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# Motion categorisation: Representing velocity qualitatively

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## Abstract

Categorising is arguably one of the first steps in cognition, because it enables high-level cognitive processing. For a similar reason, categorising is a first step—a preprocessing step—in artificial intelligence, specifically in decision-making, reasoning, and natural language processing. In this paper we categorise the motion of entities. Such categorisations, also known as qualitative representations, represent the preprocessing step for navigation problems with dynamical obstacles. As a central result, we present a general method to generate categorisations of motion based on categorisations of space. We assess its general validity by generating two categorisations of motion from two different spatial categorisations. We show examples of how the categorisations of motion describe and control trajectories. We also establish its soundness in cognitive and mathematical principles.

## 1. Introduction

Any sensor, either robotic or human, is inundated by data with no direct meaning in itself but for its numerical value. This requires simplification—reducing the amount and the degree of detail of the data—, and conceptualisation—endowing data with a more straightforward meaning. A meaningful categorisation provides both in one stroke.

This paper introduces a method for creating intuitive categorisations of motion. Its generality is its greatest asset: it can use any spatial categorisation to create new categorisations of motion. Moreover, our method is applicable in any spatial dimension; and it categorises motions even when one or both entities are motionless.

The method's effectiveness is validated by applying it, as an example, to two very different spatial categorisations: one of them dealing with overlapping, RCC (Randell, Cui, & Cohn, 1992), and the other with orientation, $\mathrm{OPRA}_1$ (Moratz, 2006). Thus, we obtain a novel categorisation of motion dealing with regions. In what follows, we show the meaningfulness of the generated categorisations: firstly, we practically show the application of the categorisations to describe trajectories qualitatively, and to control navigation; secondly, we advance cognitive and mathematical arguments.

We find categorisations of motion form a promising field, and despite their scarcity, they have already proved successful in several areas. They enhance the analysis of movements, such as pattern analysis of sport players' trajectories (Delafontaine, Cohn, & Van De Weghe, 2011), dancers' bodily movements (Chavoshi, De Baets, Neutens, De Tré, & de Weghe, 2015; Chavoshi, De Baets, Qiang et al., 2015), or animals' trajectories (Mavridis, Bellotto, Iliopoulos, & Van de Weghe, 2015). They simplify the implementation of navigation routines, notably in human-robot interaction (Bellotto, Hanheide, & de Weghe, 2013; Hanheide, Peters, & Bellotto, 2012; Lichtenthäler, Peters, Griffiths, & Kirsch, 2013), not only because they provide meaningful categories, but also by enabling decision-making (Dylla et al., 2007).

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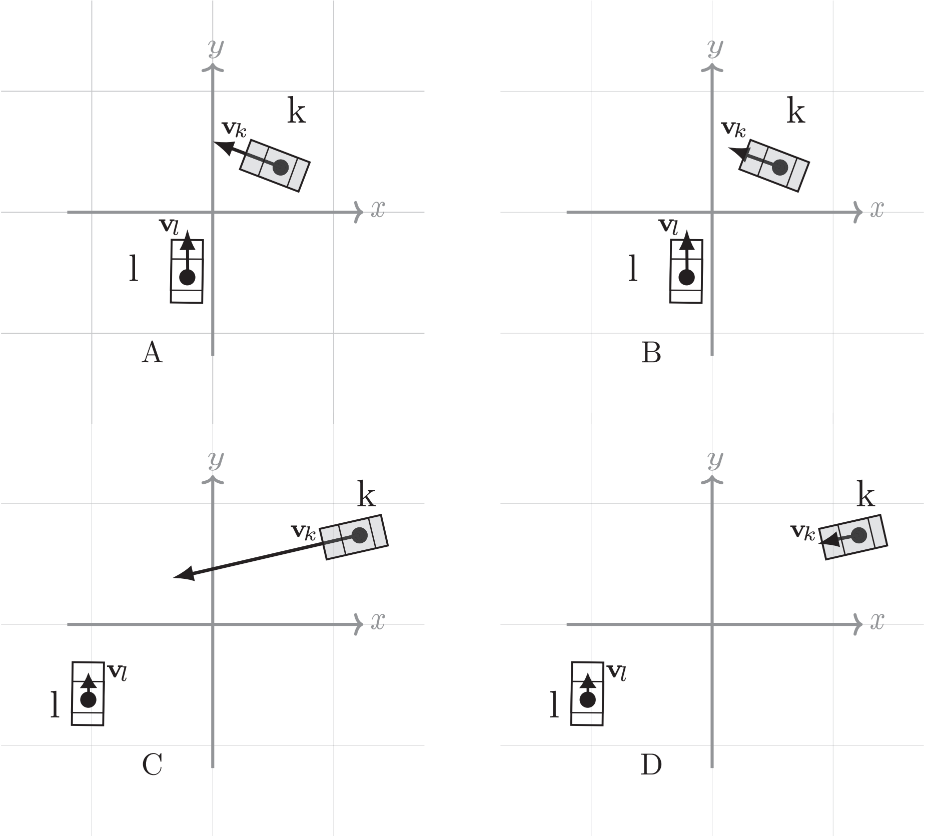

Fig. 1. A challenge for motion categorisation: 4 scenarios (A, B, C, D) with two moving vehicles $k$ and $l$, with velocity vectors $\mathbf{v}_k$ and $\mathbf{v}_l$. Each pair (A, B) and (C, D) has identical positions, velocity angles, and fulfils $\|\mathbf{v}_k\| > \|\mathbf{v}_l\|$—each pair differs only in the speed of $k$.

The difficulty of categorising motion is illustrated in Fig. 1. Which attributes should we use—and how—in order to categorise the four motion scenarios A, B, C, D, in this figure? For example, the pair of scenarios (A, B) and (C, D) are almost identical, differing only in the speed of $k$. Consequently, each pair may build a category. However, if velocities are not modified, in scenarios A and C $k$ would cross before $l$ without colliding, while in scenario B the vehicles collide, and in D $k$ crosses behind $l$. Are there then three categories (A, C), (B), and (D) more meaningful than the two previous, (A, B) and (C, D)?

The variety of possible motion categorisations originates in the variety of spatial categorisations; as we see in the example, we can differently categorise A and D, because of the spatial categories 'before' and 'behind'; we can categorise B alone, because of the spatial category 'overlap', i.e., collision. For that reason, we use spatial categorisations as the basis of our method to generate categorisations of motion from spatial categorisations, a method we presented in a preliminary version (Purcalla Arrufi & Kirsch, 2017).

## 2. Preliminaries on motion categorisation

In this section we clarify some aspects of the terminology used: the terms 'categorisation' and 'motion'. We also present the two spatial categorisations that we use as examples to create motion categorisations: RCC and OPRA$_1$.

### 2.1. Categorisation, qualitative representation, and related terms

We used the term 'categorisation' in the introduction of this paper, because it is more readily understood than other similar terms. The use of these terms depends on the field of study, for example, 'categorisation' is mostly used in cognitive science, 'conceptualisation' in language, 'classification' in machine learning, and 'qualitative representation' in artificial intelligence.

A great variety of spatial categorisations has been presented in the literature as 'qualitative spatial representations', from which we generate our motion categorisations. Consequently, in the rest of the paper we mostly use the term 'qualitative representation' (equivalent to 'categorisation') and the term 'qualitative relation' (equivalent to 'category'). As a categorisation partitions a continuum into categories, so a qualitative representation partitions it into qualitative relations.

Qualitative representations are categorisations with extended mathematical properties, which allow, for example, reasoning (Cohen & Lefebvre, 2005). As much as our motion categorisations are obtained from qualitative spa-