

## Introduction

### ● Motivations:

- Mobile videos are prevalent
  - YouTube statistics: ~20% mobile videos, ~3hours/min upload
- Increasingly geo-tagged
- Spatial-temporal video queries are demanding, e.g.,
  - “Find videos recorded in front of Tommy Trojan on the 2013 USC-UCLA football game day”

### ● Challenge:

- The fusion of location, time and direction
- Existing indexes are not efficient

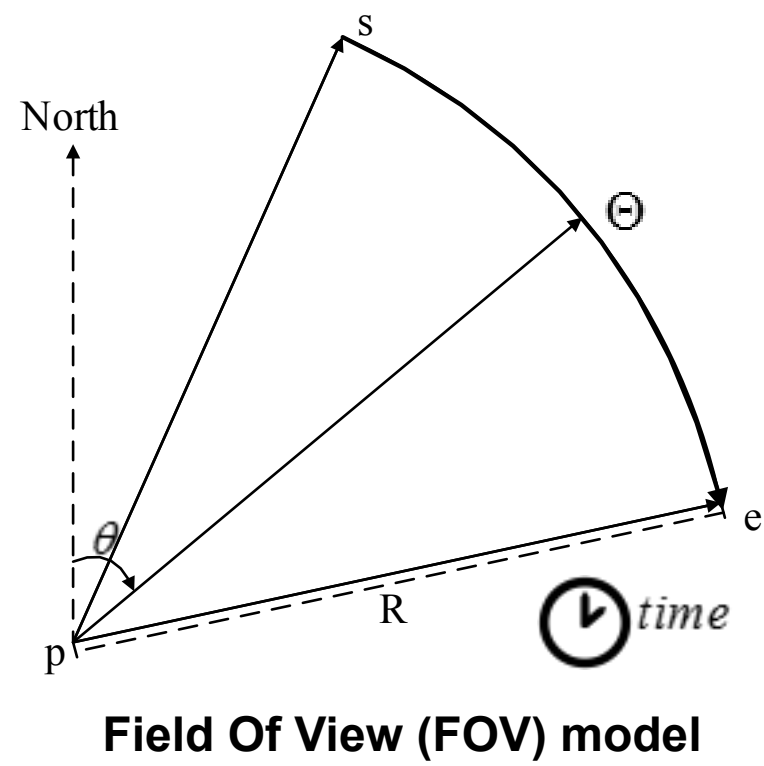


### ● How to efficiently index and search the large-scale videos by using the geo-metadata?

## Video Frame Model

### ● Model a video frame $f$ in form of $(p, \theta, R, time)$

- $p$ : camera location
- $\theta$ : view orientation
- $R$ : maximum viewable distance
- $time$ : timestamp



## Existing Indexes

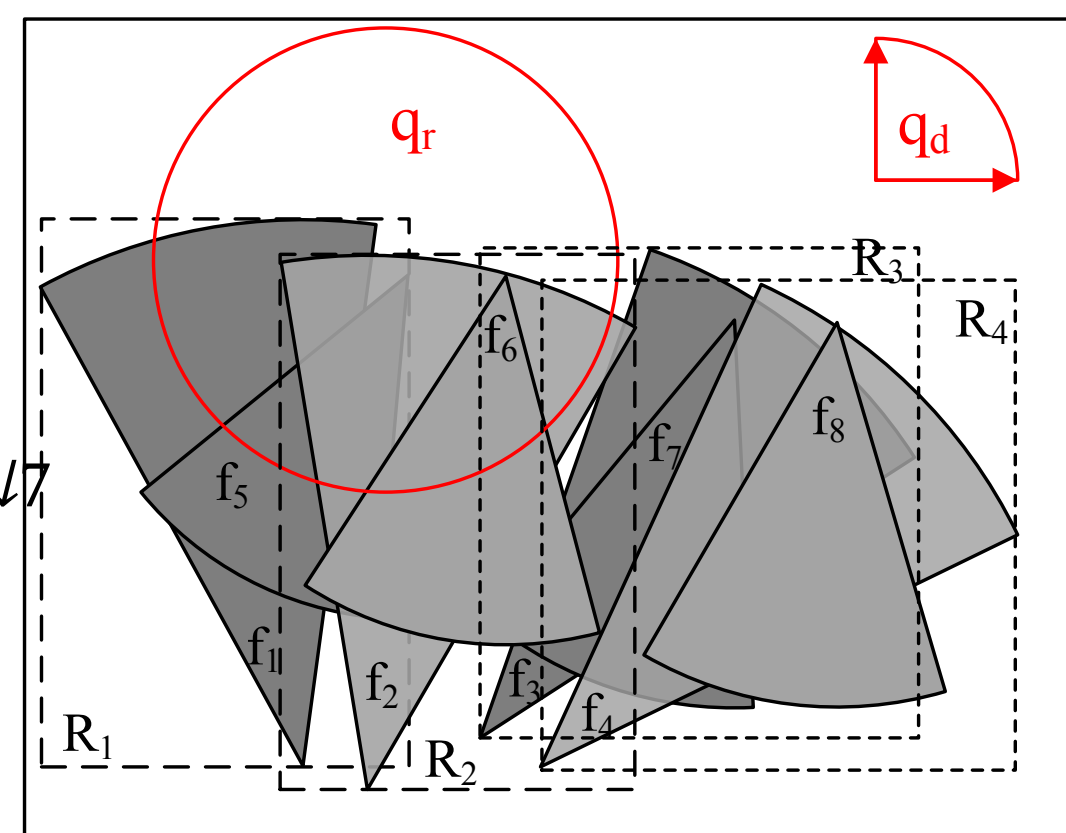
### ● R-tree [1]

#### - Range query $q_r$

- results:  $f_{11}, f_{12}, f_{15}, f_{16}$
- visit: node#=4; FOV#=7
- unnecessary visit:  $R_{13}, R_{14}, f_{13}, f_{14}, f_{17}$

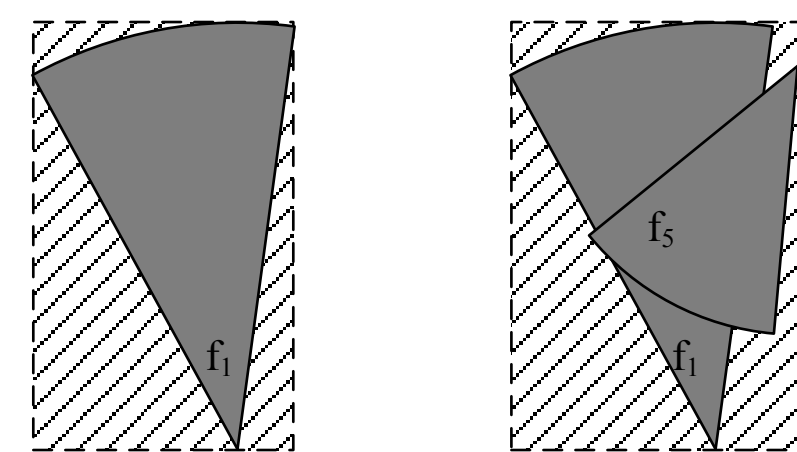
#### - Directional query $q_d$

- results:  $f_{11}, f_{12}, f_{13}, f_{14}$
- visit: node#=4; FOV#=8
- unnecessary visit:  $f_{15}, f_{16}, f_{17}, f_{18}$



#### - Drawbacks

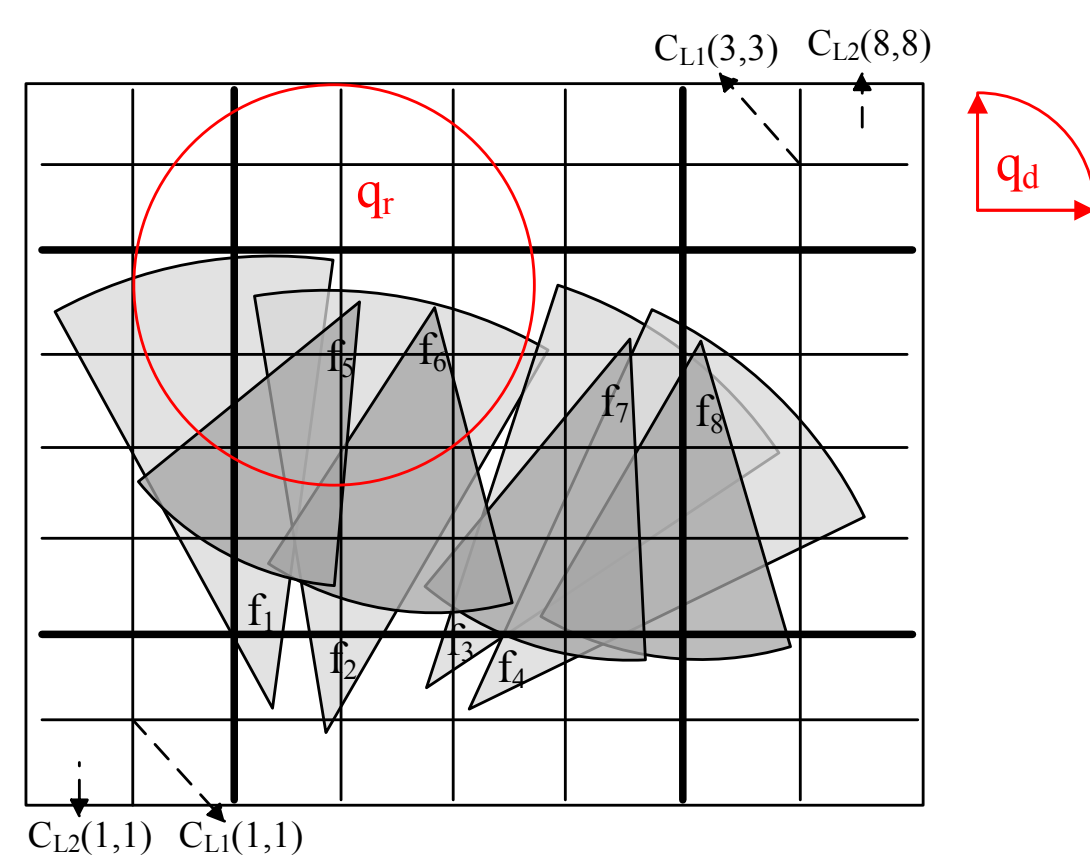
- Large “dead space”
- Large “overlap” →
- No directional info in index nodes
- Only based on area optimization criteria



### ● Grid based index [2]

#### - Drawbacks

- Need prior knowledge: cell size
- Store direction info 3<sup>rd</sup> level only
- Unnecessary visit:  $f_{15}, f_{16}, f_{17}, f_{18}$



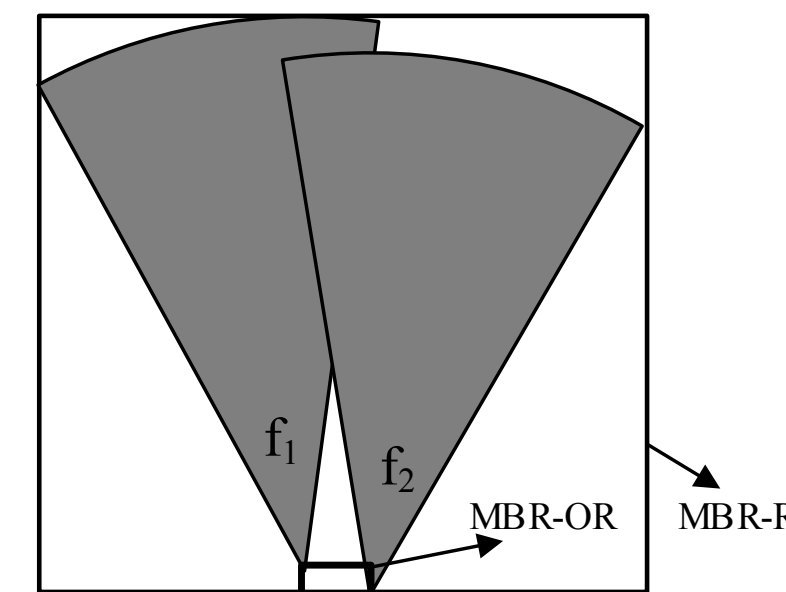
C <sub>L1</sub>	
C <sub>L1</sub> (2,1)	$f_1, f_2, f_3, f_4, f_7, f_8$
C <sub>L1</sub> (3,1)	$f_8$
C <sub>L1</sub> (1,2)	$f_1, f_5$
C <sub>L1</sub> (2,2)	$f_1, f_2, f_3, f_4, f_5, f_6, f_7, f_8$
C <sub>L1</sub> (3,2)	$f_3, f_4, f_8$

C <sub>L2</sub>	
C <sub>L2</sub> (3,1)	$f_2$
C <sub>L2</sub> (3,2)	$f_8$
C <sub>L2</sub> (4,2)	$f_3$
C <sub>L2</sub> (5,2)	$f_4$
C <sub>L2</sub> (4,6)	$f_5, f_6$
C <sub>L2</sub> (6,6)	$f_7$
C <sub>L2</sub> (7,6)	$f_8$

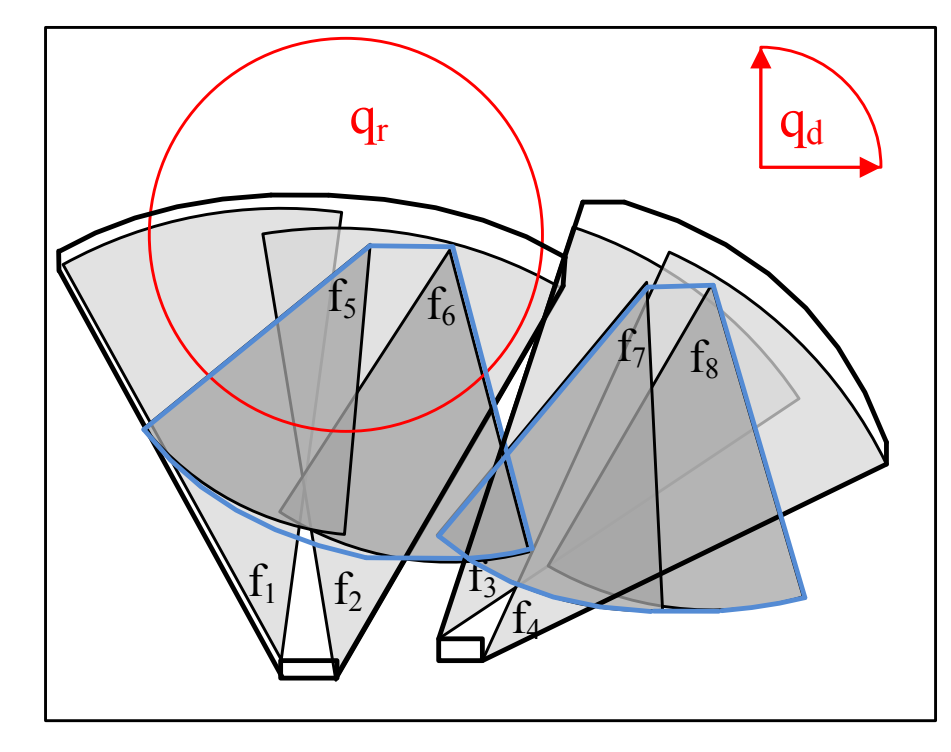
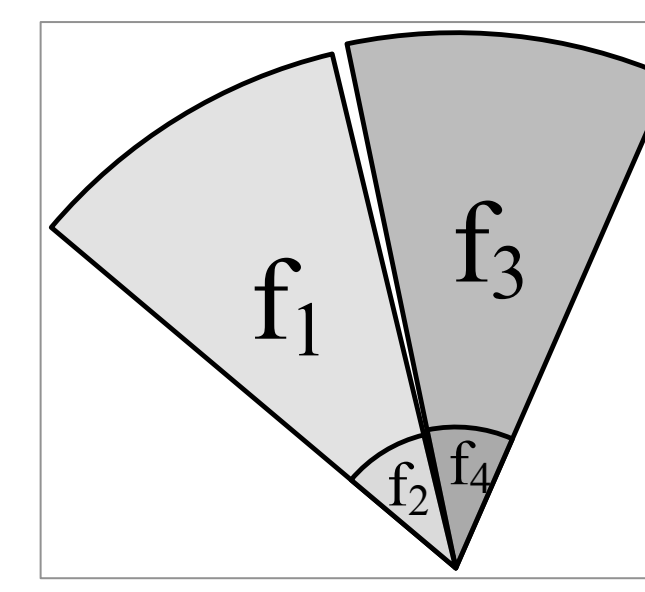
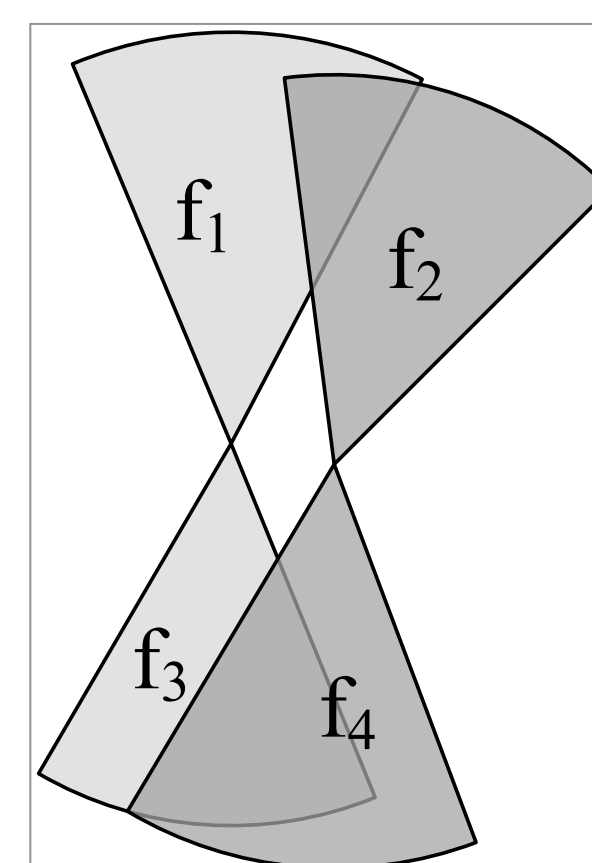
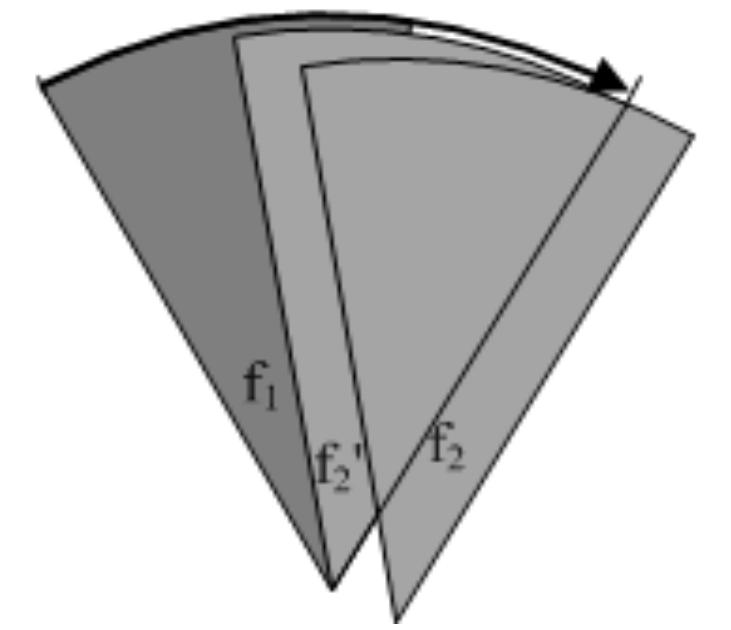
C <sub>L3</sub>	
0° - 45°	$f_1, f_2, f_3, f_4$
46° - 90°	$f_3, f_4$
91° - 180°	$f_6, f_7, f_8$
181° - 225°	$f_5, f_6, f_7, f_8$
226° - 270°	$f_5$
315° - 360°	$f_1, f_2$

## A New Index: Orientated R-tree (OR-tree)

- Store smaller MBRs
- Incorporate orientations into internal index nodes
- Incorporate combined optimization of
  - Area of camera locations
  - Orientation
  - View distance  $R$



### Minimum Bounding Orientation



### Optimization Criteria

## Experimental Results

Table 2: Datasets for the experiments

Statistics	RW	Gen
total # of FOVs	0.2M	0.1M~1B
total # of videos	1276	100~1M
FOV# per second	1	1
average time per videos	3mins	0.28hours
total time	62 hours	27.8hours~31.71years
average camera moving speed (meters/s)	1.25	7.50
average camera rotation speed (degrees/s)	30	30
maximum viewable distance $R$ (meters)	100	250
average viewable cover angle $\alpha$ (degrees)	51	51

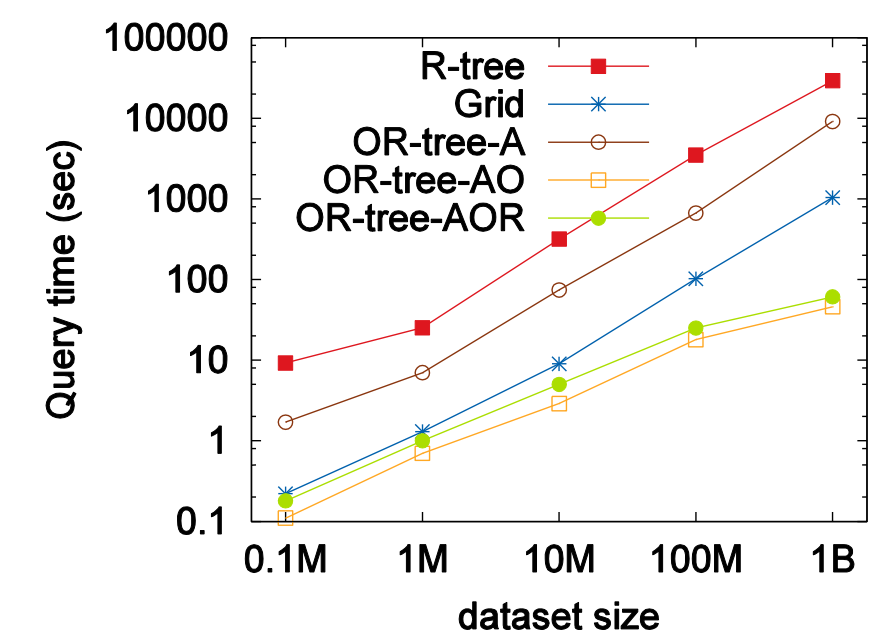
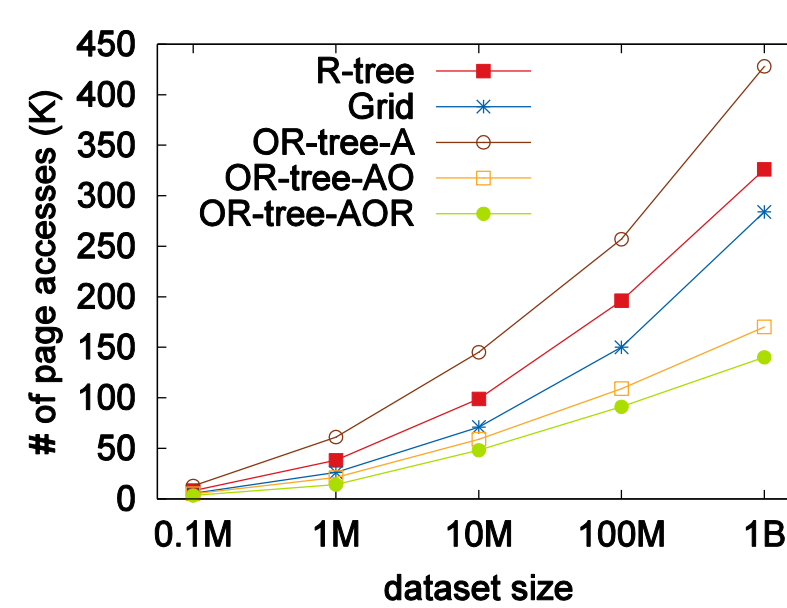
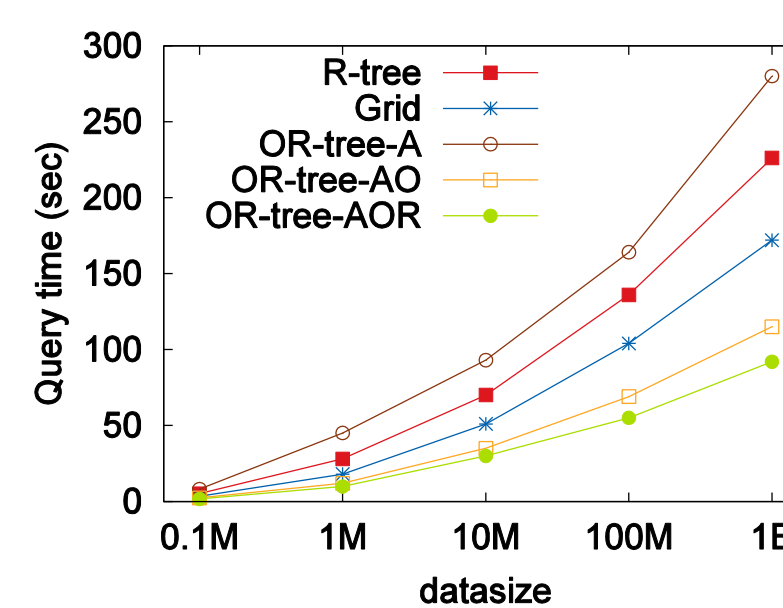
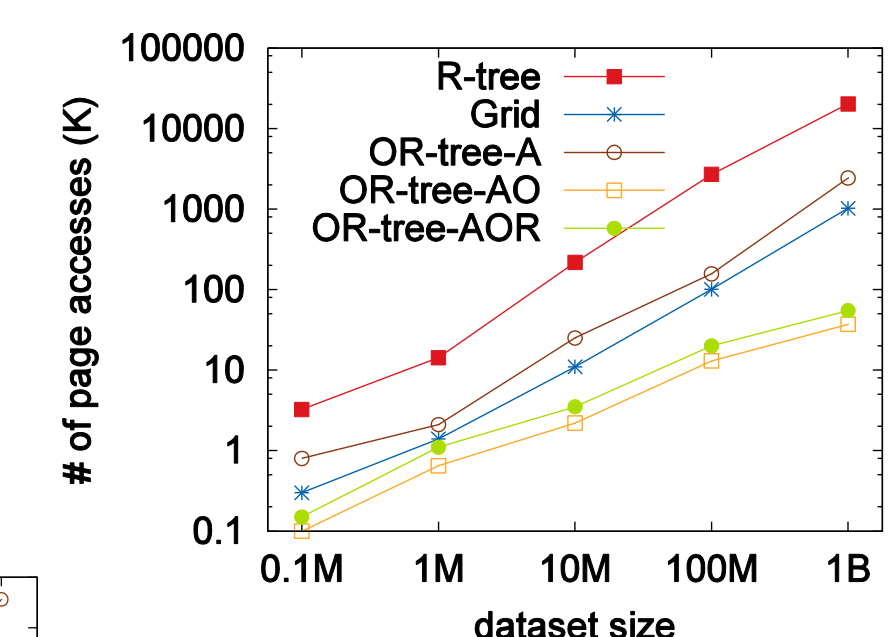


Table 3: Generated Dataset

	0.1M	1M	10M	100M	1B
total FOV#	100	1K	10K	100K	1M
total video#	27.8hours	11.6days	115.7days	3.2years	31.7years



## Related Work

1. Antonin Guttman. R-Trees: a dynamic index structure for spatial searching. In ACM SIGMOD, pages 47-57, 1984.
2. He Ma, Sakire Arslan Ay, Roger Zimmermann, and Seon Ho Kim. Large-scale Geo-tagged video indexing and queries. In Geoinformatica, pages 0362-5915, 2013.

## Conclusion and Future Work

- We proposed a new index called OR-tree to index FOVs for efficient video search.
- Our future direction is to index video considering time of videos
- Highly frequent update also need to be supported.