SCHEME FOR EVALUATION AND REDUCTION OF MOTION ARTIFACTS IN MOBILE VISION SYSTEMS

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Abstract: Artifacts like motion blur are a common problem for vision systems on mobile robots, especially when operating under low light conditions or when using high-resolution sensors. In this contribution we present a scheme for estimating the degree of motion artifacts, especially motion blur, present in a stream of individual camera images. A single quality estimate is derived per frame using data from an inertial measurement unit. Considering limited image processing capacity of resource-constrained mobile robots, we show a number of data processing strategies that are based upon the idea of congestion control by adaptive image rejection.

1 INTRODUCTION

While the presence of motion artifacts in images from moving cameras can also be exploited in several ways, it is usually a troublesome effect. Objects may become unrecognizable because of blur; visual SLAM algorithms may yield poor results because of difficulties when finding corresponding image points or due to geometric distortion of the whole image.

At the same time, image processing tasks usually require significant resources and may easily exceed the capabilities of the computer hardware present on a mobile robot.

In the following sections we describe our approach to lessen the effects of both problems. At first we evaluate motion artifacts in greater detail. After discussing related work we present our method for estimating the image quality regarding the presence of motion artifacts. We then show data processing strategies including an approach to congestion control in persistent overload situations. We also present improvements of a specific vision task achieved with our system.

2 MOTION ARTIFACTS

Cameras acquire images by exposing a light-sensitive element for a given period of time. Camera movement while the sensor is exposed may result in a number of image artifacts. Lens distortion is considered to have a negligible impact and is therefore not modeled here.

2.1 Motion Blur

Motion blur can be induced by moving either objects in the camera's field of vision or the camera itself. For simplicity we consider only a static scene and disregard any moving objects.

Camera Translation. We distinguish between two kinds of camera movement. On the one hand there is translation in direction of the optical axis; on the other hand there is motion in the plane orthogonal to that axis. In the second case, the magnitude of blur b on the image sensor for an object is in inverse proportion to the distance to the camera plane d_{cam} (See Figure 1).

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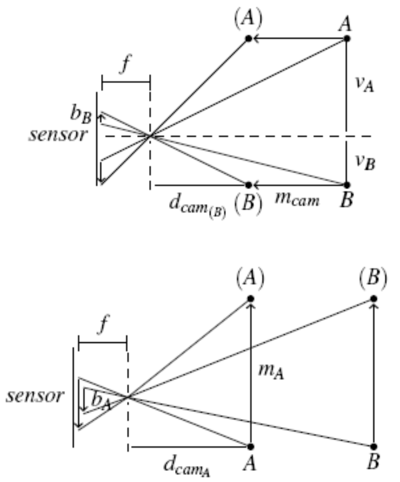

Figure 1: Motion blur in case of translation parallel to the optical axis (upper part) and vertical or horizontal translation (lower part).

For movements parallel to the optical axis the intensity of blur *b* for an object depends on its distances from line of view *v* and camera plane d_{cam} and the displacement m_{cam}. For a point at the optical axis, this kind of translation has no impact. If objects are relatively far away from the camera, translation becomes insignificant.

Camera Rotation. When rotating the camera, the magnitude of blur also depends on the position of a given object relative to the optical axis. Figure 2 shows that such a camera rotation results in a blur *b* roughly perpendicular to the axis of rotation. Its strength depends on the actual angle of rotation and on the angle between the rotation axis and the view direction. The distance to an object does not matter for rotational blur (See Figure 2).

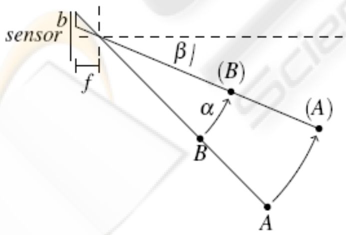

Figure 2: Motion blur in case of rotation.

2.2 Distortion

Geometrical image distortion is another common artifact that can be found with moving cameras. It occurs when different portions of the image sensor are exposed sequentially to light. This "rolling shutter"-mode is implemented in a number of CMOS-based cameras.

A sudden change in illumination may influence only portions of the image. If the camera is moved horizontally or rotated around the vertical axis, skew can be observed. Vertical lines appear to lean to the left for moving to the left or the right side for the opposite direction of movement. Vertical movements as well as rotations around the horizontal axis result in stretching respectively shrinking of objects vertically. Altering the direction of movement at a high speed (in case of vibrations) is called "wobble". When rotating the camera around the optical axis, straight lines get bent around the image center.

3 RELATED WORK

Two categories of techniques that are concerned with the problem of motion artifacts can be identified.

The first group of approaches is concerned with avoiding artifacts in the first place. Here, special hardware with accurate actuators is required. One solution is to stabilize the whole camera on a special platform, as shown in (Schiehlen, 1994). Other solutions are shiftable image sensors (Yeom, 2007), (Cardani, 2006), (Chi-Wei Chiu, 2007) that counteract camera shake or agile optical components like a variable fluid prism (Sato, 1993), a movable mirror (Günther, 2006) or an additional lens between scene and sensor.

A quite simple solution found in some recent hand-held cameras tries to delay image exposure in case of camera shaking. Camera movement is determined using acceleration sensors.

A different group of solutions is not concerned with preventing artifacts during image acquisition, but tries to undo artifacts at a later stage by using image processing techniques. For instance one approach (Choi, 2008) merges blurred and sharp but under-exposed images of the same scene to obtain an overall improved image. In general, a correction in software is time-consuming and consists of two steps. In the first step the artifacts are identified, in a second step they are removed from the image. A number of algorithms for global shutter (Ji, 2008), (Fergus, 2006) and for rolling shutter (Cho, 2008), (Nicklin, 2007), (Chun, 2008) cameras have been developed. In contrast to our implementation, most of these approaches are, beside their excessive computational cost, limited to simple motions.

4 IMAGE QUALITY ESTIMATION

We estimate motion artifacts by measuring the movement of the camera during image exposure. This eliminates the need for additional image processing to detect artifacts, which is beneficial for resource constraint mobile systems.

4.1 Sensor Configuration

In our system, motion tracking is done by an inertial sensor containing a MEMS gyroscope which can measure three-dimensional angular velocity and a MEMS three-axis-accelerometer. Measurements are discretized in time. As discussed in section 2, the effect of motion varies depending on the setup. Camera translation results only in marginal artifacts for objects at medium and large distances, which we consider prevalent in the vast majority of mobile robot scenarios. Additionally, the direction of view often is in coincidence with the driving direction. Here, camera movement as a result of the robot's linear motion can also be ignored. The position of the sensor relative to the camera is irrelevant for the measured angular speed as long as they are both firmly mounted on a rigid frame.

4.2 Tracing Motion Artifacts

In our approach we consider the intrinsic camera parameters and the position and orientation of the camera relative to the gyroscope. The direction of the view vector varies over the image. Therefore the effect of camera motion is different at every image point. It is calculated by first projecting points from image space into world space by using the camera's intrinsic matrix while considering its lens distortion (See Figure 3). The camera's depth of field could be used as a rough clue. As discussed earlier, rotation is the main cause of artifacts in many scenarios. Here, solely the view vector at the considered image points is relevant.

In a second step the measured motion is applied successively to the virtual camera while tracing the path in image space described by the projected point. The quality estimate for an image point is determined by the length of the path as well as by the maximum distance between any of two points on that path. We map the strength of motion artifacts to the interval from 0.0 to 1.0, where 1.0 stands for an immobile camera. The quality reaches 0.0 for infinitely high motion artifact strength.

As stated above, the direction of sight rays and thus the quality estimate varies over different image points. To get a single estimate for the entire image, several possibilities exist to combine the data. The simplest method is to only consider quality at the image center. Depending on the application, it is also possible to sample quality values over the entire image or from predefined areas of interest and then use the average or the lowest quality as the overall quality measure. When combining samples over a larger area it is possible to account for rotation around the optical axis, which could not be detected when only considering the image center.

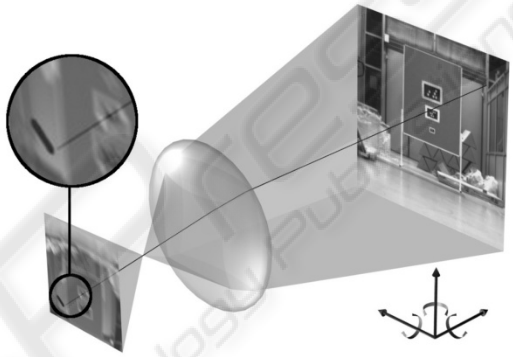

Figure 3: Basic principle of tracing motion artifacts.

5 DATA PROCESSING SCHEME

While researchers made various efforts to deal with motion artifacts, many of them are not well suited for mobile robot applications. Undoing blur is a slow and cumbersome process. Adaptive triggering of image acquisition depending on current camera movement is a promising and computationally inexpensive approach. However, a sudden increase in camera movement during exposure cannot be predicted.

In our system, we chose to continuously acquire images as well as motion data and apply a selection process at a later stage. One advantage is that the actual movement of the camera during image exposure is known for every individual image. Another advantage is that 'bad' pictures are not prevented from being acquired. A scheme for rejecting individual frames at an early processing stage is applied instead. Depending on the application, blurry images may still be used if continuous image degradation happens for a prolonged period of time.

5.1 Image Acceptance Test and Congestion Control

We consider mobile platforms to have in general a limited computing capacity. At the same time we assume that image processing tasks consume significant resources. Here, the frame rate of a camera may easily exceed the image processing capacity.

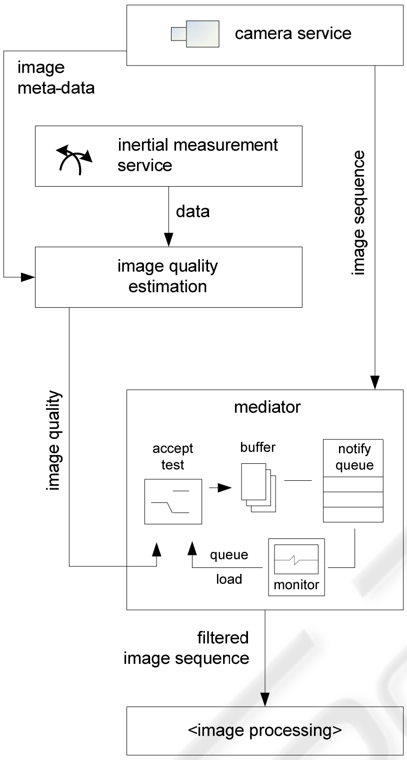

Figure 4: Structure of a system containing a mediator service for congestion control.

As shown in Figure 4, instead of dropping random frames, we can apply a simple, yet effective congestion control scheme. Having a normalized image quality value available for every frame enables us to compare it directly to the current system load. Images are only accepted for further processing if their image quality is greater than the system load indicator. This implies that in case the system is idle, even images containing heavy motion artifacts are accepted for further processing. This ensures that it is not possible to reject every image for an extended period of time. The system load indicator is derived from the percentage of utilized space in the image queue right before the image processing stage mapped to the interval from 0.0 to 1.0.

5.2 Data Processing Strategies

The basic data processing scheme has been described in the previous section. However, as in the computation of a global quality estimate for the entire image, some variations or extensions are also possible at this stage.

Minimum Quality. If an application requires that the degree of motion artifacts doesn't exceed a certain degree, it is possible to specify a minimum quality value at the mediator to prevent it from accepting low quality images.

Binning Images. Scenarios where degraded images can still be useful if they are processed in an alternative way compared to artifact-free images can also be supported. Here, the mediator shown in Figure 4 can be extended to route images with quality estimates below a certain threshold to another processing module. An example of such a scenario may be a system for visual odometry where images are too blurry to match corresponding features in successive frames but can be used to derive camera motion from blur instead. Another scenario is the combination with deblurring algorithms. To prevent starvation of image processing in case of unacceptable blurry images for a long period of time, it is possible to route individual images through a deblurring stage when the load indicator becomes low.

Reusing Quality Estimates. It may also be desirable of course to include the quality estimate or even the computed paths of movement at individual image locations in later processing stages. The overall quality measure can be easily included in the image metadata at the mediator stage. If access to more detailed data is required, it is more suitable to establish an additional connection between the quality estimation module and the processing stage and access desired data on demand.

6 SYSTEM EVALUATION

In this section we show results achieved with our approach to image quality estimation. We also present improvements of a scenario where markers are to be detected by a mobile robot while driving on a bumpy floor.

6.1 Evaluation of Motion Artifact Detection

In a first experiment we examined the correlation between motion blur in camera images and the computed quality based on angular rate measurement. A mobile robot was equipped with a front facing camera and was driving towards a board placed in front of it. The robot passed various bumps of a maximum height of 1 cm, which resulted in displacement as well as rotation of the robot. Figure 5 shows the correlation between blur radius at the image center and computed quality values. The blur radius was measured manually in each individual image.

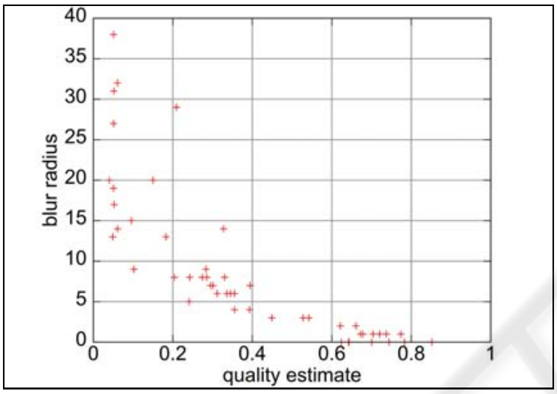

Figure 5: Correlation between quality estimate and actual strength of motion blur.

In Figure 6 small parts of a blurry and a non-blurry image is shown. The red dots indicate the motion calculated using inertial data only.

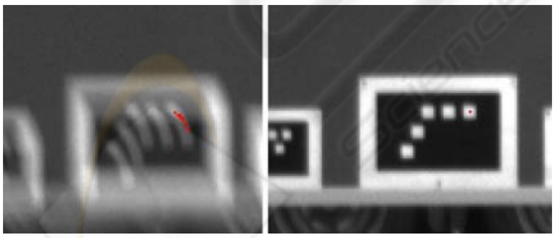

Figure 6: Motion blur traced by inertial data.

6.2 Improving a Marker Detection Scenario

We applied our approach to a scenario where optical markers were to be recognized by a moving mobile robot. The computing capacity onboard the robot is limited. Therefore not all images acquired by the onboard camera can be processed. The lights were set to about 300 lux, which resulted in an average integration time of 60 ms. A 2/3 inch monochrome CCD sensor and a 4.8 mm fixed focus C-Mount lens were used in the experiment.

The robot was approaching a board from a distance of approximately 13 meters. Markers of different sizes were attached to the board (See Figure 7). The goal when approaching the board was to recognize the markers as frequently as possible.

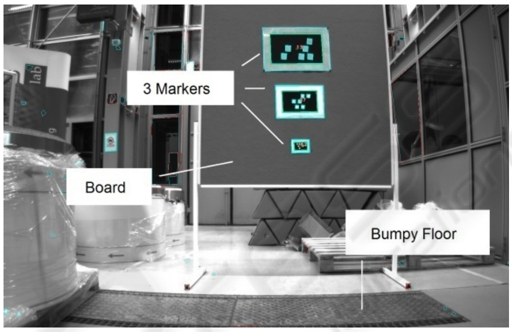

Figure 7: Test setup of the marker detection scenario.

Images and motion data were recorded in order to compare results achieved with uncontrolled frame drops due to queue overflow against results with dynamic congestion control. The total number of images acquired during the approach was 319. The average processing time per frame required by the marker detection algorithm was approximately 1.6 times the interarrival time of new images. Table 1 shows the number of images in which a marker could be identified for one particular approach. In general, markers could not be recognized in all 319 frames because at first they were too far away, went partially outside of the image, or they were obscured by motion blur. It can be seen that the improvement in the total number of images with recognized markers increases with the decreasing size of the marker. This is because smaller markers are easily obscured by blur.

Table 1: Improvements of recognition results when applying dynamic filtering.

Marker	Large	Medium	Small
recognizable	246	272	99
recognized(uncontrolled)	154	159	62
recognized(filtered)	161	178	71
Improvement [pct.]	4.5	11.9	14.5

7 CONCLUSIONS

Here we presented an approach to improve the performance of image processing tasks on mobile robots equipped with common fixed focus, low-cost cameras. The basic idea presented was to improve the quality of images processed by arbitrary vision algorithms by estimating the amount of motion artifacts for every image and rejecting bad ones while also considering a system load indicator.

Our system is suitable for resource-constrained robots where the camera's frame rate usually exceeds the processing capabilities of the onboard computer. Based on improvements we have seen in an example scenario, we are confident that the performance of a number of different image processing tasks can be improved through this approach.

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