

## The Fanbeam Projection of a Point

Consider the (directional) projection of a point  $(x_0, y_0)$  along the vector  $(x_0 - x_s, y_0 - y_s)$  onto a horizontal detector plane with center  $(x_d, y_d)$  (cf. the illustration in Figure 1). The projection

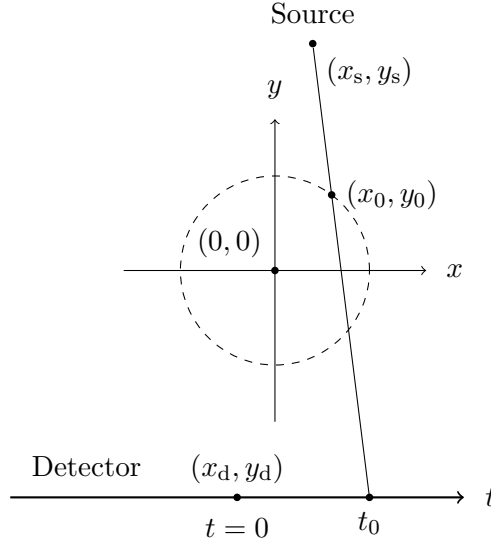


Figure 1: Fanbeam geometry: directional projection of a point.

$(x_d + t_0, y_d)$  can be expressed as the intersection of the detector plane and the line that passes through  $(x_s, y_s)$  and  $(x_0, y_0)$ , i.e., there exists a scalar  $\alpha \neq 0$  such that

$$\begin{bmatrix} x_d + t_0 \\ y_d \end{bmatrix} = \alpha \begin{bmatrix} x_s \\ y_s \end{bmatrix} + (1 - \alpha) \begin{bmatrix} x_0 \\ y_0 \end{bmatrix}.$$

The second of these two equations implies that

$$\alpha = \frac{y_d - y_0}{y_s - y_0},$$

and from the first equation we can obtain the position  $t_0$  on the detector plane

$$t_0 = \alpha(x_s - x_0) + x_0 - x_d = \frac{y_d - y_0}{y_s - y_0}(x_s - x_0) + x_0 - x_d.$$

Rewriting this expression yields

$$\begin{aligned} t_0 &= \frac{y_d - y_s + y_s - y_0}{y_s - y_0}(x_s - x_0) + x_0 - x_d \\ &= \left( \frac{y_d - y_s}{y_s - y_0} + 1 \right) (x_s - x_0) + x_0 - x_d \\ &= (x_s - x_d) - (y_s - y_d) \frac{x_s - x_0}{y_s - y_0}. \end{aligned}$$

Now if we rotate  $(x_0, y_0)$  by an angle of  $-\theta$  around origo (equivalently, rotate the source and the detector counterclockwise around the origo by  $\theta$ ), we obtain the following expression for the position on the detector plane

$$t_0(\theta; x_s, y_s, x_d, y_d, x_0, y_0) = (x_s - x_d) - (y_s - y_d) \frac{x_s - x_0 \cos(\theta) - y_0 \sin(\theta)}{y_s + x_0 \sin(\theta) - y_0 \cos(\theta)} \quad (1)$$

as a function of the source position  $(x_s, y_s)$ , the detector center  $(x_d, y_d)$ , and the point  $(x_0, y_0)$ .

## Model Calibration

The expression for the position of the projection of a point as a function of the rotation angle  $\theta$  can be used to calibrate our forward model. To this end, we will place a pin (or something that resembles a “point”) in our X-ray CT scanner and collect a number of projections from, say,  $m$  different angles. If we let  $\hat{p}_i(t)$  denote the projection at angle  $\theta_i$ , we can estimate the projection centroid as

$$\hat{\rho}_i = \frac{\int_{-w/2}^{w/2} t \hat{p}_i(t) dt}{\int_{-w/2}^{w/2} \hat{p}_i(t) dt} \approx \frac{\sum_{j=1}^r t_j b_{ij}}{\sum_{j=1}^r b_{ij}} \quad (2)$$

where  $w$  is the width of the detector,  $t_1, \dots, t_r$  are the detector pixel positions (the pixel centers), and  $b_{ij}$  is the sinogram pixel corresponding to detector pixel  $i$  and projection angle  $\theta_j$ . This is illustrated in Figure 2.

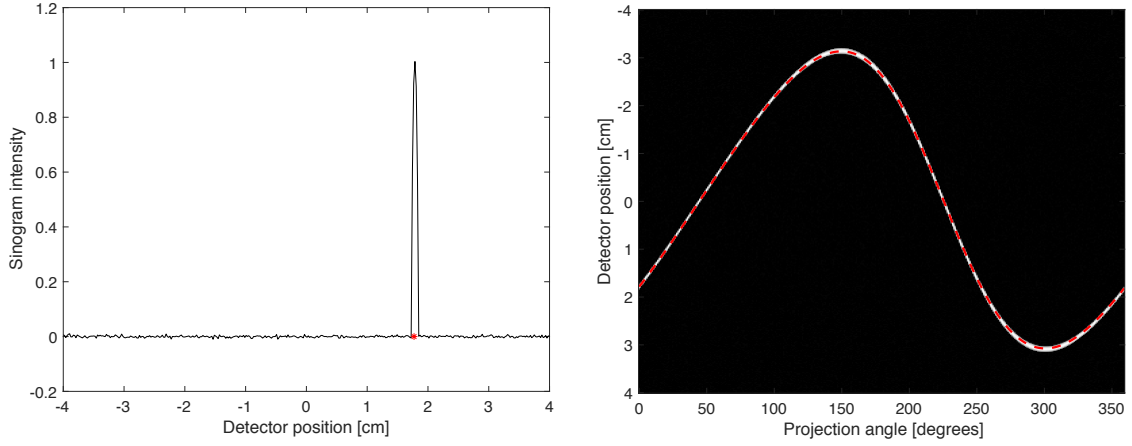


Figure 2: Centroid estimation from pin projections: (left) a single projection and the estimated centroid marked with a red asterisk; (right) sinogram with centroid estimates overlaid as a dashed red curve.

To calibrate the geometry, we will formulate a nonlinear least-squares problem

$$\text{minimize} \quad (1/2) \sum_{i=1}^m (t_0(\theta_i; \beta) - \hat{\rho}_i)^2$$

with variables  $\beta = (x_s, y_s, x_d, y_d, x_0, y_0)$ . In other words, our model  $t_0(\theta_i; \beta)$  should (approximately) agree with the centroid estimate  $\hat{\rho}_i$ . We will use the so-called Levenberg–Marquardt (LM) method to “solve” (i.e., find a local minimum) our nonlinear least-squares problem. The LM method is an iterative method, and each iteration requires the solution of a regularized (linear) least-squares problem

$$\begin{aligned} \beta^{(k+1)} &= \underset{\beta}{\operatorname{argmin}} \left\{ (1/2) \|J_{t_0}(\beta^{(k)})(\beta - \beta^{(k)}) - r(\beta^{(k)})\|_2^2 + (\gamma/2) \|\beta - \beta^{(k)}\|_2^2 \right\} \\ &= \beta^{(k)} + \underset{u}{\operatorname{argmin}} \left\{ (1/2) \|J_{t_0}(\beta^{(k)})u - r(\beta^{(k)})\|_2^2 + (\gamma/2) \|u\|_2^2 \right\} \end{aligned} \quad (3)$$

where  $r^{(k)}$  is a residual vector with elements

$$r_i^{(k)} = \hat{\rho}_i - t_0(\theta_i; \beta^{(k)}), \quad i = 1, \dots, m$$

and  $J_{t_0}(\beta^{(k)})$  is the  $m \times 6$  Jacobian matrix with rows  $\nabla_{\beta} t_0(\theta_i; \beta^{(k)})^T$ .

## Exercises

1. Verify that the gradient of  $t_0(\theta; \beta)$  (with respect to  $\beta$ ) can be expressed as

$$\nabla_{\beta} t_0(\theta; \beta) = \begin{bmatrix} \frac{y_d - y_0^{\theta}}{y_s - y_0^{\theta}} \\ -(x_s - x_0^{\theta}) \frac{y_d - y_0^{\theta}}{(y_s - y_0^{\theta})^2} \\ -1 \\ \frac{x_s - x_0^{\theta}}{y_s - y_0^{\theta}} \\ -(y_s - y_d) \frac{y_0 - x_s \sin(\theta) - y_s \cos(\theta)}{(y_s - y_0^{\theta})^2} \\ (y_s - y_d) \frac{x_0 - x_s \cos(\theta) + y_s \sin(\theta)}{(y_s - y_0^{\theta})^2} \end{bmatrix}$$

where  $x_0^{\theta} = x_0 \cos(\theta) + y_0 \sin(\theta)$  and  $y_0^{\theta} = -x_0 \sin(\theta) + y_0 \cos(\theta)$ . The MATLAB function below computes the function values  $t_0(\theta_i; \beta)$  and the Jacobian matrix:

```
function [t0,J] = t0eval(theta,beta)
% Computes function values and Jacobian matrix
% for fanbeam calibration problem. The input beta
% is the vector (xs,ys,xd,yd,x0,y0).
assert(iscolumn(theta),'theta must be a column vector');
assert(length(beta)==6,'beta must be a vector of length 6');
x0t = beta(5)*cosd(theta)+beta(6)*sind(theta);
y0t = -beta(5)*sind(theta)+beta(6)*cosd(theta);
g = beta(1)-x0t;
h = beta(2)-y0t;
t0 = beta(1)-beta(3)-(beta(2)-beta(4)).*g./h;
J = zeros(length(theta),6);
J(:,1) = (beta(4)-y0t)./h;
J(:,2) = -(beta(1)-x0t).*(beta(4)-y0t)./h.^2;
J(:,3) = -1;
J(:,4) = g./h;
J(:,5) = -(beta(2)-beta(4)).*...
    (beta(6)-beta(1)*sind(theta)-beta(2)*cosd(theta))./h.^2;
J(:,6) = (beta(2)-beta(4)).*...
    (beta(5)-beta(1)*cosd(theta)+beta(2)*sind(theta))./h.^2;
end
```

2. Download the zip-file `ExWeek3Day4.data.zip` from the course website and load one of the three mat-files. Each of the mat-files contains a regular sinogram, a pin calibration sinogram, the nominal geometry, and the projection angles. Compute a reconstruction with the nominal geometry and inspect both the reconstruction ( $x$ ) and the residual image ( $Ax - b$ ). Does the residual image tell you anything useful about your reconstruction model?
3. Estimate the geometry ( $\beta$ ) using the LM method. Use the nominal geometry (included in the mat-file) as an initial guess.
4. Check that your estimate geometry is consistent with the calibration sinogram, i.e., plot  $t_0(\theta; \hat{\beta})$  where  $\hat{\beta}$  denotes your estimated parameters and check that it is consistent with the calibration sinogram.

5. Use `fanbeamtomolinarmod.m` (included in the zip-file) or ASTRA to compute a new reconstruction with your refined geometry. With `fanbeamtomolinarmod.m` (a modified version of `fanbeamtomolinar.m`) you can input the source and detector positions as follows:

```
gs = ys/(ys-yd)*dw;    % grid size in cm
Ac = fanbeamtomolinarmod(N,theta,p,[ys,xs]/gs,[dw,xd]/gs,(ys-yd)/gs);
Ac = (gs/N)*Ac;
```

Here  $R=ys$  is the vertical distance from origo to the source and  $sd=ys-yd$  is the vertical distance from the source to the detector.

6. Inspect both the reconstruction ( $x$ ) and the residual image ( $Ax - b$ ) obtained with the refined geometry. Compare with the reconstruction and residual image obtained with the nominal geometry. Is there a noticeable difference?
7. (*Optional*) Analyze the expression  $t_0(\theta; \beta)$ . Does the parameter vector  $\beta$  uniquely determine the geometry? In other words, if  $\beta$  and  $\beta'$  are two parameter vectors and  $t_0(\theta; \beta) = t_0(\theta; \beta')$ , does that imply that  $\beta = \beta'$ ?