

Applying Case Based Reasoning Approach in Analyzing Organizational Change Management Data

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Abstract. This work is a first step towards the application of a Case Based Reasoning (CBR) model to support the management of Enterprise System Implementation (ESI) related organizational change processes. Those processes are characterized by the occurrences of unplanned problems and events, which may lead to major restructuring of the process. We rely on ESI theory developed by the BEST project. The paper's focus is the matching process within the retrieval phase. We propose a procedure for similarity assessment between current experiences and past experiences. We enhance the applicability of CBR to ESI by encoding domain knowledge, according to BEST approach. The similarity measures are based on nearest-neighbor approach and Tversky's Contrast model. The proposed method assesses the similarity between events, while accounting their context similarity. Plans for future work are outlined.

1 Introduction

Enterprise System (ES) are software packages that offer integrated solutions to companies' information needs [1]. Enterprise Systems like ERP (Enterprise Resource Planning), CRM (Customer Requirement Management), and PDM (Product Data Management) have gained great significance for most companies on an operational as well as a strategic level. An ES implementation (ESI) process, as other system development processes, is a complex and dynamic process that cannot be fixed from the start. The process is characterized by the occurrences of unplanned problems and events [2]. These situations may lead to major restructuring of the process with severe implications to the whole company.

Given the growing significance and high risk of ESI projects, much research has been undertaken to develop better understanding of such processes, in various disciplines. Yet, the literature on ESI, information technology and organizational change management do not give substantial and reliable generalizations about the process dynamics and the relationships between information technology and organizational change.

In order to fill this gap, a European FP5 project, **Better Enterprise SysTem** implementation (BEST) was launched in 2002 [7]. The aim of the BEST project is to understand the dynamics of ESI processes, and help improve organization readiness to deal with such issues by acquiring knowledge of process dynamic from existing ESI projects. The BEST project developed a general construct that can be used to capture the knowledge accumulated in existing implementation processes. This includes identification of events that occur within the implementation process, and the mapping of these events in terms of chains called Cause-Event-Action-Outcome (CEAO). Knowledge on what happens in an implementation project is documented using CEAOs and, in that way, the capability of analysts and consultants to identify and act upon unexpected or unintended events and problems is enhanced (see [9],[12]).

In this work we apply quantitative analysis to CEAO chains in order to improve ESI management by combining the ESI theory developed in BEST with a Case Based Reasoning framework.

Case Based Reasoning (CBR) is a problem-solving approach that relies on past similar cases to find solutions to problems [3]. Case-based Reasoning means to use previous experience represented as cases to understand and solve new problems. A case based reasoner remembers former cases to fit for the current problem.

In this paper we focus on the matching process within the retrieval phase and propose a procedure for similarity assessment between current experiences and past experiences. We enhance the applicability of CBR to ESI by encoding domain knowledge into several similarity measures. We propose a method to assess the similarity between events, while accounting their context similarity and outline plans for future research [21].

2 Why Case Based Reasoning to Support Organizational Change Management?

ESI related organizational change is a complex and dynamic process, with high uncertainty accompanied by unexpected problems. These potential events are related to a large number of variables that belong to organizational, human and technological aspects. In addition, the relationship among these variables is unclear. Knowledge acquisition in such an ill structured domain is very complex, so that applying Rule Based models, with problem solving algorithms expressed as rules, is highly unsuitable. In addition, even if the necessary knowledge is elicited, the representation of this knowledge would generate a multitude of rules and modeling all its interactions would be infeasible. Unlike Rule Based models, CBR models deal with case specific knowledge and do not require that the domain knowledge is modeled by rules.

The management of the ESI process is highly dependent on the ability of the people involved in the process (e.g. project manager, ES vendor, consultant, etc) to identify and solve problems. In general the solutions that are given to such problems rely on experiential knowledge and intuitive appreciation rather than on a systematic methodology. The solutions often have qualitative and subjective argumentations and sometimes cannot be characterized as effective or not. ESI experience is

difficult to formulate using rules, but easier to be viewed as distinct cases. For these reasons, we find the CBR approach a suitable paradigm for supporting the ESI process management.

3 Case Based Reasoning Background

3.1 CBR Cycle

The CBR principle is based on an analogy to the human task of “mentally searching for similar situations which happened in the past and reusing the experience gained in those situations” [4]. The underlying idea is the assumption that similar problems have similar solutions. Though this assumption is not always true, it holds in many practical domains [5]. CBR works on a set of cases derived from experience and stored in a CEAO data base. When faced with a new specific problem, CBR retrieves a case that is similar to it from a CEAO data base, and if necessary, will adapt it to provide the desired solution [6].

Although the full CBR cycle is a retrieve–evaluate–adapt–learn process, many CBR systems implement only the retrieve step, thus applying the concept of reuse of experience. Retrieval-only CBR is useful when the differences between two cases are complex, and the main request from the system is to visualize current and similar cases, and point out the important differences between them. Such systems are common in the medical domain, e.g. [8].

3.2 The Matching Process in the Retrieval Phase

The measure of success of a CBR system depends on its ability to retrieve the most relevant previous cases to support the handling of a target case, and ignore irrelevant previous cases [6]. The retrieval of more similar cases to a new problem reduces the load of adaptation and leads to more precise solution.

Thus, one of the key issues of CBR is to define how a previous case (a source case) is selected given a current case (a target case). The retrieval step is based on creating a searching mechanism to estimate the similarity between source and target case. The searching mechanism is differentiating between CBR retrieval and a simple database search. CBR retrieval is based mainly on two methods, both can be found in most commercial CBR tools [10]: Inductive methods which use an induction algorithm to produce decision trees that classifies the cases, and similarity classification methods that assess the similarity between cases by aggregation of pair-wise similarity along case’s descriptors, using predefined similarity measures [11]. Combinations between the two are common, sometimes accompanied by knowledge-guided approach applies existing domain knowledge to locate relevant cases [17].

“Matching” assesses the degree of similarity of a candidate previous case with a current case. Since the formulation of a similarity function that approximates directly the degree of similarity is usually unattainable, one tries to decompose the problem so that matching involves establishing the similarity of the representation of the current case with the representation of the previous case. The procedure usually employed to

define similarity measure is a “bottom up” approach that can be characterized as a “Divide and Conquer” strategy [14]. It assumes an attribute-value based case representation.

Two procedures that have been widely used to determine overall similarity are nearest-neighbor approach and Tversky’s contrast model [16]. Both methods assume that objects are represented as collections of attributes, so that similarity becomes an attribute matching process. A comprehensive investigation of similarity indices in the context of comparing frequency distributions of genetic characteristics of various populations is presented in [18]. Statistical properties of such indices can be derived using cross-validation and bootstrapping techniques [25], [26].

Nearest Neighbor Approach

The nearest neighbor technique is a nonparametric classification algorithm in which the similarity is based on matching a weighted sum of attributes between stored cases and the current problem case.

The feature weighting algorithms alleviate the problem of the presence of irrelevant features in the case representation. Usually, the number of attributes and the weighting coefficient of each attribute are invariant for all cases [19]. The overall similarity (SIM) determined by nearest-neighbor matching function is mathematically represented as follows [3]:

$$SIM(T, C_k) = \frac{\sum_{i=1}^n w_i \cdot sim(a_i^T, a_i^{C_k})}{\sum_{i=1}^n w_i} \quad (1)$$

where, a_i^T is the i^{th} descriptor of the target case, $a_i^{C_k}$ is the i^{th} descriptor of the k^{th} candidate source case, the superscripts T and C_k refer to the target case and the source case respectively, $sim(\cdot)$ is a function, rule, or heuristic that determines the pair-wise similarity along a descriptor; and w_i is the weight representing degree of importance of the i^{th} descriptor towards the problem.

Tversky’s Contrast Model

Tversky’s Contrast model is one of the most influential models in the psychology research [20]. The similarity between objects A and B is based on the ratio between their common and distinctive features [16]. Specifically as in [22]:

$$S(A, B) = \frac{|D_i|}{\alpha|D_i| + \beta|E_i| + \gamma|F_i|} \quad \alpha = 1, \beta, \gamma = 0.5 \quad (2)$$

with D_i the features that are common to both A and B; E_i the features that belong to A but not to B; and F_i the features belong to B but not to A.

4 Domain Knowledge – The BEST Approach

This section presents some of the BEST project outcomes [9], which serves as a basis to the knowledge we utilize in the model.

Reference Framework

The reference framework addresses the view of the overall enterprise characteristics and constitutive elements, which influence the implementation of an ES. The framework identifies important technical as well as organizational and human aspects that play a role in several processes. These processes are called dimensions and include the Business process, the Project Management process and the ES process. In addition it defines six organizational aspects: Strategy & Goals, Management, Structure, Process, Knowledge & Skills and Social dynamics. The 18 cells created by the intersection of dimension and aspect are called focus cells [12], [13].

CEAO Chains Database

CEAO chain is a mapping of a problem and solution, contains of the following items: *Event* is defined as a problem created by decisions, actions, or by events outside the control of the organization. A *cause* is an underlying reason or action, leading to the event. For each event it is possible to specify one or several causes, which are linked to the event through a parent-child relationship. An *Action* is the solution taken to resolve the event; it includes method of performing or means used. Each action is connected to *outcomes*.

The CEOA chains identified through the case studies and were captured and perceived by actors with different roles involved in an ESI-process. The mapping of causes of the CEOA chains into reference framework has led to different clusters of CEOA chains. Each cluster belongs to a focus cell in the framework.

Context of the ES Implementation

Context data provide a view of the company and ES, such as company size, type of ES, cultural region etc. It is expected that ES implementation process execution is influenced by those characteristics. Context sensitivity analysis was done in an attempt to distinguish between local pattern (occur only in specific situations due to the context characteristic), and generic pattern that can be generalized across ES implementation processes. For example, if we compare two different size companies: SME (less than 250 employees) and Large (more than 250 employees), it is expected that there are size-dependent patterns, such as greater project resources and higher complexity adoption process in a large company, that cause major differences in the ESI processes.

Readiness Scoring

The readiness scoring provides a measure of readiness according to the BEST Reference Framework. This step consists of answering the questions related to the aspects of the reference framework. Each answer is scored according to predefined scores. The scores are summed in the aspect level and create an aspect score indicating the status of the company in each aspect.

5 Knowledge-Based CBR Retrieval to Support Organizational Change Management

5.1 Domain Knowledge Utilized

We combine the knowledge gathered in BEST ESI theory to improve the matching process. The proposed matching process is based on the following constructs:

1. The problem is defined in terms of the event’s causes and not in terms of the event. The underlying assumption is that the solutions (actions in the CEO chains) are suited to handle the origin of the problem, i.e. the cause, since the same event may stem from totally different causes.
2. The search for similar events is focused by inferred local /generic patterns of the context properties, due to their considerable influence on ESI processes.
3. The company profile score in each of the six aspects is a risk indicator to the company status in this aspect. Similar scores between cases implies similar environment, and similar influence on the problem solution process.

Figure 1 describes the knowledge-based matching. It is assumed that if cases are similar, effective solution strategies adopted in past case is expected to be effective on the target case as well.

In this work we do not include the solution component (chain’s actions and outcomes) in the case representation since it is relevant to the adaptation stage which is out of scope of this paper.

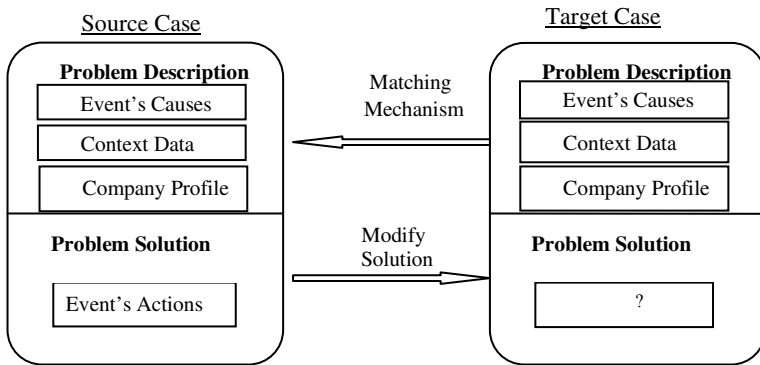


Fig. 1. Knowledge-based Matching Mechanism

5.2 Case Representation

An ordered vector of four components represents each case (C). Each element (E_i) of this vector describes a property, this property’s importance (weight), the property’s value and the property’s group $C = \{E_1, \dots, E_l\}, E_i = (P_i, W_i, X_i, G_i)$ where P_i is

the property's name, W_i is its weight, X_i is the value assigned to this property, and G_i is the property group.

The constructs of the model, distinguishes between three properties' groups (see equation (3)). The G_1 properties are the event's causes' clusters. Each event may have several causes' clusters. We compute the marginal distribution of each event causes clusters in the CEAO chain by summing the reference framework rows, resulting in the definition of event's aspect. The G_2 properties are the context data and the G_3 are the company profile scores. The property's weight (W_i) is used, in this paper, only by G_3 properties and denotes the importance of the company profile score in each aspect, with respect to event's aspects. The weights are assigned by a domain expert who estimates this importance level.

$$X_i = \begin{cases} n_{event_aspect_i} & P_i \in G_1 \quad i = 1, \dots, 6 \quad n = 1, \dots, r \\ Context_attribute_value & P_i \in G_2 \quad i = 1, \dots, m \\ Score_{profile_aspect_i} & P_i \in G_3 \quad i = 1, \dots, 6 \end{cases} \quad (3)$$

5.3 The Retrieval Phase

5.3.1 Overview

The retrieval process is described in figure 2. Based on the context properties of the target case, the case-base is searched for candidate previous cases that match the context attributes of the target case. This is done according to the existence of generic and local patterns. This search increases the efficiency of the retrieval because only a subset of the case-base is examined. However, appropriate cases may not be retrieved. This is followed by a matching process, presented in the following section, that combines similarity between the events and similarity between the company profiles [21].

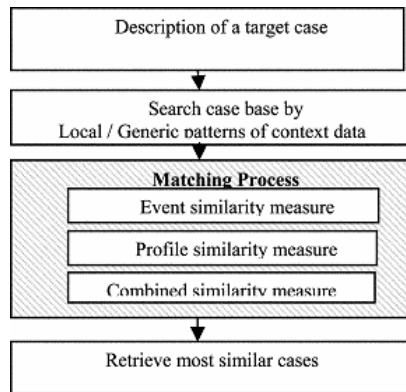


Fig. 2. The retrieval phase

5.3.2 Matching Process

Step 1 - Event Similarity Assessment

The overall event similarity measure $SIM_{event}(T, C_k)$ is based on Tversky's contrast model (equation 4):

$$SIM_{event}(T, C_k) = \frac{\alpha |D_i|}{\alpha |D_i| + \beta |E_i| + \gamma |F_i|} \quad \alpha = 1, \beta, \gamma = 0.5 \quad (4)$$

where D_i is the number of the common aspects in both events, E_i and F_i are the number of contradicting aspects. The local similarity measure between each event's aspects (cause's clusters) of a target event and a source event is defined in equation (5):

$$sim_{event_aspect_i}(T, C_k) = \begin{cases} D_i & n_{event_aspect_i}^T \geq 1, n_{event_aspect_i}^{C_k} \geq 1 \\ E_i & n_{event_aspect_i}^T \geq 1, n_{event_aspect_i}^{C_k} = 0 \\ F_i & n_{event_aspect_i}^T = 0, n_{event_aspect_i}^{C_k} \geq 1 \\ N_i & n_{event_aspect_i}^T = 0, n_{event_aspect_i}^{C_k} = 0 \end{cases} \quad (5)$$

Step 2 - Profile Similarity Assessment

The overall profile similarity measure $SIM_{profile}(T, C_k)$ is based on nearest-neighbor approach, a weighted sum of the profile similarity measures, over all six profile aspects (equation 6).

$$SIM_{profile}(T, C_k) = \frac{\sum_{i=1}^6 sim_{profile_aspect_i}(T, C_k) \cdot w_{profile_aspect_i}}{\sum_{i=1}^6 w_{profile_aspect_i}} \quad (6)$$

where $sim_{profile_aspect_i}$ is the local similarity measure between the profiles in each of the six aspects (equation 7), and $w_{profile_aspect_i}$ is its weight (equation 8).

The local profile similarity measure is a simple distance-based function [27]:

$$sim_{profile_aspect_i}(T, C_k) = 1 - \frac{|score_{profile_aspect_i}^T - score_{profile_aspect_i}^{C_k}|}{score_{profile_aspect_i}^{\max} - score_{profile_aspect_i}^{\min}} \quad (7)$$

in which $score_{profile_aspect_i}^{\max}$ and $score_{profile_aspect_i}^{\min}$ are the maximal and minimal values among all cases (including the target case), respectively.

The profile similarity measure weight $w_{profile_aspect_i}$ is a combination of the two compared case's weights (W_i), as in equation (8):

$$W_{profile_aspect_i} = weight_combination(W_{profile_aspect_i}^T, W_{profile_aspect_i}^{c_k}) \quad (8)$$

The weight combination is the method used to designate the importance of the local profile similarity in the overall profile similarity calculation, as induces by the weights of the corresponding company profile aspects in the compared cases. This method enables the assignment of an independent weight to each company and then combines it by a method such as “minimum”, “maximum”, “mean” or “l-power”[31]. The different choices of weight combination will place more or less emphasis on company profile aspects affecting strongly only one of the cases. For example, the “minimum” combination, which takes the lesser of the two cases weights, tends to give less importance to properties affecting strongly only one of the cases.

Step 3 – Combined Similarity Assessment

Based on Tversky’s Contrast Model, under the assumption proposed in [28], a function $f(\text{object})$ can be defined as an interval scale of each of the objects (D,E,F).The function reflects the salience or prominence of the various objects, thus measuring the contribution of each feature to the overall similarity.

The scale values $f(D)$, $f(E)$ and $f(F)$ associated with objects (D,E,F) are therefore measures of the overall salience of D,E,F which might depend, for instance, on intensity, frequency, familiarity or informational content [29].

We apply this logic, and define the overall salience of D, E and F to be the sum of the local profile similarity measure in this aspect. In this way the relevant profile aspect similarity is combined into the event causes similarity, expressing the “amount” of similarity between the events in a ‘wider environmental context’. This is expressed in equation (9):

$$SIM(T, C_K) = \frac{\alpha \sum_{i \in D} WS_{profile_aspect_i}(T, C_k)}{\alpha \sum_{i \in D} WS_{profile_aspect_i}(T, C_k) + \beta \sum_{i \in E \cup F} WS_{profile_aspect_i}(T, C_k)} \quad (9)$$

where, $WS_{profile_aspect_i}(T, C_k) = sim_{profile_aspect_i}(T, C_k) \cdot W_{profile_aspect_i}$ is the weighted similarity between target and source case in aspect i , and $\alpha = 1, \beta = 0.5$.

An alternative to this method is to combine between the overall event similarity-measure $SIM_{event}(T, C_k)$ (equation (4)) and the overall profile similarity measure $SIM_{profile}(T, C_K)$ (equation (6)) by ranking into order of similarity, calculating a Rank Score (RS), in the following manner [23]:

1. Ranking all the matching candidate cases in ascending order by the overall event similarity measure $SIM_{event}(T, C_k)$.
2. Ranking all the matching candidate cases in ascending order by the overall profile similarity measure $SIM_{profile}(T, C_K)$.
3. Taking an average of the two rankings, as shown in Equation (10).

$$RS = \text{round}\left(\frac{R_{SIM_{event}}(T, C_k) + R_{SIM_{profile}}(T, C_k)}{2}\right) \quad (10)$$

where: $R_{SIM_{event}}(T, C_k)$ and $R_{SIM_{profile}}(T, C_k)$ is the ascending overall event and profile similarity case's ranks, respectively.

6 Concluding Remark and Future Work

This work is a first step towards a CBR model to support the management of ESI related organizational change processes. We have used domain knowledge in order to represent an event in its wider environmental context, i.e. the characteristics of the company and the ESI process. We propose a matching process in which a linear weighting model provides a company's profile similarity measure that is combined with the events' similarity measure through Tversky's Contrast model [21]. The proposed matching approach is more of a demonstrative and confirmatory proof to the capability of CBR model, however it may not well address all problem's components. The presumed linear effect of the profile similarity measure on each aspect may be not realistic. Moreover, profile scores are taken as deterministic, and the weights assessment is a highly subjective process. This implies that more robustness evaluation methods are needed. The evaluation of methods applied to the BEST database, can rely on bootstrapping and cross-validation techniques [25, 26].

Below, we detail some planned directions to enhance the ESI CBR model. Fuzzy set theory was proved to model reality more naturally and adequately [30]. Since the ESI CBR model is connected with human judgment, evaluation and reasoning, a hybrid approach with fuzzy methods may make it more powerful.

In order to reduce the sensitivity of the nearest neighbor approach to the profile weight an Analytic Hierarchy Process (AHP) methodology can be incorporated in the CBR model [24]. AHP is an effective methodology in obtaining domain knowledge from numerous experts. It can be used for assigning relative importance of profile weighting. The sensitivity to the distance function can be handled through the use of various distance functions as demonstrated in [18].

In this work we focus on the CBR retrieval phase. The CBR adaptation phase, in which the solutions of former similar cases are modified to fit the current event will be presented in future work. A catalogue of ESI Improvement tools [9] was developed by BEST project and forms a basis for tailoring improvement actions according to a specific situation. The catalogue may enhance the expert knowledge in formulating the adaptation method.

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