E^{2}C^2: Efficient and Effective Camera Calibration in Indoor Environments

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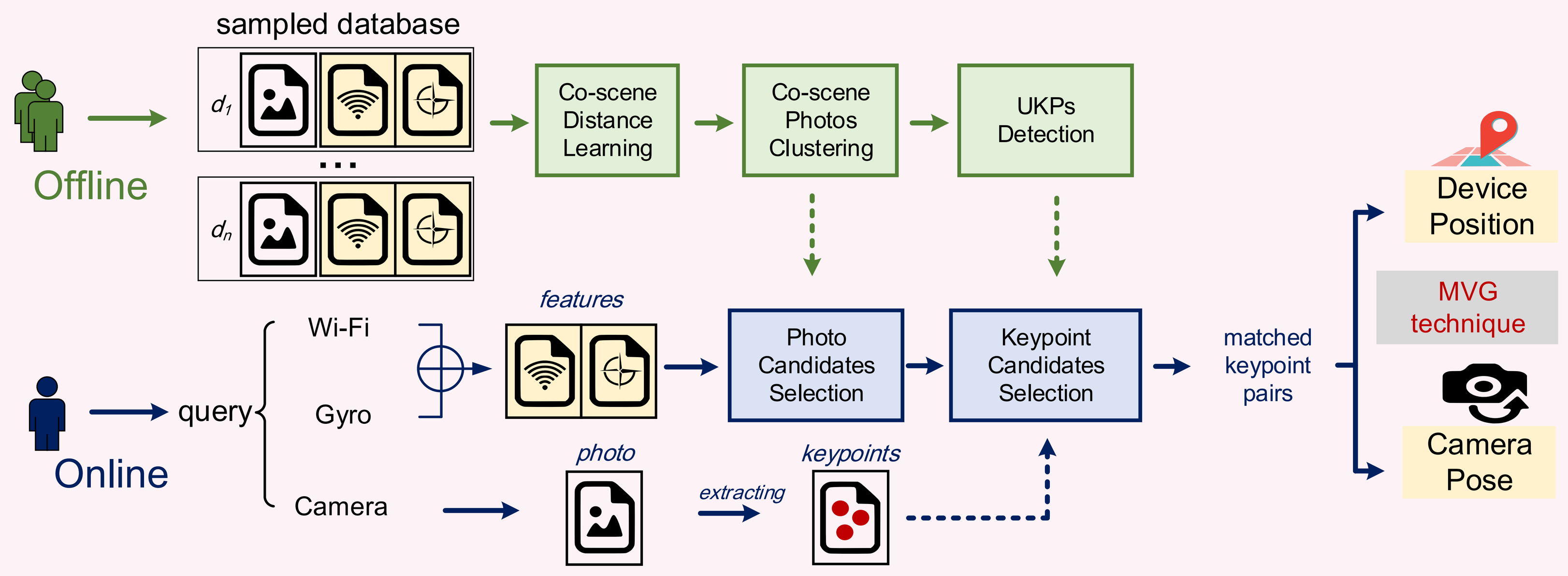
Introduction

- Mobile AR applications help people better interact with complex indoor environments, e.g., navigation in a museum.
- **Camera Calibration** requires sufficient keypoints distributed in other photos matched with the current camera view.
- Pairwise visual matching is computationally expensive.
- We are motivated to take advantage of embedded rich sensors as a way of pruning candidate photos to accelerate the calibration.

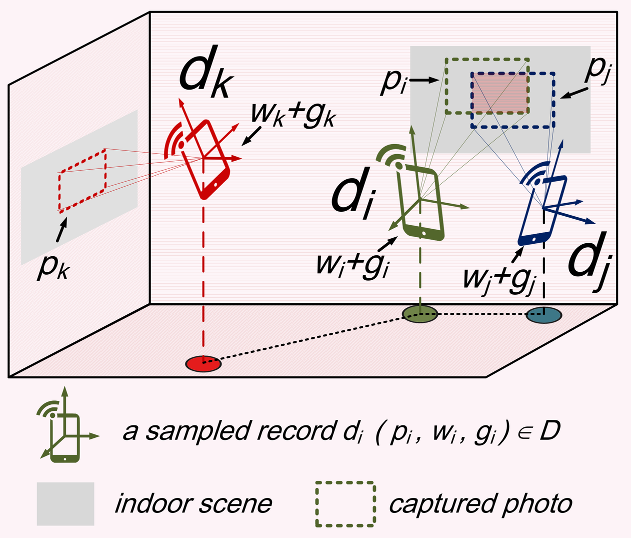
Framework Overview

- Our framework only needs a few sampled photos beforehand labeled with **Wi-Fi+gyro** information and can quickly select a small but sufficient set of SIFT points for calibration.



- **In the offline phase:**
  - capture a set of photos along with associated Wi-Fi and gyro sensor data.
  - cluster the captured photos into co-scenes according to a learned distance metric.
  - detect a subset of keypoints that are frequently appeared in each photo cluster.
- **In the online phase:**
  - select a set of photos in the nearest co-scene as photo candidates.
  - obtain several keypoint matches by only comparing with a few “useful keypoints”.
  - infer the extrinsic parameters (camera pose & position) with Multiple View Geometry(MVG) technique.

– Data Structure



- A database D, each record $d \in D$ has three fields:
  - a phone-captured photo p.
  - a set of consecutive Wi-Fi signals w.
  - device’s gyro information g.
- A constraint set C, each entry $c(d_i^{(1)}, d_i^{(2)}, y_i)$ determines if $d_i^{(1)}$ and $d_i^{(2)}$ are similar or not ($y_i \in \{-1, +1\}$). C is small-sized.

Offline Phase

- Learn a novel distance metric in order to bridge the gap between the query and the database.
- Cluster photos into distinctive clusters (each forms a *co-scene*).
- Find out “useful keypoints”(UKPs) located in each co-scene.

– Co-scene Distance Learning

- Create a synthetic feature vector ϑ by a linear combination of Wi-Fi+gyro

$$\vartheta = (w, \lambda g) = (w_1, ..., w_n, \lambda\alpha, \lambda\beta, \lambda\gamma, \lambda\omega) \quad (1)$$

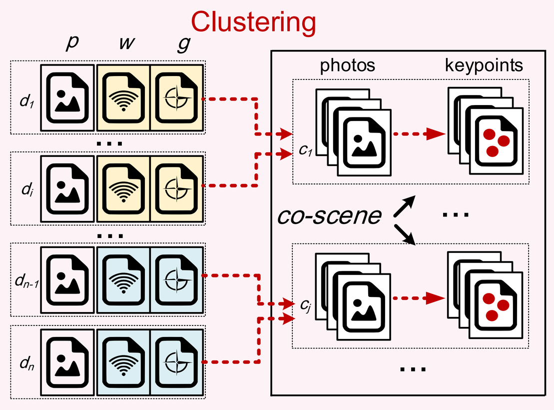
- Define the *co-scene distance* between two photos p_i and p_j by the definition of *Mahalanobis distance* as:

$$D_{cs}(p_i, p_j) = \sqrt{(\vartheta_i - \vartheta_j)^T \ M_\vartheta \ (\vartheta_i - \vartheta_j)} \quad (2)$$

- ITML is effective to optimize the distance, which is to regularize the parameter M_ϑ to be as simple as possible while satisfying the similarity and dissimilarity constraints in the set C.

– Co-scene Photos Clustering

- Cluster the photos in our database into k groups, photos in each cluster form a “co-scene”.
- k is a hyperparameter that needs to be tuned by cross validation.



– UKPs Detection

- Co-scenes help reduce photo candidates, still expensive if we iterate through all keypoints located in co-scenes.
- Detect “useful keypoints”(UKPs):
  - count the frequency of each keypoint by matching photos pairwisely in the same co-scene.
  - only frequently appearing ones are useful for further calibration.
- Consequently, UKPs (red) are selected from the whole local features (blue) by UKPs Detection.

Online Phase

- The online query contains the same structure of a sampled record d in the offline phase.
- Pick out the keypoint pairs between the query and other photos by a two-level selection.

– Photo Candidates Selection

- Compose the synthetic feature ϑ_q for the query according to Equation 1.
- Find the nearest co-scene by comparing ϑ_q with all cluster centroids based on the learned distance metric.
- As a result, all photos in that co-scene are considered as photo candidates.

– Keypoint Candidates Selection

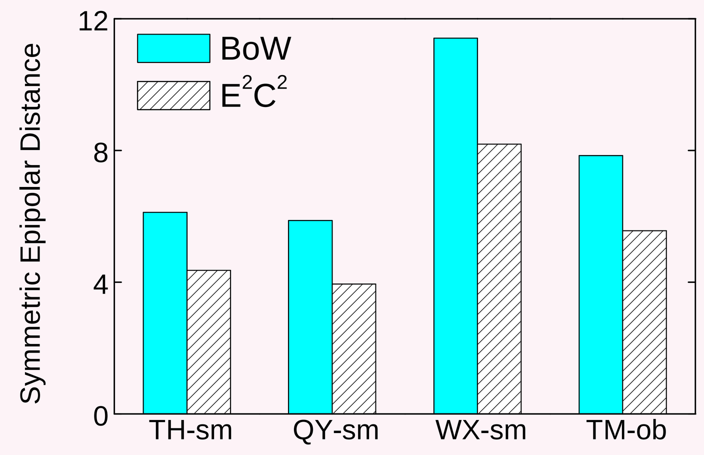
- Only need to compare keypoints in the query with these UKPs to confirm the ultimate matched keypoint pairs.
- The UKPs are only a small portion of all the keypoints, the online matching is accelerated.
- Finally, we use those few good matched keypoint pairs to estimate the query photo’s camera pose as well as the position by a MVG process.

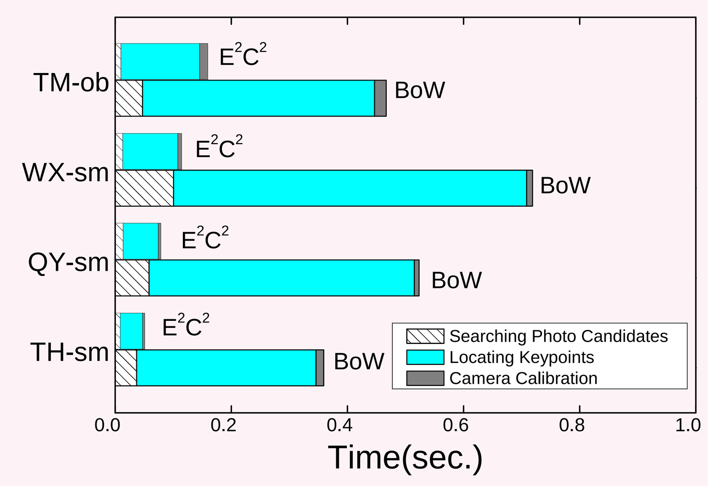
Experiments

dataset	#images	#floors
TH-sm	968	6
QY-sm	1151	6
WX-sm	1674	7
TM-ob	823	3

- An Android app was developed to collect data.
- 4 volunteers, 3 shopping malls and 1 office building.
- They were also required to indicate a few similar and dissimilar pairs to construct the constraint set C.
- 2 other volunteers collected a query set, 50 queries for each place.

– Experimental Studies





- Baseline approach:
  - a state-of-the-art bag-of-visual-words(BoW).
  - cluster all the extracted SIFT points into a dictionary with 5K visual words.
- Effectiveness of our framework:
  - lower values of SED indicate a better calibration accuracy.
  - our proposed approach outperforms BoW in each dataset.
  - the detected UKPs prove to be more robust and discriminative than simple brute-force matching.
- Efficiency of our framework:
  - our framework beats the baseline with a significantly reduced online processing cost.
  - we lower the cost of searching photo candidates since our searching space is reduced to cluster centroids instead of complete photos.
  - the cost of searching keypoints is decreased remarkably due to the UKPs detection.

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