# THREE-DIMENSIONAL RECONSTRUCTION FROM HETEROGENEOUS VIDEO DEVICES WITH CAMERA-IN-VIEW INFORMATION 

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## 1-Overview

In this work, a 3D modelization of the surrounding environment is enabled with an improvised ad-hoc camera networks of both static and mobile devices (cloud vision network).
The estimation can be significantly improved whenever one or more cameras (named here camera-in-views) can be localized within the field of view of other devices.
The locations of camera-in-views (CIV) correspond to both scene points and extrinsic parameters. Image points and synchronization associated to CIV are obtained via a VLC signaling.
As a matter of fact, it is possible to modify a standard bundle adjustment algorithm to improve the accuracy and reduce the amount of iterations. Experimental results show that this additional information can improve the accuracy of the system up to $17 \%$.


## 3-Synchronization and localization of cameras



The localization of target objects within images can be performed in different ways:

- SIFT descriptors;
- VLC.

In our implementation, the synchronization is obtained using a VLC protocol (it exploits phone screens or vehicle lights).
Feature-based synchronization is possible as well.
The required accuracy depends on the motion level of the cameras.

## 2-Scenario <br>  <br> $\mathbf{m}_{k, n}(t) \sim K_{n}\left[R_{n}(t) \mid T_{n}(t)\right] \mathbf{P}_{k}(t)$ $\boldsymbol{\mu}_{h, n}(t) \sim K_{n}\left[R_{n}(t) \mid T_{n}(t)\right] \boldsymbol{\pi}_{h}(t)$ <br> point $\mathbf{P}_{k}(t)$ and the camer $C_{h}$ are projected on camera $C_{n}$.

## 4-Bundle adjustment with camera-in-views

Given a set of points $\mathbf{m}_{k, n}$, the bundle adjustment strategy finds $\mathbf{P}_{k}, R_{n}$, and $T_{n}$

$$
\min _{R_{n}, T_{n}, K_{n}, \mathbf{P}_{k} \forall k, n} \sum_{k=0}^{N-1} \sum_{n=0}^{M-1} w_{k, n}\left\|\mathbf{m}_{k, n}-K_{n}\left[R_{n} \mid T_{n}\right] \mathbf{P}_{k}\right\|^{2}
$$

via an iterative two-steps minimization strategy.
If camera-in-views are known (i.e. $\mu_{h, n}$ ), the target function becomes

$$
\begin{gathered}
\sum_{h=0}^{M-1} \sum_{k=0}^{N-1} \sum_{n=0}^{M-1}\left\{w_{k, n}\left\|\mathbf{m}_{k, n}-K_{n}\left[R_{n} \mid T_{n}\right] \mathbf{P}_{k}\right\|^{2}+\right. \\
\left.\lambda \omega_{h, n}\left\|\boldsymbol{\mu}_{h, n}-K_{n}\left[R_{n} \mid T_{n}\right] \boldsymbol{\pi}_{h}\right\|^{2}\right\}
\end{gathered}
$$

where $\omega_{h, n}$ is equal to 1 in case the camera $C_{h}$ is "in-view" with respect to camera $C_{n}$ and 0 otherwise.

## 5-Results

Experimental tests were run both on a synthetic setting and on a real one. The first scenario allows us to evaluate the performance of the approach with different camera settings, where $N_{T}$ is the total number of cameras and $N_{C I V}\left(<N_{T}\right)$ the number of camera-in-views available. In the real scenario, we have 3 cameras with 2 CIVs.


Synthetic setting


MSE of 3D points. triangle $=$ no $B A$; square $=B A$; circle=BA-CIV.


Relative MSE improvement.

Real scenario

$C_{1}$ and $C_{2}$.

$C_{0}, C_{1}$, and $C_{2}$.

