

MOTIVATION

- Problems like absorbing, scattering and attenuation of light rays between the scene and the imaging platform degrades the visibility of image or video frames.
- Back-scattering of light rays further increases the problem of underwater video analysis, because the light rays interact with underwater particles and scattered back to the sensor.
- Extra-ordinary results Generative Adversarial Network (GAN) for various computer vision applications like image de-hazing, image super-resolution, Foreground-background segmentation, etc.

MAJOR CONTRIBUTIONS

Limitations of existing approaches and results of GAN-based approaches are motivated us to propose a novel approach for video frame segmentation for challenging videos like underwater, bad weather and dynamic background. Major contributions of the work are given below:

- The frame wise motion saliency is estimated using few initial and current video frame instead of current and previous video frames only.
- Generative adversarial network with identity mapping and dense connections is proposed for MOS of underwater videos.
- The segmentation accuracy is compared with the existing methods on benchmark Fish4Knowledge and ChangeDetection.net-2014 video database.

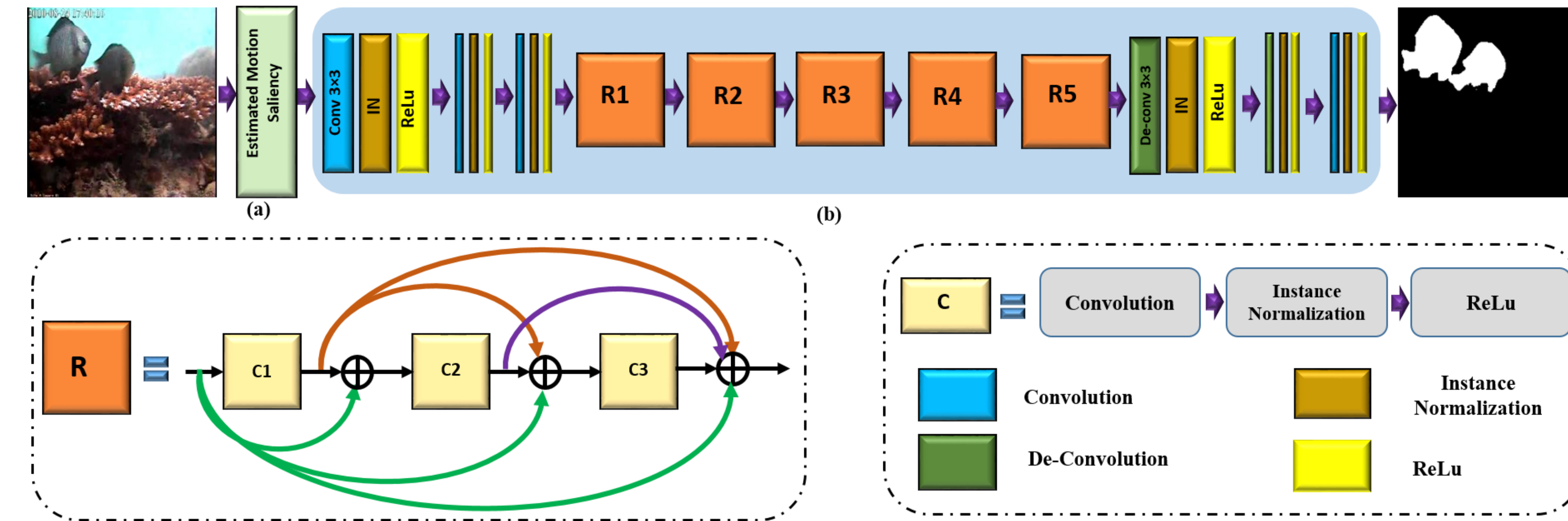


Figure 1. Flow-graph of proposed system using generative adversarial networks.

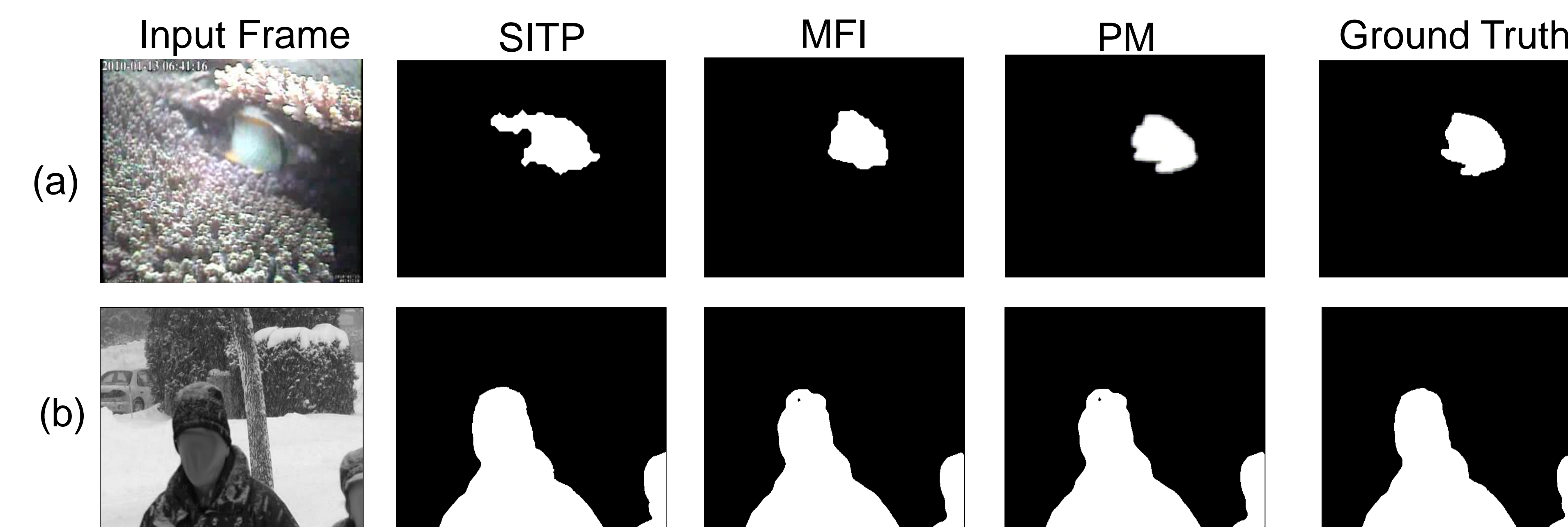


Figure 2. Qualitative comparison of existing methods on underwater and bad weather videos.

CONCLUSION

- We have proposed a novel unpaired motion saliency learning approach for foreground segmentation in underwater videos with identity mapping and dense connections.
- From experimental analysis, it is evident that the proposed approach outperforms the existing state-of-the-art methods for underwater, dynamic background and bad weather videos

REFERENCES

- Zhu et al., "Unpaired image-to-image translation using cycle-consistent adversarial networks," in **ICCV, 2017**.
- Prashant et al., "Fggan: A cascaded unpaired learning for background estimation and foreground segmentation," in **IEEE WACV, 2019**.
- Srikanth et al., "Automatic underwater moving object detection using multi-feature integration framework in complex backgrounds," **IET Computer Vision, 2018**.

Table 1. Quantitative results comparison on Fish4Knowledge dataset

Category	TBG	MCB	SEB	STP	MFI	PM
LumChg	0.91	0.85	0.82	0.84	0.92	0.96
Blurred	0.68	0.86	0.59	0.74	0.89	0.93
Combg	0.58	0.48	0.21	0.73	0.83	0.92
hybrid	0.46	0.72	0.42	0.69	0.82	0.89
CamFg	0.66	0.77	0.42	0.66	0.72	0.75
crowded	0.74	0.68	0.67	0.67	0.69	0.74
Dynbg	0.32	0.33	0.81	0.32	0.64	0.79
Average	0.62	0.67	0.56	0.66	0.79	0.85

Table 2. Quantitative results comparison on bad weather and dynamic background videos.

Category	DeepBS	GoogleNet	MSCNN	VGG	ResNet	PM
DyanBG	0.81	0.65	0.92	0.73	0.82	0.97
BadWath	0.92	0.79	0.94	0.89	0.93	0.94
Average	0.86	0.72	0.93	0.81	0.87	0.96