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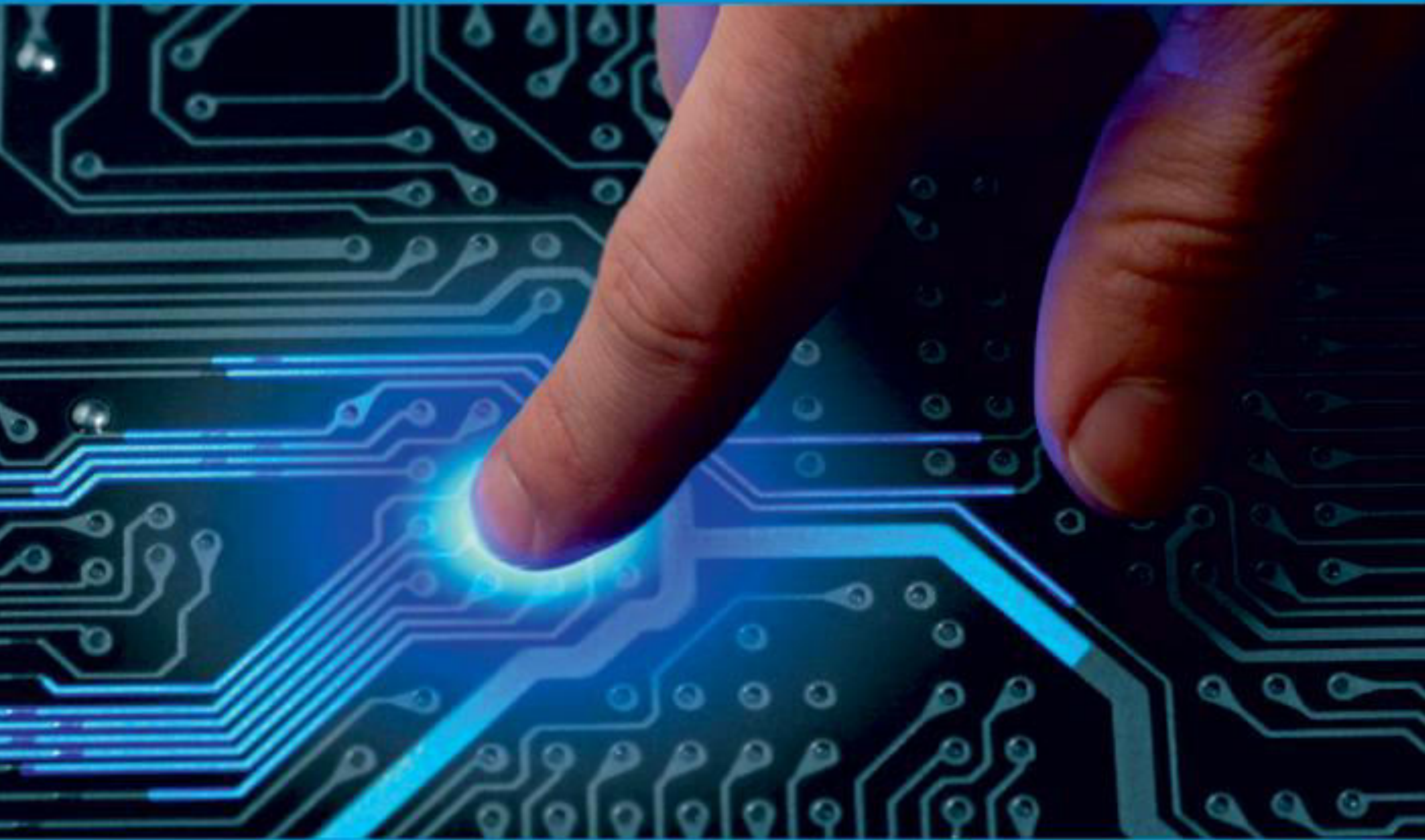

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# Underwater Image Enhancement via Medium Transmission-Guided Multi-Color Space Embedding

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**ABSTRACT:** In underwater photography, colour casts and hard-to-decipher images are common because of the wavelength and distance of the light. We came up with a network named Ucolor to address both of these issues: medium-transmission-guided multi-color area embedding for underwater photos. A multi-color area encoder network, for example, combines the properties of multiple colour areas into a single structure, increasing the number of methods to describe features. These distinct characteristics from various colour zones are brought to the foreground, in addition to the accompanying attention mechanism. We prefer to develop a medium-transmission-guided decoder network based on physical models of underwater imagery to increase the network's responsiveness in low-quality areas. By using different colour areas incorporated and the advantages of both learning-based and physical model-based methods, our network will be able to increase the visual quality of underwater images. We've run a lot of testing, and our Ucolor comes out on top in terms of both aesthetic quality and quantitative measures.

**KEYWORDS:** Color correction, Image sweetening, Single underwater image sweetening, Transmission map estimation, Scattering removal.

## I. INTRODUCTION

Attenuation and scattering, which depend on wavelength and distance, always lower the quality of images taken underwater [1]. Usually, when light travels through water, it suffers from selective attenuation, which changes the colour in different ways. Also, particles like microphytoplankton and non-algal particulate matter that are suspended in water scatter the light, which makes the contrast low. A good way to get back to the clean images underneath is very important for improving the quality of underwater photos and getting a true picture of the underwater world.


**Fig1:Visual comparison on a real under water image.**

The medium transmission, or the proportion of scene light that reaches the camera, may be used to estimate the extent

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of quality deterioration in underwater photos. According to underwater image enhancement techniques that use physical models, the most important aim is to gain an accurate assessment of how much medium is being communicated. You may achieve a clean picture with an estimated medium transmission and other important underwater imaging properties, such as a homogenous background light, by inverting an underwater imaging physical model. When used in challenging underwater conditions, physical model-based approaches may provide excellent results, but they tend to produce unstable, sensitive findings. With conventional approaches, it's difficult to estimate the medium transmission and many underwater imaging characteristics. With underwater imaging models, they don't always function.

Submarine photography has recently seen a significant improvement because to the use of deep learning technologies Deep learning approaches commonly employ networks designed for other visual tasks on photographs of the ocean. As a result, their performance lags much behind that of current deep visual models. [13]-[16]. The primary reason for this is a lack of expertise among those who create the models used to improve underwater photos.

Using extensive encoder characteristics and the advantages of physical model-based and learning-based approaches, we propose to repair underwater photos'colour cast and poor contrast. A multi-color space encoder network is employed instead of the RGB colour space encoder network used in prior deep models [10, 17, 18]. Attention mechanisms are used to emphasise the most significant aspects. As a side benefit, the character sticks of various qualities from several colour space networks are combined into a single structure, further improving the generalisation ability of deep networks. This doesn't get much attention when it comes to enhancing underwater photography. We propose a medium transmission-guided decode network to increase our network's responsiveness in areas where the quality of underwater photos is deteriorating [19]. Physical model-based approaches may be utilised in deep networks with the assistance of medium transmission, speeding up network optimization and improving enhanced performance. Deep networks. Because we solely rely on facts, our approach is robust enough to address estimation mistakes caused by too pessimistic medium transmission estimates. Figure 1 illustrates how Ucolor compares to other underwater image-enhancing techniques. According to [9](fig.1(a) and [10](fig.1(b)], both the traditional fusion-based approach and the deep learning-based method generate outcomes that are visually appealing.

## II. LITERATURE REVIEW

There are a variety of underwater approaches that may be used to create new classes. Methods that make use of specialised hardware belong in a specific class. In spite of recent advancements in underwater robotic vehicles, underwater visual detection and underwater photography remain significant challenges. Generally speaking, underwater images may be divided into two categories: Methods rooted in tradition as well as those that emphasise in-depth understanding.

### Traditional Methods:

Dynamic pixel stretching, pixel distribution adjustment and picture fusion were early efforts to improve the image by changing the values of the pixels themselves. After getting the color-corrected version and the contrast-enhanced version of an underwater picture, Ancuti et al. [9] estimated the appropriate weight maps, and then integrated the advantages of each version. Using a multiscale fusion technique, Ancuti et al. improved the fusion-based strategy for enhancing underwater photos by integrating two versions of the white-balance algorithm. Ancuti et al. have developed a pre-processing technique known as 3C, which stands for colour channel compensation. In unfavourable lighting situations like misty darkness, underwater, and artificial illumination that isn't consistent, at least one colour channel loses almost all of its information. The 3C operator has the ability to improve upon the standard procedures used in the restoration process as the initial stage.

Despite the lack of a real model, these techniques may nevertheless increase the image's quality. As a consequence, their images tend to be either too bright or lacking in colour accuracy since they don't employ underwater imaging mechanisms. Underwater pictures may be particularly challenging, and the colour correcting algorithm in [9] may not always be able to handle them. To make the improved photographs seem more natural and attractive to the eye, we used models of how underwater images develop and the great learning capacity of deep networks instead of the other approaches. Based on what we now know about underwater imaging models, most strategies for enhancing underwater photos are based on physical models that estimate these characteristics.

There are a number of these: red channel previous, underwater dark channel prior prior, blurriness prior, and so on. According to Peng and Cosman's technique, an image's blurriness and the amount of light it absorbs may be used to determine its depth underwater. Based on the blurriness and light absorption of an underwater picture, Peng and Cosman devised an algorithm for estimating image depth. Additionally, Peng et al. proposed a generalised version of the dark channel that could be used to a variety of photos captured in inclement weather. A new model for how

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pictures develop underwater was proposed based on this one. A method for correcting the colour of underwater photographs was shown using underwater RGB-D photos.

These methods based on physical models either take a long time or are sensitive to the types of underwater images. Also, it is hard to get a good estimate of complex underwater imaging parameters using physical models [3], [4]. For example, the blurriness before doesn't always hold true, especially when it comes to clear images taken underwater. Our methods, on the other hand, can bring back underwater images more accurately by taking advantage of the strengths of both model-based and data-driven methods.

**Literature Summary**

In the last 20 years, scientists have become very interested in the topic of underwater (UW) image colour correction and restoration. From marine biology to archaeology, there are a lot of fields that can and need to use the real information of the UW environment. Because of this, a lot of scientists have worked on the subject of UW image colour correction and restoration. In this, we try to look at some of the most important contributions from the last 15 years in a fair and in-depth way. After looking at the optical properties of water, how light travels through it, and the haze it makes, the focus is on the different ways that have been written about.

## III. EXISTING SYSTEM

Different algorithms for the enhancement process show that the image isn't very good because of the way light works. When light hits water, it bends and is absorbed and scattered because water is denser than air. This light drop happened because the light got into the water and spread out in all directions. Scattering of light caused by the way light blurs things and makes it harder to tell the difference between colours. Changes in the water in underwater photos are caused not just by the water itself, but also by the organisms and other things that are in the water. Blue, green, and red colours in the water cause blue, green, and red light to have different wavelengths and intensities.

**Problem Statement**

Image enhancement is the method of processing an underwater image to make it clearer and more useful for research. This technique for improving images helps make the information in the image better. This image changes the way the image looks, which helps the observer get more information from the image. It would be hard to improve an underwater image because the process of improving the image would remove some of the information that was already in the image. Image enhancement helps figure out what the image is. During the enhancement process, image features like edges and contrast are made stronger to make the photos better for research and study. For the process of enhancing, the qualitative objectives approach is used to show off the impressive images. Image enhancement can be done in many ways, such as by stretching the contrast, using the noise clipping process, giving the image a false colour, or using the noise filtering technique. The different image features that have been found have made the image's active range of features bigger.

**Proposed Solution**

As may be seen in Fig. 2, we've put Ucolor together in its entirety. The first thing that occurs to an underwater picture in the multi-color space encoder network is a shift in colour space. Encoders may take one of three routes: the HSV route, the RGB route, or the Lab route. Serial residual-enhancement modules are used in each of the three input paths. A 2x downsampling process yields three tiers of feature representations in this case. The RGB route is also being improved by linking its characteristics to those of the HSV and Lab paths. In order to create three sets of multi-color space encoder features, we combined the same level characteristics from these three parallel pathways. When we're done, we'll send all three sets of features to their respective channel attention module, which will highlight the most significant and useful elements. A medium transmission-guided decoder network highlights quality-degraded sites by delivering encoder features selected by the channel attention modules and RMT maps of the same sizes. To rebuild the decoder characteristics, three serial residual augmentation modules and two 2-by-2 upsampling operations are used, followed by passing them on to a convolution layer for reconstruction.

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## IV. SYSTEM DESIGN

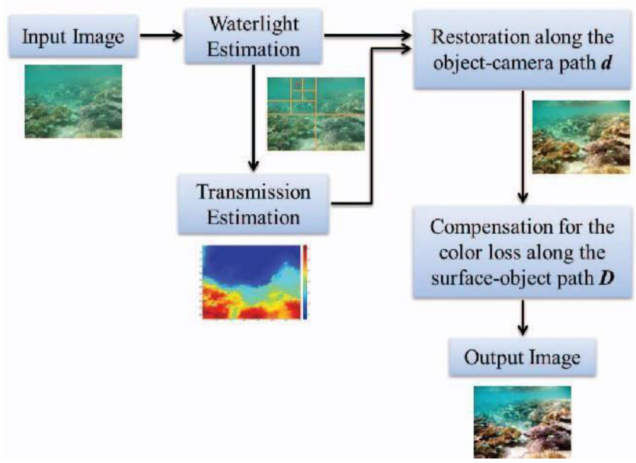


**Fig: Architecture diagram**

**Methodology Presented:**

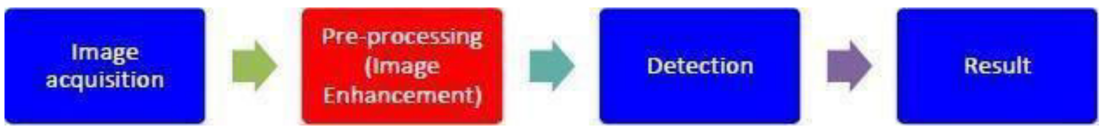


**Fig: Image processing steps**

**Detailed description of the methodology:**

**Image acquisition**:
Through the camera, an image is taken from under water. This picture was taken as an RGB image, which means it has red, green, and blue parts. The image that was captured goes through a step called "pre-processing." The bigger the pixel values, the more important the photo is. So, this algorithm picks the in-focus parts of each image by picking the best value for each pixel, resulting in very precise output. The value of each picture's pixel P I j) is taken and compared to the other pictures.

**Pre-processing:**
The number of steps in each stage of image processing depends on the image that is being processed. The pre-processing steps are done on the image that comes in from some source. The RGB image is what goes in. The RGB image is changed into a grayscale image with pixels that range from 0 to 255. The filtering process is part of the first step, which is called "pre-processing." This process of filtering gets rid of some of the noise in the image.
**Detection:**
As part of the process of detecting, the image that is used as an input is improved. The HWD transform technique is used in the proposed work improvement process. Using this method, noise can be taken away and the image can be improved more.

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## V. EXPERIMENTAL RESULTS

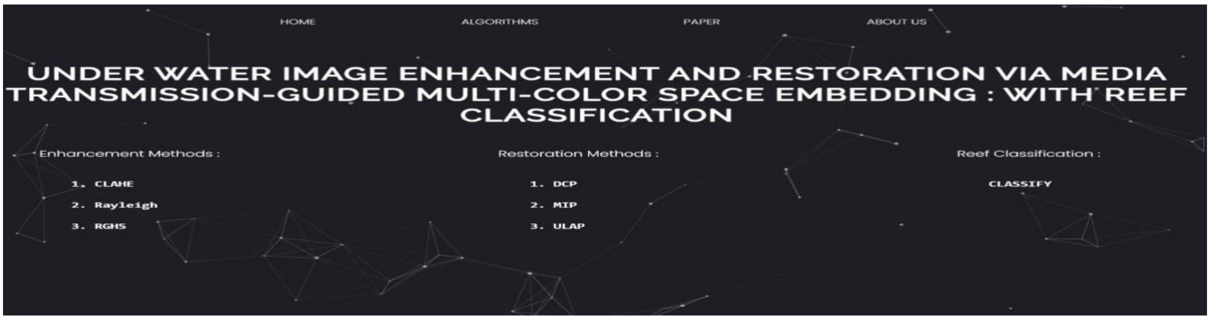


**Fig. Home Page**


**Fig:CLAHE**

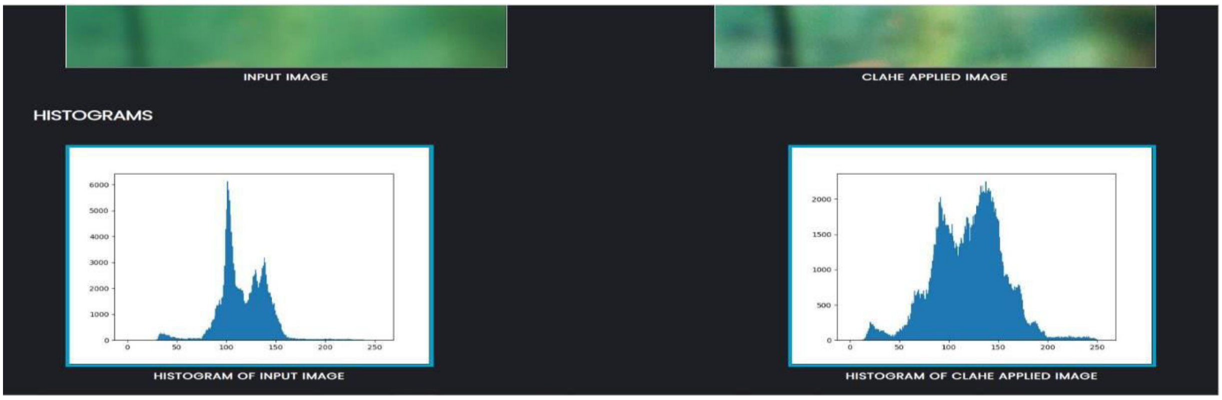


**Fig:CLAHE Histograms**

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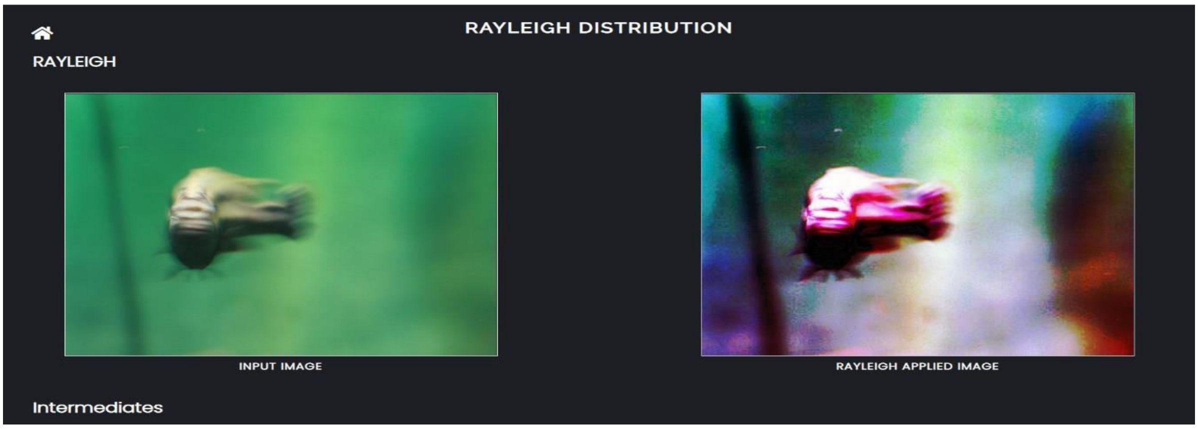


Fig: RAYLEIGH

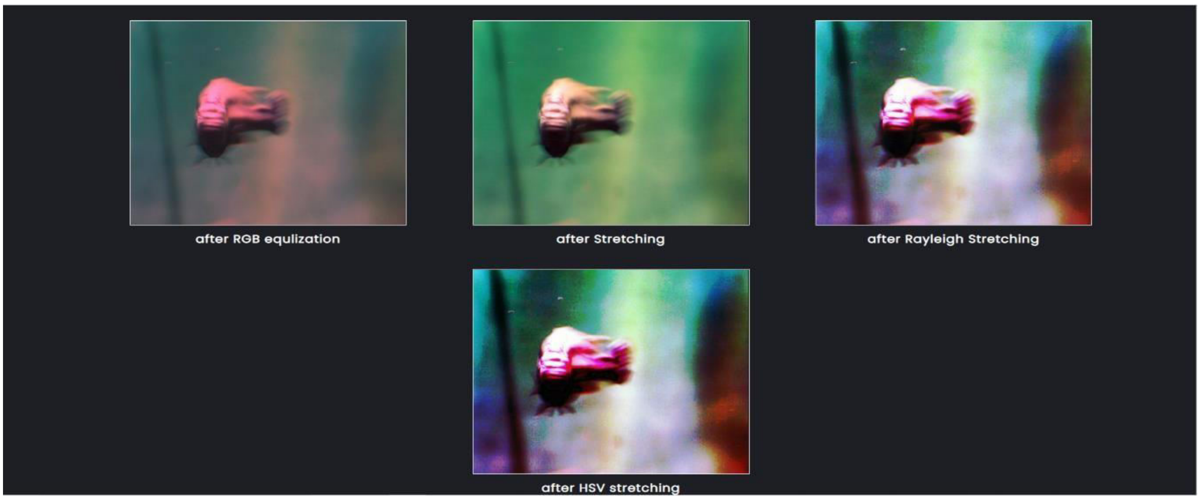


Fig:RAYLEIGH Intermediates

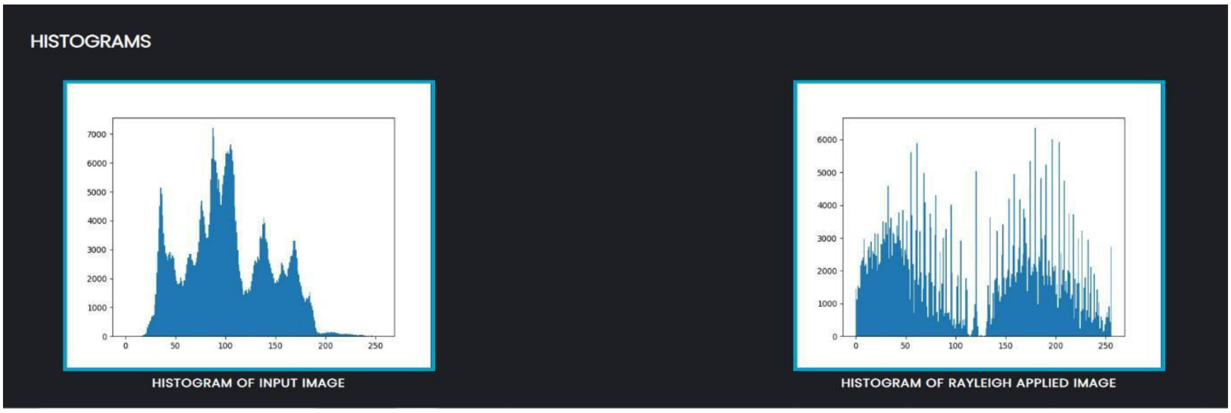


Fig:RAYLEIGH Histograms

As you can see above, we've done the same thing with all of the algorithms that are shown on the first page of our experimental results.

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## VI. CONCLUSION

We devised an algorithm to convert a smartphone video into a high-quality photograph. Our technique aligns all elements of a document to a single point of view and then merges them using a weighted average of their sharpness ratings when there are multiple viewpoints. Reflection, occlusion, and motion blur are all addressed by our approach. We were able to improve the document's picture quality and make it simpler to read than if we had taken a single photo of the whole thing.

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