

# FUSION 2018

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## *Accurate Registration of Multitemperal UAV Images Based on Detection of Major Changes*

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# OUTLINE

- **Introduction**
- **Proposed Method**
  - Coarse Registration
  - Detection of Major Changes
  - Finding the Optimal Optical Flow Field
- **Experimental Results**
- **Conclusion**

# Introduction

## Why multitemporal UAV image registration ?

**Registration of multitemperal images** refers to the process of mapping the set of multitemporal images to the same coordinate system.

- Image fusion
- Change detection
- .....



**Unmanned Aerial Vehicles (UAVs)-based imaging systems** have been rapidly developed among **low altitude** remote sensing.

- high flexibility、 low cost、 stronger survivability.....

# Introduction

## ■ The problems of multitemperal UAV image registration

- Large rotation and scale changes
- Complicated non-rigid changes
- Scene changes between the times the images are acquired

Accurate registration of multitemporal UAV images  
is challengeable!

# Introduction

## Image registration

Mathematical definition:

$$I_R(x, y) = I_I(T(x, y))$$

$T$ : geometric transformation

{ Parametric: Rigid、 Affine、 Projective.....  
Non-parametric: Thin plate Spline、 Elastic 、  
Optical flow field.....

# Introduction

## Optical flow field

Optical flow field: every pixel has its own displacement vector

⇒ Complicated non-rigid changes

The problem of solving the optical flow field is usually converted to the energy functional minimization problem.

Optical flow:

$$E(w) = \sum_p \psi(|I_1(p) - I_2(p + w_p)|^2) + \lambda \sum_p \phi(|\nabla u_p|^2 + |\nabla v_p|^2)$$

# Introduction

## SIFT flow

Objective function:

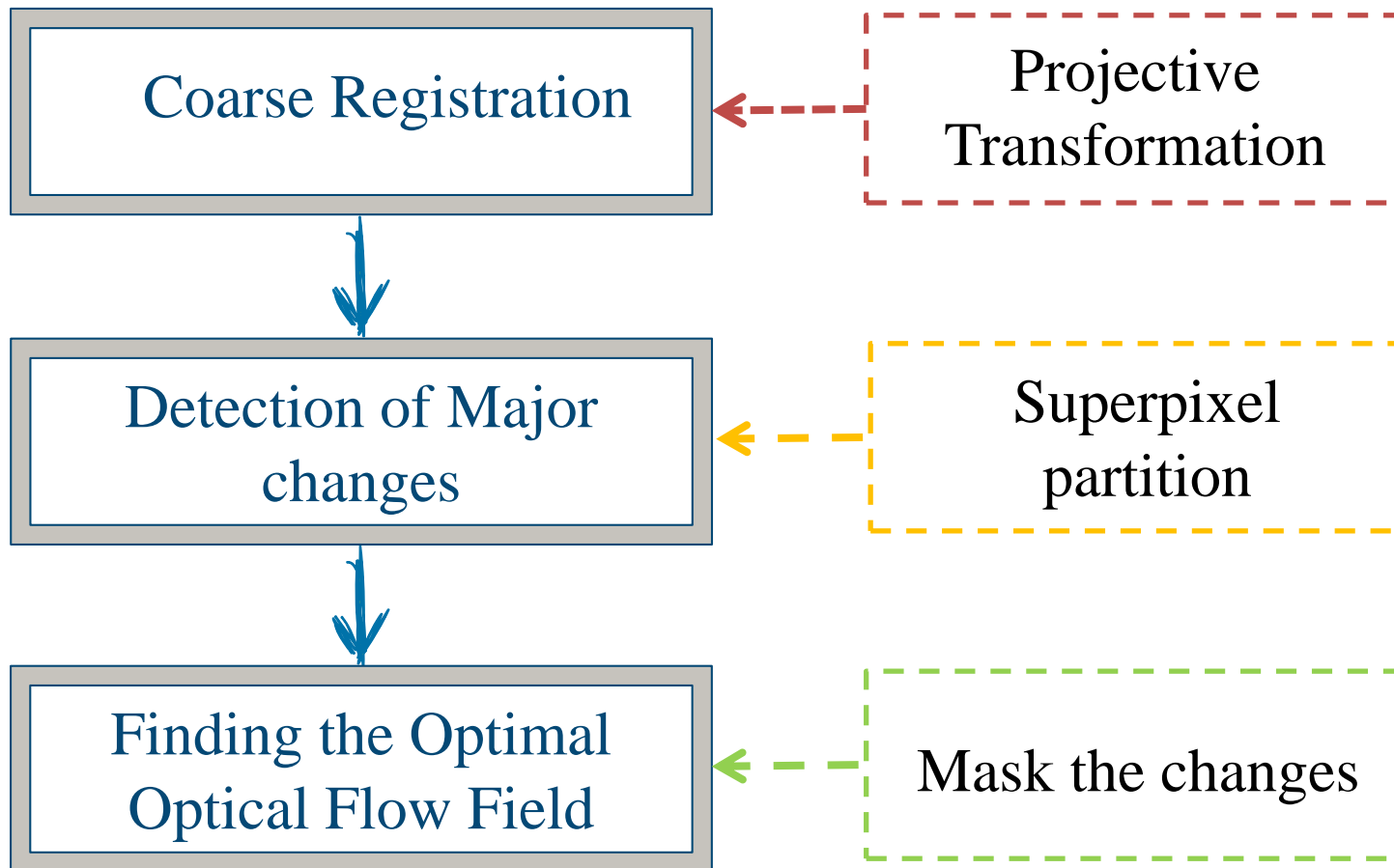
$$E(\mathbf{w}) = \sum_{\mathbf{p}} \min(\|s_1(\mathbf{p}) - s_2(\mathbf{p} + \mathbf{w}(\mathbf{p}))\|_1, t) \\ + \sum_{\mathbf{p}} \eta(|u(\mathbf{p})| + |v(\mathbf{p})|) \\ + \sum_{(\mathbf{p}, \mathbf{q}) \in \mathcal{E}} \min(\alpha |u(\mathbf{p}) - u(\mathbf{q})|, d) \\ + \min(\alpha |v(\mathbf{p}) - v(\mathbf{q})|, d)$$

Match **SIFT descriptors** instead of raw pixels.

- The dense SIFT descriptor is computed at a fixed orientation and scale.
- There should not be pixel-wise correspondence in changes while the SIFT flow algorithm wrongly match the pixels.

# Proposed Method

## Flowchart





# Proposed Method

## Coarse registration

Projective transformation:

A point  $\mathbf{p} = (x, y)$  is represented in homogeneous coordinates by  $[x_h, y_h, w_h]^T$ , both coordinates are related by  $x = x_h / w_h$  and  $y = y_h / w_h$ .

$$[x_h, y_h, w_h]^T = H[i, j, 1]^T$$

$$H = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & 1 \end{bmatrix}$$

Handle global affine transformation  
and change of perspective.

# Proposed Method

Detection of major changes

Superpixel Partition

Structure  
Information

Color  
Information

$$c(\mathbf{p}) = \begin{cases} 0, & \mathbf{p} \in \text{changes} \\ 1, & \text{others} \end{cases}$$

Change Detection

# Proposed Method

## Finding the Optimal Optical Flow Field

Modify the data term of SIFT flow:

Ignore the correspondence  
in changed areas

$$E(\mathbf{w}) = \sum_{\mathbf{p}} \min(\|s_1(\mathbf{p}) - s_2(\mathbf{p} + \mathbf{w}(\mathbf{p}))\|_1, t) \Rightarrow \sum_{\mathbf{p}} c(\mathbf{p}) \min(\|s_1(\mathbf{p}) - s_2(\mathbf{p} + \mathbf{w}(\mathbf{p}))\|_1, t)$$
$$+ \sum_{\mathbf{p}} \eta(|u(\mathbf{p})| + |v(\mathbf{p})|)$$

small displacement term

$$+ \sum_{(\mathbf{p}, \mathbf{q}) \in \mathcal{E}} \min(\alpha |u(\mathbf{p}) - u(\mathbf{q})|, d)$$
$$+ \min(\alpha |v(\mathbf{p}) - v(\mathbf{q})|, d)$$

smoothness term

# Experimental Results

## Image Set 1



(a) Image 1



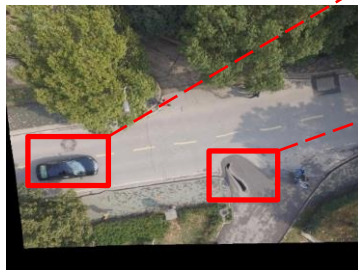
(b) Image 2



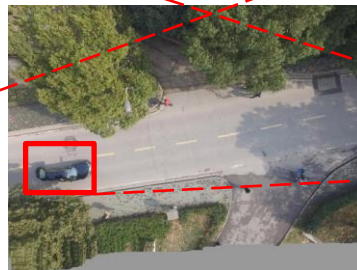
(c) Ours



(d) Projective



(e) TPS



(f) SIFT flow



# Experimental Results

## Image Set 2



(a) Image 1



(b) Image 2



(c) Ours



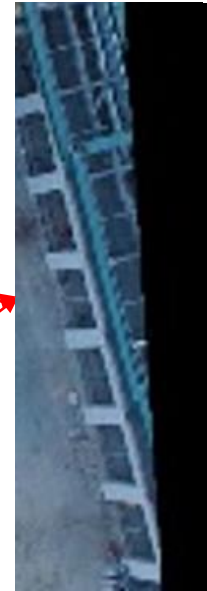
(d) Projective



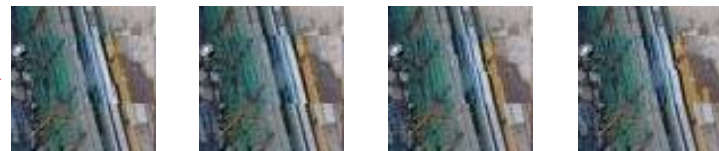
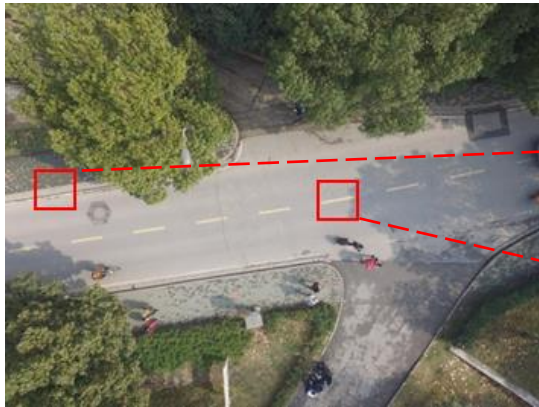
(e) TPS



(f) SIFT flow



# Experimental Results



(a) Ours    (b) Projective    (c) TPS    (d) SIFT flow

# Experimental Results

Compare the registration accuracies quantitatively by root mean square error (RMSE)

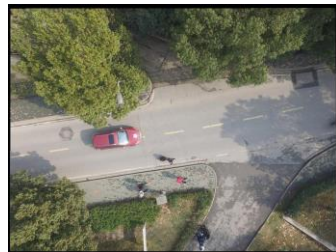
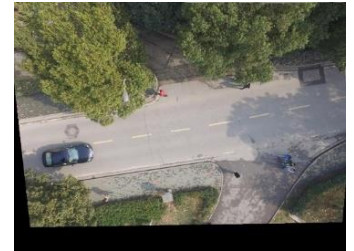
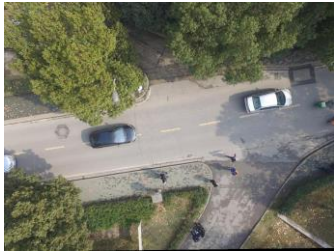
$$\text{RMSE} = \sqrt{\frac{1}{m} \sum_{i=1}^m (x_i - x'_i)^2 + (y_i - y'_i)^2}$$

Quantitative comparison (RMSE, Unit: pixel)

	<b>Ours</b>	<b>Projective-based</b>	<b>TPS-based</b>	<b>SIFT flow</b>
Image pair 1	0.4395	2.9002	1.6170	0.8738
Image pair 2	0.5722	2.4093	4.6936	1.0210

# Experimental Results

The results of registration of UAV image sequences





# Experimental Results

The results of registration of UAV image sequences



# Conclusion

## Summary

- Coarse-to-fine image registration method to align multitemporal UAV images
- Modification of SIFT flow algorithm based on masking the pixel-wise matches in major changes.

## Outlook

- Deep learning based matching to increase the efficiency.
- Exploring accurate registration of time series UAV images with abundant changes.



# Comments and Questions?