# University of Cyprus - MSc Artificial Intelligence 

## MAI644 - COMPUTER VISION <br> Lecture 9: RANSAC, Panorama Stitching

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CENTRE OF EXCELLENCE

## Last time

- Basic feature descriptor and matching
- Histogram of Oriented Gradients
- SIFT
- Image transformations
- Estimate transformations


## Today's Agenda

- Linear least-squares
- RANSAC
- Panorama Stitching


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## Linear least squares

Want to solve overdetermined linear system:

- $\mathrm{Ma}=\mathrm{b}$

Want to minimize squared error:
$||b-M a||^{2}=$

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## Linear least squares

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$||\mathrm{b}-\mathrm{Ma}||^{2}=$
$(b-M a)^{\top}(b-M a)=$
$b^{\top} b-a^{\top} M^{\top} b-b^{\top} M a+a^{\top} M^{\top} M a$

## Linear least squares

Want to solve overdetermined linear system:

- $M a=b$

Want to minimize squared error:
$||b-M a||^{2}=$
$(b-M a)^{\top}(b-M a)=$
$b^{\top} b-a^{\top} M^{\top} b-b^{\top} M a+a^{\top} M^{\top} M a=$
$b^{\top} b-2 a^{\top} M^{\top} b+a^{\top} M^{\top} M a$

## Linear least squares

Want to minimize squared error: || b-M a || $\left.\right|^{2}=$
$b^{\top} b-2 a^{\top} M^{\top} b+a^{\top} M^{\top} M a$
This is convex and minimized when gradient $=0$. So we take the derivative wrt a and set $=0$.
$-M^{\top} b+\left(M^{\top} M\right) a=0$
$\left(M^{\top} M\right) a=M^{\top} b$
$a=\left(M^{\top} M\right)^{-1} M^{\top} b$

## So what does linear least squares do?



## So what does linear least squares do?

Error based on squared residual
Very scared of being wrong, even for just one point

Very bad at handling outliers in data


Not a problem for us, our data is perfect...


Not really ...

## Today's Agenda

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## RANSAC: RANdom SAmple Consensus

- How can we fit model to inliers but ignore outliers?
- Try a bunch of models, see which ones are best!
- Inliers will all agree on a model
- Outliers are basically random, will not agree

RANSAC: RANdom SAmple Consensus



RANSAC: RANdom SA le Consensus

Inliers: 4

## RANSAC: RANdom SAmple Consensus

## RANSAC: RANdom SAmple Consensus

## Inliers: 5

## RANSAC: RANdom SAmple Consensus




## RANSAC: RANdom SAmple Consensus

- Parameters: data, model, n points to fit model, $k$ iterations, $t$ threshold, d "good" fit cutoff

```
bestmodel = None
bestfit = -INF
While i < k:
    sample = draw n random points from data
    Fit model to sample
    inliers = data within t of model
    if inliers > bestfit:
            Fit model to all inliers
            bestfit = fit
            bestmodel = model
            if inliers > d:
                return model
return bestmodel
```


## RANSAC: RANdom SAmple Consensus

- Works well even with extreme noise.



## RANSAC: RANdom SAmple Consensus

- Works well even with extreme noise.



## RANSAC: RANdom SAmple Consensus

- Parameters: data, model, n points to fit model, k iterations, $t$ threshold, d "good" fit cutoff
- Lots of tunable parameters
- Want high probability of recovering "right" model
- t: often quite small, assume "good" inliers
- n : should be just enough to fit model, no extra
- k: can be very high
- d: should be >>n


## We can estimate affine..

- How many knowns do we get with one match?
- $\mathrm{n}_{\mathrm{x}}=\mathrm{a}_{00} * \mathrm{~m}_{\mathrm{x}}+\mathrm{a}_{01} * \mathrm{~m}_{\mathrm{y}}+\mathrm{a}_{02} * 1$
- $\quad n_{y}=a_{10} * m_{x}+a_{11} * m_{y}+a_{12}^{*} 1$
- Solve linear system of equations $\mathrm{Ma}=\mathrm{b}$
- $\quad M^{-1} M a=M^{-1} b=>a=M^{-1} b$
- But $\mathrm{M}^{-1}$ does not exist in general - Why?
- Still works if overdetermined

M

| $\begin{array}{llllll} m_{x 1} & m_{1} & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & m_{x 1} & m_{y 1} & 1 \\ m_{x 2} & m_{y 2} & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & m_{x 2} & m_{y 2} & 1 \\ m_{x 3} & m_{y 3} & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & m_{x 3} & m_{y 3} & 1 \end{array}$ | $\left[\begin{array}{l}a_{00} \\ a_{01} \\ a_{02} \\ a_{10} \\ a_{11} \\ a_{12}\end{array}\right.$ | $=$ |
| :---: | :---: | :---: |

## We want projective (homography)

- What are our equations now?
- $n_{x}=\left(h_{00} * m_{x}+h_{01}{ }^{*} m_{y}+h_{02}^{*} m_{w}\right) /\left(h_{20} * m_{x}+h_{21} * m_{y}+h_{22}{ }^{*} m_{w}\right)$
- $\mathrm{n}_{\mathrm{y}}=\left(\mathrm{h}_{10} * \mathrm{~m}_{\mathrm{x}}+\mathrm{h}_{11} * \mathrm{~m}_{\mathrm{y}}+\mathrm{h}_{12}{ }^{*} \mathrm{~m}_{\mathrm{w}}\right) /\left(\mathrm{h}_{20} * \mathrm{~m}_{\mathrm{x}}+\mathrm{h}_{21}{ }^{*} \mathrm{~m}_{\mathrm{y}}+\mathrm{h}_{22}{ }^{*} \mathrm{~m}_{\mathrm{w}}\right)$

$$
\left[\begin{array}{c}
\tilde{x}^{\prime} \\
\tilde{y}^{\prime} \\
\tilde{w}^{\prime}
\end{array}\right]=\left[\begin{array}{lll}
h_{00} & h_{01} & h_{02} \\
h_{10} & h_{11} & h_{12} \\
h_{20} & h_{21} & h_{22}
\end{array}\right]\left[\begin{array}{c}
\tilde{x} \\
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\end{array}\right]
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- $n_{y}=\left(h_{10} * m_{x}+h_{11} * m_{y}+h_{12}^{*} m_{w}\right) /\left(h_{20} * m_{x}+h_{21} * m_{y}+h_{22}^{*} m_{w}\right)$
- Assume $h_{22}$ and $m_{w}$ are 1, now 8 DOF
- $n_{x}=\left(h_{00}{ }^{*} m_{x}+h_{01}{ }^{*} m_{y}+h_{02}\right) /\left(h_{20}{ }^{*} m_{x}+h_{21}{ }^{*} m_{y}+1\right)$
- $\mathrm{n}_{\mathrm{y}}=\left(\mathrm{h}_{10} * \mathrm{~m}_{\mathrm{x}}+\mathrm{h}_{11} * \mathrm{~m}_{\mathrm{y}}+\mathrm{h}_{12}\right) /\left(\mathrm{h}_{20} * \mathrm{~m}_{\mathrm{x}}+\mathrm{h}_{21} * \mathrm{~m}_{\mathrm{y}}+1\right)$

$$
\left[\begin{array}{l}
\tilde{x}^{\prime} \\
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\tilde{w}
\end{array}\right]
$$

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- $n_{y}=\left(h_{10} * m_{x}+h_{11} * m_{y}+h_{12}^{*} m_{w}\right) /\left(h_{20} * m_{x}+h_{21} * m_{y}+h_{22}^{*} m_{w}\right)$
- Assume $h_{22}$ and $m_{w}$ are 1, now 8 DOF
- $n_{x}=\left(h_{00} * m_{x}+h_{01}{ }^{*} m_{y}+h_{02}\right) /\left(h_{20}{ }^{*} m_{x}+h_{21}{ }^{*} m_{y}+1\right)$
$-n_{y}=\left(h_{10} * m_{x}+h_{11} * m_{y}+h_{12}\right) /\left(h_{20} * m_{x}+h_{21} * m_{y}+1\right)$
- More algebra on $n_{x}$
- $n_{x} *\left(h_{20}{ }^{*} m_{x}+h_{21}{ }^{*} m_{y}+1\right)=\left(h_{00}{ }^{*} m_{x}+h_{01}{ }^{*} m_{y}+h_{02}\right)$
- $n_{x}{ }^{*} h_{20}{ }^{*} m_{x}+n_{x}{ }^{*} h_{21}{ }^{*} m_{y}+n_{x}=h_{00} * m_{x}+h_{01} * m_{y}+h_{02}$
- $n_{x}=h_{00}{ }^{*} m_{x}+h_{01}{ }^{*} m_{y}+h_{02}-n_{x}{ }^{*} h_{20}{ }^{*} m_{x}-n_{x}{ }^{*} h_{21}{ }^{*} m_{y}$
- Similar for $\mathrm{n}_{\mathrm{y}}$


## We want projective (homography)

- What are our equations now?
- $n_{x}=h_{00} * m_{x}+h_{01} * m_{y}+h_{02}-n_{x} * h_{20} * m_{x}-n_{x} * h_{21} * m_{y}$
$-\mathrm{n}_{\mathrm{y}}=\mathrm{h}_{10}{ }^{*} \mathrm{~m}_{\mathrm{x}}+\mathrm{h}_{11}{ }^{*} \mathrm{~m}_{\mathrm{y}}+\mathrm{h}_{12}-\mathrm{n}_{\mathrm{x}}{ }^{*} \mathrm{~h}_{20}{ }^{*} \mathrm{~m}_{\mathrm{x}}-\mathrm{n}_{\mathrm{x}}{ }^{*} \mathrm{~h}_{21}{ }^{*} \mathrm{~m}_{\mathrm{y}}$
- New matrix equations:

$$
\begin{aligned}
& \text { M }
\end{aligned}
$$

$$
\begin{aligned}
& {\left[\begin{array}{l}
h_{00} \\
h_{01} \\
h_{02} \\
h_{10} \\
h_{11} \\
h_{12} \\
h_{20} \\
h_{21}
\end{array}\right]=\left[\begin{array}{l}
n_{x 1} \\
n_{y 1} \\
n_{x 2} \\
n_{y 2} \\
n_{x 3} \\
n_{y 3} \\
n_{x 4} \\
n_{y 4}
\end{array}\right]}
\end{aligned}
$$

## We want projective (homography)

- New matrix equations:
- Same procedure, Solve Ma=b
- Exact if \#rows of $M=8$
- Least squares if \#rows of $M>8$


## Are there any problems with this??

- New matrix equations:
- Same procedure, Solve Ma=b
- Exact if \#rows of $M=8$
- Least squares if \#rows of $M>8$


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## Panorama algorithm

Find corners in both images
Calculate descriptors
Match descriptors
RANSAC to find homography
Stitch together images with homography

## Stitching panoramas

- We know homography is right choice under certain assumption:
- Assume we are taking multiple images of planar object



## In practice



## In practice


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ing



Co-financed by the European Union

## MAI4CAREU





What's happehing?


## What's happening?



## What's happening?



## What's happening?



What's happêhing?

## What's happening?



## What's happening?



What's happêhing?


## What's happening?



## Very bad for big panoramas!



## Very bad for big panoramas!



MAI4CAREU

## Very bad for big panoramas!



Fails :-(



## How do we fix it? Cylinders!

## How do we fix it?




How do we fix it?



How do we fix it? ع-



## How do we fix it?




How do we fix it?



## How do we fix it? Cylinders!

Calculate angle and height:
$\boldsymbol{\theta}=(\mathrm{x}-\mathrm{xc}) / \mathrm{f}$
$h=(y-y c) / f$
Find unit cylindrical cóords:
$X^{\prime}=\sin (\theta)$
$Y^{\prime}=h$
$Z^{\prime}=\cos (\theta)$
Project to image plane:
$x^{\prime}=f X^{\prime} / Z^{\prime}+x c$
$y^{\prime}=f Y^{\prime} / Z^{\prime}+y c$


## Dependant on focal length!



## $f=300$



## $f=500$




## $f=1000$



## $f=1400$



## $f=10,000$



## $f=10,000$



## Does it work?



## Does it work?



## Does it work?



## Does it work?



## Does it work?



## Yes! Assuming camera is level and rotating around its vertical axis



## Thank you.

