Calibration of a vision-based system for displacement measurement in planetary exploration space missions

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Abstract. In planetary exploration space missions, motion measurement of a vehicle on the surface of a planet is a very important task. In this work a visual-odometry solution is analyzed. Particularly, a vision-based displacement instrument is described and calibrated using a simulated rocky scene. The most significant uncertainty sources are found out by experimental tests. Particular attention is dedicated to the uncertainty contributions of the feature detector and of lighting conditions. Two different motion directions are considered and the evaluated uncertainty are compared.

1. Introduction
In planetary exploration space missions motion measurement of a vehicle on the surface of a planet should be very accurate in order to track the vehicle also for long paths. The odometric evaluation of vehicle position and attitude performed measuring the rotation of wheels has wide uncertainty due to slippage of wheels on a natural, often sandy or slippery, surface. Moreover, on extraterrestrial planets GPS-like positioning systems are not yet available and inertial navigation sensors exhibit unacceptable drifts. Thus, the need of a reliable and accurate motion instrument is particularly relevant.

The use of stereo systems for visual-odometry is well known and was dealt with in several works, such as [1] - [3], and the solution can be derived also from some books, such as [4]. Stereo-processing allows estimation of the three dimensional (3D) location of landmarks observed by a stereo-camera. If the same landmarks are acquired and detected by a stereo-system that moves from an initial position to a final one, the two 3D point clouds allow to evaluate the position and orientation of the stereo-system in the final position with reference to the initial one. A recent work, i.e. [5], emphasizes the importance of a detailed and correct uncertainty evaluation, and describes a method for visual-odometry that allows to reduce the final measurement uncertainty exploiting a heteroscedastic (i.e. inhomogeneous and anisotropic) model of uncertainty sources. However, [5] does not take explicitly into account the uncertainty contribution of the feature detector that allows to find the projection of landmarks in the image plane.

Once the intrinsic and extrinsic parameters of a stereo system are carefully determined, one of the main uncertainty sources is the position on the image plane of the features detected and matched in both images. The 2D feature position is determined by the detector employed, while the matching
between images is performed using a suitable descriptor. Detectors find out regions that are projections of landmarks and can be used as features, while descriptors provide representations of the detected regions. A suitable description allows to search similar regions between stereo images and to perform their matching, which is required to measure the 3D position of features and then the position of the stereo system. Thus, several algorithms for feature extraction were considered in the preliminary phases of this work. Particularly, [4] and [6] describe a feature detector invariant to rotation and based on the assumption that an interesting feature (e.g. a corner) exhibits nontrivial gradients along two independent directions. In this approach a suitable scalar function of the spatial gradient is built and calculated in a small window moved in the image; if this function exceeds a predetermined threshold, the window position is considered a suitable feature, generally named Harris point. In [7], a similar method detects Harris-Laplace regions which are invariant to rotation and scale changes. In this case features are detected by the scale-adapted Harris function and selected in scale-space by the Laplacian-of-Gaussian operator. [8] - [10] describe a different method that detects Hessian-Laplace regions. Also these regions are invariant to rotation and scale changes. In this case, features are localized in space at the local maxima of the Hessian determinant and in scale at the local maxima of the Laplacian-of-Gaussian. Both Harris-Laplace and Hessian-Laplace regions have a corresponding version invariant also to affine image transformations. The affine adaptation is performed using the second moment matrix, see [10] and [11] for more details. Finally, [12] introduces the Maximally Stable Extremal Regions (MSER) and a watershed-like segmentation algorithm to detect them in the image. [11] compares several different detectors invariant to scale and affine transformations and finds out that the best results are obtained by the Hessian-Affine detector and the MSER one. Particularly, the last one performs well on images containing homogeneous regions with distinctive boundaries.

After features are detected, their regions have to be represented by a descriptor. Many different methods are known for describing local image regions, see [13] for details. The performance of these methods can be evaluated by the number of correct or false matches between two images. [13] uses this criterion to compare different descriptors and concludes that the scale invariant feature transform SIFT and the gradient location and orientation histogram GLOH descriptors are the best. For the reasons described above, in the present work, the selected detector is the Hessian-Affine (MSER was discarded since the simulated rocky scenes do not contain homogeneous regions with distinctive boundaries), while SIFT descriptor was chosen.

The present work focuses on the calibration of a stereo-based instrument to measure the motion of the system itself (sometimes named ego-motion). The calibration is performed according to the metrological procedures described in [14] and [15]. All main uncertainty sources, particularly the feature detector one, are analyzed taking into account a typical planetary scene.

2. Measurement algorithm

In this section, the procedure employed to perform the displacement measurement of the stereo system is described. The goal is to calculate the displacement of a calibrated stereo system using the images acquired in an initial position and in a second one. Thus, the input quantity to be measured is a displacement of the vision system and the output of the indirect measurement is a numerical evaluation of the displacement vector. The procedure begins with the detection of image features (keypoints) and the calculation of their image coordinates. Then, a triangulation phase allows to compute the 3D coordinates of the detected features and, finally, the displacement vector is calculated. In the following paragraphs, there is also a brief description of the employed camera model.

2.1. 2D points calculation

As said before, the Hessian-Affine detector was chosen for feature extraction. In the Hessian-Affine detector the image position of interest points is detected using the Hessian matrix, the scale-selection is based on the Laplacian, and the shape of the elliptical region is determined with the second moment matrix of the intensity gradient. Particularly, each feature is located at the local maximum of the determinant of the Hessian matrix:
whose components are the second derivatives of the image, expressed in levels of gray. The local image derivatives are computed with Gaussian kernels of scale \( \sigma_D \) (differentiation scale).

Then, for each local structure of the acquired scene, the detector tries to find a characteristic scale, which is useful to detect the same local structure when the relative distance between the scene and the camera is changed. To this purpose, the characteristic scale is selected as the one at which there is maximum similarity between the feature detection operator and the local image structures. In this case the selected operator is the Laplacian of Gaussians LoG:

\[
\text{LoG}(x, \sigma_D) = \sigma_n^2 [I_{xx}(x, \sigma_n) + I_{yy}(x, \sigma_n)]
\]

When the size \( \sigma_n \) of the LoG kernel matches with the size of a blob-like structure the response attains an extremum. Also in this case \( I_{xx} \) and \( I_{yy} \) are the second derivatives of the image. See [10] and [16], for details. A second advantage of this algorithm is that the size of the region is selected independently of image resolution for each point.

To obtain features with invariance to affine transformations, the iterative estimation of elliptical affine regions is applied, as in [17]. The affine shape of the point neighborhood is determined by the transformation that projects the affine pattern to the one with equal eigenvalues of the second moment matrix. The second moment matrix can be defined by:

\[
\mu(x, \Sigma_J, \Sigma_D) = \text{det}(\Sigma_D) \cdot g(\Sigma_I)^* \begin{bmatrix}
I_x(x, \Sigma_D) & I_y(x, \Sigma_D) \\
I_y(x, \Sigma_D) & I_y(x, \Sigma_D)
\end{bmatrix}
\]

where \( \Sigma_D \) is the covariance matrix that defines the Gaussian kernels used to compute the local image derivatives, and \( \Sigma_I \) is the covariance matrix of a Gaussian window \( g(\Sigma_I) \) used to smooth the derivatives.

The detector described above allows to compute the 2D position of the detected features. After that, for each feature in the image of a camera, the corresponding feature in the other camera has to be found out, if any. Moreover, corresponding features have to be found out between images acquired by the same camera but in two different positions. These correspondences are evaluated using the SIFT descriptor, which is a distribution based approach. The descriptor represents the local region around each detected feature by a 3D histogram of gradient locations and orientations, for details see [9]. The Euclidean distance is used to compare the descriptors. Each detected feature in a first image is associated with the feature in the second image that has the minimum Euclidean distance, providing that this distance is below a set threshold.

2.2. Camera model

The employed camera model can be found in [4]. The stereo system comprises two cameras, 1 and 2, each camera has a corresponding frame of reference with its z axis aligned with the optical axis. The two cameras are joined together with their optical axes substantially parallel. Considering the model of each camera, the generic position of a point feature comprised in the field of view of both cameras may be written as:

\[
^{t}X = \begin{bmatrix} X & Y & Z \end{bmatrix}^T = \lambda_i \begin{bmatrix} x_i & y_i & 1 \end{bmatrix}^T = \lambda_i x_i
\]

where \( i \) is 1 or 2, depending on which camera is considered; \(^tX\) (or \(^t\bar{X}\)) is the point position expressed in frame 1 (or 2) associated with camera 1 (or 2); \( x_i \) (or \( x_2 \)) is the projection of the point \(^tX\)
(or \(2\mathbf{X}\)) with an ideal camera aligned like camera 1 (or 2) with a focal length equal to 1 (in length units); \(\lambda_i \in \mathbb{R}^+\) is a scalar parameter associated with the depth of the point.

Each camera is characterized by a set of intrinsic parameters which are evaluated during camera calibration, and defines the functional relationship between projection \(\mathbf{x}_i\), expressed in length units, and projection \(\mathbf{x}'_i\), expressed in pixels (\(x'_i\) and \(y'_i\) are respectively the column number and row number, from the upper left corner of the sensor); an ideal pinhole camera has this direct model:

\[
\begin{bmatrix}
x'_i \\
y'_i \\
1
\end{bmatrix} = \mathbf{K} \cdot \begin{bmatrix}
x_i \\
y_i \\
1
\end{bmatrix}
\]  

(5)

The inverse model becomes:

\[
x_i = \mathbf{K}^{-1} \cdot \mathbf{x}'_i
\]

where \(S_x = \frac{\text{pixels}}{\text{length unit}}\) along \(x_i\) axis; \(S_y = \frac{\text{pixels}}{\text{length unit}}\) along \(y_i\) axis; \(f\) is the focal length in length units; \(x'_{0,i}\), \(y'_{0,i}\) are the distances (respectively in pixel columns and rows) between the upper left corner and the principal point (intersection of the optical axis with the sensor).

A stereo system is also characterized by its extrinsic parameters. Particularly, to perform triangulation and determine the 3D position of the scene points, the relative position and rotation between the two cameras have to be known. These parameters are named extrinsic and should be experimentally evaluated before any measurement with the stereo system can be performed. Generally, the procedure to evaluate the intrinsic and extrinsic parameters is referred to as calibration, which should not to be confused with the calibration of the whole measurement system described in this work.

### 2.3 3D points calculation

When both cameras of the stereo system are calibrated, the 3D position of a feature point in space may be measured by means of a triangulation algorithm. In this work, the algorithm of the middle point is used for triangulation, as in [18]. The algorithm, assuming the projected points \(\mathbf{x}_i\) as known from camera calibration, finds 3D points \(\mathbf{X}_{1,s}\), \(\mathbf{X}_{2,s}\) with the minimum distance, belonging respectively to the preimage lines of cameras 1 and 2. Points \(\mathbf{X}_{1,s}\), \(\mathbf{X}_{2,s}\) define a segment orthogonal to the two skew preimage lines. Middle point \(\mathbf{X}_m\) of this segment is selected as the measured 3D point of the feature.

Equation (4) can be used to find two generic points \(\mathbf{X}_1\), \(\mathbf{X}_2\), each belonging to the corresponding preimage line and expressed in the reference frame associated with the corresponding camera:

\[
\begin{bmatrix}
1
\mathbf{X}_1 \\
2 \mathbf{X}_2
\end{bmatrix} = \begin{bmatrix}
\lambda_1\cdot \mathbf{x}_1 \\
\lambda_2 \cdot \mathbf{x}_2
\end{bmatrix}
\]

(6)

Both points can be expressed in the reference frame 1 attached to camera 1:

\[
\begin{bmatrix}
1 \mathbf{X}_1 \\
2 \mathbf{X}_2
\end{bmatrix} = \begin{bmatrix}
\lambda_1 \cdot \mathbf{x}_1 \\
\lambda_2 \cdot \frac{1}{2} \mathbf{R} \cdot \mathbf{x}_2 + \mathbf{P}_{21}
\end{bmatrix}
\]

(7)

where \(\frac{1}{2} \mathbf{R}\) is the rotation matrix from frame 2 to frame 1, and \(\mathbf{P}_{21}\) is the origin of frame 2 with reference to the origin of frame 1 and expressed in frame 1. Points \(\mathbf{X}_{1,s}\), \(\mathbf{X}_{2,s}\) with minimum distance are calculated minimizing the following cost function:

\[
g = \left\| 1 \mathbf{X}_1 - \mathbf{X}_2 \right\|^2.
\]

The following values of \(\lambda_{1,s}\), \(\lambda_{2,s}\) are obtained:

\[
\lambda_{1,s} = \frac{\left( x'_1 \cdot \frac{1}{2} \mathbf{R} \cdot x_2 + x'_2 \cdot \mathbf{P}_{12} \right) \left( x'_1 \cdot \mathbf{x}_1 \right) + \left( x'_2 \cdot \mathbf{x}_2 \right) \left( x'_1 \cdot \mathbf{P}_{21} \right)}{\left( x'_1 \cdot \mathbf{x}_1 \right) \left( x'_2 \cdot \mathbf{x}_2 \right) - \left( x'_1 \cdot \frac{1}{2} \mathbf{R} \cdot x_2 \right)^2}
\]

\[
\lambda_{2,s} = \frac{\left( x'_2 \cdot \mathbf{x}_2 \right) \left( x'_2 \cdot \mathbf{P}_{12} \right) + \left( x'_1 \cdot \frac{1}{2} \mathbf{R} \cdot x_2 \right) \left( x'_1 \cdot \mathbf{P}_{21} \right)}{\left( x'_1 \cdot \mathbf{x}_1 \right) \left( x'_2 \cdot \mathbf{x}_2 \right) - \left( x'_1 \cdot \frac{1}{2} \mathbf{R} \cdot x_2 \right)^2}
\]

(8)
where \( \mathbf{p}_{12} = -\mathbf{p}_{21} \); \( \mathbf{P}_{12} \) is the origin of frame 1 with reference to the origin of frame 2 and expressed in frame 2. Thus, the extreme points \( \mathbf{X}_{1,s}, \mathbf{X}_{2,s} \) of the minimum distance segment and the middle point \( \mathbf{X}_m \) associated with the point feature are:

\[
\mathbf{X}_{1,s} = \lambda_{1,s} \cdot \mathbf{x}_1, \quad \mathbf{X}_{2,s} = \lambda_{2,s} \cdot (\mathbf{R} \cdot \mathbf{x}_2 + \mathbf{P}_{21}), \quad \mathbf{X}_m = \frac{\mathbf{X}_{1,s} + \mathbf{X}_{2,s}}{2}
\]

(9)

For convenience, all obtained 3D points are expressed in the frame 1 attached to the first camera.

### 2.4. Stereo system displacement

As described above, when the stereo system is calibrated (intrinsic parameters of both cameras and the position and orientation of camera 2 with reference to camera 1 are known), the middle points \( \mathbf{P}_1 \mathbf{X}_m \) can be calculated for all features detected by both cameras when the vision system is in an initial position \( \mathbf{P}_1 \). The notation \( \mathbf{P}_1 \mathbf{X}_m \) means that these points are expressed in the reference frame attached to the first camera, when the vision system is in the initial position \( \mathbf{P}_1 \). When the vision system is moved (cameras are rigidly connected) from the initial position \( \mathbf{P}_1 \) to a second position \( \mathbf{P}_2 \), the same procedure can be used to compute the 3D vectors \( \mathbf{P}_2 \mathbf{X}_m \) of the features detected by both cameras in the second position \( \mathbf{P}_2 \) and expressed in the new frame 1 attached to the first camera. For each feature that is detected by both cameras in both positions \( \mathbf{P}_1, \mathbf{P}_2 \), the following equation can be written:

\[
\mathbf{P}_1 \mathbf{X}_m = \mathbf{P}_2 \mathbf{R} \cdot \mathbf{P}_2 \mathbf{X}_m + \mathbf{P}_1 \mathbf{P}_{p2,p1}
\]

(10)

Where \( \mathbf{P}_2 \mathbf{R} \) is the rotation matrix from frame 1 in the second position \( \mathbf{P}_2 \) to frame 1 in the initial position \( \mathbf{P}_1 \); \( \mathbf{P}_{p2,p1} \) is the origin of frame 1 in \( \mathbf{P}_2 \) with reference to the origin of frame 1 in \( \mathbf{P}_1 \) and expressed in \( \mathbf{P}_1 \). These quantities are the numerical output values of the whole measurement procedure, and can be evaluated solving the equations (10) for all common features in \( \mathbf{P}_1 \) and \( \mathbf{P}_2 \). In this work, due to the availability of laboratory facilities and instrumentation, only pure translation along two orthogonal axes was imposed and measured by the stereo system. In this simplified case, rotation matrix \( \mathbf{P}_2 \mathbf{R} \) is assumed to be the identity and, thus, equations (10) becomes:

\[
\mathbf{P}_1 \mathbf{X}_m = \mathbf{P}_2 \mathbf{X}_m + \mathbf{P}_1 \mathbf{P}_{p2,p1}
\]

(11)

If there are \( n \) common features available for \( \mathbf{P}_1 \) and \( \mathbf{P}_2 \), the displacement \( \mathbf{P}_1 \mathbf{P}_{p2,p1} \) is computed as the vector that minimizes the following cost function:

\[
\sum_{k=1}^{n} \left\| \mathbf{P}_1 \mathbf{X}_{m,k} - \left( \mathbf{P}_2 \mathbf{X}_{m,k} + \mathbf{P}_1 \mathbf{P}_{p2,p1} \right) \right\|^2.
\]

### 3. Calibration procedure and uncertainty analysis

#### 3.1. Calibration

The first step to calibrate the whole measurement system is the determination of intrinsic and extrinsic parameters of the stereo system. The selected method is described in [19] and comprises a first closed form analytical evaluation of parameters for both cameras. The obtained values are then used as the starting point for a nonlinear optimization technique based on the maximum likelihood criterion. This nonlinear minimization problem, which is solved with the Levenberg-Marquardt algorithm, takes into account the lens distortion, especially radial distortion, for each camera. In our case the extrinsic parameters are the relative position and orientation between the two cameras.

After the intrinsic and extrinsic parameters of the stereo system are evaluated, the calibration of the measurement system can be performed. Thus, the stereo system is mounted on a mechanical slide.
having 2 degrees of freedom and is aimed to a simulated planetary scene obtained with crumpled brown paper. Figure 1 depicts the experimental set-up.

![Figure 1. Experimental set-up.](image)

The allowed movements are pure translations along two orthogonal axes. The slide has two graduated knobs for the movement of the stereo system. The movements of the slide and the stereo system are measured by a laser interferometer, which is used as a reference instrument. The interferometer measures the linear displacement only along one direction. Thus, the whole system is calibrated separately along two orthogonal directions: a first one substantially aligned with the optical axes of the cameras (axial displacement) and the second one substantially orthogonal to the optical axes (transverse displacement). For each direction the stereo system is moved from an initial position to a final one with 10 steps. During each step the displacement is measured by the laser interferometer and by the stereo system in order to build a calibration curve for the two considered directions of translation.

### 3.2. Uncertainty analysis

A detailed uncertainty analysis is performed (similar works can be found in [18] and [20]) and several uncertainty sources are considered. Particularly, the uncertainty associated with the following quantities are analysed and evaluated: intrinsic and extrinsic parameters of the stereo system, whose uncertainties are evaluated during the stereo calibration; the selected feature detector and descriptor, which contribute to uncertainties associated with the feature positions \( x_i \) in the image plane; the lighting of the simulated scene, which causes a not negligible uncertainty contribution to positions \( x_i \) in the image plane.

The contribution of the detector and descriptor is particularly tricky since it depends on the scene. For this reason, their contribution is evaluated using the same simulated rocky scene acquired during measurements. When the same scene is acquired in the same conditions, different images are obtained due to the uncertainty (commonly referred to as image noise in computer vision) associated with the image sensor and its electronics. This uncertainty depends on the acquired scene. Thus, for each camera, 200 images of the same scene were acquired with both cameras in fixed positions; for each pixel, the difference of the read level of gray and the corresponding mean value is calculated and the frequency histogram of all these differences of all pixels is used as an evaluation of the Probability Density Function PDF of the reading uncertainty. In our case, the two nominally identical cameras exhibit different reading uncertainties, one having a standard deviation equal to 0.9 and the other equal to 1.9, both expressed in levels of gray. The obtained PDFs are used to evaluate the position \( (x'_i) \) uncertainty of the image features detected and matched by the detector and descriptor employing a Monte Carlo simulation. This method of uncertainty propagation is selected since the feature extraction algorithms are very complex and non-linear.
The lighting uncertainty contribution to feature positions $x'_i$ is carefully evaluated moving the lamp in the experimental set-up in order to reproduce the sun movements on the surface of a planet. Since for the particular simulated scene that is used, the position of the lamp may cause wide variations of feature positions $x'_i$, the maximum allowed movement of the lamp was estimated assuming the time $t_m$ required for the stereo system to move from an initial position to a final one. Time $t_m$ should be representative of the average moving velocity of a rover on a planetary surface and allows to estimate a maximum angular variation of the lighting if the planet (e.g. Mars) rotation is known. Once the lamp is moved of the estimated maximum amount, the PDF of the image feature movements is evaluated and is used as an additional uncertainty source associated with the feature positions $x'_i$.

The uncertainties associated with the intrinsic and extrinsic parameters of the stereo system are evaluated applying a Monte Carlo simulation to the method described in [19]. Also in this case, the Monte Carlo simulation is selected due to the highly non-linear algorithm employed.

According to [14] and [15], all uncertainty sources are expressed by a probability density function (PDF) and are then propagated to the output displacement of the stereo system. Thus, the PDFs of the uncertainty contributions associated with the intrinsic and extrinsic parameters, and with 2D feature positions $x'_i$ (due to image reading uncertainty and lighting variations) are propagated to the displacement of the stereo system using a Monte Carlo simulation. In this way, both the calibration curve and its uncertainty are evaluated for the output measured displacement.

4. Experimental results and discussion

With the set-up depicted in figure 1, the numerical results shown in figures 2-5 are obtained: figures 2, 3 for the axial displacement, figures 4, 5 for the transverse displacement.

![Figure 2. Measured axial displacement: stereo system vs. laser interferometer.](image1)

![Figure 3. Difference between measurements of the stereo system and the interferometer.](image2)

![Figure 4. Measured transverse displacement: stereo system vs. laser interferometer.](image3)

![Figure 5. Difference between measurements of the stereo system and the interferometer.](image4)
For both axial and transverse directions, the displacements measured by the stereo system vs. those measured by the laser interferometer are depicted. To emphasize the variation of measurement uncertainty along the motion direction, also the difference between the measured displacements is shown. The uncertainty evaluated for axial displacements is larger than that obtained for transverse displacements. This result can be explained considering that the uncertainty of 3D points acquired by the stereo system is much wider along the axial direction than along a transverse direction, due to the small distance between the two cameras. This disadvantage along axial direction is partially compensated by the fact that the number of image features correctly matched in case of axial displacement is generally greater than the number of matched features in case of transverse displacement.

Along both directions, the evaluated uncertainty increases with the measured displacement. A possible reason of this behaviour is that the larger the displacement and the fewer the correctly matched features among images; thus, the averaging effect associated with a large number of matched features decreases along the displacement direction.

5. Conclusions
The calibration of a stereo system as an instrument for displacement measurement was described. The performed experimental analyses allowed to find out the most significant uncertainty sources, which comprise the uncertainty contribution of the feature detector. Two different feature detectors were implemented and their performances were evaluated and compared. One of the intended applications is in space missions for planetary exploration, which make the stereo system observe natural landmarks, e.g. rocky terrain or mountains. Thus, the calibration was carried out using a simulated rocky scene, that allowed to highlight advantages and drawbacks of the considered algorithms and measurement procedure.

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