A Review of Research on Dense Matching Algorithms in Digital Surface Model

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Abstract

Digital Surface Models (DSM), critical for 3D surface representation, rely on dense matching algorithms for accuracy and efficiency. This review examines two decades of advancements in feature-based, region-based, and deep learning-driven methods. Feature-based methods such as SIFT and ORB can achieve sub-pixel accuracy in high - texture scenes. However, they have a mismatch rate of approximately 20% in low - texture areas and are suitable for small - scale photogrammetry. Region - based methods like Semi - Global Matching (SGM) can achieve a Root Mean Square Error (RMSE) of ≤0.5 meters in homogeneous terrains. But in complex urban scenes, they may have errors of about 1.2 meters. These methods are used for large - scale DSM generation and have a computational complexity of $O(n^2)$. Deep learning-driven methods such as GC-Net can reduce the mismatch rate by 30-50% in low-texture regions, with F1 - scores greater than 0.9. However, they require 20-50 times more GPU memory and are applied to high - precision DSM in complex environments. Currently, the challenges include the trade-off between accuracy and efficiency and the interpretability of deep learning. Future directions include AI-driven interdisciplinary integration, enhanced data augmentation, and addressing complex scene challenges.

1 INTRODUCTION

DSM capture terrain and vertical structures, enabling applications in smart cities and disaster monitoring. Unlike DEM, DSM use grids or TIN for multi-scale modeling. LiDAR and photogrammetry are primary DSM generation methods: LiDAR achieves sub-meter accuracy via time-of-flight ranging, while photogrammetry constructs dense 3D point clouds through image matching. Dense matching algorithms, grounded in photometric consistency and geometric constraints, optimize cost functions using dynamic programming or graph-cut algorithms. SGM balances local-global optimization for robust DSM generation but struggles with regions. Deep learning enhances accuracy but suffers from computational complexity and opacity. This review synthesizes algorithmic evolution, strengths, and limitations to guide high-precision DSM advancements.

2 THEORETICAL BACKGROUND

2.1 Fundamental Principles of Digital Surface Models

DSM models 3D surface geometry and vertical structures via multi-scale grids or TIN. Generated using LiDAR (Mandlburger, Wenzel, Spitzer, et al., 2017) and stereophotogrammetry (image-matching dense point clouds), DSM capture true surface geometry unlike DEM (bare-earth only). Recent advancements integrate DSM with orthophotos to enhance 3D building reconstruction in complex urban scenes, validating its role in smart cities(Arefi, Reinartz, 2013). GIS-compatible visibility analysis further leverages DSM for environmental and spatial planning applications(Ruzickova, Ruzicka, Bitta, 2021).

As shown in Figure 1,The research on DSM has long been driven by two primary disciplines: computer vision and geomatics. Computer vision focuses on algorithm optimization to enhance the accuracy and efficiency of dense matching, particularly emphasizing robustness in complex scenes. In contrast, geomatics prioritizes precise geospatial modeling and multi-source data fusion, emphasizing reliability and standardization for practical engineering applications.

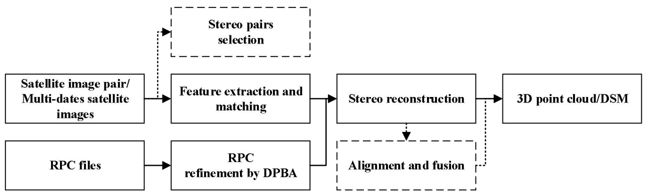

Figure 1 Generation Methods of Digital Surface Model

2.2 Core Theories of Dense Matching

Dense matching algorithms generate high-precision 3D point clouds for DSM by establishing dense pixel correspondences(Ma, Wang, Li, et al., 2019), surpassing sparse methods in density. Reliance on photometric consistency is challenged by illumination, shadows, and occlusions. To mitigate this, surface patch validation methods use LiDAR as geometric references. Zhang et al. proposed a framework integrating local photometric consistency with LiDAR spatial constraints(Zhang, Gerke, Vosselman, et al., 2018), enhancing validation accuracy in complex scenes. Matching cost metrics include NCC, SSD/SAD(Dall'Asta, Roncella, 2014). Optimization strategies span local and global methods for complex scene handling. Geometric constraints, such as disparity-depth conversion from stereo geometry, refine accuracy via spatial relationships.

3 RESEARCH STATUS

3.1 Feature-Based Dense Matching Algorithms

3.1.1 Feature Point-Based Matching

Feature matching is a fundamental technique in computer vision for establishing correspondences between images. The process involves three key steps: feature point detection, descriptor generation, and feature correspondence. In the detection phase, algorithms identify distinctive keypoints by analyzing local image structures. These keypoints are then encoded into unique and robust mathematical representations , such as SIFT's gradient histograms or binary patterns in ORB. Among them, Equation 2-1 is the calculation formula for the gradient magnitude and direction of the SIFT gradient histogram.

$$m(x,y) = \sqrt{(L(x+1,y)-L(x-1,y))^2+(L(x,y+1)-L(x,y-1))^2} \quad (1)$$

$$\arctan\left(\frac{L(x,y+1)-L(x,y-1)}{L(x+1,y)-L(x-1,y)}\right)$$

The binary pattern in ORB generates a binary code string through grayscale comparison of predefined point pairs, which is mathematically expressed as

Finally, similarity metricsare computed between descriptors, followed by outlier rejection using ratio testing and RANSAC, enabling precise cross-image correspondences.

Scharstein and Szeliski established a four-stage framework for dense stereo matching: matching cost computation, cost aggregation, disparity optimization, and disparity refinement(Scharstein, Szeliski, 2002). Z Shunyi et al. introduced a feature-based image relaxation method that enhances matching accuracy in low-texture regions(Shunyi, Zuxun, Jianqing, 2004). Wang Jingxue et al. proposed a multi-view dense matching approach integrating multiple primitives to mitigate occlusion effects(Jingxue, Qing, Weixi, et al., 2013). Dai Jiguang addressed heterogeneous high-resolution satellite image matching challenges via a progressive multi-feature fusion strategy(Jiguang, 2014). Zhao Hongrui et al. improved feature point density in blockwise matching by leveraging feature scale distribution and epipolar geometry constraints(Hongrui, Shenghan, 2018). Hou Wenguang et al. combined SURF's robust feature extraction with thin-plate spline (TPS) transformations for continuous geometric alignment, advancing stereo image matching(Wenguang, Zicui, Mingyue, 2010).

Despite widespread use, feature point matching has critical limitations: illumination variations and noise degrade local textures, destabilizing descriptors; dynamic objects and occlusions cause erroneous correspondences; perspective/scale changes distort local structures, hindering stable keypoint detection. Repetitive textures trigger mismatches; low-texture regions have sparse features. Traditional algorithms are computationally costly, while lightweight methods sacrifice precision in complex scenarios. Limited descriptor distinctiveness in ambiguous regions requires deep learning or multi-modal fusion for robustness. These challenges drive research into multi-modal fusion and end-to-end deep learning for efficient, stable matching across diverse conditions.

3.1.2 Deep Learning-Based

Deep learning-based dense matching directly learns pixel-level inter-image correspondences via end-to-end neural networks, with three core stages: feature extraction, cost volume construction, and prediction refinement. Encoders first extract multi-scale features capturing local details and global semantics. For stereo matching, 3D cost volumes are built by measuring feature similarity across disparity hypotheses between left-right image pairs, then processed via 3D convolutions or iterative optimization modules to generate disparity maps or optical flow fields with sub-pixel accuracy.

Wayne Treible et al.proposed a neural network framework, ground truth generation, and training protocols tailored for satellite image matching, accompanied by comparative analysis with existing methodologies(Treible, Sorensen, Gilliam, et al., 2018). Liu Jin et al. evaluated deep learning performance in aerial image dense matching using three CNN: MC-CNN, GC-Net, and DispNet(Liu, Ji, 2019). Teng Wu et al. established a stereo dense matching benchmark from the ISPRS Vaihingen dataset, facilitating systematic evaluation of traditional and deep learning-based methods for digital surface model (DSM) generation(Wu, Vallet, Pierrot-Deseilligny, et al., 2021). He Sheng et al. introduced a hierarchical dynamic matching strategy and constructed the GF-7 stereo dataset, training Stereo-Net and DSM-Net models to enhance satellite-derived DSM accuracy(He, Zhang, Chen, et al., 2023).As shown in Figure 2,in the generation of DSM for the built-up area in Zhongshan City, the traditional SGM algorithm leads to adhesion of buildings and blurred edges in the DSM due to occlusion. In contrast, DSM-Net and Stereo-Net, leveraging the hierarchical dynamic matching strategy and dataset advantages, clearly distinguish building clusters and preserve edges. The elevation analysis of building sections shows that the DSM generated by these methods features elevation changes more consistent with reality, fewer gross errors, and a proportion of erroneous disparity pixels <3.8%, significantly outperforming the traditional method in elevation accuracy and building morphology preservation.

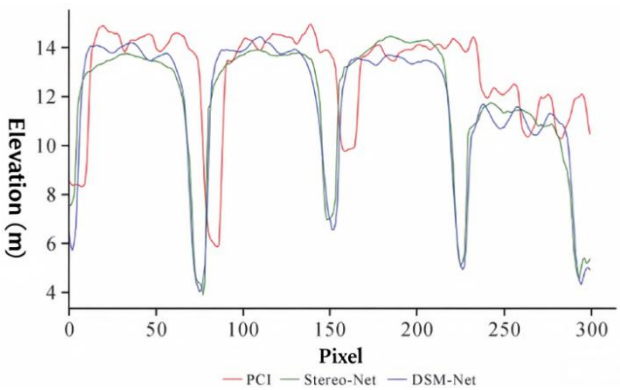

Figure 2 Elevation change curves of house section acquired from three methods

Despite superior performance, deep learning faces key challenges: high-res images need massive GPU memory for cost volume construction, and complex 3D convolutions hinder real-time deployment. Supervised learning requires costly annotated real-world data, with synthetic-to-real domain gaps limiting generalization. Moving objects violate static scene assumptions, causing prediction errors in occluded areas. Low-texture regions have ambiguous matches due to high feature similarity, and performance drops under extreme illumination, bad weather, or cross-sensor scenarios. Also, model compression often sacrifices accuracy for efficiency, failing to balance real-time processing and high precision.

3.2 Region-Based Dense Matching Algorithm

Region-based dense matching establishes inter-image correspondence via local pixel patch similarity comparison, mainly used in stereo vision disparity estimation and 3D reconstruction. Its core workflow has four steps: 1) Selecting fixed-size neighborhood windows centered on target pixels as matching units; 2) Sliding these windows pixel-wise in the reference image's candidate regions to compute similarity metrics; 3) Finding optimal matches via maximum similarity criteria and calculating disparity from pixel offsets; 4) Refining initial disparity maps with dynamic programming or Markov Random Fields to resolve local ambiguities.

Lemaire tested varying digital camera geometries and ground sampling distances (GSD) to enhance point cloud completeness(Lemaire, 2008). Alobeid A et al. compared least squares matching, dynamic programming, and semi-global matching (SGM), providing references for subsequent studies(Alobeid, Jacobsen, Heipke, 2010). G. Kuschka et al. applied SGM and total variation minimization to process ISPRS benchmark datasets(Kuschk, d'Angelo, Qin, et al., 2014). N. Yastikli et al. generated DSM from Istanbul aerial images using DLR and Microsoft software for pixel-level dense matching(Yastikli, Bayraktar, Erisir, 2014). Balenović I et al. pioneered DSM generation from Croatian digital aerial stereo imagery, evaluating vertical consistency with RMSE, mean error, and standard deviation(Balenović, Marjanović, Vuletić, et al., 2015). Wu J et al. fused SIFT and SGM for oblique image dense matching, enabling pixel-wise correspondence for automated DSM generation(Wu, Yao, Cheng, 2015). Yue Q et al. proposed an object-space semi-global optimization strategy for ZY-3 satellite imagery, improving DSM accuracy in complex terrains(Yue, Gao, Tang, 2016). Li S et al. enhanced SGM using ADCensus for UAV image dense matching(Li, Li, Wang, et al., 2017). Yang X et al. balanced computational efficiency and memory usage via systematic error compensation, block processing, and disparity map dilation-erosion algorithms(Yang, Lu, Jiang, et al., 2018). Shao C integrated geometric constraints and disparity range reduction for high-precision DSM(Shao, 2019). Zou S et al. optimized disparity maps with fast bilateral filtering to refine building edges(Zou, Zou, Pan, et al., 2020). K. Gong and D. Fritsch developed a stereo-based fusion workflow for robust DSM generation(Gong, Fritsch, 2019). Yang W et al. introduced SGBM with adaptive block matching to improve waterbody DSM accuracy(Yang, Li, Yang, et al., 2019). Wang J et al. proposed hierarchical SGM for radar-based DSM generation in vegetated and mountainous regions(Mahphood, Arefi, Hosseininaveh, et al., 2019).

Fig. 3 shows the cost aggregation in disparity space, core being minimum cost accumulation along 1D paths from all directions (e.g., 16 paths). Centered on pixel p, it illustrates how paths in different directions r undergo dynamic programming (DP) optimization under disparity d, with the specific formula as follows:

$$\begin{aligned}\min\{&L_r(p-r,d), L_r(p-r,d-1), L_r(p-r,d+1)+P_1,\\ &\min_i L_r(p-r,i)+P_2-\min_i L_r(p-r,k)\}\end{aligned} \quad (2)$$

The figure intuitively presents how the cost of each pixel achieves global optimization through the cost accumulation of adjacent pixels in the multipath aggregation, balancing the computational efficiency and matching accuracy.

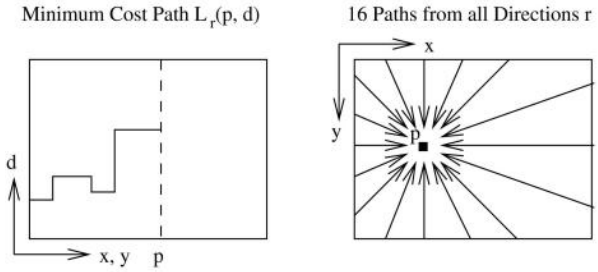

Figure 3 The multipath aggregation process of the SGM algorithm

Region-based dense matching faces inherent limitations: 1) Sliding window operations exhibit exponential computational complexity growth with window size and search range, hindering real-time processing of high-resolution images; 2) Highly uniform similarity responses across candidate windows frequently cause mismatches; 3) Window spanning depth-discontinuous regions at object boundaries leads to distorted similarity computation; 4) Metrics like SAD/SSD suffer severe performance degradation under uneven illumination or noise, while NCC only partially mitigates these issues by relying on local intensity consistency assumptions.

3.3 Other Innovative Strategies

Zhang and Gruen enhanced DSM accuracy by leveraging multi-view coverage and high-quality data from IKONOS imagery(Zhang, Gruen, 2006). Fig. 4 shows the Shaded Terrain Model generated by multi-view matching from the IKONOS triplet images . Based on the multi-view matching results (fusing feature points, grid points, and edges), this model verifies the algorithm's capability to generate DSM for large-scale complex terrains.

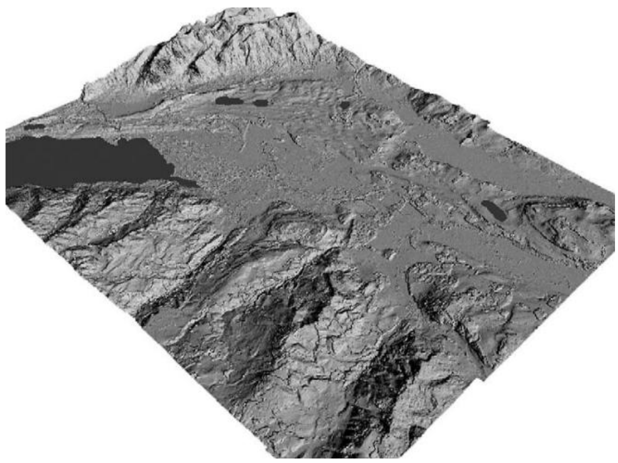

Figure 4 The shaded terrain model generated from IKONOS triplet images

Pablo d'Angelo et al. proposed region-based outlier removal for fixed-view geometry sensors like Cartosat-1 and ALOS PRISM(d'Angelo, 2010). Irschara A et al. achieved global optimization in aerial image dense matching through multi-view plane-sweep and global energy minimization(Irschara, Rumpler, Meixner, et al., 2012). Jiayuan Li et al. generated DSM via SIFT seed point matching and Poisson surface reconstruction(Li, Ai, Hu, et al., 2014). Mandlburger G et al. improved DSM quality by integrating LiDAR reliability with dense image matching (DIM) point clouds(Ma, Wang, Li, et al., 2019). Yang W et al. (2019) introduced multi-path dynamic programming with reliability estimation for efficient DSM generation(Yang, Li, Yang, et al., 2020). Mahphood A et al. implemented a DSM workflow involving epipolar image generation, registration, and SGM-based stereo matching(Mahphood, Arefi, Hosseininaveh, et al., 2019). Feng S et al. proposed a DEM generation method using multi-view image offsets on ground planes(Feng, Lin, Wang, et al., 2020). Yang W et al. addressed SGM's computational load via minimum-cost path and disparity candidate weighting(Yang, Zhang, Sun, et al., 2024). Yang X et al. employed millimeter-wave InSAR to overcome imaging challenges in inaccessible areas, generating DSM and DOM products(Yang, Kang, Wang, et al., 2024).

Innovative dense matching methods for DSM generation still face three core challenges: scenario adaptability, efficiency-accuracy trade-offs, and robustness in complex environments. For instance: Zhang and Gruen rely on multi-view, high-quality data, while Feng S assumes flat terrains, both struggling with occlusions or complex topography; Irschara et al.'s global optimization and Yang et al.'s dynamic programming suffer from high computational complexity, while SGM variants remain constrained by disparity search ranges; Mandlburger et al.'s LiDAR fusion relies on costly hardware. Future breakthroughs require lightweight architectures, adaptive multi-modal fusion, and semantic-aware enhancements to overcome current bottlenecks.

4 RESEARCH CHALLENGES AND CONTROVERSIES

4.1 The Trade-Off Challenge Between Accuracy and Computational Complexity

The accuracy-efficiency trade-off remains a critical challenge in dense matching algorithms. While Semi-Global Matching (SGM) achieves pixel-wise accuracy in 3D point clouds, its computational demands escalate exponentially with large datasets or scenes of significant depth variation due to extensive pixel storage and correspondence calculations(Rothermel, Haala, 2012). Similarly, d'Angelo's outlier removal method(d'Angelo, 2010) and commercial tools like MATCH-T DSM(Lemaire, 2008) face inherent complexity growth to maintain precision. Although optimizations like Yang Xingbin et al.'s SGM variant(Lemaire, 2008) improve efficiency for high-resolution data, excessive memory consumption and prolonged runtime persist for large-scale applications.

4.2 Matching Consistency Challenges in Complex Scenes

Matching consistency in complex scenes remains a critical challenge for dense matching algorithms, directly impacting accuracy and computational efficiency. G. Mandlburger et al. demonstrated that shadows in narrow alleys degrade image contrast, leading to mismatches(Mandlburger, Wenzel, Spitzer, et al., 2017). MahphoodA et al. identified frequent mismatches in ocean and high-rise areas due to complex geometries(Rothermel, Haala, 2012), while AlobeidA et al. observed similar issues with building occlusions and abrupt height changes in urban DSM(Alobeid, Jacobsen, Heipke, 2010). Maltezos et al. further noted that mismatches in urban scenes increase surface roughness and boundary distortions(Maltezos, Kyrkou, Ioannidis, 2016).

4.3 Interpretability Dilemma of Deep Learning Models

Deep learning-based dense matching algorithms face critical interpretability challenges that hinder practical reliability and optimization. Treible et al. demonstrated neural networks' efficacy in satellite-derived DSM generation(Treible, Sorensen, Gilliam, et al., 2018), yet their decision-making mechanisms remain opaque under complex imaging conditions . A promising solution is integrating gradient-weighted class activation mapping (Grad-CAM) into models like DSM-Net to visualize pixel-level attention mechanisms. For instance, Grad-CAM generates heatmaps indicating which image regions dominate the disparity prediction, enabling users to verify whether the model relies on geometrically meaningful features rather than spurious correlations (He, Zhang, Chen, et al., 2023). Wang et al.(Wang, Gong, Hu, et al., 2021) highlighted deep learning's dependency on extensive training data and its lack of explainability in complex scenarios, raising reliability concerns. Liu et al.(Liu, Ji, 2019) further confirmed limitations in remote sensing applications, noting immature model architectures and unintuitive decision processes.

4.4 Generalizability Limitations of Algorithms

Existing dense matching algorithms face scenario-dependent adaptability limitations, particularly in complex environments like forests and urban areas. Balenović et al. observed reduced DSM accuracy in forests due to structural complexity and sensitivity to environmental factors(Balenović, Marjanović, Vuletić, et al., 2015). Ghuffar highlighted challenges in deriving tree heights from satellite data, emphasizing texture homogeneity's impact on robustness(Ghuffar, 2016). While K. Gong and Fritsch's multi-view workflow excels in satellite data, its generalizability to heterogeneous datasets (e.g., UAV imagery) remains unverified(Gong, Fritsch, 2019).

4.5 Interlinked Challenges of Data Quality and Algorithm Robustness

Data quality critically impacts the robustness of dense matching algorithms. Kuschka et al.identified sensor oversaturation and texture scarcity as key disruptors, degrading matching reliability(Kuschk, d'Angelo, Qin, et al., 2014). Kim et al. further demonstrated that outliers and unmatched regions propagate errors into DSM reconstructions, particularly in heterogeneous terrains. Challenges like data noise, missing inputs, and sensor miscalibrations amplify ambiguities, constraining algorithmic performance(Kim, Rhee, Kim, 2018).

5 CONCLUSION

Dense matching algorithms for DSM face a persistent accuracy-efficiency-adaptability trade-off, with traditional methods like SGM balancing local-global optimization but struggling in textureless regions and large-scale datasets due to exponential computational costs. Deep learning models, while achieving superior accuracy through end-to-end feature learning, suffer from high computational demands, interpretability challenges, and domain-specific limitations. Complex scenes exacerbate these issues, as shadows, occlusions, and terrain variations degrade matching consistency. Future advancements require AI-driven optimizations: adversarial training to enhance robustness against perturbations, lightweight architectures for real-time processing, and interdisciplinary integration. Cross-domain collaboration and hybrid frameworks—combining photogrammetry, GIS, and AI—are critical to address scalability and adaptability gaps, enabling high-precision DSM generation for smart cities, disaster monitoring, and geospatial applications.

6 FUTURE DIRECTIONS

The deep integration of AI and multi-source remote sensing technologies will usher in new opportunities for the development of dense matching algorithms in DSM. Future research may focus on the following directions: First, prioritizing multimodal fusion of LiDAR and optical imagery to address accuracy and robustness challenges. This framework integrates LiDAR's geometric precision (sub-meter accuracy via time-of-flight ranging (Mandlburger, Wenzel, Spitzer, et al., 2017)) with optical imagery's dense texture information, leveraging their complementary advantages: LiDAR calibrates optical matching errors through spatial constraints, while optical data enriches LiDAR's sparse point clouds with surface details via cross-modal attention mechanisms that fuse semantic features from UNet++-based segmentation(Yang, Li, Yang, et al., 2019). Feasibility-wise, this approach requires NVIDIA A100 GPUs (40GB) for 48-72 hours of training on datasets like ISPRS Vaihingen and ZY-3+airborne LiDAR, with inference achievable on RTX 3090s (24GB) within 5 minutes per scene.

Second, constructing lightweight and adaptive deep learning architectures to balance computational efficiency and accuracy via NAS and knowledge distillation.

Third, advancing synthetic data generation driven by GAN and physics-based models to alleviate data scarcity constraints and improve cross-domain generalization.

Fourth, develop explainability techniques to boost trust and refine algorithms. Integrate edge computing and distributed processing for large-scale DSM applications in urban monitoring and disaster response. Interdisciplinary collaboration, open-source ecosystems, standardized evaluation frameworks, and shared datasets are also vital for advancing geospatial intelligence.

Fifth, addressing cross-sensor generalization challenges through a dual-stage transfer learning framework: first, pre-training a common feature extractor on the Wuhan University-Stereo dataset using contrastive learning to capture invariant features like geometric structures and semantic categories, then fine-tuning with domain adversarial neural networks (DANN) for target sensors (e.g., GF-7 satellite imagery), where gradient reversal layers minimize distribution gaps between source domains (UAV) and target domains while preserving pre-learned features.

Although certain advancements have been achieved in dense matching algorithms for digital surface models, challenges still persist. In the future, it will be necessary to conduct in-depth exploration in multiple directions, break through existing technical bottlenecks, and promote the sustained development of this field to meet practical application requirements.

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