International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 5s
DOI: https://doi.org/10.17762/ijritcc.v11i5s.6631
***Article Received**: 25 February 2023 **Revised**: 30 March 2023 **Accepted**: 14 April 2023*

Human Behaviour Recognition using Fuzzy System in Videos

Parul Saxena[1], Hemlata Arya[2]
[1]Department of Computer Science and Engineering
MITS
Gwalior, India
gaurparul2007@mitsgwalior.in
[2]Department of Computer Science and Engineering
MITS
Gwalior, India
hemlataarya21@mitsgwalior.in

Abstract— Human behavior can be detected and analyzed using video sequence is a latest research topic in computer vision & machine learning. Human behavior is used as a basis for many modern applications, such as video surveillance, content-based information retrieval from videos etc. HBA (Human behaviour analysis) is tricky to design and develop due to uncertainty and ambiguity involved in people's daily activities. To address this gap, we propose hierarchical structure combining TDNN, tracking algorithms, and fuzzy systems. As a result, HBA system performance will be improved in terms of robustness, effectiveness and scalability.

Keywords- Neuro-Fuzzy modeling, behaviour analysis, trajectories analysis, TDNN

I. INTRODUCTION

A human surveying the output of a surveillance camera may miss out on a large percentage of the footage due to limited human capabilities. Various paradigms of analysis have been designed for facing this challenge, like particularly, the approach based on top down and bottom up analysis can be deemed to be the most used in current literature on HBA or Human behavior analysis. In particular, the bottom up approach analyses and interprets the behavior of humans on the basis of features that are low level in the image or video and semantically tries to refine these by the use of a chain of methods from machine learning and artificial intelligence fields.

On the other hand, top-down approaches try to divide an entire video into a number of events whose semantic descriptions are analyzed together and may be used to recognize the human population's behavior. Despite the growing interest in HBA, this area of research is still at a nascent stage and there are several obstacles to developing a comprehensive system for analysis of human activity [1-3]. In addition, there are various approaches for analyzing a set amount of human behavior, making the system inflexible to deal with exquisite and unhindered human behavior.

There are various proposals that analyze only pixel-based information, such as a trajectory, and don't take into account the semantics of events, the scenario in which human activity occurs, and the dynamics between the actors in the scenario [4-12]. A framework for HBA is more difficult to plan and expand due to the vagueness and uncertainty that characterizes human daily activity. Due to this scenario, we suggest a scalable & effective architecture of HBA which is capable to understand the human behavior by analysis of the video information, via a framework aware of the context and based on the combined use of an algorithm for tracking in an enhanced manner and fuzzy logic [13-17].

Particularly, like other approaches we focus on various domains of application, we propose a hierarchical architecture on the basis of combination of various artificial intelligence techniques competent of benefitting both from a qualitative and quantitative point of view. An interface is proposed by combining several Fuzzy engines, each of which performs as a process that is aware of the context, enriching semantically. In this architecture, primitive behaviors are identified and refined based on context such as walking in a group, withdrawing money, meeting, fighting, and situations of danger. HBA frameworks based on this architecture have high level of scalability [24-27].

The approach used is modular to get the design of the Fuzzy systems which enable our architecture in enhancing the understanding of its human behavior capabilities with consideration of the semantic relationships which correspond to newer human activities. The distinction between the behaviors of high and low level, gives the system an improved capability in the field of behavioral learning. In this architecture, just the lowest layer which deals with raw input data depends on certain environmental properties like the view of camera with respect to its distance and angle.

As a consequence, our system is trainable to use lesser data and to reduce the effort of computing than other approaches of HBA. In addition, another benefit that is significant is given by the architecture proposed in relation with its enhanced capabilities of imprecision tracking. This property is because of the extensive use of theories in fuzzy that deal naturally with approximate or vague data. Utilizing popular datasets, this system's performance is compared with the performance of similar methods working on the same dataset in order to verify its efficiency and validity.

A. Related Research

The problem that is most challenging in HBA and understanding of human behavior is analyzed by many researchers over the years. Even then, most activities of research have their focus on the analysis of human actions at a low level, without analyzing the effect of semantic relationships of humans and their surroundings and their influence on detecting complex human behavior. Due to this, various paradigms of analysis are proposed for extending the usual human behavior to understand paradigms on the basis of an analysis at low level with extended capabilities of awareness of the context to perform behavioral understanding at a complex level.

A framework for learning object activity patterns in sequences of images was presented in 2004 [1], which was based on fuzzy maps that organized themselves to detect anomalies and predict activity using fuzzy maps. The method is more efficient than feature maps by Kohonen, which are self-organizing, in terms of efficiency. The researchers also applied Switching-Hidden Semi-Markov Model (S-HSMM) to the problems of learning about people's activities and their daily lives in order to solve the problems of recognizing and learning their activities [18], which is a dual-layered extension of Hidden Semi-Markov Model (HSMM).

The objective of the machine for HBA over here is the classification of the moving object velocity into abnormal or normal categories, for detecting anomalies in events, on account of the object class and temporal-spatial information like movements and location. This method is based on a knowledge base that is fuzzy and is generated automatically by learning algorithms on the basis of a 3 dimensional description of the environment of the installed system. Further research deals with the concept of a combined model of both complex and simple behaviors for reporting global and local human acts in a natural scenario.

In this system, there is a use of state machine method to represent activity to incorporate facts of the difficult area to provide the framework with capabilities of context awareness. Further research decomposes the intricate behavioral pattern in accordance with its temporal characters or contexts that are visual in a spatio-temporal manner. This behavior that is decomposed is then formed into a model with the use of linear CasDBN (Casecade of Dynamic Bayesian Networks) [19]. Then it introduces an approach that is bottom to top for understanding peoples' action on the basis of a multiple camera sys.

The projected method uses only normal data as a training set and determines whether the behavior is normal or abnormal based on two criteria- short term trajectory and human behavior. A single class SVM determines behavior abnormality in this system on a short term, and a constant HMM is proposed as a single class classifier in this study [20-21]. To extract the relationship between events, people, and related entities, some researchers collect data regarding people's actions along with data.

Some other researchers propose the detection of suspicious behavior on the basis of a space-context model, where a clustering algorithm with a data stream and an algorithm for inference which makes more specific detections, in particular of the suspicious behaviors in certain contexts. In some researches, the authors give an exquisite demonstration of trajectories, like ADV or activity Description Vector, based on the frequency of appearance of a human at a certain axes on the scene and also on the basis of their motion in all the directions, namely up, down, right and left.

Other researchers focus on recognizing the anomalous behavior, particularly in previous trajectories which are depicted as a chain of symbols and the trajectory similarities that is calculated through a string kernel. Here anomaly finding of trajectories is done through Abnormal Detector that is Conformal and which provide a measure of statistics of assurance for every prediction, whereas resemblance among both trajectories be calculated with the help of Hausdorff Distance. In ADVISOR project, there is an exploration of a logical language for description to try the detection of anomaly situation in intricate scenes, specifically representing using a 3D model [22].

In the OBSERVER project [23], the detection is performed of basic unusual events and basing on these events it can predict the occurring of publically abnormal behaviors, even if they are complex. In this method, there is a use of N-Tree generated classification of behavioral model requiring a large effort for computing to construct a fixed but not flexible collection of patterns of behavior.

The fuzzy approach of HBA is different from historical methods helps higher levels of robustness with respect to the

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 5s
DOI: https://doi.org/10.17762/ijritcc.v11i5s.6631
***Article Received**: 25 February 2023 **Revised**: 30 March 2023 **Accepted**: 14 April 2023*

inbuilt imperfections which characterize the algorithms for tracking. This yields a better and accurate recognition of human behavior and in addition, the system that is proposed performs a multi-level class of identification of behavior in place of the traditional dual class recognition of normal and abnormal achieved by previous approaches.

II. A Fuzzy Approach for Analyzing Human Behavior

In this research, we propose to analyze human behavior on the basis of a bottom-up artificial intelligence architecture that is hierarchical and where the different layers are specifically used to discover different components that helps in making the complex human behavior and combine these to compute a total descriptive form of activities done by the human. These layers work in combination with each other for identifying the behavior of a collective group of humans in a scenario of a temporal window with every frame, which translates the basic real time data given by the tracking algorithm for collection of labels which are semantic and are useful for description of both refined and primitive forms of human behavior [14].

Between the labels, the mapping of human activities finds description in the introduction of a namely behavioral taxonomy, which is a structure that is hierarchical one which is important to identify the various components characteristic of a given pattern of behavior and the manner in which these components depend on each other. The taxonomy of behavior specifies the human behavior in a well structured and defined way to depict a compilation of behavior components which can be aggregated and detected and can enable a complete scene to understand and characterize. Particularly, the taxonomy of behaviors is a structure with layers, as depicted in Fig 1.

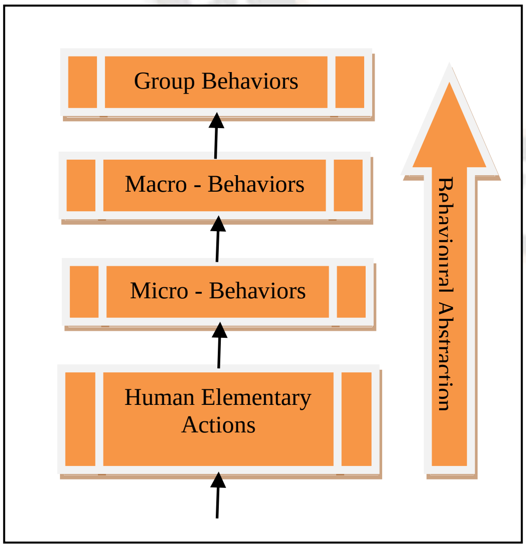

Figure 1. Taxonomy of Behaviors

In this figure, the layers below handle are responsible for managing the components of human behavior corresponding to the primitive behaviors like running and walking and fighting and these cannot be interpreted fully if they are not analyzed in a suitable context. The layers that are higher up filter these primitive human behaviors with information in context for improving the interpretation of the human behavior like fighting, reaching and following. In a detailed manner, the taxonomy of behaviors is a compilation of the behavioral components like Micro behaviors, Elementary human actions, group behaviour and macro behaviour.

Primitive Actions signify the group of immediate human activities which are incapable to provide any information about the behavior if not analyzed in an appropriate context which is spatio-temporal, like taking steps. We obtain *Micro behaviors* by putting in sequence a group of primitive actions for deriving repetitive and complex actions but are characteristic of non existence of semantics, like walking, running. *Macro behaviors* are refined micro actions by addition of contextual data, due to which they present the human behavior with semantics that are appropriate, like in taking steps to an object that is significant for the scene. Similarly moving together in the direction of object is group behavior.

In addition to representing an appropriate method of modeling of human activities formally, the taxonomy of behaviors must be used as a model of reference to develop HBA frameworks. In practice, this system is based on a group of constraint capable of analyzing nomenclature of behaviors in a manner that is bottom up from the primitive human behaviors to macro behaviors and then the human behaviors in a group. This combination of rules is called semantic behaviors. Our approach consists of tracking methodology, contextual feature extraction, FIS and semantic tagging components as shown in fig 2

This research defines these semantics of behaviors by using a layered fuzzy method which comprises of multiple components. We attempt to identify the behavior by implementation of collective semantic rules to analyze behaviors and rise up on the taxonomy of behaviors & for every stage in the given structure, computation of the group of semantic behavioral tags to describe the human behavior in a better manner for the scenario. For achieving this, the semantic rules of behavior recognize the behavior of a human by analysis of both contextual and temporal features, that is, they perform an analysis in the manner in which a human activity develops with time and how this human action acts in relation to the surrounding context.

In this system we use fuzzy logic to respectively define the rules that are contextual and temporal. After this, the information linked to the algorithm for tracking the

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 5s
DOI: https://doi.org/10.17762/ijritcc.v11i5s.6631
***Article Received**: 25 February 2023 **Revised**: 30 March 2023 **Accepted**: 14 April 2023*

classification of behaviors, and the fuzzy methods to recognize persons' behavior shall be given.

III. TRACKING APPROACH (PIXEL TO PHYSICAL-CONTEXTUAL INFO.)

The major goal of the bottom layer of the architecture proposed is the translation of the pixel data computed with a tracking algorithm into contextual and physical data representing a type of sophisticated geometric information on which the fuzzy system will perform a better analysis of behavior. To perform this translation, we use three subsystems which are tracking section, post tracking section of computation, feature extraction with context awareness.

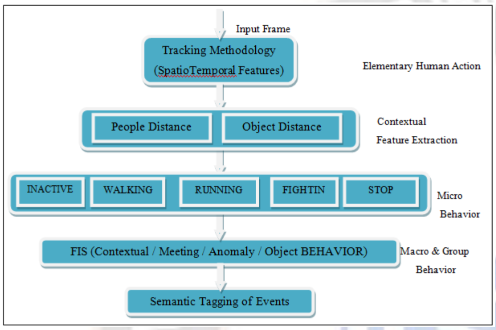

Figure 2. Architecture of Human Behavior Analysis

A. The Tracking Section

This module for tracking performs the analysis of the continuous frame obtained by the cameras, which are used for surveillance so as to extract the moving object trajectory of the scene's population, as seen in Fig 3. Particularly, it evaluates the differences in the image for reference or the background and the current image procured. The background does not have any moving objects and thus we can detect all the remaining components or blobs which correspond to the moving objects in the vision. Hence, if the blobs & the object set $|O_s|$, where $O_s=\{O_{s1}, O_{s2} \dots, O_{|Os|}\}$ which is followed up to the preceding frame t-1. The module for tracking aims at performing the association in the objects and the blobs. Then it revises this position and the appearance of every object at the present instance of time.

Figure 3. Applying Tracking Algorithm to Traditional Datasets

The sequence, in which the objects are positioned in time, is ultimately used in building the trajectory of the objects. In this scenario, the class to which the object belongs is the appearance, like a baggage, human or an animal. Even though this framework can work potentially with all types of algorithms for tracking, in our research we use the most recently proposed algorithms [13]. These have the ability of dealing with intricate occlusions including multiple simultaneously moving objects.

The idea behind this is based on the appropriate description and use of the most previous history of every individual object that is moving and is getting tracked. The history of the object is encrypted by a state and between the transitions of state; the transitions are explained using a Finite State Automata. In this way, we base the decisions for tracking on: the detected blobs in the present frame as well as the observed conditions that have been stable over longer spans of time. This is the current situation of the tracked objects in the frame analyzed previously and carried on via the Finite State Automaton.

This history of the object can be reliably used for discerning the occurrence of the most frequently occurring issues that affect the detection of the objects, which makes this method especially robust for complex scenarios.

B. Post Tracking Module of Computation

The Post tracking module of computation uses the tracking module subset and its output for computing additionally two physical measurements of each object for identification through the tracking algorithm and specifically the velocity and dissimilarity in the direction concerning the preceding frame. Particularly, in this module, velocity is computed for the object O on time T, in consideration with the location at which the entity is currently in the frame (x_O^T, y_O^T) as well as in the preceding frame $(x_O^{T-\Delta T}, y_O^{T-\Delta T})$.

$$\text{Hence, } Speed_O = \frac{\sqrt{(x_O^T - x_O^{T-\Delta T})^2 + (y_O^T - y_O^{T-\Delta T})^2}}{\Delta T} \qquad (1)$$

Here, the traditional Euclidean distance between x_O^T, y_O^T and $x_O^{T-\Delta T}, y_O^{T-\Delta T}$ *is* represented by the numerator and Δt represents the frame period under analysis in the scene, which is set as 1/30 per second, which is commonly the period that a frame sustains in a video.

C. Feature Extraction with Context Awareness

The feature extraction module with context awareness aims at identification of the relation between the group of objects as a result of computing using tracking algorithm along with the actual environment or the context in which these objects are in motion. Particularly, the subsystem for this calculates the group of values which represent the Euclidean distance between every pair of objects that are human, which are recognized by the tracking module and the other one is a

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 5s
DOI: https://doi.org/10.17762/ijritcc.v11i5s.6631
***Article Received**: 25 February 2023 **Revised**: 30 March 2023 **Accepted**: 14 April 2023*

contextual entity like baggage or some other person or escalator in a hotel or a cash counter in a bank scene.

IV. MICRO BEHAVIOR IDENTIFICATION

In this layer, we perform the task of pattern recognition for identifying the micro behaviors of humans, from the trajectory data collection which bottom layer returns. This layer specifically analyses a string of data which is calculated by the section for tracking velocity, variation and position in the direction that an object is moving and plot these in a given set of micro behavior described in the taxonomy of behaviors. Conventional modules have successfully used in various scenarios to recognize patterns but even while they are widely used, they do not possess the characteristic temporal concepts of other applications used in the video analysis field. Due to this, the architecture uses a method which is time oriented and can capture the dynamic development of a used trajectory and specifically classify these as micro behaviors. Considering this, the algorithm can improve greatly the presentation of a conventional artificial intelligence system by allowing a mechanism of learning on the basis of the facts available and the historical events available. These systems must be trained beforehand of using them in real scenarios to provide them along with realistic trajectories find in the area in which this HBA framework has being installed.

V. MACRO AND GROUP BEHAVIOR IDENTIFICATION IN THE FUZZY LAYER & RESULTS

The micro behavior layer and the layer based on tracking work provide this architecture along with quantitative segregation ability for translation of the data of pixels which is captured by the algorithm for tracking of contextual and behavioral information like appearances, object distances, people distances and micro behaviors. The main objective of the Fuzzy based layer is to augment the architecture with skills that are qualitative and to perform a task of fusing data from the dataset which comes from the lower layers for detecting the set of group and macro behaviors which are defined by the taxonomy of behaviors in fig 2.

In this scenario, the most methodological choice to achieve the previously mentioned objective is represented by fuzzy logic. Due to the ability of fuzzy logic for modeling of vagueness and uncertainties, it allows us to improve this architecture by the method of collecting FIS or Fuzzy Interface Systems. The linguistic rules of the FIS solely contribute to managing appropriately the data set of information which is imprecise and comes from the lower layer, due to which, to depict a higher accuracy level for identifying the group and macro behaviors.

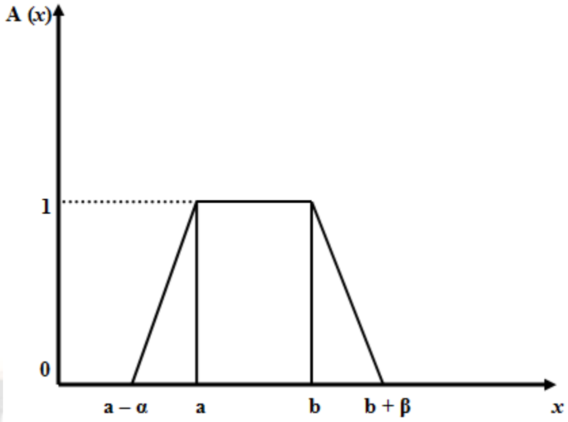

Figure 4. Modeling HBA Concepts by Fuzzy Set With Trapezoidal Tolerance Level

As seen in Fig. 4, in this module the input is a collection of data which comes from the system's lower layers, like appearances, object distances and micro behaviors, on which applied FI operators and gives an output a group of real values which correspond to the group and macro behaviors for people present in the scene. This architectural module is designed with a performance by the model of every concept related to the identification of human behavior by the method of a particularly fuzzy method and with a suitable FIE (inference engine).

Every concept in detail, like appearances, object distances, macro and micro behaviors is based on the model using a group of fuzzy sets that are trapezoidal and where every set is defined on a level of tolerance level (a, b) as explained below:

$$A(x) = \begin{cases} 1 - \frac{a-x}{\alpha} & if\ a - \alpha \le x \le \alpha \\ 1 & if\ a \le x \le b \\ 1 - \frac{x-b}{\beta} & if\ b \le X \le b + \beta \end{cases} \qquad (2)$$

In addition to enabling the framework for HBA for recognizing human behavior more efficiently than another types of fuzzy groups, the membership of trapezoidal fuzzy set may be realized in a much easy way than the usually conventional figures, like Gaussian that has lesser capability like the embedded architecture in which video surveillance systems that are intelligent are installed typically.

When the method to fuzzify is depicted i.e. the set of information that comes through the lower level of this framework, it is essential to create few choices of design which are associated with the execution of the various fuzzy system which compose the HBA system. Particularly, after investigative experiments, a group of Mamdani rules based fuzzy systems along with given feedbacks, are selected as the main part of this HBA framework's topmost layer.

These feedbacks is important for evaluation of the human activities, currently taking into consideration the preceding behavior identities and after this, avoid an instant valuation

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 5s
DOI: https://doi.org/10.17762/ijritcc.v11i5s.6631
***Article Received**: 25 February 2023 **Revised**: 30 March 2023 **Accepted**: 14 April 2023*

which may have noise and place the complete system to an incorrect stage. These choices of design improve the framework's robustness. This Mamdani approach is conventional and is preferred over the Takagi Sugeno Kang or TSK due to the linguistic capabilities which even with the high precision depicted by the TSK models, enables a direct and simple rule writing which is a part of the given behavior recognition.

This choice of design enables the system to be scalable enough for dealing with additional and unplanned research in advanced human behavior. Every Mamdani system which belongs to the HBA architecture makes use of a typical inference of MAxMin architecture engine for computing the values of fuzzy outputs with a center of gravity that is common to use the operator for defuzzification. This operator translates the fuzzy output with respect to real human activities.

VI. Results

Both the defuzzification and inference operators are selected after due consideration of some investigative experiments which involve various fuzzy operators. The present configuration of our fuzzy system architecture use Contextual, Meeting, Walking, Fighting and Stopping FISs. The *Contextual FIS* performs the analysis of the data the same as an object-distance and the values of Micro behaviors which is computed by the lower layer to identify macro behaviors of humans which strongly relative with the context of the human who is performing the activities.

Some of the contextual rules are as follows:

- If (DIST(h1,h2) is SMALL) and (STOP1 is YES) and (STOP2 is YES) then (OUTPUT is meeting)
- If (DIST(h1,h2) is SMALL) and (STOP1 is NO) and (STOP2 is NO) then (OUTPUT is meeting-walktogether)
- If (DIST(h1,h2) is HIGH) and (STOP1 is NO) and (STOP2 is YES) then (OUTPUT is approach-meet)
- If (DIST(h1,h2) is SMALL) and (STOP1 is YES) and (RUNNING2 is YES) then (OUTPUT is fight-falldown)
- If (DIST(h1,h2) is SMALL) and (RUNNING1 is YES) and (RUNNING2 is YES) then (OUTPUT is fight-chase)

Here the labels DIST(h1,h2) represents the space between the person h1 and the person h2, STOP1, STOP2, RUNNING1, RUNNING2 represents the micro behavior of both the persons respectively and OUTPUTs (meeting, meeting-walk together, approach-meet, fight-falldown, fight-chase) represents group behavior. And implemented fuzzy rules are shown in figure 5.

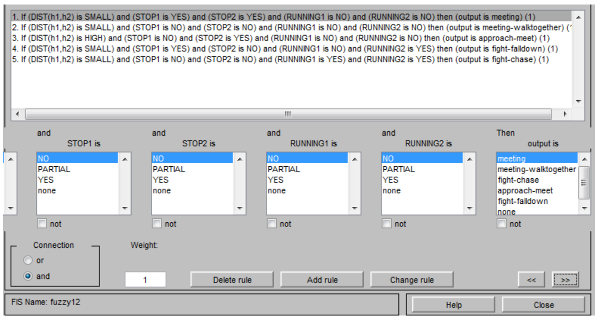

Figure 5. Implemented Fuzzy Rules

As shown in figs. 6 and 7, we can see fuzzy concept examples which relate to the FIS designed in a ways shown and there are some rules of context where the labels and the output identify the distances and the micro behaviors, respectively as in fig. 5. The object shape is detected through the scene and in the end the macro behavior is inferred. The FIS also analyses the data like distance of people and the values of their macro behavior in relation with the possible situations of danger.

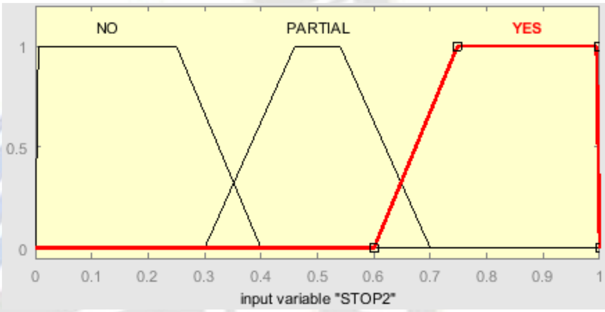

Figure 6. Stopping Trajectory Class Related Fuzzy Concept STOP2

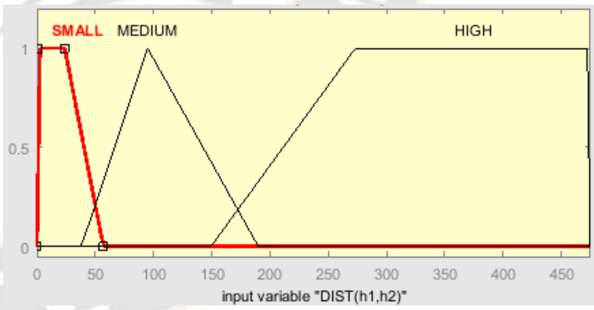

Figure 7. Contextual Variable distance related Fuzzy Concept

In relation with this FIS, the Fuzzy concept examples are constructed in the way similar to those shown in Fig 6 and Fig 7. As we can see from the outline of the architecture, every FIS is capable of using many inputs and lastly generate the output of the framework.

To realize this feature of the feedback, we describe in detail a set of variables, which are fuzzy and these variables helps in identifying human actions as implemented by the FIS by the previous time instant. The choices made in the design help the FISs in performing the analysis of behavior not by evaluation of one shot but it takes into consideration the present situation along with the behavior calculated lastly for the person mentioned earlier.

Every FIS helps to calculate a set of macro behaviors through an operator for defuzzification on the group of aggregated fuzzy data, which is refined by the rules that are fuzzy too. Consequently, for providing the users of the system a description of semantics of the abnormal behaviors, HBA architecture proposed a Semantic Tag Generator. In particular, this Semantic Tag Generator, as an input takes the actual inferred values by the previously mentioned set of FISs and returns a set of associated semantic labels.

In the figure, we can see the working of this module. For making the system more robust and more tolerant of eventual errors in FIS, the generated labels from the Semantic Tag Generator are analyzed temporarily by the ending module in the hierarchy, which is the Analysis of Temporal Behavior. In this module, we consider the labels of behavior which are computed at last second then return as the final output of the whole system according to the behavior corresponds to the label used most frequently. In the next section, we see that the temporal analysis and the feedback feature, improves strongly the proposed approach's accuracy.

VII. CONCLUSION

Today's research in HBA and video surveillance applications showing insufficiency in continuous monitoring of multiple places for visual data and recognizing quickly the behaviour of what was observed in a video and detecting the danger correctly. We are trying to diminish such shortcoming by introducing the behavioural taxonomy and fuzzy architecture so that we can support people in this situation. We use hierarchical analysis to detect and labeled them in critical behaviour. We propose a hierarchical structure that includes tracking algorithms, TDNNs, and fuzzy systems. The performance of HBA system will be improved in terms of robustness, effectiveness, and scalability. In future we will try to improve learning capabilities and detection rules so that it will work for multiple applications.

REFERENCES

[1] W.Hu, T. Tan, L Wang, S. Maybank, A survey on visual surveillance of object motion and behaviors, IEEE Trans. Syst. Man Cybernet. 34 (2004) 334-352.

[2] R. Hui, Video Content Analysis of Human Sports under Engineering Management Incorporating High-Level Semantic Recognition Models, Computational Intelligence and Neuroscience, Volume 2022, Article ID 6761857, 12 pages.

[3] F. Sulser, I. Giangreco, H. Schuldt, Crowd-based Semantic Event Detection and Video Annotation for Sports Videos, International ACM Workshop on Crowd sourcing for Multimedia, Nov. 2014, Pages 63-68.

[4] P. Borges, N. Conci, A. Cavallaro, Video-based human behavior understanding: a survey, IEEE Trans. Circ. Syst. Video Technol. 23 (11) (2013) 1993–2008.

[5] O. Brdiczka, J. Crowley, P. Reignier, Learning situation models in a smart home, IEEE Trans. Syst. Man Cybernet. Part B: Cybernet. 39 (1) (2009) 56–63.

[6] P. Dai, H. Di, L. Dong, L. Tao, G. Xu, Group interaction analysis in dynamic context, IEEE Trans. Syst. Man Cybernet. Part B: Cybernet. 39 (1) (2009) 34–42.

[7] K. Huang, D. Tao, Y. Yuan, X. Li, T. Tan, View-independent behavior analysis, IEEE Trans. Syst. Man Cybernet. Part B: Cybernet. 39 (4) (2009) 1028–1035.

[8] C.H. Lim, E. Vats, C.S. Chan, Fuzzy human motion analysis: a review, Pattern Recogn. 48 (5) (2015) 1773–1796.

[9] A. Oikonomopoulos, I. Patras, M. Pantic, Spatiotemporal salient points for visual recognition of human actions, IEEE Trans. Syst. Man Cybernet. – Part B 36 (3) (2006) 710–719.

[10] O. Popoola, K. Wang, Video-based abnormal human behavior recognition: a review, IEEE Trans. Syst. Man Cybernet. Part C: Appl. Rev. 42 (6) (2012) 865–878.

[11] S. Calderara, U. Heinemann, A Prati, R. Cucchiara, N. Tishby, Detecting anomalies in people's trajectories using spectral graph analysis, Computer Vision and Image Understanding 115 (2011) 1099-1111.

[12] Wang, H.; Schmid, C. Action recognition with improved trajectories. In Proceedings of the IEEE International Conference on Computer Vision, Kyoto, Japan, 21–23 May 2013; pp. 3551–3558.

[13] R. Di Lascio, P. Foggia, A. Saggese, M. Vento, Tracking interacting objects in complex situations by using contextual reasoning, in: 2012 International Conference on Computer Vision Theory and Applications (VISAPP), 2012.

[14] R. Di Lascio, P. Foggia, G. Percannella, A. Saggese, M. Vento, A real time algorithm for people tracking using contextual reasoning, Comput. Vis. Image Underst. (2013).

[15] D. Karras, On improved MRI segmentation using hierarchical computational intelligence techniques and textural analysis of the discrete wavelet transform domain, in: IEEE International Symposium on Intelligent Signal Processing, 2007, WISP 2007, 2007, pp. 1–6.

[16] A.T. Lawniczak, B.N.D. Stefano, Computational intelligence based architecture for cognitive agents, Proc. Comput. Sci. 1 (1) (2010) 2227–2235.

[17] Y. Lin, Affective driving, in: S. Fukuda (Ed.), Emotional Engineering, Springer, London, 2011, pp. 263–274.

[18] J. Albusac, D. Vallejo, J. Castro-Schez, L. Jimenez-Linares, Oculus surveillance system: fuzzy on-line speed analysis from 2D images, Expert Syst. Appl. 38 (10) (2011) 12791–12806.

[19] C.C. Loy, T. Xiang, S. Gong, Detecting and discriminating behavioural anomalies, Pattern Recogn. 44 (1) (2011) 117–132.

[20] J. Azorin-Lopez, M. Saval-Calvo, A. Fuster-Guillo, J. Garcia-Rodriguez, Human behaviour recognition based on

trajectory analysis using neural networks, in: International Joint Conference on Neural Networks (IJCNN), 2013, pp. 1–7.

[21] R. Laxhammar, G. Falkman, Online learning and sequential anomaly detection in trajectories, IEEE Trans. Pattern Anal. Mach. Intell. 36 (6) (2014) 1158–1173.

[22] N.T. Siebel, S.J. Maybank, The advisor visual surveillance system, in: ECCV 2004 Workshop Applications of Computer Vision (ACV), 2004.

[23] D. Duque, H. Santos, P. Cortez, Prediction of abnormal behaviors for intelligent video surveillance systems, in: IEEE Symposium on Computational Intelligence and Data Mining, 2007, CIDM 2007, 2007, pp. 362–367.

[24] B. Degardin, H. Proenca, Human Behavior Analysis: A Survey on Action Recognition. Appl. Sci. 2021, 11, 8324.

[25] L. Ballan, M. Bertini, A. D. Bimbo, Event detection and recognition for semantic annotation of video, Multimed Tools Appl (2011) 51:279-302.

[26] M. Vrigkas, C. Nikou, L. A. Kakadiaris, A review of human activity recognition methods, Front. Robot. AI, 16 November 2015.

[27] Kong, Y., Fu, Y. Human Action Recognition and Prediction: A Survey. *Int J Comput Vis* **130,** 1366–1401(2022). https://doi.org/10.1007/s11263-022-01594-9