

# Normalization for the Eight-Point Algorithm

OWEN JOW

November 17, 2019

## 1 Motivation

In the eight-point algorithm, we set up a matrix equation  $\mathbf{A}\mathbf{f} = \mathbf{0}$  based on a reformulation of the epipolar constraint, where  $\mathbf{A}$  is derived from the coordinates of corresponding points and  $\mathbf{f}$  consists of the entries of the fundamental matrix. However, in its original form,  $\mathbf{A}$  will typically be ill-conditioned because it contains both pixel coordinates (with a maximum value of, say, 1920) and final homogeneous coordinates (say, 1).

To circumvent this, we *normalize* the image coordinates upon which  $\mathbf{A}$  is based. For each image, we construct a transformation which

1. translates the centroid of the image points to the origin, and
2. uniformly rescales the image points so that the mean  $L_2$ -distance from the origin is  $\sqrt{2}$ .

## 2 Implementation

First, rescale the image points so that the third (homogeneous) coordinate is 1 in all cases.

For the first transform, we simply subtract the current centroid point  $(\mu_x, \mu_y) = (\frac{1}{n} \sum_{i=1}^n x_i, \frac{1}{n} \sum_{i=1}^n y_i)$  from each of the  $n$  image points  $(x_i, y_i)$ .

For the second transform, we divide all points by the standard deviation (making the mean distance from the origin 1) and then multiply by  $\sqrt{2}$ . The standard deviation should be computed as the square root of the expected squared  $L_2$ -distance from the current centroid point:

$$\sqrt{\frac{1}{n} \sum_{i=1}^n [(x_i - \mu_x)^2 + (y_i - \mu_y)^2]}$$

which is the same as separately computing the standard deviation  $\sigma_x$  across  $x$ -coordinates and the standard deviation  $\sigma_y$  across  $y$ -coordinates and then combining them using  $\sqrt{\sigma_x^2 + \sigma_y^2}$ :

$$\begin{aligned} \sqrt{\sigma_x^2 + \sigma_y^2} &= \sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - \mu_x)^2 + \frac{1}{n} \sum_{i=1}^n (y_i - \mu_y)^2} \\ &= \sqrt{\frac{1}{n} \sum_{i=1}^n [(x_i - \mu_x)^2 + (y_i - \mu_y)^2]} \end{aligned}$$

Overall, the second transform comes together as the following scale factor:

$$s = \frac{\sqrt{2}}{\sqrt{\frac{1}{n} \sum_{i=1}^n [(x_i - \mu_x)^2 + (y_i - \mu_y)^2]}}$$

## 2.1 Affine Transformation Matrix

As a single affine matrix, the transformation is

$$\mathbf{T} = \begin{bmatrix} s & 0 & -s\mu_x \\ 0 & s & -s\mu_y \\ 0 & 0 & 1 \end{bmatrix}$$

Note that the translations need to be multiplied by  $s$  because the scaling happens first.

## 3 De-Normalization

After computing  $\mathbf{F}$  according to the normalized image points, we will have to de-normalize it. If the transformation for the first set of image points is  $\mathbf{T}_1$  and the transformation for the second set of image points is  $\mathbf{T}_2$ , then de-normalization for  $\mathbf{F}$  will be

$$\mathbf{T}_1^T \mathbf{F} \mathbf{T}_2$$

assuming the  $\mathbf{x}_1^T \mathbf{F} \mathbf{x}_2$  form of the epipolar constraint.