ABSTRACT

Requirements engineering is frequently seen as the activity of the software engineering process with fewer tools. Usually there are only available graphic and text editing aids. This is supported by the perception that it is a human-being-intensive task. This chapter is based on the understanding that such perception is just partially true. Models used along the requirements engineering process have underlying structures holding semantic information difficult to be seen by the reader. In fact, models created with well-defined objectives were designed to maximize their expressiveness for that objective. However, they may hold some useful shadowed information. Here is where a specialized tool may become valuable. From an epistemological point of view, this situation is similar to what happens in data mining. In this chapter, a tool able to make visible any clustering existing in universe of discourse glossaries is described. It is based on the automatic constructions of graphs using references embedded in the glossary itself.

INTRODUCTION

All models created during the software development process and specifically during the Requirements Engineering Process, are created with structures and purposes clearly defined. These structures have been conceived to maximize the expressiveness of the model for its objective.

Despite this, and very possibly because of this, it may occur that this models hold information no perceptible during its routine use. From an epistemological point of view, this situation is very similar to what happens in data mining (Artz, 2009). For particular case of Requirements Engineering models, which are written in natural language, it has been observed that at least part of this hidden information can be discovered.

In this chapter, a strategy to visualize the grouping of terms in a glossary called Language Extended Lexicon (LEL) is proposed. Experiments performed on real world cases have shown that the clusters
obtained using syntactic resources of the LEL model, coincide with semantic nuclei of the application domain. The proposed strategy is based on graphs constructed using hypertext links embedded in the LEL model.

Disciplines dedicated to the comprehension of phenomena whose dominant aspect is the structural complexity instead of the essential complexity of their components have been acquiring more importance (Barabasi, 2002; Dorogovtsev & Mendes, 2003). There are many examples, in several disciplines, where the detection of groupings provides a notorious contribution to the comprehension of the phenomenon being studied (Sarmah, Kalita, & Bhattacharyya, 2011; Mo, Cao, & Wang, 2012; Zimmermann, Ntoutsi, Siddiqui, Spiliopoulou, & Kriegel, 2012). Most evident examples of this sort of problems are the organizational networks, social networks, bibliographic references networks and interest groups among many others. The classic visual representation of these networks is done by means of graphs. Actually, it happens that when the number of nodes surpasses a moderated limit, those graphs become not useful to observe the relevant characteristics of the network. Configurations of nodes and connections also occur in a great diversity of other applications. They may represent physical networks, such as electrical circuits, roadways, or organic molecules. They are also used when representing less tangible interactions as might occur in ecosystems, sociological relationships, databases, or in the flow of control in a computer program (Gross & Yellen, 2003, 2006; Kamada & Kawai, 1989).

The requirements prioritization method proposed by Duan, Laurent, Cleland-Huang, & Kwiatkowski (2009), analyzes documents of the Requirements Engineering process by means of detecting clusters of requirements. In Duan proposal, the requirements are included in clusters by means of an iterative algorithm. Those clusters are object of negotiations among the stakeholders to assign priorities. Requirements inherit the priority assigned to the cluster to which they belong.

Some of the models of the Requirements Engineering may be studied from the structural point of view. Particularly, one of the most promising is the LEL (Leite & Franco, 1990). This model records the vocabulary used in the application domain. It describes the words and phrases used by clients and users with a meaning specific to the application domain.

Observing the LEL from a structural point of view, it may be immediately seen that it can be depicted using a graph where the vertices symbolize the LEL entries and the edges represent the hypertext links among entries.

From this point of view, the LEL may be visualized as a sort of linguistic network with a complex structure; in such a way that besides the explicit information stored in each symbol, there is implicit information stored in the relationships among symbols. To build and to analyze the graph of the symbols of the LEL is a sort of knowledge mining.

The most basic knowledge acquirable from the LEL graph is the existence of clusters of entries, which become roots for any taxonomy of the business process. Intuitively it may be said that if the application domain is divided into areas of interest or organization fragments, then it may be expected some coupling among the terms used in such area.

This chapter describes a mechanism to build the graph of any LEL, offering a good visualization of the existing symbol clusters.

The following section analyses the Language Extended Lexicon (LEL), a glossary built during Requirements Engineering process. Then, a section describing force directed algorithms applied to graph visualization is included. After that, the use of these methods in LEL graph construction is studied. And finally, some results, future work and conclusions are presented.
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