Towards a More Data Efficient Sim2real Tactile Robotics Using Transfer Learning

[1], Matt Clifford*[1], Raúl Santos-Rodríguez[2], and Nathan Lepora[2, 3]

[1]Department of Computer Science, University of Bristol
[2]Department of Engineering Mathematics, University of Bristol
[3]Bristol Robotics Laboratory, University of Bristol

Abstract

Simulated environments are utilised to advance research in the area of tactile robotics. In order to use models trained in a simulated space on a real life robot, a recent approach is to use an image generator network, G, to predict the simulated sensor data given real life sensor data. G is usually trained from scratch for various sensor designs and scenarios. Importantly, the evaluation of G requires additional data collection from the real life robot. We propose a method of evaluating G that does not require additional data collection. We empirically show that the data requirements to train G can be reduced by 90% using transfer learning.

1 Introduction

Tactile robotics perform control tasks such as object pushing, grasping and edge following through touch sensors. In this work, we use optical touch sensors from the TacTip design Ward-Cherrier et al. [2018]. These sensors utilise an internally mounted camera to observe the deformation of a rubber tip. The deformation of the rubber is accentuated by internal pins, which are biometrically inspired from glabrous skin Lepora [2021]. Figure 1 shows the observed images of the sensor in different contact scenarios. The constrained distribution of images produced by the TacTip lends itself to leverage a variety of deep learning techniques Lepora and Lloyd [2020, 2021].

As in other domains, there is a move towards using a simulated environment to collect data and train models Lin et al. [2022]. Simulation increases the pace of research as there are fewer hardware requirements. Simulation also reduces the risk of damage to the robot and sensor during training. The simulated optical images are the simple depth maps shown in Fig. 1. To use models trained in the simulated space on the real life robot, the sensor images are first converted from the real to the simulated space Church et al. [2022]. Fig. 2 shows how an image generation using network, G, can take the sensor images from the real to simulated space. G uses the UNet architecture Ronneberger et al. [2015] and is trained using the conditional generative adversarial network (c-GAN) outlined in 'pix2pix' Isola et al. [2017].

Although the simulation and data domain transfer presented in Church et al. [2022] alleviate some of the research bottlenecks with regards to data collection and model training, there are two main areas for improvement. Firstly, a different generator, G, is trained from scratch per contact type (e.g., surface, edge), per TacTip design and per manufactured sensor batch. This leads to large real life data collection to train a new G from scratch. Secondly, the true evaluation of the performance of G requires an additional data collection from the real life robot using the control loops (Fig. 1c in Church et al. [2022]). This makes evaluation impractical during the training of G and limits research to robot and sensor availability.

2 Methods

Here, we propose to use transfer learning techniques to reduce the data and computational re-

*Corresponding Author: matt.clifford@bristol.ac.uk

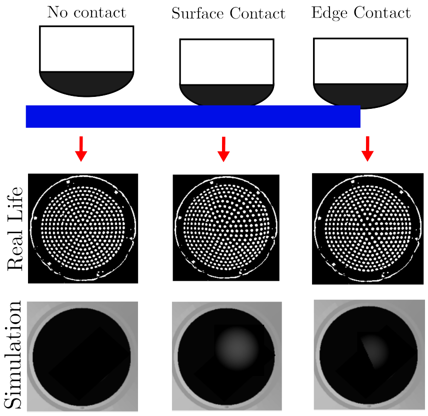

Figure 1: Real life and simulated tactile sensor images for various contact types.

quirements when training G. This reuses the knowledge acquired in a similar model to form a weak inductive bias when training. Since the network architecture for G is identical for all data scenarios, we directly apply the pre-trained weights of G trained on the edge task before training G for the surface task. We keep all training hyperparameters and loss functions identical to those used in Church et al. [2022].

To obtain a meaningful evaluation of G which does not require a control loop collecting additional data from the real life robot, we train 'PoseNet' Lepora and Lloyd [2020] in the simulated space. PoseNet is a supervised regression model that predicts the pose of the robot arm (position and rotation). We estimate the performance of G by taking the mean absolute error (MAE) between the predicted and ground truth pose for the evaluation dataset. We contextualise the MAE scores by a lower bound of the expected MAE obtained in both the real and simulated domains. We open source our implementation of 'PoseNet' in the PyTorch framework [1] . Pre-collected TacTip data for a variety of data scenarios and sensor designs is available from the open data repository [2] .

[1] https://github.com/mattclifford1/tactip-posenet-pytorch
[2] https://data.bris.ac.uk/data/dataset/110f0tkyy28pa2joru2pxxbrxd

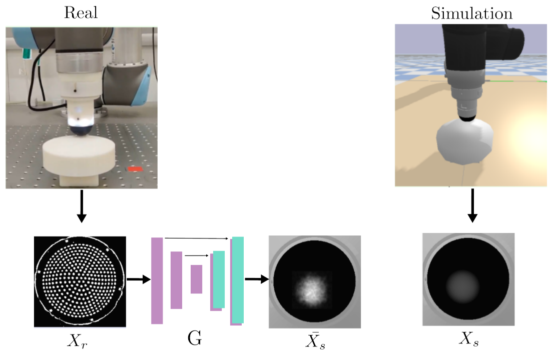

Figure 2: Real to simulated sensor data generation.

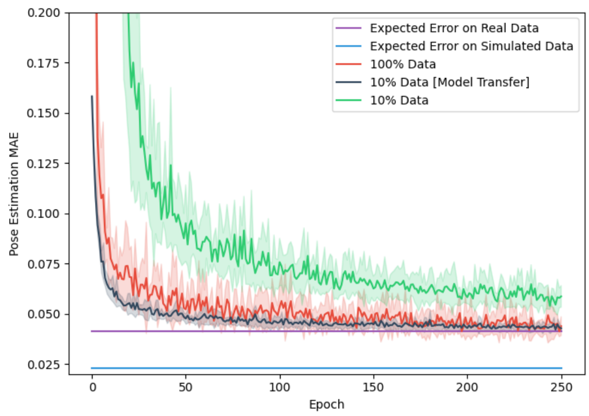

Figure 3: PoseNet evaluation during the training of G. Curves are the mean of 10 runs with the standard deviation shown in a lighter shade of colour.

3 Results

Fig. 3 shows us that by using transfer learning we can reduce the data requirements to 10% whilst maintaining the desired model performance. Transfer learning also produces a lower variance of models over the training runs due to the inductive bias. This means that there is a higher level of trust in any single training run and multiple training runs with model cherry picking are not required as is the case with training from scratch.

4 Conclusion and Further Work

We provide a method of convenient evaluation for G which does not require access to the real life robot while having meaningful, contextual values. This lowers the barriers for research into this area of tactile robotics. Also, we show that data requirements and model variance can be reduced with transfer learning. In future work the scope of model transfer can be widened to investigate if the same level of success can be achieved across different sensor designs.

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