Practical Visual Odometry for Car-like Vehicles

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Abstract—A method for calculating visual odometry for ground vehicles with car-like kinematic motion constraints similar to Ackerman’s steering model is presented. By taking advantage of this non-holonomic driving constraint we show how a single camera can be used to provide a reliable odometry measure using simple mathematics and computer vision algorithms.

I. INTRODUCTION

This paper discusses an approach to visual odometry for ground vehicles with car-like kinematic steering constraints similar to the Ackerman steering model [1]. By taking advantage of this motion constraint we show how a single camera can be used to provide a reliable odometry measure using simple mathematics and computer vision algorithms.

A. Motivation

An estimate of the vehicle’s pose is essential in most forms of autonomous navigation. Hence, localization methods for estimating the vehicle’s pose have always received strong research attention. One of the earliest methods for calculation of the motion of a wheeled ground vehicle is wheel encoder-based odometry. This method, although suffering from unbounded incremental errors and other limitations such as error calculation during wheel slippage, has been around for several decades and is still one of the main localisation sensing modules in the majority of ground vehicles [1]. If we ask ourselves how it is that this method is so popular and useful, we will come to the conclusion that it is due to simplicity and practicality.

However, one aspect of wheel odometry that sometimes limits its practicality is the difficulty of retrofitting a vehicle with wheel encoders. Retrofitting a heavy industrial vehicle with wheel encoders is challenging, time consuming, and expensive. Even after retrofitting such a vehicle, the change in tyre pressure and due to the large width of the tyres the calculated odometry is less precise. It is this issue, that has motivated us to use a different odometry method based on an alternative sensor, that is easy to mount and setup, is stand-alone, and provides a reliable estimate of the vehicle motion which we can feed into other, higher-level, localization modules.

B. Related Work

Advancements in computer hardware has finally reached a level where it is slowly becoming practical to use vision sensors as the main sensor for localization. However, vision-based localization methods for outdoor purposes are only at an evaluation stage. This was demonstrated during the recent DARPA Urban Challenge events, where it was observed that none of the finalists used vision as their main localization sensor [2] [3] [4] [5]. Similarly, the Mars Rovers use vision as a secondary localization sensor after the inertial-based systems. The Rovers are also constantly supervised by humans [6]. Vision-based localization is maturing and recent advancements indicate that it is only a matter of time before such localization systems will be deployed outdoors in unstructured environment.

One approach to visual odometry uses the Structure-from-Motion (SfM) technique. Here, the idea is to find good features in one frame and the corresponding features in the next frames, calculating the perceived motion of these features and translating that to the motion of the camera. This method can be carried out using a single camera [7] but often better results are achieved when using stereo camera [7] [8]. This is mainly due to the fact that robust features are found...
by finding the corresponding feature in the stereo pair leading to a higher chance of tracking in subsequent frames. This method is often limited by its computational complexity and its requirement for a well-calibrated stereo pair — although Johnson et al. [9] have recently demonstrated significant speed-ups in such stereo-based systems.

A slightly different approach avoids the problems of finding and tracking robust features and instead looks at the change in the brightness in the image, where this change in brightness results from the apparent motion in the image. This method, called optical flow, is much simpler and computationally cheaper than the extraction and tracking of features. However, this comes at the cost of less precision over time. One method of deriving odometry using optical flow was presented by Campbell et. al [10]. The authors mounted one camera on top of their robot and tilted it downwards to image more ground in front of the robot and less sky. They sub-divided their frame into three regions—ground, horizon, and sky—and used the optical flow calculated from the ground region to derive the robot’s motion and the optical flow from the sky region to estimate the rotation. Srinivasan [11] used an interpolation method to calculate the optical flow. Using this method, he derived the ego motion of the robot by pointing two cameras at the ceiling tracking changes in the light pattern. This interpolation technique is efficient but it only works for small displacements.

Corke et al. [12] compared a Structure-from-Motion method with an optical flow method using omni-directional vision. Their finding was that optical flow is more robust while SfM methods produce higher precision at the cost of higher computational needs.

The idea of deriving the vehicle’s ego-motion from the ceiling lights, applied by Srinivasan [11], is interesting but is not always valid as ceiling heights are not constant. It is not valid in outdoor applications either, unless we can track clouds or stars and assume they are at infinite distance and motionless in the sky. If we on the other hand flip the camera so it is pointing at the ground it is fair to assume, using a ground vehicle, that the camera-ground distance stays relatively constant.

By taking advantage of our knowledge of vehicle’s motion constraints - in our case an Ackerman-like steering model - we can limit and simplify its motion to two components; a pure forward/reverse translation and a pure rotation around the center of the rear wheel axle. It is then possible to derive these two vehicle motion parameters directly from the two camera motion parameters observed from optical flow generated in the image (Figure 1). Cars today do not apply a pure Ackerman steering model, but as we show, this assumption is still valid for our purpose.

In next section we describe our methodology; how we derive the displacement seen by the camera and how this relates to the vehicle’s own motion. In Section III we discuss how the performance of odometry systems can be measured and analyze the quality of our odometry system. Finally, in Section IV we discuss our findings and conclude.

Fig. 2. Asphalt and concrete surfaces when seen from a camera in motion approximately 0.6 m above ground.

II. METHODOLOGY

By using our knowledge of the vehicle’s kinematic motion constraints it is possible to optimize and simplify the odometry calculations. In our approach we make the following assumptions: 1) the vehicle is car-like and its motion is constrained to Ackerman’s steering model: its motion is comprised of a forward translation and a rotation around the center-of-motion of the rear axle; 2) there is no side-ways translation so we ignore any side-ways slippage; and 3) the vehicle motion can be viewed as piece-wise straight motion. This more simplified vehicle motion allows for easier odometric calculation.

We are interested in deriving the motion of the vehicle from the observed motion in the camera. We therefore mount the camera at the front of the vehicle at a fixed height looking at the ground beneath. The motion in the camera is determined by calculating the pixel displacement, ΔU and ΔV, in consecutive frames. This displacement is then translated to the actual motion seen by the vehicle, Δx and Δθ. Figure 1 shows our postulated vehicle motion figuratively.

Next we explain the method used for calculation of the pixel displacement in the camera and from that the determination of the vehicle odometry.

A. Pixel Displacement

An obvious method for measuring the displacement in two consecutive frames, ΔU and ΔV, is by calculating the optical flow. This method works well when the image contains many dominant features. In our case the camera is pointed downward looking at a small area (∼0.2 m²) of the ground directly beneath. In this case, optical flow calculation may perform poorly as distinct features can be difficult to extract. This is especially true for featureless concrete floors and asphalt roads (Figure 2).

A more robust method for calculating the image displacement in such situations is by using correlation or template matching. The idea is to take a patch from the previous frame and try to find the corresponding area in the current frame, which has a similar brightness pattern. One shortcoming of correlation matching, especially when used in stereo matching [13], is its inability to deal with foreshortening. Although we are not using this method for stereo matching this limitation is still valid. The two consecutive frames are captured with a small distance between them and therefore have a tiny difference in perspective. If the surface is uneven
where processing time 1) the size of the image and 2) the size calculated for each pixel location. Two parameters influence the processing time slightly. We can therefore choose the mask size based on another important parameter; the maximum allowable drive velocity. Figure 3 shows the dependency of the maximum drivable velocity on the mask size and available frame rate/processing rate for a camera mounted 0.6 m over the ground. This graph suggests that the smaller the mask size the higher vehicle velocity/displacement can be measured. But choosing too small a mask compromises the correlation quality due to false matches in local maximas. On the contrary, too large an area limits the velocity and the correlation quality is also compromised due to loss of resolution. We use the OpenCV implementation of template matching using CV_TM_CCOEFF_NORMED as the matching method [14], and have found that for our range of vehicle velocities and surfaces robust displacements are obtained if the length of the template window is two-third to one-forth the height of the image, depending on the details of the surface.

1) Determining the size of the correlation mask: Table I clearly demonstrates the gain in processing time achieved by using a smaller image size, whereas we have observed that the mask size only influences the processing time slightly. The size of the mask. Table I shows the influence of changing the image size.

<table>
<thead>
<tr>
<th>Image Size</th>
<th>Processing time [ms]</th>
</tr>
</thead>
<tbody>
<tr>
<td>427 × 320</td>
<td>20</td>
</tr>
<tr>
<td>320 × 240</td>
<td>10</td>
</tr>
<tr>
<td>213 × 160</td>
<td>4</td>
</tr>
</tbody>
</table>

**TABLE I**
CORRELATION PROCESSING TIMES DEPENDING ON IMAGE SIZE. THE SIZE OF THE MASK USED IS 320 × 320.

Another disadvantage of the correlation method is that it can be a time consuming process as the correlation mask has to be moved over the entire image and the correlation calculated for each pixel location. Two parameters influence foreshortening will occur and the matching can fail or give a poor result.

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<table>
<thead>
<tr>
<th>Mask size [pixels]</th>
<th>Frame rate [s⁻¹]</th>
<th>Maximum velocity [m/s]</th>
</tr>
</thead>
<tbody>
<tr>
<td>320</td>
<td>20</td>
<td>82</td>
</tr>
<tr>
<td>250</td>
<td>30</td>
<td>64</td>
</tr>
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<td>200</td>
<td>40</td>
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<td>20</td>
<td>100</td>
<td>15</td>
</tr>
<tr>
<td>10</td>
<td>150</td>
<td>10</td>
</tr>
</tbody>
</table>

**Fig. 3.** The maximum allowable velocity depends on the correlation mask size, the available frame rate, and height over ground. Here we have fixed the height to 0.6 m and present the dependency on frame rate and mask size.

2) Choosing the correlation mask: We cannot keep the correlation mask at a fixed static location in the frame but it is of interest to keep it close to the center of the frame.

\[
l_{\text{mask}} = \frac{1}{3} \cdot h_{\text{frame}}
\]

\[
u_{\text{mask}} = \frac{w_{\text{frame}}}{2} - \frac{l_{\text{mask}}}{2}
\]

\[
v_{\text{mask}} = \frac{h_{\text{frame}}}{2} - \frac{l_{\text{mask}}}{2}
\]

where \(l_{\text{mask}}\) is the length of the mask window, \(w_{\text{frame}}\) and \(h_{\text{frame}}\) are the image width and height, and \(u_{\text{mask}}\) and \(v_{\text{mask}}\) are the pixel positions of the top left corner of the mask. As the vehicle velocity increases, it is necessary to push the patch towards the edge to increase the area available to perform correlation in the next frame. A reasonable method for choosing the area mask position is to choose the area opposite to the previous match location with respect to the center of the frame.

\[
u_{\text{mask}} = \frac{w_{\text{frame}}}{2} - \frac{l_{\text{mask}}}{2} + \Delta U_{\text{prev}}
\]

\[
v_{\text{mask}} = \frac{h_{\text{frame}}}{2} - \frac{l_{\text{mask}}}{2} + \Delta V_{\text{prev}}
\]

Here \(\Delta U_{\text{prev}}\) and \(\Delta V_{\text{prev}}\) are the shifts calculated from the previous frame. This simple method takes into consideration the motion of the vehicle, pushing the mask to the top as the vehicle speeds up, towards the corners when the vehicle turns, back to center as the velocity drops, and down when the vehicle is reversing. Figure 4 shows an example of the correlation match.

3) Speeding up the correlation matching: A method by which the correlation time can be decreased is by feeding the predicted area of correlation calculated from the previous match. This reduces the region of the image that needs to be searched to achieve a template match. Assuming the velocity of the vehicle changes only slightly between two consecutive frames, this area will lie approximately opposite the location of the correlation template mirrored through the center of the frame. Using the OpenCV implementation it is not possible to feed this information to the function and we are therefore not using this speed-up.

Next we will look at how we can use the determined frame shift, \(\Delta U\) and \(\Delta V\), to calculate the motion seen by the vehicle.

![Image](image-url)
B. Odometry Calculation

In order to calculate the odometry estimate, the pixel displacement observed by the camera must be translated into vehicle motion. This translation is a four-step process:

1) Conversion from pixels to distance
2) Coordinate system transformation
3) Displacement observed by vehicle
4) Integration to global coordinate frame

These steps are explained below.

1) Conversion from pixels to distance: This first step translates the number of pixels seen on the screen to actual distance in meters and requires knowledge of camera intrinsic parameters and the camera position. Equation (6) shows this conversion.

\[
size_{\text{obj}} = \frac{d}{f \cdot size_{\text{pixel}}} \cdot size_{\text{frame}} \tag{6}\]

where \(d\) is the camera-ground-distance, \(f\) is the camera focal-length, \(size_{\text{pixel}}\) is the size of each pixel on the chip, and \(size_{\text{frame}}\) is the width/height of the frame. In our case the pixel displacements will result in a camera displacement, \(D_{\text{cam}}\):

\[
D_{\text{cam}} = \begin{bmatrix}
\Delta X \\
\Delta Y \\
0
\end{bmatrix} = \text{camConst} \cdot \begin{bmatrix}
\Delta U \\
\Delta V \\
1
\end{bmatrix} \tag{7}
\]

where \(\text{camConst} = \frac{d}{size_{\text{frame}}}\).

We use a standard radial distortion model described by Zhang [15] to calibrate and retrieve the intrinsic camera parameters.

2) Conversion from camera coordinate frame to vehicle coordinate frame: A coordinate frame transformation is necessary to convert from the camera coordinate frame, \(\{C\}\), to the vehicle coordinate frame, \(\{B\}\), \(D_{\{B\}} = T \cdot D_{\{C\}}\).

It is also at this stage that the camera misalignment with the vehicle axis, if any, is taken into consideration. A perfectly aligned camera will have the simple transformation matrix, \(T\):

\[
T = \begin{bmatrix}
0 & -1 & 0 & 0 \\
1 & 0 & 0 & 0 \\
0 & 0 & -1 & 0 \\
0 & 0 & 0 & 1
\end{bmatrix} \tag{8}
\]

3) Displacement observed by vehicle: When dealing with an Ackerman-steered vehicle we can take advantage of the motion restrictions described earlier and simplify the calculation of the vehicle displacement. The displacement seen by the vehicle then becomes:

\[
\Delta x = D_{\{B\}}(1) \tag{9}
\]

\[
\Delta y = 0 \tag{10}
\]

\[
\Delta \theta = atan2(D_{\{B\}}(2), x_{\text{cam}}) \tag{11}
\]

where \(D_{\{B\}}(1)\) and \(D_{\{B\}}(2)\) are the x and y components of the displacement in the vehicle bumper frame, and \(x_{\text{cam}}\) is the displacement of the camera along the x-axis of the vehicle, i.e. the bumper-center-of-motion distance. Here we set \(\Delta y = 0\) as we assume no sideways motion.

4) Increment vehicle displacement: The final step is to increment the robot pose. If our 3D robot pose, \(X\), is described with a \(3 \times 1\) position vector, \(t\), and a \(4 \times 1\) quaternion rotation vector, \(Q\), the calculations will be:

\[
t_n = t_p + R_p \cdot t_i \tag{12}
\]

\[
Q_n = \begin{bmatrix}
q_{1p} \cdot q_{1i} - q_{2p} \cdot q_{2i} - q_{3p} \cdot q_{3i} - q_{4p} \cdot q_{4i} \\
q_{1p} \cdot q_{2i} + q_{1i} \cdot q_{2p} + q_{3p} \cdot q_{4i} - q_{4p} \cdot q_{3i} \\
q_{1p} \cdot q_{3i} + q_{1i} \cdot q_{3p} + q_{4p} \cdot q_{2i} - q_{2p} \cdot q_{4i} \\
q_{1p} \cdot q_{4i} + q_{1i} \cdot q_{4p} + q_{2p} \cdot q_{3i} - q_{3p} \cdot q_{2i}
\end{bmatrix} \tag{13}
\]

where subscripts \(n, p, \) and \(i\) denote the new, previous, and incremental poses, respectively. \(R\) is the \(3 \times 3\) rotation matrix derived from the quaternion matrix \(Q_{\rho}\), and \(q_i\) denotes the \(i\)-th quaternion vector element.

In the next section we describe a method for calculation of the performance of the odometer and analyze our findings.

III. RESULTS

Our visual odometry system has been tested on a 20 tonne autonomous Hot Metal Carrier (HMC) forklift [16] and a standard Toyota Prado SUV. The webcam, an Unibrain Firewire camera with a resolution of \(640 \times 480\) pixels and max frame rate of 30 fps, has been mounted on the front of each vehicle looking straight at the ground beneath. The odometry calculation and data logging was done in real-time on a MacBook Santa Maria Intel Core 2 Duo 2.4 GHz with 2 GB RAM running Ubuntu Hardy Heron.

Here, we present data from the HMC, and as ground-truth we use the on-board beacon-based laser localisation system [17]. This existing localiser is based on a particle filter that uses accurately surveyed beacons in the environment for corrections.
Kelly [23] has proven that the systematic velocity scale error of an odometry module is to measure the error induced as a back at origin. Only the fraction of error, only caused by randomness, when off by meters halfway through its path can end up having origin but decreases as we loop back towards the origin. In odometry systems will increase with the distance from global scheme, this method suffers from an even larger error. Excepting the fact that the system is tested in a global context. Yet it is commonplace in the literature to calculate the error in the terms of the Euclidean distance to measure the performance of an odometry module in a global localiser system overlaid on a Google map image. Tables III and IV show the median Euclidean distance errors and heading errors between the visual odometry and the localiser and between the wheel odometry and the localiser for path lengths of 10 m, 20 m, 50 m, and 100 m while Figure 7 visualizes these errors using box plots. The box plots show the median, the 25%, and the 75% quartiles. The whiskers extend from each end of the box to the adjacent values within 1.5 times the interquartile range. Outliers are data with values beyond the ends of the whiskers and not displayed here. As can be observed, the visual odometry module is performing considerably better than the wheel encoder-based odometry module. This is especially true for the calculation of the heading over longer distances, where the wheel encoder-based odometry module has very unreliable heading—this is normally the main deficiency of odometry modules. The translational position calculation is also more precise from the visual odometry with very small error growth. The distance error for the wheel encoder-based odometry increases with the square of the distance traveled.

### IV. Conclusion

In this paper we have presented a visual odometry system using monocular vision for car-like vehicles. By taking advantage of the kinematic motion constraints introduced on these vehicles by the Ackerman-like steering model we have by Johnson et al [9]. Here they first align a short part of the odometry path with the GPS path using a least squares method, then measure the error of their odometry system over 100 m distances. The start position is shifted slightly and the procedure is repeated for the entire length of the driven path. This is a great method but it only shows the error for 100 m intervals and therefore does not indicate the error growth over distance. We will use a similar method here to analyze the performance of our system but showing the result for 10 m, 20 m, 50 m, and 100 m intervals to show the tendencies of the error increment in the odometer as the distance driven is increased. In our analysis, we find the desired segment length in our ground-truth path and using the time-stamp extract the equivalent path-segment from our odometer, align the first two meters (again using the timestamp), and then compare the two paths by calculating the Euclidean distance error between the two end points. We jump one metre in our ground-truth data and repeat the process again until the end of the path.

Next we analyze the performance of our odometry module using the method described here.

### C. Analysis

The test environment where we have carried out our tests is an industrial area with a mix of concrete and asphalt flooring. The path driven is approximately 770 m. Lighting is of high importance in these areas due to the smooth surfaces and the vehicle’s own shadow can disturb the pixel displacement calculated from the correlation matching.

Figure 6 shows the paths calculated using the proposed visual odometry, wheel odometry, and the beacon-based localiser system overlaid on a Google map image. Tables III and IV show the median Euclidean distance errors and heading errors between the visual odometry and the localiser and between the wheel odometry and the localiser for path lengths of 10 m, 20 m, 50 m, and 100 m while Figure 7 visualizes these errors using box plots. The box plots show the median, the 25%, and the 75% quartiles. The whiskers extend from each end of the box to the adjacent values within 1.5 times the interquartile range. Outliers are data with values beyond the ends of the whiskers and not displayed here. As can be observed, the visual odometry module is performing considerably better than the wheel encoder-based odometry module. This is especially true for the calculation of the heading over longer distances, where the wheel encoder-based odometry module has very unreliable heading—this is normally the main deficiency of odometry modules. The translational position calculation is also more precise from the visual odometry with very small error growth. The distance error for the wheel encoder-based odometry increases with the square of the distance traveled.

### A. System Calibration

After setting up the system and mounting the sensors, a calibration run is necessary due to the uncertainties in the mounting and sensor locations. In this step we try to determine the camera height over ground as well as the misalignment with the vehicle axis, if any. We do this by driving a figure-eight over relatively flat ground and estimate the parameters and finding the offsets so we get the vehicle back to start. The system parameters for our test vehicle estimated from the calibration run is shown in Table II. Note that this method suffers from velocity scaling error detection and is only used to derive the mentioned parameters. This shortcoming is discussed further next.

### B. Odometry Performance Measurement

Our visual odometry system is a stand-alone passive module in the sense that it is not integrated with the vehicle, cannot control the vehicle, does not have any information about the vehicle state, and receives no input from other localization modules. We call this an open-loop system. Although this module would eventually be part of a close-loop system, it is advantageous to perform open loop tests on odometry modules as these will reveal bias and velocity errors [18].

As with any other odometry system, our system also suffers from unbounded incremental errors. Due to this, odometry modules are normally not used for global localization. They are, as with INS modules, better suited to provide local estimates of short-term motion to higher level global localization methods [17] and laser and vision-based SLAM methods [19] [20]. It is therefore technically weakly founded to measure the performance of an odometry module in a global context. Yet it is commonplace in the literature to drive a vehicle in a loop, bringing it to the start position, calculate the error in the terms of the Euclidean distance from final robot pose to origin, and present that as the system error. Excepting the fact that the system is tested in a global scheme, this method suffers from an even larger error. Kelly [23] has proven that the systematic velocity scale error in odometry systems will increase with the distance from origin but decreases as we loop back towards the origin. This means that a system with systematic errors setting it off by meters halfway through its path can end up having only the fraction of error, only caused by randomness, when back at origin.

A more appropriate method to measure the performance of an odometry module is to measure the error induced as a result of the distance travelled. A similar approach is used by Johnson et al [9]. Here they first align a short part of the odometry path with the GPS path using a least squares method, then measure the error of their odometry system over 100 m distances. The start position is shifted slightly and the procedure is repeated for the entire length of the driven path. This is a great method but it only shows the error for 100 m intervals and therefore does not indicate the error growth over distance. We will use a similar method here to analyze the performance of our system but showing the result for 10 m, 20 m, 50 m, and 100 m intervals to show the tendencies of the error increment in the odometer as the distance driven is increased. In our analysis, we find the desired segment length in our ground-truth path and using the time-stamp extract the equivalent path-segment from our odometer, align the first two meters (again using the timestamp), and then compare the two paths by calculating the Euclidean distance error between the two end points. We jump one metre in our ground-truth data and repeat the process again until the end of the path.

### System Offset Parameters from the Calibration Run

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cam X</td>
<td>3.77 m</td>
</tr>
<tr>
<td>Cam Y</td>
<td>0.00 m</td>
</tr>
<tr>
<td>Cam Z</td>
<td>0.62 m</td>
</tr>
<tr>
<td>Cam θ</td>
<td>1.5°</td>
</tr>
</tbody>
</table>

**TABLE II**

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shown that the calculation of the odometry can be simplified considerably. The main advantages of our odometry system is that it is simple to implement and mount making it very practical and desirable as replacement for wheel-based odometry on large vehicles.

Analysis of the system’s performance has shown that we can expect position errors of less that 4% and heading errors of 3.5° for distances of up to 100 m. As shown, this is a considerably better achievement compared to the wheel-based odometry.

The main shortcoming of our odometry module is its inability to deal with sun/shadow regions. This was experienced during the first part of the test path, pointed out in Figure 6 with (A), where the vehicle’s own shadow was covering half of the frame over 10 m of the path. In these situations, the contrast difference between the dark area in the shadow and the light area lit by the sun exceeds a standard camera’s dynamic range of five f-stops. This means, if we expose for the light area the dark area will be represented as pure black and if we expose for the dark area the light region will be pure white. In both cases the shadow itself will be the most dominant feature in the frame. Since the shadow of the vehicle is moving with the vehicle itself there is no relative motion and the correlation matching will report this as standing still. The only way to overcome this is by bringing up the shadow using artificial lighting or repositioning the camera to a fully shaded area, e.g. under the vehicle.

We are currently able to run the odometry module at 20 fps which limits the driving velocity to 1.5 m/s. The main limitation is the correlation processing time of approximately 42 ms/frame. By implementing the suggested prediction area feeding to the correlation matching we believe the processing time can be lowered considerably allowing for more practical driving velocities.

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Fig. 7. Box plots of the A) distance error, and B) heading error for the visual odometry (Blue) and wheel odometry (Red).


