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Tool support for detection and analysis of following and leadership behavior of pedestrians from mobile sensing data

Mikkel Baun Kjærgaard, Henrik Blunck *

Department of Computer Science, Aarhus University, Denmark

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ABSTRACT

The vast availability of mobile phones with built-in movement and location sensors enables the collection of detailed information about human movement even indoors. As mobility is a key element of many processes and activities, an interesting class of information to extract is movement patterns that quantify how humans move, interact and group. In this paper we propose methods for detecting two common pedestrian movement patterns, namely individual following relations and group leadership. The proposed methods for identifying following patterns employ machine learning on features derived using similarity analysis on time-lagged sequences of WiFi measurements containing either raw signal strength values or derived locations. To detect leadership we combine the individual following relations into directed graphs and detect leadership within groups by graph link analysis. Methods for detecting these movement patterns open up new possibilities in – amongst others – computational social science, reality mining, marketing research and location-based gaming. We provide evaluation results that show error rates down to 7%, improving over state-of-the-art methods with up to eleven percentage points for following patterns and up to twenty percentage points for leadership patterns. Furthermore, we provide an analysis of the computational efficiency of the proposed methods and present visualizations for the analysis of detected patterns. Our methods are, contrary to state of the art, also applicable in challenging indoor environments, e.g., multi-story buildings. This implies that even quite small samples allow us to detect information such as how events and campaigns in multi-story shopping malls may trigger following in small groups, or which group members typically take the lead when triggered by e.g. commercials, or how rescue or police forces act during training exercises.

1. Introduction

The vast availability of mobile phones with built-in movement and location sensors enables large-scale collection of sensor data about human movement behavior, as compared to what was previously possible with dedicated devices. However, such data only becomes valuable through methods that can process and aggregate the data to extract relevant information [1]. As mobility is a key element of many human processes and activities, an interesting class of information to extract is movement patterns that quantify how humans move, interact and group [2].

In this work we target the detection of two common pedestrian movement patterns: *following* relations and group *leadership* [3,2]. A *following* pattern involves two persons and describes a relation between them, where one person is following and the other is leading. The *following* pattern occurs when a leading person's movement continuously prescribes the movement of a following person. A group *leadership* pattern is a quasi global pattern for a group of persons: it is present

* Corresponding author. Tel.: +45 22422965; fax: +45 22422965.
E-mail addresses: mikkelbk@cs.au.dk (M.B. Kjærgaard), blunck@cs.au.dk (H. Blunck).

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when a leader person's movement prescribes the movement of other persons but no other persons' movement prescribes the movement of the leader person. Both patterns are temporally and spatially constrained in so far as the persons have to be no further apart than δ m at the same point in time.

The detection of *following* and *leadership* patterns and the proposed visualization means enable new analysis methods within areas such as reality mining [1], computational social science [4], emergency research and marketing research [5], and provide new primitives for pervasive computing and location-based games. First, for computational social sciences and reality mining to extract patterns among moving co-workers including staff at hospitals, caretakers in large buildings and workers in warehouses. The detected patterns provide quantitative statistics about the relationship among co-workers. Furthermore, compared to mere proximity information the *following* and *leadership* patterns can reveal asymmetries among co-worker relationships [6]. For instance, one can deduce from such patterns whether people work independently or in teams and who leads the work. This information can then e.g. be compared with the intended working structure and help identify problems that when solved might provide e.g. gains in efficiency [7]. The clues extracted from movement and location data might also be correlated with clues extracted from audio or video data [8] or communication patterns among co-workers [1].

Second, there is a great and growing interest within marketing research to use movement data to better understand people's shopping behavior. However, methods for properly analyzing the data are lacking [5]. An important and so far less explored aspect is the impact of social interactions [5]. One example is the detection of co-shopping behaviors [9] for which the methods proposed in this paper would enable new forms of analysis, correlating *following* and *leadership* patterns with e.g. the shopping behavior of family members, product placements and store layouts.

Finally, the detection of *following* and *leadership* patterns also provides new primitives for pervasive computing and location-based games. We will later present an evaluation of our method in the context of a multi-person location-based evader game building on these primitives.

The previous work on the detection of *following* and *leadership* patterns in a spatio-temporal sense from movement and location data is mainly limited to the work of Andersson et al. [3], which focuses on computational efficient detection of such patterns from planar location data. They evaluate their geometric algorithm on synthetic data mimicking outdoor animal movements. However, as most humans spend a lot of their day indoors it is for many use-cases crucial to provide methods that are also applicable in multi-story buildings.

The previous work on visual scene understanding has addressed some elements of the problem mainly focusing on *following* patterns [10]. However, visual approaches are hampered by their need for images with a good coverage of the scene which is particularly hard to satisfy in indoor areas. Furthermore, as the identity of the subjects is often unknown, vision-based methods are not applicable in several of the above scenarios. To capture non-spatio-temporal notions of *leadership* both audio and visual methods have been applied, e.g., by analyzing audio and visual clues during a conversation [8].

Focusing on indoor environments, there have been several works focusing on further movement patterns utilizing various sensor modalities, for example, *co-moving* , proximity, flocking, user behavior modeling, crowd density and group structure detection, but not *following* or *leadership* patterns. Chandrasekaran et al. [11] proposed methods for detecting *co-moving* devices from correlation features of WiFi signal strength measurements and later applied such methods for speed estimation [12]. Several works have utilized Bluetooth [6,1,13] for proximity detection. Eagle et al. [1] proposed methods for modeling users' behavior from such data and Do et al. [4] proposed methods for utilizing it for building probabilistic models of the latent group structures. Efstratiou et al. [13] used Bluetooth data to detect social interactions in a group and Adams et al. [6] used Bluetooth and GPS data to understand proximity and then model user behavior as rhythms of place visits and social interactions. Phung et al. [14] extended this work to also consider WiFi readings in an indoor setting to quantify user rhythms. Weppner et al. [15] used Bluetooth to estimate the density of a crowd. Krumm et al. [16] used WiFi measurements for detecting proximity for their NearMe system. WiFi measurements have also been utilized for flock detection [17,18]. However, no work has so far targeted the detection of *following* and *leadership* patterns. Furthermore, technologies, e.g., Bluetooth, that can only detect proximity among moving subjects are not applicable for the problem as they cannot detect who is following who—only that the two targets are in proximity.

In this paper, we propose methods identifying *following* patterns using machine learning algorithms on features derived by using similarity metrics on time-lagged sequences of mobile sensing measurements, e.g., raw WiFi signal strength and acceleration measurements. To detect *leadership* we first combine the detected pairwise *following* relations into directed graphs and then subsequently perform a graph link analysis. We provide evaluation results showing low error rates and a clear improvement over state of the art for datasets from both a scripted and an unscripted experiment, conducted in two different multi-story buildings. In this paper we extend our earlier work [19] by including more in-depth evaluation of both the parameterization of the methods and analyzing the runtime efficiency of the methods. Furthermore, we propose and analyze both temporally, person-focused and spatially centered visualizations of the detected patterns—with the aim to provide support for the analysis of detected follower and leadership patterns.

The proposed methods support a fine-grained real-time analysis, that can detect *following* and *leadership* relations, and evolution thereof, in indoor environments of various spatial layouts. Our results imply that, for instance, when a crowd coming from a transit area diffuses into an open space, and smaller groups are heading in different directions, then our methods will be superior in identifying and analyzing these groups w.r.t. *following* and *leadership* patterns. Thus, they allow us to e.g. measure the effect of a commercial or an announcement in the transit area. Also, they allow for quick identification of leading characters in groups, when arriving at an open space—e.g. they allow us to conclude that the teenage kids who