# CS-565 Computer Vision 

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11. Transformations II: Estimation and Warping

## Estimation of Affine Transform

- We are given $N$ corresponding points

$$
\begin{aligned}
\mathrm{x}_{1} & \Longleftrightarrow \mathrm{x}_{1}^{\prime} \\
\mathrm{x}_{2} & \Longleftrightarrow \mathrm{x}_{2}^{\prime} \\
& \vdots \\
\mathrm{x}_{N} & \Longleftrightarrow \mathrm{x}_{N}^{\prime}
\end{aligned}
$$

where $\mathbf{x}_{i}^{\prime}=\mathbf{T} \mathbf{x}_{i}$ represents an affinely transformed point pair.

- Goal is to find the 6 parameters

$$
\left[\begin{array}{lll}
a & b & e \\
c & d & f \\
0 & 0 & 1
\end{array}\right]
$$

of the affine transformation $T$ that maps the $x_{i} s$ to $x_{i}^{\prime} s$.

## Estimation of Affine Transform

- By writing the transformation parameters in vector form, the $i$ th correspondence $\mathbf{x}_{i}^{\prime}=\mathbf{T} \mathrm{x}_{i}$ can be written as

$$
\left[\begin{array}{cccccc}
x_{i} & y_{i} & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & x_{i} & y_{i} & 1
\end{array}\right]\left[\begin{array}{l}
a \\
b \\
e \\
c \\
d \\
f
\end{array}\right]=\left[\begin{array}{l}
x_{i}^{\prime} \\
y_{i}^{\prime}
\end{array}\right]
$$

## Estimation of Affine Transform

- All $N$ correspondences can be written as

$$
\underbrace{\left[\begin{array}{cccccc}
x_{1} & y_{1} & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & x_{1} & y_{1} & 1 \\
x_{N} & y_{N} & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & x_{N} & y_{N} & 1
\end{array}\right]}_{2 N \times 6} \underbrace{\left[\begin{array}{c}
a \\
b \\
e \\
c \\
d \\
f
\end{array}\right]}_{6 \times 1}=\underbrace{\left[\begin{array}{c}
x_{1}^{\prime} \\
y_{1}^{\prime} \\
\vdots \\
x_{N}^{\prime} \\
y_{N}^{\prime}
\end{array}\right]}_{2 N \times 1}
$$

which can be seen as a linear system $\mathbf{A v}=\mathbf{b}$.

- Can be solved via pseudoinverse

$$
\mathbf{A} \mathbf{v}=\mathbf{b} \Longrightarrow \mathbf{A}^{T} \mathbf{A} \mathbf{v}=\mathbf{A}^{T} \mathbf{b} \Longrightarrow \mathbf{v}=\left(\mathbf{A}^{T} \mathbf{A}\right)^{-1} \mathbf{A}^{T} \mathbf{b}=\mathbf{A}^{\dagger} \mathbf{b}
$$

where $\mathbf{A}^{\dagger}=\left(\mathbf{A}^{T} \mathbf{A}\right)^{-1} \mathbf{A}^{T}$ is the $6 \times 2 N$ matrix called the pseudoinverse of A.

## Estimation of Affine Transform

## Algorithm

Input: $N$ point correspondences $\mathrm{x}_{i} \Longleftrightarrow \mathrm{x}_{i}^{\prime}$

1. Fill in the $2 N \times 6$ matrix $\mathbf{A}$ using the $x_{i}$.
2. Fill in the $2 N \times 1$ vector $\mathbf{b}$ using the $\mathbf{x}_{i}^{\prime}$.
3. Compute $6 \times 2 N$ pseudo-inverse $\mathbf{A}^{\dagger}=\left(\mathbf{A}^{T} \mathbf{A}\right)^{-1} \mathbf{A}^{T}$.
4. Compute optimal affine transformation parameters as $\mathbf{v}^{*}=\mathbf{A}^{\dagger} \mathbf{b}$.

## Detour - Cross Product

$$
\mathbf{u} \times \mathbf{v}=\left[\begin{array}{l}
u_{2} v_{3}-u_{3} v_{2} \\
u_{3} v_{1}-u_{1} v_{3} \\
u_{1} v_{2}-u_{2} v_{1}
\end{array}\right]=\underbrace{\left[\begin{array}{ccc}
0 & -u_{3} & u_{2} \\
u_{3} & 0 & -u_{1} \\
-u_{2} & u_{1} & 0
\end{array}\right]}_{[\mathbf{u}] \times}\left[\begin{array}{l}
v_{1} \\
v_{2} \\
v_{3}
\end{array}\right]
$$

- Only defined for 3-dimensional space.
- Matrix $[\mathbf{u}]_{\times}$has two linearly independent rows.
- Proof: $u_{1}$ row $1+u_{2}$ row $2+u_{3}$ row $3=\mathbf{0}^{T} \Longrightarrow$ any row can be written as a linear combination of the other two rows.
- $\mathbf{u} \times \mathbf{v}$ is another 3-dimensional vector orthogonal to both $\mathbf{u}$ and $\mathbf{v}$.
- $\|\mathbf{u} \times \mathbf{v}\|$ represents the area of the parallelogram formed by $\mathbf{u}$ and $\mathbf{v}$.


## Detour - Cross Product



- If $\mathbf{u}$ and $\mathbf{v}$ point in the same direction, then no parallelogram will be formed.
- Therefore $\|\mathbf{u} \times \mathbf{v}\|$ will be 0 .
- The only vector with norm 0 is the 0 vector.
- Therefore, $\mathbf{u} \times \mathbf{v}=\mathbf{0}$ when $\mathbf{u}$ and $\mathbf{v}$ point in the same direction.


## Estimation of Projective Transform

- We are given $N$ corresponding points

$$
\begin{aligned}
\mathrm{x}_{1} & \Longleftrightarrow \mathrm{x}_{1}^{\prime} \\
\mathrm{x}_{2} & \Longleftrightarrow \mathrm{x}_{2}^{\prime} \\
& \vdots \\
\mathrm{x}_{N} & \Longleftrightarrow \mathrm{x}_{N}^{\prime}
\end{aligned}
$$

where $\mathbf{x}_{i}^{\prime}=\mathbf{H} \mathbf{x}_{i}$ represents a projectively transformed point pair.

- Goal is to find the 8 parameters $h_{1}, h_{2} \ldots, h_{8}$ of the projective transformation H that maps the x points to the $\mathrm{x}^{\prime}$ points.
- Parameter $h_{9}$ can be fixed to be 1 .
- The $i$ th correspondence can be written as $\mathbf{x}_{i}^{\prime} \equiv \mathbf{H} \mathrm{x}_{i}$ in projective space ${ }^{1}$.

[^0]
## Estimation of Projective Transform

- This implies that the 3 -dimensional vectors $\mathbf{x}_{i}^{\prime}$ and $\mathbf{H} x_{i}$ point in the same direction.
- Their cross-product will be the zero vector.

$$
\begin{gathered}
\mathbf{x}_{i}^{\prime} \times \mathbf{H} \mathbf{x}_{i}=\mathbf{0} \\
{\left[\begin{array}{l}
x_{i}^{\prime} \\
y_{i}^{\prime} \\
w_{i}^{\prime}
\end{array}\right] \times\left[\begin{array}{l}
\mathbf{h}^{1 T} \\
\mathbf{h}^{2 T} \\
\mathbf{h}^{3 T}
\end{array}\right] \mathbf{x}_{i}=\mathbf{0}}
\end{gathered}
$$

where $\mathbf{h}^{j T}$ is the $j$-th row of $\mathbf{H}$.

- Cross-product can be performed as

$$
\left[\begin{array}{ccc}
0 & -w_{i}^{\prime} & y_{i}^{\prime} \\
w_{i}^{\prime} & 0 & -x_{i}^{\prime} \\
-y_{i}^{\prime} & x_{i}^{\prime} & 0
\end{array}\right]\left[\begin{array}{l}
\mathbf{h}^{1 T} \mathbf{x}_{i} \\
\mathbf{h}^{2 T} \mathbf{x}_{i} \\
\mathbf{h}^{3 T} \mathbf{x}_{i}
\end{array}\right]=\mathbf{0}
$$

## Estimation of Projective Transform

- After matrix-vector multiplication

$$
\left[\begin{array}{c}
y_{i}^{\prime} \mathbf{h}^{3 T} \mathbf{x}_{i}-w_{i}^{\prime} \mathbf{h}^{2 T} \mathbf{x}_{i} \\
w_{i}^{\prime} \mathbf{h}^{1 T} \mathbf{x}_{i}-x_{i}^{\prime} \mathbf{h}^{3 T} \mathbf{x}_{i} \\
x_{i}^{\prime} \mathbf{h}^{2 T} \mathbf{x}_{i}-y_{i}^{\prime} \mathbf{h}^{1 T} \mathbf{x}_{i}
\end{array}\right]=\left[\begin{array}{c}
y_{i}^{\prime} \mathbf{x}_{i}^{T} \mathbf{h}^{3}-w_{i}^{\prime} \mathbf{x}_{i}^{T} \mathbf{h}^{2} \\
w_{i}^{\prime} \mathbf{x}_{i}^{T} \mathbf{h}^{1}-x_{i}^{\prime} \mathbf{x}_{i}^{T} \mathbf{h}^{3} \\
x_{i}^{\prime} \mathbf{x}_{i}^{T} \mathbf{h}^{2}-y_{i}^{\prime} \mathbf{x}_{i}^{T} \mathbf{h}^{1}
\end{array}\right]=\mathbf{0}
$$

- After separating the unknowns

$$
\left[\begin{array}{ccc}
0^{T} & -w_{i}^{\prime} \mathbf{x}_{i}^{T} & y_{i}^{\prime} \mathbf{x}_{i}^{T} \\
w_{i}^{\prime} \mathbf{x}_{i}^{T} & \mathbf{0}^{T} & -x_{i}^{\prime} \mathbf{x}_{i}^{T} \\
-y_{i}^{\prime} \mathbf{x}_{i}^{T} & x_{i}^{\prime} \mathbf{x}_{i}^{T} & \mathbf{0}^{T}
\end{array}\right]_{3 \times 9}\left[\begin{array}{l}
\mathbf{h}^{1} \\
\mathbf{h}^{2} \\
\mathbf{h}^{3}
\end{array}\right]_{9 \times 1}=\mathbf{A}_{i} \mathbf{h}=\mathbf{0}
$$

- Matrix $\mathbf{A}_{i}$ has only 2 linearly independent rows.
- So one row can be discarded. Let's denote the resulting $2 \times 9$ matrix by $\mathrm{A}_{i}$ as well.


## Estimation of Projective Transform

- So one correspondence $\mathrm{x}_{i} \Longleftrightarrow \mathrm{x}_{i}^{\prime}$ yields 2 equations.
- Since 8 unknowns require atleast 8 equations, we will need $N \geq 4$ corresponding point pairs.

The points $\mathrm{x}_{1}, \ldots, \mathrm{x}_{N}$ must be non-collinear. Similarly, $\mathrm{x}_{1}^{\prime}, \ldots, \mathrm{x}_{N}^{\prime}$ must also be non-collinear.

## Estimation of Projective Transform

- This will yield the homogenous system $\mathbf{A h}=\mathbf{0}$ where size of $\mathbf{A}$ is $2 N \times 9$.
- It can be shown that $\operatorname{rank}(\mathbf{A})=8$ and $\operatorname{dim}(\mathbf{A})=9$.
- So nullity of $\mathbf{A}$ is 1 and therefore $\mathbf{h}$ can be found as the null space of $\mathbf{A}$.
- However, when measurements contain noise (which is always the case with pixel locations) or $N>4$, then no $h$ will exist that satisfies $\mathbf{A h}=0$ exactly.
- In such cases, the best one can do is to find an $h$ that makes $\mathbf{A h}$ as close to 0 as possible. This can be achieved via

$$
\mathbf{h}^{*}=\arg \min _{\mathbf{h}}\|\mathbf{A} \mathbf{h}\|^{2} \text { s.t. }\|\mathbf{h}\|^{2}=1
$$

Take-home Quiz 3: Show that $\mathbf{h}^{*}$ must be the eigenvector of $\mathbf{A}^{T} \mathbf{A}$ corresponding to the smallest eigenvalue.

## Estimation of Projective Transform

- This can be done via singular value decomposition.

$$
[\mathrm{U}, \mathrm{D}, \mathrm{~V}]=\operatorname{svd}(\mathbf{A})
$$

and $\mathbf{h}$ is the last column of the matrix $\mathbf{V}$.

## Estimation of Projective Transform

## Algorithm

Input: $N$ point correspondences $\mathrm{x}_{i} \Longleftrightarrow \mathrm{x}_{i}^{\prime}$

1. Fill in the $2 N \times 9$ matrix $\mathbf{A}$ using the $x_{i}$ and $x_{i}^{\prime}$.
2. Compute $[\mathbf{U}, \mathbf{D}, \mathbf{V}]=\operatorname{svd}(\mathbf{A})$.
3. Optimal projective transformation parameters $\mathbf{h}^{*}$ are the last column of matrix V .

This algorithm is known as the Direct Linear Transform (DLT). ${ }^{2}$

[^1]
## Image Warping



Original


Affine


Projective

## Image Warping

- Inputs: Image I and transformation matrix H.
- Output: Transformed image $I^{\prime}=\mathrm{H} /$.
- Obvious approach:
- For each pixel $\mathbf{x}$ in image I
- Find transformed point $\mathbf{x}^{\prime}=\mathbf{H x}$
- Divide by 3rd coordinate and move to Cartesian space
- Copy the pixel color as $I^{\prime}\left(\mathbf{x}^{\prime}\right)=I(\mathbf{x})$.
- Problem: Can leave holes in $I^{\prime}$. Why?
- Solution:
- For each pixel $x^{\prime}$ in image $I^{\prime}$
- Find transformed point $\mathbf{x}=\mathbf{H}^{-1} \mathbf{x}^{\prime}$
- Divide by 3rd coordinate and move to Cartesian space
- Copy the pixel color as $I^{\prime}\left(\mathbf{x}^{\prime}\right)=I(\mathbf{x})$.
- Problem: Transformed point x is not necessarily integer valued.


## Image Warping

Bilinear Interpolation
Find 4 nearest pixel locations around $(x, y)$

where

$$
\begin{aligned}
\underline{x} & =\lfloor x\rfloor \\
\underline{y} & =\lfloor y\rfloor \\
\bar{x} & =\lfloor x\rfloor+1 \\
\bar{y} & =\lfloor y\rfloor+1
\end{aligned}
$$

## Image Warping

Bilinear Interpolation


$$
I(x, y)=\bar{\epsilon}_{x} \bar{\epsilon}_{y} I(\underline{x}, \underline{y})+\epsilon_{x} \bar{\epsilon}_{y} I(\bar{x}, \underline{y})+\bar{\epsilon}_{x} \epsilon_{y} I(\underline{x}, \bar{y})+\epsilon_{x} \epsilon_{y} I(\bar{x}, \bar{y})
$$


[^0]:    ${ }^{1}$ Notice that $\mathbf{x}_{i}^{\prime}$ can be a scaled version of $\mathbf{H} \mathbf{x}_{i}$.

[^1]:    ${ }^{2}$ For some practical tips, please refer to slides $14-17$ from http://www.ele.puc-rio.br/~visao/Homographies.pdf

