Teach repeat description

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1 Continuous Correction

1.1 Rotational

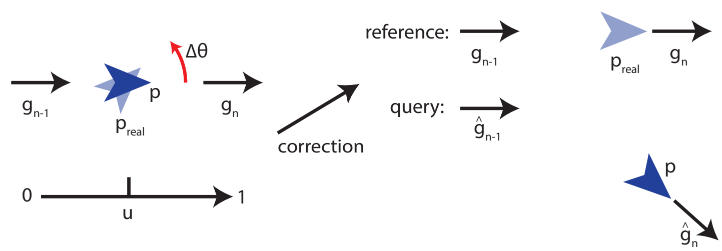

Figure 1: Rotation localisation diagram

$\boldsymbol{p}$ – pose of robot in odometry frame

$\boldsymbol{g}_n$ – goal pose (reference)

$\hat{\boldsymbol{g}}_n$ – goal pose (query)

δ_n – offset between current query image and reference image n (rad)

u – proportion of distance travelled between $\hat{g}_{n-1}$ and $\hat{g}_n$

Interpolating between previous and current goal offsets eliminates the effect of moving along the path on the image offset. For example, a large nearby visual feature could dominate the image offset calculation. Moving along the path will cause this visual feature to move left or right, depending on which side of the robot it is, and will drag the calculated offset with it. Interpolating between the previous and next reference images allows this along-path offset to be distinguished from rotational or lateral path offset, which affect both δ_{n-1} and δ_n similarly.

Measure offsets and calculate u, linearly interpolate to get offset between goals.

$$
\begin{aligned}
\delta_{n-1} &: \text{ measure offset to previous goal} \\
\delta_n &: \text{ measure offset to current goal} \\
u &= \frac{||\boldsymbol{p} \ominus \hat{\boldsymbol{g}}_{n-1}||}{||\hat{\boldsymbol{g}}_n \ominus \hat{\boldsymbol{g}}_{n-1}||} \\
\Delta\theta &= (1-u)\delta_{n-1} + u\delta_n
\end{aligned}
$$

To correct this error, the current goal is updated by rotating the offset from the previous to current goal in the opposite direction to the calculated offset:

$$
\begin{aligned}
&K_\theta = 0.01 \\
&\hat{\boldsymbol{g}}_n := \hat{\boldsymbol{g}}_{n-1} \oplus \boldsymbol{R}_{(-K_\theta \Delta\theta)}(\hat{\boldsymbol{g}}_n \ominus \hat{\boldsymbol{g}}_{n-1})
\end{aligned}
$$

1.2 Along-path

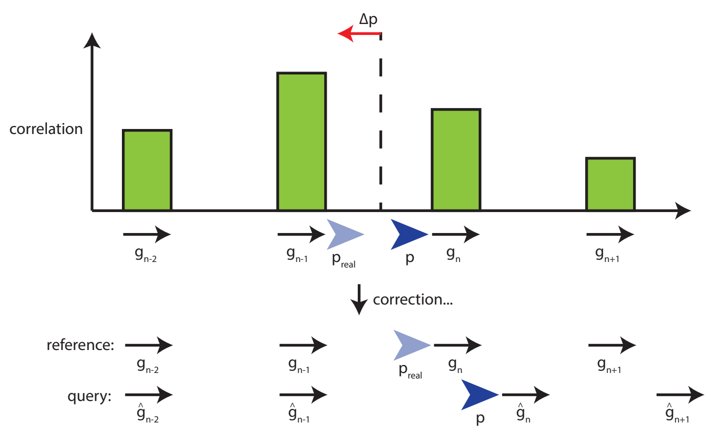

Figure 2: Along-path localisation diagram

$\boldsymbol{p}$ – pose of robot in odometry frame
$\boldsymbol{g}_n$ – goal pose (reference)
$\hat{\boldsymbol{g}}_n$ – goal pose (query)
Δg – reference target spacing (0.2 m)
ρ_n – correlation between current query image and reference image n

Along-path localisation searches a range ± 1 around the previous and current goals (ie. $\boldsymbol{g}_{n-2}$ to $\boldsymbol{g}_{n+1}$). This doesn't allow for global localisation, but makes incremental corrections to account for random and systematic odometry errors, with the assumption that the robot starts at the start of the reference path.

Peak correlations between the query and reference images are normalised to remove low correlations, scaled to have a sum of 1, then weighted and averaged to give an estimate of along-route position, relative to the middle point between the current and previous goals.

$$
\begin{aligned}
\hat{\boldsymbol{\rho}} &:= [\rho_{n-2}, \rho_{n-1}, \rho_n, \rho_{n+1}] \\
\hat{\boldsymbol{\rho}} &:= \hat{\boldsymbol{\rho}} - 0.1 \\
\hat{\boldsymbol{\rho}} &:= \max(\hat{\boldsymbol{\rho}}, 0) \\
\hat{\boldsymbol{\rho}} &:= \frac{\hat{\boldsymbol{\rho}}}{\Sigma \hat{\boldsymbol{\rho}}} \\
\Delta p &= -1.5\hat{\rho}_{n-2} - 0.5\hat{\rho}_{n-1} + 0.5\hat{\rho}_n + 1.5\hat{\rho}_{n+1}
\end{aligned}
$$

This position estimate is scaled based on the goal spacing, then used to scale the distance of the current goal to correct along-path errors.

$$
\begin{aligned}
K_p &= 0.05 \\
d &= ||\hat{\boldsymbol{g}}_n \ominus \hat{\boldsymbol{g}}_{n-1}|| \\
s &= \frac{d - K_p \Delta p \Delta g}{d} \\
\hat{\boldsymbol{g}}_n &:= \hat{\boldsymbol{g}}_{n-1} \oplus s(\hat{\boldsymbol{g}}_n \ominus \hat{\boldsymbol{g}}_{n-1})
\end{aligned}
$$

2 Discrete Correction

2.1 Rotational

$\boldsymbol{p}$ – pose of robot in odometry frame
$\boldsymbol{g}_n$ – goal pose (reference)
$\hat{\boldsymbol{g}}_n$ – goal pose (query)
δ_n – offset between current query image and reference image n (rad)

This is a simpler case because we only need to compare to one goal image. It also lets us incorporate information about the known rotational offset at the goal (due to imperfect control) without causing the correction rule to become unstable.

$$
\begin{aligned}
\delta_n &: \text{ measure offset to current goal} \\
\delta_{\theta_n} &= \theta_{\boldsymbol{p}_n} - \theta_{\hat{\boldsymbol{g}}_n} \\
\Delta\theta &= \delta_n - \delta_{\theta_n} \\
K_\theta &= 1 \\
\hat{\boldsymbol{g}}_{n+1} &:= \hat{\boldsymbol{g}}_n \oplus \boldsymbol{R}_{(-K_\theta \Delta\theta)}(\hat{\boldsymbol{g}}_{n+1} \ominus \hat{\boldsymbol{g}}_n)
\end{aligned}
$$

2.2 Along-path

$\boldsymbol{p}$ – pose of robot in odometry frame
$\boldsymbol{g}_n$ – goal pose (reference)
$\hat{\boldsymbol{g}}_n$ – goal pose (query)
Δg – reference target spacing (0.2 m)
ρ_n – correlation between current query image and reference image n

In this case we only search a range ± 1 around the current goals (ie. $\boldsymbol{g}_{n-1}$ to $\boldsymbol{g}_{n+1}$).

Peak correlations between the query and reference images are normalised to remove low correlations, scaled to have a sum of 1, then weighted and averaged to give an estimate of along-route position, relative to the middle point between the current and previous goals.

$$
\begin{aligned}
\hat{\boldsymbol{\rho}} &:= [\rho_{n-1}, \rho_n, \rho_{n+1}] \\
\hat{\boldsymbol{\rho}} &:= \hat{\boldsymbol{\rho}} - 0.1 \\
\hat{\boldsymbol{\rho}} &:= \max(\hat{\boldsymbol{\rho}}, 0) \\
\hat{\boldsymbol{\rho}} &:= \frac{\hat{\boldsymbol{\rho}}}{\Sigma \hat{\boldsymbol{\rho}}} \\
\Delta p &= -\hat{\rho}_{n-1} + \hat{\rho}_{n+1}
\end{aligned}
$$

This position estimate is scaled based on the goal spacing, then used to scale the distance of the current goal to correct along-path errors.

$$
\begin{aligned}
K_p &= 0.5 \\
d &= ||\hat{\boldsymbol{g}}_{n+1} \ominus \hat{\boldsymbol{g}}_n|| \\
s &= \frac{d - K_p \Delta p \Delta g}{d} \\
\hat{\boldsymbol{g}}_{n+1} &:= \hat{\boldsymbol{g}}_n \oplus s(\hat{\boldsymbol{g}}_{n+1} \ominus \hat{\boldsymbol{g}}_n)
\end{aligned}
$$