Modeling of Activities as Fuzzy Temporal Multivariable Problems

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Abstract

Smart Home resident may be an Alzheimer patient needing continuous assistance and care giving. Because of forgetfulness, this person may realize activities of daily living erroneously. In order to assist this person automatically in Smart Home, all his performed actions and activities are observed through the embedded sensors of Smart Home, and applying the data mining techniques his activities are analyzed. Then information about his activities is provided and in the consequence, comparing learned correct patterns and current observations the Smart Home may infer provision of assistance to this person at the appropriate moment. In this paper we propose a data-driven activity modeling approach, which supports reasoning in correct realization of the activities. Activities are presumed as the series of fuzzy events that occur shortly one after another. Per each activity, we calculate a fuzzy conceptual structure, and the model of activity is represented in form of a multivariable problem.

Introduction

Recently proposed *data-driven* works on activity recognition show effective but unreliable results on estimation of the current ongoing activities (Chen et al. 2010). For example, in (Nazerfard 2010) it is proposed how to predict the *probable* events that may occur in smart home, but no mechanism to estimate the current world state is proposed. In there, no feedback from the current home state is taken and several hypotheses without consideration of the actual state of the Smart Home Resident (SHR) are taken into account. As the result, no certain decision about the probable required assistance can be made. The mentioned approaches are still dependent on the expert's knowledge in both learning and recognition steps and do not propose a supervisor system that supports reasoning in all possible events that may occur in every time and everywhere of the ambient environment. Our conclusion is that *they do not verify correct realization of activities*.

In this paper, in order to contribute in activity recognition, we propose to calculate a virtual space that draws possible correct realization of activities, and then this space is represented in form of a multi-variable problem. This work is an extension of the research, in which we proposed modeling of activities as the series of fuzzy events (Amirjavid et al. 2012a). In there, we discussed data of smart home's temporal database can be interpreted differently depending on the details/generalities desired to be included in the inferred events. In order to present an example for this subject; please, consider the data in Table 1, in where, we have presented observations from an assumptive activity through six sensors (variables) in twenty stages. In order to describe briefly this dataset, we can make several hypotheses (concepts) and in each one we can include a level of details/generalities. In order to form these concepts in a data-driven manner, we perform the subtractive clustering (Chiu 1997) algorithm on the dataset.

observation number	Variable 1	Variable 2	Variable 3	Variable 4	Variable 5	Variable 6
1	1	1	1	10	12	10
2	2	1	2	9	11	10
3	3	1	1	4	10	10
4	4	4	2	10	9	10
5	5	4	7	19	8	10
6	6	4	8	7	8	10
7	7	7	7	7	9	10
8	8	7	8	5	10	10
9	9	7	12	17	11	10
10	10	9	13	18	12	10
11	11	9	12	20	12	10
12	12	9	14	18	11	10
13	13	20	20	2	10	10
14	14	20	19	5	9	10
15	15	20	18	2	8	10
16	16	16	19	19	11	10
17	17	16	15	14	10	10
18	18	16	14	12	9	10
19	19	12	15	5	9	10
20	20	12	13	1	8	10

Table 1 - Observation of the six world attributes in twenty stages (synthetic data)

By increasing/decreasing the cluster radius rate, bigger or smaller clusters (representing by cluster centers) are formed and the world will be described as transition of the fuzzy clusters proposed in Table 2. The mentioned algorithm according to the cluster radius rate (called also influence range) groups the similar data points in clusters. Proposal of different desired similarity degrees may lead to discovery of new clusters representing by cluster centers.

Fuzzy State Number	Variable 1	Variable 2	Variable 3	Variable 4	Variable 5	Variable 6	Influence Range
1_1	8.0 ©	7.0 ©	8.0 ©	5.0 ©	10.0 ©	10.0 ©	IR=2
2_1	7.0	7.0	7.0	7.0	9.0	10.0 ©	IR=1.5
2_2	17.0	16.0	15.0	14.0	10.0	10.0 ©	IR=1.5
3_1	12.0	9.0	14.0	18.0	11.0	10.0 ©	IR=1
3_2	7.0	7.0	7.0	7.0	9.0	10.0 ©	IR=1
3_3	14.0	20.0	19.0	5.0	9.0	10.0 ©	IR=1
3_4	2.0	1.0	2.0	9.0	11.0	10.0 ©	IR=1
4_1	12.0	9.0	14.0	18.0	11.0	10.0 ©	IR=0.9
4_2	7.0	7.0	7.0	7.0	9.0	10.0 ©	IR=0.9
4_3	14.0	20.0	19.0	5.0	9.0	10.0 ©	IR=0.9
4_4	2.0	1.0	2.0	9.0	11.0	10.0 ©	IR=0.9
4_5	20.0	12.0	13.0	1.0	8.0	10.0 ©	IR=0.9
5_1	12.0	9.0	14.0	18.0	11.0	10.0 ©	IR=0.8
5_2	7.0	7.0	7.0	7.0	9.0	10.0 ©	IR=0.8
5_3	14.0	20.0	19.0	5.0	9.0	10.0 ©	IR=0.8
5_4	2.0	1.0	2.0	9.0	11.0	10.0 ©	IR=0.8
5_5	20.0	12.0	13.0	1.0	8.0	10.0 ©	IR=0.8
5_6	5.0	4.0	7.0	19.0	8.0	10.0 ©	IR=0.8
6_1	10.0	9.0	13.0	18.0	12.0	10.0 ©	IR=0.7
6_2	7.0	7.0	7.0	7.0	9.0	10.0 ©	IR=0.7
6_3	14.0	20.0	19.0	5.0	9.0	10.0 ©	IR=0.7
6_4	2.0	1.0	2.0	9.0	11.0	10.0 ©	IR=0.7
6_5	17.0	16.0	15.0	14.0	10.0	10.0 ©	IR=0.7
6_6	20.0	12.0	13.0	1.0	8.0	10.0 ©	IR=0.7
6_7	5.0	4.0	7.0	19.0	8.0	10.0 ©	IR=0.7

Table 2 – Some possible hypotheses around the observations

In Table 2, we can see several hypotheses that explain the observations are formed, when different cluster sizes are desired. Each cluster is represented by a cluster center. At each fuzzy state, we can imagine each variable is Table and by occurrence of fuzzy event (which may be a multi-dimensional event) the world transits to a new fuzzy state. For example, one hypothesis is that activity transits four fuzzy states (coded as 3-1, 3-2, 3-3, 3-4) and the sixth variable indicates the fuzzy context (Amirjavid, Bouzouana, and Bouchard 2012c) of this activity (symbolized by © in Table 2). In Figure 1, we have illustrated this perception from the presented world.

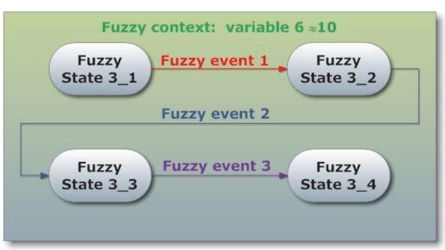

Figure 1. The world is modeled as chain of fuzzy events

In figure 1, it is illustrated that occurrence of fuzzy events would cause transition of world from one fuzzy state to another state. In (Amirjavid et al. 2012a), it is described that in the consequence of realization of a typical activity, several events occur in the ambient environment, so several world states are transited to achieve a goal. This approach includes some limitations that are the subject of the current work:

- A unique activity may be modeled through different interpretations from the fuzzy event, when different generality/details are desired.
- The beginning and ending points of the activities should be cleared at the training phase.
- The reasoning in recognition of activities can be done only when an action is performed in the world, so it does not reason in normality of the current momentum observations.

Solving the mentioned problems, we propose to integrate all the hypotheses that explain the observations by a smoothing curve in order to achieve a continuous form for activities realization possibilistic space. In other words, we propose fuzzy temporal conceptual models for activities in form of multivariable mathematical equation such as:

$$y = \alpha_1 \tilde{x}_1 + \alpha_2 \tilde{x}_2 + \ldots + \alpha_n \tilde{x}_n$$

In this equation, “y” represents the activity function, “x” represents the variable that activity depends on, and “α” is the variables’ factors in activity model. This paper is organized as the following: after making an introduction, we would discuss the essential concepts concerning to this proposal; in the consequence we introduce the formalizations and definitions applied in the modeling; then we would present a case study in which modeling and realization of activities are surveyed. Finally, after verification and validation of the experimental results, a conclusion is done.

Conceptual model for activities

Information about current status of the smart home and activities are the initials for provision of appropriate assistance in smart home (Amirjavid et al. 2013b). Therefore, our main goal in here is to propose conceptual models for activities, which leads to estimate the current state of smart home and to predict all possible events that may occur in future (Amirjavid et al. 2013b). An intelligent system such as Activity Recognition Reasoning System (ARRS) needs to perceive the real world in order to discover and create knowledge (Sowa 1984). In other words, ARRS would perceive the real world by creating the concepts who may explain the occurring events. Generally, the “concept” is a perceived regulatory or pattern in events or objects, or records of events or objects, designated by a label[1] (Novak 1984). In the next sections, we would discuss how to generate the concepts in a data-driven manner so that ARRS perceives the real world.

[1] Label in here refers to the “name” or the “word” that a concept is called with.

Data-driven conceptual models for an activity

In modeling process; we apply the explanative hypotheses (cluster centers) as the entities that form the conceptual structure of activities. To do so will calculate a function that represents the behavior of the sensors (variables) during the activity's realization through a smoothing process and finally a function representing the activity's characteristics is estimated.

Considering that observations in Table 1 are part of a bigger dataset, so it can be inferred that an activity is a special concept hidden in a temporal dataset. In Figure 2, we have demonstrated how a typical activity can be perceived as a set of world state transitions when different rates of details are desired.

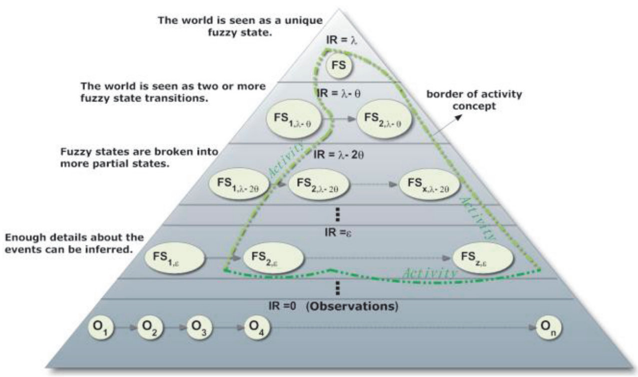

Figure 2. Hypotheses to perceive an activity

In Figure 2, we show that a typical activity from a view point at the data (observations) level is viewed as a dynamic entity that transits quickly a lot of world states. In observations level, on one hand relatively very high level of details is provided, and on the other hand very low level of generality is desired. Therefore, partial changes such as "one second elapse of time" would lead to creation of new world states. The result is the quantity of transition states increases to the maximum possible. Performing clustering, the observations those are partially similar to each other are grouped (by selection of a bigger cluster radiuses), we can decrease the number of transitional world states and perceive the world through data-drivenly made clusters. Naturally, at this level, fewer details for world description are included and more general characteristics of the activity are focused.

In clustering process, we can define a level for the desired details by decreasing/increasing of the cluster sizes. The bigger clusters would include fewer details, but more generality and of course less world states are transited. Selection of the biggest possible cluster "IR=λ" leads to *perceive the world as a single unique world state*, which describes an activity as a special world quality (Amirjavid et al. 2013a). In Figure 2, it is illustrated that we can consider "IR=ε" as the level of minimum desired details from the observations. Generally, a higher level of world description may be broken into more partial explanations at lower levels. It justifies why we propose all activity's explanative hypotheses in a pyramidal schema.

Characterization of an activity

Long-term observation of the Activities of the Daily Living (ADLs) leads to formation of a huge data warehouse in smart home. The reality is that in data level, we have no idea about beginning and ending points of the activities. In order to distinguish an activity with its time-dependent (dynamic) borders in dataset, we propose to consider an activity as a set of fuzzy events that occur with an approximate but special fuzzy time interval. This fuzzy interval can be represented by a cluster center. In other words, we label a subset of data points as an activity if and only if we find a *fuzzy temporal interval* representing the possible measures of delays between occurring fuzzy events. Therefore, an activity is a set of fuzzy events that occur in special temporal intervals**.**

These intervals are dependent to both real daily time and the beginning/ending times of other activities, while the clusters are estimated considering the real time and delays between occurring events. In subtractive clustering (Chiu 1997) the cluster centers are discovered by two types of comparisons: the first comparison is done between the data points of a variable, so the data points' interrelations are subjected, so the beginning/ending points of the activities, which are kinds of interrelations between data points of an activity, are calculated. The second comparison is done between data points of a variable with other variables' data points, so when "real time" is included in the observations properties, the cluster centers would be calculated considering this property too.

Activity Recognition Model

In this section, we present some definitions and formalizations to learn the activities. The "world" of the proposed learning problem is observed through set of applied sensors "S". "s_i" represents sensor "i" from the set of applied sensors; "n" refers to the number of sensors or variables and "a" refers to a typical activity from the set "A" (set of activities). Goal "G" is achieved when "a" is realized, so we can consider that a goal achievement is equivalent to an activity realization. In formalizations it is presumed that the world is observed for "T" times through "n" sensors, when a goal from the set "G" was intended.

Definition 1 (*observation matrix*). This is the set of digitized numeric values taken from each sensor and registered into a temporal dataset, which indicates the observed world qualities in a continuous frequent observation from the world. If the observations concern to an activity realization then a temporal dataset consisting from multi-attribute observations is formed. We formalize the set of observations in a matrix format. It may be sorted by a world attribute such as time:

$$O_{S,G} = \begin{array}{c} \overbrace{\phantom{V_{1,1} \quad . \quad . \quad .}}^{s_i} \\ \begin{bmatrix} V_{1,1} & . & . & . \\ . & . & . & . \\ . & V_{i,t} & . & . \\ . & . & . & V_{n,T} \end{bmatrix} \end{array}$$

Equation 1 – Observation matrix

In equation 1, the columns represent the sensors (variables or world features) and the rows represent the observed values at time "t". "$V_{i,t}$" represents the value of the variable (sensor) 'i' in time 't'. "T" is the total time of observation and "n" refers to the number of sensors.

Definition 2 (*cluster center*). It is a set of observations representing groups of observations that are similar to each other, that are discovered through the subtractive clustering process:

$$CC_{i,t} = subtract(O_{S,G})$$

In definition 2, "$CC_{i,t}$" is the matrix of cluster centers that represent their own group of similar data points. In subtractive clustering process, the cluster centers are discovered based on two parameters: first one is the similar observations of a single sensor (a column in ($O_{S,G}$")) are clustered and per each cluster (containing similar data points) a cluster center is discovered in order to represent its concerning cluster members. This process is done through discovery of fuzzy time intervals in which a set of data points do not vary significantly and the result is discovery of the *fuzzy sensors' states*. The second parameter in cluster estimation is the inferred similarity between rows of the observation matrix. The result is formation of n-dimensional cluster centers, which represent the *fuzzy world states*. For detailed information about the cluster center estimation using subtractive clustering approach, which is not in the main subjects of this work please refer to (Chiu 1997).

Definition 3 (*fuzzy world state*). It is a set of observations concerning to all applied sensors, which represents one group of similar observations. It represents an approximate evaluation from a world state shown by ("$FS_{a,IR,k}$"). Fuzzy state is formed from groups of similar world states. The formalization of the fuzzy state is presented in the following:

$$FS_{a,IR,k} = \{(s_i, \tilde{v}_i, \tilde{t}) \mid i = 1,2,..,n,\ s_i \in S, \tilde{V}_i \in O_{S,G=a}$$
$$, \tilde{V}_i = CC_{i,t}.V_i\ , \tilde{t} = CC_{i,t}.t, 0 \le IR \le 1,\ 1 \le k \le T\}$$

In definition 3, "a" refers to the followed goal or activity; "IR" refers to the range of influence or the relative similarity degree, and "k" refers to the k'th (out of "T" possible fuzzy classes) data point that absorbs similar data points around at the influence range of IR; "k" also represents the number of fuzzy states that are transited, so that activity "a" is realized. A fuzzy state may include (subsume) one or more rows of the $O_{S,G}$ matrix. In Table 2 we have shown that if at cluster radius is selected as IR =0.7 then the world would be divided into seven fuzzy states. If at the running time a relatively high similarity between the current observations and the learned fuzzy cluster centers be observed, then it can be inferred that the observations may belong to realization of the surveyed activity.

Definition 4 (*Fuzzy context*). Fuzzy context is referred to as "$\tilde{C}$" and it is the set of variables that do not play any significant role in both realization and recognition of the activity "a":

$$\tilde{C}_{a,IR} = \{(s_i, \tilde{v}_i) \mid s_i \in S,\ \tilde{v}_i \in O_{S,G=a}, \forall t \in T \rightarrow v_{i,t} \approx \tilde{v}_i\}$$

In definition 4, the variable "s_i" during the time of the activity "a" realization does not vary significantly and it is fixed to value "$\tilde{v}_i$" and this value is calculated through the cluster center discovery process (definition 2).

Fuzzy context indicates the surrounding circumstances that scenarios or activities are realized in it. The fuzzy contexts of the activities indicate the conditions and presumptions that activities' models are valid in them and a change in the fuzzy context may cause invalidity of the system's perception from the activities; so, it will be taken into account as a new activity model. Therefore, any knowledge extracted from the observations is valid only if the similar context is met (Amirjavid, Bouzouana, and Bouchard 2012c)

Proposition 1 (*Fuzzy temporal concept*). Fuzzy temporal concept is a set of discovered fuzzy world states that are discovered in a range from high value of "IR" (which is indicated by "λ") to low value of "IR" (which is indicated by "Ɛ"). This set represents all possible hypotheses that may explain an activity. In a normalized dataset, the value "λ=1" returns a single data point as the result. Also, "Ɛ" represents the level of the desired details to be considered in modeling. In a normalized dataset "Ɛ=0.5" indicates the data points inside a cluster are at least fifty percent; regarding to the total data points, similar to the cluster centers.

$$FTC_{a,IR_{low=\varepsilon}^{high=\lambda}} = \int_{IR=\varepsilon}^{IR=\lambda} FS_{a,IR}.d_{IR}$$

Equation 2 – integration of all hypotheses in a matrix

In proposition 1, the FTC is a set that its constituting elements are possible cluster centers discoverable from a temporal dataset, so it contains all explanative hypotheses that can describe the temporal dataset. Technically, we are not able to load continuous values of IR into clustering algorithm; however, we can load discrete values of IR into the clustering algorithm. For example, at the implementation we can select "d_{IR}=0.1" as the step length for calculation of the hypotheses explaining the activities.

Proposition 2 (*Fuzzy Activity Function*). Fuzzy activity function symbolized by "y_a" represents that a typical realization of activity "a" would cause possibly which world states. In other words, it indicates the space that observations of "a" can be valid in them. The logic in reasoning is the estimated inferred similarity degree between observations "$v_{i,t}$" and the activity function "y_a". In order to calculate the "y_a" at first we estimate the line or curve that traverses the FTC members, then we calculate the function that proposes the similarity degree to this line.

Property 2.1 (*smoothing FTC members*). The line or curve that traverses the fuzzy states of the activity "a" can be resulted from a linear smoothing technique such as linear regression, polynomial estimation or Savitzky-Golay (Simonoff 1998) and it is symbolized by "z_a". Generally, these methods are different in the way they treat the existing noise of the data and in the linearity of the smoothing curve. Calculation of this line is not a main subject of the current paper and we suffice to a generic representation of smoothing technique:

$$z_a = smoothing(\{x \mid x \in FTC\})$$

In property 2.1, "z_a" represents the line or curve that traverses possible world states that may be created while "a" is realized.

Property 2.2 (*similarity to "z_a"*). The reasoning in membership of an observation to a member of FTC is done based on the distance factor. The closer an observation is to an "TFC_a" member, the more similarity to "z_a" is resulted, so more certainty in recognition of "a" is inferred. The distance of an observation to the "z_a" is estimated according to this formula:

$$\text{distance } (v_{i,t}, \mathrm{z_a}) =$$

$$\min((\sqrt{\sum_{i=1}^{n}(FTC_a - v_{i,t})^2})\Big|_{from\ row=first}^{to\ row=last})$$

$$= \min(\sqrt{\sum_{i=1}^{n}((\int_{IR=\varepsilon}^{IR=\lambda} FS_{a,IR}.d_{IR}) - v_{i,t})^2})\Big|_{from\ row=first}^{to\ row=last})$$

In property 2.2, the distance of all FTC rows (members) to the observation is calculated and out of these distances, the minimum distance represents the similarity that "a" is getting realized or in other words: $v_{i,t} \in a$.

Property 2.3 (*ranking of points similar to "z_a"*). Regardless from the distance of observation to the "z_a", there is another parameter that affects the possibility of membership to an activity, which is closeness to bigger cluster centers. If an observation is closed to a bigger cluster center, then it would take more possibility degree than a point which is closed to a smaller cluster center. The reason is that a bigger cluster center represents itself a set of more data points, so it justifies assignment of more possibility degree to the points that are closed to the bigger cluster centers. In order to take this parameter into account, in this work, we propose to establish a direct relationship between cluster radius and distance to the "z_a":

$$rank_a(v_{i,t}) = \max(\sqrt{\sum_{i=1}^{n}((\int_{IR=\varepsilon}^{IR=\lambda} \frac{FS_{a,IR}.d_{IR}}{IR}) - v_{i,t})^2})\Big|_{from\ row=first}^{to\ row=last})$$

In property 2.3, $rank_a(v_{i,t})$ represents how much the "$v_{i,t}$" provides certainty in recognition of activity "a" as a candidate out of all activities in "A".

In order to calculate the "y_a", which represents the fuzzy activity function or the space of activity "a" validity, a function indicating the relation between the $rank_a(v_{i,t})$ and distance ($v_{i,t}$, z_a) is established:

$$y_a = smooth(rank(v_{i,t}), \text{distance } (v_{i,t}, \mathrm{z_a}))$$

In here, "y_a" represents the activity function. Smoothing function may include linear or polynomial regression methods or other famous smoothing methods such as Kalman filter.

Recognition of concept border

In a huge temporal dataset, which includes data of ADLs, gathered by continuous observation of the activities for a relatively long time, the borders of activities should be known or labeled in order to model automatically the activities. In fact, in the presented formalizations and definitions we have been presuming that the expert is performing the modeling process on observations of a known activity. As it was mentioned earlier, in clustering process, we can find a definitive cluster radius or influence range, which represents each activity as a set of singular world states at a definitive influence range. *Therefore, each activity is a special temporal quality out of all observed world temporal qualities*. Considering a range from zero to one: [0-1] for the influence range, then at a special cluster radius for example, "IR = q, 0 ≤ q ≤ 1", we can find the cluster centers that each of them represent a special world quality as an activity. Therefore, data-driven interpretation of activity "a" is every cluster center discovered at "IR=q".

Validation and experimental results

In order to validate the proposed ideas we realized three activities of "coffee making", "studying" and "hand washing" in LIARA smart home. The matrix operations are validated applying MATLAB facilities (www.mathworks .com). Each activity was performed four times and their realizations were observed through more than 500 sensors, which most of them are the RFID tags that estimate the objects' locations. Applying the fuzzy context filter (refer to definition 5), we calculated the sensors presented in Table 3 are the ones that play role in realization and recognition and the rest of sensors should be taken into account as fuzzy context members:

S_i	Variable title	description
s_1	Time	Daily time
s_2	Tag44_RFID5	Object localization
s_3	Tag45_RFID5	Object localization
s_4	Tag53_RFID5	Object localization
s_5	Tag54_RFID5	Object localization
s_6	Tag33_RFID6	Object localization
s_7	Tag34_RFID6	Object localization
s_8	Tag42_RFID6	Object localization
s_9	Tag43_RFID6	Object localization
s_{10}	CE2	Doors open/close
s_{11}	DB1	Water temperature
s_{12}	DB2	Water temperature
s_{13}	MV1	Motion sensor
s_{14}	MV4	Motion sensor
s_{15}	MV5	Motion sensor

Table 3 – Role playing variables in case study

The observations of the activities are attached together and synthetic delays are put between activities. The rate of "q" and delay between activities is illustrated in Figure 3.

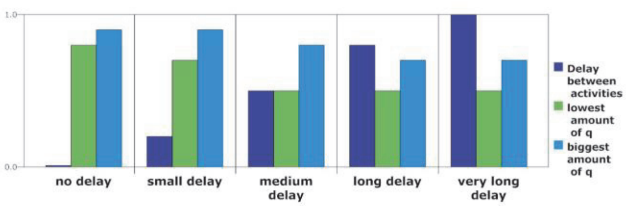

Figure 3. Estimation of "q"

In Figure 3, the rate of influence ranges in which the activities can be seemed as unique world states are shown. According to our experimentation in "q=0.7" all the activities can be seen as unique world states.

In the consequence, the three activities are modeled and as a sample, in equation 3, we have presented the normalized equation of the coffee making activity:

$$Y_{\text{coffee making}} = (7.944\cdot10^{-2} \times \tilde{s}_1) - (5.307\cdot10^{-2} \times \tilde{s}_{12}) + (2.187\cdot10^{-1}\times \tilde{s}_2)$$
$$- (1.196\cdot10^{-2}\times \tilde{s}_{10}) + (0.154\cdot10^{-1}\times \tilde{s}_9) + (- 4.501\cdot10^{-2}\times \tilde{s}_{12}) + (3.206\cdot10^{-2}\times \tilde{s}_{13})$$
$$- (1.459\cdot10^{-2}\times \tilde{s}_{14}) - (1.213\cdot10^{-2}\times \tilde{s}_{15}) + (1.405\cdot10^{-1}\times \tilde{s}_8) - 1.729\cdot10^{-2}$$

Equation 3 – integration of all hypotheses in a matrix

In here, it is proposed to consider nine variables (or sensors) in order to recognize the "coffee making" activity. The results of recognition of the activities using linear regression are demonstrated in Figure 4:

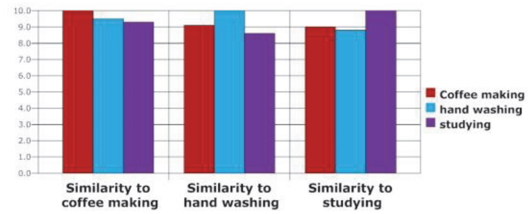

Figure 4. Recognition of activities with the activities functions applying linear regression estimation

In Figure 4, we have illustrated the models accept their own observations (in average) with which similarity degree. Although, applying linear regression technique the concepts are correctly recognized, but we can see the concepts are recognized *highly similar* to each other. In Figure 5, we have illustrated how the dissimalirties between concepts are recognized if different curve estimation techniques are applied:

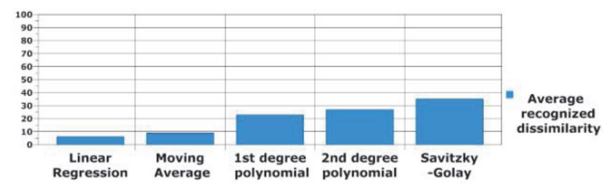

Figure 5. Average recognized dissimilarities between concepts

In Figure 5, we have illustrated the rate of inferred dissimilarity between concepts when the activities functions are estimated by Linear regression, Moving average, 1st degree polynomial, 2nd degree polynomial and Savitzky-Golay (Draper and Smith 1998).

Conclusion

In this paper, we proposed to consider the activities as sorts of multivariable problems that can data-drivenly be modeled. Applying fuzzy logic the data clusters representing the hypotheses who describe the activity's observations are formed and then they traversed through a smoothing curve or line in order to calculate the activity function. One application of the proposed approach is to calculate how much an activity is similar to a correct realization. The experimental results confirmed the basic idea by which we proposed to consider a typical activity as a set of events that occur in a special temporal context.

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