SEAMLESS SOFTWARE DEVELOPMENT FOR SYSTEMS BASED ON BAYESIAN NETWORKS

An Agricultural Pest Control System Example

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Abstract: This work presents a specific solution for the development of software systems that embed functionalities based and not based on knowledge, concerning the decision support process and the information management processes, respectively. When constructing a knowledge model, the processes to be performed are mainly focus on the description of the steps necessary to build it. Usually, all approaches concentrate on adapting the software engineering lifecycle to develop a knowledge model and forget the problem of integrating it in the final software system. We propose a process model that allows developing software systems that use a Bayesian network as knowledge model. In order to show how to apply our software process model, we have included a partial view of the development process of a knowledge-based system, related to decision making in an agricultural domain, specifically with pest control in a given crop.

1 INTRODUCTION

There is not a successful method that can solve the development of software systems that integrate software components based and not based on knowledge. Several solutions have been proposed to solve this problem partially. Some of them customize lifecycles (Alonso et al, 2000), or propose alternative process models (Acuña et al, 1999). Other propose to distinguish between a system definition at contents level, (bound to knowledge) and a definition at a container level (bound to software) (Gachet and Haettenschwiler, 2003), or propose the use models integrating components based and not based on knowledge (Águila et al, 2006). But all of them are descriptive proposals that should be developed in detail.

On the other hand, the development of knowledge-based systems (KBS) is a modelling activity which requires a methodology that ensures well-defined knowledge-models that are able to manage the complexity of the symbol-level in the construction process (Studer et al, 1998). Bayesian networks (Pearl, 1988; Cowell et al, 1999; Jensen and Nielsen, 2007; Kjaerulff and Madsen, 2008) can be used as knowledge-models to represent expert knowledge on an uncertain domain. Several authors have defined the process of constructing Bayesian networks (BNs) focusing on the steps to build the knowledge model (Laskey and Mahoney, 2002; Korb and Nicholson, 2003). But this works only adapt the software engineering lifecycle to the development of BNs models and forgets the problem of integrating them in the final software system.

Figure 1 shows the vision of a software development project from the points of view of a customer, a software engineer and a knowledge engineer. The knowledge engineer (Fig. 1A) makes use of knowledge engineering to define what is needed to be done (tasks) to build the software product, relegating to the background the tasks defined by software engineering. The software product that results is a KBS. The software engineer (Fig. 1B) applies its skills, tools and software engineering methods to develop a software product (system), where the knowledge is only another element. Finally (Fig. 1C), the customer focuses on quality and the need of cooperation between engineerings (Juristo and Acuña, 2002; Aguila et al. 2006; Studer et al., 1998) so that the final software properly covers all her/his needs. Thus, software components based and not based on knowledge must be integrated homogeneously. The lack of cooperation leads to a useless software product.

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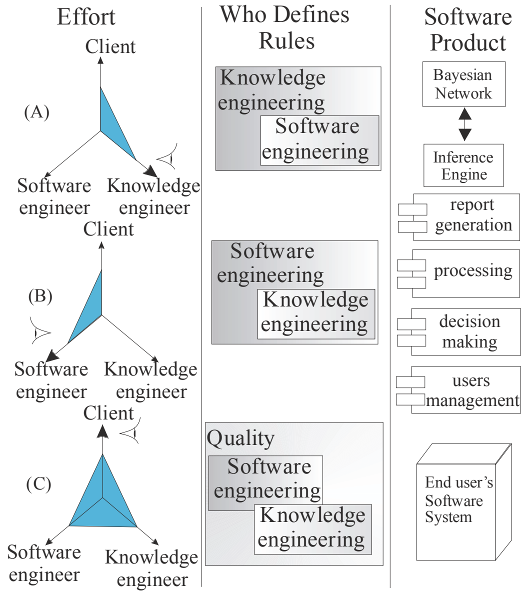


Figure 1: Views of the software development process.

In this paper we define a process model that allows the development of software systems in which BNs are used as the knowledge-based part of the system. Our goal is to define the tasks in order to manage the development of a software project which in turn includes the development of a knowledge model which, in our case, is a BN.

This paper is organized in three sections. Section 2 describes how to integrate the tasks for modelling knowledge in the software development project, defining our process model. Section 3, we have included a partial view of a KBS system development for decision making in agricultural pest control domain, as an application to a real world. Finally, conclusions are given in Section 4.

2 BN CONSTRUCTION IN THE SOFTWARE PROCESS

A software project has as goal to manage and translate the user needs into software. In order to do that, developers need to apply a methodological development approach following a well-defined process model, starting from business modelling and ending with the delivery of the software product. A software process model is a complete and well-defined set of activities required for converting user needs into a set of consistent artefacts making up a software product (Juristo and Acuña, 2002).

Our software process model integrates knowledge modelling as a workflow. Our goal is to construct, as homogeneously as possible, a software product in which a knowledge model is integrated as any other client needs. This is achieved through the execution of workflows. Our model has six workflows (Figure 2): Requirement Modelling (RM), Expert Modelling (EM), Specification of the Software Solution (SSS), Design of the Software Solution (DSS) Coding and Debugging (CD), and Software Evaluation (SE). These workflows are broken down in activities (Figure 3).

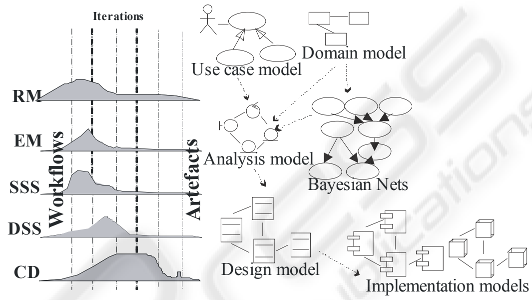


Figure 2: The process model proposed.

Requirement modelling (RM) characterizes the client's needs and the organisational context in which the software system has to operate. Working with requirements is a critical and complex process. The system scope has to be clearly identified, considering any benefit or impact of the software solution on the whole organisation, in terms of processes and domain concepts.

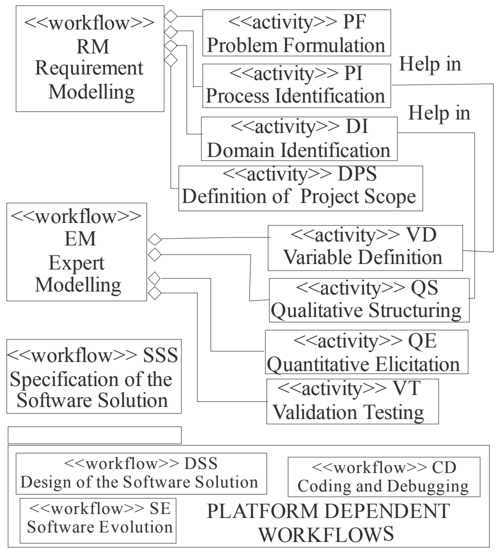


Figure 3: The process model proposed.

Expert Modelling (EM) is related to the artificial intelligence techniques applied in order to build the knowledge model. The methods used are interaction with experts (e.g. interviews) and 'learning' from databases when they are available. We focus on modelling knowledge as a BN, but our process model can be easily modified to integrate any other knowledge model (rules, neural networks,...) by redefining the activities needed for the specific type of knowledge model (Águila et al, 2006).

EM and Specification of the Software Solution (SSS) model the software in an implementational independent level. While EM focuses on knowledge, SSS focuses on requirements defining the set of functionalities. Some of these functions correspond to the knowledge model that is being defined during the EM. SSS activities are engaged in building a software model in which functionalities have a unified representation, without taking into account whether they are based on knowledge or not.

The design of the software solution (DSS), coding and debugging (CD), and software evolution (SE) workflows, are dependent on the coding language and on issues related to the hardware platform and they are out of the scope of this paper.

Through the execution of RM, EM and SSS workflows we can develop seamlessly a software product that embeds a BN as knowledge model.

2.1 Requirement Modelling

A software project starts by focusing on some of the business problems that can be improved by means of software systems to assist the business processes of the organization. The RM workflow is more than just a specification of future functionalities of the system. It extends the "what the system must do" approach to "why the system is like this" (Rolland and Prakash, 2000). If the improvements identified involve a non-software solution (e.g., an improvement in knowledge management, worker training tasks), then the software project is stopped. The RM workflow is broken down into four activities: problem formulation (PF), process identification (PI), domain identification (DI), and definition of project scope (DPS).

PF faces up to the description of the processes applied to solve the problem. The benefit, cost and impact that the software system has on the entire organization, must be identified. Here, any information analysis and elicitation techniques can be applied: joint application development, interviews and/or brainstorming.

Business processes are the set of processes defined in an organization in order to achieve its business goal. Each of them is characterized by a dataset produced and manipulated by a set of operations performed by actors. Here is where PI fits. PI techniques are those that express what must be done, such as functional analysis or protocol analysis. The artefacts used can be expressed by templates in natural language, or by diagrams (e.g. use cases, activities, state transitions or data flows).

Each of the business processes identified during PI manages data and information. DI activity is related with the process of building a domain model that describes the relevant concepts for the organization. Those techniques related to data modelling (e.g. glossaries, entity/relationships diagrams, class diagrams, etc.) are applicable in DI.

DPS activity has as goal to achieve a commitment about the project limits. With the artefacts previously defined, we must identify what are the business areas that can be improved by a software solution. DPS includes the task of building a feasibility study and the definition of a contract that reflects the scope of the software project.

2.2 Expert Modelling using BNs

Our aim is to model knowledge using only BNs, leaving other methodologies out of the scope of this paper. Formally, a BN (Pearl, 1988; Cowell et al, 1999; Jensen and Nielsen, 2007; Kjaerulff and Madsen, 2008) is a pair ***(G, P)***, where ***G*** *=(**U**, **A**)* is a directed acyclic graph (DAG), where the set of nodes $U = \{V_1, V_2, \ldots, V_n\}$ (i.e. the variables), and the set of directed edges (or arcs) ***A*** is the set of direct dependence relations between variables. ***P*** is a joint probability distribution over ***U***, given by: $P(V_1, V_2, \ldots, V_n) = \prod_{i=1}^{n} P(V_i|pa(V_i))$, where the conditional probability of each variable V_i in ***U*** given its set of parents, $pa(V_i)$, in the DAG is $P(V_i|pa(V_i))$.

Research on BNs research was initially focused on inference algorithms. Next research attention shifted to the difficulties of finding domain experts willing to share their knowledge and enter it in a software system. This developed into automated learning methods. Nonetheless, what is needed from a practical point of view is a methodology (Laskey and S. M. Mahoney, 2000; Korb and Nicholson, 2003) enabling the construction of BNs.

A BN has qualitative and quantitative components: a DAG and a set of conditional probability distributions. Thus, the EM workflow for BNs comprises four activities: variable definition (VD), qualitative structuring (QS), quantitative elicitation (QE), validation and testing (VT).

Normally, the process of building such a BN model is perceived by the expert as a tedious and time consuming effort. So it is desirable to get an early commitment between the expert and the engineer in order for them to have time enough to learn. The expert has to know what knowledge models are and what they can do, whilst the engineer must learn about the domain. Such aspects must have been previously tackled during RM in DI and PI activities. Once it is decided that BN modelling is plausible, the results obtained during PF and DI, can be used to identify variables. During VD hypothesis events, are detected and grouped into sets of mutually exclusive and exhaustive events to form hypothesis variables. Achievable information relevant to the hypothesis must also be collected. Then these pieces of information are grouped into information variables.

QS is in charge of representing relations between variables under the form of a DAG. A link represents dependence or influence between variables. The most usual techniques for modelling a BN based on its structure are *undirected dependence*, *parent divorcing* and *functional dependence* (Jensen and Nielsen, 2007; Kjaerulff and Madsen, 2008; Korb and Nicholson, 2003). QE must acquire the conditional probability distributions $P(Vi|pa(Vi))$ (Jensen and Nielsen, 2007; Kjaerulff and Madsen, 2008). QS and QE are activities intrinsically related, because the greater the number of parents of a variable, the greater the complexity of its associated conditional probability distribution. In those cases in which there are enough data available, machine learning techniques can be used in QS and QE (Neapolitan, 2004).

Finally, VT activity checks that the BN model meets specifications and that it fulfils its intended purpose. Validation can be expressed by 'Are you building the right BN model?' and testing by 'Are you building the BN model right?'

2.3 Specification of the Software Solution

This workflow is similar to the analysis task in the development of software that is not based on knowledge. The result is a model described in developer language that provides a conceptual view of the software system. Requirements must be refined as software functionalities, removing inconsistencies, and taking into account that some of these functionalities are related to the inference tasks carried out by the BN model developed in EM.

Any of the modelling languages used in software development may be used to describe this model. If an object-oriented approach is applied, the interface, entity, control, (Jacobson et al, 1992) and knowledge (Águila et al, 2006) stereotype classes can be used. An interface class models interactions between software system and actors. An entity class models long-term data or data persistent in the software system. A control class represents a use case or process coordination, calculations or controls. A knowledge class represents the inference tasks. The specification of the software solution implies thinking about the structure of the system and must serve also as a good starting point when dealing with its design. This modelling activity entails allocating the system behaviour in different object classes.

3 CASE STUDY

This section shows how to apply our software process model, giving a simplified description RM, EM, SSS workflows. We want to emphasize the collection of products that will be generated.

Our case is related to pest control in a given crop under the regulation of Integrated Production Quality standard (Águila et al, 2003). This standard is adopted by a group of growers in order to achieve a quality production certification. It involves intervention by technicians, marketing controls, and periodical inspection by the certification agencies.

Software project development starts with RM. The first activity consists of collecting, structuring and organizing all the relevant data for a concise and accurate definition of the problem to be solved by the software system (problem formulation–PF). Integrated production involves handling and storing a huge amount of information, and making decisions about all actions performed to fulfil the quality regulations. During PF, all of the business actors were interviewed and we identified the major improvements that could be achieved by applying new technologies. As result, we found that in an integrated production system, decisions are made at two levels. First, a decision is made on whether crop control action is necessary by sampling pests and estimating risk of attack. Then if it is decided that crop control action is required, the product (chemical or biological) to be applied has to be selected. The treatment advised has to respect natural enemies.

PI is done at the same time as PF. This activity generates a model of the processes identified which, in this case, are represented as use cases. The typical processes in an integrated production problem are shown in Figure 4. All tasks related to pest control are performed by growers and agronomists in the

Monitor crop process. Use cases, Market Produce, Act in Crop, Certify Crop Quality, and Finish Growing Season, are out of scope because they are all related to information required for quality management standards. DI models the data used in the processes. In the case, a crop is a complex system consisting of a plot of land, plants, a set of diseases and pests, and natural enemies that may be able to control them. The problem is to decide what treatment to apply, in order to maintain a balanced system. Figure 5, shows the diagram obtained as result of DI activity.

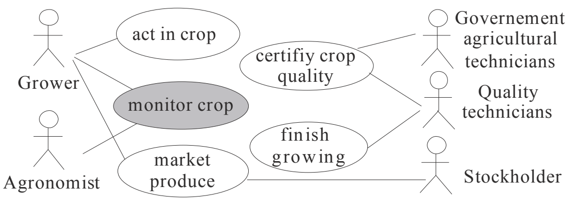


Figure 4: Processes in an Integrated Production system.

DPS is concerned with achieving a commitment that has to take the form of a contract. In this project our attention is focused on all the pest control processes performed in Monitor Crop. This use case can be described as the following informal scenario: “Each week, the agronomist samples the crop’s condition and makes an estimation of the risk of pest attack. Crop sampling consists of direct observation and count of harmful agents in randomly selected plants. Where imbalance is detected, the agronomist advises a treatment.”

As result of the RM a set of requirements and domain concepts have been defined. The scope of the project has been limited to estimating the risk of pest attack in grapes omitting the process of choosing a control action.

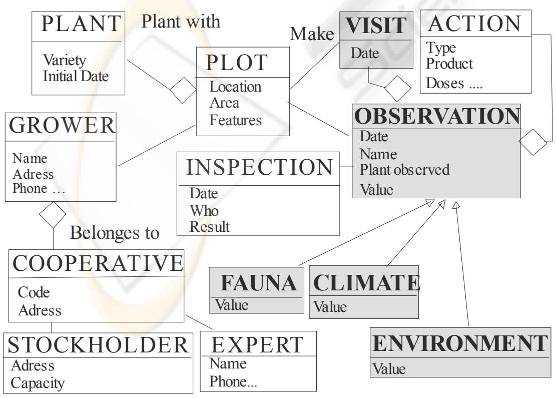
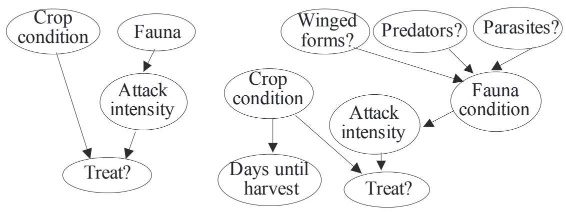


Figure 5: Domain identified.

The next workflow is EM and its first activity concerns to select the set of relevant variables. One of the benefits of our development approach is that the results found in the previous workflow RM, are reused during EM and help to reduce knowledge modelling effort. More precisely, DI activity helps in VD by identifying the main concepts to be considered for inclusion in the BN, whereas PI activity helps to identify relations between variables that can be used when defining the QS of the BN.

Within the scope of integrated production systems, the knowledge domain is shown shaded in Figure 5. When an agricultural expert visits a greenhouse, he writes down the date of the visit and samples the crop, including information about fauna, weather (wind, rain, etc.) and environment (weeds).

For each crop-harmful agent pair, we need only to consider an instantiation of the knowledge domain model represented. The general schema for a crop-harmful agent pair consists of observing the crop’s condition and fauna. Crop condition is measured in terms of its phenology. The presence of fauna is important to estimate the intensity of the attack. The crop condition, along with the intensity of pest attack, determines the need for applying a plant health treatment or not. Figure 6(a) shows the general BN structure elicited from the knowledge of the domain expert, whilst Figure 6(b) illustrates its application to the grape flea. Once the BN structure has been established, the probabilities are estimated (QE) based on a database of cases, completing the construction of the BN model. This expert modelling process has been successfully applied to determine the need of applying a treatment for the olive’s fly (dacus olae) (Sagrado and Águila, 2007).



(a) DAG for a general Integrated Production system

(b) A BN structure for the grape’s fly case

Figure 6: BN for Integrated Production Systems.

The SSS workflow produces the software model that has to be designed, coded and debugged. The model produced can be represented using the class stereotypes. A partial view of this model is shown in Figure 7. Action begins when an actor calls up a use case by sending a message to the system. In this case we begin with a *new visit* message. The agronomists interact with the system by entering a new visit and some sample data, and get a therapeutic action plan as the result. This interaction is done through the interface, *visit*, *sampling template* and *therapeutic plan* classes. The *toss* class performs the calculations necessary for selecting which plants a sample should be taken from. The *estimate pest risk* and *treat pest* classes make the inference. The information obtained is sent to the user by interface classes.

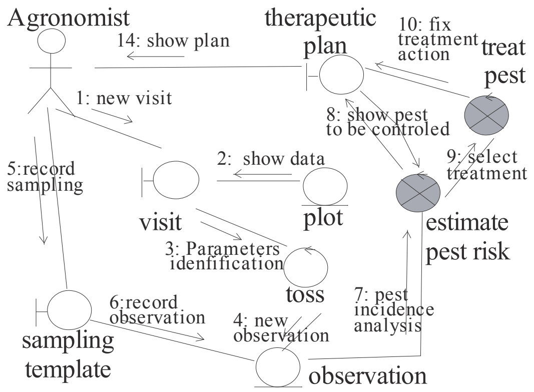


Figure 7: Partial view of a class diagram.

4 CONCLUSIONS

This work shows how to integrate methods of software and knowledge engineering into a unified perspective in which components, independently if they are based on knowledge or not, are integrated in shaping the software system for the end user. We have chosen BNs as technique to handle uncertainty in decision-making problems due to the non-existence of a software development process for systems that used them as knowledge model. Our process model allows the seamless inclusion of BNs into a final software solution for an organizational environment. The applicability of our solution has been tested in a real world problem: integrated production in agriculture.

In future works, it would be of interest to test the applicability of our approach to other real cases and attempt to adapt the EM to other knowledge modelling techniques in order to verify that we will substantially reduce the software development effort required, including the study of the horizontal dimension of the project (time and iterations).

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