# A Study on Motion Knowledge Visualization

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## ABSTRACT

*While information technology is rapidly developing, the volume of digital information has significantly increased over the Internet. This challenges human's limited capability to acquire and absorb domain knowledge efficiently and accurately. From this issue, it is obvious that representing the document contents effectively for knowledge receivers to easily acquire the domain knowledge has become a necessary requirement in enterprise knowledge management. Our paper brings out a three-phase methodology (including automatic thesaurus definition (ATD), target sentence extraction and formatting (TSEF) and motion knowledge visualization (MKV)) for motion knowledge extraction, representation and visualization is developed. Furthermore, the proposed approach shall influence enterprise e-training and knowledge management enviornments by enhancing reuse of domain knowledge.*

**Keywords:**
Knowledge Representation, Motion Knowledge, Visualization, Visual, Knowledge Management

## 1. Introduction

Traditional schemes for explicit knowledge representation within the enterprise and academic circles are mostly text-oriented and therefore much time and efforts are required for knowledge receivers to recognize the knowledge contents. Recently, approaches such as Information Extraction (IE) techniques have been developed [8][9][11][12] to automatically extract and format core knowledge within large quantity of text-oriented documents, and facilitate the knowledge receivers to understand and absorb domain knowledge more efficiently and sufficiently. Moreover, if the extracted and formatted knowledge is represented via knowledge visualization (KV) mechanisms, the domain knowledge can be more concretely expressed and the efficiency and accuracy for knowledge acquisition can be enhanced [13][14][15][16]. Both technologies, the information extraction techniques and the knowledge visualization mechanisms, are based on certain thesauri, which are defined as listings of words or phrases with similar, related, or opposite meanings.

Information extraction techniques could facilitate the recognition of core information out of large amount of original document. The general process of information extraction systems could be classified into the following steps including syntactic analysis, semantic tagging, discourse analysis and rule reasoning [1]. However, abstractive knowledge, such as motion knowledge, may still be hard to absorb or even misunderstandings; Knowledge Visualization (KV) would be a solution to the lack of concrete expression of knowledge contents. KV can be regarded as "the process of transforming data, information, and knowledge into visual form making use of humans' natural visual capabilities [2]", and the general process includes raw data transformation, transformed data and visual structure mapping, and the final visual representation, as shown in Figure 1 [3].

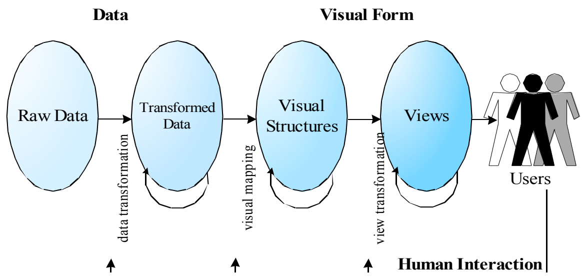


Figure 1. The general process of knowledge visualization [3]

By integrating information extraction and knowledge visualization technologies, domain knowledge or user queries could be visually displayed after being automatically and efficiently extracted from the text-oriented documents, so that knowledge receivers can accurately acquire the domain knowledge, improving the efficiency and accuracy of knowledge acquisition, and enhance reuse of domain knowledge.

The related works of thesaurus technology, information extraction and visualization technology will be introduced in Section 2. Section 3 will propose an approach for visual representation of motion knowledge. Last, contributions and future studies of this research will be conclued in Section 4.

## 2. Related Works

The goal of this study is to extract the motion knowledge out of the motion knowledge containing document, and represent the knowledge in a motional visual display, so that knowledge receivers can view the knowledge in a concrete, realistic way instead of having to read off the abstract free-form documents. This not only improves the efficiency and accuracy of knowledge acquisition, but will also enhance domain knowledge reuse. Because extracting knowledge from the free-form documents requires techniques such as information extraction, representing the knowledge in visual display requires Information Visualization (IV) technology, and both are based on the thesaurus technology, we will sequentaially bring out the related works of thesaurus technology, Information Extraction and Information Visualization.

**2.1 Thesaurus Technology**

Thesauri are traditionally established and maintained manually by domain experts who frequently insert new domain phrases into the thesauri which is restricted and over-relies on the experts' knowledge. To overcome the restriction, there are now new methods for thesauri to construct and grow automatically including combining the Neural Network Technology with Latent Semantic Indexing [4], using self learning systems to build a Dynamic Thesaurus [5], etc. Self learning technologies are required to be combined with the thesaurus in order to conquer the downside of the limited phrases in the thesaurus. Approaches such as combination of thesaurus and neural network technology [6], applying Bayesian networks in thesauri automatic construction [7], an AutoSlog System which automatically constructs and expands thesauri, etc., have been brought out. The approaches allows processes that require application of thesauri to be unlimited by the thesauruses' content. In this paper, thesauri automatic construction and expansion is also an important issue we focus on, it is also the first phase of our methodology (the automatic thesaurus definition (ATD) phase); therefore, we take the previous works as reference to establish our methodology.

**2.2 Information Extraction**

The most important task in information extraction is word segmentation [8][9]. Character-based language segmentation basically included two main methods, which are the Dictionary-based Method and the Statistical-based Method [9].

The most commonly seen Dictionary-based Method is the Maximum Matching Method, it is often used with other mathematical calculations to overcome problems caused by obscure phrases. Ge et al. [10] uses the Dictionary-based Method with Statistical-based Method: by matching each sentence in the free-form document with phrases in the thesauri, there would be different ways for segmentation; also, each phrase has its own show-up-rate (the possibility of showing up in a sentence), therefore, the maximum value of multiplying each show-up-rate would correspond to the most possible segmentation way of the sentence.

Besides using a dictionary (or a thesaurus), Nie et al. [11] states that in character-based language, certain characters or phrases that are preposition or conjunctions could also be used to segment a sentence by applying a pre-defined pattern rule. Chen et al. [12] uses the Bigram Indexing method, also dictionary regardless, which is based on mathematical calculation; this method is usually faster, yet less accurate than other Dictionary-based Methods, because no special processing is required to deal with ambiguities, even in the case of overlapping ambiguities.

In our study, the extracted information will be used for further visualization application, therefore, the accuracy of the method would be seriously considered. We will build our information extraction method based on the Dictionary-based Method, taking the previous related works as reference.

**2.3 Knowledge Visualization**

Knowledge visualization is to improve the knowledge understandability for human. Hence, to make the visual representation in a more realistic, understandable and human-familiar display is an important issue. Studies reveal that adding in "motion" or "movements" may in some cases, enhance the visualization performances.

The "motion" (or "movements") of objects reveals the information of the relationship between the target object, the environment (which includes the viewer), and the related time; the information contains an important element which static displays cannot reveal, "speed". Researches on "object motion" in visualization started when the "Mental Rotation Paradigm" experiment was brought out by Shepard et al. [13]. The experiment finds a more realistic way of displaying a rotation movement. Subsequent studies show that "Wire Frame Objects" result in higher error rates and slower response times compared to "Solid Objects", and rotation movements using 3D visual displays are easier to recognize than those using 2D visual displays, also greatly contributing to the techniques in rotation-movements visualization.

Sollenberger et al. [14] and Ware et al. [15] also show that 3D displays (instead of 2D displays) and continuous motions (instead of interval static displays) used together show a higher performance than merely applying 3D displays or only concerning continuous motions. In addition, [16] noticed that concerning the changes of the objects' surface color or burnish during the rotation or other movements would also enhance the realness of the object motion, hence, the understandability.

As a whole, concerning the object motions in visualization could enhance the accuracy for the viewers in absorbing and understanding the displayed knowledge, the accuracy and understandability would be even higher if represented in a 3D display with surface color or burnish changes.

## 3. Proposed Approach

In this section, we will propose an approach for visual representation of motion knowledge which can extract target sentences that contain motion knowledge from the free-form documents, convert the sentences into formatted representation, and then display the formatted sentences into visualized display. The methodology consists of three main phases, including Automatic Thesaurus Definition (ATD), Target Sentence Extraction and Formatting (TSEF) and Motion Knowledge Visualization (MKV). Since predefined thesauri are required for motion knowledge extraction, completeness of each thesaurus will affect the accuracy target sentence extraction. Therefore, we establish an automatic thesaurus definition algorithm to automatically extract the domain phrases from the free-form documents. Afterwards, by looking up the predefined thesauruses, the target sentences that contain motion knowledge can be extracted from the free-form documents and converted into formatted information matrix. By mapping the formatted matrix to the visualization database, the corresponding graphs and visualization information could be acquired to generate the visualized display of the motion knowledge. The conceptual process of the methodology is shown in Figure 2.

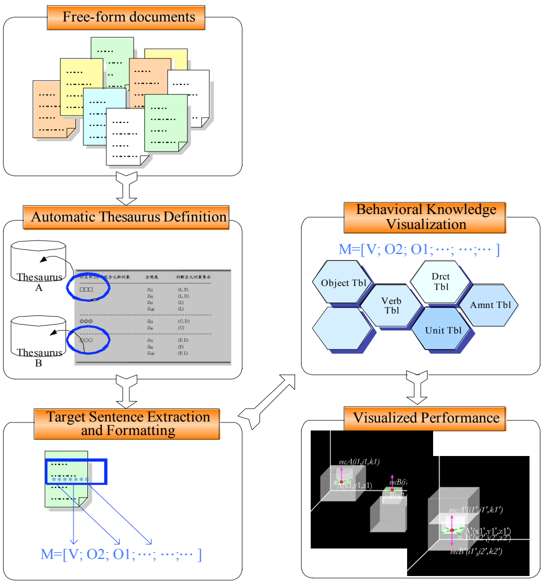


Figure 2. Visualization of motion knowledge

### 3.1 Phase 1: Automatic Thesaurus Definition (ATD)

The objective of ATD is to automatically extract the domain phrases from the free-form documents and add the phrases into the predefined thesaurus. This not only reduces the time required for thesaurus definition, but also reduces relies on domain experts. All sentences in the target document would be fragmented and the fragmented phrases will be mapped to the thesaurus to mark each phrase with its type. Compare the sentences that contain unknown phrases with the sentence pattern rules to find the candidate types of the unknown phrases. A predefined threshold is used to determine the final types of the unknown phrases. Each unknown-phrase can be added to the corresponding thesaurus to enhance completeness of the predefined thesaurus (Figure 3).

The method would be based on a thesaurus, *Judge_Base*, which is used to define the motion knowledge in the target document that is used for further visualization. The *Judge_Base* contains 11 subsets, including *Position* Set, *Connection* Se, *Object* Set, *Movement Verb* Set, *Rotation Verb* Set, *Connection Verb* Set, *Number* Set, *Movement Direction* Set, *Rotation Direction* Set, *Movement Unit* Set and *Rotation Unit* Set.

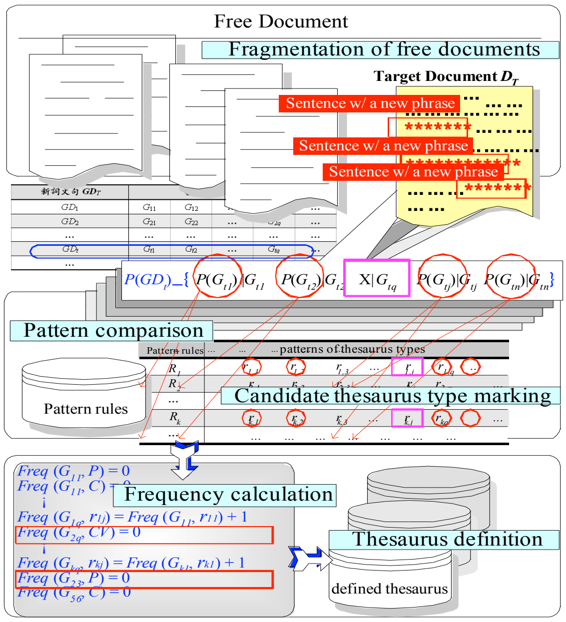


Figure 3. Procedure for ATD

**Step (1-a): Unknown phrase detection and candidate sentence tagging**

We assume that the acquired target document is composed with the candidate sentences. Based on the fragmentation rule [17][18], each sentence can be divided into the phrases segmented phrases.

To identify the corresponding thesaurus subset of each phrase, each phrase is compared with all predefined thesaurus subsets and marked with a corresponding phrase tag. If a phrase does not belong in any thesaurus subset, mark it as an unknown-phrase with a tag “X”. As all phrases in sentence are marked, all the phrase tags can be combined into a tag sequence of sentence.

**Step (1-b): Acquisition of new-phrase sentences**

A list of tag sequences can be derived after Step (1-a), and only sentences which contain unknown phrases (with tag “X”) should be concerned; moreover, these sentences are gathered in a new sentence group namely “new phrase sentences”. Each new phrase sentences sequentially includes the phrases, and its tag sequence is the same as the tag sequence of the corresponding candidate sentence.

**Step (1-c): Thesaurus definition for the document**

After Step (1-b), we compare the tag sequence with sentence rules; if all tags excluding the tag “X” are matched and the unknown phrase corresponds to the tag in the sentence rule, we will know that the unknown phrase is possible to be in the thesaurus subset which the matched tag represents. After determining the frequency of each posible tag, the probability of unknown phrase belonging in the thesaurus subset which a certain tag represents can be calculated.

**Step (1-d): Add unknown phrases into corresponding thesaurus subsets**

A threshold is defined to be compared with the probability that the unknown-phrase belongs to each thesaurus subset, if the probability is greater than the threshold, the unknown-phrase can be added in the corresponding subset. The greater the threshold is set, the higher the accuracy (of the unknown-phrase being in the correct subset) would be.

### 3.2 Phase 2: Target Sentence Extraction and Formatting (TSEF)

With ATD, each unknown phrase in the target document can be automatically added in the corresponding subset in the predefined thesaurus, automatically asuring its completeness. The purpose of TSEF is to extract the target sentences that contain motion knowledge by looking up the predefined thesaurus. Simultaneously, the extracted sentences can also be converted into formatted information matrix for further visualization. The conceptual process of the methodology is shown in Figure 4.

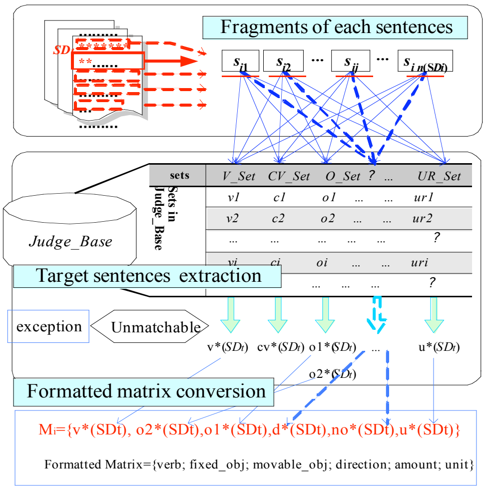


Figure 4. Procedure of TSEF

**Step (2-a): Target sentence extraction**

All sentences in the target document will be fragmented after phase one. The purpose of this step is to compare each sentence with the predefined thesaurus to indetify sentences that include motion knowledge. If a sentence includes motion knowledge, it is considered as a target sentence and will go on to the next step (2-b). This step contains three sub-steps:

- Step (2-a.1): Determine whether the target sentence includes a verb. If not, skip to the next sentence and start over from Step (2-a.1); otherwise, move on to Step (2-a.2).
- Step (2-a.2): Determine whether the target sentence is a complete motion sentence by checking if the sentence includes a connection verb, a moving object and a fixed object. If either one does not exist, then mark the sentence as an exceptional sentence for other special procedures; otherwise, move on to Step (2-a.3).
- Step (2-a.3): Compare the target sentence with the predefined thesauruses to check if the sentence includes the motion direction, amount and unit. Assign the default values for the ones that are lacked.

**Step (2-b): Target sentence formatting**

After extracting the motion-related phrases of sentence in previous step (2-a), the purpose of this step is to insert these phrases into a formatted motion information matrix. The matrix content includes the motion, fixed object, moving object, direction, motion amount and motion unit of the motion knowledge sentence (Figure 5).

$M_i$={v'(SDt), o2'(SDt),o1'(SDt),d'(SDt),no'(SDt),u'(SDt)}

M={verb, fixed-object, moving-object, direction, motion amount, motion unit

Figure 5. The formatted motion knowledge matrix

### 3.3 Phase 3: Motion knowledge Visualization (MKV)

Now that the target sentences are extracted from the document and converted into formatted matrix, we can use the matrixes contents to map to the mapping tables in order to acquire the corresponding graphs and visualization information for visualized display of the motion knowledge. The conceptual process of this algorithm is shown in Figure 6. The visualization procedure requires data and information such as the graph of the object, the object characteristics, the feature of the motions, etc. Thus, certain mapping tables are required to identify contents of the information matrix. The mapping tables include the object table, the character table and the motion table.

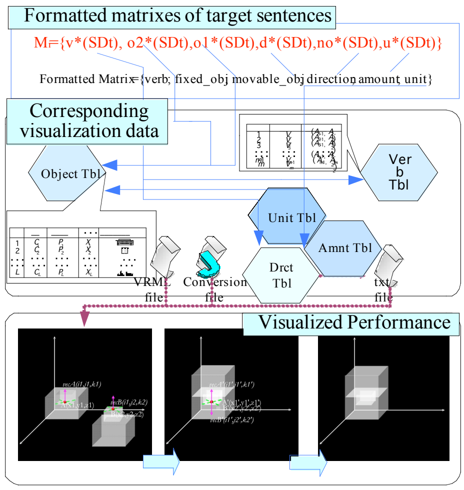


Figure 6. Procedure for MKV

**Step (3-a): Acquiring the original coordinate & vector of the moving object**

To enhance readability of the motion in visualization display, the locations of the two objects before assembly (or before the motion) should be clear and observable. Therefore, the fixed object is placed at the origin and the moving object is placed some distances beside it. From the formatted matrix, we can acquire the moving object and fixed object. By looking up the character table, the central point of the fixed object can be obtained. Similarly, the central point of the moving object can also be obtained. Since the starting point of the moving object should be located near the fixed object, the central point of the moving object should be translated via a translate vector. Moreover, scale of the vector must exceed maximum{length, width} values of both objects in order to avoid impractical conditions such as objects overlapping.

**Step (3-b): Acquiring the coordinate & vector of the moving object after assembly**

Now that the coordinate and vector of the object before assembly is known, the coordinate and vector after assembly should be derived in order to calculate the route of the objects motion. Since the fixed object will be fixed at the same position throughout the motion, only the coordinate and vector of the moving object after assembly should be determined. The motion can be acquired from the formatted matrix and the relative coordinate and vector of the objects after assembly can be derived by looking up the mapping tables.

Before moving the object to the terminal position, we first shift it to a key position, which is the position where the main motion actually starts, to enhance readability of the visualized motion. Based on the acquired final point, the key point can be obtained by using the motion direction and the motion amount of the formatted matrix.

**Step (3-c): Calculating movement and rotation amount of the moving object**

Through the previous steps we've acquired the starting point and key point of the moving object, now the purpose of this step (3-c) is to use a transform matrix to calculate the movement amount *Mamount* and rotation amount *Ramount* between the two points. The route of the moving object from the starting point to the key point could be defined by the *Mamount* and *Ramount*. By inserting the values of the starting point, starting vector, key point and key vector into the transform matrix, we can acquire the values of *Mamount* and *Ramount*.

**Step (3-d): Knowledge visualization**

The knowledge visualization step can be divided into two phases: the first phase is the motion of the moving object shifting from the starting point to the key point and the second phase is to move the moving object from the key point to the final position. By setting the variables *Ramount* and *Mamount* acquired from Step (3-c) into corrospoding visualization funtional lauguage codes, the visualization display could be generated.

## 4. Conclusion and Future Works

In this paper, we've proposed a motion knowledge representation and visualization approach to automatically extract and format core information within large quantity of text-oriented documents. The extracted and formatted motion knowledge will be represented via a knowledge visualization approach so that the domain knowledge could be more concretely expressed and knowledge acquisition efficiency can be enhanced. Via the three main phases (i.e., ATD, TSEF and MKV), target sentences that contain motion knowledge can be extracted from the free-form documents and converted into formatted representation by looking up the predefined thesaurus. Based on the formatted contents, visualized display of the motion knowledge can be generated via visualization fuctional languages.

Different from other studies, our paper focuses thoroughly from thesaurus construction, natural languages processing, to visual representation; for being a sequential process, all phases are tightly connected. Morover, in ATD, our thesauri could automatically expend when a new document is inserted, which is more efficient that other thesauri constructing methods with additional training phases required. In TSEF, we merely use a simple dictionary-based method with a sequential matching algorithm for information retrival, reducing complexity and time compared with other sophisticated mathematical IR methods. Last, though in the visualization field, there have already been various studies on how motions in visualization could affect the understandability and realness of the view, seldom application has taken this into account. Thus, in our MKV phase, the visualization processes could transform the motion knowledge into actual moving views, which would result in a better performance than the former static representations.

In the near future, we may establish a motion knowledge representation and management system based on our proposed approach. The main purpose of the system is to manage documents with motion knowledge systematically and efficiently and to facilitate knowledge receivers to acquire and absorb the knowledge accurately. The main functions would include document sharing, domain thesaurus maintaining, visual structure maintaining, user data maintaining and correspoding parameter setting. The main tasks of each function are listed as below:

- Document Sharing: This function includes tasks such as document uploading, full-text search, formatted motion knowledge search and visualized motion knowledge search. Users can upload free-form documents that contain motion knowledge to share with other users. Users can view the uploaded knowledge in original text form, formatted form or visualized display.

- Domain Thesaurus Maintaining: The tasks include domain thesaurus search, new domain phrase suggestion and domain phrase approval. Users can choose either to automatically derive or manually add new motion knowledge phrases in the domain thesaurus.
- Visual Structure Maintaining: Tasks such as visual structure search, new visual structure suggestion and approval. Users can recommend visual structure insertion to the system database and the suggestion will be approved by the system administrator.
- User Data Maintaining: Tasks include user data search and modification.
- System Parameter Setting: System administrators are authorized to setup correspoding parameter.

The architechture of this To-Be system is designed as in Figure 7.

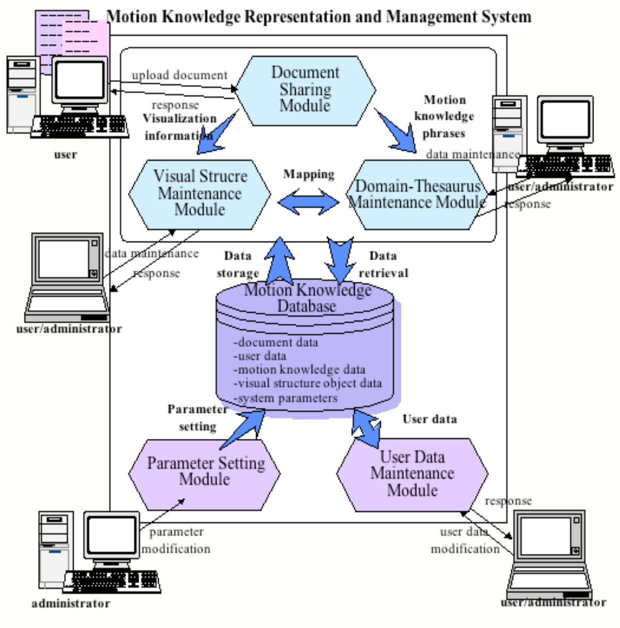


Figure 7. To-Be system based on the motion knowledge visaulization approach

The proposed approach and the To-Be system can be futurely established and validate. After the accuracy and efficiency is ensured, it could be applied in enterprise e-training and knowledge management, long-distance self-learning environments, and any other knowledge acquiring environments in order to lower the knowledge management cost, to improve knowledge acquisition efficiency, and to enhance domain knowledge reuse.

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