discovery algorithms based on artificial neural networks, and a Markovian approach in his later work. Agrawal *et al.* (1998) developed a method to derive a workflow graph from event logs for the first time.

Fig. 4. A process model (M1) discovered from an event log (L1), by a process mining algorithm (α -algorithm).

Table 1. The simplified log data for the process described in Fig. 4

Case ID	Log Traces
Case 4	ABCD
Case 5	ACD

Herbst (2000) dealt with a problem with duplicated tasks. In these earlier researches, concurrent processes were not taken into account. Aalst *et al.* (2004) solved this problem, by suggesting the α -algorithm. However, the α -algorithm could not handle noise and incompleteness of event logs properly, resulting in over-fitting or under-fitting. Later, in order to solve these problems, Heuristic Mining (Weijters *et al.*, 2006), Genetic Process Mining (Medeiros *et al.*, 2007), and Region-based Mining (Bergenthum *et al.*, 2007; Sole and Carmona, 2010) were proposed.

Conformance-type research is about the comparative analysis of an existing process model, and the event log (Aalst, 2011). Table 1 shows the sequence of events for each process instance of the M1 process model explained in Fig. 4. As compared to the M1 process model, we can conclude that Case 5 does not conform to the corresponding model. By using this type of test, we can pinpoint the difference between two processes, and explain the reason as well. Then we can make effective use of these analysis results, in order to improve exiting processes. Rozinat and Aalst (2008) proposed two conformance evaluation measures - fitness and appropriateness, and suggested algorithms to calculate these measures.

Enhancement-type research is about the improvement and extension of existing processes, based on process event log data. Process improvement utilizes the conformance test results to revise an existing process model to reflect the real situation (represented in the form of event logs), while process extension extends an existing process model, by taking into account not only a control-flow perspective but also the perspectives of organization, case,

Fig. 5. A sociogram based on the event log shown in Table 1.

and time. For example, Fig. 5 depicts the analysis result drawn from the L1 event log in Fig. 4, showing the organizational aspect of the process. Until now, there have been various researches carried out from the different perspectives. From the organization's perspective, Song and Aalst (2008) extends process mining techniques to social network analysis, by extracting the structure of organizations and communication among workers from process event logs. Rozinat *et al.* (2009) extends the process mining technique, from the case perspective, to estimate the next following activities, in order to support operational decision making based on the past event log analysis. From the time perspective, Aalst *et al.* (2011) estimated the execution time of a process instance, and analyzed bottleneck activities from event logs.

RFID-based Supply Chain Process Mining

Workflow is the automation of a business process, dur-

ing which documents, information, or tasks are passed from one participant to another for action, according to a set of procedural rules. Similarly, in a supply chain, raw materials or products are passed among partners, according to trading contracts, thereby forming a material flow. There are some similarities between workflow and RFID-based material flow, in the sense that (1) workflow events (including the start and the end of a task) change the state of tasks, while RFID read events change the state of the products; and (2) in both cases, the process steps proceed driven by events.

Our system model for an RFID-based supply chain process mining is composed of the EPCglobal network, Generic Traceability Services (GTS) (Kang and Lee, 2013) and process mining applications, as shown in Fig. 6. The EPCglobal network plays the role of storing and providing an RFID event data related to products. GTS provides supply chain process instances, by restructuring a complete history of a product. Process mining applications has three components - Process Instance Transformer, Process Instance Repository, and Business Process Mining Framework (Dongen *et al.*, 2005). A Process Instance Data Transformer converts GTS event data format to MXML format (Dongen and Aalst, 2005). A Process Instance Repository stores process instances, by each product class. A Process Mining Framework (ProM), which has various plug-ins, provides a graphical process analysis environment.

Fig. 6. The RFID-based process mining architecture framework.

Collecting process instance data

In order to collect the complete history of beef's life cycle (in the form of supply chain process instances), we utilize the pedigree query of GTS. The pedigree query is to reconstruct the complete history of individual products or other logistic units like boxes and containers. This query may be performed at the end of the supply chain (e.g., at point of sale), although it can be done at any point of time in the commodity life cycle. Table 2 explains pedigree query's overall procedure, in which GTS invokes the `getHistory()` function repetitively for all the EPCIS's those the EPC passed through. First, GTS query about the address of a DS (`dsAddress`) to ONS (line 2). Next, GTS receives `DSEventList`, which includes the address of the EPCIS's and when the EPC entered and left the EPCIS's boundary (line 3). Now, for all EPCISs in each `DSEvent` (DSE), GTS searches the history of the target EPC from receiving time to shipping time (lines 4-5). This loop is executed in parallel rather than in sequence thanks to the designated algorithm of `getHistory()`. Finally, GTS transforms `EPCISEventList` to `TSEventList` (line 6). The pedigree query of GTS can collect complete history of an object, even with nested multiple aggregations. This paper omits the detailed algorithm of `getHistory()` function, which is explained in detailed level in Kang and Lee (2013).

Mapping from GTS event type to MXML

In order to use ProM, workflow logs should be complied in MXML schema. Since ProM can't interpret the `TSEventList` type of GTS directly, type-casting process is needed. Fig. 7 depicts the structure of MXML schema. The root element of MXML is `WorkflowLog`. A `WorkflowLog` has one `Process` or more. A `Process` includes multiple `AuditTrailEntry`. `AuditTrailEntry` means the events of business process and has four sub-elements: `WorkflowModelElement`, `EventType`, `Timestamp`, and `Originator`. In this study, we mapped data elements in GTS to appropri-

Fig. 7. UML expression of MXML (Dongen *et al.*, 2005).

ate ones in MXML, referring to Gerke *et al.* (2009) as shown in Table 3. Since the main purpose of RFID-based supply chain process mining is to extract the process structure of supply chains, we selected `WorkflowModelElement` as the `readPoint` that indicates object's identification place. Also, `bizStep`, which means a distribution process step in GTA, is mapped to `EventType`, since `bizStep` is similar to workflow event in the sense that it changes the status of objects. `TSEventList` does not have any attribute that can be mapped to `Originator` directly because `EventType` data does not include any worker's information. Instead `readPoint` is mapped to `Originator` because RFID detection is performed by RFID readers. Finally event-Time is well matched to `Timestamp`. Fig. 8 explains the semantics mappings between workflow and RFID-based material flow.

Process Mining Application to the Imported Beef Supply Chain

Process and Simulation Model

We demonstrate how process mining techniques can be applied to the imported beef supply chain, by using ProM and simulation data. For this purpose, we need to understand the characteristics of the supply chain network of

Table 2. Pedigree query algorithm of GTS

Algorithm : pedigreeQuery
Input : EPC
Output : TSEventList
1: $EPCISEventList = \phi$
2: $dsAddress := queryToONS(EPC)$
3: $DSEventList := queryToDS(EPC, dsAddress)$
4: for all $DSE \in DSEventList$ do // in parallel
5: $EPCISEventList := EPCISEventList \cup getHistory(DSE, EPC, DSE.receivingTime, DSE.shippingTime)$
6: $TSEventList := transformToTSEventList(EPCISEventList, DSE.epcisAddress)$
7: return $TSEventList$

Table 3. Schema mappings from GTS event schema to MXML schema

GTS Event Schema		MXML Schema	
TSEventList		ProcessInstance	
	<code>readPoint</code>	<code>WorkflowModelElement</code>	
<code>TSEventType</code>	<code>bizStep</code>	<code>EventType</code>	<code>AuditTrailEntry</code>
	<code>eventTime</code>	<code>Timestamp</code>	
	<code>readPoint</code>	<code>Originator</code>

Fig. 8. Semantic mappings between a workflow and a material flow.

imported beef. Fig. 9 shows a generic distribution network of imported beef. The imported beef supply chain consists of about 5 tiers, which include different types of participants - importer, large distributor, small distributor, butcher's shop, and restaurant. As shown in the figure, basically, later tiers have more participants, and the beef stocks move from one tier to the next. Usually, distribution is completed in tier 4, or tier 5. Particularly in tier 3 and tier 4, some beef stocks move to the participant within the same tier, or even to the previous tier. Such a reverse sale occurs, when small distributors without enough cash asset, cannot afford the inventory cost and/or warehouse operation cost.

Currently, there exists no exact distribution network

information and RFID event log data available for imported beef. Hence we used a computer-generated supply chain network, and event data. Fig. 10 shows the procedure to generate nodes (i.e., participants) of the network, and path linking rules.

Once a distribution network has been built, as explained above, we generate one thousand commodity (beef stocks) flow instances, using a simulation program. We assume that all the commodities are identified every time they are received and shipped by RFID tag reads, thereby generating RFID events. The dwell time of a commodity within a node (warehouse for example) is defined by a random variable of exponential distribution, with $\lambda = 24$. Inter-node transportation time is modeled by a random variable

Fig. 9. Illustration of a generic distribution network of imported beef.

Fig. 10. Steps of generating distribution network instances for imported beef.

of normal distribution, with $\mu = 3$ (hours) and $\sigma = 1$. If a node has more than one subsequent node, the probability of the commodity moving to the “main” arc is 0.7. In addition, one out of ten commodities shipped from the nodes in Tier 3 and Tier 4 are to be lost, in order to model the commodity shrinkage (for example, lost during transportation, or RFID read errors while receiving).

Supply Chain Network Discovery

The ProM provides various algorithms as a plug-in,

which can be used to extract processes from event log data. The most fundamental algorithm is the α algorithm (Aalst *et al.* 2004). Fig. 11 shows the result of extracting the distribution network by using a ProM’s Alpha Algorithm Plug-in. As shown in the figure, the imported beef distribution network has an unstructured “spaghetti” process structure. In such cases, people can hardly understand the overall network structure to analyze, due to the complexity of the network, and therefore require some ways to simplify them.

Supply Chain Network Simplification

In order to simplify a complicated supply chain network, we can use Fuzzy Minder in ProM, as shown in Fig. 12. Fuzzy Miner aggregates (or clusters) less significant, but highly correlated behaviors, into an abstract one. In addition, Fuzzy Miner removes less significant and less correlated behaviors. The significance is measured by the frequency of the instances, while the correlation is measured by seeing how closely the two nodes are linked. The color and width of the connections indicate their strength i.e., more significant relations are darker and wider. This visualization aid enables analysts to focus on the most significant participants and paths in the distribution network.

Fig. 11. Discovery of the Overall Distribution Network of Imported Beef.

Fig. 12. Simplification of an unstructured supply network.

Analysis of anomaly in the distribution network

Products experience abnormal incidents in a supply chain, deviating from the predefined process model, due to product losses, RFID reading failures, etc. If such abnormal situations happen frequently, we need to think of them as evidence of the abnormality of the supply chain

network itself. The ProM's Conformance Checker Plug-in is an evaluation tool for compatibility between an extracted process structure, and process instances. From the supply network's viewpoint, it helps finding abnormally distributed products, lost products, or products with abnormally long periods of dwell/transportation time. Fig. 13

Fig. 13. Analysis of abnormal situations in the supply chain.

Fig. 14. Average duration times for each participant.

demonstrates a sample case of abnormality detection via ProM's Conformance Checker Plug-in. The numbers on the arrows mean the number of objects (or commodities) passing through the route. In this specific example, 401 units of beef stocks were received by Cluster 81, while only 319 of the units were shipped from the cluster. Similarly, in Cluster 78, 400 units were received, and only 260 units were shipped out. These phenomena are caused by intentionally lowering the RFID recognition rate in our simulation model, as explained in the earlier section, and the Conformance Checker Plug-in successfully detected these problems.

Similarly, as shown in Fig. 14, the Basic Performance Analysis plug-in can be used for supply chain participants to analyze average inventory periods, or to identify bottlenecks. Inventories with exceptionally long inventory period must be investigated, to see if there are any problems.

Conclusion

In general, it is not easy to analyze the processes of distribution networks with complicated structure, such as in imported beef distribution. The RFID-based supply chain process mining model proposed in this paper will make it possible for enterprises and researchers to analyze such distribution networks as a whole, and accordingly, to make decisions very effectively. In our approach, we demonstrated that well-established process mining and analysis models in the workflow management society can effectively be used in the analysis of complicated distribution networks, including the imported beef distribution industry in Korea. However, in order to use the approach in the imported beef industry in Korea, a traceability system,

such as MeatWatch, must be used broadly and actively. Traceability systems are very important foundations for customers' benefits and their right to know. In this sense, both the government efforts to make it mandatory, and systems support, such as the proposed solutions in this paper, are necessary.

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