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Modelling the Point Spread Function of Wide Field Small Aperture Telescopes with Deep Neural Networks – Applications in Point Spread Function Estimation

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Abstract

The point spread function (PSF) reflects states of a telescope and plays an important role in development of smart data processing methods. However, for wide field small aperture telescopes (WFSATs), estimating PSF in any position of the whole field of view (FoV) is hard, because aberrations induced by the optical system are quite complex and the signal to noise ratio of star images is often too low for PSF estimation. In this paper, we further develop our deep neural network (DNN) based PSF modelling method and show its applications in PSF estimation. During the telescope alignment and testing stage, our method collects system calibration data through modification of optical elements within engineering tolerances (tilting and decentering). Then we use these data to train a DNN. After training, the DNN can estimate PSF in any field of view from several discretely sampled star images. We use both simulated and experimental data to test performance of our method. The results show that our method could successfully reconstruct PSFs of WFSATs of any states and in any positions of the FoV. Its results are significantly more precise than results obtained by the compared classic method - Inverse Distance Weight (IDW) interpolation. Our method provides foundations for developing of smart data processing methods for WFSATs in the future.

Key words: telescopes – methods: numerical – techniques: image processing

問題設定

視野を M = m×m のグリッドに分割
グリッド内では PSF は不変とする.
各グリッドでの PSF を求めることを
目標とする.

Fig.1 (使用した Neural Network の構造)

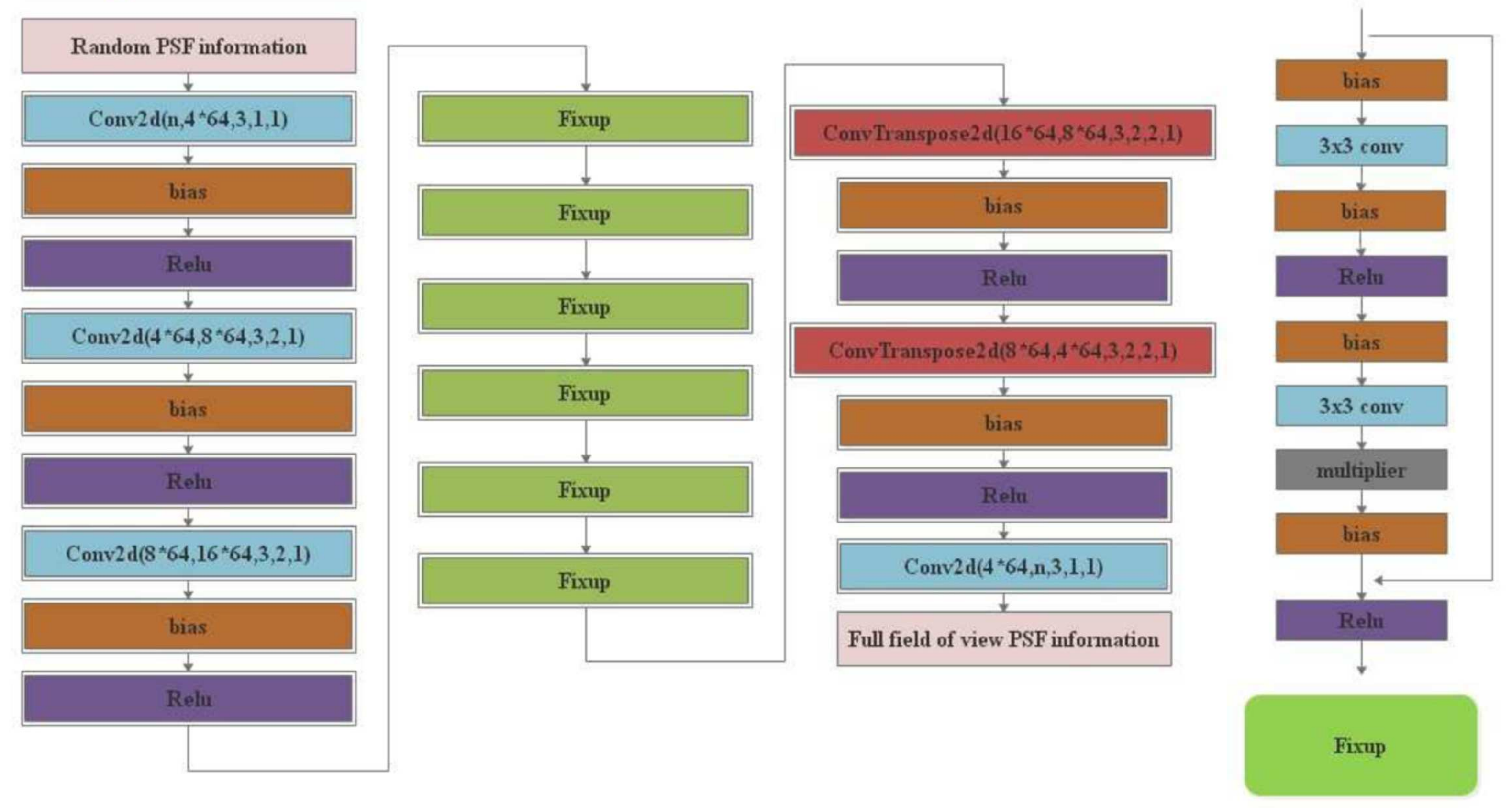


Figure 1. The structure of the Tel–Net. The Tel–Net consists of convolutional layers (Conv2d in blue), Bias layers (Bias in brown), Activation layers (Relu in purple), Conv-transpose layers (ConvTranspose2d in red), multiply layers (multiplier in grey) and Fixup blocks (Fixup block in green). The structure of Fixup block is shown in the right part of this figure.

DNN の入力は各グリッドの PSF.
(NAXS3 = M の データキューブ)
ただし, PSF が測定できなかった グリッド では
ゼロで 埋めた画像とする

DNN の出力も各グリッドの PSF
つまり, N×N×M の データキューブのうち,
欠損したデータを推定する補完問題を
DNN で解いていることになる

論文中では 2種類の実験を実施

(理想的な状況でうまくいくかをテスト)

(実験1) ZEMAX ベースのシミュレーション. 2番目のレンズを 公差の範囲 で動かしてモデルPSFを作成 (2000パターン)
61×61 のグリッドに分割. 入力ではランダムに選んだ 60個の PSF のみ有効化

(実験2) 実際の光学系での試験. 鏡の配値をわずかに変えて 40 パターンの PSF キューブを作成.
グリッドは 5×5. 入力では 8個の PSF のみ有効化した

Points

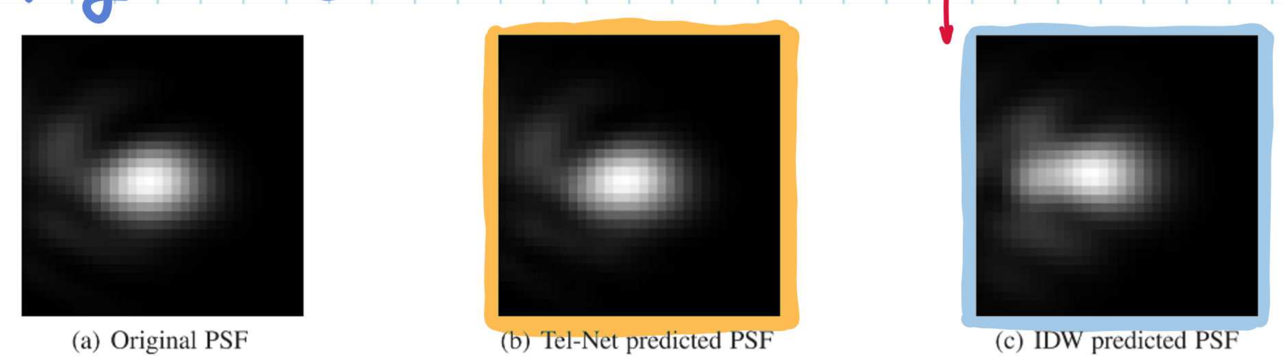
WFSATs (10°×10° の広視野カメラ) の視野の任意の場所での PSF を計算したい.

- 収差が大きい & カメラそのものが不安定 (PSF が変わる) → 観測データから推定する必要がある
- PSF fitting ができるほど明るい星は視野内でも限られる → 視野全体で PSF の直接測定は困難

視野内の限られた明るい星の画像から視野全体での PSF を推定する関数を DNN で作成

→ 本論文はそのための手続きを提案 & テスト

Fig.4 & 5 (実験1の結果)



(a) Original PSF (b) Tel-Net predicted PSF (c) IDW predicted PSF

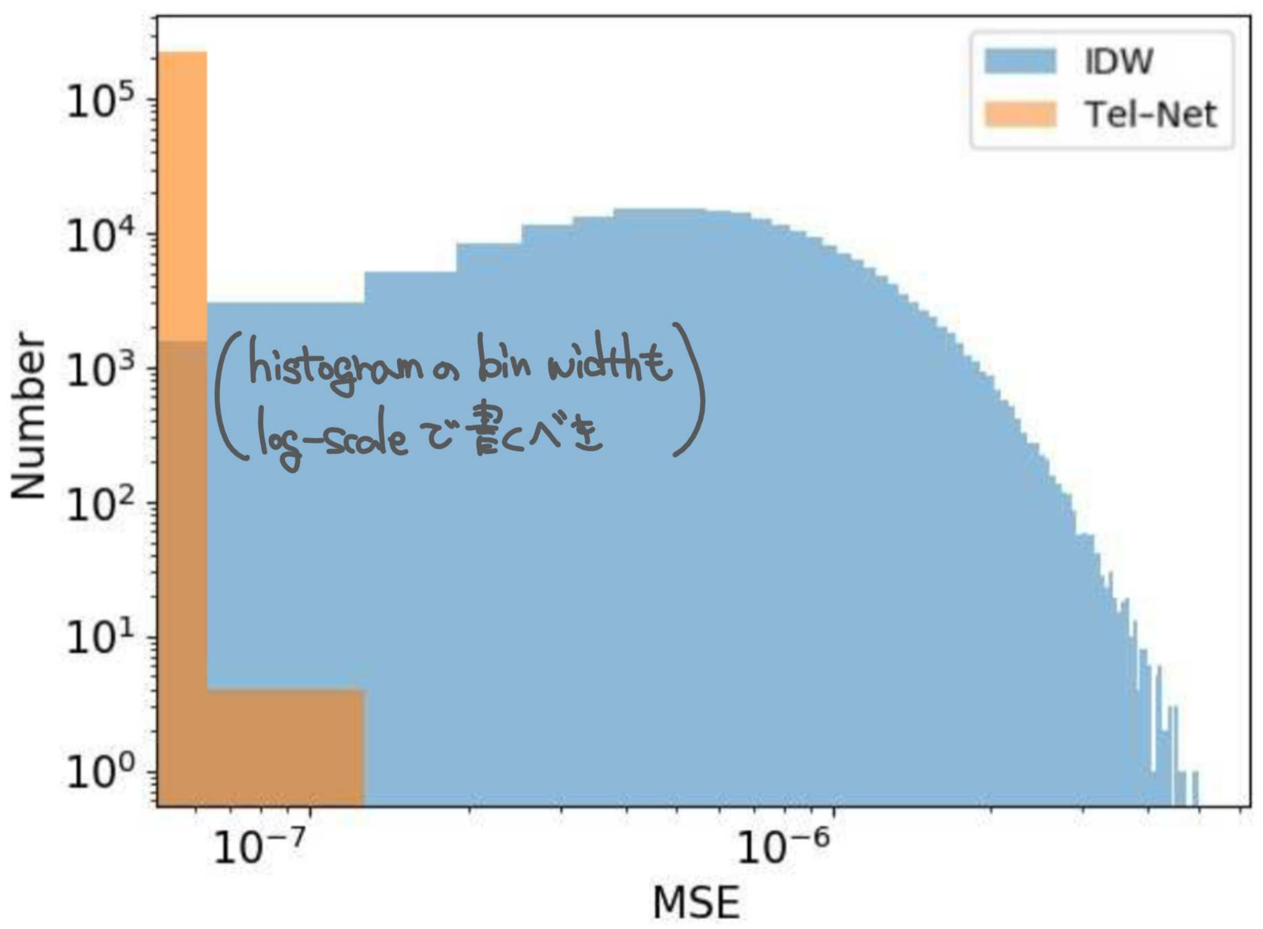
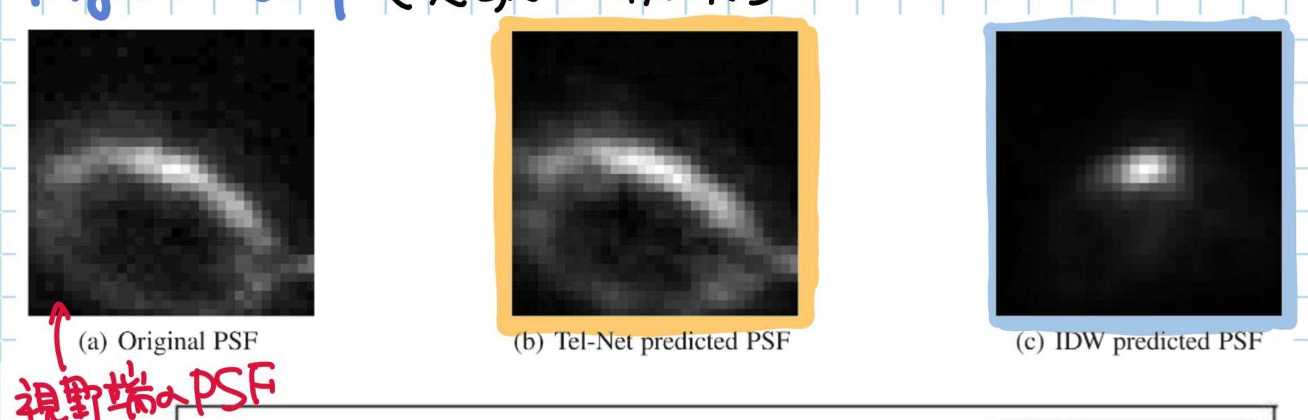


Table 2. MSE between predicted PSFs (estimated by the Tel–Net and the IDW) and original PSFs. The Tel–Net is trained by 2000 training PSF–Cubes and tested by 100 test PSF–Cubes.

Predicted Method	MSE mean	MSE variance
Tel-Net	1.49×10^{-8}	5.81×10^{-17}
IDW	7.79×10^{-7}	2.04×10^{-13}

Fig.8 & 9 (実験2の結果)



(a) Original PSF (b) Tel-Net predicted PSF (c) IDW predicted PSF

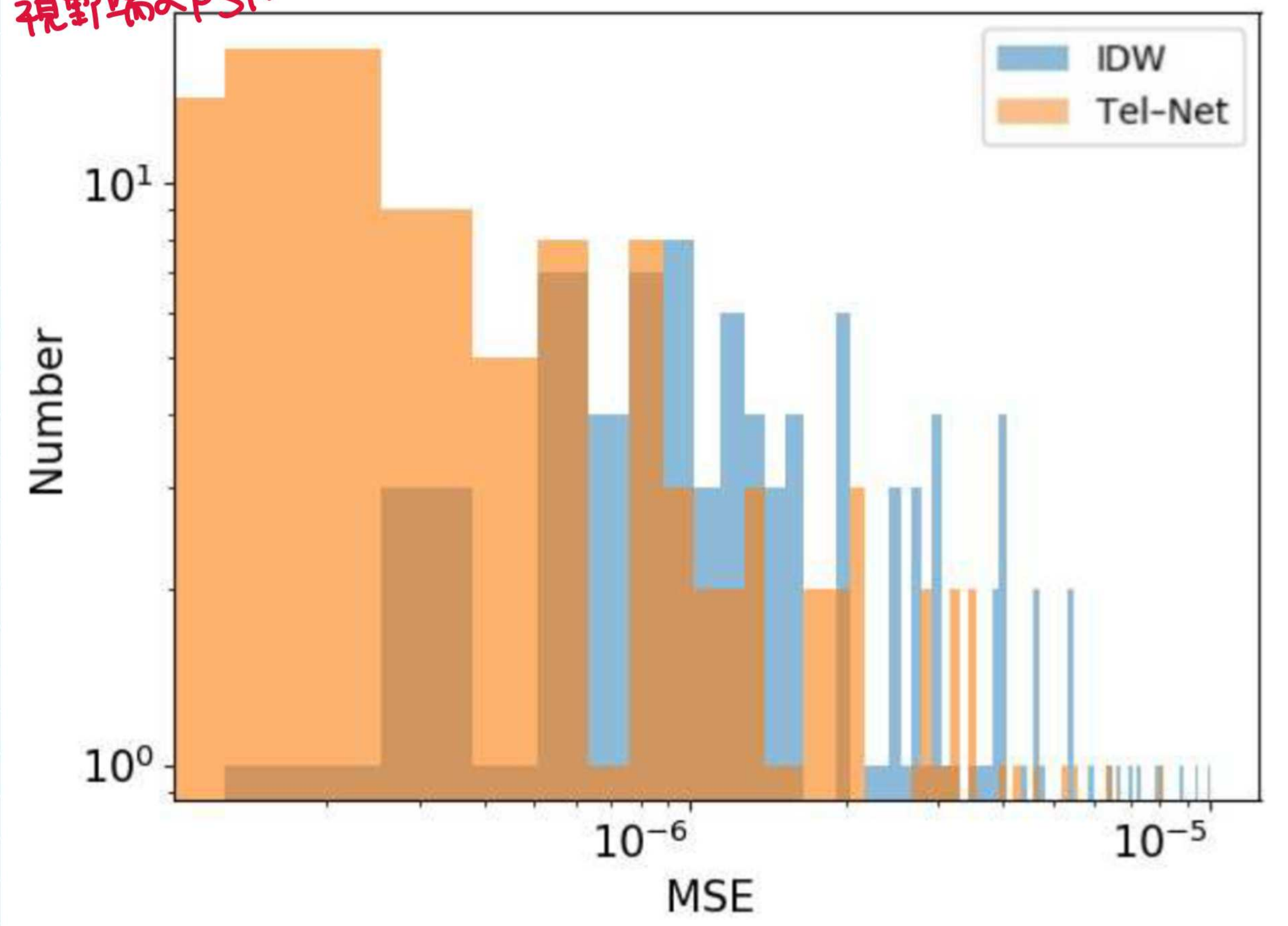


Table 3. MSE between predicted PSFs (estimated by the Tel–Net and the IDW) and original PSFs. The Tel–Net is trained by 36 training PSF–Cubes and tested by 4 PSF–Cubes.

Type	mean	var
Tel-Net	1.29×10^{-6}	3.07×10^{-12}
IDW	2.83×10^{-6}	5.60×10^{-12}

Fig.7 (実験2のセットアップ)

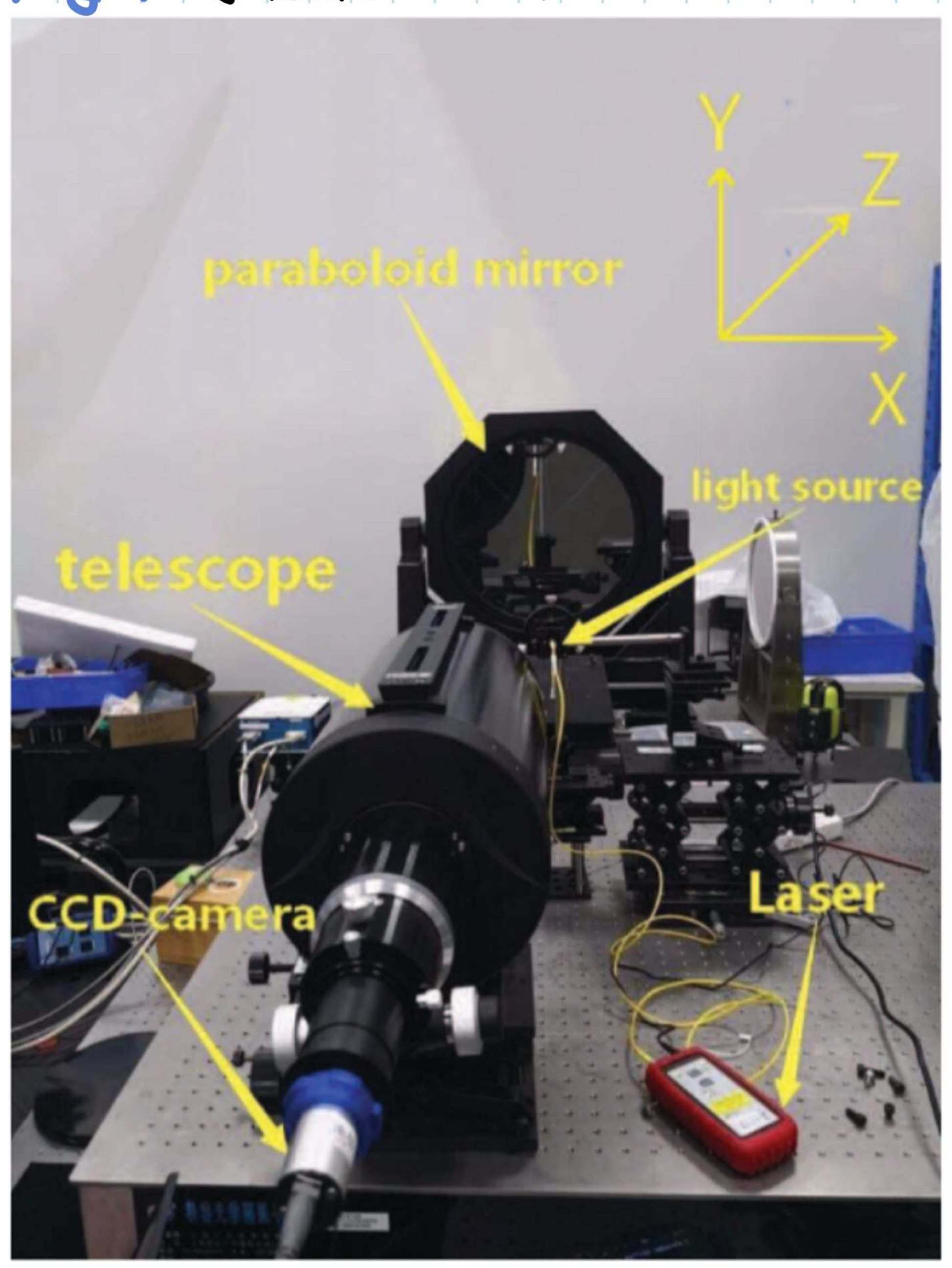


Fig.2 (WFSATs の ZEMAX モデル)

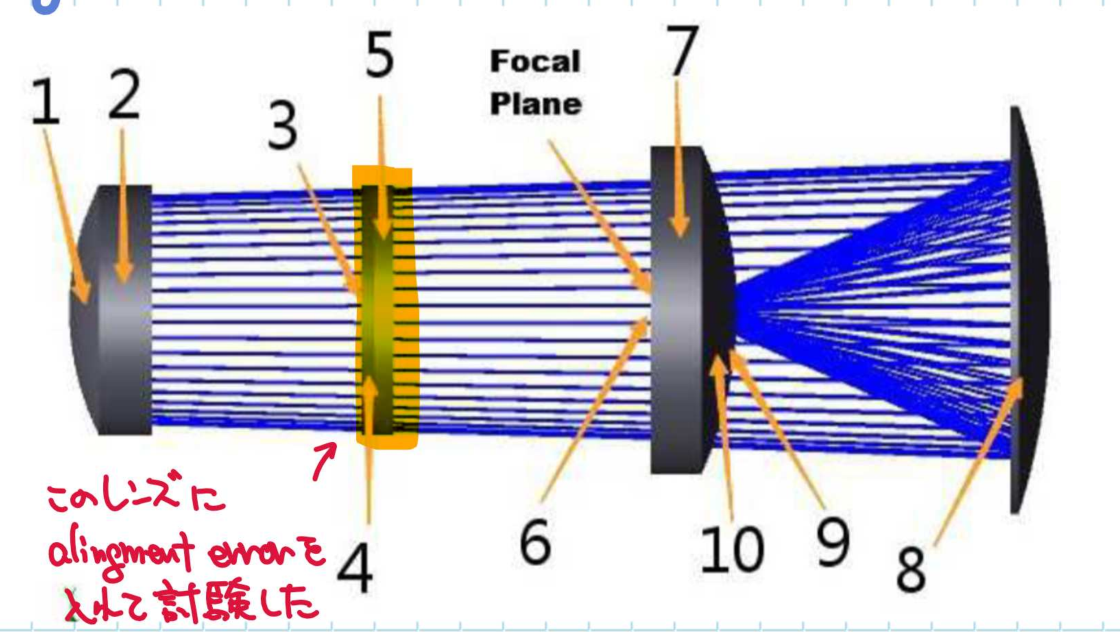


Fig.6 (実験2のコンセプト図)

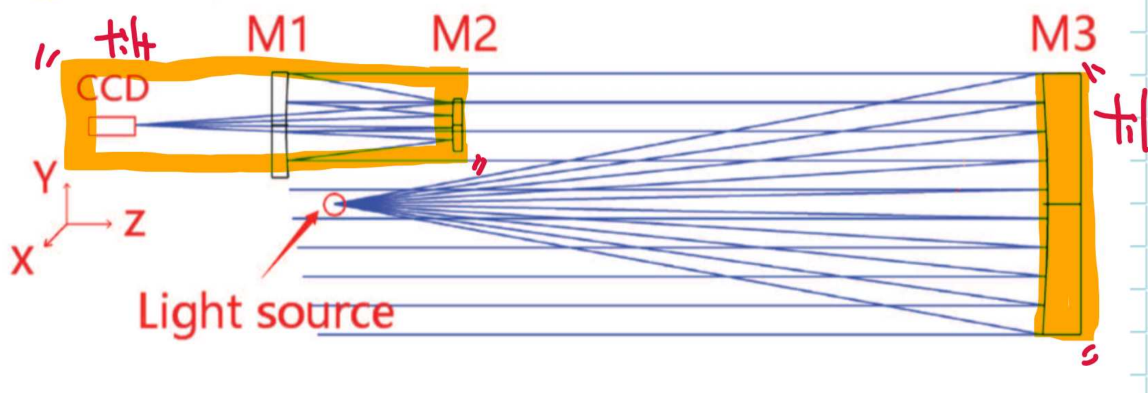


Figure 6. The concept design of the optical path in our experiment.