Modelling and Predicting Rhythmic Flow Patterns in Dynamic Environments

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Abstract

In this paper, we introduce a time-dependent probabilistic map able to model and predict future flow patterns of people in indoor environments. The proposed representation models the likelihood of motion direction by a set of harmonic functions, which efficiently capture long-term (hours to months) variations of crowd movements over time, so from a robotics perspective, this model could be useful to add the predicted human behavior into the control loop to influence the actions of the robot. Our approach is evaluated with data collected from a real environment and initial qualitative results are presented.

Introduction

Representation of the environment dynamics is seen as one of the key challenges to enable autonomous navigation in real-world scenarios, since this representation will help to define how and where the robot should move. This is especially important when deployed in a human-populated context, where significant variations are often observed. Some authors have proposed representations to model the typical (average) motion patterns of dynamic objects[1]. However, human activities tend to change over time, meaning that static models usually do not capture the real behavior of the environment, leading to inaccuracies over time.

Thus, our method includes the temporal dimension on top of the spatial structure, but unlike previous approach using an occupancy grid map[2], we assume that the observed activities follow some underlying patterns due to the periodic nature of human activities, such as leaving home and returning after work at approximately the same time, or, as in the experiments presented here, people going in one direction or another in a shopping centre depending on the time of day. In the proposed approach, we model the temporal dimension of activities using periodic functions, going from hours to weeks, allowing prediction of future environment states with a compact representation, even during long-term operation.

Spatio-Temporal Model

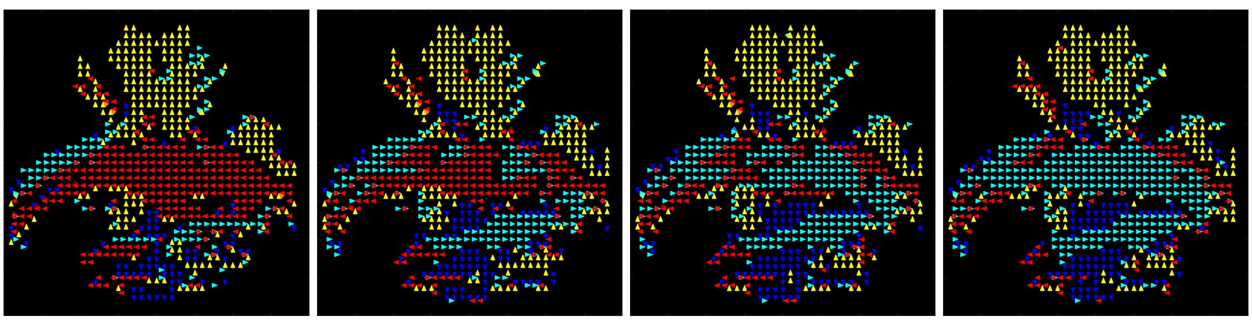
The geometric space is defined using a grid-based representation, where each cell in the grid has 8 associated transitions to the neighbouring cells, and due to our interest is only on the cell change, the case of remaining in the same cell is not considered. So in total, we model the likelihood of $8 * n_{cells}$ transitions over time. We consider that a cell is occupied if a person can be found within its boundaries, and the transitions are performed exclusively to neighbouring cells in one time step. To achieve that we have discretized the space and time according to the well-known Nyquist-Shannon theorem and knowing the average walking speed of people in the dataset used for experimentation, giving one meter side cells and half a second of sampling time.

In order to handle the temporal dynamics we use the FreMEn framework[3]. FreMEn is a mathematical tool based on the Fourier Transform, which considers the probability of a given state or event as a function of time and represents it by a combination of harmonic components. Such a model not only allows representation of environment dynamics over arbitrary timescales with constant memory requirements, but also prediction of future environment states or events. Assuming the transitions follow some periodic patterns over time as a consequence of the natural human activities, we can apply the FreMEn model over each transition, obtaining a probabilistic prediction of each transition happening at any instant of time. Similarly to earlier work[4], our approach counts the number of transitions happening in each direction during an interval of time, and normalises these counts so that the most frequent transition is assigned the value of 100. If some periodic patterns can be found, after some training we should observe that some transitions have higher probabilities than others during certain periods of time.

Experiments

To evaluate the model, we used a pedestrian tracking dataset recorded from the ATC shopping center in Osaka, Japan[5]. The perception system consists of multiple 3D range sensors, covering an area of approximately 900 m^2, so we can follow the same person around the place in every instant of time. The data was recorded every Wednesday and Sunday during a timespan of one year. From all these data, we employed the first 20 consecutive Wednesdays as our training set to learn the model, using the 21^{st} Wednesday as the evaluation day. The recording of each day provides people trajectories starting from approximately 9 a.m. to 9 p.m., so for the rest of day we have set all transitions to 0 simulating the shopping center being closed.

After comparing the predicted model for the evaluation day with the ground truth, we found that the best model was obtained using one FreMEn component, corresponding to a period of one day. In Fig. 1, for better visualization, only a subset of the whole map is plotted, where for each cell the transition with the highest probability for that time is shown. Within this region, the upper and lower zones remain stable throughout the day, but the middle area presents a noticeable change in the flow direction. In the morning the number of people entering the mall tends to be higher than those leaving, hence the arrows to the left (red), but in the afternoon (Fig.1c and 1d) there are more people leaving so the transition to the right neighboring cell (cyan) tends to have higher probability. Thus the model learned that most of the cells in the centre present a daily change, and is able to predict future states with good generalization of the dynamics.



(a) 10 a.m. **(b)** 2 p.m. **(c)** 6 p.m. **(d)** 9 p.m.

Figure 1. Model predicted at 4 different times during the evaluation day. Each colour (yellow, green, cyan, blue, dark blue, dark red, red and orange) represents one of the eight possible transition orientations.

Discussion

We have proposed an approach to model the dynamics of human motion in an indoor environment, which is able to generate predictions of future crowd movement at a given time. From a robotics perspective, this representation could be very useful to add the predicted human behavior into the control loop to influence the actions taken by the robot, for example, to navigate and plan robot paths with a more natural and harmonious movement with respect to the crowd, moving with the flow and obtaining fewer face-to-face encounters. The model could be also used for semantic clustering or studying motion patterns.

For the experiments presented in this paper, we assumed that the environment is fully observable. However, we know this is almost unfeasible in a real-world scenario using only the sensors of a mobile robot. So using the capability of FreMEn to work with sparse data[3], allowing us to update only the transitions actually observed by the robot, we are planning to study robot exploration strategies to actively keep the spatio-temporal representations up-to-date. These strategies need to take into account not only the spatial domain, but also the temporal dimension, as we need to know if new rhythmic patterns appear in some areas of the map, and the most important ones when they do. Future work will also include testing the model in other scenarios such as warehouse operations to check the method's generalization capabilities.

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