# Efficient Augmentation of the EKF Structure from Motion with Frame-to-Frame Features 

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## Outline

(1) Introduction
(2) Proposed Approach (High-level Overview)
(3) Proposed Approach: The Details
(4) Experimental Results

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## Introduction

- Frame-to-Frame Features
- Provide additional constraints on the velocity.
- Abundant (Under Gaussian noise assumption, consistent estimation leads to higher accuracy).
- Have been used earlier in:
- bundle adjustment.
- Particle Filtering (only in weighting the particles).
- Their direct insertion in the EKF is very costly (cubic complexity).


## Problem Formulation

- 3D Parameters to estimate
- Motion:
- Pose $[\vec{\Omega} ; \vec{T}]$
- Velocity $[\vec{\omega} ; \vec{V}]$
- Structure (3D points): $\overrightarrow{\mathbf{X}}=\left[\vec{X}^{1} ; \ldots ; \vec{X}^{N}\right]$
- $\vec{S}=\left[\vec{S}^{1} ; \vec{S}^{2}\right]$
- $\vec{S}^{1}=[\vec{\Omega} ; \vec{T} ; \overrightarrow{\mathbf{X}}]$
- $\vec{S}^{2}=[\vec{\omega} ; \vec{V}]$
- Measurements
- Tracked Features: $\overrightarrow{\mathbf{y}}(t)=\left[\vec{y}^{1}(t) ; \ldots ; \vec{y}^{N}(t)\right]$
- Frame-To-Frame features:

$$
\overrightarrow{\mathbf{z}}(t)=\left[\vec{z}^{1}(t-1) ; \vec{z}^{1}(t) ; \ldots ; \vec{z}^{K}(t-1) ; \vec{z}^{K}(t)\right]
$$

## Dynamical System

- Transition Equations:

$$
\left\{\begin{array}{l}
\overrightarrow{\mathbf{X}}(t+1)=\overrightarrow{\mathbf{X}}(t) \\
\vec{T}(t+1)=e^{[\vec{\omega}(t)]_{\times} \vec{T}(t)+\vec{V}(t)} \\
\vec{\Omega}(t+1) \\
\vec{V}(t+1) \\
\overrightarrow{L_{0}} \log _{S O 3}\left(e^{[\vec{\omega}(t)]_{\times}} e^{[\vec{\Omega}(t)]_{\times}}\right) \\
\vec{\omega}(t)+\vec{a}_{V}(t) \\
=\vec{\omega}(t)+\vec{a}_{\omega}(t)
\end{array}\right.
$$

- Measurement Equations:

$$
\left\{\right.
$$

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(1) Introduction
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3 Proposed Approach: The Details

44 Experimental Results

## Proposed Approach

- Fold the Frame-to-Frame information in a separate filtering Step
- By capitalizing on the special structure of the covariance matrix, the computational complexity can be reduced from cubic to linear
- Can be divided into several steps
- Can be done in a Random Sample Consensus way to get rid of outliers
- Steps can be computed in parallel



## Flowchart



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## Efficient Implicit Extended Kalman Filtering

- Implicit measurement equation: $h\left(\overrightarrow{\mathbf{Z}}, \vec{U}^{1}\right)=0$

$$
\begin{aligned}
\vec{U}^{1 u} & =\vec{U}^{1}+L h\left(\vec{U}^{1}, \vec{z}\right) \\
\Sigma_{\vec{U}^{1}}^{u} & =\Gamma \Sigma_{\vec{U}^{1}} \Gamma^{T}+L R_{\vec{Z}} L^{T} \\
R_{\vec{Z}} & =H_{\vec{z}} \Sigma_{\vec{z}} H_{\vec{z}}^{T}
\end{aligned}
$$

$$
\begin{aligned}
& \Lambda=H_{\vec{U}^{1}} \Sigma_{\vec{U}^{1}} H_{\vec{U}^{1}}^{T}+R_{\vec{Z}} \\
& L=-\Sigma_{\vec{U}^{1}} H_{\vec{U}^{1}}^{T}(\Lambda)^{-1} \\
& \Gamma=I_{K}-L H
\end{aligned}
$$

- Sherman-Morrison-Woodbury formula + some manipulations:

$$
\begin{aligned}
L & =-A+B\left(I_{6}+B\right)^{-1} A \\
L H_{\vec{U}^{1}} & =-B+B\left(I_{6}+B\right)^{-1} B
\end{aligned}
$$

$$
\begin{aligned}
& A=\left(\Sigma_{\vec{U}^{1}} H_{\vec{U}^{1}}^{T}\right) R_{\overrightarrow{\mathbf{z}}}^{-1} \\
& B=\left(\Sigma_{\vec{U}^{1}} H_{\vec{U}^{1}}^{T}\right)\left(R_{\overrightarrow{\mathbf{z}}}^{-1} H_{\vec{U}^{1}}\right)
\end{aligned}
$$

## Reduced Cost: Number of Multiplication Operations

| $R_{\overrightarrow{\mathbf{z}}}^{-1} H_{\vec{U}^{1}}$ | $6 K$ |
| :---: | :---: |
| $\Sigma_{\vec{U}^{1} 1} H_{\vec{U}^{1}}^{T}$ | $36 K$ |
| $A=\left(\Sigma_{\vec{U}^{1}} H_{\vec{U}^{1}}^{T}\right) R_{\mathbf{z}}^{-1}$ | $6 K$ |
| $B=\left(\Sigma_{\vec{U}^{1}} H_{\vec{U}^{1}}^{T}\right)\left(R_{\overrightarrow{\mathbf{z}}^{-1}}^{-1} H_{\vec{U}^{1}}\right)$ | $36 K$ |
| $L$ | $36 K+216$ |
| $L H_{\vec{U}^{1}}$ | 432 |
| $\Sigma_{\vec{U}^{1}}^{u}$ | $42 K+432$ |
| $\vec{U}^{1} 1 u$ | $6 K$ |
| Total | $162 K+1080$ |

## Update Propagation Using the Covariance Matrix

- $\vec{\mu}$ and $\Sigma$ partitioned as follows:

$$
\vec{\mu}=\left[\begin{array}{c}
\vec{\mu}^{1} \\
\vec{\mu}^{2}
\end{array}\right] \quad \Sigma=\left[\begin{array}{cc}
\Sigma^{11} & \Sigma^{12} \\
\Sigma^{21} & \Sigma^{22}
\end{array}\right]
$$

- then if $\vec{\mu}^{2}$ and $\Sigma^{22}$ are updated to be $\vec{\mu}^{2 u}$ and $\Sigma^{22 u}$, then $\vec{\mu}^{11}, \Sigma^{11}$ and $\Sigma^{12}$ should be updated as follows:

$$
\begin{array}{r}
\vec{\mu}^{1 u}=\vec{\mu}^{1}+\Sigma^{12}\left(\Sigma^{22}\right)^{-1}\left(\vec{\mu}^{2 u}-\vec{\mu}^{2}\right) \\
\Sigma^{12 u}=\Sigma^{12}\left(\Sigma^{22}\right)^{-1} \Sigma^{22 u} \\
\Sigma^{11 u}=\Sigma^{11}-\Sigma^{12}\left(\Sigma^{22}\right)^{-1}\left(\Sigma^{22}-\Sigma^{22 u}\right)\left(\Sigma^{22}\right)^{-1} \Sigma^{21}
\end{array}
$$

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44 Experimental Results

## Pose Error




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## Velocity Error




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## 3D Points Error



## Reprojection Error on Real Images




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## Thank you

## Questions and comments?

