EXTRACTING KEY FRAMES FROM FIRST-PERSON VIDEOS IN THE COMMON SPACE OF MULTIPLE SENSORS

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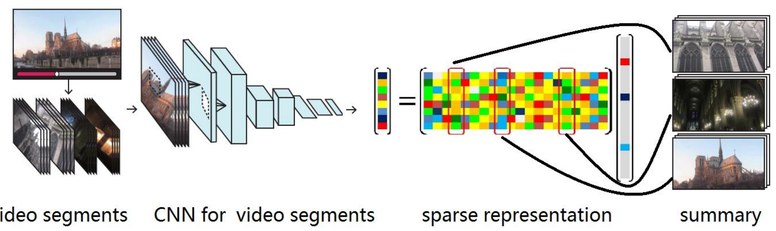
INTRODUCTION

Selecting authentic scenes about activities of daily living (ADL) is useful to support our memory of everyday life. Key-frame extraction for first-person vision (FPV) videos is a core technology to realize such memory assistant.

FPVs
√ Shift background
√ With much noise
√ Only parts of subjects

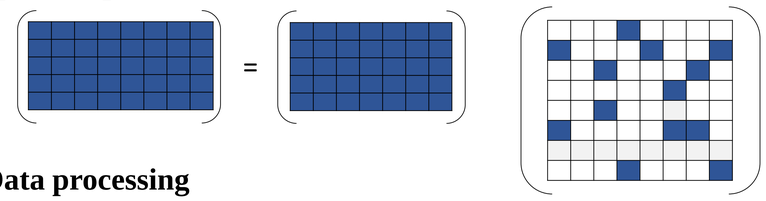
Normal videos
√ Stable background
√ With less noise

➢The overview of the video feature selection.



PROPOSED METHOD

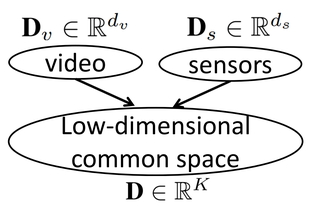
➢Sparse representation: Y=DH.



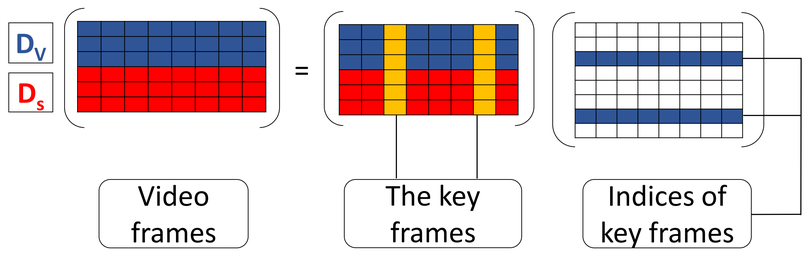
➢Data processing

In our situation, we use (Probabilistic Canonical Correlation Analysis) PCCA to embed the multi-sensor integration data (video and sensors) to a common space.

$$\min\left(\frac{1}{2}\sum_{n_v=1}^{N_v}\sum_{n_s=1}^{N_s} w_{ij}^{n_v n_s}\|\mathbf{A}^v\mathbf{x}_i^v-\mathbf{A}^s\mathbf{x}_j^s\|^2 + \frac{1}{2}\sum_{n_s=1}^{N_s}\sum_{n_v=1}^{N_v} w_{ij}^{n_s n_v}\|\mathbf{A}^s\mathbf{x}_i^s-\mathbf{A}^v\mathbf{x}_j^v\|^2\right)$$



➢Sparse model based key frame extraction.



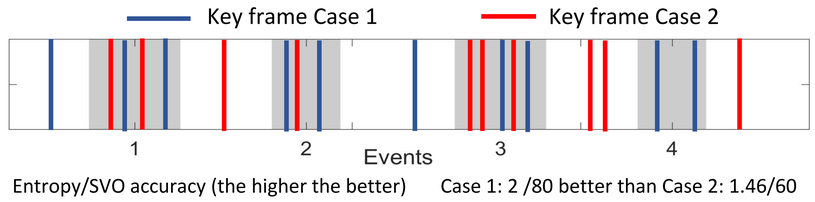
$$\min_{\mathbf{H}}\|\mathbf{Y}-\mathbf{Y}\mathbf{H}\|_2^2+\alpha\|\mathbf{H}\|_{1,2} \quad \text{s.t. } \mathbf{1}^T\mathbf{H}=\mathbf{1}^T, \text{where } \|\mathbf{H}\|_{1,2}=\sum_{i=1}^{N}\|\mathbf{h}_i\|_2$$

EXPERIMENTS AND DISCUSSION

➢Evaluation

We use accuracy (A) and entropy (S) as metrics for the extraction experiments.

$$A=\frac{N_{\text{Correct}}}{N_{\text{Whole}}} \qquad S=-\sum_{i=1} p_i \log_2 p_i$$



Entropy/SVO accuracy (the higher the better) Case 1: 2 /80 better than Case 2: 1.46/60

➢Experimental results.

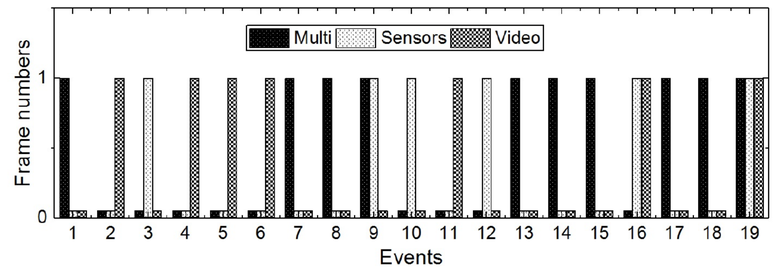
Table 1. The accuracy various kinds of information

Session	α	Video	Sensors	Multi
1	$4\sqrt{2}$	0.15	0.13	**0.23**
2	4	0.21	0.16	**0.23**
3	$8\sqrt{2}$	**0.24**	0.19	0.22
4	$8\sqrt{2}$	**0.19**	0.07	0.15
5	$4\sqrt{2}$	0.15	0.13	**0.24**
6	$4\sqrt{2}$	0.13	0.15	**0.20**
7	$8\sqrt{2}$	**0.22**	0.08	**0.22**
8	$8\sqrt{2}$	0.13	0.13	**0.15**
9	8	0.13	0.18	**0.20**
10	$2\sqrt{2}$	0.10	0.10	**0.14**

Table 2. The entropy various kinds of information

Session	α	Video	Sensors	Multi
1	$4\sqrt{2}$	2.81	2.59	**3.46**
2	4	2.81	2.81	**3.00**
3	$8\sqrt{2}$	**3.59**	3.32	3.32
4	$8\sqrt{2}$	**3.32**	2.00	3.00
5	$4\sqrt{2}$	3.32	3.17	**3.46**
6	$4\sqrt{2}$	2.32	2.59	**3.00**
7	$8\sqrt{2}$	**3.46**	2.00	3.32
8	$8\sqrt{2}$	2.59	**2.81**	**2.81**
9	8	2.81	3.17	**3.32**
10	$2\sqrt{2}$	2.00	2.00	**2.32**

➢The number of representatives found by our method for each of the events in the video.



CONCLUSION

➢We proposed a novel framework for key frame extraction of FPVs by sparse modeling representation selection from multisensory integration.

➢We use video features from DNN instead of raw frames.

➢Experimental results show that our proposed approach achieves modest improvements over a pure video information and the accuracy and entropy results predict the efficient of the proposed algorithm.

➢Moving forward, we plan to improve our method by using other nonvideo information such as audio and eWatch information.

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