Texture-Independent Feature-point Matching (TIFM) from Motion Coherence

Ping Li[1,2], Dirk Farin[1], Rene Klein Gunnewiek[2], and Peter H. N. de With[1,3]
[1] Eindhoven University of Technology / [2] Philips Research Europe / [3] CycloMedia Technology B.V.

1 Introduction

- Finding feature-point correspondences between two images by maximizing the smoothness of local motion fields.
- No texture information is required for matching.
- Reliable due to the reliability of the smoothness constraint.
- Efficient due to the simplicity of the smoothness computation.
- Works well for tracking feature points in image sequences with small or moderate motion.

2 Algorithm

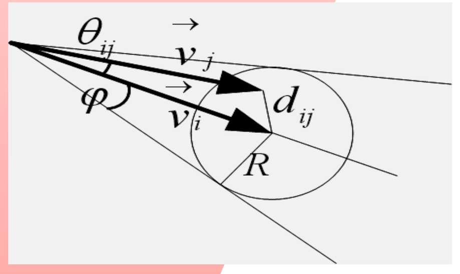

Fig.2: Two coherent vectors

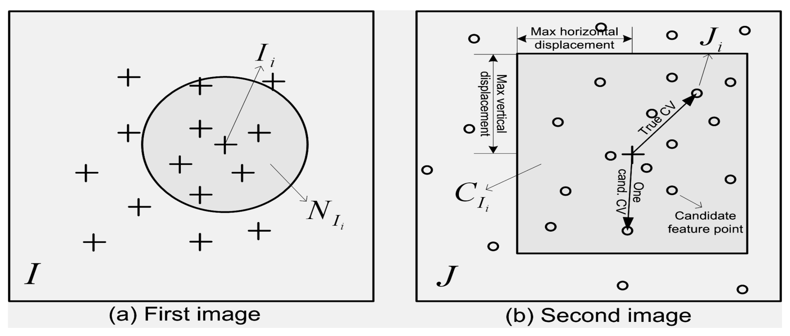

Fig.1: Neighborhood set and candidate set

- *Coherent Vectors (CV)* have similar directions and similar magnitudes.
- *Smoothness* of a neighborhood is defined as:
  #coherent vectors / #feature points

- 2.1 Steps

- For each candidate vector, count the #coherent vectors in the neighborhood.
- The set of coherent vectors that gives the maximum smoothness are considered correct.

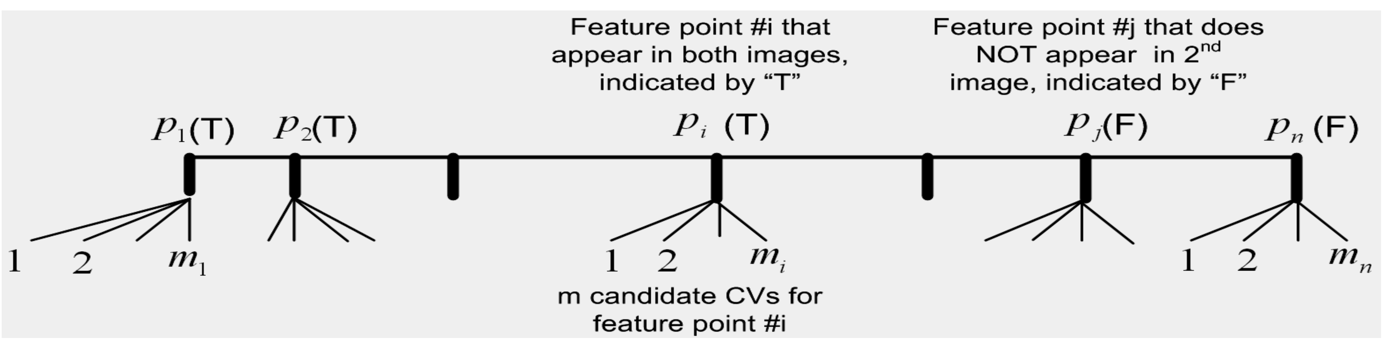

Fig.3: Possible matching combinations

2.2 Rationale

- Along the true CV, smoothness equals the repetition ratio of the feature points by Harris corner detector.
- Finding another set of coherent CVs that give a higher smoothness than the repetition ratio is difficult (feature points appear randomly along any other CV due to random textures).

True CV⇔ maximum smoothness, i.e., smoothness constraint alone is able to give sufficient constraint on feature-point matching.

3 Experiment

Compare TIFM with

- Scale-Invariant Feature Transform (SIFT)
- Kanade-Lucas-Tomasi feature tracker (KLT)
- Block Matching (BM)

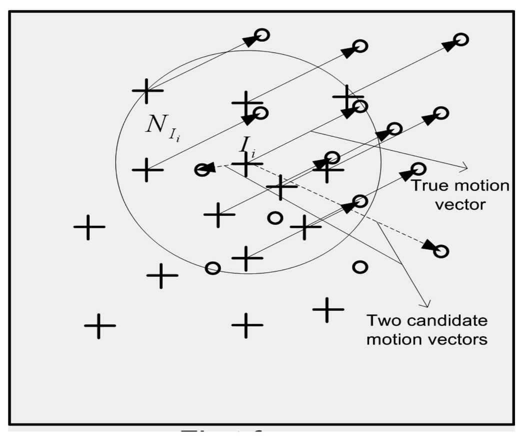

Fig.4: Local motion field

Table 1. test sequences

Seq ($\#frm$)	Description
medusa (194)	from www.cs.unc.edu/~marc/; small motion
castle (26)	from www.cs.unc.edu/~marc/; moderate motion
lab (150)	by hand-held DV; small motion
kspoort (22)	by hand-held DC; moderate motion
house (16)	by hand-held DC; moderate motion
church (25)	by hand-held DC; moderate motion
leuven (6)	from www.robots.ox.ac.uk/~vgg/research/affine/; big light change + small motion

Table 2. test image pairs

ImagePair	Description
L01	two brightest images from leuven
L05	the brightest and darkest images from leuven
IP1	extracted from castle; moderate motion
IP2	extracted from house; moderate motion
IP3	extracted from medusa; small motion
IP4	Fig. 6(b); by hand-held DC

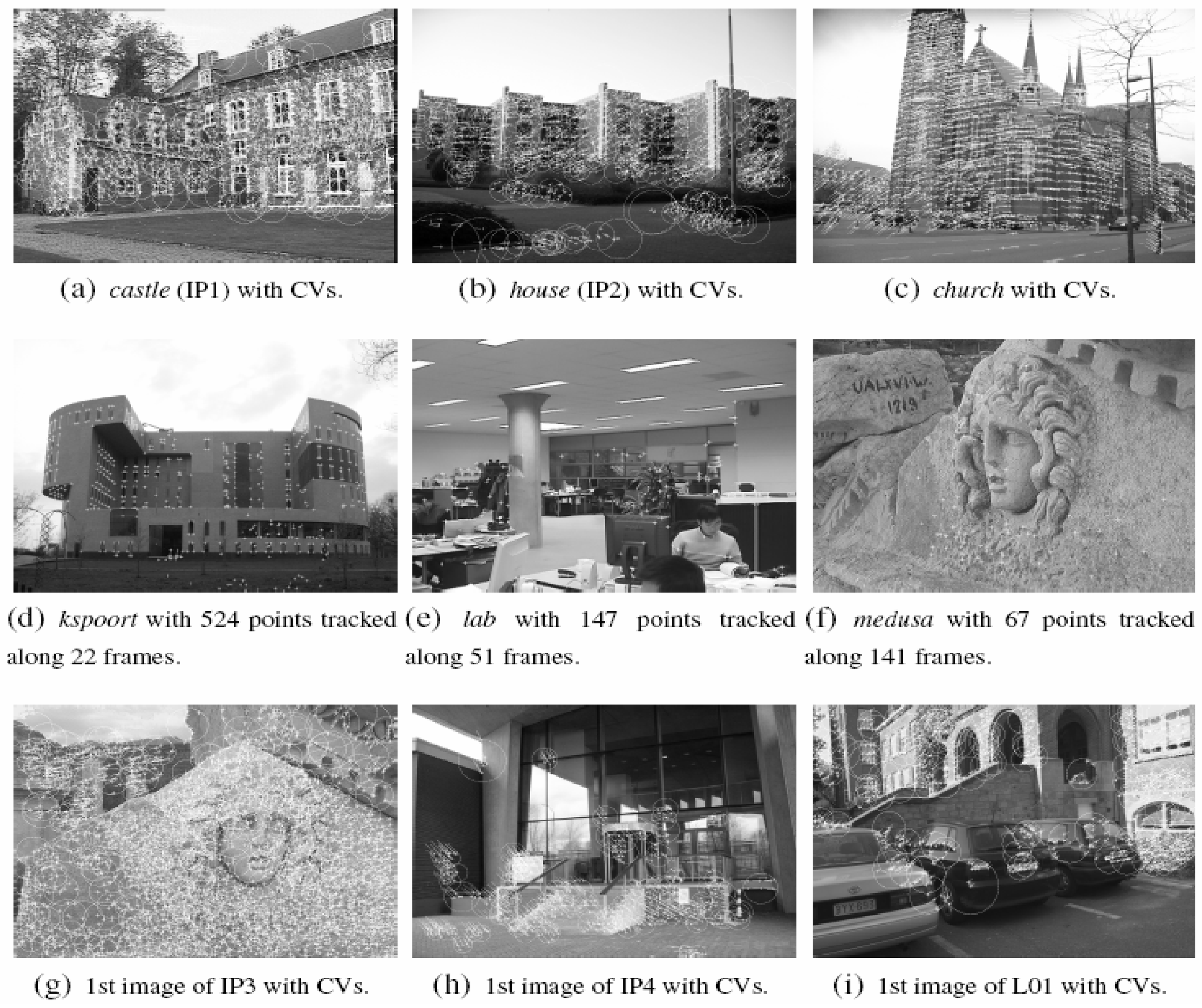

Fig.5: Test data and results

3.1 Two-frame matching

– *#CorrectMatches* = #Inliers to Homogray or F matrix
– *Recall* = #CorrectMatches / #DetectedMatches
– *Precision* = #CorrectMatches / #DetectedFeaturePoints

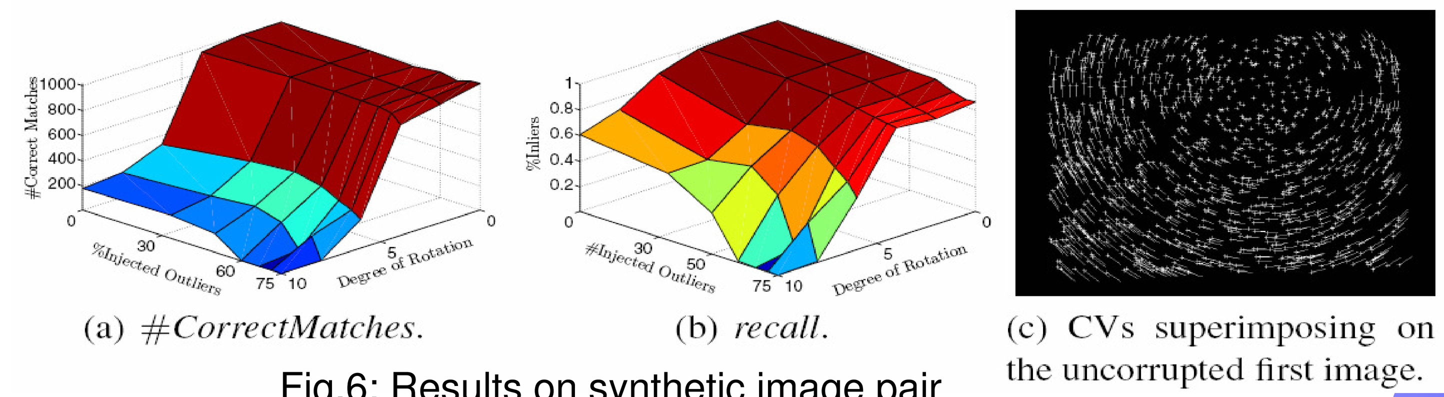

Fig.6: Results on synthetic image pair

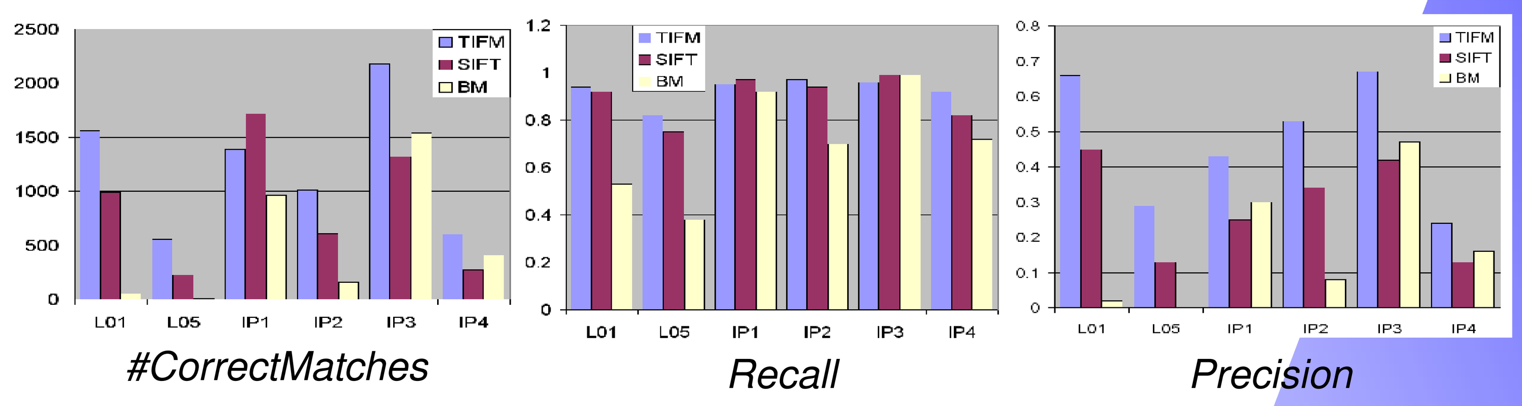

Fig.7: Results on all real image pairs

3.3 Tracking & structure reconstruction

– *#TrackedPoints*
– *Success of Fail of reconstruction*

Table 3. tracking and reconstruction results for 6 sequences

	Kspoort (0-21)	Castle(0-25)	Medusa (0-30)	Medusa (0-100)	House(0-5)	House(0-15)
TIFM	524S	242S	616S	156S	1152S	156S
SIFT	68F	19S	120S	13F	591F	179S
BM	3F	7F	14F	X	430F	79F
KLT	X	X	388F	70F	X	X

4 Conclusion

- We proposed a texture-independent feature-point matching algorithm that bases purely on the smoothness constraint
- TIFM is efficient and reliable, and outperforms SIFT, KLT, and BM for feature-point tracking in image sequences with small or moderate motion.

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