Integrated Intelligent Research (IIR) International Journal of Communication and Networking System
Volume: 08, Issue: 01, June 2019, Page No.43-49
ISSN: 2278-2427

# Evolutionary model and Fuzzy Finite State Machine for Human activity recognition

R.Karthigasri[1], M.Sornam[2]
[1 2] Department of Computer Science, University of Madras, Guindy Campus, Chennai
Email: karthigasrimurali.918@gmail.com, madasamy.sornam@gmail.com

**Abstract** - Human activity recognition (HAR) aims to acknowledge activities from a series of observations supported the actions of subjects and therefore the environmental conditions. The HAR research is the basis for many applications including video surveillance, health care, and human-computer interaction (HCI). In this research work, proposed sequential classification problems with evolutionary model and with fuzzy finite state machine. The approach is employed to process and analyze data sets, like activities of daily living (ADL) and activities of daily working (ADW) and later applied with machine learning algorithms namely support vector Classification (SVC), Decision Tree to classify the activities. The technique fuzzy finite state machine and genetic algorithm (G-FFSM) shows better results in terms of performance measures accuracy, precision, recall, f1-scores with 96% average.

**Keywords**: Human Activity Recognition, human-computer interaction, Machine learning techniques, Genetic algorithm, FSM, G-FFSM.

## I. INTRODUCTION

Human activity recognition (HAR) is a new technology that may acknowledge human activities or gestures through automatic data processing system. Signals can be obtained from various types of detectors, such as audio sensors, image sensors, barometers, and accelerometers. With the rapid development of human-computer interaction (HCI) and wireless networks (WNs), lot of technologies and strategies [1, 4] are applied to the sensor-based human action recognition. Meanwhile the machine learning algorithms has made human activity recognition widely used in athletic competition, medical care for smart home and health care for the old people. Human Activity Recognition consists of identifying the different activities of a human being. This research field has attracted considerable attention as a basis for the detection of user's behavior [5], which could provide new context aware services. Example of applications range from proactive care [2] for elderly people to applications of health Engineering. There are two well distinguished approaches to tackle this problem: the sensor-based and the computer vision approach. The sensor-based approach consists of using small sensors (usually accelerometers) placed in the body of the person. Basu et al. [4], showed how acceleration data can aid the recognition of pace and incline.

The main advantages of this approach are the possibilities of embedding these sensors into clothes or electronic devices such as mobile phones due to the advances in miniaturization [3], the capabilities of communication between sensors through wireless connections, and the low cost [3] and energy consumption is the principal drawback of the user's need of wearing the sensors. The computer vision approach [2] is based on the use of video cameras installed in the scenario. While the sensor-based approach made the user to wear sensors, in this case, an additional hardware [1, 5] must be installed in each room of the environment. This approach usually works in labs but fails in real world scenarios due to clutter, variable light intensity, and contrast. Moreover, the video cameras are sometimes perceived as invasive and threatening by some people. Another important drawback is the computational cost of working with video signals. In this work, proposed the use of fuzzy finite state machines (FFSMs) for recognizing activities of humans by the sensor-based approach. FFSMs [7] are especially useful tools for modeling dynamical processes which change in time, becoming an extension of classical finite state machines (FSM). The main advantage of FFSMs is the use of Fuzzy Logic (FL), which provides semantic expressiveness by the use of linguistic variables [3] and rules [4] close to natural language (NL). The hybridization of fuzzy inference rule based systems [11] are able to perform nonlinear mappings between inputs and outputs, allowing FFSMs to handle imprecise and uncertain data, which learns automatically the fuzzy rules and membership function which is a form of fuzzy states and transitions. In previous studies [6, 7], FFSMs are suitable tools for modeling signals that follow an approximately repetitive pattern. different machine learning algorithms like SVC (Support Vector Classification), Decision tree algorithms [12] and Discriminant analysis, were investigated and proved it as a complex task and modeled for this problem of HAR (Human activity recognition) by experts. Hence here the dynamic nature of FFSMs increases the complexity of the process. For that reason, the proposed method defines a new automatic learning [8], using the fuzzy Knowledge Base (KB) of FFSMs based on the use of genetic algorithms (GAs) [6]. GA's [10] has proven largely their effectiveness and efficiency in the last two decades in the so-called genetic fuzzy systems (GFS) [12] area of application. The fuzzy states and transitions are defined by the expert in order to keep the knowledge that she/he has over the whole system, while the fuzzy rules [11] and membership functions regulating the state changes will be derived automatically by the GFS. This combined action thus results in a robust, accurate, and human friendly model called genetic fuzzy finite state machine (GFFSM) [8].

In this proposed method the use of a GFFSM for the human activity recognition problem, the final goal is to obtain a specific model (GFFSM) in such way that this FFSM can generalize well under different subject's situations. Moreover, the obtained GFFSM will result in an accurate and human friendly linguistic description of this phenomenon, with the capability of identifying the abnormal activity of the user. The experimentation results are developed to test the performance of the new proposal, comprising a detailed analysis of results which shows the advantages of the proposed method in comparison with another classical technique called FFSM. Furthermore, also compare this new proposed model against a FFSM and various types of machine learning algorithms previously developed models for human activity recognition, who's KB [13] had been defined by the experts. The paper is organized as follows. Section II explains existing model FFSM. In Section III explained about the proposed approach, the Datasets used using genetic algorithm and various machine learning classification model categories and methods discussed. In Section IV presents the experimentation and comparison of the obtained results. Finally, Section V concludes with conclusions and future research works.

## II. EXISTING SYSTEM

In this section, the main concepts and elements of the system model described by the experts to build comprehensible fuzzy linguistic models is given. The *FFSM* defined as (Q, U, f, Y, g), which is quintuple of,

- Q is the state of the system.
- U is the input vector.
- f is the transition function which calculates the state of the system.
- Y is the output vector.
- g is the output function which calculates the output vector.

### a) Fuzzy States (Q)

The state of the system (Q) is defined as a linguistic variable [3] that takes its values using set of linguistic labels $\{q_1, q_2, \ldots, q_n\}$, where n being the number of fuzzy states, representing the pattern [6] of a repetitive situation and it is represented numerically by a state activation vector: n

$S[t] = (s_1 [t], s_2 [t], \ldots, s_n[t])$, where $s_i[t] \in [0, 1]$ and $s_i[t] = 1$.

$S_0$ is defined as the initial value of the state activation vector, i.e., $S_0 = S[t = 0]$.

### *b) Input Vector (U)*

U is the input vector $(u_1, u_2, ..., u_{nu})$, with $n_u$ being the number of input variables. U is a set of linguistic variables obtained after fuzzification of numerical data. Typically, $u_i$ can be directly obtained from sensor data or by applying some calculations to the raw measures, e.g., the derivative or integral of the signal, or the combination of several signals. The domain of numerical values that $u_i$ can take is represented by a set of linguistic labels, $A_{ui} = \{ A^1_{ui}, A^2_{ui}, \ldots, A^n_{uii} \}$, with $n_i$ being the number of linguistic labels of the linguistic variable $u_i$.

### c) Transition Function (f)

The next value of the state vector is calculated by using transition function (f) at each instances of time.

$$S[t + 1] = f (U [t], S[t]) \qquad (1)$$

It is implemented by means of a fuzzy KB. Once the knowledge base (KB) has identified the relevant states in the model, she/he must define the allowed transitions among states. There are rules $R_{ii}$ to remain in a state $q_i$, and rules $R_{ij}$ to change from state $q_i$ to state $q_j$. If a transition is prescribed in the FFSM, it will have no fuzzy rules associated. A generic expression rule is of the form,

$$R_{ij}: \text{IF } (S[t] \text{ is } q_i) \text{ AND } C_{ij} \text{ THEN } S[t+1] \text{ is } q_j \quad (2)$$

where,

- The term ($S[t]$ is $q_i$) computes the degree of activation of the state $q_i$ in the time instant t, i.e., $s_i[t]$. With this mechanism, the FFSM to change from the state $q_i$ to the state $q_j$ (or to remain in state $q_i$, when i = j) done.
- The term $C_{ij}$ describes the constraints imposed on the input variables in disjunctive normal form (DNF) [10]. For example:
- $C_{ij}$ = ($u_1[t]$ is $A^3_{u1}$ ) AND ($u_2[t]$ is $A^4_{u2}$ OR $A^5_{u2}$ ).
- S[t+1] defines the next value of the state activation vector, consists of a vector with a zero value in all of its components but in $s_j[t]$, where it takes value one.

To calculate the next value of the state activation vector (S[t + 1]), a weighted average using the firing degree of each rule $k(\omega_k)$ is computed as defined in Equation 3.

$$S[t+1] = \begin{cases} \dfrac{\sum_{k=1}^{k} \omega_k \cdot S(t)}{\sum_{k=1}^{k} \omega_k} \; if \displaystyle\sum_{k=1}^{k} \omega_{k \neq 1} \\ S(t) if \displaystyle\sum_{k=1}^{k} \omega_{k=0} \end{cases}$$

where ($\omega_k$) is calculated using the minimum for the AND operator and the bounded sum for the OR operator.

**d) Output Vector (Y )**

Y is the output vector: ($y_1$, $y_2$, ..., $y_{ny}$ ), $n_y$ be the number of output variables.

**e) Output Function (g)**

The symbol g represents output function which calculates, at each time instant, the next value of the output vector: Y [t] = f (U [t], S[t]). The simple implementation of g is Y [t] = S[t].

## III. THE PROPPOSED APPROACH

*A. Fuzzy finite state machine to model the human activity recognition*

In the proposed method with main elements model has been built FFSM for Human activity recognition. Here the fuzzy transition function used to map a current state in to a next state upon input and attributing values of fuzzy intervals with in (0,1). The membership value associated with each transition is called weight of the transition.

**a) Fuzzy States**

In this application, define six different fuzzy states with activities as follows:
{q1 →laying, $q_2$ → sitting, $q_3$ →standing, $q_4$→walking, $q_5$→walking upstairs, $q_6$→ walking downstairs}

**b) Input Vector**

In these experiments, the embedded accelerometer and gyroscope, 3-axial linear acceleration and 3-axial angular velocity at a constant rate of 50Hz $a_x$, $a_y$, $a_z$ were the parameters. In order to distinguish between the three different states, created three linguistic variables {$a_x$, mov, tilt} with these numerical values [3]:

- $a_x$ is the acceleration as it was obtained from the sensor.
- mov measures the amount of movement. It is the sum of the difference between the maximum and minimum of $a_x$, $a_y$, and $a_z$, respectively, contained in an interval of 1 second.

- tilt is a variable that measures the tilt of the activity. It is calculated as the sum of the absolute value of the ay and az axial signal, i.e., |ay | + |ay |.

The term sets for each linguistic variable are: {$S_{ax}$ , $M_{ax}$ , $B_{ax}$ }, {$S_{mov}$ , $M_{mov}$ , $B_{mov}$ }, and {$S_{tilt}$, $M_{tilt}$, $B_{tilt}$}, where S, M , and B are linguistic terms representing small, medium, and big, respectively.

**c) Transition Function**

The definition of which transitions are allowed to calculate the next state vector S[t+1], at each time instant. The transition function f controls the allowed transitions between relevant states in the system. The rules defined to be followed as, it can be recognized that there are 20 fuzzy rules overall in the system: 4 rules remain in each state and other 16 rules to change between states. Therefore, the RB (Rule Base) will have the following structure:

$R_{11}$: IF (S[t] is $q_1$) AND $C_{11}$ THEN S[t + 1] is $q_1$
$R_{22}$: IF (S[t] is $q_2$) AND $C_{22}$ THEN S[t + 1] is $q_2$
$R_{33}$: IF (S[t] is $q_3$) AND $C_{33}$ THEN S[t + 1] is $q_3$
$R_{44}$: IF (S[t] is $q_3$) AND $C_{44}$ THEN S[t + 1] is $q_4$
$R_{55}$: IF (S[t] is $q_3$) AND $C_{55}$ THEN S[t + 1] is $q_5$
$R_{66}$: IF (S[t] is $q_3$) AND $C_{66}$ THEN S[t + 1] is $q_6$
$R_{12}$: IF (S[t] is $q_1$) AND $C_{12}$ THEN S[t + 1] is $q_2$
$R_{21}$: IF (S[t] is $q_2$) AND $C_{21}$ THEN S[t + 1] is $q_1$
$R_{23}$: IF (S[t] is $q_2$) AND $C_{23}$ THEN S[t + 1] is $q_3$
$R_{32}$: IF (S[t] is $q_3$) AND $C_{32}$ THEN S[t + 1] is $q_2$
$R_{34}$: IF (S[t] is $q_3$) AND $C_{34}$ THEN S[t + 1] is $q_4$
$R_{43}$: IF (S[t] is $q_4$) AND $C_{43}$ THEN S[t + 1] is $q_3$
$R_{45}$: IF (S[t] is $q_4$) AND $C_{45}$ THEN S[t + 1] is $q_5$
$R_{54}$: IF (S[t] is $q_5$) AND $C_{54}$ THEN S[t + 1] is $q_4$
$R_{53}$: IF (S[t] is $q_5$) AND $C_{53}$ THEN S[t + 1] is $q_3$
$R_{56}$: IF (S[t] is $q_5$) AND $C_{56}$ THEN S[t + 1] is $q_6$
$R_{57}$: IF (S[t] is $q_4$) AND $C_{57}$ THEN S[t + 1] is $q_6$
$R_{65}$: IF (S[t] is $q_6$) AND $C_{65}$ THEN S[t + 1] is $q_5$
$R_{64}$: IF (S[t] is $q_6$) AND $C_{64}$ THEN S[t + 1] is $q_4$
$R_{67}$: IF (S[t] is $q_6$) AND $C_{67}$ THEN S[t + 1] is $q_3$

$C_{ij} \rightarrow$ ($a_x$ is $S_{ax}$ ) AND (mov is $M_{mov}$ ) AND (tilt is $M_{tilt}$ OR $B_{tilt}$).

**d) Output Vector and Output Function**

Consider Y [t] = S[t], i.e., the output of the FFSM is the degree of activation of each state. Fig.1 depicts the state diagram of FFSM human activity recognition.

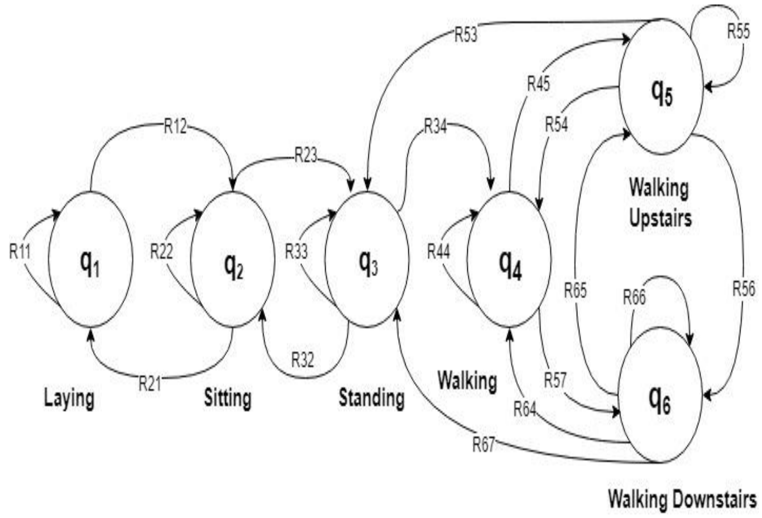


Fig. 1: State Diagram for FFSM human activity recognition

**e) Genetic Fuzzy System**

In this case, learning the KB (Knowledge Base) of the FFSM is designed for human activity recognition. This contains the linguistic label's membership functions (MFs) which collects the fuzzy if-then rules. Then fitness function is applied for calculation.

**f) Fitness Function**

Since the computation of the next state is based on the previous state, the tentative FFSM definition encoded in each over data set be evaluated, the Mean absolute error (MAE) measure has been chosen as fitness function, defined in Equation 5:

$$\frac{1}{n} \cdot \frac{1}{T} \cdot \sum_{i=1}^{n} \sum_{j=0}^{T} |S_i \text{ j} \; S_i^*[j]|$$

where:

- n is the number of states, i.e., n = 3.
- T is the dataset size (i.e., the considered time interval duration).
- $S_i$[j] is the degree of activation of state qi at time t = j.
- $S_i$*[j] is the expected degree of activation of state $q_i$ at time t = j.

The MAE directly measures the difference between the actual state activation vector (S∗ [t]) and the obtained one (S[t]). However, define S∗ [t] for each input data set that has to be learnt. This definition could be problematic and must be done carefully because, more than one state can be defined at each time instant, each of those states activated with certain degree in the interval [0, 1]. In the following subsection, this issue is explained in detail.

**g) Data Collection**

The datasets is publicly available from the UCI Machine learning repository [13] database. The dataset have been collected by observing behavior of inhabitants inside their home or office using wearable sensors like accelerometer and gyroscope built from the recordings of 30 subjects performing activities of daily living. The objective is to classify activities into one of the six activities performed viz labelled as, LAYING, SITTING, STANDING, WALKING, WALKING_UPSTAIRS, WALKING_DOWNSTAIRS.

## IV. RESULTS

Human activity datasets are often imbalanced where some activities appear much more frequently. The experiment is done using software Anaconda prompt and Integrated Development Environment (IDE) is Spyder version 3.3. All the source code [14] is written in python 3. The dependencies of libraries are tensorflow, keras, numpy, pandas, matplotlib, seaborn, sklearn, itertools, date time. Datasets used here is evident that if dominant activities are not well recognized, then cross- validation of each activity applied for the whole model. Table 1 shows the recall, precision and accuracy obtained using genetic algorithm (GFFSM). Confusion matrix plot also represented precision and accuracy, f-scores over the whole model illustrated in the Equation 6, 7 and 8. The expression that were used to calculate accuracy, precision, and recall are given below,

$$\text{Accuracy} = \frac{1}{\mathrm{N}} \sum_{\mathrm{i}=1}^{\mathrm{c}} \mathrm{tp_i} \tag{6}$$

$$\text{Precision} = \frac{1}{\mathrm{C}} \sum_{\mathrm{i}=1}^{\mathrm{C}} \frac{\mathrm{tp_i}}{\mathrm{tp_i}+\mathrm{fp_i}} \tag{7}$$

$$\text{Recall} = \frac{1}{\mathrm{C}} \sum_{\mathrm{i}=1}^{\mathrm{C}} \frac{\mathrm{tp_i}}{\mathrm{tp_i}+\mathrm{fn_i}} \tag{8}$$

where:

N is the total number of events N = $tp_i+tn_i+fp_i+f_{ni}$ for $i^{th}$ activity in the source data. C is the number of activities for which their accuracy, recall, and precision are calculated. For this study, $tp_i$, $tn_i$, $fp_i$ and $fn_i$ were defined [2] as follows:

- True positive ($tp_i$): the case when $i^{th}$ activity is correctly recognized as being the $i^{th}$ activity.
- True negative ($tn_i$): the case when all the other activities are correctly recognized as being not theith activity.
- False positive ($fp_i$): the case when all the other activities are incorrectly recognized as being the $i^{th}$ activity.
- False negative ($fn_i$): the case when the ith activity is incorrectly recognized as being not the $i^{th}$ activity.

International Journal of Communication and Networking System
Volume: 08, Issue: 01, June 2019, Page No.43-49
ISSN: 2278-2427

***Machine learning algorithm***

The machine learning models on the dataset. As the dataset is a 3-D matrix which converted it to a (7352 X 1152) data frame to implement these models. Table 1 depicts the accuracy of algorithms from existing models.

Table 1: Accuracy of machine learning algorithms

| **Algorithm** | **Accuracy** |
|---|---|
| Decision Tree | 71.97 % |
| K Nearest Neighbors | 61.89 % |
| SVC | 76.95 % |
| Gaussian Naïve Bayes | 72.48 % |
| Quadratic Discriminant Analysis | 48.45 % |

***Evolutionary algorithm***

The proposed work involves in hybridizing FFSM with GA model. The parameters of genetic algorithm are trapezoidal membership functions and state transitions fuzzy rules. The best results of accuracy, recall, precision and models based on GFFSM are shown in Table 2 and confusion matrix plot is shown in Fig 2.

Table 2: Accuracy result of GSSM

| ***Activities*** | **Results by GFFSM** | | | |
|---|---|---|---|---|
| | ***Precision*** | ***Recall*** | ***F1-Score*** | ***Support*** |
| LAYING | 1.00 | 1.00 | 1.00 | 537 |
| SITTING | 0.97 | 0.87 | 0.92 | 491 |
| STANDING | 0.90 | 0.98 | 0.94 | 532 |
| WALKING_ DOWNSTAIRS | 1.00 | 0.97 | 0.99 | 496 |
| WALKING_ UPSTAIRS | 0.97 | 0.95 | 0.96 | 471 |
| accuracy | | | 0.96 | 2947 |
| Macro avg | 0.97 | 0.96 | 0.96 | 2947 |
| weighteravg | 0.97 | 0.96 | 0.96 | 2947 |

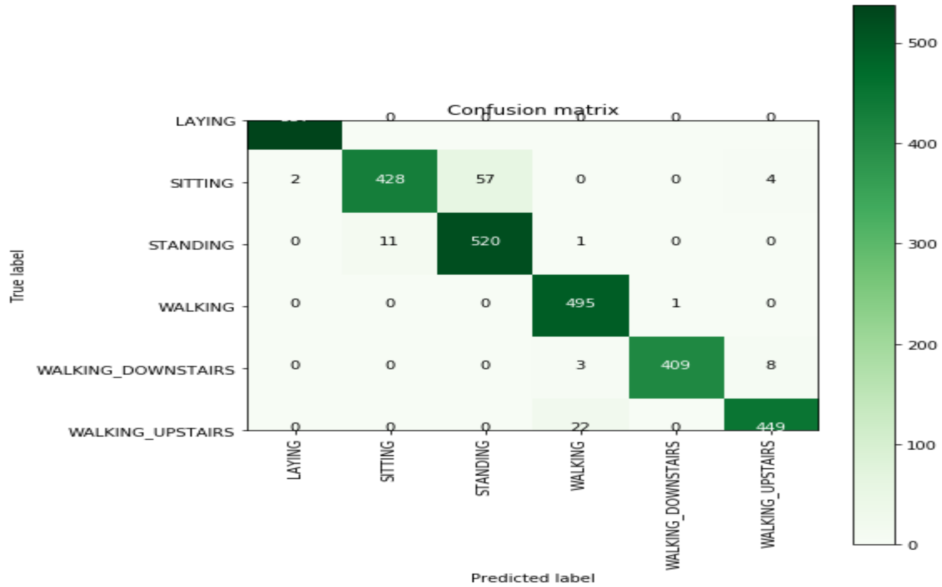


Fig. 2: Confusion matrix plot for predict model of activity

Volume: 08, Issue: 01, June 2019, Page No.43-49
ISSN: 2278-2427

## V. CONCLUSION

Human activity recognition remains to be an important task for many applications such as video surveillance, health care, and human-computer interaction. This hybrid of GA_FSM can obtain automatically the fuzzy rules and fuzzy membership functions. The results obtained by the GFFSM showed the goodness of our proposal. Moreover, its ability by combining the available expert knowledge with the accuracy achieved by the learning process shows the effectiveness of human activity recognition model. To increase the effectiveness of recognition rate of human activity this can be further extended by applying of evolutionary models like PSO (Particle Swarm Optimization) algorithms.

**References**

[1] T.L.M. van Kasteren, G. Englebienne, and B.J.A. Kröse, "Human Activity Recognition from WirelessSensor Network Data: Benchmark and Software", Chapter 8, Activity Recognition in Pervasive Intelligent Environments, Atlantis Press, 2011.

[2] H.Karamath Ali, D. I. George Amalarethinam, "Activity recogntion with Multi-tape Fuzzy Finite Automata automata", I.J.Modern Education and Computer Science, 5, 60-65. 2013.

[3] Gadelhag Mohamed, A. L, Ahmed Lotfi, Amir Pourabdollah " Human Activities Recognition based on Neuro-Fuzzy Finite state machine", Switzerland, MDPI, 17, 2018.

[4] Basu. D, Giovanni Moretti, Gourab Sen Gupta, Stephen Marshlands, "Wireless Sensor Networks Based Smart Home: Sensor Selection, Deployment and Monitoring". IEEE Sensors Applications Symposium Proceedings, Galveston, TX, USA, February 2013; pp. 49–54.

[5] Langensiepen. C., Lotfi. A., Puteh. S," Activities Recognition and Worker Profiling in the Intelligent environment using a fuzzy finite state machine", IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), Beijing, China, 6–11 July 2014; pp. 873–880

[6] Alvarez-Alvarez, A., Trivino, G., Cordon. O, "Body posture recognition by means of a genetic fuzzy finite state machine." IEEE 5th International Workshop on Genetic and Evolutionary Fuzzy Systems (GEFS), Paris, France, 11–15 April 2011; pp. 60–65

[7] Mohmed. G., Lotfi. A., Langensiepen. C.; Pourabdollah. A," Unsupervised Learning Fuzzy Finite State Machine for Human Activities Recognition." 11th Pervasive Technologies Related to Assistive Environments Conference, Corfu, Greece, 26–29 June 2018.

[8] Alberto Alvarez, Gracian Trivino, Oscar Cordon, "Human Gait Modeling Using a Genetic Fuzzy Finite State Machine". IEEE Trans. Fuzzy System. 2012, 20, 205–223.

[9] Ignatov, Andrey "Real time Human Activity Recognition from accelerometer data using Convolutional Neural Networks". Elsevier Inc. "Application of Soft Computing" 2018, 62, 915–922.

[10] Rodriguez-Benitez. L, C. Solena-cipres, J.Moreno-Gracia. "Approximate reasoning and finite state machine to the detection of actions in video sequences", 2011, 52, 526-540., Elsevier Inc.

[11] Jyh-Yeong Chang, Chien-Wen Cho "Fuzzy Rule Inference Based Activity Recognition" IEEE Conference. Saint Petersburg, Russia, July 2009.

[12] K. De Jong, W. M. Spears, and D. F. Gordon, "Using Genetic Algorithms for Concept Learning," from Machine Learning, vol. 13, no. 2-3, pp. 161–188, 1993.

[13] UCI Machine Learning Repository- L. Reyes-Ortiz, David Anguita, Alessandro Ghio, Luca Oneto and Xavier Parra– Smart lab-- Non-Linear Complex Systems Laboratory DITEN - University degli Studi di Genova, Genoa (I-16145), Italy.2 - CETPD – "Technical Research Centre for Dependency Care and Autonomous Living University" at Politècnica de Catalunya (BarcelonaTech). VilanovailaGeltrú (08800), Spain activity recognition '@' smartlab.ws

[14] Python 3.7.1 (default, Dec 10 2018, 22:54:23) [MSC v.1915 64 bit (AMD64)]. Type "copyright", "credits" or "license" for more information. Python 7.2.0 -- An enhanced Interactive Python.