Towards an uncertainty interchange format based on fuzzy numbers

Pietro Baroni, Giovanni Guida
Università di Brescia - Dipartimento di Elettronica per l'Automazione
Via Branze 38, I-25123 Brescia Italy
Phone: +39-30-3715455, Fax: +39-30-380014
email: {baroni,guida}@ing.unibs.it

ABSTRACT: In a variety of applications, such as multi-agent systems and heterogeneous knowledge-based systems, there is the need to exchange uncertain information between distinct and independently developed software components. This requires that such components share a common uncertainty interchange format and poses, therefore, a serious and still poorly considered problem, in face of the variety of existing uncertainty theories and of related representation formalisms. In fact, while imposing that all components adopt the same uncertainty theory is often unrealistic and, more importantly, is against the very reasons that support modularization and distribution. Defining a common uncertainty interchange format, able to guarantee compatibility with the different existing approaches (and possibly also with future ones) is an open research problem. In this paper we discuss the basic issues that need to be dealt with for the definition of a sufficiently general uncertainty interchange format and formulate an initial proposal of generic belief representation based on fuzzy numbers.

KEYWORDS: Multi-agent Systems, Heterogeneous Knowledge-Based Systems, Distributed Systems, Uncertainty Interchange Format, Uncertainty Representation, Uncertainty Transformation, Uncertain Reasoning.

1 INTRODUCTION

One of the key issues in the development of multi-agent system is the definition of an interchange format for communication and information exchange among different agents. As to our knowledge, existing proposals of interchange formats for agent communication, such as KIF [Genesereth and Fikes 92] do not address the case where the information to be exchanged is affected by uncertainty. This clearly represents a severe limitation, which restricts their applicability to the (few) application contexts where the importance of uncertainty is negligible and leaves out the (many) domains where there is the need to exchange uncertain information between agents.
A similar need is present in the area of heterogeneous knowledge-based systems [Steier et al. 93] which address domains where expert problem-solving activity is characterized by the integrated use of different types of competencies. These systems are expected to be able to integrate different types of knowledge representation and reasoning mechanisms: if any of these knowledge sources are affected by uncertainty, the need to exchange and integrate uncertain reasoning results produced by distinct knowledge-based components arise.
One simple solution to the problem pointed out above would be to impose that all the agents in a multi-agent system (or all components of an heterogeneous knowledge-based system) adopt the same uncertainty theory and a uniform internal representation format. This solution is however in strong contrast with the requirement of allowing heterogeneous knowledge representation and reasoning schemes in distinct software components, which is widely recognized as a fundamental need both in multi-agent systems and in heterogeneous knowledge-based systems.

In this paper we address the problem of defining a generic uncertainty interchange format to be used for exchange of uncertain information between heterogeneous agents or knowledge-based components, each one featuring a specific, individual uncertain reasoning paradigm. The main objective of this effort is generality, namely the ability to guarantee compatibility with different existing theories and approaches (and possibly also with future ones).

The paper is organized as follows. In section 2 we provide a synthetic background on uncertainty representation and uncertain reasoning. Section 3 discusses the basic issues in uncertainty representation. Sections 4, 5, and 6 illustrate the main aspects of our proposal, namely the representation of belief degrees in terms of fuzzy numbers associated to linguistic labels, their interpretation in terms of amount of evidence, and the absence of constraints binding belief degrees concerning truth and falsity of the same proposition. Inter-format translation issues are discussed in section 7. Section 8 summarizes and concludes the paper.

2 BACKGROUND

The topics of uncertainty representation and uncertain reasoning have been intensively studied for years and have received special attention in the area of artificial intelligence, being considered a crucial factor for the development of intelligent systems (see [Shafer and Pearl 90] and [Clark and Krause 93] for ample and general surveys). Many different theories have been developed and are currently investigated in the area of uncertain reasoning including (just to mention the most known ones), the now obsolete certainty factors [Buchanan and Shortliffe 84], Bayesian networks [Pearl 91], belief function theory [Shafer 76], possibility theory [Zadeh 78] [Dubois et al. 94a], and various forms of nonmonotonic logics (see [Léa Sombé 90] for a survey on this field). The general validity, the practical applicability and the limitations of the different theories proposed in the literature have been and still are the subject of a (sometimes strong) scientific debate between their supporters. Some attempts to propose very general formalisms able to include several specific proposals as special cases have also been made [Shenoy 92], but a universally recognized and general theory of uncertainty does not exist yet and seems to be far from being achieved. Moreover, also the definition of a precise applicability scope for the different theories available, stating which theory should be adopted to face a specific uncertain reasoning problem, is lacking. In fact, it should be noted that the selection of a suitable formalism for uncertain reasoning is not independent from the features of the knowledge that characterizes a problem solving domain. A first step in this largely unexplored direction is represented by the distinction between factual and generic knowledge proposed in [Dubois et al. 96]; other basic considerations related to this point can be found in [Baroni et al. 95].

The remarks reported above have a significant impact on the issue of introducing uncertain reasoning in the context of a heterogeneous distributed problem-solving architecture. In particular, since distinct software components, let say agents (or components, knowledge sources, modules, etc.), are devoted to face different classes of problems, they generally exploit different types of knowledge and adopt different knowledge representation and reasoning formalisms. Therefore, it seems natural to assume that they must be allowed to use different uncertainty representation and uncertain reasoning formalisms as well. Given this freedom left to individual agents, the problem arises of defining a common concept and format for uncertainty representation, in order to allow effective exchange of uncertain information between agents. This problem calls for a series of questions to be faced, which are orderly discussed in the following sections.

3 FUNDAMENTAL ISSUES IN REPRESENTING UNCERTAINTY

In presence of uncertainty, the truth value of a proposition is associated to a judgment. The truth (or falsity) of propositions can, therefore, be qualified as "certain", "likely", "possible", "extremely unlikely", etc. A *belief* is an evidential judgment about the credibility of a truth value assigned to a proposition. Beliefs may assume values in an ordered set of *belief degrees*. Belief degrees are not a property of a proposition but a property of the pair (proposition, truth value). A belief degree represents, in very general terms, how much it is reasonable to believe in the association between a proposition and a given truth value, on the basis of the available evidence. In general, we will denote as $\underline{bel}_E(P, X)$ the belief degree in the association of a truth value X to a proposition P, given a body of evidence E.

If we now consider a proposition and compute the belief degrees for all its possible truth values, we obtain a complete representation of the uncertainty about which truth value should be assigned to the proposition, on the basis of the available evidence, called the *belief state* of the proposition. In the following, we assume that propositions belong to a classical two-valued logic, the possible truth values being therefore the set {$\underline{true}$, $\underline{false}$}. Clearly this is a very restrictive assumption, which is however useful to limit the extension and the complexity of the present work; the extension to multi-valued logics, such as fuzzy logic, will be dealt with in future work.

Therefore, the belief state of a proposition is a pair [$\underline{\text{bel}}_E$(P, true), $\underline{\text{bel}}_E$(P, false)]. The belief state represents how much one is authorized to believe in the association between a given proposition and all its possible truth values, on the basis of the available evidence. A proposition appended with the relevant belief state is called a *quantified proposition*.

The considerations presented above are quite general by nature and are basically shared by all thories and approaches to uncertainty representation. Significant differences between theories are found instead in the following aspects:
(i) the actual representation of belief degrees;
(ii) the meaning ascribed to belief degrees;
(iii) the constraints imposed on the pair of belief degrees concerning the truth and the falsity of the same proposition.

Considering point (i), a first distinction concerns the so-called symbolic versus quantitative approaches. In symbolic approaches, that is the various families of nonmonotonic logic, an explicit quantification of uncertainty is not provided, whereas in quantitative approaches a (numerical or qualitative) uncertainty quantification is given. As a matter of fact, in symbolic approaches a simple set of belief degrees including two elements only, namely {unknown, believed}, is implicitly assumed, whereas in quantitative approaches a set of belief degrees with greater cardinality is explicitly adopted. Therefore, the symbolic approaches can be regarded as the binary counterpart of the quantitative ones and the cardinality of the set of belief degrees represents a first fork where different theories diverge. Moreover once the cardinality has been stated, the choice between a numerical or a qualitative representation has to be made. Many approaches, such as probability theory and belief function theory assume the real interval [0 1] as the set of belief degrees, whereas other researchers support the use of discrete qualitative scales [Bonissone and Decker 86]. Interestingly enough, both numerical and qualitative versions have appeared in the literature for the same uncertainty theory; for example, qualitative versions have been proposed for probability theory [Goldszmidt and Pearl 96] or for possibility theory [Dubois and Prade 97]. Therefore, this choice is in a sense independent of other features of a formalism. To sum up, as far as point (i) is concerned, two basic choices characterize an uncertainty formalism:

- the binary or not binary cardinality of the set of belief degrees;
- in case of a non binary cardinality, the use of a numerical or qualitative representations.

Point (ii) is probably the most fundamental and debated one, since it concerns the very meaning ascribed to the concept of uncertainty in a given formal framework. It has to be stressed that even in the context of the same formalism different (and strongly contrasting) interpretations may exist. For instance, in probability theory, both a subjective and a frequentist interpretation do exist, whereas belief functions have been interpreted either as a special case of upper and lower probabilities or as an autonomous concept related to the representation of evidence. Given the fact that no general consensus exists about what a probability value (or a belief function) means, it is clearly difficult to achieve a general consensus about how the concepts underlying different formalisms should be compared and related among them. However some formal correspondences between different theories have been identified. As mentioned above, belief function theory can be interpreted in terms of upper and lower probabilities, whereas possibility and necessity quantifications envisaged by possibilistic logic can be interpreted as a special case of belief functions [Dubois et al. 94a]. Moreover, the issue of possibility-probability conversion has been the subject of specific studies [Delgado and Moral 87] [Dubois et al. 93]. These studies may represent the basis for a general and unifying theory of uncertainty which is however, at present, a long-term open research goal.

Turning to point (iii), one of the most important and distinguishing features of an uncertainty theory is represented by the constraints that bind the belief in the truth and in the falsity of the same proposition. In probability theory there is one very tight constraint: the two values must sum up to 1, so that p(not A) can be derived from p(A) and vice versa, and a single number is enough to represent the belief state of a proposition.
The property of additivity of belief degrees is, in turn, a debated subject: it is considered too strong by many researchers and has been relaxed in other theories. In belief function theory, the constraint reduces to bel(A) + bel(not A) <= 1, whereas in possibility theory we have min(N(A), N(not A)) = 0 - or equivalently: max (Π(A), Π(not A)) = 1. Given this looser constraint, in both theories a couple of numbers is necessary to represent a belief state.

Starting from this background, we will now discuss how we propose to face the three points mentioned above. Our choices have been directed by the need of guaranteeing the highest level of interoperability between different agents and, therefore, are aimed at obtaining the most expressive and least restrictive representation.

4 REPRESENTATION OF BELIEF DEGREES

The definition of the actual representation of belief degrees involves two non independent choices: the cardinality of the set of belief degrees (two or more) and the choice between a numerical and a qualitative scale. A binary representation has been discarded, since it is not really expressive and can in any case be recovered as a special case from a more general one.

The choice between a numerical and a qualitative scale is more difficult. On one hand, a numerical scale (for instance the [0, 1] interval) offers an infinite variability of belief degrees, with the possibility of expressing very precise quantifications. Moreover, it is possible to rely on the usual operations on real numbers in order to define operators on uncertainty quantifications. As a matter of fact, the [0, 1] interval is adopted as the scale of belief degrees in probability, possibility and belief function theories. However, the adoption of a numerical scale as a common belief representation has also some significant drawbacks. First of all, the meanings ascribed by different theories to the same numerical values (and in particular to the extreme values 0 and 1) are very different. Thus, the use of the same number may hide very different interpretations: for instance a 1 probability value represents a certain event, whereas a 1 possibility value represents a fully possible (but not certain at all) event. Another difficulty concerns the precision to be ascribed to a numeric value, which should be the subject of an explicit agreement among agent developers. A related, but distinct, issue concerns a suitable management of roundoff errors. Finally, it should also be remarked that in many application domains some of the uncertainty quantifications an agent has to deal with, namely those concerning the uncertainty of domain knowledge, have to be acquired from human experts. However, as it is well known, it is often unnatural for an expert to express a belief judgment in numerical term. It is generally much easier and more reliable to use linguistic labels, like for example {very-low, low, ..., high, very-high}, than choosing a number in the real interval [0, 1].

All issues mentioned above make evident the various difficulties inherent to the adoption of a numerical scale. For these reasons, we propose to adopt a qualitative scale of linguistic labels for the representation of belief degrees. This choice, though still not widely adopted, has been suggested in the past as the result of a series of detailed studies [Szolovits and Pauker 78] [Beyth-Marom 82] [Bonissone 87] and is still a largely unsatisfied desideratum according to [Zadeh 95].

In our approach, belief degrees are symbols, called *linguistic labels*, that represent concepts defined in intuitive terms [Bonissone 82]. For example, in ASTRA, a successful application of an heterogeneous knowledge-based system (see [Baroni et al. 97] [Baroni et al. 98] for details), we have assumed the following scale of nine linguistic labels, derived (with minor modifications) from [Bonissone and Decker 86]. Each label is denoted by a full name carrying an intuitive meaning and by a symbol to be used as a short-hand form:

UNINFORMED	E_1
EXTREMELY UNLIKELY	E_2
MOST UNLIKELY	E_3
UNLIKELY	E_4
IT MAY	E_5
LIKELY	E_6
MOST LIKELY	E_7
EXTREMELY LIKELY	E_8
CERTAIN	E_9.

The intuitive semantics of these labels is in terms of the amount of evidence that supports a belief and will be better discussed in the next subsection. So, for example:

- $\underline{bel}_E$(P, $\underline{true}$) = UNINFORMED = E_1 means that the available evidence supporting $\underline{bel}_E$(P, $\underline{true}$) is negligible;
- $\underline{bel}_E$(P, $\underline{true}$) = CERTAIN = E_9 means that the available evidence supporting $\underline{bel}_E$(P, $\underline{true}$) is fully satisfactory.

The formal semantics of the linguistic labels is provided through fuzzy numbers. To each linguistic label a fuzzy number defined on the interval [0, 1] is associated. In the case of ASTRA, we have assumed, for the nine linguistic labels introduced above, the semantics proposed by [Bonissone and Decker 86] based on trapezoidal fuzzy numbers. Thus, linguistic labels provide an intuitive meaning, which is especially useful in case of interaction with domain experts, whereas fuzzy numbers are used for the internal implementation of reasoning mechanisms.

The use of a qualitative linguistic scale limits of course the granularity of the possible quantifications. On the other hand, however, it provides a framework where uncertainty quantifications are represented in a fuzzy rather than in a crisp way, so achieving all the universally recognized advantages of fuzzy representations, such as cognitive plausibility, robustness, and insensitivity with respect to small numerical variations.

5 INTERPRETATIONS OF BELIEF DEGREES

In order to provide a general interpretation of the concept of belief degree, we start from a basic assumption: beliefs can not derive from a mere subjective, a priori judgment. They must always be justified on the basis of some concrete evidence. We express this assumption as the "*no belief without evidence*" principle. According to this principle, since a belief is based on a given body of evidence, if this body of evidence changes (for example, new evidence is collected or old evidence is discarded), the belief must also change in order to be consistent with the available evidence.

As already mentioned above, a belief degree is a property of a pair (proposition, truth value) and represents how much it is reasonable to believe in the association between a proposition and a given truth value, on the basis of the available evidence. In this view, the value of a belief degree is related to the concept of amount of evidence. In order to understand this concept, consider the following representation of the dynamics of uncertain reasoning.

In absence of any evidence about a specific subject, let say a proposition P, a reasoner should not have any belief about either the truth or the falsity of P. Therefore the belief state of P should be [UNINFORMED, UNINFORMED] (or [0, 0] for those who prefer a numerical representation): this kind of belief state is in accordance with the concept of total ignorance, proposed in [Dubois et al. 96], which corresponds, in our approach, to the absence of any evidence.

Starting from a state of total ignorance, the reasoner collects evidences from the world and can then ascribe a truth value to some propositions he is interested in. As far as evidence collection proceeds, the initial state of ignorance converts into a state where the reasoner has some, more or less strong, motivations to believe in the truth or in the falsity of a proposition. The belief degree for a given truth value will be in some way proportional to how much cogently (according to the knowledge and opinion of the reasoner) the collected evidence supports such truth value. Following [Shafer 76], we "do not pretend that there exists an objective relation between given evidence and a given proposition that determines a precise degree of support". As a matter of fact, different individuals may express even very different degrees of belief, starting from the same body of evidence: clearly this does not mean that, in general, belief degrees are completely arbitrary, but that a univoque objective and absolute way of deriving belief degrees from evidence can not be defined.

This conceptual model of uncertain reasoning is quite general and, with minor variations, lies at the heart of different uncertainty theories. For instance, Shafer [Shafer 76] introduces the concept of weights of evidence as the primitive quantifications from which belief functions are derived: "it would seem that the degrees of support for the various propositions [...] ought to be determined by the weight of the items of evidence attesting to those propositions". Kleiter [Kleiter 93][Kleiter 96] recalls that probability density functions represented by beta distributions, which are at the core of imprecise probability theory, can be defined in terms of two parameters whose intuitive interpretation is in term of weights of evidence supporting the truth and falsity of a proposition. Moreover this conceptual model in perfectly in accordance with the research trend focusing on the treatment of conditional events, that is of knowledge items representing the impact of a piece of evidence on a given belief [Dubois et al. 94b]. On the basis of these considerations, the interpretation of degree of belief as related to the concept of amount of evidence seems to be reasonably general and acceptable.

6 CONSTRAINTS ON BELIEF DEGREES CONCERNING THE SAME PROPOSITION

Different uncertainty theories also differ in the constraints they put on belief degrees concerning the truth and falsity of the same proposition. These constraints are an essential part in the definition of an uncertainty theory: they reflect its peculiarities and, at the same time, significantly affect its expressiveness. For instance the constraint P(a) + P(not A) = 1 represents a crucial feature of probability theory, namely the fact that the overall amount of belief should be entirely distributed between a hypothesis and its negation. However, this constraint severely limits the expressiveness of the theory since it prevents the possibility to represent ignorance and contradictory evidence, as repeatedly remarked in the literature [Shafer 76] [Dubois et al. 96]. As a matter of fact, one of the declared (and achieved) goals of belief function theory [Shafer 76] is to allow a representation of ignorance. However the representation of contradiction in such theory is less easy; in fact Dempter's rule of combination, by enforcing normalized belief functions, simply discards contradiction, by redistributing the belief ascribed to the empty set among other hypotheses. However, this approach may lead to paradoxical conclusions in some cases and validity of Dempster's rule of combination is highly debated [Voorbraak 91]. In order to overcome these difficulties unnormalized belief functions have been proposed [Smets 92], but this alternative solution is not universally accepted.

Coherently with our goal of maximum generality, we decided to put no constraints at all on the pair of belief degrees constituting the belief state of a proposition, allowing them to assume independently any value. This choice is in accordance with our interpretation of belief degrees in terms of amount of evidence: as a matter of fact, both weights of evidence [Shafer 76] and the parameters identifying a beta distribution [Kleiter 93] for a single proposition are a couple of independent values, ranging in the real interval [0 +∞], where 0 represents null evidence, and +∞ represents the limit case of innumerable concordant evidences. In contrast with the [0 +∞] interval, we adopted, however, a sort of normalized representation where a finite value (in our case the label E_9) represents a sort of belief saturation value. In other words, we assume that, after collecting a sufficiently large amount of evidence, the belief degree can not increase further. A representation very similar to ours has been proposed in [Benferhat et al. 95].

7 EXCHANGING UNCERTAIN INFORMATION

The definition of a common uncertainty representation shared among different agents is a key feature to allow the exchange of uncertain information. Of course, each agent, is required to be able to carry out conversions from the common uncertainty interchange format to its internal representation of uncertainty and vice versa. Since the uncertainty interchange format is very general and little specific it has to be taken into account that:

- in the conversion from the uncertainty interchange format to a more specific internal representation, some specific features, not entailed by the common representation, might remain undefined or have to be added in the representation (inevitably somewhat arbitrarily as it happens, for example, when using default values);
- in the conversion from a specific internal representation to the more general uncertainty interchange format, some of the peculiarities of the internal representation can not be preserved and might be lost.

In particular, there are three kinds of aspects to be considered:

- semantic aspects, concerning the armonization among interpretations of belief quantifications;
- representational aspects, concerning the conversion between different forms of expressing belief quantification;
- constraint aspects, concerning the adaptation of belief states which do not respect the constraint imposed by a specific theory.

Any uncertainty conversion should be driven first of all by semantic considerations relating the meaning ascribed to the internal representation with the meaning of the uncertainty interchange format, which is based on the notion of amount of evidence supporting the attribution of a given truth value to a considered proposition. In other words, proper mappings between the internal quantifications and those of the uncertainty interchange format have to be defined in such a way that the semantic meaning of quantifications is preserved.

For instance, in the case of probability theory, the value of p(A), can be considered as a representative of the amount of evidence supporting the truth of A, and therefore p(A) should be mapped into $\underline{bel}_E$(A, <u>true</u>), and similarly p(not A) should be mapped into $\underline{bel}_E$(A, <u>false</u>). In other cases however conversion may require some more articulated considerations. For instance, in possibility theory a possibility value Π(A) = 1, actually should be interpreted as the fact that there is no evidence supporting the falsity of the proposition, whereas a necessity value N(A) = 1 should be interpreted as the fact that there is cogent evidence for believing in the truth of the proposition. Hence, a necessity value N(A) should be directly mapped into $\underline{\text{bel}}_E$(A, true), whereas $\underline{\text{bel}}_E$(A, false) should be mapped into the complement of a possibility value, namely 1 - Π(A). Similar considerations can be drawn about belief and plausibility values in belief function theory.

Once semantic criteria for uncertainty conversion have been identified, the issue of format conversion has to be faced. This may involve:

- the translation from an internal numerical representation to the fuzzy representation of the uncertainty interchange format and vice versa;
- the translation from an internal qualitative representation to the fuzzy representation of the uncertainty interchange format and vice versa.

These kinds of conversions are a well-known problem and several standard solutions exist.

As far as numeric-fuzzy translations are concerned:

- the translation of a numeric value *v* into a fuzzy number *f* to be selected from a fixed set *F*, may be carried out selecting *f* such that $\mu_f(v)$ is maximum or such that the distance between the centroid of *f* and *v* is minimum, in any case the precision and sharpness of the value is somewhat diluted by the fuzzy representation;
- the translation of a fuzzy number *f* into a numeric value *v* may be carried out by calculating the mean of maxima or the centroid of *f*, in any case the information carried by the shape of *f* is lost.

In the case of qualitative-fuzzy translation, one has to define a mapping between internal qualitative values and fuzzy numbers (and vice versa), according to criteria dependent on the specific features of the internal representation. For instance, if the internal representation is based on fuzzy numbers, each fuzzy number of the internal representation may be mapped into the fuzzy number of the uncertainty interchange format with the nearest centroid. Also in this case some distortion is unavoidable.

Such kind of limitations are intrinsic to any conversion between uncertainty representations having different features and have been pointed out in [Dubois et al. 93] for the case of possibility/probability transformations. In particular, the fact that an agent using a specific formalism has to sacrifice the peculiarities of its own representation is just the price to pay in order to allow effective communication and cooperation. Clearly such limitations could be avoided if a unique internal representation formalism were adopted for all agents: this would however be in strong contrast with the requirement of allowing heterogeneous knowledge representation and reasoning schemes for each individual agent, which represents the basic raison d'être of agent systems.
A final problem is represented by the fact that the uncertainty interchange format we propose does not involve any constraint between quantifications concerning the truth and falsity of the same proposition, whereas other theories enforce more or less strict constraints. Clearly this represents a problem only in the translation from the uncertainty interchange format to a specific internal representation, as the result of translation may be incompatible with the constraints imposed by the internal theory.
For instance a belief state expressing some contradiction in the available evidences about a proposition A, might be translated in an unacceptable probability assessment, where p(A) + p(not A) > 1. On the other hand, a belief state expressing a global lack of evidence would result in another unacceptable probability assessment where p(A) + p(not A) < 1.
In these cases a normalization procedure is required for each theory imposing internal constraints. A simple and relatively natural choice (though not the only possible one) is to increase or decrease both unacceptable values by the same normalization factor, so that the respect of constraints is ensured. Clearly this entails some distortion in the uncertain information conveyed, but, again, this is just the price to pay in order to achieve interoperability between different theories.

8 CONCLUSIONS

In this paper we have addressed the problem of defining an uncertainty interchange format to support uncertain information communication between distinct and independently developed software components such as agents in a multi-agent system or knowledge sources of an heterogeneous knowledge-based system. As to our knowledge, this issue has received only poor attention in past years, though its importance will significantly

increase in next future, as witnessed by the growing diffusion of distributed and multi-agent applications.
The issue of proposing an uncertainty interchange format is made especially complex by the large variety of existing uncertainty theories and by the strong differences existing among them both at semantic and syntactic level.
Our proposal for an uncertainty interchange format is grounded on the following main assumptions:

- belief quantification should adopt a fuzzy, rather than numerical, representation, as this ensures robustness and cognitive plausibility;
- the basic meaning of uncertainy quantifications should be related to the notion of amount of evidence;
- uncertainty about the truth value of a proposition should be represented through two independent quantifications, concerning its truth and falsity.

In this context, translation from and into the proposed uncertainty interchange format can be defined in terms of:

- a semantic mapping, which relates the meaning of a specific representation to the notion of amount of evidence;
- a format conversion method, which deals with the translation of numeric or qualitative quantifications into linguistic labels associated to fuzzy numbers and vice versa;
- a normalization procedure, to be applied to translation results which do not respect the constraint imposed by a given theory.

The translation process may involve some unavoidable distortion in the carried information, mainly due to differences in the expressiveness of different theories. This is however just the price to pay in order to achieve interoperability between different theories and effective communication and cooperation between different software agents.

This work is just a first initial step in the direction of defining a general interchange format for uncertainty, among the main issues for future work we mention:

- a detailed investigation about the issues of translation and normalization with respect to the most known uncertainty theories;
- the extension to the case of non-binary truth-values, i.e. to multi-valued logics;
- the definition of a protocol for allowing agents to negotiate some aspects of the interchange format, such as, for example, the scale of linguistic labels to adopt.

REFERENCES

[Baroni et al. 95] P. Baroni, G. Guida, and S. Mussi, Modeling uncertain relational knowledge: The AV-quantified production rules approach. *Proc. of ECSQARU 95, 3rd European Conf. On Symbolic and Quantitative Approaches to Uncertainty and Reasoning*, Fribourg, CH, 1995, 18-27

[Baroni et al. 97] P. Baroni, G. Guida, S. Mussi, State assessment and preventive diagnosis of power transformers: a knowledge-based approach, *International Journal of Engineering Intelligent Systems*, 5(2), 1997, 91-105

[Baroni et al. 98] P. Baroni, G. Guida, S. Mussi, Enhancing cognitive plausibility of uncertainty calculus: a common-sense-based approach to propagation and aggregation, *IEEE Trans. on Systems, Man, and Cybernetics-Part A*, 28 (4), 1998, 394-407

[Benferhat et al. 95] S. Benferhat, D. Dubois and H. Prade, A local approach to reasoning under inconsistency in stratified knowledge bases, *Proc. ECSQARU 95 3rd European Conf. on Symbolic and Quantitative Approaches to Reasoning and Uncertainty*, Fribourg, CH, 1995, 36-43

[Beyth-Marom 82] R. Beyth-Marom, How probable is probable ? A numerical taxonomy translation of verbal probability expressions, *J. Forecasting*, 1, 257-269, 1982

[Bonissone 82] P.P. Bonissone, A fuzzy sets based linguistic approach: theory and applications, in M.M. Gupta and E. Sanchez (Eds.), *Approximate Reasoning in Decision Analysis*, North Holland, New York, NY, 1982, 329-339.

[Bonissone 87] P. Bonissone, Summarizing and propagating uncertain information with triangular norms, *International Journal of Approximate Reasoning* 1, 1987, 71-101.

[Bonissone and Decker 86] P.P. Bonissone and K.S. Decker, Selecting uncertainty calculi and granularity: an experiment in trading-of precision and complexity, in L.Kanal and J.Lemmer (Eds). *Uncertainty in Artificial Intelligence*, North-Holland, Amsterdam, NL, 1986, 217-247.

[Buchanan and Shortliffe 84] B.G. Buchanan and E.H. Shortliffe, *Rule-based Expert Systems - The MYCIN Experiments of the Stanford Heuristic Programming Project*, Addison Wesley, Reading, MA, 1984

[Clark and Krause 93] D. Clark and P. Krause, *Representing uncertain knowledge: an artificial intelligence approach*, Intellect, Oxford, 1993

[Delgado and Moral 87] M. Delgado and S. Moral, On the concept of possibility-probability consistency, *Fuzzy sets and systems*, 21, 311-318, 1987

[Dubois et al. 93] D. Dubois, H. Prade, and S. Sandri, On possibility/probability transformations, in R. Lowen, M. Roubens (eds), *Fuzzy Logic - State of the art*, Kluwer, 1993, 103-112

[Dubois et al. 94a] D. Dubois, J. Lang, and H. Prade, Automated reasoning using possibilistic logic: Semantics, belief revision, and variable certainty weights, *IEEE Trans. on Knowledge and Data Engineering* KDE-6(1), 64-71

[Dubois et al. 94b] D. Dubois, I.R. Goodman and P.G. Calabrese (eds), Special Issue on Conditional Event Algebra, *IEEE Trans. on Systems, Man and Cybernetics*, vol. 24, n. 12, 1994

[Dubois et al. 96] D. Dubois, H. Prade and P. Smets, Representing partial ignorance, *IEEE Trans. on Systems, Man and Cybernetics*, vol. 26, n. 3, 1996, 361-377

[Dubois and Prade 97] D. Dubois and H. Prade, Qualitative possibility theory and its applications to reasoning and decision under uncertainty, *Proc. of ESIT 97, European Symposium on Intelligent Techniques*, Bari, Italy, 1997, 301-308

[Genesereth and Fikes 92] M. R. Genesereth, R. E. Fikes (Editors) Knowledge Interchange Format, Version 3.0 Reference Manual.Computer Science Department, Stanford University, Technical Report Logic-92-1, June 1992

[Goldszmidt and Pearl 96] M. Goldszmidt and J. Pearl, Qualitative probabilities for default reasoning, belief revision, and causal modeling, *Artificial Intelligence*, 84 (1996) 57-112

[Kleiter 93] G. D. Kleiter, Expressing imprecision in probabilistic knowledge, *Journal of Italian Statistical Society*, 2 , 1994, 213-232

[Kleiter 96] G. D. Kleiter, Propagating imprecise probabilities in Bayesian networks, *Artificial Intelligence*, 88, 1996, 143-161

[Léa Sombé 90] Léa Sombé Group. Reasoning under incomplete information in artificial intelligence: A comparison of formalisms using a single example, *International Journal of Intelligent Systems* 5(4), 1990, 323-472.

[Pearl 91] Pearl J. *Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference*, Morgan Kaufmann, San Mateo, CA, 1991.

[Shafer 76] G. Shafer, *A Mathematical Theory of Evidence*, Princeton University Press, Princeton, NJ, 1976.

[Shafer and Pearl 90] G. Shafer, J. Pearl (eds.), *Readings in Uncertain Reasoning*, Morgan Kaufmann, 1990

[Shenoy 92] P.P. Shenoy, Valuation-based systems: a framework for managing uncertainty in expert systems, in L.A. Zadeh, J. Kacprzyk (eds.), *Fuzzy Logic for Management of Uncertainty*, John Wiley & Sons, 1992, 83-104

[Smets 92] P. Smets, The nature of unnormalized beliefs encountered in the transferable belief model, *Uncertainty in AI 92*, 292-297, 1992

[Steier et al. 93] D. M. Steier, R.L. Lewis, J.F. Lehman, and A.L. Zacherl, Combining multiple knowledge sources in an integrated intelligent system, *IEEE Expert*, 8(3), 1993, 35-44

[Szolovits and Pauker 78] P. Szolovits and S.G. Pauker, Categorical and probabilistic reasoning in medical diagnosis, *Artificial Intelligence*, 11, (1978) 115-144

[Voorbraak 91] F. Voorbraak, On the justification of Dempster's rule of combination, *Artificial Intelligence*, 48, (1991) 171-197

[Zadeh 78] L. Zadeh, Fuzzy sets as a basis for a theory of possibility, *Fuzzy Sets and Systems* (1)1, 1978, 3-28.

[Zadeh 95] L.A. Zadeh, Computing with words - A paradign shift, Invited lecture at *25th IEEE International Conference on Systems, Man, and Cybernetics*, Vancouver, B.C., 1995.