

method	venue	high-level summary
CtxSyn [5]	CVPR 2018	estimate $F_{0 \rightarrow 1}$ and $F_{1 \rightarrow 0}$ , extract features and splat them to time $t$ , synthesize the output $I_t$ using a neural network
Super SloMo [3]	CVPR 2018	estimate $F_{0 \rightarrow 1}$ and $F_{1 \rightarrow 0}$ , obtain $F_{t \rightarrow 0}$ and $F_{t \rightarrow 1}$ and visibilities using a network, backwarp and merge $I_0$ and $I_1$
DAIN [1]	CVPR 2019	estimate $F_{0 \rightarrow 1}$ and $F_{1 \rightarrow 0}$ , splat flows subject to $Z$ , extract and backwarp features to time $t$ , obtain $I_t$ using a network
SoftSplat [6]	CVPR 2020	estimate $F_{0 \rightarrow 1}$ and $F_{1 \rightarrow 0}$ , extract feature pyramids and splat them to time $t$ , synthesize $I_t$ using a neural network
EDSC [2]	arXiv 2020	estimate kernels as well as masks and offsets at $t$ using a network, apply deformable convolutions and merge the images
BMBC [7]	ECCV 2020	estimate $F_{t \rightarrow 0}$ and $F_{t \rightarrow 1}$ as well as $F_{0 \rightarrow 1}$ and $F_{1 \rightarrow 0}$ , extract features and splat them to $t$ , obtain $I_t$ using a network
AnimeInterp [4]	CVPR 2021	estimate coarse $F_{0 \rightarrow 1}$ and $F_{1 \rightarrow 0}$ , refine flows recurrently, extract feature and splat them, synthesize $I_t$ using a network
XVFI [8]	ICCV 2021	extract features, estimate $F_{0 \rightarrow 1}$ and $F_{1 \rightarrow 0}$ , splat flows and refine them, backwarp features and obtain $I_t$ using a network
Ours	N/A	estimate $F_{0 \rightarrow 1}$ and $F_{1 \rightarrow 0}$ , optionally upsample them, splat flows to get $F_{t \rightarrow 0}$ and $F_{t \rightarrow 1}$ , backwarp and merge $I_0$ and $I_1$

Table 1: Overview of recent video frame interpolation approaches that take two images as input and yield an interpolation result at an arbitrary time. For brevity we use the term features in the high-level summary to refer to various feature representations such as the input images themselves, contextual features, feature pyramids, depth maps, edge maps, occlusion masks, and visibility maps.

## References

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