Ubiquitous Computing Laboratory
Kyung Hee University, Korea

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KYUNG HEE UNIVERSITY

Evolutionary Learning Models *for* Indoor and Outdoor Human Activity Recognition

Ph.D. Dissertation Defense

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Outline

- Introduction
- Motivation
- Problem Statement
- Thesis Contribution
- Related Work
- Proposed Methodologies
- Experiment and Results
- Conclusion and Future Directions
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Introduction

Background

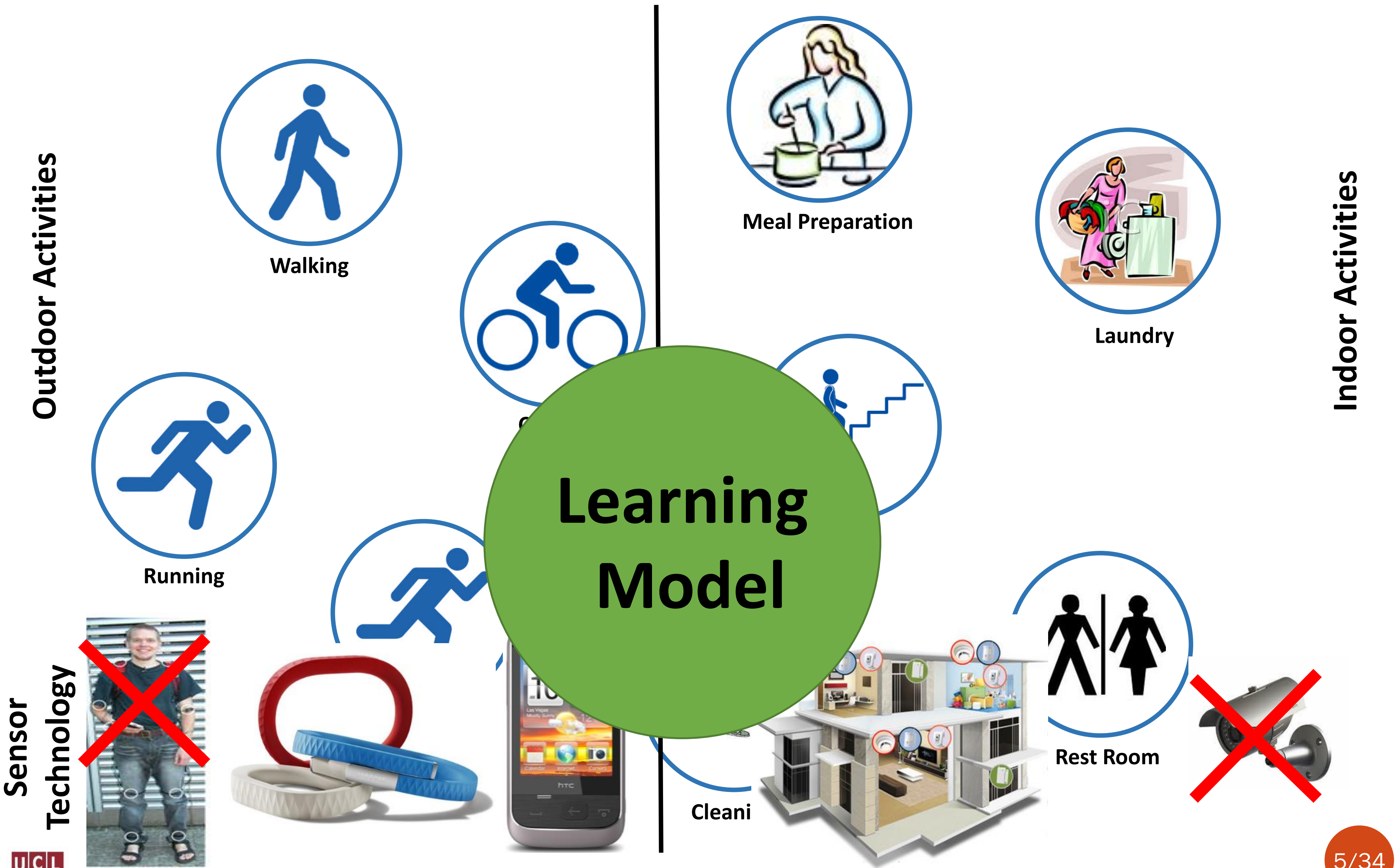
- Human activity recognition is an attempt to **recognize human actions** by **observations** using **various sensors.**
- It has many different **potential applications** and the possible connection to many different fields of study.
  - Healthcare Applications
  - Games and Robotics Industry
  - Virtual Reality
  - Home and Office Automation
  - Security and Surveillance

Human Activity Recognition





Indoor and Outdoor Activities



Motivation

- Consider the **simple sensors** to recognize the human activities.
- To overcome the domination of **major over the minor** activities, **novel models are needed** which make human activity recognition more significant.
- Previous approaches do not consider the activity structure, just utilized the sensor events sequence. Thus, **considering activity structure** would provide **more vital information** for better human activity recognition.
- There is a need for methodologies to recognize the human activities **without domain experts knowledge:** develop methodologies to embed experts knowledge from new models.

Problem Statement

We analyzed and wants to solve the following existing problems

- The domination of **major activities** over **minor activities.**
  - **Major Activities:** Meal preparation, Bathing, or Walking etc.
  - **Minor Activities:** Doing Laundry or Cleaning.
- To handle activities **non-deterministic** nature.
  - Due to **culture differences** and **lifestyles**.

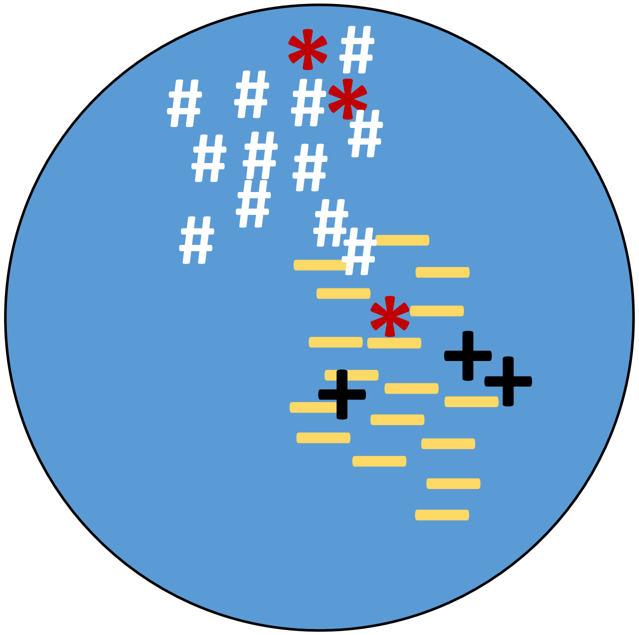


Figure: Domination of major over the minor activities

Problem Statement

- **Resolve the uncertainties** which are associated with motion of the body related activities. For Instance:
  - **Fast Walking:** is it jogging?
  - **Slow Jogging:** is it walking?
- Requires **human expert** to remove uncertainties by **defining boundaries and rules** in Fuzzy Inference systems.

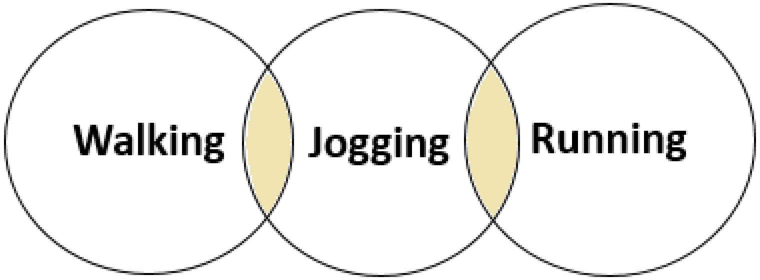


Figure: Uncertainties associated with the motion of the body.

Thesis Contribution

- We introduce **ensemble learners** to process the information by giving equal importance to **minor and major activities.**

- Our proposed model has ability to **embed activity structures** via **Genetic Algorithm** and provide **viable information** to recognize the activities.

- We **measure the uncertainties** associated with the motion of the body related activities by analyzing and estimating the **natural grouping of data.**

- Consequently, we relax the **domain knowledge constrains** to define the fuzzy sets and rules.

Related Work

Related Work

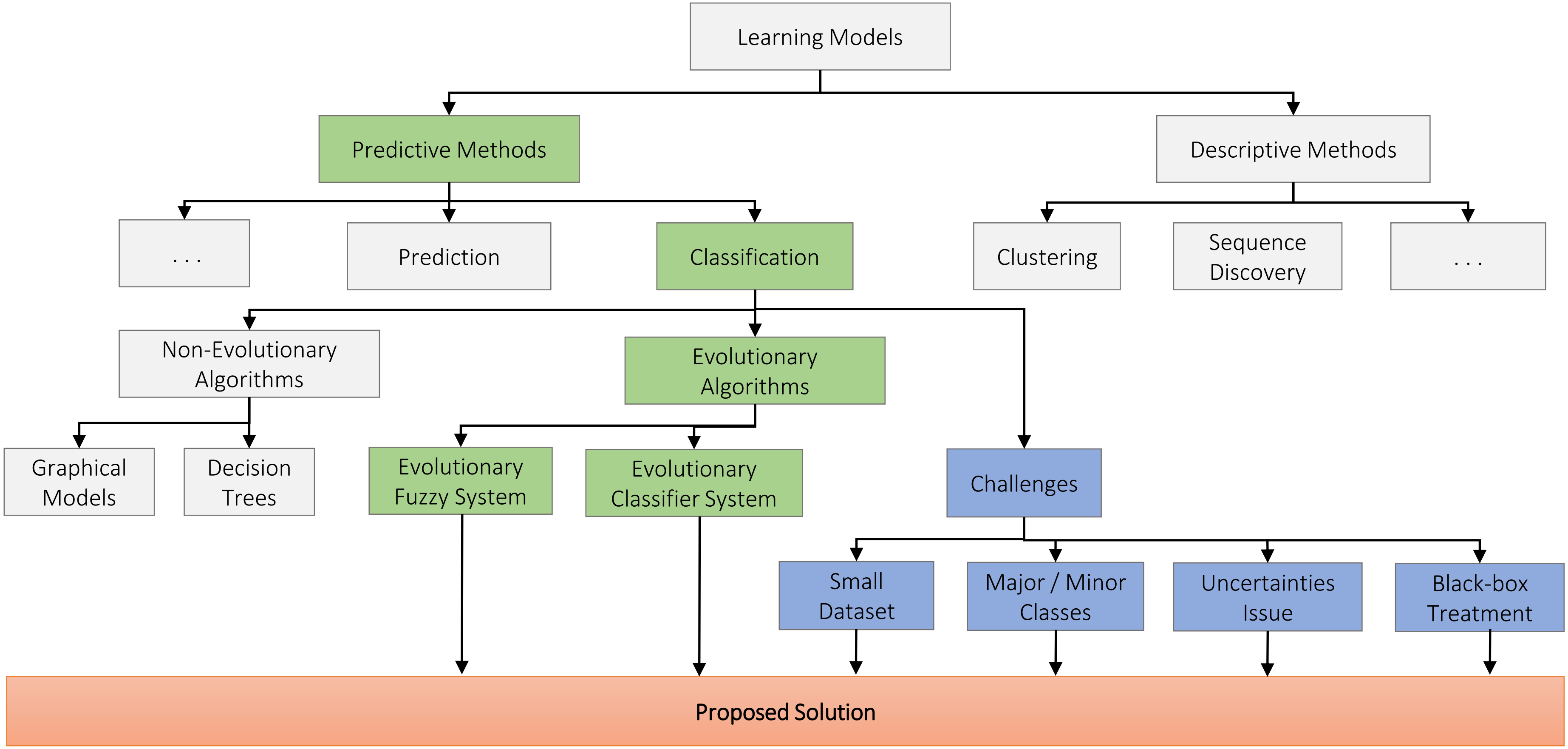
- Tapia *et al.* [1] works on activity recognition in the home using simple and ubiquitous sensors. They highlight the **activities with more examples** were recognized **more accurately.**
- Similarly, Ravi *et al.* [2] also mentioned that it would be interested to find out how effectively recognized the **"short activities".**
  - **Limitations:** Low accuracy
- Evolutionary ensemble learning paradigm can solve the limitations of low accuracy rate.
- It has successfully solved **well-known problems** such as:
  - Intrusion Detection [3]
  - Classification and data mining tasks [4]
  - Robot Control [5]

In order to apply **evolutionary algorithms**, problem is converted to **genetic representation** and then evolve by **stochastic operators**.

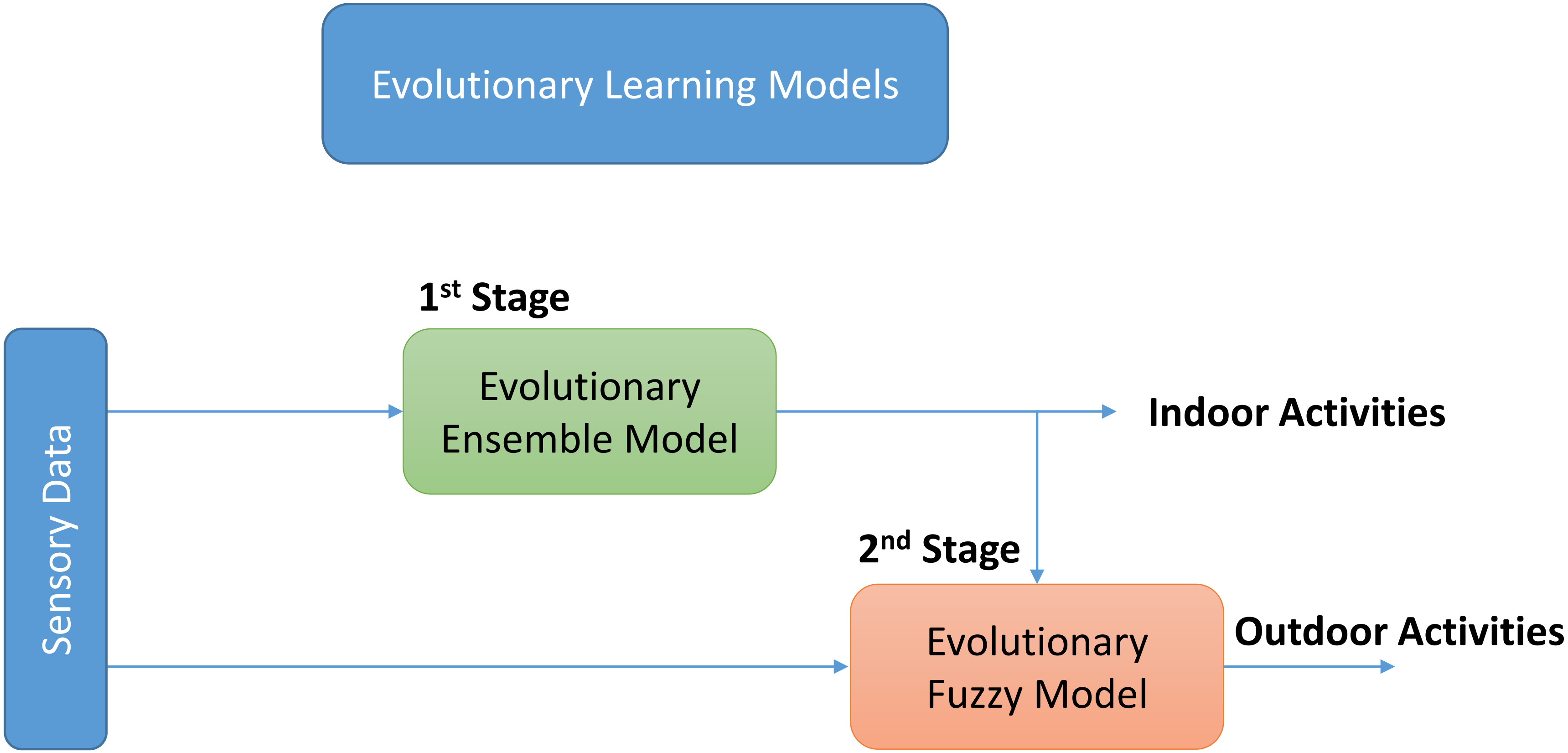
Related Work

- **Uncertainties** are associated with the motion of the body related activities and mix with each other **near the boundaries.**
- Preece *et al.* [6] provide detail **comparison of position** of the accelerometer with **feature extraction methods** to classify the activities.
- Lara *et al.* [7] system is composed of a **wearable device** and a Bluetooth-enabled Android phone; experiments were performed in a **sequential fashion** which recognized walking, running and sitting activities.
- Helmi *et al.* [8] proposed human activity recognition using a **fuzzy inference system** to recognize walking, jogging and stairs.
- **Limitations**
  - The rules and membership functions are **defined manually.**
  - The are based on the experiences of **domain experts.**
  - They used **multiple accelerometers.**
  - Activities are performed in **sequential manner (i.e., Restricted Environment).**

Proposed Solution



Thesis Philosophy



Proposed Methodology

Evolutionary Ensemble Model*

- Let $\Omega = \{S_1, \dots, S_n\}$ be a set of ***n* embedded sensors.**
- Characterized by ***m* attributes** $a = [a_1, \dots, a_m]^T$
- In order to recognize the performed activities, we divide the daily life activities into a set of ***c* classes** $C = \{C_1, \dots, C_n\}$
- For each ensemble node, **search space** is defined as $S = \{c, [S_{1a}, \dots, S_{na}]\}$
- **Rule space** is defined as $R = (c, [S_{1a'}, \dots, S_{na'}])$
- An evolutionary ensemble learner (EL) for class *c*

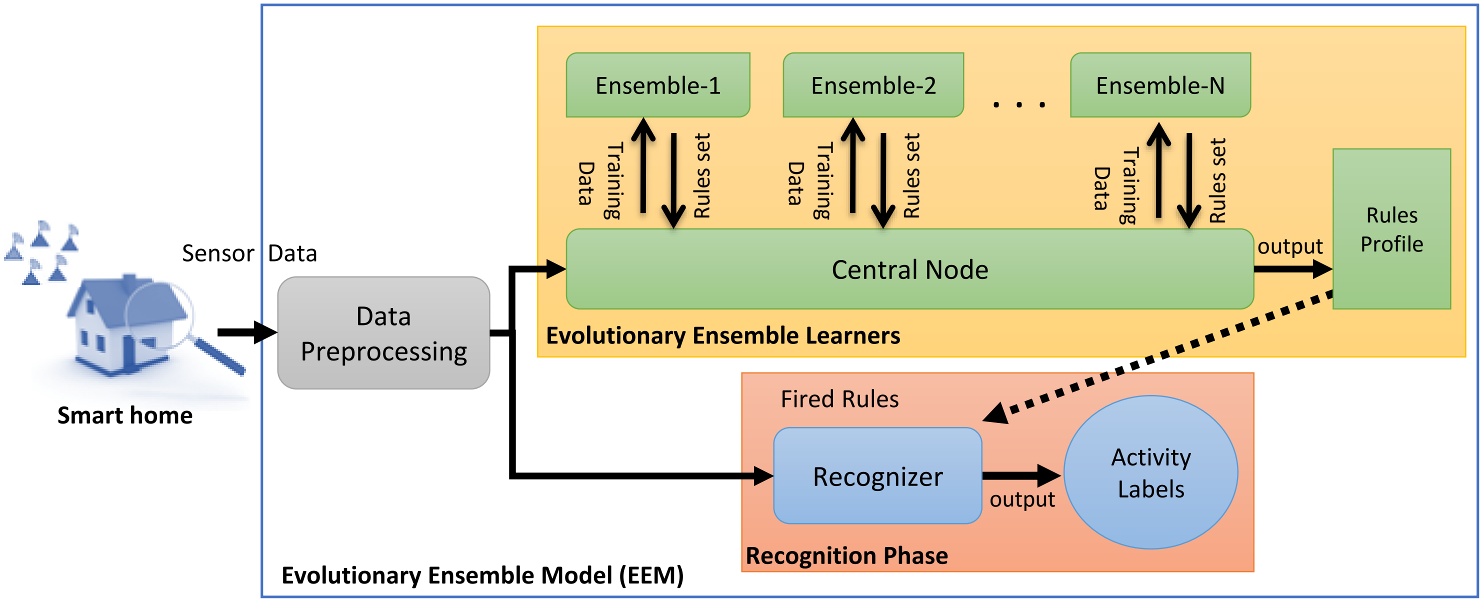
$$EL_{en}^{c} = S \rightarrow R$$

- The output of *c*-evolutionary ensemble learners are **aggregated on the central node (cn)** as **rule profile (RP):**

$$RP_{cn} = \sqcup_c EL_{en}^{c}$$

* Muhammad Fahim, Iram Fatima, Sungyoung Lee, and Young-Koo Lee, **"EEM: Evolutionary Ensembles Model for Activity Recognition in Smart Homes"**, Applied Intelligence - Springer (SCI, IF: 1.853), vol. 38(1), 2012

Proposed Architecture

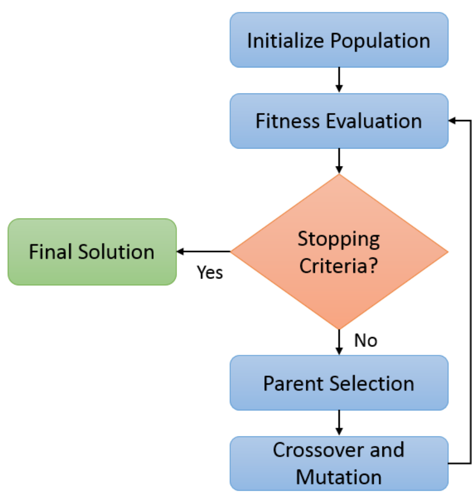


Ensemble

$$EL_{en}^{c} = S \rightarrow R$$

$$S = \{c, [S_{1a}, \dots, S_{na}]\}$$

$$R = (c, [S_{1a'}, \dots, S_{na'}])$$



Central Node

$$RP_{cn} = \bigsqcup_{c} EL_{en}^{c}$$

Ensemble Node

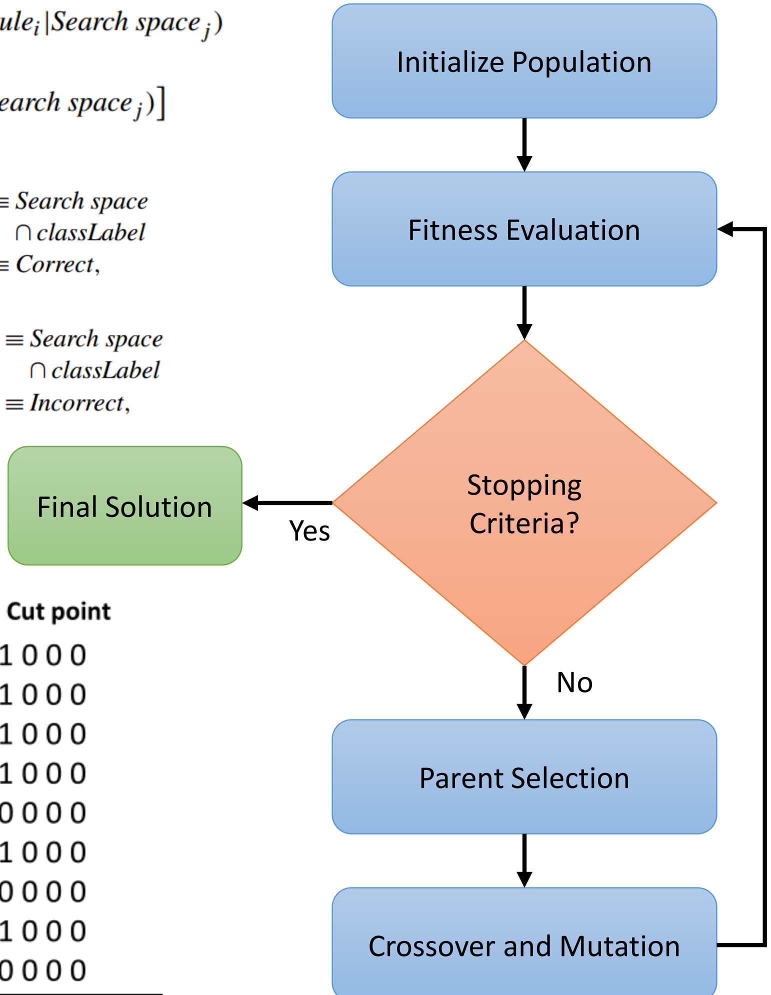
Fitness Evaluation

$$F = \sum_{i}^{n}\sum_{j}^{m}\left[reward\ (Activity\ rule_i\,|Search\ space_j) - payoff\ (Activity\ rule_i\,|Search\ space_j)\right]$$

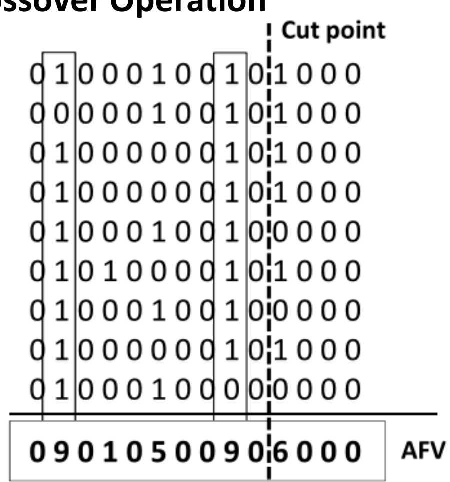
where,

$$reward = \begin{cases} 1 & if\ Activity\ rule \equiv Search\ space \cap classLabel \equiv Correct, \\ 0 & otherewise. \end{cases}$$

$$payoff = \begin{cases} -1 & if\ Activity\ rule \equiv Search\ space \cap classLabel \equiv Incorrect, \\ 0 & otherewise. \end{cases}$$



Crossover Operation



Sensor Encoding

	Stove Sensor	Microwave Sensor	Fridge Sensor	Dishwasher Sensor	Freezer Sensor	Light Sensor	.	.	.	n-sensors	Activity Class
value	1	1	0	1	1	1	.	.	.	n	4
locus	1	2	3	4	5	6	.	.	.	n	-

Stopping Criteria

- The stopping criterion is either all training instances passed correctly or
- evolved over a fixed number of generations.

Parent Selection

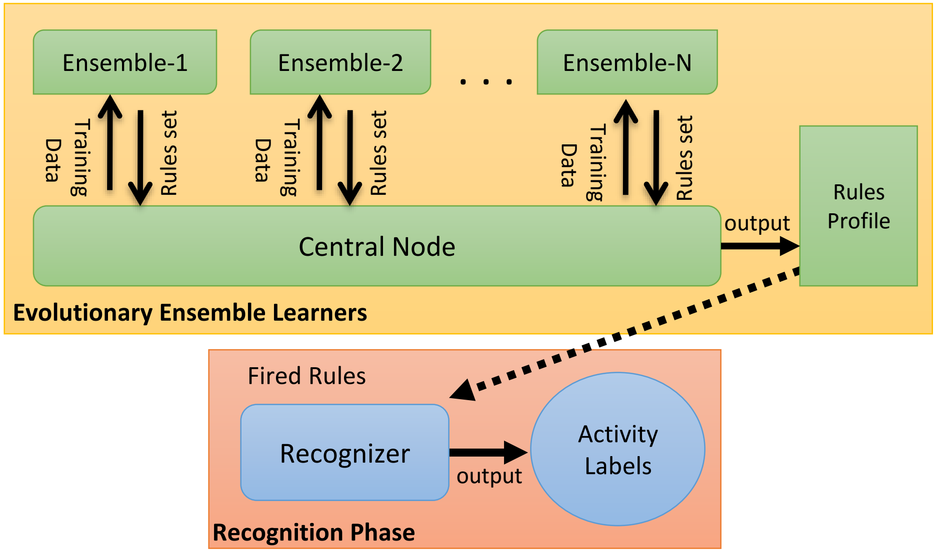
- Apply ranked-based selection method
- After ranking, one parent is randomly selected from the **top 50%.**
- While the other is randomly selected from the **remaining population.**
- This **guarantees exploration** of the **whole search space** for producing better offspring in the next generation.

Central Node

Central Node

- n ensemble nodes are aggregated on the central node.

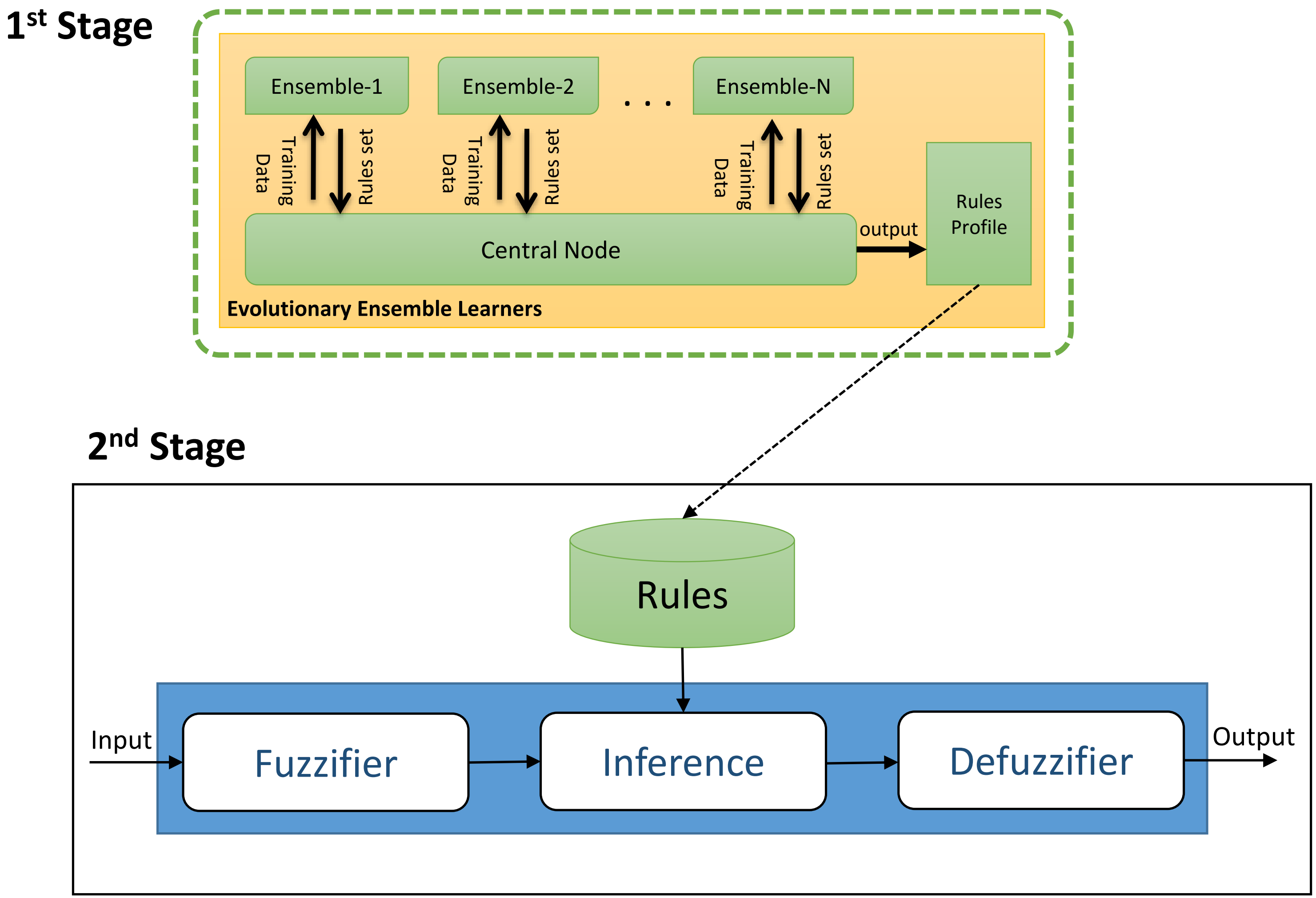
$$RP_{cn} = \bigsqcup_c EL_{en}^c$$



Recognition phase

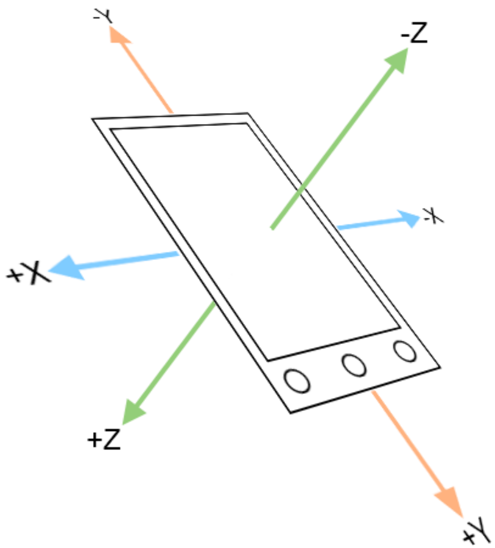
- For a particular set of sensor observations, **rules are fired** to recognize activity class labels
- In the special case when more than one rule is fired then conflicting class labels are resolved by **majority voting**.

Evolutionary Fuzzy Model*



* Muhammad Fahim, Iram Fatima, Sungyoung Lee, and Young-Tack Park, "**EFM: Evolutionary Fuzzy Model for Dynamic Activities Recognition using a Smartphone Accelerometer**", Applied Intelligence - Springer (SCI, IF: 1.853), 2013.

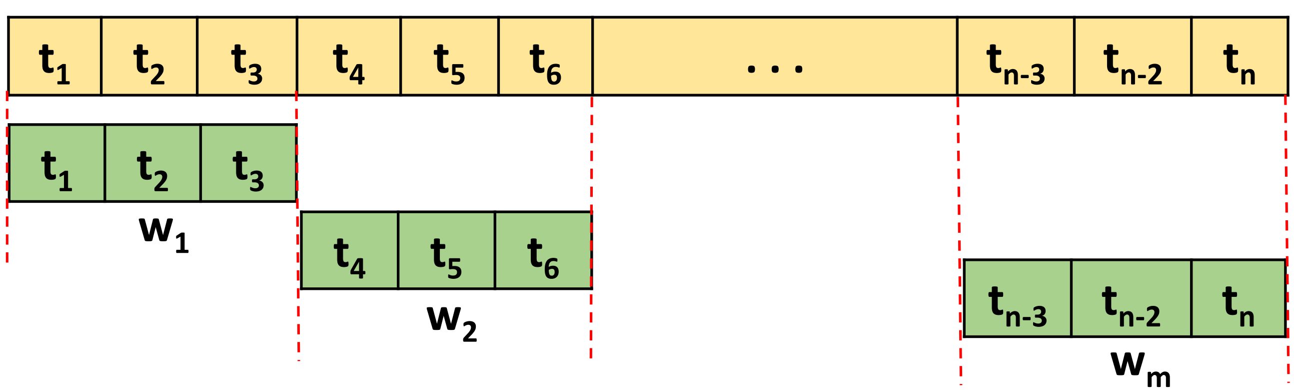
Features Extraction



- $\mathrm{RMS} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}$
- $\delta^2 = \frac{1}{n}\sum_{i=1}^{n} x_i - \bar{x}$
- $E = \frac{1}{n}\sum_{i=1}^{n} |\mathrm{FFT}_i|^2$
- $\mathrm{Corr}(x_i, x_j) = \frac{\mathrm{Cov}(x_i, x_j)}{\delta_i \delta_j}$

12 Features (i.e., 4 x 3-axis)

No overlapping sliding window

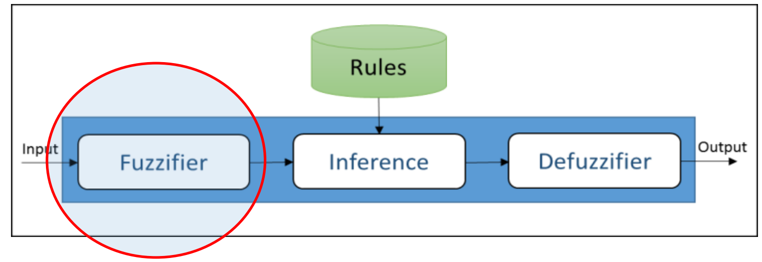


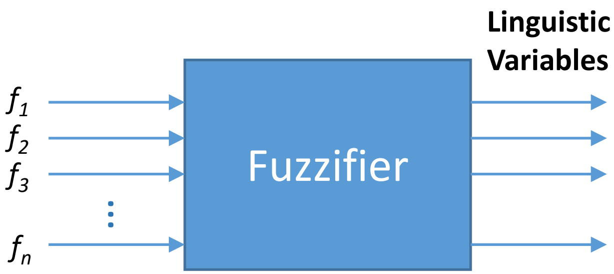
50 Hz

Frequency Rate

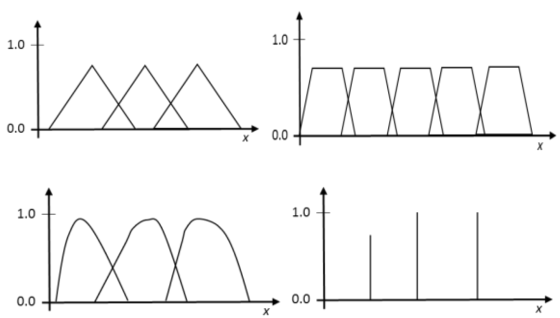
Fuzzifier

- Fuzzifier change the **real scalar features** into **fuzzy values** over the defined fuzzy sets.





Very low | Low | Medium | High | Very high



Low | Medium | High

Very low | Low | Medium | High | Very high

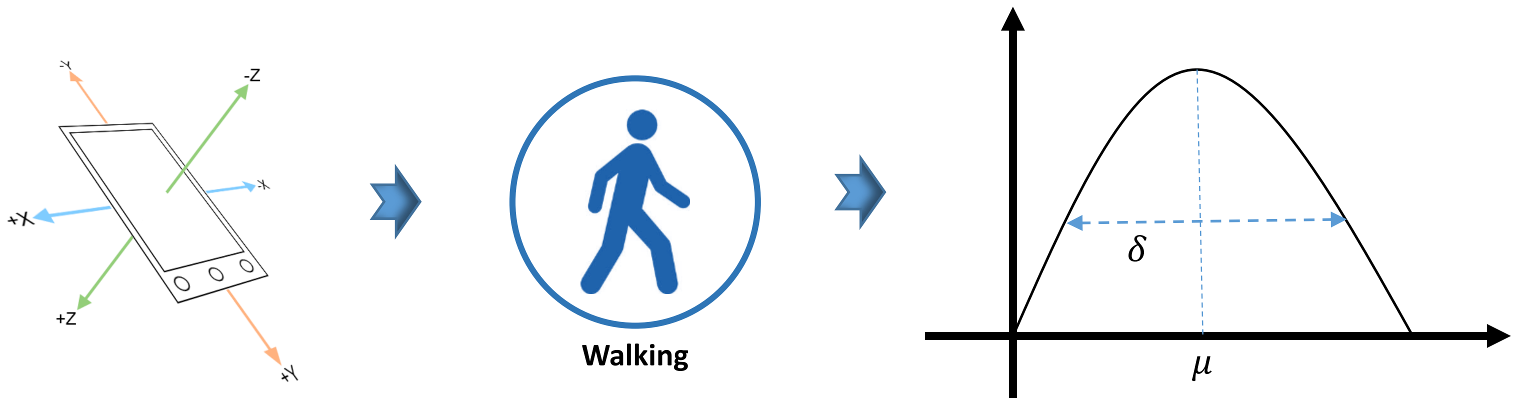
Hedge **Hedge**

Human expert's define the boundaries of **membership functions**

Fuzzifier

Assumption

- The acceleration pattern of an activity has a **Gaussian-like distribution.**



- Although the assumption is not always true but it is **reasonable.**
- Since, most activities have a **fairly consistent** mean value around the **distinguishing features.**

Gaussian Membership Functions Estimation

Initialization and Estimation

- Numbers of Gaussian distributions **are equal** to the number of defined fuzzy sets.
- Initialization is done by **finding the range** and dividing it into **equal parts.**
- To estimate the parameters of each Gaussian, an **Expectation-Maximization (EM)** algorithm is applied.

$$p_k(Y_m \mid \mu_k,\ \delta_k) = \frac{1}{\sqrt{2\pi\delta_k^2}} \exp\left\{-\frac{(y_m-\mu_k)^2}{2\delta_k^2}\right\}$$

$$\mu_k = \frac{\sum_{m=1}^{M} w_{mk} y_m}{\sum_{m=1}^{M} w_{mk}}$$

$$\delta_k = \sqrt{\frac{\sum_{m=1}^{M} w_{mk}(y_m-\mu_k)^2}{\sum_{m=1}^{M} w_{mk}}}$$

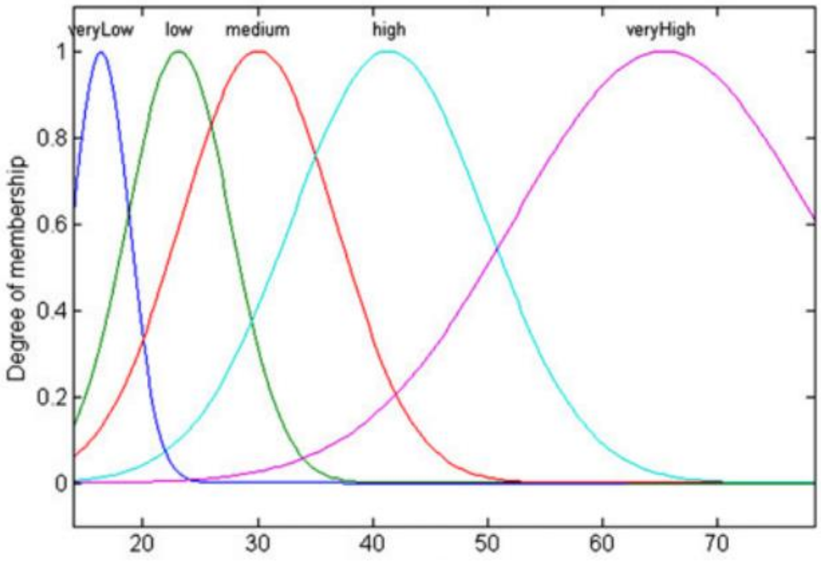
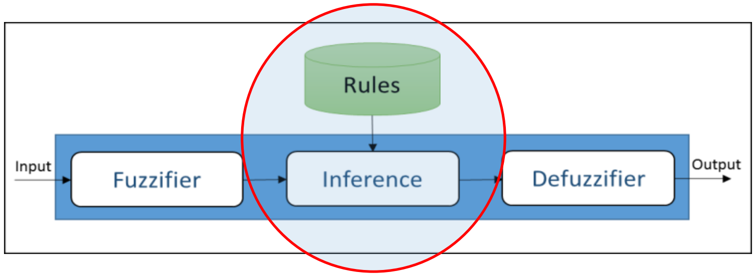
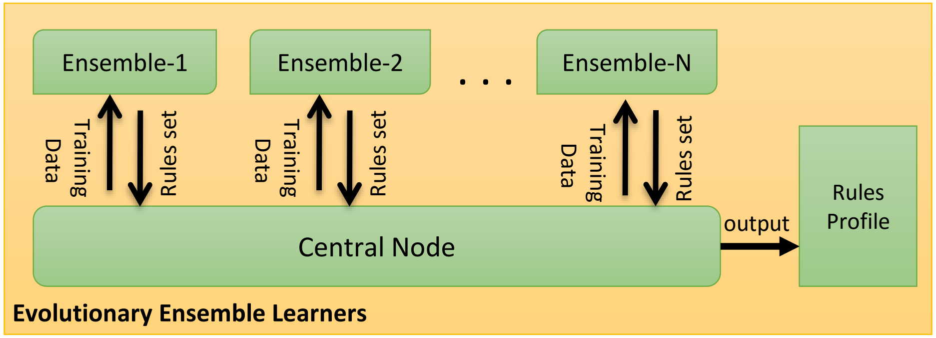


Figure: Fuzzy input variable with five fuzzy sets

Fuzzy Inference and Defuzzification



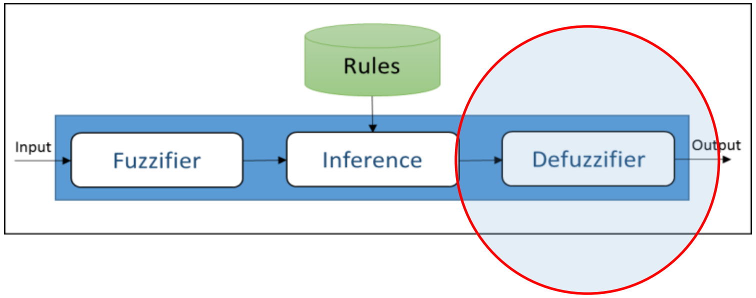
Rule Generation



Inference

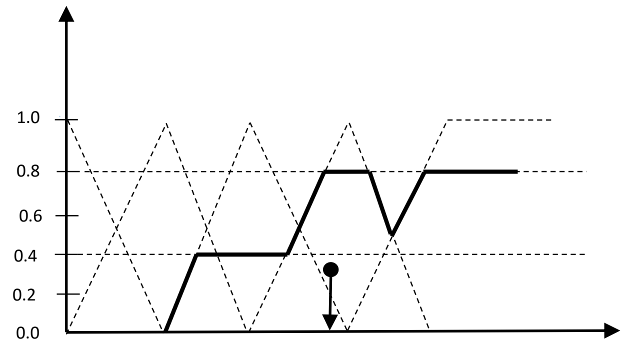
- A set of **rules are fired** during the fuzzy inference.
- The output of each rule is aggregated by an **implication method** that is based on a **union operator.**

Fuzzy Inference and Defuzzification



Defuzzification

- We apply the **fuzzy Centroid method.**
- Each membership function is clipped at the **corresponding strengths** of the activated rules.
- The **centroid of the composite area** is calculated and the horizontal coordinate is the recognized activity.



Activity	Crisp output
Walking	0.00–0.29
Jogging	0.30–0.45
Running	0.46–0.60
Cycling	0.61–0.80
Downstairs	0.81–0.86
Hopping	0.87–0.90
Upstairs	0.91–1.00

Table: Activity recognition from the crisp output

Experiment and Results

Data Sets Description

- Experiments are performed on three smart home datasets
- MIT's House N
  - **Dataset:** MITADS1
  - **Apartment:** 1-Bedroom
  - **Duration:** 14 Days
  - **Participant:** 30-year-old woman

  - **Dataset:** MITADS2
  - **Apartment:** 1-Bedroom
  - **Duration:** 14 Days
  - **Participant:** 80-year-old woman
- Intelligent System Laboratory
  - **Dataset:** ISL dataset
  - **Apartment:** 3-rooms
  - **Duration:** 28 Days
  - **Participant:** 26-year-old man

Activity	MITADS1			MITADS2		
	Num.	Time	Sensor	Num.	Time	Sensor
Toileting	85	128185.7	4084	40	60494.48	1599
Washing dishes	7	10534.42	274	21	31796.88	713
Preparing breakfast	14	21307.7	645	18	27511.95	702
Preparing lunch	17	25940.1	784	20	31006.33	733
Preparing dinner	8	12385.05	329	14	21538.88	549
Preparing a snack	14	21308.83	715	16	24214.25	581
Preparing a beverage	15	22850.68	599	–	–	–
Dressing	24	36033.93	1038	–	–	–
Bathing	18	27546.28	848	–	–	–
Grooming	37	55969	1682	–	–	–
Cleaning	8	12319.98	223	–	–	–
Doing laundry	19	28950.58	945	–	–	–
Going to work	12	17997.03	584	–	–	–
Taking medication	–	–	–	14	21183.23	590
Watching TV	–	–	–	15	23223.25	667
Listening to music	–	–	–	18	28469.97	701

Table: MITADS1 and MITADS2 activity dataset statistics

Activity	Num.	Time	Sensor
Idle	–	3507.27	38
Going out	33	17304.78	83
Toileting/toilet downstairs	114	198.7833	388
Bathing	23	219.8	52
Sleeping/going to bed	24	12335.25	173
Prepare breakfast	20	55.65	122
Prepare dinner	10	325.0333	125
Get a drink	20	17.75	62

Table: ISL activity dataset statistics

Results and Analysis

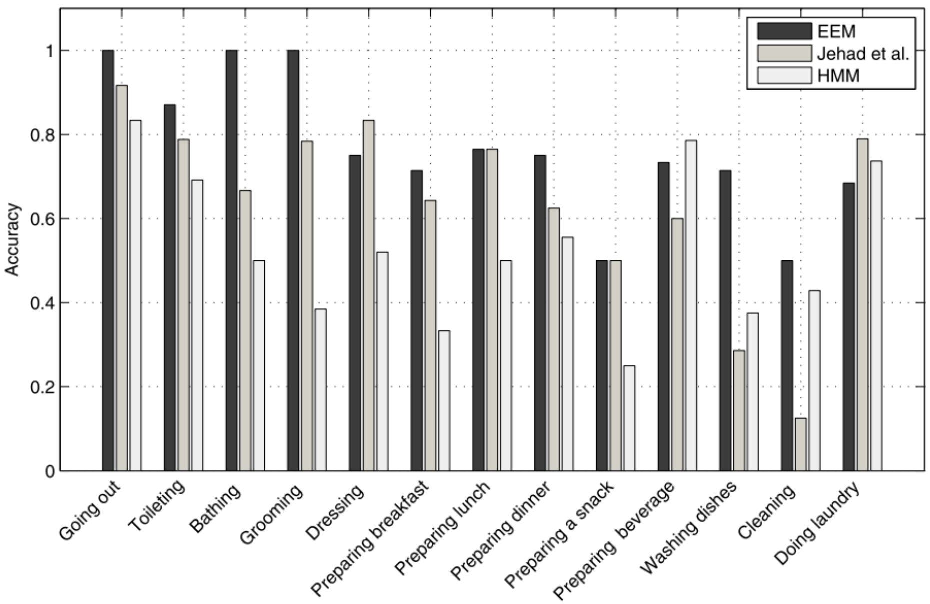


Figure: The MITADS1 activity recognition results

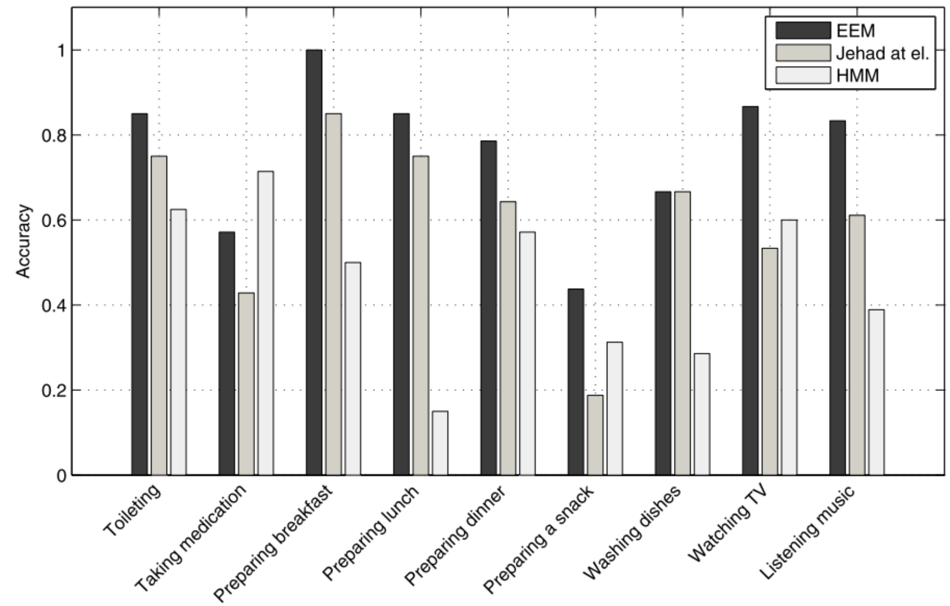


Figure: The MITADS2 activity recognition results

MITADS1

- We achieved remarkable improvement for **"Bathing", "Grooming"** and **"Toileting"** as major activities.
- For minor activity **"Washing dishes"** and **"Cleaning"** as compared to existing methods.

MITADS2

- The most noticeable improvements for major activities are in case of **"Preparing breakfast" ,"Preparing a snack", "Watching TV"** and **"Listening to music".**
- In case of minor activity **"Preparing Dinner"**, our accuracy is high as compared to existing methods.

Results and Analysis

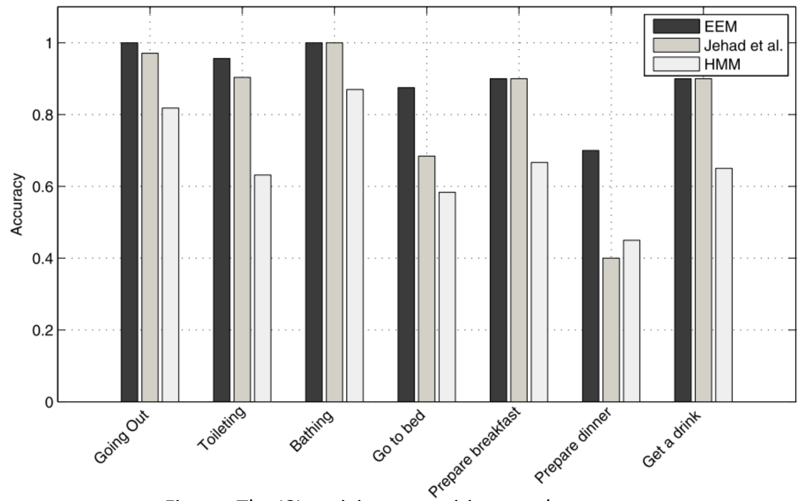


Figure: The ISL activity recognition results

Dataset	Model	Precision	Recall	F-measure	Accuracy
MITADS1	EEM	0.7515	0.6909	0.7199	0.7678
	Jehad et al.	0.6668	0.6401	0.6532	0.6401
	HMM	0.5308	0.5321	0.5314	0.5303
MITADS2	EEM	0.7721	0.7624	0.7672	0.7623
	Jehad et al.	0.6550	0.6204	0.6372	0.6022
	HMM	0.5015	0.4587	0.4792	0.4608
ISL	EEM	0.8997	0.9044	0.9020	0.9044
	Jehad et al.	0.8264	0.8065	0.8163	0.8226
	HMM	0.7130	0.6575	0.6843	0.6670

Table: Model, Precision, Recall, F-measure and Accuracy

Statistical Significance Test

We performed the statistical significance test and our EEM achieves significant improvement **(p-value < 0.005)** regarding to the classification accuracy.

Stability Test

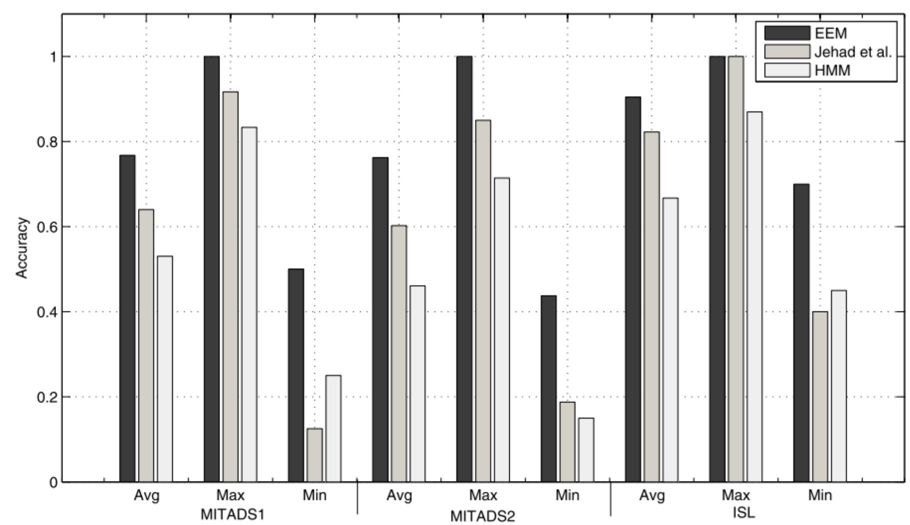


Figure: Accuracy comparison (Avg, Max and Min)

Results and Analysis

We used **"10-fold cross validation"** method to perform the experiments.

Activity	Walking	Jogging	Running	Hopping	Cycling	Up stairs	Down stairs
Walking	**6585**	145	5	–	–	–	–
Jogging	4	**3628**	56	–	–	–	–
Running	3	25	**2572**	–	–	–	–
Hopping	2	24	14	**990**	21	–	22
Cycling	–	19	14	11	**2819**	10	22
Up stairs	9	5	2	15	6	**1084**	48
Down stairs	10	6	2	14	9	20	**572**

Table: Confusion Matrix of recognized activities

Model	Precision	Recall	F-Measure
EFM	0.9551	0.9540	0.9545
NB	0.8350	0.8619	0.8482

Table: Model, Precision, Recall, F-measure and Accuracy

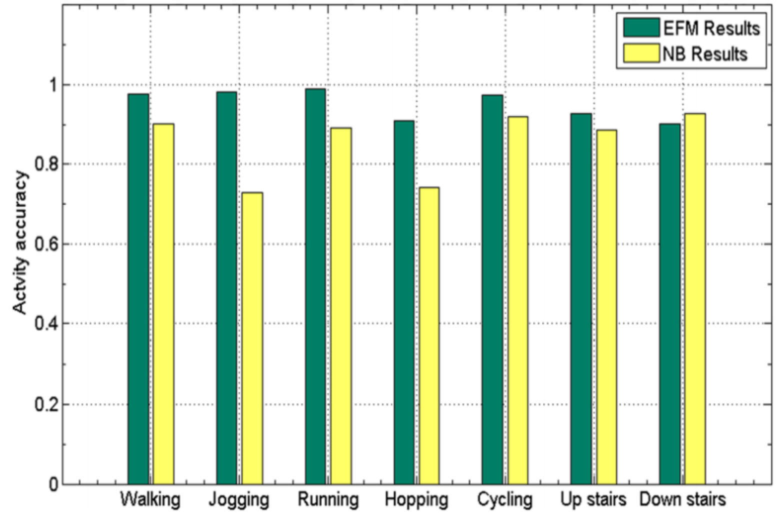


Table: Comparisons of EFM and Naïve Bayes Classifier

Stability Test

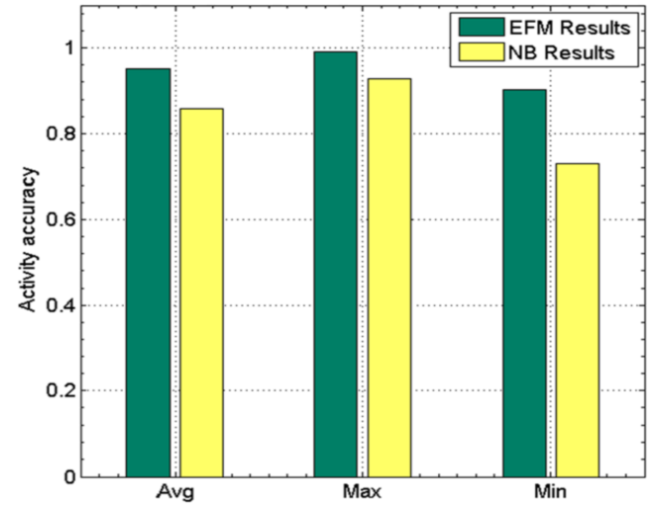


Figure: Accuracy comparison (Avg, Max and Min)

Wilcoxon Signed-Ranks Test

- The p-value is computed **(i.e., p-value=0.0313)** for the pairwise comparison.
- It shows our model achieves a significant improvement over the existing Naïve Bayes method with a **level of significance α=0.05**

Conclusion

- To solve the limitations of learning **major/minor activities,** evolutionary ensemble learners are proposed.
- Existing methods **unable to model the activity structure** such as location, and type of sensors, thus, GA based method is designed for learning.
- During fuzzy inference system, defining rules and fuzzy sets through domain experts **is not feasible method**. Thus natural grouping of data is estimated by assuming **Gaussian like distribution.**
- Experimental results demonstrated that handling the discussed issues consistently **increased accuracy** for indoor and outdoor activities.

Achievements

Korean Patents	Two Patents	**2**
SCI/E Journal Papers	Two Frist Author | Four Co-author	**6**
Non-SCI/E Journal Papers	Two Co-author	**2**
International Conference Paper	Six First Author | Six Co-author	**12**
Domestic Conference Paper	One First Author | Two Co-author	**3**

Total Publications: 25

Work in progress!

A Light-weight Physical Activity Recognizer based on Multimodal Sensors in Smartphone

IEEE Transactions on Mobile Computing

ATHENA: A Platform to Support Ambient Assisted Living based on Activities, Emotions and Social Interactions

Journal of Sensors

Thank you

Appendix

Selected References

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Future Directions

- For Indoor activity recognition, only a **single inhabitant** is considered at a time.
- Our future plan includes handling multiple residents and recognize the activities under the framework of evolutionary ensembles.
- In outdoor activity recognition study, We consider **fixed position** of a smartphone. Complications may arise due to **different positions**
- However, the generic nature of training and implementation will lead to the **success** of EFM for **conceivable complex situations**.
- Our future plan includes handling **position-independent** recognition by deriving novel features **using the proposed framework**.

Data Collection

- **Samsung** Galaxy S
- Google **Android OS** version **Gingerbread**
- 10 healthy adult subjects (7 male and 3 females) participated in this study
- Walking, Jogging, Running, Cycling, Going up stairs, Going down stairs, and Hopping
- We analyzed and recorded the data **at 50 Hz**
- We collected approximately **18,794 data samples** over the two months.

	Min	Max	Mean	Std. deviation
Age (year)	22	32	27.18	3.3710
Height (cm)	167	180	173.6	4.7806
Weight (kg)	48	92	64.8	13.3553

Table: Characteristics of the participants

Figure: Dataset collection application

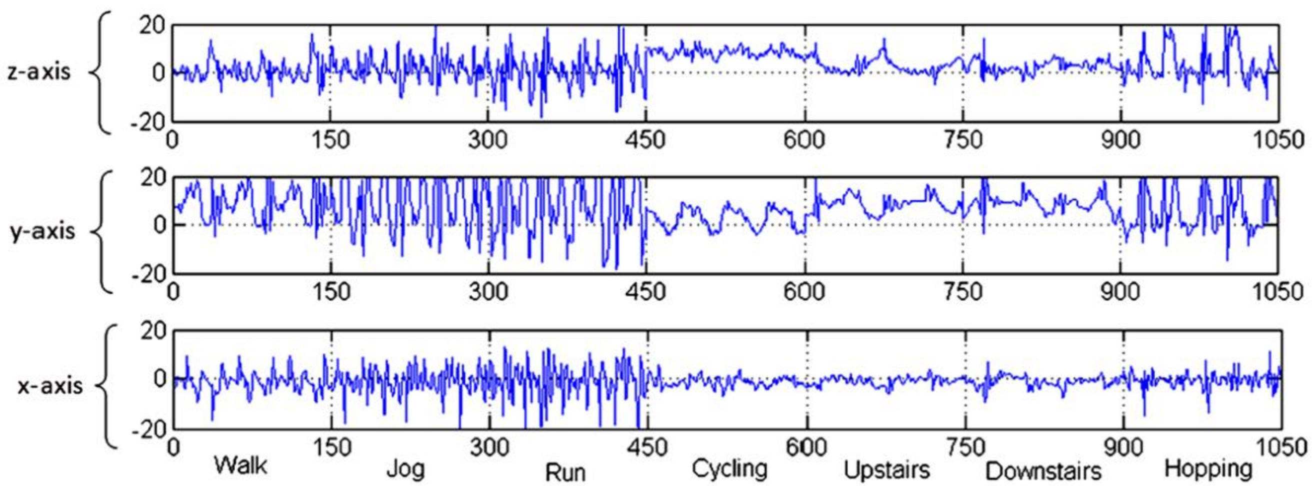

Figure: Representative raw signals of activities

Parameter Estimation

In this section, we present details of the parameters for Gaussian membership estimation for expectation maximization algorithms, which are used for computing μ_k and δ_k. The log-likelihood of the observed data $Y = \{Y_m\}$, $m = 1, \ldots, M$ is calculated as:

$$l(\Theta) = \sum_{m=1}^{M} \log p_{mix}(Y_m|\Theta) \tag{12}$$

Expectation Step (E-Step)

$$p_{mix}(Y_m \mid \Theta) = \sum_{k=1}^{K} p(Y_m \mid \theta_k) w_{mk} \quad \text{and} \quad \sum_{k=1}^{K} w_{mk} = 1 \tag{13}$$

Inserting (13) into (12) gives,

$$l(\Theta) = \sum_{m=1}^{M} \log \sum_{k=1}^{K} p(Y_m \mid \theta_k) w_{mk}$$

For Expectation step, use Jensen's inequality,

$$l(\Theta) \geq \sum_{m=1}^{M} \left[\sum_{k=1}^{K} w_{mk} \log p(Y_m \mid \theta_k) \right] \Rightarrow E\left[\log\left(p(Y_m \mid \theta_k)\right)\right]$$

At the Maximization step (M-Step)

$$\nabla_{\theta_k} \sum_{m=1}^{M} \sum_{l=1}^{K} w_{mk} \log p(Y_m \mid \theta_l) \tag{14}$$

At maximum, the partial derivations w.r.t. all parameters vanish:

$$\nabla_{\theta_k} l(\Theta) = \sum_{m=1}^{M} \frac{w_{mk}}{p(Y_m \mid \theta_k)} \nabla_{\theta_k} p(Y_m \mid \theta_k) \tag{15}$$

In order to find the parameters of accelerometer data, our problem is a similar problem to the one dimensional Gaussian mixture, where we do not know the variances or mixture portions either. The parameter vector is $\theta_k = [\mu_k, \delta_k]$ is computed as:

$$p(Y_m \mid \theta_k) = \frac{1}{\sqrt{2\pi\delta_k^2}} \exp\left\{-\frac{(Y_m - \mu_k)^2}{2\delta_k^2}\right\} \tag{16}$$

The Expectation step is easily defined by inserting (16) into (13). For Maximization, inserting (16) into (15) and taking the derivative w.r.t. μ_k gives,

$$\begin{aligned} 0 &= \frac{\partial}{\partial \mu_k} l(\Theta) \\ &= \sum_{m=1}^{M} \frac{w_{mk}}{p_k(y_m|\theta_k)} * \frac{1}{\sqrt{2\pi\delta_k^2}} \exp\left\{-\frac{(y_m - \mu_k)^2}{2\delta_k^2}\right\} \\ &\quad * \frac{-2(y_m - \mu_k)}{2\delta_k^2} \\ &= \sum_{m=1}^{M} w_{mk}(y_m - \mu_k) \end{aligned}$$

$$\mu_k = \frac{\sum_{m=1}^{M} w_{mk} y_m}{\sum_{m=1}^{M} w_{mk}} \tag{17}$$

Parameter Estimation

Taking the derivative w.r.t. δ_k

$$\frac{\partial}{\partial \delta_k} l(\Theta) = \sum_{m=1}^{M} \frac{w_{mk}}{p_k(y_m|\theta_k)} * \frac{1}{\sqrt{2\pi\delta_k^2}} \exp\left\{-\frac{(y_m-\mu_k)^2}{2\delta_k^2}\right\}$$

$$\times \left[-\frac{1}{\delta_k} + \frac{(y_m-\mu_k)^2}{\delta_k^3}\right]$$

$$= \sum_{m=1}^{M} \frac{w_{mk}}{p(y_m|\theta_k)} \left[-\frac{1}{\delta_k} + \frac{(y_m-\mu_k)^2}{\delta_k^3}\right] * p(y_m|\theta_k)$$

$$\Rightarrow \quad \sum_{m=1}^{M} w_{mk} \left[\frac{-\delta_k^2 + (y_m-\mu_k)^2}{\delta_k^3}\right] = 0$$

$$\delta_k^2 = \frac{\sum_{m=1}^{M} w_{mk}(y_m-\mu_k)^2}{\sum_{m=1}^{M} w_{mk}}$$

$$\delta_k = \sqrt{\frac{\sum_{m=1}^{M} w_{mk}(y_m-\mu_k)^2}{\sum_{m=1}^{M} w_{mk}}} \tag{18}$$

Equations (17) and (18) are required parameters for the Gaussian membership function.

Membership Estimation (EFM)

Parameter estimation		μ_x	δ_x	μ_y	δ_y	μ_z	δ_z
RMS	Very low	2.0806	0.3311	6.2331	0.2867	2.5325	0.2764
	Low	3.6014	0.5759	9.7983	0.4489	3.5286	0.3247
	Medium	4.3237	0.9352	10.5287	0.5916	4.1769	0.9129
	High	5.6829	1.6944	11.1824	0.8412	4.6374	1.1508
	Very high	10.0838	2.5517	12.5821	1.7337	7.5937	1.7096
δ^2	Very low	2.164	0.8859	9.0882	3.6385	1.03	0.7101
	Low	9.4408	2.6224	20.1302	4.0457	5.857	1.3976
	Medium	13.1113	3.5358	26.613	7.1513	9.7751	2.5971
	High	25.8409	9.701	70.5636	10.0789	22.3297	8.8136
	Very high	82.031	34.5779	92.6388	15.0831	44.6485	20.7813
$\mathrm{Corr}(x_i, x_j)$[a]	Very low	−0.3585	0.0855	−0.3844	0.076	−0.4061	0.0694
	Low	−0.0462	0.103	−0.1854	0.0797	−0.1372	0.0775
	Medium	0.023	0.1112	0.0865	0.1119	0.0067	0.093
	High	0.1509	0.1613	0.2507	0.1424	0.1531	0.1593
	Very high	0.4391	0.2539	0.4138	0.211	0.3982	0.1851
E	Very low	14.623	3.7203	22.5516	4.7044	16.344	2.4627
	Low	29.0289	3.944	43.6205	4.8321	23.2049	4.5916
	Medium	31.0961	5.305	49.4905	5.9332	30.1824	6.7669
	High	45.6145	9.9425	66.0577	6.8354	41.65	8.7217
	Very high	70.3286	16.7727	74.1976	15.804	65.2823	13.0504

[a] $(x_i, x_j) = (xy,\ xz,\ yz)$

Results and Analysis (EFM)

Subjects	Walking	Jogging	Running	Hopping	Cycling	Up stairs	Down stairs	Avg.
Subject 1	0.9958	0.9947	0.9714	0.8596	0.9932	0.9152	0.9012	0.9473
Subject 2	0.9452	0.9673	1.0000	0.9382	0.9930	1.0000	0.8889	0.9618
Subject 3	0.9958	0.9947	0.9821	0.8596	0.9932	0.9491	0.9012	0.9537
Subject 4	0.9736	0.9934	1.0000	0.9459	0.9430	0.8739	0.9230	0.9504
Subject 5	0.9734	0.9618	0.9852	0.9444	0.9671	0.9145	0.9125	0.9513
Subject 6	0.9452	0.9673	1.0000	0.9496	0.9930	1.0000	0.8888	0.9634
Subject 7	0.9901	1.0000	0.9810	0.8260	0.9967	0.9056	0.8235	0.9318
Subject 8	0.9945	0.9869	1.0000	0.8765	0.9449	0.8956	0.9491	0.9496
Subject 9	0.9736	0.9934	1.0000	0.9459	0.9430	0.9159	0.9230	0.9564
Subject 10	0.9734	0.9618	0.9852	0.9444	0.9671	0.8974	0.9125	0.9488

Table: Individual subject activity recognition

EFM

Rule Learner using Genetic Algorithm

Representation

- Each fuzzy variable-defined linguistic value of the fuzzy set is mapped onto a value 1–5 to represent each of the five terms and 0 for the “don’t care” term.
- A **dynamic single point** crossover is applied as a reproduction operator.

xRMS	yRMS	zRMS	xVar	yVar	zVar	xyCorr	xzCorr	yzCorr	xEnergy	yEnergy	zEnergy	Activity label
1	5	0	2	4	0	4	5	1	4	2	1	6

Figure: Chromosome Encoding

Selection

- The whole population is sorted from **best to worst** according to the **ranked fitness values**.
- After ranking, one parent is randomly selected from the **top 50%** of the ranked population, while the other is randomly selected from the **remaining population.**

Fitness function

$$F = \sum_{i}^{n} \sum_{j}^{m} \big[reward\ (Activity\ rule_i | Search\ space_j) - payoff\ (Activity\ rule_i | Search\ space_j) \big]$$

where,

$$reward = \begin{cases} 1 & if\ Activity\ rule \equiv Search\ space \cap classLabel \equiv Correct, \\ 0 & otherewise. \end{cases}$$

$$payoff = \begin{cases} -1 & if\ Activity\ rule \equiv Search\ space \cap classLabel \equiv Incorrect, \\ 0 & otherewise. \end{cases}$$

EFM

Stochastic Operators

Crossover

- Crossover is performed on the **selected parents** to create new offspring.
- A **dynamic single point** crossover is applied as a reproduction operator.

Mutation

- The proposed approach also inaugurates diversity in activity rules by using a uniform mutation operator.
- It assigns a “don’t care” term— a value of 0 or any other membership value—on randomly selected genes of the activity rule.

Stopping Condition

- The stopping criterion is either a fixed number of generations or
- all training instances passed correctly.

GA Optimal Parameters

- Crossover Rate: 0.8
- Mutation Rate: 0.1
- Population Size: 55
- Generation Size: 500

Ensemble Optimal Parameters

- Population Size: 35
- Generation Size: 125

- Crossover Rate: 0.4
- Mutation Rate: 0.005