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Optical Speed Measurement and applications

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1. Introduction

Mobile robot navigation is a well researched discipline, looking back to a relatively long history however it is still a rich, active area for research and development. The ultimate goal for robots and intelligent vehicles seems to be autonomous navigation in complex real life scenarios. In order to achieve higher levels of autonomy sophisticated sensors and a sound understanding of the robot and its interaction with the environment is needed. The tasks involved can be divided to two basic categories; internal tasks involve keeping track of internal dynamic parameters, like speed accelerations, internal states etc. On the other hand the vehicle needs to be aware of external factors like obstacles, points of interest, possible routes from a to b and the respective costs. This is generally called robotic mapping.

Intelligent Vehicle stands for a vehicle that senses the environment and provides information or control to assist the driver in optimal vehicle operation. Intelligent Vehicle systems operate at the tactical level of driving (throttle, brakes, steering) as contrasted with strategic decisions such as route choice, which might be supported by an on-board navigation system. (Bishop, 2005)

Optical sensors supply by far the most information and as greater and greater processing capabilities become readily available their use becomes more widespread. Many researchers and companies have made more or less successful attempts at creating optical sensors for speed measurement, however to the knowledge of the authors no accurate high speed solution exist at the low price range. The aim of this article is to introduce a novel method for optical speed measurement and put it into perspective by summarizing other navigation methods and reviewing recent related work and possible applications. Also an introduction to optical flow calculation is given and practical considerations on texture analysis and sensor parameters are discussed backed up with simulation results.

2. Motion measurement techniques

The development of navigation and dynamic sensors has always had a prominent place in mobile robotics research, as the key to accurate trajectory tracking and precise movements is the exact knowledge of the dynamic parameters of the mobile platform.

2.1 Incremental techniques

The first class of movement measurement methods - called incremental techniques - uses only sensors located on the mobile platform. In this case the actual position is calculated from the previous pose-information and the relative displacement measured by the motion-sensors. This navigation mode is often called "dead reckoning navigation".

On wheeled vehicles the most straightforward method is to measure wheel movements and calculate displacement accordingly. Rotations can be measured with optical encoders, proximity sensors and cog wheels or magnetic stripes with Hall sensors etc. Heading information can be derived from differential odometry, which means calculating the direction based on the distance difference travelled by the left side and right side wheels of the vehicle. In addition to optical encoders, potentiometers, synchros, resolvers and other sensors capable of measuring rotation can be used as odometry sensors. In the last few years in the wake of the invention of the optical mouse optical navigation found its way to mobile robotics, and other similar methods emerged in the transportation industry.

(Borenstein et al. 1996) describes thoroughly the various aspects related to odometry including typical error sources. Many of the systematic errors come from the errors of the kinematical model (wheelbase, wheel radius, misalignment etc.), some depend on the electronics (finite sampling rate, resolution). Non systematic errors occur when the wheel slips due to uneven surface or overacceleration etc. Some of these problems can be eliminated by the use of inertial methods, when accelerations and rotations are measured in three dimensions and integrated over time to derive position, speed and heading information. These methods are very sensitive to sensor quality since the double integration in position determination is prone to drift. (Mäkelä 2001) Due to accumulated errors measurements loose accuracy over time therefore position and speed information is usually periodically updated from an absolute source.

2.2 Absolute methods

In this case the actual position can be calculated without any previous information about the motion of the agent. The global pose is estimated directly (with one measurement) by means of external – artificial or natural – beacons which are totally independent from the platform.

Artificial beacons are objects which are placed at known positions with the main purpose of being used for pose determination. According to this definition, setting up the working environment for a robot using artificial beacons almost always requires a considerable amount of building and maintenance work. In addition, using active beacons requires a power source to be available for each beacon. GPS positioning is one of the major exceptions since the system is almost constantly available for outdoor navigation. Although the ultimate goal of research is to develop navigation systems which do not require beacons to be installed in the working environment, artificial beacons are still preferred in many cases. The reason is that artificial beacons can be designed to be detected very reliably which is not always the case when using natural beacons. For pose estimation in two dimensions, one can either measure the distances or bearings to at least three beacons and calculate the position and the heading by simple geometry. The calculation is called trilateration if it is based on known distances, and triangulation if it is based on bearings. Distance from the beacons can be measured by using several different methods like triangulation, time of flight, phase-shift measurement, frequency modulation, interferometry, swept focus, or

return signal intensity etc. The sensors used can be radio or laser based ultrasonic, or visual. The advantage of artificial beacon based systems is that they can be made very accurate as the environment is controlled, however this same controlled environment is the biggest disadvantage as it decreases flexibility. In certain cases system complexity becomes a problem, as was the case with GPS before mass production of receiver chips started. Artificial beacons are relatively simple to use and pose estimation based on them is straightforward and reliable. However, there are various applications where they can not be used. Natural beacons are objects or features of the environment of the robot that can be used for pose estimation. These beacons can be man made; natural means they were not built for navigation purposes. Navigation using a map is also related to natural beacons, when the map is matched to raw sensor data the whole environment can be considered as a beacon. (Mäkelä 2001)

2.3 Fusion

Through sensor fusion we may combine readings from different sensors, remove inconsistencies and combine the information into one coherent structure. This kind of processing is a fundamental feature of all animal and human navigation, where multiple information sources such as vision, hearing and balance are combined to determine position and plan a path to a goal. While the concept of data fusion is not new, the emergence of new sensors, advanced processing techniques, and improved processing hardware make real-time fusion of data increasingly possible (Bak 2000).

Incremental and absolute navigation techniques have somewhat complementing advantages and disadvantages so developers usually combine them to benefit from the advantages of both. In case of absolute techniques like for example GPS, the navigation system can directly calculate the absolute position of the platform therefore the error of the actual pose comes only from the current measurement and does not accumulate over time. But unfortunately in some cases these methods are unusable for direct positioning or speed measurement, for lack of signal or unacceptable latency. Incremental techniques are usually simpler and have greater data rates, but accumulate error over time.

In addition the ability of one isolated device to provide accurate reliable data of its environment is extremely limited as the environment is usually not very well defined in addition to sensors generally not being a very reliable interface. Sensor fusion seeks to overcome the drawbacks of current sensor technology by combining information from many independent sources of limited accuracy and reliability to give information of better quality. This makes the system less vulnerable to failures of a single component and generally provides more accurate information. In addition several readings from the same sensor are combined, making the system less sensitive to noise and anomalous observations.

Basically motivations for sensor fusion can be categorized into three groups (Bak 2000).

Complementary. Sensors are complementary when they do not depend on each other directly, but can be combined to give a more complete image of the environment.

Competitive. Sensors are competitive when they provide independent measurements of the same information. They provide increased reliability and accuracy. Because competitive sensors are redundant, inconsistencies may arise between sensor readings, and care must be taken to combine the data in a way that removes the uncertainties. When done properly, this kind of data fusion increases the robustness of the system.

Cooperative. Sensors are cooperative when they provide independent measurements, that when combined provide information that would not be available from any one sensor. Cooperative sensor networks take data from simple sensors and construct a new abstract sensor with data that does not resemble the readings from any one sensor.

The tool of choice for sensor fusion and vehicle state estimation has often been the Kalman filter. It is an efficient recursive filter that estimates the state of a dynamic system from a series of incomplete and noisy measurements. The classic linear Kalman filter is very attractive for low-cost applications due to its simplicity and low computational demand. Its main disadvantage is that it can only estimate linear plants. The advantage of the nonlinear Kalman filters is that they can directly estimate the vehicle dynamics (which are non-linear in most cases). Both the vehicle states and the sensor measurement equations can have nonlinear terms. This results in better estimation accuracy, over a wider range of operating conditions. The main disadvantage of the nonlinear Kalman filters is that the algorithms are more complex than the linear implementation, therefore requiring more computational resources. A wide body of literature is available on sensor fusion and Kalman filtering (Gustaffson 2007, Grewal et al. 2007, Bak 2000); however it is out of the scope of this article as in this chapter we only wanted to emphasize the importance of using measurements from a variety of different sensors, to achieve better accuracy and reliability.

2.4 Summary

As we can see automated navigation is a research area with a long history and many achievements, however there is still much to be done, both in the area of sensor technology and processing algorithms. In this section we have shown that for an accurate and reliable measurement it is necessary to use both absolute and incremental techniques. With the development of visual sensor technology and the availability of more computing power, the potential in visual sensors can be exploited. The authors feel that there is a need for new solutions in that field.

3. Introduction to optical motion measurement

As mentioned in the previous section incremental methods hold a prominent place in the area of motion measurement. The main purpose of this chapter is to introduce a cheap, easy to use, but accurate dead reckoning sensor-system based on visual information acquired from the ground.

First we review the techniques to extract motion from image sequences then we review related work in the field of motion measurement, both industrial and academic.

3.1 Optical flow

Visual movements are caused by the relative displacement of the observer (eye, camera) and the objects of the world. The measurement of these motions can be used in several areas of robotics, like object tracking and segmentation, navigation, and optical speed measurement etc.

Most techniques of visual motion measurement are based on the well researched discipline called "optical flow". The basic idea is to compare consecutive images of a scene produced by camera and calculate a vector field for each image which shows the displacements of the

pixels to get the next image of the scene. This vector field is often called optical flow or optical flow field (Fig. 1.).
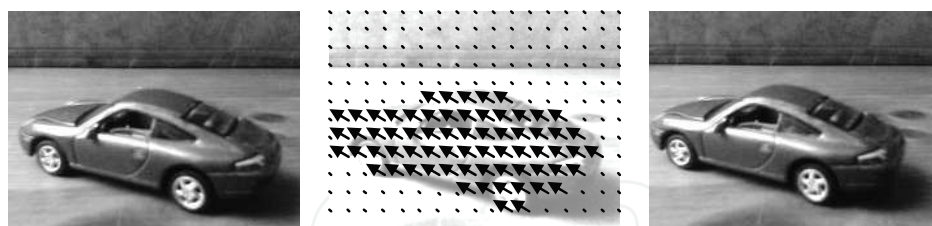

Fig. 1. The principle of optical flow

Since the first algorithm presented by Horn and Schunck (Horn & Schunck 1980) several techniques have been published to determine optical flow field. The common base of these techniques is the optical flow constraint (Horn & Schunck 1980) which presumes that the related points in the consecutive images have the same intensity value. Putting it in another way, a spatial point projected in the image plane has constant (time-invariant or projection-invariant) intensity value:

$$E(x(t+\Delta t), y(t+\Delta t), t+\Delta t) = E(x(t), y(t), t) \qquad (1a)$$

$$\frac{dE}{dt} = 0 \qquad (1b)$$

where $E(x,y,t)$ is the intensity of the (x,y) point in time t.
From a Taylor expansion of (1a) or from the dependencies between the total and partial derivative using (1b) the general form of constrains is easily derived:

$$\frac{\partial E}{\partial x}\frac{\partial x}{\partial t} + \frac{\partial E}{\partial y}\frac{\partial y}{\partial t} + \frac{\partial E}{\partial x} = 0 \qquad (2)$$

where $\frac{\partial x}{\partial t}$ and $\frac{\partial y}{\partial t}$ refer to the coordinates of the velocity vector (the two unknowns of the equation), $\frac{\partial E}{\partial t}$ denotes time change of the intensity value, $\frac{\partial E}{\partial x}$ and $\frac{\partial E}{\partial y}$ denote components of the spatial gradient vector of intensity field.

This constraint is not sufficient to determine both components of the velocity vector, only the component in the direction of local gradient can be estimated. As a consequence, to compute the optical flow field it is necessary to introduce additional constraints.

The method of Horn and Schunck (Horn & Schunck 1980) starts from the observation that the points of the image plane do not move independently, if we view opaque objects of finite size undergoing rigid motion or deformation. Therefore the neighbouring points of moving objects have quite similar velocities and the vectors of the optical flow field vary smoothly almost everywhere. This smoothness constrain represent the following equation:

$$\min\left\{\left(\frac{\partial u}{\partial x}\right)^2 + \left(\frac{\partial u}{\partial y}\right)^2 + \left(\frac{\partial v}{\partial x}\right)^2 + \left(\frac{\partial v}{\partial y}\right)^2\right\} \tag{3}$$

where u and v are the coordinates of the velocity vector.

Therefore the purpose is to determine a velocity vector field which minimizes the optical flow and the smoothness constrain together:

$$\min\left\{\iint_D \left(\frac{\partial E}{\partial x}\frac{\partial x}{\partial t} + \frac{\partial E}{\partial y}\frac{\partial y}{\partial t} + \frac{\partial E}{\partial x}\right) + \alpha^2\left(\left(\frac{\partial u}{\partial x}\right)^2 + \left(\frac{\partial u}{\partial y}\right)^2 + \left(\frac{\partial v}{\partial x}\right)^2 + \left(\frac{\partial v}{\partial y}\right)^2\right)dxdy\right\} \tag{4}$$

It seems that to compute individual velocity vectors it is necessary to take the whole image into consideration, because every vector depends on every other vector. Therefore this method is classified as a global technique (Beauchemin 1995).

Another approach presented by Lucas and Kanade assumes the velocities are the same in a small local area (local techniques) (Barron 1994). Therefore to calculate the velocity vector of a point it is possible to write more than one optical flow constraint because the points in the small region have the same velocity:

$$\mathbf{WAv} = \mathbf{Wb}, \text{ where}$$

$$\mathbf{A} = \begin{bmatrix} \nabla E(x_1, y_1) \\ \nabla E(x_2, y_2) \\ ... \\ \nabla E(x_{m\times m}, y_{m\times m}) \end{bmatrix}; \quad \mathbf{v} = \begin{bmatrix} u \\ v \end{bmatrix}; \quad \mathbf{b} = -\begin{bmatrix} E_t(x_1, y_1) \\ E_t(x_2, y_2) \\ ... \\ E_t(x_{m\times m}, y_{m\times m}) \end{bmatrix}; \quad \mathbf{W} = \begin{bmatrix} w_1 & 0 & 0 & 0 \\ 0 & w_2 & 0 & 0 \\ ... & ... & ... & ... \\ 0 & 0 & 0 & w_{m\times m} \end{bmatrix} \tag{5}$$

In this case the local region has m×m points and $\mathbf{W}$ is a weight matrix.

Because the equation system is over constrained and has no solution (in general) therefore the velocity estimates are computed by minimizing

$$\sum_{\mathbf{x}\in\Omega(m\times m)} \mathbf{W}^2(\mathbf{x})[\nabla E(\mathbf{x})\cdot\mathbf{v} + E_t(\mathbf{x})]^2 . \tag{6}$$

After using the least mean squares method, the solution is the following:

$$\mathbf{v} = \left(\mathbf{A}^T\mathbf{W}^2\mathbf{A}\right)^{-1}\mathbf{A}^T\mathbf{W}^2\mathbf{b} \tag{7}$$

This method can only measure relatively small displacements therefore it is often called the iterative Lucas-Kanade algorithm.

The previous two algorithms are directly based on the gradients of scenes therefore these techniques are often called differential methods. Unfortunately these techniques suffer from

a serious disadvantage: accurate numerical differentiation is sometimes impractical because of small temporal support (only a few frames) or poor signal-to-noise ratio (Barron 1994). Region-based techniques define velocity as the shift **d** that yields the best fit between image regions at different times. Finding the best match amounts to maximizing (or minimizing) a similarity measure (over **d**), such as the sum of square distances (SSD), normalized cross correlation, etc. The optical flow constraint (namely the related points in consequent images have the same intensity value) can also be found in these techniques indirectly because the best match tries to minimize the difference of the intensity values of the points.

One of the well-known techniques belonging to this group is published by Anandan in 1987 (Barron 1994) which combines the Laplace-pyramid (to decrease the correlation between the pixels of the images) and the "coarse-to-fine" SSD matching method. Another region-based algorithm presented by Singh is also built on the SSD metric but uses three consequent images from the scene to calculate the displacement of the regions in the second image. Therefore the inaccuracy caused by noises and periodical texture is decreased (Beauchemin 1995).

A third class of optical flow techniques is based on the frequency domain of the image-sequence. One of the advantages brought by these methods is that motion-sensitive mechanisms operating on spatiotemporally oriented energy in Fourier space can estimate motion in image signals for which matching approaches would fail. A good example is the motion of random dot patterns, which are difficult to capture with region-based or differential methods, whereas, in frequency domain, the resulting oriented energy may be rapidly extracted to determine optical flow field (Beauchemin 1995).

These methods can be classified in two groups: energy-based approaches are built on the amplitude, phase-based techniques use the phases of the Fourier space to determine the optical flow field. The method developed by Heeger (Heeger 1988), formulated as a least square fit of spatiotemporal energy to a plane in frequency space belongs to the first group. An example for the phase-based methods is the algorithm by Fleet and Jepson (Fleet 1990).

3.2 Basics of optical navigation sensors

As previously discussed, the principle of optical flow can be used in several areas of robotics. For example it is possible to obtain distance information, avoid collision with obstacles, track patterns on the image etc. (Davies 2005). This chapter focuses on one application, motion measurement of a mobile platform based on optical flow field.

The working principle of an optical speed sensor is quite simple: an optical sensor (photo-detector, camera, etc.) is attached to the mobile platform facing the ground. From the periodically captured visual information it is possible to estimate the real velocity of the agent relative to the ground. (Fig. 1.)
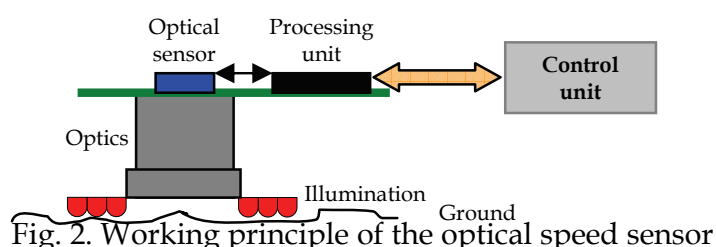

Fig. 2. Working principle of the optical speed sensor

3.3 Related work

Optical speed measurement is an emerging discipline, with existing commercial solutions and research activity in the academic sector, however many problems remain unsolved. As for commercial technologies the most widely known example is the optical mouse, which on the other hand has generated a fair amount of academic research. The optical mouse uses two distinct but essentially similar techniques for displacement calculation. The classical method uses LED illumination and relies on the micro texture of the surface. The more advanced method is laser speckle pattern technology. Laser speckle patterns can be observed when a rough surface (rough, relative to the wavelength) is illuminated with a coherent light and the interference of the reflected light waves creates a surface dependent random intensity map on the detector. When the detector is moved relative to the surface, the speckle pattern changes accordingly and optical flow can be calculated. The advantage over surface texture based methods is its accuracy and ability to function properly on relatively textureless smooth surfaces.

Frequency analysis is a less frequently used method. The light reflected from the surface travels through an optical grating, and is focused on a pair of photo-detectors. The surface elements, passing in front of the grating generate a certain signal frequency in the detectors depending on the sampling frequency, ground speed, grid graduation, ratio of the image, size of the surface elements and the size of the picture on the grating. The difference of the two signals is computed and the frequency of the difference signals corresponds to the true ground speed.

Indoor dead reckoning solutions for small mobile robots using optical mice were suggested by several authors (Palacin et al. 2006, Bonarini et al. 2004, Sorensen 2003) T.W. Ng investigated the usability and accuracy of optical mice for scientific measurements in several articles (Ng 2003, Ng & Ang 2004) with good results. It was found that the readings possessed low levels of error and high degrees of linearity. The mean square error for measurements in the x-axis increased significantly when the distance between the surface and the detector was increased possibly caused by the illumination direction of the mouse. Several researchers proposed the use of optical mice as a dead reckoning sensor for small indoor mobile robots in one and two sensor configurations. By using one sensor and kinematical constraints from the model of the platform, a slip free dead reckoning system can be realized. The kinematic constraint originates from the sensors inability to calculate rotation. By using two sensors the constraint can be removed and the measurements become independent of the platforms kinematics. Systematic errors originate from measurement errors, alignment errors and change of distance from the ground. (Bonarini et al. 2004) achieved results comparable to other dead reckoning systems up to a speed of 0.3 m/s by using the UMB benchmark test (Borenstein & Feng 1994). Sorensen found that the error of the two mice system was smallest when the sensors were as far as possible from the centre of rotation, and when good care were taken of maintaining constant height. He found that when these constraints were met, the system performed significantly better than other dead reckoning systems (Sorensen 2003). In their work Palacin et al. found that if measurements from an array of sensors were averaged the error became independent from the distance traveled. They also found that the sensor needed a different calibration when moving in an arc, possibly due to the sideways illumination used in computer mice. Another problem was the extreme height dependence of the sensor, which made it impossible for them to use it on carpet. They proposed a modified sensor for they found mice to be unfit for mobile robot

navigation (Palacin et al. 2006). The results of the authors of this article were similar to other researchers, they found that one way to make mouse sensors useful for navigation is to equip them with telecentric lens, to avoid magnification changes, to use homogeneous illumination, to avoid directional problems and to use two sensors to get rid of kinematic constraints. (Takács, Kálmán 2007) By using different magnification larger portions of the ground will be projected on the sensor making higher speeds possible, but this is limited by ground texture (section 4.4).

Mouse sensors are cheap and readily available and with certain modifications they can be used for low speed mobile robot dead reckoning. However they are limited by their low resolution and speed and their algorithm can only be changed by the factory.

Horn et al. aimed at developing a sensor system for automobiles. They used a fusion approach with two cameras and a Kalman filter. One of the cameras is a forward looking stereo camera to estimate yaw rate and forward velocity, the other camera is facing the ground and used to estimate two dimensional velocity. It was found that the camera facing the ground gave better results for lateral and longitudinal velocity than the stereo camera. The fusion approach provided good results even when one of the sensors was failing. The system was tested at slow (< 1 m/s) speeds on a towed cart in a lab (Horn et al. 2006). Chhaniyara et al. followed a somewhat similar approach and used a matrix camera facing the ground to estimate speed over ground. They used a mechanism that moved the camera over sand and compared optical flow speed estimates with measurements from an encoder attached to the mechanism. They used Matlab and the Lukas and Kanade algorithm to compute optical flow. They obtained good results at low speeds (0-50 mm/s), however the suitability of the algorithm they used is questionable (Chhaniyara et al. 2008).

This technology has already found its way to the transportation industry as well. Corrsys - Datron has a one-of-a-kind optical speed sensor (Correvit 2001) used for testing the dynamics of passenger vehicles before mass production. The sensor is claimed to be working on any surface, including water and snow, but it is priced for the big automotive manufacturers. It uses the frequency analysis method. OSMES by Siemens is an optical speed measurement system for automated trains (Osmes 2004). It uses the principle of laser speckle interferometry mentioned above, and "looks" directly on the rails to measure the trains speed.

It is clear that much work has been done in the field of optical navigation however several issues remain open for research. Current industrial solutions are somewhat bulky and definitely not priced for the average mobile robot. Solutions by academic researchers have not matured to the level of really useful applications. Mouse chips are the mostly the sensors of choice. With some modifications their problems of ground distance, lighting and calibration can be helped, but their current speed and resolution is simply not enough for high speed (the order of ten m/s) applications.

More work in the area of texture analysis, optics design and image processing hardware is needed.

4. Optical correlation sensor

In this section we outline the basics of the motion measurement system proposed by the authors. First we introduce basic problems and some assumptions on which we based our investigations: the sensor is facing the ground, which is relatively flat, the field of view is constant due to telecentric optics and our sensor can only measure movements along a

straight line. Then we describe a multisensor setup that is capable of providing two dimensional velocity measurements independent of the platform. Finally we introduce a simulator which we created to verify the feasibility of different sensor embodiments, and the validity of our basic assumptions.

4.1 Basics

The distance between the sensor and the ground is continuously changing because of the macroscopic unevenness of the surface and the movement of the suspension of the platform causing variable field of view which can be a serious source of errors in speed measurement. The use of *telecentric optics* can eliminate this problem in a certain distance range as telecentric optics has constant magnification. In this range the field seen by the camera does not change its size. This approach does not solve the problem of the change in depth of field but blurriness only causes loss of accuracy while change of magnification causes miscalibration.

Two important parameters of the sensor are sampling rate and the size of the image seen by the camera (field of view). Frame rate and field of view determine the maximal measurable velocity of the platform. If the speed of the mobile agent is higher than this limit, there is no correlation between the consequent images as they do not overlap. This can cause false readings thus estimation of the real velocity is impossible. Fortunately a mobile robot or car has a well-determined limit for velocity therefore it is possible to calculate these parameters based on apriori information (Fig. 3.).
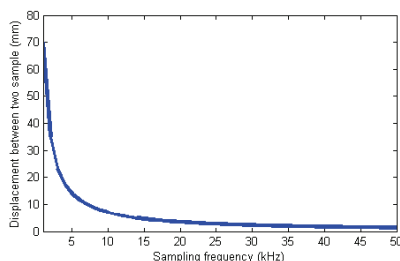

Fig. 3. Displacements between samples (sensor-speed: 70 m/s)

Let's illustrate the effects of limited dynamics with a simple example: the best racing cars in Formula-1 have 4-5 G deceleration at most. If we take a very modest estimation for frame rate like 100 Hz, then the difference between the two measured velocity-values is 0.05 m/s (0.18 km/h) in the worst case. Knowing this a plausibility check can be conducted and erroneous measurements caused by noise or "difficult" texture can be discarded. Also state variables of a vehicle such as speed cannot change abruptly, that is measurements in neighbouring sampling instants have to be close in value.

If the visual information about the motion comes from a camera and the displacement-estimations are calculated from the optical flow field of the captured scene, then some additional apriori information facilitates determination of the velocities. First of all it is important to determine what kind of displacement occurs in the image plane. Image movements can be categorized in two groups.

The first class, called *local image movement* belongs to the principle of optical flow presented in the previous section. Several objects of various sizes, velocities are moving in the visual field of the camera in different directions. Therefore the motion in the image plane can be

described with vectors corresponding to individual pixels. With this vector field the motion, shape etc. of the different objects can be estimated.

a.) Local image movements
(http://of-eval.sourceforge.net/)
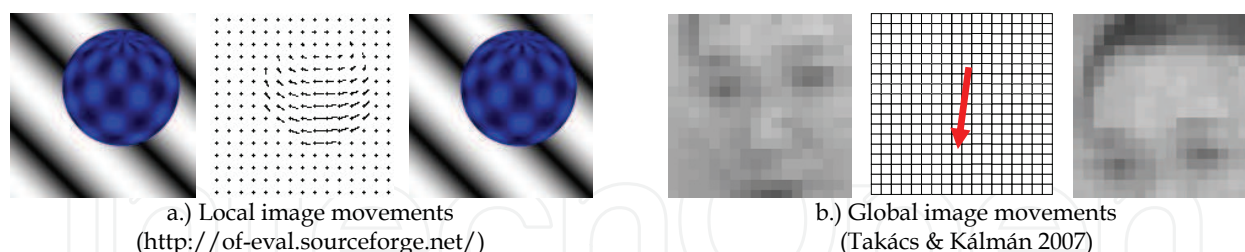
b.) Global image movements
(Takács & Kálmán 2007)

Fig. 4. Local and global image movements

But in our case it is necessary to measure the relative movement of the camera to a single object, so the class of *global image movement* is introduced. In this case the motion of all pixels of the image corresponds to the relative movement of the camera and exactly one object with smooth surface covering the whole field of view. The constraint about covering the whole field of view causes a very close relationship between the motion vectors (they have the same length and direction; they can only change smoothly, etc.). This is the reason for the name "global". The condition of smooth surface guarantees that the distance between the camera and every point of the object are quite the same therefore the effect of motion parallax can not cause sharp differences between velocity vectors (Fig. 4.).

These two strict constraints of global image movement can be approximated by a camera facing the ground and taking pictures of it periodically. If a general mobile platform like a car or mobile robot is assumed, and the camera has a sufficiently high frame rate, it is possible to disregard the orientation change between successive images as the arc travelled can be approximated with a straight line, and therefore all vectors in the optical flow field have the same length and direction. The great advantage of this approach is that there is no need to determine the motion of each pixel because they are all the same; therefore the calculation of optical flow is simpler, faster and more accurate.

From the field calculation techniques presented previously region-based methods fit this application best. In this case the window of the region contains the whole image and the comparison is between the two consecutive images. Other solutions which calculate the velocity vectors in pixel level and try to determine the camera movement from the heterogeneous motion vector field, avoid the use of this very important piece of apriori information. Therefore the application of these techniques in optical speed measurement with a camera facing the ground has marginal significance.

4.2 Measurements with multiple sensors

In case of using only one sensor - unless it is placed in the point of interest - the displacement measured needs to be transformed to platform coordinates. Additionally - unless kinematics of the platform is taken into account - rotation information is lost. In the extreme case, if the origin of the rotation is in the centre of the sensor the angle of rotation can not be estimated because the sensor does not measure any displacement.

In consequence it is necessary to apply multiple sensors and calculate the displacement from their geometry.
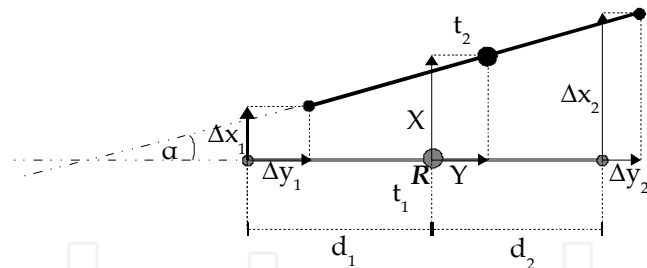
Fig. 5. Multiple sensor displacement model

Figure 5. shows a possible case of sensor placement. As mentioned above the orientation of the coordinate system is constant between two sampling instances because we approximate the movement of the sensors with a straight line. This introduces a small quantization error which can be modelled as noise. d_1 and d_2 are the distances of the sensors from the reference point R, Δx_1, Δy_1, Δx_2 and Δy_2 are the displacement values measured by the sensors 1 and 2 respectively. From this model the displacement and orientation change of the reference point X, Y and α can be easy derived:

$$X = \frac{d_1 \Delta x_2 + d_2 \Delta x_1}{d_1 + d_2}; \quad Y = \frac{d_1 \Delta y_2 + d_2 \Delta y_1}{d_1 + d_2}; \quad \alpha = \arcsin\left(\frac{\Delta x_2 - \Delta x_1}{d_1 + d_2}\right); \quad (8)$$

Displacement of any other point of the platform can be calculated with a simple geometrical transformation.

If the reference point is in the origin of sensor #1 (namely $d_1 = 0$), then the equations in (8) became simpler: X = Δx_1, Y = $\Delta y1$ and $\alpha = \arcsin\left(\frac{\Delta x_2 - \Delta x_1}{d_2}\right)$. This shows that the system is over determined the y component of the second sensor is not needed.

The equations show another very important property, in particular, that the calculation of the motion information does not depend on the kinematical model of the platform. This is one of the greatest advantages of the method. This property has been noted by others too. (Palacin et al. 2006, Bonarini et al. 2004, Sorensen 2003)

Another very important question is the connection between the distance of the sensors and the accuracy of the measurement. From the equations (8) it is clear that with greater sensor distance higher accuracy can be achieved. The distance required for a given angular resolution can be reduced by increasing the sampling rate and/or resolution as smaller displacements will be detectable.

In real applications parallel mounting of the sensors is not always guaranteed. This alignment error introduces systematic errors in odometry that can be eliminated by calibration as described in the literature (Borenstein 1996).

4.3 Advanced experiments

In the first stage of our experiments a mouse chip was used as image sensor. It quickly became clear that mouse chips are not fit for the purpose of high speed velocity

measurement as they lack both the necessary resolution and speed. This is similar to what other experimenters found.

Our basic assumptions to start with were the following: low speed displacement measurement is most accurate if we look at a relatively small area on the ground with a high resolution image sensor to detect small movements accurately. But for high speed measurements we need to look at a bigger area to ensure that the consecutive images overlap. Also sampling rates need to be higher, but resolution can be lowered to achieve the same relative error rates. This contradiction can be resolved by using a variable image size by changing the magnification rate of the optics. Unfortunately this raises cost, causes calibration and accuracy problems, so we need to assume it to be constant. Therefore it is necessary to find a compromise to be able to measure the whole speed range.

Matrix cameras are very practical for the purpose of movement measurement as two dimensional displacement and even rotation can be calculated from the images (if it is necessary). However they have certain disadvantages. With commercial matrix cameras high (several kHz) sampling rates are currently unachievable and the data rate at high speeds makes processing challenging. We claim that accurate two dimensional measurements can be made with line-scan cameras. The most important advantages of this type of camera in respect of displacement measurement are relatively high – several mega pixels - resolution in one dimension, frame rates at the order of 10 to 100 kHz and relatively low prices.

In this case the field of view is projected to a single line of detectors therefore line-scan cameras with appropriate optics (e.g. cylindrical lens) or with wide pixels can realize an integrating effect (Fig. 6.). This property is very important and useful for our purposes (see details later).

Fig. 6. Projection of matrix and line-scan camera (illustration)

Naturally a line-scan camera can measure the motion only in the direction parallel with its main axis. If two cameras are used perpendicular to each other, two dimensional motion can be detected. Inherently the motion component orthogonal to the main axis causes errors in the calculation of parallel displacement (Fig 7.).
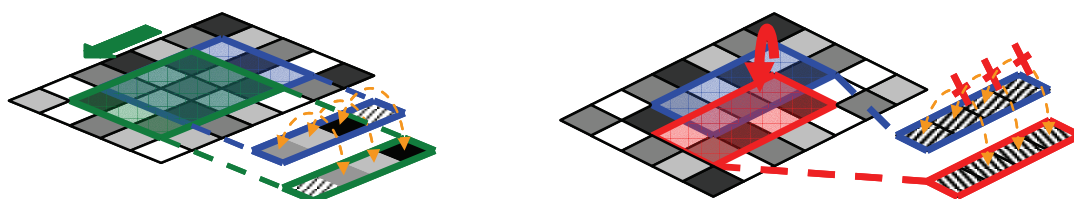
Fig. 7. Illustration of the problem of sideways motion

This error can not be totally eliminated but it is possible to decrease this effect with high frame rate and larger field of view of the camera. If the sampling frequency is high (which is easy to reach with line-scan cameras) then the perpendicular displacement between two consecutive images can be small enough that they will be taken of essentially the same texture element, making correlation in the parallel direction possible. This is of course a texture dependent effect and has to be investigated with texture analysis. Also this effect can be enhanced by widening the field of view of the detector, i.e. by integrating the image in the orthogonal direction. By doing this the images can overlap, giving higher correlation values. (More on this in the experimental results.)

A negative effect of this method is that the integration of the wider field of view can cause contrast in the image to reduce to the level of noise or completely disappear, making estimation of displacement in the parallel direction impossible. For that reason great care should be taken in the choice of pixel shapes and field of view of the line detector.

In order to find the sensor parameters we created an experimental computer program with a simple camera model that simulates a moving line-scan camera over a virtual surface. These surfaces are represented by simple greyscale images taken of real textures (e. g. concrete, soil, stone, PVC etc.) with very high resolution (Fig. 8.). Available, widely used texture databases were not fit for our purposes for they had insufficient resolution and were not calibrated for size. Our pictures were taken with an upside down flatbed scanner to ensure uniform conditions. By using this method we created a controllable environment, light, distance, image size, pixel/mm ratio and viewing angle were equivalent for all pictures taken. These images have different properties in respect to texture-size, contrast and brightness.

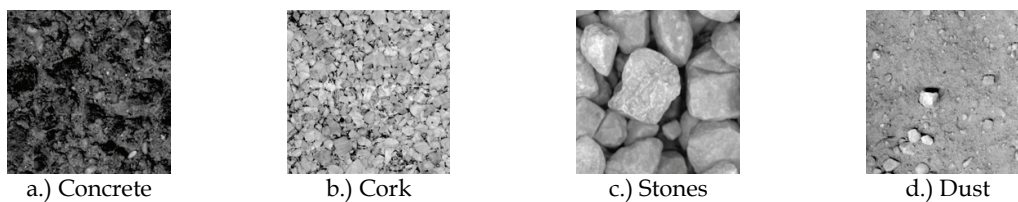| a.) Concrete | b.) Cork | c.) Stones | d.) Dust |

Fig. 8. Some of the ground textures used in the experiment

The virtual camera implemented in the simulator has several adjustable parameters: movement speed, frame rate, field of view in two dimensions, signal to noise ratio and resolution. Using the virtual surfaces and line-scan cameras it is possible to simulate different movement scenarios. The maximum virtual speed is over 100 m/s, the limit of frame rate is higher than 100 kHz and the size of field of view is greater than 100 mm in both directions.

The simulator – written in Matlab - works the following way: the ground is represented by a high resolution image, an image detector is chosen by defining an n X m resolution and a pixel size. Then the field of view is determined: a k X l mm rectangle. The image on the detector is created by resampling a k X l mm portion of the high resolution image onto the n X m detector image with additional white noise with an expected value of 0 and a standard deviation of choice. The consecutive image is chosen by translating the k X l mm window on the ground image with a certain amount of pixels according to the pre-defined movement speed, frame rate and direction. Three directions can be chosen, zero, 45, and 90 degrees. The two neighbouring images are then compared according to a distance measure of choice

such as correlation, least squares, Manhattan and cosine distances. As the exact distance in pixels is known the error of the measurement can be obtained easily.

The purpose of the simulator was to determine the feasibility of using line-scan cameras for optical velocity measurement. Because of the huge size of the parameter space and various requirements and conditions it is hard to determine the exact properties of the sensor immediately. In this chapter we show the most important results and experiments which are available at this phase of our research. All the following tests were conducted with the simulated velocity of 100 m/s and the direction of movement was 45 degrees.

The first interesting property is the connection between measurement accuracy and the frame rate of the camera. The sampling frequency determines the amount of light needed, the maximal processing time and the quality (and price) of the camera.

Figure 9. shows the measurement error versus the frame rate. The simulated velocity of the platform is 100 m/s and the direction of movement was 45 degrees. This sampling frequency range is usual for common line-scan cameras.
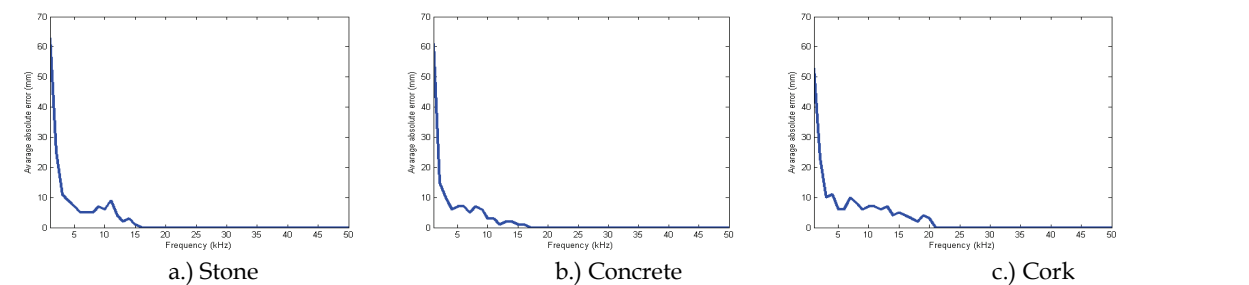

a.) Stone   b.) Concrete   c.) Cork

Fig. 9. Error versus frequency for different textures

From the figure the tendency can be seen that for "bigger" texture size the errors converge to zero at smaller frequencies, however more experiments are needed with different textures to verify this assumption. The idea is that with bigger texture larger sideways movements (lower frame rates) are tolerated as the texture elements correlate for a greater distance. At this point no quantitative measure was used for texture size, "bigger" or "smaller" was determined by subjective methods.

A very important parameter of the sensor is the field of view and the shape factor of the optics. As we modeled our imaging system with rectangular frames a practical shape factor choice is width/length of the field of view in %. A sensor with a small field of view is more compact and cheaper. If it is possible to avoid the use of cylindrical lens the optics will be simpler and easier to develop. Therefore another purpose of the tests was to obtain the connection between the accuracy and the field of view.

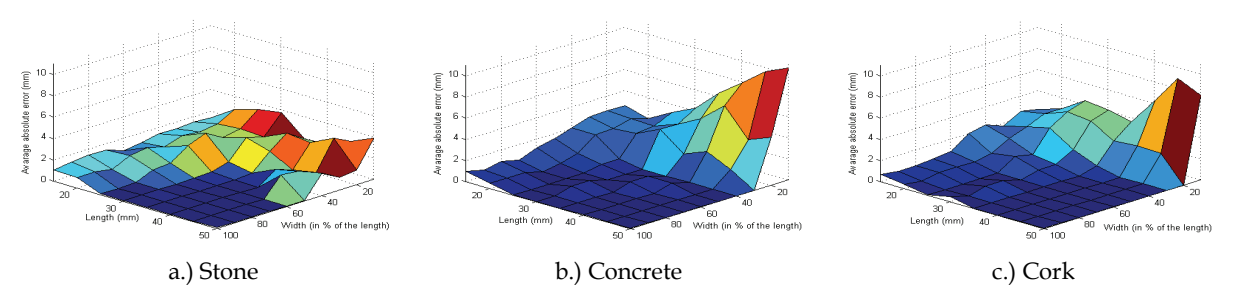

a.) Stone   b.) Concrete   c.) Cork

Fig. 10. Error surfaces as a function of field of view ratio (width/length) @ 15kfps

Figure 10. shows the error surface as a function of the two dimensions of the field of view. The main axis of the line detector is called length; width of the sensor is scaled in percentage of the length, 100% meaning a square field of vision. It is clear from the images that increasing the length alone does not decrease the error, image ratios of 40% or larger are needed to obtain acceptable measurements. However increasing frame rate allows us to choose ratios around 20% which is demonstrated on figure 11. These results seem logical as an increase in frame rate means smaller displacements between frames making correlation possible for narrower images too.
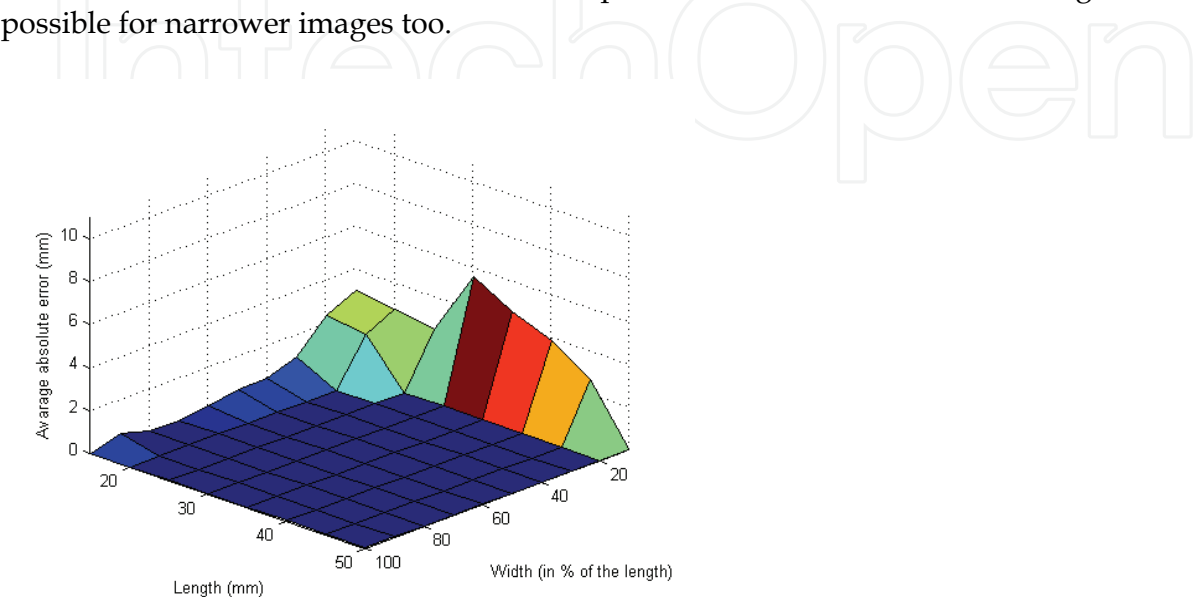

Fig. 11. The effect of increased frame rate Cork @ 30kfps

As mentioned earlier widening the field of view has a negative effect on contrast. This can be seen on figure 11.

a) Consecutive images with wider field of view   b) Consecutive images with narrow field of view
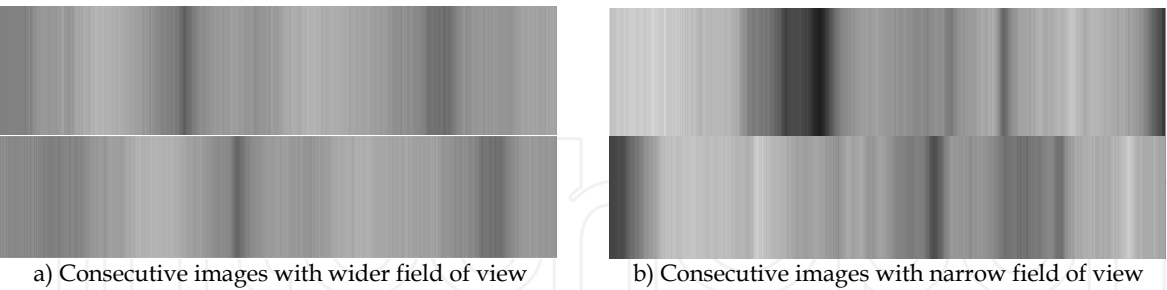
Fig. 12. The effect of field of view shape factor

On figure 12. a.) a wider field of view was used than on b.). Both image pairs are one sampling period apart taken on the same surface (Stone) at the same speed, and frame rate. It is clearly visible that a.) has less contrast, due to the integration effect, but the samples correlate, b.) on the other hand has more contrast but a lower cross correlation value. It is important to note here that increasing image width much further leads to total loss of contrast making measurements impossible. However on this particular surface that limit is higher than 100% width/length, which seems impractical anyway.
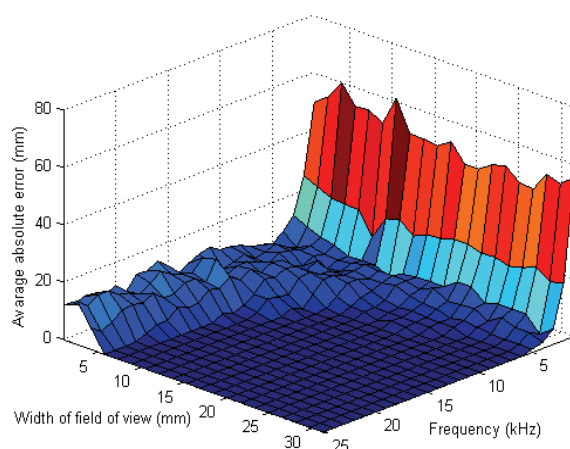
Fig. 13. Error versus frame rate and width of image @ fixed 50mm length (Cork)

Figure 13. shows that we can not reach zero error just by increasing the frame rate, however by increasing the field width we can obtain good results at relatively low frame rates for the given texture.

The experiments conducted with the simulator show that using a line-scan camera for optical speed measurements is a viable idea. Practical parameter choices have lead to exact displacement calculations for most of the investigated textures in the presence of simulated noise. To be fair we have to mention that there were a few textureless surfaces (e.g. plastic tabletop) for which no amount of tuning made correlation work. This shows that experiments with different lighting methods need to be done to be more independent from color based texture. Our initial tests justify further research to find the optimum of the parameters of our sensor. Optimization methods should be used to determine the most cost effective solution in terms of frame rate, resolution and optics. Future work will include hardware implementation of the sensor and the development of texture analysis methods.
(You can read more information about this research and development project on the website http://3dmr .iit.bme.hu/opticalflow)

4.4 Texture analysis
For purely image based systems the importance of texture can not be overlooked as it affects sensor qualities like precision and resolution and determines the necessary criteria the sensor parameters have to meet, like sampling frequency, magnification, resolution, pixel size and shape. Sampling frequency and magnification affect the maximal speed measurable as the consequent images have to overlap. Texture size might be the most important feature of a given texture as it determines the size of the area the sensor needs to look at i.e. the magnification. Texture size can be hard to define as it depends on how closely we look at a given surface. If we look at a gravel road the small stones form the basis of the texture or, if we look closer the rough surfaces on the stones do. The latter might be a better option as micro texture is usually available on otherwise homogeneous surfaces – laser speckle correlation takes advantage of this – but if we use a small image with great magnification, we limit the maximal speed measurable as for a given frame rate we might not get

overlapping images. Several methods exist in the literature to determine texture size. One of the main applications is grain size measurement in chemical or other industrial processes, and some of the methods can be readily adapted for our purposes. For example asphalt and gravel textures can be modelled by a mixture of different sized grains. Lepistö et al. used a histogram based quantifier. They calculated the distances of maximal intensity differences for a given direction on a greyscale image and took the center of gravity of the resulting distance histogram as a good measure to predict average grain size. This method is computationally cheap but suffers from inaccuracies in the presence of noise and areas without grain (Lepistö et al. 2007). Another popular method is to binarize the image and use segmentation on the resulting black and white shapes to determine average particle size (Pi & Zhang 2005), however the result depends greatly on the choice of the binarizing level.

The theoretical limit of geometrical precision of movement calculation also depends on the texture, only the presence of sufficient high frequency components will guarantee precise correlation (Förstner 1982). Sampling frequency and resolution of the instrument has to be chosen to capture these high frequency components. The highest frequency of interest can be determined from the energy spectrum of the image. According to Förstner precision can be estimated by examining the curvature (2nd derivative) of the cross correlation function in the neighborhood of the maximum.

Some of the problems associated with textures can be eliminated by changing the illumination. Optical mice illuminate the surface at a low angle creating long shadows of miniature surface irregularities, making measurement possible on surfaces of homogeneous colour. Laser speckle interferometry – known since the seventies - offers another alternative: In laser speckle correlation the object is illuminated with laser light so that its image is modulated by a fine, high-contrast speckle pattern that moves with the surface. This movement is tracked by cross-correlation of the intensity distribution in successive images (Feiel & Wilksch 2000). This method offers unprecedented resolution and total independence from surface texture. A serious drawback of both the above mentioned illumination methods is that both the shadows created by sideways illumination and the speckle pattern changes with the distance between the light source and the object. This effect makes displacement measurement hard, if not impossible.

In the field of texture analysis many questions remain open such as a quantitative relation between texture and detector parameters and a good measure of texture frequency that determines resolution parameters. The problem of illumination also offers itself to application oriented research.

5. Applications

There are many possible applications of true ground speed measurement. In the following we will outline some of the areas that the authors think are most important.

5.1 Slip measurement

When a wheel contacts the ground usually two kinds of slip can occur, lateral and longitudinal. Longitudinal slip is the difference between the velocity of the centre of the wheel and the velocity of the circumference of the wheel. The difference is usually caused by acceleration or deceleration when there is not enough friction between the wheel and the ground, so slip is heavily dependent on the friction coefficient.
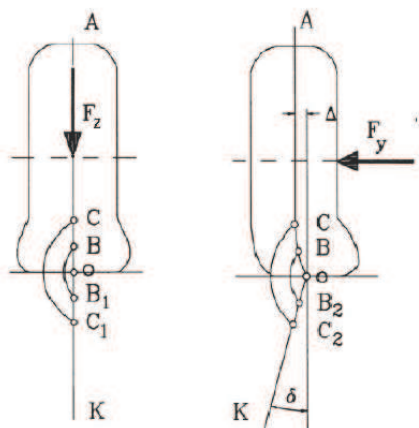
Fig. 14. Lateral slip

Lateral slip occurs if the wheel's angular displacement differs from the path the tire is following. It is caused by wheel deformation. When lateral forces act on the wheel - cornering, driving on a slope or in crosswind – the wheel changes its shape and starts to "crawl" to the side. The angle that corresponds to the rate of sideway movement is called the slip angle. It should be noted that the slip angle is not the same as the steering angle. Knowledge of the sideslip of a vehicle is indispensable for the exact description of its dynamics and kinematics.

The importance of longitudinal slip: in agricultural and off road applications it is considered as a predictor of the tractive efficiency of a given wheel set-up. The other main application is tire road friction estimation which is a discipline with a long history (Gustafsson 1997). Many researchers have worked on the problem of determining tire- road friction on line, (Müller et al. 2003) give a good overview on the literature and propose a method, based on slip curve steepness to estimate maximal available friction. (Miller et al. 2001) also conducted research on slip estimation using GPS and wheel speed sensors, their results show that tire slip and wheel radius can be estimated with good accuracy from these two measurements. By using optical speed sensors the disadvantages of GPS such as latency and limited reception could be eliminated and on-line measurements are possible.

Off road and agricultural applications could greatly benefit from the use of a simple non contact speed sensor, as it could provide speed over ground measurements on rough or slippery surfaces. (Lindgren et al. 2002) describe an odometry model for autonomous agricultural vehicles in which a relation between torque and slip is established. To estimate slip they used laser rangefinders and reflective beacons to obtain ground truth velocity measurements, limiting their application to level surfaces and a calibrated environment. By the use of an optical speed sensor their method can be extended and on line measurements without the use of external beacons can be conducted.

(Hutangkabodee et al. 2008) present a method to identify the set of soil parameters required to predict drawbar pull and wheel drive torque from measurements of slip, sinkage, and drawbar pull for a wheeled vehicle traversing unknown terrain. Knowledge of the terrain characteristics helps the driver to have a better control of the vehicle. From wheel-terrain interaction dynamics, it is seen that soil parameters play a vital role in determining vehicle drawbar pull which can, in turn, be utilized for developing traversability prediction criteria and traction control algorithms.

The importance of lateral slip: Vehicle safety is highly active research topic as car manufacturers keep pushing the boundaries of intelligent vehicle systems. Governments world wide have started programs to promote road safety to lessen the effect of traffic accidents; probably the most ambitious is vision zero from Sweden, trying to achieve zero fatalities on the roads. (Bishop 2005) Vehicle stability systems are among the most researched topics as they provide superior handling in extreme conditions. Modern ESP -s use yaw rate and steering angle as their main input, but in certain cases these are insufficient for correct intervention and knowledge of the slip angle of the vehicle is necessary. A good example would be a cornering vehicle, which is sliding at the same time. Its yaw rate might be considered adequate to its steering angle but it might still leave the road due to its sideways movement. The importance of sideslip is twofold; it allows better description of vehicle dynamics and on the other hand it plays an important role in wheel-road interaction, allowing us to determine friction or cornering forces. (Bevly et al. 2001) proposes a method to integrate inertial sensors with GPS to estimate sideslip angle and cornering stiffness. Sensor fusion is essential to solve this problem since GPS sensors have high noise and low sample rates, inertial sensors are fast and accurate but their measurements need to be integrated leading to unbounded errors. Using an optical speed sensor in the fusion system could provide a fast low noise speed estimate. Errors caused by textureless surfaces or other anomalies could be corrected by inertial sensors.

Big car manufacturers have been working on projects to estimate and use the sideslip angle in their stability systems (Nishio et al. 2001).

By measuring the sideslip angle at individual wheels important parameters of the suspension and wheel alignment can be determined. For example at high slip angles, the rear of the tire footprint actually slides laterally along the surface of the road, which contributes to less capacity for lateral force and reduces the stabilizing self-aligning torque. It may be important to realize that when not completely sliding, the lateral force is not dependent on the coefficient of friction, although this provides the upper limit; instead, it depends on the foundation stiffness. An alternate way to look at this is to say that the lateral force is not dependent on coefficient of friction until the tire has "broken away", indicating a large slip angle (Smith 2003).

5.2 Mapping

Robotic mapping is an active research area with lots of problems open to research. Thrun conducted a survey of the major mapping methods used by researchers in the last decade (Thrun 2002). Although the survey was six years old when this article was written its statements and general assumptions were still valid.

Intelligent mobile robots navigate around in their environment by gathering information about their surroundings. The most common approach is to use ranging sensors mounted on the robot to form occupancy grids or equivalent. Other approaches avoid this metric division of space and favour topological mapping. By combining these mapping techniques it is possible to form a hierarchical map that has the advantages of both methods while some of the disadvantages can be avoided (Thrun, 1998). The map categories proposed by Dudec and Jenkin overlap with the ones mentioned above, but they are somewhat more differentiated (Dudec & Jenkin 2000):

Sensorial. Raw data signals or signal-domain transformations of these signals.

Geometric. Two- or three-dimensional objects inferred from sensor data.

Local relational. Functional, structural or semantic relations between geometric objects that are near one another

Topological. The large-scale relational links that connect objects and locations across the environment as a whole (for example, a subway map).

Semantic. Functional labels associated with the constituents of the map.

Occupancy grids classify the individual cells based on range data and possibly other features such as colour or surface texture or variation. This becomes very important in outdoor mobile robotics when the robot needs to distinguish between real obstacles and traversable terrain. An extreme case is given by navigation in a field of tall grass. The elevation map will represent the scene as a basically horizontal surface above the ground level; that is, as a big obstacle in front of the vehicle. It is apparent that only by integrating the geometry description with terrain cover characterization will a robot be able to navigate in such critical conditions (Belluta, 2000). This is the case when semantic information would prove useful. Topological maps describe the world in terms of connections between regions. This is usually enough indoors, or in well structured environments, but when travelling through more complex terrain a different representation might be necessary. For example a sloping gravel road or sand dune may only be traversable at a certain speed or only one way, up or downwards. By applying information from the inertial navigational unit, such as slope angle, wheel slippage, actual movement versus desired movement, these characteristics can be learned (or used from apriori information) and the connections of the topological graph can be updated accordingly. Terrain characteristics (and those of our vehicle) determine the maximum safe speed, braking distance curve radius at a given speed, climbing manoeuvres etc. It is obvious that the more information we have about a certain region we are planning to travel through, the more driving efficiency we can achieve, as it is generally unsafe to drive at high speed through bumpy terrain or make fast turns on a slippery surface. By incorporating the data from the navigational unit into the world map, we can associate driving guidelines to a given map segment. Also on the higher, topological or relational level - using apriori information - we can identify the type of the terrain for a given point of our topological graph, as office environment, forest, urban area, desert etc. By doing so, we narrow down our choices when making decisions about terrain coverage. For example it is unlikely to encounter sand, water or foliage in an office environment. If we know the type of terrain ahead we can make a more accurate estimate of the drivability of the area thus increasing driving efficiency. In this section a hierarchical map making method was proposed which uses data from a multi-sensor navigation unit that supplies information about vehicle dynamics. This unit heavily relies on the optical correlation sensor described in the preceding sections. By measuring wheel slip and vehicle slip angle we are able to associate drivability guidelines such as safe speed, friction coefficient, minimal driving speed etc. to a given map segment or type of terrain. A higher level of environment recognition was also proposed: based on apriori information, or sensor data the vehicles control system decides the type of environment (e.g. office, forest, desert) the robot traverses at the time, and changes the probability of terrain types, characteristic of the type of environment, thus simplifying terrain classification. (Takács & Kálmán 2007)

6. Conclusion

An overview on optical speed measurement was presented with a special focus on measurement methods with an image sensor facing the ground. The second section gave a

short overview on motion measurement in general, section 3 described the basics of optical flow and image correlation, and related work in the field of optical motion measurement. The following section described the foundations of a high speed optical correlation sensor based on line-scan cameras. Special attention was given to texture properties, possible problems and their solutions. A simulator was created and several experiments were conducted to verify the assumptions made earlier. The results show that it is possible to use a line-scan camera for one dimensional speed measurement and a range of parameters was defined for independent measurements in orthogonal directions. The last chapter gave a brief overview on possible applications of the sensor. Possible applications include slip free platform independent dead reckoning sensor for mobile robots, slip measurement for vehicles, that can be used for on line friction estimation, wheel geometry alignment and stability systems. A method was proposed to incorporate slip and handling data into maps created by autonomous agents to enhance driving efficiency and facilitate cost effective route planning.

In the future the authors plan to do extensive testing on the simulator as the tests conducted were not exhaustive in the sense of optimizing sensor parameters, and also plan to create a working prototype to address real world problems absent from the simulation and solve them.

Problems to be solved, possible areas of contribution: to create a truly useful sensor for mobile platforms further research and development is needed. One group of problems come from environmental effects. If it was to be mounted on an automobile the sensor has to operate in an environment with constant vibration, high temperature changes and lots of dirt. To counter the effects of dirt several methods might be used: mounting inside a protective tube, blowing air away from the sensor, using protective water repellent coating on the housing, shaking the lens with high frequency to prevent adhesion of dirt and using special image processing techniques to achieve graceful degradation of performance, however viability of these methods is still to be verified.

The effects of highly reflective surfaces such as ice snow and water, and the effects of fog and rain need to be investigated too.

In section 4.4 several aspects of texture processing have been mentioned, however there is still a need for a qualitative measure for texture that shows how good a texture is for movement detection. This measure could incorporate factors such as contrast, texture size and density, number of edges per unit of area and spectral information.

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