A CNN-Inertial-based Odometry for Agile 6D Pose Estimation.

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Abstract—In this work, we present a CNN-inertial-based Odometry system that fuses Visual 3D pose estimation with inertial-based orientation estimation. For the visual 3D pose, we propose an Inception-based architecture that takes a sequence of two consecutive images and predicts the relative 3D motion between them. As the FPV VIO Challenge require, our system can estimates 6D pose at real-time up to 50 Hz allowing the estimation of agile flights.

I. SYSTEM OVERVIEW

The proposed system is based on the integration of 3D pose (translation) estimated by a CNN and the orientation estimation by IMU data (see figure 1). The network developed is a two-branch architecture based on inception modules that take as input a sequence of two consecutive images, one for each branch, and predicts by regression the relative motions between them. The inertial data is used as input for the orientation estimation algorithm. The combination of the translation estimated by CNN and orientation is taken by a module that calculates work 6D pose.

$\mathbf{p}_c^i = \text{Rot}^T(q_{i-1})(\mathbf{p}_w^i - \mathbf{p}_w^{i-1})$ \hspace{1cm} (1)

where $\mathbf{p}_c^i$ is the relative motion between $\mathbf{p}_w^i, \mathbf{p}_w^{i-1}$; $\mathbf{p}_w^i$ is the position in the world; $q_{i-1}$ is the orientation in the world and $\text{Rot}^T$ is the transpose rotation matrix of $\mathbf{q}$.

The pose $\mathbf{p}_c^i$ is relative to camera motion, to generate the motion in the world we use the world orientation $\mathbf{q}_w^i$, thus:

$\mathbf{p}_w^i = \text{Rot}(\mathbf{q}_w^i) \ast \mathbf{p}_c^i + \mathbf{p}_w^0$ \hspace{1cm} (2)

III. ORIENTATION ESTIMATION

The orientation is calculated by Madgwick algorithm [2], that fuse accelerometer and gyroscope data to estimate Inertial Measurement Unit (IMU) orientation using a gradient descent algorithm. The IMU’s world orientation is expressed as quaternion $\mathbf{q}_w^i_{\text{imu}}$. Figure 2, shows a diagram of the orientation estimation.

IV. RESULTS

For the experiments, we train and test in a Laptop with a GTX860m (640 CUDA cores, 2GB VRAM), Intel i7 – 4710HQ (Octa-core 2.5GHz) and 16GB ram.

We work with the bag files to trajectory estimation, we process each pose as soon as it is published by image\_raw topic (about 30Hz); but our system is not limited by this frequency, our system can process data up to 50Hz by the use of the GPU.

Figure 3 shows the estimated trajectories for outdoor face forward dataset.
<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Optimiser</td>
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<td>Batch size</td>
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<td>Learning rate</td>
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Fig. 3. Estimated trajectories for Outdoor face forward datasets.

REFERENCES
