

# On the Collaborative Development of Para-consistent Conceptual Models

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## Abstract

*There have been various proposals for the formalization of appropriate viewpoint-based frameworks. Each of these approaches have been devised with a specific motive and to address an important concern. The model that we propose in this paper attempts to provide a basis for conceptual model integration particularly with the existence of partial ignorance and uncertainty. The model attempts to formalize the degree of uncertainty present in experts' expressions, and proposes tools for conceptual model integration and formal consensus building between the involved viewpoints. Metrics for measuring integration effectiveness have also been proposed in this paper. The model proposed in this paper has been employed in a case study to collaboratively develop a conceptual model for the Pet Store application.*

## 1 Introduction

Software engineers have been interested in using information from multiple sources to create a concrete, consistent and complete compilation of software requirements. Sources of information are mainly known as viewpoints. Nuseibeh defines viewpoints as 'loosely coupled, locally managed distributed objects which encapsulate partial knowledge about a system and its domain, specified in a particular, suitable representation scheme, and partial knowledge of the process of development' [3]. Although not all models of viewpoint-based requirement engineering conform to this definition, most of them roughly agree on this basis. The intuition behind this practice is that various information sources, more specifically human evidences in this case, have different areas and amount of knowledge that may help in better analyzing the problem. They may also each use different styles of knowledge expression that can itself be helpful in beating the concern.

In this paper, we propose a model for the process of collaborative conceptual model design. We explicitly capture the degree of uncertainty that the participating viewpoints

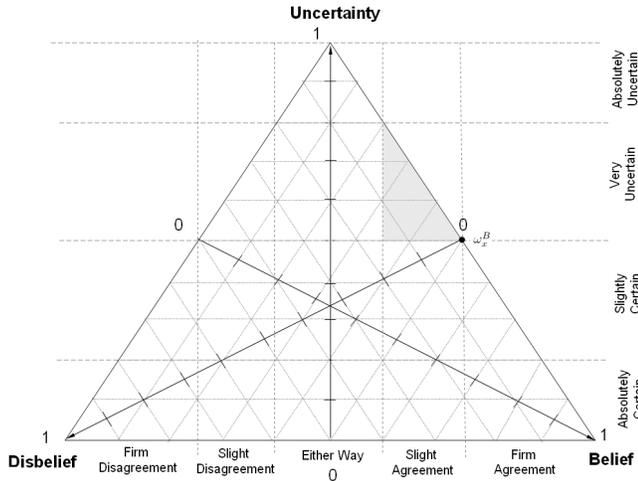
may have in certain aspects of the design and exploit the quantified degree of uncertainty to devise models for merging the developed conceptual models. We employ Subjective logic (an extension to the Dempster-Shafer theory of evidence that incorporates an explicit notion of uncertainty) to represent the belief of the viewpoints in their design i.e. each element of the model is annotated with belief values. We also propose methods for converting quantitative belief values into linguistic terms. Models for measuring the reliability of the involved viewpoints and the efficiency and effectiveness of the model merge process has also been proposed. The paper is organized as follows: Section 2 discusses some of the fundamental developments of the work, and Section 3 continues with the proposal for the model merge, consensus formation, effectiveness evaluation, reliability analysis and model pruning problems. In Section 4 the proposed model is evaluated through a case study, and the paper is then concluded in Section 5.

## 2 Formal Basis

In this section, we will discuss the theoretical basis of our approach [1].

### 2.1 Opinion Foundation

In the process of modeling with the involvement of various experts, each piece of gathered information can be represented in the form of a declarative expression. As an example, consider a case in the design of an electronic learning system where one of the analysts ( $A_i$ ) has defined the concept of 'course' as a UML class. This can be expressed as ' $belief(A_i, class(course))$ '; which means that expert  $A_i$  believes that a course should be modeled as a class in the conceptual model. Based on this model, since the analyst does not have any doubt (uncertainty) about the expressed specification, he/she is completely certain that he/she does not believe in modeling a course as an attribute of a larger class. It can be seen from the example that the set of hypotheses only consists of  $x$  and its complement ( $\bar{x}$ ); there-



**Figure 1. Experts' Linguistic Opinions are Bound to the Interior Space of an Equal-sided Triangle.**

fore, the frame of discernment is binary, which means that there are only two hypotheses here that can receive belief masses in the framework of belief calculus. It is logical to employ Subjective logic an extension of the Dempster-Shafer theory of evidence that supports belief representation and reasoning in binary frames of discernment. Subjective logic explicitly defines uncertainty as a separate dimension which is actually implicit in the definition of belief in the Dempster-Shafer theory. This is a major advantage for our purpose since we intend to capture experts' uncertainty about their expressions. A belief expression in Subjective logic is defined as a 3-tuple  $\omega_x^A = (b_x^A, d_x^A, u_x^A)$ , also known as the opinion of expert  $A$  about hypothesis  $x$ . It can be shown with this definition that belief, disbelief, and uncertainty elements of an opinion should satisfy:  $b_x^A + d_x^A + u_x^A = 1$ . This equation restricts the possible values that can be expressed as an opinion by an expert only to the points placed in the interior surface of an equal-sided triangle. The three constituent elements determine the position of an opinion within the triangular space. Figure 1 shows the three axis that can be used to identify the position of an opinion point in the triangle. In the opinion triangle, the line connecting absolute belief and absolute disbelief corners (right and left corners) is called the probability axis. This is because the removal of uncertainty from Subjective logic will result in a pure probabilistic interpretation of belief (i.e.  $b_x^A + d_x^A = 1$ ).

### 2.1.1 Linguistic Opinions

Domain experts and analysts are generally uncomfortable with expressing their opinions in an exact probabilistic form. They prefer to use common linguistic terms to articulate their opinions in a rough manner. For this reason, it is required to convert linguistic expressions of the experts into a mathematical format so that calculations can be performed and then re-convert the mathematical values into linguistic terms for expert comprehension.

As it can be seen in Figure 1, the uncertainty axis and the probability axis have been divided into four and five sections, respectively. Each of these divisions represent a linguistic term. For example, the partitions on the uncertainty axis have developed the absolutely uncertain, very uncertain, slightly certain, and absolutely certain terms that can be used by the experts. On the other hand, the divisions on the probability axis has created five linguistic terms, namely firm disagreement, slight disagreement, either way, slight agreement, and firm agreement. If we consider the spaces that are created by the intersection of these two divisions, we will have various sub-spaces within the triangle that roughly represent certain linguistic expressions. For example, the gray area in Figure 1 represents the kind of opinions by the experts where the expert is rather ignorant of the correctness of the proposition but thinks that the proposition is more likely to be correct; therefore, an opinion like  $\omega_x^C = (0.3, 0.05, 0.65)$  is located in the gray area and is interpreted as 'expert  $C$  is very uncertain about  $x$ ; however, at the same time, prefers to slightly agree with it'. Once an opinion has been expressed in a linguistic form, it can be converted into its mathematical representation by first finding its correct location in the triangle, and then taking the value of the belief elements of the center of gravity of the corresponding sub-space as the representative of the expressed opinion.

### 2.2 The Core Representation Model

The integration of conceptual models is the issue of many different application domains such as requirement engineering, database schema development, and ontology creation to name a few. For this reason, it would be enticing to create an integration model which is independent of the actual conceptual modeling formalism that has been used to create the specifications. To achieve this, a lower level modeling construct is required so that the higher level conceptual models can be mapped through it and the reasoning process be performed based on the lower level belief structures. The results of the operation on the lower level models can then be mapped back to the higher level conceptual models.

Construct is a low level modeling notion that we propose for processing higher level models. It has the capa-

bility to be decorated with belief elements that can be used for reasoning and integration. Construct has four segments: Attributes, Opinion, Pre-condition, and Post-condition. Attributes are the set of elements that are needed in the higher level model. Construct has three default attributes that can be extended by analysts. These attributes are Name, Cardinality, and Contributors. The name attribute allows each construct to have a unique name, cardinality defines the number of identical instances that are permissible, and the contributors attribute is used to identify the list of experts (viewpoints) that have affected the definition of this instance of the construct used for traceability purposes.

The belief segment consists of three elements namely belief, disbelief, and uncertainty that are employed to assign subjective opinions to each instance of the construct. Pre-conditions and post-conditions are the set of circumstances that need to hold before and after the creation of an instance of a specific construct. Suppose that a group of analysts each representing a different viewpoint have agreed upon using the class diagrams of the unified modeling language as the high level conceptual modeling language. In order for them to be able to use our proposed integration model, the underlying construct model should be customized for the class diagram of the unified modeling language. Here, we show how the class, notion from the set of all concepts in the class diagrams can be defined in the construct format. The definition of the rest of the concepts in the UML, ERD, OWL, etc. are very similar to what is shown in the following.

```

Construct Class (instanceName)
Attributes
  name= instanceName
  Cardinality=1
  Contributors=*
Opinion
  belief=1
  disbelief=0
  uncertainty=0
Pre-condition
  belief(X, this.name)<disbelief(X, this.name)
  + uncertainty(X, this.name)
Post-condition
  if (belief(Class, this.name)>0.5) {
    disbelief(X-{Class}, this.name)=belief(Class, this.name)
    uncertainty(X-{Class}, this.name)=disbelief(Class, this.name)
    +uncertainty(Class, this.name)
    belief(X-{Class}, this.name)=0
  }
End Construct

```

As it can be seen in the definition, the name of each instance is to be assigned by the analyst, and only one instance of each concept with the same specification is permitted. Opinions are set to complete belief by default that will be over-riden by the belief values that are provided by the analysts. If no belief value is assigned to the concepts, a full degree of belief is assigned to it; therefore, in cases where the modelers feel that assigning belief values are a big burden they can ignore it and a full belief value will be assigned automatically.

The most important section of the definitions are the pre

and post-conditions. In the Class construct, it should be made sure that if a different construct instance has been created with the same name, the belief of the analyst is lower than the sum of the uncertainty and the disbelief for that instance. This pre-condition makes sure that there exists a certain degree of belief that can be assigned to this construct. In the definitions above,  $X$  is a variable that can be unified with any defined construct.

Post-conditions are propositions that should hold having expressed an instance of the construct. For example, the post-conditions for the Class construct are that if the belief value assigned to an instance construct is higher than 0.5, all other constructs instances with a similar signature other than the Class construct should be assigned the complement of the belief value assigned to this instance of the construct. This condition does not apply to constructs with a belief lower than 0.5, since a person may disagree with multiple construct instances which does not mean that he/she agrees with the other constructs and therefore the other constructs should not receive the complement of the belief.

## 2.3 Expert Reliability Analysis

In our perception of viewpoint-based specification, concerns are one of the most important aspects of the model. The definition of concern in our model is similar to what has been defined in [5]. Based on this definition, each viewpoint may be responsible for considering the information regarding several specific concerns of the system. Since not all analysts have the same degree of expertise in all of the different concerns that are considered in the elicitation process, a reliability metric needs to be defined. This reliability metric can be used to discount the information which is expressed by that viewpoint. According to the fact that we employ concerns ( $n$  concerns), each viewpoint can be assigned a set of different reliability measures (one for each concern).

The set of reliability values attributed to each viewpoint have two faces. Firstly, the analysts involved in the creation of the specifications for each viewpoint are asked to express their degree of confidence in their understanding and knowledge of that area of concern. Secondly, a third-party understanding of the reliability of each viewpoint in a specific concern is taken into consideration. The third-party reliability values can be set equally for all viewpoints if no extra information about the viewpoints are available.

Viewpoint analysts are initially asked for the perception of their own reliability. They can state their opinion from within the range of  $[0, 1]$ . It is rather intriguing to interpret the reliability values assigned to each viewpoint as the amount of belief mass that has been assigned to each viewpoint. The ascribed mass (assigned either by the viewpoint itself or the third-party) represents the degree of belief in the

fact that the viewpoint is going to reveal the correct specification; therefore, the combination of the two reliability values reduces to the problem of combining two belief mass assignments. We propose the use of Yager's rule of combination which is actually the application of Dempster's rule of combination without normalization. Yager's rule can be considered as an epistemologically honest interpretation of the belief masses since it does not change the value of the belief masses through normalization. Instead of normalization, Yager's rule assigns the conflicting belief mass to the universal set  $\theta$ .

According to Yager's rule, the mass assigned to each hypothesis shows the degree of belief in that hypothesis in cases where the hypothesis is a singleton; however, since we are not totally ignorant of the reliability hypothesis space, we can re-distribute the ignorance mass assigned to  $\theta$  over the belief of the set of viewpoints. The re-distribution is performed proportionally to the degree of belief mass that has been assigned to each viewpoint by Yager's rule. The remaining belief mass can be attributed to uncertainty, and since we believe each viewpoint to be honest, no degree of disbelief is ascribed to them.

### 3 The Merge Procedure

The provided information by each viewpoint should be in the form of an agreed conceptual model. These models need to be consolidated into one single model that correctly represents the perspective of all the viewpoints. In this section, we will describe how various conceptual models originating from different viewpoints can be merged on the basis of negotiation, consensus building, and model pruning.

#### 3.1 Model Integration

Conceptual models need to be mapped onto the belief layer using the underlying construct layer before they can be merged. As was explained in the previous sections, the conversion process can be performed automatically based on the defined pre and post-conditions of the related constructs. Upon conversion of the conceptual models, merging can take place. There have been various proposals for combining belief masses among which we choose the consensus operator [2] to merge various conceptual models. The choice of the consensus operator has been due to three facts. Firstly, the consensus operator has been designed specifically for binary frames of discernment which are the types of frames that we have also chosen for our model. Secondly, the operator has been shown to have a stable behavior under various conditions and even while merging conflicting dogmatic beliefs [2]. Finally, it is an appealing choice since it satisfies two important algebraic properties i.e. commutativity ( $A \oplus B = B \oplus A$ ), and associativity

( $A \oplus [B \oplus C] = [A \oplus B] \oplus C$ ). These two properties are of great significance since the merging process of conceptual models should neither be affected by the order used for the merge process nor the order of models while being manipulated by the merging operator. The employment of the consensus operator can provide a basis for merging conceptual models that are in essence uncertain. We employ the consensus operator along with a widely used model called discount and combine (aka the tradeoff model) [4]. This model discounts the information provided by each viewpoint related to a certain concern with the reliability values of that viewpoint in that specific concern.

#### 3.2 Consensus Effectiveness

The process of belief revision and combination in conceptual model integration is repeated iteratively until a desirable degree of stability is reached. Measuring the degree of stability requires some quantitative measure for evaluating the combined model. Stephanou and Lu have proposed a quantitative metric called the generalized entropy criterion which measures the degree of consensus effectiveness obtained as a result of combining evidences from multiple sources through the application of the Dempster's rule of combination [6].

It has been shown that the generalized entropy criterion decreases with consensus; therefore, the amount by which it decreases as a result of consensus can be considered as the degree of consensus effectiveness. Inspired by the generalized entropy criteria, we propose three similar metrics for measuring consensus effectiveness, namely ambiguity ( $\zeta$ ), indecisiveness ( $\psi$ ), and conflict ( $\delta$ ). Each of the metrics are calculated separately for all of the present concerns in the analysis process. The metric values for each concern are superscripted with the corresponding concern indicator. For instance,  $\zeta^k$  depicts the ambiguity value with regards to concern  $k$ . Ambiguity is defined as:

$$\zeta^k = - \sum_{i=1..n_k} \left( \frac{1}{e^{1-(b_{x_i^k}+d_{x_i^k})}} - 1 \right). \quad (1)$$

Ambiguity is similar to belief entropy in that it provides the basis to calculate the degree of confusion in the overall viewpoints knowledge about the exact fraction of belief that they should assign to each hypothesis. The indecisiveness metric is a measure of the ability of the viewpoints to firmly state a given proposition. For this purpose, the further away the degree of belief and disbelief of a given hypothesis are, the stronger and more decisive the hypothesis is:

$$\psi^k = \sum_{i=1..n_k} \left( \frac{2}{e^{(b_{x_i^k}-d_{x_i^k})} + e^{(d_{x_i^k}-b_{x_i^k})}} - \frac{2e}{e^2 + 1} \right). \quad (2)$$

The third metric that we define for consensus stability analysis is the conflict metric. Conflict defines the degree of inconsistency between the beliefs of the different viewpoints. Therefore, analogous to the previous two metrics, conflict should also be minimized for reaching a more stable conceptual model as a result of consensus.

$$\delta^k = \sum_{j=1..n_k} (b_j d_j^{\text{consensus}} + d_j b_j^{\text{consensus}}) / 2. \quad (3)$$

where  $n_k$  is the number of propositions in viewpoint  $k$ . To create a unified view for each of the three metrics, the value of the metrics in each concern should be aggregated. The aggregation process is a weighted sum of each metric. The applied weight is proportional to the number of propositions in the corresponding concern. As mentioned earlier, the process of belief revision and integration is repeated until a stable and agreeable model is reached.

### 3.3 Finalizing Model Integration

The integration of various conceptual models can result in inconsistencies that may have not been present in the initial conceptual models. It is recommended that these inconsistencies be tolerated until the situation under which a final decision must be made on the ultimate conceptual model. This means that inconsistencies, and conflicts should be resolved at some point in time; however, consistency enforcement is usually one of the last activities that are performed in the model integration process.

In the model that we have proposed in this paper, inconsistencies and conflicts arise as a result of the difference in the belief mass assigned to different hypotheses by various viewpoints. The conflict may be resolved through the consensus building process. Briefly, the employed consensus building process is a recommendation scheme which is defined as follows. Let  $\otimes$  and  $\oplus$  be the discount and consensus operators, and  $B^{\text{Recommended}}$ ,  $B^{VP_i}$ , and  $B^{\text{Consensus}}$  be the recommended belief base, viewpoint  $i$ 's belief base, and the consensus belief base, respectively, the recommendation process can be expressed as:

$$B^{\text{Recommended}} = [\otimes (\mathbb{R}_{VP_i}^{C_j}, B^{VP_i})] \oplus [\otimes (\mathbb{R}_{\text{Consensus}}^{C_j}, B^{\text{Consensus}})] \quad (4)$$

The recommendations are made to all viewpoints so that consensus is formed more easily and quicker. In cases where conflict still exists, a decision must be made as to which proposition to select from amongst the conflicting opinions. Here, it is possible to select the proposition with the highest degree of potency. Potency of each proposition is defined as:

$$\text{Potency}_x = \begin{cases} 0 & \text{if } u_x = 1 \\ \frac{b_x - d_x}{1 - u_x} & \text{else} \end{cases} \quad (5)$$

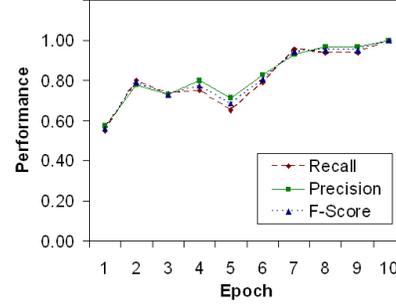


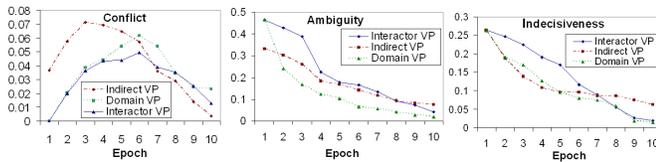
Figure 2. Precision, Recall and F-score of the Merged Model in Each Epoch.

The inconsistent propositions are ordered based on their degree of potency, and the proposition with the highest degree of potency is selected as the appropriate one, and the rest are removed. In cases where several propositions have the same degree of potency, the one with the higher value of belief, and lower uncertainty is selected.

## 4 Performance Evaluation

To evaluate the proposed model, we followed the setting proposed by Sommerville and Sawyer [5]. They have proposed three main viewpoints, namely domain, interactor, and indirect stakeholder viewpoints that in their belief can cover most of the aspects of a software design process. These authors also propose four major concerns that need to be considered which are safety, availability, functionality, and maintainability. Following the same setting, we selected different viewpoints that represented these three types of viewpoints. Each viewpoint was given the same textual definition of the Pet Store application. The viewpoints were required to identify the requirements of the Pet Store application from the textual information. According to their own requirement definitions, each viewpoint then designed a conceptual model in the form of UML class diagram. They were also asked to initially specify the degree of their own reliability in each of the four concerns.

To support the negotiation, and model integration process, a plug-in incorporated into Eclipse and developed on top of EMF was provided to the viewpoints (Integration Client). A separate plug-in was also developed that managed the server-side processing of information that are gathered from each individual viewpoint (Integration Server). The class diagrams developed by each viewpoint were stored on the server-side plug-in in Ecore format. Using these tools, each of the viewpoints started to specify their requirements and then design their conceptual model. In this process, recommendations were constantly provided to the viewpoints. Furthermore, based on the agreement of the



**Figure 3. The Behavior of the Effectiveness Metrics in Each Epoch.**

viewpoints the developed conceptual models were merged automatically and stored on the server and the individual models were versioned and also kept on the server. This process was repeated for ten epochs. In each epoch, the final merged model was compared with a reference conceptual model that had been developed prior to the case study by a set of experienced modelers for the Pet Store application. This reference model was considered as a sound model designed based on the given textual information to be compared to; therefore, the aim of the case study was to see if the viewpoints can finally achieve this model or not (the participating viewpoints were blind to the reference conceptual model).

In each epoch, four metrics were measured, namely True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN). TP is the number of design entities that existed in the reference model and also did exist in the merged model, FP is the number of model elements that did not exist in the reference model, but did exist in the merged model. On the other hand, TN is the number of model elements that did not exist in neither the merged model nor the reference model, and FN is the number of elements that did exist in the reference model but were omitted (or did not appear) in the merged model. Using these four metrics, Precision and Recall are defined. Precision (quality of the merged model) is the ratio of correctly labeled elements in the merged model over all of the elements in the merged model, and recall (coverage of the merged model) is the average number of correctly classified elements over all elements.

The weighted harmonic mean of precision and recall (F-score) was also measured. Figure 2 shows the result of this process. As it can be seen the precision and recall rates of the merged model increases gradually until the model reaches the fully correct state in the tenth epoch. This shows that the proposed framework consisting of the merge model, reliability evaluators, and belief recommender is able to formally guide the viewpoints through the conceptual modeling process and enable the viewpoints to form consensus and develop a correct final product. During the study, the three consensus effectiveness measures were also observed. Figure 3 shows the behavior of these three measures in each epoch. As it can be seen the degree of ambiguity and in-

decisiveness of all the viewpoints has gradually decreased which shows that they have been able to gain a better understanding of the target system based on the formal collaboration in the integration framework throughout the modeling process and hence reduce the amount of uncertainty in their models. Figure 3 also shows that the degree of conflict between the viewpoints increased as the study progressed and more elements were added to the individual viewpoints' models (until epoch 5); however, as time progressed (from epoch 5 to 10) and more recommendations were made to the viewpoints, the disagreements in the form of conflicting belief masses were resolved and a good degree of mutual understanding was reached at the end which led to a correct final conceptual model. As it can be seen in Figure 3, some degree of conflict still exists in the tenth epoch, but the final model is correct. This shows that the pruning model is also successful in detecting the incorrectly defined models and removing them from the final product.

## 5 Concluding Remarks

In this paper, we have proposed a formal model for integrating various conceptual models expressed by different analysts on the same domain of discourse. The model introduced in this work is based on Subjective logic, and explicitly addresses the degree of uncertainty which may be present in experts' opinions. Various operators for translating linguistic expert opinions into mathematical representation, translating various conceptual models into a core representation, analyzing experts' reliability, model merging, and model pruning have been introduced in this paper to enhance the process of conceptual model merging.

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