Evaluation of Cross-View Matching to Improve Ground Vehicle Localization with Aerial Perception

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Abstract—Cross-view matching refers to the problem of finding the closest match to a given query ground-view image to one from a database of aerial images. If the aerial images are geotagged, then the closest matching aerial image can be used to localize the query ground-view image. Recently, due to the success of deep learning methods, a number of cross-view matching techniques have been proposed. These techniques perform well for the matching of isolated query images. In this paper, we evaluate cross-view matching for the task of localizing a ground vehicle over a longer trajectory. We use the cross-view matching module as a sensor measurement fused with a particle filter. We evaluate the performance of this method using a city-wide dataset collected in photorealistic simulation using five parameters: height of aerial images, the pitch of the aerial camera mount, field-of-view of ground camera, measurement model and resampling strategy for the particles in the particle filter.

I. INTRODUCTION

Consider a ground vehicle that is navigating in an environment. Localizing this vehicle in the global frame of reference (geolocalization) is critical for efficient planning. Geolocalization can be achieved by using the GPS onboard the vehicle. However, GPS can be noisy and unavailable at times, especially when operating in urban environments with tall building canopies [1]. In such cases, the localization is improved by using onboard vehicle perception (e.g., stereo, inertial sensors, and LIDAR). In this paper, we study a technique to complement onboard perception with cross-view matching for localization in a global frame.

Cross-view matching is the problem of finding an aerial image in a database of aerial images that is a closest match to a given ground-view query image [2] [3]. This requires learning to match images that are taken from different view points. This has widespread applications in situations such as identifying the location where a photo was taken from [4] and guiding ground-based navigation. Specifically, cross-view matching can be used for cross-view localization if the aerial images are geo-referenced. The aerial images can be satellite images or can be images that were taken from a lower altitude by an aerial vehicle. Every aerial image has latitude and longitude information of where the image was taken from. By matching a ground view to an aerial database we can predict the location of the query image.

Prior work has shown the potential for cross-view matching for localizing ground vehicles using satellite imagery [5], [6], [7], [8], [9]. In this paper, we perform a thorough evaluation of this technology. Specifically, we evaluate a recently proposed architecture for cross-view matching, called CVM-NET [10], in the context of localization of a ground robot over time. CVM-NET uses a Siamese neural network [11] that is trained on a database of paired aerial and ground images. The network learns to predict a similarity measure between two input aerial and ground images. This can be used during test time to take a ground-view query image and find its similarity to each image in the database of aerial images. Then, the highest similarity score (or the top-k highest scores) are used to retrieve the closest matching aerial images. The resulting system was shown to yield about 37% accuracy using Top 1 and 91.4% accuracy using Top 80 image retrievals from the aerial dataset.

The output of CVM-NET can be thought of as a noisy position observation of the ground vehicle at a given time instance. Over time, these noisy position observations can be fused using, for example, a particle filter [12]. Project Autovision [13] showed one way of integrating the output from CVM-NET in a particle filter to localize a ground vehicle. Their results yield a localization error of 9.92 meters in an urban environment and 9.29 meters in a rural environment over a route of 5km, indicating that this is a promising approach in situations where onboard perception is not reliable. However, their evaluation was restricted to one specific dataset, and one specific method of integrating CVM-NET and particle filtering. In general, there are a number of design choices one has to make that will affect the localization performance of the resulting system. The goal of this paper is to conduct an empirical analysis of exactly these design choices.

We focus on the following five design choices that may affect the localization performance:

1) The height at which the aerial images are obtained from. Prior evaluation was limited to images taken from one altitude. We expect that higher altitudes will lead to lower resolution images but ones that cover a larger area and therefore containing more information that could be useful in matching.

2) The field-of-view of the ground-view image. Prior evaluation only used a panoramic ground-view image (which can see more local information). It is not clear how regular images with narrower fields-of-view will...
affect performance.

3) The camera pitch of the aerial images. Prior work only used top-down images.

4) The output of CVM-NET is a similarity score with all the images in the database. When integrating it in a particle filter, one has the choice of using only the top 1 match, top k match, or use all the similarity scores (as was the case in the prior work).

5) The resampling strategy used within the particle filter.

The goal of this paper is to evaluate CVM-NET in the context of these five design choices. Specifically, we collected a large dataset of ground and geotagged aerial images in AirSim [14], a photorealistic simulator. Using this dataset, we conduct numerous numerical experiments to study the performance of CVM-NET localization. Our results can be helpful for a practitioner who is interested in using CVM-NET for supporting onboard localization and eliminating guesswork that is typically involved when making such design choices.

The rest of the paper is organized as follows. We begin by describing the related work in Section II. Then, we describe the overall architecture of the system that integrates CVM-NET and particle filtering in Section III. The experimental setup and results are discussed in Section IV. Finally, we conclude with a discussion of the related work in Section V.

II. RELATED WORK

Several prior work exists that exploit the large amount of geotagged images to address the geolocalization problem. Research on identifying the location of an image has been mostly studied as an image retrieval problem [15]. In a retrieval problem, one image from a database must be retrieved closely matching the query image. In [16], a vocabulary tree approach [17] typically used for object detection, is used to determine which features are best dependent on the location. Hays et al.[18] proposed a technique, termed IM2GPS, which uses geotagged photos from Flickr and then modeled the query image as a probabilistic distribution over the entire world. IM2GPS uses both the geographic location and the appearance of the query image to find a matching image that will have the geolocation information. In [19], the authors developed a system that could match and reconstruct three dimensional scenes of a city. This kind of three-dimensional model is used in [20] and [21] for localization. In all the above approaches, both the query and the database to be searched have the same view.

The second approach to geolocalization is the cross-view approach which is the focus of our work here. Cross-view, as defined earlier, involves taking images from different viewpoints to solve the problem of geolocalization. Recently, there has been significant progress on cross-view matching. Zhang et al. [22] used SIFT-based image matching and use the average of top three images to obtain the geotags for the query image. A more recent result is [15] where the authors use Faster R-CNN [23] to identify buildings in the query image and the testing set. They achieve cross-view matching using building identification and building matching. They observe that neural networks perform poorly for full-scale matching (a limitation that has since been overcome). They cluster the predictions together and take the mean of the geolocations of the reference building in the dominant set.

Hu et al. used a novel technique of using a generalized VLAD (Vector of Locally Aggregated Descriptors) layer called NetVLAD on top of CNN (Convolutional Neural Network) in order to extract view-point invariant image descriptors. They do it in a two step procedure. First, the local features from the image are extracted using a CNN and then the locally extracted features are converted into global image descriptors by clustering using a NetVLAD layer.

More recently, Regmi et al. [24] used Generative Adversarial Networks (GANs) to generate an aerial-view image, given a query ground-view image. They combine the features from the synthesized aerial-view and the ground-view image through a joint-feature-fusion network, to get a more robust representation. They show that this technique performs better than CVM-NET. Nevertheless, we chose CVM-NET over the GAN one, since the GAN based approach requires the query image to be passed through two networks for feature aggregation. This increases the overhead in computation which is particularly important for resource-constrained systems. Nevertheless, our focus here is not so much in designing a new cross-view matching algorithm, and is instead in evaluating how cross-view matching performs when it comes to localizing a mobile ground vehicle. We note that none of the aforementioned work evaluate the effect of cross-view matching on estimating a trajectory of the vehicle.

III. CROSS-VIEW MATCHING BASED LOCALIZATION FRAMEWORK

In this paper, geolocation refers to the 2D position of an agent with respect to some global frame of reference. Our framework for tracking a ground vehicle using cross-view matching and particle filter is shown in Figure 1. We assume that the ground vehicle has an initial estimate of its own position in the global frame, is equipped with an Inertial Measurement Unit (IMU) sensor, and has a forward-facing RGB camera. We also assume that there is an aerial-view dataset collected from a drone (or some low-altitude aircraft) equipped with a downwards-facing camera. Each image in the aerial-view dataset is a top-down view of the environment with associated geolocation or geotag.

As shown in Figure 1 a ground-view query image from the forward-facing camera is given as an input to the system along with the geotagged aerial-view dataset. The output produced by the localization system is the estimated position of the ground vehicle. Our proposed localization approach is a two-step procedure. First, we convert the ground-view query image and the aerial-view image into view-point invariant image descriptors for assessing the similarity between them. This is achieved using a Siamese based neural-network CVM-NET-I [10]. Secondly, we use a particle filter. Particle filters have three primary steps; sampling, prediction, and update. First, M particles are sampled from the prior distribution. In the prediction step, the IMU information
from the ground robot is used to propagate the particles at each time step. Our system uses the similarity information from the first step to update the weights of the particles in accordance with their posterior likelihood. Then, a new set of particles is sampled from this weighted distribution of particles. The estimated ground robot position is a weighted mean of resampled particles at every time step.

We propose two strategies for updating the weights of the particles and resampling. We will call these techniques Prediction-based Particle Filtering (PPF) and Compare-All Particle Filtering (CAPF).

**Prediction-based Particle Filtering (PPF):** CVM-NET solves a retrieval problem. The primary aim of retrieval is to find the $k$ nearest neighbours for a ground view query image in an aerial-view dataset. In PPF, the posterior distribution is updated using retrieval of the $k$ nearest neighbors from the aerial-view dataset, for a predetermined value of $k$. In the extreme case $k = 1$, in which case only the Top 1 retrieved image is used to update the posterior distribution. Figure 2 indicates the top 3 retrievals for the ground-view query image shown on the left.

We pass the query image and all the aerial-view images through the CVM-NET to convert them to image descriptors. Then at every time step, we retrieve the top $k$ nearest neighbours for the ground-view for that time step using the distance metric (Equation 1).

$$\text{Dist} = 2 - 2 \cdot \text{Grd\_descriptor} \cdot (\text{Sat\_descriptors})^T$$  \hspace{1cm} (1)

Here $\text{Sat\_descriptors}$ refers to the global descriptors of all the aerial view images in the test set while $\text{Grd\_descriptor}$ refers to the global descriptor of the ground-view image. The descriptors are learned by the CVM-NET and have individual dimension of $1 \times 4096$.

Once we have these predictions we use them as measurements in the particle filter estimations to update the posterior weights. The weight assigned to each particle is inversely proportional to the product of Euclidean distance between the particle and the position of each of the top $k$ predictions.

**Compare-All Particle Filtering (CAPF):** The CAPF methodology is adapted from project Autovision [13]. In this approach, the weight assigned to each particle is inversely proportional to the Euclidean distance between the image descriptors of the ground-view query image and the aerial-view image descriptor with a geotag closest to the particle position.

In the next section, we show an empirical comparison between these two methods (for different values of $k$) as well as study of a number of other design issues.

### IV. EMPIRICAL EVALUATIONS AND RESULTS

#### A. Dataset

![Fig. 3. Plot of the trajectories traversed by the aerial and ground robot. The trajectories used for training and testing are marked with red and blue colour.](image)

For training and evaluation, we generated our dataset using the photorealistic simulation API AirSim [14] which is a simulator for drones and cars built on the Unreal Engine. It
TABLE I
AIRSIM DATA COLLECTION PARAMETERS FOR AERIAL AND GROUND-VIEW IMAGE

| Altitude (meters) | 30 | 50 | 60 | 70 | 80 |
|-------------------|----|----|----|----|----|
| Field of View (degrees) | 90 | 120| 180|
| Pitch of downward facing camera (50 meter Altitude only) | -50 | -90 |

provides the functionality of spawning multiple agents in the environment and provides full control over their movements. It also makes it possible to model different weather and temporal conditions. Our current setup makes use of the pre-compiled binaries from City Environment in AirSim which is a large environment with moving vehicles and pedestrians. Figure 3 shows a plot of all the training and test data collection trajectories within the city. Our dataset consists of images collected from 5 different altitudes and 3 different fields of view (FOV) for a single scene. Hence, overall it consists of $5 \times 3 \times 2546$ pairs of aerial and ground view images spanning an area of approximately 1544.75 meters diagonally over the trajectories shown in Figure 3. We also collected the same number of images for two different pitch values for the downward-facing camera on the UAV flying at an altitude of 50 meters.

For any one run, we use 1679 images for training ad 867 images for testing. The dataset was collected by flying cameras at two different altitudes on the same trajectory and then fetching the images from these vehicles along with the positional information. However, the ground and aerial images are not perfectly synced; the paired positions are corrupted with a noise of $4.58 \pm 2.44$ meters. The combination of settings are shown in Table I.

A few sample images from the Airsim dataset are shown in Figure 3. When evaluating geotracking, we investigate the performance on the Complete dataset (which includes training and test images since it represents a complete trajectory through the city) and one that includes only the Test dataset (Figure 3).

B. Experiments

In this section, we present the experiments conducted to evaluate the performance of particle filter localization. The primary theme of this section is to test the performance of the localization system across system-level design choices and various data collection settings. The system level parameters include altitude of aerial images, Field of View (FOV) of ground images, and pitch of the aerial-view camera. For evaluation of design choices, we compare the PPF and CAPF methodology mentioned in Section III.

1) Prediction Particle Filter versus Compare-All Particle Filter: We initialize the particle filter by sampling 200 particles around the initial location from a Gaussian distribution with a standard deviation of 4 meters. The ground truth velocity obtained from the IMU data is artificially corrupted by a diagonal covariance matrix of standard deviation 1 meter to simulate real-world noise. This is used for propagating the particles in the update step.

As described in Section III PPF, and CAPF methodologies primarily differ in the weighting scheme for the particles. In PPF, the weight assigned to the particle is inversely proportional to the L2 norm of the particle position minus the top 1 prediction. In CAPF, the weight assigned to the particle is inversely proportional to the L2 norm of the image descriptor of the aerial image closest to that particle and the ground-view query image. Figure 5 shows the performance of CAPF over the AirSim dataset with stochastic resampling while Figure 6 shows the performance of PPF with top 1 prediction over Airsim dataset with rejection sampling. We will explain in Section IV-B.2 why...
Fig. 5. Localization performance for CAPF particle filter with Importance sampling

Fig. 6. Localization performance for PPF particle filter with Rejection sampling
rejection sampling is used with the PPF application. It can be observed from Figures 5a, 5b, 6a and 6b that even though PPF was very close to the CAPF in terms of localization error, CAPF is more consistent than the PPF approach.

2) Resampling Strategy: The basic strategy used for resampling particles in a particle filter is called rejection sampling [25]. In rejection sampling, we make use of a function \( f(x) \) with a value between 0 and 1 and a threshold value, \( t \) which is sampled at every time step from a range \([0, 1]\). If the particle \( x \) sampled has \( f(x) > t \) it is kept, else the particle is discarded. However, this strategy requires the particle filter to be initialized with a very high number of particles. This makes it slow to use in practice. Stochastic importance is a practical sampling method meant to alleviate this issue. Importance Sampling (IS) is a well-known Monte Carlo technique. Given a distribution \( g \) we can use another distribution \( f \) to generate samples from \( f \). Importance weight \( w = \frac{f}{g} \) accounts for the difference between \( g \) and \( f \). \( f \) is called the target distribution while \( g \) is called a proposal. In a particle filter a Cumulative Distribution Function (CDF) of the particles is used as the target distribution. In implementation, a random number is chosen from a range \([0, 1]\). Then a binary search is performed on the CDF to find which bin the number falls into. Then, the particle is selected [26]. This makes importance sampling faster than rejection sampling. Thus, we decided to use importance sampling with the CAPF. However, it did not work well for the PPF filter which can be seen from the Table I.

We observed that importance sampling made the filter very sensitive to the outlier incorrect predictions, which made the filter perform poorly. Hence, we resorted to using rejection sampling as the sampling technique for PPF. We modified it as follows: whenever the effective number of particles becomes less than half of the initial value all the previous weights should be discarded. A new set of particles is sampled around the current estimate with a higher variance and equal weights are assigned to each particle. This made the PPF robust in case of outlier measurements/predictions. All the values reported in Table I are averaged over 5 runs.

3) Evaluation across different altitudes: We performed five different experiments to analyze the effect of the altitude of aerial image collection on the localization performance. For each altitude, we trained a separate network for cross-view matching and then used the aerial and ground view descriptors generated by this network to do the particle filter localization. It is important to assess the trade-off between altitude and cross-view localization performance as it might not always be possible to fly the aerial robot at a given altitude.

It can be seen from Figure 7 that the top 1% recall accuracy was highest for an altitude of 30 meters. This is the accuracy of individual measurements. However, the localization error is approximately the same for both Complete and Test datasets as shown in Figure 8a and Figure 8b respectively. The results presented are averages over five runs of the particle filter.

![Fig. 7. Comparison of recall accuracy for test data for different altitude values. All values are averaged over epoch 20 to 100 and the standard deviation in accuracy indicate the convergence of the model.](image)

![Fig. 8. Plot for localization error (L2 norm) and dead reckoning for comparison of particle filter performance across different altitudes.](image)
4) Evaluation over different Fields-of-View: Field-of-view of the ground vehicle also plays an important role in cross-view scene understanding. Thus, we analyzed the performance of our localization pipeline across three different fields of view and assessed the trade-off between FOV, recall accuracy, and localization error. The performance of all of these FOV is analyzed for an altitude of 50 meters. For 1% recall accuracy, the 120-degree field of view performed the best as seen from Figure 9. However, when it came to the localization errors, all three FOV performed approximately the same, as seen in Figure 10a and Figure 10b.

5) Pitch: Changing the pitch of the camera mount is a small adjustment that can change the amount of information contained in an image and thus the performance of both retrieval and localization. This hypothesis was justified by our experiments conducted for two different pitch values for an altitude of 50 meters. Changing the pitch from -90 degrees (top-down) to -50 degrees (look-ahead) gave a significant boost in the retrieval performance as seen from the Table III. This also resulted in better localization performance.

V. DISCUSSION

In this paper, we investigated the performance of cross-view matching as it is applied to localization of a moving vehicle. Prior work had shown that cross-view matching techniques, such as CVM-NET, can successfully retrieve aerial images that are closest to a given query ground-view image. In this paper, we show how this can be used, along with a particle filter, to improve the localization of a ground vehicle. In our experiments, cross-view matching was the only perception module used. However, in practice, one would combine cross-view matching along with onboard perception.

We evaluated CVM-NET through five design choices. We have the following conclusions: (1) We find that instead of choosing top $k$ nearest neighbors, using all the images in the aerial database to weigh the particles performs better. The localization error is similar but the consistency of the latter is better. We conjecture that this is due to the susceptibility of the top $k$ retrievals to outliers. (2) We find that stochastic importance sampling is better suited for the CAPF approach. (3) We find that although the retrieval accuracy improves as the altitude of aerial images decreases, the localization performance over a trajectory is unaffected. This is because the retrieval accuracy only depends on the top $k$, whereas the localization accuracy depends on how close the global descriptors are. Along a trajectory, we expect similar aerial views. Say there are two aerial images taken close to each other. Similar views will get similar global descriptors. Therefore, in the CAPF approach, they will give similar weights to nearby particles. However, unless you select the exact image from the top, the retrieval accuracy will be hampered. We believe this is why although the retrieval accuracy decreases with increasing altitude, the localization performance is largely unaffected. (4) Similar conclusions can be reached for fields-of-view. Higher field-of-view leads
to better retrieval (only marginally) but similar localization performance. (5) However, the pitch of the aerial images has a significant impact. Top-down aerial images perform poorly as compared to front-facing ones.

We expect the observations from this paper can eliminate some of the guesswork in deploying cross-view matching for localization. An immediate avenue for future work is to evaluate this through field experiments. Since cross-view matching has been extensively evaluated with real-world data, we expect the results to be similar.

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