

#### **Functional model:**

Measured from "i" to "k"

$$s_{ik} = \sqrt{(x_k - x_i)^2 + (y_k - y_i)^2}$$

# Sih Pk

## **Observation equations:**

$$s_{ik} + v_{s_{ik}} = \sqrt{(\hat{x}_k - \hat{x}_i)^2 + (\hat{y}_k - \hat{y}_i)^2}$$

#### Nonlinear functional model

- → for least squares adjustment we need a linearised functional model
- → Jacobian matrix with partial derivatives



#### Partial derivatives:

$$\frac{\partial s_{ik}}{\partial x_k} = \frac{1}{2\sqrt{}} \cdot 2(x_k - x_i) = \frac{x_k - x_i}{s_{ik}} = \frac{\Delta x_{ik}}{s_{ik}}$$

$$\frac{\partial s_{ik}}{\partial x_i} = \frac{1}{2\sqrt{}} \cdot 2(x_k - x_i) \cdot (-1) = \frac{-\Delta x_{ik}}{s_{ik}}$$

$$\frac{\partial s_{ik}}{\partial y_k} = \frac{\Delta y_{ik}}{s_{ik}}$$

$$\frac{\partial s_{ik}}{\partial y_i} = \frac{-\Delta y_{ik}}{s_{ik}}$$

→ See handout (Partial derivatives of geodetic observation equations)

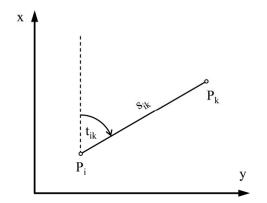


#### Partial derivatives of geodetic observation equations

Given: Observation Equations

Searched: Partial derivatives with respect to the unknowns for the linearization of the observation equations

**1. Distances** 
$$s_{ik} = \sqrt{(x_k - x_i)^2 + (y_k - y_i)^2}$$



Notation information:

Index *i*: Station Index *k*: Target

measured from i to k

Partial derivatives can be further simplified by using the equations for the grid bearing  $t_{ik}$  and distance  $s_{ik}$ .

Partial Derivatives:

$$\frac{\partial s_{ik}}{\partial x_k} = \frac{x_k - x_i}{s_{ik}} = \frac{\Delta x_{ik}}{s_{ik}} = \cos t_{ik}$$

$$\frac{\partial s_{ik}}{\partial x_i} = -\frac{x_k - x_i}{s_{ik}} = \frac{-\Delta x}{s_{ik}} = -\cos t_{ik}$$

$$\frac{\partial s_{ik}}{\partial y_{k}} = \frac{y_{k} - y_{i}}{s_{ik}} = \frac{\Delta y_{ik}}{s_{ik}} = \sin t_{ik}$$

$$\frac{\partial s_{ik}}{\partial y_i} = -\frac{y_k - y_i}{s_{ik}} = -\frac{\Delta y_{ik}}{s_{ik}} = -\sin t_{ik}$$

Adjustment\_Theory\_I\_Derivatives.pdf



## Weights in trilateration networks

• Precision for distances from electronic distance measurement given in

$$\sigma_{s_i} = a_1 + a_2 \cdot d_i$$

 $a_1$ : constant part of precision

 $a_2$ : standard error per unit sight distance length

 $d_i$ : length of sight distance



Typical values for the precision of an EDM:

$$3 \text{ mm} + 2 \text{ ppm}$$

→ Standard deviation for a distance of

500 m: 4 mm

1000 m: 5 mm

2000 m: 7 mm



Variance matrix of the observations

$$\mathbf{\Sigma}_{LL} = egin{bmatrix} \sigma_{S_1}^2 & & & 0 \ & \sigma_{S_2}^2 & & \ & & \ddots & \ 0 & & & \sigma_{S_n}^2 \end{bmatrix}$$

- With reference variance  $\sigma_0^2$
- Cofactor matrix of observations:  $\mathbf{Q}_{LL} = \frac{1}{\sigma_0^2} \mathbf{\Sigma}_{LL}$
- Weight matrix of observations:  $\mathbf{P} = \mathbf{Q}_{LL}^{-1}$



## **Example**

The measurements of the trilateration network depicted in Figure 1 are listed in Table 2. The points 1, 2 and 3 are control points (error-free) and their Gauss-Krueger coordinates are given in Table 1. Calculate the adjusted Gauss-Krueger coordinates of point 100 using least squares adjustment.

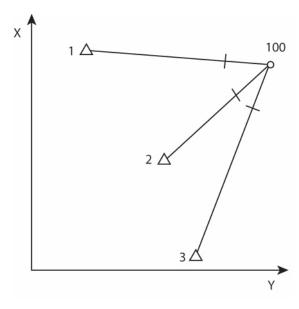


Figure 1: Trilateration network

Table 1: Gauss-Krueger coordinates of control points

Point No.	y [m]	<i>x</i> [m]
1	865.400	4527.150
2	2432.550	2047.250
3	2865.220	27.150

Approximate values for the coordinates of point 100:

$$y_{100}^0:6861.3; x_{100}^0:3727.8$$

(graphical coordinates from a map)



Table 2: Observed reduced distances

From	То	s [m]
100	1	6049.000
100	2	4736.830
100	3	5446.490

- The distance measurements have been performed with a precision of 1 mm + 2 ppm
- The distances are uncorrelated and already reduced into the Gauss-Krueger projection
- Set up an appropriate functional model as well as the observation equations
- Set up the stochastic model
- Choose appropriate values for the break-off conditions arepsilon and justify your decision
- Solve the normal equation system and determine the Gauss-Krueger coordinates of point 100 as well as their standard deviations
- Calculate the residuals and the adjusted observations as well as their standard deviations



#### **General considerations:**

- What are our unknowns?
  - $\rightarrow$  Coordinates of point 100
  - $\rightarrow$  We introduce  $y_{100}$ ,  $x_{100}$
- What are our observations?
  - → Distances
  - $\rightarrow s_{100,1}, s_{100,2}, s_{100,3}$
- Observations reduced into projection?
  - $\rightarrow$  Yes!
- What are our fixed values?

$$\rightarrow y_1, x_1; y_2, x_2; y_3, x_3$$

• Redundancy? 
$$\rightarrow r = n - u \rightarrow r = 3 - 2 \rightarrow r = 1$$



#### **Functional model:**

$$s_{100,1} = \sqrt{(x_1 - x_{100})^2 + (y_1 - y_{100})^2}$$

$$s_{100,2} = \sqrt{(x_2 - x_{100})^2 + (y_2 - y_{100})^2}$$

$$s_{100,3} = \sqrt{(x_3 - x_{100})^2 + (y_3 - y_{100})^2}$$

## **Observation equations:**

$$s_{100,1} + v_1 = \sqrt{(x_1 - \hat{x}_{100})^2 + (y_1 - \hat{y}_{100})^2}$$

$$s_{100,2} + v_2 = \sqrt{(x_2 - \hat{x}_{100})^2 + (y_2 - \hat{y}_{100})^2}$$

$$s_{100,3} + v_3 = \sqrt{(x_3 - \hat{x}_{100})^2 + (y_3 - \hat{y}_{100})^2}$$



#### **Observation vector:**

$$\mathbf{L} = \begin{bmatrix} 6049.000 \\ 4736.830 \\ 5446.490 \end{bmatrix}$$

#### Stochastic model of the observations:

$$\sigma_1 = 1 \text{ mm} + 2 \frac{\text{mm}}{\text{km}} \cdot 6.049 \text{ km}$$

$$\sigma_2 = 1 \text{ mm} + 2 \frac{\text{mm}}{\text{km}} \cdot 4.73683 \text{ km}$$

$$\sigma_3 = 1 \text{ mm} + 2 \frac{\text{mm}}{\text{km}} \cdot 5.44649 \text{ km}$$



$$\mathbf{\Sigma}_{LL} = \begin{bmatrix} \sigma_1^2 & 0 & 0 \\ 0 & \sigma_2^2 & 0 \\ 0 & 0 & \sigma_3^2 \end{bmatrix}$$

$$\mathbf{Q}_{LL} = \frac{1}{\sigma_0^2} \mathbf{\Sigma}_{LL}$$

with

$$\sigma_0^2 = 1$$

$$\mathbf{Q}_{LL} = \mathbf{\Sigma}_{LL}$$

$$\mathbf{P} = \mathbf{Q}_{LL}^{-1}$$



## **Vector of adjusted unknowns:**

$$\widehat{\mathbf{X}} = \begin{bmatrix} \widehat{x}_{100} \\ \widehat{y}_{100} \end{bmatrix}$$

Nonlinear functional model

- → Solution from iterative computing with linearised functional model
- $\rightarrow$  Introduction of approximate values  $x_{100}^0, y_{100}^0$



## → Vector of starting values:

$$\mathbf{X}^0 = \begin{bmatrix} x_{100}^0 \\ y_{100}^0 \end{bmatrix}$$

Vector of adjusted reduced unknowns:

$$\hat{\mathbf{x}} = \hat{\mathbf{X}} - \mathbf{X}^0 = \begin{bmatrix} d\hat{x}_{100} \\ d\hat{y}_{100} \end{bmatrix} = \begin{bmatrix} \hat{x}_{100} - x_{100}^0 \\ \hat{y}_{100} - y_{100}^0 \end{bmatrix}$$

**Vector of reduced observations:** 

$$\mathbf{l} = \begin{bmatrix} 6049.000 - \sqrt{(x_1 - x_{100}^0)^2 + (y_1 - y_{100}^0)^2} \\ 4736.830 - \sqrt{(x_2 - x_{100}^0)^2 + (y_2 - y_{100}^0)^2} \\ 5446.490 - \sqrt{(x_3 - x_{100}^0)^2 + (y_3 - y_{100}^0)^2} \end{bmatrix}$$



#### Jacobian matrix:

$$\mathbf{J} = \begin{bmatrix} x_{100}^{0} & y_{100}^{0} \\ S_{100,1} & \frac{\partial s_{100,1}^{0}}{\partial x_{100}^{0}} & \frac{\partial s_{100,1}^{0}}{\partial y_{100}^{0}} \\ \frac{\partial s_{100,2}^{0}}{\partial x_{100}^{0}} & \frac{\partial s_{100,2}^{0}}{\partial y_{100}^{0}} \\ S_{100,3} & \frac{\partial s_{100,3}^{0}}{\partial x_{100}^{0}} & \frac{\partial s_{100,3}^{0}}{\partial y_{100}^{0}} \end{bmatrix}$$



with

$$\frac{\partial s_{100,1}^0}{\partial x_{100}^0} = \frac{1}{2\sqrt{(x_1 - x_{100}^0)^2 + (y_1 - y_{100}^0)^2}} \cdot 2(x_1 - x_{100}^0) \cdot (-1)$$

$$= \frac{-(x_1 - x_{100}^0)}{s_{100,1}^0}$$

:

$$\frac{\partial s_{100,3}^0}{\partial y_{100}^0} = \frac{1}{2\sqrt{(x_3 - x_{100}^0)^2 + (y_3 - y_{100}^0)^2}} \cdot 2(y_3 - y_{100}^0) \cdot (-1)$$

$$= \frac{-(y_3 - y_{100}^0)}{s_{100,3}^0}$$



**Design matrix:** 

$$A = J$$

**Normal equations:** 

$$\mathbf{A}^{\mathrm{T}}\mathbf{P}\mathbf{A}\hat{\mathbf{x}} = \mathbf{A}^{\mathrm{T}}\mathbf{P}\mathbf{I}$$

**Solution of normal equations:** 

$$\hat{\mathbf{x}} = \left(\underbrace{\mathbf{A}^{\mathrm{T}}\mathbf{P}\mathbf{A}}\right)^{-1}\mathbf{A}^{\mathrm{T}}\mathbf{P}\mathbf{I}$$

Adjusted unknowns:

$$\widehat{\mathbf{X}} = \mathbf{X}^0 + \widehat{\mathbf{x}}$$

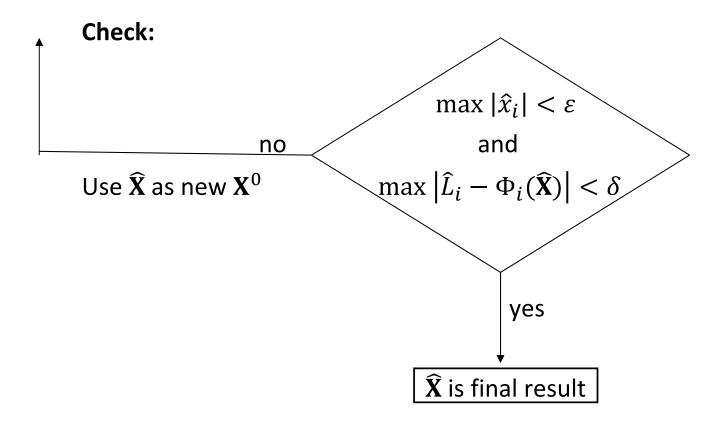
**Residuals:** 

$$\mathbf{v} = \mathbf{A}\hat{\mathbf{x}} - \mathbf{l}$$

**Adjusted observations:** 

$$\hat{\mathbf{L}} = \mathbf{L} + \mathbf{v}$$







### **Empirical reference standard deviation:**

$$s_0 = \sqrt{\frac{\mathbf{v}^{\mathrm{T}} \mathbf{P} \mathbf{v}}{n - u}}$$

#### VCM of adjusted unknowns:

$$\mathbf{\Sigma}_{\hat{X}\hat{X}} = \mathbf{s}_0^2 \cdot \mathbf{Q}_{\hat{X}\hat{X}}$$
 with  $\mathbf{Q}_{\hat{X}\hat{X}} = \mathbf{N}^{-1}$ 

#### Standard deviation of unknowns:

$$\mathbf{\Sigma}_{\hat{X}\hat{X}} = s_0^2 \cdot \begin{bmatrix} q_{\hat{X}\hat{X}} & q_{\hat{X}\hat{Y}} \\ q_{\hat{Y}\hat{X}} & q_{\hat{Y}\hat{Y}} \end{bmatrix}$$

 $q_{\hat{x}\hat{x}}$ : Cofactor of unknown value  $x_{100}$ 

 $q_{\hat{y}\hat{y}}$ : Cofactor of unknown value  $y_{100}$ 

$$s_{\hat{\chi}_{100}} = s_0 \cdot \sqrt{q_{\hat{\chi}\hat{\chi}}}$$

$$s_{\hat{y}_{100}} = s_0 \cdot \sqrt{q_{\hat{y}\hat{y}}}$$

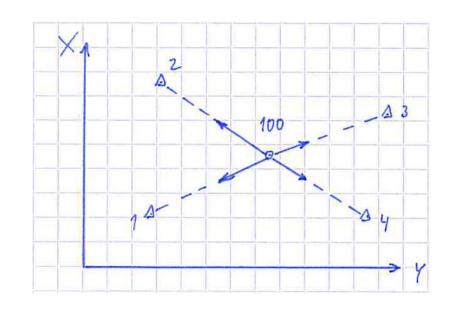


## **Basic idea of triangulation:**

Determination of 2D coordinates of points in a plane Cartesian coordinate system from <a href="https://doi.org/10.2016/journal.com/">observed directions</a>

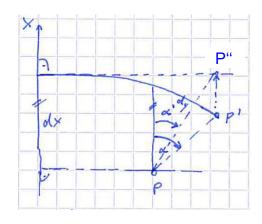
#### Cartesian coordinates in 2D

- Gauss-Krueger coordinates
- UTM coordinates
- → Projected coordinates into a plane
- → Conformal mapping



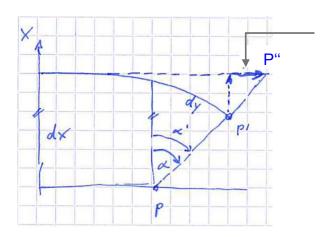


## Non-conformal and conformal mapping



$$\alpha' \neq \alpha$$

e.g. Soldner coordinates



Ordinate difference is elongated → elimination of angular distortion

$$\alpha' = \alpha$$

e.g. Gauss-Krueger coordinates, UTM coordinates



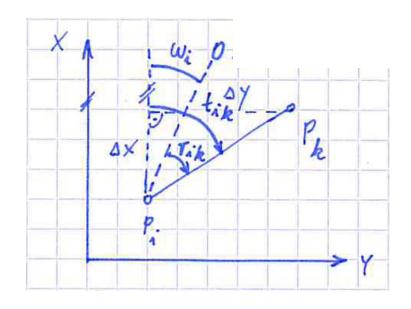
- A conformal mapping keeps a differential similarity between the original elliptic situation and the maps image
  - → We can use our measured directions without corrections and reductions and combine them with GK or UTM coordinates
- $\blacktriangleright$  Directions  $r_{ik}$  are our observations with corresponding precision / weight
- For an adjustment within the Gauss-Markov Model (parametric adjustment)

$$\mathbf{L} = \mathbf{\Phi}(\mathbf{X})$$

we have to introduce appropriate unknowns to express our observations as functions of the unknowns

→ We introduce 2D coordinates as unknowns





0: zero direction of our instrument (tacheometer, theodolite)

i: instrument station

*k*: foresight station

 $r_{ik}$ : measured direction from i to k

 $t_{ik}$ : azimuth from i to k

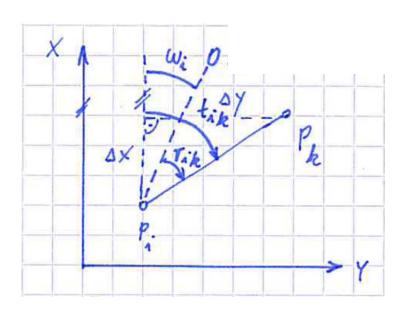
 $\omega_i$ : orientation unknown

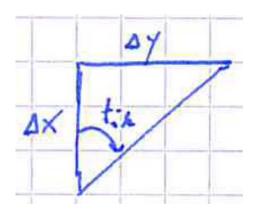
#### **Functional model:**

$$r_{ik} = t_{ik} - \omega_i$$



## How to obtain $t_{ik}$ ?





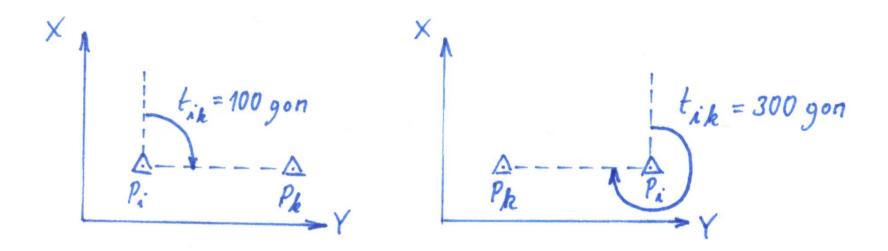
$$tan t_{ik} = \frac{\Delta y}{\Delta x}$$

$$\Rightarrow t_{ik} = \arctan \frac{\Delta y}{\Delta x}$$

$$\Rightarrow t_{ik} = \arctan \frac{y_k - y_i}{x_k - x_i}$$



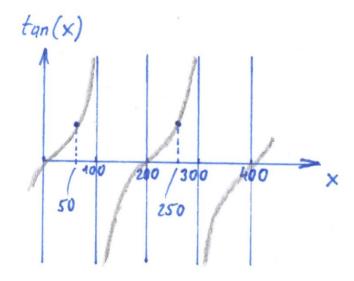
- ► Attention 1: What happens if  $\Delta x = 0$ ?
  - → Cannot use formula
  - → two cases possible





#### ► Attention 2:

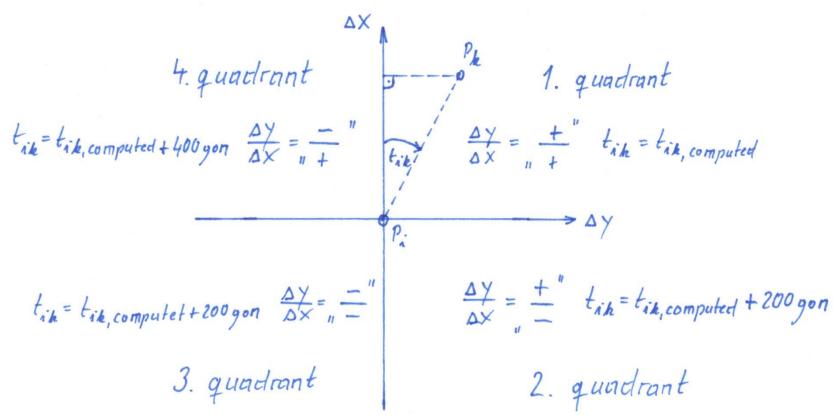
e.g. 
$$tan 50 gon = 1$$
  
 $tan 250 gon = 1$ 



Problem: Which value is the desired one?



Solution: Analysis of the quadrants,  $t_{ik, \text{computed}} = \arctan \frac{\Delta y}{\Delta x}$ 



Remark: "atan2"



#### **Functional model:**

Measured from "i" to "k"

$$r_{ik} = \arctan \frac{y_k - y_i}{x_k - x_i} - \omega_i$$

Attention: Quadrants!

## **Observation equations:**

$$r_{ik} + v_{ik} = \arctan \frac{\hat{y}_k - \hat{y}_i}{\hat{x}_k - \hat{x}_i} - \hat{\omega}_i$$

#### Nonlinear functional model

- → for least squares adjustment we need a linearised functional model
- → Jacobian matrix with partial derivatives