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A Knowledge Fusion Pattern and its Evolution Processes in a Decision Support System

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Abstract. The aim of a decision support system (DSS) is to enhance the course of decision-making by furnishing a decision episode and support during the decision-making and enforcing procedure. Inspired by management information systems, the DSS assists policy makers to reach a decision by man-machine interaction through data, models and knowledge. Knowledge fusion is an effective means of enhancing the efficiency of a DSS. Thus, this paper presents a three-layer, six-step knowledge fusion pattern from the perspective of interaction and the three procedures used to arrive at a decision. For better understanding, an evaluation of the knowledge state with knowledge objects in the fusion pattern is also presented. Furthermore, we briefly examine a case study of a Fire Rescue DSS(FRDSS).

1. Introduction

Decision support systems (DSS), proposed by Keen and Scott in the 1970s and based on management information systems [1], are typically systems that are dedicated to the support of decision-making and problem-solving [2]. A DSS is designed to analyze and process all accessible compatible data, information, and knowledge about a particular aspect [3]. The emphasis of a DSS is on processing large amounts of data, information and knowledge. Thus, scholars often introduce data, information and knowledge related techniques into the DSS to improve performance. As discussed in [2], data warehouses and data mining are two powerful tools that have emerged for building DSSs. March and Hevner aimed to provide researchers with a clear view of the challenges and opportunities arising from applying data warehousing technology to support all levels of management decision-making [2]. Park and Kim [4] presented a DSS for the management of sewer infrastructure using data warehousing technology, while Khan et al. used data mining and data fusion for enhanced decision support [5]. Moreover, a classification framework for financial fraud detection by applying data mining techniques has been proposed [6]. In terms of information processing, Nilsson and Ziemke ensured the effectiveness of information fusion systems as DSSs [2], while in [7], the authors presented an information fusion system to produce information from different sources to support the decision-making process. Today, knowledge fusion has become a new trend in improving a DSS's ability to solve problems since the integration and combination of multi-source data and information reduces ambiguity [8] [9].

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We present a new knowledge fusion pattern for a DSS. The proposed pattern divides knowledge fusion in the DSS into three layers. Similar works in the domain of data fusion have been realized in [10] and [11], categorizing data fusion with multiple sensors into three levels: data level, feature level, and decision level. Similarly, but not identically, the pattern is presented here from an interaction perspective. On another hand, the proposed knowledge fusion pattern tries to analysis potential knowledge fusion processes through decision-making assisting.

Usually, a DSS is involved in a decision process to affect the process and its outcome [12]. A DSS is actually a dynamic interactive computer support system. At the highest level of abstraction, the system can be considered as a black box, which requests the decision context and provides a decision episode. Within the box, the process of decision-making is realized. Thus, the pattern is divided into three layers: one for knowledge fusion before knowledge is delivered to the decision-making process, one for the decision-making process, and the third one for fusion after decision-making. In this way, the three-tier architecture corresponds to the three fusion processes, i.e., input-layer fusion, interface-layer fusion, and output-layer fusion, encapsulating the knowledge fusion processes through the DSS.

Typical decision-making processes are often described as consisting of intelligence, design, choice, and implementation phases [12, 13]. Decision-makers and individuals responsible for solving problems expect support in these four phases to achieve a single or multiple goals. The course of decision-making can be decomposed into four steps: determine decision objects, contrive schemes, select a scheme, and execute the plan, thereby defining the responsibility of each layer. Each layer corresponds to one aspect of the decision-making process, except the third one. Regarding the selection of the best decision, this is done by the decision-makers and not the DSS. The proposed three-layer model actually corresponds to the three phases of assisting production. Merrill presented a series of instructional strategies based on knowledge objects. In his correlation study, a knowledge object is defined as a container for the information components thought to be required to adequately solve a particular type of problem [14, 15]. Drawing on previous knowledge, the authors introduce a knowledge object into the three-layer knowledge fusion pattern. The knowledge object presented in this paper contains knowledge, the content resources of which can be organized in such a way that a given algorithm can be executed on it. Moreover, based on the theory in soft engineering, three evolution types for knowledge objects are proposed.

According to the proposed pattern, this article uses the Fire Rescue Decision Support System (FRDSS) as a case study. The FRDSS is a non-project measure that can efficiently mitigate the casualties of a fire disaster and reduce economic damage due to fire rescue system. Usually, a FRDSS contains information acquisition and analysis and so on. FRDSS proposes fire engine scheduling according to the gathered real-time information. Then the plan is put into practice. Through the implementation process of the decision, the system is supposed to give optimal scheme based on practical situation. For a better understanding of the proposed three-layer fusion pattern, the pattern is applied in this DSS. Some processes of decision support in the FRDSS with the presented fusion pattern is discussed.

The rest of this paper is organized as follows. In the next section, we provide an introduction to some typical knowledge fusion processes, and the background for knowledge fusion using a DSS. Then, the three-layer knowledge fusion pattern specific to the DSS is introduced. Next, evolution of the knowledge fusion pattern with knowledge object is described. Finally, the feasibility is discussed with the results of our predecessor and a case study involving the use of the presented fusion structure in the FRDSS. A brief discussion concludes the paper.

2. Related Work

Decisions depend largely on the substantial amount of data, knowledge and information arriving from the distributed resources. The introduction of knowledge fusion underpins the DSS since it not only transforms, integrates and fuses knowledge to acquire new knowledge, but also optimizes the structure of existing knowledge to provide decision services based on the knowledge [16].

2.1. Knowledge Fusion Process

Current academic research has distinguished seven knowledge fusion processes [8] [9] [17]: creating new knowledge from data/ information/ knowledge through fusion with heterogeneous data/ information/ knowledge obtained from distributed sources. New knowledge types or products can result from the integration of knowledge obtained from different sources. Hidden knowledge can be uncovered by reasoning about the knowledge/ information. Existing knowledge can be combined in a variety of different ways and scenarios to discover new relations between knowledge objects or resources. New capabilities or competencies can be applied to a knowledge object once the sources have been reconfigured. Sometimes, the exchange of knowledge during the process of learning, interacting, and discussing can also improve competencies and capabilities. Finally, scholars have also introduced knowledge (from different sources) into problem-solving resulting in new solutions to a problem.

Besides the fusion processes defined by Smirnov et al. in their studies, there are also various other types. Dong et al. extracted knowledge with a certain structure through knowledge fusion [18]. In a study analyzing Avian Influenza H5N1 in East and Southeast Asia, knowledge fusion provided a framework for integrating the formation from different research domains [19]. Knowledge fusion has the ability to transform, integrate, and fuse distributed information resources such as databases, knowledge bases, and data warehouses to obtain useful new knowledge elements. In [20], using a detailed knowledge fusion algorithm based on a genetic algorithm and semantic rules, a distributed knowledge source was shared and integrated. In studies on cloud manufacturing, knowledge fusion is proposed to combine distributed and heterogeneous knowledge and fully exploit these in a dynamic way to find solutions [21]. With the advances in associated research, knowledge fusion has increasingly been applied to interdisciplinary research such as learning style diagnosis [22] and in the agro-environmental field [23] , among others.

2.2. Knowledge Fusion in a DSS

A DSS has a target-oriented and model-based framework, including four data resources, namely, a question base, knowledge base, model base, and method base. The DSS assists resolving semi-structured or unstructured decision problems. Data, information, knowledge, artificial intelligence and modeling techniques are applied in the DSS, since it relies heavily on a large amount of data, information, knowledge, and model elements [2] [24]. Of all these techniques, knowledge fusion is one of the most effective methods.

Ontology-based knowledge fusion is a promising method since it satisfies semantic heterogeneity, which contains synonyms (different items referring to the same concept) and homonyms (the same items with different meanings) [25]. Smirnov et al. combined an ontology with knowledge logistics and proposed a user-oriented ontology-driven knowledge fusion methodology [26]. Then, this laboratory presented a context-based knowledge fusion pattern for emergency responses in a DSS [27]. The proposed pattern was further improved into a seven-step knowledge fusion pattern for context-aware DSSs based on the use of an ontology [8] [9] [17].

Knowledge fusion is such an effective means of increasing the efficiency of a DSS that many scholars have considered combining a DSS with it. A knowledge fusion toolkit to assist decision-making has been realized using Java Enterprise technology [28] [29]. Regarding procurement fraud detection in Brazil, Rommel et al. combined a probabilistic ontology and knowledge fusion (the automated fraud detection system used as the case study is intended to be a DSS) [30], while an inference structure was proposed for diagnostic problem solving incorporating knowledge reuse from knowledge bases covering various domains [31].

3. Three-layer Fusion Pattern

A DSS provides a user interface to gain instant access and offers candidate decisions and alternatives. Regarded as a black box, the DSS connects with data, knowledge and information arriving from distributed sources, drives the decision-making mechanism considering the actual situation, and then proposes candidate sets. Thus, this paper proposes a three-layer knowledge fusion pattern for use in a DSS. The presented architecture includes fusion in the input layer, within the DSS, and through the output layer. These three layers correspond to fusion before knowledge is input into the system, inside the system, and after decisions have been presented to users. Details of the fusion process in each layer are presented in the following sections.

The proposed pattern is actually based on the decision-making process. As mentioned above, the process of making a decision can be divided into four steps: first, determining what decision-makers expect to accomplish under certain conditions; second, formulating multi-wrap alternative plans; third, weighing the advantages and disadvantages and selecting the most optimized program; and fourth, carrying out the implementation of the alternatives identified and selected in the previous steps. A DSS provides effective support for decision-making. Thus, the knowledge fusion pattern elaborated below includes the four steps mentioned above. However, the third step, referring to the choice of a solution, is excluded from the pattern, since the decision is actually made by people and not by the system. Thus, the proposed pattern considers knowledge fusion in the other three steps.

To better understand the knowledge fusion process in the pattern, in the part processes emergency DSS is introduced for case description. Emergency DSS is proposed for assisting decision making in a sudden occurrence. This system is supposed to draw up feasible countermeasures based on practical situation. With the tracking of performance, system is expected to correct the mistakes of chosen decision in time.

3.1. *Input-layer Fusion*

Making a decision is based on certain conditions. This means that to provide effective support for decision systems, a DSS should first acquire data/ information/ knowledge about the topic of interest. For example, a clinical DSS uses patient clinical data to generate case specific advice [32]; emergency DSSs provide emergency responses based on incident scenarios [33], and so on.

DSSs are usually data-based to some extent. One of the problems with these systems is that data does not exist naturally but has to be collected, stored and processed. Thus, a DSS tends to have its own underlying information service subsystem, also called a data acquisition systems (DAS). Data, information, and knowledge from heterogeneous knowledge sources are vital in terms of creating a foundation. Therefore, the first layer of the proposed knowledge fusion pattern considers knowledge fusion that occurs before the data/ information/ knowledge access to decision-making stage, that is, input-layer fusion. Fusion in this layer comprises two steps: reconstruction and connection.

3.1.1. *Reconstruction*

Data, information, and knowledge are input into the DSS through a human computer interaction (HCI) interface and the DAS. Then, reconstruction, which can also be regarded as pre-processing, is applied to some extent to the data/ information/ knowledge. As presented in [34], two main operations are recommended in a distributed knowledge fusion system: knowledge retrieval and problem solving. Reconstruction, in fact, merely supports the retrieval of knowledge. Data/ information/ knowledge obtained from different resources usually have different structures. Reconstruction extracts and reconstructs the data/ information/ knowledge into a structure acceptable to the system.

Analysis of reconstruction from knowledge fusion processes' view, knowledge fusion in this part may create new knowledge object. Heterogeneous data/ information/ knowledge obtained from distributed sources are engaged in the intelligent fusion and result in new knowledge. This new knowledge is then become the foundation of the decision making.

3.1.2. *Connection*

The main task of connection is to innovate new knowledge based on the realization of knowledge fusion between the collected distributed data, information, and knowledge, and even knowledge sources. Discovering hidden associations of knowledge sources and relations between knowledge is the goal of this phase (as shown in Fig. 1). Mined relationships are regarded as new knowledge and are accessible to the system together with the original knowledge, data, and information.

For instance, an emergency DSS contains basic information, disaster information, hazard management, and many other subsystems. When an emergency arises, a lot of the data, information and knowledge

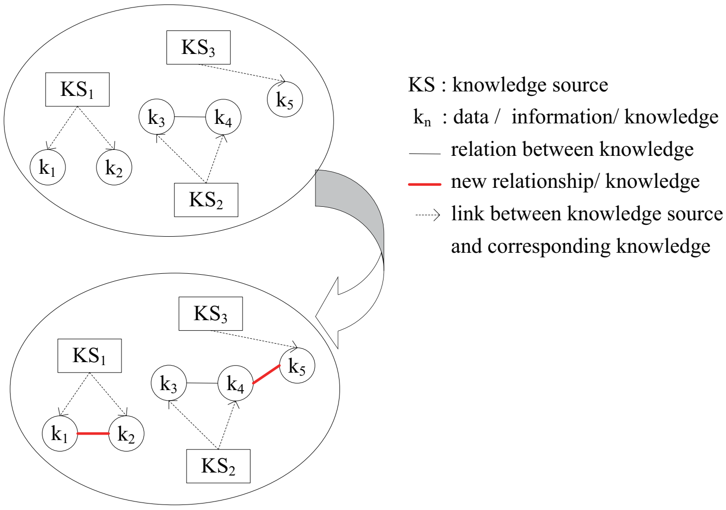

Figure 1: schematic of Connection

are transferred to the system. Before decision-making, fusion of the input layer takes place. First of all, reconstruction result into new knowledge object.Then comes to connection which tends to discovered hidden relation between knowledge. For example, the place where the incident occurs (as obtained from the knowledge source for disaster information) is part-of the geographic information and could relate to public facilities belonging to another knowledge source.

3.2. *Interface-layer Fusion*

As a knowledge-based HCI system, the DSS receives an operation request and responds to the user input. From this perspective and as presented above, this layer lifts the veil on knowledge fusion within the DSS; in other words, knowledge fusion happens inside the black box. The previous layer describes knowledge fusion after the knowledge has been input into the system but before it reaches the decision-making process. The next layer, which is called the output layer, incorporates knowledge fusion after the candidate solution set has been drawn up and the selected scheme has been implemented.

From another perspective, during the process of decision-making, the DSS is expected to assist in determining the decision objects, contriving schemes, and executing the selected plan. In this section, interface-layer fusion is proposed to assist the contrived schemes. After completion of this process, foundational information is turned into candidate decisions.

In any case, this layer serves as a link between the previous and subsequent layers. It receives and processes knowledge from the input layer and provides enforceable detailed operation plans for the output layer. In this study, we divide fusion in this layer into three main steps: combination includes knowledge fusion of this layer at an abstract level, while instantiation expounds knowledge fusion by creating concrete decisions for selection. Finally, recycling infers from existing knowledge, and instantiation instantiates concrete executable solutions.

3.2.1. *Combination*

The knowledge arriving from the upper layer becomes the source in this stage. Once a decision needs to be made, the first step is to select a related problem-solving model (the ontology describes problem-solving methods). Then, to assist users in the decision-making process, the DSS is expected to suggest a series of measures, which become the objectives in this step. The scenario description obtained from the input layer is combined with the chosen problem-solving models. A guide to the action alternative is given in this phase.

The fusion method for this stage consists of integration of the knowledge obtained from the different sources, which results in new ideas about how to solve the problem, and the involvement of knowledge in the problem-solving, which comes out in the solutions. Considering the whole architecture, knowledge fusion at this stage comes down to making alternative decisions for the first time. The candidate sets under layers of abstraction are then instantiated to specific scenarios.

Consider once again the emergency DSS, which presents various problem-solving models for emergency response. After an accident has occurred and the relevant knowledge have arrived in this layer, the combination function is invoked. Suppose that a traffic accident occurs, through knowledge fusion, the DSS will pick up traffic-accident related problem-solving models in this procedure. Each of these models contains a set of methods indicating concrete solution procedures.

The result of knowledge fusion resembles that given below:

Step 1 path planning (place A, place B)

Step 2 send fire-engines to the fire location (license-set N, path-plan PP)

Step 3 dispatch firefighters (firefighters-set F, engine-dispatch ED)

Here, A, B, N, PP, F, ED corresponds to parameter required by each step. Furthermore, PP as the parameter of path-plan is a return result of path planning of Step 1. Similar to it, engine-dispatch ED result from Step 2. And as for each parameter, A and B denote the location of the fire department and the site of the fire, respectively. N the license-plate number set of the fire-engines, and F is a set of firefighters who are able to execute this task.

3.2.2. Recycling

A DSS may contain more than one subsystem. Each subsystem sends data/ information/ knowledge to the controlling system and requires an associated response. Frequently, the DSS is a distributed one composed of cooperating subsystems, which necessitates knowledge interaction among the distributed systems. The subsystems are not independent, but overlap one another. Thus, interactions between systems, the systems daily operation, and data exchanges with the outside world accumulate much recorded history. Recycling of this knowledge can result in interesting outcomes.

Furthermore, to utilize the existing resources of the DSS more rationally, the main task of knowledge fusion at this stage is divided into two steps: reasoning about the existing knowledge and combining historical knowledge through a number of scenes. New hidden knowledge and relationships can be uncovered in this way.

Through recycling, hidden functional relations can be discovered. Suppose function a() obtains input data from function b() and returns some output. Moreover, assume that there is another function c(), which has the same input as function a() and provides output to function b(). Recycling shows that the execution of functions a() + b() is the same as function c(). Similarly, knowledge fusion mines the association between the knowledge; ascertains the output effect that one subsystem has among the other subsystems; and discovers new knowledge.

3.2.3. Instantiation

After the combination process, alternative solutions are acquired. Instantiation is then carried out to make the solutions more specific. In this step, objects of certain class are instantiated. For example, the process flow given in the Combination section is transformed into the steps below after knowledge fusion for this stage has taken place:

Step 1 path planning (place a, place b)

Step 2 send fire-engines to the fire location (license-set n, path-plan pp)

Step 3 dispatch firefighters (firefighters-set f, engine-dispatch ed)

Unlike the previously mentioned, here, these small letters correspond to those capitals. Not represented as a parameter, but a concrete value of this parameter.

Knowledge fusion during instantiation involves a conceptual problem-solving strategy and concrete data/ information/ knowledge. This means that after combination, the DSS provides a series of candidate function sets like the one given above. Knowledge fusion in this stage instantiates objects of classes and supplies parameters from other aspects. Instantiation is the final process in the interface layer. After this stage, specific alternative decisions are provided to the users for selection as the final solution. Contrary to the abstract decisions supplied by the combination process as an input for knowledge fusion, the instantiation process offers operable and human understandable solutions as answers to the users requests.

If a traffic accident occurs, as per our example, after the previous steps the DSS presents alternative solutions and reaches instantiation. The knowledge fusion occurring here takes place using the knowledge from the input-layer fusion and solutions obtained through combination.Thus, the procedure Send a police car to the scene of the accident is changed to Send police car a to place b. Here, a denotes a specific police car and b is the actual location where the traffic accident occurred. The other traffic accident-related procedures are influenced in a similar manner by the fusion in this layer.

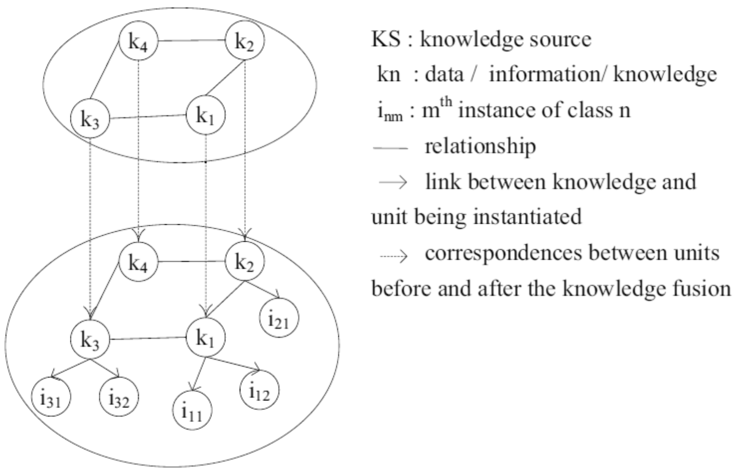

Figure 2: schematic of Instantiation

3.3. Output-layer Fusion

For any decision, there may be several choices of which decision-makers can select one or more [34]. To aid decision-making, the DSS must offer a series of candidate solutions. The user finally selects the one that is seen to be the optimum alternative. Then, the whole process gears up to implement the chosen scheme.

From the perspective of knowledge fusion in the DSS, this is an optional process. Certainly, the proposed pattern is expected to incorporate most of the knowledge fusion in the DSS. Therefore, output-layer fusion has been proposed, most likely as an emergency measure or a precaution. After the implementation of interface-layer fusion, the decision process needs to select a scheme. As mentioned above, the DSS has nothing to do with this. Then, the flow moves on to execute the chosen plan at which stage knowledge fusion of the output layer occurs.

The DSS offers mainly assistant decision support functions for complicated problems, which means that the effect of the system is to provide decision support, but not to make the decisions. The DSS offers a series of candidate items to aid decision-making. Although a human is responsible for making the decision, thereafter, the process may be hampered by curve balls. To ensure that decision-making is carried out smoothly, knowledge fusion before the decisions are presented to the users is quite necessary in case of recall. During this stage, alternatives are provided in case an exception occurs. Knowledge fusion at this level exchanges knowledge during learning and interacting to improve specific competencies and capabilities.

If a police car assigned to the site of the accident breaks down, output-layer fusion is executed. The broken car keeps a record of the decisions about the car made by the DSS. This may contain a series of task instructions as well as the relevant knowledge. Because of the broken car, implementation of the decision for this part fails. To support the decision, the DSS system provides an alternative for this part. Through knowledge fusion in the output layer, another police car is given the competencies and capabilities of the broken car and performs the corresponding task.

4. Evolution in Three-layer Knowledge Fusion Pattern

In the previous section, we proposed a three-layer knowledge fusion pattern based on a decision process. From the perspective of interaction, the pattern is illustrated in Fig. 3. In this section, knowledge objects and a knowledge state are incorporated in the proposed knowledge fusion pattern.

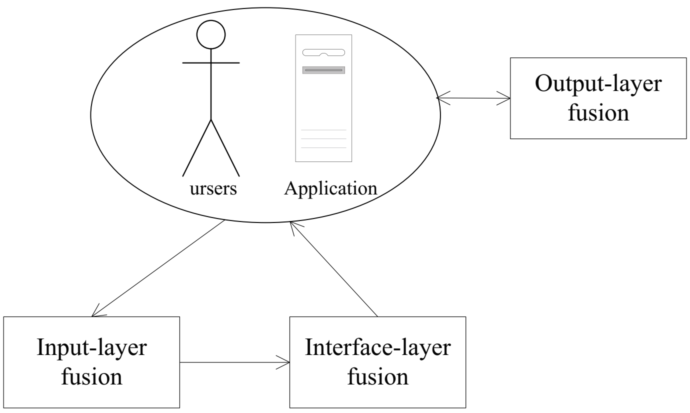

Figure 3: Interaction diagram of the fusion pattern

4.1. Knowledge Objects and Knowledge State

A knowledge object here, is defined as knowledge whose content resources can be organized in such a way that a given algorithm is able to execute on it; in other words, knowledge that can be coded as a particular data structure. For example, knowledge can be represented as IF-THEN rules:

IF *the temperature is higher than* 45°C

THEN *turn on the air conditioning*

Using some coding scheme, this IF-THEN rule can easily be used by an algorithm. Obviously, the content is contained within the above-mentioned rule. However, presenting the IF-THEN rule as an example of a knowledge object does not mean all knowledge objects are represented as IF-THEN rules. Knowledge organized as triples in the form (*subject*, *predicate*, *object*) or as a semantic network, or any other knowledge that can be identified in a specific way can also be considered as a knowledge object.

The knowledge object defined in the knowledge fusion process is akin to a node in a graph. Since the knowledge state is defined as a collection of knowledge objects under certain constraints, it changes during the processes of knowledge fusion. Knowledge state KS_i containing knowledge object k under constraints (f_c, T_c) is depicted as follows:

$KS_j : \{k_i | f_c(k_i) \in T_c\}$

By incorporating the knowledge state into the proposed three-layer knowledge fusion pattern, interaction within the pattern can be illustrated as in Fig. 5. Knowledge processes KF-1 to KF-6 correspond to the proposed knowledge fusion processes: reconstruction, connection, combination, recycling, instantiation, and reconfiguration, respectively. Consider, as an example, the knowledge state transition in the input layer (Fig. 4(a)) containing three knowledge states and two knowledge fusion processes. With regard to the entire layer, the transition entry and transition exit are KS_1 and KS_3, respectively. KS_1 first changes into KS_2 after KF-1 (reconstruction) takes place and then, into final state KS_3 for KF-2 (connection). The other two layers are similar to the input layer.

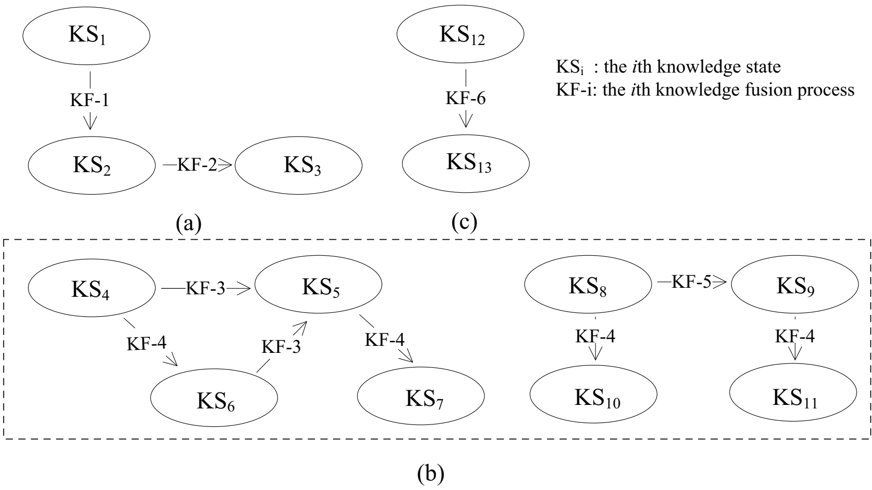

Figure 4: Knowledge state transition of the three layers: (a) input layer; (b) interface layer; and (c) output layer

4.2. Evolution of Knowledge Objects

Change in the knowledge state actually comprises the evolution of the knowledge objects. Evolution is a characteristic of knowledge systems. Regarding the proposed knowledge fusion pattern, evolution is regarded as continually changing the external structure and internal relations of the knowledge objects. There are three evolution rules in the three-layer knowledge fusion pattern: coalition, migration, and coevolution.

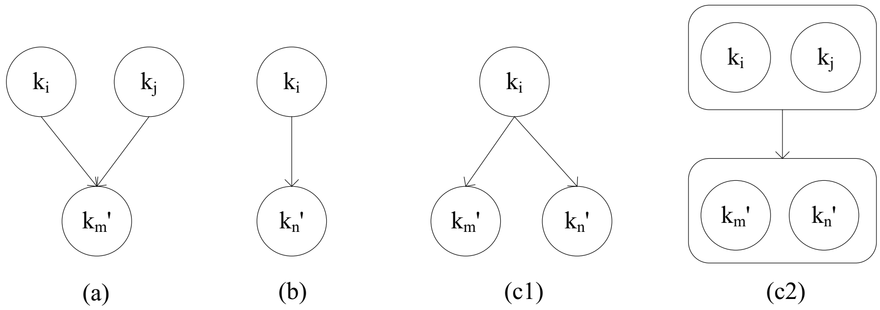

Figure 5: Evolution of knowledge objects

Coalition refers to the formation or synthesis of new knowledge objects from particular knowledge objects under certain restrictions and control rules. The new knowledge object can satisfy the demands of problem-solving at a higher level. Migration refers to the processes of redefinition from a knowledge object into another new one under certain restrictions and control rules. Migration is usually caused by inconsistencies between existing representations of knowledge and structure, which is actually needed. Finally, coevolution refers to the creation of new knowledge object(s) from interaction between other knowledge under certain restrictions and control rules. Coevolution is actually a many-to-many process, where mergers and extinctions sometimes accompany creation and migration.

4.3. Evolution in the Three-layer Fusion Pattern

As detailed above, the three evolution types refer to the proposed three-layer knowledge fusion pattern with six knowledge fusion processes involved in this pattern. Evolution of the six knowledge fusion processes is described in detail as a pattern in Table 1.

Table 1: Pattern for Evolution Description.

Fusion layer	layer of the current fusion process
Name	a name that refers to the fusion process
Initial knowledge state	knowledge state that leads to the procedure for the knowledge fusion process
Target knowledge state	knowledge state resulting from the procedure for the knowledge fusion process
Related evolution	evolution through this fusion
Effect in DSS	the effect the knowledge fusion process has on the DSS

The evolution of the entire knowledge fusion pattern is then described as bellow.

Table 2: Evolution Description of the Three-layer Fusion Pattern

Fusion layer	Name	Initial knowledge state	Target knowledge state	Related evolution	Effect in DSS
Input-layer	reconstruction	heterogeneous knowledge obtained from various subsystems	knowledge objects in a common format that the system can understand and operate	Migration	new knowledge created from existing knowledge
	connection	knowledge objects in a common format that the system can understand and operate	new relations between knowledge as knowledge objects	Coalition	new relationships
Interface-layer	combination	knowledge objects related to the current problem being solved	knowledge objects describe abstract solutions for the current problem being solved	Coevolution	abstract solutions for problem solving
	recycling	any knowledge state in the interface layer	hidden knowledge inside the initial knowledge will be found and becomes new knowledge objects	Coalition	new knowledge created from existing knowledge
	instantiation	knowledge describes abstract solutions for the current problem being solved	knowledge objects describe specific solutions for the current problem being solved	Coevolution	specific solutions for problem solving
Output-layer	reconfiguration	unspecific solutions	knowledge objects describe specific solutions for the current problem being solved	Coalition	remedial actions

The input layer contains two knowledge fusion processes. Reconstruction is one of these in the input layer, but is also the first knowledge fusion process in the entire knowledge fusion pattern. As previously stated, reconstruction fuses heterogeneous knowledge obtained from distributed sources into a recognizable format for the system. Connection is the second knowledge fusion process in the input layer. Unlike reconstruction, connection creates relations between existing knowledge as new knowledge by means of the knowledge fusion.

The interface layer is the essence of the whole pattern. This layer considers three knowledge fusion processes: combination, recycling, and instantiation. Combination takes problem solving into consideration and fuses the related knowledge to find abstract solutions. Recycling is ubiquitous in the interface layer, which is why there are four knowledge states (KS_6, KS_7, KS_{10}, and KS_{11} in Fig. 4) concerned with this knowledge fusion process. It can take place before and/or after combination and instantiation. Recycling can discover tacit knowledge from the codified knowledge. Instantiation, which always occurs after combination, presents a list of abstract solutions. However, the target knowledge state of combination is part of the initial knowledge state of this knowledge fusion process but not always. Since the occur of recycling after combination and before instantiation. This procedure also considers objects of subjects in the abstract solutions fused by combination.

Reconfiguration takes place in the output layer. This knowledge is special in that it is sometimes not necessary. Reconfiguration takes place only when the chosen solution does not execute well. In the case of unexpected condition, fusion in this process achieves new configuration with new ability for substitute knowledge.

5. Case Study

The previous section described the architecture of the three-layer knowledge fusion and its evolution based on knowledge objects. In this section, for better understanding, the flowchart of the proposed knowledge fusion pattern shown previously is replicated in Fig. 6. Thereafter, practicability analysis of the fusion pattern for algorithm implementation is discussed. Then, the implementation of the proposed knowledge fusion framework over the Fire Rescue Decision Support System(FRDSS) is given in the second subsection. FRDSS relies heavily on weather, date and time, and the available of fire stations as well as various other relevant information, knowledge. Introduction of knowledge fusion is an effective measure to assist the DSS in dealing with such a vast amount of data/ information/ knowledge and models.

5.1. Feasibility Study

The proposed decision process-based knowledge fusion architecture is actually a three-layer, six-step fusion pattern. The three layers are the input layer, interface layer and output layer as discussed previously, while the six steps correspond to reconstruction, connection, combination, recycling, instantiation, and reconfiguration. This section discusses practicability from the perspective of algorithm implementation.

For reconstruction in the input layer, the translation methods proposed in [35] and [36] have proven to be valid measures. Chalupsky presented OntoMorph [35], a translation system for knowledge with different representations. OntoMorph transforms a source knowledge base into a target knowledge base using the combination of two mechanisms: syntactic and semantic rewriting. In [36], a knowledge resource item (KRI) is represented as a triple with three attributions. Using KRI, heterogeneous knowledge can be transformed into a uniform knowledge representation model. Another step in the input layer is connection.

Recycling in the interface layer is actually the fusion and optimization of multi-source knowledge. In current studies of knowledge fusion, various researches have focused on this aspect. For example, some have tried to incorporate an optimization algorithm into knowledge fusion, which is indeed a very efficient method. Huang et al. applied a particle swarm optimization algorithm and cat optimization to the fusion process to integrate knowledge from different sources [22] [37]. As a result, tacit knowledge can be abstracted as new knowledge. Besides, a genetic algorithm is also an effective measure of this process. Owing to the algorithms capability as a powerful search mechanism, the authors in [38] used it to discover new knowledge.

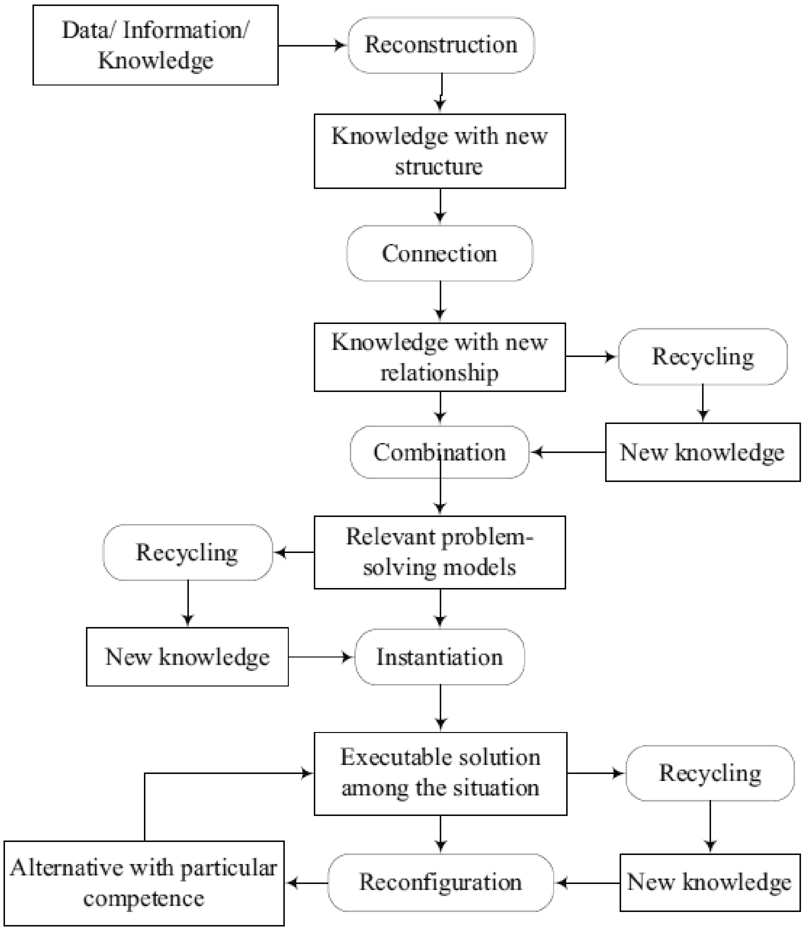

Figure 6: Process flow in the three-layer knowledge fusion pattern.

The last layer in the fusion pattern contains reconfiguration. Inspiration for this was derived from Smirnovs work on knowledge source network configuration [39]. In the proposed study, new capabilities of knowledge are realized through re-configuration of the knowledge source. In addition, in research on the configuration of knowledge sources, the authors in [40] presented their own approach (KSNet-approach) to knowledge fusion.

5.2. Three-layer Knowledge Fusion in FRDSS

Every year, large number of economic loss and casualties due to fire disaster. Scientific and effective FRDSS have great significance to reduce the casualties and economic losses. In FRDSS, rescue scheduling means how to reach the fire rescue scene as soon as possible. Here, we select the following factors to briefly explain: the location of the fire incident, the fire stations distribution , weather, time and historical data. For the candidate path, we use commonly Maps API. For better understanding, description of a fire rescue system is given below in Fig. 7.

Complete complexion about fire stations' distribution, fire stations' availability, weather, time and historical data is necessary to create the foundation of FRDSS. When data/information/knowledge are obtained from distributed knowledge sources, the input-layer fusion comes into play. First, reconstruction extracts knowledge and reconstructs data/information/knowledge in various representations. Relationships between the weather, time, historical data are discovered during connection. The FRDSS is able to provide a scene description.

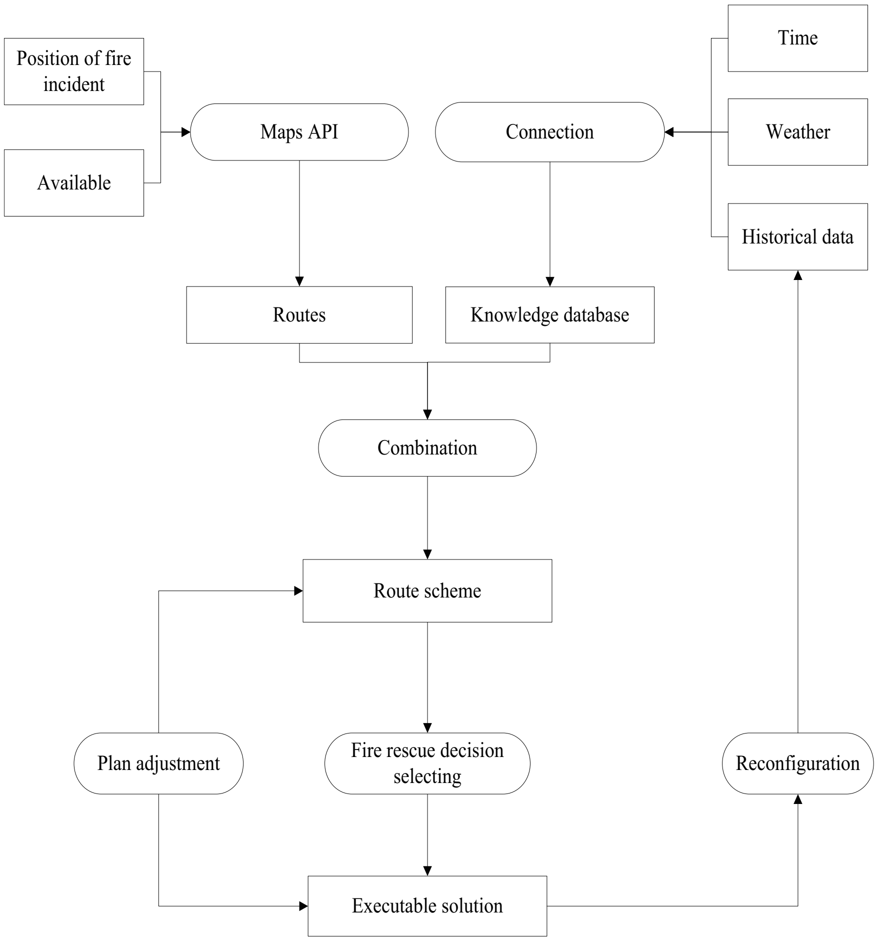

Figure 7: Description of fire rescue system

Combined with weather, time and historical factors discover hidden information. Through knowledge fusion of this stage, hidden knowledge and associations are mined. This can affect the further decision making. For instance, if there is rain and snow in weather, the extra time for all the routes is proportional to the distance. If it takes more time than the usual to go through a certain location area (for example, primary and secondary schools) in the historical route data, then we can consider to find a new knowledge from the historical data, and the knowledge is added to the historical knowledge database. It's be added to the factors that influence the route cost which will increase the time required to pass the route or avoid passing the road section.

The system then continues to decision-making. In FRDSS, this phase is decision-making. The knowledge within the system and that obtained from the input layer are joined in the interface-layer fusion. First knowledge of the situation description starts combination, which outputs solutions for the current problem. Sending the fire incident and fire stations' available information to the map application interface, and then the map application interface return some different route which is the fire stations reach fire incident. Then, combine with knowledge database,FRDSS update every route. Finally, we combine all the factors to estimate the possible time to reach and select a few less time-consuming routes as a decision-making reference.

After instantiation, solutions change to be workable plans. That is, dispatch fireman and fire-engines to the fire incident according to fire rescue decision. And then based on the actual situation on the rescue route, added congestion and other information into historical data, for subsequent analysis.

Figure 8: Distribution of fire stations

Output-layer fusion is actually precaution. When one of the alternative decision is chosen, the solutions can being executed. However, when the execution of the decision service is interrupted, the DSS is required to provide another substitution, which should satisfy the relevant capabilities and competence. This is what the knowledge fusion does in this layer. In fact, it is a fault-tolerant mechanism. When encounter the fatal traffic jam or the rescue team does not arrive in time for some other reasons, this layer has a role to play.

We select Xiamen City as the experimental research object. Through commonly Maps API we get altogether six fire stations as shown in Fig. 8 (number 4 and number 6 are the same point,so we consider these two stations as number 4 following). Assume that the fire incident is MingFa Commercial Plaza, at 12 o'clock on Monday noon, sunny day. Then we can get six routes from the map's API(as shown in Fig.9). First we analyse Route 1. There are two schools,a middle school and a primary school in this line. Assume we obtain the knowledge that the primary school always affect traffic in 12 oclock from the historical knowledge database. Through the analysis of historical knowledge, it can be deduced that it may take more 5 minutes than common in this section. So we estimate the total time is using mean up time added 5 more minutes. In Route 2, there is a primary school, but according to historical knowledge we found that the primary school on this path does not have impact, so we estimate the total time is mean up time. About Route 3, there is a common part line in the first route and the remaining lines without influencing factors. So will we estimate the total time is using mean up time added 5 more minutes too. In Route 4, the whole road is relatively smooth. There is no factors that impacts traffic. So the total time is mean up time. The Route 5 is abandoned because the distance is far greater than the previous four roads. Route 7 is also be abandoned similarly.

Speed of urban roadway is generally limited to 50KM/H, taking into account the traffic lights, avoid pedestrians, etc., we assume that the average speed is 30KM/H. And in future calculations, we can use the historical data to adjust the average speed. Therefore, we can estimate and calculate the time spent on each route (as Table 3 show). According to the above analysis, we select Route 2 and Route 4 as the candidate routes. And Route 2 is prior to Route 4.

Table 3: estimated time of each route

Route	distance(km)	average speed(km/h)	distance estimated time(min)	extra estimated time(min)	total estimated time(min)
1	3.3	30	6.6	5	11.6
2	2.7	30	5.4	0	5.4
3	4.8	30	9.6	5	14.6
4(6)	2.9	30	5.8	0	5.8
5	10.8	30	21.6	0	21.6
7	8.3	30	16.6	0	16.6

6. Conclusion

This paper presented a knowledge fusion architecture for a DSS. The proposed three-layer knowledge fusion pattern is the main contribution of the paper. The proposed knowledge object and knowledge state incorporate the theory of software engineering into knowledge fusion. Evolution throughout the entire pattern was discussed in detail. A case study involving the FRDSS showed that the methodology can be applied in the system and processes it more efficiently.

The knowledge fusion pattern covers most of the executive procedure for the DSS. Further research is needed to identify a better knowledge fusion model for the DSS. Moreover, use of an ontology and agent would strengthen the study substantially. A detailed algorithm for each pattern also needs to be defined in future study.

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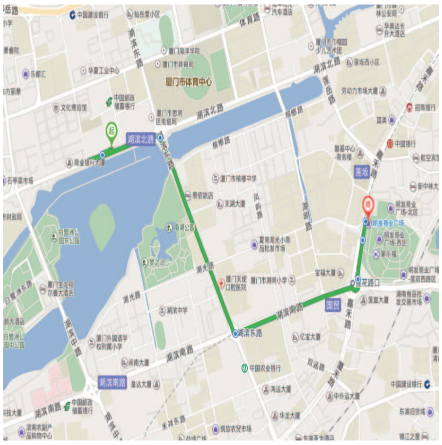
(a) Route 1


(b) Route 2


(c) Route 3


(d) Route 4


(e) Route 7


(f) Route 5

Fig. 9 Route of Map's API return