High-Fidelity Simulation for Evaluating Robotic Vision Performance

John Skinner[1], Sourav Garg[1], Niko Sunderhauf[1], Peter Corke[1], Ben Upcroft[1], Michael Milford[1]

***Abstract*— Robotic vision, unlike computer vision, involves processing a stream of images from a camera with time varying pose operating in an environment with time varying lighting conditions and moving distractor objects. The consequence is that no robot vision experiment can ever be repeated and the performance of different algorithms cannot be compared since they are conducted under different conditions. For machine learning applications a critical bottleneck is the limited amount of real world image data could be captured and labelled for both training and testing purposes.**

In this paper we investigate the use of a photo-realistic simulation tool to address these challenges for the problems of: robust place recognition, visual SLAM and object recognition. For the first two problems we generate generate images from a complex 3D environment with repeatable camera paths and lighting conditions. For the first time we able to show how the peformance of these algorithms falls off as paths and lighting conditions change. We also compare algorithm results for a camera in a real environment and a simulated camera in a simulation model of that real environment. For object recognition we generate labelled image data to train a deep network which we demonstrate is able to robustly recognize the real-world version of the simulated objects.

I. INTRODUCTION

Robotic vision involves processing a stream of images from a camera attached to a robot moving through a physical environment. The pose of the robot's camera is controlled and is a function of previous images. The environment typically has a complex 3D structure with transient distractor objects of unknown type and motion, as well as time varying lighting conditions. An important consequence is that no robot vision experiment can ever be repeated. Nor can the performance of different algorithms be compared, as they are in computer vision research, since they will be evaluated under different conditions: the robot initial conditon may vary, the lighting may vary, and the camera path which is a function of previous images may vary.

In contrast, progress in computer vision research is driven by datasets of images which are are static, not temporally related and there is no scope for the algorithm to request a slightly different view of the scene as is possible in robotic vision. Computer vision research has recently made giant strides in performance through the use of deep learning, but this is fundamentally limited by the amount of representative real world image data could be captured and labelled for training and testing purposes.

In this paper we propose the use of a state-of-the-art photo-realistic simulation tool, the Unreal Engine 4 by Epic Games, to address these challenges. This tool, developed for gaming, allows the creation of complex 3-dimensional worlds that are realistically rendered. The view from a camera at any arbitrary pose can be obtained and this allows us to mimic the motion of a robot through the environment, and the robot can one or many cameras. We can also change the illumination conditions, adjusting the position of the sun, the cloud conditions, artificial light sources and atmospheric conditions such as fog. A particular advantage is that ground truth is known, camera poses and object positions estimated by robotic vision algorithms can be compared against the simulation state.

The key contribution of this paper is studying the efficacy of this new tool for robotic vision, in particular evaluating algorithms in a systematic and repeatable manner, and generating synthetic data for training deep networks. We test our ideas for three common robotic use cases. Firstly, robust place recognition using the SeqSLAM[11] algorithm. We capture a reference path through the world at a particular time of day and then evaluate precision-recall (which we summarise as F1 score) for different paths through the world and for different lighting conditions. The simulation allows us to change the path and the lighting independently – something that cannot be done when capturing image sequences from the real world. Secondly, for visual SLAM we evaluate the performance of OrbSLAM in an environment where the ground truth is known (the simulation model and camera path) and the camera path and lighting conditions are varied. Thirdly, we look at object recognition. We use the simulator to render millions? of training and test images which we use to teach a deep network for object recognition. The images vary in camera pose, object color and texture, and shape. We evaluate the performance of that network on real images of the same objects captured under different conditions.

The next section presents prior work in the area and introduces the tools that we use. Sections ??-?? evaluate our approach for robust place recognition, visual SLAM and object recognition. Finally Section ?? presents our conclusions and future work.

II. PRIOR RESEARCH

A. Simulation

The use of simulation in robotics is not a new idea. Popular robot simulators such as Gazebo [7] and Player/Stage [5] have existed for many years, and are commonly used to test robot motion and control. The use of game engines for robot simulation is also not new, with the USARsim project based on the Unreal Tournament 3 engine [1], and other projects

[1] Australian Centre for Robotic Vision, Queensland University of Technology, 2 George St, Brisbane, Australia

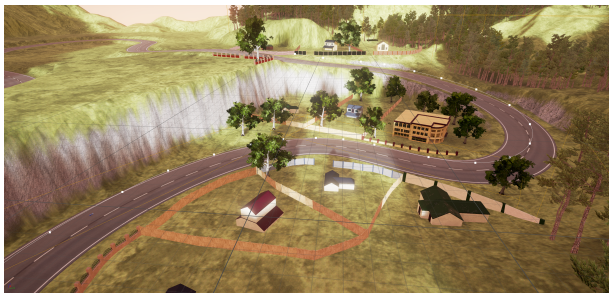

Fig. 1. The street scene used to capture the image datasets that were used for testing the place recognition algorithms. The line of white dots shows the baseline path followed by the camera when generating the datasets to test Sum of Absolute Differences matching and SeqSLAM. OrbSLAM test datasets follow a slightly different path so that they can loop their way around and end where they started.

using the Unity engine [8]. Nobody has yet made use of modern, high-fidelity engines such as Unity 5 or Unreal Engine 4 (the successor to the Unreal Tournament 3 engine).

The more specific field of robotic vision has not seen much application of simulation at all, it instead prefers to work from image datasets captured from the real world. The key requirement for simulation in computer vision is that the simulator is capable of photo-realistic rendering and lighting, which has historically been out of reach for older platforms, including the Unreal Tournament 3 engine or Gazebo. Unreal Engine 4 however has powerful tools for realistic materials and lighting [6], which make it possible to create simulated environment that produce images similar to the real world.

Unreal Engine 4 has a number of additional advantages that make it suitable as a simulator platform for computer vision. It is developed and maintained by Epic Games Inc, and uses physics and modelling tools from nVidia, which allow for complex and interactive dynamic environments. It also allows full access to it's source code, allowing a stimulation designer complete control over the simulation. It is also free for non-commercial uses, including research.

B. Place Recognition and Visual SLAM

A place is defined as a distinct 2D or 3D location in the representation map of environment. In robotic vision, visual places are described using the image features which can be broadly classified into local and global image descriptors. The most common and efficient approaches for recognizing a place revisited by a robot make use of Bag of Words approach with features, for example, SURF in FAB-MAP [3] and ORB in ORB-SLAM [12] etc. Some extensions of such methods also include building vocabulary online in an incremental fashion or incorporating geometric constraints between words for better performance. These methodologies allow a wide baseline matching of places, but they are brittle towards vast changes in appearance of the environment. On the other hand, use of global image descriptors like BRIEF-GIST [17] or patch-normalized downsampled images as in SeqSLAM [11] allows matching across change in conditions, but lacks robustness towards viewpoint variations. There are some place recognition methods which have proven to work well with both condition and viewpoint variations as in [9], [10] and [14]. Some of the methods describe places in 3D using only monocular camera by employing Structure from Motion (SfM) techniques. This helps in sparse [12], semi-dense [4], [15] or dense [13] reconstruction of environment for visual SLAM and other similar applications.

The main challenges in place recognition lie in robustness towards both change in conditions and viewpoint of a place. The environments with bland and texture-less images, motion blur, and effects introduced by camera properties like rolling shutter, granular noise etc. make it even more challenging to develop a strong place recognition algorithm. The visual S-LAM systems apart from performing visual place recognition also comprise of visual odometry and a mapping backend. The overall challenges for such systems are related to consistently calculating camera motion between keyframes/frames, relocalizing camera position when tracking fails, handling dynamic changes in the environment, performing efficient loop closures to get rid of scale drift in the map, and efficient 3D map construction.

A robust place recognition or SLAM system needs to be tested for all the challenges mentioned above and in different types of enviroments for a complete analysis of its performance. Such an in-depth analysis is often limited by lack of variety in the test datasets or bias towards chosing a test set that works for the assumptions made by the particular algorithm. The existence of high fidelity simulated enviroment where the content of it can be fully controlled thus provides a great tool for thorough performance analysis and is not being currently done to the extent we present in this paper.

III. ANALYSIS OF PLACE RECOGNITION

To demonstrate the effectiveness of high-fidelity simulation as an analysis tool for computer vision, we performed an in depth analysis of the viewpoint and time-of-day invariance of two different state-of-the-art place recognition algorithms, SeqSLAM [11] and OrbSLAM [12]. Then, to demonstrate the versatility of we performed an analysis of the viewpoint dependence of object recognition.

A. Simulation Setup: Unreal Engine 4

The simulation tool used in this paper was the Unreal Engine 4, developed by Epic Games Inc.

All of the test images used were generated from the same street scene, shown in Figure 1. The 3D models used were either sourced for free from TurboSquid (www.turbosquid.com), with significant manual clean up, or were produced manually. The landscape was produced using the basic version of WorldMachine (http://www.world-machine.com). All lighting is as computed by the Unreal Engine, using standard sky and light assets provided with the engine.

To generate the image data, the camera was made to move along a specified path and produce images at fixed intervals. The simulator allows us to precisely repeat the same path, and introduce calculated and precise variations upon it. In

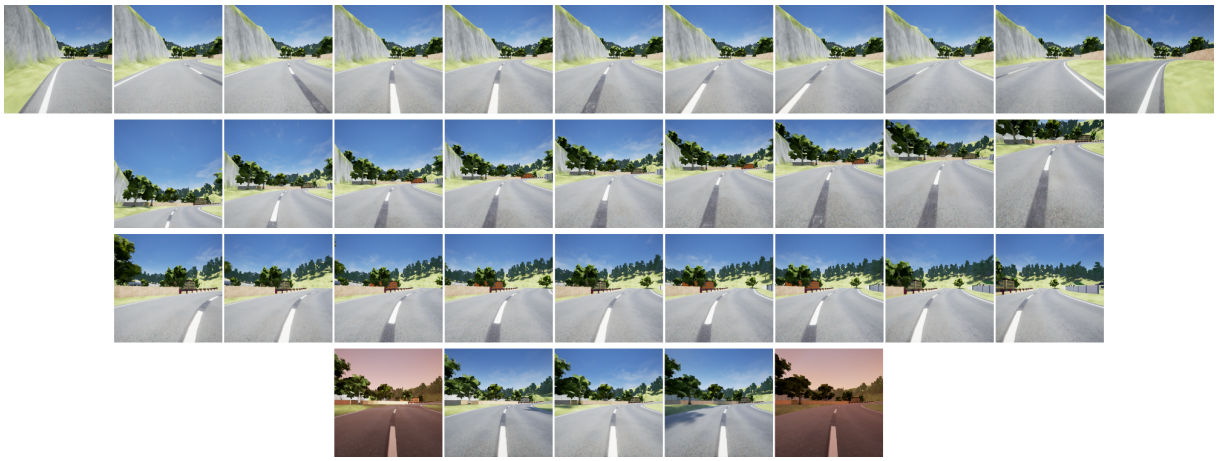

Fig. 2. A Sample of the variation found in the datasets used for testing. The first row shows lateral offset, from left to right, images are offset are left 3.5m, 2m, 1m, 0.4m, 0.2m, Then the baseline, then offset right 0.2m, 0.4m, 1m, 2m, and 3.5m. The second row shows vertical orientation change, left to right, images are angled are up 30°, 15°, 10°, 5°, Then the baseline, then angled down 5°, 10°, 15°, and 30°. The third row shows horizontal orientation change, from left to right, images are angled are left 30°, 15°, 10°, 5°, Then the baseline, then angled right5°, 10°, 15°, and 30°. Finally, the lowest row shows samples of time of day variation, from left to right, images are taken at dawn, in the morning, at noon, in the afternoon, and at sunset.

order to explore how the performance of place recognition changes with time of day and viewpoint change, passes along the path were generated for 5 different times of day in combination with increasing lateral offsets or camera tilts (Figure 2).

B. Place Recognition: Sum of Absolute Differences

The first test we did was on simple place recognition using simple sum-of-absolute-differences (SAD) based image matching. While this is neither state-of-the-art nor particularly effective, sum-of-absolute-differences is a common metric which is used in many computer vision algorithms, including SeqSLAM discussed below. As such, an analysis of its performance characteristics is potentially interesting.

Before matching, each image is down-sampled to 64x64 pixels and reduced to greyscale, in order to save computation time. The matcher used compares each image in a query dataset to each of those in a reference dataset, and considers the reference image with the lowest sum of absolute difference to be a match. The performance is then the percentage of images for which the matched reference image is taken from a place close to the query image.

The matcher is tested using 130 different combinations of time of day and viewpoint changes, so that we can see how the performance falls off as both increase. The results are summarized in Figure 3.

Figure 3 shows that SAD-based matching seems to be relatively robust against small lateral offsets, falling of after approximately $2m$. There is similar falloff as time of day approaches sunrise or sunset, and seems to be relatively symmetrical. The small number of samples makes this change seem relatively smooth, but it also seems plausible that it may instead change rapidly around dawn and sunset when the lighting change has the most effect. Resolving this is simply a matter of sampling the distribution further.

Interestingly, matching rate falls off similarly with angle change irrespective of the direction of change (compare the lower two plots in Figure 3). Matching performance seems to follow an exponential decay with angle, but additional sampling would need to be performed to verify that hypothesis. It may also be worth investigating the effects of multiple orientation offsets combined together to see how they compound. Were it the aim of this paper, it would be relatively simple to generate additional required sample passes to properly evaluate, but it is beyond the current scope.

C. Place Recognition: SeqSLAM

The first full place recognition algorithm we investigated was SeqSLAM, first described by Milford and Wyeth [11]. SeqSLAM is a place recognition algorithm that searches for loop closures by attempting to match sequences of similar images. It measures image similarity using sum of absolute differences as analysed in the previous section.

To perform the test, we generated 130 passes across 5 times of day and 26 different viewpoint variations from the street scene used in the other tests (figure 2. We chose the baseline pass at noon as the reference dataset, and compared it to all 130 of the other datasets (including itself). For each dataset we calculated the maximum F1 score, the results are summarized in Figure 4.

The first immediately obvious result is the anomalous low performance values for a left 0.2m offset in the morning and at sunset, and the low performance across all times of day at a 10°vertical orientation change. All of these changes are sudden and extreme, so the initial inclination is to sample around these points to see if there is a smooth or sudden decline. Based on the results of tweaking the parameters however, it seems more likely that SeqSLAM performance is sensitive to having achieved a certain level of matching, and that it will either perform very well or badly, rather than smoothly transition.

The other feature of note in the performance characteristics is the way the F1 score plateaus for translational offsets

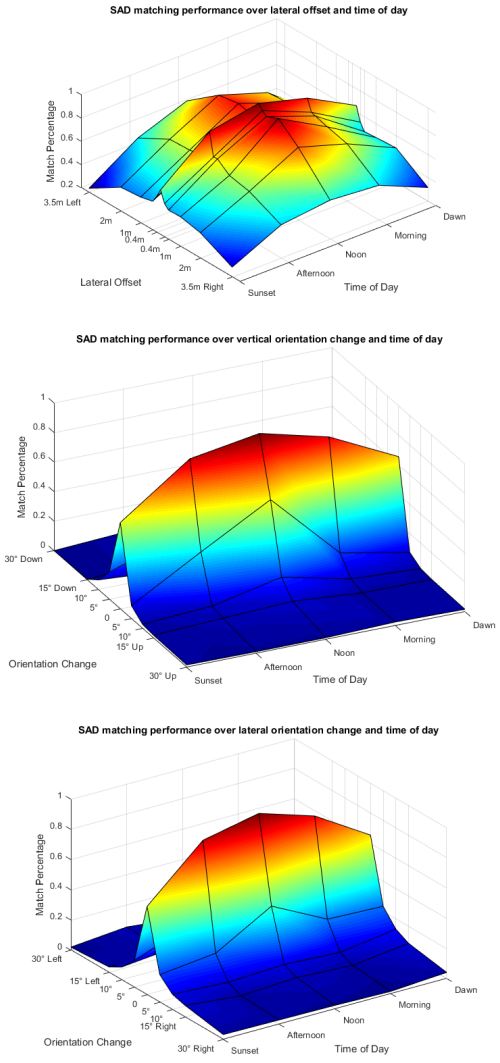

Fig. 3. Match percentage for Sum of Absolute Differences for, from top to bottom, lateral offset, vertical orientation change (pitch), and lateral orientation change (yaw). Each offset was tested across several times of day.

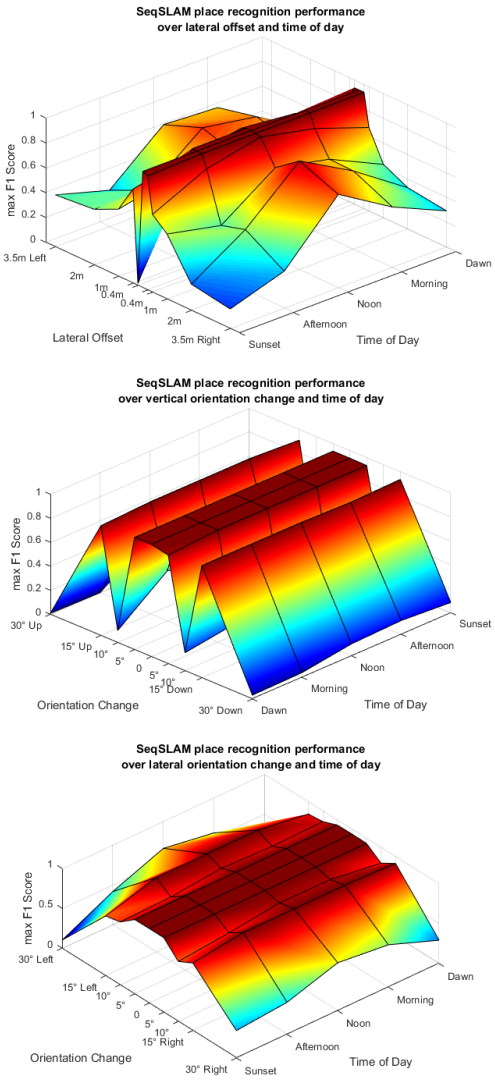

Fig. 4. SeqSLAM performance over, from top to bottom, lateral offset, vertical orientation change (pitch), and horizontal orientation change (yaw). Each viewpoint change is captured over 5 times of day to show how performance degrades over both viewpoint and condition change

of less than 1 and orientation changes of 5°. When the algorithm performs well, it seems to do so irrespective of the time of day. Strong condition invariance has been noted in previous work as a particular feature of SeqSLAM [11], so it is good to see it confirmed here. Note however that when the performance falls off, it becomes less condition invariant, falling off further toward sunset and sunrise.

Using high-fidelity simulation has allowed us to explore the behaviour of SeqSLAM more comprehensively than ever before, and has revealed new details of its behaviour. Further investigation will be required to find the reason for this, which will lead to it becoming more reliable and even more robust.

D. Visual SLAM: ORB-SLAM

The second algorithm tested was ORB-SLAM [12]. ORB-SLAM is a feature-based monocular SLAM system, that performs feature-based visual feature tracking, place recognition, mapping and loop closure using ORB features.

To test OrbSLAM, we again generated a variety of image datasets from the same street scene, with 5 different times of day, a baseline pass and 20 different viewpoint variations. Due to the mapping element of OrbSLAM, all datasets were made to start and end in the same place. To test the performance, each of the datasets was appended to the noon baseline dataset (acting as a reference pass), and camera trajectories were generated. These trajectories were then compared with the ground truth to calculate the Absolute Trajectory Error after aligning their scale. Results are summarised in Figure 5.

The observed performance of ORB-SLAM is patchy, error seems to range inconsistently, irrespective of the viewpoint or conditions. Even the baseline datasets with no viewpoint change between the passes have trouble sometimes, such as

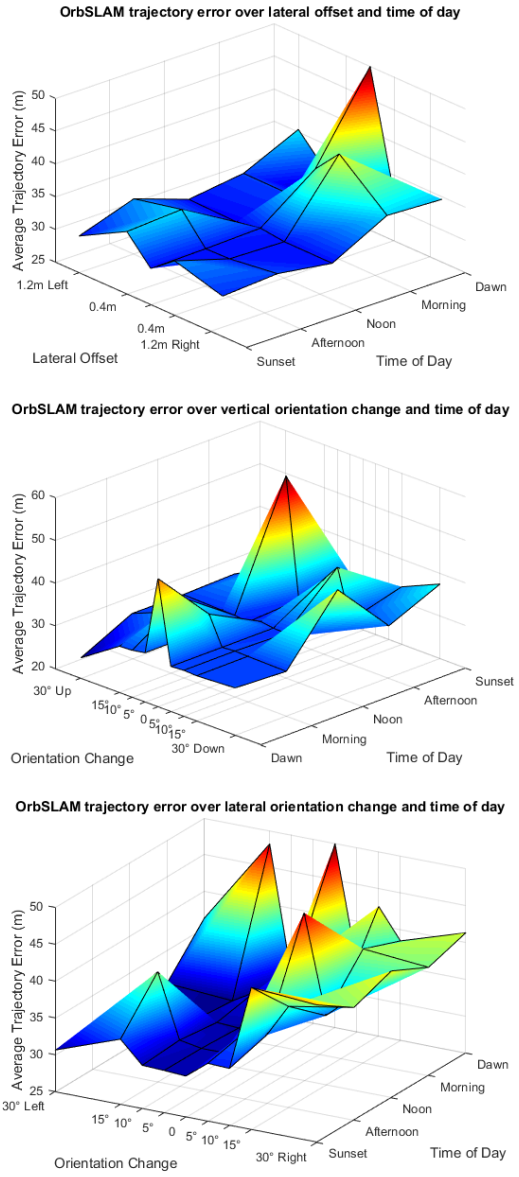

Fig. 5. ORB-SLAM average trajectory error over, from top to bottom, lateral offset, vertical orientation change (pitch), and horizontal orientation change (yaw). Each viewpoint change is captured for 5 different times of day.

in the morning pass. On the other hand, the performance of the algorithm doesn't seem to depend on viewpoint or time of day at all, but on other factors not controlled in our data. In the end, the inconsistent performance of ORB-SLAM under comprehensive testing is a question for the developers.

E. SeqSLAM parameter tuning

The detailed analysis we have performed can be used to inform subsequent actions, including parameter tuning. To demonstrate this, we again tested the performance of Sum of Absolute Differences on the noon datasets across the range of lateral offsets shown in Figure 2 with a variety of different offset window parameters. SeqSLAM uses Sum of Absolute Differences combined with an offset window parameter that

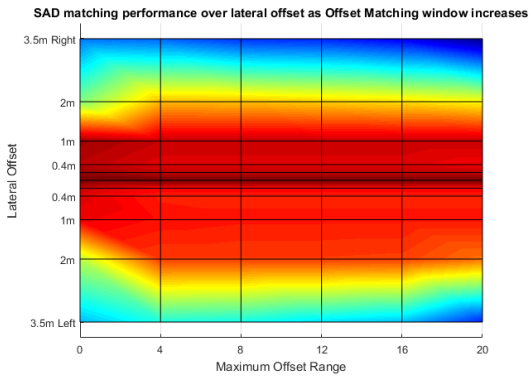

Fig. 6. Sum of Absolute Difference matching rate as the maximum offset window is increased. This result helps us choose a maximum offset appropriate for a given lateral offset

shifts the image pixels to achieve a better matching image. The results of this test can be seen in Figure 6.

This data suggests that for distances up to 3.5m offset from the reference location, it is best to use the smaller 4 pixel window range. The use of an offset window shows clear improvement in performance, but larger windows may introduce false matches. Larger windows may be appropriate to larger offset, and if necessary we could easily have tested this by generating more data and extending the experiment.

Benefits of Simulation: The performance curves generated using simulated datasets for SeqSLAM show a peculiar behaviour for certain parameter values. This enables a comprehensive evaluation of the algorithm for such cases which is not expected in general. The corresponding input parameters of SeqSLAM which might have caused the unexpected intermittent performance drop as shown in the Figure 4 could be the *Offset Matching Range* and/or *Patch Normalization* factor.

F. Comparison to real-world

It is important to verify that performance change in simulation is representative of performance change in the real world. To test this, we compared performance drop over lateral viewpoint change using SeqSLAM for data from a real street and for data generated from a simulation of a similar street. The results can be seen in Figure 7.

Unsurprisingly, observed performance is consistently better in simulation; we ascribe this to a lack of sufficient realism in the simulation, which was built simply and quickly. However, the performance follows the same trends in both environments, falling off smoothly as the offset difference increases. This demonstrates that performance results obtained in simulation obey similar trends to data obtained from even simplistic simulations.

IV. Analysis of Object Recognition Viewpoint Dependency

Another area of robotics research that can benefit from high fidelity simulation is visual object recognition and detection. Much of the recent progress in this field has

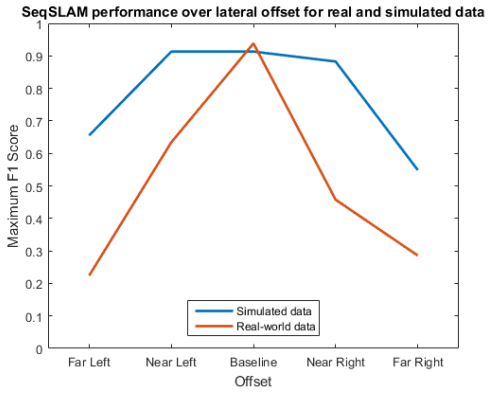

Fig. 7. Comparison of SeqSLAM performance falloff between simulated and real-world environments as lateral offset increases. As is often the case, simulated performance is better in an absolute sense, but the trend is the same in both cases. This data was not compared across multiple times of day.

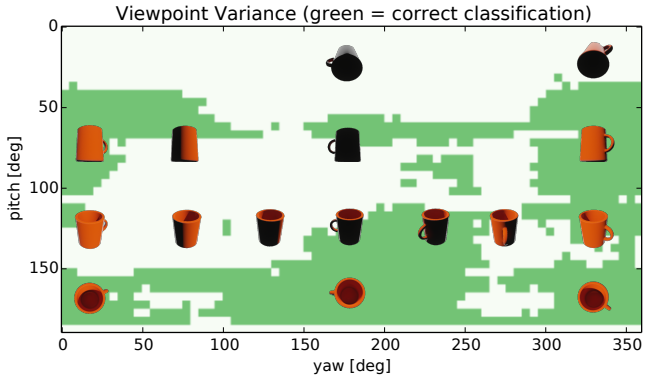

Fig. 8. Simulated viewpoint-dependency test for the `vgg_s` convolutional network [2] on a coffee mug object. Successful recognition (green) requires the mug handle to be clearly visible and the object to be well-illuminated.

been driven by the computer vision community's intensive race to achieve ever improving performance on large image recognition datasets like ImageNet [16] that is curated from large online photo repositories. State-of-the-art deep learning techniques now rival or surpass human performance and often approach perfect performance on these test sets. Rationally, related research fields such as robotics should be the beneficiary of such significant advances, but with a few exceptions, deep learning techniques have made little headway into the robotics field. Perhaps the primary reason for this disconnect is that robots operating in unpredictable, real world environments encounter visual imagery with very different characteristics and biases (or lack of biases) to that seen in traditional computer vision datasets.

The high-fidelity simulation framework discussed in this paper allows to render realistic views of arbitrary objects from different viewpoints, under different lighting conditions, backgrounds, and occlusions. Such a dataset enables an in-depth analysis of current object recognition approaches to understand under which conditions and viewpoints good performance can be expected, and to inform and improve the training process to address the discovered challenges.

To demonstrate the potential of such analyses, we perform a viepwoint dependency test for an exemplary state-of-the-art convolutional network for object recognition. We use the simulation framework to generate views of a coffee mug object by moving the camera around the object on a sphere. We increment pitch and yaw in 5 degrees steps while letting the camera point at the object centre. The generated images were then classified by the `vgg_s` convolutional network [2] and we record successful or wrong classification. Fig. 8 illustrates the results and reveals the object-specific viewpoint dependency: The mug could only be correctly identified when the handle was clearly visible, sticking out to the side. Furthermore, even with the handle visible, the classification failed under insufficient lighting conditions (e.g. in the area around pitch 175, yaw 100). Interestingly the mug can be identified correctly if seen from above, i.e. looking inside the mug (pitch 175 degrees), but not when observing the mug from below. Such insights can help improve the training process of object classifiers and the simulation framework can even be used to generate more training data from viewpoints or under conditions that are hard to replicate in reality.

V. DISCUSSION

The most difficult and time consuming aspect of using high-fidelity simulation is creating the scene in the first place. Scenes are built of 3d models and textures, which are first time consuming to create, and then take even more time to arrange in the scene. The more realistic a scene is required to be, the longer both of these stages take. The creation of high quality 3D models and scenes is the speciality of a professional 3D artist, so if a particular problem requires large or realistic scene it may be necessary to hire a 3D artist to construct it. It can also be extremely difficult to maintain a consistent scale throughout the scene. Examination of our scene in Figure 1 will reveal a myriad of scale flaws, note for instance the height of the houses relative to the width of the road.

However, once a particular simulation has been created, it can be used to generate arbitrary amounts of image data. Once we had constructed the street scene and the tools set up, actually capturing each dataset can be specified programatically and takes relatively little time. Indeed, when we initially created the datasets used to test the place recognition algorithms above, we tested orientation change at 30° and 15° only. However, after observing the way matching performance falls off with angle in Figure 3, we were able to very easily add tests for 5° and 10° orientation changes as well. The very fact that we can exactly repeat a movement through a scene with a precise orientation change is a powerful advantage of high-fidelity simulation.

It can in some sense be too easy to capture data. Since capturing additional data is often simply a matter of adding a new modifier to a path, increasing a sample range or decreasing a sample increment, it can be very easy to generate too much data. For instance, it may be tempting

to sample a street scene such as ours at every offset up to 4m either side in 1m increments, and at each location take all vertical and horizontal changes up to 30° in 5° intervals. This is relatively simple to specify, but when multiplied out, produces $9 \times 13 \times 13 = 1521$ images per forward step down the path. The path we used with a step distance of 1m as well requires 612 forward steps, for a total therefore of 1965132 images. When capturing datasets ourselves, we averaged about 6 frames per second, so collecting all this data would take approximately 91 hours. It's easy to see how tweaking any of the specified numbers could multiply this number even further.

Rather than sampling densely with a large initial dataset, we recommend initial testing be done relatively sparsely over the test domain, and then using the initial results to choose a second round of test values. For instance, given the distribution for vertical orientation change in Figure 3, it makes more sense to generate new test data at 2.5° and at 7.5° than at 25°. In the future, it should be possible to automate this iterative testing, automatically choosing new test datasets based on the results of previous testing.

It is also important to note that the difficulty of a particular change to the simulation can be non-intuitive. For instance, it is very easy in the simulation to change the location or orientation of an object or the camera; or to change the base colour of a flat-coloured object. For this reason, it was very easy for us to add additional variations on the camera path, since this simply changes the camera's location and orientation. On the other hand, changing the lighting is simple manually, but for good quality lighting a lot of data needs to be recalculated, which takes a lot of time and is not designed to be triggered programatically. As such, it takes longer to generate data across different times of day, and it would be more time-consuming for us to test at an additional time of day.

VI. CONCLUSIONS AND FUTURE WORK

In this paper we investigated the use of photo-realistic gaming engine simulation tool to address important challenges in robotic vision: that experiments cannot be repeated, that algorithms cannot be quantitatively compared, and that for object recognition the lack of labelled training and test is a bottleneck for training deep networks. The simulation allows us to create high realistic images from an arbitrary camera or cameras in a complex 3-dimensional world in which lighting and atmospheric conditions can be set at will. We showed how we can systematically evaluate some standard robotic vision algorithms (robust place recognition and visual SLAM) in ways which have not been previously possible. These algorithms are broadly representive of the classes of image-based and feature-based methods. We also showed how we can synthetically generate a large number of images to evaluate a deep network for object recognition.

We have only just begun to scratch the surface of this new approach to robotic vision. So far our paths through the environment are set manually rather than being driven by a robotic vision algorithm. Integrating the game engine into the ROS environment would simplify this, allowing us to run a robotic vision algorithm in a manner analagous to a hardware-in-the-loop simulator, its output commands the camera pose in the simulator and the rendered image becomes its input. The fidelity of the simulation approach needs to be tested on a wider variety of common vision algorithms. Creating complex 3D worlds is time consuming and we are investigating modern 3D reconstruction techniques to create a first draft of a simulated world. It should also be possible to procedurally generate many parts of the environment, establishing rules for the generation of roads, cities, and other environments allowing variations to be produced quickly. Finally, many assets need only be created once, and a wider community using simulation and sharing work should reduce the initial costs of setting up a simulation.

APPENDIX

Appendixes should appear before the acknowledgment.

ACKNOWLEDGMENT

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