Consistent Ground-Plane Mapping: A Case Study Utilizing Low-Cost Sensor Measurements and a Satellite Image

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Abstract— Vision-aided localization systems are often utilized in urban settings to take advantage of structured environment, high availability of unique visual features, as well as complimenting aiding measurements from Global Navigation Satellite System (GNSS). In this paper, we present a case study for roadway texture mapping that combines low-cost sensor measurements that are already available on many production vehicles (e.g. single frequency GPS, wheel odometry, and a forward looking camera) together with a satellite image. The aim of the method presented here is to obtain high resolution texture of the ground plane that is consistent with the low-resolution satellite image through an optimization process that estimates the smooth vehicle trajectory using Maximum-a-Posteriori (MAP). The main benefit of this system comes from the facts that: (1) it utilizes only low-cost sensors and information that are readily available, (2) it can be easily embedded into existing maps. Data and analysis of a drive captured around a block is used in this study.

I. INTRODUCTION

Autonomous vehicle has become an important topic in both robotics and intelligent transportation communities in recent years. Accurate estimation of the vehicle state is amongst one of the core problems that needs to be solved. Knowledge of the driving environment is essential for a robotic vehicle to accurately recover its state, hence successfully carrying out desired tasks such as complying with traffic rules and ensuring driving safety.

Satellite (aerial) imagery is an useful resource for providing driving environment information. It has advantages in two aspects. Firstly, taking images from high altitude observing point naturally yields high global consistency. Secondly, satellite image databases are well maintained and easy to gain access (e.g. Google maps, Bing maps, etc.). However, satellite images, especially the publicly available ones, suffer from the problem of limited resolution. This makes them less desirable to be directly used in advanced driver assistance systems. Current mainstream precise digital map generation systems provide maps in high quality, but they usually rely on expensive and dedicated sensor set as well as great efforts in manual data analysis. These properties limit their benefits to normal commercial cars.

We present a study for high resolution lane image generation. We use publicly available low resolution satellite images and widely installed low-cost sensors such as single frequency GPS, wheel odometry computed in the Electronic Stability Program (ESP) system, and a forward looking camera. Our method produces high quality lane images

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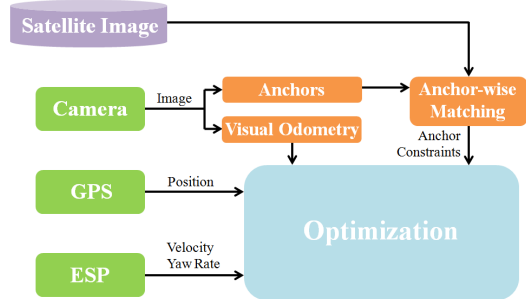
Fig. 1: An overview of our framework.

that are consistent with the satellite image, that can be easily embedded into existing maps. The use of low-cost sensors allows standard vehicles to serve as probe cars, which provides fast and inexpensive coverage of large accessible areas as well as up-to-date information.

Fig.1 shows the framework overview of our method. We propose to identify anchors and match with the satellite image in the unit of anchor. An anchor is a set of consecutive frames that have highly identifiable structured features. Anchors are identified using orthographic views obtained by the camera. Only identified anchors are matched with the satellite image to compute anchor-wise location constraints. Vehicle states are optimized by minimizing the sum of the weighted residuals in: positions measured by GPS, velocity and yaw rate measured by ESP, visual odometry, and the computed anchor constraints. The anchor-based scheme works more effectively than directly correlating camera and satellite images for each single frame due to the high uncertainty in single frame matching.

II. RELATED WORK

Previous work have shown that a great amount of effort is needed to generate high-precision digital maps. However most existing map generation systems commonly require specialized sensors [12, 15] and intense manual analysis [1]. This makes them difficult to be applied in large scale and maintain up-to-date. In another category of work [2], digital maps are generated using satellite images exclusively. Such method has the disadvantages of expensive data acquisition and unable to recover details that can only be observed in close distance.

In recent years road orthographic image construction systems using only commodity sensors have been developed. The methods in [3] and [4] use vision sensor exclusively. Though visual odometry works fully automatically

and produces generally accurate local state estimation, it relies heavily on visual cues and does not work well when insufficient texture is observed in the image. Furthermore, vision exclusive methods suffer from accumulated errors, which reduces global consistency by a large margin. The method in [17] uses visual odometry in complement to GPS. However it fails to create road images that are in pixel-level alignment with the satellite image due to limited precision of GPS.

In the work of [5], GPS and Inertial Navigation System (INS) sensors are coupled and then used for absolute localization. In its recent successor [6], visual odometry and road network topologies are also added to improve localization accuracy. These methods show promising results as well as state-of-the-art accuracy. However, as GPS may suffer from insufficient number of visible satellites and multipath reflections, it is essentially unable to guarantee high absolute positioning accuracy. Besides, though road network structure information is used in [6] to improve accuracy, sections between road segment intersections are not precisely constrained and thus not accurately mapped.

Methods in [7], [8], and [14] create maps that are consistent with satellite image priors. The satellite image is matched with 3D range scans of outdoor building structures in [7] and [14], and in [8] matched with reconstructed 3D point clouds of the road plane. Although these methods ensure high consistency with the satellite image, the usage of 3D range scanner or stereo 3D reconstruction systems significantly increases the implementation cost and decreases the number of probe vehicles. The method in [16] uses only low-cost sensors along with pre-existing map priors. However it requires labeled digital lane marks, which requires manual efforts and limits the method's usability in large scale.

The main novelties and contributions of this paper are: (1) a study that uses conventional low-cost sensors to create high resolution roadway images that are consistent with the publicly available satellite image, and (2) improved global consistency by identifying anchor points that are common in both the forward looking camera and the satellite image.

III. Approach

The method includes three major components: a preprocessing preparation stage, an anchor-based method for consistent roadway high resolution image generation, and an incremental optimization algorithm that is more computationally efficient.

A. Preprocessing

Two preprocessing steps are carried out. The first one is to compute the GPS-to-image projection. The projection is defined as a homography transformation that transforms a *longitude-latitude* GPS coordinate into its corresponding *x-y* image coordinate, where we assume no distortion in the satellite image. To do this, we survey GPS positions along with image coordinates of 20 points randomly scattered in a $1.5km \times 1.5km$ region. The homography matrix is then computed using Random Sample Consensus (RANSAC).

Fig. 2: An example of the shadow removing preprocessing, (a) original satellite image, (b) processed image.

The second preprocessing is detecting and removing shadows in the satellite image. Tree or building often project shadows on the lane, which interferes matching camera images because shadow position varies in different time of the day. To detect shadows, we apply watershed segmentation on the image region within a constant distance to the road centerline. Segments with dark color appearances are treated as shadows. We remove the detected shadows by linear interpolation along the road direction. Fig.2(a) shows an example of the original satellite image, Fig.2(b) shows the processed image after shadow removal.

It should be noted that both preprocessing steps can be easily automated and thus will not impose requirements for extra manual analysis.

B. Anchor-based Method for Consistent Roadway Image Generation

The orthographic views are obtained by applying homography transformation on a fixed region in the forward-looking (zero-tilt) images. We compute edges from the preprocessed satellite image and orthographic view inputs using the random-forest-based edge detection method [9], which is robust to illumination changes and computationally efficient. For an initial state, edge maps of transformed orthographic camera input and the nearby satellite image region centered at initial location are computed and matched. The matching correlation is used to compute the optimal position the current frame should be shifted to. This aligns the orthographic view with the satellite image. This is a nontrivial task because optimizing directly using computed correlations of all single frames will not work. Fig.3 shows examples of orthographic camera inputs. Fig.3(a) and (b) show clear lane marks. These images often provide useful matching results, e.g. Fig.3(a) provides accurate match result in the direction perpendicular to vehicle heading; Fig.3(b) provides useful positioning information in both vehicle heading and perpendicular directions. However, not all observed orthographic views contain meaningful textures, such as Fig.3(c). In that case, matching fails to provide useful alignment information, sometimes even shows strong correlation at wrong locations.
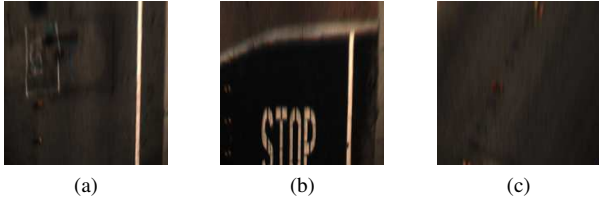
Fig. 3: Examples of transformed road orthographic views. When matched with the satellite image (a) and (b) produce useful location information. In the contrast images like (c) often fail to provide helpful positioning information.
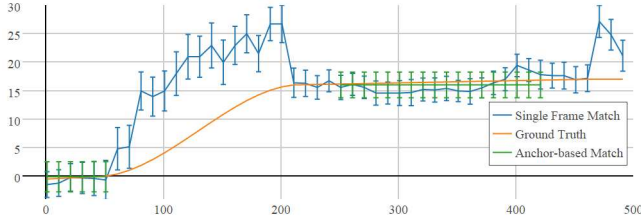

Fig. 4: An illustration of different matching methods. *x-axis*: time as frame number, *y-axis*: adjustment Δx produced by image matching, bars show standard deviations. The anchor-based method automatically turns off bad matching results, also produces smoother and more accurate location constraints than single frame matching within turned on anchor sections.

We further demonstrate why directly matching in single frames fails to produce accurate results by the example in Fig.4. Fig.4 shows the estimated Δx (the optimal adjust distance in the direction perpendicular to vehicle heading) of different methods from an actual data sequence. At frame 80-200, as input images are textureless similar to Fig.3(c), single frame matching shows strong correlation at wrong locations. To address this problem, we propose to use an anchor-based method. An anchor consists of a set of continuous anchor frames, anchor frames are frames that have highly identifiable structured textures. In the example of Fig.4 two anchors are found. Frames within an anchor are adjusted uniformly based on all single frame matching correlations. In this way, our method achieves three benefits: (1) it automatically turns off unhelpful matching results; (2) it computes more accurate position constraints by taking into account all correlations within each anchor; (3) it produces smooth adjustment by moving anchors uniformly, which improves final mapping quality.

In the next, we will describe the method we use for anchor identification, visual odometry, obtaining the optimal state estimation by incorporating anchor constraints and all other measurements , as well as the final image generation using estimated states.

1) Anchor Identification: In this step, the goal is to find whether an orthographic view contains identifiable texture in vertical (vehicle heading or image y) or horizontal (perpendicular to vehicle heading or image x) directions. First, we sum up edge potentials of the orthographic view along two

TABLE I: List of features used in anchor frame identification.

Feature	Definition
mean	$f_1 = \mu\{E_{1D}\}$
variance	$f_2 = \sigma^2\{E_{1D}\}$
peak value	$f_3 = max\{E_{1D}\}$
peak-mean ratio	$f_4 = f_3/f_1$
3 dimensional histogram	$f_5 = 1\{E_{1D} \geq 0.7f_1\}$ $f_6 = 1\{0.3f_1 < E_{1D} < 0.7f_1\}$ $f_7 = 1\{E_{1D} \leq 0.3f_1\}$

axes into two 1D signals, i.e.

$$Ex_j = \sum_{i=1}^{h} E_{ij} \qquad (1)$$

$$Ey_i = \sum_{j=1}^{w} E_{ij} \qquad (2)$$

where E_{ij} is edge potential of the orthographic view, h,w are image height and width. To identify anchor frames, we define and extract 7 features from the 1D edge signal. Table 1 lists the features, where E_{1D} can be either Ex or Ey.

We collect two anchor/non-anchor training sets corresponding to the two axes respectively. Then a standard k-nearest neighbours (k-NN) classifier is applied using the normalized feature vector to determine whether an input should be treated as an anchor frame. We further apply a round-robin buffering scheme to filter the computed labels. This process rejects lone outliers and ensures the continuity of identified anchor sections. Each set of continuous anchor frames forms an anchor, anchor constraints are then computed by averaging matching correlations within anchors.

As road images show limited number of repetitive patterns, it is possible to collect a sufficient dataset that can be used for anchor identification in larger areas. However, such large scale experiment is beyond the scope of this study.

2) Visual Odometry: As we already have ESP that measures vehicle motion, we want the visual odometry process to produce motions that has greater, or at least comparable accuracy to ESP. However, most traditional image feature based methods fail to meet this requirement. Thus we use a pixel-level dense stereo optimization approach to achieve high-precision visual odometry.

We follow the method introduced in [6] and [10]. The lower half of the transformed orthographic view is used as the region-of-interest (ROI) to optimize the 2D vehicle motion $\boldsymbol{\beta}_{vo} = (\Delta x_{vo}, \Delta y_{vo}, \Delta \alpha_{vo})^T$, where $\Delta x_{vo}, \Delta y_{vo}, \Delta \alpha_{vo}$ are the estimated vehicle translations and yaw angle change. The optimal motion vector is obtained as

$$\hat{\boldsymbol{\beta}}_{vo}^t = \underset{\boldsymbol{\beta}_{vo}}{\operatorname{argmin}} \sum_{p \in ROI} \sum_{k} \lambda_k (\boldsymbol{\Phi}_k^{t+1}(p) - \boldsymbol{\Phi}_k^t(p')) \qquad (3)$$

where p' denotes the pixel corresponding to p under the current motion $\boldsymbol{\beta}_{vo}$. $\boldsymbol{\Phi}_k^t$ denotes the k-th feature at frame t, with weight λ_k. We use three feature types: image intensity

values, edge potential values, and distance transform values of the edge map. A Nelder-Mead simplex routine is used for minimizing the objective function. Also linear interpolation is used for non-integer pixel coordinates. We use the ESP measurement as initial estimation of $\boldsymbol{\beta}_{vo}$.

3) State Estimation: At this point, we have derived anchor constraints by matching satellite and camera images at anchor frames, visual odometry derived by matching two consecutive frames, along with GPS and ESP readings. GPS provides noisy absolute location measurement, and it is refined by anchor constraints. Similarly, ESP provides initial relative motion measurement, and it is refined by visual odometry. All measurements and constraints are then used for the final optimization.

The optimization starts with an initial state estimate using an Extended Kalman Filter (EKF) on GPS aiding odometry measurements. We then identify anchors using only input images. For a frame inside an anchor, we match its (Ex, Ey) with (Ex', Ey') that are computed similarly but using the satellite image patch centring and oriented at the initial state. Matching correlations are averaged within each anchor to obtain the unified anchor constraints, which gives anchor-wise optimal adjustments and covariances. Note that here we assume error propagation inside anchors is negligible.

The optimal trajectory $\boldsymbol{s}^{1:M}$ can be computed iteratively as a nonlinear weighted least squares problem as shown in [11] and [12]. The objective function is defined as

$$E(\boldsymbol{s}^{1:M}) = \sum_{i=1}^{M-1} (\boldsymbol{p}_{esp}^{i}{}^{T} \boldsymbol{C}_{esp}{}^{-1} \boldsymbol{p}_{esp}^{i} + \boldsymbol{p}_{vo}^{i}{}^{T} \boldsymbol{C}_{vo}^{i}{}^{-1} \boldsymbol{p}_{vo}^{i})$$
$$+ \sum_{i=1}^{N} \boldsymbol{p}_{gps}^{i}{}^{T} \boldsymbol{C}_{gps}^{i}{}^{-1} \boldsymbol{p}_{gps}^{i}$$
$$+ \sum_{i=1}^{K} \sum_{j=1}^{L_i} \boldsymbol{p}_{anchor}^{ij}{}^{T} \boldsymbol{C}_{anchor}^{i}{}^{-1} \boldsymbol{p}_{anchor}^{ij} \quad (4)$$

$$\boldsymbol{p}_{esp}^{i} = \boldsymbol{s}^{i+1} - \boldsymbol{s}^{i} - \boldsymbol{\beta}_{esp}^{i} \quad (5)$$
$$\boldsymbol{p}_{vo}^{i} = \boldsymbol{s}^{i+1} - \boldsymbol{s}^{i} - \boldsymbol{\beta}_{vo}^{i} \quad (6)$$
$$\boldsymbol{p}_{gps}^{i} = \boldsymbol{s}^{u_i} - \boldsymbol{s}_{gps}^{i} \quad (7)$$
$$\boldsymbol{p}_{anchor}^{ij} = \boldsymbol{s}^{v_{ij}} - \boldsymbol{s}_{init}^{v_{ij}} - \delta\boldsymbol{s}_{anchor}^{i} \quad (8)$$

where $\boldsymbol{C}_{esp}$, $\boldsymbol{C}_{vo}^{i}$, $\boldsymbol{C}_{gps}^{i}$, and $\boldsymbol{C}_{anchor}^{i}$ are respectively error covariances of ESP measurements, visual odometry at the i-th frame, the i-th GPS measurement depending on number of visible satellites, and the i-th anchor constraint. M, N, and K are numbers of frames, GPS measurements, and identified anchors. L_i is the frame length of the i-th anchor. u_i is the time for the i-th GPS measurement, and v_{ij} is the time of the j-th anchor frame in the i-th anchor, all in frame unit. $\delta\boldsymbol{s}_{anchor}^{i}$ denotes the i-th anchor constraint, i.e. unified optimal adjustment of all frames in the i-th anchor. We set the yaw dimension in all $\delta\boldsymbol{s}_{anchor}^{i}$ zero as the 2-axis 1D matching does not count orientation change. We use the version of Levenberg-Marquardt solver implemented in GTSAM [11,13] to optimize the final objective function.

Algorithm 1 The incremental optimization procedure for map updating

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1: **for** $t = 1 : M$ **do**
2:    **if** $t == 1$ **then**
3:       Set $\boldsymbol{s}^1$ as $\boldsymbol{s}_{gps}^1$
4:    **else**
5:       **if** Detect the end of anchor i, i.e. $t == v_{iL_i}$ **then**
6:          **if** $i > k_{opt}$ **then**
7:             Compute anchor constraints $\delta\boldsymbol{s}_{anchor}^{(i-k_{opt}):i}$, set $\delta\boldsymbol{s}_{anchor}^{i-k_{opt}-1}$ zeros
8:             Optimize and update $\boldsymbol{s}^{v_{(i-k_{opt}-1)1}:v_{iL_i}}$
9:          **else**
10:            Compute anchor constraints $\delta\boldsymbol{s}_{anchor}^{1:i}$
11:            Optimize and update $\boldsymbol{s}^{v_{11}:v_{iL_i}}$
12:          **end if**
13:       **else**
14:          Propagate $\boldsymbol{s}^M$ using EKF with $\boldsymbol{s}_{esp}^t$, $\boldsymbol{s}_{vo}^t$, and $\boldsymbol{s}_{gps}^{u_{k'}=t}$ if has new GPS reading
15:       **end if**
16:    **end if**
17: **end for**

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4) Final Image Generation: After the optimal states have been estimated, we render all orthographic views onto the initial satellite image background to generate final high resolution roadway image. To deal with overlapping areas, we first compute weights for every pixel in each frame, in inverse proportion to the pixel's distance to the camera. Only the pixel with the highest weight will be used in the final map. This is because areas closer to the camera have higher resolution and they are not as effected by the changes in roll and pitch angles during the drive. We also find out that keeping only the highest weighted pixel usually yields better image quality than other strategies such as weighted averaging.

C. Anchor-wise Incremental Optimization

The global optimization framework we just described requires all measurement being collected. However this is not desirable in practical mapping applications, especially when the data sequence is long. Therefore we further design an anchor-wise incremental optimization algorithm that allows map updating to be more efficient, as described in Algorithm 1. We combine our above method with EKF. Anchor-based matching and optimization are only triggered at anchor end frames. In addition, we apply optimization and updating only for the most recent k_{opt} anchors, one fixed anchor is also added to ensure continuity of the final trajectory. In our implementation we set k_{opt} as 3.

IV. EXPERIMENTAL RESULTS

In this section we present experimental results. We use an Audi A7 as our test platform, its original GPS, ESP, and an extra added forward looking (zero-tilt calibrated) color camera are used for data collection. Frame rates (fps) of the used GPS, ESP, and camera are respectively 1, 50,

TABLE II: Quantitative results of different methods.

	EKF	SFC	CI[6]	**Proposed**
mean error(m)	4.02	2.94	1.16	**0.16**
max error(m)	6.04	12.32	2.74	**0.78**
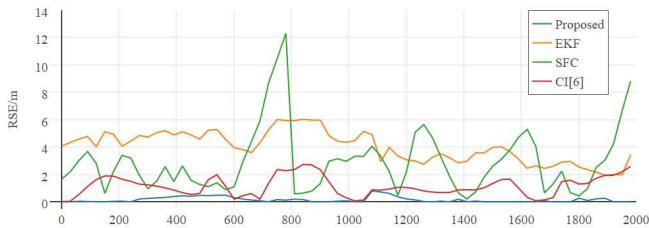
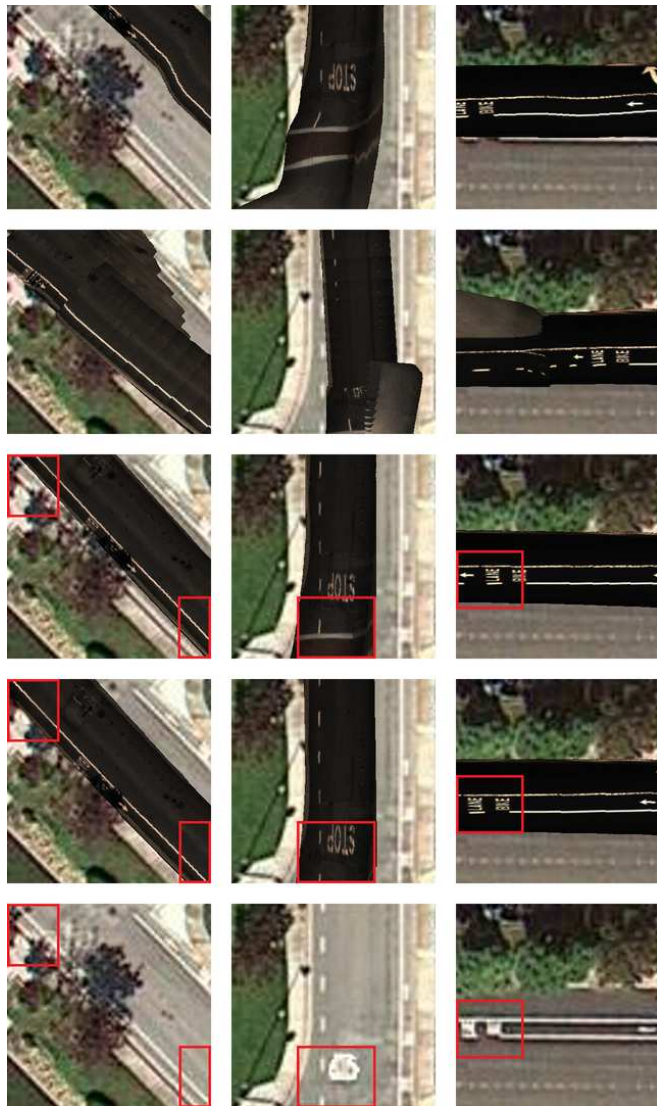Fig. 5: Diagram of errors over time.

Fig. 6: Qualitative results of different methods. Top to fourth row: results produced by EKF, SFC, CI[6], and proposed method. Bottom row: the original satellite image. Areas marked red show that the proposed method has better consistency with the original satellite image.

and 30. We stitch image patches from Google maps as the low resolution satellite image prior, assuming no distortion. The stitched map has resolution of $23.5cm/pixel$. We test our algorithm at Clipper Drive near Belmont, CA. The test sequence has duration of $215s$ and length of $1443m$.

We first evaluate the accuracy of our algorithm. To measure accuracy quantitatively, we select a 2000 frame subsequence (first $66.7s$ in attached video, length $439m$) and set one measure point every second. We manually align input orthographic views of measure points with the satellite image, and use them as ground truths. As comparison to our method, we also evaluate 3 other methods using the same data. The compared methods are: (1) Extended Kalman Filtering (EKF): applying EKF on GPS and ESP, without using any image information. (2) Single-Frame Correlation (SFC): using GPS, ESP, visual odometry, and camera-satellite image matching. Rather than anchor identification and anchor-wise constraints, single frame matching correlations are directly used for final optimization. (3) Calibrated Intersections (CI): this is similar to the method described in [6]. GPS, ESP, and visual odometry are used for positioning. The road network is divided into road segments, with the intersections of segments localized accurately. Table 2 and Fig. 5 show quantitative results of all evaluated methods.

From Table 2 and Fig.5, it can be seen that our method achieves higher accuracy than all three compared methods. In the EKF method no image information is used, thus high accuracy localization cannot be achieved due to limited precision of the low-cost GPS. In the SFC method, in addition to GPS and ESP, visual odometry and camera-satellite image matching are also used. This improves overall accuracy and produces lower mean error than EKF. However as no anchor strategy is used and all single frame correlations are directly sent to optimization, the final estimated states are severely affected by frames that are highly ambiguous and inaccurate. This explains why SFC produces high maximum error. In the CI method [6], 3 road segment intersections (around frame 10, frame 810, and frame 1680) are detected. While intersections are localized accurately, the distance between two intersections are relatively long and drifting error propogates

without being refined by any precise location constraints. This leads to error accumulation between intersections and impairs the final performance of CI. Our proposed method outperforms CI as it is able to detect anchors adaptively and calibrate itself using detected anchors. Our proposed anchor strategy automatically turns off inaccurate image matching results, thus avoids the problem of SFC. In this sub-sequence 8 anchors are identified.

In Fig.6, we show qualitative results of final maps generated by different methods. It can be seen that EKF produces low accuracy and images are not satisfactorily positioned, mainly due to GPS does not have sufficient precision. In SFC sometimes the images are positioned more accurately but sometimes not, also the final map appears to be jagged or twisted. This demonstrated that SFC fails to generate
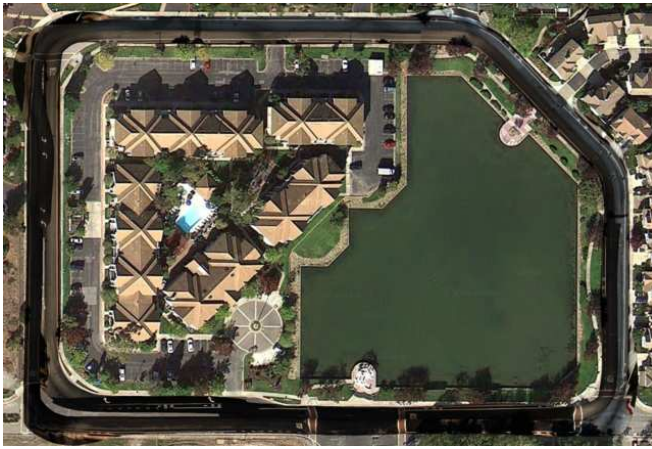
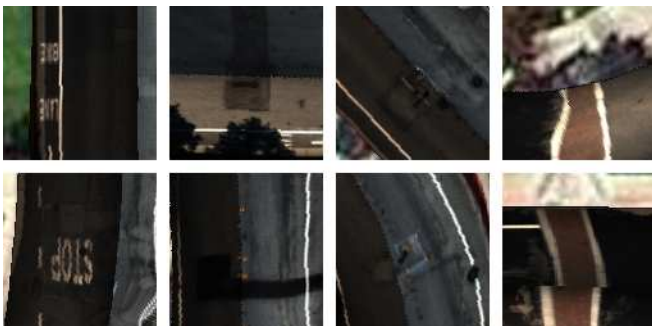Fig. 7: The final high resolution road image generated in our study.

Fig. 8: Examples from the final generated high resolution road image.

accurate map because inaccurate single frame correlations severely interferes final state estimation. Both CI [6] and the proposed method generate high quality maps. The proposed method has better consistency with the original map as aligned anchors impose stronger consistency constraints than calibrated intersections.

Fig.7 shows the final generated high resolution roadway image and Fig.8 shows example patches from Fig.7. In Fig.8, the first column shows two examples where the generated map shows clear lane marks, the second and third columns show examples that the generated map provides new detailed textures that cannot be observed from the satellite image. These examples imply the usefulness of the generated map in applications such as vehicle localization and intelligent self driving.

Though we are able to create generally satisfactory and useful maps, our method still has a drawback. As shown in the last column in Fig.8 some parts in the final map are distorted. This is mainly caused by the curvature of the road and/or sudden vehicle speed change. One way to solve this problem is to estimated full 3D camera poses including pitch and roll angles in visual odometry, instead of only 2D poses in Eq.3. However we choose not to do so as estimating 3D poses from stereo requires intensive computational power [10], which would significantly increase the hardware

requirements.

The multimedia attachment shows an example of our incremental optimization procedure, as well as detailed anchor positions.

V. Conclusions and Future Work

A case study for generating high resolution roadway images that are consistent with an existing satellite image was presented. Our method uses publicly accessible map resources and conventional low-cost sensors, indicating more potential probe vehicles and lower mapping cost. Our generated maps can be easily embedded into existing maps due to its high consistency. An anchor-based method was proposed to improve state estimation accuracy and mapping consistency.

This work can be extended to deal with curvature on the road, compensating for roll and pitch effects, and generating high resolution image that is invariant to lighting condition. Such a map can be used as vision aiding cue in localization methods.

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