## Finding Corner Points



## Normalized Cross-correlation

Let $w_{1}=I_{1}\left(x_{1}+i, y_{1}+j\right)$ and $w_{2}=I_{2}\left(x_{2}+i, y_{2}+j\right)$,
$i=-W, \ldots, W, j=-W, \ldots, W$ be two square image windows centered at locations $\left(x_{1}, y_{1}\right)$ and $\left(x_{2}, y_{2}\right)$ of images $I_{1}$ and $I_{2}$, respectively.
Normalized cross-correlation of $w_{1}$ and $w_{2}$ is given by

$$
N C C\left(w_{1}, w_{2}\right)=\frac{\left(w_{1}-\bar{w}_{1}\right) \cdot\left(w_{2}-\bar{w}_{2}\right)}{\left\|w_{1}-\bar{w}_{1}\right\|\left\|w_{2}-\bar{w}_{2}\right\|}
$$

where $w_{1}$ and $w_{2}$ are treated as vectors. $(a \cdot b$ stands for inner product of vectors $a$ and $b, \bar{a}$ for the mean value of vector elements and $\|a\|$ for the 2 -norm of vector $a$.)

For two windows whose pixel values differ by a scale factor only NCC will be equal to 1 ; if the windows are different NCC has value lower than 1 .

For two non-zero binary patterns which differ in all pixels NCC is -1 .

Normalized cross-correlation corresponds to the cosine of the angle between $w_{1}$ and $w_{2}$; this angle varies between $0^{\circ}$ and $180^{\circ}$ - the corresponding cosines vary between 1 and -1 .

Corner points differ from other points - have low NCC with all other points.

## Corner Point Candidates



## Corner Point Selection





Cross-correlation results for $9 \times 9$ neighborhoods of the three image points on the previous slide.

Corresponding similarity functions shown from an $80^{\circ}$ viewing angle. Two outside points are good feature point candidates, while the center point is not

## Selected Corner Points



Selected feature points for $1 / 2$ resolution: each point is shown with its $9 \times 9$ neighborhood.

## Selected Corner Points



Selected feature points for $1 / 4$, and $1 / 8$ resolutions: each point is shown with its $9 \times 9$ neighborhood.

## Problems with NCC

We need something more efficient for a practical corner detection algorithm.

An NCC-based algorithm detects posints that are different from their neighborhood. We need a measure of "cornerness".

Alternative: use a measure based on local structure.

## Local Structure Matrix

Consider the spatial image gradient $\left[E_{x}, E_{y}\right]^{T}$, computed for all points $(x, y)$ of an image area (neighborhood). The matrix $M$, defined as

$$
M=\left(\begin{array}{cc}
\Sigma E_{x}^{2} & \Sigma E_{x} E_{y} \\
\Sigma E_{x} E_{y} & \Sigma E_{y}^{2}
\end{array}\right)
$$

where the sums are taken over the image neighborhood, captures the geometric structure of the gray level pattern. Note that the sums can be replaced by Gaussian smoothing.
$M$ is a symmetric matrix and can therefore be diagonalized by rotation of the coordinate axes, so with no loss of generality, we can think of $M$ as a diagonal matrix:

$$
M=\left(\begin{array}{cc}
\lambda_{1} & 0 \\
0 & \lambda_{2}
\end{array}\right)
$$

where $\lambda_{1}$ and $\lambda_{2}$ are the eigenvalues of $M$.
We can choose $\lambda_{1}$ as the larger eigenvalue so that $\lambda_{1} \geq \lambda_{2} \geq 0$.
If the neighborhood contains a corner, then we expect $\lambda_{1}>\lambda_{2} \geq 0$, and the larger the eigenvalues, the stronger (higher contrast) their corresponding edges.

A corner is identified as two strong edges; therefore as $\lambda_{1}>\lambda_{2}$, a corner is a location where $\lambda_{2}$ is sufficiently large.

Solve: $\operatorname{det}(M-\lambda I)=0$ to obtain $\lambda_{1}$ and $\lambda_{2}$.
There are three cases:
No structure: (smooth variation) $\lambda_{1} \approx \lambda_{2} \approx 0$
1D structure: (edge) $\lambda_{2} \approx 0$ (direction of edge), $\lambda_{1}$ large (normal to edge)

2D structure: (corner) $\lambda_{1}$ and $\lambda_{2}$ both large and distinct
The eigenvectors $\vec{n}$ of $\mathrm{M}(M \vec{n}=\lambda \vec{n})$ correspond to the direction of smallest and largest change at $(x, y)$.

## Computing Cornerness

Identify the corner points using the measure described earlier.
Consider all image points for which $\lambda_{1} \geq \tau$ and $\lambda_{1} / \lambda_{2} \leq \kappa$.
(For example, use $\tau$ equal to one-twentieth of the maximum $\lambda_{1}$ in the entire image and we use $\kappa=2.5$.)

Decreasing $\tau$ or increasing $\kappa$ will typically result in a larger number of candidate points.

## Example: selected corner points




Selected corner points for full resolution.


Selected corner points for $1 / 2$ and $1 / 4$ resolutions.

