



Incremental Reconstruction based Bayesian learning

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June 9, 2012

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Context

◆ Background

- 3D Model
- Insights into some problems

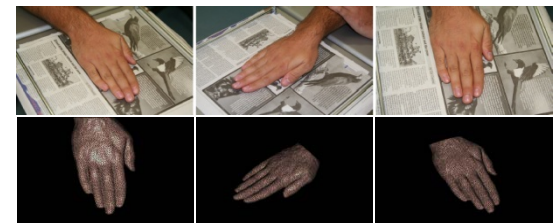
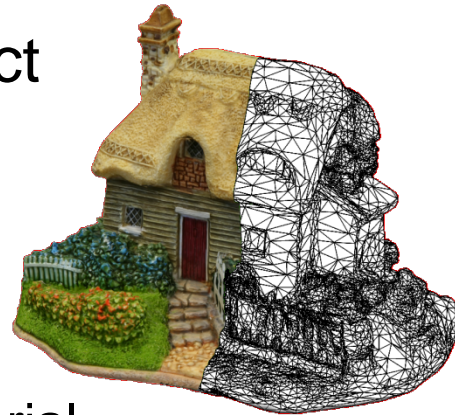
◆ Incremental reconstruction

- Goal
- PMVS
- Model
- Algorithm

◆ Experiments

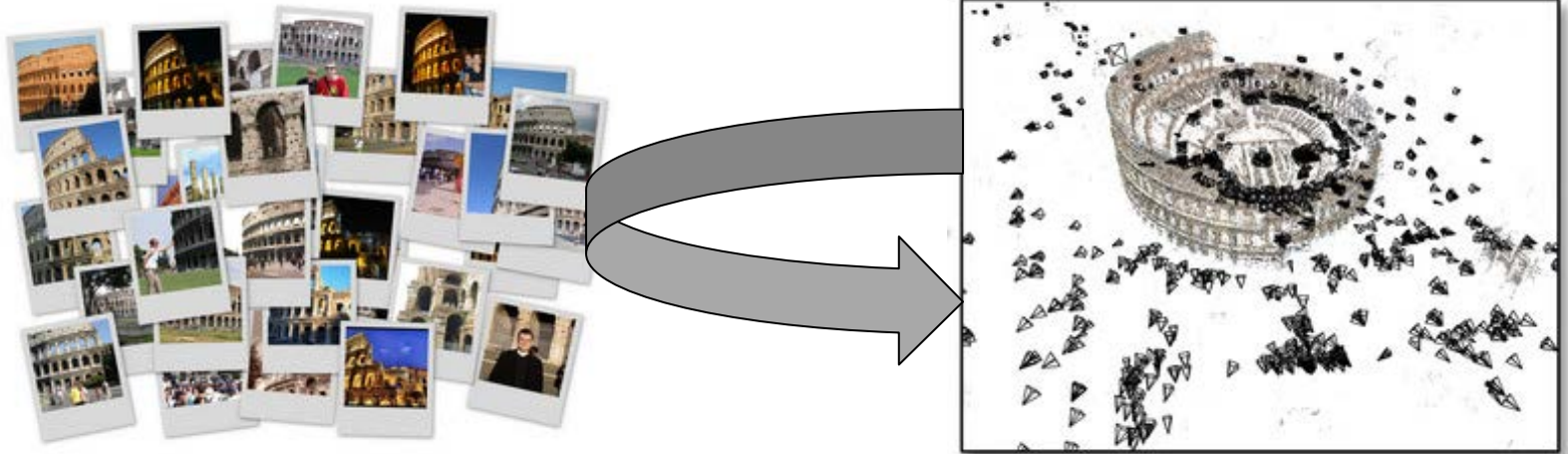
3d model

- ▣ “Digital copy” of real object
- ▣ Allows us to
 - Inspect details of object
 - Measure properties
 - Reproduce in different material
- ▣ Many applications
 - Cultural heritage preservation
 - Computer games and movies
 - City modelling
 - E-commerce
 - 3d object recognition/scene analysis



3D Reconstruction

Building 3D object or scene from images and videos obtained in different views



Build Rome In a day

Problems

- Dataset
 - illumination, images from Internet, videos



- Applications
 - Real-time reconstruction
- Update of 3D model
 - Multi-resolution reconstruction

Incremental reconstruction

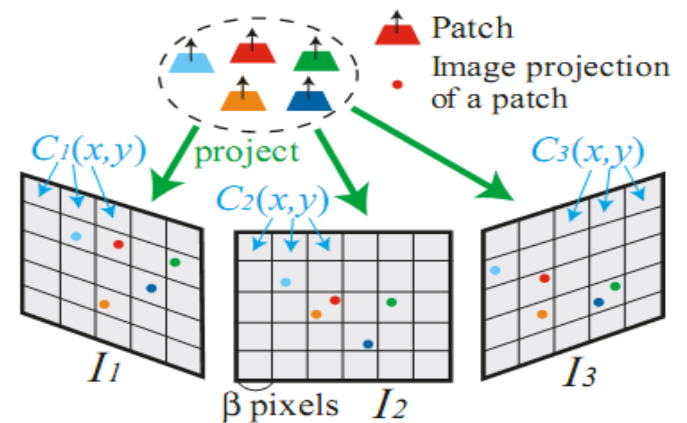
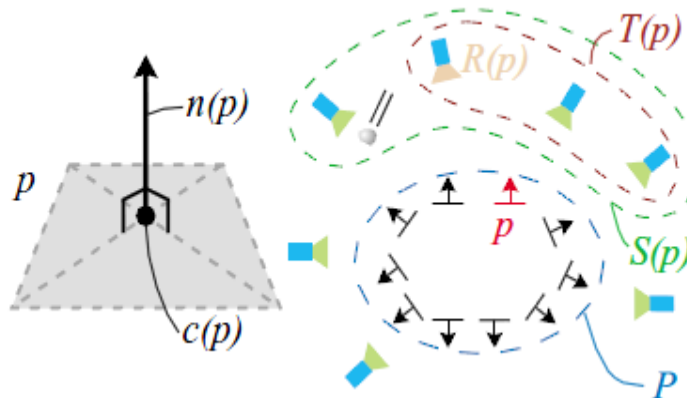
Incremental reconstruction

- Goal
 - Asynchronous input
 - Update of 3D model
- Incremental reconstruction
 - Exploiting the input images
 - Refine the model under geometric constraints

Bayesian Model

PMVS

- Patch-based multi-view stereopsis
 - A 3D representation Model
- A patch p
 - ✓ $c(p), n(p), V(p), R(p)$



From Yasutaka Furukawa and Jean Ponce's paper

Bayesian model

- Observation

- An input image is a measurement of 3D model
- The most likely surface is obtained by maximizing the posterior.

- Model

$$p(S | i_{new}) = \frac{1}{Z} p(i_{new} | S) p(S), S \in \Omega$$

$$S_{MAP} = \arg \min (-\log p(i_{new} | S) - \log p(S))$$

- Prior and likelihood function

- $P(i_{new}|S)$ ——likelihood function,
- $P(S)$ ——geometric prior

Likelihood function

- Representation

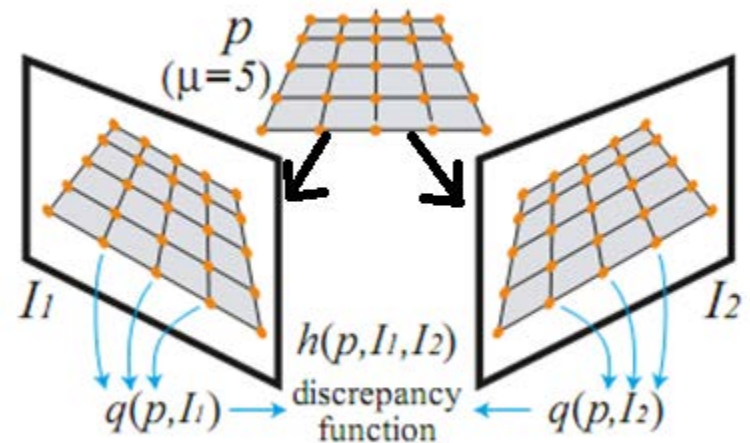
$$p(i_{new} \mid S) \propto \exp(-\eta E_p)$$

- Photometric consistency

- visual compatibility

$$E_p = \frac{1}{|S|} \sum_{p \in S} \frac{1}{|V(p)| - 1} \sum_{i \in V(p)/i_{new}} h(p, i_{new}, i)$$

- Discrepancy function



Prior

- Representation

$$p(S) \propto \exp(-\{\lambda E_1 + \zeta E_2\})$$

- E_1

$$E_1 = \frac{1}{|S|} \sum_{p \in S} \frac{1}{|N(p)|} \sum_{v \in N(p)} f(p, v)$$

- Function of curvature

- Square-root prior

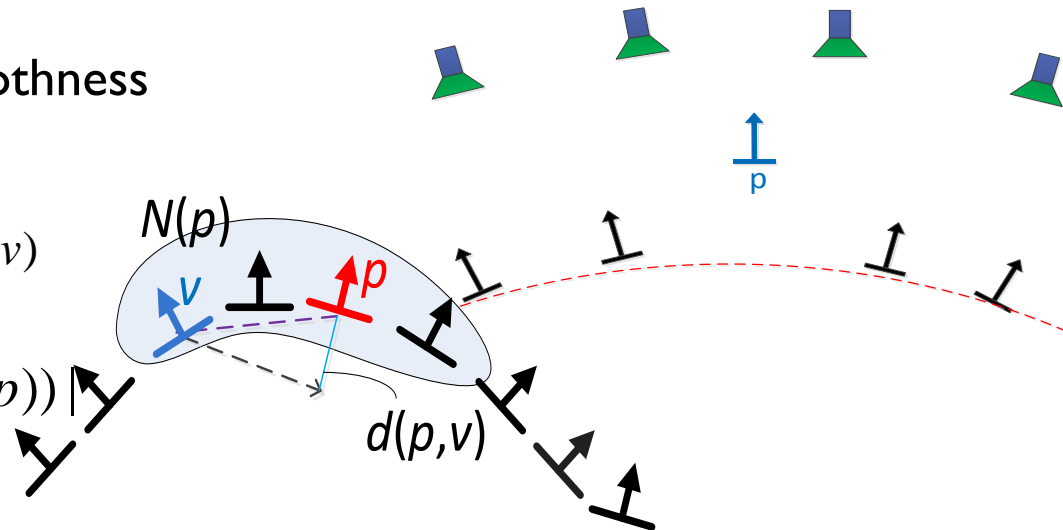
$$f(p, v) = \sqrt{(n(p) - n(v))^T (n(p) - n(v))}$$

- E_2

- Enhance the smoothness

$$E_2 = \frac{1}{|S|} \sum_{p \in S} \frac{1}{|N(p)|} \sum_{v \in N(p)} d(p, v)$$

$$d(p, v) = |n(p) \cdot (c(v) - c(p))|$$



Algorithm

- **Step 1: Initialization**

- Goal

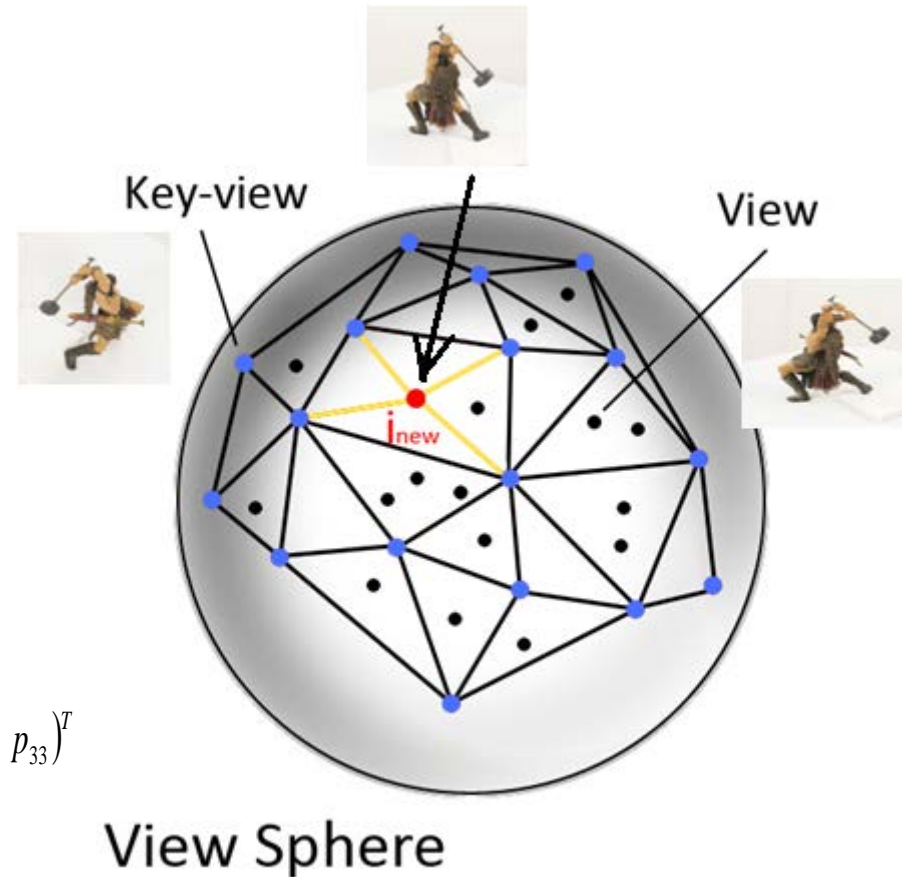
- View sphere
- 3D model

- Process

- Sample key views

$$P = \begin{bmatrix} p_{11} & p_{12} & p_{13} & p_{14} \\ p_{21} & p_{22} & p_{23} & p_{24} \\ p_{31} & p_{32} & p_{33} & p_{34} \end{bmatrix} \quad N = (p_{31} \quad p_{32} \quad p_{33})^T$$

- Delaunay triangulation
- 3D reconstruction from key views
 - PMVS(Patch-based multi-view stereopsis)



Algorithm

- **Step2:** Locate the new view

- SIFT

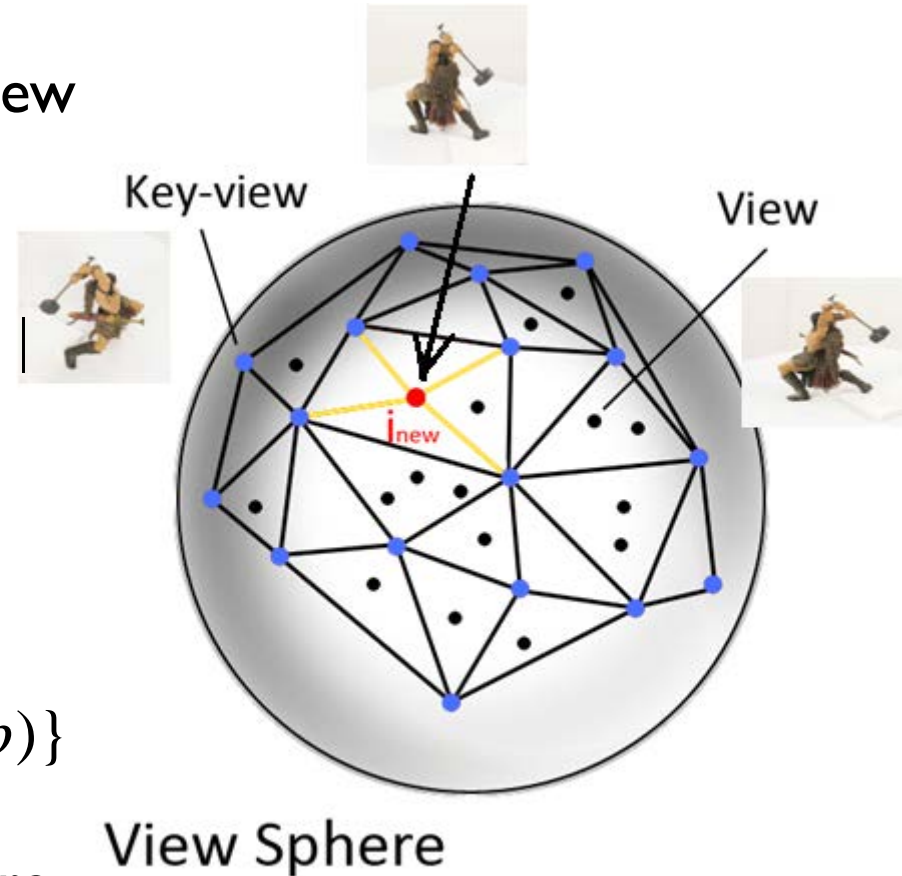
$$T \leftarrow \arg \max_T \sum_{v \in T} |x_{i_{new}}^v|$$

- P_{update}

- ⊙ A subset of patches
- ⊙ Reduce the dimensionality without loss of accuracy

$$P_{update} = \bigcup_{v \in T} \{p \mid v \text{ is } R(p)\}$$

- **Step3:** Update view sphere



Algorithm

- **Step 4: Extension**

- Goal

- Increase resolution
- Make patches uniform

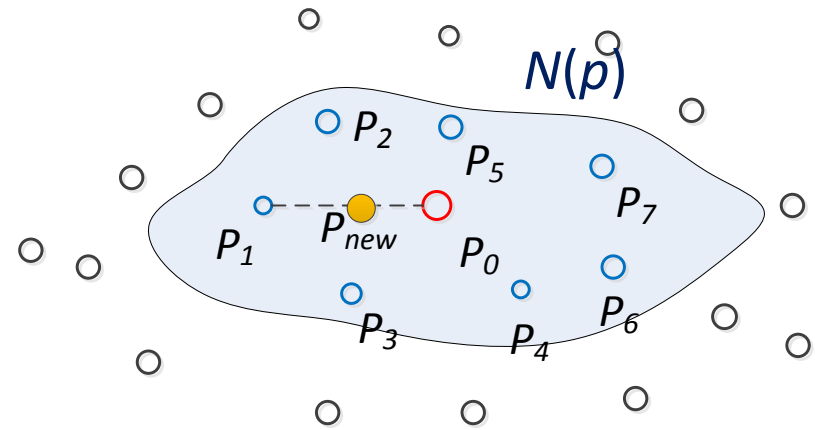
- Method

- Density

$$N(p) = \{p' \mid p' \in \bar{S}, |(c(p) - c(p')) \cdot n(p)| + |(c(p) - c(p')) \cdot n(p')| < \rho\}$$

- Procedure

- SMOTE (Synthetic Minority Over-sampling Technique)



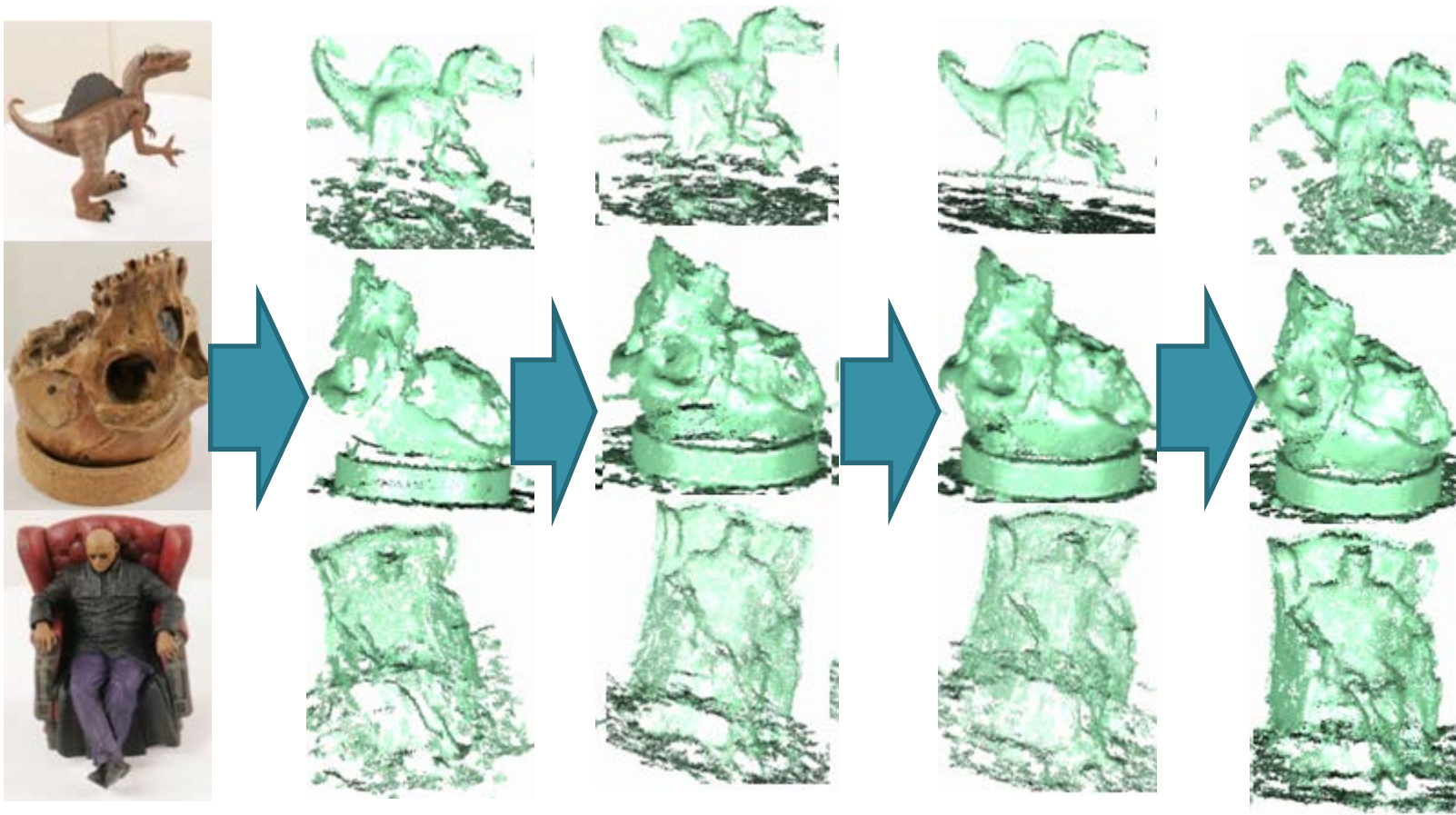
Algorithm

- **Step 5:** Maximize the posterior
 - Global optimization

$$c(p), n(p) \leftarrow \arg \min(\lambda E_1 + \zeta E_2 + \eta E_p), p \in P_{update}$$

Experiment

- Incremental reconstruction
 - Intuitive effects with new images input

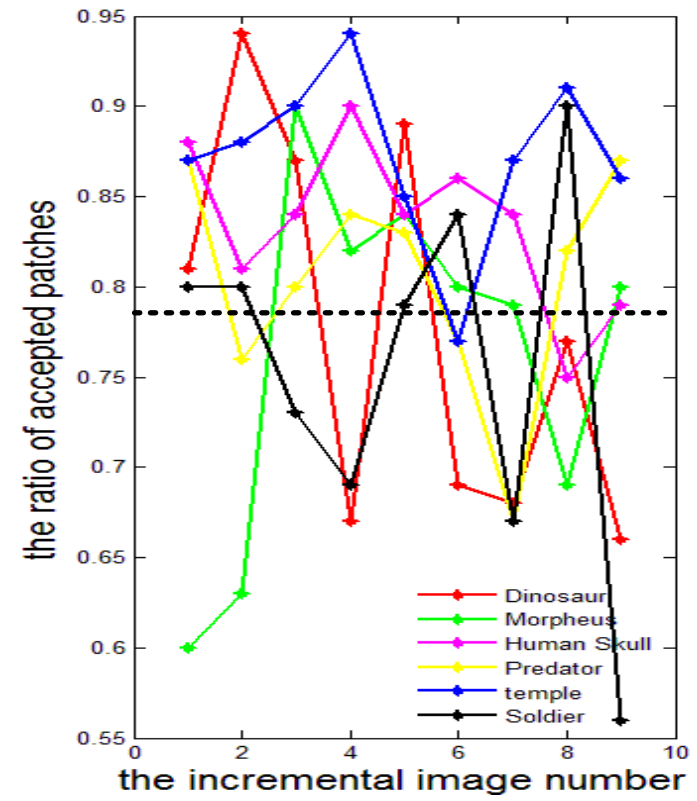
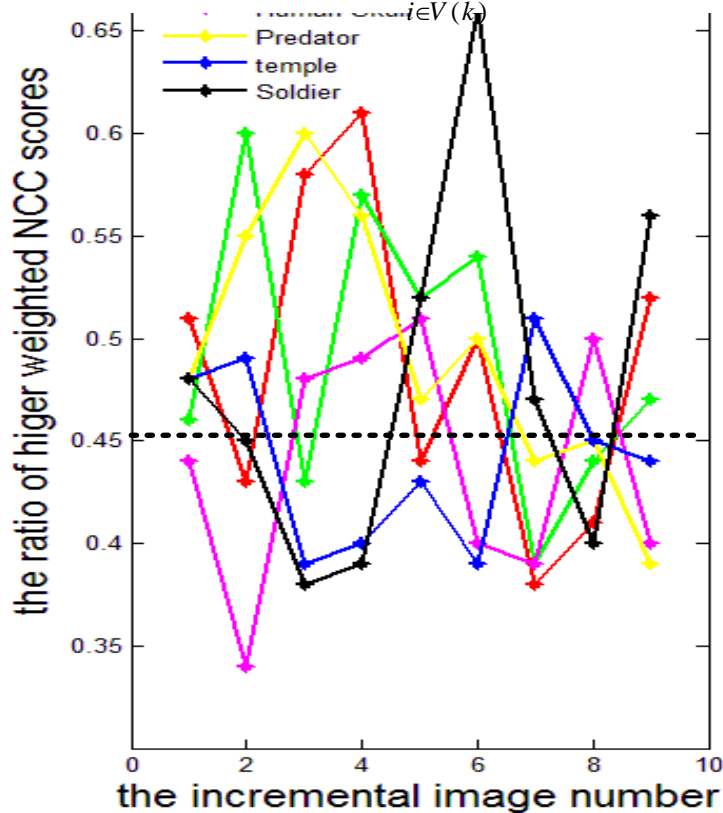


Experiment

- Statistical analysis

- Measure of accuracy

$$P_k = \frac{1}{\sum_{i \in V(k)} r(k,i)} \sum_{i \in V(k)} \frac{h(k, R(k), i)}{r(k,i)}$$





Ends

ANY QUESTIONS?