



## 多传感器融合讲评



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# 补全代码

第十章需要补全的代码主要有两大类。第一类是实现预积分、地图匹配、边缘化、帧间匹配四种优化因子。对应文件如下：

```
✓ factor_prvag_imu_pre_integration.hpp sensor-fusion-for-localization-and-mapping\workspace\assig
// TODO: get square root of information matrix
// TODO: compute residual:
// TODO: compute jacobians:
// TODO: correct residual by square root of information matrix:
✓ factor_prvag_map_matching_pose.hpp sensor-fusion-for-localization-and-mapping\workspace\ass
// TODO: get square root of information matrix:
// TODO: compute residual:
// TODO: compute jacobians:
// TODO: correct residual by square root of information matrix:
✓ factor_prvag_marginalization.hpp sensor-fusion-for-localization-and-mapping\workspace\assignme
// TODO: Update H:
// TODO: Update b:
// TODO: Update H:
// TODO: Update b:
// TODO: Update H:
// TODO: implement marginalization logic
// TODO: compute residual:
// TODO: compute jacobian:
✓ factor_prvag_relative_pose.hpp sensor-fusion-for-localization-and-mapping\workspace\assignment
// TODO: get square root of information matrix:
// TODO: compute residual:
// TODO: compute jacobians:
// TODO: correct residual by square root of information matrix:
```

# 补全代码

第十章需要补全的代码主要有两大类。第二类是将上述四种约束因子，加入滑窗，进行优化。对应文件如下：

```
✓ sliding_window.cpp sensor-fusion-for-localization-and-mapping\workspace\assignments\10-sliding-window\src\lidar_localization\src\matching...
// TODO: add init key frame
// TODO: add current key frame
// TODO: add constraint, GNSS position:
// TODO: add constraint, lidar frontend / loop closure detection:
// TODO: add constraint, IMU pre-integration:
✓ ceres_sliding_window.cpp sensor-fusion-for-localization-and-mapping\workspace\assignments\10-sliding-window\src\lidar_localization\src\m... 10
// TODO: create new sliding window optimization problem:
// TODO: a. add parameter blocks:
// TODO: add parameter block:
// TODO: add residual blocks:
// TODO: b.2. map matching pose constraint:
// TODO: add map matching factor into sliding window
// TODO: b.3. relative pose constraint:
// TODO: add relative pose factor into sliding window
// TODO: b.4. IMU pre-integration constraint
// TODO: add IMU factor into sliding window
```

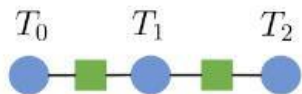
# 里程计约束关系

## (1) 里程计示意图

3) 激光里程计相对位姿和优化变量的残差

该残差对应的因子为激光里程计因子。

一个因子约束两个位姿，其模型如下：



残差关于优化变量的雅可比，可视化如下：

	$T_0$	$M_0$	$T_1$	$M_1$	$T_2$	$M_2$
$r_{L0}$						
$r_{L1}$						

因此，对应的Hessian矩阵可视化为：

	$T_0$	$M_0$	$T_1$	$M_1$	$T_2$	$M_2$
$T_0$						
$M_0$						
$T_1$						
$M_1$						
$T_2$						
$M_2$						

# 里程计约束关系

## (2) 里程计残差函数和雅可比矩阵

3.b. relative pose from lidar frontend.

Residual:

$$\begin{aligned} \therefore T_i^{-1} T_j &= \begin{bmatrix} R_i^T & -R_i^T t_i \\ 0 & 1 \end{bmatrix} \begin{bmatrix} R_j & t_j \\ 0 & 1 \end{bmatrix} \\ &= \begin{bmatrix} R_i^T R_j & R_i^T (t_j - t_i) \\ 0 & 1 \end{bmatrix} \end{aligned}$$

$$\therefore r_p = R_i^T (t_j - t_i) - t_{obs}$$

# 里程计约束关系

## (2) 里程计残差函数和雅可比矩阵

$$\begin{aligned} r_q &= \ln(R_i^T R_j R_{obs}^T)^V \\ \text{Jacobian, pos:} \quad \frac{\partial r_q}{\partial t_i} &= -R_i^T \\ \text{Jacobian, ori:} \quad \frac{\partial r_q}{\partial R_i} &= \lim_{\phi \rightarrow 0} \frac{\ln[\exp(-\phi^\wedge) R_i^T R_j R_{obs}^T]^V - \ln[R_i^T R_j R_{obs}^T]^V}{\phi} \\ \frac{\partial r_q}{\partial t_j} &= R_i^T \\ &= \lim_{\phi \rightarrow 0} \frac{\ln[R_i^T R_j R_{obs}^T \cdot \exp(-R_{obs} R_j^T R_i \phi)^\wedge]^V - \ln(R_i^T R_j R_{obs}^T)^V}{\phi} \\ &= -J_r(r_q) \exp(r_q^\wedge).inverse() \end{aligned}$$

# 里程计约束关系

## (2) 里程计残差函数和雅可比矩阵

$$\begin{aligned}\frac{\partial r_q}{\partial R_j} &= \lim_{\phi \rightarrow 0} \frac{\ln(R_i^T R_j \exp(\phi \hat{R}_{obs})^V) - \ln(R_i^T R_j R_{obs}^T)^V}{\phi} \\ &= \lim_{\phi \rightarrow 0} \frac{\ln[R_i^T R_j R_{obs}^T \cdot \exp(R_{obs} \phi)^V]^V - \ln(R_i^T R_j R_{obs}^T)^V}{\phi} \\ &= J_r^{-1}(r_q) R_{obs}\end{aligned}$$

$J_r$  should be implemented.



# 里程计约束关系

```
//  
// TODO: get square root of information matrix:  
//  
Eigen::Matrix<double, 6, 6> sqrt_info = Eigen::LLT<Eigen::Matrix<double, 6, 6>>(  
    I_  
)>.matrixL().transpose();  
  
//  
// TODO: compute residual:  
//  
Eigen::Map<Eigen::Matrix<double, 6, 1>> residual(residuals);  
  
residual.block(INDEX_P, startCol: 0, blockRows: 3, blockCols: 1) = ori_i.inverse() * (pos_j - pos_i) - pos_ij;  
residual.block(INDEX_R, startCol: 0, blockRows: 3, blockCols: 1) = (ori_i.inverse()*ori_j*ori_ij.inverse()).log();  
  
//
```



# 里程计约束关系

```
// TODO: compute jacobians:
//
if ( jacobians ) {
    // compute shared intermediate results:
    const Eigen::Matrix3d R_i_inv = ori_i.inverse().matrix();
    const Eigen::Matrix3d J_r_inv = JacobianRInv( w: residual.block(INDEX_R, startCol: 0, blockRows: 3, blockCols: 1));

    if ( jacobians[0] ) {
        Eigen::Map<Eigen::Matrix<double, 6, 15, Eigen::RowMajor>> jacobian_i( dataPtr: jacobians[0] );
        jacobian_i.setZero();

        jacobian_i.block<3, 3>(INDEX_P, INDEX_P) = -R_i_inv;
        jacobian_i.block<3, 3>(INDEX_R, INDEX_R) = -J_r_inv*(ori_ij*ori_j.inverse()*ori_i).matrix();

        jacobian_i = sqrt_info * jacobian_i;
    }

    if ( jacobians[1] ) {
        Eigen::Map<Eigen::Matrix<double, 6, 15, Eigen::RowMajor>> jacobian_j( dataPtr: jacobians[1] );
        jacobian_j.setZero();

        jacobian_j.block<3, 3>(INDEX_P, INDEX_P) = R_i_inv;
        jacobian_j.block<3, 3>(INDEX_R, INDEX_R) = J_r_inv*ori_ij.matrix();

        jacobian_j = sqrt_info * jacobian_j;
    }
}
```

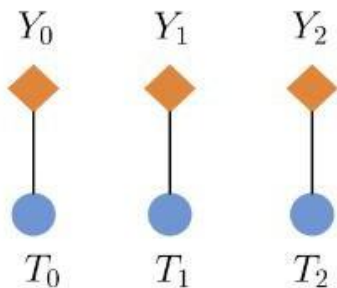
# 补全代码

## (3) 地图匹配示意图

2) 地图匹配位姿和优化变量的残差

该残差对应的因子为地图先验因子。

一个因子仅约束一个位姿，其模型如下：



残差关于优化变量的雅可比，可视化如下：

	$T_0$	$M_0$	$T_1$	$M_1$	$T_2$	$M_2$
$r_{Y0}$	■					
$r_{Y1}$			■			
$r_{Y2}$					■	

因此，对应的Hessian矩阵的可视化：

	$T_0$	$M_0$	$T_1$	$M_1$	$T_2$	$M_2$
$T_0$	■					
$M_0$						
$T_1$			■			
$M_1$						
$T_2$					■	
$M_2$						

# 地图匹配约束关系

3. a. pose from map matching / GNSS position

Residual:

$$r_p = t - t_{obs}$$

$$r_q = \ln(R \cdot R_{obs}^T)^V$$

Jacobian:

$$\frac{\partial r_p}{\partial t} = I_3$$

# 地图匹配约束关系

$$\begin{aligned}\frac{\partial r_q}{\partial R} &= \lim_{\phi \rightarrow 0} \frac{\ln(R \exp(\phi^T R_{obs})) - \ln(R R_{obs}^T)}{\phi} \\&= \lim_{\phi \rightarrow 0} \frac{\ln(R R_{obs}^T R_{obs} \exp(\phi^T R_{obs})) - \ln(R R_{obs}^T)}{\phi} \\&= \lim_{\phi \rightarrow 0} \frac{\ln[R R_{obs}^T \cdot \exp(R_{obs} \phi)] - \ln(R R_{obs}^T)}{\phi} \\&= \lim_{\phi \rightarrow 0} \frac{\ln(R R_{obs}^T) + J_r^{-1} R_{obs} \phi - \ln(R R_{obs}^T)}{\phi} \\&= J_r^{-1}(r_q) R_{obs}\end{aligned}$$

$J_r$  should be implemented.

# 地图匹配约束关系

```
//  
// TODO: compute residual:  
//  
Eigen::Map<Eigen::Matrix<double, 6, 1>> residual(residuals);  
  
residual.block(INDEX_P, startCol: 0, blockRows: 3, blockCols: 1) = pos - pos_prior;  
residual.block(INDEX_R, startCol: 0, blockRows: 3, blockCols: 1) = (ori*ori_prior.inverse()).log();  
  
//  
// TODO: compute jacobians:  
//  
if ( jacobians ) {  
    if ( jacobians[0] ) {  
        Eigen::Map<Eigen::Matrix<double, 6, 15, Eigen::RowMajor> > jacobian_prior( dataPtr: jacobians[0] );  
        jacobian_prior.setZero();  
  
        jacobian_prior.block<3, 3>(INDEX_P, INDEX_P) = Eigen::Matrix3d::Identity();  
        jacobian_prior.block<3, 3>(INDEX_R, INDEX_R) = JacobianRInv(  
            w: residual.block(INDEX_R, startCol: 0, blockRows: 3, blockCols: 1)) * ori_prior.matrix();  
  
        jacobian_prior = sqrt_info * jacobian_prior;  
    }  
}
```

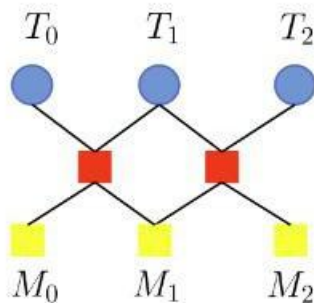
# 补全代码

## (3). 预积分示意图

### 4) IMU预积分和优化变量的残差

该残差对应的因子为IMU因子。

一个因子约束两个位姿，并约束两个时刻 IMU 的速度与 bias。



残差关于优化变量的雅可比，可视化如下：

	$T_0$	$M_0$	$T_1$	$M_1$	$T_2$	$M_2$
$r_{M0}$						
$r_{M1}$						

因此，对应的Hessian矩阵可视化为：

	$T_0$	$M_0$	$T_1$	$M_1$	$T_2$	$M_2$
$T_0$						
$M_0$						
$T_1$						
$M_1$						
$T_2$						
$M_2$						

# 预积分约束

3.c IMU pre-integration:

The residual, when parameterized using so3, is as follows:

$$\textcircled{1} \quad r_p = R_i^T (p_j - p_i - v_i T + \frac{1}{2} g T^2) - \alpha_{ij}$$

$\propto p_i, v_i, b_{ai}, b_{gi} \quad / \quad p_j, b_{aj}, b_{gj}$

$$\therefore i \quad \frac{\partial r_p}{\partial p_i} = -R_i^T$$

$$\therefore j \quad \frac{\partial r_p}{\partial p_j} = R_i^T$$

$$\frac{\partial r_p}{\partial v_i} = [R_i^T (p_j - p_i - v_i T + \frac{1}{2} g T^2)]^{\wedge}$$

$$\frac{\partial r_p}{\partial v_j} = 0$$



# 预积分约束

$$\frac{\partial r_p}{\partial v_i} = -T \cdot R_i^T$$

$$\frac{\partial r_p}{\partial v_j} = 0$$

$$\frac{\partial r_p}{\partial b_{ai}} = -J. \text{block}_{\langle 3,3 \rangle}(P, A)$$

$$\frac{\partial r_p}{\partial b_{aj}} = 0$$

$$\frac{\partial r_p}{\partial b_{gi}} = -J. \text{block}_{\langle 3,3 \rangle}(P, G)$$

$$\frac{\partial r_p}{\partial b_{gj}} = 0$$

# 预积分约束

②

$$r_r = \ln(R_{ij}^T R_i^T R_j)^V$$

$$\propto r_i, b_{gi} \quad r_j, b_{gj}$$

$$\therefore \frac{\partial r_r}{\partial r_i} = \lim_{\varphi \rightarrow 0} \frac{\ln[R_{ij}^T R_i^T R_j \exp(-R_j^T R_i \varphi)]^V - r_r}{\varphi} = -J_r^{-1}(r_r) R_j^T R_i$$

$$\frac{\partial r_r}{\partial b_{gi}} = \lim_{\delta b_{gi} \rightarrow 0} \frac{\ln[\exp(-J_{b_{gi}}^q \delta b_{gi}) R_{ij}^T R_i^T R_j]^V - r_r}{\delta b_{gi}}$$

$$= -J_r^{-1}(r_r) \exp(r_r^{\wedge}).\text{inverse}(\omega).J.\text{block}(3,3)(R, G)$$

$$\therefore \frac{\partial r_r}{\partial r_j} = \lim_{\varphi \rightarrow 0} \frac{\ln[R_{ij}^T R_i^T R_j \exp(\varphi)]^V - r_r}{\varphi} = J_r^{-1}(r_r)$$

$$\frac{\partial r_r}{\partial b_{gj}} = 0$$

# 预积分约束

③.

$$r_u = R_i^T (v_j - v_i + g^T) - \beta_{ij}$$

$\propto r_i, v_i, b_{ai}, b_{gi}$        $v_j, b_{aj}, b_{gj}$

$$\therefore \hat{z}: \frac{\partial r_u}{\partial r_i} = [R_i^T (v_j - v_i + g^T)]^A$$

$$\frac{\partial r_u}{\partial v_i} = -R_i^T$$

$$\frac{\partial r_u}{\partial v_j} = R_i^T$$

$$\frac{\partial r_u}{\partial b_{ai}} = -J.\text{block}\langle 3,3 \rangle(V,A)$$

$$\frac{\partial r_u}{\partial b_{aj}} = 0$$

$$\frac{\partial r_u}{\partial b_{gi}} = -J.\text{block}\langle 3,3 \rangle(V,G)$$

$$\frac{\partial r_u}{\partial b_{gj}} = 0$$

# 预积分约束

$$\textcircled{4}: r_a = b_{aj} - b_{ai}$$

$$r_g = b_{gj} - b_{gi}$$

$$\frac{\partial r_a}{\partial b_{ai}} = -I \quad \frac{\partial r_a}{\partial b_{aj}} = I$$

$$\frac{\partial r_g}{\partial b_{gi}} = -I \quad \frac{\partial r_g}{\partial b_{gj}} = I$$

# 预积分约束

```
//  
// TODO: compute residual:  
//  
Eigen::Map<Eigen::Matrix<double, 15, 1>> residual(residuals);  
  
residual.block<3, 1>(INDEX_P, startCol: 0) = ori_i.inverse().matrix() * (pos_j - pos_i - (vel_i - 0.50 * g_ * T_) * T_) - alpha_ij;  
residual.block<3, 1>(INDEX_R, startCol: 0) = (Sophus::SO3d::exp(theta_ij).inverse()*ori_i.inverse()*ori_j).log();  
residual.block<3, 1>(INDEX_V, startCol: 0) = ori_i.inverse().matrix() * (vel_j - vel_i + g_ * T_) - beta_ij;  
residual.block<3, 1>(INDEX_A, startCol: 0) = b_a_j - b_a_i;  
residual.block<3, 1>(INDEX_G, startCol: 0) = b_g_j - b_g_i;  
  
//  
// TODO: compute jacobians:  
//  
if ( jacobians ) {  
    // compute shared intermediate results:  
    const Eigen::Matrix3d R_i_inv = ori_i.inverse().matrix();  
    const Eigen::Matrix3d J_r_inv = JacobianRInv( w: residual.block(INDEX_R, startCol: 0, blockRows: 3, blockCols: 1));  
  
    if ( jacobians[0] ) {
```

# 预积分约束

```
// a. residual, position:
jacobian_i.block<3, 3>(INDEX_P, INDEX_P) = -R_i_inv;
jacobian_i.block<3, 3>(INDEX_P, INDEX_R) = Sophus::S03d::hat(
    omega: ori_i.inverse() * (pos_j - pos_i - (vel_i - 0.50 * g_ * T_) * T_)
);
jacobian_i.block<3, 3>(INDEX_P, INDEX_V) = -T_ * R_i_inv;
jacobian_i.block<3, 3>(INDEX_P, INDEX_A) = -J_.block<3,3>(INDEX_P, INDEX_A);
jacobian_i.block<3, 3>(INDEX_P, INDEX_G) = -J_.block<3,3>(INDEX_P, INDEX_G);

// b. residual, orientation:
jacobian_i.block<3, 3>(INDEX_R, INDEX_R) = -J_r_inv * (ori_j.inverse() * ori_i).matrix();
jacobian_i.block<3, 3>(INDEX_R, INDEX_G) = -J_r_inv*(
    Sophus::S03d::exp( omega: residual.block<3, 1>(INDEX_R, startCol: 0))
).matrix().inverse()*J_.block<3,3>(INDEX_R, INDEX_G);

// c. residual, velocity:
jacobian_i.block<3, 3>(INDEX_V, INDEX_R) = Sophus::S03d::hat(
    omega: ori_i.inverse() * (vel_j - vel_i + g_ * T_)
);
jacobian_i.block<3, 3>(INDEX_V, INDEX_V) = -R_i_inv;
jacobian_i.block<3, 3>(INDEX_V, INDEX_A) = -J_.block<3,3>(INDEX_V, INDEX_A);
jacobian_i.block<3, 3>(INDEX_V, INDEX_G) = -J_.block<3,3>(INDEX_V, INDEX_G);

// d. residual, bias accel:
jacobian_i.block<3, 3>(INDEX_A, INDEX_A) = -Eigen::Matrix3d::Identity();

// d. residual, bias accel:
jacobian_i.block<3, 3>(INDEX_G, INDEX_G) = -Eigen::Matrix3d::Identity();

jacobian_i = sqrt_info * jacobian_i;
```

# 预积分约束

```
if ( jacobians[1] ) {
    Eigen::Map<Eigen::Matrix<double, 15, 15, Eigen::RowMajor>> jacobian_j( dataPtr: jacobians[1]);
    jacobian_j.setZero();

    // a. residual, position:
    jacobian_j.block<3, 3>(INDEX_P, INDEX_P) = R_i_inv;

    // b. residual, orientation:
    jacobian_j.block<3, 3>(INDEX_R, INDEX_R) = J_r_inv;

    // c. residual, velocity:
    jacobian_j.block<3, 3>(INDEX_V, INDEX_V) = R_i_inv;

    // d. residual, bias accel:
    jacobian_j.block<3, 3>(INDEX_A, INDEX_A) = Eigen::Matrix3d::Identity();

    // d. residual, bias accel:
    jacobian_j.block<3, 3>(INDEX_G, INDEX_G) = Eigen::Matrix3d::Identity();

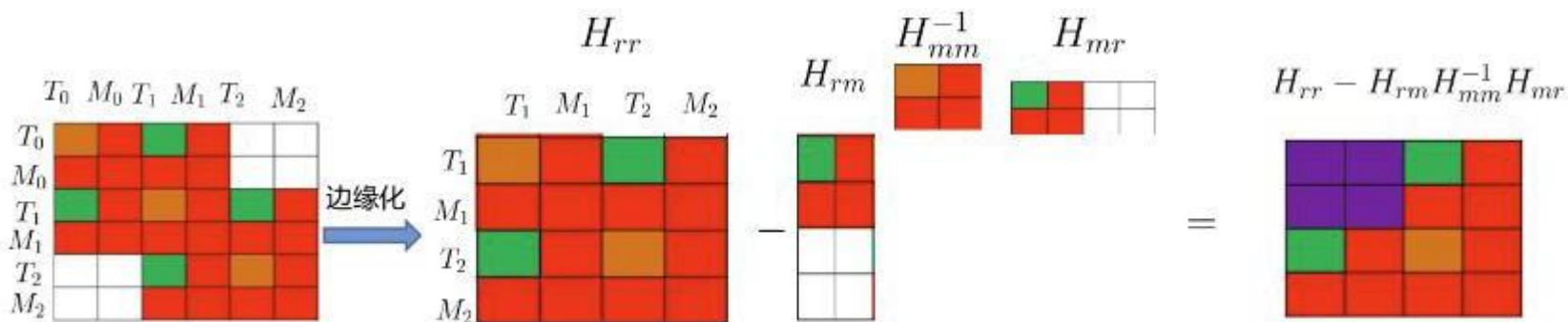
    jacobian_j = sqrt_info * jacobian_j;
}
```



## 边缘化因子

### 1) 移除老的帧

上述过程，通过可视化可以表示为



# 边缘化因子

Marginalization的实现理念参考关键计算步骤的推导

4. In order to adapt Marginalization to Ceres  
solver

a. When the sliding window has been  
filled, start to create Marginalization  
factor for next optimization

# 边缘化因子

b. In order to fit into Ceres solver  
marginalization has to be implemented  
as follows:

$$\therefore \begin{cases} H_{rr} - H_{rm} H_{mm}^{-1} H_{mr} = \tilde{H} = J^T J \\ b_r - H_{rm} H_{mm}^{-1} b_m = \tilde{b} = -J^T r \end{cases}$$

$$\therefore \tilde{H} = V \Lambda V^T$$

$$\therefore J = \sqrt{\Lambda} V^T \quad \rightarrow \text{Marg. Res. Block. Jacobians}$$

$$\therefore r = J^{-T} \tilde{b} = \sqrt{\Lambda}^{-1} V^T \tilde{b} \rightarrow \text{Marg. Res. Block. Residuals.}$$

# 边缘化因子

c. Add the Marg. Factor directly to next Ceres problem.

Marginalization Residual Block Building, PRVAG in SO3

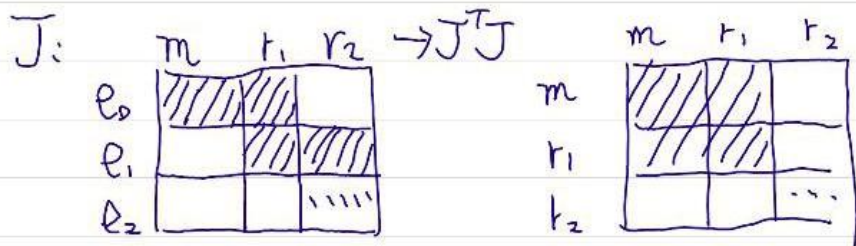
for the to-be-marginalized param block  $m$   
and its next param block  $r_1$

a. Map Matching:

$$J: \begin{array}{c} m \quad r_1 \quad r_2 \\ \begin{array}{|c|c|c|} \hline e_0 & \text{///} & \\ \hline e_1 & & \text{///} \\ \hline e_2 & & \dots \\ \hline \end{array} \end{array} \rightarrow J^T J \begin{array}{c} m \quad r_1 \quad r_2 \\ \begin{array}{|c|c|c|} \hline m & \text{///} & \\ \hline r_1 & & \text{///} \\ \hline r_2 & & \dots \\ \hline \end{array} \end{array}$$

# 边缘化因子

## b. Relative Pose & IMU Pre Integration



$\therefore$  The marginalization res. block is only relevant to param block  $r_1$

and  $H_{rr}, H_{rm}, H_{mm}, H_{mr}, b_r, b_m$

should be computed using res. block

$$\begin{cases} \text{Map/Matching}(m) \\ \text{Relative Pose}(m, r_1) \\ \text{IMU}(m, r_1) \end{cases}$$

# 边缘化因子

$$\frac{1}{2}(\mathbf{r} + \mathbf{J}\Delta\alpha)^T(\mathbf{r} + \mathbf{J}\Delta\alpha) = \frac{1}{2}\Delta\alpha^T \mathbf{J}^T \mathbf{J} \Delta\alpha + \mathbf{r}^T \mathbf{J} \Delta\alpha + \mathbf{r}^T \mathbf{r}$$

$$\mathbf{J}^T \mathbf{J} \Delta\alpha + \mathbf{J}^T \mathbf{r} = 0$$

$$\mathbf{J}^T \mathbf{J} \Delta\alpha = -\mathbf{J}^T \mathbf{r}$$

# Sliding Window Marginalization

```
//  
// TODO: Update H:  
//  
// a. H_mm:  
H_.block<15, 15>(INDEX_M, INDEX_M) += J_m.transpose() * J_m;  
  
//  
// TODO: Update b:  
//  
// a. b_m:  
b_.block<15, 1>(INDEX_M, startCol: 0) += J_m.transpose() * residuals;
```

```
//  
// TODO: Update H:  
//  
// a. H_mm:  
H_.block<15, 15>(INDEX_M, INDEX_M) += J_m.transpose() * J_m;  
// b. H_mr:  
H_.block<15, 15>(INDEX_M, INDEX_R) += J_m.transpose() * J_r;  
// c. H_rm:  
H_.block<15, 15>(INDEX_R, INDEX_M) += J_r.transpose() * J_m;  
// d. H_rr:  
H_.block<15, 15>(INDEX_R, INDEX_R) += J_r.transpose() * J_r;  
  
//  
// TODO: Update b:  
//  
// a. b_m:  
b_.block<15, 1>(INDEX_M, startCol: 0) += J_m.transpose() * residuals;  
// a. b_r:  
b_.block<15, 1>(INDEX_R, startCol: 0) += J_r.transpose() * residuals;
```



# Sliding Window Marginalization

```
//  
// TODO: Update H:  
//  
// a. H_mm:  
H_.block<15, 15>(INDEX_M, INDEX_M) += J_m.transpose() * J_m;  
// b. H_mr:  
H_.block<15, 15>(INDEX_M, INDEX_R) += J_m.transpose() * J_r;  
// c. H_rm:  
H_.block<15, 15>(INDEX_R, INDEX_M) += J_r.transpose() * J_m;  
// d. H_rr:  
H_.block<15, 15>(INDEX_R, INDEX_R) += J_r.transpose() * J_r;  
  
//  
// Update b:  
//  
// a. b_m:  
b_.block<15, 1>(INDEX_M, startCol: 0) += J_m.transpose() * residuals;  
// a. b_r:  
b_.block<15, 1>(INDEX_R, startCol: 0) += J_r.transpose() * residuals;
```

# Sliding Window Marginalization

```
// TODO: implement marginalization logic
// save x_m_0:
Eigen::Map<const Eigen::Matrix<double, 15, 1>> x_0(raw_param_r_0);
x_0_ = x_0;
// marginalize:
const Eigen::MatrixXd &H_mm = H_.block<15, 15>(INDEX_M, INDEX_M);
const Eigen::MatrixXd &H_mr = H_.block<15, 15>(INDEX_M, INDEX_R);
const Eigen::MatrixXd &H_rm = H_.block<15, 15>(INDEX_R, INDEX_M);
const Eigen::MatrixXd &H_rr = H_.block<15, 15>(INDEX_R, INDEX_R);

const Eigen::VectorXd &b_m = b_.block<15, 1>(INDEX_M, startCol: 0);
const Eigen::VectorXd &b_r = b_.block<15, 1>(INDEX_R, startCol: 0);

Eigen::MatrixXd H_mm_inv = H_mm.inverse();
Eigen::MatrixXd H_marginalized = H_rr - H_rm * H_mm_inv * H_mr;
Eigen::MatrixXd b_marginalized = b_r - H_rm * H_mm_inv * b_m;
// solve linearized residual & Jacobian:
Eigen::SelfAdjointEigenSolver<Eigen::MatrixXd> saes(H_marginalized);
Eigen::VectorXd S = Eigen::VectorXd(
    x: (saes.eigenvalues().array() > 1.0e-5).select(saes.eigenvalues().array(), elseScalar: 0)
);
Eigen::VectorXd S_inv = Eigen::VectorXd(
    x: (saes.eigenvalues().array() > 1.0e-5).select(saes.eigenvalues().array().inverse(), elseScalar: 0)
);

Eigen::VectorXd S_sqrt = S.cwiseSqrt();
Eigen::VectorXd S_inv_sqrt = S_inv.cwiseSqrt();

J_ = S_sqrt.asDiagonal() * saes.eigenvectors().transpose();
e_ = S_inv_sqrt.asDiagonal() * saes.eigenvectors().transpose() * b_marginalized;
```

# Sliding Window Marginalization

```
//  
// parse parameters:  
//  
Eigen::Map<const Eigen::Matrix<double, 15, 1>> x( dataPtr: parameters[0]);  
Eigen::VectorXd dx = x - x_0_;  
  
//  
// TODO: compute residual:  
//  
Eigen::Map<Eigen::Matrix<double, 15, 1>> residual(residuals);  
residual = e_ + J_ * dx;  
  
//  
// TODO: compute jacobian:  
//  
if ( jacobians ) {  
    if ( jacobians[0] ) {  
        Eigen::Map<Eigen::Matrix<double, 15, 15, Eigen::RowMajor> > jacobian_marginalization( dataPtr: jacobians[0] );  
        jacobian_marginalization.setZero();  
  
        jacobian_marginalization = J_;  
    }  
}
```

# sliding window optimization problem

```
// TODO: create new sliding window optimization problem:
ceres::Problem problem;

// TODO: a. add parameter blocks:
for ( int i = 1; i <= kWindowSize + 1; ++i) {
    auto &target_key_frame = optimized_key_frames_.at( n: N - i);

    ceres::LocalParameterization *local_parameterization = new sliding_window::ParamPRVAG();
    // TODO: add parameter block:
    problem.AddParameterBlock(target_key_frame.prvag, size: 15, local_parameterization);

    if ( target_key_frame.fixed ) {
        problem.SetParameterBlockConstant(target_key_frame.prvag);
    }
}
```

# sliding window optimization problem

```
// TODO: add residual blocks:
// b.1. marginalization constraint:
if (
    !residual_blocks_.map_matching_pose.empty() &&
    !residual_blocks_.relative_pose.empty() &&
    !residual_blocks_.imu_pre_integration.empty()
) {
    auto &key_frame_m = optimized_key_frames_.at( n: N - kWindowSize - 1);
    auto &key_frame_r = optimized_key_frames_.at( n: N - kWindowSize - 0);

    const ceres::CostFunction *factor_map_matching_pose = GetResMapMatchingPose(
        res_map_matching_pose: residual_blocks_.map_matching_pose.front()
    );
    const ceres::CostFunction *factor_relative_pose = GetResRelativePose(
        res_relative_pose: residual_blocks_.relative_pose.front()
    );
    const ceres::CostFunction *factor_imu_pre_integration = GetResIMUPreIntegration(
        res_imu_pre_integration: residual_blocks_.imu_pre_integration.front()
    );

    sliding_window::FactorPRVAGMarginalization *factor_marginalization = new sliding_window::FactorPRVAGMarginalization();

    factor_marginalization->SetResMapMatchingPose(
        factor_map_matching_pose,
        parameter_blocks: std::vector<double *>{key_frame_m.prvag}
    );
}
```

# sliding window optimization problem

```
factor_marginalization->SetResRelativePose(  
    factor_relative_pose,  
    parameter_blocks: std::vector<double *>{key_frame_m.prvag, key_frame_r.prvag}  
);  
factor_marginalization->SetResIMUPreIntegration(  
    factor_imu_pre_integration,  
    parameter_blocks: std::vector<double *>{key_frame_m.prvag, key_frame_r.prvag}  
);  
factor_marginalization->Marginalize(key_frame_r.prvag);  
  
// add marginalization factor into sliding window  
problem.AddResidualBlock(  
    factor_marginalization,  
    loss_function: NULL,  
    key_frame_r.prvag  
);  
  
residual_blocks_.map_matching_pose.pop_front();  
residual_blocks_.relative_pose.pop_front();  
residual_blocks_.imu_pre_integration.pop_front();  
}
```

# sliding window optimization problem

```
// TODO: b.2. map matching pose constraint:
if ( !residual_blocks_.map_matching_pose.empty() ) {
    for ( const auto &residual_map_matching_pose: residual_blocks_.map_matching_pose ) {
        auto &key_frame = optimized_key_frames_.at(residual_map_matching_pose.param_index);

        sliding_window::FactorPRVAGMapMatchingPose *factor_map_matching_pose = GetResMapMatchingPose(
            residual_map_matching_pose
        );

        // TODO: add map matching factor into sliding window
        problem.AddResidualBlock(
            factor_map_matching_pose,
            loss_function: NULL,
            key_frame.prvag
        );
    }
}

// TODO: b.3. relative pose constraint:
```



# sliding window optimization problem

```
// TODO: b.3. relative pose constraint:
if ( !residual_blocks_.relative_pose.empty() ) {
    for ( const auto &residual_relative_pose: residual_blocks_.relative_pose ) {
        auto &key_frame_i = optimized_key_frames_.at(residual_relative_pose.param_index_i);
        auto &key_frame_j = optimized_key_frames_.at(residual_relative_pose.param_index_j);

        sliding_window::FactorPRVAGRelativePose *factor_relative_pose = GetResRelativePose(
            residual_relative_pose
        );

        // TODO: add relative pose factor into sliding window
        problem.AddResidualBlock(
            factor_relative_pose,
            loss_function: NULL,
            key_frame_i.prvag, key_frame_j.prvag
        );
    }
}
```

# sliding window optimization problem

```
// TODO: b.4. IMU pre-integration constraint
if ( !residual_blocks_.imu_pre_integration.empty() ) {
    for ( const auto &residual_imu_pre_integration: residual_blocks_.imu_pre_integration ) {
        auto &key_frame_i = optimized_key_frames_.at(residual_imu_pre_integration.param_index_i);
        auto &key_frame_j = optimized_key_frames_.at(residual_imu_pre_integration.param_index_j);

        sliding_window::FactorPRVAGIMUPreIntegration *factor_imu_pre_integration = GetResIMUPreIntegration(
            residual_imu_pre_integration
        );

        // TODO: add IMU factor into sliding window
        problem.AddResidualBlock(
            factor_imu_pre_integration,
            loss_function: NULL,
            key_frame_i.prvag, key_frame_j.prvag
        );
    }
}

// solve:
```

感谢各位聆听！  
Thanks for Listening

