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Towards a Computational Theory of Perceptions under Neutrosophic Environment

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Abstract

Computing and reasoning with perceptions in AI are shifting from traditional methods to those that mimic human cognitive processes. Humans intuitively measure and evaluate without explicit computations, using sensory input and past experiences for quick judgments. The theory of perceptions can enhance AI's ability to replicate human-like assessment by providing a framework for handling the nuances of human reasoning. Traditionally, information granularity is either crisp (c-granular) or fuzzy (f-granular), focusing on measurement-based and perception-based information. This paper outlines a neutrosophic-based computational theory of perceptions (n-CTP), introducing neutrosophic granular (n-granular) information and neutrosophic constraint-centered semantics of natural languages (n-CSNL). Based on the neutrosophy theory, which deals with truth, falsity, and indeterminacy, managing uncertainties and vagueness in real-world data can be done more effectively than with traditional methods. The n-CTP has the potential to enhance AI's ability to process and reason with complex, uncertain, and ambiguous information.

Keywords: Artificial Intelligence; Computational Theory of Perceptions; Information Granularity; Soft Computing; Neutrosophic Logic.

1 | Introduction

From Plato's dialogues, where the question "What is knowledge?" was first posed, to the present day, questions about the nature of knowledge have puzzled philosophers for thousands of years. For more than 2000 years philosophers such as Aristotle, Heraclitus, Descartes, and others have tried to describe the mechanism of learning, memorizing, sight, perception, and reasoning. At that time Aristotle laid down the rules of conventional logic in an attempt to clear things up. Aristotelian logic provided some rules for the foundations of logical inductive reasoning, but it failed to deal directly and satisfactorily with the vague nature of many things.

Although researchers in mathematical logic had already worked with multi-valued logic, it wasn't until 1965 that a scientific approach to the issue of ambiguity was mentioned. Science aims to make things as clear as possible and to provide convincing answers for the various phenomena of our world. Ambiguity was seen as the enemy, as the goal was to clarify anything unclear. To admit that something was questionable and to accept and treat it as such went against the aims of science.

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In 1965, Zadeh introduced the idea of fuzzy logic and fuzzy sets [1]. Zadeh had to convince the scientific community that he was not proposing a way to compromise real problems but an ingenious new approach that could yield new results. Fuzzy logic is an extension of conventional logic. According to conventional logic, something is either completely true or completely false. However, there are many cases where this is not the case. In these instances, it would be better if we could use expressions like “almost true” or “almost false”.

Information granulation plays a key role in both human and machine intelligence. It involves breaking down complex information into easier-to-comprehend, coarse-grained portions or granules. Within this framework, to enable computers to process and reason with imprecise and vague information similarly to how humans do, Zadeh proposed the computational theory of perceptions (CTP) [2]. This framework involves translating perceptions, expressed in natural language, into computational representations utilizing fuzzy logic.

Neutrosophic logic, an advanced extension of classical and fuzzy logic, changes how we perceive and handle uncertainty, indeterminacy, and contradictions in complex systems [3]. Neutrosophic logic proposes three functions: truth-membership, indeterminacy-membership, and falsity-membership, to address limitations in classical logic when faced with incomplete, imprecise, or contradictory information. The ability of neutrosophic logic to capture and formalize this inherent complexity makes it a valuable tool in various fields, including artificial intelligence, decision sciences, engineering, and philosophy.

Neutrosophic logic's versatility and ability to handle uncertainties, contradictions, and vague information find applications across various domains. It has been successfully applied to decision-making systems [4-6], medical diagnosis and healthcare [7-9], pattern recognition and image processing [10-11], control systems and robotics [12-13], engineering and risk management [14-16] and environmental studies [17-18].

This paper aims to introduce in related literature an extension of the fuzzy CTP, namely a neutrosophic CTP (n-CTP). Our proposed framework enhances the accuracy of information granulation by managing truth, untruth, and indeterminacy simultaneously. This leads to the creation of more precise and detailed granules that precisely represent the complexity of the real world. In addition, n-CTP improves decision-making by ensuring that granules are based on the underlying data and allows for greater flexibility in handling uncertainty. Its connection with human cognition enables the development of more intuitive and granular computer systems.

2 | A Neutrosophic Computational Theory of Perceptions

2.1 | The Need for a Neutrosophic Computational Theory of Perceptions

Information granulation is important in human intelligence because it allows people to digest complicated information more effectively. By dividing enormous volumes of data into digestible, coarse-grained bits or granules, humans may concentrate on vital aspects while ignoring irrelevant information. This simplicity allows for greater comprehension, decision-making, and issue resolution. C-granular modes of information granulation (Figure 1) are essential in a variety of methodologies, approaches, and techniques, including interval analysis, qualitative process theory, decision trees, semantic networks, and constraint programming.

Despite its major impact on numeric measurement-based approaches, crisp information granulation fails to reflect the fact that in most human reasoning and idea production, the granules are fuzzy (f-granular) rather than crisp. Fuzzy sets represent confusing concepts by enabling items to have varying degrees of membership in a set. To do this, each element is assigned a membership degree to the set, which ranges from 0 to 1, yielding a membership function. While the concept of fuzzy logic has proven useful in resolving ambiguities and imprecision, it has a fundamental flaw when dealing with scenarios that include not only uncertainty but also indeterminacy, as well as the coexistence of truth, falsehood, and indeterminacy within the same assertion.

Smarandache [19] proposed Neutrosophy, a new discipline of philosophy based on many-valued logic that combines non-standard analysis with a tri-component logic/set/probability theory. Neutrosophy holds that any idea/concept/thesis, etc., has a degree of truth, as well as untruth and indeterminacy, which must be addressed separately. As a result, he created the theory of neutrosophic logic (NL) as a generalization of many-valued logic. Fuzzy logic is thought to be incapable of producing indeterminacy on its own, therefore NL was created to be more human-like. NL refers to the imprecision of information or linguistic inexactitude acquired by diverse observers, the uncertainty caused by inadequate knowledge or acquisition mistakes, and the vagueness caused by a lack of defined bounds or boundaries.

In neutrosophic logic, propositions are represented using triples *(T, I, F),* where *T* represents the degree of truth, *I* represents the degree of indeterminacy, and *F* represents the degree of falsehood. These degrees range from 0 to 1, indicating the extent to which each component is present. Mathematically, a neutrosophic proposition can be represented as:

Proposition $p = (T, I, F)$ (1)

If we observe expression (1) in greater detail, it becomes clearer that this representation is closer to how the human mind thinks. The subsets T, I, and F represent imprecise knowledge or linguistic inexactitude obtained by various observers, as well as uncertainty caused by incomplete knowledge or acquisition errors. The presence of subset I is due to stochasticity, while subsets T, I, and F exist because of a lack of clear boundaries [20].

It should be emphasized that for engineering issues, the traditional unit interval [0, 1] is employed. When T, I, and F are independent, there is the opportunity for inadequate information (sum < 1), paraconsistent and contradicting information (sum > 1), or complete information (sum = 1) [21].

In a more formal sense, let U be a universe of discourse and M a set within U. An element x from U is marked concerning the set M as $x(T,I,F)$ and belongs to M in the following way: it is t% true in the set, i% indeterminate (unknown whether it is) in the set, and f% false.

Thus, when we denote as $p = (0.6,0.2,0.2)$ we mean that proposition p belongs to M (which means, with a probability of 60% x is in M, with a probability of 20% x is not in M and the rest 20% is undecidable or undefined);

In this perspective, we believe that the introduction of a n-CTP could be viewed as a new and promising direction of AI to address problems in which the information that decisions are based on is perceptual.

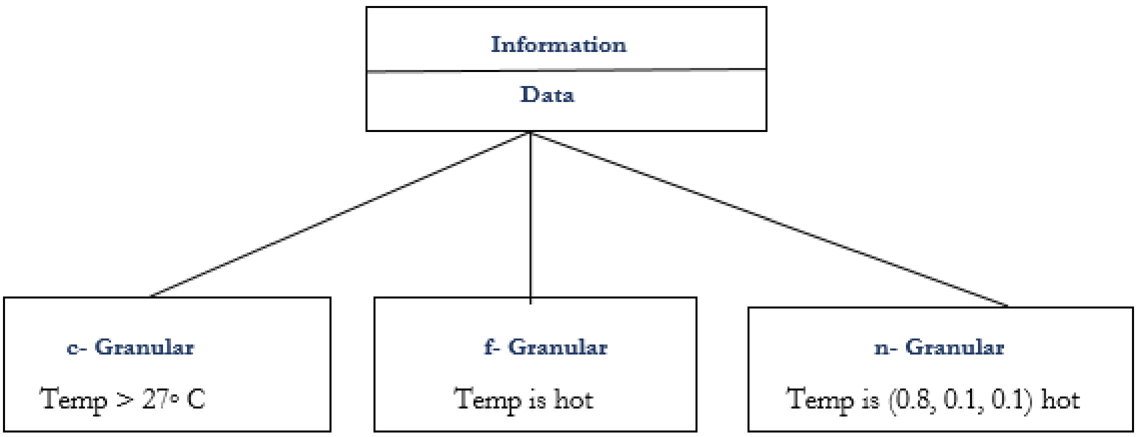

Figure 1. Classification of modes of granulation.

2.2 | Computing with Words in a Neutrosophic Environment

Computing frequently involves manipulating numbers and symbols. Humans, on the other hand, typically employ words in computing and reasoning, obtaining conclusions expressed as words based on premises articulated in natural language or taking the form of mental impressions.

The following is a simple general problem in the process of calculating with words. The initial data set (IDS) comprises natural language assertions. Our objective is to derive an answer to a natural language query from the original dataset. The response, expressed in regular English, is known as the terminal data set (TDS). The difficulty is to derive TDS from IDS (Fig. 2), which was adopted and modified from the seminal work discussed in [22]. In our article, TDS refers to the needed actions that have to be undertaken to successfully compute with IDS.

IDS {p} ⟶ **Computing with words** ⟶ **TDS {q}**

p, q: propositions expressed in natural language

Figure 2. Process of computing with words.

To reason about perceptions, one must first have a way to describe their meaning in a form that can be computed. Conventional meaning representation languages based on predicate logic lack the expressive capability needed for this task. Towards this direction, Zadeh proposed a CTP based on fuzzy logic [2, 22]. However, due to the inherent limitation of fuzzy logic in efficiently handling indeterminacy, it lacks the capability for a more thorough analysis of ambiguous or incomplete information.

In CTP, meaning representation entails capturing and recording the semantic content of perceptions in a computational form. This representation seeks to bridge the gap between human comprehension of language and machine analysis of data. Constraint-centered semantics in natural language processing (CSNL) [23] employs constraints to convey the meaning of linguistic expressions rather than standard formal semantics. It emphasizes the importance of limits in determining the meaning of words and phrases in a specific context, allowing for a more flexible and dynamic interpretation of natural language.

The main ideas and assumptions behind CSNL can be summarized as follows [24]:

- Natural-language propositions are used to describe perceptions.
- A proposition, p, can be interpreted as a response to a question.
- A proposition serves as a means of communication.
- A proposition's meaning is expressed as a generalized constraint that determines the information it conveys.

In this work, we propose an extension of CSNL, namely a neutrosophic CSNL (n-CSNL) which includes the following key concepts:

- Constraint-Based Representations: language meanings are represented by constraints that encompass a variety of language events, including word meanings, syntactic structure, and pragmatic restrictions. Neutrosophic logic provides for the modeling of these restrictions using degrees of truth, indeterminacy, and falsity, which accommodates ambiguous and conflicting data.
- Constraint Satisfaction: Interpreting language expressions requires meeting these constraints, ensuring that the meaning drawn from the statement is consistent with the limits imposed by the context. n-CSNL enables flexible constraint satisfaction while accepting variable levels of uncertainty and ambiguity in the interpretation process.
- Dynamic Interpretation: n-CSNL offers dynamic interpretation of verbal statements, allowing the interpretation process to adjust to changes in context or information availability. This dynamicity guarantees that the interpretation is both culturally appropriate and semantically meaningful.

When calculating with words in n-CSNL, two major issues arise. The first challenge is encoding neutrosophic limitations. More specifically, how may neutrosophic restrictions that are implicit in claims expressed in common language be made explicit? The second issue is neutrosophic constraint transmission, which investigates how neutrosophic constraints in premises, also known as antecedent constraints, may be spread to conclusions, or consequent constraints. These difficulties are addressed in the next subsection.

2.3 | Representation of Neutrosophic Constraints and Generalized Constraints

In a neutrosophic environment, generalized constraints are extended to handle the inherent uncertainty, indeterminacy, and inconsistency found in many real-world problems. A neutrosophic generalized constraint can be expressed as:

$$X\ is\ (T, I, F) \tag{2}$$

where: X is the variable or quantity being constrained

T is the degree of truth (how true the constraint is)

I is the degree of indeterminacy (how indeterminate or unknown the constraint is)

F is the degree of falsity (how false the constraint is)

As a simple example consider the proposition *p: The temperature in the room is moderate*. In this case, there are two possible questions: (1) What is the temperature of the room? and (2) What temperature is moderate? Assuming that the question is the first one, the meaning of *p* could be represented as

$p \longrightarrow$ *Temperature (room)* is *moderate*

where *Temperature (room)* is the constrained variable; *moderate* is the considering relation and the constraint defines the neutrosophic possibility distribution Π_x of *Temperature (room)*.

In schematic form, adopted and modified from [21]:

$X\ is\ (T, I, F) \longrightarrow \Pi_x = (T, I, F)$

$\longrightarrow$ Poss (X=u) = $(\mu_T\ (u), \mu_I\ (u), \mu_F(u))$

At this point, it is useful to define what we mean with the term neutrosophic possibility as first discussed in [25]. Assume p is represented as a neutrosophic proposition in the form X is P, where X takes values in a space U and P is a neutrosophic set in U with a given truth membership function μ_T, indeterminacy membership function μ_I, and falsity membership function μ_F. Assume F is represented as a neutrosophic statement of the form X is F, where F is a neutrosophic set in U, with a defined truth membership function (ν_T), indeterminacy membership function (ν_I), and falsity membership function (ν_F). Let u be a generic value of X. Denote the neutrosophic possibility that

X =u as $Poss_N$ (X=u).

Definition 1 [25]. $Poss_N$ (X=u) is defined as the grade of (t, i, f)-membership of u in P, i.e.

$$Poss_N\ (X=u) = (\mu_T\ (u), \mu_I\ (u), \mu_F(u)) \tag{3}$$

If we return to the above example and if we assume that the truth membership function of, say, 20°C in *moderate* is 0.7, the indeterminacy membership function and falsity membership function are 0.1 and 0.2 respectively, then the possibility that the temperature of the room is 20°C given that the temperature is (0.7, 0.1, 0.2)-moderate.

If the question is the second one, the meaning of *p* would be represented as

$p \longrightarrow$ *(moderate)* is V *(temperature in room)*

in which the constrained variable is (*moderate)*, and is V is a veristic constraint. Thus, if the temperature of the room is 20°C and the grade of truth/indeterminacy/falsity membership of 20°C in *moderate* is (0.7, 0.1, 0.2), then the neutrosophic verity of the proposition "the temperature of the room is moderate" is (0.7, 0.1, 0.2).

2.4 | Reasoning with Perceptions Based on Neutrosophic Generalized Constraint Propagation

When reasoning with perceptions using neutrosophic generalized constraint propagation, the goal is to handle indeterminacy and uncertainty more effectively. Perceptions are expressed using neutrosophic logic, allowing each perception to be associated with degrees of truth, indeterminacy, and falsity. These perceptions are then formulated as generalized constraints. For example, the perception "The room temperature is high" can be expressed as a constraint *(room) is High.*

The generalized constraints are propagated through a system of rules or models. This involves combining constraints using logical operations (AND, OR, NOT) and other operators specific to neutrosophic logic. For example, if we know "If the temperature is high, then the air conditioner should be on," we can propagate the constraint related to temperature to derive the constraint related to the air conditioner's state.

Consider the following example to illustrate this process:

Proposition p: "It feels warm in the room."

This can be represented in neutrosophic terms as *Warm* $_{room}$ $(T_W,,w)$ where *T*, *I*, and *F* represent the degrees of truth, indeterminacy, and falsity respectively.

Generalized Constraint: (room) is Warm

Propagation Rule: "*If (room) is Warm, then* AC_{state} *is On.*"

To better understand the propagation rule let us delve into the detailed steps involved:

Let *(room) is Warm* be represented as $(T_W,,w)$ where T_W, I_W, and F_W are the truth, indeterminacy, and falsity values, respectively. Similarly, let AC_{state} *is On* be represented as (T_{AC},I_{AC},F_{AC})

Establish a rule that links the perception to the action. For example, the rule can be expressed as *IF T(room) is Warm THEN* AC_{state} *is On*

Given the rule, *if (Troom) is Warm* is represented by $(T\ ,F_W)$, then the corresponding AC_{state} *is On* can be represented by a similar neutrosophic triplet (T_{AC},I_{AC},F_{AC}).

The transformation typically follows some predefined logic that dictates how the truth, indeterminacy, and falsity values propagate through the rule. For simplicity, let's assume the transformation preserves the levels of uncertainty, meaning: $T_{AC}=T_W$, $I_{AC}=I_W$, and $F_{AC}=F_W$. This implies that the truth, indeterminacy, and falsity of the room being warm directly map to the truth, indeterminacy, and falsity of the AC being on.

Suppose we have the following neutrosophic values for the perception "Warm": (T_W=0.7, I_W=0.2 F_W=0.1). Given the rule: *IF (room) is Warm THEN* AC_{state} *is On.* The propagation results in: (T_{AC}=0.7, I_{AC}=0.2, F_{AC}=0.1)

So, the propagated constraint for the air conditioner's state being "On" is: AC_{state} is *On* ≡ (0.7,0.2,0.1)

In more complicated situations, the propagation rules use sophisticated transformations to account for the various linkages and interactions between multiple perceptions and actions. This complexity stems from the necessity to deal with the combined ambiguity, indeterminacy, and vagueness of various perceptions and how they impact each other in a more nuanced way.

For instance, in the above example, the decision to turn on an air conditioner might depend on both the room temperature and humidity levels so on this occasion we will have the following propositions:

p_1: *T(*room) is Warm

p_2: H(room) is Humid and

q: AC_{state} is On

The rule in this instance might be: If p_1 AND p_2 THEN q (4)

In order to compute the above rule we will first need to define the neutrosophic conjunction connective to handle neutrosophic values.

Definition 2 [26]. Given two sentences p_1, p_2 and a neutrosophic valuation v such that v $(p_1) = (t_1, i_1, f_1) \in$ N , and $v(p_2) = (t_2, i_2, f_2) \in \mathcal{N}$, the truth value of the conjunction $p_1 \wedge p_2$ may be defined as:

$$v(p_1 \wedge p_2) = (\min(t_1, t_2), \max(i_1, i_2), \max(f_1, f_2)) \quad (5)$$

Now, if we assume that we have:

p_1: *T(*room) is Warm = (0,7, 0.2, 0.1) and

p_2: H(room) is Humid = (0.6,0.3, 0.1) then by applying equation (5) we have

$v(p_1 \wedge p_2) = (\min(0.7, 0.6), \max(0.2, 0.3), \max(0.1, 0.1)) = (0.6, 0.3, 0.1)$

So the propagated constraint for the air conditioner's state being "On", based on the if-then rule shown in (4), would be, q: AC_{state} is *On* = (0.6, 0.3, 0.1).

3 | Concluding Remarks

The integration of neutrosophic logic into the computational theory of perceptions (n-CTP) represents a major advancement in artificial intelligence, specifically in enhancing its ability to mimic human cognitive processes. We introduce a framework that adequately manages the inherent uncertainties, vagueness, and indeterminacies present in real-world data by introducing the notion of neutrosophic granular (n-granular) information and formulating neutrosophic constraint-centered semantics of natural languages (n-CSNL).

Unlike prior suggested methods, which rely primarily on crisp (c-granular) or fuzzy (f-granular) approaches, n-CTP uses three-valued neutrosophic logic of truth, falsity, and indeterminacy. This allows for a more intricate and comprehensive representation and processing of information, which is similar to how people naturally perceive and reason about their surroundings. The versatility of neutrosophic logic to deal with varying degrees of uncertainty makes it an ideal conceptual instrument for dealing with the specifics of perceptional knowledge. This advancement has far-reaching implications for a wide range of applications, including natural language processing and decision-making systems, in which understanding and interpreting complicated human perspectives is crucial.

However, this article only outlines the basic key concepts of a computational theory of perceptions under a neutrosophic environment. In more complex scenarios, the propagation rules involve even more sophisticated transformations to account for the intricate relationships and interactions between multiple perceptions and actions. Actions may be influenced not just by present perceptions but also by their history and evolution over time. In the latter, temporal dynamics provide a further layer of complexity, as propagation algorithms must account for trends and rates of change. In other cases, there may be conditional dependencies and nonlinear interactions between perceptions and actions. For example, the feeling of comfort might be influenced by both temperature and humidity, but with distinct weights and perhaps non-linear interactions that represent how humans experience comfort.

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Data Availability

The datasets generated during and/or analyzed during the current study are not publicly available due to the privacy-preserving nature of the data but are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that there is no conflict of interest in the research.

Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors.

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