The utilization of spherical camera in simulation for service robotics

Krystian Chachuła
Warsaw University of Technology
Institute of Control and Computation Engineering
Warsaw, Poland,
Email: krystian.chachula.stud@pw.edu.pl

Maciej Stefańczyk
Warsaw University of Technology
Institute of Control and Computation Engineering
Warsaw, Poland,
Email: maciej.stefanczyk@pw.edu.pl

Abstract—Safety is one of the most critical factors in robotics, especially when robots have to collaborate with people in a shared environment. Testing the physical systems, however, must focus on much more than just software. One of the common steps in robotic system development is the utilization of simulators, which are very good for tasks like navigation or manipulation. Testing vision systems is more challenging, as the simulated data often is far from the real camera readings. In this paper, we show the advantages of using the spherical camera for recording the sequences of test images and a way to integrate those with existing robotic simulator. The presented system also has the possibility to be extended with rendered objects to further improve its usability.

Index Terms—spherical camera, service robotics, robot simulation, ROS

I. INTRODUCTION

A. The problem

People use their sight as the most important sense when they move through their surroundings. It is therefore essential for service robots to use image processing. When robots coexist with humans, safety is highly important [1]. One of many measures to be taken is software testing, which requires test data and, in the domain of computer vision, this data consists of images or videos from a robot’s camera [2]. However, using a real robot for testing can be dangerous. The danger stems from the fact that, while testing, the robot is controlled by yet untested software, which, in case of service robots, can be complicated [3]. This can lead to damaging the environment, the robot itself or in the worst case scenario can harm the people. Using a real robot for testing can also be tedious – after each test iteration one has to return the environment to the initial state and move robot back to the staring pose. To speed up the process it is possible to run the application on multiple robots [4], but this is not the cost-effective solution. This creates the need to simulate the tested robot [5] and, specifically, its one or more cameras. In this article, we examine the existing robotic simulators as a tool for testing vision algorithms and propose their extension with the use of spherical images.

This work was funded within the INCARE AAL-2017-059 project „Integrated Solution for Innovative Elderly Care” by the AAL JP and co-funded by the AAL JP countries (National Centre for Research and Development, Poland under Grant AAL2/2/INCARE/2018).

B. State of the art

A practical method of gathering image data for testing is recording a video while the robot is executing a given path in the testing environment for future use. Another way is using simulators such as Gazebo [6] or UnrealROX [7]. Gazebo is meant to be a universal simulator, with physics and 3D rendering engine. It allows for accurate robots and environment modeling and robot behavior simulation. Its integration with the Robot Operating System makes it very popular amongst the research and industry community. It lacks the most in the vision field. Although the 3D rendering is possible, environments created in the simulation are often filled with repetitive objects with very simple textures (Fig. 1). The lighting system is also very simplified, without any shadows and reflections, which makes the renders unsuitable for the vision algorithms evaluation.

On the other hand, simulators like UnrealROX are designed to be used as a tool for training visual algorithms, especially those based on deep learning, requiring a lot of training data. Simulator, based on Unreal Engine, is able to produce photorealistic scenes in real-time (Fig. 2). To prepare such scenes, however, an artist is required most of the time. A solution like this would be perfect, but lack of integration (and no possibility thereof) with robotics systems makes it a tool only for off-line learning, not interactive testing.

From this short review, we can point out some features that are desired in simulators [8] apart from the photorealism. One is the capability to modify the world model used for
image generation quickly. This allows the tester to create new test scenarios rapidly. Another essential feature is the ability to edit the robot’s path dynamically. Of course, this is not possible when simulating using a prerecorded video, but should be achievable in every generic simulator, as well as the capability of simulating robot’s interactions with the environment, such as collisions and manipulation. Integration with ROS is also important. From the summary in Tab. I we can see that fulfilling all the requirements at once is hard to achieve.

TABLE I: Comparison of different camera simulation methods

| Feature                           | Gazebo | video | UnrealROX |
|-----------------------------------|--------|-------|-----------|
| environment modification          | yes    | no    | yes       |
| editable robot path               | yes    | no    | yes       |
| interaction with the environment  | yes    | no    | yes       |
| photorealism                      | no     | yes   | yes       |
| ROS integration                   | yes    | yes   | no        |

C. The solution

Using pre-recorded video/images has the biggest photorealism (as those are photos). Using the 3D simulators gives possibility of free robot movement and interaction with the environment. To combine both worlds, we study the possibility of using the photos as a source for the camera image in the simulation. To give the robot the possibility to look around, photos should cover the full sphere (360° panorama or full spherical photo). To have freedom of movement images from (almost) all possible robot locations should be available. The position of the virtual camera can be used to select exactly one (the closest) spherical image from the set. Finally, to not limit the solution to only a single pre-recorded environment state, there has to be a way of adding the simulated/rendered objects to the scenes. This will also allow for interaction. Schematic diagram of the proposed system is presented in Fig. 3.

The rest of the paper is structured as follows. In section II we show the methods of creating a single photo from a spherical image. Section III introduces a way of dealing with the robot movement. Integration with the 3D simulator and merging with the rendered overlays is presented in section IV. A case study for a prepared system is presented in section V, followed by the conclusions.

There are different camera types used throughout the article. A **spherical camera** is a type of camera with a field of view that covers the entire sphere, and a **regular camera** is a type of camera with a field of view close to 90 degrees. The camera that belongs to a robot in simulation is referred to as a **virtual camera**. A **projection camera** is an entity that projects a 3D scene to a 2D image in computer graphics.

II. Transforming spherical images

In order to transform a spherical image into a regular image, one can utilize 3D computer graphics. Not only is this method simple, but its implementation can utilize hardware acceleration. A sphere is a 3D closed surface where every point on the sphere is the same distance from its origin. Since only a finite number of points can be drawn, a sphere will need to be approximated by drawing a subset of its points. Those points can be selected by creating a UV Sphere. A UV Sphere consists of vertices that are created by performing angular steps in the spherical coordinate system (Fig. 4). Cartesian points are generated using these equations:

\[
\begin{align*}
  x &= r \cdot \cos \phi \cdot \cos \theta \\
  y &= r \cdot \cos \phi \cdot \sin \theta \\
  z &= r \cdot \sin \phi
\end{align*}
\]

where \(r\) is the radius of the sphere, \(\phi \in [0, \pi]\) – polar angle, and \(\theta \in [0, 2\pi)\) – azimutal angle.

Fig. 4: Sphere coordinates generation

Then the sphere has to be textured with the spherical image (Fig. 5). Most spherical cameras create images in the form of equirectangular projections, and, without the loss of the generality of the solution, we assumed images in that format are available. The process of texturing a UV sphere with an
image in the form of this projection is fairly straightforward [9]. Every point on the sphere can be mapped to a point on the texture by simply assigning angles to texture coordinates \( x_t = \theta \) and \( y_t = \phi \).

![Sphere textured with equirectangular photo](image)

Fig. 5: Sphere textured with equirectangular photo

Having textured the sphere, now a projection camera can be placed in its center (Fig. 5b). Its parameters (field of view and resolution) are set to match the robot’s virtual camera. The image from this camera is a regular image as seen by the robot looking in a given direction.

III. INTERPOLATION

The fact that always the nearest spherical image is used for rendering poses a significant issue. If two virtual camera positions are close to each other it is possible, that both of them will use the same spherical image to create the projected camera view. Moreover, if those cameras have the same orientation relative to the global reference frame then exactly the same regular image would be produced for both cameras.

![Sphere textured with a spherical image](image)

![Projection camera](image)

![Result](image)

Fig. 6: The method of interpolating camera views inside the single spherical image

A simple solution to this problem would be to mimic the position of the virtual camera relative to a region with the position of the projection camera, thus creating the illusion of moving closer to certain objects as visualized in Fig. 6. This solution is not perfect, as there will be no parallax visible, but with the photos sampled sufficiently dense the effect is satisfactory.

IV. 3D OBJECTS OVERLAY

So far, the robot can look around and move through the prepared environment. Generated images can be further processed in order to make this solution more versatile. As the position and orientation of virtual camera is known, and its parameters are the same as the projection camera, objects generated using 3D rendering software can be overlaid onto the photo. Fig. 7 depicts an example of such a process.

In our solution, we decided to stick with the Gazebo simulator for this purpose. In order to remove unwanted objects from the image, additional plugin to the Gazebo simulator was prepared to hide the objects from rendering in a virtual camera, keeping them visible for other sensors (like laser scanner or sonars), thus keeping the obstacle avoidance still working. This provides additional simulation features mentioned in the introduction. It enables the tester to modify the testing environment and provides the means of interaction of the simulated robot with the environment utilizing the Gazebo simulator.

![Result](image)

Fig. 7: Rendered object (can) overlaid on the photo

V. EVALUATION

The simulation system presented above was tested in our robotics laboratory. At first, individual modules and system parameters were evaluated, followed by the partial scan of the room. Prepared environment is meant to be used with the TIAGo robot applied to service tasks related to Elderly care and assistance.

A. Camera selection

In order to acquire a full spherical photo, a dedicated camera setup is required. Nowadays, there are different possibilities to achieve that, without the need for building multiple camera rig from scratch. If the price doesn’t matter, Ladybug5+ from Flir is the option. Its precalibrated six cameras provide 360° panorama with 8K resolution. Custom solutions use single camera with specially shaped mirror [10] to achieve the omni-directional field of view. On the consumer side of the market, there are a few different devices to choose from, most of them built from two fish-eye cameras facing in opposite directions. We chose the Theta V camera from Ricoh. This camera is
Fig. 8: Example images generated with grid resolutions of 20, 100 and 200 cm.

capable of on-board image stitching to the equirectangular projection with final resolution $5376 \times 2688$ pixels (created from two 4K photos). Another useful feature is the possibility to capture and transfer photos using WiFi. The average angular resolution of the selected camera is around 15 px/°, which is more than the 10 px/° of a robot’s camera.

B. Rendering performance

All the advantages of even the most advanced and photorealistic simulation are useless if its performance doesn’t allow for (near)real-time work. There are two independent factors in photo rendering that can limit the simulation performance. When the robot moves inside a single cell (in range of a single spherical photo), only the rendering time is important. For our system, it takes on average 0.365 ms to render a single VGA view. This allows us to simulate the camera with 2740 FPS.

The other latency is a result of loading the spherical photo from disk, decoding it, and loading it into the memory of the video card. A single $5376 \times 2688$ pixels JPEG image takes on average $t = 198.672 \text{ ms}$ to load and decode on our system. This further limits the FPS to 5 if the images are loaded synchronously. However, if the images can be loaded in advance, this would mitigate the negative impact of the load latency on the robot’s maximum speed. In this case simulated robot’s maximum speed $v_{max}$ depends on the amount of primary memory.

To achieve scaling $v_{max}$ with memory, one can utilize a pool of threads or processes. Now a significant problem is choosing which spherical images should be cached in RAM. The most straightforward strategy is to always store four images that were taken closest to the current position of the robot. Such a solution often loads many images that will not be used for simulation. A more sophisticated method would be to predict the movement of the robot. For example, the robot’s velocity vector could be projected forward until it intersects the border of a cell. Then, this image would be decoded and loaded in advance.

With just one thread or process for decoding images, the grid resolution of 20 cm and image load time of 200 ms, the theoretical aggregated speed limit of the simulated robot is equal to $1 \text{ m/s}$. According to TIAGo’s datasheet, this value coincides with real robot’s maximum speed.

C. Grid resolution and interpolation parameters

Proper distance between consecutive photos is not easy to decide and depends on the actual environment. Photos captured to sparse will result in big jumps when the camera moves between different grid points. Too dense and image loading and decoding times will limit the speed of the robot in simulation to unacceptable values.

In order to make such a decision, we created a relatively small but dense spherical photo set. After that, example images were generated for a given position and orientation of the virtual camera using that set. Next, we made the grid more sparse by selecting every second, third, and so forth photo from the set and generated images for each step. Some of the generated images can be seen in Fig. 8 (notice the vertical line distortions for too large step). The grid resolution of 20 cm provided a good balance between the quality of the simulation and the time needed for the creation of the photo set.

D. Collecting the photos of the target environment

Finally, when all the parameters are selected, a set of spherical images can be created. To facilitate the whole process, we’ve created helper hardware and software. For accurate photo capture and straight camera movement, the device in Fig. 9 was used. It consists of a rail and a cart to which a monopod has been fixed. At the other end of the monopod, there is a mounting point for the camera. A grid marks were put on the rail in order to allow precise positioning of the cart. Similar marks were put on the floor in order to guide the rail.

To simplify the process and keep track of photos that are already taken and still waiting to be captured, an application was created (Fig. 9). It allows for selecting points and sending requests to the camera for taking pictures using the Open Spherical Camera API. It also automatically tags the images with the correct position. In the selected room, 404 pictures were taken in 20 cm intervals, covering the living room part, the kitchen, and part of the corridor. The whole process took 2 hours and 17 minutes, which yields approximately 3 pictures taken per minute.

The whole solution was evaluated by comparing generated images with images from a real robot. For this purpose, the TIAGo robot was used. It was booted up and manually controlled in order to take pictures. Then the proposed solution
Manual photo capturing results also in slight misalignments between consecutive frames. Photo stabilization techniques could be implemented to calculate angular offsets for each image.

Created photo collection could be extended with depth information calculated from multiview structure estimation. This would make the interpolation process work better and allow for, possibly, grid with bigger steps.

VI. CONCLUSIONS

The article presented the idea and application for the spherical camera-based simulator for service robots. The system was tested by comparing images generated in simulation with those gathered by the real robot. Those results prove that using the proposed solution a set of spherical images can be used to replace a real robot in software testing. One important feature of presented system is that it doesn’t replace existing simulators, but rather coexists with them and provides additional features. Presented system in its current form can be utilized to test the robotic vision algorithms involving visual inspection [12] or even objects grasping [13] when the 3D overlays are used.

There are some issues in the system that can be improved. The process of photo acquisition at the moment is highly manual labor. For each photo, one has to move the camera, hide from the camera view, and capture a photo. In its current form, it takes around 8 minutes per square meter. The natural extension would be to utilize a robotic platform to move the camera around and take photos automatically.

REFERENCES

[1] S. Haddadin, A. Albu-Schäffer, and G. Hirzinger, “Safety evaluation of physical human-robot interaction via crash-testing,” in Robotics: Science and Systems, vol. 3. Citeseer, 2007, pp. 217–224.
[2] J. Skinner, S. Garg, N. Sünderhauf, P. Corke, B. Upcroft, and M. Milford, “High-fidelity simulation for evaluating robotic vision performance,” in 2016 IEEE/RSJ International Conference on Intelligent Robots and Systems, 2016, pp. 2737–2744.
[3] W. Dudek, M. Węgierek, J. Karwowski, W. Szykiewicz, and T. Winiarski, “Task harmonisation for a single-task robot controller,” in 12th International Workshop on Robot Motion and Control (RoMoCo). IEEE, 2019, pp. 86–91.
[4] S. Levine, P. Pastor, A. Krizhevsky, J. Ibarz, and D. Quillen, “Learning hand-eye coordination for robotic grasping with deep learning and large-scale data collection,” The International Journal of Robotics Research, vol. 37, no. 4-5, pp. 421–436, 2018.
[5] D. Seredyński, K. Banachowicz, and T. Winiarski, “Graph-based potential field for the end-effector control within the torque-based task hierarchy,” in 2016 21st International Conference on Methods and Models in Automation and Robotics (MMAR). IEEE, 2016, pp. 645–650.
[6] N. Koenig and A. Howard, “Design and use paradigms for Gazebo, an open-source multi-robot simulator,” in 2004 IEEE/RSJ International Conference on Intelligent Robots and Systems, vol. 3, Sep. 2004, pp. 2149–2154.
[7] P. Martinez-Gonzalez, S. Oprea, A. Garcia-Garcia, A. Jover-Alvarez, S. Orts-Escolano, and J. Garcia-Rodriguez, “UnrealROX: an extremely photorealistic virtual reality environment for robotics simulations and synthetic data generation,” Virtual Reality, pp. 1–18, 2019.
[8] A. Staranowicz and G. L. Mariottini, “A survey and comparison of commercial and open-source robotic simulator software,” in Proceedings of the 4th International Conference on PErvasive Technologies Related to Assistive Environments, ser. PETRA ’11. Association for Computing Machinery, 2011.
[9] N. Greene, “Environment mapping and other applications of world projections,” IEEE Computer Graphics and Applications, vol. 6, no. 11, pp. 21–29, Nov 1986.
[10] M. Waś, M. Rostkowski, and P. Skrzypeczynski, “Embedded, gpu-based omnidirectional vision for a walking robot,” in Advances in cooperative robotics. World Scientific, 2017, pp. 339–347.
[11] J. Pages, L. Marchioni, and F. Ferro, “Tiago: the modular robot that adapts to different research needs,” in International workshop on robot modularity, IROS, 2016.
[12] T. Winiarski, W. Kasprzak, M. Stefańczyk, and M. Wałęcki, “Automated inspection of door parts based on fuzzy recognition system,” in 21th IEEE International Conference on Methods and Models in Automation and Robotics. MMAR’2016. IEEE, 2016, pp. 478–483.
[13] D. Seredyński and W. Szykiewicz, “Fast Grasp Learning for Novel Objects,” in Recent Advances in Automation, Robotics and Measuring Techniques, ser. Advances in Intelligent Systems and Computing (AISC), vol. 440. Springer, 2016, pp. 681–692.
Fig. 10: Images generated in simulation (first row) and taken by the robot (second row). Last two rows presents sample source spherical photos.