WaterGAN: Unsupervised Generative Network to Enable Real-time Color Correction of Monocular Underwater Images

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2018.12.21

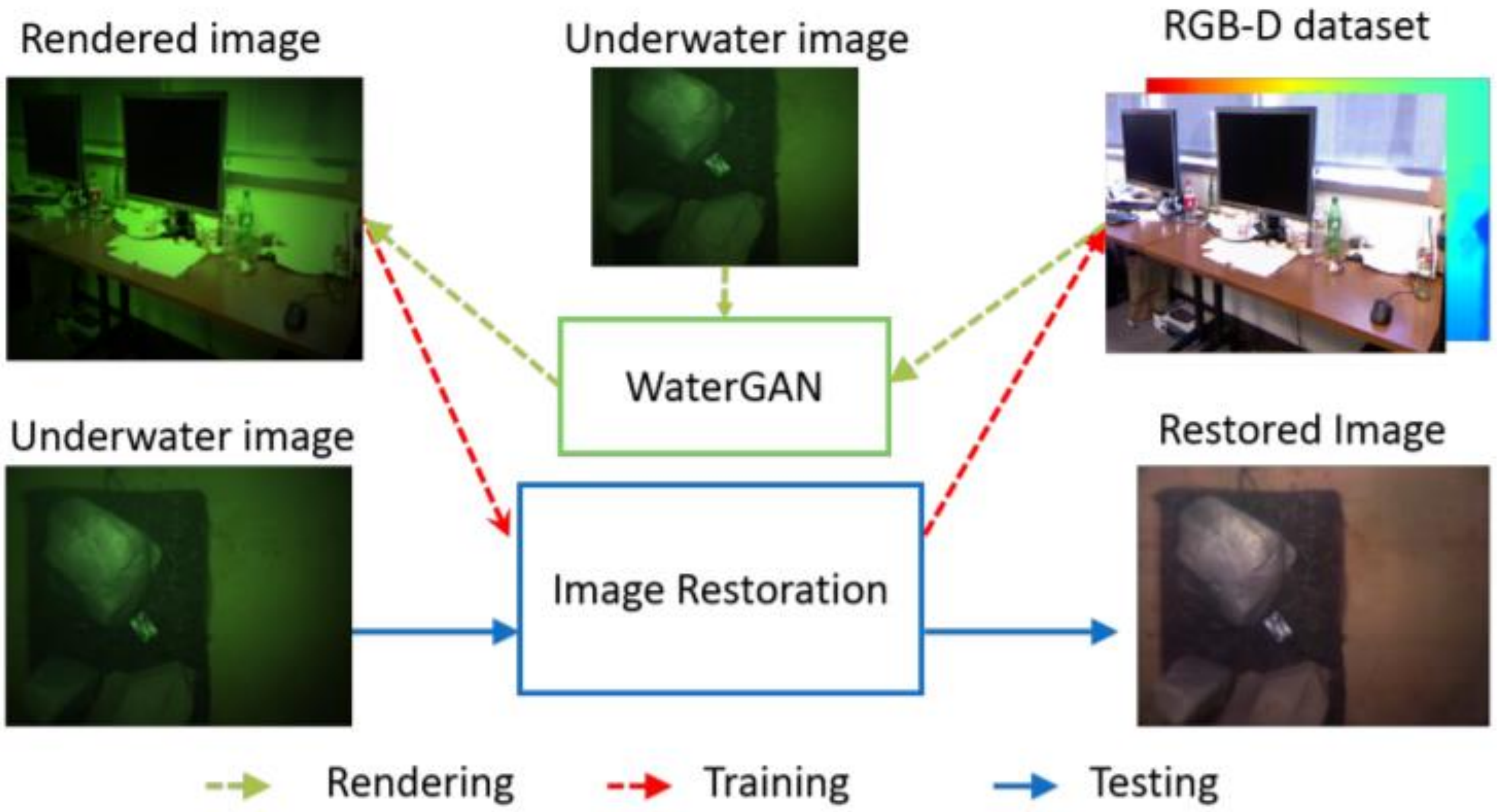

Fig. 1: Flowchart displaying both the WaterGAN and color correction networks. WaterGAN takes input in-air RGB-D and a sample set of underwater images and outputs synthetic underwater images aligned with the in-air RGB-D. The color correction network uses this aligned data for training. For testing, a real monocular underwater image is input and a corrected image and relative depth map are output.

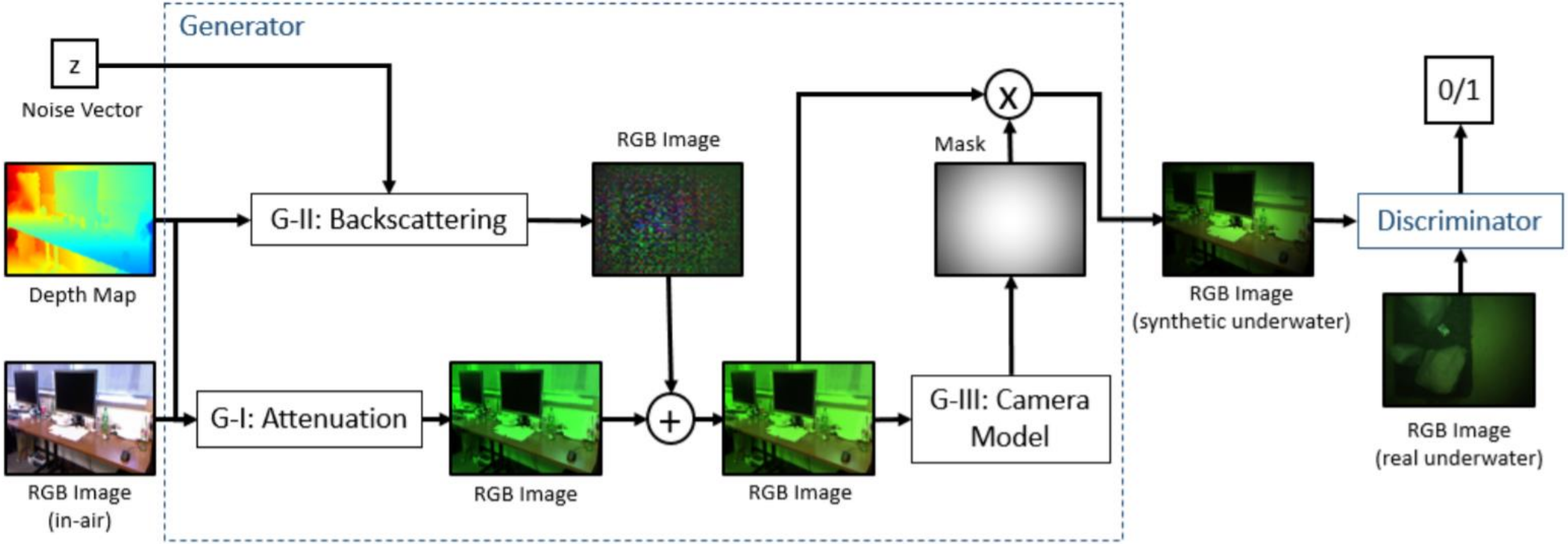

Fig. 2: WaterGAN: The GAN for generating realistic underwater images with similar image formation properties to those of unlabeled underwater data taken in the field.

A. Generating Realistic Underwater Images

$$log(D(G(z)).$$

$$log(D(x)) + log(1 - D(G(z))).$$

G-I: Attenuation

$$G_1 = I_{air} e^{-\eta(\lambda) r_c},$$

G-II: Scattering

$$B = \beta(\lambda)(1 - e^{-\eta(\lambda) r_c}), \quad G_2 = G_1 + M_2.$$

G-III: Camera Model

$$V = 1 + ar^2 + br^4 + cr^6, \qquad M_3 = \frac{1}{V} \qquad G_3 = M_3 G_2.$$

$$G_{out} = kG_3.$$

B. Underwater Image Restoration Network

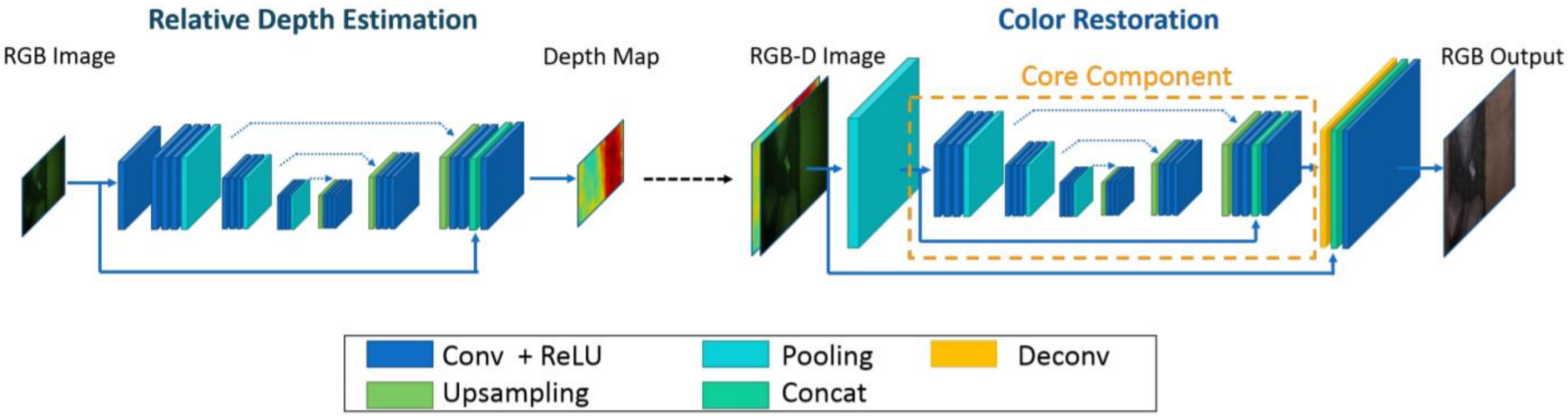

Fig. 3: Network architecture for color estimation. The first stage of the network takes a synthetic (training) or real (testing) underwater image and learns a relative depth map. The image and depth map are then used as input for the second stage to output a restored color image as it would appear in air.

Results：

(a) Raw image patch (b) Restored image without skipping layers (c) Proposed output

Fig. 6: Zoomed-in comparison of color correction results of an image with and without skipping layers.

Fig. 5: Results showing color correction on the MHL, Lizard Island, and Port Royal datasets (from top to bottom). Each column shows (a) raw underwater images, and corrected images using (b) histogram equalization, (c) normalization with the gray world assumption, (d) a modified Jaffe-McGlamery model (Eqn. 3) with ideal attenuation coefficients, (e) Shin et al.'s deep learning approach, and (f) our proposed method.

Two quantitative metrics for evaluating the performance of color correction：

	Raw	Hist. Eq.	Gray World	Mod. J-M	Shin[13]	Prop. Meth.
Blue	0.3349	0.2247	0.2678	0.2748	0.1933	**0.1431**
Red	0.2812	0.0695	0.1657	0.2249	0.1946	**0.0484**
Mag.	0.3475	0.1140	0.2020	0.298	0.1579	**0.0580**
Green	0.3332	**0.1158**	0.1836	0.2209	0.2013	0.2132
Cyan	0.3808	**0.0096**	0.1488	0.3340	0.2216	0.0743
Yellow	0.3599	**0.0431**	0.1102	0.2265	0.2323	0.1033

TABLE I: Color correction accuracy based on Euclidean distance of intensity-normalized color in RGB-space for each method compared to the ground truth in-air color board.

	Raw	Hist. Eq.	Gray World	Mod. J-M	Shin[13]	Prop. Meth.
Red	0.0073	0.0029	0.0039	0.0014	0.0019	**0.0005**
Green	0.0011	0.0021	0.0053	0.0019	0.0170	**0.0007**
Blue	0.0093	0.0051	0.0042	0.0027	0.0038	**0.0006**

TABLE II: Variance of intensity-normalized color of single scene points imaged from different viewpoints.

Dataset	Red	Green	Blue	Depth RMSE
Synth. MHL	0.052	0.033	0.055	0.127
Synth. Port Royal	0.060	0.041	0.031	0.122
Synth. Lizard	0.068	0.045	0.035	0.103

TABLE III: Validation error in pixel value is given in RMSE in RGB-space. Validation error in depth is given in RMSE (m).