PA-FlowNet: Pose-Auxiliary Optical Flow Network for Spacecraft Relative Pose Estimation

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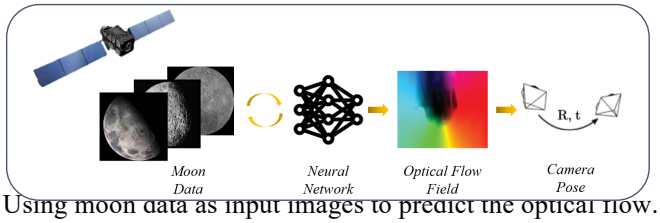
Abstract

During space travelling, spacecraft attitude estimation is the indispensable work for navigation. Since there are not enough satellites in space, the computer vision technique is adopted to address the issue. The most crucial task for localization is the extraction of correspondences. In computer vision, optical flow estimation is often used for finding correspondences. In this paper, we present PA-FlowNet, an end-to-end pose-auxiliary optical flow network using the predicted relative camera pose to improve the performance of optical flow. With the concept of curriculum learning, PA-FlowNet also use the foreground-attention approach to avoid backgrounds from flow prediction error . Furthermore, we simulate aerial photography on a 64K moon model to generate Moon64K dataset. PA-FlowNet significantly outperforms all existing methods on the proposed Moon64K dataset. Additionally, we also predict the relative pose and accomplish the remarkable performance.

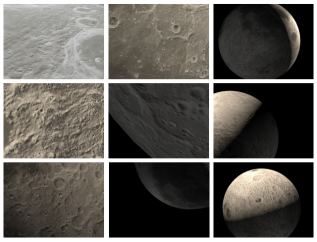
Objectives



- Using moon data as input images to predict the optical flow.
- Determining correspondences via optical flow field to estimate the relative camera pose.

Experimental Results

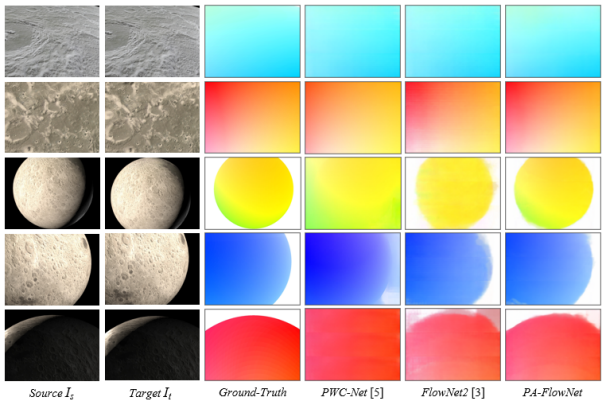
A. Moon64K Dataset



Height (km)	Training Data	Testing Data	Total
50~100	400	100	500
100~1,000	2,000	500	2,500
1,000~2,000	2,000	500	2,500
2,000~3,000	2,000	500	2,500
3,000~4,000	1,600	400	2,000
Aggregate	8,000	2,000	10,000

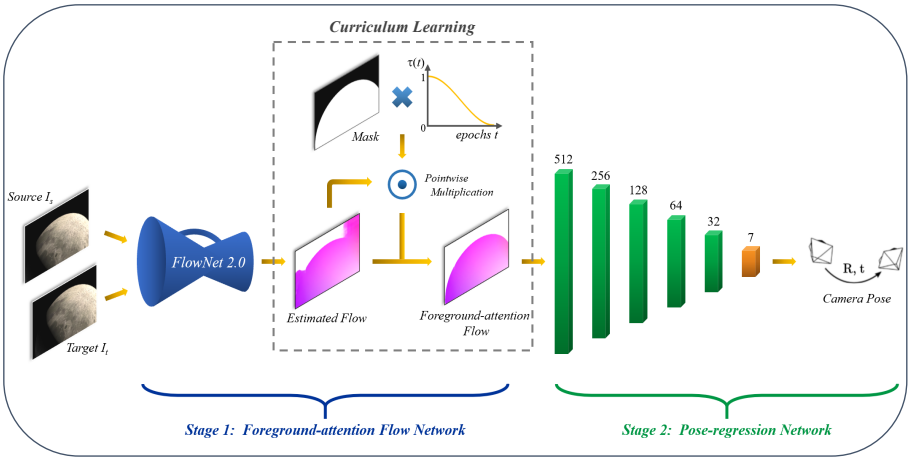
B. Results

Methods	Optical Flow error	Relative Pose Error	
	AEPE	Orientation Error	Translation Error
FlowNet2 [3]	6.682	0.987°	0.701
PWC-Net [5]	10.059	1.025°	0.783
PA-FlowNet	**2.409**	**0.918°**	**0.648**



Proposed PA-FlowNet

※ PA-FlowNet Architecture :



※ Curriculum Learning :

$$f'_{(c,i,j)} = f_{(c,i,j)} + \tau(t)[M_{(i,j)} \cdot f_{(c,i,j)}] \quad (1)$$

$f_{(c,i,j)}$: Estimated Flow
$f'_{(c,i,j)}$: Foreground−attention Flow
$M_{(i,j)}$: Mask

※ Training Strategy :

Training Stage	Model	Loss Function	Total Epochs
1	Foreground-attention flow network	M-epeLoss & epeLoss	50+10
2	PA-FlowNet	totalLoss	150

※ Loss Function :

$$M\text{-}epeLoss = \sum_{l=0}^{n} \alpha_l \sum_x \left\| flow_{est}^{(l)}(x) - flow_{gt}^{(l)}(x) \right\|_2 \quad (2)$$

$$epeLoss = \sum_x \left\| flow_{est}(x) - flow_{gt}(x) \right\|_2 \quad (3)$$

$$poseLoss = \beta \left\| Q_{gt} - (Q_{est}/|Q_{est}|) \right\|_2 + \left\| t_{gt} - t_{est} \right\|_2 \quad (4)$$

$$totalLoss = epeLoss + \gamma \times poseLoss \quad (5)$$

Reference

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