

# Crops as Time-Invariant Keypoints

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# Problem Introduction



Drone Images



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Orthophoto

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Orthophoto

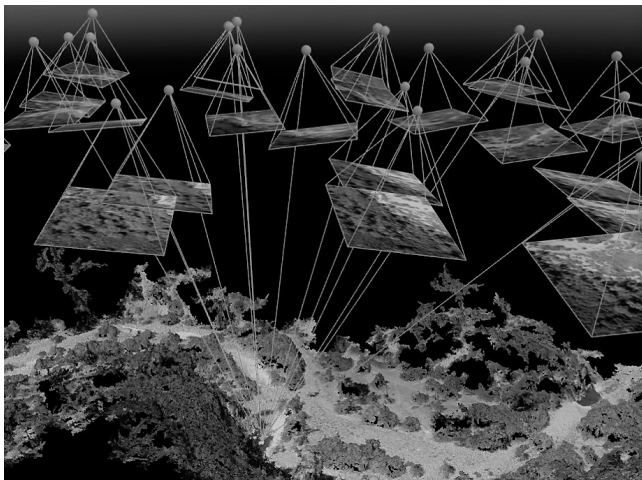


Time-Series

- 1 Problem Introduction
- 2 Creating an Orthophoto
- 3 Time Alignment of Orthophotos
- 4 Results & Discussion

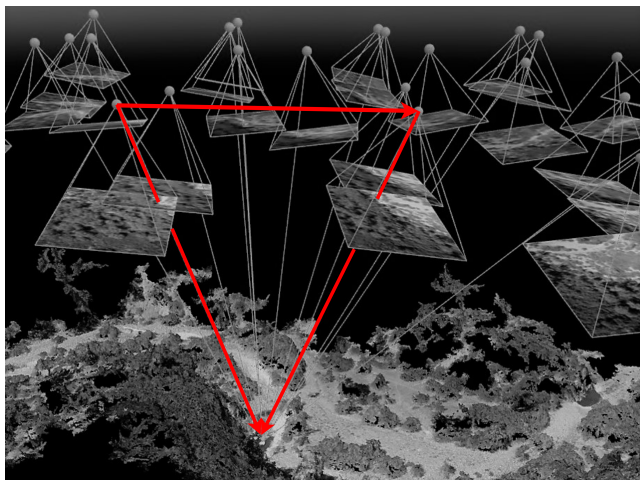
# Creating an Orthophoto

- Aim to unite image data into a common reference frame.
  - Use 3D geometry of the problem.

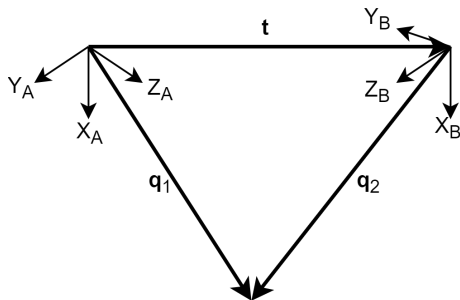


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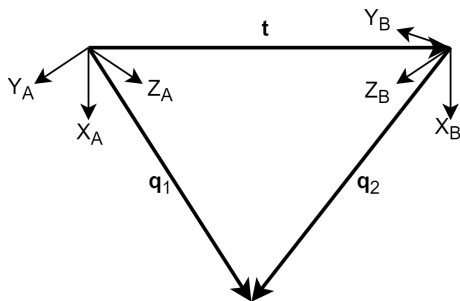
# Essential Matrix



- $\mathbf{q}_1 \cdot (\mathbf{t} \times R\mathbf{q}_2) = 0$

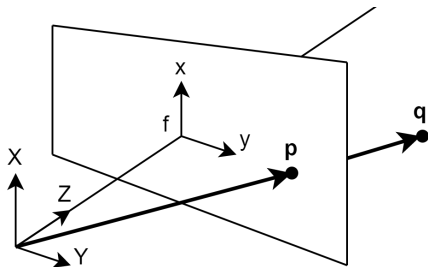
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- $\mathbf{q}_1^T E \mathbf{q}_2 = 0$ 
  - by defining *essential* matrix  $E = \mathbf{t} \times R$ , or  $E = R[\mathbf{t}]_{\times}$ .

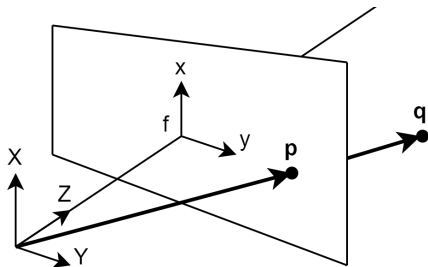
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- $\mathbf{q}_1^T E \mathbf{q}_2 = 0$  becomes  $\mathbf{p}_1^T E \mathbf{p}_2 = 0$

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- Can be solved for  $\mathbf{e}$  using a singular value decomposition of  $\mathbf{A}$ .

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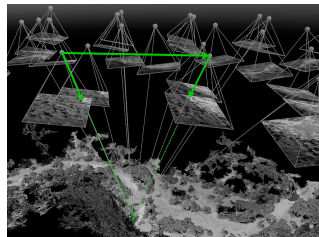
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- For example using the scale-invariant feature transform (SIFT).



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  - $\iota = \arg \min_{\tau \in S^B} \|\mathbf{f}_i - \mathbf{f}_\tau\|$ .
- Accept candidate if there is no 'close' second-nearest neighbour:
  - $\|\mathbf{f}_i - \mathbf{f}_\iota\| < C \min_{\tau \in S^B \setminus \{\iota\}} \|\mathbf{f}_i - \mathbf{f}_\tau\|$  with  $C \leq 1$ .



# Point Correspondences

- Image pair with a set of matches ( $\mathbf{p}_i \leftrightarrow \mathbf{p}_i$ )

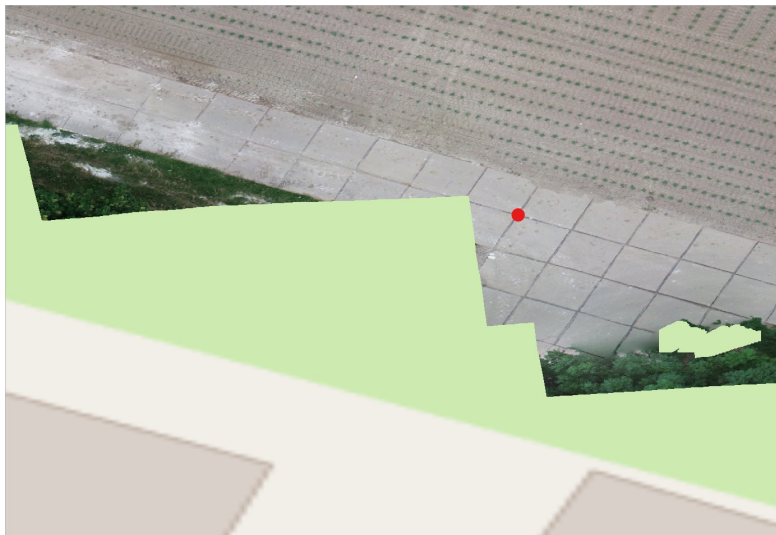
# Point Correspondences

- Image pair with a set of matches  $(\mathbf{p}_i \leftrightarrow \mathbf{p}_l)$
- Filter data and fit  $E$  using random sample consensus (RANSAC):
  - 1: **for**  $N$  iterations **do**
  - 2:   select random subset of  $(\mathbf{p}_i \leftrightarrow \mathbf{p}_l)$  and determine  $\tilde{E}$
  - 3:   count inliers on all data that satisfy  $(\mathbf{p}_i)^T \tilde{E} \mathbf{p}_l < \varepsilon$
  - 4:   **if** count  $>$  best count **then**
  - 5:      $E \leftarrow \tilde{E}$
  - 6:   **end if**
  - 7: **end for**

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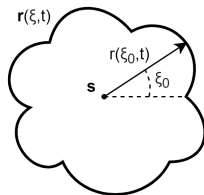
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- Do not require e.g. scale-invariance, but time-invariance.
- **Use crops as time-invariant keypoints.**
  - Guaranteed to be present.
  - Evenly distributed.

# Model Growth

- Polar parametrization of crop:

$$\mathbf{r}(\xi, t) = r(\xi, t)\mathbf{n}(\xi) + \mathbf{s}, \quad \mathbf{n}(\xi) = \langle \cos \xi, \sin \xi \rangle.$$



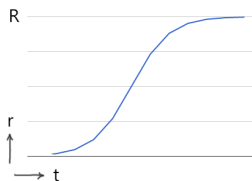
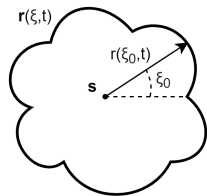
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- Assume logistic growth model:

$$\frac{\partial r}{\partial t} = \alpha r \left(1 - \frac{r}{R}\right).$$



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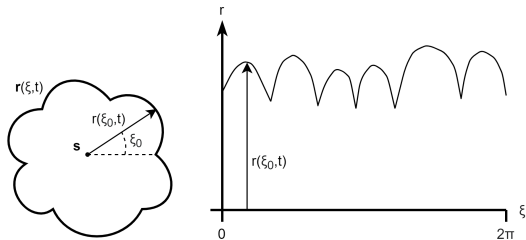
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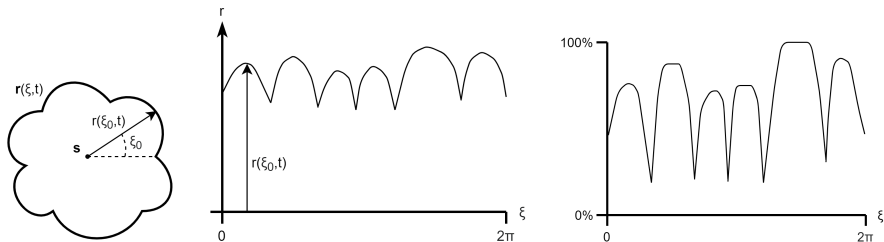
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- Position  $\mathbf{p}_i$  is ideally selected as the stem  $\mathbf{s}$ , which is time-invariant.
- Two possible descriptors  $\mathbf{f}_i$  are suggested:
  - Shape and size based descriptor
  - Planting pattern based descriptor

# Shape and Size Descriptor

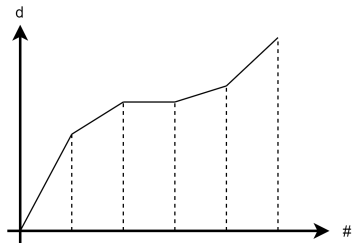
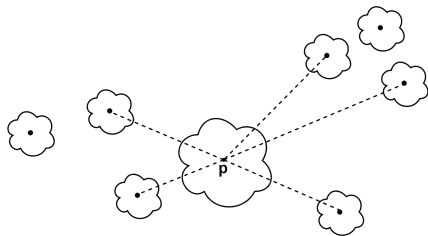


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- Tested effectiveness on a time-series of seven orthophotos.





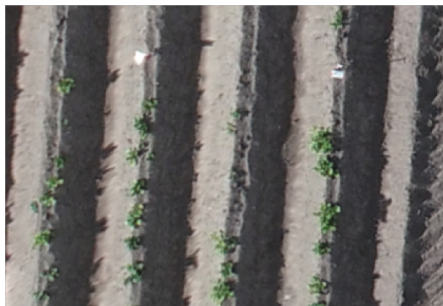
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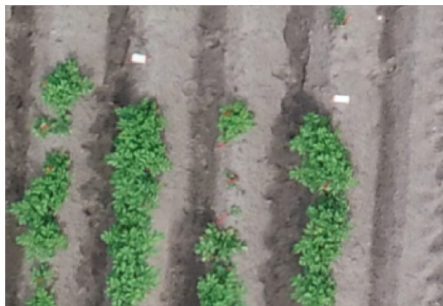
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  - Split connected components by shrinkage and buffer operations.
  - Account for merging in the model → planting pattern descriptor.
  - Identify crops not by image thresholding but by e.g. convolutional neural networks.