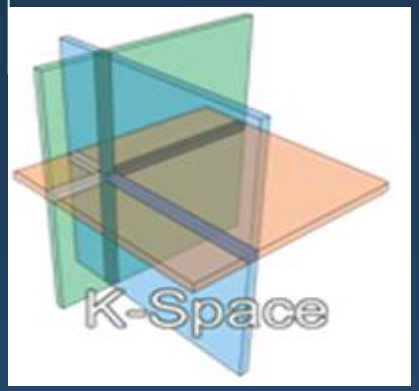


Clustering of Visual Data using Ant-inspired Methods

Tijana Janjusevic

Multimedia and Vision Group,
Queen Mary, University of London

Supervisor: Prof. Ebroul Izquierdo

Overview

- Introduction
- Biologically Inspired Optimization Systems
- ACO – based image classifier
  - Ant Colony Optimization (ACO)
  - Subspace clustering by Ants
  - Experimental Results
- Ant-tree for video summarization
  - Ant-tree - new model for clustering
  - Experimental Results
- Future work

Image Classification

- **Data Mining tasks:** feature extraction,
  pattern recognition,
  segmentation,
  feature selection,
  classification,
  optimization,
  annotation, ...

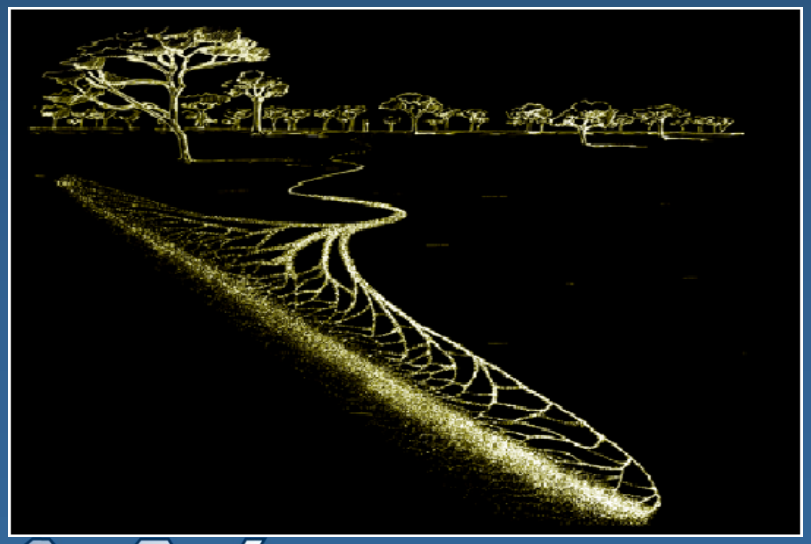
- **Image Classification**
  - the task is to learn to assign images with same semantic content to predefined classes
  - two types of classification schemes: *supervised* and *unsupervised*.

- **Supervised classification**
  - requires relevance feed-back from a human annotator and training data
- **Unsupervised classification - Clustering**
  - without training or need for knowledge about the data

The performance of the image classification algorithms relies on the efficient optimisation techniques

Biologically Inspired Optimisation techniques

- **Recent developments in applied and heuristic optimisation have been strongly influenced and inspired by natural and biological system.**
- **Biologically Inspired systems:** Artificial Immune Systems,
  Particle Swarm,
  Ant Colony Systems



Ant Colony Optimisation (ACO)

- Meta-heuristic that uses strategies of ants to solve optimization problems.
- An important and interesting behavior of ant colonies is their foraging behavior, and, in particular, how ants can **find shortest paths** between food sources and their nest, using **pheromone** driven communication.

Ant Colony System

- **The Ant System algorithm (AS) was first proposed to solving the Traveling Salesman Problem (TSP).**
  - Given a set of *n* points and a set of distances between them, we call d_{ij} the length of the path between points *i* and *j*.

o **The probability of choosing next *j* node:**

$$p_{ij}^{\ k}(t) = \begin{cases} \dfrac{(\tau_{ij}(t))^{\alpha}(\eta_{ij})^{\beta}}{\sum_{k \in allowed}(\tau_{ij}(t))^{\alpha}(\eta_{ij})^{\beta}} \\ 0 \quad , \text{otherwise} \end{cases}$$

o **Heuristic information :**

$$\eta_{ij} = \frac{1}{d_{ij}}$$

o **Pheromone value :**

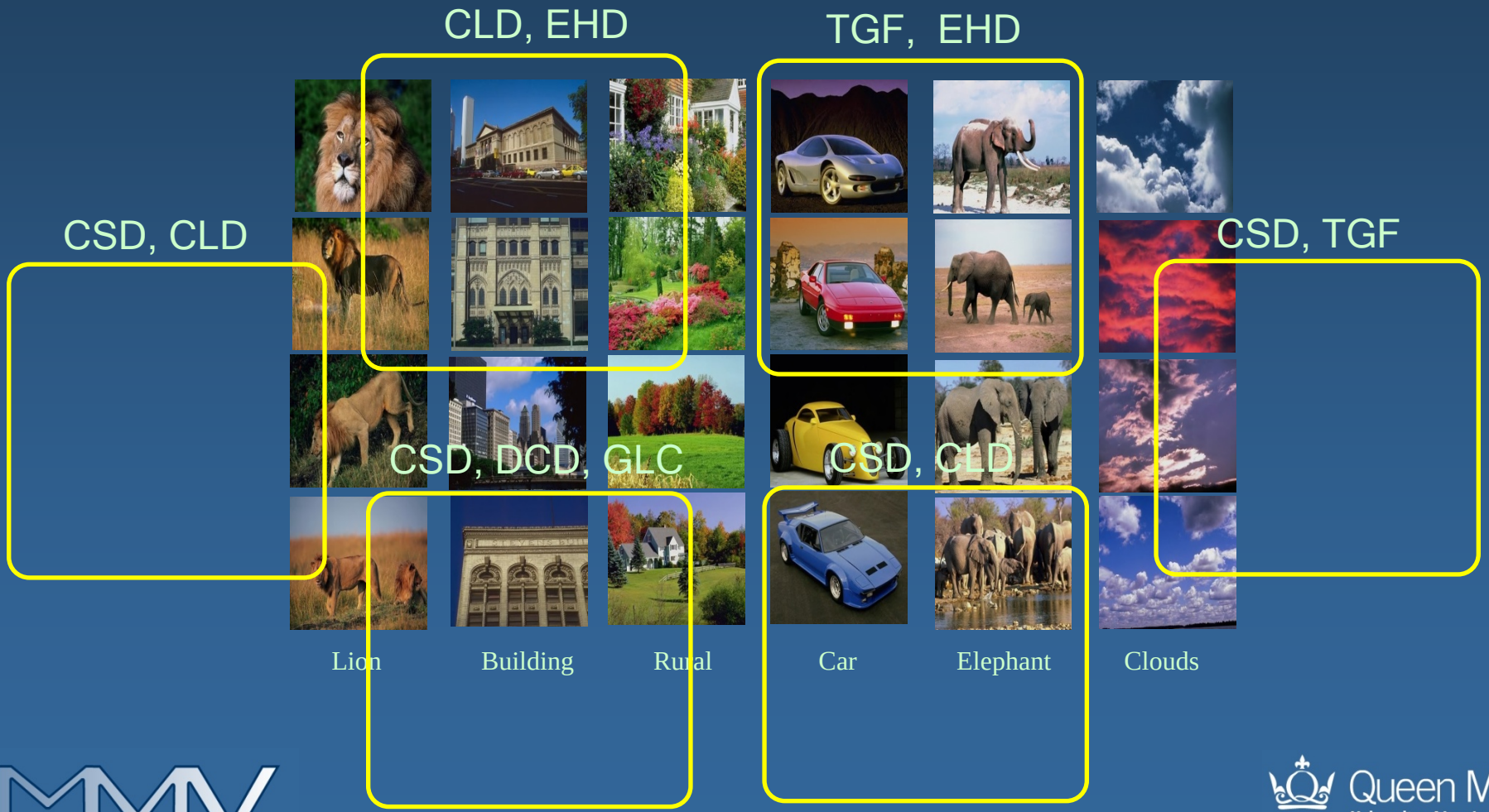
$$\tau_{ij}(t) = \rho \cdot \tau_{ij}(t-1) + \Delta\tau_{ij}$$

$$\Delta\tau_{ij} = \sum_{k=1}^{m} \Delta\tau_{ij}^{\ k}$$

$$\Delta\tau_{ij}^{\ k} = \begin{cases} \dfrac{Q}{L_k}, \text{if k - th ant use edge(i, j)} \\ 0 \quad , \text{otherwise} \end{cases}$$

Problem Definition

- Combination of low-level visual features in Clustering
  - Each group of images may correlate with respect to different set of important features, and each group may contain some irrelevant features



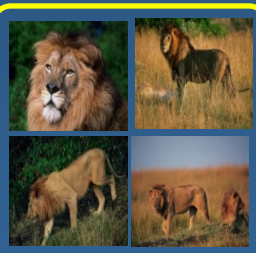
Subspace Clustering using ACO

- Ant Colony Optimisation and its learning mechanism is implemented for **optimizing feature weights for each cluster** of images.

Each ant clusters images according to:

- different local feature weights
- pheromone value from previous solutions

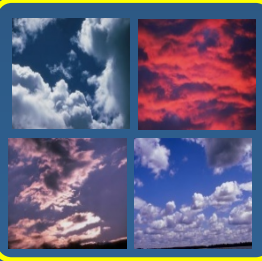
CSD, CLD



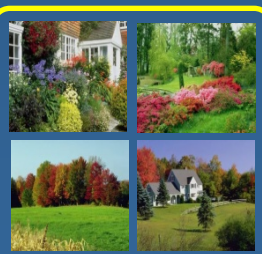
CLD, EHD

TGF, EHD

CSD, TGF



CSD, DCD, GLC



CSD, CLD

Subspace Clustering using ACO

Multi-feature Combination: $D^{\alpha}(x,\tilde{x}) = \sum_{l=1}^{m} \alpha_l D_l(F_l, \tilde{F}_l)$

Proposed Algorithm

I. Each ant will assign each image x_i, $1 \le i \le n$ to the cluster π_u, $1 \le u \le k$, with the probability $P_{(x_i,\pi_u)}$ obtained from:

$$p_{(x_i,\pi_u)} = \frac{\tau_{(x_i,\pi_u)}\eta_{(x_i,\pi_u)}}{\sum_{u=1}^{K} \tau_{(x_i,\pi_u)}\eta_{(x_i,\pi_u)}} \qquad \eta_{(x_i,\pi_u)} = \frac{B}{D^{\alpha_u}(x_i, c_u)}$$

II. Computation of weights: $\alpha_{(u,l)} = \frac{e^{-R\cdot AD_{(u,l)}}}{\sqrt{\sum_{s=1}^{m} e^{-2\cdot R\cdot AD_{(u,s)}}}} \qquad AD_{(u,l)} = \frac{1}{|\pi_u|}\sum_{x\in\pi_u} D_l(x, c_u)$

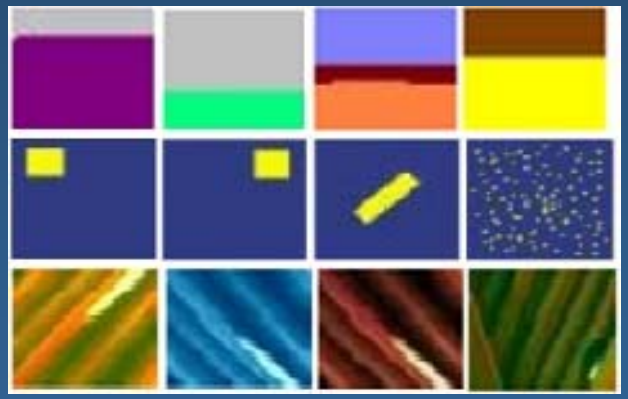
III. Computation of centroids.

IV. Pheromone Update: $\tau_{(x_i,c_u)}(t) = \rho\cdot\tau_{(x_i,c_u)}(t-1) + \sum_{A=1}^{S} \Delta\tau_{(x_i,c_u)}{}^{A}(t)$

$$\Delta\tau_{(x_i,c_u)}{}^{A} = \begin{cases} \frac{\Lambda^A(\alpha_u)}{n\cdot\Gamma^A(\alpha_u)}, & \text{if } x_i \text{ belongs to cluster } \pi_u \\ 0, & \text{otherwise} \end{cases}$$

Experimental Evaluation

- Low-level features (descriptors) used For visual representation of images:
  - Colour Layout (CLD),
  - Colour Structure (CSD),
  - Dominant Colour (DCD),
  - Edge Histogram (EHD)
  - Grey Level Co-occurrence Matrix (GLC)
- **Synthetic Data**



Group A

Group B

Group C

Results:

	Feature Weighting			
Descriptors	CLD	DCD	EHD	GLC
Group A	0.03	0.01	0.91	0.05
Group B	0.11	0.76	0.08	0.05
Group C	0.05	0.01	0.10	0.84

Method	Average Error Rates
SC-ACO	0.06±0.02
PROCLUS	0.09±0.04
GFS-K-Means	0.62±0.07
K-Means	0.33±0.08

Experimental results

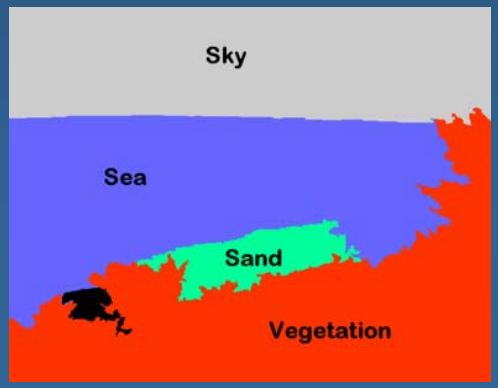
- **The Corel image database** - 600 images with 6 semantic concepts

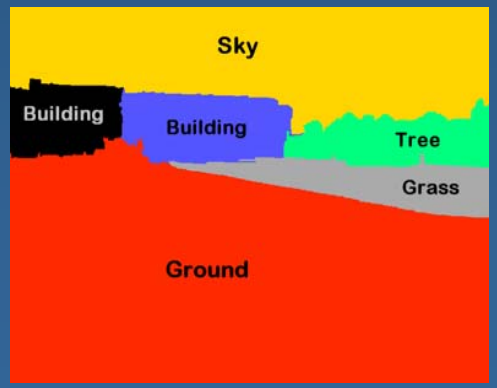
Lion Building Rural Car Elephant Clouds

Method	Average Error Rates
SC-ACO	0.30±0.02
PROCLUS	0.37±0.05
GFS-K-Means	0.47±0.07
K-Means	0.52±0.09

Experimental results

- **Flickr Image Database** - 500 images segmented into regions.
- **Semantic Concepts:** *Sand*, *Sea*, *Vegetation*, *Building*, *Sky*, *Person*, *Rock*, *Tree*, *Grass*, *Ground*, and.





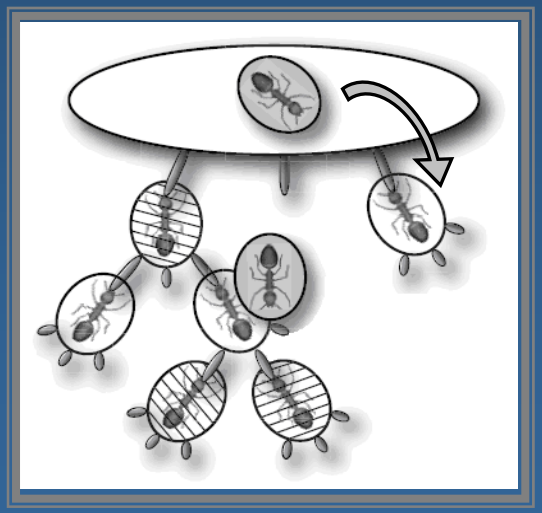
Method	Average Error Rates	
	5 concepts	10 concepts
SC-ACO	0.21±0.03	0.31±0.04
PROCLUS	0.28±0.06	0.32±0.05
GFS-K-Means	0.36±0.07	0.45±0.08
K-Means	0.39±0.08	0.5±0.1

Ant-tree for video summarisation

Ant-Tree clustering method

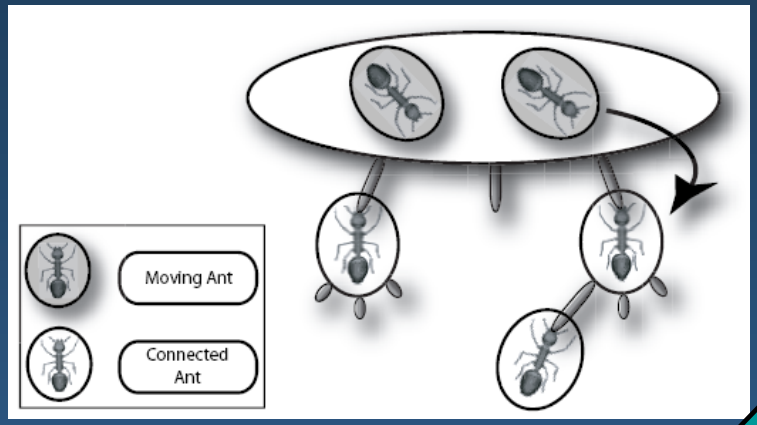
- Inspired by self-assembling behavior of African ants and their ability to build chains (bridges) by their bodies in order to link leaves together.

- We model the ability of ants to build live structures with their bodies in order to discover, in a distributed and unsupervised way, a tree-structured organisation and summarisation of the video data.



AntTree: New model for clustering

- General principles

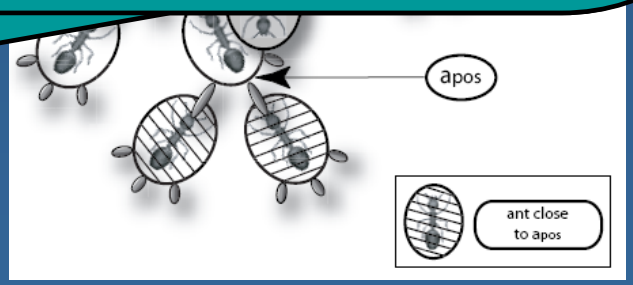


- Main algorithm

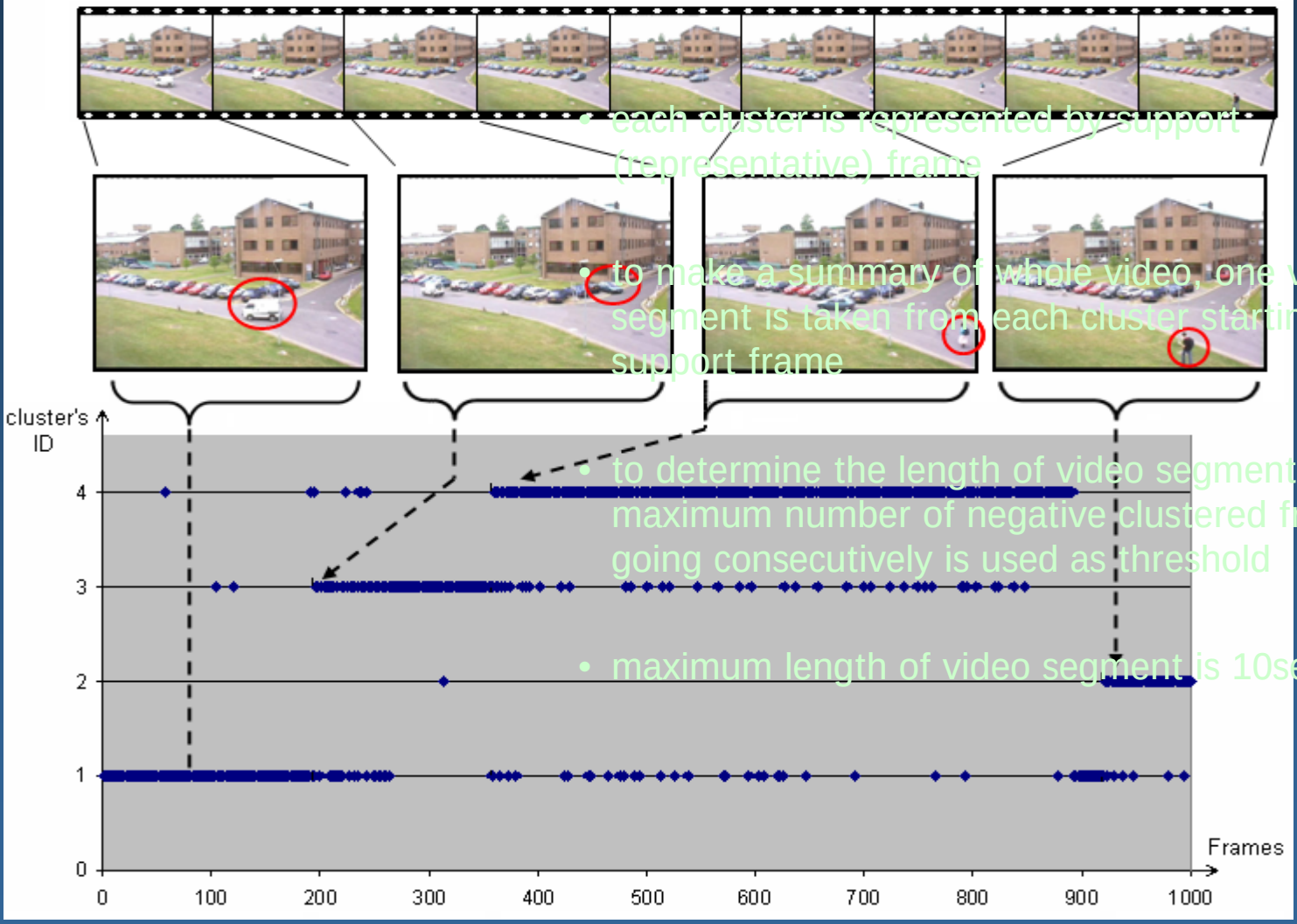
1. all ants placed on the support;
   initialization: $T_{sim}(a_i)=1$, T_{di}
2. While there exists non co ted ant a_i Do
3. If ai is located on t support Then ***Support case***
4. Else ***Ant case***
5. End While

Ant case

1. let a_{pos} denote the ant on which a_i is located and let a_k denote a randomly selected neighbour of a_{pos}
2. If $Sim(a_i,a+)>T_{sim}(a_i)$ Then connect a_i to a_{pos} Else decrease $T_{dissim}(a_i)$, increase $T_{sim}(a_i)$ and move a_i toward a_k
3. Else randomly move a_i toward a_k



Surveillance video

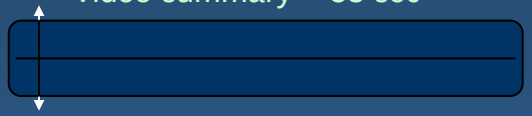


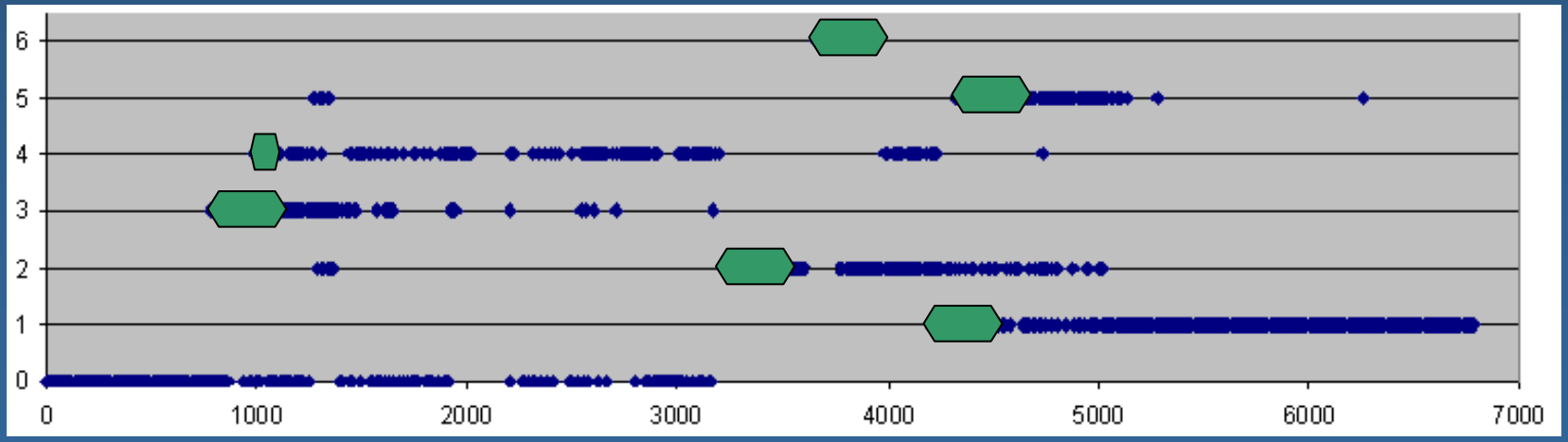
- each cluster is represented by support (representative) frame
- to make a summary of whole video, one video segment is taken from each cluster starting with support frame
- to determine the length of video segment the maximum number of negative clustered frames going consecutively is used as threshold
- maximum length of video segment is 10sec.

Summarization results (PETS2001)

Camera video – 4 min 30 sec (duration)

Video summary – 53 sec





Future work

- Improvement of SC Method

  Pheromone driven mechanism of ACO will be used for optimization of clustering

  task by searching for number of clusters that leads to best clustering.

- Implementation of FS for Video Summarization and Scene Detection

  The aim of this task is to detect and classify events from video using intelligent combination of multiple low-level visual features.

Thank you for your attention!

tomas.piatrik@elec.qmul.ac.uk