

# Medical Image Processing for Interventional Applications

## Ultrasound

Online Course – Unit 37

Andreas Maier, Joachim Hornegger, Frank Schebesch  
Pattern Recognition Lab (CS 5)

# Topics

## Ultrasound

Historical Remarks

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## Historical Remarks

**1942:** Discovery of medical ultrasound by [Theodore Dussik](#)

**1984:** First 3-D ultrasound system reported by [Kazunori Baba](#)



Figure 1: First applications of sound  
(echometry due to Aristoteles)

# Generation of Ultrasound Waves

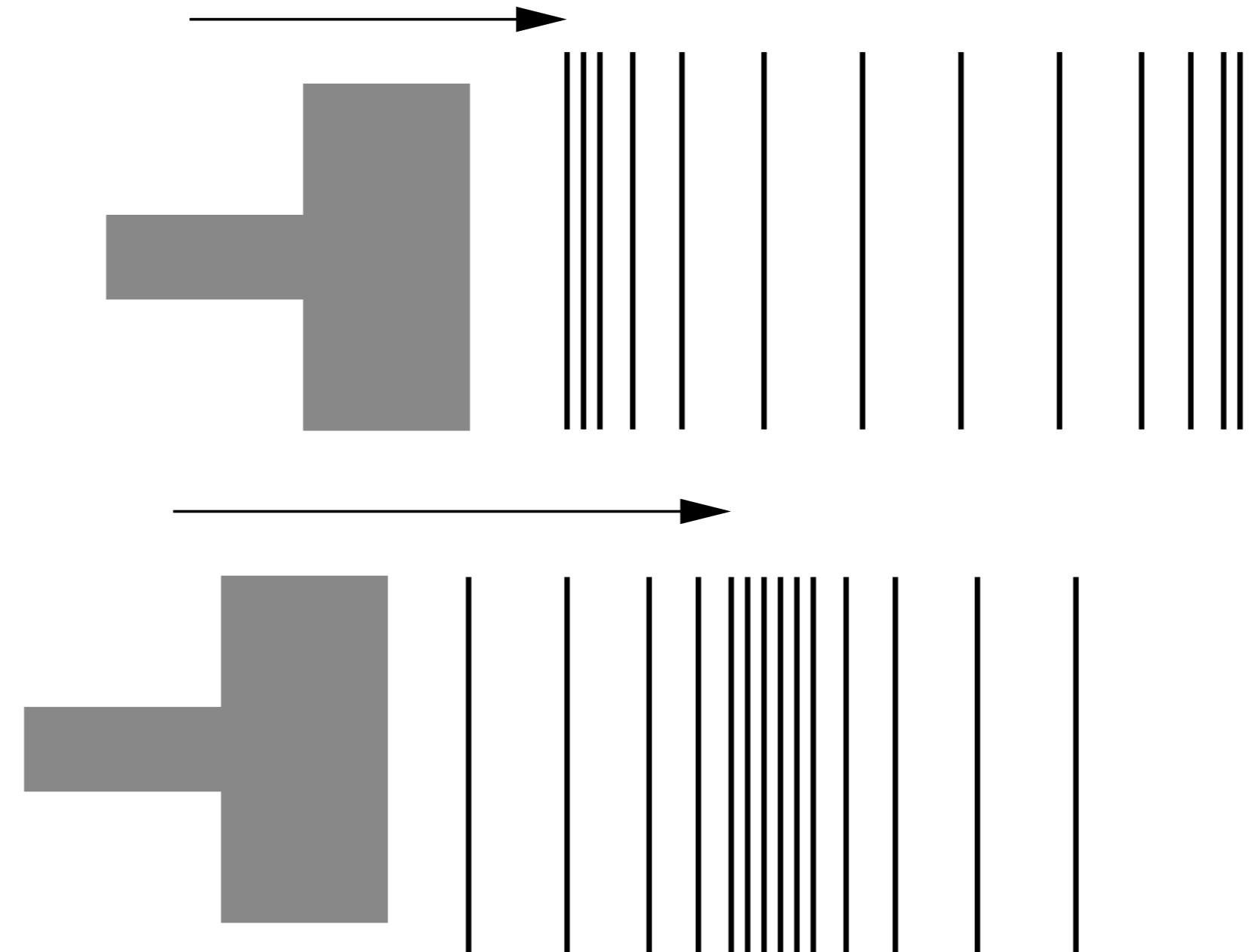


Figure 2: Pressure waves generated by periodic motion

# Properties of Waves

- **Reflection:** At the boundary of two media waves are not transmitted, but reflected.
- **Refraction:** At the boundary of two media waves are bended.
- **Absorption:** Conversion of acoustic energy to heat causes attenuation of waves.



Figure 3: Siemens-ACUSON Aspen Echo System (left),  
Siemens-ACUSON US CV 70 (right)

## 2-D Ultrasound Images



Figure 4: Portable ultrasound system (Siemens Healthcare)

## 2-D Ultrasound Images

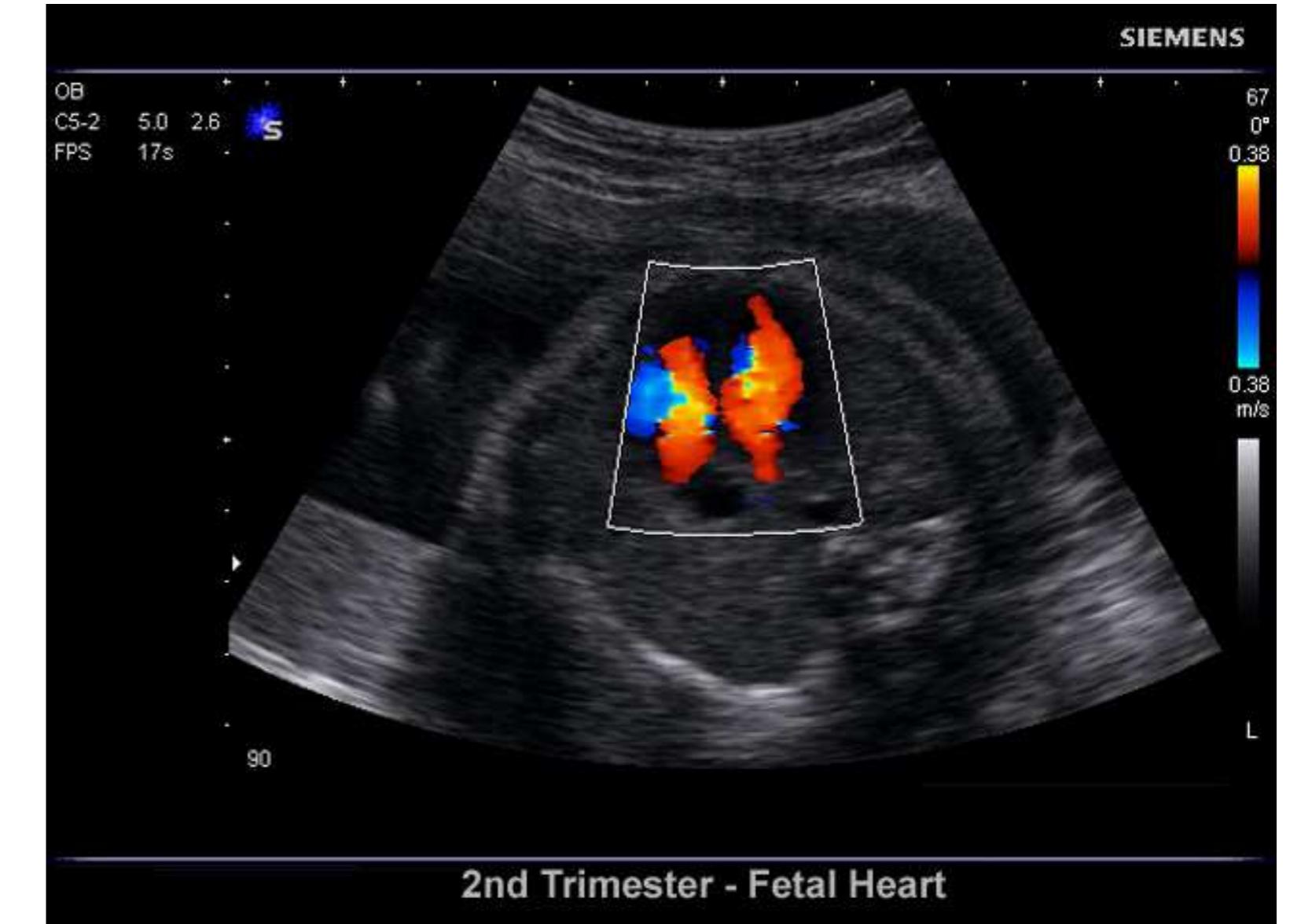
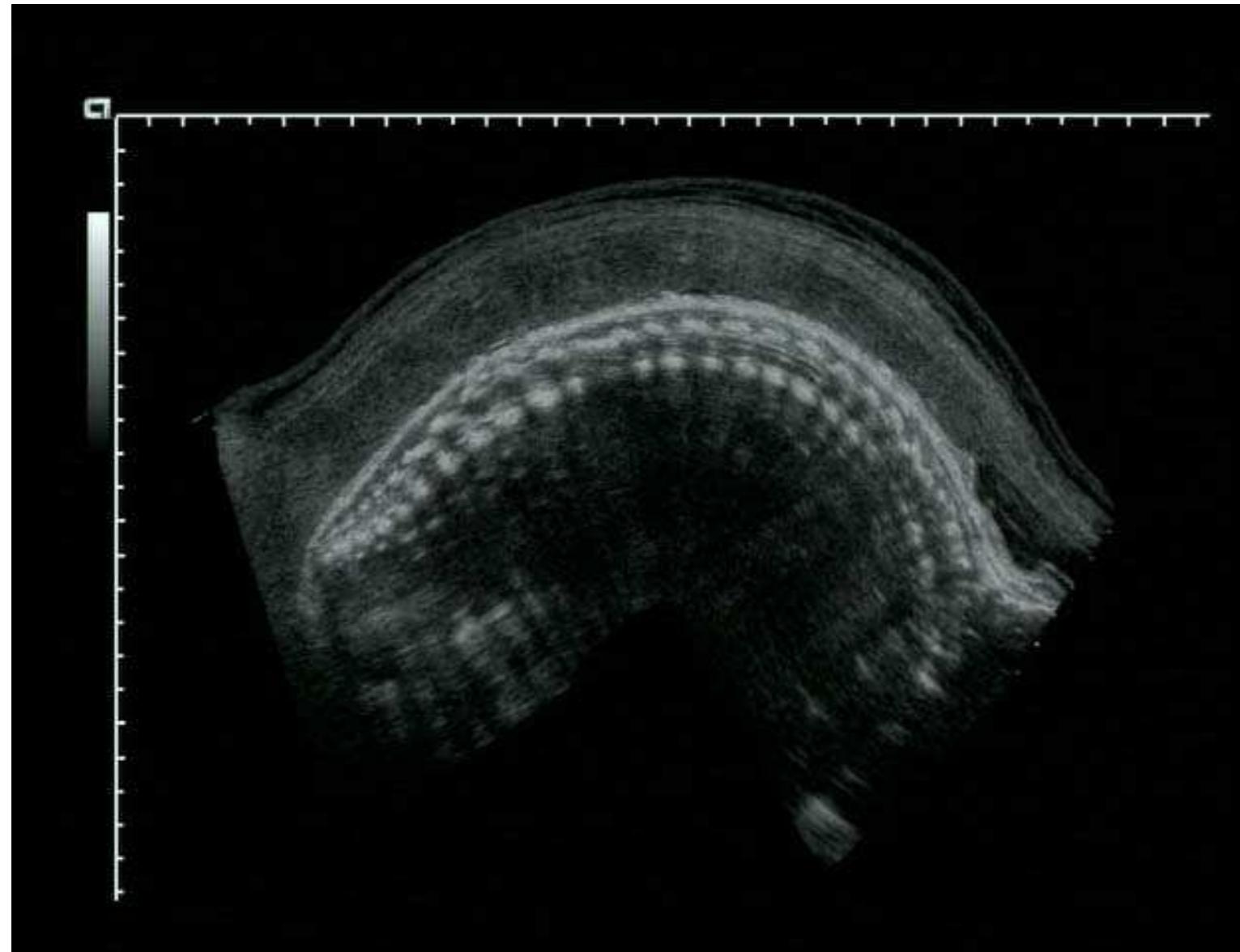


Figure 5: 2-D ultrasound showing a fetal spine and heart (images courtesy of Siemens Healthcare)

## 3-D Ultrasound Images



Figure 6: 3-D ultrasound images of a fetus (images courtesy of Siemens Healthcare)

# Carotid Artery

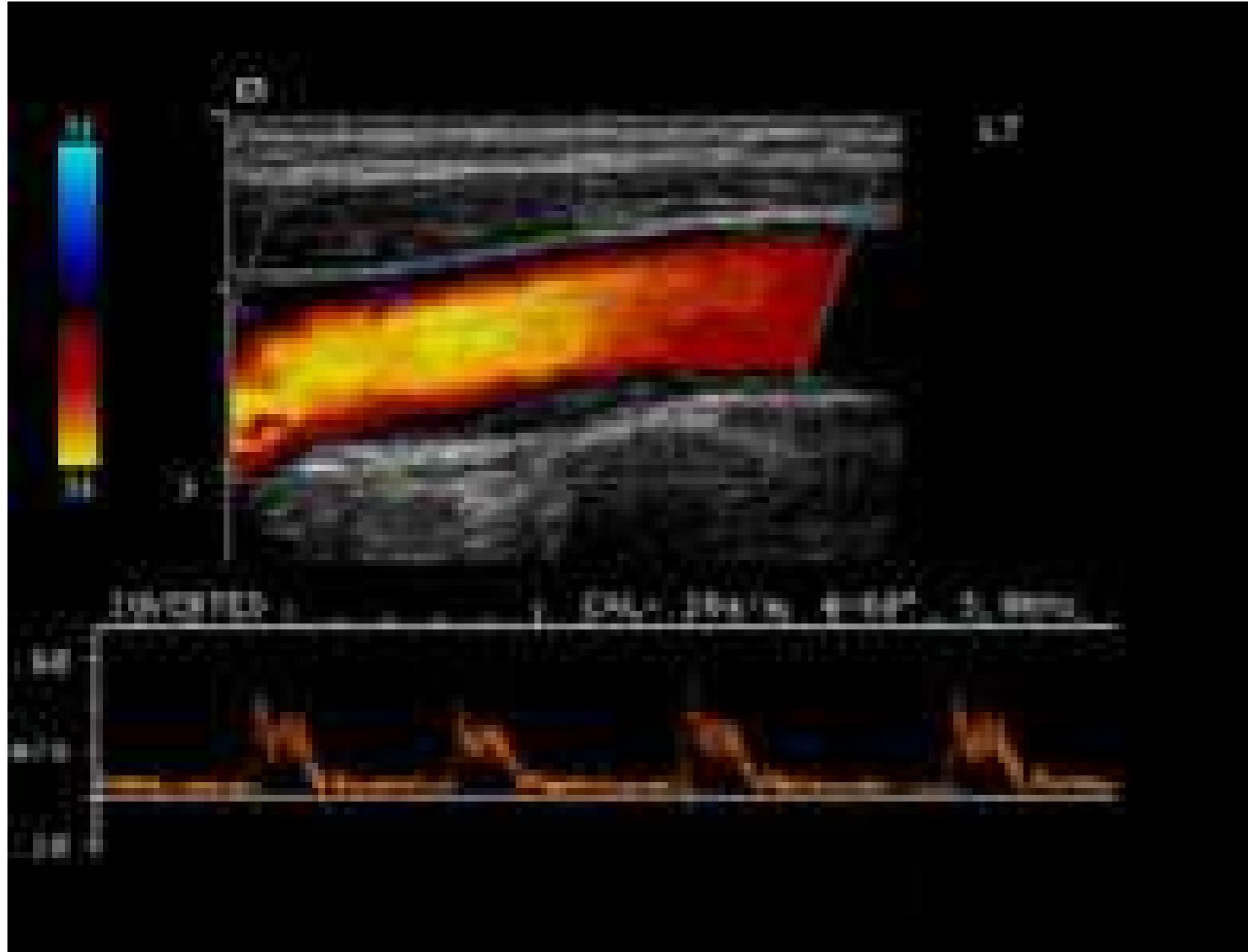


Figure 7: Carotid artery and 3-D ultrasound image of vessels (images courtesy of Siemens Healthcare)

# Basics from Physics

- Physical medium can vibrate and produce sound.
- Sound waves are due to tissue vibrations.
- Sine waves: peak represents the maximum, nadir represents the minimum pressure.
- Characteristics of sound waves: period, frequency, speed, amplitude, power, intensity, wavelength
- Propagation speed in human tissue:  $\sim 1500 \text{ ms}^{-1}$
- Hearable sound: 20–20000 Hz
- Clinical ultrasound: 1–10 MHz

# Biological Media

<b>medium</b>	<b><math>c</math> [ms<math>^{-1}</math>]</b>	<b><math>Z</math> [gcm<math>^{-2}s^{-1}</math>]</b>	<b><math>\rho</math> [gcm<math>^{-3}</math>]</b>
air	331	430	0.013
grease	1470	$1.42 \times 10^5$	0.97
water	1492	$1.48 \times 10^5$	0.9982
brain tissue	1530	$1.56 \times 10^5$	1.02
muscles	1568	$1.63 \times 10^5$	1.04
bones	3600	$6.12 \times 10^5$	1.7

Table 1: Data of different biological media (speed of sound in the medium, acoustic impedance, density)

# Basics from Physics

## Important observations:

- Medium determines the speed of sound.
- Sound of different frequencies propagates at the same speed in the same medium.

# Basics from Physics

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- Sound of different frequencies propagates at the same speed in the same medium.

## Definition

The ***acoustic impedance***  $Z$  is:

$$Z = \rho \cdot c,$$

where  $\rho$  is the density of the medium, and  $c$  the speed of sound waves in the medium.

# Basics from Physics

**Reflection at the boundary of two different tissue classes** can be described by:

$$I_R = I_I \frac{1 - \frac{Z_2}{Z_1}}{1 + \frac{Z_2}{Z_1}},$$

where

- $I_I$ : intensity of incoming wave,
- $I_R$ : intensity of reflected wave,
- $Z_1$ : impedance of tissue class 1,
- $Z_2$ : impedance of tissue class 2.

# Basics from Physics

The **relationship of speed  $c$ , frequency  $f$  and wavelength  $\lambda$**  is:

$$c = f \cdot \lambda .$$

- The denser a medium, the higher the speed of sound through the medium.  
→ Sound propagates faster through bones than liquids.
- The higher the frequency, the lower the wavelength.  
→ Echocardiographic imaging: Higher image resolution due to smaller wavelength; deeper penetration results from larger wavelength.

# Basics from Physics

The **distance between ultrasound source and boundary** can be computed as

$$d = \frac{1}{2}ct,$$

where

- $d$ : distance between source and tissue boundary,
- $t$ : runtime of signal,
- $c$ : speed of sound.

**Note:** Factor 0.5 results from the fact that the signal moves from the source to the tissue boundary and back.

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# Take Home Messages

- Ultrasound is using sound waves to generate images. This is possible due to different acoustic characteristics of the tissue materials.
- There are various medical applications and, in contrast to X-ray imaging, US does not depend on possibly harmful radiation.

## Further Readings

- Carlo Tomasi and Takeo Kanade. “Shape and Motion from Image Streams Under Orthography: A Factorization Method”. In: *International Journal of Computer Vision* 9.2 (Nov. 1992), pp. 137–154. DOI: [10.1007/BF00129684](https://doi.org/10.1007/BF00129684)
- C. J. Poelman and T. Kanade. “A Paraperspective Factorization Method for Shape and Motion Recovery”. In: *IEEE Transactions on Pattern Analysis and Machine Intelligence* 19.3 (Mar. 1997), pp. 206–218. DOI: [10.1109/34.584098](https://doi.org/10.1109/34.584098)
- Mei Han and Takeo Kanade. “A Perspective Factorization Method for Euclidean Reconstruction with Uncalibrated Cameras”. In: *The Journal of Visualization and Computer Animation* 13.4 (2002), pp. 211–223. DOI: [10.1002-vis.290](https://doi.org/10.1002-vis.290)
- Peter Sturm and Bill Triggs. “A Factorization Based Algorithm for Multi-Image Projective Structure and Motion”. In: *Computer Vision — ECCV '96: 4th European Conference on Computer Vision Cambridge, UK, April 15–18, 1996 Proceedings Volume II*. ed. by Bernard Buxton and Roberto Cipolla. Vol. 1065. Lecture Notes in Computer Science. Berlin, Heidelberg: Springer Berlin Heidelberg, 1996, pp. 709–720. DOI: [10.1007/3-540-61123-1\\_183](https://doi.org/10.1007/3-540-61123-1_183)

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## 3-D Ultrasound

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# 3-D Reconstruction

- 3-D reconstruction requires computation of relative positions and orientations of acquired 2-D ultrasound images.
- 3-D volume results from interpolation of voxel values.
- Adjustment of 2-D images:
  - Feature-based reconstruction
  - Intensity-based reconstruction

# 3-D Ultrasound: Principle

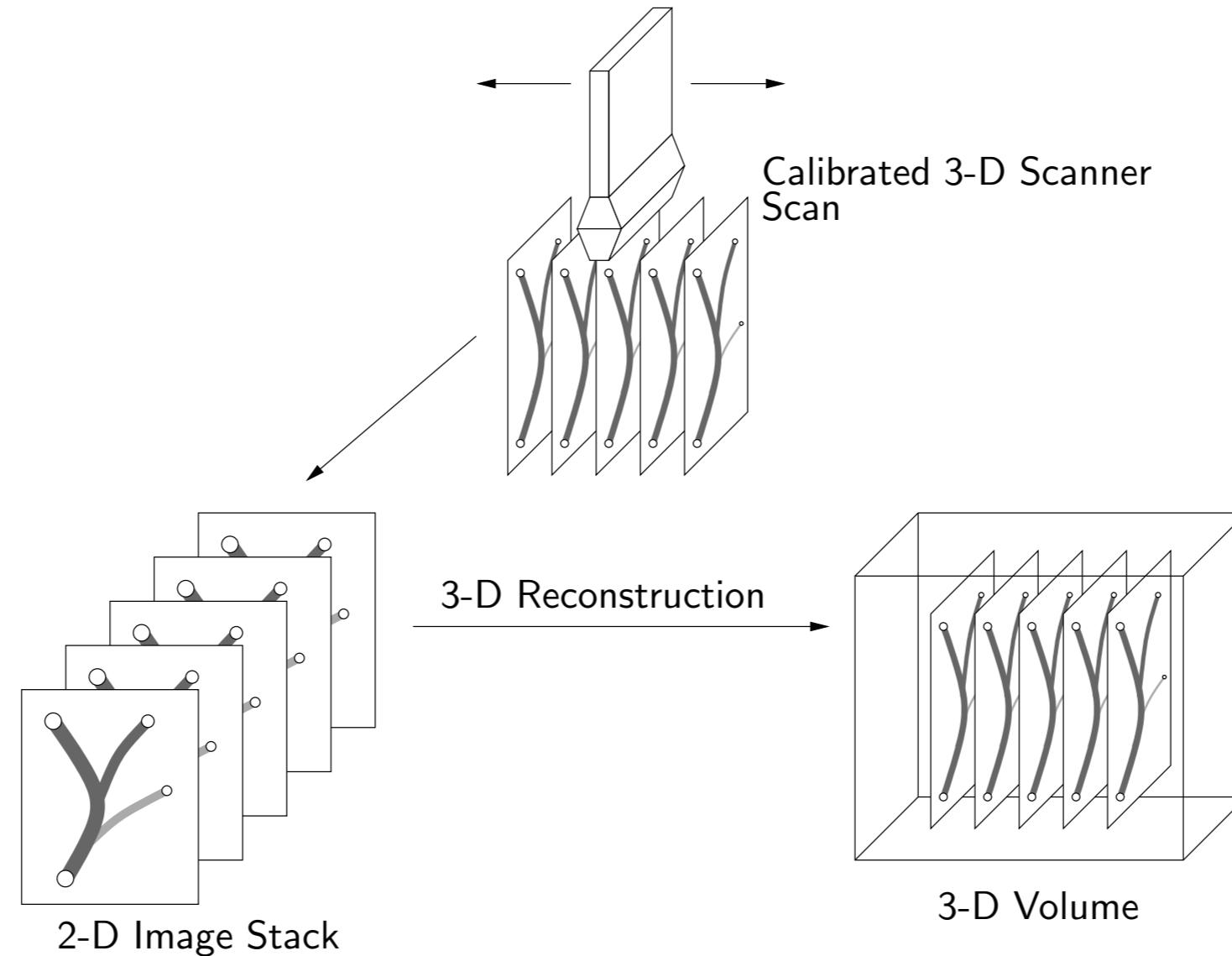


Figure 1: Ideal 3-D ultrasound acquisition

## 3-D Ultrasound: Principle

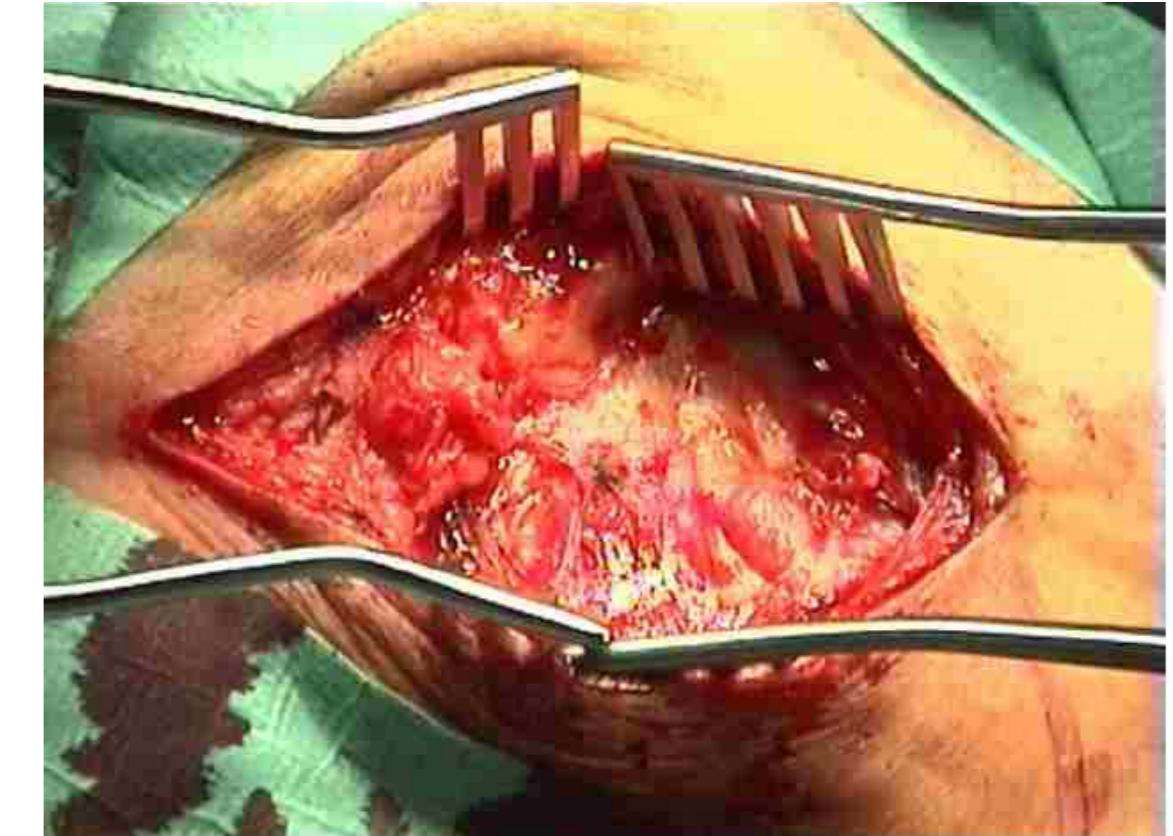
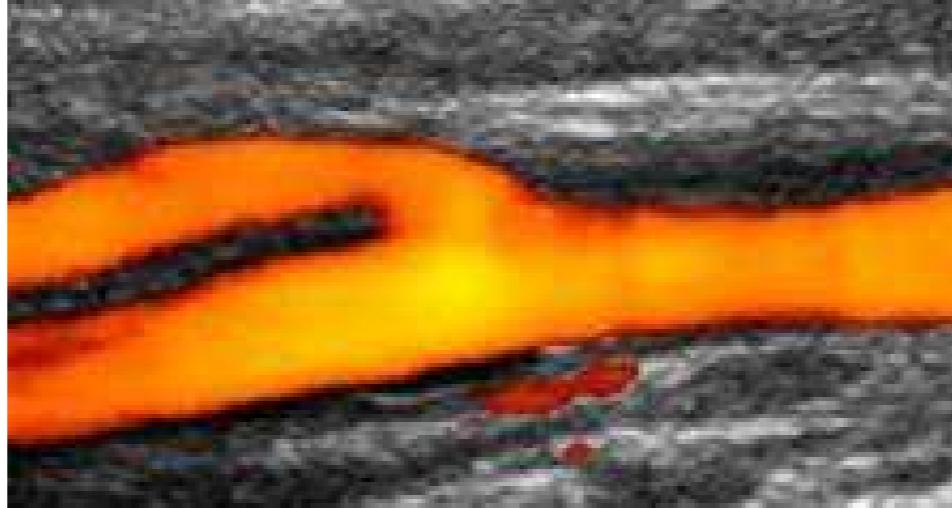
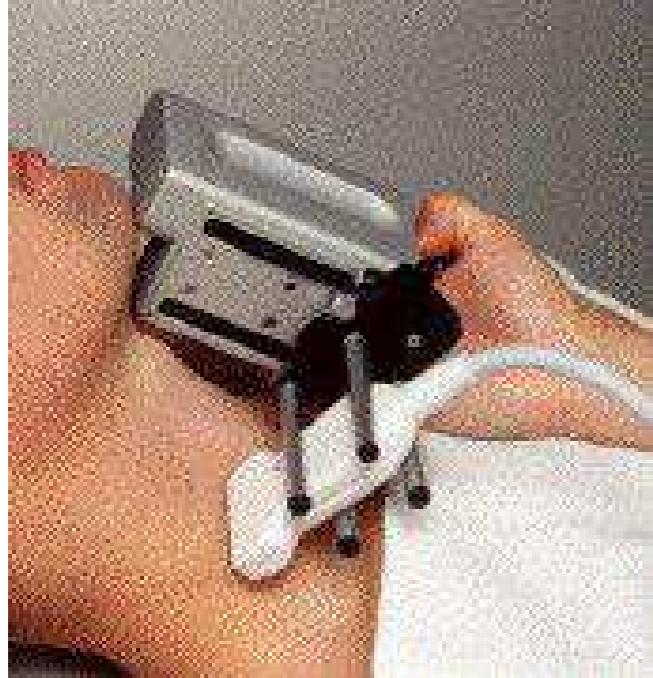


Figure 2: Special device for 3-D ultrasound acquisition (left) (image courtesy of A. Fenster & D. B. Downey), ultrasound image of carotis bifurcation (middle), surgery of carotis (right) (image courtesy of Schön Klinik Vogtareuth)

# 3-D Ultrasound: Principle

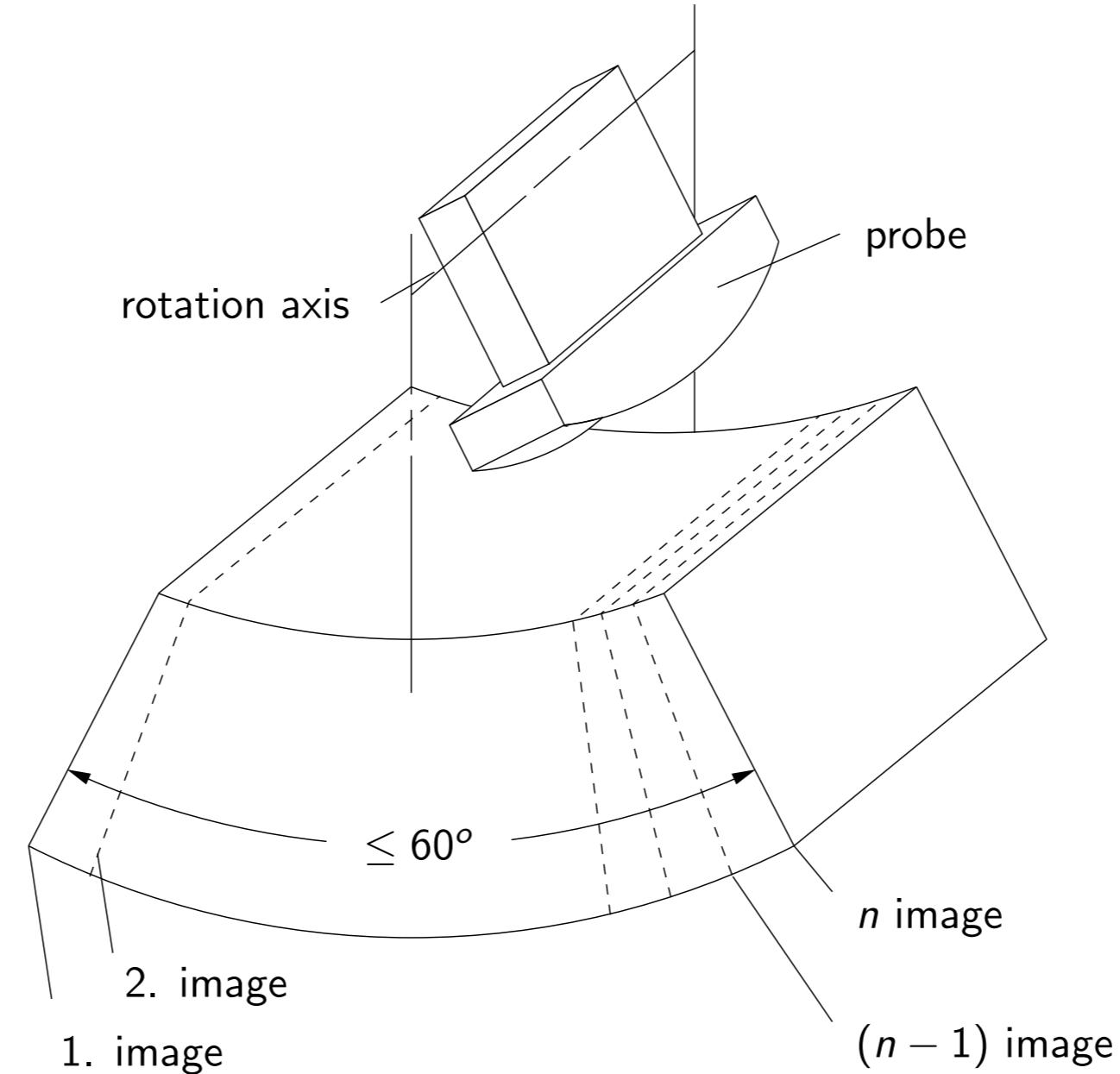


Figure 3: 3-D ultrasound acquisition

# 3-D Ultrasound: Principle

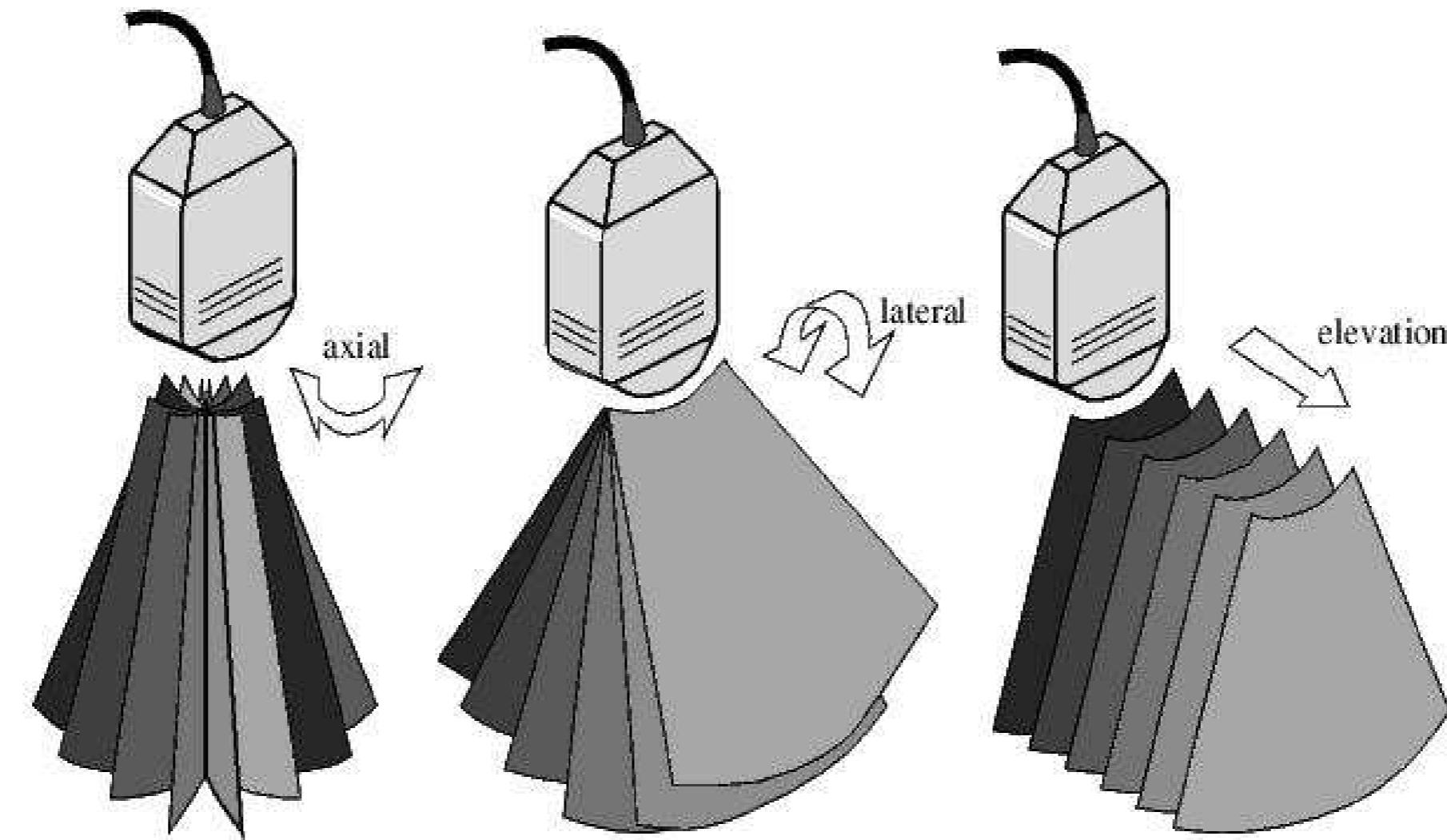


Figure 4: Mechanical sweep motion for 3-D US acquisition

# 3-D Ultrasound: Principle



Figure 5: Mechanical motion of the probe by a rotation device (left), a sweep device (middle), or a pullback device (right) ([TOMTEC](#), Munich)

# 3-D Ultrasound: Principle

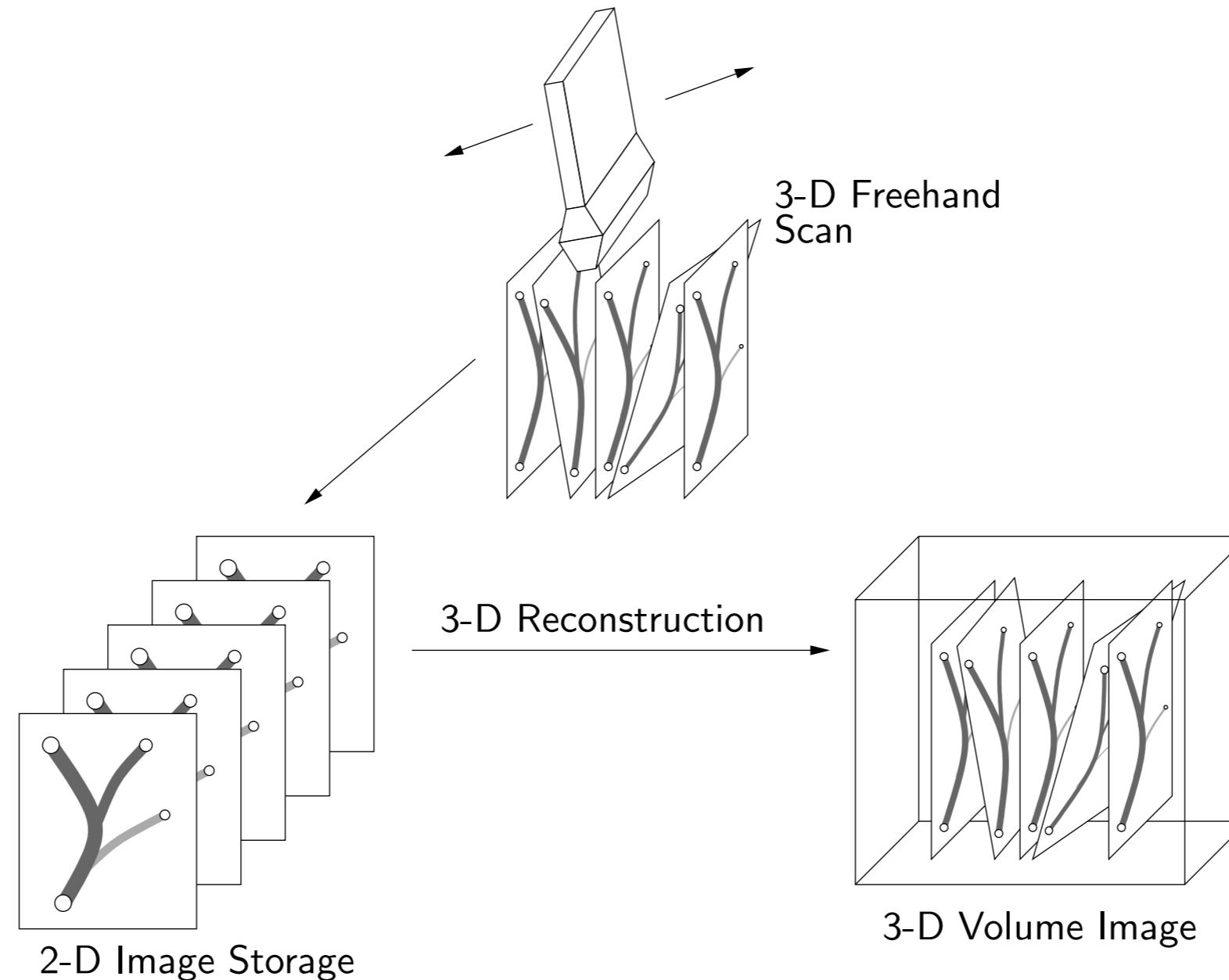


Figure 6: Freehand ultrasound 3-D acquisition

## 3-D Ultrasound: Principle



Figure 7: Markers for automatic pose estimation of the probe (left), stereo camera system (right)

**Exercise:** Describe an algorithm that computes the rotation and translation parameters between two different positions of the probe (use fundamental and essential matrix).

# ECG Triggered US Reconstruction

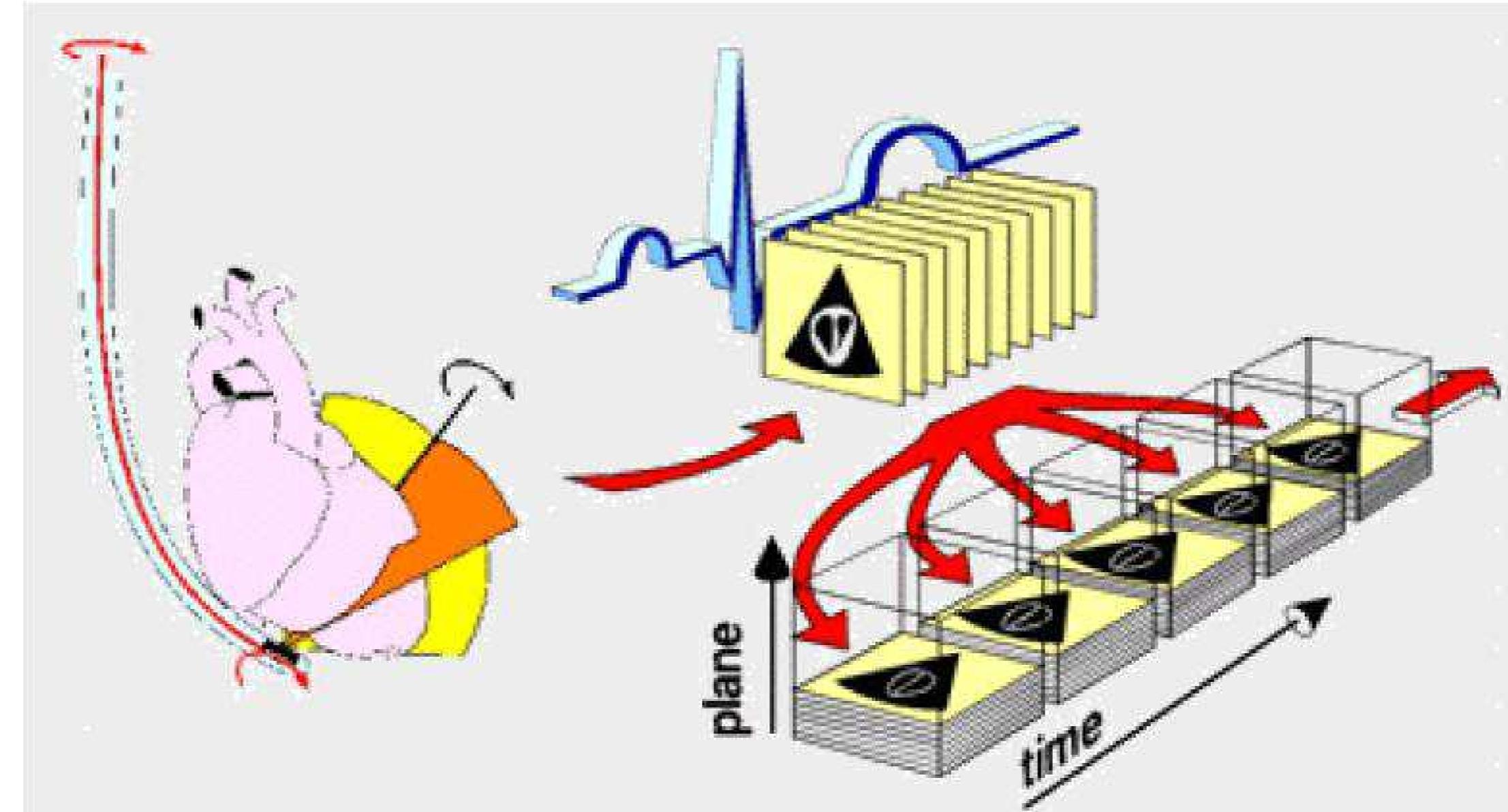


Figure 8: ECG triggered US reconstruction ([TOMTEC, Munich](#))

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# Interpolation Techniques

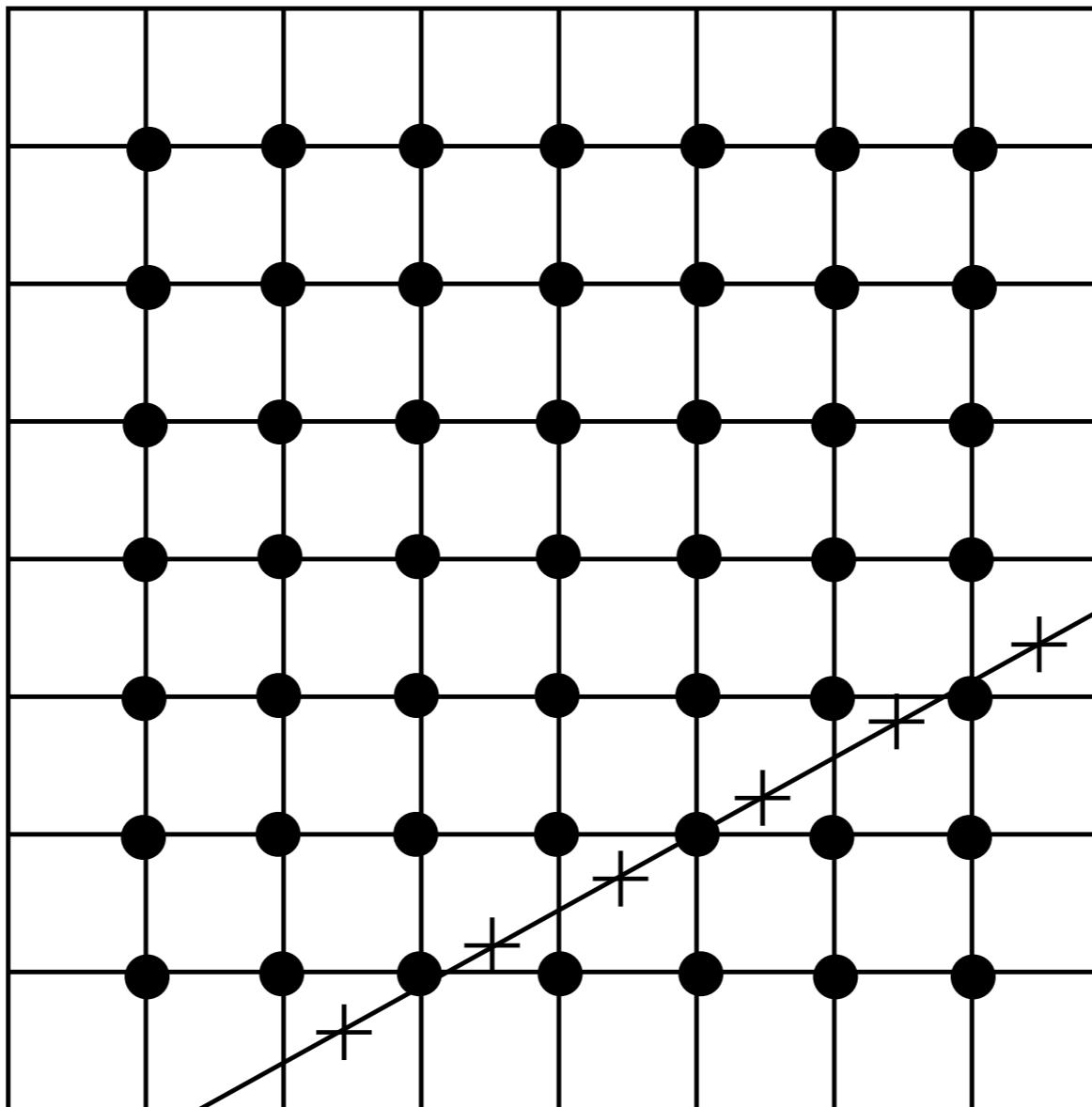


Figure 9: Interpolation

# Interpolation Techniques

## Voxel nearest neighbor:

- Assign voxel to nearest pixel.
- No parameterization is required.
- Avoid gaps in the reconstruction.

# Interpolation Techniques

## Nearest neighbor interpolation:

- Run through all pixels.
- Fill the nearest voxel with the intensity value.
- Multiple contributions are averaged or use maximum value alternatively.
- Gap filling is done in a second step.

# Interpolation Techniques

## Distance weighted interpolation:

- Sampling is done voxel by voxel.
- Voxel values are assigned the averaged sum of nearby voxels.
- For example, consider a spherical neighborhood centered around each voxel.

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# Take Home Messages

- There are several ways to acquire US data for 3-D reconstruction, some of them even involve freehand acquisition.
- Implementing 3-D ultrasound reconstruction requires interpolation methods, where there is also a variety of methods to choose from (differing in runtime and accuracy).

## Further Readings

- Carlo Tomasi and Takeo Kanade. “Shape and Motion from Image Streams Under Orthography: A Factorization Method”. In: *International Journal of Computer Vision* 9.2 (Nov. 1992), pp. 137–154. DOI: [10.1007/BF00129684](https://doi.org/10.1007/BF00129684)
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- Mei Han and Takeo Kanade. “A Perspective Factorization Method for Euclidean Reconstruction with Uncalibrated Cameras”. In: *The Journal of Visualization and Computer Animation* 13.4 (2002), pp. 211–223. DOI: [10.1002-vis.290](https://doi.org/10.1002-vis.290)
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## Factorization for Orthographic Projections

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# Topics

Factorization Methods for Orthographic Projections

Preliminaries

Registered Measurement Matrix

Factorization of the Measurement Matrix

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# Factorization Methods

## Preliminaries:

- Orthogonal projection model
- Number of frames  $N_F \geq 3$
- Each world point  $\tilde{\mathbf{p}}_j^w$  is visible in **all** frames.
- The world points are **not** all coplanar.
- $(x_{ij}, y_{ij})^\top \in \mathbb{R}^2$  is the  $j$ -th image point in the  $i$ -th frame.

# Factorization Methods

## Idea:

- Put all image points together in one matrix  $\mathbf{M}$ ,
- then **factorize**  $\mathbf{M}$  into a product of two matrices, a projection-matrix  $\mathbf{R}$ , and a matrix  $\mathbf{S}$  (world-points):

$$\mathbf{M} = \mathbf{RS}.$$

In general we have:

- $\mathbf{R}$  is a  $3N_F \times 4$  matrix containing all projection matrices,
- $\mathbf{S}$  is a  $4 \times N_p$  matrix containing all world points ( $N_p$  = number of all points).

In the case of orthogonal projections, the homogeneous form is not necessary, thus:

- $\mathbf{R}$  is  $2N_F \times 3$ ,
- $\mathbf{S}$  is  $3 \times N_p$ .

# Measurement Matrix

Form the so-called ***measurement matrix***  $\mathbf{M}$  of size  $2N_F \times N_p$  from the image points:

$$\mathbf{M} = \begin{pmatrix} \mathbf{X} \\ \mathbf{Y} \end{pmatrix},$$

where

$$\mathbf{X} = \begin{pmatrix} x_{11} & x_{12} & \dots & x_{1N_p} \\ \vdots & \vdots & \ddots & \vdots \\ x_{N_F1} & x_{N_F2} & \dots & x_{N_FN_p} \end{pmatrix}, \quad \mathbf{Y} = \begin{pmatrix} y_{11} & y_{12} & \dots & y_{1N_p} \\ \vdots & \vdots & \ddots & \vdots \\ y_{N_F1} & y_{N_F2} & \dots & y_{N_FN_p} \end{pmatrix}.$$

# Registered Measurement Matrix

For factorization we need the **registered** measurement matrix  $\hat{\mathbf{M}}$  containing all 2-D points  $(x_{ij}, y_{ij})^T$  shifted so that their mean is 0, i. e.,

$$\hat{\mathbf{M}} = \begin{pmatrix} \hat{\mathbf{X}} \\ \hat{\mathbf{Y}} \end{pmatrix},$$

where the entries of  $\hat{\mathbf{X}}, \hat{\mathbf{Y}}$  are:

$$\hat{x}_{ij} = x_{ij} - \bar{x}_i, \quad \hat{y}_{ij} = y_{ij} - \bar{y}_i,$$

with

$$\bar{x}_i = \frac{1}{N_p} \sum_{j=1}^{N_p} x_{ij}, \quad \bar{y}_i = \frac{1}{N_p} \sum_{j=1}^{N_p} y_{ij}.$$

# Representation of 2-D Image Points

Now consider the following representation of image points:

$$x_{ij} = \mathbf{u}_i^T (\tilde{\mathbf{p}}_j^w - \mathbf{t}_i), \quad y_{ij} = \mathbf{v}_i^T (\tilde{\mathbf{p}}_j^w - \mathbf{t}_i),$$

where

- $\mathbf{u}_i, \mathbf{v}_i$  are unit vectors of image reference frame  $i$  (3-D vectors),
- $\mathbf{t}_i$  is the translation vector from world-origin to frame origin,
- $\tilde{\mathbf{p}}_j^w$  is a 3-D world point,
- the world coordinate system is object-centered:

$$\frac{1}{N_p} \sum_{j=1}^{N_p} \tilde{\mathbf{p}}_j^w = 0.$$

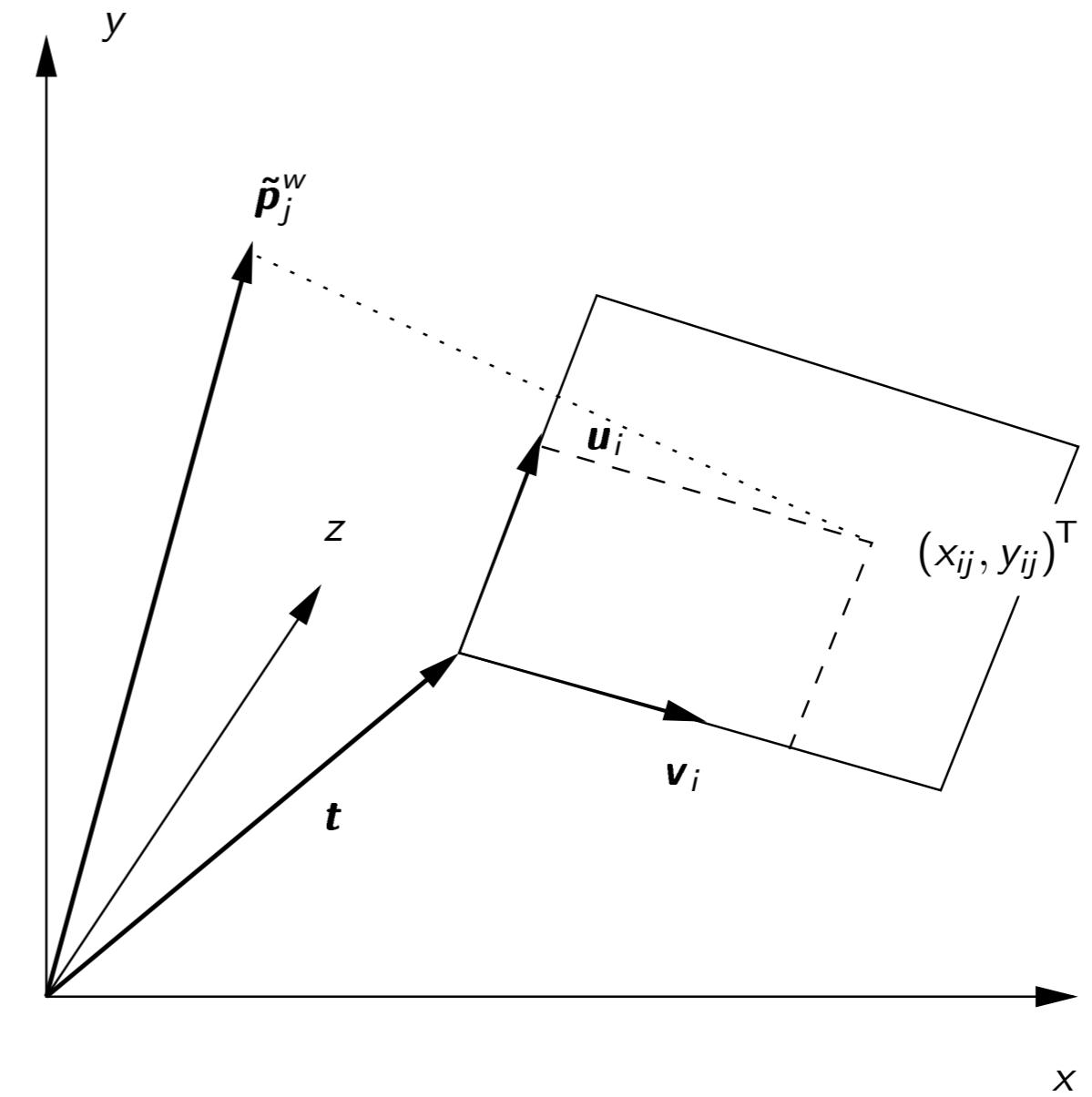


Figure 1: Image planes in 3-D

# Representation of 2-D Image Points

Thus we get:

$$\begin{aligned}\hat{x}_{ij} = x_{ij} - \bar{x}_i &= \mathbf{u}_i^\top (\tilde{\mathbf{p}}_j^w - \mathbf{t}_i) - \frac{1}{N_p} \sum_{m=1}^{N_p} (\mathbf{u}_i^\top (\tilde{\mathbf{p}}_m^w - \mathbf{t}_i)) \\ &= \mathbf{u}_i^\top \tilde{\mathbf{p}}_j^w - \mathbf{u}_i^\top \mathbf{t}_i - \mathbf{u}_i^\top \left( \left( \frac{1}{N_p} \sum_{m=1}^{N_p} \tilde{\mathbf{p}}_m^w \right) - \mathbf{t}_i \right) \\ &= \mathbf{u}_i^\top \tilde{\mathbf{p}}_j^w.\end{aligned}$$

# Computation of Registered Image Points

With  $\hat{x}_{ij} = \mathbf{u}_i^T \tilde{\mathbf{p}}_j^w$  and  $\hat{y}_{ij} = \mathbf{v}_i^T \tilde{\mathbf{p}}_j^w$  the registered measurement matrix looks as follows:

$$\hat{\mathbf{M}} = \begin{pmatrix} \mathbf{u}_1^T \tilde{\mathbf{p}}_1^w & \mathbf{u}_1^T \tilde{\mathbf{p}}_2^w & \dots & \mathbf{u}_1^T \tilde{\mathbf{p}}_{N_p}^w \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{u}_{N_F}^T \tilde{\mathbf{p}}_1^w & \mathbf{u}_{N_F}^T \tilde{\mathbf{p}}_2^w & \dots & \mathbf{u}_{N_F}^T \tilde{\mathbf{p}}_{N_p}^w \\ \mathbf{v}_1^T \tilde{\mathbf{p}}_1^w & \mathbf{v}_1^T \tilde{\mathbf{p}}_2^w & \dots & \mathbf{v}_1^T \tilde{\mathbf{p}}_{N_p}^w \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{v}_{N_F}^T \tilde{\mathbf{p}}_1^w & \mathbf{v}_{N_F}^T \tilde{\mathbf{p}}_2^w & \dots & \mathbf{v}_{N_F}^T \tilde{\mathbf{p}}_{N_p}^w \end{pmatrix} = \begin{pmatrix} \mathbf{u}_1^T \\ \vdots \\ \mathbf{u}_{N_F}^T \\ \mathbf{v}_1^T \\ \vdots \\ \mathbf{v}_{N_F}^T \end{pmatrix} \left( \tilde{\mathbf{p}}_1^w \ \tilde{\mathbf{p}}_2^w \ \dots \ \tilde{\mathbf{p}}_{N_p}^w \right).$$

# Notes

- $\hat{M}$  can be factorized into:
  - a  $2N_F \times 3$  matrix  $R$  containing camera movement,
  - and a  $3 \times N_p$  matrix  $S$  containing 3-D points.
- $\hat{M}$  is always of rank 3, since
  - $u_i, v_i, \tilde{p}_j^w$  are 3-vectors,
  - and the world points are **not** all coplanar.
- Factorization can be done using the SVD.
- The factorization is not unique.

**Rank theorem:**  $\hat{M}$  has rank 3.

# Factorization of the Measurement Matrix

If the factorization is  $\hat{\mathbf{M}} = \mathbf{RS}$ , then

$$\hat{\mathbf{M}} = (\mathbf{RQ})(\mathbf{Q}^{-1}\mathbf{S})$$

is also a valid factorization. The matrix  $\mathbf{Q}$  is an invertible  $3 \times 3$  matrix.

The following constraints are useful:

- $\mathbf{u}_i, \mathbf{v}_i$  are orthogonal,
- $|\mathbf{u}_i| = |\mathbf{v}_i| = 1$ .

# Tomasi's Factorization Algorithm

1. Track points.

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3. Set all  $\sigma_k$  for  $k \geq 4$  to zero, since  $\text{rank}(\hat{\mathbf{M}}) = 3$ .
4. Let  $\mathbf{U}'$  be the  $2N_F \times 3$  submatrix of  $\mathbf{U}$ , and  $\mathbf{V}'$  the  $3 \times N_p$  submatrix of  $\mathbf{V}$  corresponding to  $\sigma_1$ ,  $\sigma_2$ , and  $\sigma_3$ .  
Let  $\Sigma' = \text{diag}(\sigma_1, \sigma_2, \sigma_3)$ , then compute:

$$\hat{\mathbf{R}} = \mathbf{U}' \Sigma'^{\frac{1}{2}}, \quad \hat{\mathbf{S}} = \Sigma'^{\frac{1}{2}} \mathbf{V}'^T.$$

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$$\hat{\mathbf{R}} = \mathbf{U}' \Sigma'^{\frac{1}{2}}, \quad \hat{\mathbf{S}} = \Sigma'^{\frac{1}{2}} \mathbf{V}'^T.$$

5. Solve the following (nonlinear) equations for  $\mathbf{Q}$ :

$$\begin{aligned}\hat{\mathbf{u}}_i^T \mathbf{Q} \mathbf{Q}^T \hat{\mathbf{u}}_i &= 1, \\ \hat{\mathbf{v}}_i^T \mathbf{Q} \mathbf{Q}^T \hat{\mathbf{v}}_i &= 1, \\ \hat{\mathbf{u}}_i^T \mathbf{Q} \mathbf{Q}^T \hat{\mathbf{v}}_i &= 0.\end{aligned}$$

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5. Solve the following (nonlinear) equations for  $\mathbf{Q}$ :

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6. Compute the output:

$$\mathbf{R} = \hat{\mathbf{R}} \mathbf{Q}, \quad \mathbf{S} = \mathbf{Q}^{-1} \hat{\mathbf{S}}.$$

## Remarks

- Nonlinear optimization for  $\mathbf{Q}$  is not very pleasant.
- Elegant “democratic” method: All points are treated equally.
- It is mathematically simple and stable.
- The algorithm yields only the **rotation** of the world points.
- It is used in industry.
- Translation parallel to the image plane is proportional to the translation of the image centroid between two frames.
- The translational component along the optical axis cannot be computed because of the orthogonal projection model.
- Adding new frames is easy and gives a more stable reconstruction.
- *Problem:* All 3-D points must be visible in all frames.
- Check the assumption that the camera gives an orthogonal image.

# Topics

Factorization Methods for Orthographic Projections

Preliminaries

Registered Measurement Matrix

Factorization of the Measurement Matrix

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# Take Home Messages

- If we put all image points from several ultrasound acquisitions into a single measurement matrix for 3-D reconstruction, we can perform a factorization of this matrix.
- One of the factorized matrices contains the projective information, the other contains the world points.
- We need to register a given measurement matrix towards the centroid center of the image points.
- Tomasi's algorithm can be used to compute a factorization in case of orthogonal projections.

## Further Readings

- Carlo Tomasi and Takeo Kanade. “Shape and Motion from Image Streams Under Orthography: A Factorization Method”. In: *International Journal of Computer Vision* 9.2 (Nov. 1992), pp. 137–154. DOI: [10.1007/BF00129684](https://doi.org/10.1007/BF00129684)
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# Medical Image Processing for Interventional Applications

## Factorization for Perspective Projections

Online Course – Unit 40

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# Topics

## Perspective Factorization

### Summary

Take Home Messages

Further Readings

# Perspective Factorization

## Historical remarks:

- Projective factorization method introduced by Sturm and Triggs (1996)
- Algorithm very similar to orthographic factorization

# Perspective Factorization

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## Preliminaries:

- Perspective projection model
- Projection matrix for the  $i$ -th frame is denoted by  $\mathbf{P}_i \in \mathbb{R}^{3 \times 4}$ .
- Number of frames  $N_F \geq 3$
- $j$ -th world point  $\tilde{\mathbf{p}}_j^w \in \mathbb{R}^4$  is represented in homogeneous coordinates and is visible in **all** frames.
- World points are **not** all coplanar.
- $\tilde{\mathbf{q}}_{i,j}^l = (x_{i,j}, y_{i,j}, 1)^T \in \mathbb{R}^3$  is the homogeneous vector associated with the  $j$ -th image point in the  $i$ -th frame.
- $\lambda_{i,j}$  is the scaling factor (**projective depth**) of the  $j$ -th image point in the  $i$ -th frame.

# Perspective Factorization

## Factorization using homogeneous coordinates:

The world point is projected to the image point by perspective projection:

$$\lambda_{i,j} \tilde{\mathbf{q}}_{i,j}^i = \mathbf{P}_i \tilde{\mathbf{p}}_j^w.$$

In components:

$$\lambda_{i,j} \begin{pmatrix} x_{i,j} \\ y_{i,j} \\ 1 \end{pmatrix} = \begin{pmatrix} p_{i,1,1} & p_{i,1,2} & p_{i,1,3} & p_{i,1,4} \\ p_{i,2,1} & p_{i,2,2} & p_{i,2,3} & p_{i,2,4} \\ p_{i,3,1} & p_{i,3,2} & p_{i,3,3} & p_{i,3,4} \end{pmatrix} \begin{pmatrix} x_j \\ y_j \\ z_j \\ 1 \end{pmatrix}$$

# Perspective Factorization

Considering all points simultaneously, matrix notation gives us the following factorization of the measurement matrix  $\mathbf{M}$ :

$$\begin{pmatrix} \lambda_{1,1} \tilde{\mathbf{q}}_{1,1}^i & \lambda_{1,2} \tilde{\mathbf{q}}_{1,2}^i & \dots & \lambda_{1,N_p} \tilde{\mathbf{q}}_{1,N_p}^i \\ \lambda_{2,1} \tilde{\mathbf{q}}_{2,1}^i & \lambda_{2,2} \tilde{\mathbf{q}}_{2,2}^i & \dots & \lambda_{2,N_p} \tilde{\mathbf{q}}_{2,N_p}^i \\ \vdots & \vdots & \ddots & \vdots \\ \lambda_{N_F,1} \tilde{\mathbf{q}}_{N_F,1}^i & \lambda_{N_F,2} \tilde{\mathbf{q}}_{N_F,2}^i & \dots & \lambda_{N_F,N_p} \tilde{\mathbf{q}}_{N_F,N_p}^i \end{pmatrix} = \begin{pmatrix} \mathbf{P}_1 \\ \mathbf{P}_2 \\ \vdots \\ \mathbf{P}_{N_F} \end{pmatrix} \left( \tilde{\mathbf{p}}_1^w, \tilde{\mathbf{p}}_2^w, \dots, \tilde{\mathbf{p}}_{N_p}^w \right).$$

# Perspective Factorization

**Assumption:** Projective depth  $\lambda_{i,j}$  is known.

- In the perspective case the measurement matrix has rank 4, since it is a product of two matrices where the first factor has 4 columns and the second one 4 rows.
- Rank criterion can be enforced by SVD: all but the first four singular values are set to zero.

# Perspective Factorization

- Use the SVD of the rank enforced measurement matrix

$$\mathbf{M} = \mathbf{U}\Sigma\mathbf{V}^T.$$

- Up to a  $4 \times 4$  projective transform we get the following motion and scene parameters:
  - projection matrices result from:

$$\begin{pmatrix} \mathbf{P}_1 \\ \mathbf{P}_2 \\ \vdots \\ \mathbf{P}_{N_F} \end{pmatrix} = \mathbf{U}\Sigma,$$

- 3-D scene points are:

$$(\tilde{\mathbf{p}}_1^w, \tilde{\mathbf{p}}_2^w, \dots, \tilde{\mathbf{p}}_{N_p}^w) = \mathbf{V}^T.$$

# Perspective Factorization

## Estimating projective depths:

Apply the following iterative scheme:

1. Initialize  $\lambda_{i,j} := 1$ .
2. Normalize projective depths by scaling  $M$  such that column and row vectors have norm 1.
3. Enforce the rank criterion for the measurement matrix.
4. Use SVD to estimate projection matrices and 3-D structure.
5. Project estimated points anew into each frame and update all  $\lambda_{i,j}$ .
6. If the projective depths change significantly, go back to step 2.

# Topics

Perspective Factorization

## Summary

Take Home Messages

Further Readings

# Take Home Messages

- In many ways, perspective factorization is similar to orthogonal factorization, but here we additionally need to estimate the projective depths.
- The projective depths are estimated iteratively along with the factorization algorithm.

## Further Readings

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