



Enhancement of Motion Deblurring Algorithms in single images

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- **Abstract**

One of the key problems of restoring a degraded image from motion blur is the estimation of the unknown blur filter. Several algorithms have been proposed utilizing image intensity or gradient information. The unknown blur filter could be linear, shift in-variant filter that could be characterized with only two parameters; the motion direction and the blur length. Or it could be non-linear, shift-variant filter that has no specific behavior. There has been much work dealing with motion blur with both of its types.

This thesis proposes an algorithm for restoring the motion blurred image using Genetic Algorithms. It works on both, the linear and the non-linear motion blur, separately. In the linear part, the direction and the length of the motion blur are used as the parameters of the Genetic Algorithm. The method assumes a uniform linear camera blur over the image. In the non-linear part, the blur kernel has no specific behavior, so each pixel value in the kernel is considered as a parameter to the algorithm.

A Graphics Processing Unit Accelerated version of the Genetic Algorithm is presented at the end of the thesis that achieved a huge speedup in the running time. The accelerated algorithm works 12.6x faster than the standard Genetic Algorithm.

Experiments on a wide data set of standard images degraded with different length kernels demonstrate the efficiency of the proposed approach especially in small blur lengths compared to other algorithms.

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List of Abbreviations

GA: Genetic Algorithm

PSF: Point Spread Function

LCD: Liquid Crystal Display

MAP: Maximum A Posteriori

MDF: Motion Density Function

ISD: Iterative Support Detection

SNR: Signal to Noise Ratio

IID: Independent and Identical Distributed

RMSE: Root Mean Squared Error

IOAC: Index Of Area Coverage

GPU: Graphics Processing Unit

Chapter 1 Introduction

1.1 Problem Definition

One of the most common artifacts in digital photography is motion blur caused by the relative motion between the camera and the scene during image exposure time. The problem is particularly apparent in low light conditions when the exposure time can often be in the region of several seconds, and the inevitable result is that many of our snapshots come out blurry and disappointing [1]. Many photographs capture ephemeral moments that cannot be recaptured under controlled conditions or repeated with different camera settings. If camera shake occurs in the image for any reason, then that moment is lost. One solution that reduces the degree of blur is to capture images using shorter exposure intervals. This, however, increases the amount of noise in the image as the required amount of light is not collected.

Motion Deblurring is a problem that has been extensively studied recently, to restore a close estimate to the original image from its blurred version only. That is called blind deconvolution, which is a very difficult problem because there will be larger number of unknowns.

Applications of Motion Deblurring:

- ***Common Photography:*** to restore Images and videos corrupted by the motion blur while capturing them by normal cameras.
- ***Surveillance:*** to clarify images of moving objects or humans [2].
- ***Radars:*** to restore the blurry numbers of license plates of fast moving vehicles on the roads and highways [3].
- ***Text Recognition:*** can be used as a part of the text recognition problem to enhance and sharpen the output text [4].

1.2 Target of the Thesis

In this thesis, restoration of a motion blurred image is investigated. It is required to find the blurring kernel that caused the degradation from a single input blurred image without previous knowledge about the original image. Genetic Algorithm (GA) is used to optimize the solution and reach the best blurring kernel. The work is divided into two main categories: linear motion blur estimation, and non-linear motion blur estimation, as the linear blur kernel has much less parameters than the non-linear kernel, which leads to less computational time and less needed resources.

GA has been used recently in image restoration in general, but not in particular for motion blur removal. The algorithm has to be well suited for each problem that is being investigated, while still having its general structure. Some modifications to normal GA had to be added in order to suite the nature of our problem.

As slow running time is a main disadvantage to GA, a Graphics Processing Unit-Accelerated version of the Genetic Algorithm is presented. The accelerated version achieved a huge speedup in the running time as it works 12.6x faster than the standard GA. Experiments on a wide data set of standard images degraded with different kernels of different sizes demonstrate the efficiency of the proposed approach especially in small blur lengths compared to other algorithms.

1.3 Thesis Organization

The thesis is organized as follows:

Chapter 2 explains the meaning of motion blur, how it happens and how to model it in image processing. It introduces brief description of point spread functions (PSFs) and the main types of motion blur, the linear motion blur, and the non-linear motion blur with a survey of the most important algorithms.

Chapter 3 presents image deconvolution, with a survey of the most common techniques used, focusing on the lucy-richardson algorithm used in the proposed approach.

Chapter 4 introduces GA, where a detailed explanation for the different stages of the algorithm as the reproduction, crossover, and mutation is given. This is followed by a demonstration for the algorithm that is used in our study. Effects of the different parameters affecting the operation of the algorithm as the probability of mutation and the size of population are all investigated.

Chapter 5 presents how GA is used for linearly blurred images. The chapter includes the different trials of the goal function till the final attempt, and how the algorithm behaves in small and large blur lengths. Then the problem of ringing artifacts is discussed. Finally, experimental results of the GA are compared to some selected algorithms.

Chapter 6 introduces how GA is used to remove non-linear motion blur. This chapter also includes the different trials of the goal function, and how the image gradients histogram is used in the final goal function. Then it introduces experimental results and comparisons with the other algorithms.

Chapter 7 presents the accelerated version of the GA using Graphics Processing Unit (GPU) and includes the results that show the great speed-up achieved.

Chapter 8 contains the final conclusions of this work together with any possible improvements and further investigation for unsolved problems.