RELIABLE LOCALIZATION AND MAP BUILDING BASED ON VISUAL ODOMETRY AND EGO MOTION MODEL IN DYNAMIC ENVIRONMENT

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Keywords: Visual Odometry (VO), Ego Motion Model, Ego Motion Control, Localization, Map Building, Temporal Filter.

Abstract: This paper presents a robust method for localization and map building in dynamic environment. The proposed localization and map building provide general approaches to use them both in indoor and outdoor environments. The proposed localization is based on the relative global position starting from initial departure position. In order to provide reliable positioning information, Visual Odometry (VO) is used instead of ego robot's encoder. Unlike general VO based localization, the proposed VO does not use iterative refinement in order to select inliers. The suggested VO uses ego motion model based on the motion control. The rotation and translation values of tracked features are guided by the estimated rotation and translation values obtained by motion control. Namely the estimated motion provides upper and lower limits of motion variation of VO. This estimated boundary of motion variation helps to reject outliers among tracked features. The rejected outliers represent tracked features of fast/slow moving objects against ego robot movement. The map is built along with ego robot path. In order to get rich 3D points in each frame accumulated dense map based temporal filter method is adapted.

1 INTRODUCTION

The stable and accurate position estimation is a key issue of the robot/vehicle navigation. The related researchers have proposed absolute/relative global position estimation. They have used GPS and INS (Inertial Navigation System) to estimate robot/vehicle position. Recently vision based new approaches have been introduced for localization. They have been called Visual Odometry (VO). The VO provides stable position and rotation estimation comparing with Encoder raw data.

Nister(2004) gives one of the first solutions for Visual Odometry. He presents implementation results using single camera and stereo camera in order to estimate vehicle pose. He uses a feature tracking method and the 5 point algorithm with RANSAC to select the motion model in both single camera and stereo camera. The result of Visual Odometry is compared to result of INS/DGPS.

Howard(2008) presents a different approach to Visual Odometry. Features tracked only in two consecutive frames are triangulated to obtain 3D points that are used in Visual Odometry. For computing the rotation and translation parameters, a back projection equation connecting the 3D tracked points from the previous frame with the corresponding 2D image points from the current frame is optimized. The algorithm is verified outdoor on many different robot platforms.

Agrawal(2007) presents Visual Odometry in rough terrain environment. They track features in multiple frames rather than just in two consecutive frames. A two step camera motion computation process is used on a bundle of frames considering each camera pose a different camera observing the same points in space. Re-projecting the same 3D points on each camera in turn tests for convergence. Visual Odometry pose is corrected by considering the gravity normal from IMU (Inertial Measurement Unit) and the yaw from GPS to maintain global pose consistency.

Konolige(2006) presents outdoor mapping and navigation based on stereo vision. They use Visual Odometry integrated with IMU/GPS for robustness in difficult lighting or motion situation and for overall global consistency. The ground surface

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model is determined with RANSAC and used in obstacle detection. They use an offline learning method for finding the paths and the extended road surface.

The related works are mainly focused on VO based localization. Their methods have problems with inliers selection in dynamic environment and with visual information loss in fast changing situations.

In this paper, for localization, an ego-motion model based special data filter method is proposed for selecting as inliers only the static features from the dynamic environment and for overcoming visual information loss in fast changing situations.

The 3D images are registered along with position estimated by VO and ego-motion model in order to build 3D map. The 3D map also consists of 3D road surface. Especially road surface extraction is a tough task for vision.

There are two major problems for the road surface extraction.

1) The road surface extraction is strongly influenced by non-uniform illumination, variant road surface textures, and road surface conditions. Many researchers have proposed methods of road surface determination (Guo, Sofman and Dahlkamp, 2006). However there are still open issues in terms of accuracy and time cost efficiency.

2) The road surface, many times, consists of homogeneous textures. It means that there are no 3D reconstructed points on the road surface.

In this paper, simple X-Y (Front-view) projection method is proposed for road surface extraction, and accumulated dense map (temporal filter) is used for obtaining 3D positions of road surface. The method of accumulated dense map along with robot path provides rich 3D information even though features of road surface are not textured.

This paper consists of three main sections. The localization is presented in the section 2.The map building is presented in the section 3. The experiments and their results are presented in the section 4.

The conclusions highlight the achievements of the work.

2 PROPOSED LOCALIZATION

2.1 Pre-processing for Selecting Good Tracking Features

The VO is based on the 3D points obtained by triangulation of features determined by feature tracking method (Shi, 1994). In this paper we do not use our own triangulation method. We directly used the 3D points provided by Tyzx (Tyzx.com) dense stereo engine. Unfortunately the 3D points are affected by noise due to different reasons. It causes inaccurate translation/rotation estimation of VO. Therefore 3D noise elimination procedure is required before determining inliers for translation/ rotation estimation. This 3D noise is filtered following image projection procedure. The coordinate system is configured as X (west-east), Y (north-south), and Z (current position to ahead)). There are three ways in which the projection can be achieved: X-Y projection (Front-view), Y-Z projection (Side-view), and X-Z projection (Top-view). The X-Y projection method is adopted in this paper because noise points and object points are easily separated. Scoring map (500 x 312) in the X-Y projection is achieved by following equation:

$$c = \frac{(X_i - X_{\min})}{\Delta X}, r = \frac{(Y_i - Y_{\min})}{\Delta Y}, \quad (1)$$
$$\because \Delta X = (X_{\max} - X_{\min})/500, \Delta Y = (Y_{\max} - Y_{\min})/312$$

where c and r are column and row of 500 x 312 image, X_i and Y_i are 3D point coordinates, and $X_{\min}$ and $Y_{\min}$ are the minimum values of X_i and Y_i respectively.

Each cell of the scored map is filled with number of projected 3D points by corresponding Equation (1). The cells which have smaller scored number than the threshold ($N_{threshold}$) are eliminated. The $N_{threshold}$ is determined by following off-line recursive iterations only at the beginning. The $N_{threshold}$ starts with “0”, it increments until the average Y value of X-Y projected points becomes a positive floating point value. Due to the down orientation of the Y axis and due to the positioning of the origin of the world coordinate system on the road surface, the initial average values are negative floating point values. In each iteration, the cells which have smaller scored number than the threshold are eliminated. After iteration is finished, the remaining 3D points are restored from scoring map. These 3D points will be used for VO.

2.2 Inliers Selection for Visual Odometry

In dynamic environments, the selection of inliers in Visual Odometry is very important. Unlike other Visual Odometry approaches (Nistér, Howard, Agrawal, Konolige), the proposed Visual Odometry avoids influences of non-static objects. We select static features to compute translation/rotation estimation of robot in terms of X, Z, and yaw (X - Z plane) angle.

1) In the first step we extract good features in the intensity image by well-known (Shi-Tomassi, 1994) method: For tracking these features in two consecutive images the pyramidal Lukas-Kanade optical flow based tracking method is used (Lucas, 1981). As a result, we obtain between 300-400 pairs of features.

2) The ego motion model is used to determine maximum-and minimum-variation boundary of translation/rotation.

The ego motion model is based on the kinematics and dynamics model of a differential-drive robot. The kinematics and dynamics model is derived from point to point movement. It is descried in Figure 1.

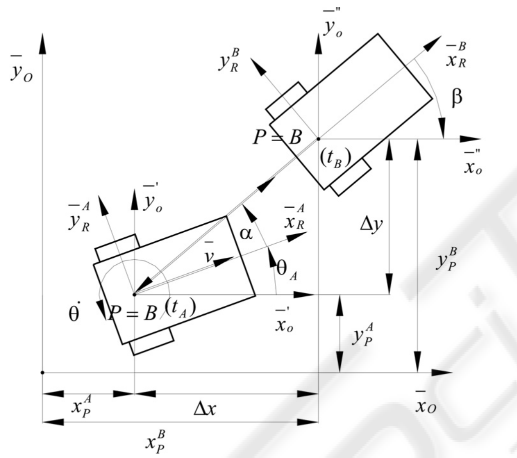


Figure 1: The point $B(t_A)$ to point $B(t_B)$ movement.

During point to point movement, translation ($\Delta x, \Delta y$) and rotation (α and /or β) is obtained. In addition, translation velocity $\bar{v}$ and rotational velocity $\dot{\theta}$ are also obtained.

The rotation estimation is induced from the ego robot's rotational velocity and complex motion control equation during two consecutive image frames. The rotational angle follows:

$$\Delta\theta = \pm\sqrt{(|\dot{\theta}| \times \Delta t \times E_r * 180)/(4 * E_t)} \qquad \begin{cases} + : \dot{\theta} \geq 0 \\ - : \dot{\theta} < 0 \end{cases} \qquad (2)$$

where Δt is the elapsed time between two consecutive frames, E_r and E_t is rotation and translation error. These E_r and E_t are determined experimentally.

$|\dot{\theta}| = \left(\sum_{i=1}^{n} \left| \dot{\theta}_i \right| \right) \big/ n$. where n is the number of rotation velocities during Δt.

The Δx and Δy are induced from forward kinematics.

$$\begin{aligned} \Delta x &= -(v_r + v_l)/2 \times \Delta t \times \sin(\Delta\theta) \\ \Delta y &= (v_r + v_l)/2 \times \Delta t \times \cos(\Delta\theta) \end{aligned} \qquad (3)$$

The x_0 and y_0 of Figure. 1 are equivalent to X direction of camera coordinates and Z direction of camera coordinates respectively.

From equation (2) and (3), the physical movement of ego robot is determined in terms of translation and rotation. These translation value and rotation angle are used to filter out features of VO. Namely the features which have bigger rotational angles and translation values than the equation (2) and (3) will be excluded for VO. The excluded features represent fast moving objects comparing to movement of ego robot. The remaining features after excluding fast moving features are used for computing mean (μ_T , μ_R) and Absolute Standard Deviation (ASD: σ_T , σ_R) in terms of translation and rotation. As a result of computing ASD, two ASDs (+/- ASD: $\pm\sigma_T$, $\pm\sigma_R$) are obtained. The features that have bigger translation values than $\mu_T - \sigma_T$ and bigger rotational angle than $\mu_R - \sigma_R$ will be kept as inliers for VO. Therefore finally we can compute a pair of mean inliers, one corresponding to the previous frame and the other to the current frame:

$$\left(\bar{X}_{t-1}, \bar{Z}_{t-1}\right), \left(\bar{X}_t, \bar{Z}_t\right)$$

They are used for computing translation and rotation of robot as part of VO.

2.3 Hybrid Filter for Localization

The localization in this paper is relative global. The robot's position is accumulated from starting position along with robot's path. This relative global position is obtained by hybrid filter. The hybrid filter consists of Visual Odometry (VO)-based motion estimation and ego motion model based motion estimation. The hybrid filter switches VO estimation to ego motion estimation according to current situation. The VO is mainly used for robot's localization. The ego motion estimation is used when visual information is lost and no tracking features exist in the scene. The case of loss of visual information especially appears in clumsy and compact indoor environment when the scene is too close. The case of no available tracking features appears in the poor illuminated or in the no textured image scenes.

The proposed hybrid-filter-based localization can be used in both indoor and outdoor environment.

The equation of the relative global localization follows:

We choose the *X*, *Z* coordinates of the 3D feature points from the previous and current frames, $(\overline{X}_{t-1}, \overline{Z}_{t-1})$, $(\overline{X}_t, \overline{Z}_t)$. The position estimation of robot in terms of *X*, *Z* is:

$$\begin{aligned} X_{curr} &= \sqrt{\|\bullet\|}\sin(-\Delta\theta), \quad Z_{curr} = \sqrt{\|\bullet\|}\cos(-\Delta\theta) \\ X_{accum} &= X_{accum} + X_{curr}, \quad Z_{accum} = Z_{accum} + Z_{curr} \end{aligned} \tag{4}$$

where

$\|\bullet\| = (\overline{X}_{t-1} - \overline{X}_t)^2 + (\overline{Z}_{t-1} - \overline{Z}_t)^2$

$\Delta\theta = \arccos\left((A \cdot B)/(\|A\|\|B\|)\right) * 180/\pi$,

$\Delta\theta = [-\pi, \pi]$ is yaw angle.

$A \cdot B = \overline{X}_{t-1}\overline{X}_t + \overline{Z}_{t-1}\overline{Z}_t$,

$\|A\| = \sqrt{(\overline{X}_{t-1})^2 + (\overline{Z}_{t-1})^2}$, $\|B\| = \sqrt{(\overline{X}_t)^2 + (\overline{Z}_t)^2}$.

X_{curr} is X axis mapping of $\sqrt{\|\bullet\|}$, Z_{curr} is Z axis mapping of $\sqrt{\|\bullet\|}$.

3 PROPOSED MAP BUILDING

The 3D map is registered along with robot's path. Tyzx's stereo camera is used for proposed 3D map building. The proposed map-building method generates complete road surface as well as 3D environment. Two map building algorithms are introduced to solve the above mentioned problems. The 3D road pixel determination is based on X-Y projection. The 3D environment is built through temporal fusion using a dense accumulation–based temporal filter.

For the 3D road pixel determination, the row position with the maximum pixel number in the filtered X-Y projection map is determined by searching. Lets call it r_{road_index}.

The 3D points which are in the r_{road_index} row cells of scoring map are assumed as the 3D points of the road surface. From experiments the 3D points of road surface are between $r_{road\_index} - 1$ and $r_{road\_index} + 1$. This approach was proved to be very simple and very robust in the structured environment.

For the 3D environment building, the successive depth images are fused using a temporal filter. The temporal filter is implemented by exploiting two information: position height and its time stamp. At each step we replace the current position height if a new height is provided for that position, or discard the height having a time step older than the current one with a pre-defined threshold.

The pixels of road surface which are extracted in the first case, but also the pixels corresponding to the other elements of the environment are accumulated by the temporal filter. Consequently the accumulated 3D environment surface is generated. This 3D relative environment surface is registered by 2D translation and rotation on the 3D world coordinates.

The obtained local 3D road surface is registered based on the following equation.

$$\begin{bmatrix} X_t^i \\ Y_t^i \\ Z_t^i \end{bmatrix} = \begin{bmatrix} \cos\theta_r & 0 & -\sin\theta_r \\ 0 & 1 & 0 \\ \sin\theta_r & 0 & \cos\theta_r \end{bmatrix} \begin{bmatrix} X^i{}_{env} \\ Y^i{}_{env} \\ Z^i{}_{env} \end{bmatrix} + \begin{bmatrix} X_t \\ Y_t \\ Z_t \end{bmatrix} \tag{5}$$

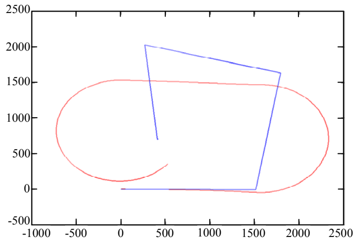
where (X_t, Y_t, Z_t) is the global position of the robot at time t, and θ_r is relative yaw at time t, ($X^i{}_{env}, Y^i{}_{env}, Z^i{}_{env}$) is the relative environment pixel position at time t (i goes from 0 to the total number of 3D pixels) and ($X^i{}_t, Y^i_t, Z^i{}_t$) is the new position of the pixel relative to the global coordinate system. The global position (X_t, Z_t) and relative yaw (θ_r) comes from $\{X_{accum}, Y_{accum}, \Delta\theta\}$ of equation (4).

The proposed Hybrid-filter-based localization and map building can be run in real-time conditions and variant environments (indoor and outdoor).

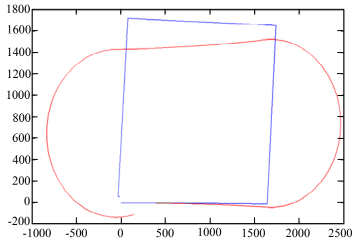
4 EXPERIMENTS

As mentioned in Section 2.2, the ego robot is modeled as differential drive robot, and empirical parameters determination for translation error and rotational angle error is required. These errors mainly come from robot's weight load. In order to determine translation error and rotational error, robot navigates pre-defined path with constant commanded velocity (100 mm/sec). The pre-defined path is a rectangle (1500 mm x 1500 mm).

As varying empirical parameters (E_r and E_t), the actual robot trajectory is varying too. The parameters are determined when the robot trajectory has the smallest error against pre-defined path. The behavior of the robot navigation looks like car due to differential drive modeling. The results corresponding to different sets of translation and rotation error parameters are presented in Figure 2.

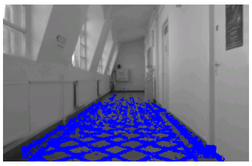


(a) In case of $E_r = 0.08$ and $E_t = 940$

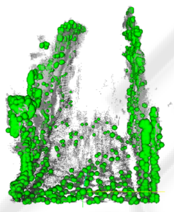


(b) In case of $E_r = 0.08$ and $E_t = 1010$

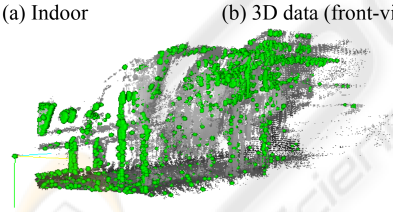
Figure 2: Ego motion calibration (blue: encoder data, red: estimated trajectories according to translation and rotation velocity)



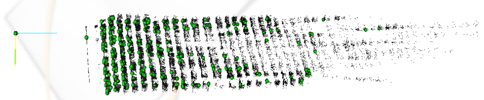
(a) Indoor



(b) 3D data (front-view)



Fusion with Temporal filter: 3475509 points (gray and green);
No fusion: 7192 points (green)
(c) 3D data (side-view) after 1000 frames accumulation



Fusion with Temporal filter: 99571 points (gray and green);
No fusion: 353 points (green)
(d) 3D Road data (side-view) after 1000 frames accumulation

Figure 3: 3D data acquisition in variant environments.

The parameter of rotation error is fixed to 0.08, and only the parameter of translation error changes from 940 to 1020. The blue line (rectangle) represents raw encoder data that is obtained in each four corners of pre-defined rectangle path.

The red line represents robot's trajectory that is computed by translation value and rotation angle along with time stamps. The minimum mismatched value (10 cm between departure position and returned position) is obtained when the parameter of translation error is about 1000. This case can be seen in Figure 2(b). These obtained error parameters are used in Equation (2) in order to provide maximum accuracy of VO.

The road surface extraction by X-Y projection and temporal filter is presented in Figure 3. The extracted road surface pixels by X-Y projection is presented in blue color on the original image (e.g. (a)). Their corresponding 3D positions are displayed in (b), (c), and (d). The green spheres in the (b), (c), and (d) represents the 3D points before temporal filtering. The gray points represent the 3D points added by fusing 10.000 images using temporal filtering.

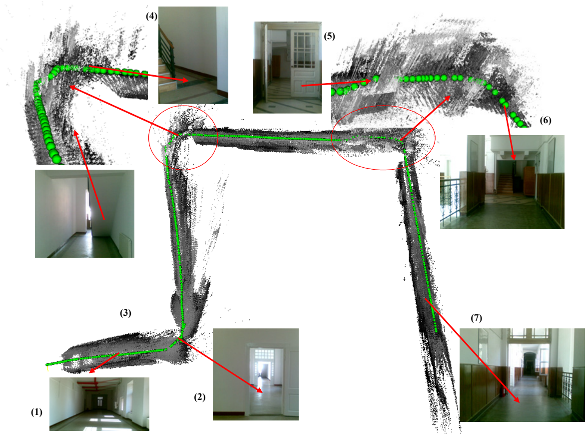
The fusion of successive images has as consequence the increase of the density of the 3D representation together with the increase of the representation accuracy.

To evaluate accuracy of localization, robot passes though 3 known points (2 meters, 6 meters, and 10 meter) in 5 turns. It is presented in Table 1. We obtained 1.5875 percentages of average error.

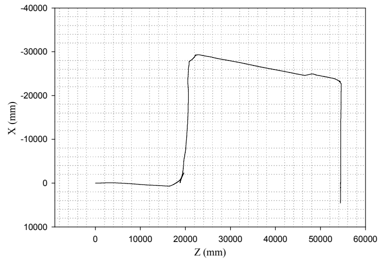
As final experiment, the robot navigates in long indoor environment. When the robot navigates indoor, the robot met many different environment variations (non-uniform illuminations Figure 4. (1-3), narrow paths Figure 4. (3-6), and non textured road surface Figure 4. (6-7)). In spite of these facts 3D road surface and 3D environment is well registered along with the robot path.

5 CONCLUSIONS

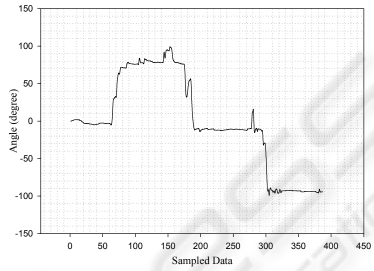
This paper proposed a new robust localization and map building method based on VO and ego motion model. Robot navigates in dynamic environment hat contains moving objects, non-uniform illumination, and non textured road surfaces. The achieved accuracy of position estimation is 1.5875 errors percentage in 10 meters.



(a) Raw accumulated image and reconstructed 3D road surface and 3D environment.



b) Distance variation along with navigation path.



(c) Angle variation along with navigation path.

Figure 4: Result Localization and map building in the long distance navigation (about 110 meter).

Table 1: Accuracy comparison at each known position.

Measuring Nr.	**2 meters (mm)**			**6 meters (mm)**			**10 meters (mm)**			**Remark Error (%)**
	X	Z	Yaw	X	Z	Yaw	X	Z	Yaw	
1	35.65	1847.5	-1.82	259.46	5625.01	-3.78	789.82	9703.77	-10.57	2.617
2	80.29	2066.14	-4.23	416.25	5981.49	-5.46	900.35	10118.09	-6.98	0.766
3	39.9	2062.2	-2.52	329.59	6095.2	-9.2	1298.73	10270.26	-14.44	1.729
4	95.14	1901.13	-4.98	541.43	5704.66	-6.18	1442.69	9646.03	-15.59	2.042
5	62.85	1975.55	-2.97	305.59	6018.14	-3.99	1063.45	10130.03	-16.25	0.783

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