Spatio-temporal Representation of Time-varying Pedestrian Flows

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INTRODUCTION

Recent advances in robotics have allowed services robots to begin to enter domestic environments. However, their deployment is not always perceived as useful, and their presence can be rejected by the people the robots are supposed to help. The work of [1] points out that a critical factor of robot acceptance is their ability to navigate around humans in a socially compliant manner.

The problem with this is that traditional navigation methods represent the environment as a static structure, and dynamic objects, such as humans, are treated separately. Therefore the robots assume a reactive approach, where they estimate people's velocities by tracking them and then replan their trajectory accordingly.

To overcome the limitations of reactive approaches, a robot could learn to avoid areas likely to be congested [2], and several authors [3], [4], [5] have proposed models to represent the characteristic movements of people. However, pedestrian flows are not stationary, but, as shown in [6], [5], they change over time. A robot, capable of predicting future distributions of pedestrian flows, would be able to plan a congestion-free, socially-compliant trajectory in advance, minimising the likelihood of having to alter its route in order to avoid collisions.

We present a method capable of learning the natural flows of people and *how they change over time*. The core idea of the method is to model the time domain by several dimensions wrapped into themselves, which can efficiently represent the periodicities of the pedestrian flow characteristics. Using a real-world dataset of several weeks, we compare the method's performance to state-of-the-art algorithms [5], [7], [4] for pedestrian flow modelling. To promote reproducible and unbiased comparisons, the dataset, code and supporting materials have been made publicly available [8], and the methods were applied to the dataset by their authors.

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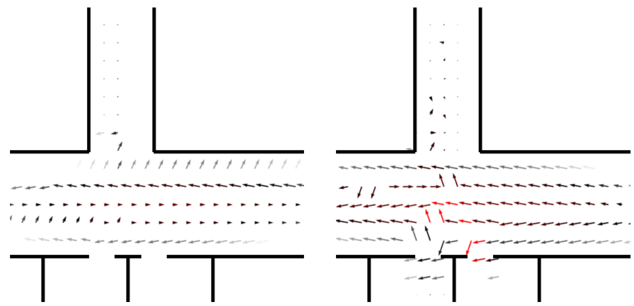

Fig. 1. Directions of pedestrian movement at 9:15 and 16:30 predicted by the proposed model. The arrow lengths correspond to flow intensity, i.e. number of people walking in the directions indicated by the arrows. See a video at https://youtu.be/ANbEODdFnR8.

METHOD

The aim of the proposed method is to find an estimation of the probabilistic distribution of an occurrence of a spatio-direction-temporal event for a given time, position, speed and angle. We assume that the distribution of the events is influenced by a set of cyclostationary processes influenced by people habits. Thus, in accordance of our previous works [9], [10], [11], [12], we proposed to use a "warped-hypertime" projection of the timeline into a constrained subset of multidimensional vector space with topology derived from the periodicities identified in the training data. This space allows to model distributions of quasi-periodic spatio-temporal events using the Expectation Maximisation algorithm for estimating Gaussian Mixture Models (EM GMM). The idea behind the aforementioned projection is that events which occur with similar periodicity will form clusters in the hypertime space even if they are isolated in the (linear) temporal domain. An intuitive example, shown in Figure 2, demonstrates how the "warped-hypertime" projection allows to represent cyclostationary probabilistic distribution.

A. Warped Hypertime Projection

Let us assume that the pedestrian tracking system on the robot provides us with a vector indicating detected people's positions, velocities and orientations as well as the timestamp of the observation. We apply the spectral decomposition method derived from the Frequency Map Enhancement [13], identify the most prominent temporal periodicities in the provided data, and determine the parameters for the warped

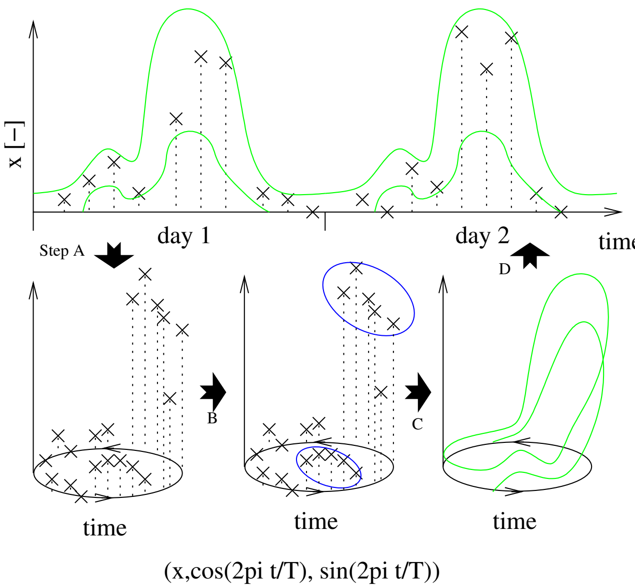

Fig. 2. Example of the warped hypertime projection for one periodicity **T** and one dimensional data x_i. The numbers x_i observed at t_i are projected into a 3d vector space as $(\mathbf{x_i}, cos(2\pi t_i/T), sin(2\pi t_i/T))$, (step A) where they form clusters because they exhibit a periodic behaviour with a period T (step B). Distribution of the clusters allows to model the probabilitic distribution of the x in the hypertime space (step C) as well as in the original domain (step D). In the warped hypertime, time dimensions define the base of a cylinder, and values of x_i define the side of the cylinder. Courtesy of [12].

hypertime projection. Then, we project every measurement into a new constrained subset of multidimensional vector space, as described in [9].

B. Model of the probability distribution

We assume that the time-dependent occurrences of events projected into the warped hypertime space are distributed in a way which allows us to model their distribution by Gaussian mixtures. Since in this particular case, we model the probabilities of people movement directions by Bernoulli distribution, we split the dataset into occurrences and non-occurrences (that are mutually exclusive), and we estimate the parameters of the ditribution of each of these phenomena separately using an Expectation Maximisation algorithm (EM GMM). To estimate the probability of the Bernoulli distribution of occurrences at one specific point, we compare the probability of occurrence to probability of non-occurrence derived from these two distributions [14].

C. Experiment

The approach described was evaluated using a temporally expansive dataset, covering 9 separate ∼10-hour sessions starting before the usual working hours over four weeks. This covered approximately 30000 detections of people walking, and 70000 non-detections.

On this dataset, and with the aid of the co-authors of several of the alternative methods [5], [7], [4], we evaluated and compared our method. We found during our experiments that we achieved a significantly lower Mean Squared Error compared to the other state-of-the-art methods and that memory-wise, our model was being magnitude(s) smaller, making it suitable for representation of large environments.

Conclusion

The important advantage of the techinique presented is that as it can predict the future directions, intensities and speeds of the pedestrian flows. It doesn't need to base its predictions on recent observations, and therefore the robot can plan its collision-free trajectory through a given location before it arrives there, minimising the risk of breaking natural flows of pedestrians. This will allow the robot to naturally merge into the predicted flows, and thereby behave in a more socially acceptable way.

In the experiments, we showed significant improvement in predicting the probability of occurrences over the other methods. However the STeF [5] and CLiFF [4] methods showed better prediction at estimating the conditional probability of flow directions.

In the future work, we will evaluate the impact of compared methods to the robot's ability to predict the collision-free trajectories in a real world scenario.

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