Subspace Clustering via Graph Regularized Sparse Coding

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1. Problem

- **Objective:**
  - **Segment videos using sparse coefficients and graph regularization.**
- **Applications:**
  - **Tracking**
  - **Supervoxel and superpixel segmentation**
  - **Efficient clustering**

2. SegTrack 2011 Dataset

- **Diverse array of videos with various amounts of objects, object sizes, and backgrounds.**

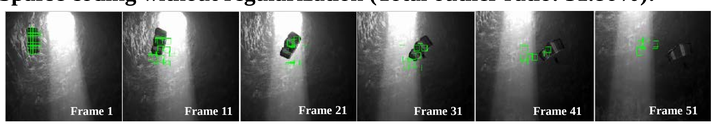


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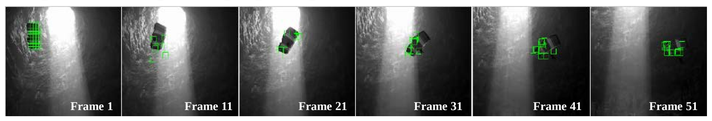
3. Motivation

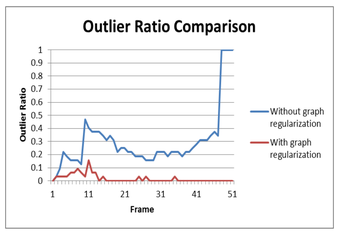
- **Attempts to track image patches in a video using sparse coding with and without graph regularization yielded very different results and demonstrated that graph regularization can improve accuracy by exploiting the geometric interpretation of the data.**

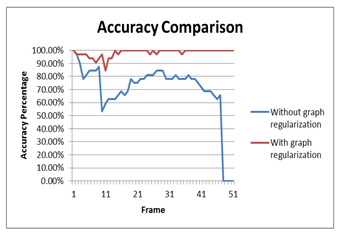
Sparse coding without regularization (Total outlier ratio: 31.86%):



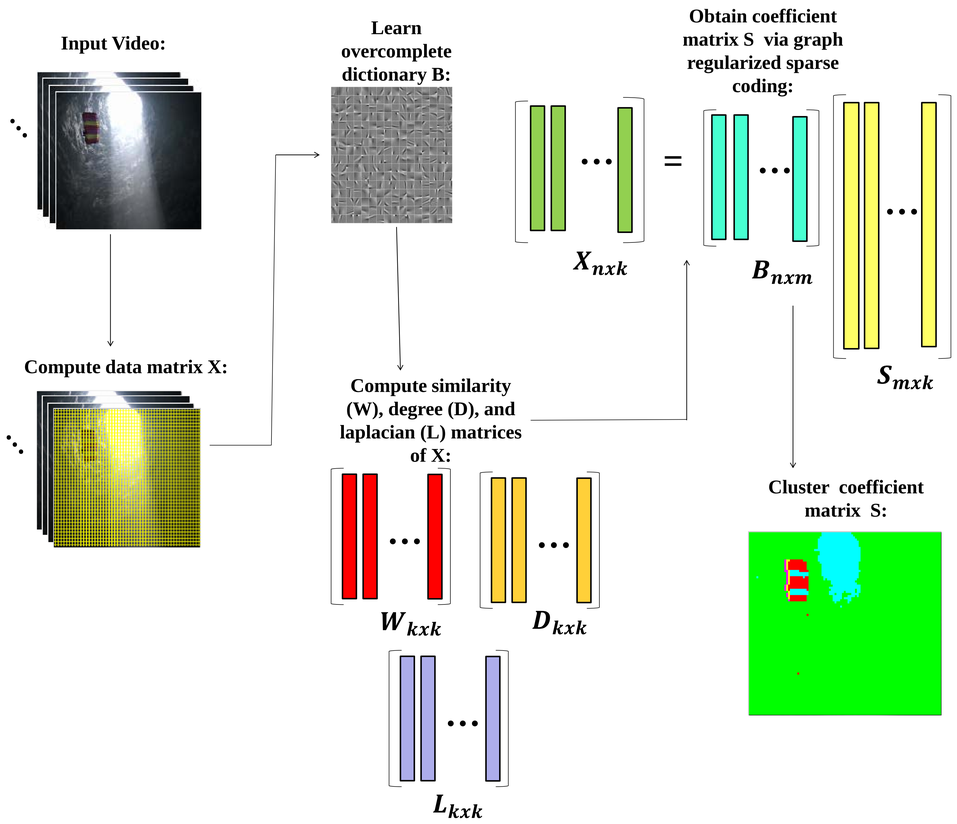
- **Sparse coding with graph regularization (Total outlier ratio: 1.65%):**







4. Framework



Compute data matrix X

- **Each vector of X consists of a q-by-q-by-q RGB cuboid.**
- **Let m = $3q^3$. X will be an m-by-k matrix, where k is the number of cuboids.**

Learn overcomplete dictionary B:

- **K-SVD was used.**
- **B will be an n-by-m matrix, where m is the number of atoms and m > n.**

Obtain a sparse coefficient matrix S:

- **Compute similarity matrix W between cuboids.**
  - **W will be a k-by-k matrix.**
  - **We use the Heat Kernel metric to compute for similarity.**
  - **An indicator function I is also used.**
    - **$I_{x_i \in N(x_j)}$ = 1 if x_i is a nearest neighbor of x_j; zero otherwise.**
- **Compute degree matrix D.**
  - **D will be a k-by-k matrix.**
- **Compute Laplacian matrix L.**
  - **L is the difference between the degree and similarity matrices.**
- **S results from minimizing the objective function in section 5.**
  - **S will be an m-by-k matrix.**

Cluster coefficient matrix S:

- **Hierarchical clustering was used.**

5. Algorithm

- **Input: Image volume Ω, cuboid size q, sparsity constraint T_0, number of clusters c.**
- **Output: Cluster indices Θ**

For t = 1 to $\lfloor dim(\Omega, 3) \rfloor$

X ← Cuboids in Ω, where X_i is the column-wise vectorization of the i^{th} cuboid

$$B \leftarrow \min_{B,S} \|X - BS\|_F^2 \; s.t. \; \forall i, \|x_i\|_0 \leq T_0$$

$$L \leftarrow D - W; \text{ where } W_{ij} = I_{x_i \in N(x_j)} * e^{-\frac{\|x_i - x_j\|^2}{\sigma}}$$

$$\text{and } D_{ij} = \begin{cases} \sum_j W_{ij}; & i = j \\ 0; & otherwise \end{cases}$$

$$S \leftarrow \min_S \|X - BS\|_F^2 + \alpha Tr(SLS^T) + \beta \sum_{i=1}^{m} \|s_i\|_1$$

Θ_t ← Cluster S

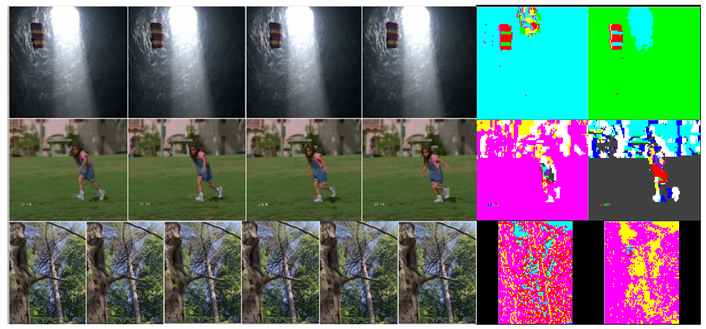
t ← t + q

End for

6. Results

- **We tested our framework against sparse coding without graph regularization and obtained the following results:**

Without Graph Regularization: With Graph Regularization:



7. Future Work

- **Further testing needs to be performed to prove the benefit of this framework. On a side note, there are a lot of clustering algorithms but none that fully exploit the sparse graph-regularized data generated through our method. Max-Voting has proven useful in exploiting the distribution of elements in graph-regularized sparse data, as seen in section 3, and so further research in creating our own clustering algorithm that utilizes Max-Voting as the main criterion for computing clusters could be worthwhile.**