LiteFlowNet360 - Revisiting Optical Flow Estimation in 360 Videos

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Texas State University
By
Keshav Bhandari, Ziliang Zong & Yan Yan
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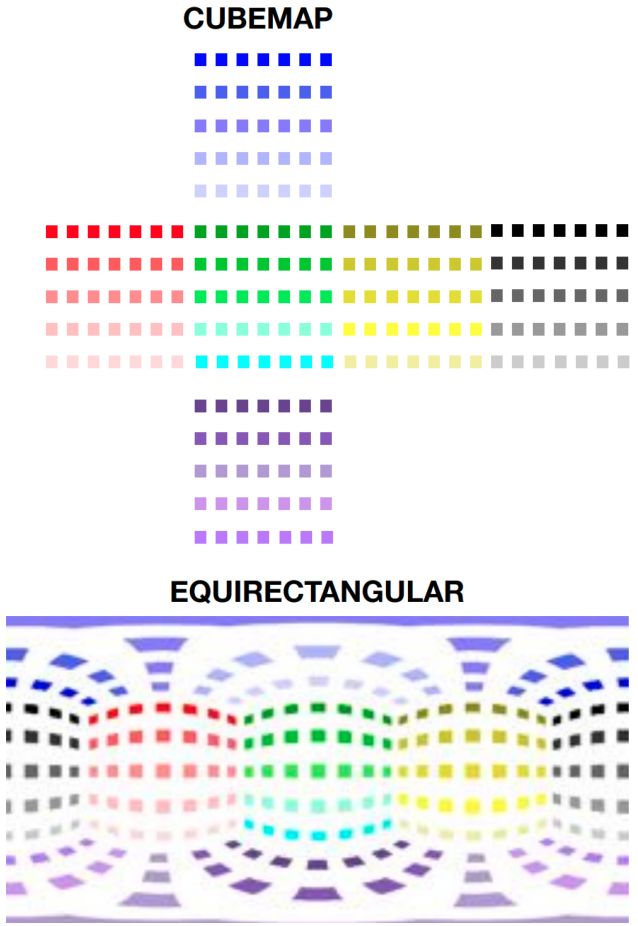
MOTIVATION

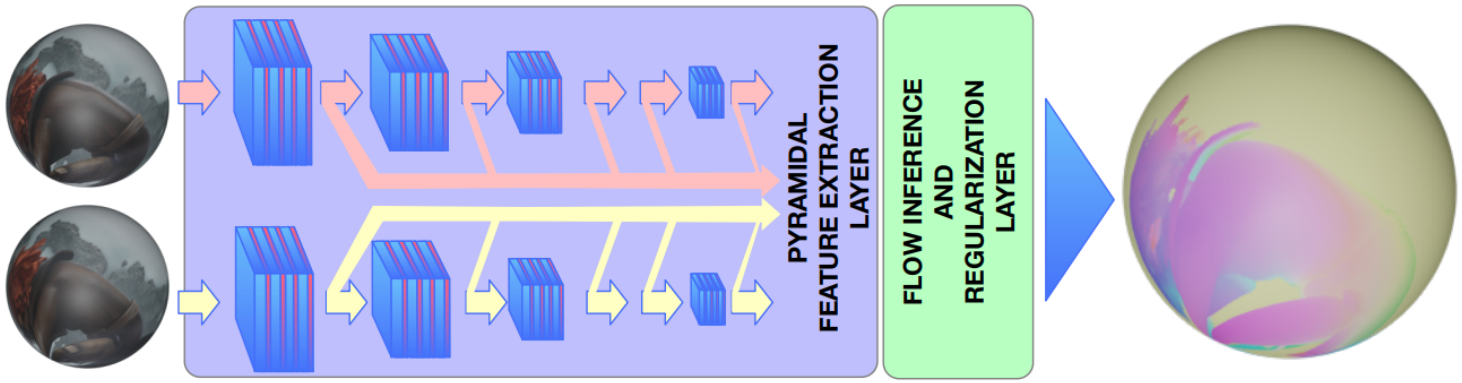
Are optical flow representation for normal and 360 videos are same?

How to exploit existing architecture to compute optical flow for 360 videos?

Do we have labelled data?

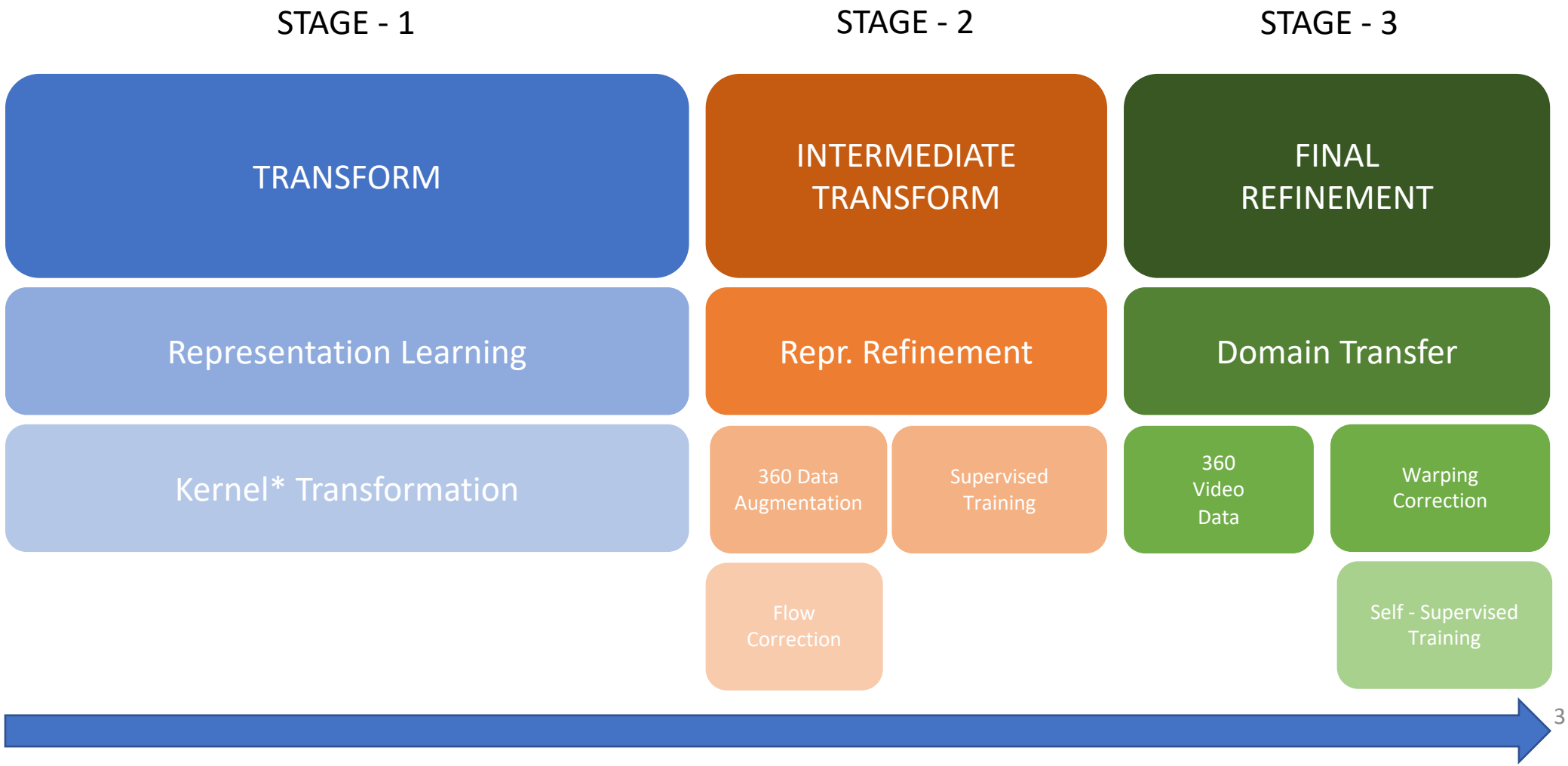


Architecture-Overview

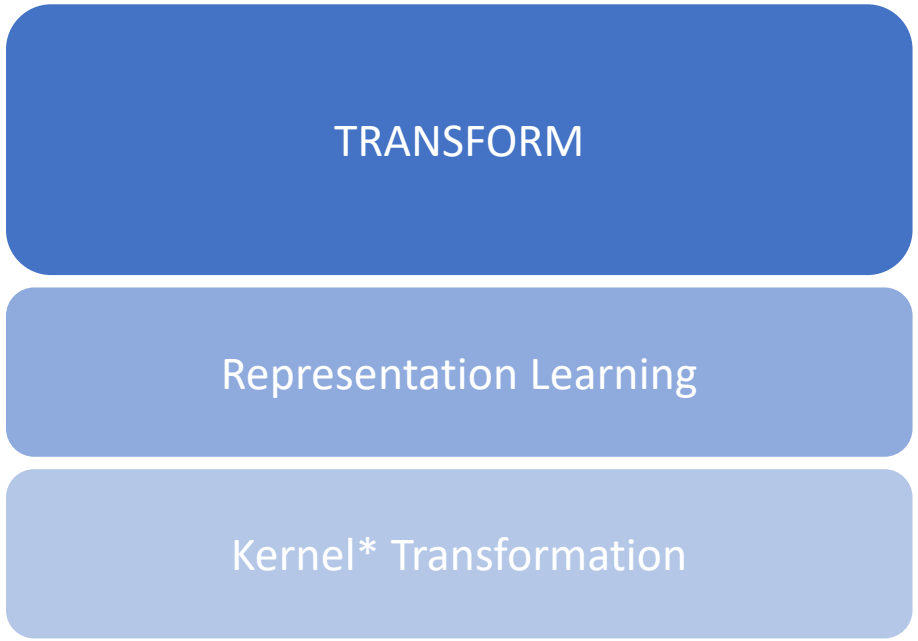


Architecture - ***LiteFlowNet360*** is inspired by Lite-FlowNet. Feature Extractions Layers are replaced with **"Spherical Convolution Learnable Layers"** using transformer network. We did flow inference by projecting the feature map to *tangential plane, rather than learning inference/regularization layer.*

Approach


STAGE - 1
STAGE - 2
STAGE - 3
TRANSFORM
INTERMEDIATE TRANSFORM
FINAL REFINEMENT
Representation Learning
Repr. Refinement
Domain Transfer
Kernel* Transformation
360 Data Augmentation
Supervised Training
360 Video Data
Warping Correction
Flow Correction
Self - Supervised Training

Representation Learning



$$F_k(X) = \begin{cases} F_0(X) & : k = 0 \\ (F_k \circ F_{k-1})(X) & : n > k > 0 \end{cases} \quad (1)$$

$$F'_k(X) = \begin{cases} F'_0(F_0(X), \Omega) & : k = 0 \\ (F'_k(F_k, \Omega) \circ F'_{k-1}(F_{k-1}, \Omega))(X) & : n > k > 0 \end{cases} \quad (2)$$

$$Y_k = F_k(X), Y'_k = F'_k(F_k(X), \Omega)$$

$$L_k = ||Y'_k - Y_k||^2$$

This is done in tangential planes, so multiple L_k

$$L'_k = \frac{1}{n_g} \sum_i^{n_g} L_k(\Omega(Y'^i_k), Y^i_k)$$

* Multiple variable size kernels are learned, these kernels are used to perform convolution in Spherical domain(that is in projected tangential planes)

Representation Refinement

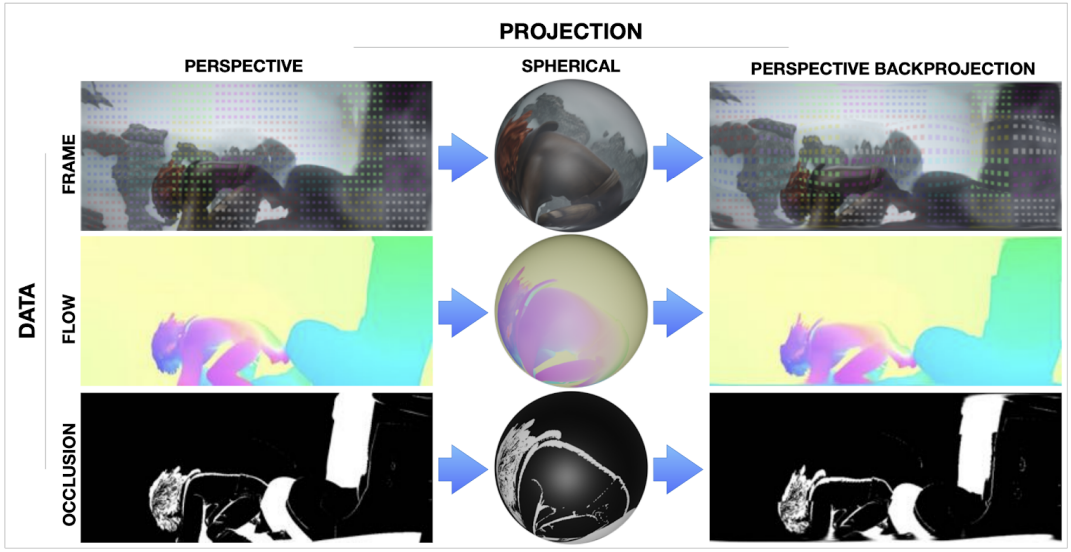
INTERMEDIATE TRANSFORM

Repr. Refinement

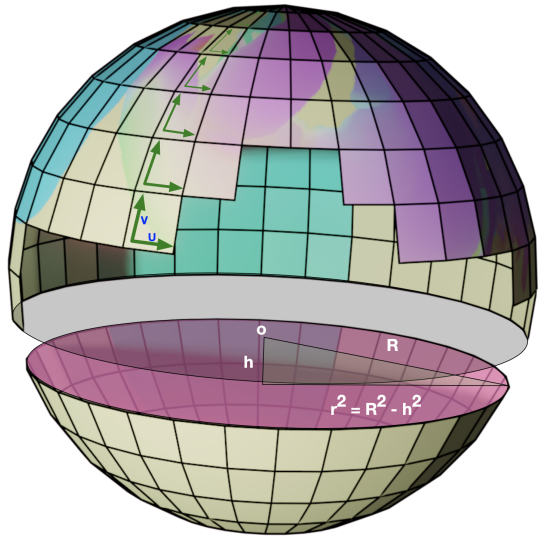
360 Data Augmentation

Supervised Training

Flow Correction



360 Data Augmentation



Flow Corrections

Domain Transfer

FINAL REFINEMENT

Domain Transfer

360 Video Data

Warping Correction

Self - Supervised Training

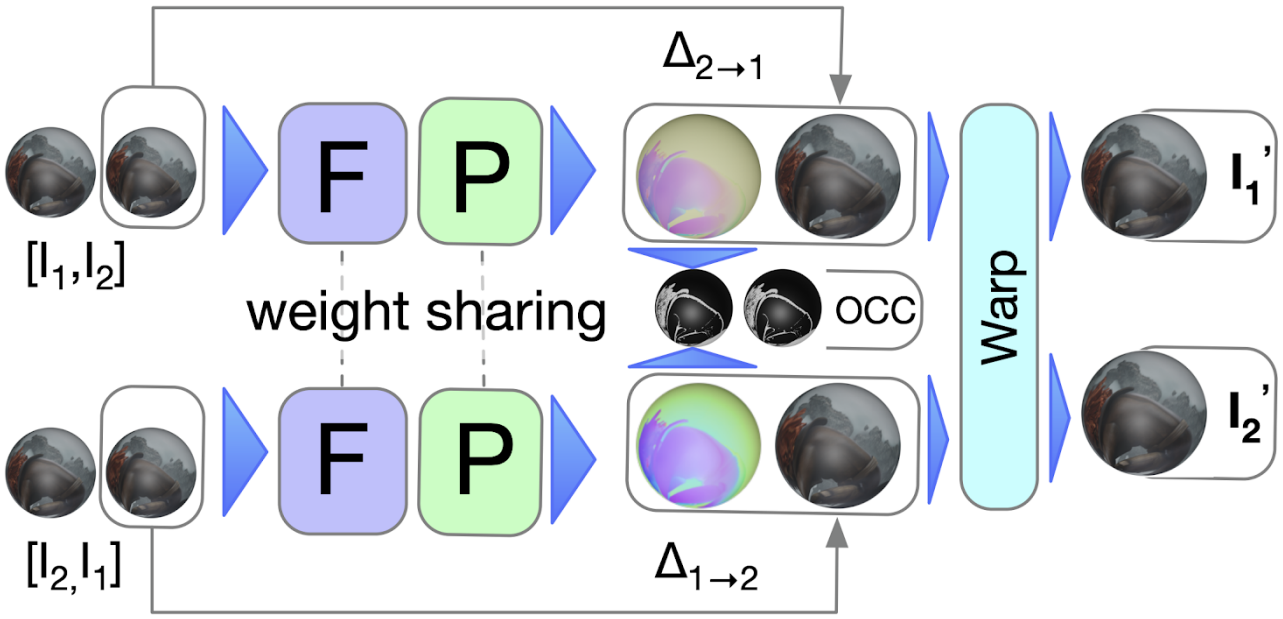


Fig. 5. Final Refinement process. Network from second stage is extended to have two parallel weight sharing architecture.

$$M_i = \begin{cases} 0 \\ 1 \quad if, |\Delta_{i\to j}| \leq \epsilon \end{cases}$$

$$\tilde{O}_{i\to j} = M_i \odot ((1 - M_j) + \tilde{O}_{j\to i})$$

$$L_p = \sum_{i,j} \frac{\sum \psi(I_i - I_i') \odot (1 - O_{i\to j})}{\sum 1 - O_{i\to j}}$$

*There is no boundary case for warping.
*Warping in 2D domain doesn't make sense
*Warping must be done in spherical domain.

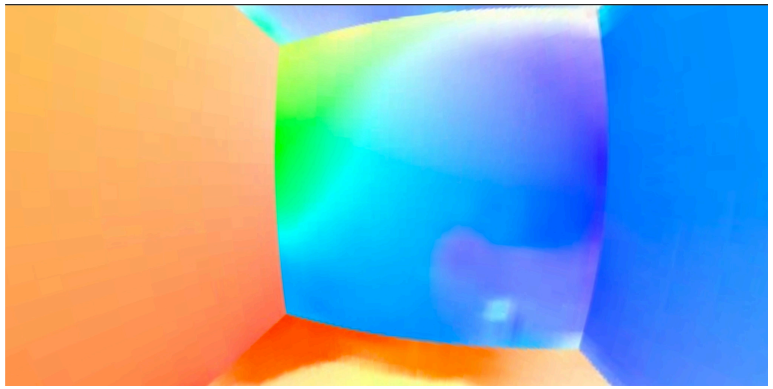
Quantitative Results

RESULTS ON SINTEL360 DATASET.

Model	Data	#Layers	EPE	L_p^*
LiteFlowNet[9]	Sintel360	0	$\sim$ 6.35	$\sim$ 1.30
LiteFlowNet +[14]	Sintel360	> 4	$\geq$ 17	$\geq$ 3.06
Ours, Stage-2	Sintel360	4	$\sim$ 6.35	$\sim$ 0.70
Ours, Final	Sintel360	4	$\sim$ 3.95	$\sim$ 0.60

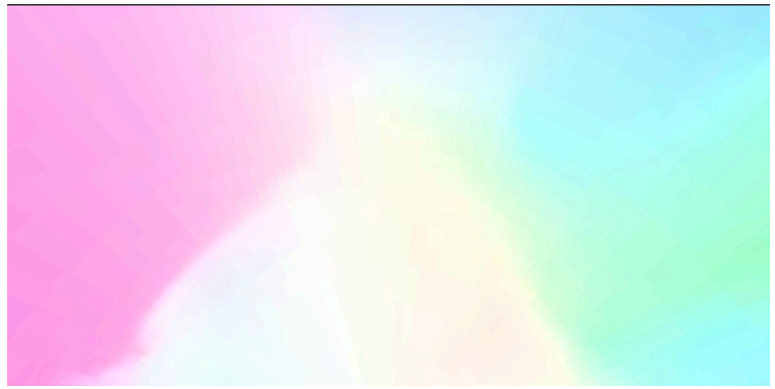
Qualitative Results

Conclusion



Flow Using Cube-maps only

Cube map using Lite-Flownet
Flow representations adapt to represent 360 properties
STAGE-2
(Equirectangular Projection)



OURS
(Equirectangular Projection)

<Conclusion>

LiteFlowNet360 is more of a domain adaption approach to estimate Optical flow for 360 Videos. The core idea is to light on fundamental considerations before exploiting off-the-shelf trained models.

<Thank You!!>

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