

# FAST HYPOTHESIS FILTERING FOR MULTI-STRUCTURE GEOMETRIC MODEL FITTING

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## MOTIVATION

- Performance of clustering based robust multi-model fitting algorithms depends on quality of hypotheses generated.
- Sampling based hypothesis generation leads to a significant proportion of irrelevant hypotheses.

## CONTRIBUTIONS

- We propose a novel fast and efficient two-stage hypothesis filtering technique that can improve performance of clustering based robust multi-model fitting algorithms.
- Our approach leverages the asymmetry in the distributions of points around the inlier/outlier boundary via the sample skewness computed in the residual space.
- The output is a set of promising hypotheses which aid multi-model fitting algorithms in improving accuracy as well as running time.

## ILLUSTRATIVE EXAMPLE- MULTIPLE LINE FITTING

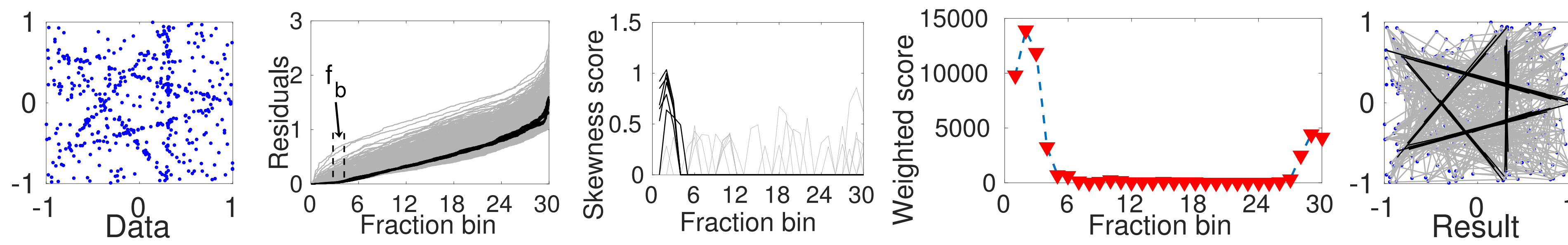


Figure 1: FHF pipeline: **Grey:-** Bad hypotheses, **Black:-** Good hypotheses

## RESULTS- QUANTITATIVE

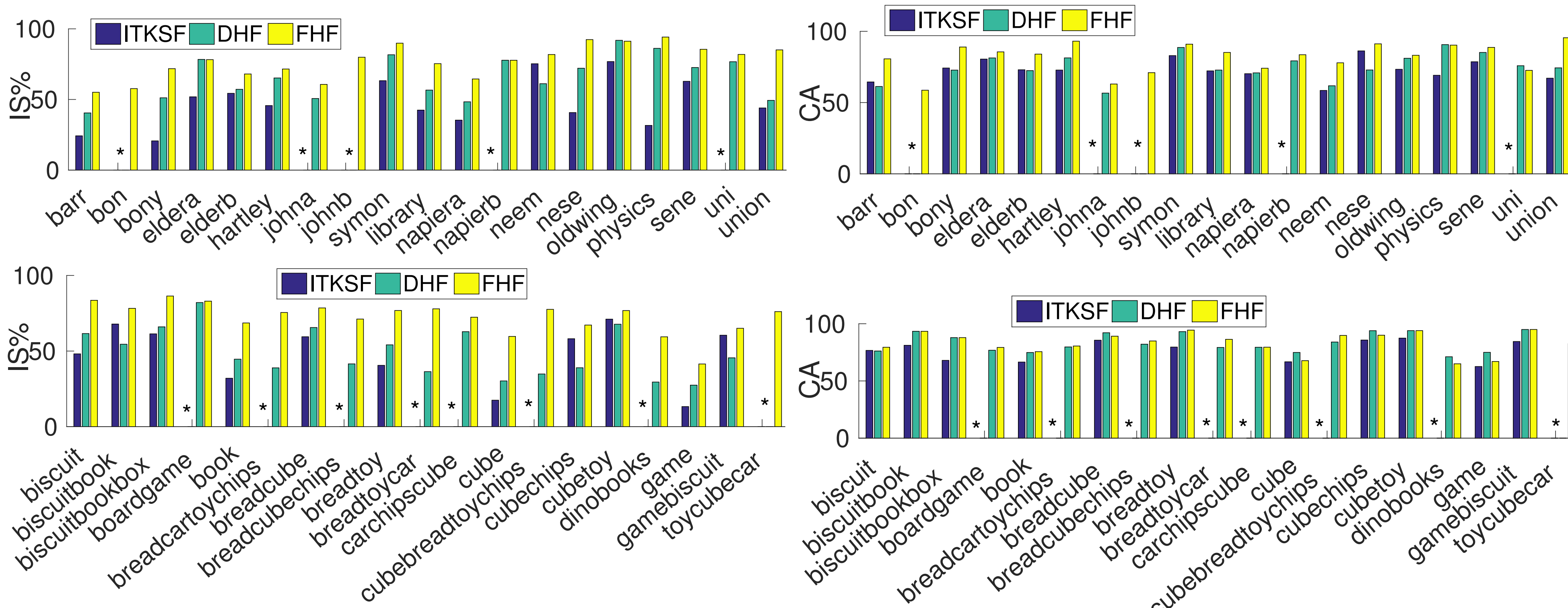


Figure 2: Comparison with ITKSF[1] and DHF[1]. **Row-1:** Homography fitting, **Row-2:** Fundamental matrix fitting. Clustering Accuracy(CA in %) of T-Linkage[3] when the input was the set of hypotheses retained by FHF. (AdelaideRMF[2] dataset).

## SAMPLE RESULTS- QUALITATIVE

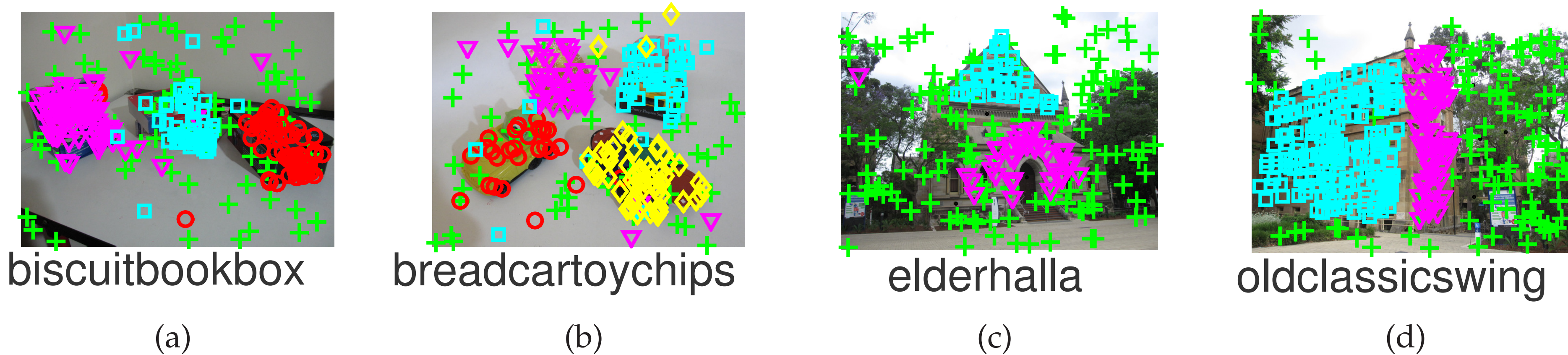


Figure 3: Fundamental matrix fitting(a,b), Homography fitting(c,d)

## REFERENCES

- [1] H. S. Wong, T. T. Chin, J. Yu, D. Suter. A simultaneous sample-and-filter strategy for robust multi-structure model fitting In CVIU'13
- [2] H. S. Wong, T. T. Chin, J. Yu, D. Suter. Dynamic and hierarchical multi-structure geometric model fitting In ICCV'11
- [3] L. Magri, A. Fusiello. T-linkage: A continuous relaxation of j-linkage for multi-model fitting In CVPR'14

## PROPOSED APPROACH

**Data:**  $\mathcal{X} = \{x_j\}_{j=1}^N$

**Initial hypotheses:**  $\vartheta = \{\theta_i\}_{i=1}^M$

**Absolute residuals:**  $r_i^j = \phi(\theta_i, x_j)$

### Stage-1 Skewness Based Filtering

- compute skewness score  $S_{iq}$  at each  $q^{th}$  fraction bin,  $q = 1, \dots, Q$ .
- $S_{iq} = \frac{1}{|wN|} \sum_{j \in f_i^q} \left( \frac{\phi(\theta_i, x_j) - \mu}{\sigma} \right)^3$
- for each hypothesis retain only top three skewness scores  $\bar{S}$ .
- skewness threshold  $\tau = \min_q \max_i \bar{S}_{iq}$
- $\mathcal{H}_q$  be the index set of hypotheses at the  $q^{th}$  fraction bin that yield a skewness value at least  $\tau$ .
- weighted score  $c_q = |\mathcal{H}_q| \sum_{i \in \mathcal{H}_q} \bar{S}_{iq}$
- largest fraction bin  $\hat{q} = \arg \max_q c_q$
- $\vartheta_1 = \{\theta_i | \bar{S}_{iq} \geq \tau, \theta_i \in \vartheta, q = 1, \dots, \hat{q}\}$

### Stage-2 Preference Based Pruning

- $\mathcal{X}^{\vartheta_1} \subset \mathcal{X}$ , comprising all minimal subsets corresponding to hypotheses in  $\vartheta_1$ .
- $\mathcal{I}_k^{\theta_j^1}$  be the index set of points in  $\mathcal{X}^{\vartheta_1}$  with the smallest  $k$  residuals with respect to  $\theta_j^1 \in \vartheta_1$ .
- $\beta$  is the overlap threshold.
- $\alpha$  is the minimum similar hypotheses.

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1 Input:  $\{\mathcal{I}, \vartheta_1, k, \beta, \alpha\}$ 
2 Output:  $\{\vartheta_{II}\}$ 
3 begin
4   for  $j \leftarrow 1$  to  $|\vartheta_1|$  do
5      $\vartheta_{temp} \leftarrow \{\emptyset\}, c \leftarrow 0$ 
6     for  $l \leftarrow 1$  to  $|\vartheta_1|; l \neq j$  do
7        $olap = \left( \left| \mathcal{I}_k^{\theta_j^1} \cap \mathcal{I}_k^{\theta_l^1} \right| \right) / k$ 
8       if  $olap \geq \beta$  then
9          $c \leftarrow c + 1$ 
10         $\vartheta_{temp} \leftarrow \{\vartheta_{temp} \cup \theta_l^1\}$ 
11      if  $c \geq \alpha$  then
12         $\vartheta_{II} \leftarrow \{\vartheta_{II} \cup \vartheta_{temp} \cup \theta_j^1\}$ 
13         $\vartheta_1 \leftarrow \vartheta_1 \setminus \vartheta_{II}$ 
14 return  $\vartheta_{II}$ 

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## SOURCE CODE

The source code is available at author's webpage



<https://www.iiitd.edu.in/~lokendert/>