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NEUTROSOPHIC CONCEPT LATTICE BASED APPROACH FOR COMPUTING HUMAN ACTIVITIES FROM CONTEXTS

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Abstract- Complex human activity recognition suffers from ambiguity of interpretation problem. A novel neutrosophic formal concept analysis method has been proposed to quantify non-determinism leading to ambiguity of interpretation and utilize it in activity recognition. The method works by penalizing performance of non-deterministic activities and rewarding the deterministic ones. Thus, non- deterministic activities are identified during testing due to significantly reduced performance and contexts can be redesigned to improve their description. The proposed method has been implemented on benchmark dataset having both types of activities. Our approach successfully identified non-determinism in activities description without compromising recognition performance of deterministic activities. It has also been shown that other approaches fail to identify non deterministic activities. Overall accuracy of activity recognition of our approach was comparable to other approaches.

Index terms*:* Sensors Data Streams, Concept Lattice, Neutrosophic Logic, Situation Inference, Activity Recognition.

I. INTRODUCTION

Regular performance of Activities of Daily Living (ADL) has been established as major indicator of wellbeing in humans [1]. Video based monitoring with miniature cameras provide rich information about the environment being monitored. They are however, not preferred in monitoring ADLs because of privacy and ethical issues. Unobtrusive sensors are more easily acceptable by human beings as they don't appear to directly invade their privacy. This has given rise to significant increase in research reported on sensor based Activity Recognition (AR) [2].

In this work, an activity has been described by a set of symbolic information called "contexts", obtained from real time raw sensor data processing [3]. Significant success has been achieved in extracting low level contexts from sensor data [4]. However, machine based AR from Contextual Information (CI) is still challenging due to several reasons [5]. 1) Humans rarely follow a fixed sequence while doing any activity. Same sequence of actions in an activity is further unlikely when different humans do same activity. 2) More than one activity may take place at same place and within same time frame. Location and time thus can't distinguish these activities. 3) Humans may interleave several activities together. For example, cooking and answering phone call may be interleaved. 4) Contextual description of activities can be ambiguous when same contexts are present in different activities.

A formal concept lattice based solution approach to handle first three problems has been suggested by us in [6]. In this paper, we focus on addressing the last challenge. Contexts, as perceived in this work, are middle level abstractions obtained as semantic interpretation of raw numeric sensor data. For example, data from relevant sensors for the context *left_arm_action* can be interpreted as move, release, open, close, cut, bite and stir etc. Activities can be described as co-occurrence of specific unique set of values of various such contexts. However, on observing real activity datasets it is found that combination of context values describing some activities may not be unique. This leads to non-determinism in contextual description of that activity. Non-determinism occurs either due to small number of possible contexts or due to inherent variation in the way person/s performs an activity each time. For example, left_hand_action - '*move'* can be present in many activities done by a person at home. If at least one distinguishing context value is not present than the activity description becomes ambiguous.

In this paper, we propose a new neutrosophic formal concept analysis based AR model to handle the challenge of ambiguity in context based interpretation of activities. The method works by penalizing performance of non-deterministic activities and rewarding the deterministic ones. Thus, non-deterministic activities are identified during testing due to significantly reduced performance and contexts can be redesigned to improve their description. A benchmark data set of mid-level abstractions and corresponding activities has been used for validation [7]. On testing, activity recognition method successfully recognized well defined activities and identified non-determinism in description of other activities. Upon identification, more number and types of sensors can be deployed to deterministically define those activities.

The rest of paper is organized as follows. In the next Section, features and drawbacks of existing activity recognition methods have been discussed. In Third Section, preliminaries of concept lattice and neutrosophic logic are described. Neutrosophic concept lattice based activity model has been proposed in Section 4. Method of utilizing the model for activity recognition has been described in the same section. Proposed methods were validated on third party datasets. Description of the datasets, model obtained for the dataset and other validations have been presented in Section 5. The paper is finally concluded in Section 6.

II. RELATED WORK

There has been recent research interest in automatic activity recognition in pervasive computing environments [2]. Existing literature was surveyed to explore related existing methods. For activity model creation, foremost requirement is to model relationships between contexts and activities quantitatively. One class of methods proposed in literature use annotated datasets of actual AR environments to train and learn probabilistic or statistical activity models based on machine learning techniques [8- 12]. Mahmod et al [8] examined the ability of recurrent neural networks for modelling sensory data to ADLs of an occupant in inhabited intelligent environments. Behavioral model of each occupant was built using this technique. The model predicted future activities and expected occupancy.

Hidden Markov Model has been applied for predicting activity series from low rate sensor signals obtained from wearable accelerometer sensors in [9]. Dynamic Bayesian Networks (DBN) has been used in Assisted Cognition project [10] to provide directional guidance to a user navigating through a city. This system uses a three-level hierarchical Markov model represented as a DBN to infer user's activities from GPS sensor readings. Movement patterns based on GPS localization signals are translated into a probabilistic model using unsupervised learning. Brdiczka et al. [11] have recently used Support Vector Machine (SVM) to locate and recognize social interactions of subjects from multiple sensors, including video and audio. High precision and recall was obtained in identifying low-level interactions like shaking hands, touching, pushing, and kicking. Ravi *et al.* investigated multiple base-level classifiers namely decision tables, decision trees, K-NNs, SVM, and Naive Bayes applied through a variety of techniques such as boosting, bagging, voting, cascading, and stacking on worn accelerometer data[12]. Boosted SVM was shown to perform best for difficult settings in recognizing activities like standing, walking, running, going up/down stairs etc.

The task of AR with respect to establishing wellness of monitored person has been discussed in [13 – 15]. Similar to our assumption, Suryadevara et al assume activities to be some sequence of sub activities derivable from sensors [13]. The sub activities have been determined using naïve bayes model. Maximum likelihood estimate have been used to estimate activity from the given sequence of sub- activities within a given time frame. Similarly, emotional state of person was determined from other related sensors. Wellness was computed from these two by defining and calculating wellness indices. Such an indoor tracking system has been implemented in [14] and has been shown to determine irregular health conditions correctly. The wellness indices based on usage duration and time of household appliances were designed in [15]. Use of wellness indices helps in increasing the objectivity of all AR methods. There is still scope of research in defining custom wellness indices using individual parameters.

Apart from the discussed data-driven machine learning based methods, recently, ontology based formalization of activity models has also gained popularity. Riboni and Bettini [16] investigated the use of activity ontologies to model, represent, and reason complex activities using rule representation and rule-based reasoning of Web Ontology Language (OWL).

Generic ontologies for situations were defined by making use of intrinsic and extrinsic contexts. Use of existing and new ontologies has been suggested to map multiple terms used across methods to defined contexts and activities [17]. Ontology based approaches address problem of contextual non-determinism to some extent by grouping them into a super activity say "Kitchen activity" and present that as result of AR. However, such answer is not appreciable when there is a need to identify each ADL separately.

Ontology based activity recognition methods are semantically more clear and understandable for human beings than data driven methods. However, experimental evaluation of these techniques has been limited and their actual effectiveness is still unknown. To the best of our knowledge, none of the existing methods addresses ambiguity of interpretation problem in composition of activities in terms of high-level context information.

Use of fuzzy logic to capture uncertain constituent information of activities has been proposed by few researchers. Fuzzy Cognitive Maps (FCM) for describing behaviour of a system in terms of concepts; each one representing an entity, a state, a variable or a characteristic of the system has been proposed in [18]. FCMs indicated the relationships between the environmental variables and the emotions. What-if simulations and forecasting emotions according to previous environmental conditions were shown. Fuzzy logic based approach measures uncertainties as degree of truthness of membership of contexts in a situation. However, the problem of non-determinism mentioned in Section 1 cannot be handled by fuzzy logic. An activity modeling method based on descriptive Formal Concept Analysis (FCA) has been proposed by us in [6]. To handle non-determinism, FCA has been enhanced with neutrosophic logic and comparisons are made with conventional fuzzy concept lattices.

Neutrosophic logic has been a topic of interest among mathematicians but has not been applied much in applications [19]. Use of neutrosophic logic in classification problems has been limited. One significant work towards use of neutrosophic logic has been presented in [20], where neutrosophic logic based extension of fuzzy classifier has been designed. Although, fuzzy concept lattices have been worked upon by many researchers, this is the first attempt to further generalize concept lattices with neutrosophic logic.

III. NEUTROSOPHIC LOGIC AND FORMAL CONCEPT ANALYSIS

In this section, preliminaries of neutrosophic logic and neutrosophic formal concept analysis have been defined.

a. Preliminaries of Neutrosophic Logic

Neutrosophic Logic (NL) proposed recently by mathematician F. Smarandache [19] is an extension or generalization of fuzzy logic. Conventional fuzzy logic represents a logical variable, *l* as ordered pair l= (t,f) where *t* is considered the degree of truth and *f* is the degree of falsity, such that $t+f=1$. In neutrosophic logic, a logical variable *x* is described by an ordered triple composed of neutrosophic components, x= (t, i, f) where *t, f* are same as defined in fuzzy logic and *i* is the level of indeterminacy. In its most general form, each neutrosophic component can vary individually in the interval [0,1].

This generic definition thus allows neutrosophic logic to be able to deal with paradoxes, which are propositions that are true and false in the same time. Formally, a NL(paradox)=(1, I, 1). Fuzzy logic cannot do this because in fuzzy logic the sum of fuzzy components should be 1.

However, to maintain consistency with fuzzy logic and probability, in our adaption of neutrosophic logic, it is assumed that

$$t+f=1.0 \tag{1}$$

and the indeterminacy component is allowed to vary independently in interval [0,1]. Thus,

$$t+i+f>=1.0 \tag{2}$$

The added indeterminacy component is useful to characterize imprecision of possessed knowledge which is common in AR.

Combination of two or more neutrosophic values can be interpreted by logical connectives. For any two neutrosophic variables $x_1 = (t_1, i_1, f_1)$ and $x_2 = (t_2, i_2, f_2)$,the logical connectives not (~), conjunction (∧) and disjunction (∨) are defined as follows:

$$\text{if, } x_3 = \sim x_1 \qquad \text{then } x_3 = (f_1, i_1, t_1) \tag{3}$$

$$\text{if, } x_3 = x_1 \wedge x_2 \qquad \text{then } x_3 = (min(t_1, t_2), i = max(i_1, i_2), f = max(f_1, f_2)) \tag{4}$$

$$\text{if, } x_3 = x_1 \vee x_2 \qquad \text{then } x_3 = (max(t_1, t_2), i = max(i_1, i_2), f = min(f_1, f_2)) \tag{5}$$

Conjunction and disjunction connectives can be similarly defined for many neutrosophic variables as both max and min are group operators. As with fuzzy logic, falsity dominates in conjunction and truthness in disjunction. Neutrosophic logic has been used to extend fuzzy classification in [20]. In this work, we make use of neutrosophic logic to extend our FCA based activity model.

b. Neutrosophic Formal Concept Analysis

Formal Concept Analysis has been used for AR in [6]. In this section, key definitions of formal concept analysis have been modified by including concepts of neutrosophic logic.

Definition 1: A Neutrosophic formal context, N, is defined as a triplet$\{S,\gamma, R\}$, where S is a set of situations, γ is the set of conceptually scaled contexts, and R is a relation in domain $S \times \gamma$. Each member $(s, \gamma_i) \in R$ has a membership value, μ, defined as a triplet $\{\mu_t(s, \gamma_i), \mu_i(s, \gamma_i), \mu_f(s, \gamma_i)\}$each in interval [0,1]. Each element of R represents, context 'γ_i' determining situation 's_i' is $\mu_t(s, \gamma_i)$ true, $\mu_i(s, \gamma_i)$ indeterminate and $\mu_f(s, \gamma_i)$ false.

For AR, exact membership values have been calculated from the training dataset as per equations (6 -8):

$$\mu_t(s, \gamma_i) = \frac{\mathrm{freq}(s|\gamma_i)}{\mathrm{total\_freq}(s)} \tag{6}$$

$$\mu_i(s, \gamma_i) = \max\left\{\frac{\mathrm{freq}(\gamma_i|s_j)}{\mathrm{total\_freq}(s_j)}\right\} \text{ where } j \in \{S - s\} \tag{7}$$

$$\mu_f(s, \gamma_i) = \max\left\{\frac{\mathrm{freq}(\gamma_i|s)}{\mathrm{total\_freq}(s)}\right\} \forall\, i \in \{\gamma - \gamma_i\} \tag{8}$$

With respect to the training set, the frequency of context 'm' for a given activity, s, that is, freq(s| m) is the number of times the given value is present in that situation. The total_freq(s) is total instances of *s*, present in the training dataset. Another way of defining membership values for each instance in *R* is to obtain them from a domain expert or other mining approaches [21].

Definition 2: Given a Neutrosophic formal context, N = {S, γ, R}, A⊆ S and B ⊆ γ and truth membership threshold, TM

Neutrosophic extent, NE (B) = $\{s \in A \mid \forall c \in B: \mu_t(s,c) \geq TM\}$ (9)

Neutrosophic intent, NI (A) = $\{c \in \gamma \mid \forall s \in A: \mu_t(s,c) \geq TM\}$ (10)

Definition 3: For a Neutrosophic formal context, N, a Neutrosophied Concept, NC is a pair (∅ (A), ∅(B)) where ∅ (A) ⊆ A and ∅ (B) ⊆ B such that,

NI(∅(A)) = ∅(B) and NE(∅(B))= ∅(A)

∀g ∈∅ (A) has values of neutrosophic components as follows:

$$\mu_t = \min (\mu_t (g, c)) \ \forall c \in \emptyset(B) \tag{11}$$

$$\mu_i = \max (\mu_i (g, c)) \ \forall c \in \emptyset(B) \tag{12}$$

$$\mu_f = \max (\mu_f (g,c)) \ \forall c \in \emptyset(B) \tag{13}$$

Given an intent set ∅(B), μ_t, μ_i and μ_f represent truthness, indeterminacy and falsity values of the occurrence of each situation in the extent. Algorithms to extract and organize the set of neutrosophic concepts and organize them as neutrosophic concept lattice are given in next section.

IV. NEUTROSOPHIC CONCEPT LATTICE BASED ACTIVITY MODEL AND ACTIVITY RECOGNITION

In this section, creation of activity model based on neutrosophic concept lattice has been described. Model is constructed in two parts, first of these is the creation of list of all neutrosophic concepts. Second part is about arranging the concepts in form of lattice.

a. Neutrosophic Concept Lattice based Activity Model

Neutrosophic concept lattice based model is obtained by creating a list of neutrosophic concepts and organizing them in lattice order. Algorithm 1 calculates all neutrosophic concepts. For implementation of the algorithm, few Abstract Data Types (ADTs) have been defined. *neutro_mem* has been defined to represent the membership triplet of an object. A generic object has been defined by the ADT *Object* characterized by its name and membership values. Attribute that possesses a name has also been defined as an ADT. *Extent* and *Intent* are another ADTs used to represent neutrosophic extents and intents as defined earlier. Using these ADTs, Concept data structure has been defined in terms of extent and intent.

```
ADT  neutro_mem { true_mem; indeterminacy_mem; false_mem, bal_score }
ADT Object {Name, neutron_mem; }
ADT Attribute {Name };
ADT Extent {Set of Objects;}
ADT Intent {Set of Attributes;}
ADT Concept {Extent; Intent;}
```

Algorithm 1: Compute_Set_of_All_Concepts

Input: Neutrosophic Context (O, γ, R)

Output: Set_All_Concepts

Method:

Const TM: truth membership threshold

1. Set_All_Concepts := Φ
2. New_Concept.Extent := Cal_Neutro_Extent(γ)
3. New_Concept.Intent := γ;
4. New_Concept. Extent.neutro_mem := Cal_Neutro_Mem (New_Concept.Extent , New_Concept.Intent)
5. Set_All_Concepts := New_Concept ∪ Set_All_Concepts
6. for $A \subset \gamma : \forall a \in A, \mu_t(a) \geq TM$
7. temp_extent := Cal_Neutro_Extent (A)
8. flag:=1

```
9.        for each concept ∈ Set_All_Concepts
10.            if concept. Extent = temp_extent
11.                flag:=0
12.            end if
13.       end for
14.       if (flag)
15.          New_Concept.Extent := temp_extent
16.          New_Concept.Intent := A
17.          New_Concept. Extent .neutro_mem := Cal_Neutro_Mem (New_Concept.Extent ,
                                                      New_Concept.Intent)
18.          Set_All_Concepts := New_Concept ∪ Set_All_Concepts
19.       end if
20. end for
```

Function Cal_Neutro_Extent(A)

Input: Subset of Attributes, A

Output: Extent of A

Method:

```
Extent = O;
for each a ∈ A
        attribute_extent := Φ
        for each obj ∈ O
                if (R[obj][a].true_mem ≥ Mem_Threshold)
                        attribute_extent := attribute_extent ∪ obj
                end If
        end for
Extent = Extent ∩ attribute_extent;
end for
```

Function Cal_Neutro_Mem ()

Input: X, Y: Concept.extent and Concept.Intent

Output: Neutro_Mem of Neutrosophic concept (X, Y)

Method:

```
for each x∈ X
    min_t= 1.0          // minimum truth value for all attributes of an object
    max_i=0.0           // maximum indeterminate value for all attributes of an object
    max_f = 0.0         // maximum false value for all attributes of an object
    for each y ∈ Y
        if( R[x][y].true_mem < min_t) then
            min_t: = R[x][y].true_mem
        if(R[x][y].indeter_mem > max_i)
            max_i:= R[x][y].indeter_mem
        if (R[x][y].false_mem > max_f)
            max _f := R[x][y].false_mem;
    end for
    x. neutro_mem.true_mem := min_t;
    x.neutro_mem. indeterminacy_mem := max_i;
    x. neutro_mem. false_mem = max_f;
    return neutro_mem_bal= 0.5 * x. neutro_mem.true_mem - 0.5 * x.neutro_mem.
                                                                  indeterminacy_mem
end for
```

The relation R, has been implemented as a two dimensional array of size '*number of objects * number of attributes*'. Each element of array, R[i][j], is assigned membership triplet if *'i'* possesses '*j'* else zero.

Algorithm 1 takes as input neutrosophic formal context, described by set of objects, set of attributes and relation R. The algorithm then works as follows:

- Set of all concepts is initialized to be empty in line 1.
- In lines (2-5), the first concept is calculated as taking Intent as complete set of attributes and calculating its corresponding extent. It is added to overall concept set. This concept will act as the infimum to create a complete lattice [21].

- Lines (6 -20) describe generation of new concepts. Iterations to calculate all possible intents, find their extent and add to the set of all concepts, if it is already not there are defined.
- Line 6 each time generates a possible intent as proper subset of attributes such that each element has truth membership greater than threshold. Extent of generated intent is calculated in Line 7 and saved in a temporary extent. This is done as, it is yet to be decided whether a new concept has been found or not.
- In Lines (8 -13) temporary extent is compared with extents of existing concepts and a flag is reset if so found. No new concept is added in this case.
- Lines (14 -19) execute if concept has not been generated before. New concept is created by calculating neutrosophic membership of each object of extent using memberships of each attribute of intent.
- The algorithm ends with concept generation loop in line 20

Algorithm 1 makes use of two functions. *Cal_Neutro_Extent()* takes as input neutrosophic intent and calculates neutrosophic extent as per definition 2. *Cal_Neutro_Mem()* calculates neutrosophic membership triples for each object in a given extent according to memberships of attribute in intent.

For AR problem, objects are considered as *activities* and their attributes are relevant *contexts*. Both truthness and indeterminacy membership values have been given equal weights to decide membership of a context in an activity. The indeterminacy score penalizes the membership of a context in any activity. Computation of fuzzy lattice was also been done using same algorithm, but only true membership is utilized for extent calculation.

In FCA, set of concepts are organized as lattice representing sub concept and concept relation [18]. However, here instead of lattice construction, it suffices to create a partially ordered list of concepts arranged in descending order of cardinality of extents of each concept. The complexity of computation of ordered set of extent in lexicographic order is $O(|n|^2)$ while that of lattice construction is typically is $O(|n|\,|A|\,(|O| + |A|))$ [22], where $|n|$ is number of concepts, A is the set of attributes and O is the set of objects. The neutrosophic formal context, partial ordered list of concepts and neutrosophic membership of each extent forms our sought activity model that can be stored in suitable data structures for real time AR.

b. Activity Recognition

In the testing phase, the contexts at a given time instance, t, are used to infer activities. An activity query is denoted by $A_q = \{C_1,.. C_i\}$, the set of current contexts. Query is input to Algorithm 2 and recognized activity is obtained as output. In case, the query context is not present in intent of any of the concepts, user will get an estimate of actual activity as most likely or probable.

Algorithm 2 iterates over complete set of concepts in lines (1-9) to find exact match of activity corresponding to queried context set, Aq.

Algorithm 2: Predict_Activity_Set

Input: C:= Set_All_Concepts, Queried Context Description Aq:= { C_1,.. C_i}

Output: Recognized Activity

Method:

1. for each concept, c
2.   if Aq ⊆ c.Intent then
3.   if |c.Extent|= 1 then β:= c.Extent
4.   else for each o in c.Extent
5.   find o such that, o.neutromem = max(c.Extent.neutromem)
6.   β:= o
7.   end if
8.   end if
9. end for
10. if β:= ∅
11.   c':= ∅
12.   for all , c ∈ C, find c such that max $\left(\frac{|Aq \cap \text{c.Intent}|}{|Aq \cup \text{c.Intent}|}\right)$
13.   c':= c'∪ c
14. end if
15. β' = $\bigcap_{i=1}^{|c'|} c'_i$ for all c'_i ∈ c'
16. β'' = $\bigcup_{i=1}^{|c'|} c'_i$ for all c'_i ∈ c'

17. S(precise)= β //set of currently occurring situations
18. S(most_likely) = β' //most likely set of situations
19. S(probable) = β'' //as the probable set of situations
20. End

The algorithm works as follows:

- Lines (2-3) represent the simplest case when Aq is found as subset of intent of one of the concepts with single activity in its extent. Extent of this concept is output as recognized activity.
- Lines (4-8) consider the case when Aq is found as subset of an intent whose extent has more than one activity. The recognized activity is then considered as the one have maximum neutrosophic value. Activity that has maximum truthness and minimum indeterminacy membership in Aq is considered as one having maximum neutrosophic value.
- Lines 10 -16 are executed if Aq is not found in any of the concept intent. An approximate answer is sought then. In line 10-14, the list of concepts is traversed again to generate a set of concepts, c', having concepts maximally similar to Aq. Similarity is computed by calculating Jaccard's coefficient with respect to Aq and each intent.
- In lines 15-16, set of most likely is calculated as activities common in extents of c'. The set of probable activities are calculated as all possible activities present in any of the extents of c'.
- All sets of recognized activities are finally output in lines 17-19 and algorithm is terminated in line 20.

The time complexity of Algorithm 2 is linear and computed as O (|N|) in case of exact match and as O (2|N|) in case of most probable and possible matches. In the next section, the proposed algorithms are evaluated on publicly available datasets.

V. RESULTS AND PERFORMANCE ANALYSIS

AR model developed in earlier section have been validated on publicly available multi modal sensor based dataset called *"OPPORTUINITY"* [23]. It has been used by several researchers to examine their methods of activity recognition [24].

Database has multi-modal sensor data annotated with two types of ground truths recorded from four subjects in five run of each. One is low level actions and other is high level activities. Low level actions, as described in Table 1, have been used as contexts in which the actual activity takes place. Activities annotated in the dataset are described in Table 2. Table 2 also gives general description of how an activity was performed in the said environment. Numeric names used for contexts and each activity in concept set construction are enclosed in parenthesis in respective tables.

Table 1: Activity Context, their Possible Values and Id of each Value

Contexts	**Abstract Values**
Locomotion	Null (1), Stand (2), Walk (3) , Sit (4), Lie (5)
Left Arm Actions	Null (6), Unlock (7), stir (8), lock (9), close (10), reach (11), open (12), sip (13), clean (14), bite (15), cut (16), spread (17), release (18), move (19)
Right Arm Actions	Null (44), Unlock (45), stir (46), lock (47), close (48), reach (49), open (50), sip (51), clean (52), bite (53), cut (54), spread (55), release (56), move (57)
Object Used with Left Arm	Null (20), Bottle (21), Salami (22), Bread (23), Sugar (24), Dishwasher (25), Switch (26), Milk (27), Lower Drawer (28), Spoon (29), Knife for cheese (30), Middle Drawer (31), Table (32), Glass (33), Cheese (34), Chair (35), Door1 (36), Door2 (37), Plate (38), Top Drawer (39), Fridge (40), Cup (41), Knife for salami (42), Lazy chair (43)
Object Used with Right Arm	Null (58), Bottle (59), Salami (60), Bread (61), Sugar (62), Dishwasher (63), Switch (64), Milk (65), Lower Drawer (66), Spoon (67), Knife for cheese (68), Middle Drawer (69), Table (70), Glass (71), Cheese (72), Chair (73), Door1 (74), Door2 (75), Plate (76), Top Drawer (77), Fridge (78), Cup (79), Knife for salami (80), Lazy chair (81)

Table 2: Activities Done and Their Descriptions

Activity (Activity Id)	**General Process of Doing Activity**
Idle (0)	No activity
Relaxing (101)	Close doors, Lie down and no other action or object usage
Coffee time(102)	Prepare Coffee using utensils like cup, spoon etc., ingredients like milk ,sugar, appliance like Coffee Machine and accessing drawers, Subject is standing most of the time and walks to fetch things
Early Morning (103)	Goes out of the room for a walk, walks around in the room, standing occasionally to use some objects
Cleanup (104)	Cleans the table, put soiled dishes in dishwasher , put remaining food in fridge and drawers
Sandwich Time (105)	Fetch ingredients cheese, salami , bread etc. from drawers and fridge, sit on table , prepare and eat sandwich

On observing the datasets it was found that when annotated activity was idle random values of contexts were occurring. Thus any instance of activity “Idle” was not used in training and testing of activity model.

a. Learnt Activity Model and its Interpretation

Activity Models were created for each subject using data of four runs for training the model and fifth run for testing. Twenty experiments including five for each of the four subjects using each run at a time for testing and remaining for training were performed. Figure 1 represents the concept lattice obtained by using first four runs of Subject 1 as training data.

Lattice Navigator software has been utilized to visualize the lattice in Figure 1 [25]. Each node has been labelled using reduced labelling [22]. Lattice has two extreme concepts. The topmost concept represents the context values that are found in all activities. The bottommost concept represents the activity which has all possible contexts values in its description. All lattices generated with given datasets had empty extent for these concepts. Twenty lattice models were obtained for testing the models. Results presented in next section are average performance over all these models.

The lattice is stored in memory as graph data structure and accessed in breadth first manner for context query matching using Algorithm 2. In case the matched concept has an extent with more than one activity, recognition of activity is resolved by maximizing neutrosophic membership.

For example, on breadth first traversal of lattice, a queried context description,

A_q = {Locomotion: *Stand (2)*; Left Arm Actions: *Reach (11)*; Right Arm Actions: *Lower Drawer (28)*; Object Used with Left Arm: *Null (44)*; Object Used with Right Arm: *Null (58)}* matches the 6^{th} node in 4^{th} level of lattice with extent {*Coffee Time and Sandwich Time*}. The actual activity is recognized by computing neutrosophic score for each activity and output the one with higher score.

Validation of activity models was done by testing with activity run data of same subject for which the model was trained as well as for other subjects. For establishing the advantage of proposed approach, performance of neutrosophic concept lattice model has been compared against conventional fuzzy concept lattice based activity model.

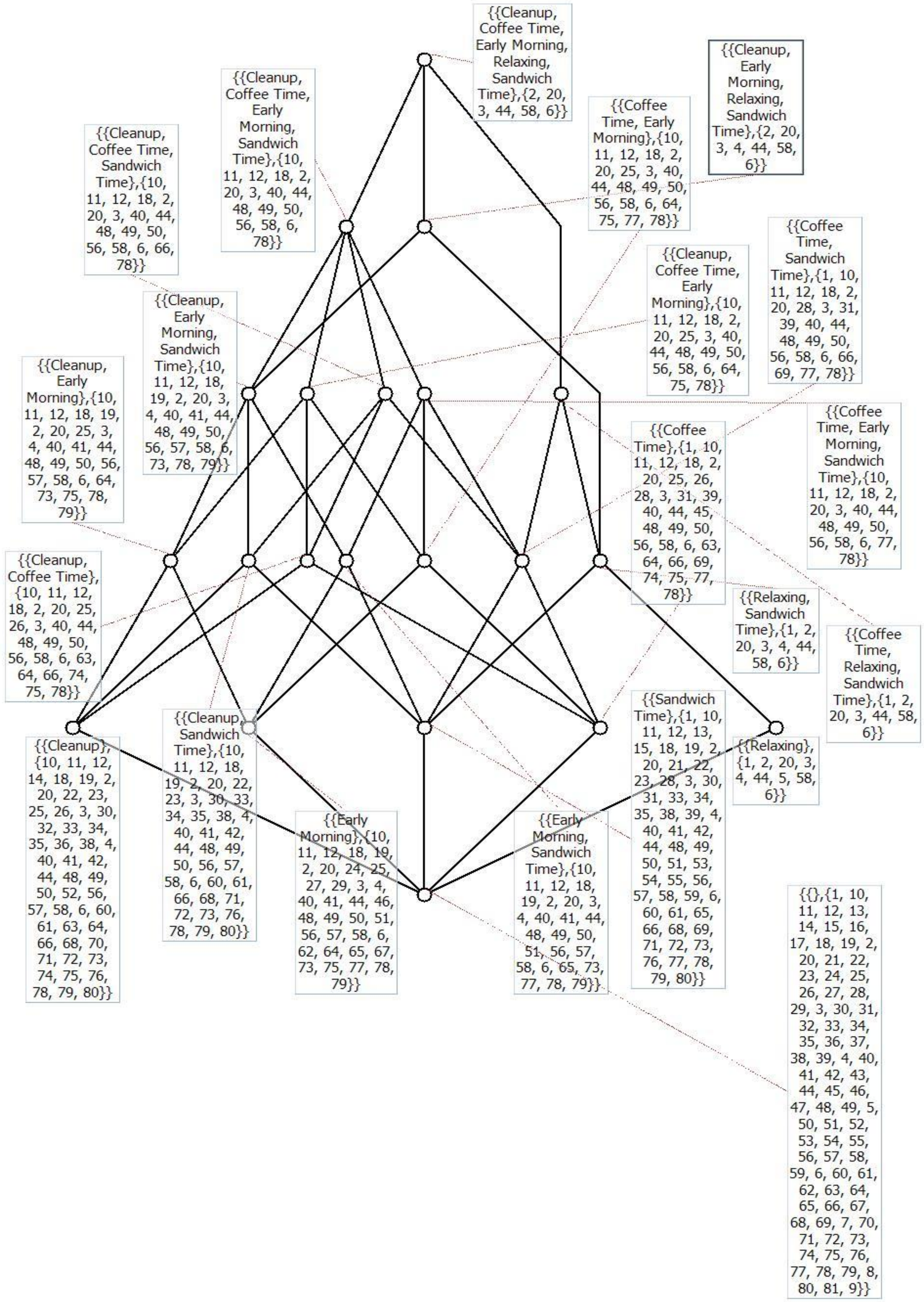

Figure 1: Lattice Based Activity Model Learnt from data of Subject 1 (Visualized in Lattice Navigator)

b. Validation of Activity Recognition on Same Subject

Experiments without Null Contextual Information:

As can be seen in Table 1, each context has been labelled as *'NULL'* at times. This value doesn't have any clear cut meaning in dataset. Thus, in the first experiment all data instances where value of even one of the contexts was *'NULL'* were discarded. Confusion matrix of Table 3 shows recognition results when 80% data of Subject 1 was used for training and remaining 20% for testing. Activity recognition was very encouraging with 93.3% accuracy obtained. These instances represent best quality data of dataset. It can be observed from Table 3 that only contextual information obtained from sensors embedded in objects is presenting confusing results as same objects are touched in many activities.

A major concern here is complete elimination of '*Relaxing*' and partial elimination of '*Early Morning*' activities from the dataset.

Table 3: Confusion Matrix Obtained By Ignoring All Null Values of Contexts

		Predicted Situations				
		Relaxing	Coffee Time	Early Morning	Cleanup	Sandwich Time
Actual Situations	Relaxing	0	0	0	0	0
	Coffee time	0	701	0	28	0
	Early morning	0	0	45	0	0
	Cleanup	0	0	22	1025	44
	Sandwich Time	0	0	191	55	1501

This is due to the fact that in relaxing activity once the subject lies down, values of all other contexts becomes null as he neither does any action nor uses any object. Similarly in "Early Morning" activity the subject goes out of room for walk, thus making all other contextual values as *'NULL'*.

Experiments with Null Contextual Information:

Due to the problem of elimination of two activities from activity model, the next set of experiments considered *'Null'* as possible context values for each type of contexts. Activity model was trained with conventional fuzzy lattice method and proposed neutrosophic lattice method.

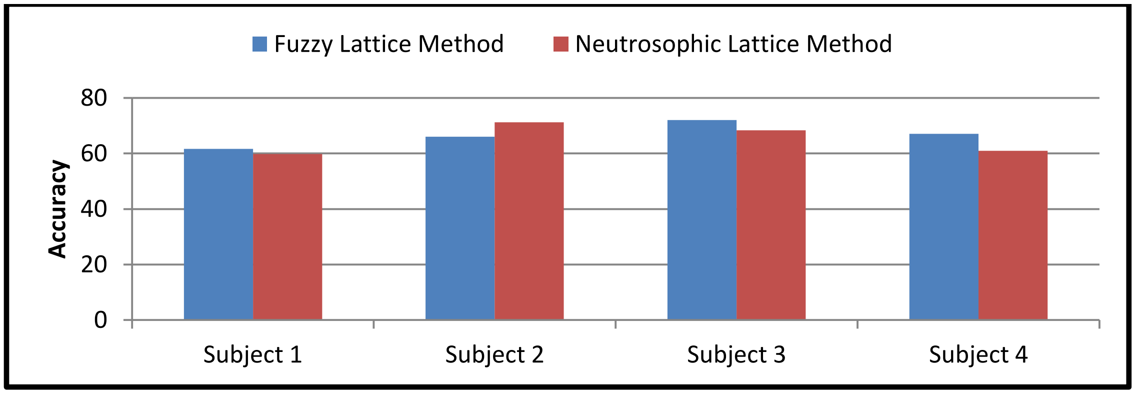

Figure 2: Mean accuracy of classification over five runs of each subject

Models were trained and tested five times for each subject by taking four of the runs as training data and remaining for testing. Subject wise mean accuracy of recognition of each activity was evaluated for each run and has been presented in Figure 2.

It can be seen that neutrosophic lattice performs at par with activity recognition of fuzzy lattice. Inclusion of indeterminacy component in neutrosophic logic has increased its semantics while not affecting the recognition accuracy. Dataset is imbalanced in terms of number of occurrences of each activity. Thus, validation results were analysed for activity wise recognition rate of each run of each subject.

Table 4: Confusion Matrix of one Runs of Subject 3

		Predicted Activities				
		Relaxing	Coffee Time	Early Morning	Cleanup	Sandwich Time
Actual Situations	Relaxing	822	0	2	255	404
	Coffee time	0	2004	205	473	103
	Early morning	0	459	4431	2117	0
	Cleanup	0	327	103	3032	542
	Sandwich Time	0	648	342	1420	8175

In Table 4, one of the confusion matrices obtained while testing a run of subject 3 has been shown. Inclusion of null values for each type of context has increased spill overs to neighbouring activities. This is because each context's values are *'NULL'* in many activities.

Other observation from this confusion matrix is about the Cleanup activity (Recall rate: 41.5%). This activity is often mistaken as coffee time, early morning and sandwich time. It is the usage of dishwasher that separates Cleanup from other three activities. Thus, only those instances of cleanup where usage of dishwasher is made are correctly recognized, while others are recognized to other activities depending on the neutrosophic membership value of that activity for a given test data.

In Figure 3, mean recall rate of each activity has been shown. Recognition of *Sandwich time* and *Early Morning* activity is improved greatly in our method due to their lopsided truth membership values and less indeterminacy. Locomotion context with *'sit'* value is unique and most common to Sandwich Time activity. Similarly, '*Null'* values for locomotion context has high truth membership in *Early Morning* activity. In both cases, the use of indeterminacy factor enhances the recognition rate of these activities.

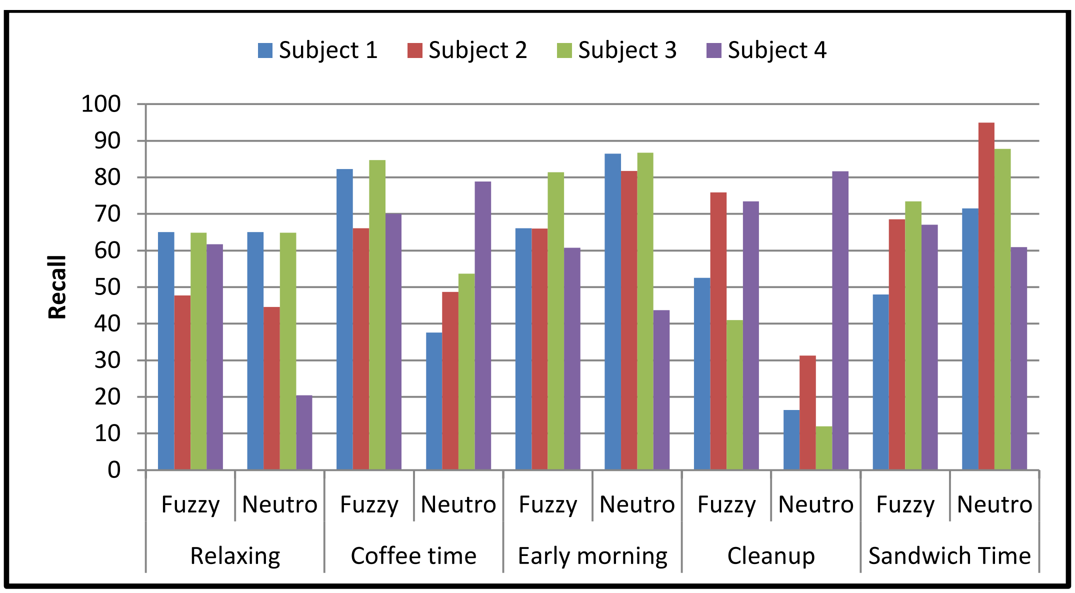

Figure 3: Activity wise mean recall over five runs of each subject

A loss in recall of indeterminate activities like '*Cleanup'* and '*Coffee Time'* and gain in recall of distinguishable activities like Sandwich Time and Early Morning proves the efficacy of approach in achieving its objective of highlighting non-deterministic activities.

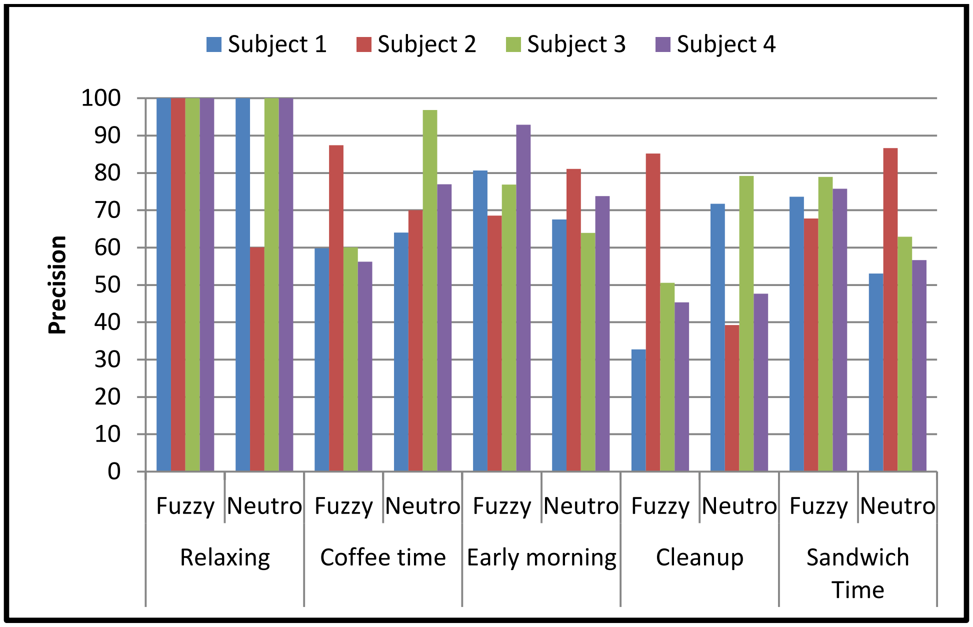

Figure 4: Activity wise mean Precision over five runs of each subject

Recall gave an idea of how many times each activity was correctly recognized. Next set of analysis over obtained results was to find precision of each class of activity. Precision is important for getting information on exactness or quality of recognition of each class (activity here) in imbalanced datasets.

In Figure 4, activity wise precision of each activity for all four subjects has been reproduced. For *Relaxing* activity, precision is perfect hundred except for one case using neutrosophic logic. For understanding this result, raw data of subject 2 was examined closely for this activity particularly. In *Relaxing* activity, a subject typically lies down on the lazy chair for most of the duration. It was found that Subject 2 was sitting most of the time during one of the runs of *Relaxing.* Sitting, however, is typical to *Sandwich Time* activity, thus the proposed neutrosophic lattice captured this as indeterminacy and low precision was observed for this case. It can be noted that fuzzy lattice could not capture this anomaly in training data.

Similarly, for *Sandwich Time* which is otherwise deterministic activity, significant drop in precision was noticed for Subject 1 and 3. It was again explainable through raw data of these subjects where during more than one runs these subjects have interleaved coffee sipping and cleaning with *Sandwich Time* activity. Thus, using our lattice, the non-determinism in the way an activity is carried has been identified well, which was not possible using fuzzy lattice approach.

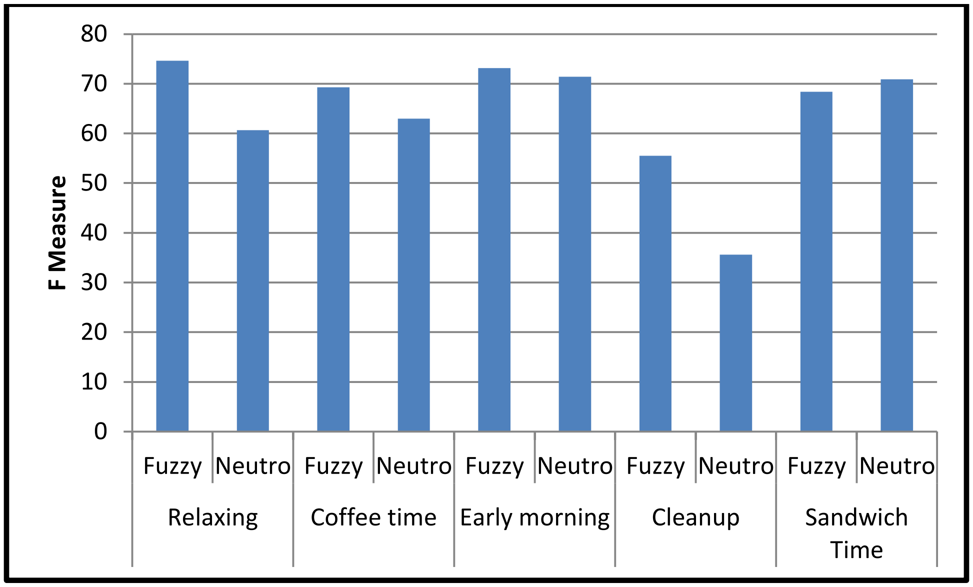

Figure 5: Overall Activity Wise F Measure for Our Approach and Fuzzy Lattice

Overall F-measure analysis of all subjects has been represented in Figure 5. As expected the F-measure for non- deterministic *Cleanup* activity is low. However, for other such activity that is *Coffee Time*, F measure is comparable to other activities due to improved precision of this activity for subjects 1, 3 and 4. Low precision of Subject 2 for *Relaxing* activity has contributed to reduced F measure of this activity.

There were only about 0.5% instances where the test data did not match the intent of any of the concepts, thus calculation of most likely and probable activities for these were dropped.

c. VALIDATION OF ACTIVITY RECOGNITION ACROSS SUBJECTS

In activity recognition, it is important to analyse the validity of learnt model when applied over different users. For this analysis, datasets of all runs of one subject was used for training and tested on dataset of other subjects one by one. One of the results where activity model was trained on subject 1 and tested on all other subjects has been shown in Figure 6.

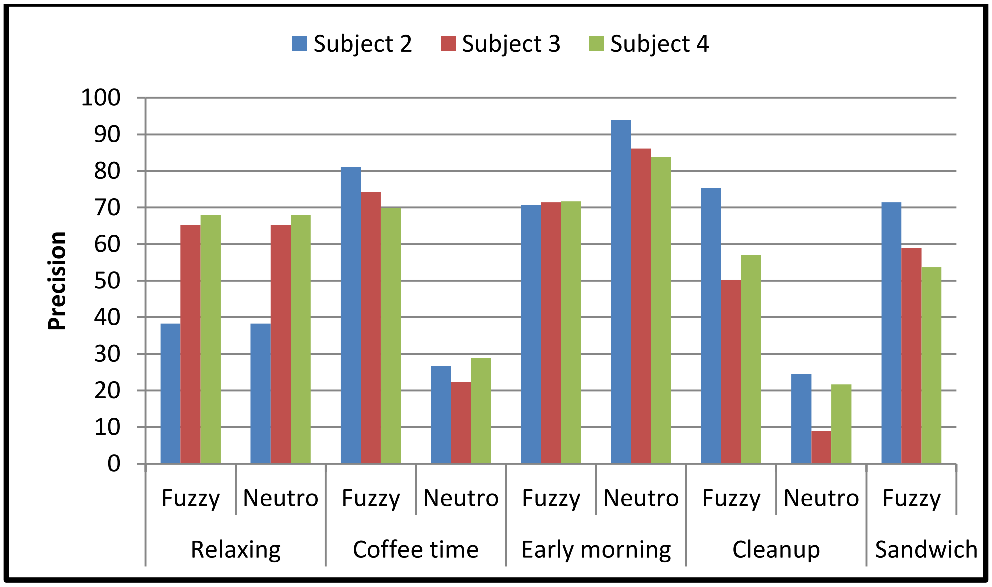

Figure 6: Activity Wise Mean Precision on Applying Activity Model across Subjects

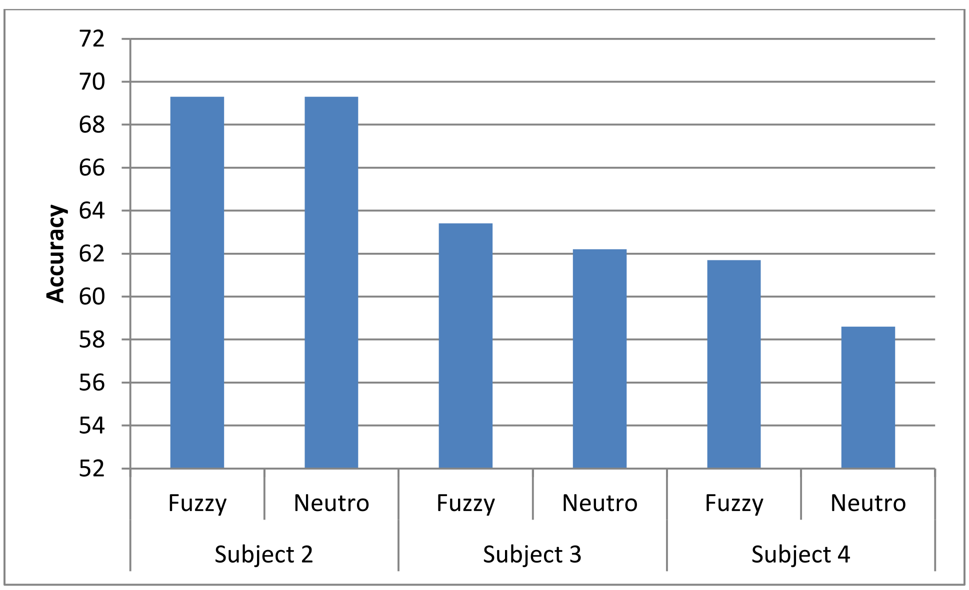

Figure 7: Subject Wise Accuracy over application of Models across Subjects

Average precision has decreased as compared to fuzzy approach. However, for deterministic activities, neutrosophic method gave far better results. However, very low precision of *Cleanup* and *Coffee Time* is a concern and thus sensor sources for these activities need to be enhanced urgently. It can be concluded that neutrosophic lattice based classifier helps in addressing ambiguity of interpretation of activities by highlighting them due to significantly reduced recognition (down to 10% in some cases).

In Figure 7, overall accuracy of activity recognition obtained, when activity models learnt using Subject 1's data are tested over other subjects' data is shown. The overall accuracy indicates consistent performance of the model. It can be thus concluded that if activity wise precision issues are handled well, lattice based models can withstand variations of activity dissemination by different persons. Thus, need for training the model for every new user is eliminated. This is a big advantage while designing ready to use sensor based activity recognition solution.

d. Comparison of Activity Recognition with Other Approaches

Study of effectiveness of context data in describing activities on same dataset was also found in [26]. Purpose of evaluation was to select the relevant set of contexts. J48 decision tree, Hidden Naïve Bayes and simple instance based learner IBK classifiers were used in that study. The paper did not clarify about which subset of dataset was taken in their study. Therefore, their methods could not be verified by us on our own and evaluation results mentioned in their paper have been used directly. The comparison results of their reported accuracy and against mean performance of proposed method is shown in Figure 8.

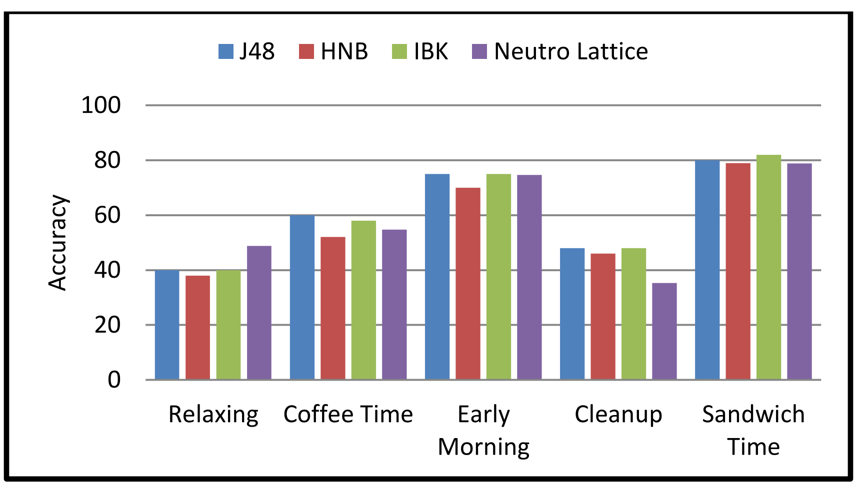

Figure 8: Evaluation of Proposed Model against results published in [26]

The accuracy of deterministic activities *Relaxing*, *Early Morning* and *Sandwich Time* is higher or equivalent to machine learning based approaches. The accuracy of non-deterministic approaches is slightly lesser, as our approach penalizes the recognition in such activities. The recognition algorithms used in [26] work like a black box and recognition process is not explainable. In our case the recognition process is semantically clear and self-explanatory.

While strength of proposed model is in identifying non determinism, it has few limitations also. It is based on similarity computation to recognize activities and cannot perform reasoning to derive new information such as those supported by ontology based activity models. Other shortcoming is its inability to only highlight and not improve performance of non-deterministic activity. The proposed method can't differentiate between non-determinism due to non - availability of contextual information from non- determinism caused due to interleaving of otherwise deterministic activities. These shortcomings can be worked upon by further enhancing the proposed method.

For large scale usage, AR methods across similar homes in a building can be investigated. One such study with respect to scalability of home monitoring systems, determining wellness through AR, to smart buildings has been presented in [27].

VI. CONCLUSIONS

In this paper, human activity recognition from sensor derived low level abstract information that is "contexts" has been studied. Existing approaches for solving this problem have shown good results for recognizing simple actions. Recognition of high level activities defined by certain sequence of contexts and taking place at different times or place has also been attempted. However, humans do activities in their own manner and seldom follow known sequence while doing certain activity. Activities taking place at same place within same time frame and having similar context values can become non-deterministic if at least one distinguishing context value is not present in it. Such activities give poor recognition results with almost all existing approaches. In this paper, Neutrosophic logic, a generalization of fuzzy logic has been utilized to quantify non-determinism and include it in Formal Concept Analysis based activity model. The proposed method does not increase the accuracy of recognition of non-deterministic activities but it works towards highlighting them during recognition. This is done by calculating non-determinism associated with contextual description of activities and utilizing it as penalizing factor in recognition. Thus, recognition performance of non-deterministic activities gets significantly reduced while is increased for deterministic activities. The algorithms were tested on benchmark context and activity datasets. Difference in recognition performance of deterministic and non-deterministic activities was not significant in other approaches. The proposed approach also successfully revealed anomalies in input data which was not apparent in other methods.

It is thus concluded that our approach can be effective for testing correctness of context based activity determination before on site installations. New relevant contexts can be added for activities which are not recognizable with current set of contexts. This may require deployment of more number or types of sensors.

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