Learning Navigational Maps by Observing the Movement of Crowds

Simon T. O'Callaghan
Australian Centre for Field Robotics
University of Sydney
Australia, NSW 2006
s.ocallaghan@acfr.usyd.edu.au

Surya P. N. Singh
Australian Centre for Field Robotics
University of Sydney
Australia, NSW 2006
spns@acfr.usyd.edu.au

Fabio T. Ramos
Australian Centre for Field Robotics
University of Sydney
Australia, NSW 2006
f.ramos@acfr.usyd.edu.au

Abstract

Modelling and predicting the movement of people through different environments offer important benefits to a wide range of applications from estimating intent to security. The study of human motion patterns is also crucial for the development of social robots that share their surroundings with people. Here we present a methodology to learn socially informed trajectories by observing pedestrian positional traces and we apply it to enable a robot to navigate in complex environments. A continuous probabilistic function is determined using Gaussian process learning and used to infer the direction a robot should take in different parts of the environment. The approach learns and filters noise in the data producing a smooth underlying function that yields more natural movements. Our method combines prior conventional planning strategies with the most probable trajectories followed by people in a principled statistical manner, and adapts itself online as more observations become available. The use of learning methods is automatic and requires minimal tuning as compared to potential function or spline function regression. This approach has been tested against a cluttered office and an open forum datasets using laser and vision sensing modalities. It yields interactive paths that are similar to the expected behaviour of people (e.g., crossing a street at a pedestrian crossing) without any *a priori* knowledge of the environment or explicit programming.

1 Introduction

As robots start to share the environment with people, the study of human motion patterns becomes increasingly important. In the robotics community, the social interaction between humans and robots has been the object of numerous studies [1], [2], [3]. It presents significant challenges and has proved vexing for numerous reasons – not least of which being that such interactions are often qualitative and difficult to measure.

However, human locomotion is incredibly informative. Considering the paths people transit not only informs how to navigate, but also improves interaction. Consider, for example, navigating around spilled coffee. Trying to sense this is incredibly difficult, yet following the cues of people walking around it is relatively much easier. That is, understanding and generalising peoples' behaviour is paramount to defining better decision making rules and improve safety of humans and robots. This, however, can be difficult as the variability of human motion patterns is immense even in structured environments such as offices and corridors. Also challenging is estimating and modelling the uncertainty in these motions from noisy sensors, which are generally subject to occlusions and misdetections.

In this work we study how preferred course trajectories can be learnt for an environment by observing the motion pattern of people and consider its use for navigation. Given a set of traces from pedestrians walking in a populated area, we seek to learn a function that maps any arbitrary location to a direction of travel – we call this the navigational map. This navigational map reflects people's behaviour in a statistical manner and helps the robot to understand the environment. For example, people (almost) always avoid obstacles when walking. By learning how humans walk in a closed area, a robot can avoid obstacles without relying solely on perception. Equally, assumed social boundaries such as personal workspaces or the area between a television and a viewer often mean that the shortest path is not always the optimum.

Traditionally, integrating such behaviour into the path planner is challenging as the definitions of preferred spaces are mostly qualitative, hence making metrics (and sensing) difficult [4]. However, learning the motion pattern can lead to trajectories that incorporate a very abstract level of reasoning on the environment without explicitly understanding the underlying principles influencing them.

We rely on a machine learning technique to develop a model of how people traverse the environment. Using traditional path planning techniques as a prior, the resulting navigational map emulates human-like motion trajectories in a sound, statistical manner. In order to learn this map from pedestrians' traces, we explore the benefits of Bayesian learning and, in particular, a popular regression technique known as a Gaussian process [5]. A key aspect of this approach is the manner in which the problem is formulated. By modelling human motions as a deviation from a prior path plan, it becomes possible to infer preferred areas (a subsequently areas of repulsion) all within the Bayesian statistical framework.

2 Problem Formulation

Intuitively, the proposed approach seeks to produce a navigational map, a function which maps a location to a normalized velocity in a manner that incorporates the motion patterns of people. This would enable the trajectory taken by a person travelling to a destination to be estimated at any location allowing the robot to navigate in a human-like manner. Essentially, this is achieved by learning a continuous function that describes how people deviate from some prior belief on the path to a destination. This deviation function, Ψ, is combined with the prior navigational map to produce a navigational map that captures the general trends of how humans traverse the environment.

2.1 Learning the Motion Patterns of People

Generally speaking, our technique can be divided into two main segments. Initially, the outputted paths of a people tracking algorithm are used in an offline learning phase to estimate Ψ for a given destination. Subsequently, an online algorithm uses the generated function to traverse the environment in a way that reflects the tendencies of people. Fig. 1 shows the traces from simulated data of people using a zebra-crossing that would be chosen, represented in blue, when generating a navigational map for the indicated destination.

The training data's target vector used for learning the underlying deviation function is obtained from the selected raw data by initially approximating the trajectory of the pedestrians at each observed location and subtracting it from some predetermined prior prediction, Fig. 1(b). A Gaussian process, GP, is then trained to estimate a non-parametric probabilistic model of Ψ. The predictive mean, Fig. 1(c), represents the model's estimate of how much the human motion pattern deviates from the expected direction of navigation (the prior). An associated variance function also exists to quantify the model's confidence in each prediction.

Once a model for Ψ has been trained, it becomes possible to predict the motion pattern of people at any location in the environment. The robot can query the probabilistic model with its current location and receives an estimate of the deviation angle. This is then added to the original prior to produce a prediction of the direction that a human would take in that position. The robot moves along the trajectory given by the navigational map until the destination is reached. Fig. 1(b) & (d) compare the prior navigational map with the posterior map produced after incorporating the information gathered from observing how people move through the environment. The social context

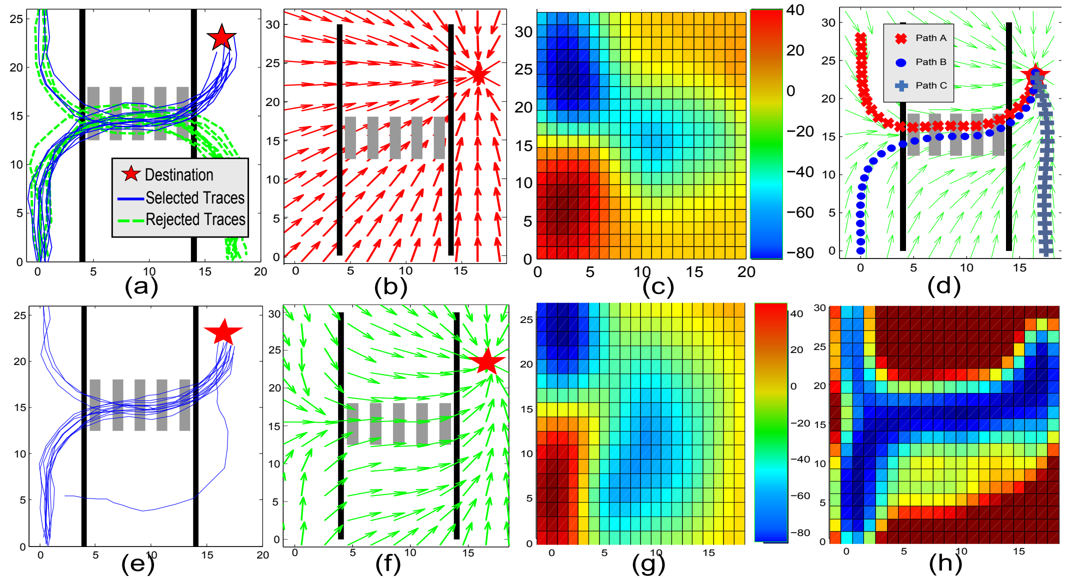

Figure 1: (a) Plan view of zebra-crossing with the path traces of simulated pedestrians using it to get from one sidewalk to another. (b) Prior navigational map. (c) Predictive mean of the deviation function. (d) Posterior map with 3 sample trajectories generated from different starting locations. (e) Path traces with added jaywalker. (f) Updated posterior navigational map. (g) Updated predictive mean. (h) Updated predictive variance.

of the zebra-crossing is reflected in the posterior map and it has the effect of channelling the flow from left to right through the designated crossing zone.

2.2 Integrating New Observations into the Model

After the training phase, incorporating additional observations into the model can be done online by updating the inverted covariance matrix of the GP. Fig. 1(f) illustrates the effects on the outputs of our method when the observation of a jaywalker's path trace is integrated into the map.

Interestingly, the direction of the updated navigational map's normalised velocity vectors below the zebra-crossing adapt to reflect the behaviour of a person walking in that region (i.e., to get to the other side of the road as directly as possible) compared to the quiver plot in Fig. 1(d). Importantly, however, the variance, Fig. 1(h), in this same region although lower than areas where no observations were made, is still higher than the section over the zebra-crossing and the route preferred by the majority of pedestrians. The variance could correspond directly to the level of caution that the robot should exercise in each region and indicate how it should adjust its speed or perceptiveness accordingly.

3 RESULTS

The proposed approach was tested on a number of different datasets. Here we present the results from the UTS RobotAssist Project [6] in which the motion patterns of people were recorded in an office environment over the course of three hours. Once again, a naïve potential function was used as the prior map, Fig. 2(d). Samples from the resulting predictive mean after learning are shown in Fig. 2(c). The posterior navigational map, represented as a quiver plot in Fig. 2(e), merges the observations of path traces into the prior map to generate more socially-informed routes to the destination. Three typical starting locations were chosen and the resulting paths generated by the posterior navigational map were plotted.

An important advantage to incorporating the motions of people into the navigational map is the ability to indirectly sense obstacles that may be occluded or even undetectable to the robot's sensors. The large table on which one of the laser rangefinders used to track people is placed, seen in Fig. 2(a) close to the center of the image, is below the sensor's plane and hence does not appear in the laser returns plotted in Fig. 2(b) & (d). Observing that people avoid this area leads to trajectories

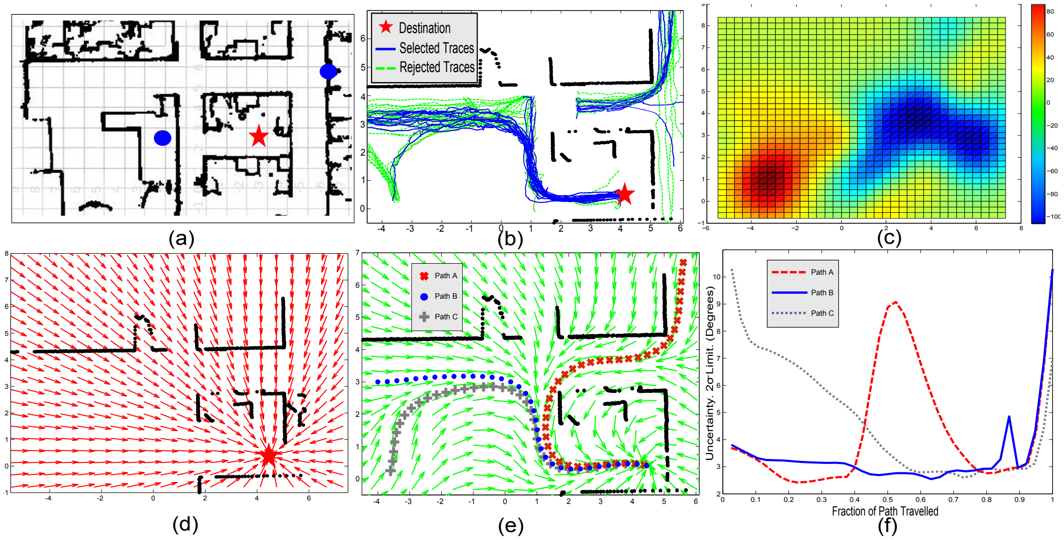

Figure 2: (a) Occupancy grid of office area - positions of laser rangefinders marked in blue. (b) Path traces of pedestrians detected by lasers. (c) Predictive mean function of Ψ. Sparsely sampled quiver plot of the prior (d) and posterior (e) navigational maps with examples of resulting routes to the destination taken from three different starting locations using the latter. (f) 2σ boundary (degrees) vs. fraction of route travelled for each sample route.

like Path C which also circumvent the obstacle without ever requiring to reason about the boundaries or type of the obstruction. Although in this case the obstacle is quite tangible, our approach would just as easily handle more abstract obstructions such as a restricted area due to a slippery surface or paths that may impinge on the work areas of other people.

A key feature of the Gaussian process is its capacity to infer the most likely value of the Ψ at any point in the map based on the trends of observed motion patterns in the region. The benefit of this is clearly illustrated in the region occluded to both rangefinders - around $\mathbf{x}_* = [2, 3.5]$ m in Fig. 2 (b). Despite a lack of path traces in this area, the GP correctly predicts the most likely trajectory of pedestrians in the vicinity. Crucially, an associated variance is also produced for each prediction and can be used as an indicator of the caution that should be exercised in each particular region. Fig. 2 (f) illustrates the 2σ boundary for each of the sample paths. The area occluded from both sensors is made apparent by the large peak in uncertainty approximately halfway along the curve of Path A. Similarly, the variance associated with the planned trajectory of Path C is initially quite high due to a low density of observations in the region as only 2 pedestrians were observed here. However as the trajectory brings the robot into the more populated corridors, the uncertainty on the predicted value of the deviation from the prior falls to within a 2σ boundary of approximately 3 degrees.

4 CONCLUSIONS

We introduce a powerful tool for modelling the motion patterns and inherent preferences of people. Incorporating this knowledge into the the path planners of robots helps to address several important challenges currently facing robotic navigation such as perceiving obstacles that are traditionally difficult to observe and motion planning in a manner that conforms to social assumptions. The proposed approach is illustrated and tested on a variety of datasets which demonstrate the algorithm's capacity to encapsulate social context in navigation.

Handling this problem within the framework of the Gaussian process avoids the necessity to discretise the world or the resulting trajectories. Crucially, an associated predictive variance exists along each trajectory which can be used to dictate the the level of confidence the robot should have in the model for each region of the map. An additional benefit of adopting a Bayesian approach is the ability to learn the sensor noise levels and characteristics of the underlying function in tandem through the optimisation of the marginal likelihood function without the requirement of hand-tuning the model's parameters We believe that this work is an initial step towards integrating conventional decision making algorithms and path planning with the complex decision making processes in humans and their social behaviours.

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