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A Concise Comparative Analysis of Ambiguous Set Theory in Relation to Fuzzy, Intuitionistic Fuzzy, and Neutrosophic Sets

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ABSTRACT

Uncertainty, vagueness, indeterminacy, and ambiguity are fundamental challenges in representing information arising from complex real-world environments, particularly when human perception and decision-making involve indistinct boundaries between truth and falsity. This article presents a conceptual review and comparative analysis of Ambiguous Set (AS) theory in relation to Fuzzy Set (FS), Intuitionistic Fuzzy Set (IFS), and Neutrosophic Set (NS). The objective is to clarify the structural and representational characteristics of AS and identify situations in which its formulation may provide additional flexibility for uncertainty modeling. The comparison considers the basic components, mathematical constraints, relationships among parameters, interpretation of uncertainty, and capability to represent human perception. FS represents uncertainty through a single membership degree, whereas IFS incorporates membership, non-membership, and hesitation. NS further introduces independently characterized truth, indeterminacy, and falsity components. In contrast, AS employs four interrelated components: true membership, false membership, true-ambiguous membership, and false-ambiguous membership, allowing partially true and partially false conditions to be explicitly represented. The reviewed literature indicates that AS has been explored in image processing, multi-criteria decision-making, ambiguous logic, mathematical modeling, complex analysis, and time-series applications. However, its additional parameters may increase computational and interpretational complexity. Therefore, AS should not be regarded as universally superior to FS, IFS, or NS; its suitability depends on the characteristics of the uncertainty and application context. This review provides a balanced assessment of the strengths, limitations, and potential applications of AS while identifying future research opportunities in machine learning, hybrid decision-making, temporal ambiguity modeling, cognitive artificial intelligence, optimization, and formal mathematical development.

1. INTRODUCTION

Recently, one of the major issues for data science researchers is the precise assessment of uncertainty and vagueness of attributes. To deal with this issue, Fuzzy Set (FS) theory was developed by Zadeh [1]. The FS theory uses a non-probabilistic method to handle the vagueness associated with events. It assigns a single

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membership value within the range [0,1] to represent the degree to which an event belongs or does not belong to a specific fuzzy set.

Atanassov [2] introduced the concept of an IFS, which simultaneously captures both the degree of membership and non-membership of an element. In IFS theory, these are referred to as the true membership degree and the false membership degree, respectively [3]. The false membership degree is defined as the complement of the true membership degree with respect to 1. Additionally, a third parameter, known as the hesitant membership degree, is used to represent the uncertainty between the true and false membership values. This hesitant degree is also the remaining portion when the true and false membership degrees are subtracted from 1.

Table 1. Comparative analysis of FS, IFS, NS, and AS theories.

Aspect	Fuzzy Set (FS)	Intuitionistic Fuzzy Set (IFS)	Neutrosophic Set (NS)	Ambiguous Set (AS)
Introduced by	L. A. Zadeh (1965) [1]	K. T. Atanassov (1986) [2]	F. Smarandache (1998) [4]	P. Singh et al. [6]
Primary Objective	To model vagueness in data using a single membership degree.	To capture both membership and non-membership simultaneously, including hesitation.	To represent truth, falsity, and indeterminacy independently.	To handle blurred boundaries between truth and falsehood by introducing partial components.
Basic Components	One component: membership degree (μ).	Three components: membership (μ), non-membership (ν), and hesitation (π).	Three independent components: truth (T), falsity (F), and indeterminacy (I).	Four components: true membership (μ^t), false membership (μ^f), true-ambiguous (μ^{ta}), and false-ambiguous (μ^{fa}).
Mathematical Representation	FS = $\{\langle x, \mu(x)\rangle \mid x \in X, \mu(x) \in [0,1]\}$	IFS = $\{\langle x, \mu(x), \nu(x)\rangle \mid x \in X, \mu(x), \nu(x) \in [0,1], \mu(x)+\nu(x) \leq 1\}$	NS = $\{\langle x, T(x), I(x), F(x)\rangle \mid x \in X, T,I,F \in [0,1]\}$	AS = $\{x, \mu^t(x), \mu^f(x), \mu^{ta}(x), \mu^{fa}(x)\rangle \mid x \in X, \text{total} \leq 2\}$
Nature of Components	Single and dependent (only one value).	Dependent: hesitation depends on membership and non-membership.	Independent: all three values are mutually independent.	Interrelated: true and false components coexist with their partial (ambiguous) counterparts.
Constraint Condition	$0 \leq \mu(x) \leq 1$	$0 \leq \mu(x) + \nu(x) \leq 1$	No dependency; T, I, F $\in$ [0,1]	$\mu^t, \mu^f, \mu^{ta}, \mu^{fa} \geq 0$, total ≤ 2
Interpretation of Uncertainty	Represented by partial membership in the set.	Represented by hesitation between truth and falsity.	Represented by independent indeterminacy value.	Represented by gradations of truth and falsity, including partial (ambiguous) zones.
Flexibility	Least flexible; only one parameter.	Moderate flexibility through hesitation.	Highly flexible due to independent parameters.	Most flexible; captures both conscious and unconscious ambiguity.
Handling of Human Perception	Limited; assumes crisp boundaries for membership.	Partially considers hesitation in human reasoning.	Considers full independence of uncertainty.	Specifically models unconscious human perception and indistinct boundaries.

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Smarandache [4] introduced the concept of NS theory, which extends the framework of intuitionistic fuzzy sets (IFS). In NS theory [5], the components representing truth, falsity, and indeterminacy are treated as independent values within the interval [0, 1]. This independence marks a key distinction from IFS, positioning NS as a generalization of IFS theory. While both frameworks describe uncertainty using degrees of truth, falsity, and hesitation, Smarandache redefined the hesitant component as the indeterminacy degree. He emphasized that, unlike in IFS, these three components in NS are not constrained by interdependence, allowing for a more flexible and comprehensive representation of uncertainty.

The complexity increases when attempting to represent the partially true and partially false aspects of an uncertain event, as this results in indistinct boundaries between: (a) true and partially true membership degrees, and (b) false and partially false membership degrees.

To manage this complexity, Singh et al. [6] introduced the Ambiguous Set (AS) Theory, which accounts for the unconscious subtleties present in human perception, where the line between truth and falsehood is naturally blurred. The theory defines four interrelated membership degrees to represent an uncertain event: true membership, false membership, true-ambiguous membership, and false-ambiguous membership. These degrees are organized within a structured dimensional system that facilitates clearer analysis of vague boundaries. As a result, AS theory is especially effective in uncommon scenarios where unconscious human perception plays a critical role in decision-making. Table 1 provides a comparative analysis of FS, IFS, NS, and AS theories.

2. BACKGROUND ON AMBIGUOUS SET

Let $X = \{x\}$ represent the universe for a fixed event x. An AS, denoted by J, for $x \in X$, is defined as:

$$J = \{x, \mu^t(x), \mu f(x), \mu^t a(x), \mu f a(x) | x \in X\} \tag{1}$$

Here

- $\mu^t(x)$: X → [0,1] is the true membership degree,
- $\mu f(x)$: X → [0,1] is the false membership degree,
- $\mu^t a(x)$: X → [0,1] is the true-ambiguous membership degree, and
- $\mu f a(x)$: X → [0,1] is the false-ambiguous membership degree.

These membership degrees must satisfy the condition:

$$0 \leq \mu^t(x) + \mu f(x) + \mu^t a(x) + \mu f a(x) \leq 2 \tag{2}$$

In Eq. (1), the functions μ^t, μf, $\mu^t a$, and $\mu f a$ are referred to as the true membership function, false membership function, true-ambiguous membership function, and false-ambiguous membership function, respectively. Collectively, these four functions are termed the ambiguous membership functions.

3. LITERATURE REVIEW

Recently, many research articles have been published on ambiguous set theory. They are reviewed as follows:

- Theoretical Foundation: Singh [6] proposed the AS theory to better model the unconscious and ambiguous nature of human perception, distinguishing between true, false, true-ambiguous, and false-ambiguous membership degrees. This foundational work laid the groundwork for further extensions and applications of ambiguous logic and sets in decision-making and uncertainty modeling [10][16].
- Image Processing Applications: Ambiguous set theory has been effectively applied to medical image analysis, particularly for COVID-19 CT scans, where traditional clustering techniques face challenges due to noise and low resolution. The Ambiguous D-Means Fusion Clustering Algorithm (ADMFCA) and Ambiguous Kernel Distance Clustering (AKDC) demonstrated superior performance by capturing grayscale ambiguities in CT images [7][15][13].
- Decision-Making: Singh and Huang developed ambiguity-aware membership functions, aggregation operators, and distance measures for ASs and demonstrated their efficacy in multi-criteria decision-making, such as selecting the most suitable college under uncertain preferences [8].
- Logical Extensions: The development of a four-valued ambiguous logic system further enriched the theory, enabling the design of ambiguous inference systems. This logic allows for a more nuanced interpretation of vague and partially understood rules, with direct applications in fuzzy control systems [9].

- Mathematical Extensions: Singh proposed generalized ambiguous sets, single-valued ambiguous numbers, and aggregation operators, enhancing the mathematical expressiveness of the theory. Furthermore, lattice-based ambiguous sets provide a structured framework for handling partial ordering and hierarchy in uncertain environments [11][12].
- Cross-Disciplinary Applications: Building upon mathematical extensions, Singh introduced single-valued ambiguous complex numbers, with applications in Mandelbrot set generation and vector field analysis, showing that AS theory can extend to complex analysis and physics [14]. This section presents the results and validation of the experiments along with a detailed discussion. Tables and figures are explained in paragraphs. The author needs to add more detailed analysis. Authors need to adjust the use of equations based on the journal template.

4. FUTURE DIRECTION CONCLUSION AND LIMITATION

Based on the reviewed literature, several promising future directions for ambiguous set theory can be envisioned:

a) Enhanced Machine Learning Integration: Future research can explore the integration of ambiguous sets with advanced machine learning models such as deep learning [17]-[20], ensemble methods [21]-[24], or reinforcement learning [25]-[28]. By encoding ambiguity in input features, models could learn to handle uncertainty more effectively, especially in high-stakes domains such as healthcare diagnostics or financial forecasting.
b) Hybrid Frameworks for Decision-Making: Building upon the success of ambiguous sets in multi-criteria decision-making [29]-[32], future studies can develop hybrid frameworks combining ASs with FSs, rough sets [33]-[35], or NSs to create more robust decision-support systems that accommodate multiple types of uncertainty.
c) Temporal Ambiguity Modeling in Time-Series Analysis: An emerging avenue is the application of AS to time-series data where ambiguity changes over time [36]. This would involve defining dynamic ambiguous membership functions capable of modeling evolving uncertainty, which could benefit climate forecasting, energy demand prediction, or epidemiological modeling.
d) Ambiguous Logic in Cognitive Systems and AI: The four-valued ambiguous logic system could be further explored in artificial cognitive architectures and AI agents [37]. This would help simulate human-like reasoning under ambiguous conditions, with applications in natural language understanding, autonomous decision-making, human-robot interaction, and IoT [38].
e) Formalization and Topological Structures: There is scope to further formalize the algebraic and topological properties of ASs. Developing metrics, continuity, compactness, or convergence concepts under the ambiguous framework could lead to a deeper mathematical theory akin to topological fuzzy sets.
f) Ambiguity-Based Optimization Algorithms: Inspired by applications in image processing, optimization algorithms can be extended using ASs to enhance robustness in ambiguous environments, especially in areas such as swarm intelligence, genetic algorithms, and bio-inspired metaheuristics [39]-[41].
g) Expansion to Quantum and Complex Systems: The introduction of single-valued ambiguous complex numbers offers a new paradigm for modeling uncertainty in quantum mechanics and complex systems. Future research can delve into ambiguous quantum states, ambiguous probability amplitudes, or ambiguous transformations for applications in quantum information and signal processing.
h) Software Tools and Visualization Techniques: Developing open-source libraries and visualization tools for ambiguous set operations, inference systems, and membership distributions would greatly support broader adoption and educational use of the theory across disciplines.In this section, the author explains as stated in the "INTRODUCTION" section which ultimately leads to the "RESULTS AND DISCUSSION" section, so there is a connection. Apart from that, the author can add limitations and prospects for future research development (based on the results and discussion).

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