LIMO The Detector: A Service Robot for   
Object Detection

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*Abstract*—This paper introduces "LIMO Detector," a programmable robot that can recognise and count colourful things while navigating children's rooms on its own. The robot, based on ROS2 components and Python scripts for mapping, inspection, and navigation, performs well in a simulation. Colour object recognition and collision-free navigation are two important achievements. The system's effectiveness and scalability are confirmed by quantitative measurements, which also show that it has the potential for wider service robotics applications.

Keywords—Gazebo Simulation, Mobile Robots, OpenCV, Autonomous.

# Introduction

Robots are noticeably expected to work in dynamic environments and beside non-expert users. To meet this required demands, Robot Learning from Demonstration (LfD) has appeared as a promising approach that enables the robots to have new skills by observing the human behaviour. In contrast with the traditional programming methods that ask for manually controlling, the LfD offers a more flexible framework for learning more complex behaviours from the data given.

In the context of a trajectory learning, the LfD is often used to model time movement patterns that a robot can learn and repeat the tasks across varying scenarios [1]. Two main studied techniques in this area are: Dynamic Movement Primitives (DMPs) and Stable Estimator of Dynamical Systems (SEDS), where Both of them aim to produce demonstrated trajectories but also achieving stability and generalization, however they differ in their mathematical formulations and guarantees. In the DMP it represents the trajectories through dynamical systems that are modulated by forcing terms, which allow for a time scalability and. In contrast, the SEDS models a general stable dynamical system using Gaussian Mixture Models (GMMs) and applies convergence through the Lyapunov constraints.

This report aims to explore and compare both approaches using a set of 2D demonstrated trajectories of varying complexity between them. The goal is to discuss their theoretical foundations based on two relevant papers and their practical implementation, while the rest of the report applies both methods to a real dataset, highlighting key differences in stability, generalization, and performance.

# Literature Review

Robot Learning from Demonstration (LfD) enables the robots to learn more skills by understanding human provided instructions, avoiding the need for task specific programming for each scenario. This method has been widely used in robot manipulation, motion planning, and also in human-robot applications. Among the LfD methods two adopted frameworks have been widely used: Stable Estimator of Dynamical Systems (SEDS) and Dynamic Movement Primitives (DMPs) by demonstrating a strong ability for trajectory modelling where each of these methods has its own distinct advantages.

Khansari-Zadeh and Billard have introduced the SEDS framework in which described the motion learning as the estimation of a nonlinear time invariant dynamical system [1]. The system models the flow of velocity vectors across the state space using the Gaussian Mixture Model (GMM) and trained to produce the observed behaviour while also ensuring that all the trajectories is reaching to a desired goal. In contrast with the time dependent systems, this formulation enables more robustness and allows the system to respond dynamically without relying much on time indexed trajectories. The key concept of the SEDS is its use of the Lyapunov stability theory to include global stability limitations directly into the GMM parameter optimization, which is described as a convex optimization problem [1]. This method ensures the theoretical convergence while keeping the computationally efficient.

The demonstration data for SEDS typically consists of position and velocity pairs, obtained using the kinaesthetic teaching or teleoperation technique [1]. The output of the learning is a usually stable and continuous velocity field to guide the system to reach the goal. However, this model is sensitive to the number of GMM parameters, which have to be tuned carefully to avoid any overfitting. Moreover, because the SEDS is a time invariant, it is usually lacks the mechanisms for encoding the time dependent behaviours which can be one of the limitations when temporal modulation is required.

In order to locate the SEDS within a wider landscape, Ravichandar et al. provided a comprehensive survey of LfD approaches, by offering some methods based on their learning outputs, generalization capabilities, and demonstration modalities [2]. They distinguish between the low-level primitives like those that are used in SEDS and DMPs, and the high-level task policies that abstract away from specific trajectories. The survey also emphasizes the power of SEDS in its ability to be stability, and real time application, especially in collaborative robotics.

In contrast, the DMPs represent motor skills using the second-order differential equations with spring damper dynamics, which allows for temporal modulation and a smooth trajectory generation [2]. Furthermore, the DMPs can be adapted to different goal positions or durations of motion execution which make them suitable for the tasks when changing in the temporal or spatial conditions are required. However, DMPs lack the built-in stability guarantees in contrast with SEDS, and extra effort is needed to ensure that the trajectories do not diverge or having unstable behaviour under any noisy [2].

Ruan et al. [3] has proposed PRIMP which refers to Probabilistically Informed Motion Primitives, a recent framework that combine the probabilistic modelling into the motion primitive learning. PRIMP captures the distribution of 6D trajectories and enables flexible adaptation to new task usage such as varying viewing perspectives. It is addressing a key limitation of the other LfD models. By combining the probabilistic trajectory modelling with the optimized planning, PRIMP supports the obstacle avoidance and the task generalization in random environments. Experiments demonstrated that PRIMP outperformed the traditional methods in both trajectory accuracy and the learning efficiency [3].

The survey also discusses the other ways through which demonstrations are introduced: the passive observation, teleoperation, and the kinaesthetic teaching and how each one of these affect the model performances [2]. For instance, kinaesthetic teaching produces a highly aligned input data, which suits the SEDS stability framework, but can be physically limited in scalability improvement. The DMPs, in contrast offer more variance to noisy or less consistent demonstrations because of their dynamic modulation capabilities [2].

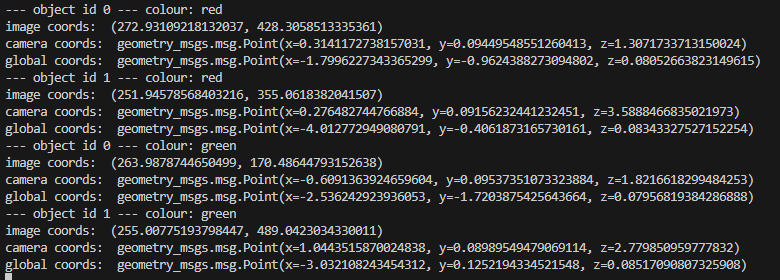
From a machine learning perspective, both the SEDS and the DMPs are classified as non-deep, prioritizing transparency over raw model complexity [2]. This makes them especially suitable for the applications with a limited training data or real time control requirements, as in human robot collaboration. In contrast, the deep learning methods may offer better performance in more complex systems and datasets, but they for sure require greater computational resources.

In summary, SEDS provides a basic approach to learning converging motions from demonstrations, offering more formal guarantees of stability, generalization across initial conditions, and efficient learning [1]. While the DMPs are more flexible in encoding and adapting motion systems, they lack convergence assurances and require tuning to match the task goals [2]. PRIMP, as a recent advancement, using the probabilistic modelling with task the adaptation [3]. These trade-offs build the basis for the comparative evaluation of this report, where both methods the SEDS and the DMPs are applied to real-world 2D trajectory datasets and assessed in terms of accuracy and stability.

# Methodology

Dynamic Movement Primitives (DMPs) are a widely-used framework for encoding robot trajectories as nonlinear dynamical systems. The core idea is to represent a movement using a system of differential equations that can be modulated to adapt to different goals and execution speeds, while maintaining the general shape of the trajectory.

A DMP consists of two subsystems: the canonical system and the transformation system.



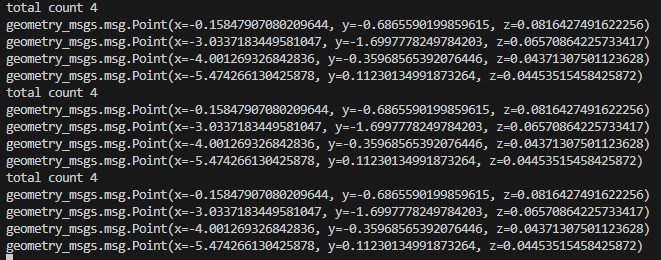


Figure 5 the four objects detecting and counting respectively

Future improvement is to create adaptive thresholds based on object sizes or add additional filtering methods to pick the exact object location while removing the others.

Several simulation trials were carried out, and it was found that the total number of objects detected changed with every trial. Object position, overlapping objects, and complex computational processes that happen during the detection process are some of the causes of this difference.

The outputs, which are collected in Table I, show that the system's object counting accuracy was acceptable. In particular, the detection accuracy was high in the basic map scenario, with 80% of properly detected objects.

However, the advanced map scenario produced a lower accuracy of 60%, mainly because the more complex environment needs more waypoints, which causes the robot to pause and adjust its position and direction more frequently, which may affect its field of view and object detection reliability; additionally, the physical complexity of the advanced map, such as the hidden area, further complicate these issues.

Table I dataset of detection outputs for both worlds

|  |  |  |
| --- | --- | --- |
| Trial | Basic world  (4 red objects) | Advance world  (6 red and green objects) |
| 1 | 4 objects detected | 10 objects detected |
| 2 | 4 objects detected | 6 objects detected |
| 3 | 4 objects detected | 6 objects detected |
| 4 | 6 objects detected | 5 objects detected |
| 5 | 4 objects detected | 6 objects detected |
| 6 | 4 objects detected | 6 objects detected |
| 7 | 4 objects detected | 6 objects detected |
| 8 | 3 objects detected | 6 objects detected |
| 9 | 4 objects detected | 8 objects detected |
| 10 | 4 objects detected | 6 objects detected |

Although the adjustable navigation parameters specifically the inflation radius, the path planning and the obstacle avoided weren’t as much as expected. One of the main reasons why more waypoints were used is that the robot navigation system chose a narrow path ignoring the wider space which led to obstacle hit several times.

Mapping with the SLAM toolbox is a reliable way to create the maps but, it might need more parameter adjustability for a chance of a higher precision map. Increasing the number of waypoints led to more stable robot navigation without hitting the walls and the objects.

# Conclusion

The "LIMO Detector" project effectively addresses the real-world difficulties parents have in their children's playrooms by showcasing the capabilities of a programmable robot for identifying and counting coloured toys. The robot was able to navigate, avoid obstacles, and map effectively in simulated environments by utilizing ROS2 components and Python programming. The system's excellent accuracy in simple scenarios was validated by quantitative evaluations, although computing restrictions and simulation noise caused slight performance limitations in more complicated environments.

The system's scalability was further demonstrated by the effective functioning in both organized and random layouts with LiDAR sensors and camera reading. The robot frequently produced reliable outputs, indicating its potential for wider service robotics applications, even if there were frequent errors in counting. To increase performance in the real world, future research might concentrate on improving detection accuracy and navigation processes.

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