HOPE: Shape Matching Via Aligning Different K-hop Neighbourhoods

[1]Barakeel Fanseu Kamhoua, [1]Huamin Qu
[1]The Hong Kong University of Science and Technology

THE HONG KONG UNIVERSITY OF SCIENCE AND TECHNOLOGY

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- Learned vs Optimization based

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- Challenges in current optimization-based techniques
- New refinement strategy

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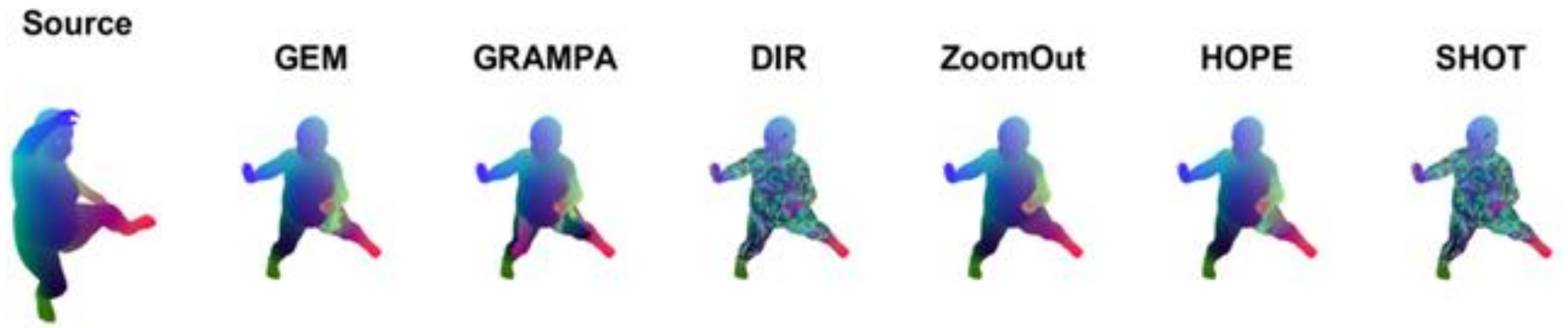
Introduction



Problem Definition: Shape Matching

- Given two shapes M and N, find the pointwise map $\pi_{M,N}$ that matches vertices (points) from M to vertices (points) on N

Problem Definition: Shape Matching

- Given the shapes M and N, we define vertex signatures (descriptors). These descriptors can be pairwise (P_M, P_N) or pointwise (Q_M, Q_N).
- Using pointwise descriptors, the shape matching problem becomes:
  - $\pi_{M,N} = argmin_{\pi_{M,N}} \left|\left| Q_M - \pi_{M,N} Q_N \right|\right|_F$
- Using pairwise descriptors, the shape matching problem becomes:
  - $\pi_{M,N} = argmin_{\pi_{M,N}} \left|\left| P_M \ \pi_{M,N} - \pi_{M,N} P_N \right|\right|_F$

Learned Vs Optimization Shape Matching

- **Optimization based Shape matching:** Initializes the map using descriptors, and use an iterative refinement strategy (using other shape descriptors)
  - $\pi_{M,N}^{k+1} = argmax_{\pi_{M,N}^{k+1}} Tr(\pi_{M,N}^{k+1} Q_M Q_N + \pi_{M,N}^{k+1} P_M \pi_{M,N}^{k} P_N)$

- **Learned shape matching:** Data dependent, learns the descriptors, then uses ***KNN*** or ***rounding (sinkhorn, softmax)*** to compute the final map. May explicitly use the ground-truth map for training (supervised) or may use other supervision signals such as functional maps.

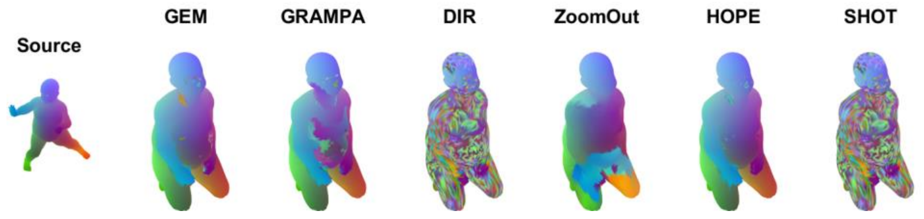
Paper's Contribution

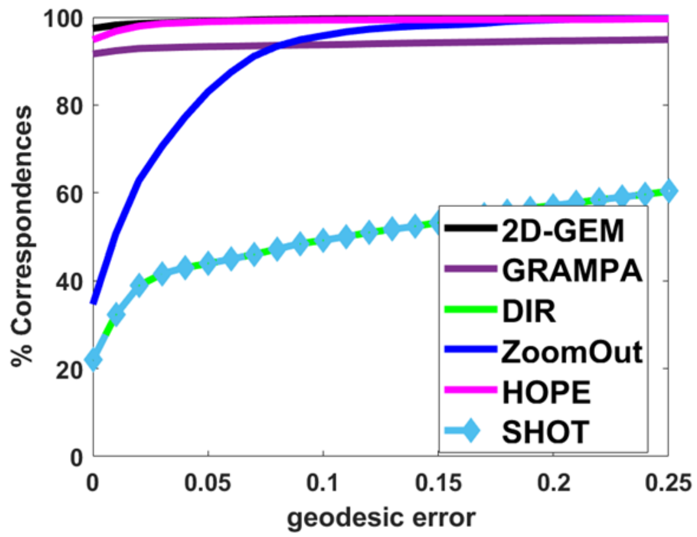
Challenges:

- Most current methods use LBO bases as descriptors ($Q_M, \; Q_N$) for refining an initialized map via the concept of functional maps:
  - $\pi_{M,N}^{k+1} = argmin_{\pi_{M,N}^T} \left|\left| Q_M \pi_{M,N}^{k+1} - Q_N C^T \right|\right|_F$
- Where the functional map C used to transport functions from shape N to shape M is obtained as
  - $C^T = min_{C^T} \left|\left| Q_M \pi_{M,N} - Q_N C^T \right|\right|_F$
- As such these methods can be seen as refining the map using well aligned soft clusters. Where the functional map aligns the clusters and a ***rounding*** or ***KNN*** is used to recover the map from the aligned soft clusters

Challenges:

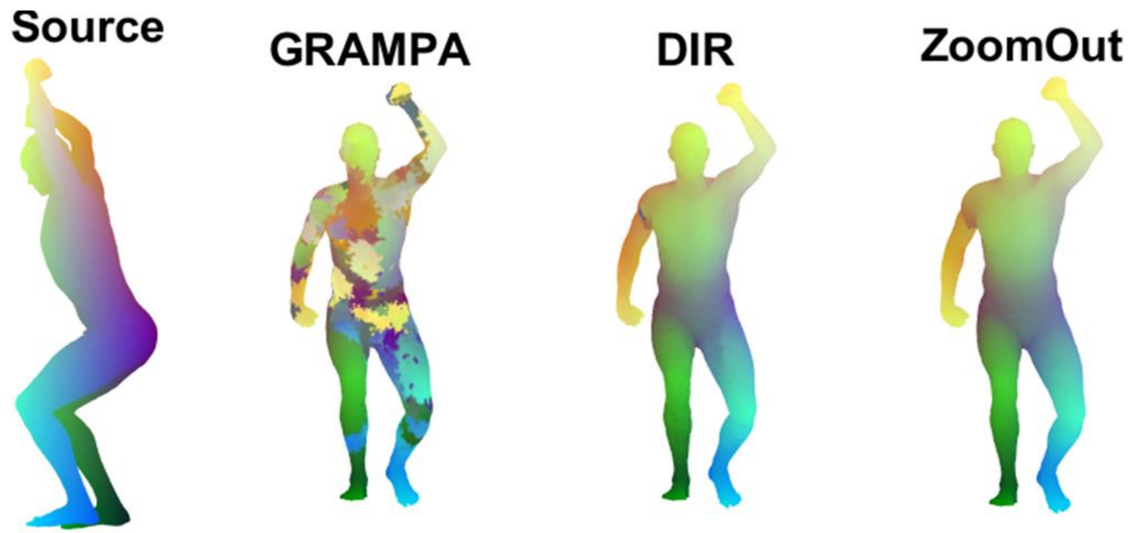
- **Not robust to noise nor to non-isometric deformations since:**
  - Noise can cause flips in the soft clusters
  - Lead to noisy functional map computation and noisy map recovery
- **Accuracy problem:**
  - Soft cluster indicators may not provide a unique enough description of a point since similar points may have sane (or indistinguishable) soft cluster indicator





Challenges:

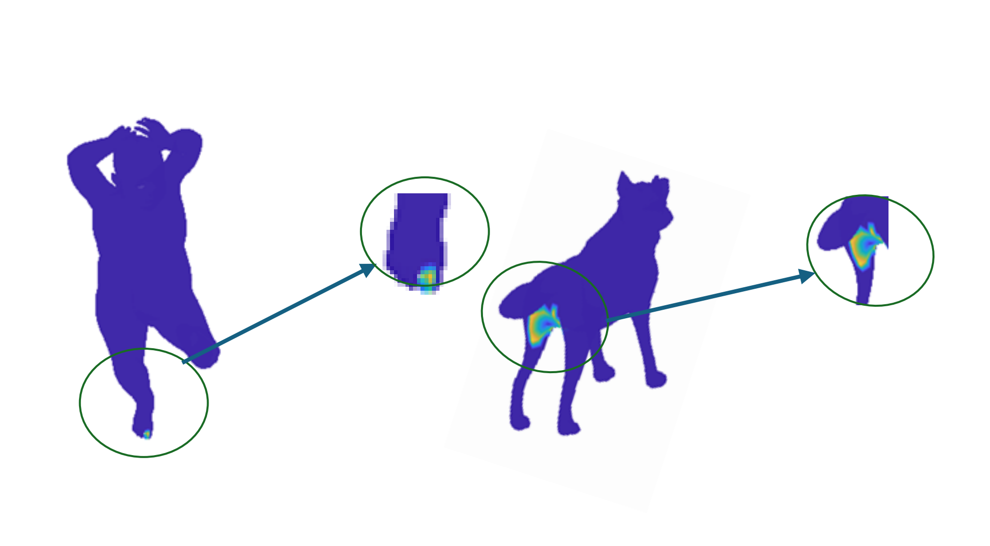
- **Generalization Problem:**
  - Methods (GRAMPA, GEM) which try to address noise suffer in near isometric scenarios, because most of them rely on triangulations which may not suitable especially in the presence of intrinsic symmetries and similar neighborhoods



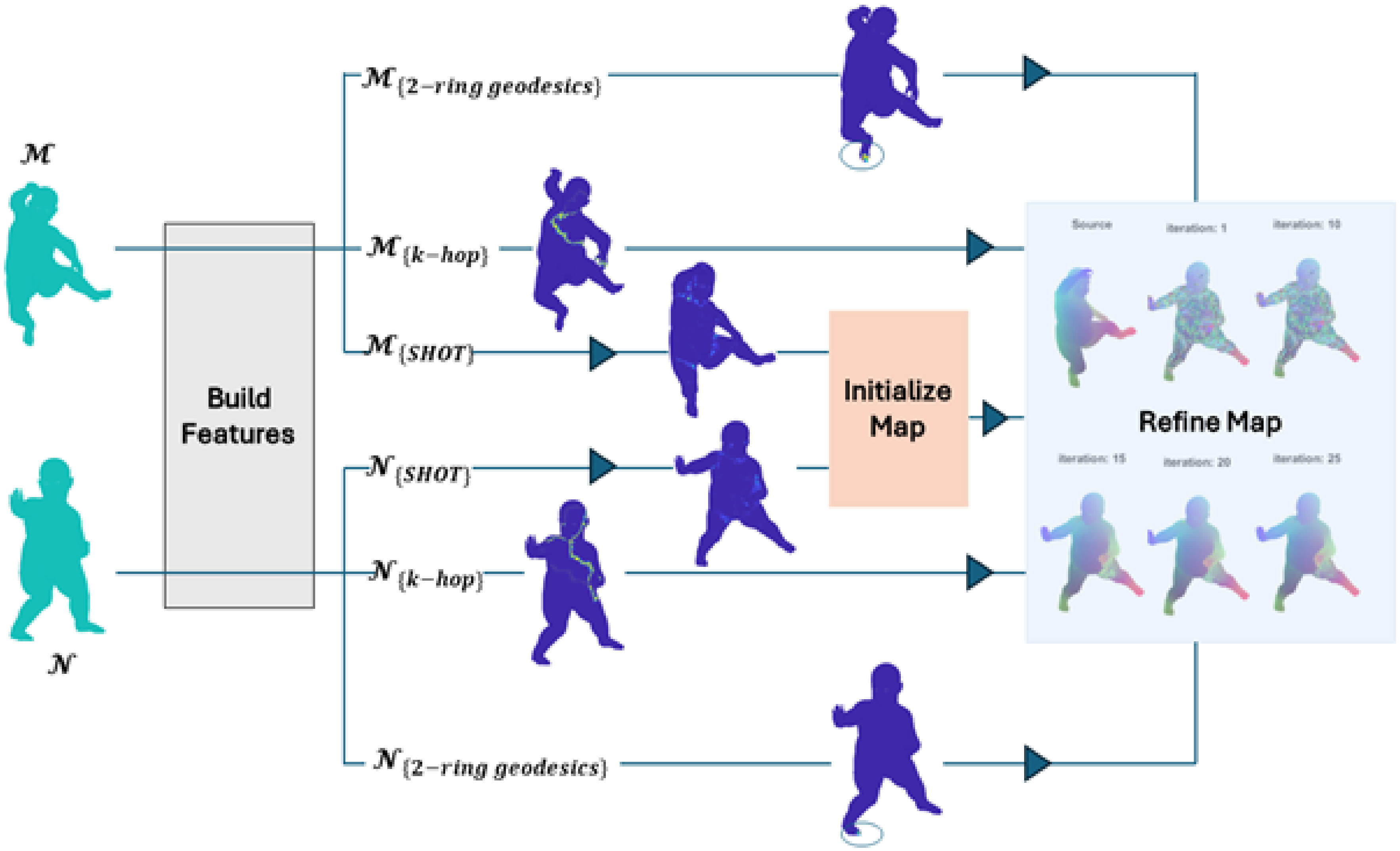
New Refinement Strategy:

- Use LMD to identify poorly matched points (Z) i.e., points whose 2-ring geodesic ball are extremely distorted by the map

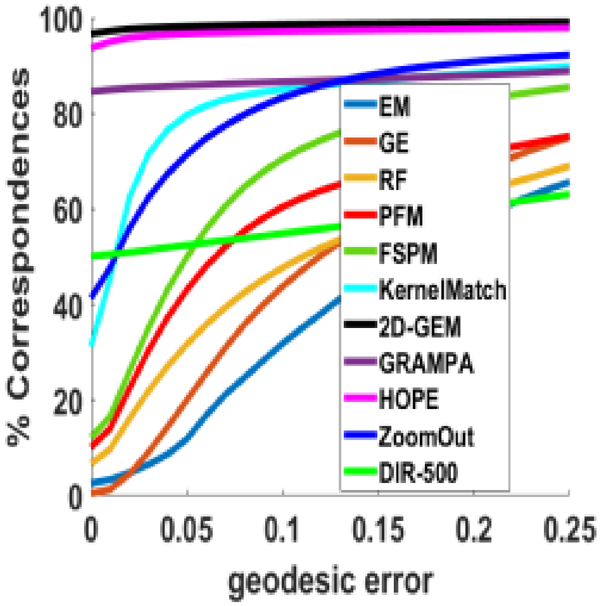
- Use robust K-hop neighborhoods to refine the map via:
- $\pi_{M,N}^{k+1}(Z) = \ argmax_{\pi_{M,N}^{k+1}(Z)} \ Tr(\pi_{M,N}^{k+1}(Z)P_M\pi_{M,N}^{k} \ P_N)$



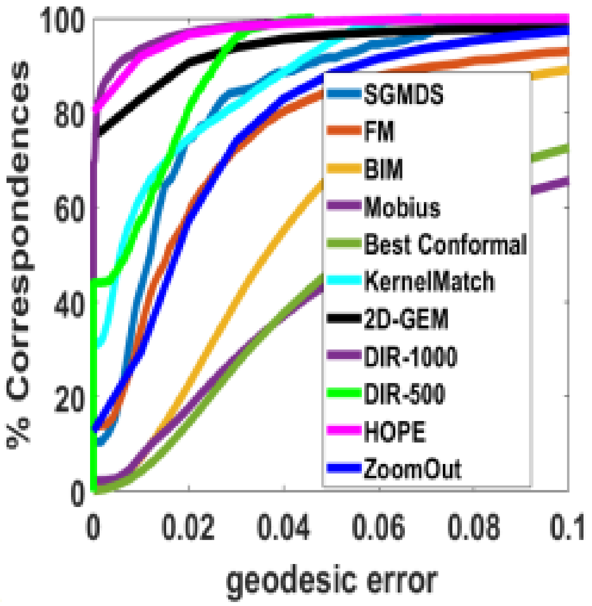
New Refinement Strategy: Pipeline



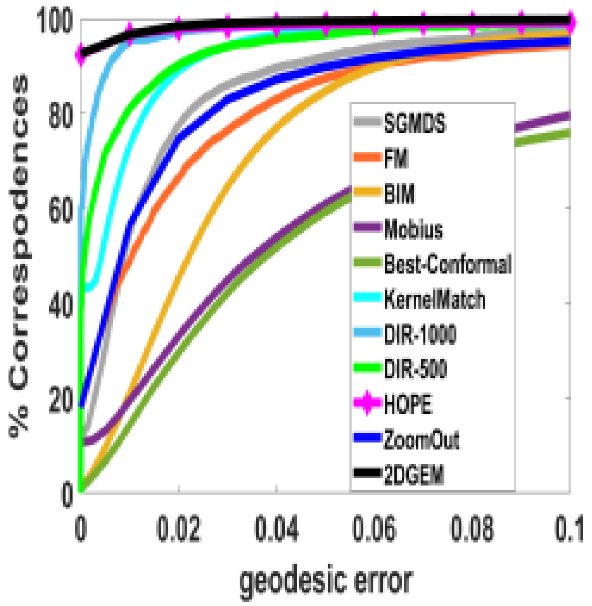
Experimental Results



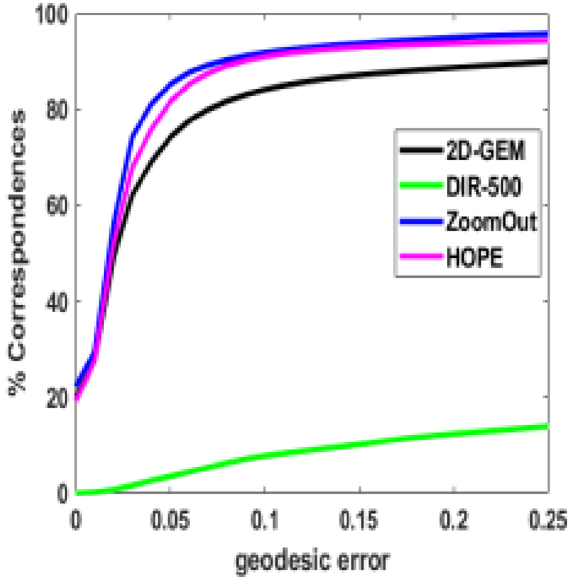
(a) TOPKIDS



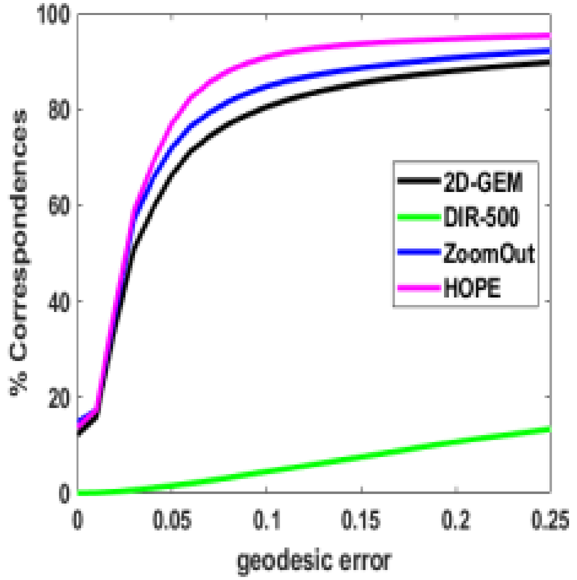
(b) SCAPE



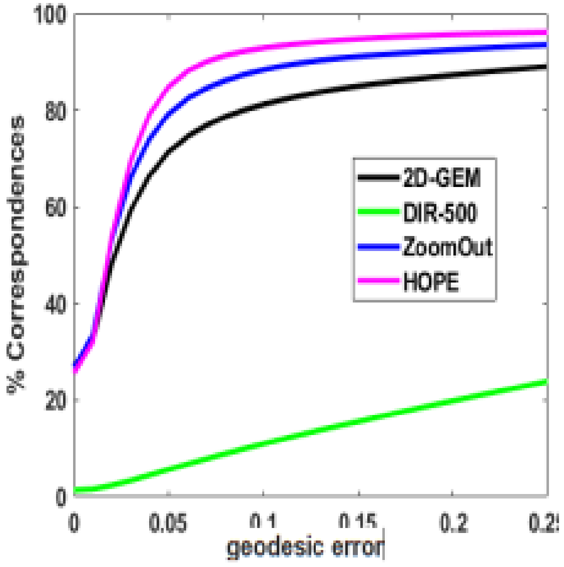
(c) TOSCA



(a) FAUST_r



(b) SCAPE_r



(c) TOSCA_r