Classification of regional dominant movement patterns in trajectories with a convolutional neural network

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1 Introduction

Various movement patterns have been discovered in trajectories, which are valuable in studying the contextual behavior of tracked objects [15]. Most of the previous studies have been concentrated on detecting of specific patterns in trajectories, such as flock, leadership and convergence [9] or sequential patterns [14]. In practice, movement patterns can be much more diverse and complex, e.g., clockwise, and zigzag, which calls for a unified, effective and robust approach for classification.

In deep learning field, convolutional neural network (CNN) have achieved superior performance in classification of image [8], video [6], text [7] and voice data [4]. In terms of vector data, computer vision approaches have been designed to process point set data for shape matching and classification [1, 11, 12, 13]. However, applying CNN for classification of trajectory data is relatively unexplored, which confronts two challenges. Firstly, trajectory data includes two additional pieces of information, namely the connectivity between points and direction, which can be primary features in movement pattern classification. Secondly, both the number of trajectories in a set and points in a trajectory can be variable. They should be considered together with the variations in point positions.

To address the above two challenges, this paper proposes a deep learning approach for classifying *regional dominant movement pattern* (RDMP), which is defined as the movement pattern followed by the *majority* of a trajectory set within a target *region*. To achieve this objective, the proposed approach defines a *directional flow image* (DFI) by mapping a trajectory set to a grid space according to its extent and storing *local directional flow* in multiple channels at each grid, i.e., the pixel of DFI. The benefit is that a trajectory set with the aforementioned variations can be transformed into an image in *fixed* shape. Subsequently, a CNN called TR-Net is designed for classification of DFI, which is trained on synthetic trajectory data and a considerably high accuracy is achieved. In summary, the approach adds a bridge between deep learning and trajectory pattern classification.

2 Methodology

2.1 RDMP category definition

Based on the commonly encountered movement patterns summarized in [3], this paper firstly defines 10 RDMP categories as move straight, turn left, turn right, converge, diverge, cross, reverse, zigzag, clockwise and counter-clockwise. Some examples are displayed in Figure 1.

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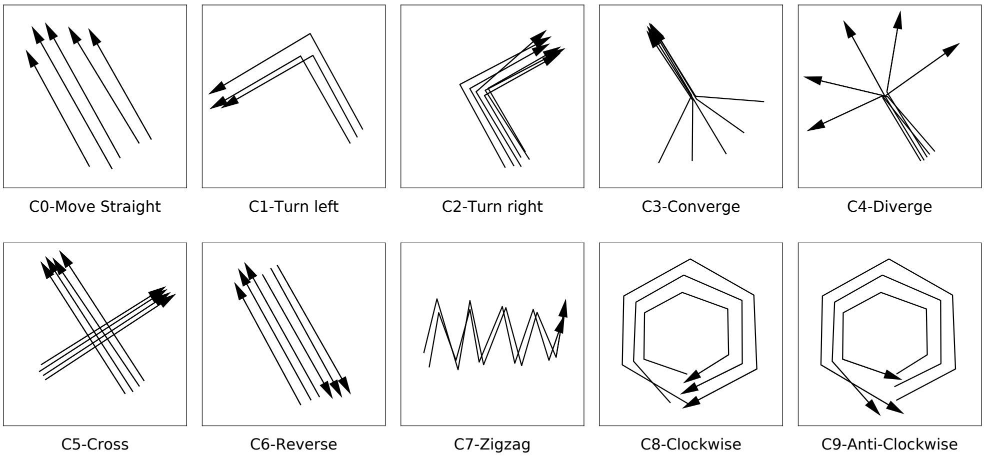
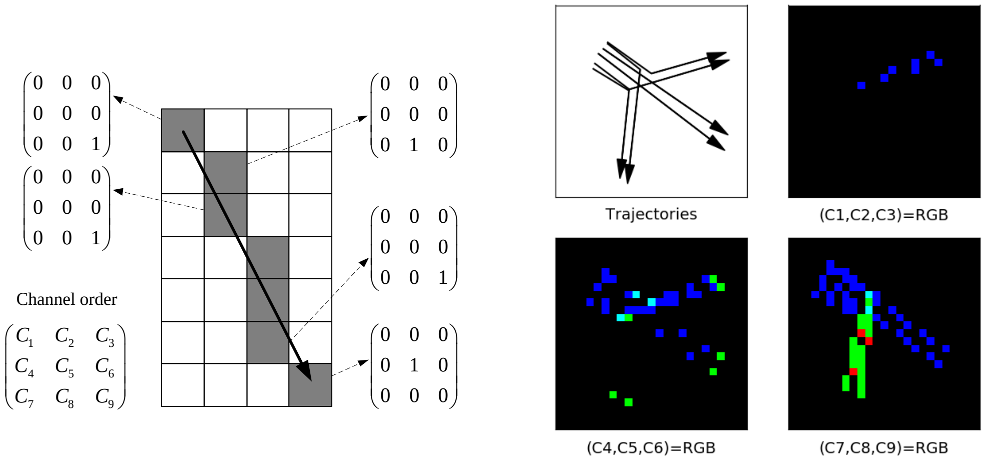


Figure 1 Category definition of regional dominant movement pattern (category ID and name)



(a) DFI of a single trajectory

(b) DFI (25×25) of a trajectory set

Figure 2 Illustration of directional flow image.

These definitions are highly conceptual and fuzzy where variations in shapes, the number of points and the number of trajectories are tolerated.

2.2 Directional flow image and TR-Net

A DFI is created from a trajectory set to store the local directional flow information. Given a trajectory set, its extent can be firstly partitioned into a grid space G in shape of $H \times W$ indicating the number of grids in height and width. From G, a DFI is created as an image with 9 channels where each pixel represents a grid $g \in G$. The shape of DFI is written as $9 \times H \times W$. The channel C_i at grid g stores the number of traversals in the trajectory set from g to its neighbouring grid indexed by C_i as illustrated in Figure 2(a). The 9 channels cover the $\mathcal{N}_8$ neighbours and the grid itself, where C_5 represents traversals to the grid itself indicating the end of a trajectory.

When it comes to classification of DFI, the task is similar to the handwritten digit recognition problem studied in [10] where a CNN called LeNet was designed. TR-Net adjusts

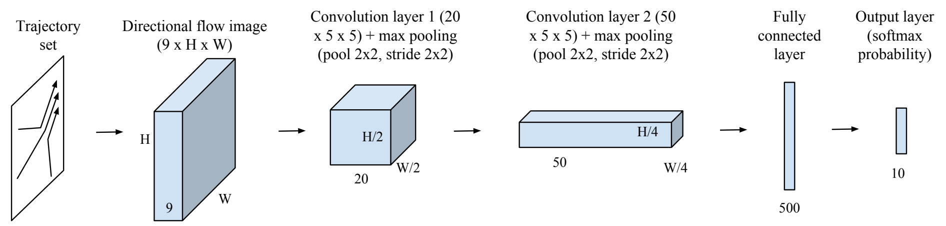


Figure 3 Architecture of TRNet

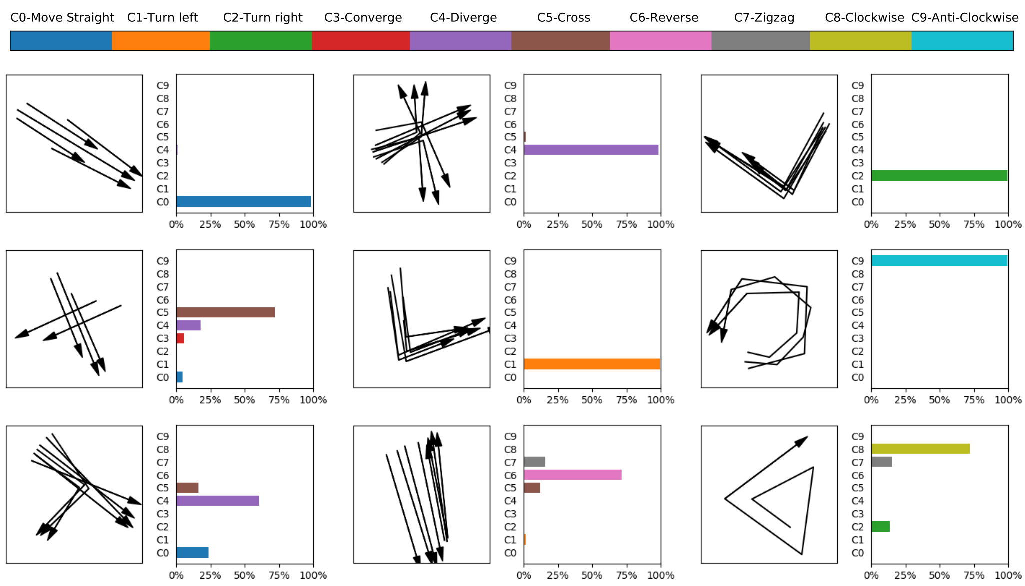


Figure 4 Demonstration of some classification results using DFI size of 10×10

LeNet by replacing the first input layer as a $9 \times 10 \times 10$ DFI. The detailed information is shown in Figure 3. In this paper, TR-Net is implemented with Keras [2].

2.3 Synthetic training data generation

The synthetic training data generation is divided into two steps. In the first step, trajectory seeds are drawn manually according to the definition of 10 categories, as shown in Figure 1. Each seed is a set of trajectories following a specific RDMP. Different types of variations in a trajectory set are considered including the number of points inside a trajectory, the number of trajectories in a set and variations in shape. To reduce the complexity, all the trajectory seeds are draw within a fixed area bounded by point (0,0) and (10,10) in the Cartesian coordinate system. By setting a grid size of 1.0, the shape of DFI is thus fixed to be $9 \times 10 \times 10$. When applying TR-Net to other datasets, an adaptive grid size can be set proportional to the extent of a trajectory set.

In the second step, data augmentation is performed by rotating the trajectory seeds. It can be observed from Figure 1 that all the classes are invariant to rotation. In other words, a group of trajectories rotated by angle α still belong to the same class. Given a specific α, sample size can be increased by $360/\alpha$ times. In this paper, 34 seeds are drawn manually for each of the 10 classes and rotated by 20 degrees. Finally, $34 \times 10 \times 360/20 = 6120$ trajectory sets and DFIs are generated.

3 Results and discussion

In training TR-Net, the 6120 DFIs generated from the synthetic trajectory sets are shuffled and split into a validation dataset (60%) and a test dataset (40%). The accuracy on test dataset increases from 20% to 90% after 9 epochs of training and finally arrives at 99.3% after 20 epochs. Some results are displayed in Figure 4, which demonstrates the effectiveness of the approach.

Several limitations of TR-Net are discussed below. In this paper, all the training data are created within an extent of (10,10) and the shape of DFI is fixed to be $9 \times 10 \times 10$. The restriction primarily comes from the consideration that a conventional CNN generally requires a fixed input layer in order to train the weights of fully-connected layer. Advanced architecture such as spatial pyramid pooling layer [5] has been designed recently to eliminate the constraint. Improving TR-Net along this direction will be planned as a future work. In addition, the patterns currently classified are regional dominant, which implies that it cannot discover a small area exhibiting a different pattern inside a regional dominant one. Similarly, a common phenomenon is that a large trajectory set can exhibit multiple patterns at different scales in space, which cannot be discovered by TR-Net. These problems may be addressed with by introducing object detection approaches, which is also left as a future work. Moreover, the performance of TR-Net will be further evaluated with different types of real-world data.

4 Conclusion

The paper proposed a deep learning approach to discover regional dominant movement patterns in a trajectory set. A directional flow image was firstly defined to store local movement information of trajectories in a multi-spectral image. Subsequently, a convolution neural network called TR-Net was designed for classifying that type of image. Experiments on synthetic data demonstrated that the approach achieved a considerably high accuracy that was robust to different types of variations in trajectories.

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