Postprint on Multi-level Recognition and Reasoning Based on Probabilistic Soft Logic

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Abstract

As the global aging population continues to grow, the monitoring and care of daily behaviors among older adults has emerged as a highly challenging social issue. To address this escalating societal demand, we propose a data- and knowledge-driven approach that employs Probabilistic Soft Logic (PSL) and multi-level analysis to model the daily activities of older adults, thereby solving the activity recognition problem in elderly care. Experimental results demonstrate that the proposed method achieves higher accuracy than Hidden Markov Models in both activity recognition and anomalous activity detection, while also exhibiting faster response speeds compared to non-hierarchical recognition methods.

Full Text

Preamble

Multi-level Recognition and Reasoning Using Probabilistic Soft Logic

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Abstract: With the global aging population increasing, the daily behavior monitoring and care of elderly individuals has become a challenging social problem. To address this growing societal demand, this paper proposes a method that is driven by both data and knowledge, using Probabilistic Soft Logic (PSL) and multi-level analysis to model the daily activities of elderly individuals, thereby solving activity recognition problems in elderly care. Experiments demonstrate that this method achieves higher accuracy than Hidden Markov Models in both activity recognition and abnormal activity detection, while also providing faster response times than non-hierarchical recognition methods.

Keywords: probabilistic soft logic; elderly care; multi-level recognition method; machine learning

0 Introduction

According to statistics from the "Development of China' s Aging Cause" white paper [1], the population aged 65 and above will reach 240 million by 2020, accounting for 17.17% of the total national population, and is projected to double again by 2050. Consequently, the daily behavior monitoring and care of elderly individuals has become an extremely challenging social issue. To meet this growing societal demand, there is a need to design a care system capable of detecting abnormal activities among elderly individuals anytime and anywhere. The recognition and reasoning of daily behaviors are critical components of such systems, and designing elderly care systems based on daily activities represents a significant challenge [8].

Designing an effective elderly care system that can classify normal and abnormal activities requires two key steps. First, sensors deployed in the living environment must collect real-time data to provide a basis for determining specific activities. Second, the system must identify the activities being performed by the subject based on this data to recognize abnormal activities. In this second step, the model for judging abnormal activities must possess the ability to handle uncertainty factors such as incomplete behavior records and temporal records, as well as perform reasoning about preceding and subsequent events. This necessitates combining data with knowledge and introducing probabilistic reasoning models to address these challenges. Knowledge-driven reasoning is particularly important throughout the care system, as it requires domain experts or physicians to provide foundational knowledge—referred to as common sense. Integrating this common sense into our model helps the system perform reasoning more effectively. Since Probabilistic Soft Logic (PSL) can effectively express reasoning processes using syntax based on first-order logic, it is a suitable method for modeling elderly care systems.

Simultaneously, this paper models factors such as activity objects, time, location, and duration through multi-level analysis to identify abnormal activities. The advantages of multi-level analysis include: distributed decision-making with high speed, where each subsequent layer only executes if the previous layer identifies normal activity; improved reasoning capability through knowledge integration; and the ability to perform reasoning based on uncertain factors and preceding/subsequent events.

The remainder of this paper is organized as follows: Section 2 presents our proposed multi-level activity recognition method based on probabilistic soft logic;

Section 3 provides experimental results and analysis; and Section 4 concludes with a discussion of future research directions.

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1 Multi-level Activity Recognition Using Probabilistic Soft Logic

1.1 Related Work on Activity Recognition

Activity recognition is a complex task involving monitoring, modeling, and judgment processes. Current research on activity recognition primarily focuses on data-driven and knowledge-driven approaches [2]. Data-driven techniques build systems based on existing data. Common data-driven methods include Naive Bayes Classifiers (NBC) [18], Hidden Markov Models (HMM) [7], Dynamic Bayesian Networks (DBN) [19], and Support Vector Machines (SVM) [17]. Naive Bayes Classifiers model dependencies as probability functions and map them to activity labels to determine the most likely activity. However, they only achieve good performance with large amounts of training data and cannot model temporal information crucial for smart home applications [2]. Khan Z A et al. [6] used image data for abnormal activity recognition, achieving good results for activities with large differences but less ideal performance when activities are highly similar. Hidden Markov Models are well-suited for smart home applications as they can model temporal information in sensor data and easily simulate temporal relationships. HMM is the most commonly used method for modeling human activities in smart homes. Assam R et al. [7] proposed a method based on HMM and wavelet transforms that effectively recognizes highly similar activities, though it performs poorly for complex activities with strong temporal correlations. HMM can also be considered an example of Dynamic Bayesian Networks. SVM, the most commonly used activity recognition technique in machine learning [2], possesses strong generalization capabilities and can achieve superior results from small training samples compared to other algorithms. He Z et al. [17] used SVM, Discrete Cosine Transform (DCT), and Principal Component Analysis (PCA) to classify different human activities with high accuracy, yet it can hardly express causal relationships between events. The essence of these methods is activity classification; however, they fail to adequately represent relationships among spatial, temporal, or uncertain factors, and suffer from poor reusability—requiring repeated data collection and analysis for different subjects.

Knowledge-driven methods can associate human behaviors with activity objects, space, time, and other factors, with knowledge obtainable from domain experts and online sources [10]. Since knowledge about similar objects is largely comparable, the reusability efficiency of knowledge-driven methods is evident. These methods can be constructed through logic and ontologies and expressed as a series of rules for reasoning [2], largely considering relationships among various factors, but they still have limitations in handling uncertain factors and temporal inputs [7].

In summary, purely data-driven and knowledge-driven methods both have significant shortcomings in handling temporal, spatial, logical relationships, and uncertain factors. Therefore, this paper proposes a multi-level activity recognition method driven by both data and knowledge using probabilistic soft logic to avoid these problems.

1.2 Probabilistic Soft Logic (PSL)

Probabilistic Soft Logic (PSL) is a machine learning framework proposed and developed by SH Bach et al. for constructing probabilistic models [3]. PSL uses syntax based on first-order logic to define logical structures and relational features. Like Markov Logic Networks (MLNs) and other statistical relational learning methods, PSL employs weighted rules to model dependencies in problems [5]. However, unlike MLNs and other methods, PSL represents logical relationships using probabilistic soft truth values in the interval [0,1] rather than Boolean values.

1.2.1 PSL Syntax Rules in PSL are composed as follows:

P1 and P2 are called predicates [3], used to define relationships between random variables X, Y, and Z. The weight represents the importance of each rule in reasoning. For example, in this paper, obj(S,O) indicates that the usage object of record S is O, and isactivity(O,A) indicates that the activity state corresponding to usage object O is A. Then, based on the combination of these two predicates, the probability that record S is activity A can be expressed.

1.3 Multi-level Activity Recognition and Anomaly Detection Using PSL

Activity recognition analyzes individual activity states through a series of observations of the subject' s behaviors and environmental conditions [4] to achieve the research objective. In this paper, our research goal is to combine multiple factors such as time and spatial location to recognize elderly individuals' activities and thereby identify abnormal activities to assist in elderly care.

Based on domain knowledge, we establish PSL rules for activity space, time, activity duration, and other factors, categorizing these rules into five layers. Each layer only executes the next layer if the activity is identified as normal. The process is shown in Figure 1 [Figure 1: see original paper]. The specific functions of each layer are:

- **Layer 1:** Identify abnormal activities using sensors
- **Layer 2:** Identify abnormal activities based on activity start time
- **Layer 3:** Identify abnormal activities based on activity simultaneity
- **Layer 4:** Identify abnormal activities based on activity location
- **Layer 5:** Identify abnormal activities based on activity duration

Each layer can have a different number of rules. Some logical rules are established based on domain knowledge. The following subsections explain the rationale for rule establishment in each layer.

1.3.1 Layer 1: Sensor-based Anomaly Detection Rules 1-1 and 1-2 map usage objects to activities [9], inferring the probability of possible activities. If the probability is very low, the system judges that an abnormal activity may be occurring with the object.

Scenario Example 1: Elderly person A uses cooking utensils and pots at 2:00 AM for cooking activities. Layer 1 identifies the activity "cooking" as normal. Layer 2 begins identification and outputs a low probability for "starting cooking at 2:00 AM," identifying it as an abnormal activity.

1.3.2 Layer 2: Start Time-based Anomaly Detection Rules 2-1 and 2-2 map object usage start times to activities. Layer 1 uses object-to-activity mapping, while Layer 2 extends this with start time considerations. The weight of each rule can be learned from known data.

Scenario Example 2: Elderly person A begins cooking at 8:00 AM, suddenly leaves the kitchen without turning off the stove, and goes to the bedroom to sleep. Events in the kitchen and bedroom are identified as cooking and sleeping activities through Layer 1. These activities are identified as normal in Layer 2 because occurring at 8:00 AM are high-probability events. Cooking and sleeping are a pair of forbidden simultaneous activities and will be identified as abnormal in Layer 3.

1.3.3 Layer 3: Simultaneity-based Anomaly Detection In Layer 3, Rule 3-1 incorporates domain knowledge into the rules. Forbiddenactivity represents knowledge about activities that should not occur simultaneously.

Scenario Example 3: Elderly person A enters the kitchen at 1:00 PM and lies on the floor. Layers 1 and 2 identify "lying" as "sleeping," which is considered normal. Layer 3 identifies no concurrent activities, Layer 4 identifies that generating a "sleeping" activity at the "kitchen" location is abnormal.

1.3.4 Layer 4: Location-based Anomaly Detection Layer 4 associates location information to identify activities and detect abnormal activities. Rules 4-1 and 4-2 link location and activity recognition, while Rule 4-3 comes from common-sense knowledge, functioning to identify abnormal activities by returning a low probability based on contradictory forbidden information.

1.3.5 Layer 5: Duration-based Anomaly Detection Layer 5 associates the duration of object usage with activity recognition. According to domain knowledge, when the duration of using an object exceeds the average standard, it is fed back as abnormal.

Scenario Example 4: Elderly person A enters the bathroom at 8:10 AM to shower, and at 8:50 AM, sensors still detect water flowing. Layers 1 and 2 identify this as "showering," which is normal. Layer 3 identifies no forbidden simultaneous activities and feeds back normal. Layer 4 identifies that the location information for showering is also reasonable and feeds back normal. Layer 5 identifies that the duration exceeds the average showering time and feeds back abnormal.

This section has elaborated on the design of an activity recognition and anomaly detection system driven by both data and knowledge, using PSL and employing multi-level analysis.

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2 Experiments

2.1 Experimental Data

The dataset used in this paper is the daily activity dataset provided by the UCI Machine Learning Repository[1]. This dataset contains daily activity data from two users over 35 days, collected through 12 types of sensors. The detailed dataset description is shown in Table 6 . Data samples are shown in Table 7 . Based on the start and end times of activities provided in the dataset, activity duration can be easily obtained; information about spatial location, activity objects, and start times can be directly read from the data.

For evaluation, we conduct ten experiments on each layer. In each experiment, 70% of the data is randomly selected as training data for rule weight learning, with the remaining 30% used as test data. For abnormal activities corresponding to elderly individuals, we introduce anomaly factors in location, activity objects, start time, and duration to generate abnormal activity test cases for each layer, achieving the purpose of simulating abnormal activities among elderly individuals.

The method' s accuracy is measured using Precision, Recall, and F1-score averaged over ten experiments, as shown in Equations 2, 3, and 4. In these formulas, TP represents the number of abnormal activities correctly identified in each experiment, FP represents the number of normal activities incorrectly identified as abnormal, and FN represents the number of abnormal activities incorrectly identified as normal. Precision is the ratio of correct judgments to the total number of activities identified as abnormal, Recall is the ratio of correct judgments to the total number of activities that should have been identified as abnormal, and F1 is the harmonic mean of Precision and Recall.

2.2 Activity Recognition Using Hidden Markov Model (HMM)

To verify the performance of our proposed PSL multi-level recognition method, we first model the activity recognition system using Hidden Markov Model

(HMM). Since HMM does not provide methods for modeling common-sense knowledge, Layers 3 and 4 cannot be completely modeled using HMM.

Figure 2 [Figure 2: see original paper] shows the F1-score of HMM for activity recognition in Layer 1, while Table 8 displays the average F1-score for abnormal activity detection across layers using HMM. There are no results for Layer 3 because domain common-sense knowledge cannot be modeled by HMM. The data in the table shows that the F1-scores obtained without the participation of domain common-sense knowledge are not high, which motivates us to use PSL to improve these deficiencies.

2.3 Multi-level Recognition Method Using Probabilistic Soft Logic (PSL)

In PSL, for each layer, every rule is written according to the forms given in Tables 1, 2, 3, 4, and 5, and the weight of each rule can be learned using PSL' s built-in weight learning command. We evaluate its performance based on abnormal activity detection capability.

Figures 3 and 4, along with Tables 9 and 10, show the recognition effectiveness of the PSL-based multi-level analysis method across layers. The data in Figure 5 [Figure 5: see original paper] indicates that PSL and HMM have comparable stability. Table 11 compares the average F1-scores of HMM and our PSL multi-level analysis method across layers. The F1-score comparison demonstrates that using PSL to model elderly care systems achieves better recognition accuracy than HMM.

2.4 Comparison Between PSL Multi-level and Non-hierarchical Recognition Methods

We remove Rules 3-1 and 4-3, which require domain knowledge support, from the multi-level recognition model, and combine the remaining rules using PSL to form a non-hierarchical recognition model. We gradually increase the number of test samples, conduct multiple experiments for each group, and record the average time required for each experiment, forming Table 12 .

The results in Table 12 show that the multi-level method requires less time than the non-hierarchical method to identify abnormal activities.

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3 Conclusion

This paper proposes a multi-level recognition method based on PSL, applying it to the recognition of elderly individuals' daily activities using a data- and knowledge-driven model. The introduction of domain knowledge assigns higher priority to key factors affecting abnormal activity recognition. Experiments on standard datasets demonstrate that compared with HMM, the PSL-based multi-level recognition method produces higher accuracy in activity recognition and abnormal activity detection. Additionally, the multi-level recognition method, by modeling high-priority abnormal activity detection rules within the system, achieves higher detection efficiency and shorter response times. Therefore, the PSL-based multi-level recognition method is feasible and effective for daily activity recognition and abnormal activity detection in elderly care.

In future work, we will incorporate more domain knowledge and more effective temporal relationships to further improve the accuracy of activity recognition and abnormal activity detection from both knowledge structure and model hierarchy perspectives. Additionally, we will explore the applicability of our method in domains such as patient care and child supervision.

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Note: Figure translations are in progress. See original paper for figures.