Energy Based Fast Event Retrieval in Video with Temporal Match Kernel

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Outline

- Introduction
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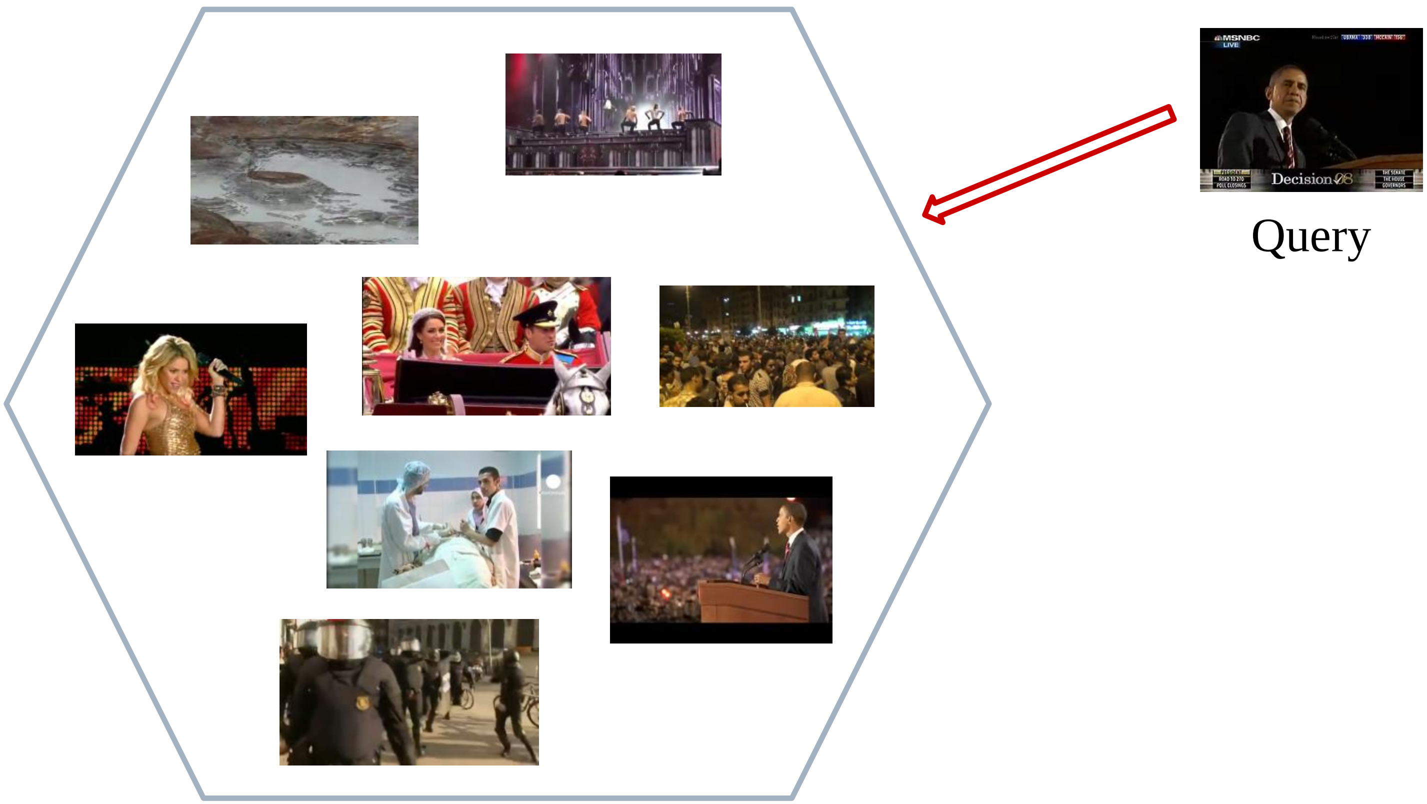
Introduction

- Approach for fast content-based search in large video database



Database

Introduction

- Related work
  - Jerome Revaud, et al., Event retrieval in large video collections with circulant temporal encoding, CVPR, 2013
  - Matthijs Douze, et al., Stable hyper-pooling and query expansion for event detection, ICCV, 2013
  - **Sebastien Poullot, et.al, Temporal matching kernel with explicit feature maps, ACM MM, 2015**
- Contribution
  - Simplify the similarity metric by calculating the energy of the score function
  - Derive the energy formulation by Parseval's theorem
  - Accelerate the computation with product quantization

Background

$\mathbf{x} = (\boldsymbol{x}_0, \ldots, \boldsymbol{x}_t \ldots)$ $\mathbf{y} = (\boldsymbol{y}_0, \ldots, \boldsymbol{y}_t \ldots)$ time offset: Δ

A kernel defined with $\mathbf{x}$, $\mathbf{y}$, and Δ

$$\kappa_\Delta(\mathbf{x},\mathbf{y}) \propto \sum_{t=0}^{\infty} \boldsymbol{x}_t^T \boldsymbol{y}_{t+\Delta} = \underbrace{\left(\sum_{t=0}^{\infty} \boldsymbol{x}_t \otimes \varphi(t)\right)^T}_{\psi_0(\mathbf{x})} \underbrace{\left(\sum_{t'=0}^{\infty} \boldsymbol{y}_{t'} \otimes \varphi(t'+\Delta)\right)^T}_{\psi_\Delta(\boldsymbol{y})}$$

$$\varphi(t) = \begin{bmatrix} \sqrt{a_0} \\ \sqrt{a_1}\cos(\frac{2\pi}{T}t) \\ \sqrt{a_1}\sin(\frac{2\pi}{T}t) \\ \vdots \\ \sqrt{a_m}\cos(\frac{2\pi}{T}mt) \\ \sqrt{a_m}\sin(\frac{2\pi}{T}mt) \end{bmatrix}$$

$$\psi_0(\mathbf{x}) = \left[\mathbf{V}_0^T, \mathbf{V}_{1,c}^T, \mathbf{V}_{1,s}^T, \ldots, \mathbf{V}_{m,c}^T, \mathbf{V}_{m,s}^T\right]^T$$

$$\mathbf{V}_0 = a_0 \sum_{t=0}^{\infty} \boldsymbol{x}_t \in \mathbb{R}^D,$$

$$\mathbf{V}_{i,c} = a_i \sum_{t=0}^{\infty} \boldsymbol{x}_t \cos(\frac{2\pi}{T} it) \in \mathbb{R}^D$$

$$\mathbf{V}_{i,s} = a_i \sum_{t=0}^{\infty} \boldsymbol{x}_t \sin(\frac{2\pi}{T} it) \in \mathbb{R}^D$$

a_i: the fourier coefficients

Background

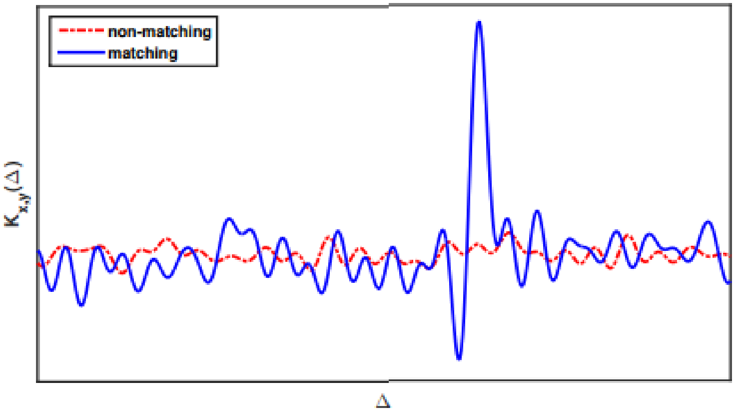
- Final Formulation

$$\kappa_{\mathbf{x},\mathbf{y}}(\Delta) = \left\langle \mathbf{V}_0^{(\mathbf{x})}, \mathbf{V}_0^{(\mathbf{y})} \right\rangle + \sum_{n=1}^{m} \cos(n\,\Delta)\left(\left\langle \mathbf{V}_{n,c}^{(\mathbf{x})}, \mathbf{V}_{n,c}^{(\mathbf{y})} \right\rangle + \left\langle \mathbf{V}_{n,s}^{(\mathbf{x})}, \mathbf{V}_{n,s}^{(\mathbf{y})} \right\rangle\right) + \sum_{n=1}^{m} \sin(n\,\Delta)\left(-\left\langle \mathbf{V}_{n,c}^{(\mathbf{x})}, \mathbf{V}_{n,s}^{(\mathbf{y})} \right\rangle + \left\langle \mathbf{V}_{n,s}^{(\mathbf{x})}, \mathbf{V}_{n,c}^{(\mathbf{y})} \right\rangle\right)$$

- Similarity Score

$$S(\mathbf{x}, \mathbf{y}) = \max_{\Delta} \kappa_{\mathbf{x},\mathbf{y}}(\Delta)$$

$$t_m = \arg\max_{\Delta} \kappa_{\mathbf{x},\mathbf{y}}(\Delta)$$



Our Method

- Matching with energy

$$E(\kappa_{\mathbf{x},\mathbf{y}_1}) > E(\kappa_{\mathbf{x},\mathbf{y}_2}) \quad \text{if } S(\mathbf{x},\mathbf{y}_1) > S(\mathbf{x},\mathbf{y}_2)$$

$$\Downarrow$$

$$\tilde{S}(\mathbf{x},\boldsymbol{y}) = E(\kappa_{\mathbf{x},\mathbf{y}}(\Delta))$$

Denote the Fourier series of $f(x)$ as

$$f(x) = \frac{1}{2}c_0 + \sum_{n=1}^{m} c_n \cos(nx) + \sum_{n=1}^{m} s_n \sin(nx)$$

The energy of $f(x)$ is

$$E(f(x)) = \int_{-\infty}^{\infty} [f(x)]^2 \, dx$$

According to the Parseval's Theorem

$$\frac{1}{2\pi}\int_{-\infty}^{\infty} [f(x)]^2 \, dx = \sum_{i=1}^{n} (c_i^2 + s_i^2) + c_0^2$$

Our Method

- Matching with energy

The final form of the energy $\tilde{S}(\mathbf{x},\mathbf{y})$ for $\kappa_{\mathbf{x},\mathbf{y}}(\triangle)$ is

$$\tilde{S}(\mathbf{x},\mathbf{y}) = E\left(\kappa_{\mathbf{x},\mathbf{y}}(\triangle)\right)$$
$$= \sum_{n=1}^{m}\left[\left(\left\langle \mathbf{V}_{n,c}^{(\mathbf{x})}, \mathbf{V}_{n,c}^{(\mathbf{y})}\right\rangle + \left\langle \mathbf{V}_{n,s}^{(\mathbf{x})}, \mathbf{V}_{n,s}^{(\mathbf{y})}\right\rangle\right)^2\right.$$

- Generalized formulation

$$S^{(p)}(\mathbf{x},\mathbf{y}) = \sqrt[p]{\sum_{i=1}^{m}\left(c_i^2 + s_i^2\right)^p}$$

$$S^{(\infty)}(\mathbf{x},\mathbf{y}) = \lim_{p\to\infty}\frac{1}{M}\sqrt[p]{\sum_{i=1}^{m}\left(c_i^2 + s_i^2\right)^p} = \max_n\{(c_n^2 + s_n^2)^p\}$$

Our Method

- Matching with energy
  - Given a query video, go through the candidate in database
  - Calculate the $\tilde{S}(\mathbf{x}, \mathbf{y})$ between query and candidate
  - Retrieval with $\tilde{S}(\mathbf{x}, \mathbf{y})$

- Advantages
  - More stable (maximum of $S(\mathbf{x}, \mathbf{y})$ is sensitive to noise)
  - Lower computational complexity
  - Further accelerate the computation using approximate nearest neighbor method such as PQ

Our Method

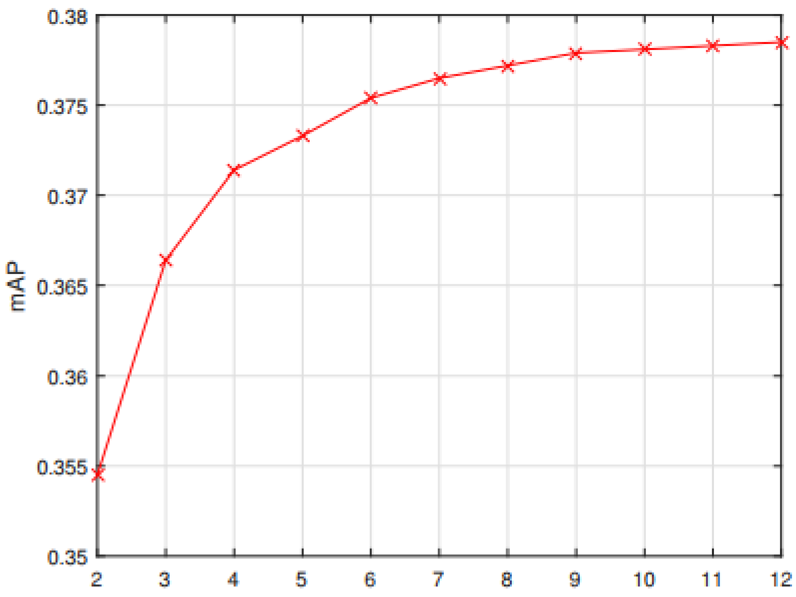
- Algorithm speedup with PQ
  jth codebook $\boldsymbol{c}_{j*}$ generated from

$$\left\{\mathbf{V}_{j,c}^{(\mathbf{x}_i)}: i \in \{1, \dots, N\}\right\} \cup \left\{\mathbf{V}_{j,s}^{(\mathbf{x}_i)}: i \in \{1, \dots, N\}\right\}$$

- Searching steps
  - Quantize query q to its ω nearest neighbors with $\tilde{S}(\mathbf{x}, \mathbf{y})$
  - Compute the squared distances and dot product for each subquantizer j and each of its centroid $\boldsymbol{c}_{ji}$
  - Using the subvector-to-centroid distance, calculate the similarity score $\tilde{S}(\mathbf{x}, \mathbf{y})$
  - Order the candidates by decreasing $\tilde{S}(\mathbf{x}, \mathbf{y})$

Experiments

- EVent VidEo (EVVE) dataset [CVPR'13]
  - 620 queries, 2375 database videos, 13 events
  - 1024-D multi-VLAD frame descriptor
- Experimental results



The average mAP using $S^{(p)}(\mathbf{x},\mathbf{y})$ for different p

$p\uparrow \longrightarrow \text{mAP}\uparrow$

$$S^{(p)}(\mathbf{x},\mathbf{y}) = \sqrt[p]{\sum_{i=1}^{m}\left(c_i^2 + s_i^2\right)^p}$$

Experiment

- Results on EVVE and comparison

Table 1: Performance (mAP and time) on EVVE. The bold values show the best score.

Event No.	Baseline	Ours $\widetilde{S}$	Ours $\widetilde{S}$ +PQ	Ours $S^{(\infty)}$ +PQ
#1	0.1521	0.2013	0.1985	**0.2483**
#2	0.2424	0.2503	**0.2621**	0.2133
#3	**0.1186**	0.1130	0.0651	0.0905
#4	0.1370	0.1390	0.1419	**0.1467**
#5	0.2486	0.2538	**0.2675**	0.2671
#6	0.2913	0.3189	0.3511	**0.3917**
#7	**0.1856**	0.1854	0.1177	0.1139
#8	0.2004	0.2216	0.2128	**0.2736**
#9	0.6119	0.6351	0.6276	**0.6728**
#10	0.3737	0.4519	0.4913	**0.5529**
#11	0.7979	0.7879	**0.8584**	0.8218
#12	0.2295	0.3084	0.3224	**0.4344**
#13	0.6187	0.6331	**0.6915**	0.6762
ave-mAP	0.3237	0.3461	0.3545	**0.3772**
time	9.31s	1.74s	≈ **0.3s**	≈ **0.3s**

Table 2: Comparison with state of the art.

methods	state of the art				Ours
	MMV	CTE	SHP	MMV+CTE	
ave-mAP	0.334	0.352	0.363	0.376	**0.377**

Baseline (temporal match kernel): MM’15

MMV (mean-multiVLAD): CVPR’13

CTE (circulant temporal encoding): CVPR’13

SHP (stable hyper-pooling): ICCV’13

Conclusion

- Propose a fast event retrieval method in video database with temporal match kernel
- Use the energy of the score function as similarity metric
- Derive the simplified energy formulation by using Parsevals's theorem
- With the energy formulation, we use PQ to accelerate the computation
- Achieve competitive performance with the-state-of-the-art

Thank you! ☺