# Multiple View Geometry: Exercise Sheet 8 

Prof. Dr. Daniel Cremers, Julia Diebold, Robert Maier, TU Munich<br>http://vision.in.tum.de/teaching/ss2015/mvg2015

Exercise: June 30th, 2015

## Part II: Practical Exercises

In this exercise you will implement direct image alignment as Gauss-Newton minimization on SE(3). Download the package ex8.zip provided on the website. It contains a code-framework, test-images and the corresponding camera calibration.

1. Implement a function $[I d, D d, K d]=$ downscale(I, D, K, level) which (recursively) halves the image resolution of the image $I$, the depth map $D$ and adjusts the corresponding camera matrix $K$ per pyramid level (see slides). For an input frame of dimensions $640 \times 480$ (level 1), level 2 corresponds to $320 \times 240$ pixels, level 3 correspondes to $160 \times 120$ pixels and so on. For the intensity image, downscaling is performed by averaging the intensity, that is

$$
\begin{equation*}
I_{d}(x, y):=0.25 \sum_{x^{\prime}, y^{\prime} \in O(x, y)} I\left(x^{\prime}, y^{\prime}\right) \tag{1}
\end{equation*}
$$

where $O(x, y)=\{(2 x, 2 y),(2 x+1,2 y),(2 x, 2 y+1),(2 x+1,2 y+1)\}$.
For the depth map, downscaling is performed by averaging the depth of all valid pixels (invalid depth values are set to zero), that is

$$
\begin{equation*}
D_{d}(x, y):=\left(\sum_{x^{\prime}, y^{\prime} \in O_{d}(x, y)} D\left(x^{\prime}, y^{\prime}\right)\right) /\left|O_{d}(x, y)\right| \tag{2}
\end{equation*}
$$

where $O_{d}(x, y):=\left\{\left(x^{\prime}, y^{\prime}\right) \in O(x, y): D\left(x^{\prime}, y^{\prime}\right) \neq 0\right\}$.
2. Implement a function $r=\operatorname{calcErr}(I 1, D 1, I 2, x i, K)$ that takes the images and their (assumed) relative pose, and calculates the per-pixel residual $\mathbf{r}(\xi)$ as defined in the slides. $r$ should be a $n \times 1$ vector, with $n=w \times h$. Visualize the residual as image for $\xi=\mathbf{0}$.
Hint: work on a coarse version of the image (e.g. $160 \times 120$ ) to make it run faster.
3. Implement a function $[J, r]=$ deriveNumeric (I1, $D 1, I 2, x i, K)$ that numerically derives $\mathbf{r}(\xi)$ on the manifold, i.e., for each pixel $i$ computes

$$
\begin{equation*}
\frac{\partial r_{i}(\xi)}{\partial \xi}=\left(\frac{r_{i}\left(\left(\epsilon \mathbf{e}_{1}\right) \circ \xi\right)-r_{i}(\xi)}{\epsilon}, \ldots, \frac{r_{i}\left(\left(\epsilon \mathbf{e}_{6}\right) \circ \xi\right)-r_{i}(\xi)}{\epsilon}\right) \tag{3}
\end{equation*}
$$

where $\epsilon$ is a small value (for Matlab $\epsilon=10^{-6}$ ), and $\mathbf{e}_{j}$ is the $j$ 'th unit vector). J should be a $n \times 6$ matrix. Additionally, the per-pixel residuals $\mathbf{r}(\xi)$ are returned as $r$.
4. Implement Gauss Newton minimization for the photometric error $E(\xi)=\|\mathbf{r}(\xi)\|_{2}^{2}$ as derived in the slides. Use only one pyramid level $(160 \times 120)$ in the beginning, and then add the others.
5. Implement a function $J=$ deriveAnalytic (I1, D1, I2, xi, K) which analytically derives $\mathbf{r}(\xi)$ (see slides). Using it instead of the numeric derivatives in the minimization from the previous task should result in a significant speed-up.

