Asian Journal of Information Technology 15 (3): 608-613, 2016
ISSN: 1682-3915

Enhanced Image Processing for Blurred Images Using GA Based Image Extraction

V. Premchandran and P. Poongodi
[1]Department of Electronics and Communication Engineering,
PPG Institute of Technology,
[2]Department of Electronics and Communication Engineering,
Karpagam College of Engineering, 641032 Tamil Nudu, India

Abstract: We propose a novel method for combined de-blurring and depth estimation in a variation framework. Our goal is to retrieve a de-blurred image and the corresponding depth map by only using information from a single blurred image. In many practical applications, for example for defocus or camera motion, the shape of the blurring remains constant but only its spatial extent is varying. A new blurring model based on this assumption in which the depth is included explicitly, is introduced. Depth is related to the spatial extent of the blur by assuming that the stronger an object is blurred, the closer it is to the camera. We also present a reduction of the model to one-dimensional blurring, as it is present for example in motion blur. The de-blurred image and the depth map is then estimated variation by means of gradient descent, where a novel partial equation occurs. Our method is evaluated experimentally and the results that the combination of de-blurring and depth estimation from just one image is possible.

Key words: Explicitly, gradient, experimentally, image, India

INTRODUCTION

Image de-blurring and depth estimation are both tasks with a long tradition in image processing. In de-blurring, as the name already indicates, we want to recover a sharp image back from an image that is deviated under some blur. Depth estimation is about retrieving 3 dimensional information out of one or several 2 dimensional images.

Everyone who has already taken images with a small hand-held camera knows what image blur is. It appears very frequently in practice that images are blurred. The reasons range from the shaking hands with a small camera over ordinary defocus to images taken from a moving vehicle or even atmospheric perturbations when a telescope is used. It is very desirable for a photographer to have a de-blurring algorithm to get nice and sharp images out of blurry ones. Unfortunately, de-blurring is a very hard problem and it appears in many different variants. The blur may be the same for the whole image or it may vary over space. We may know how the blur was caused or not. We may know the shape of the blur or not or we may know it only approximately. Additionally, even the simplest de-blurring task where the blur is everywhere the same and we know it exactly is an ill-posed problem.

But anyway, there is still a great demand in having a good de-blurring algorithm. This fact has attracted many researches and a lot of papers have been written about de-blurring. They dier in what assumptions they make, what variant of the problem they actually want to solve, how they cope with the ill-pose de-blurring and t modeling techniques they use. Some of these approaches are mentioned in the next section. No method works well in all cases and so all the de-blurring techniques have their right to exist.

Depth estimation is also a very important task. We live in a 3 dimensional environment but are only able to take 2 dimensional images (at least with a standard camera). Therefore, we want to bring these two worlds together. If the camera position is fixed, then we should not expect an algorithm to reconstruct the complete 3-D space because we cannot look behind objects. In this setting a depth map for an taken image is the best what we can hope for.

Many divergent information cues have been investigated to retrieve 3-D information from 2-D images. These cues include stereo images, shading, motion, focus, texture and some more. Also, the depth reconstruction from blur has been already investigated including defocus and motion blur. Basically, any way to retrieve depth is useful because often just a single cue is available.

Corresponding Author: V. Premchandran, Department of Electronics and Communication Engineering, PPG Institute of Technology, 641032 Tamil Nadu, India

Assumptions exactly such devices can be used for example in medical imaging or robotics where it is very important to know the real 3-D world instead of a simple 2-D projection.

De-blurring and depth estimation are indeed highly related, if the right setting is chosen. Imagine for example a car driving by a house. If one takes a picture out of a moving car, it will be blurred because the car is driving. But, a tree in front of the house will be stronger blurred than the house because it is closer to the camera and a aircraft in the sky will be probably not blurred at all. In this case, the assumption that the closer an object to the camera is the more it is blurred, is true. But, this assumption can also simply be violated. If a child is running next to the tree, it will be blurrier than the tree, even if it is at the same depth.

The assumption that closer objects are more blurred is nevertheless true in many practical situations, as for example in the described car scene. If this is filled then depth and blur are basically in a one-to-one relation: if we know the depth then we can estimate the blurriness of an object and if we know its blur then we can reconstruct its depth. Our goal is to use this observation to design an algorithm that combines de-blurring and depth estimation in a variation framework.

Literature review: As already stated before, de-blurring is a very research-intensive topic and there are still improvements and novel methods.

The most classical methods are linear approaches, that are based on the Fourier trans-form. They are only applicable to spatially invariant blur because they use the convolution theorem which says that the convolution of two signals turns out to be a multiplication in Fourier space. The most prominent example of this lter class is the Wiener lter (Wiener, 1949).

Another often used approach is the Richardson-Lucy algorithm that was introduced by Lucy (1974) and Richardson (1972). It is based on Bayes theorem and performs de-blurring in an iterative way. The Wiener lter as well as the Richardson-Lucy algorithm assume that the blur is known exactly.

There are also methods that try to estimate spatially invariant blur and the un-blurred image from a single image. Fergus *et al*. (2006) model their method using probability distributions and by means of Bayes theorem. They include prior knowledge in assuming that the de-blurred image follows natural image statistics. These statistics are also modeled by Shan *et al*. (2008) but they also introduce some other interesting concepts that makes their algorithm quite successful. Even though, they motivate their model in a Bayesian way, the resulting energy is very similar to the ones in pure variation approaches.

These variation approaches include the methods from You and Kaveh (1996, 1999) that focus on the regularization of the smoothness terms. Images are also de-blurred in a spatially variant and blind way where is reduced by parameter the blur. The most in until methods for this thesis are the researches by Welk *et al*. (2005) and Welk (2008). They perform spatially invariant and variant de-blurring under known blur. The use of robust data terms for de-blurring and they propose the stepwise reduction of the smoothness weights during image evolution. Boundaries are treated in a detailed way and (Welk, 2008) derives stability conditions for the gradient descent. Bar *et al*. (2005) introduced the notion of robust data terms. Money and Kang (2008) try to improve the de-blurring result by using a shock ltered version of the blurred image as initialization.

We now come to approaches that include some notion of depth into de-blurring. In Jin and Favaro (2002) a variation energy is not based on a 2 dimensional model as in the methods before but on a 3 dimensional one. They already try to estimate a depth map and an un-blurred image but they are using multiple de-focused images. Multiple images are also used by Favaro *et al*. (2003, 2004, 2008) where they assume that the blur for defocus has Gaussian shape which is a quite strong assumption.

Therefore, they are able to use the relation between Gaussian convolution and dilution to use this in their variation energy to recover some 3-D shape from blurred images. The focus of Lin and Chang (2006) is on geometric optics, they show in a detailed way why the relation between depth and blur is reasonable for defocus and motion blur. Their depth estimation method only estimates one depth value for the whole image by trying to detect the blurriness of edges, it is therefore spatially invariant. The method can only handle quite restricted test patterns with strong edges. Bae and Durand (2007) also try to detect the blurriness of edges to get some blur measure for the image, but they do it in a spatially variant way, such that they get a “blurriness map”. They actually do not use this for de-blurring but for defocus imagination to increase the quality of a photograph. The blurriness of edges is detected by a variant of the edge detector from Elder and Zucker (1996) that is based on Gaussian derivatives. Levin (2006) does blind spatially variant de-blurring of motion blurred images with a hands-on approach. She compares the image statistics in the direction of the blur to the statistics in the direction rectangular to it which is not blurred. Doing this she gets a measure how well a certain blur ts to the image and she uses this measure in a segmentation algorithm to get regions with di erent blur extents.

Machine learning approaches have been used to perform depth estimation, as well. Favaro and Soatto (2002) follow a quite discrete idea where they interpret the blurring process as matrix multiplication and use singular value decomposition to detect the blurriness.

Saxena *et al*. (2008) perform classical supervised learning, by constructing a reasonable feature vector and using a Markov random field. They do not even assume that their images are blurred, because they just train their algorithm with ground truth images taken with a 3-D scanner and hence try to reconstruct depth with a single un-blurred image. The machine learning approaches have in common that they need a ground truth set of images to train their method.

That the relation between blur and depth exists is one more time justied by Schechner and Kiryati (2000). They show that depth recovery from stereo images is actually very similar to depth recovery from blurred images.

MATERIALS AND METHODS

Proposed system: The images pixel values are pre loaded in genetic function as parent array and child array the optimal values are calculated and stored in the array. The child array is compared with the actual image and any deviation in the comparison is calculated and the image pixel value is adjusted in accord as shown in Table 1. A generic selection procedure is implemented as follows:

- The fitness function is evaluated for each individual, providing fitness values, which are the parent 1 one and parent 2. Normalization means getting the best fitness value from parent array
- The population is sorted by fitness values
- Accumulated normalized fitness values are computed (the accumulated fitness value of an individual is the sum of its own fitness value plus the fitness values of all the previous individuals). The accumulated fitness of the last individual should be 1 (otherwise something went wrong in the normalization step)
- A random number child class between 0 and infinite is chosen
- The selected individual is the first one whose accumulated normalized value is optimal value (Favaro *et al*., 2004) (Fig. 1-5)

Table 1: Child array extraction using parent class

Parent array 1 (px)	Parent array 2 (px)	Child array (px)	Actual image (px)
144	144	144	139
162	158	162	154
132	136	136	132
172	178	178	180
140	150	150	160
152	162	162	162
171	170	171	169
188	181	188	179
130	123	130	133
143	133	143	133
133	130	133	134

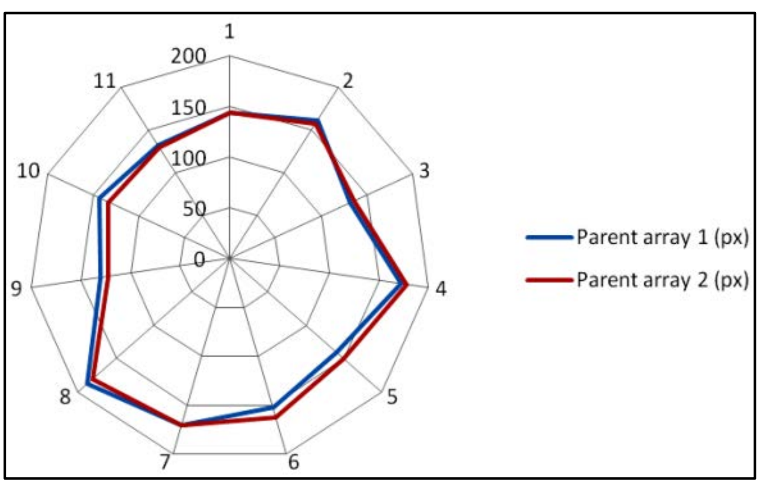

Fig. 1: Analysis of parent array 1 vs parent array 2

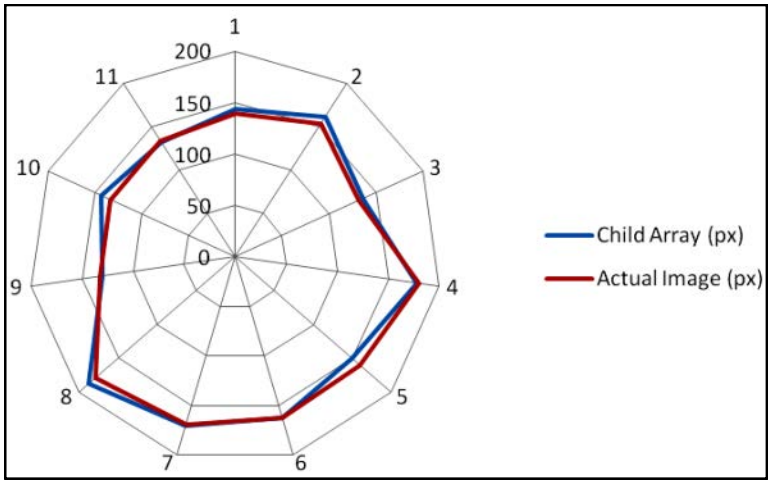

Fig. 2: Analysis of child array vs actual

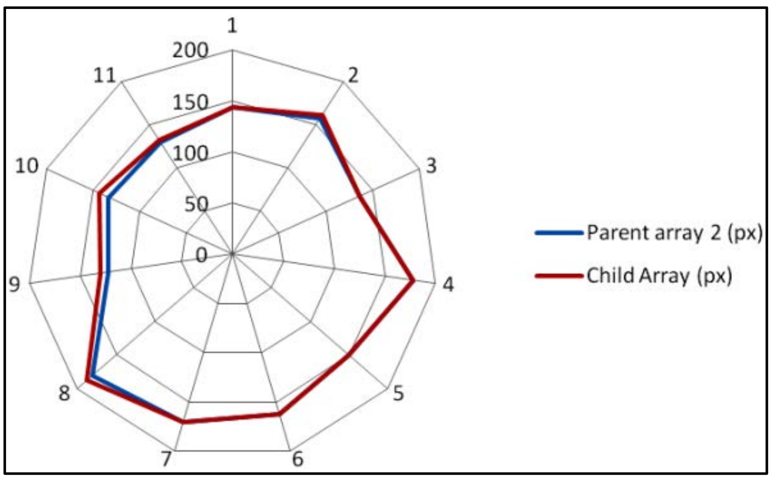

Fig. 3: Analysis of child array vs parent array 2

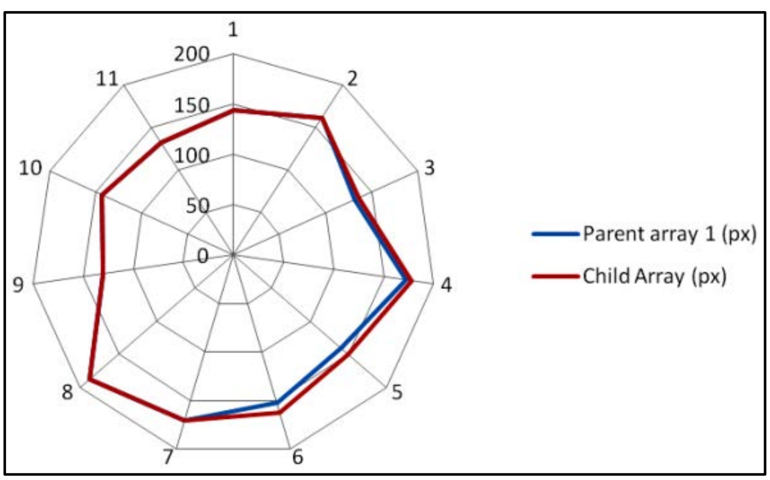

Fig. 4: Analysis of child array vs parent array 1

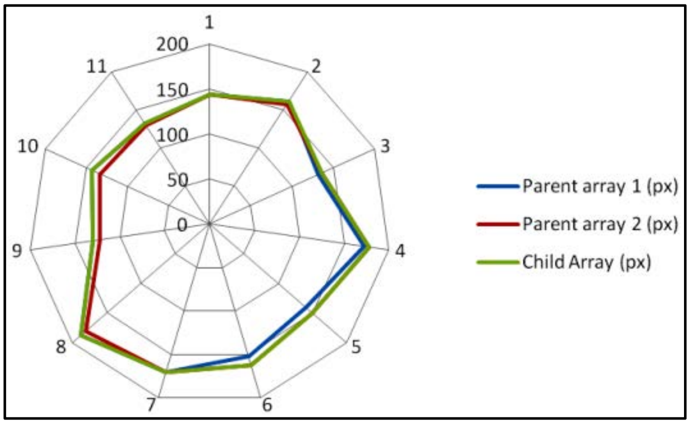

Fig. 5: Analysis of child array vs parent array 1 and 2

RESULTS AND DISCUSSION

By analysis parent child and actual data point no 4, 8 and 6 has a indication of divergence in this case the values of 4, 6 and 8 are taken as blur points and the values are shaded with optimal value and the parent array is updated for the same. The iteration will take place till reduction of error. The analysis of child array shows in the points 5,6 and 10 the child array has an optimum value compared to parent array value and in the comparison between child array and parent array one the points 5 and 6 has a optimal clarity. Thus, it is been observed that the child value is 20% more optimal than parent class which in turn works on avoiding blur in image.

CONCLUSION

For a large number of individuals, the above algorithm might be computationally quite demanding. A simpler and faster alternative uses the highest fitness value. If this procedure is repeated until there are enough selected individuals, this selection method is called high fitness selection. If instead of a single pointer spun multiple times, there are multiple, equally spaced pointers on a wheel that is spun once, it is called fitness sampling. Taking the best half, third or another proportion of the individuals is fitness selection.

REFERENCES

Bae, S. and F. Durand, 2007. Defocus magnification. Comput. Graphics Forum, 26: 571-579.

Bar, L., N. Sochen and N. Kiryati, 2005. Image Deblurring in the Presence of Salt-and-Pepper Noise. In: Scale Space and PDE Methods in Computer Vision. Kimmel, R., N. Sochen and J. Weickert (Eds.). Springer Berlin Heidelberg, Berlin, Germany, pp: 107-118.

Elder, J.H. and S.W. Zucker, 1996. Local Scale Control for Edge Detection and Blur Estimation. In: Computer Vision-ECCV'96. Bernard, B. and C. Roberto (Eds.). Springer Berlin Heidelberg, Berlin, Germany, pp: 55-69.

Favaro, P. and S. Soatto, 2002. Learning Shape from Defocus. In: Computer Vision-ECCV 2002. Heyden, A. (Ed.). Springer Berlin Heidelberg, Berlin, Germany, pp: 735-745.

Favaro, P., M. Burger and S. Soatto, 2004. Scene and Motion Reconstruction from Defocused and Motion-Blurred Images via Anisotropic Diffusion. In: Computer Vision-ECCV 2004. Pajdla, T. and J. Matas (Eds.). Springer Berlin Heidelberg, Berlin, Germany, pp: 257-269.

Favaro, P., S. Osher, S. Soatto and L.A. Vese, 2003. 3D shape from anisotropic di usion. Proc. IEEE. Intl. Conf. Comput. Vision Pattern Recognit., 1: 179-186.

Favaro, P., S. Soatto, M. Burger and S.J. Osher, 2008. Shape from defocus via diffusion. Pattern Anal. Mach. Intell. IEEE. Trans., 30: 518-531.

Fergus, R., B. Singh, A. Hertzmann, S.T. Roweis and W.T. Freeman, 2006. Removing camera shake from a single photograph. ACM. Trans. Graphics, 25: 787-794.

Jin, H. and P. Favaro, 2002. A Variational Approach to Shape from Defocus. In: Computer Vision-ECCV 2002. Heyden, A. (Ed.). Springer Berlin Heidelberg, Berlin, Germany, pp 18-30.

Levin, A., 2006. Blind motion deblurring using image statistics. Adv. Neural Inf. Process. Syst., 19: 841-848.

Lin, H.Y. and C.H. Chang, 2006. Depth Recovery from Motion and Defocus Blur. In: Image Analysis and Recognition. Campilho, A. and M. Kamel (Eds.). Springer Berlin Heidelberg, Berlin, Germany, pp: 122-133.

Lucy, L.B., 1974. An iterative technique for the recitations of observed distributions. Astron. J., 79: 745-754.

Money, J.H. and S.H. Kang, 2008. Total variation minimizing blind deconvolution with shock filter reference. Image Vision Comput., 26: 302-314.

Richardson, W.H., 1972. Bayesian-based iterative method of image restoration. J. Opt. Soc. Am., 62: 55-59.

Saxena, A., S.H. Chung and A.Y. Ng, 2008. 3-d depth reconstruction from a single still image. Intl. J. Comput. Vision, 76: 53-69.

Schechner, Y.Y. and N. Kiryati, 2000. Depth from defocus vs. stereo: How different really are they?. Intl. J. Comput. Vision, 39: 141-162.

Shan, Q., J. Jia and A. Agarwala, 2008. High-quality motion deblurring from a single image. Proc. ACM Trans. Graphics, Vol. 27. 10.1145/1360612.1360672.

Welk, M., 2008. Dynamic and geometric contributions to digital image processing. Habilitaion thesis, Saarland University, Germany.

Welk, M., D. Theis and J. Weickert, 2005. Variational deblurring of images with uncertain and spatially variant blurs. Lect. Notes Comput. Sci., 3663: 485-492.

Wiener, N., 1949. Extrapolation, Interpolation and Smoothing of Stationary Time Series. MIT Press, Cambridge, MA.

You, Y. L. and M. Kaveh, 1999. Blind image restoration by anisotropic regularization. Image Proc. IEEE. Trans., 8: 396-407.

You, Y.L. and M. Kaveh, 1996. A regularization approach to joint blur identification and image restoration. Image Proc. IEEE. Trans., 5: 416-428.