An Autonomous Agent for Learning Spatiotemporal Models of Human Daily Activities

(Extended Abstract)

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ABSTRACT

Activities of Daily Living (ADLs) refer to activities performed by individuals on a daily basis. As ADLs are indicatives of a person's habits, lifestyle, and well being, learning the knowledge of people's ADL routine has great values in the healthcare and consumer domains. In this paper, we propose an autonomous agent, named Agent for Spatia-Temporal Activity Pattern Modeling (ASTAPM), being able to learn spatial and temporal patterns of human ADLs. ASTAPM utilises a self-organizing neural network model named Spatiotemporal - Adaptive Resonance Theory (ST-ART). ST-ART is capable of integrating multimodal contextual information, involving the time and space, wherein the ADL are performed. Empirical experiments have been conducted to assess the performance of ASTAPM in terms of accuracy and generalization.

General Terms

Algorithms, Design, Experimentation

Keywords

Fusion ART, Activity pattern, spatiotemporal features

1. INTRODUCTION

Activities of daily living (ADLs), as used by health care professionals, refers to daily self care activities performed by an individual in his or her place of residence, outdoor, or both. In elderly health care, ADLs are usually used to measure the functional status of elderly. Researchers, e.g. [2] [3], have used the topic model approach to discover activity patterns, wherein topics are pulled from a document using a bag-of-words approach. However, these works mainly study the relationships between low level activities and ADLs. We have proposed ADLART architecture [1] which incorporates the fusion ART (Adaptive Resonance Theory) model [5] to learn ADL sequence patterns. Although ADLART made various applications possible, there are some limitations. Firstly, ADLART could not associate personalized ADL spatial and temporal information to the ADL categories. Secondly, due to its data structure, ADLART uses only the starting time of ADLs and does not capture the ADL duration information.

In this paper, we propose a self-organizing neural model named SpatioTemporal - Adaptive Resonance Theory (ST-ART). ST-ART is capable of learning the personalized spatial temporal information of ADLs by encoding the space, time, and activity information across multimodal pattern channels. With the extended spatiotemporal feature, compared with ADLART, the ST-ART model has a better accuracy on classification in spatiotemporal domains. Based on ST-ART, we propose an autonomous agent named Agent for Spatia-Temporal Activity Pattern Modeling, or ASTAPM, which performs daily ADL pattern learning and spatiotemporal information retrieval.

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2. FUSION ART

Various models of ART and their supervised learning versions are used in the pattern analysis and recognition tasks [4]. Within the family of ART models, there is a group of networks known as Fusion ART [5] or multi-channel adaptive resonance associative map (multi-channel ARAM) [7], which formulates cognitive nodes associating multi-modal patterns across multiple input channels. Fusion ART models can also be used for reinforcement learning. For example, a three channel fusion ART called FALCON is described in [6] [8]. Self-organizing is another important feature of fusion ART. When no learnt node is matched, the network could autonomously use the uncommitted node to represent the new pattern. The architecture of a typical fusion ART model is shown in Figure 1.

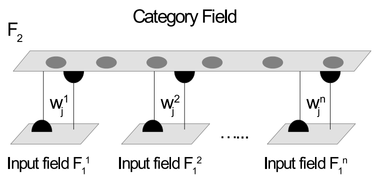

Figure 1: The generic fusion ART architecture.

3. ST-ART ARCHITECTURE

SpatioTemporal - Adaptive Resonance Theory (ST-ART) is a four-layer neural network, as shown in Figure 2. The first layer represents the low level temporal information in two input fields, namely the time field and the day field. The second layer is the ADL spatiotemporal layer, consisting of the ADL type field, temporal field, and spatial field. The third layer is the spatiotemporal ADL (ST ADL) layer, wherein the ST ADL category nodes encode the associations of ADL types and spatiotemporal information. Finally, the highest layer is the ADL routine layer, wherein the ADL routine nodes encode the sets of ST ADLs over a day.

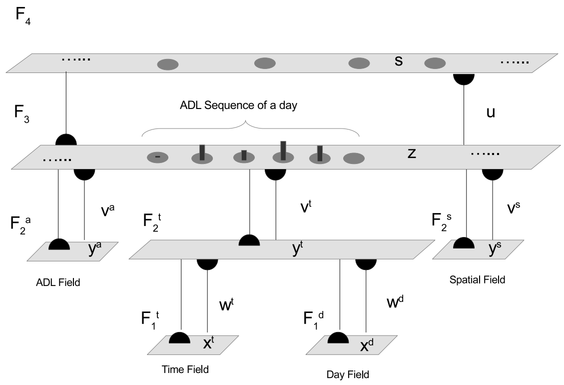

Figure 2: ST-ART model

4. ASTAPM

Based on ST-ART described in Section 3, ASTAPM proactively learns the spatiotemporal patterns of ADLs and ADL daily routines through a training process. At each level, if there is one wining node satisfies the match function, e.g., resonance occurred, related weights will be updated, otherwise a new node is created for the input pattern. The process of learning spatiotemporal patterns and daily routine across the four layers is summarized in Algorithm 1.

Algorithm 1 ASTAPM training process

Require: A sequence of ADLs each in the form of $(\mathbf{x}^t, \mathbf{x}^d, \mathbf{y}^a, \mathbf{y}^s)$
Ensure: Learn an ADL routine

for each input ADL $(\mathbf{x}^t, \mathbf{x}^d, \mathbf{y}^a, \mathbf{y}^s)$ **do**
    Compute activity vector $\mathbf{y}^t$ in F_2^t layer using input patterns $\mathbf{x}^t$ and $\mathbf{x}^d$
    The winning F_2^t node learns a temporal category from $\mathbf{x}^t$ and $\mathbf{x}^d$
    Update activity vector $\mathbf{z}$ in F_3 layer using input patterns $\mathbf{y}^t, \mathbf{y}^a$, and $\mathbf{y}^s$
    The winning F_3 node learns a ST ADL category from $\mathbf{y}^t, \mathbf{y}^a$, and $\mathbf{y}^s$
end for
Update activity vector $\mathbf{s}$ in F_4 layer using input patterns $\mathbf{z}$
The winning F_4 node learns an ADL routine category from $\mathbf{z}$

5. EXPERIMENTS

5.1 Methodology

To evaluate the performance of ST-ART, we designed a simulation environment to conduct experiments. The simulator generates daily ADL samples based on a person's profile over a period of one year. The purpose of the experiment is to study the spatiotemporal ADL categories created in the F_4 layer by using different vigilant values.

5.2 Daily routine categories generation

In this experiment, we look at the learning process from F_3, the ADL category layer containing the learnt spatial temporal ADL categories that a person performed in his daily life, to F_4, the ADL daily routine category layer. This step is to learn ADL daily sequences or ADL daily routines that could be used to describe his personal behaviour or lifestyle. After training with the simulation data of 365 samples, the F_3 layer learnt the spatiotemporal ADL categories. In order to obtain generalized personal daily routine patterns, we aim to identify a low vigilance value, for generating roughly 50 or less ADL routine categories. After conducting experiments with different vigilance values, we found by using a vigilance value of 0.8, ST-ART learnt a total of 46 ADL daily routine categories. The top frequency categories are listed in Table 1.

Table 1: Top frequency ADL daily routines learnt by ST-ART

Index	Count	Routine Interpretation
1	64	Normal Weekday
2	49	Normal Weekend
3	41	Exercise on Weekday
4	28	Outing on Weekend
5	19	No breakfast day

6. CONCLUSION

In this paper, a spatiotemporal fusion ART neural network model (ST-ART) is used to model the spatial and temporal information of human ADLs. The ST-ART model is capable of learning multimodal contextual information. An autonomous agent utilizing the ST-ART model is proposed and named Agent for Spatia-Temporal Activity Pattern Modeling, or ASTAPM. Simulation experiments are conducted to evaluate the ASTAPM agent. In the future, experiments on real data will be conducted.

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