An Experimental Approach to Motion Blur Estimation in Legged Mobile Robot Platforms

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Abstract

Determining how much an image is blurred is crucial in many computer vision applications. This study focuses on obtaining the amount of motion blur induced by rotating camera looking into a static scene. A reference based motion blur metric using standard deviation is proposed. This metric is developed experimentally by working on different image samples taken from a legged mobile robot. The reference frame is selected automatically among the sharpest frames detected in a streaming video frames. The results show that the proposed method can yield enough accuracy to classify the frames captured on a legged robot platform according to the motion blurring magnitudes.

Key words: Motion Blur Metric, Image Sharpness, Legged Robots

Özet

Bir resmin bulanıklık miktarının tespiti birçok bilgisayar görüntü uygulamaları için büyük önem taşımaktadır. Bu çalışmanın odağı dönen bir kameranın hareketsiz bir sahneye uyguladığı bulanıklık miktarının elde edilmesidir. Bir referansa dayalı ve standart sapmayı kullanan bir metrik öne sürülmüştür. Bu metrik bacaklı hareketli robottan alınan farklı görüntüler üzerinde deneysel olarak çalışılarak geliştirilmiştir. Referans karesi kesintisiz akan video karelerinin içinden en net olan karelerden otomatik olarak seçilmiştir. Sonuçlar önerilen metodun hareket bulanıklılığının büyüklüğüne göre bacaklı robot platformundan elde edilen karelerin sınıflandırılmasında yeterli doğruluğu sağlayabildiğini göstermektedir.

1. Introduction

The camera mounted on a legged robot which is moving with a high speed and on a rough terrain is mostly exposed to high mechanical vibrations. These vibrations during a video capture prevent obtaining sharp images from the camera. This results in a corruption or loss of information by means of a blurring on the image. An example image captured during the walking motion of a hexapod robot [1] that includes motion blur is shown in Figure 1. As can be noticed easily from the figure, the captured image is neither visually pleasant for human perception for remote controlling by a human operator nor suitable for gathering high frequency components of scene such as edges, corners etc. The use of motion blurred images mostly degrades the performances of computer vision techniques and causes erroneous results. Therefore, determining the amount of motion blur of a captured image frame becomes important.

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Figure 1. A motion blurred image frame taken from the camera mounted on our hexapod robotic platform while it is running using the alternating tripod gait on a rigid flat surface.

The motion blurring of images captured from a legged mobile robot platform shows some particular properties. The blur is caused by the interaction between the leg and the surface while the robot is walking. This surface-leg interaction induces some mechanical vibrations on the robot body and so on the camera. However these vibrations are not continuous and fade out with time. Therefore, the magnitude of motion blur changes while the robot walks. The analysis of image frames shows that there are captured both very sharp, very blurred frames and different level of blurring in-between. In this study, a metric is obtained to determine how much an image is blurred.

Motion blur term is as old as the invention of the camera. Therefore, a large body of literature is available on motion blur because of the wide application area of cameras. Detection of motion blur magnitude, in other words how much an image is blurred, is generally a common preprocess in most of the applications related with motion blur. There are many methods proposed in literature to determine the motion blur magnitude. However, each method has different pre-assumptions and has its own disadvantages when compared to each other. Therefore, the method to use should be selected based on the application.

The motion blur detection methods in literature can be analyzed mainly in two groups according to the reference. The first group of methods assumes that there is only one motion blurred frame of the scene. These methods try to extract the motion blur using only the single blurred image itself. These methods are referred as “no-reference” methods since there is no reference frame available which represents the sharp snapshot of the considered scene. A popular method in this group is based on the just noticeable blur approach proposed in [2]. This metric is generally used to compare visual quality and it is applicable for relatively small blur amounts. Another no-reference metric is presented in [3]. Their metric is based on a cumulative probability of blur by taking into account the Human Visual System. In [4] a blur metric based on the analysis of the spread of the edges in an image is given. Wavelet transform coefficients are utilized in [5] claiming that blurring disrupts the phase coherence. The study in [10] utilizes contrast based blur invariant features together with local standard deviations to determine spatially varying blur in images. In [6], the authors utilize the gradient profile sharpness of image edge and the histogram of sharpness distribution. In [9], they consider both the defocus and motion blur artifact. They use local edge blur to estimate the overall image blur. Although this group of methods has more application area because of the lack of reference need, their performances depend much on the scene type since there is no information available about the sharp representation of the scene.

The second group of methods depends on the knowledge of a reference frame which is not exposed to any motion blur and therefore a sharp representation of the scene. Because of the use of a reference frame, this group of methods is called "reference based" methods. These methods try to determine the amount of motion blur that causes the reference scene to appear as the motion blurred frame captured of that scene. Generally these methods perform better than the no-reference based methods since there is more information available about the scene. However, there are fewer studies in this group available in literature since the cases where the reference frame is available are rare. An important study in this group is presented in [7]. They assume the existence of global motion blur and a sharp reference frame. They use linear least squares fit approach in a wavelet-based Haar filters and claim the real-time operation of the algorithm. A study on the motion blur removal for humanoid robots is presented in [8]. They first classify the images as less blurred and severely blurred by using Just Noticeable Blur Metric [2] as a quantitative criterion. For less blurred images, they propose a maximum a posteriori framework by taking advantage of the previous sharp image as reference. Our work can be classified in the second group as a reference based method and it is similar to the study given in [8] in classifying the frames and finding the sharpest one among them.

2. Motion Blur Analysis in Legged Mobile Robot Platforms

In legged robots, images that are taken from a camera mounted on the moving platform are affected by the vibrations due to both rugged terrain and the legs of the robot. These introduced distortions may occur in different forms depending upon the direction and speed of the movement. Translational and rotational camera motions yields a rich content of motion blur. In this study, the motion blur is assumed to be induced by the camera rotation around pitch and yaw axes which are the dominant motion involved in motion blur while the legged robot is walking. This assumption yields a uniform motion blur in the captured image frames.

For the analysis of the image texture in the point of blur amount, several methods can give information on the high frequency content available in the image data. A motion blurred image is poor in high frequency components since they are smoothed out. Therefore analyzing the statistical properties of the texture of the images captured from the same scene can give information on which one is sharper. In development of this metric, a synthetic checkerboard pattern is first used as an experimental input image since it has both horizontal and vertical sharp edges and it is easier to find the ground truth blur amount visually. In the proceeding step, several functions are tested to detect the one which has more linear relation with respect to blur magnitude. The tested functions are entropy function that takes the entropy of the gray-scale image, the correlation function that calculates the correlation coefficient, the edge detection function that finds edges in gray-scale image and the standard deviation function that finds the standard deviation of image pixel values. Among all, the standard deviation function gives the most linear blur change for the different amount of blurred checkerboard images. The maximum blur amount that is applied to the checkerboard image is adjusted to satisfy the linearity such that the ratio of the size of the original image and amount of the blur is almost 10.

Hata! Başvuru kaynağı bulunamadı. indicates the performances of mentioned image analysis functions in terms of linearity behavior when they are applied to images which are blurred in different magnitudes. In order to decide the function which yields most linear behavior, the R-square value and the root-mean square error value (RMSE) are considered as the criteria by fitting a linear line. If the figures are examined, it can be seen that standard deviation ensures the highest R-square value of 0.9957. Therefore, being founded of the assumptions, it can be concluded that standard deviation function has a better linearity relation with respect to the motion blur magnitude. The equation that is used in the calculation of standard deviation is given by expression (1).

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2} \quad (1)$$

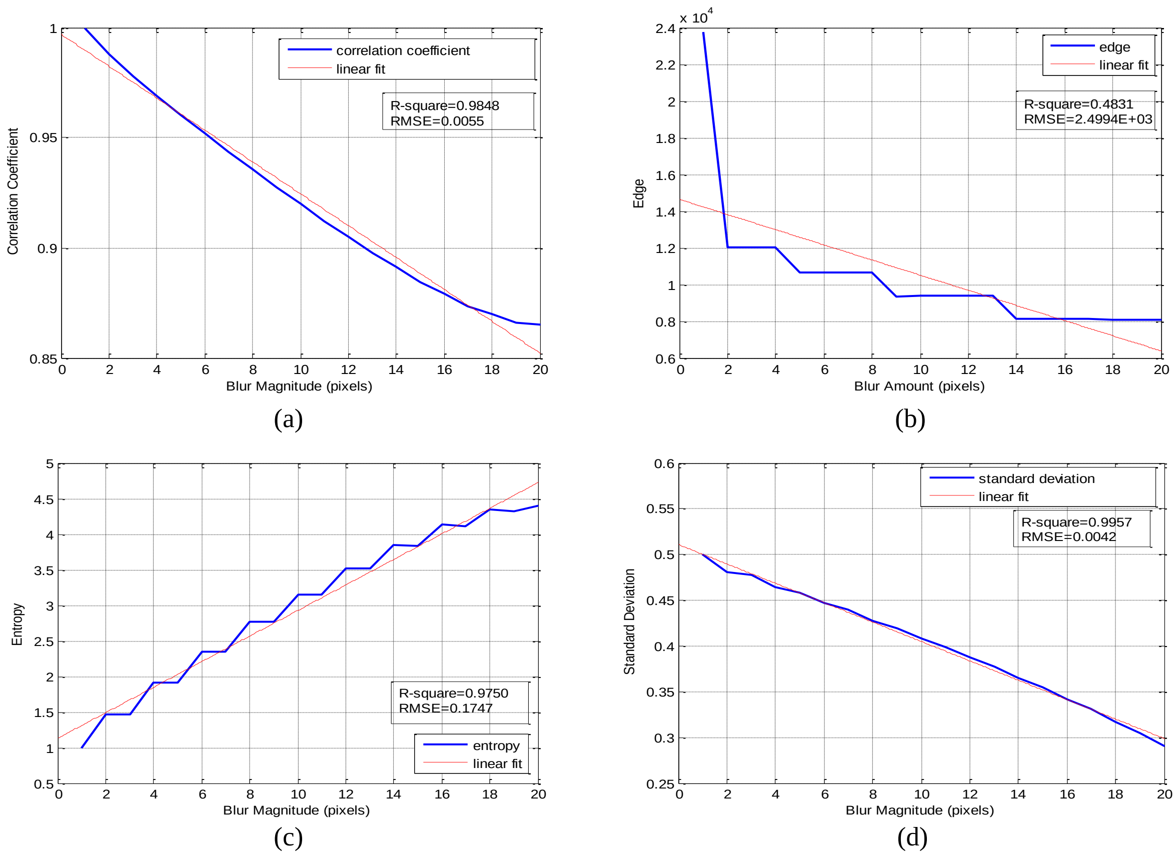

Figure 2. : Variation on blur magnitude (pixels) vs. correlation coefficient (a), edge number (b), entropy (c) and standard deviation (d) of the synthetically generated checker board pattern. Same synthetic checker board pattern used in all plots.

In order to gain an insight into the motion of the legged robot, we need to observe the amount of the motion blur by calculating the standard deviation of the blurred images. Figure 3 demonstrates the variation of standard deviation for 50 consecutive images captured at 25 fps from the camera mounted on the legged robot platform. Coarsely, it can be said that frames having higher standard deviation are relatively sharper than the frames having lower standard deviation values. From the graph, it can be realized that there are both sharp and blurred images in the video sequence obtained while the robot is walking in a periodic manner. The sharp frames can be used as a reference frame representing the non-blurred representation of the scene. Actually, the reference of each motion blurred frame is different. However, the consecutive image frames are not changing too much with respect to its neighboring frames. Therefore, it can be assumed that a reference frame is valid among its neighboring frames collected in a window. The window size should be selected properly so as to both there exists a sharp frame to be selected as the reference frame and the reference frame still remains valid for all the other frames in the window. In our case, we selected a window of 10 consecutive image frames. Therefore, this observation will shape our approach during the calculation steps.

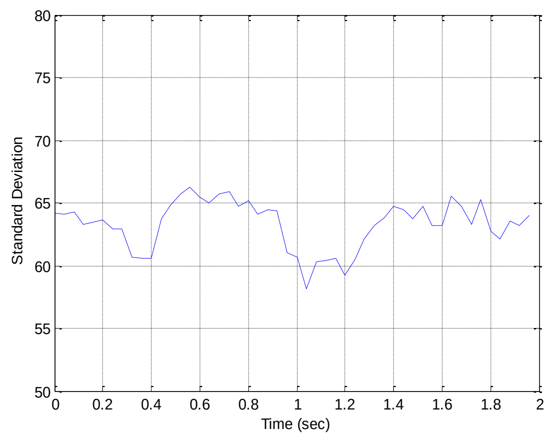

Figure 3. . Standard deviation vs. time of the 50 consecutive images captured from a camera mounted on a legged mobile robot platform.

3. Motion Blur Metric Calculation

The calculation of any motion blur, mainly the magnitude of the blur in both directions, is performed with the assumption that the standard deviation of the motion blurred image changes linearly as a new, synthetic filter is applied on, as previously mentioned. The algorithm used in this article predicts the blur amount based on a comparison of each frame to a reference frame, the sharpest frame, in a window of frames containing a predefined number of frames taken in time.

Before we continue with the estimation of the blur the camera is exposed to, let us mention how the sharpest frame is selected among the others in a time window of n frames. The image that the program chooses as the reference image in a time slot is simply the image which has the highest standard deviation in the window that is examined. During the testing of the operation of the function, we used a fixed time window of 10. Therefore, inside of the window, the reference image chosen for each image is unique and the reference input changes as the window slides in time. One drawback of this kind of operation is that during the real-time operation it needs several image frames to be buffered to find the reference frame. This means that the algorithm calculates the blurring of a frame only after n previous frames are available in the buffer. This of course, is related only to the choice of the time window, so the type of application and can be adjusted accordingly.

After determining the sharpest image taken in a fixed time window, the function utilizes the valid assumption of linearity of standard deviation against motion blur amount. At this stage, the algorithm fits a linear function to the graph of standard deviation versus motion blur magnitude. At the next step, it determines the inverse function of the line obtained, i.e. the function from the set of standard deviations to the set of motion blur amount, called the motion blur function which is linear by definition.

At the last step, the function estimates the blur amount of any non-reference image coupled to that reference image as the output of the motion blur function. The input variable of the metric is the calculated standard deviation of the considered blurred image. valid assumption that the images, prior or posterior to the coupled references, are alike in terms of content and therefore can be used as a starting point for the calculations.

As a result, our blur metric separates the operation time into frame window of a given length and determines the sharpest frames for the frames in that window to use them as reference. Then, blurs each reference image to determine a linear relation between the blur amount and change in standard deviation and refers to this relation estimating the blur amount of any image. The steps of the algorithm are given by the flow chart in Figure 4.

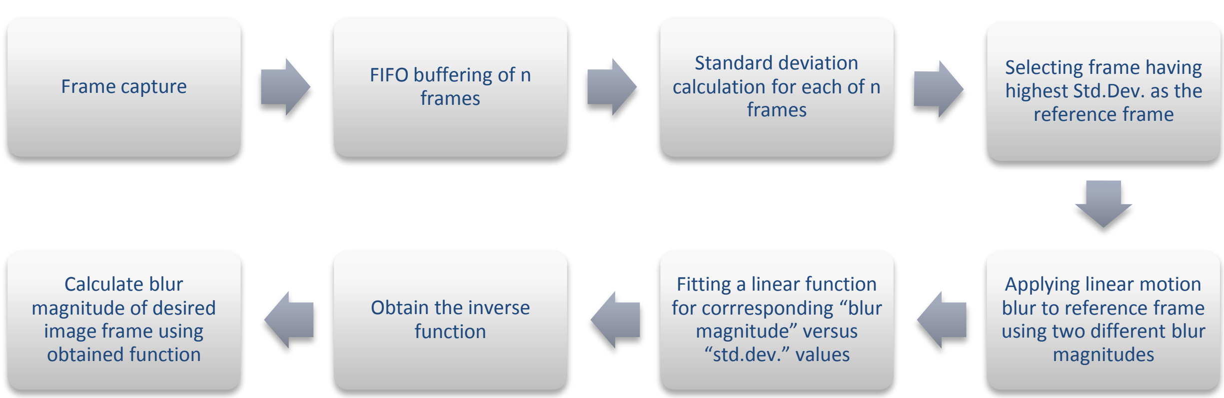

Figure 4. Flow chart of the proposed motion blur detection method.

4. Results

After constitution of theoretical structure and enhancement of the operation of the function, it is tested on the consecutive image frame samples taken from a camera mounted on a legged robot. Comparison between theoretical and real values of blur amount for two different images which are selected randomly is as follows.

The experimental blur magnitude of the first randomly chosen image is calculated as 7.9 pixels while the corresponding ground truth value is 8.9 pixels. The image frame is visualized in Figure 5 together with a magnified image patch which shows the blurring of pixels around the edge.

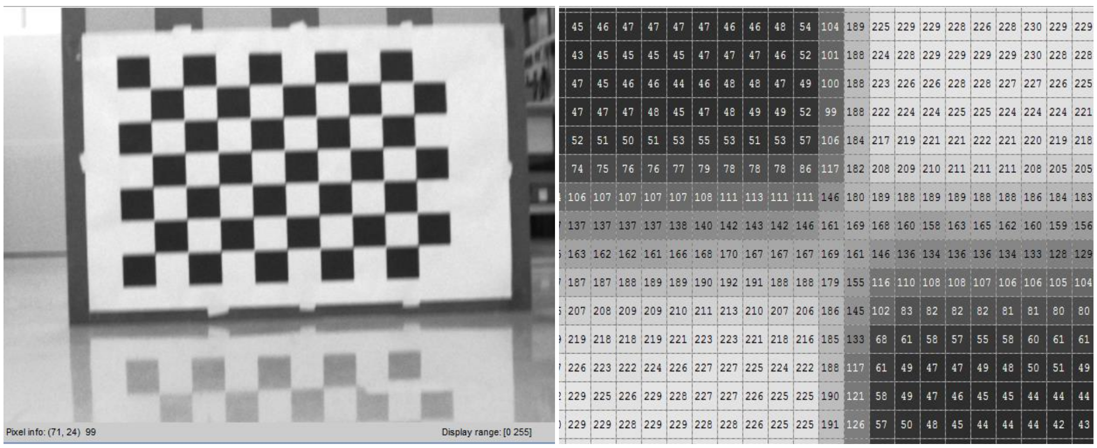

Figure 5. First randomly chosen image taken from camera mounted on a legged robot platform and its blown-up version. The experimental blur magnitude is calculated as 7.9 pixels while the ground truth value is 8.9 pixels.

The experimental blur magnitude of the second chosen image is calculated as 1.69 pixels while the corresponding original value is 2.23 pixels. The image frame is visualized in Figure 6 together with a magnified image patch which shows the blurring of pixels around the edge.

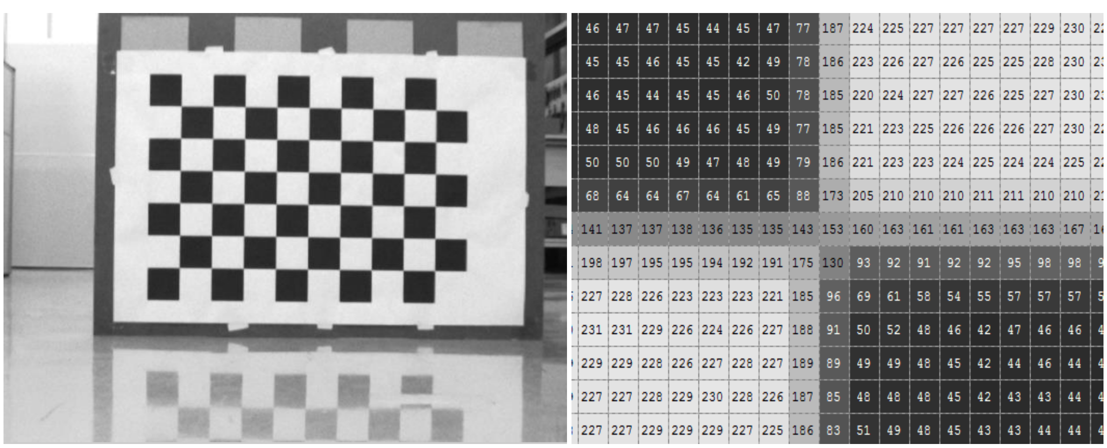

Figure 6. Second randomly chosen image taken from camera mounted on a legged robot platform and its blown-up version. The experimental blur amount value is 1.69 pixels while the original value is 2.23 pixels.

The mean error and the standard deviation of error of the metric are provided as criteria of accuracy and preciseness. The mean error is calculated as 1.2598 while the standard deviation of error is found as 2.9042.

The theoretical and real values of blur amount taken from a random frame window consisting of 20 consecutive frames are provided in Figure 7.

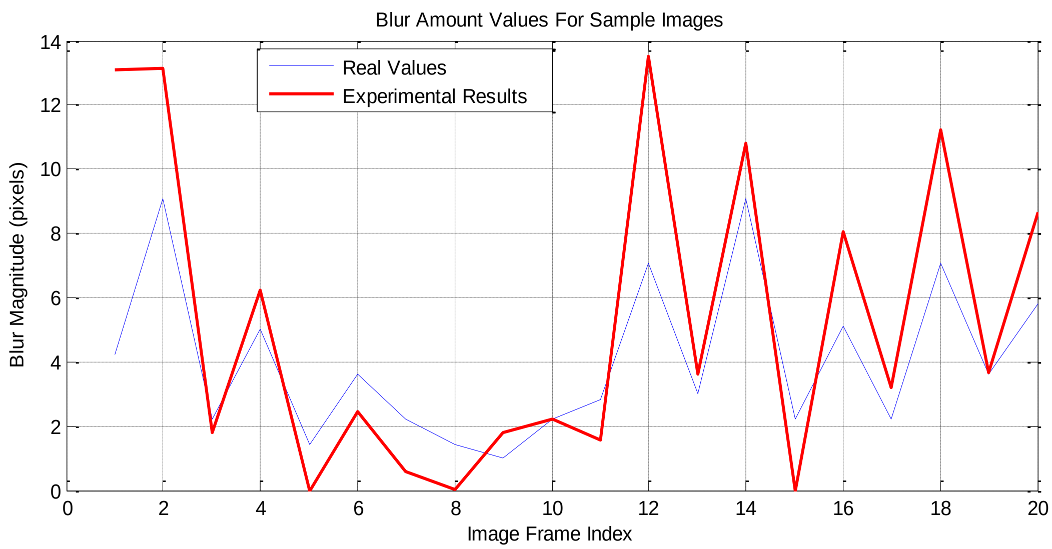

Figure 7. Comparison of experimental and real values of blur magnitude for a randomly selected image frame index which are taken from images captured from a camera mounted on a legged mobile robot platform.

5. Discussion

After the implementation of metric to the consecutive image frame samples taken from a camera (Point Grey Flea2 640x480 resolution) mounted on a legged robot, it is observed that the metric definitely give a deep understanding about the comparison of the blur amounts of frames between each other. However, some errors occur in the computation of blur amount globally as can be seen in Fig 7. These errors can be minimized by proper selection of the size of frame window. The window size must be chosen such that it should be as large as possible to include a sharp frame for the sake of accuracy of the calculated motion blur magnitudes. On the other hand, it must also be not so large since the comparison of standard deviations of two images which are too much far from each other is meaningless. In this study, the window size is kept at a selected constant value. However, using an adaptive window size can improve the accuracy of the results. Another approach may be to utilize more than one reference frame to reduce the dependence on the proper selection of a single reference.

Regarding the computation time of the algorithm, the tests on a 1.73GHz computer having 0.99

GB RAM have shown that for a file containing 10 test images, the time interval the first results are computed, i.e. the first estimations appear, is from 0.8s to 1.1s while after characterizing the time window by its sharpest image and motion blur function it takes about 30ms to compute each frame's amount of motion blur estimation separately.

6. Conclusion

In this study, a motion blur metric is proposed to measure the blurring of an image captured from a camera mounted on a legged mobile robot platform. The metric measures the motion blurring of an image within a video sequence, based on a reference sharp frame. The reference frame is obtained among the captured frames having the highest standard deviation value. Then the motion blur metric is derived as a linear function that maps the standard deviation to the motion blur magnitude. The experiments show that the metric calculates the motion blur magnitude with a mean error of 1.2598 pixels and the standard deviation as 2.9042 pixels. This metric, as a fast estimate, can be utilized in many legged robotic platforms for a variety of computer vision applications.

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