Computer Vision
Assignment 2

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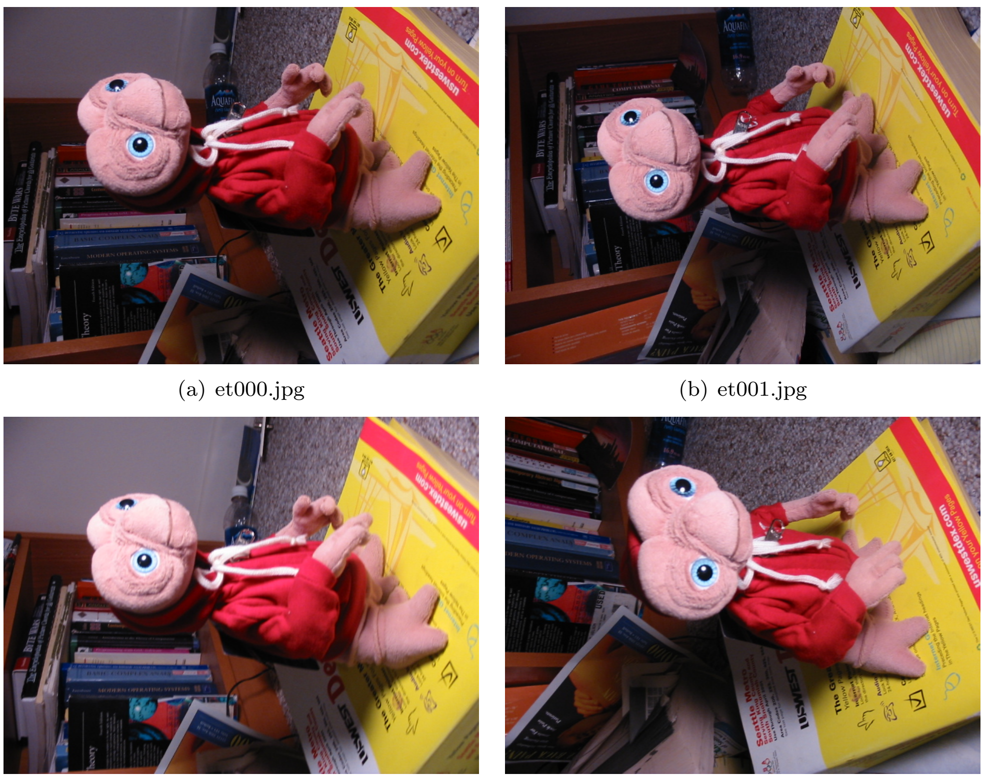
1 Camera Calibration

In this assignment we have learnt how to determine the intrinsic camera matrix for a pin-hole camera model. Using the world points and their respective projections onto the image plane we get the a linear equation of the form $Ap = 0$ subject to the constraint that $\|p\|^2 = 1$ (where p is vector of all parameters of the P matrix). We have used the opencv solver *SolveZ()* to estimate the P matrix. Further, decomposition of the P matrix is done using *decomposeProjectionMatrix()* function in opencv to find the K, R, t values of the camera matrix.

This report is an analysis of Direct Linear Transformation, Singular Value Decomposition and RANSAC Algorithm which are commonly used camera calibration techniques. In our analysis we have used the images in Figure 1.



(a) et000.jpg

(b) et001.jpg

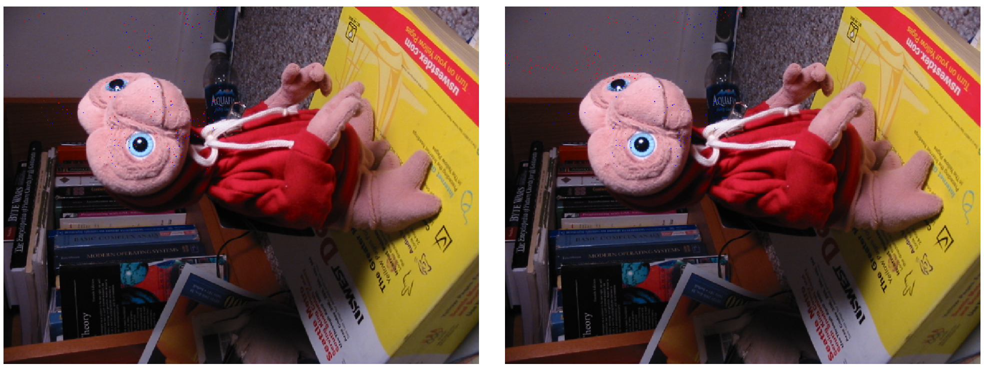
(c) et003.jpg

(d) et004.jpg

Figure 1: Images used in our experiments.

2 Direct Linear Transformation

In Direct Linear Transformation we use 6 point matches to estimate K, R, t. In our implementation, we have randomly selected 6 point matches and estimated the P matrix. We have noticed arbitrarily large re-projection errors in many of the cases. This is an indication of the presence of outliers in the given point matches.



(a) (b)

Figure 2: Original image points of e000.jpg are marked blue and re-projections are marked red. Estimated P matrix on e000.jpg using DLT resulted in Re-projection error= 41.19 in (a) and a Re-projection error = 5751.43 in (b) (*Zoom-in here to see the re-projections.*)

3 Singular Value Decomposition

Using SVD for camera calibration we choose arbitrary number of point matches to estimate K, R, t. In our experiments, we estimated the P matrix by randomly selecting point matches and noticed large re-projection errors due to outliers. In order to see the variation of the re-projection error with number of point matches, we estimated P for 10 different random selections in each case. The mean of the average least square error is calculated and the plot is shown in Figure 3.

4 RANSAC Algorithm

RANSAC algorithm is a robust method to estimate the parameters of a mathematical model to a set of observations which may contain outliers. Iteratively, the algorithm produces either a model which is rejected because too few points are classified as inliers or a refined model

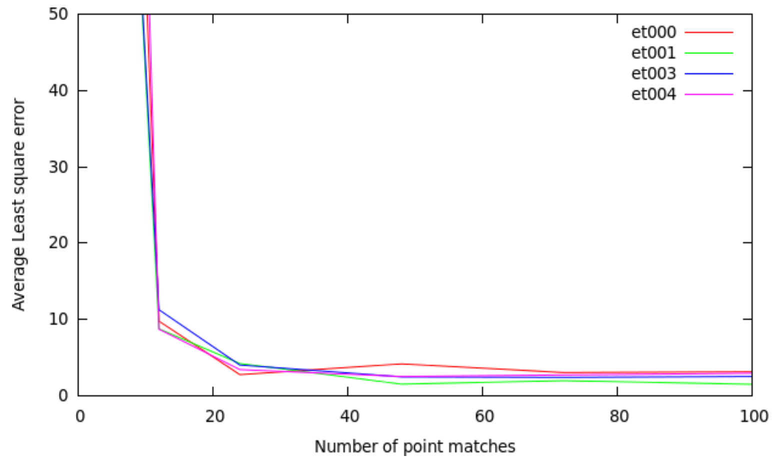


Figure 3: Average least square obtained for the 12, 24, 48 and 72 point matches of the four images. *Gradually, increase in number of point matches resulted in low re-projection errors i.e., SVD finds better models given more point matches.*

together with a corresponding error measure. In the latter case, we keep the refined model if its error is lower than the last saved model.

However, the accuracy of the obtained model depends on the parameter t, a threshold value for determining when a datum is classified as inlier to a model.The number of iterations(N) depends on the parameter d, the number of close data values required to assert that a model fits well to data. Figure 4 shows our analysis while tuning the parameters t and d.

5 Decomposition of Projective matrix

In our experiments on multiple images, we decomposed the estimated P matrix into $K, Randt$. In our experiments, we obtained the K_1 matrix for et000.jpg, et003.jpg and K_2 matrix for et001.jpg, et004.jpg images. The obtained matrices correspond to least square error in the range (1.4, 2.5).

$$K_1 = \begin{bmatrix} 0.187 & -0.00013 & 0.0074 \\ 0 & 0.186 & 0.00045 \\ 0 & 0 & -0.00027 \end{bmatrix}; K_2 = \begin{bmatrix} 0.223 & 0.00028 & -0.003 \\ 0 & 0.222 & 0.0033 \\ 0 & 0 & 0.00033 \end{bmatrix}$$

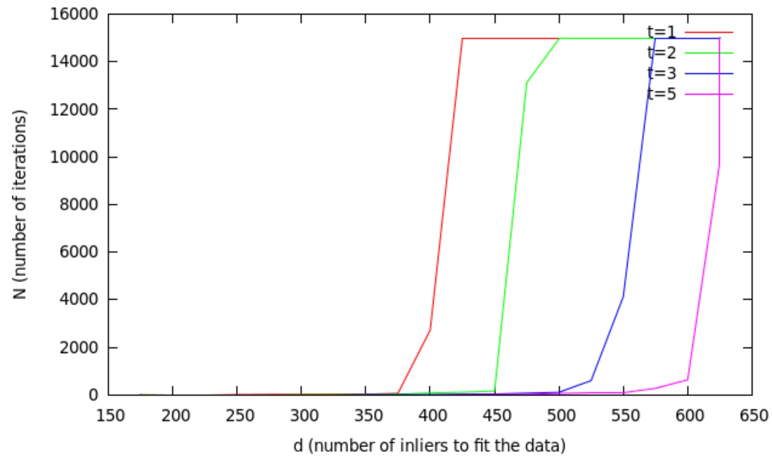


Figure 4: Effect of the parameters t and d on N is reflected in this plot. For small values of t, finding a reasonably good model requires more number of iterations. *RANSAC offers a trade-off i.e., by computing a greater number of iterations the probability of a reasonable model being produced is increased.*

6 Conclusions

In our experiments, we found the RANSAC algorithm producing better models than DLT and SVD implementations. The following table supports this conclusion.

Image Id	DLT Error	SVD Error	RANSAC Error
0	24.3817	2.74086	2.67924
1	28.5399	2.03772	1.53178
3	28.1573	2.2035	2.38449
4	20.1222	3.30922	2.39597