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Survey on Human Activity Prediction based on Temporal and Spatial Patterns

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Abstract: The machine learning and persistent sensing expertise found into smart environment present extraordinary chances for presenting wellbeing examining and support to persons undergoing complexities surviving autonomously at residence. The purposes system makes a survey to examine the practical wellbeing of smart-environment inhabitants; technology which could identify and follow behavior that people generally make as their every day schedules is developed. Even methodologies are present for identifying actions, the proposed method is implemented to captured movements which are preselected and which is useful based on the sample learning information presented in various researches.

Key Words: Data Mining, Temporal Data Mining, Spatio-Temporal Data Mining.

I. INTRODUCTION

A convergence of technologies in machine learning and persistent computing as well asDevelopment of robust sensors and actuators has caused interest in the development of *smartenvironments* to emerge [1]. The need for development of such technologies is underscored by the aging of the population, the cost offormal health care, and the import that individuals place on remaining independent in theirown homes. To function independently at home, individuals need to be able to complete Activities of Daily Living (ADLs) such as eating, dressing, cooking, drinking, and taking medicine. The BehaviorsReasoning algorithm that achieved good results even when errors were present in the data.[8] However, all of the model data in that study had been labeled (mapped onto the correct corresponding activity) in advance by the experimenter. The challenge remains, then, how to *efficiently* and *accurately* annotate sensor data with the corresponding activity. Because the user will need to process a large amount of sensor data, efficient data annotation is necessary [10].Because the annotated data will be used to train a machine learning algorithm, accurate data annotation is paramount. Individuals perform activities differently due to physical, mental, cultural, and lifestyle differences, so sample data needs to be efficiently and accurately annotated for many individuals before the learned models can generalize well.

II. LITERATURE REVIEW

A. Learning Spatio Temporal Graphs of Human Activities .*B. Reisberg, S. Finkel, J. Overall, N. Schmidt-Gollas, S. Kanowski, H. Lehfeld, F. Hulla, S.G. Sclan, H.-U. Wilms, K. Heininger, I. Hindmarch, M. Stemmler, L. Poon, A. Kluger, C.Cooler, M. Bergener, L. Hugonot-Diener, P.H. Robert, and H. Erzigkeit, "The Alzheimer's Disease Activities of Daily Living International Scale (ADL-IS)," Int'l Psychogeriatrics, vol. 13, no. 2, pp. 163-181, 2001 [1].*They proposed Complex human activities occurring in videos can be defined in terms of temporal configurations of primitive actions. Prior work typically hand-picks the primitives, their total number, and temporal relations (e.g., allow only followed-by), and then only estimates their

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relative significance for activity recognition. They represent videos by spatiotemporal graphs, where nodes correspond to multiscale video segments, and edges capture their hierarchical, temporal, and spatial relationships. Access to video segments is provided by our new, multiscalesegmenter. Given a set of training spatiotemporal graphs,learn their archetype graph, and pdf's associated with model nodes and edges. The model is used for parsing new videos in terms of detecting and localizing relevant activity parts For example, activity structure has been modeled by HMMs , dynamic Bayesian nets, prototype trees, spatiotemporal graphs, context-free (AND-OR) grammars, CRFs , and compilations of first-order logic to graphical models . These issues have recently been addressed by learning relevant contextual relations between individual actions of people in a group movement. However, their model encodes a fixed number of primitive actions.

B. Learning Context for Collective Activity Recognition*R.Begleiter,R.El-yaniv,andG.Yona, "On prediction using variable order markov models," J.Artificialintelligence research,vol.22,pp.385-421,2004[2].*Has proposed a framework for the recognition of collective human activities. A collective activity is defined or reinforced by the existence of coherent behavior of individuals in time and space. This enables a methodology for modeling crowd context. The useof 3D Markov Random Field to regularize the classification and localize collective activities in the scene. They express the flexibility and scalability of the proposed framework in a number of experiments and show that our method outperforms state-of-the art action classification techniques. They represent crowd context by adaptively binning the spatio-temporal volume as well as the attribute space using a novel random forest (RF) classification scheme. A Randomized Spatio- Temporal Volume (RSTV) classifier. In their framework, the feature that the trees in a RF operate on is calculated over a random spatio-temporal volume. The approach of Random Forest classifier to associate each individual with a collective activity label, performing local classification.

C. Observing Human-Object Interactions: Using Spatial and Functional Compatibilityfor Recognition. *D.J. Cook and P. Rashidi, "The Resident in the Loop: Adapting the Smart Home to the User," IEEE Trans. Systems, Man, and Cybernetics, Part A: Systems and Humans, vol. 39, no. 5, pp. 949- 959, Sept. 2009 [3].*Have described Interpretation of images and videos containing humans interacting with different objects is a daunting task. It involves understanding scene/event, analyzing human movements, recognizingmanipulable objects, and observing the effect of the human movement on those objects. While each of these perceptual tasks can be conducted independently, recognition rate improves when interactions between them are considered. Motivated by psychological studies of human perception, they present a Bayesian approach which integrates various perceptual tasks involved in understanding human-object interactions.Moreover they demonstrate the use of such constraints in recognition of actions from static images without using any motion information. Interactions between different perceptual analyses allow us to recognize actions and objects when appearances are not discriminative enough. Consider two objects, such as the spray bottle and a drinking bottle. When interaction movements are too subtle to observe using computer vision, the effects of these movements can provide information on functional properties of the object. For example, when lighting a flashlight, recognizing the pressing of a button might be very difficult. However, the resulting illumination change can be used to infer the manipulation.

D. Action Recognition based on Human Movement Characteristics.*Q.Fan et al.,"Recognition of Repetitive Sequentinal Human Activity," Proc.IEEE Conf.Computer Vision and Pattern Recognition, pp.943-950, 2009. [4].*has proposed a motion descriptor for human action recognition where appearance and shape information are unreliable.

Unlike other motion-based approaches, they leverage image characteristics definite to human movement to achieve better robustness and lower computational cost. The proposed descriptor is used for both classification and detection of action instances, in a nearest-neighbor framework. The descriptor on the KTH action database and obtain a recognition rate of 90% in a relevant test setting, comparable to the state-of-the-art approaches that use other cues in addition to motion. Understanding human behavior at a investigate counter of a department store is a challenging application and current statistics on revenue loss due to illicit cashier actions make it an important problem. Typical motion-based representations compute optical flow over a video volume of interest and classify the action in the volume without assuming a particular model for the resulting set of motion vectors. But ignoring the characteristics of human movement in these and other motion-based approaches limits performancein terms of both robustness and computational cost.

E. Recognizing Human Activities from Partially Observed Videos.*R. Wray and J. Laird, "Variability in Human Modeling of Military Simulations," Proc. Behavior Representation in Modeling and Simulation Conf., pp. 160-169, 2003. [5].* Recognizing human activities in partially observed videos is a challenging problem and has many practical applications. When the unobserved subsequence is at the end of the video, the problem is reduced to activity prediction from unfinished activity streaming, which has been studied by many researchers. Thetwo approaches describe (SC and MSSC) on various real videos. They evaluate the proposed methods on two special cases: 1) activity prediction where the unobserved subsequence is at the end of the video, and 2) human activity recognition on fully observed videos. One widely used approach for human activity recognition is to train and classify the spatiotemporal features extracted from videos with different activities. By using the bag-of-visual-words technique, spatiotemporal features within a video can be combined into a feature vector that describes the activity presented in the video.

TABLE 1: Comparison of to Predict Human Activity by Temporal and Spatial Patterns

Sl.No	Author	Algorithm	Features	Problems
1	B. Reisberg, S. Finkel,	HMMs , dynamic Bayesian nets, prototype trees, spatiotemporal graphs, context-free (AND-OR) grammars, CRFs	Capture particular activity in well-organised manner.	Not good accuracy.
2	R.Begleiter,R.El-yaniv,and G.Yona	Markov Random	1.Identify the human activities. 2.Number of techniques were use	Establish robustness. To clutter and able to incorporate other verification
3	D.J. Cook and P. Rashidi	Bayesian Approach	Motion less images by means of any motion information.	Very difficult for viewing an actions.
4	Q.Fan et al	Nearest-neighbo	Used for classification and detections of action instances.	Robustness and computational cost.
5	R. Wray and J. Laird	SC and MSSC	Reduced the activity prediction from incomplete activity streaming	Robustness and usefulness.

III. Conclusion

This paper as presented different algorithm of data mining.These huge collections of spatio temporal data often hide possibly intresting information and expensive knowledge. Spatio-temporal data mining is an emerging research area that is dedicated to the development of Bayesian algorithm computational techniques for the successful analysis of large spatio-temporal databases. Spatial and temporal databases are an existing quickly advancing field and we have outlined exceeding a few areas. Many methods have been proposed for mining sequential data, including mining frequent sequences , mining frequent patterns using regular expressions , constraint-based mining, and frequent-periodic pattern mining . One limitation of these approaches is that they do not discover discontinuous patterns, which can appear in daily Behaviour data due to the erratic nature of human activities. This paper aims at bringing together research and practitioners of spatial, temporal and spatio-temporal data mining.

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