INTEGRATION OF NOVEL EVENT RECOGNITION USING SPN (SEMANTIC-PROBABILISTIC NETWORK)

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ABSTRACT Integration of novel event recognition using SPN is describe the events and scenarios pre defined ontology is utilized. The Bayesian network is obtained when simple variables and concepts are decomposed into automation conversion. Depend on the concept of ontology, novel approach is introduced. This will calculate the weighted relationship using SPN. By using novel approach gestures are recognized in human gesture recognition system. In this initially multiple layers are given as input. Next these layers are segmented using segmentation. After the layers are segmented data is classified. Once classification is done then event detection is performed. After event detection features are extracted using feature extraction. At last for obtained data, sequence analysis is performed. From results it can observe that precision, recall, average processing time and accuracy will give effective outcome.

KEY WORDS: Semantic-Probabilistic Network (SPN), Feature extraction, segmentation, Classification, Event detection and Sequence Analysis.

I.INTRODUCTION

In the last several decades, a considerable growth of human-computer interaction systems using video cameras as input has been observed. This includes human gesture recognition systems as well as intelligent surveillance systems that have various applications, from crime prevention to taking care of the elderly. Automatic event recognition plays a key role in these applications [1]. A large number of existing related works focused on basic human action/activities recognition (like “walking”, “turning around” etc.) in clean backgrounds using datasets such as KTH, Weizmann, and HOHA.

This led to the necessity of the improvement of existing software and hardware video processing and analysis systems, context recognition and context search systems [2]. The existing event recognition methods can be divided into feature (descriptor) and model-based approaches. Feature based approaches use HOG feature and the spatio-temporal features such as the spatio-temporal interest point (STIP) features and optical flow based features that capture local appearance or motion patterns near the interest points or optical flows. Model-based methods include probabilistic graphical models such as Hidden Markov Models, Dynamic Bayesian Networks, Conditional Random Fields, and their variants. They use models to encode semantic and temporal relationships and combine it with image features.

Despite these efforts, video event recognition still faces difficulties even with the well-constructed descriptors or models for describing the events. A very promising tool for event recognition are the Bayesian networks, which are indispensable for determining the probability of events influenced by various components [3]. The creation of Bayesian networks requires solving three tasks: determining relevant influence factors, determining relationships between them and calculating of the conditional probability tables for each node.

We build the domain ontology by decomposing the events recognized by our system into a hierarchical set of ontological concepts, separated into several layers. The first layer contains the variables, which are the properties derived as the visual descriptors computed from the observed scene. These represent the possible states and values that an input variable of the Bayesian network can assume and are defined as concepts of the ontology.

They are grouped into one variable by having a relation to the “variable” concept. The nature of the relation signifies how high the probability (likelihood) of the variable assuming that number is. For this we incorporate three gradations of likelihood: “low”, “medium” and “high”. These gradations are then used to calculate the weighs of the Bayesian network initial nodes [4].

The next layer of the ontology consists of a set of states, in which the observed object can find itself and is mainly used to aggregate the output of the variables layer in order to simplify the ontology and decrease the amount of connections. These concepts are grouped into states by having a connection to a “state” concept. The third layer of the ontology is reserved for a set of events occurring in the scene.

A set of concepts in the ontology is grouped into one event by having connections to an “event” concept. In the case, when the scene contains objects with a more complex behavior, a fourth layer can also be used to describe overall scenarios, which are composed of a set of events occurring at the same time.

The relations between the concepts in the ontology describe how a combination of states of objects as well as variables assuming certain values can mean with a certain probability that a certain event, a set of events or a scenario is happening in the observed scene [5]. Every one of these relations is marked by the strength of the connection, which is then used to calculate the weights of the Bayesian network nodes and can be negligible (“none”), “weak” or “strong”.

II. POSSIBLE APPROACHES

The conventional approach to this problem is image-level segmentation, i.e., if all single object behavior patterns present in the input image sequence are successfully extracted, a simple classification method can be applied to each extracted pattern [6]. Whether the input is a temporal pattern or not, this approach, i.e., bottom-up segmentation followed by classification, is the standard framework for multiobject recognition in computer vision.

A behavior analyzer based on this principle can be realized by an architecture named selective attention mechanism consisting of the following components: State-Dependent Event Detector. An event is a predicate representing whether an image region2 called focusing region is filled up by anomalous pixels obtained by background subtraction or not. Since the event detection is performed in a limited image region, it is not affected by image variation outside of the region (outliers) [7]. Each focusing region is switched according to the corresponding active states in the event sequence analyzer described below. The event can be regarded as a positive evidence of a certain behavior at a certain behavior stage.

Event Sequence Analyzer. A state transition model representing the order relationship between the behavior stages is necessary to generate the assumptions. We call the state transition model

driven by the detected events the sequence analyzer [8]. In this paper, we employ Nondeterministic Finite Automaton (NFA) as a sequence analyzer, because NFA is a simple example satisfying the following properties: Instantaneousness. States are instantaneously activated whenever an input is injected. This is because
1) The focusing region depends on active states and
2) The start and the end of each behavior can be detected by monitoring state activation patterns without using bottom-up temporal segmentation.

Pure-Non determinism: All feasible states can besimultaneously activated for each input to realize multicontext search. This property is sufficient for the multiple object behavior recognition and necessary to guarantee the feasibility [9]. The reason why we use the word purenondeterminism instead of nondeterminism is of state transition models.

Nondeterministic as a model, but deterministic in optimization stage, e.g., HMM. Nondeterministic as both of a model and a state machine, e.g., NFA. This architecture iterates the following loop:
1. Focusing region! Event detection
2. Event detection! State transition (activation)
3. Activated state! Focusing region.

This loop produces mutual interactions between these two components, which tightly bind them [10].

III. NOVEL EVENT RECOGNITION USING SPN

The Fig.1 shows the flow chart of novel event recognition using SPN. In this initially multiple layers are given as input. Next these layers are segmented using segmentation. After the layers are segmented data is classified. Once classification is done then event detection is performed. After event detection features are extracted using feature extraction. At last for obtained data, sequence analysis is performed.

ALGORITHM:

STEP-1: In this initially multiple layers are given as input.
STEP-2: Next these layers are segmented using segmentation.
STEP-3: After the layers are segmented data is classified.
STEP-4: Once classification is done then event detection is performed.
STEP-5: After event detection features are extracted using feature extraction.
STEP-6: At last for obtained data, sequence analysis is performed.

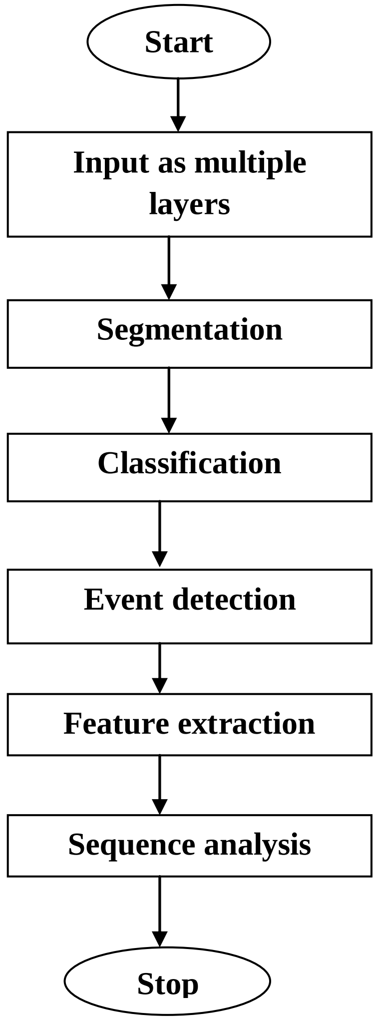

Fig. 1: FLOW CHART NOVEL EVENT RECOGNITION USING SPN

The ontology serves as a basis for constructing a network of Bayesian inference. The structure of a Bayesian network consists of a directed acyclic graph (DAG) whose connectivity matrix defines the conditional (in) dependence relationships among its constituent nodes and hence defines the form of the conditional probability tables. Each node in the domain ontology is grouped with others into sets of variables, states, events and scenarios by means of aggregation. These aggregating concepts serve as nodes of the Bayesian network, and the concepts, grouped by the aggregator, are used as values of the Bayesian's network node.

Subsequent to the node creation, the dependencies among the nodes have to be set up. Ontology relations starting and ending between the selected concepts are used to establish the links between the Bayesian network nodes. For each relation of each concept selected in the previous phase it has to be checked if the considered relation starts and ends at a concept, which has been selected in the previous phase. If this is true for the considered relation it can be used to connect the corresponding Bayesian network nodes.

The Table.1 shows comparison of event recognition using SPN and novel event recognition using SPN. The parameters used in this are precision, recall, average processing time and accuracy. Compared withevent recognition using SPN and novel event recognition using SPN, precision, recall, average processing time and accuracy.

Table. 1:COMPARISON TABLE

S.No	**Parameter**	**Event recognition using SPN**	**Novel event recognition using SPN**
1	Precision	14%	93%
2	Recall	19%	96%
3	Average Processing Time	94%	11%
4	Accuracy	43%	98%

Fig.2 shows the comparison of precision and recall for event recognition using SPN and novel event recognition using SPN. Compared with event recognition using SPN, novel event recognition using SPN improves the precision and recall in effective way.

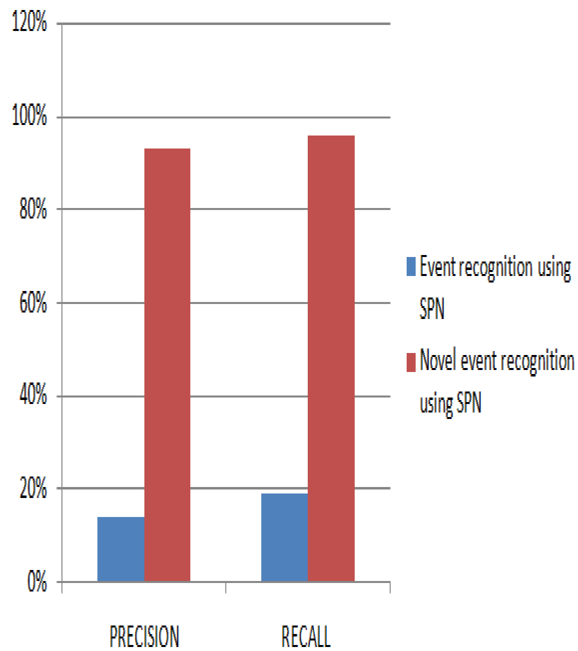

Fig. 2: COMPARISON OF PRECISON AND RECALL

The Fig.3 shows the comparison of average processing time for event recognition using SPN and novel event recognition using SPN. Compared with event recognition using SPN, novel event recognition using SPNreduces the time in effective way.

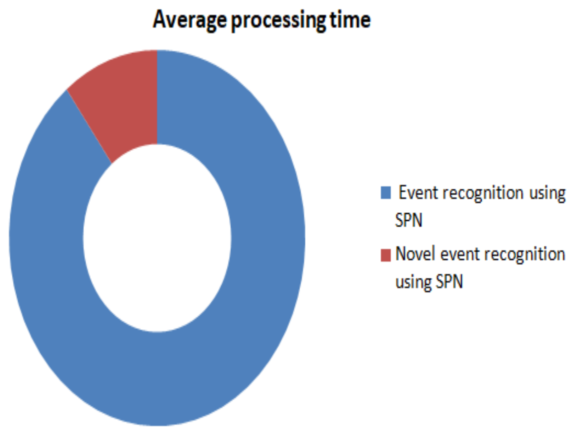

Fig. 3: COMPARISON OF AVERAGE PROCESSING TIME

The Fig.4 shows the comparison of accuracy for event recognition using SPN and novel event recognition using SPN. Compared with event recognition using SPN, novel event recognition using SPN improves the accuracy in effective way.

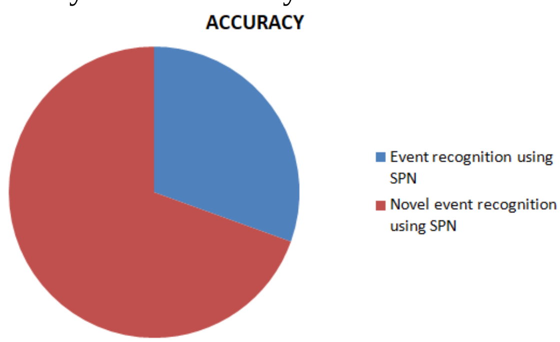

Fig. 4: COMPARISON OF ACCURACY

IV. CONCLUSION

Here Integration of novel event recognition using SPN was implemented. The approach involves using a predefined domain ontology that describes the events and scenarios as a hierarchical decomposition of simple concepts and variables and weighted relation between them. The ontology is then used for automated Bayesian network generation, which allows us to infer the events and scenarios in the observed scenes. The transition graphs for the input variables serve to predict events and scenarios. We also introduced a novel approach for gradually recalculating the probabilities of the Bayesian network nodes' in order to reduce the sensitivity of the system to errors appearing during the low-level video frame processing. The proposed approaches were then tested on a human gesture recognition system and showed very good results compared to other modern human gesture recognition systems, in both processing speed and recognition accuracy. Other possible applications of the proposed event recognition system include automatic human behavior recognition in intelligent surveillance systems and automatic video annotation.

V. REFERENCES

[1] Chang, X.; Ma, Z.; Yang, Y.; Zeng, Z.; Hauptmann, A.G. Bi-Level Semantic Representation Analysis for Multimedia Event Detection. IEEE Trans. Cybern. 2017, 47, 1180–1197.

[2] Qian, S.; Zhang, T.; Xu, C.; Shao, J. Multi-modal event topic model for social event analysis. IEEE Trans. Multimed. 2015, 18, 233–246.
[3] Qian, S.; Zhang, T.; Xu, C.; Hossain, M.S. Social event classification via boosted multimodal supervised latent dirichlet allocation. ACM Trans. Multimed. Comput. Commun. Appl. (TOMM) 2015, 11, 1–22.
[4] F. Zhu, L. Shao, and M. Lin. Multi-view action recognition using local similarity random forest and sensor fusion. Pattern Recognition Letters, 2013
[5] A.S. Ghotkar and G.K. Kharate, “Hand Segmentation Techniques to Hand Gesture Recognition for Natural Human Computer Interaction,” International Journal of Human Computer Interaction (IJHCI) 3, pp. 15–25, 2012.
[6] A.S. Ghotkar and G.K. Kharate, “Hand Segmentation Techniques to Hand Gesture Recognition for Natural Human Computer Interaction,” International Journal of Human Computer Interaction (IJHCI) 3, pp. 15–25, 2012
[7] J. Wang, Z. Chen, and Y. Wu. Action recognition with multi scale spatiotemporal contexts. In CVPR, pages 3185 –3192, june 2011.
[8] G. Yang, Y. Lin, and P. Bhattacharya. A driver fatigue recognition model based on information fusion and dynamic Bayesian network. Information Sciences, 180(10):1942–1954, 2010.
[9] M. Marszalek, I. Laptev, and C. Schmid. Actions in context. In CVPR, pages 2929 –2936, june 2009.
[10] P. Bao, N. Binh and T. Khoa, “A new Approach To Hand Tracking and Gesture Recognition by a New Feature Type and HMM,” International Conference on Fuzzy Systems and Knowledge Discovery, 2009
[11] M. Lei, T. Yuan and S. Hong qi, “A Small Target Tracking Algorithm Based on Monte Carlo Method,” Journal of Image and Graphics.2008, Vol.13, pp. 445–449.
[12] D. L. Vail, M. M. Veloso, and J. D. Lafferty. Conditional random fields for activity recognition. In Proceedings of the 6th international joint conference on Autonomous agents and multiagent systems, p. 235, 2007.
[13] L. Gorelick, M. Blank, E. Shechtman, M. Irani, and R. Basri. Actions as spacetime shapes. PAMI, IEEE Transactions on, 29(12):2247 –2253, dec. 2007.
[14] F. Lv and R. Nevatia. Recognition and segmentation of 3-D human action using HMM and multi-class AdaBoost. In ECCV, pages 359–372. Springer, 2006.
[15] P. Viola and M. Jones, “Robust Real-Time Object Detection,” Intl. Journal of Computer Vision, Vol. 57, No. 2, 2004.