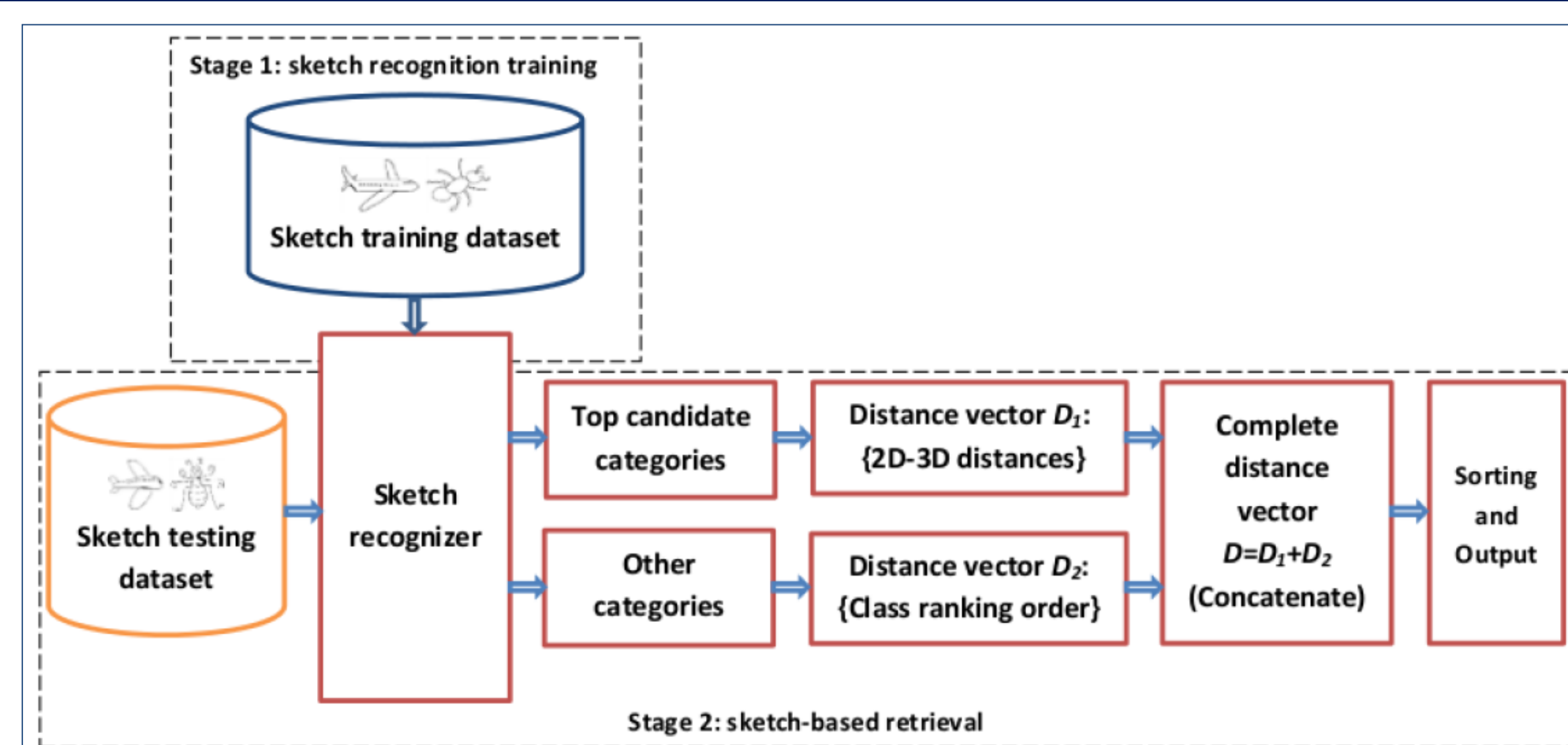


Overview

- Research Topic:** Query-by-Sketch is an intuitive scheme; promising in game design, 3D animation and human computer interaction, etc
- Problem:** Big semantic gap exists between human-drawn sketches and 3D models
 - ❖ *2D human-drawn sketch:* an iconic representation of an object; several simplified and exaggerated curves; arbitrary styles; high-level abstraction; drastic simplification
 - ❖ *3D model of an object:* accurate representation of the geometry information
- Consequence:** Such big semantic gap makes the search based on a direct 2D-3D comparison suffer low accuracy and high computational cost
- Motivation:** Bridge the semantic gap
- Our Semantic Sketch-Based 3D Model Retrieval Approach:** First recognizing the potential semantic meanings of the user sketch and then performing 2D-3D matching for the 3D models within the predicted categories
- Overview of Our Results:** Significant improvements in both search accuracy and efficiency

Framework



Algorithm

- Stage 1: Sketch Recognition Training**
 - ❖ (1) *Sketch feature extraction. Hybrid features:* Eitz et al.'s [2] 500-dimensional *local* feature vector + our proposed 119-dimensional *global* feature vector, which comprises 9 distance histograms:
 - ✓ 5 radial distance histograms of the sketch pixels with respect to 5 selected reference points/lines
 - ✓ 2 radial distance histograms of the first intersection points
 - ✓ 2 radial angle histograms of the sketch pixels with respect to the two centers C and FPC

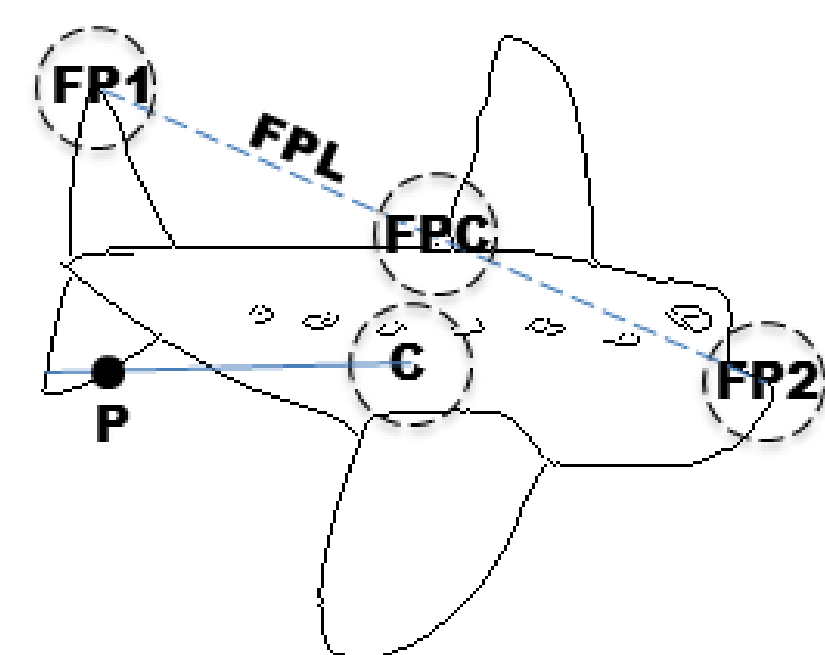


Fig. Illustration of our 5 reference points or lines for the global features: C, FP1, FP2, FPL and FPC, where C is the centroid of a sketch, FP1 and FP2 are the two farthest points with respect to the centroid C, FPL is the line between the two farthest points; and FPC is the center of the FPL line. P is an example of first intersection point.

Algorithm (Cont.)

- ❖ (2) *Sketch classifier training.* Support Vector Machine: adopt same parameter settings as [2] including local feature definitions, "soft" kernel-codebook coding choice, vocabulary size, and 3-fold cross-validation selection except for RBF kernel ($\gamma=0.1$ and $C=20$)
- Stage 2: Sketch-Based Retrieval**
 - ❖ (3) *Sketch classification.* Predict all the possibilities of the input sketch belonging to all the categories
 - ❖ (4) *2D-3D matching.* The state-of-the-art sketch-based retrieval approach SBR-2D-3D [4] is applied on all the models in the top L candidate categories, which makes our approach SBR_SVM-2D-3D. The distances between the models and the input sketch, named D_1 , are calculated
 - ❖ (5) *Distance vector generation.* Assign distances between the input sketch and the models in the left categories as the second part of D, named D_2 : set to be the ranking orders of their respective categories. Concatenate D_1 and D_2 into D
 - ❖ (6) *Ranking and output.* All the distances in D are sorted and the relevant models are listed accordingly

Experiments

- SHREC'13 Sketch Track Benchmark:** A large scale sketch-based shape retrieval benchmark
 - ❖ 7200 hand-drawn sketches: uniformly distributed on 90 classes
 - ❖ 1258 relevant 3D models: selected from the PSB benchmark, as the target 3D dataset
 - ❖ "Training" and "Testing" datasets: randomly selecting 50 sketches per class for training and the rest 30 sketches for testing; while the complete target model dataset is remained as a whole for both training and testing purpose

Sketch Recognition Results

Table 1. Average classification performance comparison in terms of eight metrics. The first two rows are for the SHREC'13 Sketch Track Benchmark; the last two rows (*) are for the Eitz et al.'s [2] complete sketch benchmark.

	TP	FP	P	R	F	MCC	ROC	PRC
Our	0.613	0.004	0.623	0.613	0.614	0.612	0.982	0.664
LSR	0.594	0.005	0.597	0.594	0.593	0.590	0.974	0.637
Our*	0.545	0.002	0.549	0.545	0.544	0.544	0.772	0.326
LSR*	0.520	0.002	0.523	0.520	0.519	0.518	0.759	0.298

- ❖ *Timing:* averagely 0.1 second is needed to classify a sketch

Sketch-Based Retrieval Results

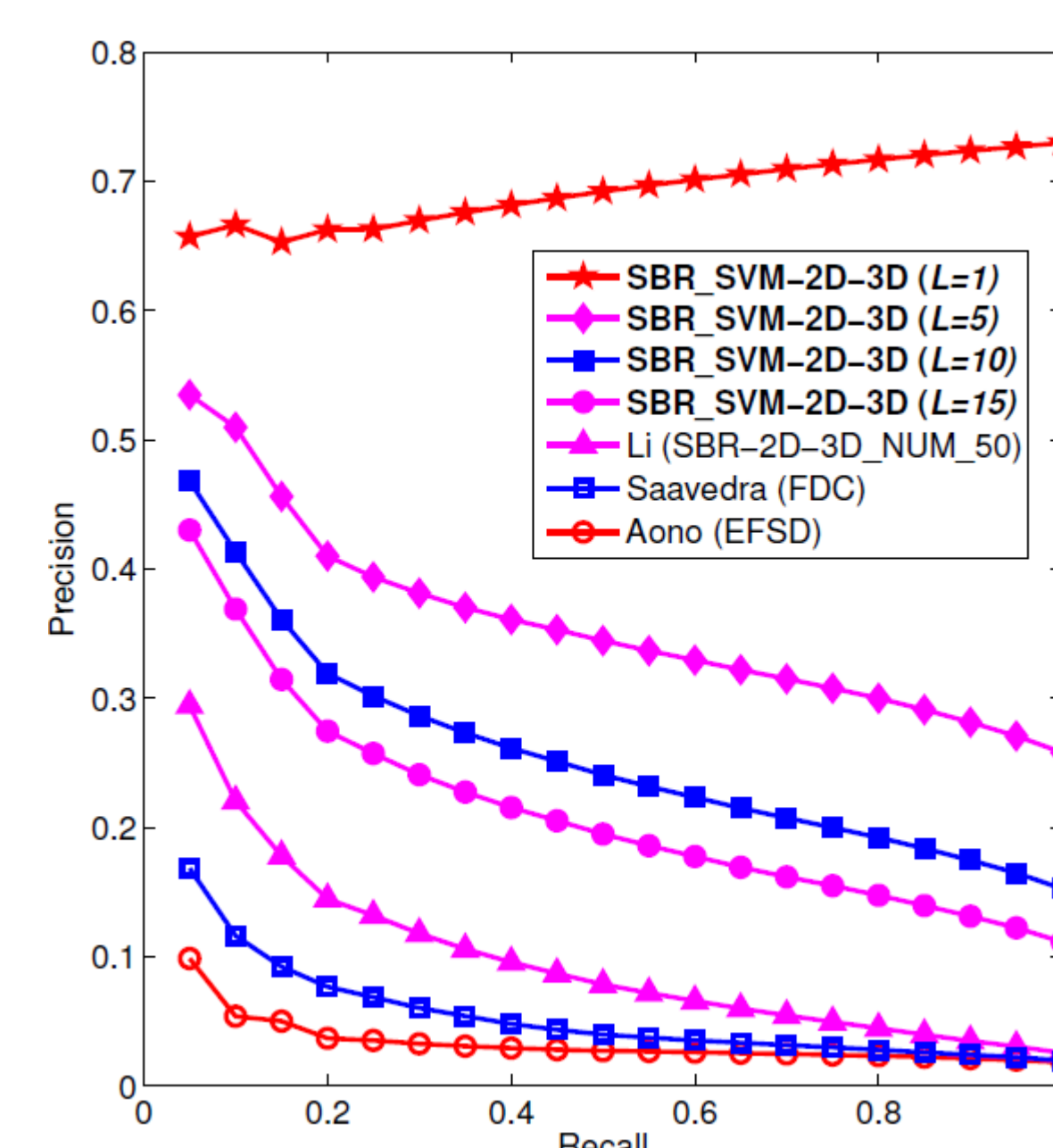


Fig. Precision-Recall diagram performance comparison between our SBR SVM-2D-3D (different L values) method and the participating approaches in the SHREC'13 Sketch Track Contest on the "Testing" dataset.

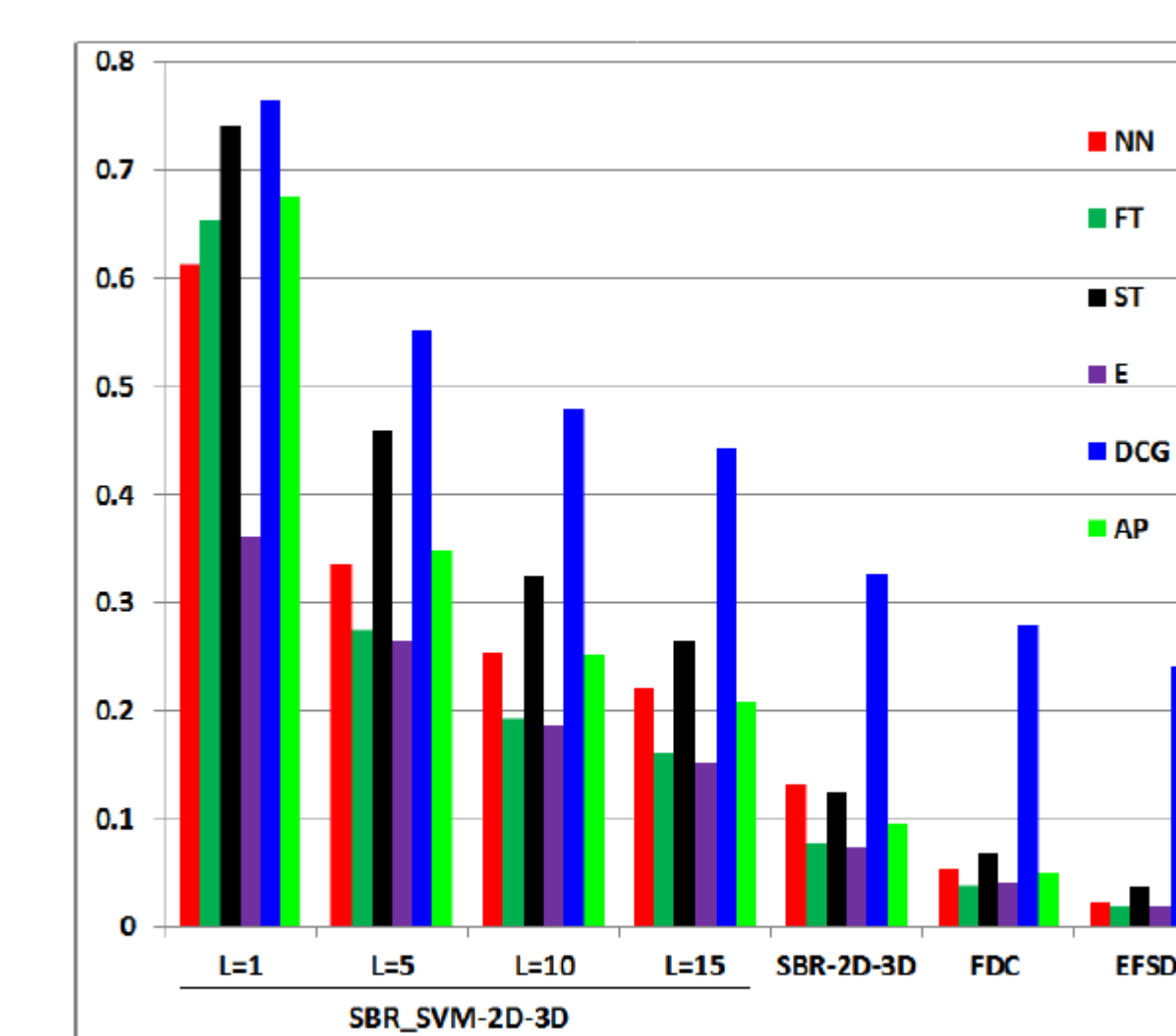


Fig. Other performance metrics comparison between our semantic algorithm SBR SVM-2D-3D (different L values) and the participating approaches in the SHREC'13 Sketch Track Contest on the "Testing" dataset.

Experiments (Cont.)

Table 2. Timing information comparison: t is the average response time per query based on a modern computer.

Method	SBR_SVM-2D-3D				SBR-2D-3D	FDC	EFSD
	L=1	L=5	L=10	L=15			
t (s)	1.43	4.88	9.32	13.26	43.93	0.02	20.24

- ❖ (1) Our semantic retrieval approach *significantly* improves the retrieval performances (100%~700% better accuracy) than other state-of-the-art sketch-based retrieval algorithms
- ❖ (2) In this experiment, keeping only the top *first* candidate category is the best choice in terms of both accuracy and efficiency. However, for other datasets, the situation may be *varied* due to different sketch recognition performances
- ❖ (3) Sketch-based 3D model retrieval based on semantic information will have broad application *potentials* on the applications which require *real-time* response time

Conclusions

- Our semantic sketch-based 3D model retrieval algorithm is an important improvement to encompass the semantic gap between the sketches and models.
 - ❖ It achieves the *significant* improvements in both retrieval accuracy and computationally efficiency
- Future work:* study the integration of unsupervised or semi-supervised sketch recognition module when the label information of the target 3D model dataset is not available

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