Pattern recognition in pedestrian movement trajectories

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ABSTRACT

Interpretation of pedestrian behavior in public, camera-supervised areas (e.g., train stations, sports stadiums) has become a popular research topic in the last years (see [1]). Today's camera-based surveillance systems are often live monitored and analyzed by trained security staff members responsible for visually detecting restricted or security critical behavior of individuals or groups. Increasing security needs result in an increase of the number of cameras used for surveillance of public areas, both total as well as per responsible security staff member. Extrapolating this trend of providing a single security staff member with a continuously increasing amount of parallel video data leads to a point where the cognitive load needed to process all data exceeds human capabilities resulting in a lower overall-quality of visual inspection resulting in a lower detection rate of security critical behavior.

The surveillance personnel's task typically consists of three steps: visual detection of potentially critical behavior in the video scene (one of several video streams provided by a number of cameras), inspection and interpretation of the detected action's context and finally classification as either security critical or uncritical, resulting in an appropriate response. (Partial) automation of this task would yield high benefits in terms of both easing the security staff's task as well as increasing the quality of video analysis itself, e.g., in a higher detection rate of critical behavior due to a priori filtering of the information input.

The CamInSens project funded by the German Ministry of Technology and Research (BMBF) deals with this scenario: public open areas are supervised using a set of stereo smart cameras detecting and tracking objects – mainly pedestrians – within the scene, generating interpretations for individual behavior as result of an in-situ analysis task mainly based on pedestrian movement trajectories. Results of this analysis are then available for both controlling the network of surveillance cameras to automatically focus attention to areas with potentially security critical activity (i.e. without the need to manually handle camera control for better visual inspection), as well as for giving appropriate visual output to security staff personnel.

The idealized vision of the project is the aforementioned security staff member sitting in front of a grid of surveillance monitors which are basically turned off or dimmed down as long no security critical action takes place in the observed area. Whenever pattern analysis based on the detected pedestrians' trajectories results in detection of potentially security critical behavior, the corresponding monitor(s) become active, providing additional hints on the trajectory analysis results as well as the current context (e.g., by highlighting the critical area inside the scene or giving additional information to individual or group actions requiring human attention and human cognitive interpretation capabilities). After visual inspection, the responsible security staff member may then manually classify the observed behavior, providing feedback for the pattern module which is then used as either positive or negative example in terms of machine learning.

Our part in the project CamInSens covers the in-situ analysis task, that is searching for patterns in pedestrian movement trajectories. The task itself is subdivided into three main modules. The first module deals with the analysis of individual movement behavior. After preprocessing for reducing noise and fine-granular sinuosity, primary movement features (e.g., speed, curvature, sinuosity) are extracted from the trajectories and used for classification of the observed movement, trying to identify the observed person's current mode of locomotion (e.g., detection of circular movement). Derivatives of those features, e.g., sudden changes in direction or speed of movement, are indicators for potentially security critical behavior.

The second module deals with the identification of groups of homogenously (with respect to primary movement features, their derivatives and spatial proximity among group members) moving individuals within the observed scene. Like in the above case, primary features of homogenous groups (e.g., diameter, density) can be extracted and used as indicators for security critical behavior as well. Detection of group movement patterns, i.e. domain-specifically interesting relations between single individuals or groups with homogenous movement behavior, allow for a high-level interpretation of the observed activity, e.g., a meeting/interaction between several persons (see [2]) or a group following a designated leader (see [3]). This includes interpretation of observed movement behavior with respect to influences of other pedestrians' movement, e.g., anticipatory avoidance of collision with other pedestrians or formation of lanes with homogenous movement direction to maximize movement speed inside crowds (see [4]).

The third module deals with the analysis of identified pattern (of individuals and groups) in the spatio-temporal context. This includes collection and aggregation of previously detected movement features and patterns, both for individual as well as group movement, in correlation with the parameters time and location (of the observation). The idea here is unsupervised learning of typical scene-specific space- and/or time-dependent behavior which is then used to detect abnormal behavior, i.e. patterns not critical by themselves but uncommon in a certain location or at a certain time (see [5]). Particularly interesting in this context is the need for a mechanism allowing to integrate changes in pedestrian behavior resulting from changes in the physical environment (e.g., a barrier preventing access to a popular area inside the scene thus forcing pedestrians to walk around the obstacle) into the previously learned model of scene-typical behavior.

The result is a behavioral model of the observed scene storing detailed information of typical pedestrians' movement, which not only contains models of typical movement paths within the scene but also information regarding area and time where/when specific primary movement features or specific movement patterns can typically be observed. This model can be used for spatio-temporal semantic queries like "When and where do crowds with a given density occur?" or "What are the places inside the scene where people tend to stay while not moving?", allowing for other applications besides search for security critical behavior. It can as well be used for counting customers of shops or automats within the scene or for conflict-detection due to the building layout of the scene (e.g., detection of bottlenecks near entrances/exits).

In the project, first investigations have been conducted with respect to filtering the initial data and reducing noise (see Fig. 1a). Furthermore, first analysis methods have been implemented to

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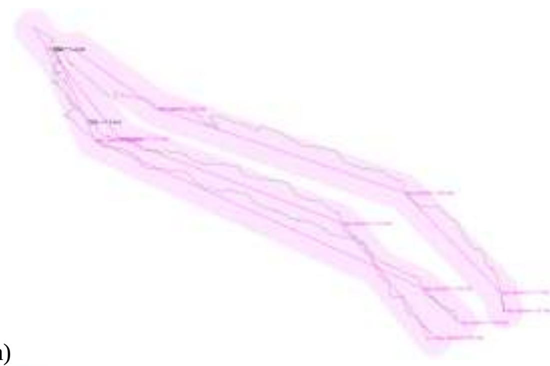
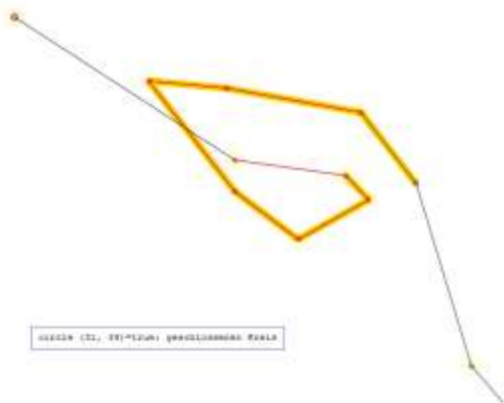


(a)



(b)

Fig. 1. Two steps of the single trajectory analysis: Figure 1a shows the preprocessing step reducing noise and the intrinsic movement sinuosity of the original trajectory (black), resulting in a smoother representation (magenta). Figure 1b shows a circular movement (yellow) as a result of geometric analysis.

classify the observed movement in terms of the observed person's mode of locomotion. Fig. 1b) shows the result of identifying a circular movement. Note that the circularity is not defined in terms of a perfect circle, but also allows (typical) deviations of it. In the paper, the current state of the project will be presented, and the developed algorithms will be described in more detail.

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REFERENCES

[1] D. Makris and T. Ellis. "Finding paths in video sequences". In *Proc. Brit. Machine Vision Conf.*, vol. 1, Manchester, U.K., Sep. 2001, pp. 263–272.

[2] D. Orellana, M. Wachowicz, N. Andrienko, G. Andrienko. "Uncovering Interaction Patterns in Mobile Outdoor Gaming". In *International Conference on Advanced Geographic Information Systems & Web Services, 2009*, pp.177-182, 1-7 Feb. 2009.

[3] S. Dodge, R. Weibel and A.-K. Lautenschütz. „Towards a taxonomy of movement patterns". *Information Visualization*, (7):240–252, 2008.

[4] W. Daamen and S.P. Hoogendoorn. *"Qualitative results from pedestrian Laboratory experiments"*. PED2003 proceedings 121-132 (2003).

[5] D. Makris and T. Ellis. "Spatial and Probabilistic Modelling of Pedestrian Behaviour". *British Machine Vision Conference BMVC2002*, Cardiff University, UK, vol. 2, pp. 557-566, September 2002.