# Light field reconstruction using shearlet transform in tensorflow



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# LIGHT FIELD RECONSTRUCTION USING SHEARLET TRANSFORM IN TENSORFLOW

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**ABSTRACT**

Shearlet Transform (ST) is one of the most effective approaches for light field reconstruction from Sparsely-Sampled Light Fields (SSLFs). This demo paper presents a comprehensive implementation of ST for light field reconstruction using one of the most popular machine learning libraries, *i.e*. TensorFlow. The flexible architecture of TensorFlow allows for the easy deployment of ST across different platforms (CPUs, GPUs, TPUs) running varying operating systems with high efficiency and accuracy.

***Index Terms—*** Light Field Reconstruction, Shearlet Transform, TensorFlow, Epipolar-Plane Image, Light Field Sparsification

## 1. INTRODUCTION

Shearlet Transform (ST) [1, 2] is designed for reconstructing a Densely-Sampled Light Field (DSLF) from a Sparsely-Sampled Light Field (SSLF) using Epipolar-Plane Image (EPI) sparse representation in shearlet domain. Typically, ST is composed of four steps, which are (1) pre-shearing, (2) shearlet system construction, (3) sparsity regularization and (4) post-shearing. For step (1), (2) and (4), ST requires the information of minimum disparity $d_{min}$, maximum disparity $d_{max}$ and disparity range $d_{range}$ of the input SSLF, so that this input SSLF can be pre-sheared with new $d'_{min} = 0$ and $d'_{max} = d_{range}$. Besides, a shearlet system for the input SSLF can be constructed with $\xi$ scales, where $\xi = \lceil \log_2 d_{range} \rceil$. Regarding sparsity regularization, it typically consists of analysis transform, hard thresholding and synthesis transform as introduced in [1]. In addition, the double overrelaxation (DORE) algorithm in [2] can efficiently accelerate the convergence speed of sparsity regularization.

## 2. IMPLEMENTATION

The sparsity regularization step of ST is re-implemented here using TensorFow as shown in Fig. 1 (a). The original implementation [2] of ST using Matlab and the presented TensorFlow ST implementation are also compared here. For a fair comparison, the fifth row of "Dishes" in 4D Light Field Dataset [3] is extracted and decimated with an interpolation rate $\delta = 2$. In other words, the input SSLF contains 5 horizontal-parallax images. Since the "Dishes" light field has ground-truth $d_{min}$ ($-3.1$ pixels) and $d_{max}$ (3.5 pixels), the disparity condition of the input SSLF can be derived. The pre-shearing step is performed as illustrated in Fig. 1 (b) and (c). An Nvidia Titan Xp is exploited to process these 512 sparsely-sampled EPIs with resolution of $608 \times 128$ pixels and the number of iterations is set to 30.

**Table I**. Computation time comparison of different implementations.

| ST implementation | Time (s) |
|---|---|
| Matlab (with CUDA) [2] | 87.635 |
| TensorFlow (with CUDA) | 91.574 |

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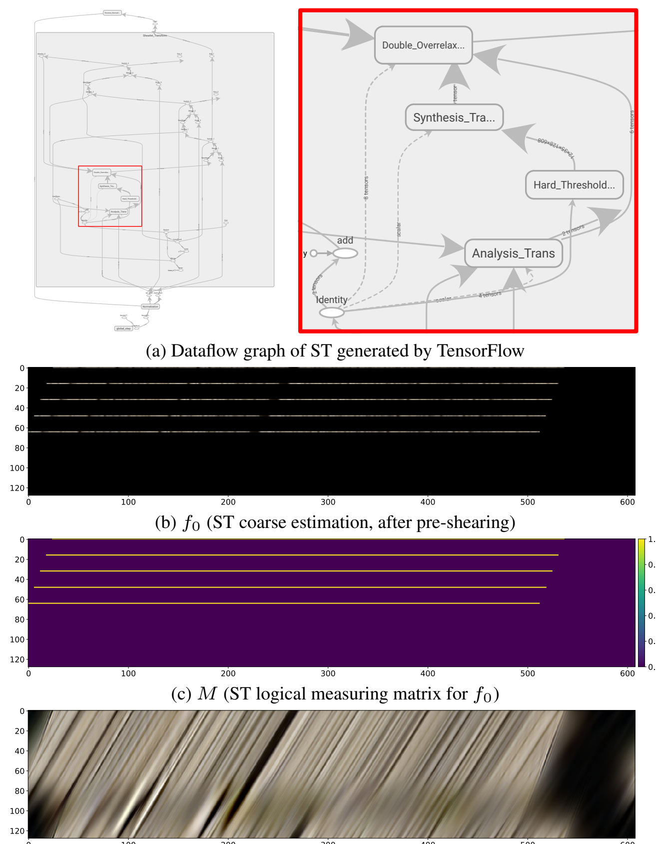


(a) Dataflow graph of ST generated by TensorFlow

(b) $f_0$ (ST coarse estimation, after pre-shearing)

(c) $M$ (ST logical measuring matrix for $f_0$)

(d) $f_{30}$ (ST estimation refinement, after 30 iterations)

**Fig. 1**. The coarse estimation, logical measuring matrix and estimation refinement for densely-sampled EPI reconstruction using ST.

The computation time of different implementations are compared in Table I. As can be seen in this table, the presented TensorFlow implementation achieves comparable performance to the original Matlab implementation. An example of reconstructed densely-sampled EPI is displayed in Fig. 1 (d). The source code of this demo will be released to facilitate learning-based light field research using ST.

## 3. REFERENCES

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