

Linguistic Summarization Of Long-Term Trends For Understanding Change In Human Behavior

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Abstract—In this paper, we propose a linguistic summarization procedure for describing long-term trends of change in human behavior. Our objective consists of defining methods that provide information to elders, caregivers, social workers or even family in an understandable language. We adapt a measure that we defined in previous work on soft cluster partition similarity for comparing behaviors that are adapted over time. From that measure, we are able to produce a time series that numerically describes change in behavior over time. In this article, the resulting time series is partitioned and linguistically summarized depending on a user's (caregiver, social worker, etc.) desired time resolution. Simulated resident behavior is used in order to explore a range of different scenarios and the response of the proposed linguistic summarization process is investigated.

Keywords- *comparing soft partitions, human behavior, anomaly detection, fuzzy linguistic summarization*

I. INTRODUCTION

In recent years, successful aging has become one of the most important problems in our society. Life expectancy has improved, and along with it the resources required to maintain quality and style of life. Emerging applications combining *technology* and *medicine* provide one possible solution. Multiple large scale projects combine these subjects. One such project is the center for Eldercare and Rehabilitation Technology (CERT) [1] and the TigerPlace facility [2]. This effort is a large interdisciplinary collaboration between electrical and computer engineers, gerontological nurses, social workers, physical therapists and others at the University of Missouri. This group has installed multiple sensing technologies in the homes of elders. One goal of these technologies includes assisting residents with "aging in place" as independently as possible. Other projects include the MavHome project [3], iDorm [4], CASAS [5] and the Georgia Tech Aware Home [6]. In addition, in [7] eight other relevant projects in this field are summarized.

Important advantages of behavior analysis in the eldercare domain include: reducing dependency, enhancing personal comfort and safety and delaying the process of moving to a nursing home. Many projects are centered around Activities of Daily Living (ADL) [8]. From the set that focus on the ADL, we emphasize [9], an approach based on multiple behavioral

hidden Markov models (MBHMM). The authors propose the creation of multiple HMMs for each variation of an action. The most important advantage of this proposal is that the system is able to determine which tasks are currently active, even if the user has not yet completed the activity.

A related fuzzy approach is [10]. In that work, the authors propose an Aml fuzzy computing system, which is a multilayer architecture to learn and model human behavior. They attempt to join the advantages of a multi-agent based framework with fuzzy control techniques to improve the recognition process and continuously enrich the knowledge about the user and environment.

The majority of existing efforts are focused on the detection of normal and abnormal behaviors at the moment the resident is performing them. In previous work [11], we introduced a method to identify changes in patterns of behavior over longer periods of time (days, weeks or months). Identification of changes in behavior over such time frames is significant in the regard that it can be used to help predict cognitive and/or functional decline that affects overall quality of life [12, 13, 14]. If significant change in human behavior can be recognized early, then caregivers can take action to help avoid or postpone catastrophic events. However, the information obtained is a numerical data set. In this article our objective consists of developing a method to produce linguistic information that is of greater use to users. Our approach is based on the concept of linguistic summarization. A linguistic data summary is a concise, human-consistent description of a (numerical) data set [15, 16, 17]. This process allows us to summarize a data time series by segmenting and describing long-terms trends of change in behavior.

In the existing literature, there are different approaches to deal with time series summarization. The application range is very assorted, but the business field stands out over the rest. In [18, 20] Kacprzyk and Wilbik deals with time series used for an analysis of the past performance of investment (mutual) funds and extracts summaries to help to make future investment decisions. Focusing on human activities, in [19] the authors propose a novel method for recognizing human

activity from linguistic summarizations of temporal fuzzy inference curves representing the states of a three-dimensional object called voxel person. However, the approach taken in this article is most similar to that of Kacprzyk et al. [20]. Primarily, they focus on stock market analysis and finance applications. They propose a way to summarize trends identified with straight line segments of a piecewise defined linear approximation of time series of change in long-term human behavior. They employ a set of features (attributes) to characterize the trends such as the slope of the line segment. They then use a linguistic quantifier driven aggregation of trends to perform the linguistic summary. In addition, they also study the description of duration and variability.

Herein, we introduce a method to obtain a natural language description about change in long-term adapted behavior. The user selects a time period amount (resolution) to summarize, e.g., day, week, month, etc. A resident history is partitioned according to this time window and we extract features to characterize the change. In particular, we look for decreasing, constant, or increasing change (similarity) in behavior. This makes it possible to monitor cases such as a degenerative disease or a rehabilitation process without the need to continuously bother an elder.

This paper is organized as follows. Section 2 is previous work, which is required in order to understand this article. Next, in section 3 we introduce the linguistic summarization process, specifying the parameters used and the structure of the sentences. Section 4 is experiments. We present simulated user behavior in order to demonstrate a wide range of different possible scenarios and the response of our proposed approach.

II. RELATED WORK

A. Modeling Human Behavior

Modeling human behavior in eldercare is a field that studies computational techniques to represent and analyze human daily activities in order to provide people with services if required, but without loss of independence. In this article, our objective is to extract a linguistic description of trends in long-term change of human behavior. This approach depends on the choice of representation. Here, we focus on a computational framework investigated by our research team in unpublished [21, 22]. The choice of representation is a sequence of cascaded AND gates with an underlying probability distribution that characterizes temporal dependency requirements over a set of actions for the different ways in which a user can perform a behavior. The work in [21, 22] is summarized in this subsection.

An abnormal situation occurs when a person does not perform the behavior as expected, i.e., forgetting things, performing actions in a dangerous order, etc. Example 1 demonstrates the role of detecting abnormal situations in the context of the goals of this work.

Example 1: Suppose that every morning a resident wakes up, goes to the bathroom, takes his pajamas off, takes a

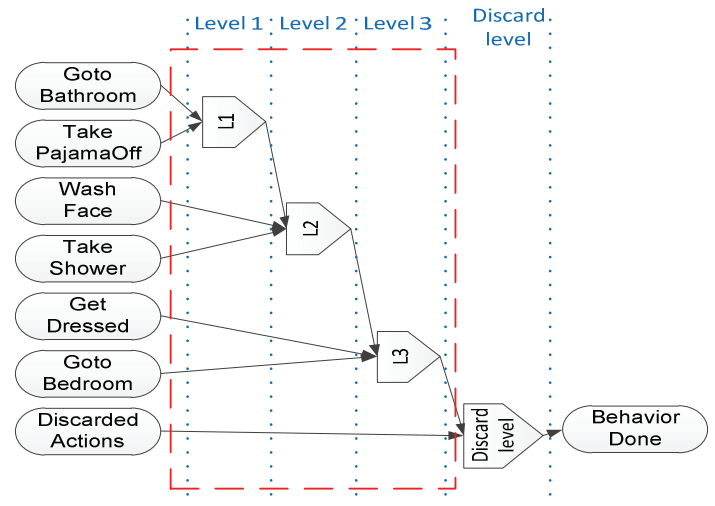


Fig. 1. Morning routine behavior model (example 1).

shower, washes his face, gets dressed and returns to the bedroom. All of these actions could be embraced as a single behavior concept, “morning routine”. However, suppose that for a period of time the person does not take a shower. This is considered as a change in the “morning routine” behavior. This abnormal situation needs to be identified and the behavior model needs to be updated accordingly.

In example 1, two important concepts are introduced, *action* and *behavior*. Informally, an action is the output of a sensor or a low-level algorithm interpreting sensor firings, e.g., the refrigerator door is closed, the front door is opened, a person is sitting on the couch, etc. Behavior is the set of actions and the order in which the actions need be performed. Formally, these concepts are characterized as follows.

Definition 1 (Human Action) [21, 22]: A human action h_i is a triple $h_i = \langle l_i, s_i, t_i \rangle$, where l_i is a label used to identify the action, s_i is a sensor event and t_i is a time stamp in which the action occurs.

Definition 2 (Behavior) [21, 22]: A human behavior B_i is a quadruple $B_i = \langle H, R_i, C_i, \prec \rangle$, where $H = \{h_1, h_2, \dots, h_n\}$ is a set of available human tasks, $R_i = \{r_1^i, r_2^i, \dots, r_{|R_i|}^i\} \subseteq H$ is the subset of available human tasks that are required to complete the behavior, and C_i is a set of temporal constraints between the tasks in R_i defined over a partial order relationship operator $\prec$. The partial order relationship $\prec$ defines the temporal dependency requirements over the actions of a behavior, and its formal definition is

$$r_a^i < r_b^i \leftrightarrow t_a < t_b. \quad (1)$$

Thus, a behavior is represented as a set of relevant actions, which maintain a specific order of performance between them. In [21, 22], we demonstrated that a behavior can be represented as a set of cascaded AND gates. An action in the system corresponds to an input of a specific AND gate. Each input is true if the action has been performed, or false if not. On the other hand, although all the tasks in the H set may be taken into consideration for a specific behavior, only those

actions that are included in the R set are really required for it. To handle this situation, we introduced a discard-level in which those actions that are irrelevant are assigned.

Besides relevant actions, this representation contains more knowledge about a specific behavior, such as the order relationship between diverse actions. As previously pointed out, a behavior is designed as a set of actions that maintains an order relationship between them. The level-representation for a behavior simulates the order relationship between the actions in such a way that those actions that are the input to an AND gate in Level_n have to be done previously to those that are the inputs to the following AND gate, in Level_{n+1} . Fig. 1 shows the sequence of AND gates obtained from example 1.

Nevertheless, a behavior does not have a single way to be performed. Hence, there may be several combinations of the same set of actions for a behavior, i.e., that some tasks may be performed in different levels of the structure without loss of meaning. For instance, in example 1, the action “wash face” could be performed either in level 2 or in the level 3 and be a legitimate Morning Routine. To deal with this disparity, in [21, 22] a probability matrix, $P(i, j)$, was computed, whose rows, $1 \leq i \leq |H|$, are actions, H set, and columns, $1 \leq j \leq |L|$, are available levels in the sequence of ANDs. Each element represents the probability of an action being performed in a particular level. Therefore, the behavior model represents, for each action, the most expected level for it being carried out. Next, keeping on with the prior example, an achievable matrix is presented below.

Continuation of example 1: Let us suppose that we want to study a “morning routine” behavior. In addition, let us suppose that we have the actions presented in example 1, plus the action “go to kitchen”. Then, if the maximum number of levels was fixed to four, a possible P matrix to represent the model presented in fig. 1 could be

	L_1	L_2	L_3	L_4	$L_5(\text{discard level})$
go to bathroom	0.7	0.2	0	0	0
take pajama off	0.6	0.4	0	0	0
take shower	0.2	0.7	0.1	0	0
wash face	0	0.5	0.3	0	0.2
get dressed	0	0.2	0.6	0.2	0
go to bedroom	0	0.1	0.5	0.3	0.1
go to kitchen	0	0	0	0	1

Among the advantages of our approach, the independence between the behavior representation and the method used to learn, recognize or adapt is the most important. This separation allows us to achieve better system modularization and to use a higher number of learning methods for the same activity model [21]. In [21, 22] we constructed a learning and recognition/adaptation process that will be used in this article to obtain the input to the process presented here. However, as this is not the focus of our article, we refer the reader to our previous work [11, 21, 22].

B. Comparing Soft Partitions

The next tool used in this investigation comes from the field

of clustering. This method is used herein to compute the similarity between two behaviors according to how closely actions group into levels. Let $O = \{o_1, \dots, o_n\}$ denote n objects. When each object in O is represented by a (column) vector x , the set $X = \{x_1, \dots, x_n\} \subset \mathbb{R}^p$ is an *object data representation* of O . When each object in $o_i \in O$ has a *physical label*, O is a set of *labeled data*; otherwise, O is unlabeled. Let integer c denote the number of groups, $1 < c < n$. Clustering in unlabeled data is the assignment of one of four types of labels to each object in O . After clustering, the label vectors of the objects are the columns of c -partitions of O , which are sets of (cn) values $\{u_{ik}\}$ that can be conveniently arrayed as $(c \times n)$ matrices, $U = [u_{ik}]$. These labels can be crisp, probabilistic, fuzzy, or possibilistic.

When clustering produces more than one candidate for partitioning a finite set of objects O , there are two approaches to validation, i.e., selection of a “best” partition, and implicitly, a best value for c , the number of clusters in O . First, one could use an internal index, which evaluates each partition separately. Second, one could compare pairs of candidate partitions to each other, or to a reference partition that purports to represent the “true” cluster structure in the objects. In [23], we generalized many of the classical indices that have been used with outputs of crisp clustering algorithms so that they are applicable for candidate partitions of any type, i.e. crisp or soft, soft comprising the fuzzy, probabilistic and possibilistic cases. In particular, we concentrated on the Rand index and its modifications. We showed that our extension of the Rand index is $\mathcal{O}(n)$.

Let U and V be crisp partitions of O . Here, U and V need not possess the same number of clusters, i.e., r need not equal to c ($r \neq c$). The four classical combinations for pairs of objects from $O \times O$ in clusters of U and V are: (a) paired in U and V ; (b) not paired in U nor in V ; (c) paired in V but not in U ; and (d) paired in U but not in V [24]. The comparison of U to V with a similarity measure s begins with the $r \times c$ contingency matrix $N = UV^T$ that contains counts of the number of occurrences of each of the four types over the $n(n-1)/2$ distinct, unordered pairs in $O \times O$. Entry n_{ij} is the number of objects common to subgroups U_i and V_j . The building blocks of many similarity measures for $s(U, V)$ are the four expressions (a)-(d) below. These four calculations count the number of occurrences amongst the $n(n-1)/2$ pairs of each of the four types of unordered pairs:

$$a = \frac{1}{2} \sum_{i=1}^r \sum_{j=1}^c n_{ij}(n_{ij}-1); \quad (2)$$

$$d = \frac{1}{2} n^2 + \sum_{i=1}^r \sum_{j=1}^c n_{ij}^2 - \left(\sum_{i=1}^r n_{i\bullet}^2 + \sum_{j=1}^c n_{\bullet j}^2 \right); \quad (3)$$

$$b = \frac{1}{2} \sum_{j=1}^c n_{\bullet j}^2 - \sum_{i=1}^r \sum_{j=1}^c n_{ij}^2; \quad (4)$$

$$c = \frac{1}{2} \sum_{i=1}^r n_{i\bullet}^2 - \sum_{i=1}^r \sum_{j=1}^c n_{ij}^2. \quad (5)$$

where $n_{i\bullet}$ and $n_{\bullet j}$ referring respectively to the number of objects in classes U_i and V_j , using standard “dot” notation for row and column sums.

The sums $(a + d)$ and $(b + c)$ are usually interpreted, respectively, as (the total number of) *agreements* and *disagreements* between U and V . Anderson et al. [23] tabulate a (non-exhaustive) list of 14 coefficients that have been proposed for $s(U, V)$ based on functions of a, b, c and d ; Sokal and Sneath list many others [25]. In addition, Anderson et al. also present a scaling value in the case of possibilistic labels. Here, we focus on the Rand, the classical form of which is

$$s_R(U, V) = (a + d) / (a + b + c + d). \quad (6)$$

The measure $s(U, V)$ can be used to address a variety of clustering problems [23]. For example, it can be used to compare a *clustering* to a reference partition that purports to represent the “true cluster structure”, measure the effect of noise or missing data with respect to a specific clustering algorithm, study the convergence of a clustering algorithm at successive iterations, perform prediction (regression), as well as compare two different clustering algorithms.

C. Similarity measure for comparing human behavior

In [11], a similarity measure is introduced for comparing pairs of learned behavior and subsequently anomaly detection. Our new measure for analyzing long term human activity tends includes three different components: (1) comparing partitions, (2) subethood of non-discarded actions, and the (3) similarity of partial order relations.

- *Comparing soft partitions*

We determine the similarity between pairs of behaviors according to the strength of actions grouping into similar levels. Specifically, $s(U, V)$ is used, where U and V are behavior probability matrices acquired using the procedures described in subsection IIA, i.e. $U(i, j)$ is the probability that action i belongs to level j . In [11], we presented a scaling of $s(U, V)$ to produce a $[0, 1]$ value that is more appealing to human interpretation. The formula used to compare two different behaviors is

$$s_{cp}(U, V) = s(U, V) / \text{maximum}(s(U, U), s(V, V)) \quad (7)$$

- *Subethood of Non-Discarded Actions*

This term is included to reduce the influence of the discarded level on $s_{cp}(U, V)$. This is because U and V generally share many actions in that level, independently of the represented behavior. First, the most likely level, $L_{i, \max} = \text{argmax}_j P(i, j)$, for each action is found. Next, the crisp sets, $R_U \subseteq H_U$ and $R_V \subseteq H_V$, of actions in which $L_{i, \max}$ does not equal the discard level is found. The matrix P contains evidence about the importance of actions to a behavior and the criteria of picking all actions

that are not most likely in the discard level is feature selection. The subethood measure of non-discarded actions over R_U and R_V is

$$s_{sub}(U, V) = |R_U \cap R_V| / |R_U \cup R_V| \quad (8)$$

where $\cap$ is intersection, $\cup$ is union and $|\cdot|$ is cardinality. The resulting similarity is

$$s_{cp_sub}(U, V) = s_{cp}(U, V) \times s_{sub}(U, V). \quad (9)$$

- *Similarity of Partial Order Relations*

The definition of $s_{cp_sub}(U, V)$ does not take into account the similarity between the partial order relations. That is, two behaviors may share a set of non-discarded actions and have a strong similarity of actions grouping into levels (clusters), but the order of levels is not consistent. Hence, to truly compare two behaviors, the partial order relations need to be factored into the measure. We resolve this by counting the number of disagreements between U and V and weight the disagreements by their individual importance.

First, a $|H| \times |H|$ matrix, E_U , is created for behavior matrix U . For each action, the level with the greatest probability (most likely explanation) is found, i.e. $L_{i, \max}$. Next, $E_U(i, j)$ is assigned a label from the set $\{B, A, S\}$, where ‘B’ (before) means $L_{i, \max} < L_{j, \max}$, ‘A’ (after) means $L_{i, \max} > L_{j, \max}$, and ‘S’ (same) means $L_{i, \max} = L_{j, \max}$. Cell $E_U(i, i) = ‘S’$ and if $E_U(i, j)$ is ‘B’ (‘A’) then $E_U(j, i)$ is ‘A’ (‘B’). Remember, $L_{i, \max}$ is the most likely level that action i belongs to. For that reason, we cannot just count the number of disagreements in E_U . Instead, we calculate an importance value per action. For action i , $P_{U,i}$ measures the ability to decide that action i belongs to some particular level,

$$P_{U,i} = \max_j (P_U(i, j)) - \max_{j \neq k} (P_U(i, k)) \quad (10)$$

The significance weighted calculation of the similarity of partial order relations, $s_{por}(U, V)$, is based on the set of off-diagonal upper triangular indices of E_U , i.e. all (i, j) where $j > i$. In particular, the measure uses only the subset of indices, I' , in which actions i and j are not most likely discarded. Based on $P_{U,i}$ and $E_U(i, j)$, the similarity of partial order relations is now defined as

$$s_{por}(U, V) = 1 - (\sum_{(i, j) \in I'} \phi(E_U(i, j), E_V(i, j))) / |I'|, \quad (11)$$

where

$$\phi(E_U(i, j), E_V(i, j)) = \begin{cases} 0 & \text{if } E_U(i, j) = E_V(i, j) \\ \min(P_{U,i}, P_{V,i}) & \text{else} \end{cases}, \quad (12)$$

and the final measure for comparing human behaviors is

$$s_{final}(U, V) = s_{cp}(U, V) \times s_{sub}(U, V) \times s_{por}(U, V) \quad (13)$$

With this measure, we are able to detect longer time period changes in the *same* behavior (days, weeks, months, etc). The anomaly detection approach in this article is independent of the success of any short time period recognition algorithm. That is, if a serious short-term event is undetected, we still expect significant change in longer time period behavior. In [11], we also presented a time series normalization of $s(U, V)$,

$$norm_1(U, V) = \text{maximum}(s(U, U), s(V, V)), \quad (14)$$

$$norm_2(U, \{V_1, \dots, V_n\}) = \text{maximum}(\{norm_1(U, V_1), \dots, norm_1(U, V_n)\}), \quad (15)$$

$$s_{cp2}(U, V_i) = s(U, V_i) / norm_2(U, \{V_1, \dots, V_n\}), \quad (16)$$

where U is the reference behavior and V_i ($1 \leq i \leq N$) is an adapted behavior. We update the behavior model each day. The final measure presented in [11] is

$$s_{final2}(U, V_i) = s_{cp2}(U, V_i) \times s_{sub}(U, V_i) \times s_{por}(U, V_i) \quad (17)$$

Fig. 2 is an example time series from [11] for the behavior ‘Wake up’. The annotations describe what the person was doing during the one year time period. We see that the proposed similarity measure captures these important changes.

III. LINGUISTIC SUMMARIZATION

Using the measure discussed in section 2c, we are able to study longer time period changes in behavior. However, this representation is not the most understandable by nurses, social workers, families or residents. Our objective is to produce linguistic summarizations of the time series. Example summarizations include “the quality of the ‘wake up’ behavior

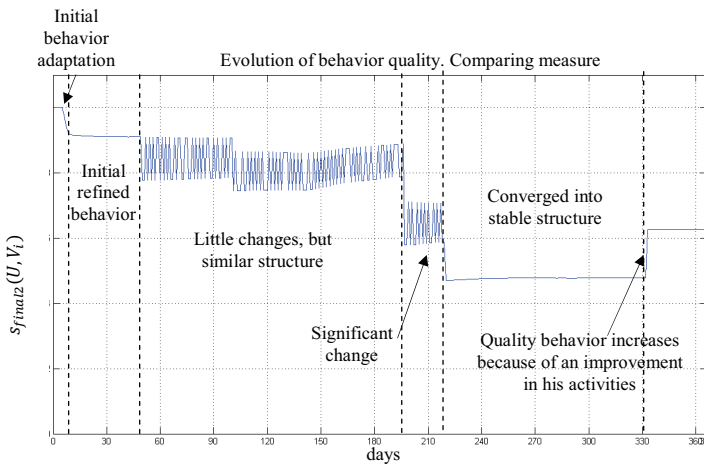


Fig 2. Output of our comparing behavior approach [10] for 360 days of adapted behavior for the activity “Wake up” (which is reported in table 1). Annotations show what happened in this year. Each day is compared to an initial base refined behavior (the base-line behavior).

is decreasing in the last month”, “the quality of the ‘have breakfast’ behavior is slowly increasing in the last week”, or “the quality of ‘morning routine’ is constant but highly unstable in the last month”. These examples illustrate cases in which less information is more useful. That is, summarization identifies the important trends and it is understandable by a domain expert. In the following sections, we present a method to measure the type and amount of change as well as the stability in comparing behavior time series. We then present a fuzzy set theoretic approach for linguistically interpreting the numeric values for the eldercare problem domain.

A. Temporal resolution of summarization

As already discussed, in Kacprzyk et al. [20] a time series is algorithmically segmented. The proposed technique can address identifying trends that take varying amounts of time to occur, but only one set of summarizations are produced. That is, different summarizations could be produced if the problem is viewed in different ways, like being sampled differently. For example, a summary of increasing might be produced if we analyzed day by day, while a summarization of constant might be produced if the time scale is month. Our objective is not to study automatically segmented global trends, rather trends for a user specified time scale. We are interested in detecting gradual changes in the elder’s behavior as soon as possible. Kacprzyk et al. differentiate between global trends, which concern the entire time series (or some, probably large, part of it), and partial trends concerning a smaller time span (e.g. a window). Our focus is on the second (partial trends). We provide the person with the option of selecting the time period that he/she would like summarized. That defined time window has a considerable influence on the linguistic summarizations produced. Thus, the user will select it based on a specific hypothesis to be tested. For example, has there been change this week, this month, etc.

B. Partial trend summarization using linear regression

The global trend segmentation and resulting variability calculations of Kacprzyk et al. did not work particularly well for our problem domain. Their focus is stock market analysis and financial domains. The particular trends that we are looking to identify are not reliably segmented using their technique. Instead, we rely on the well-known method of linear regression in order to numerically summarize a partial trend time window. Linear regression is used here to fit a predicted model (linear equation) to observed data, a window of our time series. We calculate the slope of the estimated linear equation, which resides in $[-90^\circ, 90^\circ]$. Additionally, we compute the mean squared error (mse), which varies in $[0, 1]$. This simple but effective method provides us with the two desirable quantities, the angle of the line segment that characterizes the rate of change of the time series and the variability of the samples to the estimated linear equation.

Herein, linguistic summarization of change in human

behavior over long time periods according to a reference baseline model for a given user time resolution consists of the generation of understandable sentences of the form:

Behavior [X] is [angle] with [mse] in a time period equal to [time window].

C. Fuzzy sets

In this article, we leverage the concept of *dynamics of change* (or speed of change) identified by Kacprzyk et al [20]. The authors propose linguistic terms corresponding to various inclinations of a trend line: *quickly decreasing*, *decreasing*, *slowly decreasing*, *constant*, *slowly increasing*, *increasing* and *quickly increasing*. Each term represents a fuzzy granule of direction. Following the authors' indication, we define the following trapezoidal fuzzy sets on the angle domain in degrees, and illustrated in fig. 3:

- *Quickly decreasing* [-90 -90 -80 -60]
- *Decreasing* [-75 -60 -40 -25]
- *Slowly decreasing* [-40 -30 -20 -10]
- *Constant* [-20 -10 10 20]
- *Slowly increasing* [10 20 30 40]
- *Increasing* [25 40 60 75]
- *Quickly increasing* [60 80 90 90].

Next, we define a linguistic variable for the concept stability of a time series in a user defined time window. While this is similar to Kacprzyk's notion of variability, they are calculated differently. Our terms for stability are defined using linear regression, specifically mse. The fuzzy sets represent the possible levels of instability existing in a time window. We define five terms: *no instability*, *low instability*, *medium instability*, *high instability* and *extreme instability*. The trapezoidal membership functions for these fuzzy sets are (see fig. 4 for a graphical representation):

- *no instability* [0 0 0.0001 0.0012]
- *low instability* [0.0001 0.0005 0.001 0.0014]
- *medium instability* [0.0001 2 0.002 0.004 0.0048]
- *high instability* [0.004 0.009 0.04 0.07]
- *extreme instability* [0.05 0.071 1 1].

These fuzzy sets have been defined as a generalization of a wide range of cases studied, using the trial and error technique.

IV. EXPERIMENTS

Our experiments study different common elderly behaviors, such as Wake Up, Morning Routine or Have Breakfast. Here, we show results for *Wake Up* and *Morning Routine*, but more results can be found in [11].

As previously indicated, the behavior model is an abstract architecture completely independent of method used to learn, recognize or adapt it. Therefore, our outcomes will be also independent of the type of sensors used to detect the user activities required to those processes. In order to test a wide range of human behavior scenarios, we have developed an

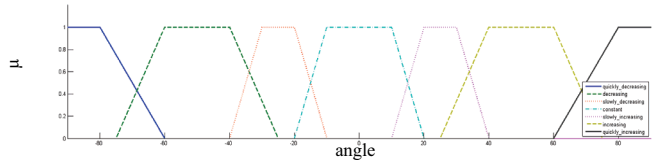


Fig. 3: Fuzzy sets for the angle of the estimated linear equation.

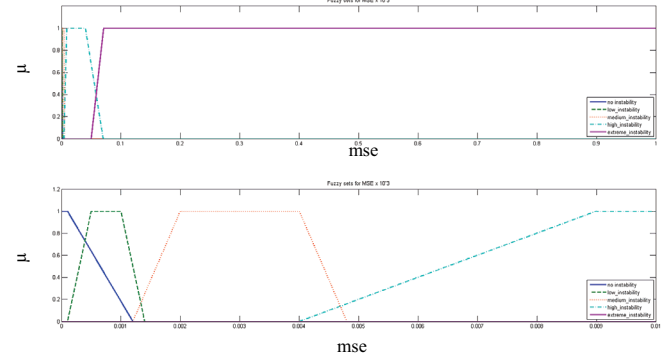


Fig. 4: Fuzzy sets for the mse in the user specified time window.

algorithm that takes action and temporal constraints and generates *synthetic data sets* [21, 22]. The input to this algorithm consists of a set of constraints (table 1), where the partial order relations between the actions are defined. These data sets are used in both learning and recognition [21]. We generated the following data sets to explore how the proposed measure responds to different scenarios.

- DS₁: The resident always performs the behavior correctly, i.e. normal behaviors. Herein, DS₁ is used to learn the initial baseline model. It has 365 days worth of behavior.
- DS₂: The resident has a degenerative disease, and his behavior deteriorates continuously and slowly.
- DS₃: The resident has a *catastrophic event*, e.g. a fall. This event is severe and it results in restricted mobility. After the event, a user's routine has changed significantly as a result. However, after a period of time the user is able to start *rehabilitation*, and his behavior improves. There

TABLE 1: BEHAVIOR AND TEMPORAL CONSTRAINTS

Behavior	Order relationship constraints	Temporal constraints
B_1 (Wake up)	AsleepInBed < AwakeInBed AwakeInBed < GetOutOfBed GetOutOfBed < GetSlippers GetSlippers < GotoBathroom	6:50 to 7:10
B_2 (Morning Routine)	GotoBathroom < { UseToilet, TurnShowerOn } { UseToilet, TakePijamaOff, TurnShowerOn } < TakeShower TakeShower < { TurnShowerOff, UseTowel, BrushTeeth, WashFace, CombHair } UseTowel < GetDressed { TurnShowerOff, UseToilet, BrushTeeth, CombHair, WashFace } < GotoBedroom	7:00 to 7:40

TABLE 2: BEHAVIOR CONSTRAINTS AFTER CATASTROPHIC EVENT

Behavior	Order relationship constraints
B_1^* (Wake up)	AsleepInBed < AwakeInBed AwakeInBed < GetOutOfBed GetOutOfBed < GotoBathroom
B_2^* (Morning Routine)	GotoBathroom < { GetDressed, UseToilet, BrushTeeth, CombHair, WashFace } { UseToilet, BrushTeeth, CombHair, WashFace } < GotoBedroom

are 110 days before the event, 1 day in which the event occurred (day 111), 139 days of convalescence and others 115 days of different behavior afterwards when the user is undergoing rehabilitation. During the rehabilitation, his behavior is improving slowly.

The changes in behavior due to the catastrophic event are shown in table 2.

A. Experiment 1. Degenerative disease

In the first experiment, we show how our system is able to detect a degenerative disease. First, we learn a correct behavior using DS_1 . After that, we use DS_2 as input to the recognition and adaptation process. Once the process has finished, the evolution graph is generated using the method in [11]. This time series is used as input to our linguistic summarization method. First of all, we define the *time window resolution*. Although the system is able to deal with different resolutions, here we study the results monthly in order to simplify the problem.

The results for *Wake up* behavior are shown in fig. 5. The graph represents the measured change in behavior. The continuous curve is the similarity measure, while the discontinuous lines are the linear regression results at each non-overlapping window. The related linguistic summarization is presented in table 3.

Fig. 5 shows a behavior whose quality is decreasing very slowly. This corresponds to a resident with a degenerative disease reducing the resident mobility and, therefore, changing his normal activity. However, there are time periods when his/her behavior is considered constant although not stable. Our summary is able to detect those moments of instability, describing it as medium in *February* or low in *November*, when the behavior has a little decrease and later an increase.

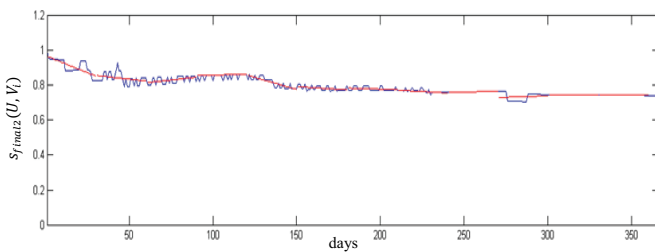


Fig. 5: Similarity of adapted behavior to a learned reference behavior for “Wake up” behavior. In this situation, we simulate a user with a degenerative disease. The rate of change for this behavior is slow.

TABLE 3: LINGUISTIC SUMMARIZATION OF TIME SERIES IN FIGURE 5

Days	Linguistic Summarization
1-30	B_1 is slowly decreasing in a time period equal to 30 days
31-60	B_1 is constant with medium instability in a time period equal to 30 days
61-90	B_1 is constant with low instability in a time period equal to 30 days
91-120	B_1 is constant with no instability in a time period equal to 30 days
121-150	B_1 is slowly decreasing in a time period equal to 30 days
151-180	B_1 is constant, with no instability in a time period equal to 30 days
181-210	B_1 is constant, with no instability in a time period equal to 30 days
211-240	B_1 is constant, with no instability in a time period equal to 30 days
241-270	B_1 is constant, with no instability in a time period equal to 30 days
271-300	B_1 is constant, with low instability in a time period equal to 30 days
301-330	B_1 is constant, with no instability in a time period equal to 30 days
331-365	B_1 is constant, with no instability in a time period equal to 30 days

B. Experiment 2. Catastrophic event and rehabilitation

For the second experiment, once again DS_1 is used to learn a reference behavior. However, DS_3 is used during the recognition and adaptation process. The database represents user activities for a year. The user suffers a *catastrophic event*, as a fall. This event provokes the elder to change his/her activity significantly, and then undergo *rehabilitation*. The linguistic summarization for *Morning Routine* behavior obtained from these results is presented in table 4 regarding fig. 6.

We would like to emphasize how the linguistic summarization is able to delineate the important changes occurring during the year. During the first three months, the behavior is *constant* because the elder maintains his/her normal activities. When the catastrophic event happens, at the middle of the fourth month, the behavior model adapts to the new normal. The model requires some time period to adapt completely. However, it does reflect those little changes, as does the linguistic summary. The fourth month is characterized as *medium instability*, since the behavior is summarized as *constant*. During the fifth and sixth months, the behavior changes significantly (declines), resulting in *behavior decreasing* and *behavior slowly decreasing* respectively. These months are included in the convalescence period: the user stabilizes her behavior and she recovers from the catastrophic event. The ninth month is when the elder starts rehabilitation. As expected, rehabilitation is not an instant process, it requires effort and time. During the ninth and tenth months, she is changing her behavior slowly without great advance (*behavior constant* and *low instability*). Nevertheless, after two months undergoing rehabilitation, the elder improves her behavior more rapid than before (*behavior increasing*), until a point where the behavior is stable again (*behavior constant* and *low instability*).

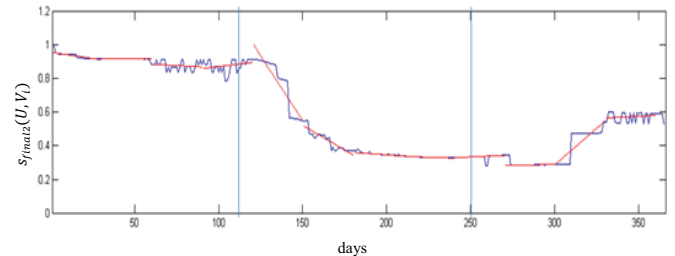


Fig. 6: Similarity of adapted behavior to a learned reference behavior for “Morning Routine” behavior. This event, e.g. a fall, results in a large change in subsequent behavior (i.e. table 2). We also simulate a scenario in which the user undergoes rehabilitation and his/her behavior improves but never goes back to what it was before.

TABLE 4: LINGUISTIC SUMMARIZATION OF TIME SERIES IN FIG. 6

Days	Linguistic Summarization
1-30	B_2 is constant, with no instability in a time period equal to 30 days
31-60	B_2 is constant, with no instability in a time period equal to 30 days
61-90	B_2 is constant with low instability in a time period equal to 30 days
91-120	B_2 is constant with medium instability in a time period equal to 30 days
121-150	B_2 is decreasing in a time period equal to 30 days
151-180	B_2 is slowly decreasing in a time period equal to 30 days
181-210	B_2 is constant, with no instability in a time period equal to 30 days
211-240	B_2 is constant, with no instability in a time period equal to 30 days
241-270	B_2 is constant with low instability in a time period equal to 30 days
271-300	B_2 is constant with low instability in a time period equal to 30 days
301-330	B_2 is increasing in a time period equal to 30 days
331-365	B_2 is constant with low instability in a time period equal to 30 days

V. CONCLUSIONS

In this paper, we presented a method to produce a linguistic summarization about the quality of an elder's behavior as it adapts over time. In previous work, we presented a method to obtain behavior representations [21, 22] and a measure to analyze change in behavior models [11]. This paper is focused on defining a fuzzy set-based method to summarize the measured information, with the goal of reporting information in a natural language to nurses, doctors or social workers, which makes it simpler for them to understand what is going on. We introduced a user-defined time resolution approach that allows the expert to investigate different time specific health queries. In addition, we defined a set of features that allows us to detect if the behavior is changing, the speed of the change and the stability of the behavior. Finally, we tested our method in a simulated resident scenario to show how the method helps a person (e.g. elder, caregiver, social workers or even family member) to monitor the activities of an elderly resident.

Future work includes the following. First, a synthetic data set was used to test different behavior scenarios. We will investigate using the LA approach from the University of Granada, Spain on real sensor data collected from the assisted living facility, TigerPlace [2], in Columbia MO, USA. Secondly, we propose to obtain the expert opinion to evaluate the method and improve it by adding more attributes. Both the membership functions and the methods of producing the linguistic summarization can be learned.

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REFERENCES

- [1] M. Skubic and M. Rantz. (2011) Active elders: Center for eldercare and rehabilitation technology. [Online]. Available: <http://eldertech.missouri.edu/>
- [2] M. Rantz, M. Aud, G. Alexander, D. Oliver, D. Minner, M. Skubic, J. Keller, Z. He, M. Popescu, G. Demiris, and S. Miller, "Tiger place: An innovative educational and research environment," AAAI in Eldercare: New Solutions to Old Problems, Tech. Rep, November 2008.
- [3] D. Cook, M. Youngblood, I. Heierman, E.O., K. Gopalratnam, S. Rao, A. Litvin and F. Khawaja. "Mavhome: An agent-based smart home", in *Pervasive Computing and Communications, 2003. (PerCom 2003). Proceedings of the First IEEE International Conference on*, march 2003, pp. 521 – 524.
- [4] F. Doctor, H. Hagra, and V. Callaghan, "A fuzzy embedded agentbased approach for realizing ambient intelligence in intelligent inhabited environments," *Systems, Man and Cybernetics, Part A: Systems and Humans. IEEE Transactions on*, vol. 35, no. 1, pp. 55–65, jan. 2005.
- [5] P. Rashidi and D. Cook. "Keeping the resident in the loop: Adapting the smart home to the user". *Systems, Man and Cybernetics, Part A: Systems and Humans. IEEE Transactions on*, vol.39, no.5, pp.949 –959. sept.2009
- [6] J.A. Kientz, S.N.Patel, B. Jones, E. Price, E.D. Mynatt, G.D. Abowd, "The georgia tech aware home", in *CHI '08: CHI '08 extended abstracts on Human factors in computing systems*, ser CHI EA '08. New York, NY, USA: ACM, 2008, pp. 3675–3680.
- [7] R.-M. Droe, M. Mulvenna, C. Nugent, D. Finlay, M. Donnelly, M. Mikalsen, S. Walderhaug, T. v. Kasteren, B. Krose, S. Puglia, F. Scanu, M. O. Migliori, E. Ucar, C. Atlig, Y. Kilicaslan, O. Ucar, and J. Hou, "Healthcare systems and other applications," *Pervasive Computing, IEEE*, vol. 6, no. 1, pp. 59 –63, jan.-march 2007.
- [8] M. Philipose, K. P. Fishkin, M. Perkowitz, D. J. Patterson, D. Fox, H. Kautz, and D. Hahnel, "Inferring activities from interactions with objects," *Pervasive Computing, IEEE*, vol. 3, no. 4, pp. 50 – 57, oct.-dec. 2004.
- [9] U. Naeem and J. Bigham, "A comparison of two hidden markov approaches to task identification in the home environment," in *Proceedings of the 2nd International Conference on Pervasive Computing and Applications*, 2007, pp. 383–388.
- [10] Acampora, G., Loia, V. "Fuzzy control interoperability and scalability for adaptive domotic framework". *Industrial Informatics, IEEE Transactions on*, vol. 1, no. 2, pp. 97 – 111, may 2005.
- [11] Derek T. Anderson, Maria Ros, James M. Keller, Manuel P. Cuéllar, Mihail Popescu, Miguel Delgado and Amparo Vila. Similarity measure for anomaly detection and comparing human behaviors. Submitted to *IEEE Transactions on Knowledge and Data Engineering*, 2011.
- [12] Stone E, Anderson D, Skubic M & Keller J, "Extracting Footfalls from Voxel Data," *Engineering in Medicine and Biology Society(EMBC), 2010 Annual International Conference of the IEEE*, vol.1, no. 1, sept. 2010, pp. 1119 –1122.
- [13] Wang F, Skubic M, Abbott C & Keller J, "Body Sway Measurement for Fall Risk Assessment Using Inexpensive Webcams," *Engineering in Medicine and Biology Society(EMBC), 2010 Annual International Conference of the IEEE*, vol.1, no.1, sept 2010, pp. 2225 –2229.
- [14] Wang F, Stone E, Dai W, Skubic M & Keller J, "Gait Analysis and Validation Using Voxel Data," in *Engineering in Medicine and Biology Society, 2009 EMBC. Annual International Conference of the IEEE*, sept, 2009, pp. 6127–6130.
- [15] R.R. Yager. "A new approach to the summarization of data". *Information Sciences*, vol. 28, no. 1, pp. 69 – 86, 1982.
- [16] J. Kacprzyk, RR. Yager, "Linguistic summaries of data using fuzzy logic". *International Journal of General Systems* vol. 30, no. 2, pp. 133 – 154, 2001.
- [17] J. Kacprzyk, RR. Yager, S. Zadrozny, "A fuzzy logic based approach to linguistic summaries of database". *International Journal of Applied Mathematics and Computer Science*, vol. 10, pp. 813–834, 2000.
- [18] Kacprzyk, Janusk and Wilbik, Anna. "Temporal Linguistic Summaries of Time Series Using Fuzzy Logic", in *Information Processing and Management of Uncertainty in Knowledge-Based Systems. Theory and Methods*, ser. Communications in Computer and Information Science, 2010, vol. 80, pp. 436–445.
- [19] Derek Anderson, Robert H. Luke, James M. Keller, Marjorie Skubic, Marilyn Rantz, and Myra Aud. "Linguistic summarization of video for fall detection using voxel person and fuzzy logic". *Computer Vision and Image Understanding*, vol. 113, no. 1, pp. 80 – 89, 2009
- [20] J. Kacprzyk, A. Wilbik, and S. Zadrony. "Linguistic summarization of time series using a fuzzy quantifier driven aggregation". *Fuzzy Sets Syst.*, vol. 159, pp. 1485–1499, June 2008
- [21] Cuellar, MP., Ros M., Delgado M, Vila A, Detection of abnormal human activities by means of learning automata. Submitted to *IEEE Trans. on Systems, Man and Cybernetics, Part A* .
- [22] Ros M., Cuellar, MP., Delgado M, Vila A, Online recognition of human activities and adaptation to habit changes by means of learning automata and fuzzy temporal windows. Submitted to *Spec. Iss.: On-Line Fuzzy ML and DM. Information Sciences*.
- [23] D. T. Anderson, J. C. Bezdek, M. Popescu, and J. M. Keller, "Comparing Fuzzy, Probabilistic, and Possibilistic Partitions," *Fuzzy Systems, IEEE Transactions on*, vol. 18, no. 5, pp. 906 –918, oct. 2010.
- [24] Hubert, L. and Arabie, P., "Comparing partitions". *Journal of Classification*, vol. 2, pp. 193–218, 1985.
- [25] Sneath, P. H. A. and Sokal, R. R.. *Numerical Taxonomy - The Principles and Practice of Numerical Classification*, Freeman, 1973.