METHODS FOR SIMULTANEOUS SELF-LOCALIZATION AND MAPPING FOR DEPTH CAMERAS

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Abstract: This work deals with the extension of the existing implementation of RGBD Visual SLAM with additional data source from wheel odometry of robot's chassis, on which RGBD sensor is located. Each of these two position estimation methods has a different character measurement uncertainty. By combining these methods together we could be able to suppress the disadvantages of both approaches, and in the result we would be able to create more accurate model of the robot's environment, which was unknown at the beginning of the measurement. Also accuracy of position estimation in created model can be improved.

Keywords: SLAM, Visual SLAM, Odometry, Kinect, 3D Mode, Position Estimation

1 INTRODUCTION

These days we can see an ever-accelerating automation of all human activities. For the machines to be able to carry out any human tasks, they have to be equipped with systems which provide them with feedback from its surroundings, allowing them to orientate in it.

In the field of autonomous machine orientation in the known and the unknown environment, there are many different techniques and approaches to give the robot capability to perceive its surroundings. We can mention for example: various proximity sensors, laser scanners, or for example random space passing and mapping based on Markov chains. Another option is called a Visual Odometry (Visual SLAM).

2 VISUAL SLAM

Visual Odometry is a technique of position estimation within the specified environment map that is inspired by human way of orientation. In this approach the robot is equipped with a set of image sensors and based on the data obtained from these sensors it is trying to create a model of the surroundings (unless is not given in advance) and in this model it tries to estimate its own position.

This work builds on the basis of a state-of-art project called Elastic Fusion [1], which has been tested on Linux Ubuntu 14.04. This project uses as input sensor RGBD camera. It is a device which combines classical RGB chip with matrix distance sensor, often called a depth camera. The position estimation in this project is divided into two domains. First, color domain, is based on illumination correlation of RGB images with environment model while the second, space domain performs ICP technique of spatial information from depth camera over the model (environment map).

The original project works with older type of RGBD sensor. As part of this project the software API to communicate with RGBD sensor, which is built on the basis of the OpenNI library, has been modified so that the program is now able to works with a newer model of RGBD camera, Kinect v2.

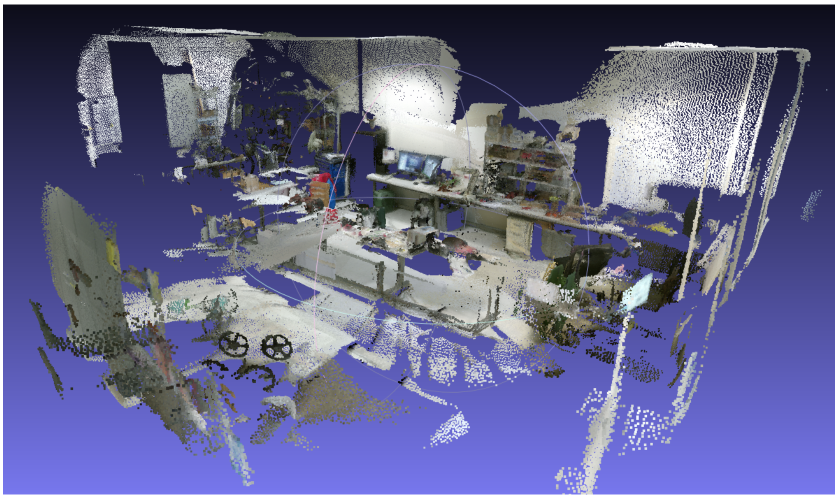

Figure 1: Model of laboratory created by extended Elastic Fusion project and Kinect v2 sensor

To use Kinect v2, in SLAM measurement it is necessary to perform sensor calibration to be able to interpret measured data into 3D space.

The main problem of Visual SLAM is to simultanously building a map and self-localizating in it. These are two contradictory problems that must be solved iteratively. Due to this fact, when robot is passing through unknown terrain there is constantly increasing cumulated error of position estimation and also the created map's deformation to the original surrounding. That when the measurement begins at point A, then robot travels a certain distance and again physically returns to point A, but according the SLAM it will be located in different place. However this problem can be solved by Loop Closing technique, but it often fails and it is better to prevent this map deformations.

3 WHEEL ODOMETRY

Wheeled odometry, often called Dead Reckoning [2], is the method of position estimation of the robot based on the information on the distance it passed. Typically, this problem is solved by quadrature encoders mounted on the wheels of the robot that measures the number of wheel's rotations.

As part of my work the measuring vehicle has been constructed. It has two wheels on the main axle with RI58-O / 5000AS.41RB quadrature encoders mounted. Furthermore, the vehicle is equipped with STM32F4 Discovery module, which is fitted into the extending shield. This computing unit functions as a collector of data from the encoders, which are then passed to the PC through the emulated USB serial line or a Bluetooth virtual serial line.

The PC is running the background daemon, which performs a model calculation of the vehicle odometry and through a POSIX system pipes it provides output of Dead Reckoning telemetry to the Visual SLAM process, which is able to reduce cumulative position estimation error.

$$d' = f(x,y,\Phi,\Delta d_r,\Delta d_l) = \begin{bmatrix} x \\ y \\ \Phi \end{bmatrix} + \begin{bmatrix} \frac{\Delta s_r + \Delta s_l}{2} cos(\Phi + \frac{\Delta s_r - \Delta s_l}{2b}) \\ \frac{\Delta s_r + \Delta s_l}{2} sin(\Phi + \frac{\Delta s_r - \Delta s_l}{2b}) \\ \frac{\Delta s_r - \Delta s_l}{b} \end{bmatrix} \tag{1}$$

where x and y are robots space coordinations, Φ is robot orientation. Δd_r and Δd_l are right and left wheel distance changes and b is robot's chassis base.

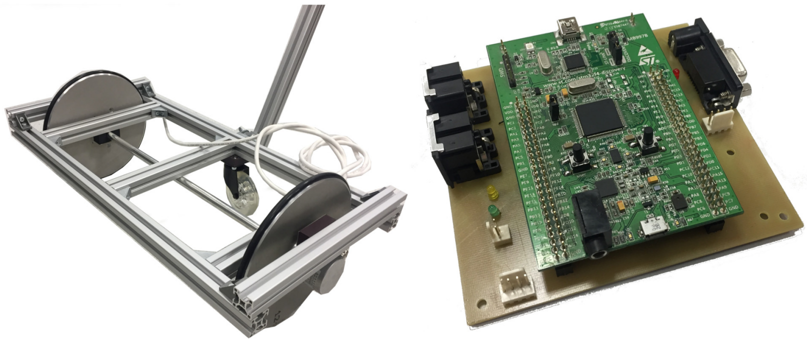

Figure 2: Detail of measurement vehicle and STM32F4 shield

4 DATA FUSION

For mutual compensation of uncertainties of both previously mentioned methods, Kalman Filter [3] has been implemented. It performs a linear combination of input data from both data sources in such a way that the measurement matrix gives larger weight on short-term accurate data from Wheel Odometry and smaller weight on the longer term reliable data from Visual Odometry. The most interesting part of Kalman Filter implementation [3] is placed in measurement matrix H, which looks as follows.

$$z_k = \begin{bmatrix} x_{z,k} \\ \dot{x}_{z,k} \end{bmatrix} = Hx_k + v_k = \begin{bmatrix} C & (1-C) & 0 & 0 \\ \frac{C}{\Delta t} & \frac{1-C}{\Delta t} & \frac{-C}{\Delta t} & \frac{-(1-C)}{\Delta t} \end{bmatrix} \begin{bmatrix} x_{wheel,k} \\ x_{visual,k} \\ x_{wheel,k-1} \\ x_{visual,k-1} \end{bmatrix} + v_k \quad \text{for} \quad 0 << C < 1 \tag{2}$$

5 CONCLUSION

In this paper the extension of Elastic Fusion project has been described. It includes the software modules for Kinect v2 data input adaptation, RGBD camera calibration, modules to calculate and receive data from position estimation of the Wheel Odometry of vehicle on which the RGBD camera is mounted and all these extensions are used to create more accurate Visual SLAM positioning process.

In conclusion, the implementation with extended data sources shows less accumulated error over time and produces more accurate models of unfamiliar surroundings.

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