

Weakly-Supervised Temporal Action Alignment Driven by Unbalanced Spectral Fused Gromov-Wasserstein Distance

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Objectives

Predict frame labels, when the ground truth in training is limited and specifies only the actions appearing in the video, instead of their temporal ordering and frequency.

Introduction

How to characterize videos and textual labels?

How to match between two modalities?

How to train in the weakly-supervised setting?

Our contributions:

1. A novel optimal transport-based solution to set-supervised temporal action alignment.
2. A new contrastive learning paradigm based on US-FGW distance.
3. An algorithm for efficient calculation of US-FGW distance leveraging the Bregman ADMM algorithm.

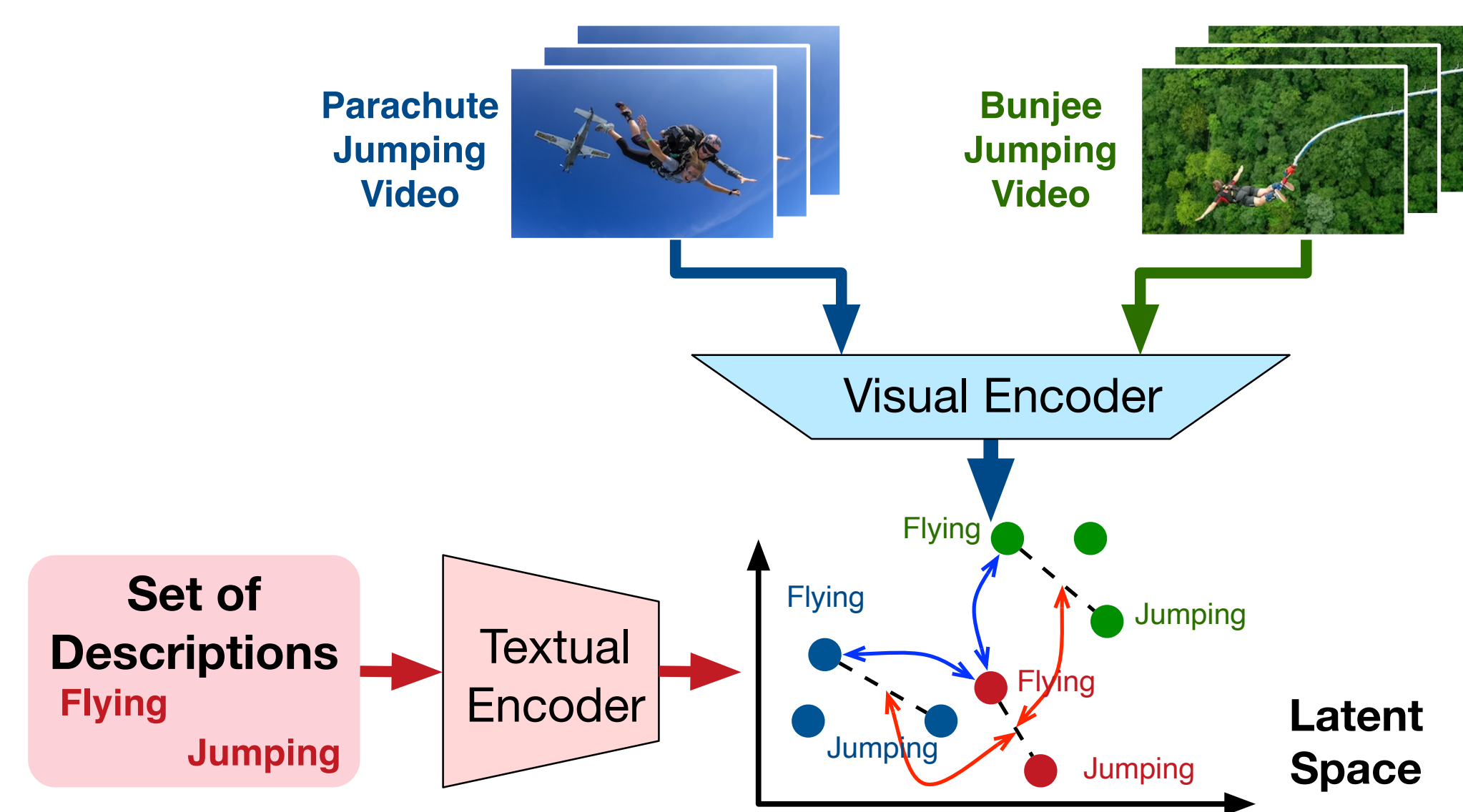


Figure 1: An illustration of the FGW distance, which not only considers the pointwise comparison between the latent codes of different modalities, but also considers the pairwise comparison between the latent relations of different modalities.

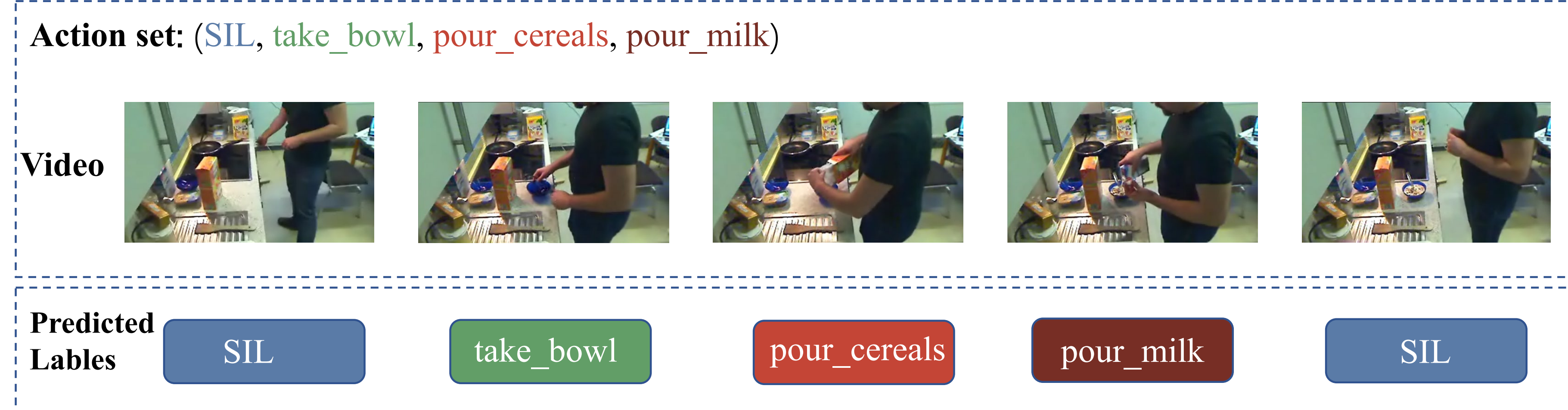


Figure 2: An illustration of the proposed method.

Considering the input video \mathcal{V} , the text set \mathcal{W} , we obtain the proposed unbalanced spectral FGW (US-FGW) distance:

$$d_{\text{us-fgw}}(\mathbf{V}, \mathbf{W}; \beta, \tau) = \min_{\mathbf{T}} \underbrace{(1 - \beta) \langle -\mathbf{K}_{vw}, \mathbf{T} \rangle}_{\text{Wasserstein term}} + \underbrace{\beta \langle -\mathbf{K}_v \mathbf{T} \mathbf{K}_w^T, \mathbf{T} \rangle + \tau \left(\text{KL}(\mathbf{T} \mathbf{1}_J \| \frac{1}{J} \mathbf{1}_I) + \text{KL}(\mathbf{T}^T \mathbf{1}_I \| \frac{1}{J} \mathbf{1}_J) \right)}_{\text{GW term}}.$$

Taking the negative text set \mathcal{W}'_n into account, the overall learning strategy is as follows:

$$\min_{f_v, g_v, f_w, g_w} \sum_{(\mathcal{V}_n, \mathcal{W}_n, \mathcal{W}'_n) \in \mathcal{D}} \left(\underbrace{\ell_v(\mathcal{V}_n, g_v(f_v(\mathcal{V}_n)))}_{\text{Reconstruction loss of frames}} + \underbrace{\ell_w(\mathcal{W}_n, g_w(f_w(\mathcal{W}_n)))}_{\text{Reconstruction loss of words}} + \underbrace{\gamma(d_{\text{us-fgw}}(f_v(\mathcal{V}_n), f_w(\mathcal{W}_n); \beta, \tau))}_{\text{Positive US-FGW distance}} - \underbrace{d_{\text{us-fgw}}(f_v(\mathcal{V}_n), f_w(\mathcal{W}'_n); \beta, \tau)}_{\text{Negative US-FGW distance}} \right).$$

Experiments

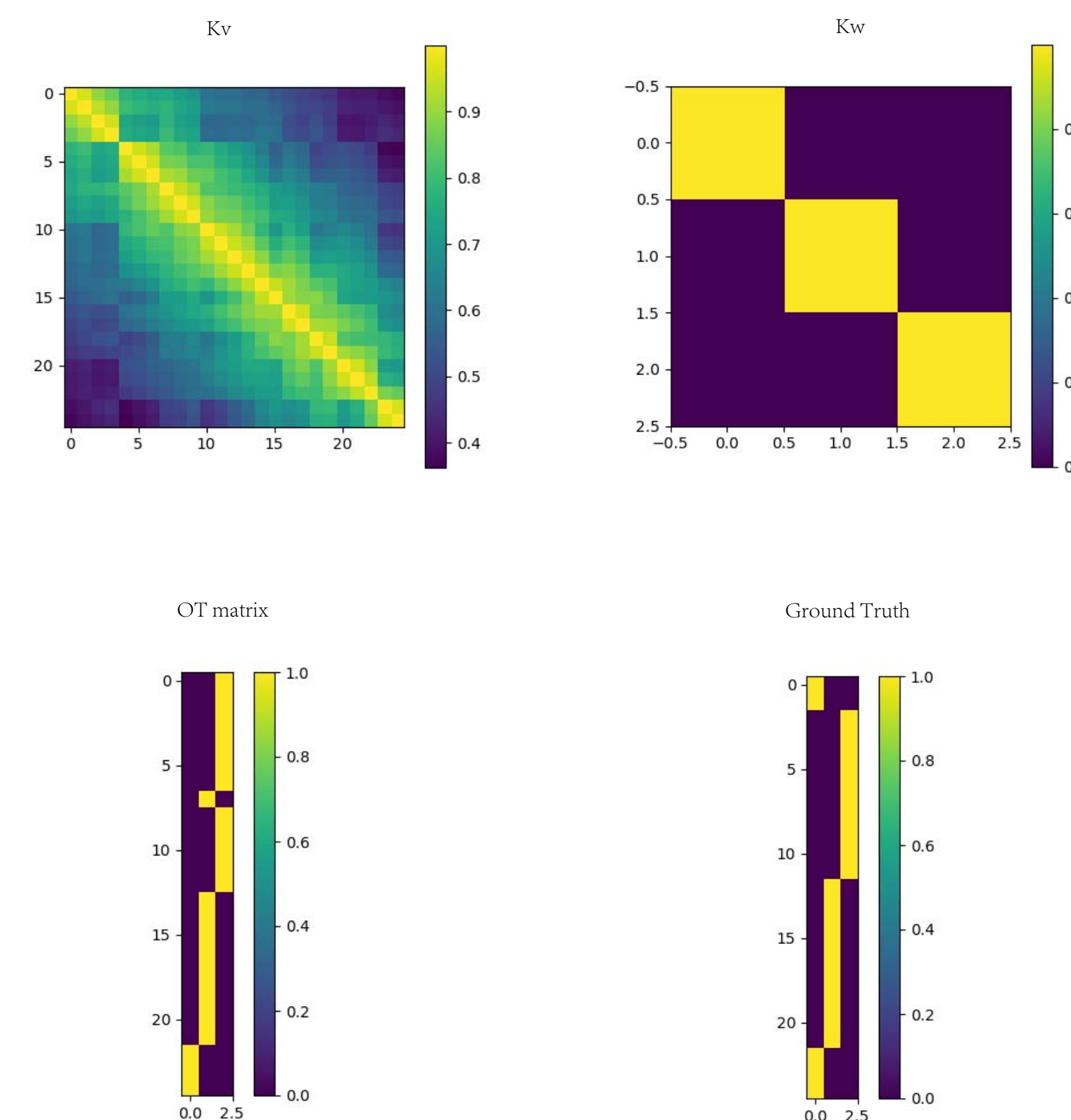


Figure 3: Visualization on distance matrix \mathbf{K}_v , \mathbf{K}_w , optimal transport matrix \mathbf{T} and ground truth matrix.

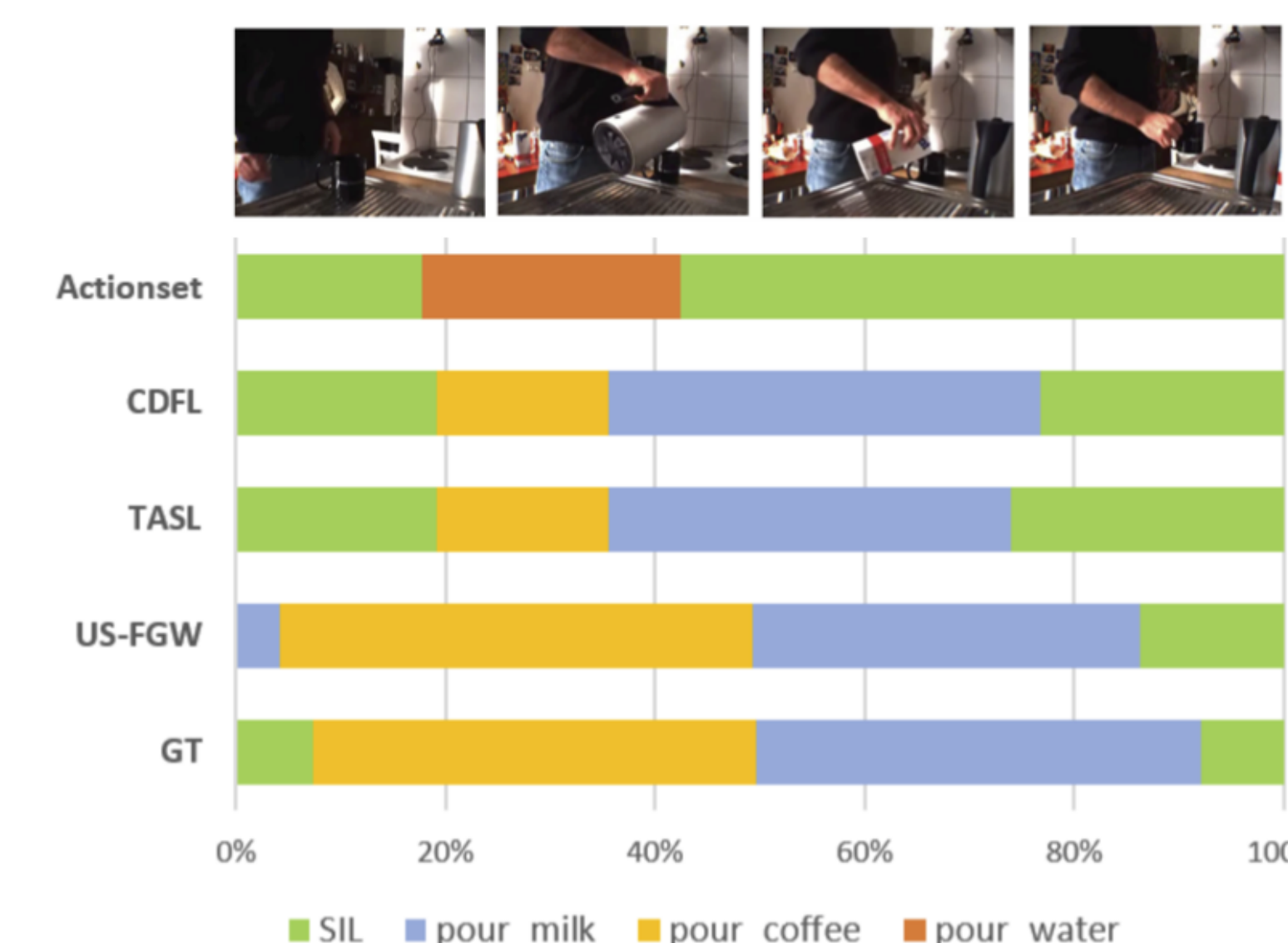


Figure 4: A qualitative alignment result comparison between our US-FGW and Actionset, CDL and TASL.

Methods	Breakfast (MoF)	Hollywood (IoD)
Transcript-Supervised		
ISBA _{ED-TCN}	0.4548	0.3878
ISBA _{TCFPN}	0.4825	0.3958
NNV	0.5404	0.4692
CDL	0.5940	0.5009
TASL	0.6042	0.4959
Set-Supervised		
Actionset	0.2137	0.1833
*SCT	0.2660	0.1770
*SCV	0.3020	0.3020
*ACV	0.3340	0.2090
US-FGW(Ours)	0.3357	0.4001

Conclusion

- A new set-supervised paradigm for temporal action alignment based on optimal transport.
- Unified learning of the visual and textual auto-encoders within the new contrastive learning framework.
- Experimental results show that our method achieves encouraging performance for set-supervised temporal action alignment.

Acknowledgements

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Contact Information

- Code and data:
<https://github.com/hhhh1138/Temporal-Action-Alignment-USFGW>
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