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Improved Dehazing Techniques for Maritime Surveillance Image Enhancement

Branka Stojanović[1], Saša Milićević[1], Srđan Stanković[1,2]

Abstract: The subjective quality of images (human interpretation) is very important in long-range imaging systems, where the presence of haze directly influences visibility of the scene, by reducing contrast and obscuring objects. Image enhancement techniques – dehazing techniques, are usually required in such systems. This paper compares the most significant single image dehazing approaches, proposes three additional enhancement steps in dehazing algorithms, compares performance of the algorithms and additional enhancement steps, and presents test results on maritime surveillance images, which represent one special case of long-range images.

Keywords: Dehazing, Image enhancement, Surveillance imaging, Long-range imaging.

1 Introduction

The subjective quality of images (human interpretation) is very important in surveillance systems, and especially in long-range imaging systems, where the presence of haze directly influences visibility of the scene, by reducing contrast and obscuring objects. Haze is usually defined as a slight obscuration of the lower atmosphere, typically caused by fine suspended particles. The haze can be caused by various types of particles, usually classified in one of two classes – dry haze (dust, smoke…) and wet haze (fog, mist, rain, snow…). Scene depth seems to influence the scene visibility in hazy conditions – far objects are more obscured than near objects (Fig. 1).

Image enhancement techniques are usually required for surveillance video enhancement, especially for scenes taken under bad weather conditions and/or scenes that contain objects at distant ranges from the surveillance sensor. There are two types of video enhancement techniques in such systems – *online* and *offline* video enhancement. Online video enhancement is performed in real-time, while offline video enhancement can be applied to a video segment taken

[1]Institute Vlatacom, Milutina Milankovića 5, 11070 Belgrade, Serbia;
E-mails: branka.stojanovic@vlatacom.com; E-mail: sasa@vlatacom.com; srdjan.stankovic@vlatacom.com
[2]School of Electrical Engineering, University of Belgrade, Bulevar kralja Aleksandra 73, 11120 Belgrade, Serbia; E-mail: stankovic@etf.rs

in some specific circumstances, for example, triggered by some predefined events, like new object appearance on the scene.

Fig. 1 – *Typical hazy image* [1].

This paper presents a comparative study of three most important approaches to the dehazing problem – DCP [2], CAP [3], and DNET [4], applied to the special case of long range maritime surveillance systems (Fig. 2), and proposes three complemental image enhancement techniques, that add additional value to the existing dehazing algorithms.

The driving force and final goal of this research is to find a dehazing solution that is suitable for real-time high resolution multi-sensor electro-optical maritime surveillance systems.

Multi-sensor electro-optical monitoring and surveillance systems integrate various high definition imaging sensors and provide ultra-long range target detection, recognition and identification, based on sensors, optics and image processing. Imaging sensors included in this type of systems are usually color (low-light), thermal (Medium Wavelength Infrared – MWIR and Long Wavelength Infrared – LWIR) and Short Wavelength Infrared (SWIR) imaging sensors. Thermal and SWIR imaging sensors have the grayscale output and are not very prone to the haze problem, while color imaging sensors are very sensitive to this type of visual obstacles, and cannot be enhanced only with the well-known image enhancement techniques (like contrast adjustment), that are successfully used for grayscale images. Long range surveillance systems are designed to detect various objects at very large distances (more than 20 km), where the influence of various atmospheric disturbances is very high.

The haze removal algorithms applied to compressed image signal adds additional unwanted artefacts; because of that image enhancement algorithms should be applied directly on the row image signal, prior to compression, in processing units embedded in the multi-sensor platforms. Dehazing can also be performed prior to the image stabilization algorithms, which is very important for long-range imaging systems. The dehazing algorithms help electro-optical systems to get the most of features from the images, which are used for image stabilization (for example, corners).

Fig. 2 – *Maritime surveillance hazy images exemples.*

The paper is organized as follows. Section 2 describes the haze imaging model, Section 3 describes the related work in this field, and Section IV describes the existing dehazing approaches, together with typical dehazing algorithm components. Sections 5 and 6 present statistical and visual comparison of the tested dehazing methods. Section VII proposes complemental enhancement steps to the existing approaches and presents visual results for these additional steps. Section 8 lists conclusions and indicates directions for future work in this research area.

2 Haze Imaging Model

This section describes mathematical representation of the haze on a hazy image. This model is used in the most significant approaches to the dehazing problem, as the basis for algorithm design.

The *haze imaging equation* that describes the haze imaging model (Fig. 3) is given by:

$$I(x) = J(x)t(x) + A(1 - t(x)), \tag{1}$$

where all the variables are described in **Table 1**.

Table 1
Haze imaging equation variables.

x	$x = (x,y)$ represents **coordinates** (x,y) of a pixel's position in the image; it is a 2D vector.
I	The **hazy image**; it is a 3D vector of color (RGB) at a pixel.
J	The **scene image radiance**; it is a 3D RGB vector of the color of the light reflected by the scene; it represents the image that needs to be reconstructed - the haze-free image.
t	The **transmission map** or thickness of the haze; it is a 2D vector of scalars in the range [0, 1]; for example $t(x) = 0$ means a completely hazy and opaque pixel, $t(x) = 1$ means a haze-free pixel.
A	The **atmospheric light**; it is a 3D RGB vector usually assumed to be spatially constant. It is often considered as "the color of the atmosphere, horizon, or sky".

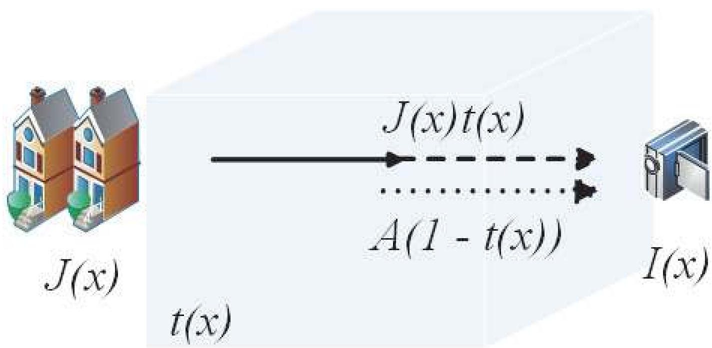

Fig. 3 – *Haze imaging model.*

Regardless of the obstacles' source (smoke, dust, sand, water droplets, ice crystals…), the haze is formed by the particles in the atmosphere absorbing and scattering light, like numerous tiny light sources.

The term $J(x)t(x)$ in (1) is called **direct attenuation** – the light reflected from an object is partially absorbed by the particles in the atmosphere and is attenuated.

The **airlight** $A(1 - t(x))$ is due to particles playing the role of light sources.

Thickness of the haze $t(x)$ is directly related to the **scene depth** - the distance of the scene objects to the observer $d(x)$.

It is found that the haze transmission ***t*** is physically related to the depth ***d*** in a following manner:

$$t(x) = \exp\left(- \int_{0}^{d(x)} \beta(z)\,\mathrm{d}z \right), \tag{2}$$

where β is the **scattering coefficient** of the atmosphere (determined by the physical properties of the atmosphere).

All the proposed approaches to the dehazing problem assume that the physical properties of the atmosphere are homogenous, which means that the scattering coefficient β is spatially constant, which leads to the following:

$$t(x) = \exp\left(-\beta d(x)\right), \tag{3}$$

or equivalently:

$$d(x) = -\frac{\ln t(x)}{\beta}. \tag{4}$$

3 Related Work

All the existing approaches require, in order to dehaze a single image, some additional information regarding the image itself – additional images of the same scene, or adoption of some assumptions (priors) related to the hazy image settings. Two distinct categories of the existing approaches [2] can be selected according to the type of this additional information; they are described in **Table 2.**

Table 2
Categories of dehazing approaches.

Multi-image approaches	Require multiple images of the same scene, taken under different settings (like polarization); unsuitable for real-time applications [1].
Prior-based approaches	All required data for dehazing is present on the hazy image itself; these approaches impose extra constraints using some "**priors**" – some knowledge or assumptions known beforehand; the main goal is to find a suitable prior, which can be based on some statistical/physical properties, or heuristic assumptions.

The multi-image approaches require strict scene conditions, which may not be available in practice (fail in processing dynamic scenes, taken by moving cameras) [2]. Because of this, together with the additionally required processing time and setup complexity for multi-image approaches, the prior-based approached have been found more suitable for real-time applications [1].

There are three most important prior based approaches for color image dehazing – DCP [2], CAP [3] and DNET [4]. These approaches are presented in **Table 3**, and described in detail in the next section.

Table 3
Prior-based dehazing approaches.

Dark channel prior (DCP) model [2], [5]	Originally proposed in [2] by He et al., and significantly improved in [5] by the same group of authors. It is based on certain statistics of haze-free outdoor images - the authors assume that in most of the image local regions which do not cover the sky, very often some pixels have very low intensity (close to zero) in at least one of the RGB color channels. A number of variants of the original DCP model have been proposed in the literature [6-14].
Color attenuation prior (CAP) model [3]	Proposed by Zhu et al.; it constructs a linear relationship between the scene depth and the hazy image, with parameters of the model learned by a supervised learning method.
DehazeNet (DNET) model [4]	Proposed by Cai et al.; it utilizes a trainable CNN (Convolutional Neural Network) based end-to-end system for medium transmission estimation. DehazeNet takes a hazy image as input, and outputs its medium transmission map that is subsequently used to recover the haze-free image.

4 Dehazing Algorithms Description

As previously stated, the basis of the most significant dehazing algorithms is the haze imaging equitation (1). The logic behind dehazing is very clear – since a hazy image contains two major sources – scene radiance and radiance of additional light sources (haze particles) that obscure objects of interest, called airlight, the influence of the airlight should be minimized. The airlight is defined by thickness of the haze (***t***) and atmospheric light (***A***).

The goal of haze removal algorithms based on the given equitation is the following: given the input hazy image ***I***, recover the scene radiance image ***J***, and usually ***t*** and ***A*** – the typical dehazing workflow includes the calculation of the transmission map and atmospheric light, used to restore the haze-free images.

A wide class of dehazing algorithms can be decomposed into the following three components (Fig. 4).

1. The **transmission map estimator** computes ***t*** in the haze imaging (1).
2. The **atmospheric light estimator** calculates ***A*** in haze imaging (1).
3. The **haze-free image generator** generates the haze-free image ***J*** based on the estimated ***t*** and ***A***.

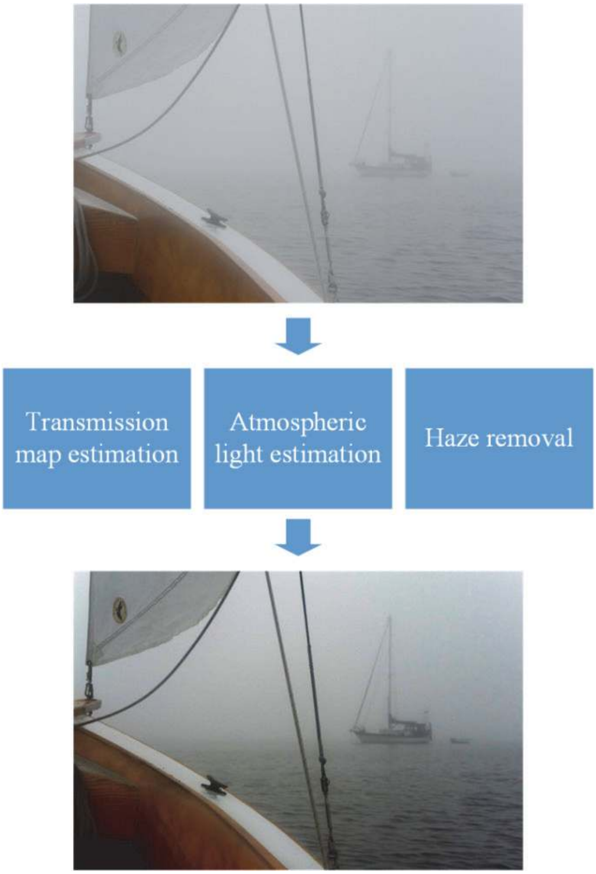

Fig. 4 – *Dehazing procedure.*

4.1 Transmission/depth map estimator

Thickness of the haze (transmission map) is represented by the depth of the scene with the following logic – far objects are more obscured since more particles are presented between the imaging sensor and the object itself. This spatial inconsistency, and dependency of scene content, is what makes this step the most demanding from the algorithmic point of view.

Transmission map estimator computes the transmission map or the depth map (Fig. 5) from a hazy image. This part of algorithm is the most important and specific for each approach, and as such will be explained in more detail for the most significant approaches in the following text. This is the heart of the algorithm, where prior-based calculation comes in place – based on some statistical assumption, the goal is to calculate the depth of the scene from the hazy image alone. It is also the most processing time demanding part of the dehazing algorithm pipe.

The transmission map estimator also provides the basic processing data for the atmospheric light estimation. If the atmospheric light is required in the process of the transmission map estimation, it is temporarily assumed that it takes the value of 1 [2].

Fig. 5 – *Depth and transmission maps examples.*

DCP approach

In the DCP approach [2], the transmission $t(x)$ is estimated based on color channel I_C of the hazy image I, and atmospheric light of the color channel A_C using the following relation:

$$t(x) = 1 - \min_{y \in \Omega(x)} \left(\min_{C} \frac{I_C(y)}{A_C} \right). \qquad (5)$$

The dark channel prior is based on the following statistics of haze-free outdoor images – in most of the local regions which do not cover the sky, it is noted that some pixels (called ”dark pixels”) have very low intensity in at least one color (RGB) channel. In a hazy image, intensity of these dark pixels in a certain color channel is mainly contributed by airlight. Therefore, these dark pixels can directly provide accurate estimation of the haze transmission map.

Using this prior in the haze imaging model, one can directly estimate thickness of the haze and recover high quality haze-free image.

CAP approach

The CAP approach [3] calculates the transmission map based on the linear coefficients ω_0, ω_1 and ω_2, the value channel v and saturation channel s by:

$$t(x) = \exp(-\beta(\omega_0 + \omega_1 v(x) + \omega_2 s(x))) . \quad (6)$$

The color attenuation prior is very simple and powerful prior that helps to create a linear model for the scene depth of the hazy image. The authors concluded that brightness and saturation of pixels in a hazy image vary sharply along with the change of the haze concentration, meaning that the difference between brightness and saturation can approximately represent the concentration of haze.

By learning the parameters of the linear model using a supervised learning method, the bridge between the hazy image and its corresponding depth map is built effectively.

With the recovered depth information, the haze can be removed from a hazy image on the basis of the haze imaging model.

DNET approach

The DNET approach [4] directly estimates the transmission map from the hazy image, based on a previously trained end-to-end system, called *DehazeNet*:

$$t(x) = \text{DehazeNet}(I(x)) . \quad (7)$$

DehazeNet takes a hazy image as input, and outputs its medium transmission map that is subsequently used to recover a haze-free image via the haze imaging model. DehazeNet adopts the Convolutional Neural Networks (CNN) based deep architecture, whose layers are specially designed to embody the established assumptions/priors in image dehazing. Specifically, layers of Maxout units are used for feature extraction, which can generate almost all haze-relevant features. DehazeNet approach also proposed a novel nonlinear activation function, called Bilateral Rectified Linear Unit (BReLU), which is able to improve quality of the recovered haze-free image.

4.2 Refining transmission/depth map

The previously explained transmission/depth map estimation techniques have one common problem – the resulting transmission/depth maps have blocking artifacts. According to the authors of the three above given approaches [2 – 4], guided image filtering [5] represents the most suitable transmission/depth map refining technique.

Derived from a local linear model, the guided filter computes the filtering output by considering the content of a guidance image, which can be the input image itself or another different image. The guided filter can be used as an edge-preserving smoothing operator like the popular bilateral filter [15], but it has better behavior near edges. The guided filter is based on a more generic concept, going beyond smoothing – it can transfer the structures of the guidance image to the filtering output, enabling new filtering applications, like dehazing and guided feathering. Moreover, the guided filter naturally has a fast and nonapproximate linear time algorithm, regardless of the kernel size and the intensity range. It is claimed by the authors that the guided filter is one of the fastest edge-preserving filters.

Fig. 6 – *Refining depth map – example.*

4.2 Atmospheric light estimator

Atmospheric light estimator computes the atmospheric light (Fig. 7) from the hazy image. This part of the algorithm is commonly derived from the physical model described in (1) in the following manner: when $\boldsymbol{t}$ tends to zero, (1) becomes $A = I(x)$. This shows that A can be estimated by $I(x)$ at pixel x where $t(x)$ is small enough:

$$A = I(x), \quad t(x) < t_{threshold} . \tag{8}$$

Given the described model in (8), the atmospheric light estimator utilizes the hazy image and its estimated transmission map as an input for computation of the atmospheric light A.

Fig. 7 – *Position of the atmospheric light marked in red color.*

All three described approaches [2 – 4] estimate the atmospheric light according to the following procedure (with small modifications): the algorithm picks the top **0.1%** brightest pixels in the transmission map, and the algorithm then selects the pixel with the highest intensity in the corresponding hazy image I among these brightest pixels (on *t*) as the atmospheric light *A* (Fig. 7).

During testing of dehazing maritime surveillance images, it has been noted that 0.1% of the brightest pixels can mislead the algorithm in the way to choose pixels from big bright objects, like boats (which are usual in described surroundings), as atmospheric light pixels. It has also been noted that the field of view of maritime surveillance images usually contain large sky and sea areas (most commonly more than 50% of the field of view). Because of these two reasons, it was decided to use the same atmospheric light estimation procedure, with the following modifications – the algorithm picks the top **10%** of the brightest pixels in the transmission map, then the algorithm calculates the **median** value of the pixels in the corresponding hazy image *I* among these brightest pixels (on transmission map *t*), and considers this value as the atmospheric light *A*.

4.3 Haze-free image generator

The haze-free image generator computes the haze-free image *J* from the previously estimated transmission map ***t*** and the atmospheric light ***A***. *J* is derived from the physical model described in (1) as follows:

$$J(x) = \frac{I(x) - A}{t(x)} + A, \tag{9}$$

$t(x)$ is usually [2 – 4] restricted by a lower bound $t_0(x) = 0.1$, in order to avoid too much noise:

$$J(x) = \frac{I(x) - A}{\max\{t(x),\, t_0\}} + A\,. \tag{10}$$

The haze-free image generator is common and generally used in all the described dehazing methods [2 – 4], with only small modifications (similar to the atmospheric light estimator).

5 Comparative Analysis of Dehazing Algorithms

In order to estimate whether the described algorithms can be used for real-time video processing in surveillance systems, they were tested in order to measure the average processing time of the algorithm components. Testing was performed on 100 hazy images in HD resolution (1280×720 pixels), on quad-core CPU. The results of this testing are given in **Table 4**.

Table 4
Dehazing average processing time comparison.

	Processing time (s)	Transmission map (%)	Atmospheric light (%)	Scene radiance (%)
DCP	4,45	94.7	3.1	2.2
CAP	4,17	93.2	3.3	3.5
DNET	8,62	96.9	1.6	1.5

The results in table above show that the CAP method is the fastest algorithm among the tested algorithms, generally speaking. This conclusion is expected, because the CAP method is computationally the simplest one – it is based on a linear relation between pixels of the hazy image and haze thickness itself.

On the other hand, DNET, as the most complex and nonlinear, is the most time consuming method.

The most time consuming process is the transmission map estimation, which takes more than 90% of the processing time for all three approaches.

It can also be concluded that these methods, in order be used for real-time video processing in the frame-by-frame processing manner, must include certain amount of process parallelization. The optimal parallelization methods will be a part of our future research goals. In the actual setup, these methods can be used for offline video processing.

6 Dehazing Algorithms - Maritime Surveillance Images

The results of described dehazing methods applied to maritime surveillance images are presented on Fig. 8 and 9.

It can be concluded from these examples that the DCP method provides more details on the objects on the scene, but the other two methods (CAP and DNET) provide more real-life like images, where CAP has a slightly more stable output.

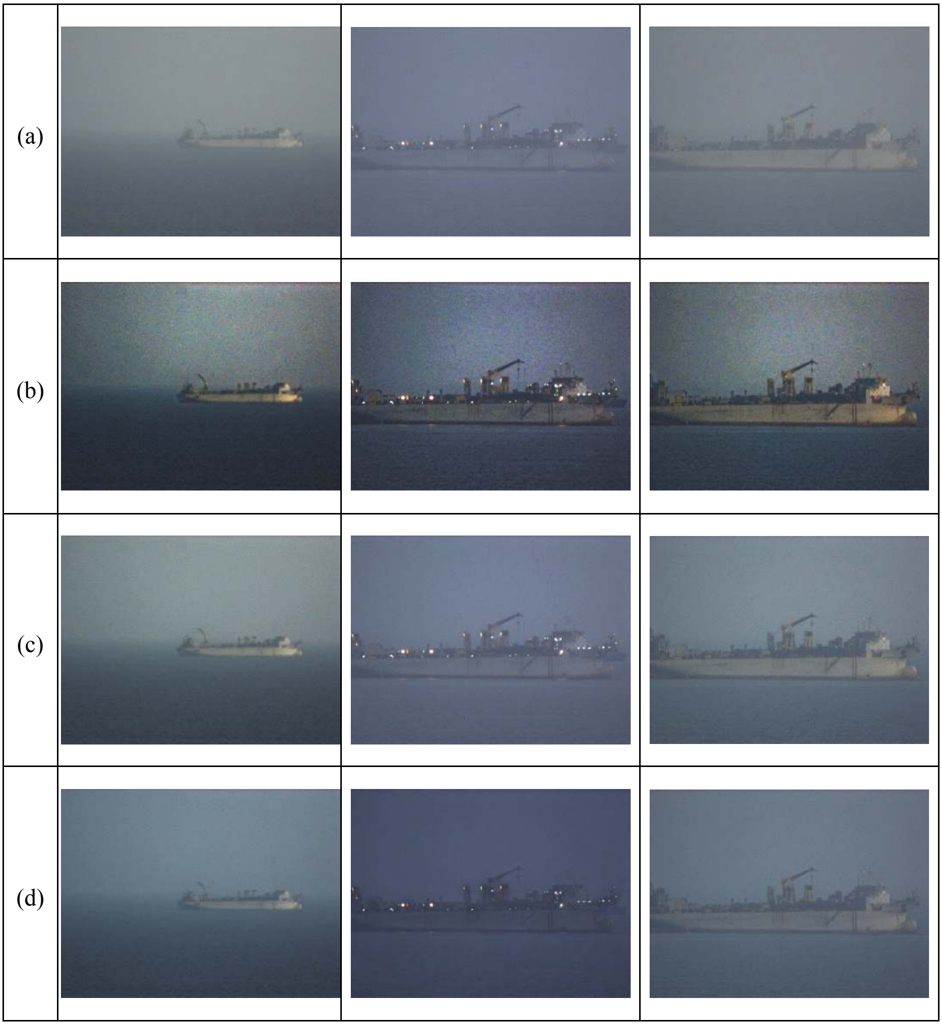

Fig. 8 – *Dehazing methods applied to maritime images. (a) Original image, (b) DCP dehazed image, (c) CAP dehazed image, (d) DNET dehazed image.*

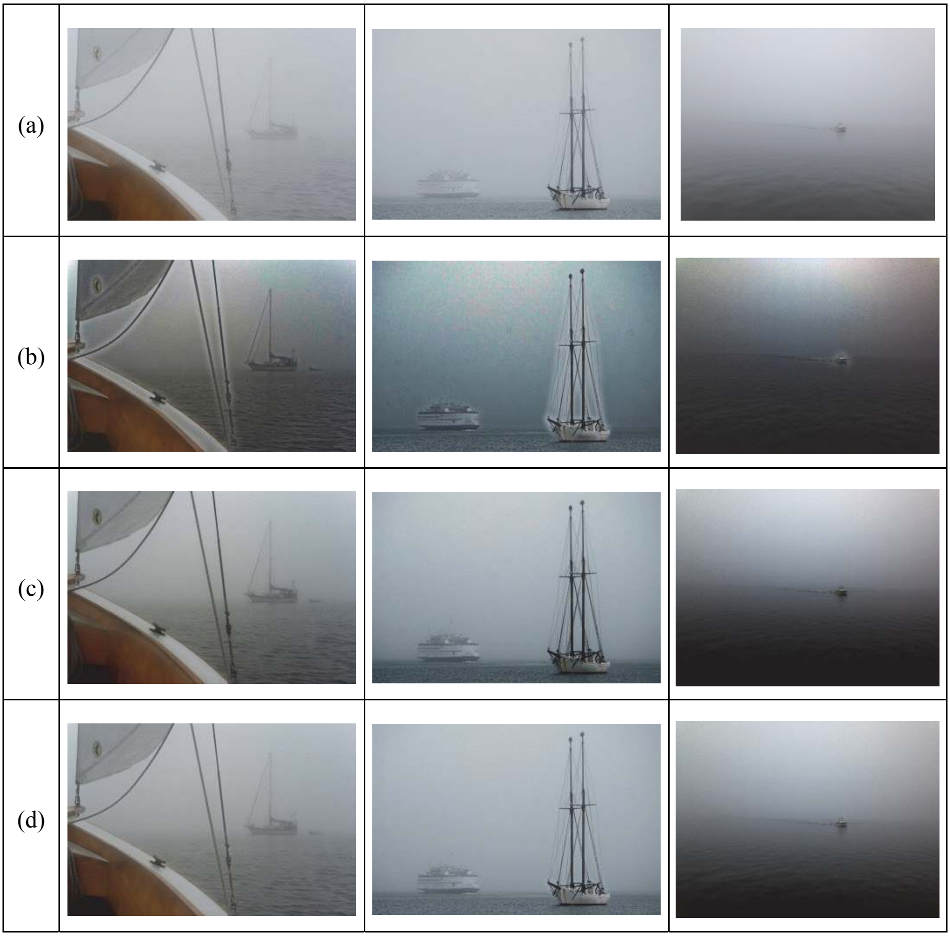

Fig. 9 – *Dehazing methods applied to maritime images - cont. (a) Original image, (b) DCP dehazed image, (c) CAP dehazed image, (d) DNET dehazed image.*

7 Complemental Image Enhancement Techniques

Since different hazy images, taken under different weather conditions (snow, fog, rain, dust…), suffer from common problems, like blurred objects, low contrast, noise… this paper proposes additional image enhancement steps, related to these common problems. These steps bring additional value to image dehazing and the whole work toward the final goal of getting the most of information from the image itself. All such steps can be used within any of the existing dehazing approaches.

Contrast adjustment

The haze on the image is usually manifested by light regions with high saturation. This makes contrast in the image very low, and degrades the quality in a significant way. Although dehazing algorithms themselves help in solving this problem in certain amount, additional contrast adjustment is a meaningful step.

This paper proposes additional contrast adjustment of a color image, and tests it on maritime hazy images. The contrast adjustment is performed in the following manner - in all three color channels (RGB) of the image, the bottom 1% and the top 1% of all pixel values are saturated. This operation increases the contrast of the output image.

Median filtering

Beside low contrast, hazy images also suffer from the presence of noise that remains on image in a certain amount, even after applying dehazing procedures. This is usually the case with the haze originated from large particles, like snow, but can be present with any type of haze.

This paper proposes median filtering as an additional enhancement step related to image denoising. Median filtering is performed on all three color channels (RGB) of the image, in two dimensions. Each output pixel contains the median value in a 3-by-3 neighborhood around the corresponding pixel in the input image. This operation removes the noise and makes the output image smoother than input image.

Image sharpening

The common problem related to hazy images that cannot be resolved very well with dehazing approaches is connected to blurred objects. This paper proposes the unsharp-mask method as an additional sharpening technique incorporated in the dehazing procedures.

The unsharp-mask method [16] utilizes an adaptive filter in the correction path. The objective of the adaptive filter is to emphasize the medium-contrast details in the input image more than large-contrast details, such as abrupt edges, so as to avoid overshoot effects in the output image [16]. This simple step takes around additional 3 seconds of processing time (HD images, quad-core CPU), but provides sharpened images, that visually look better than the images dehazed without this enhancement step.

It can also be concluded that all the proposed additional enhancement techniques bring a visible enhancement to the images, with an additional processing cost.

The original images, and examples obtained with additional enhancement steps after the original dehazing process (CAP based), are presented on the Fig. 10.

Original Image		
CAP		
CAP and Contrast Adjustment		
CAP and Median Filtering		
CAP and Image Sharpening		

Fig. 10 – *Additional enhancement techniques.*

8 Conclusion

The subjective quality of images is very important in outdoor surveillance systems, especially for long-range imaging, where there exists a strong need to extract as much of a detail as possible from images of objects at long distances, for example, more than 20 km. Maritime surveillance application of such systems can be considered as a special case, because of the presence of a large amounts of sky and sea regions in the field of view, and because the objects of interest are usually brighter than the surrounding (boats, vessels…).

This paper gives a review of the most significant image dehazing algorithms, proposes modifications in atmospheric light estimation making them better adapted to the special case of maritime surveillance, tests the described methods on a large amount of images from both visual and processing time perspectives, and proposes three complemental image enhancement steps that are independent of the dehazing algorithm itself.

It can be concluded that modifications of atmospheric light estimation helps algorithms to adapt better to the special case of maritime image surveillance.

It can also be concluded that additional enhancement techniques - contrast adjustment, median filtering and unsharp-mask - bring visible enhancement of the images with an insignificant processing cost.

Both the visual and statistical results presented in this paper shows that the tested dehazing methods can be successfully used for offline video processing applications, in the frame-by-frame processing manner. Offline applications are usually triggered by some predefined events, like new object appearance in the scene, or sudden visibility degradation, caused, for example, by fog or smoke.

Applications in real-time video processing systems require process parallelization that should include usage of multi-core GPU units and FPGA platform.

Dehazing methods for real-time video processing, including optimal parallelization methods, will be a part of our future research activities.

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