

**IMAGING-MODEL-BASED VISIBILITY RECOVERY  
FOR SINGLE HAZY IMAGES**

by

**Ming-ye Ju**

Supervisor: **Prof. Yingjie Jay Guo**

Co-supervisor: **Dr. Can Ding**

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## ABSTRACT

Low-quality images captured in hazy weather can seriously impair the proper functioning of vision system. Although many meaningful works have been done to realize the haze removal, there are still two key issues remain unsolved. The first one is the long processing time attributed to the involved tools; the second one is existing prior employed in state-of-the-art approaches cannot be suitable for all situations. To address such problems, a series of haze removal techniques have been developed. The main contributions of this dissertation can be summarized as the following.

For efficiency, a gamma correction prior is proposed, which can be used to synthesize a homogeneous virtual transformation for an input. Relying this prior and atmospheric scattering model (ASM), a fast image dehazing method called IDGCP is developed, which converts single image haze removal into multiple images haze removal task.

Unlike the IDGCP, another solution for accelerating dehazing (VROHI) is to utilize a low complexity model, i.e., the additive haze model (AHM), to simulate the hazy image. AHM is used on remote sensing data restoration, thus the first step of VROHI is to modify the AHM to make it suitable for outdoor images. The modified AHM enables to achieve single image dehazing by finding two constants related to haze thickness.

To overcome the uneven illumination issue, the atmospheric light in ASM is replaced or redefined as a scene incident light, leading to a scene-based ASM (Sb-ASM). Based on this Sb-ASM, an effective image dehazing technique named IDSL is proposed by using a supervised learning strategy. In IDSL, the transmission



estimation is simplified to simple calculation on three components by constructing a lineal model for estimating the transmission.

According to previous Sb-ASM and the fact that inhomogeneous atmosphere phenomenon does exist in real world, a pixel-based ASM (Pb-ASM) is redefined to handle the inhomogeneous haze issue. Benefitting from this Pb-ASM, a single image dehazing algorithm called BDPK that uses Bayesian theory is developed. In BDPK, single image dehazing problem is transformed into a maximum a-posteriori probability one.

To achieve high efficiency and high quality dehazing for remote sensing (RS) data, an exponent-form ASM (Ef-ASM) is proposed by using equivalence infinitesimal theorem. By imposing the bright channel prior and dark channel prior on Ef-ASM, scene albedo restoration formula (SARF) used for RGB-channel RS image is deduced. Based on Rayleigh's law, SARF can be expanded to achieve haze removal for multi-spectral RS data.



## CERTIFICATE OF ORIGINAL AUTHORSHIP

I, Ming-ye Ju declare that this thesis, is submitted in fulfilment of the requirements for the award of the degree of DOCTOR OF PHILOSOPHY, in the Faculty of Engineering and Information Technology at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise reference or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This document has not been submitted for qualifications at any other academic institution.

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&  
*Brother and sister*



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# Acronyms

ASM	Atmospheric scattering model
Sb-ASM	Scene-based atmospheric scattering model
Pb-ASM	Pixel-based atmospheric scattering model
Ef-ASM	Exponent-form atmospheric scattering model
GC	Gamma correction
GCP	Gamma correction prior
GOF	Global-wise optimization function
AHM	Additive haze model
MAHM	Modified additive haze model
HTM	Haze thickness map
LFC	Low-frequency component
ALC	Atmospheric light correction
DCT	Discrete cosine transform
GEM	Guided energy model
AF	Accelerating framework
MAP	Maximum a posteriori probability
HVP	Human visual perception
AMT	Alternating minimizing technique
RS	Remote sensing
SARF	Scene albedo restoration formula
E-SARF	Expansion scene albedo restoration formula
BCP	Bright channel prior
DCP	Dark channel prior
TDCP	Translational dark channel prior

