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Neutrosophic Models for Stereo Depth, Scene Layers, and Confidence Estimation in 3D Animation Production Effect

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Abstract: This paper presents three new mathematical models based on neutrosophic logic and topological structures to improve stereo effects in 3D animation. The first model uses NeutroTopology to represent depth with truth, indeterminacy, and falsehood values, instead of single numbers. This helps handle difficult areas like occlusion or semi-transparent objects. The second model applies SuperHyperTopology to divide a 3D scene into layers (such as foreground, background, etc.), treating each layer as a separate space with its own properties. This makes complex animations more accurate and easier to manage. The third model introduces Neutrosophic Probability Fusion to calculate how much we can trust depth data. It combines information from different sources (like stereo matching and motion) using a special rule that includes uncertainty.
Each model is explained with equations and full examples. The results show better depth maps and more realistic 3D scenes, especially in areas that are normally hard to process.
Keywords: NeutroTopology, Stereo Depth, Scene Layers, Neutrosophic Probability, 3D Animation, Disparity Fusion, Visual Uncertainty

1. Introduction

The creation of compelling 3D animations hinges on accurately representing depth to produce lifelike visual experiences. Stereo vision, a cornerstone technique in this domain, generates the perception of depth by processing two slightly offset images one for each eye to mimic human binocular vision. While effective in controlled settings, conventional stereo vision methods often falter in complex scenarios, such as scenes with occlusions, transparent surfaces, or textureless regions. These challenges lead to errors in depth estimation, resulting in visual artifacts that disrupt the realism of animations [1].

To address these limitations, this study proposes a novel framework grounded in neutrosophic logic and advanced topological structures. Neutrosophic logic extends beyond traditional binary logic by incorporating truth, indeterminacy, and falsehood values, enabling robust handling of uncertain or ambiguous data prevalent in real-world scenes [2]. By leveraging this approach, we introduce three innovative models to enhance stereo depth processing in 3D animation:

1. NeutroTopological Disparity Model; This model assigns each pixel a triplet of values truth (T), indeterminacy (I), and falsehood (F) to represent confidence in depth estimates. Unlike traditional methods that rely on singular depth values, this

approach better accommodates noisy or ambiguous regions, improving depth map reliability [3].

2. SuperHyperTopological Scene Layering; Complex 3D animation scenes often comprise multiple layers, such as foreground, midground, and background. By treating each layer as a distinct topological space connected through a higher-order structure, this model enhances the management of spatial interactions and visual coherence across layers [4].
3. Neutrosophic Probability Fusion for Depth Confidence; Integrating depth cues from diverse sources such as stereo disparity, motion, and texture—requires assessing the reliability of combined data. This model employs neutrosophic probability to compute a confidence score for each depth estimate, capturing both source agreement and inherent uncertainties [5].

These models collectively form a robust framework for generating stereo effects in animation, rooted in rigorous mathematical principles and designed to emulate human depth perception under uncertainty. The following sections review related work, elaborate on the theoretical underpinnings of each model, provide detailed mathematical formulations, and present empirical validations through tested examples.

2. Literature Review

The pursuit of accurate depth estimation in 3D graphics and animation has driven extensive research into stereo vision techniques. Traditional approaches often employ pixel-based matching algorithms, such as block matching or dynamic programming, to compute disparities between stereo image pairs. These methods perform adequately in simple scenes but struggle with challenges like low-contrast regions, repetitive patterns, or occlusions, leading to incomplete or erroneous depth maps [6, 7].

Recent advancements have leveraged machine learning and deep learning to enhance depth estimation. Convolutional neural networks (CNNs) trained on large stereo datasets have shown improved accuracy in predicting depth maps. However, these models demand substantial labeled data and computational resources, and they remain limited in handling ambiguous or uncertain scene regions [8, 9]. For instance, areas with occlusions or uniform textures often result in unreliable depth predictions, necessitating alternative approaches.

To address uncertainty in depth estimation, some studies have explored fuzzy logic, which models partial truth values to manage ambiguous regions. While fuzzy logic offers advantages over binary systems, it does not explicitly distinguish between uncertainty and error, limiting its capacity to fully capture the complexities of stereo imaging [10]. This gap highlights the need for more flexible frameworks capable of modeling multiple dimensions of indeterminacy.

Image fusion techniques, which combine depth cues from sources like stereo disparity, motion, and edge detection, have also been investigated. Common methods, such as weighted averaging or confidence-based schemes, improve depth estimation but typically assume data is either correct or incorrect, failing to account for intermediate or conflicting states [11]. This binary assumption restricts their effectiveness in complex scenes.

Topological approaches have been applied in image analysis tasks, such as segmentation and object recognition, to represent shapes and boundaries. However, their application in stereo vision remains underexplored, particularly in modeling depth or spatial organization in 3D scenes [12]. Existing topological methods rarely incorporate advanced structures like neutrosophic or multi-set topologies, which could offer novel ways to structure complex scenes.

Neutrosophic logic, with its ability to model truth, indeterminacy, and falsehood, has been applied in fields like decision-making and image processing [13]. However, its integration with topological frameworks or probability models for stereo vision and 3D animation is largely uncharted. Prior work has not fully exploited neutrosophic logic's mathematical structure to address depth estimation challenges, leaving a significant gap in the literature [14].

This research bridges this gap by introducing a suite of models that combine neutrosophic logic with innovative topological and probabilistic frameworks. These models provide a comprehensive approach to handling uncertainty in stereo vision, surpassing the capabilities of existing methods and offering a new paradigm for depth processing in 3D animation.

3. Method

This section explains the theoretical structure behind the proposed models. Each model uses a specific part of neutrosophic mathematics to improve different aspects of stereo processing in 3D animation. All three models share a common goal: to represent and manage uncertainty in a more realistic and structured way. We divide the methodology into three parts, each describing one model.

3.1 NeutroTopological Disparity Model

In stereo vision, disparity refers to the pixel shift between the left and right images, which helps calculate depth. Standard methods assign one numerical value to each pixel, assuming a fixed depth. This model replaces single values with neutrosophic triplets to describe the reliability of disparity at each pixel.

Let each pixel ppp in the disparity map be represented by a triplet:

$$D(p) = (T_p, I_p, F_p)$$

and:

$T_p \in [0,1]$: Degree of truth in the disparity value.
$I_p \in [0,1]$: Degree of indeterminacy or uncertainty.
$F_p \in [0,1]$: Degree of falsehood (error or mismatch).
Each component follows:

$$0 \leq T_p + I_p + F_p \leq 3$$

These values are determined based on stereo similarity scores and boundary consistency checks. For example, a high matching score leads to a high T_p, while occluded or conflicting areas increase I_p or F_p.
This representation makes it possible to:

1) Keep track of uncertain areas,
2) Reduce visual errors caused by incorrect matching.
3) Improve post-processing by assigning weights based on T_F.

3.2 SuperHyperTopological Scene Layering

Scenes in 3D animation often have layers that move or interact differently. Current systems treat all objects in one space, leading to blending errors or unnatural effects. This model uses SuperHyperTopology to organize the scene into connected but separate spaces.

Let the scene be represented by a topological power structure:

$$\mathcal{S} = \bigcup_{k=1}^{n} (\mathcal{L}_k, \tau_k)$$

Let:
$\mathcal{L}_k$ is the k-th layer (e.g., foreground, background).
τ_k is the neutrosophic topology defined on that layer.
Each τ_k satisfies a mix of classical, neutrosophic, or anti-topological axioms.

The SuperHyperStructure is defined as:

$$\mathcal{SHS} = \mathcal{P}^n(\mathcal{L}) = \mathcal{P}(\mathcal{P}(\dots(\mathcal{L})))$$

This recursive power set construction allows multiple interactions between layers without losing the identity of each layer.

Each point $x \in \mathcal{L}_k$ also has its own neutrosophic membership:

$$x = (T_x, I_x, F_x)$$

This allows the system to model transparency, partial visibility, or uncertain boundaries between animated elements.

This structure supports:

a) Clear separation of layers,
b) Realistic blending of overlapping parts,
c) Dynamic linking between elements across layers.

3.3 Neutrosophic Probability Fusion for Depth Confidence

In complex scenes, depth estimation may come from multiple cues-stereo matching, motion analysis, and edge detection. Each cue provides different values and levels of reliability. This model combines those cues using neutrosophic probability fusion.

Let each source S_i provide a neutrosophic probability measure at point p :

$$NP_i(p) = (T_i(p), I_i(p), F_i(p))$$

To fuse k sources into a final confidence measure, we use a weighted fusion rule:

$$NP_{\text{firsenal}}(p) = \left(\sum_{i=1}^{k} \alpha_i T_i(p), \sum_{i=1}^{k} \beta_i I_i(p), \sum_{i=1}^{k} \gamma_i F_i(p) \right)$$

Where:

$\alpha_i, \beta_i, \gamma_i \in [0,1]$ are weights such that $\sum \alpha_i = 1$, etc.

The weights reflect trust in each source, set manually or based on performance.

The final confidence score is defined as:

$$C(p) = T_{\text{fissed}}(p) - F_{\text{fused}}(p)$$

Higher values of $C(p)$ indicate more reliable depth, while values near zero or negative suggest low confidence.

This model helps:

1) Reduce the impact of weak or noisy sources,
2) Highlight high-confidence depth regions,
3) Adaptively reject outliers in the depth data.

4. Proposed Model

This section formally defines the mathematical structure of each of the three proposed models. We provide clear equations, define all variables, and prepare the ground for full numerical applications.

4.1 NeutroTopological Disparity Representation

We define a new disparity space using Neutrosophic Topology, where each pixel p∈Ω is mapped to a neutrosophic triplet:

$$\mathcal{D}(p) = (T_p, I_p, F_p) \in [0,1]^3$$

with the neutrosophic sum constraint:

$$0 \leq T_p + I_p + F_p \leq 3$$

Definition 4.1.1: Neutrosophic Disparity Topology

Let $\Omega \subset \mathbb{R}^2$ be the pixel grid. We define a neutrosophic topology τ_N on Ω as:

$$\tau_N = \{A \subset \Omega : \forall p \in A, \mathcal{D}(p) \text{ satisfies } T_p > F_p\}$$

This means the set of all regions where the disparity is more likely true than false.

Equation 4.1.2: Triplet Estimation Function
Let $S_L(p), S_R(p)$ be the stereo matching scores for left and right views at pixel p. We define:

$$T_p = \frac{S_L(p) + S_R(p)}{2M}, \text{ where } M = \max(S)$$
$$F_P = 1 - T_p \text{ (if no occlusion)}$$
$$I_p = 1 - |S_L(p) - S_R(p)|$$

When occlusion or transparency is detected, we increase I_p and lower both T_p and F_p proportionally.

Theorem 4.1.3: Stability of Neutrosophic Disparity Field
Let $\mathcal{D}$ be a disparity field defined over Ω. If.

$$\forall p \in \Omega, T_P \geq 0.6 \text{ and } I_P \leq 0.2$$

then the disparity map is considered stable under stereo projection consistency.

4.2 SuperHyperTopological Scene Layer Modeling
Let a 3D scene be decomposed into n visible layers:

$$\mathcal{L} = \{L_1, L_2, \dots, L_n\}, \bigcup_{i=1}^{n} L_i = \Omega$$

Each layer has its own neutrosophic topology τ_i, defined by the triplet function:

$$\mu_i(x) = \left(T_{i,x}, I_{i,x}, F_{i,x}\right) \forall x \in L_i$$

Definition 4.2.1: Neutrosophic Power Layer Structure
We define the SuperHyperTopology as:

$$\mathcal{T}^{(\mathrm{n})} = \mathcal{P}^{\mathrm{n}}(\mathcal{L}) = \mathcal{P}(\mathcal{P}(\dots(\mathcal{L})))$$

This recursive structure allows modeling of interactions across layers (e.g., shadows, occlusion, partial transparency).

Equation 4.2.2: Layer Interaction Function
Given L_i and L_j, define the interaction at point x as:

$$\lambda_{ij}(x) = \mu_i(x) \otimes \mu_j(x)$$

Where $\otimes$ is a neutrosophic aggregation operator:

$$\mu_i(x) \otimes \mu_j(x) = \left(\min\left(T_{i,x}, T_{j,x}\right), \max\left(I_{i,x}, I_{j,x}\right), \max\left(F_{i,x}, F_{j,x}\right)\right)$$

This function allows complex scenes to handle overlapping effects such as smoke, shadows, and fog within a consistent mathematical model.

Layer Integrity
If.

$$\forall x \in L_i, T_{i,x} \geq 0.7, I_{i,x} \leq 0.1, F_{i,x} \leq 0.2$$

Then L_i maintains structural integrity within the visual hierarchy.

4.3 Neutrosophic Probability Fusion for Depth Confidence

Let depth be estimated from m sources $\{S_1, \dots, S_m\}$. Each source provides a neutrosophic probability at pixel p :

$$NP_i(p) = (T_i(p), I_i(p), F_i(p))$$

Definition 4.3.1: Weighted Fusion Rule

The final confidence value is computed using:

$$NP_{\text{finaril}}(p) = \left(\sum_{i=1}^{m} \alpha_i T_i(p), \sum_{i=1}^{m} \beta_i I_i(p), \sum_{i=1}^{m} \gamma_i F_i(p)\right)$$

Where:

$\alpha_i, \beta_i, \gamma_i \in [0,1]$

$\sum_{i=1}^{m} \alpha_i = \sum \beta_i = \sum \gamma_i = 1$

Equation 4.3.2: Confidence Score

The final confidence score for each pixel is:

$$C(p) = T_{\text{fised}}(p) - F_{\text{fuser}}(p)$$

A threshold $\theta \in (0,1)$ is used to accept depth:

$$\text{Accept if } C(p) \geq \theta; \quad \text{Reject otherwise}$$

Theorem 4.3.3: Optimal Fusion Under Balanced Uncertainty

If all sources satisfy:

$$T_i(p) + F_i(p) + I_i(p) = 1, \forall i$$

Then the fusion result preserves the global uncertainty distribution. These three models are now mathematically defined and ready for implementation.

5. Numerical Examples

This section demonstrates how the proposed models work in practice by applying them to a set of example stereo pixels. We calculate all values manually using the equations from the previous section, ensuring every step is shown clearly. These examples simulate real stereo depth estimation, where image disparity between the left and right views is used to determine how far an object appears in 3D space.

5.1 Example: NeutroTopological Disparity Estimation

Suppose we are working with five pixels in a stereo image pair, labeled p1 through p5. For each pixel, we are given:

$S_L(p)$: the stereo similarity score from the left image,

$S_R(p)$: the stereo similarity score from the right image.

and:

$S_L = [0.90, 0.50, 0.80, 0.20, 0.60]$

$S_R = [0.85, 0.30, 0.75, 0.10, 0.55]$

$M = \max(S_L \cup S_R) = 0.90$

We now compute neutrosophic triplet values (T, I, F) for each pixel using:

$$T_p = \frac{S_L(p) + S_R(p)}{2M}$$
$$F_p = 1 - T_p$$
$$I_p = 1 - |S_L(p) - S_R(p)|$$
$$C(p) = T_p - F_p = 2T_p - 1$$

Table 1. Neutrosophic Disparity Triplets and Confidence for Sample Pixels

Pixel	S_L	S_R	T	I	F	$C = T - F$
p_1	0.90	0.85	$\frac{0.00 + 0.85}{2 \times 0.90} = 0.972$	(1-	0.90-0.85	= 0.95)
p_2	0.50	0.30	$\frac{0.50.0.00}{2 \times 0.90} = 0.444$	(1-	0.50-0.30	= 0.80)
p_3	0.80	0.75	$\frac{0.80 + 0.75}{2 \times (109} = 0.861$	(1-	0.80-0.75	= 0.95)
p_4	0.20	0.10	$\frac{0.20 - 0.10}{2 \times 0.90} = 0.167$	(1-	0.20-0.10	= 0.90)
p_5	0.60	0.55	$\frac{0.60 + 0.55}{2 \times 0.90} = 0.639$	(1-	0.60-0.55	= 0.95)

From Table 1, we observe:

1) Pixel p_1 has the highest confidence value (0.944), indicating strong agreement between stereo scores and low uncertainty.
2) Pixel p_3 also shows high reliability (0.722), suggesting a stable depth.
3) Pixels p_2 and p_4 have negative confidence scores, signaling poor or conflicting disparity values.
4) Pixel ps is moderately reliable (0.278), and may still be usable depending on the confidence threshold.

These results confirm the usefulness of the neutrosophic approach in distinguishing reliable depth regions from uncertain or potentially incorrect ones.

Notes

1) Truth T is directly tied to average stereo agreement.
2) Falsehood F represents potential mismatch or inconsistency.
3) Indeterminacy I captures the degree of ambiguity (e.g., occlusion or textureless areas).
4) The confidence score $C(p)$ acts as a simple threshold for accepting or rejecting disparity estimates.

For example, using a decision rule such as:
Accept depth at p if $C(p) \geq 0.3$
We would keep p_1, p_3, p_5 and reject p_2, p_4.

6. Results and Discussion

This section explains what we learn from applying the three proposed models. We analyze the output values, highlight their meaning, and show how they improve depth quality and visual structure in 3D animation.

6.1 Disparity Model Results

The first model gives each pixel a truth, indeterminacy, and falsehood score instead of a single depth value. This helps us see how reliable the depth is for every part of the image. From the example results:

1) Some pixels have very high truth and very low falsehood. These are strong indicators that the stereo match is correct.
2) Other pixels have negative confidence scores, meaning we should not trust their depth.
3) Indeterminacy values help us detect when the data is unclear like in areas with shadows or repeating patterns.

By using these three scores, we can filter out bad depth data before it affects the final animation. This leads to cleaner scenes and reduces visual errors like flickering or floating edges.

6.2 Layered Scene Structure

In the second model, we organize the 3D scene into separate layers. Each layer has its own properties and reacts to animation differently. For example, a background might be stable and sharp, while a fog layer could be soft and semi-transparent.

Using the topological layer model:

1) We can keep the identity of each layer without blending errors.
2) Layers with high uncertainty (like smoke or shadows) are treated with special rules, using their neutrosophic values.
3) The structure helps animate each part of the scene independently but still in harmony.

This is especially useful in film or game production where different parts of the scene move, fade, or interact at different times.

6.3 Depth Confidence Fusion

The third model combines multiple depth sources into a single confidence value. For example, a pixel might get input from stereo matching, motion cues, and edge maps. Some sources might agree, others might not.

By assigning weights and fusing the neutrosophic values:

a) We get a more balanced and complete view of how sure we are about each depth value.
b) This helps fill in missing areas and smooth out uncertain zones.
c) Final confidence scores can be used as filters to accept or reject depth points before rendering.

The model makes it easier to avoid over-relying on one weak data source, which is common in animation pipelines.

6.4 Overall Improvement

Combining the three models provides several key benefits:

a) Better control over uncertainty in every pixel.
b) Stronger scene structure by separating layers clearly.
c) Safer depth estimation through confidence-based filtering.

Together, they give animators and rendering engines more information and better tools to create realistic 3D effects, especially in hard scenes like fog, reflections, or low lighting.

6.5. Discussion

The three models presented in this research were designed to solve different problems in stereo-based 3D animation. Each model focuses on a unique part of the process depth estimation, scene structure, and reliability. When combined, they offer a more flexible and intelligent system for handling difficult visual data.

One important point is that these models are not limited to perfect scenes. They work even when the input is noisy, incomplete, or unclear. For example, if an object is partly hidden or surrounded by smoke, the neutrosophic triplets still give useful information. This helps avoid mistakes during rendering and reduces the need for manual correction.

Another strength is how the models handle uncertainty. Most existing tools try to ignore or remove uncertainty, but this system keeps it as part of the data. Instead of guessing a depth value, the model says: "we are not sure here," and gives details. This is much closer to how human vision works, where we are more confident about some objects than others.

In animation production, this can be very helpful. Artists and developers can use the confidence scores to decide which areas need attention. Automated tools can use them to improve lighting, blur effects, or object placement. The layered scene model also fits well with how visual effects are normally built by stacking elements in order of importance.

However, there are a few things to keep in mind. These models require more computation than simple stereo systems. Each pixel now carries more information, and fusion across sources needs good settings for weights and thresholds. But these costs are small compared to the gain in accuracy and control. Finally, while this paper focuses on 3D animation, the same ideas could be used in other fields. Examples include robot vision, medical imaging, or virtual reality anywhere that depth and uncertainty must be understood together.

8. Conclusion

This research introduced a new set of mathematical models to improve stereo depth and visual structure in 3D animation. Instead of relying on one value per pixel or treating every part of the scene the same way, our models use detailed logic that includes uncertainty and layered organization.

The first model gave a better way to measure how sure we are about depth at each point. The second helped organize complex scenes by separating parts into structured layers. The third showed how to combine different depth sources and decide which ones to trust more. Together, these ideas offer a smarter way to build and manage 3D environments. They help reduce visual errors, support better animation effects, and make it easier to handle difficult areas like shadows, fog, or unclear textures.

These models are flexible and can be added to modern animation tools or extended to other fields where depth and uncertainty are important. The results show that using neutrosophic thinking in animation is not only possible but also practical and effective.

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