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THE ECLECTIC QUADRANT OF RULE BASED SYSTEM VERIFICATION: WORK GROUNDED IN VERIFICATION OF FUZZY RULE BASES

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ABSTRACT

In this paper, we used a research approach based on grounded theory in order to classify methods proposed in literature that try to extend the verification of classical rule bases to the case of fuzzy knowledge modeling. Within this area of verification we identify two dual lines of thought respectively leading to what is termed respectively static and dynamic anomaly detection methods. The major outcome of the confrontation of both approaches is that their results, most often stated in terms of necessary and/or sufficient conditions are difficult to reconcile. This paper addresses precisely this issue by the construction of a theoretical framework, which enables to effectively evaluate the results of both static and dynamic verification theories. Things essentially go wrong when in the quest for a good affinity, matching or similarity measure, one neglects to take into account the effect of the implication operator, an issue that rises above and beyond the fuzzy setting that initiated the research. The findings can easily be generalized to verification issues in any knowledge coding setting.

Keywords : fuzzy logic, rule based expert system, validation & verification, anomaly detection

ISRL Categories : HA04 Expert Systems - UF Knowledge Based Systems / HB27 Strategic Intelligence IS / HC07 Knowledge Base / HD02 Database Characteristics - UF database requirements

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1. INTRODUCTION

Assuring the reliability of knowledge based systems (KBS) is known to be of the utmost importance. Until recently, most of the research results have been achieved in the field of classical knowledge based systems. Renewed interest in the modeling power of Lotfi Zadeh's fuzzy set theory [20]-[21] and the possibility it provides in reasoning with vague concepts seem to alter this. During the last half decade, much of the research attention has shifted towards the verification issue in a fuzzy rule based systems context.

In this paper, we identify two dual lines of thought encountered in the literature in search for methods to tackle the problem of verifying a fuzzy rule base. These two main classes of verification will be termed static and dynamic. The discussion is built up gradually to allow the reader to follow the distinctive steps that were taken in the process towards the final result of this paper. This is perfectly in line with the on grounded theory based approach used to uncover the main findings presented in this discussion.

The motivation for the confrontation of the identified branches in literature relating to the verification of fuzzy rule bases, stems from the fact that the results of the respective approaches mainly stated in terms of necessary and/or sufficient conditions to identify anomalies, are rather difficult to reconcile. Moreover, this duality in approach seems to have translated into a duality in results in terms of necessary and/or sufficient conditions to identify knowledge base (KB)-anomalies. Things will be shown to essentially go wrong when in the quest for a good verification approach, one neglects to take into account the inference mechanism underlying the reasoning of the fuzzy expert system.

The paper is organized as follows. In section 2 the essential role of grounded theory in the research underlying this paper is clarified. In section 3 the feasibility of verification by anomaly detection is addressed. Section 4 introduces and exemplifies two dual lines of thought, respectively a static and a dynamic one, as to anomaly detection for fuzzy rule bases by empathizing way of reasoning stated in terms of motives, goals and key concepts. In section 5, a zone of potential conflict will first be identified by means of a framework called the duality scheme. The principles underlying this framework will enable us in a next phase to explain the duality in outcome between both anomaly detection approaches identified in section 4. In section 6 we generalize the main findings of the constructed framework. Section 7 sums up the discussion.

2. A GROUNDED APPROACH UNDERLYING THE RESEARCH

Grounded theory [6] is a perception towards conducting research that seeks to develop theory that is *grounded* in data systematically gathered and analyzed. Martin and Turner [11] describe grounded theory as "an inductive, theory discovery methodology that allows the researcher to develop a theoretical account of the general features of a topic while simultaneously grounding the account in empirical observations or data." Therefore, Grounded Theory resorts under the label of Qualitative Research [3, 13].

The way 'qualitative' is integrated in the research effort as presented in this paper can best be explicated by the presentation of an adapted version of the 'Interacting Model' of Qualitative Data Analysis (QDA) by M.B. Miles & A.M. Huberman [13], as depicted in Figure 1.

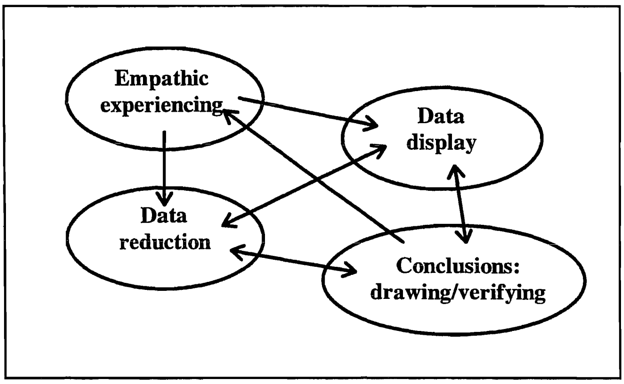

Figure 1 : Interactive Model of QDA (revised)
Miles, M.B. and Huberman, A.M. (1994)

The richness and holism of the constructed theoretical framework is the well balanced product of the four concurrent flows of activity in the Interactive Model.

Empathic experiencing : The data collection activity mainly consisted in a build-up of hands-on experience with the verification methods at hand, at the same time trying to 'enter' the researcher's mental model by reviewing papers, research reports, mainly any kind of document at hand. Where possible we also engaged in dialogue. We actually tried to go through all the phases of coming to each specific approach.

Data reduction & display : Focusing on concepts, motives, goals and basic insights, leading to the proposed approach, enabled us to isolate the factors that gave rise to each verification theory. In order to obtain this information a coding approach in which fuzzy set paradigmatic elements functioned as main drivers in reducing, contextualizing and displaying the basic elements during this process.

Conclusion drawing & verification : Linking the phases of classical verification to the elements uncovered in the fuzzy verification scheme, which essentially came down to opening a 'black box', we identified what drivers gave rise to what type of verification approach. This eventually lead to a classification into static and dynamic methods. In a next phase, the elements of the constructed framework emerging from the data were tested against the collected evidence for their plausibility, sturdiness and 'confirmability'. Through the formal nature of the problem we were finally able to formulate normative advice in addition to and in relation to the proposed classification.

3. FEASIBILITY OF VERIFICATION BY ANOMALY DETECTION IN FUZZY RULE BASED EXPERT SYSTEMS

Fuzzy set theory constitutes a superset of classical binary (crisp) set theory. It introduces a form of continuous logic, for now we are able to handle real number membership values μ in the continuous interval [0..1]. This is illustrated in Figure 2. The figure depicts the membership of a person measuring 1m70 to the fuzzy set labelled 'tall' on the universe of discourse X, 'length of a person'. Clearly the membership value is situated somewhere in between the perfect-fit, i.e. value 1, and the no-fit, i.e. value 0.

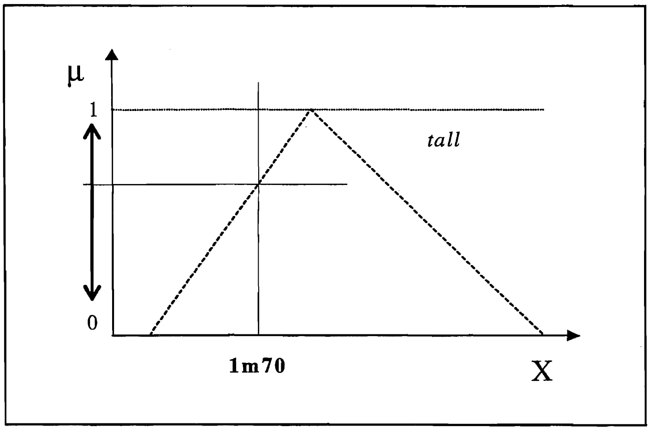

Figure 2 : Membership is 'fuzzified'

Within our particular rule based context, basically composed of IF THEN type of rules with fuzzy, i.e. linguistic labels included in the condition and/or action part op the rules[1], it should be possible to use both classical or binary and fuzzy sets in the knowledge modeling phase. This not only requires the new modeling formalism to still be able to handle classical input sets, but it also means that inference results in the case of crisp, i.e. binary input into the fuzzy system should be in accordance with results that would have been obtained from a classical rule based inference system when subjected to the same crisp input.

[1] In most cases, the inclusion of fuzzy sets (labels) in the condition and/or action part of the IF THEN type rules amounted to a form of conjunction and/or disjunction of propositional statements of the form *x is A*, where A is a fuzzy label defined on the universe of discourse X.

e.g. *Length of person x* is *tall*

The requirement stated above has a direct implication on the construction of the inference engine of the expert system : it should make use of what Dubois & Prade [4] called an *implication-based rule* design. In essence this means that results are guaranteed to be compliant with the truth table of the classical implication. Basically only these types of rules conform to the causality based reasoning scheme of classical reasoning.

Out of a verification perspective, this has some interesting consequences. In designing a fuzzy rule based system that for any crisp input *reproduces* the same *results* as a classical system, one guarantees that erroneous inference results that appear out of the classical system persist when the same inputs are offered to the fuzzy system. Classical verification research has succeeded in attributing *errors*, that spring from the inference process after certain input has been subjected to the system, to a set of *set-anomalies* within the constructed knowledge base. The anomalies were classified as inconsistency (i.e. incoherence), redundancy, circularity and deficiency of knowledge. It should be clear that an anomaly is not an error. Errors spring from the inference process. Anomalies are but symptoms within the knowledge base of a knowledge system that point out the fact that the inference process could produce errors.

The concept of anomaly can in fact be connected to the knowledge base sets at a conceptual level, independent of any knowledge coding formalism (*non paradigmatic drive*). However, because knowledge based systems do not work at a conceptual level, but are designed in a specific knowledge representation formalism, both syntax and semantics of anomalies have to be (re)stated in terms of syntax and semantics of the knowledge representation language used to express the KB, i.c. fuzzy set theory. To be able to verify a knowledge model for anomalies, one has to discover the *manifestation* of the anomaly within the context of the chosen knowledge representation formalism. The set of anomalies identified out of research conducted in the context of classical rule based systems remains both relevant and exhaustive in a fuzzy rule based environment. Even though the kind of anomalies is unaltered, the manifestation of the anomalies is not.

4. DYNAMIC VERSUS STATIC ANOMALY DETECTION : MAIN IDEAS, MOTIVES, GOALS AND BASIC INSIGHTS

We introduce two main lines of thought distinguished in fuzzy rule base verification literature. Identification is realized by means of uncovering the main idea, the motives, goals and insights upholding each identified approach. In this way we restrict the discussion intentionally to only the purely necessary elements of understanding needed to fruitfully pave the way to section 5, the very heart of this paper.

4.1 Verification as a Static Process

Central to the mental model sustaining this type of verification attempt is the fundamental concern to produce an intuitively appealing approach. The strong commitment to intuition that transpires from it lies directly in line with the ambition of Zadeh's fuzzy set theory. To be able to not only formally capture 'common sense reasoning' but also produce a theory that embodies this common sense element itself covers the essence of its roots. A second major characteristic of any static anomaly detection attempt is the pragmatism it embodies.

The fact that fuzzy set theory is 'merely' a generalization of classical or crisp set theory, allowing for a system to reason with *vague* concepts, opens further perspectives in a fuzzy verification context. The idea of trying to transpose the major realizations from the area of classical rule base verification to a fuzzy context thus seems not unfeasible. After all, there exists a wide on the job experience with anomaly detection in rule bases of classical rule based systems.

However, reuse of classical results or tools might be not that straightforward a task. By using fuzzy sets to represent knowledge, one gives rise to the possibility of partial equality between sets, an issue that has been covered by several authors [1,2,8,10,17] and is illustrated in Figure 3.

In fuzzy systems, partial resemblance between sets is allowed, whereas in the context of classical systems a comparison between sets always either leads to an exact match or to a no-match. This implies that in a classical context a person is either tall or small, but never both, if we suppose these two labels define a partition of the length range. However, by considering 'tall' and 'small' as fuzzy labels, describing a fuzzy variable 'length', the outcome of a comparison in terms of the resemblance of sets now depends completely on the positions of their set-support[2], as can be seen in Figure 3. A person measuring 1m70 is

[2] The support S of a fuzzy set A is defined as $S(A) = \{x \in X / \mu_A(x) > 0\}$, with μ the membership value of x to set A.

now both tall and small, be it to a different extent, indicated by the membership value of this specific height value within the considered fuzzy sets.

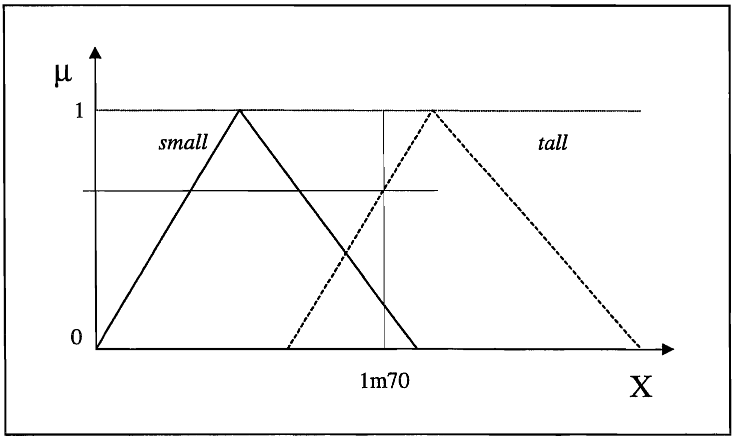

Figure 3 : Person's length 1m70, both tall and small

The relevance of this observation stems from the fact that about all classical formal anomaly definitions rely on the concept of equality between sets or on some very similar concept, like an 'is part of'-relationship. With this in mind, one has obtained a potential key to conceive a fuzzy rule base verification theory out of classical verification results : classical formal anomaly definitions can simply be *transposed* to their fuzzy counterparts, by introducing a good fuzzy *equivalence* concept. The ultimate goal consists of transposing what is generally considered to be the strength of the approach in classical anomaly detection in verifying crisp rule based systems : independent verification of the knowledge base and the inference engine. In a classical rule base environment, anomalies are detected by examining the syntax of the KB, where the properties of the inference engine are assumed but not verified.

The lever element that enables the transposition of verification results from a classical towards a fuzzy context, is the ubiquitous presence of the concept of equivalence of sets in classical formal anomaly descriptions. The discovery of a fuzzy counterpart to the concept of crisp equivalence of sets would enable the knowledge engineer to simply duplicate the anomaly detection methods from the crisp environment, with the slight adaptation of having to 'fuzzify' the concept of equivalence. Static anomaly detection essentially tries to use what is termed as similarity, affinity or matching measures to identify anomalies within a fuzzy rule base. It is assumed that the detection methods can be the same as those used in a non-fuzzy environment, except that the formerly mentioned measures indicate the degree of matching of two fuzzy expressions. Examples, or at least traces of this type of approach in fuzzy rule base verification literature can be found in [7,9,15,16,18].

4.2 Getting the Feel of It : an Example

The analysis is based upon a specific result taken from the paper by Leung and So [9] : the case of parallel conflicting rule pairs.

The specific rule model that we consider, consists of two rules of the following form

R1 : IF U is A1(x) THEN V is B1(y)

R2 : IF U is A2(x) THEN V is B2(y)

where A1 and A2, respectively B1 and B2 are fuzzy labels describing fuzzy variables U and V. U and V are defined on respective one-dimensional universes of discourse X and Y. We further assume that both rules are modeled as implication-based rules, cf. [8,9].

The authors start from the definition of a conflicting rule pair in the classical case. Assuming A1, A2, B1 and B2 are all crisp sets, it is stated that {R1,R2} is a conflicting rule pair if $A1 = A2 \ \& \ B1 \neq B2$

In a next step this definition is 'fuzzified' to handle fuzzy sets by introducing an *affinity measure A*, which replaces the equality of classical sets to come to the statement that fuzzy rule set {R1,R2} is contradictory or conflicting, if $A(A1,A2) \geq 0.5 \ \& \ A(B1,B2) < 0.5$

The affinity measure introduced by Leung and So is defined as $A(A1,A2) = M(A1 \wedge A2 \mid A1 \vee A2)$[3], where $M(A1 \mid A2)$ is a similarity measure calculated by the following algorithm working on the fuzzy sets involved.

4.3 Verification as a Dynamic Process

A well founded formal theory of verification is a condition sine qua non for guaranteeing reliable functioning of a fuzzy rule based system. This covers a strong plea for a verification theory that should be well embedded within the theoretical foundations of fuzzy set theoretic constructs. Any verification theory has to earn itself a place within the modeling formalism underlying the built knowledge system.

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3 $\mu A1 \wedge A2 = \min(\mu A1, \mu A2)$ and $\mu A1 \vee A2 = \max(\mu A1, \mu A2)$

A dynamic anomaly detection method explicitly starts from the idea that anomalies are symptoms within the KB of a KBS, pointing to potential erroneous output of the inference mechanism (cf. section 3). Identification of erroneous inference results, for short the *errors*, therefore provides an excellent means of defining *anomalies* formally. By imposing some type of constraint on the result of inference, that guarantees that the error does not occur, the possibility is offered to reason backwards and discover conditions to which the static knowledge base has to comply in order not to produce these errors. This states that anomaly detection *always* passes via the inference process, the dynamics of the system, to eventually, if possible, come to static demands in terms of necessary and/or sufficient conditions which need to be imposed on the knowledge base in order not to manifest a specific anomaly.

The main proponents of a dynamic verification approach are Yager & Larsen [19], Dubois, Prade & Ughetto [5]. Yager & Larsen were the first to introduce this type of verification in a fuzzy rule base. Their method of 'reflecting on the input' allows to test a rule base for consistency. This in essence describes some sort of backward inferencing mechanism, that allows to translate the demand for *normality*[4], imposed on the fuzzy relationship that results from inference when one wishes it to be coherent, into a constraint on the input sets to be fed into the rule base. Dubois, Prade & Ughetto thus use the method

[4] Normality of a fuzzy relationship (i.e. a fuzzy set in multiple variables) : the fact that a fuzzy set you use or produce has at least one element of its support that shows a perfect fit with the modeled label. In other words $\exists x \in X : \mu(x)=1$. The essential demand for normality imposed on the result of inference in order not to be inconsistent, when using normal input sets, is an inherent and guaranteed quality of the inferred results at the level of a single rule due to the use of *implication based* rule design (cf. section 3).

of reflection on the input essentially to try to obtain necessary and/or sufficient conditions for several scenarios within the rule base.

4.4 Indicative Example

To be consistent with the example that was used to illustrate static anomaly detection approaches in section 4.2, we here stick to illustrating the same case : the case of parallel conflicting rule pairs. The included consideration is based upon the ideas proposed by Dubois, Prade & Ughetto [5]. We just briefly take a peek, without even briefly getting into details. Just to get a feel of things.

What Dubois, Prade & Ughetto state about the conflicting rule pair K={R1,R2}, is that for the set of implication-based rules K to be *inconsistent*, assuming all fuzzy sets involved are normalized, the following statement has to be fulfilled[5]

$\exists\, x \in X : \mathrm{Sup}_y \min_{i=1\ldots2}(\mu_{Ai}(x) \rightarrow \mu_{Bi}(y)) < 1$, i.e. there exists input data that together with K makes an inconsistent fuzzy knowledge base, since the corresponding inferred[6] possibility distribution – the 'Sup-min' part – is not normalized.

5. IDENTIFICATION OF A CONFLICT

The framework presented in this section of the text, immediately points out a potential zone of conflict between the static and the dynamic approach described in section 4. We

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[5] deduced from the reflection-on-the-input method [1].

[6] using a Generalized Modus Ponens reasoning scheme.

claim that it is precisely this potential conflict that manifests itself when confronting most of the results of both approaches in fuzzy verification literature.

5.1 The Duality Scheme

The duality scheme in Figure 4 positions dynamic and static anomaly detection methods in relation to the evolution of anomaly detection in a context of classical rule bases.

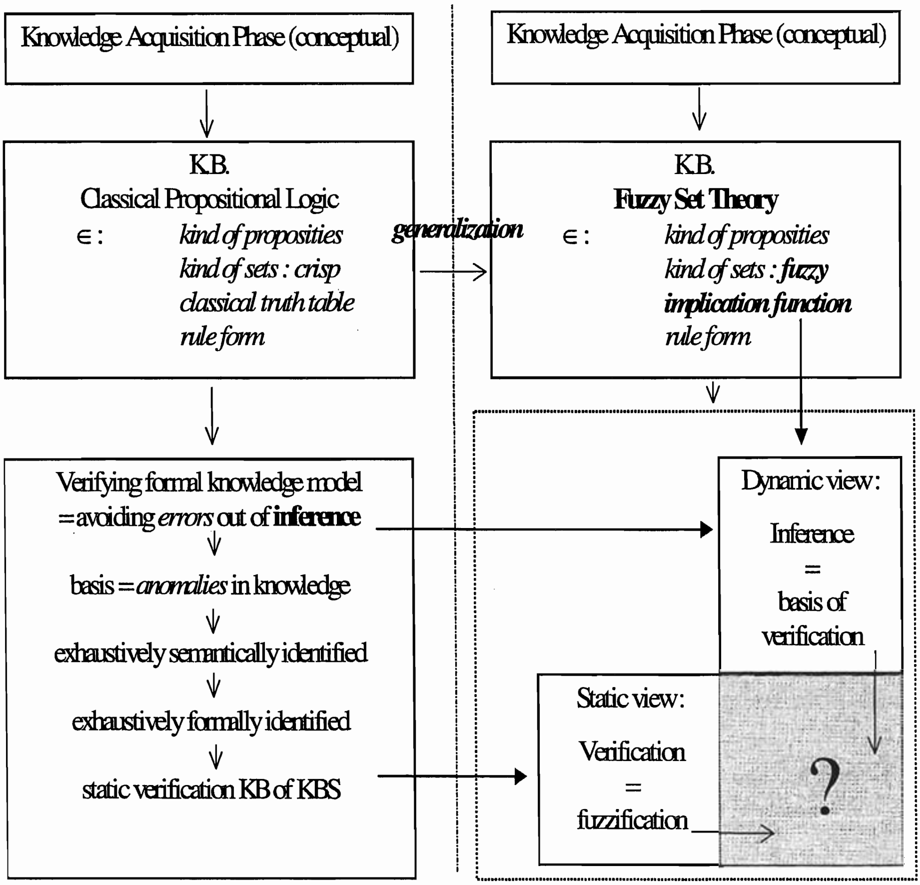

Figure 4. The duality scheme

The framework in Figure 4 is constructed as follows :

The left half of the figure, i.e. left of the vertically dotted line, represents the classical zone. This side encloses all the major realizations in the field of verification of classical propositional rule bases. These major realizations can be summarized by three principles [12,14] :

- Principle P1 : *Verification is done in function of the syntax and semantics of the specific knowledge representation formalism.*
- Principle P2 : *Verification is done in order to avoid errors out of inference. The means to prevent those errors from occurring is found in the detection of their symptoms in the KB : anomalies.*

These first two principles imply that one has to explicitly take into account the way of inferring results in order to obtain valid anomaly definitions. Principle P2 lies at the origin of the fact that it is always possible, by means of a dynamic analysis of the knowledge system, to impose a constraint on the results of inference in order to assure that a specific anomaly does not occur in the knowledge system, i.e. the dynamic verification approach. Yager & Larsen [29] illustrate this for a vast number of rule based logic encoding schemes, under which simple first order propositional logic and fuzzy logic, by using their method of *reflecting on the input* to detect any *inconsistency* in a rule based KB. They hereby create a definition of the anomaly, that is then verified by involving the inference process, thus the fuzzy inference operator, in the analysis, even without having to feed a representative set of inputs to the system.

- Principle P3 : *Anomaly detection is performed on the KB of the KBS. Certain properties of the inference engine are assumed but not verified any more.*

This last principle, one of the major contributions of classical verification research, allows for independent verification of inference engine and knowledge base. However, it remains necessary to specify those aspects of the inference mechanism upon which the results of this static kind of approach rely, whereas explicit testing of these inference engine properties is left behind. Verification research has succeeded in specifying anomalies in terms of the equivalence of the classical sets occurring in the rule base, or in terms of some related concept, e.g. the relationship 'is part of'.

When turning to the right hand side of the vertically dotted line in the duality framework, we enter the zone where fuzzy set theory makes its appearance in knowledge modeling. The introduction of fuzzy set theory engenders two major changes in the construction of a formal knowledge model : on the one hand there is the novelty of fuzzy sets, thus a new set formalism, on the other hand a adapted reasoning mechanism is introduced in the form of a fuzzy implication function.

The zone in the lower right half of Figure 4, represented by means of the dotted frame, constitutes the relevant range in the context of fuzzy rule base verification via the technique of anomaly detection. From the discussion in the previous part of this paper and from the insight in the principles governing the left part of the duality framework of Figure 4, it should now be clear where the duality in verification literature essentially finds its origin : dynamic anomaly detection methods are directly inspired upon principle P2, whilst the static counterparts of fuzzy verification literature try to directly transpose the acquirements underlying principle P3 to a fuzzy context.

5.2 Compatible Motives, Incompatible Realizations

It is a fact that literature on the verification of fuzzy rule based systems reveals that the current realisations of the dynamic and the static anomaly detection methods are very often quite incompatible with one another. This clearly points in the direction of a potential conflict between both lines of thought. The power of the above described duality framework now enables us to put the observed difficulty to reconcile results in the right perspective. The potential zone of conflict within the above discussed duality scheme, is indicated by the light-gray zone in the lower right corner of Figure 4.

The origin of an in literature identified conflict between results that stem from a dynamic anomaly analysis and those that emerge from a static point of view on verification in fuzzy rule bases, in most cases relies on the fact that principle P2 and principle P3 can never be realised separately. This is because they can be but the respective deliverables of two consecutive steps in one and the same sequential verification research project. This basic insight will in fact provide us not only with an explanation of why results in verification literature seem to differ according to the line of thought a verification theory belongs to, it also foresees in a means to normatively judge any proposed verification theory initiative. Now, both types of verification approach in section 4 can be evaluated.

With as main and direct motive the realisation of principle P3, the static anomaly detection methods identified in fuzzy verification literature try to transpose the static anomaly detection methods from a non-fuzzy or classical environment into a fuzzy rule base environment by *fuzzifying* the concept of equivalence of sets. They essentially try to use similarity, affinity or matching measures to identify anomalies within a fuzzy rule base. It is assumed that the static detection methods can be the same as those methods encountered in a non-fuzzy environment, except that the formerly mentioned measures indicate the degree of matching of two fuzzy expressions. In this way, these verification theory initiatives de facto uncouple verification and inference. By doing so, the probability of violating the major idea underlying principle P2, in that the specific inference mechanism cannot be omitted from any verification analysis, is not unthinkable. This is synthesized in Figure 5.

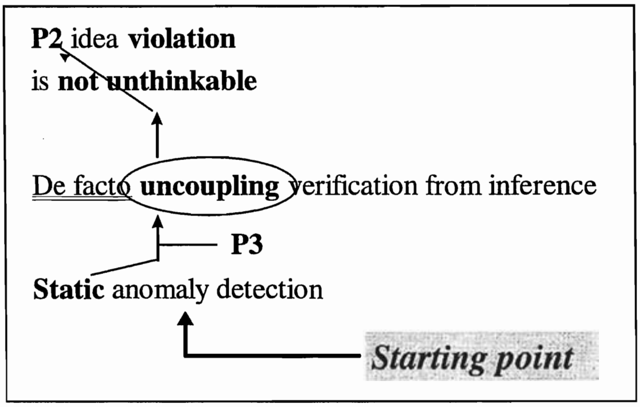

Figure 5 : static tactics to reach P3

Taking principle P2 as a starting point in conceiving a verification theory for a fuzzy rule base environment, i.e. the idea behind the dynamic line of thought, causes no problems of the former kind. It's even one of the main objectives of a P2-verification-analysis to be able to in the end realize principle P3, and obtain a static checking procedure in terms of necessary and/or sufficient conditions for verifying the KB of a rule based system. Unfortunately this is not yet the case, even though some major contributions have already been made by Dubois, Prade & Ughetto [5]. The gist of things for dynamic verification is again schematized in the next display, Figure 6.

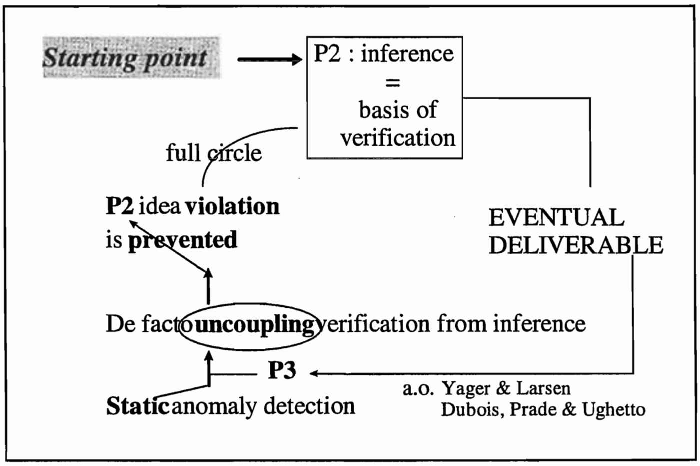

Figure 6 : dynamic tactics to reach P3

The foundations underlying both views on verification proposed in literature are not incompatible with one another. The incompatibility lies completely within the realizations of the motives governing both approaches and is due to the fact that static anomaly detection methods in general make abstraction of the semantics of the rules and thus leave the implication operator which is used out of the analysis.

6. GENERALIZING THE FINDINGS

Attentive readers will undoubtedly notice that the reasons that seem to underlie the fact that results in fuzzy rule base verification literature tend to differ between the two identified approaches, in se have nothing to do whatsoever with the fact that knowledge is modeled by means of fuzzy set theoretic constructs. The framework that was uncovered and that we used to grasp what was going on in the fuzzy verification literature, is of a very general nature.

Indeed, transposition of verification ideas from classical binary rule based reasoning towards an inferencing setting made up by any non-classical knowledge coding formalism, could potentially have lead to the situation that manifested itself to us in the specific area of fuzzy rule based knowledge modeling. Concretely, this means that the right hand side of the duality scheme could be populated by let's say any coding paradigm, not necessarily fuzzy set theory.

Focusing on what has happened over time within the classical rule base verification research area proves to be enlightening in this respect. This history of things is summarized by means of the next figure which is very similar to Figure 6, and this is not a coincidence.

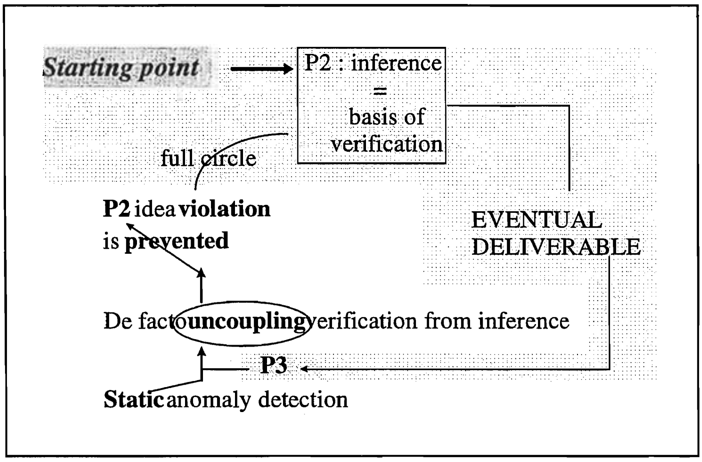

Figure 7 : black boxing the dynamic part of the verification effort

Classical verification research started out with the full picture, being lead by principles P1 and P2. Gradually, verification researchers were able to formulate verification checks in terms of necessary and sufficient conditions purely on the sets included in the rules. Part of the picture was beginning to get black boxed – the gray zone – in the process, giving birth to the statement in principle P3.

Then a new, intriguing and very promising knowledge coding formalism is introduced, in this case fuzzy set theory and the corresponding fuzzy logic. People are faced with the same expert system verification issues as before. Pragmatic as some are, most of them simply try to transpose the static verification definitions to the new context.

This is where things get really intriguing. Proposed verification theories do not always seem to be compatible. There are those who still are able to see the full picture, there are others who only notice the gray outside of what has been 'black boxed' through classical tradition. In the end some researcher inevitably will get intrigued by the diverse propositions. In his/her quest for understanding he/she uncovers the roots of the domain. Finally, relieved from all 'shades of gray', he/she takes up his/her pen and states to the whole world that he/she has opened yet another black box.

7. CONCLUSION

We identified dual lines of thought, static and dynamic, underlying the construction of the in literature proposed verification models that try to extend the verification of classical rule bases to the case of fuzzy knowledge modeling, without needing a set of representative input. This essentially is the result of applying an on grounded theory based research approach in order to grasp the complex multitude of verification approaches promoted in fuzzy verification literature.

The major outcome of the confrontation between both approaches is that their results, most often stated in terms of necessary and/or sufficient conditions are difficult to reconcile.

The analysis presented in this paper points out that the foundations underlying both views on verification proposed in literature are not incompatible with one another. At the origin of the observed duality in realizations of both rationale lies an error in the conception of the in literature proposed static approaches towards verification of rule bases. Things essentially go wrong when in the quest for a good affinity, matching or similarity measure, one neglects to take into account the effect of the implication operator, an issue that rises above and beyond the fuzzy setting that initiated the research.

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