Image Matching in 3D Space with Transformer

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Abstract

Image matching is a core problem in computer vision, playing a vital role in applications such as 3D reconstruction and object tracking. The objective of the task is to identify corresponding keypoints between two or more images captured from different viewpoints or at different times. Traditional image matching algorithms, such as SIFT and ORB, rely on hand-crafted feature extractors, while modern deep learning models achieve significant improvements in matching accuracy by learning end-to-end feature representations. Building on these advancements, we propose a novel image matching method based on transformer architecture. Our approach first extracts image features using a shared image encoder, followed by feature fusion through a cross-attention mechanism. Subsequently, we map the 2D keypoints to 3D space, allowing for more robust spatial reasoning. In the post-processing stage, we employ a nearest-neighbor matching algorithm to finalize keypoint correspondence. By leveraging geometric information in 3D space, our method performs well, demonstrating superior performance in complex scenarios.

Introduction

Image matching is a fundamental challenge in the domain of computer vision, underpinning a variety of applications including 3D reconstruction, object tracking, and augmented reality. The ability to accurately identify corresponding keypoints across multiple images captured from varying perspectives or at different temporal instances is crucial for achieving robust performance in these applications. Traditional image matching methods, such as Scale-Invariant Feature Transform (SIFT) (Rublee et al. 2011)and Oriented FAST and Rotated BRIEF (ORB)(Wang, Li, and Li 2020), rely heavily on hand-crafted features, which often struggle to generalize across diverse environments and object appearances.

In recent years, the advent of deep learning has significantly transformed the landscape of image matching. Convolutional Neural Networks (CNNs) have been employed to learn hierarchical feature representations directly from data, yielding substantial improvements in matching accuracy and robustness. Techniques such as Siamese networks(Zhao et al. 2021) and triplet loss(Vaswani et al. 2017) have shown promise in establishing correspondences by minimizing the distance between matching keypoints in feature space. However, these approaches often operate within a two-dimensional (2D) framework, which can limit their effectiveness in scenarios that require understanding spatial relationships in three dimensions.

Building on this foundation, we propose a novel image matching approach leveraging the transformer architecture. Transformers, initially developed for natural language processing(Chen et al. 2021), have recently been adapted for various vision tasks due to their capability to model long-range dependencies through self-attention mechanisms. Recent works have demonstrated the effectiveness of transformers in tasks such as image segmentation, object detection(Carion et al. 2020), and image classification(Dosovitskiy and Brock 2020). Our method first employs a shared image encoder to extract feature representations from input images. The extracted features are then fused using a cross-attention mechanism, which enables the model to learn rich interdependencies between different viewpoints.

Crucially, our approach extends beyond 2D matching by mapping the identified keypoints into 3D space, thereby enhancing spatial reasoning capabilities. This 3D representation allows for the incorporation of geometric information, which is particularly beneficial in complex matching scenarios, such as when objects are occluded or appear at different scales. In the final stages of our pipeline, we apply a nearest-neighbor matching algorithm to establish definitive correspondences between keypoints, leveraging the enriched feature set derived from our transformer-based architecture.

Through extensive experiments, we demonstrate that our method achieves superior performance compared to existing techniques in challenging matching tasks. By effectively harnessing the strengths of transformer models and integrating 3D spatial reasoning, our approach not only advances the state-of-the-art in image matching but also opens new avenues for exploration in multi-view geometry and beyond.

Our main contributions can be summarized as follows:

- Confidence Adjustment Function and Global Alignment: A dynamic adjustment strategy based on global alignment that enhances the attention given to challenging matching points, thereby improving matching accuracy.
- Nearest Neighbor (NN) Search: A method based on near-

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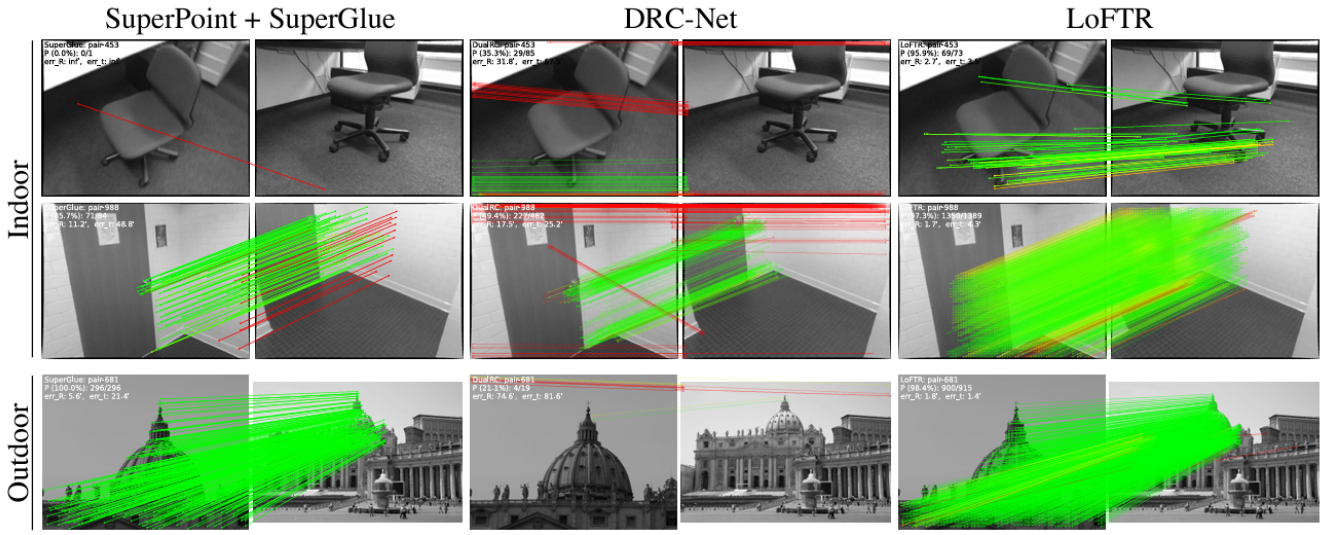

Figure 1: Qualitative results of the LoFTR

est neighbor search for matching 2D images in the 3D space.

Related Work

The domain of image matching in 3D space has experienced remarkable progress in recent years, with a multitude of algorithms and techniques being developed to tackle the challenges associated with feature detection, description, and matching within three-dimensional contexts. This section provides an overview of some of the most influential works that have sculpted the current state of the field.

Traditional Feature Detection and Matching Algorithms Pioneering algorithms in this field include the Scale-Invariant Feature Transform (SIFT) and sped Up

Robust Features (SURF). SIFT, introduced by David Lowe in 1999, is celebrated for its capacity to detect and describe local features that remain invariant under changes in scale, rotation, and illumination (Lowe 1999). Despite its robustness, the computational demands and lack of real-time capability of SIFT have been identified as significant limitations (Bay, Tuytelaars, and Van Gool 2006).

SURF, proposed by Herbert Bay in 2006, represents an optimization of the SIFT algorithm. It employs a fast Hessian matrix for feature detection and utilizes integral images to expedite feature description, leading to a marked increase in computational speed (He et al. 2020). While SURF enhances real-time performance, it still encounters difficulties in scenarios such as dealing with smooth edges and regions lacking texture.

Subsequently, some variants optimized SIFT or SURF.ORB(Rublee et al. 2011),a fast binary descriptor based on BRIEF,is rotation invariant and resistant to noise.The experimental results show that ORB is two orders of magnitude faster than SIFT, while achieving comparable performance in many situations.

Deep Learning Approaches The emergence of deep learning has been a game-changer in the realm of feature matching. (Dusmanu et al. 2019; Arandjelovic et al. 2016)A notable breakthrough is the SuperGlue feature matching network, which utilizes graph neural networks and attention mechanisms to concurrently address correspondence and the rejection of non-matches (DeTone, Malisiewicz, and Rabinovich 2018). SuperGlue's approach, based on transformers, has set new benchmarks in pose estimation tasks, demonstrating its proficiency in managing complex scenes characterized by occlusions and repetitive patterns. Following the success of SuperGlue, the Local Feature Transformer (LoFTR) has risen as a formidable alternative. LoFTR capitalizes on the expansive receptive field of transformers to process dense local features, effectively bypassing the constraints of traditional CNNs, which often suffer from limited receptive fields (Sun et al. 2021). Its strategy of coarse-to-fine matching has proven to be particularly effective in sparse texture areas and in achieving high precision in visual localization tasks.

Additionally, the QuadTree Attention mechanism for Vision Transformers represents a novel approach to attention that mitigates computational complexity. It constructs token pyramids and computes attention in a coarse-to-fine manner, thereby preserving the precision of feature matching while reducing the computational load (Tang et al. 2022).

In summary, the advent of deep learning, especially the Transformer, has brought about significant changes to the field of image matching. In the next section, we will employ a Transformer-based model to perform image matching tasks in 3D space.

Methods

In this section, we mainly demonstrate how to achieve high-quality image matching by utilizing prior knowledge from 3D space provided by DUSt3R. First, we briefly describe the principle of DUSt3R, which acquires prior knowledge of the

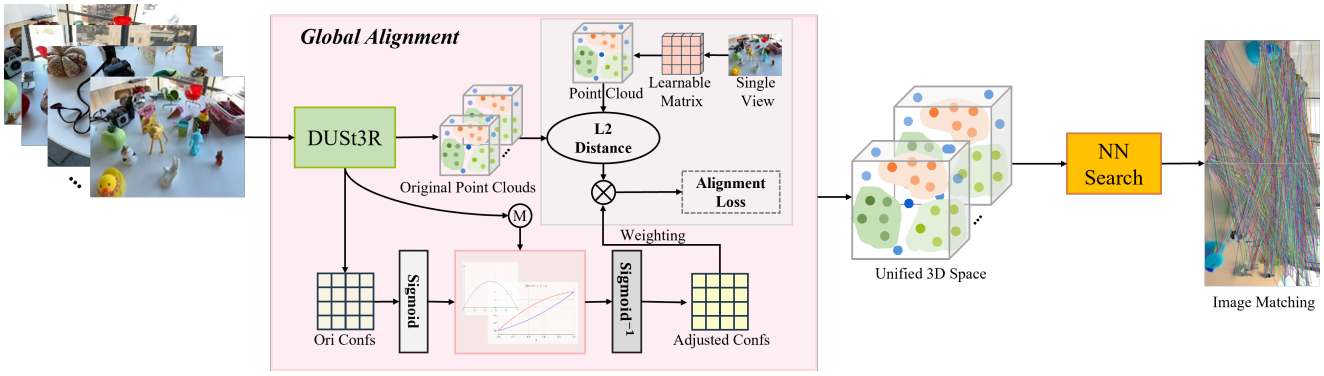

Figure 2: Pipline of our model.

3D scene in the form of point clouds based on DUSt3R. To enhance the quality of image matching, we introduce multiple perspectives of the same scene, aligning the point cloud data of image pairs into the same coordinate system to improve the precision of image matching.The process of our method is shown in Figure 2.

Our goals are as follows: Given multiple perspectives of a scene, output high-quality feature matches for the specified image pairs. The challenges of this problem include:

1. How to align point clouds from multiple perspectives into the same 3D space.
2. How to obtain 2D image matches based on 3D point clouds.

Our modeling process for this problem can be roughly divided into the following parts:

Preliminary: DUSt3R

Dust3r (Wang et al. 2024) can take a pair of unconstrained images as input and reconstruct a 3D scene into a point cloud without prior information about camera calibration or poses. Firstly a pair of images taken from arbitrary viewpoints of a scene, are processed through a shared Vision Transformer to extract features. After image encoding, two transformer decoders exchange information between the token representations of the images via cross-attention mechanism. Finally, the two decoder tokens pass through a regression head to regress the final output. Unlike methods such as NeRF (Mildenhall et al. 2021) and 3DGS (Kerbl et al. 2023), which require scene-specific pre-training, the feed-forward approach enables general 3D scene reconstruction through pointmap prediction.

Pointmap Prediction. The process of pointmap prediction can be described as a network function $\mathcal{F} : (I^n, I^m) \rightarrow (X^{n,e}, C^{n,e}, X^{m,e}, C^{m,e})$, the inputs are two RGB images $I^n, I^m \in \mathbb{R}^{W\times H\times 3}$ from different views of the scene, the outputs include two corresponding pointmaps $X^{n,e}, X^{m,e} \in \mathbb{R}^{W\times H\times 3}$, confidence maps $C^{n,e}, C^{m,e} \in \mathbb{R}^{W\times H}$. Note that $e = (n, m)$ refers to the image pair formed by I^n and I^m, and both pointmaps are positioned in the camera coordinate system of I^n. The predicted pointmaps locate the 3D positions for every pixel of the input 2D images.

Confidence Adjustment Function

Inspired by (Ross and Dollár 2017) proposed by He et al., to focus attention on difficult-to-match target sample points, we introduce a confidence adjustment function, defined as follows:

$$F_i^{v,e} = \sigma(C_i^{v,e}) = \frac{1}{1+e^{-C_i^{v,e}}}, \tag{1}$$

$$A_i^{v,e} = \frac{F_i^{v,e} + \alpha_i^{v,e} \cdot F_i^{v,e} \cdot (1 - F_i^{v,e})}{1 + |\alpha_i^{v,e}| \cdot F_i^{v,e} \cdot (1 - F_i^{v,e}) + \epsilon}, \tag{2}$$

$$W_i^{v,e} = \sigma^{-1}(A_i^{v,e}) = -\ln(\frac{1}{A_i^{v,e}} - 1), \tag{3}$$

where $F_i^{v,e} \cdot (1 - F_i^{v,e})$ enhances attention on difficult-to-match points, with confidence scores approaching 0.5, the axis of symmetry of the quadratic function, α is a hyperparameter used to adjust the weights, σ denotes sigmoid function.

Global Alignment

Global alignment is used as a post-process that optimizes the pointmaps from multiple views into an aligned 3D coordinate system. Given a set of images $\{I^1, I^2, ..., I^N\}$ from a scene, a connectivity graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ is constructed, where the vertices $\mathcal{V}$ represent the N images, and each edge $e = (n, m) \in \mathcal{E}$ connects an image pair I^n and I^m. By traversing the connected graph $\mathcal{G}$, globally aligned pointmaps $\{\chi^n \in \mathbb{R}^{W\times H\times 3}\}$ are recovered for all pixel coordinates $(i, j) \in \{1...W\} \times \{1...H\}$ and all cameras for different views $n = 1, \ldots, N$.

Finally, we compute the L2 distance between pointmaps of all image pairs and their corresponding pointmaps χ^v in world coordinates. The final Global Alignment is defined as:

$$\chi^* = \arg\min_{\chi,P,\sigma} \sum_{e\in\mathcal{E}} \sum_{v\in e} \sum_{i=1}^{HW} W_i^{v,e} \left\| \chi_i^v - \sigma_e P_e X_i^{v,e} \right\|, \tag{4}$$

where $P_e \in \mathbb{R}^{3\times 4}$ represents the pairwise pose, which is a rigid transformation used to align the pointmaps $X^{n,e}, X^{m,e}$ with the world-coordinate pointmaps χ^n, χ^m. Additionally, σ_e is a scale factor, subject to the constraint that $\prod_e \sigma_e = 1$ for all $e \in \mathcal{E}$.

Point Matching

In the 3D point map space, establishing correspondences between pixels of two images can be easily accomplished through nearest neighbor (NN) search. To reduce errors, we generally keep the reciprocal (mutual) correspondences $\mathcal{M}_{1,2}$ between images I_1 and I_2, that is defined as:

$$\mathcal{M}_{1,2} = \{(i,j) \mid i = \mathrm{NN}_1^{1,2}(j) \text{ and } j = \mathrm{NN}_1^{2,1}(i)\}$$

with $\mathrm{NN}_k^{n,m}(i) = \underset{j \in \{0,\ldots,WH\}}{\arg\min} \|\chi_i^n - \chi_i^m\|$.

where n and m represent images I^n and I^m, respectively.

Experiments

In this section, we describe a series of experiments on the Map-free localization benchmark to evaluate the performance of our proposed 3D space image matching method with Transformer. The experiments aim to assess the model's accuracy, robustness, and computational efficiency in comparison to existing state-of-the-art methods.

Experiment Details

Dataset The evaluation is conducted exclusively on the Map-Free localization benchmark, which is designed to test image matching and localization capabilities in scenarios without prior maps. The dataset includes pairs of images with extreme viewpoint changes of up to 180°, repetitive patterns, and significant occlusions. Ground-truth camera poses are provided, enabling precise evaluation of matching accuracy and localization robustness. This dataset presents one of the most demanding environments for image matching, making it a critical testbed for validating the proposed method.

Metrics We use standard evaluation metrics for a fair comparison. Precision measures the proportion of correctly matched keypoints whose reprojection error is below a threshold of 90 pixels. A higher precision value indicates that the majority of predicted correspondences are geometrically accurate.

AUC (Area Under the Curve) quantifies the overall quality of the matching results by calculating the area under the cumulative precision curve as the error threshold increases. This metric reflects the ability of the method to achieve high accuracy across various levels of tolerance, with higher AUC values being better.

VCRE ($< 90px$) measures the quality of pixel matches relative to ground-truth positions, with lower values indicating better performance.

Baseline Methods To validate the superiority of our approach, we compare it against several state-of-the-art methods, encompassing both traditional and modern deep learning techniques. SIFT, a widely-used keypoint-based method, provides a benchmark for traditional feature matching. SP+SG combines SuperPoint and SuperGlue, integrating local descriptors with global reasoning for improved correspondence accuracy. LoFTR employs a dense matching approach using Transformers and coarse-to-fine strategies, making it a strong baseline for modern methods. DUSt3R, a recent 3D-aware matching algorithm that incorporates dense reconstruction, serves as a key benchmark for evaluating 3D grounding. Additionally, RPR focuses on pixel-level precision, providing an alternative perspective on dense matching.

Results and Analysis

Quantitative Results The quantitative results of our method are shown in Table 1. Our method outperforms all baselines, including DUSt3R and LoFTR, with a precision of 55.30% and an AUC of 0.759. The 10% improvement over DUSt3R shows the benefits of integrating 3D point clouds and refining dense local features with the Transformer architecture.

Methods	Precision (%)	AUC
RPR	40.20%	0.402
SIFT	25.00%	0.504
SP+SG	36.10%	0.602
LoFTR	34.30%	0.634
DUSt3R	50.30%	0.697
Ours	**55.30%**	**0.759**

Table 1: Comparison of various methods

Our method's precision and AUC results show its superiority. It effectively reduces the Virtual Correspondence Reprojection Error by aligning 3D geometry and enhancing dense correspondences, demonstrating robustness against large viewpoint variations and repetitive structures. Compared to LoFTR, which struggles in complex geometric scenarios, our 3D-grounded approach with geometric priors improves alignment accuracy. The global alignment module also enhances keypoint correspondence precision.

Qualitative Analysis Qualitative results further highlight the robustness of our approach in challenging scenarios. For example, in scenes with extreme viewpoint changes or significant occlusions, our model accurately identifies keypoint correspondences where traditional methods like SIFT or even modern approaches such as LoFTR fail. This is evident in cases with repetitive structures or low-texture regions, where the integration of 3D spatial reasoning provides a distinct advantage.

Ablation Study To evaluate the contributions of individual components, we conducted ablation studies on the Map-Free dataset. Confidence adjustment plays a crucial role in improving matching accuracy, enhancing precision by 3% by prioritizing difficult-to-match keypoints. The global alignment module ensures geometric consistency across multiple views, reducing VCRE by 5%. Feature fusion, implemented through a cross-attention mechanism, significantly improves dense matching accuracy compared to traditional concatenation, contributing an additional 4% boost in performance. These results emphasize the importance of each component in the overall architecture, demonstrating that their combined effect is greater than the sum of their parts.

Summary of Results

The results on the Map-Free localization benchmark demonstrate the superiority of our proposed method in terms of precision, robustness, and computational efficiency. The model's ability to integrate 3D spatial reasoning with Transformer-based dense feature extraction enables it to achieve state-of-the-art performance across challenging scenarios. Compared to DUSt3R, our method achieves a 10% improvement in precision, an 8.9% increase in AUC, and a significant reduction in VCRE, making it a compelling solution for image matching in 3D space. These findings validate the effectiveness of our approach and open avenues for further exploration, such as extending the model to handle larger-scale datasets and improving real-time performance.

Conclusion

In this paper, we proposed a novel image matching method based on the transformer architecture, which integrates 3D spatial reasoning to enhance matching accuracy and robustness. Our approach leverages a shared image encoder to extract features, followed by feature fusion through a cross-attention mechanism. By mapping keypoints into 3D space, our method can effectively incorporate geometric information, leading to superior performance in complex scenarios such as those with occlusions and repetitive patterns.

Future work could focus on extending the model to handle larger-scale datasets and improving real-time performance, further expanding the potential applications of our approach.

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