Similarity Evaluation of Sets of Linguistic Summaries

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Creating linguistic summaries of data has been a goal of the artificial and computational intelligence communities for many years. Summaries of written text have garnered the most attention. More recently, creating summaries of imagery and other sensed data has become important as a means of compressing large amounts of data and communicating with humans. In this paper, we consider the question of comparing sets of summaries generated from sensed data. In an earlier work, we developed a metric between individual protoform-based summaries; and here, as a next step, we propose aggregation methods to fuse these individual distances. We provide a case study from eldercare where the goal is to compare different nighttime patterns for change detection. © 2012 Wiley Periodicals, Inc.

1. INTRODUCTION

Advances in information technology cause more and more data to be stored and analyzed. The amount of data is beyond human cognitive capabilities and comprehension skills. There is an urgent need to process those data into knowledge. To meet those needs, the fields of data mining and knowledge discovery are developing rapidly. Many powerful data mining and knowledge discovery techniques are available, but they still require constant human supervision.[1] Moreover, we believe that the outputs of such techniques are not human centric enough as they, for the most part, do not use natural language, the only fully natural means of communication and articulation for human beings. Therefore, we think that there is an urgent need for an "intelligent" and human-centric data summarization system. This work is a step in that direction. Acknowledging this problem, several approaches for linguistic summarization were investigated.[2–8] The resulting summaries should be generated so that the people reading them will take appropriate actions. For instance, summaries

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of sensor data on elderly residents in independent living including, nighttime motion activity and restlessness while lying in bed provide indications of potential abnormal conditions.[9] However, as the number of sensors grows, so does the complexity and quantity of the set of linguistic descriptions. Hence, it is necessary to perform some automated analysis to condense this information. In Ref. 10, we defined a dissimilarity measure between two single summaries represented in a protoform format[11] and proved that it is a metric. But even in the simple case mentioned above (restlessness and bedroom motion), several summaries can be generated over a given night. If our desire is to make decisions such as "today is normal for Mr. Smith" or "Mrs. Jones is much better this week than she was last week," we need methods, not only to compare single summaries from different days, but to compare the entire groups of summaries that are generated. Therefore, we have to be able to compute the similarity of the sets of the summaries. That is the content of this paper. Although the approach is general, we will refer to the eldercare example previously described to demonstrate the techniques developed herein. We begin by generating the sets of summaries for the sensor data on two or more time windows (two different nights for the elder). The linguistic summaries can be exemplified by "many 15-minute slots are of high restlessness" or "most of high restlessness 15-minute slots are of medium motion." Next, we use our similarity/–dissimilarity measure[10] on pairs of summaries under examination, one from each time window, and aggregate those values to evaluate the similarity of the sets. There are several possibilities for how to aggregate them, and we present and analyze a few of them in this paper.

We demonstrate the results of this fusion in a real-case example and show that those proposed similarity values can help us distinguish some changes of behavior of the resident.

2. LINGUISTIC SUMMARIES AND THEIR DISTANCE

A protoform-based linguistic summary (cf., Yager,[11,12] Kacprzyk and Yager,[13] or Kacprzyk, Yager, and Zadrożny[14]) is usually a short (quasi-)natural language sentence that captures the very essence of the set of data that is numeric, large, and because of its size, difficult for human comprehension.

It contains the following elements:

- summarizer P, i.e., an attribute together with a linguistic value (fuzzy predicate) defined on the domain of attribute (e.g., low for attribute restlessness);
- quantifier Q, e.g., most;
- truth-value T, number form the interval [0,1] assessing the truth (validity) of the summary;
- optionally, qualifier R, another attribute together with a linguistic value determining a fuzzy subset of interest (e.g., high for attribute motion).

The core of linguistic summaries is the linguistic quantified proposition,[15] which is

$$Q\ y\text{'s are } P \tag{1}$$

and in the case with qualifier

$$Q\ R\ y\text{'s are } P \tag{2}$$

Examples of the linguistic summaries may be "Most 15-minute windows of the resident are of low restlessness" with truth-value $T = 0.9$ or "Many medium motion 15-minute windows of the resident are of high restlessness" with the truth-value of $T = 0.95$.

The truth-value, in the example from Section 4, is computed using original Zadeh's calculus of quantified propositions,[16] i.e.,

$$T(Q\ y\text{'s are } P) = \mu_Q\left(\frac{1}{n}\sum_{i=1}^{n}\mu_P(y_i)\right) \tag{3}$$

$$T(Q\ R\ y\text{'s are } P) = \mu_Q\left(\frac{\sum_{i=1}^{n}\mu_P \wedge \mu_R}{\sum_{i=1}^{n}\mu_R}\right) \tag{4}$$

The truth-value is the basic quality criterion; however, there are many more. A very useful one is the degree of focus,[17] which gives the proportion of objects satisfying the property R to all objects. It is calculated as

$$d_{\text{foc}}(Q\ R\ y\text{'s are } P) = \frac{1}{n}\sum_{i=1}^{n}\mu_R(y_i) \tag{5}$$

More information on linguistic summaries can be found in Ref. 18.

The similarity of two protoform summaries that was developed in Ref. 10 is the minimum of the four elements that create the summary, i.e., similarity of summarizers, quantifiers, truth-values, and qualifiers, and is given by

$$\begin{aligned}
&\text{sim}(Q_1R_1\ y\text{'s are } P_1,\ Q_2R_2y\text{'s are } P_2)\\
&\quad= \min\left(\min\left(\frac{a}{b}, \frac{\int(\mu_{P_1}\cap\mu_{P_2})}{\int(\mu_{P_1}\cup\mu_{P_2})}\right), \frac{\int(\mu_{Q_1}\cap\mu_{Q_2})}{\int(\mu_{Q_1}\cup\mu_{Q_2})}, 1-|T_1-T_2|,\right.\\
&\left.\min\left(\frac{\int(\mu_{R_1}\cap\mu_{R_2})}{\int(\mu_{R_1}\cup\mu_{R_2})}, 1-|d_{\text{foc}}(Q_1R_1\ y\text{'s are } P_1) - d_{\text{foc}}(Q_2R_2y\text{'s are } P)|\right)\right)
\end{aligned} \tag{6}$$

We have shown in Ref. 10 that $1 - \text{sim}(Q_1R_1\ y\text{'s are } P_1,\ Q_2R_2y\text{'s are } P_2)$ is a metric.

Table I. Matrix of the similarities of two sets of summaries.

	s_{11}	s_{12}	$\cdots$	s_{1n}
s_{21}	$\mathrm{sim}(s_{11}, s_{21})$	$\mathrm{sim}(s_{12}, s_{21})$	$\cdots$	$\mathrm{sim}(s_{1n}, s_{21})$
s_{22}	$\mathrm{sim}(s_{11}, s_{22})$	$\mathrm{sim}(s_{12}, s_{22})$	$\cdots$	$\mathrm{sim}(s_{1n}, s_{22})$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
s_{2m}	$\mathrm{sim}(s_{11}, s_{2m})$	$\mathrm{sim}(s_{12}, s_{2m})$	$\cdots$	$\mathrm{sim}(s_{1n}, s_{2m})$

3. SIMILARITY BETWEEN THE SETS OF LINGUISTIC SUMMARIES

Now our task is to evaluate the similarity of two sets of linguistic summaries. Consider two sets of linguistic summaries: S_1 and S_2. Suppose that the set S_1 contains n summaries: $\{s_{11}, s_{12}, \ldots, s_{1n}\}$ while set S_2 contains m summaries: $\{s_{21}, s_{22}, \ldots, s_{2m}\}$. There are several methods to measure the likeness of the sets of summaries, and we present our proposals below.

We will employ a few well-known aggregation methods, and show how they can be used in our context.

3.1. Similarity Based on the Matrix of Similarities/Distances

On the basis of the similarity/distance of two summaries, we can create the matrix of similarities of two summaries s_{1i} and s_{2j}, $i = 1, \ldots, n$ and $j = 1, \ldots, m$. An example of such matrix is shown in Table I.

One of the possibilities is finding, for every summary in S_1 and S_2, the most similar summary from the other set together with its degree of similarity. Then, we average those values as

$$\mathrm{sim}_M(S_1, S_2) = \sum_{i=1}^{n} \frac{\max_{j=1,\ldots,m} \mathrm{sim}(s_{1i}, s_{2j})}{n+m} + \sum_{j=1}^{m} \frac{\max_{i=1,\ldots,n} \mathrm{sim}(s_{1i}, s_{2j})}{n+m} \tag{7}$$

Here, $d(S_1, S_2) = 1 - \mathrm{sim}\ (S_1, S_2)$ is a semimetric, but not a metric, because the triangle inequality is not satisfied.

However, this is not the only option. We can say that two sets of summaries are similar if *most* (or *almost all*) summaries from one set have a similar summary in the other set. We will explore now different possibilities that match this definition.

3.2. *Soft Degree* of the Similarity

The above definition is somewhat similar to the *soft degree* of consensus proposed by Kacprzyk and Fedrizzi[19] or Kacprzyk et al.[20] and defined as the degree to which most of the individuals agree to almost all (relevant) issues.

Hence, we define a *soft degree* of similarity between two sets of summaries as the degree to which *most* (or *almost all*) summaries from one set have *at least one* comparable summary in the other set.

The soft degree of similarity is calculated as

$$\mathrm{sim}_Q(S_1, S_2) = \mu_Q\left(\sum_{i=1}^{n} \frac{\max_{j=1,\ldots,m} \mathrm{sim}(s_{1i}, s_{2j})}{n+m} + \sum_{j=1}^{m} \frac{\max_{i=1,\ldots,n} \mathrm{sim}(s_{1i},\ s_{2j})}{n+m}\right) \tag{8}$$

where Q denotes the quantifier *most* and is represented by an appropriate fuzzy set over the nonnegative integers, and max corresponds to the quantifier *at least one*.

Besides changing the definitions of the quantifiers in Equation 8, ordered weighted averaging (OWA) operators provide a more general method for aggregation across the matrix of individual similarities.

3.3. Aggregation Using the OWA Operators

An OWA operator[21] of dimension n is a mapping $F_w : [0,\ 1]^n \to [0,\ 1]$ such that $W = [w_1, w_2, \ldots,\ w_n]^T$ is a weighting vector with

1. $w_i \in [0,\ 1]$ for all $i = 1, \ldots, n$
2. $\sum_{i=1}^{n} w_i = 1$

and

$$F(a_1, a_2, \ldots, a_n) = W^T B = \sum_{j=1}^{n} w_j b_j \tag{9}$$

where b_j is the jth largest element in the set $\{a_1, a_2, \ldots, a_n\}$ and $B = [b_1, b_2, \ldots b_n]$.

For normal nondecreasing quantifiers Q, Yager[22] generates the weighting vector $W = [w_1, w_2, \ldots, w_n]^T$ as

$$w_i = \mu_Q\left(\frac{i}{n}\right) - \mu_Q\left(\frac{i-1}{n}\right), \quad i = 1, \ldots, n \tag{10}$$

and as, by definition, $\mu_Q(0) = 0$ and $\mu_Q(1) = 1$, then $w_1 + w_2 + \cdots + w_n = 1$.

This procedure for determining the weighting vector is simple and intuitively appealing.

So, in our context, the similarity of two sets of linguistic summaries is

$$\mathrm{sim}_{\mathrm{OWA}}(S_1, S_2) = \sum_{l=1}^{m+n} w_l b_l \tag{11}$$

where $w_l = \mu_Q(\frac{l}{m+n}) - \mu_Q(\frac{l-1}{m+n})$ and b_j is the lth largest element in the set $\{a_1, a_2, \ldots, a_{m+n}\}$, $a_k = \max_{j=1,\ldots,m} \mathrm{sim}(s_{1k}, s_{2j}) k = 1, \ldots, n$ and $a_k = \max_{i=1,\ldots,n} \mathrm{sim}(s_{1i}, s_{2(k-n)}) k = n+1, \ldots, n+m$, i.e., a set containing the biggest similarity values for every summary from both sets with a summary from the other set. To generalize further, we can employ the Sugeno or Choquet fuzzy integrals to perform the fusion.[23]

3.4. Aggregation by Fuzzy Integrals

Let $X = \{x_1, x_2, \ldots, x_n\}$ be a finite set. Then fuzzy measure[24] on X is a function $g : P(X) \to [0,\ 1]$ such that

- $g(\emptyset) = 0$
- $g(X) = 1$
- If $A \subseteq B$ then $g(A) \leq g(B), \forall A, B \in P(X)$

where $P(X)$ denotes the set of all subsets of X.

Let g be a fuzzy measure and h be a function $h : X \to [0,\ 1]$. Moreover, assume that $\{x_i\}$ are ordered so that $h(x_1) \geq h(x_2) \geq \ldots \geq h(x_n)$.

Then the discrete Sugeno integral[25] of a function h with respect to g is a function $S_g : [0,\ 1]^n \to [0, 1]$ such that

$$S_g(h) = \max_{i=1,\ldots,n} [\min(h(x_i), g(A_i))] \tag{12}$$

where $A_i = \{x_1, x_2, \ldots, x_i\}$.

Similarly, the discrete Choquet integral[25] of a function h with respect to g is a function $C_g : [0, 1]^n \to [0, 1]$ such that

$$C_g(h) = \sum_{i=1}^{n} [h(x_i) - h(x_{i+1})] \cdot g(A_i) \tag{13}$$

where $h(x_{n+1}) = 0$.

In our context, $X = S_1 \cup S_2$, i.e., it is the set of summaries from the set S_1 and S_2.

Here, a fuzzy measure $g : P(X) \to [0, 1]$ is defined as $g(A) = \mu_Q(\frac{|A|}{|X|})$, where $|\cdot|$ denotes cardinality of the set, and μ_Q is the membership function of the quantifier, in our case "most."

The partial support function $h : X \to [0,\ 1]$, is defined as

$$h(s) = \begin{cases} \max_{j=1,\ldots,m} \mathrm{sim}(s,\ s_{2j}) & \text{if} \quad \in S_1 \\ \max_{i=1,\ldots,n} \mathrm{sim}(s_{1i}, s) & \text{if} \quad s \in S_2 \end{cases} \tag{14}$$

i.e., the maximal degree of similarity between a summary s and a summary form the other set.

Then the similarity value found using the Sugeno integral is expressed as

$$S_g(h) = \max_{i=1,\dots,n} \left[\min \left(\alpha, \mu_Q \left(\frac{|A_\alpha|}{n+m} \right) \right) \right] \tag{15}$$

and $|A_\alpha|$ is the number of summaries from S_1 and S_2 that have their biggest similarity value with a summary from the other set larger than α.

Similarly, we can formulate the aggregation by the Choquet integral. For this choice of measure, however, the Choquet integral reduces to the OWA operator given above.[26] Of course, the Choquet integral is more general and offers a rich family of fusion techniques as the measures are changed. Both of the integral aggregation operators are semimetrics.

Clearly, the methods shown above are not the only possibilities how to evaluate similarity of two sets of linguistic summaries, as there are many aggregation operators,[27] such as linguistic aggregation operators.

4. NUMERICAL EXAMPLE

We give an example based on eldercare research activity at TigerPlace, an "ageing in place" facility in Columbia, Missouri.[28] Linguistic summaries were generated for a male resident, about 80 years old. He has a past history of syncope, bradycardia with pacemaker placement in 2002. He suffered from stenosis of carotid arteries, hypertension, and probable transient ischemic attacks. He had a bypass surgery (CABG) in December 2005 and a stroke in December 2006.

Our data come from two sensors only: bed restlessness and bedroom motion, which illustrates the bed movement while lying in the bed and movement around the bedroom during the night (from 9 pm to 7 am).

In Figure 1, we display the plot of the nighttime sensor firings for both types of sensors: bed restlessness and bedroom motion. Some data are missing, like in November 2005 or from mid November till mid December 2006. Note that in February 2006 as well as in January 2007, there are longer periods with no restlessness sensor firings. Nursing care coordinators determined the resident did not sleep in bed during these times; in fact, for some of these dates he was not present and was admitted to the hospital, or he was staying with family. The motion sensor firings on those days could be caused by housekeeping.

On the basis of the resident's medical history, we will focus on two periods:

- after CABG—(January, 2006) referring to the about one month period after the surgery that was in December 2005,
- stable time—(March—November, 2006) referring to the 9-month period when no serious health events occurred.

We analyzed five nights after CABG and five nights during the stable time, and we show the both the linguistic summaries obtained, and the set similarities between

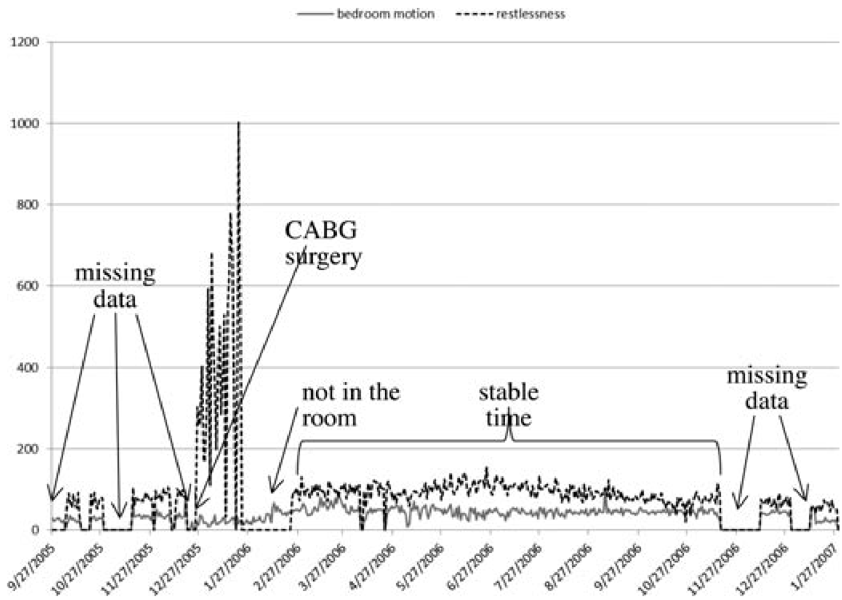

Figure 1. Plot of the nighttime sensor firings.

them. We summarize the number of sensor firings in 15-minute slots during the nighttime.

First, we describe the linguistic terms we use. All the linguistic values are modeled with trapezoidal membership functions, as they are sufficient in most applications. Moreover, they can be very easily interpreted and defined by a person not familiar with fuzzy sets and fuzzy logic, for instance, healthcare providers. To represent a fuzzy set with a trapezoidal membership function, we need to store four numbers only, a, b, c, and d. An example of such a function Trap[a,b,c,d] is shown as in Figure 2.

We use five linguistic quantifiers: *almost all* (Trap[0.9, 0.95, 1, 1]), *most* (Trap[0.7, 0.8, 1, 1]), *many* (Trap[0.6, 0.7, 1, 1]), *about a half* (Trap[0.3, 0.45, 0.55, 0.7]), and *a few* (Trap[0.1 0.2 0.3 0.45]). To describe motion and restlessness,

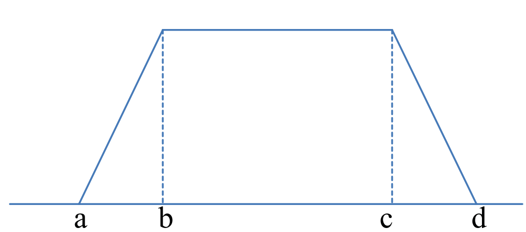

Figure 2. Trapezoidal fuzzy membership function used in the numeric examples, denoted by Trap[a,b,c,d].

Table II. Similarity matrix of linguistic summaries for the nights of January 12, 2006 and August 15, 2006.

	s_{11}	s_{12}	s_{13}	s_{14}
s_{21}	0.035	0	0	0
s_{22}	0.3	0	0	0
s_{23}	0	0	0	0
s_{24}	0.035	0	0	0
s_{25}	0	0	0	0
s_{26}	0	0.052	0.0732	1

we use three linguistic values: *low* (Trap[0,0,2,5]), *medium* (Trap[2,5,12,15]), and *high* (Trap[12,15,50,50]).

For the comparison, we have chosen only the summaries with the truth-value higher than 0.75 and the degree of focus higher than 0.1.

An example of a set of linguistic summaries generated for a night from after CABG time (January 12, 2006) is

- *almost all* 15-minute slots are *low* motion, $T = 1.0$, $d_{\text{foc}} = 1.0$;
- *about a half* of the15-minute slots are *high* restlessness, $T = 1.0$, $d_{\text{foc}} = 1.0$;
- *a few* 15-minute slots are *low* restlessness, $T = 1.0$, $d_{\text{foc}} = 1.0$;
- *a few15*-minute slots are *medium* restlessness, $T = 1.0$, $d_{\text{foc}} = 1.0$

and an example of a set of linguistic summaries generated for a night from the stable time (August 15, 2006) is

- *almost all low* restlessness 15-minute slots are *low* motion, $T = 1.0$, $d_{\text{foc}} = 0.72$;
- *most* 15-minute slots are *low* motion, $T = 1.0$, $d_{\text{foc}} = 1.0$;
- *most low* motion 15-minute slots are *low* restlessness, $T = 0.94$ $d_{\text{foc}} = 0.87$;
- *many* 15-minute slots are *low* motion and *low* restlessness $t = 0.91$, $d_{\text{foc}} = 1.0$;
- *many* 15-minute slots are *low* restlessness, $T = 1.0$, $d_{\text{foc}} = 1.0$;
- *a few* 15-minute slots are *medium* restlessness, $T = 1.0$, $d_{\text{foc}} = 1.0$.

The similarity matrix of linguistic summaries for the two nights listed above is shown in Table II. This matrix compares two nights that are dissimilar. Hence, the linguistic summaries for those two nights are different, and we observe many zero values.

In Table III we present the similarities of two nights from the stable time. Notice that the matrix is denser. The three linguistic summaries describing this night are

- *almost all* 15-minute slots *low* restlessness are *low* motion, $T = 1.0$, $d_{\text{foc}} = 0.66$;
- *most* 15-minute slots are *low* motion, $T = 1.0$, $d_{\text{foc}} = 1.0$;
- *many low* motion 15-minute slots are *low* restlessness, $T = 1.0$, $d_{\text{foc}} = 0.88$.

In Tables IV–VII, we present the values of the similarity of the sets of the summaries obtained for different methods presented in Section 3.

Table III. Similarity matrix of linguistic summaries for the night of March 18, 2006 and August 15, 2006.

	s_{11}	s_{12}	s_{13}
s_{21}	0.9431	0.035	0
s_{22}	0.035	1	0
s_{23}	0	0	0.7143
s_{24}	0.035	0.035	0.035
s_{25}	0	0	0.035
s_{26}	0	0	0

Table IV. Similarity matrix of the sets of the summaries—based on matrix of similarities.

	4-Jan	9-Jan	12-Jan	15-Jan	22-Jan	18-Mar	10-May	15-Aug	20-Sep	3-Nov
4-Jan	1.00	0.64	0.85	0.85	0.95	0.11	0.30	0.30	0.30	0.27
9-Jan	0.64	1.00	0.80	0.80	0.69	0.11	0.09	0.09	0.09	0.08
12-Jan	0.85	0.80	1.00	1.00	0.80	0.09	0.27	0.27	0.27	0.25
15-Jan	0.85	0.80	1.00	1.00	0.80	0.09	0.27	0.27	0.27	0.25
22-Jan	0.95	0.69	0.80	0.80	1.00	0.11	0.30	0.30	0.30	0.27
18-Mar	0.11	0.11	0.09	0.09	0.11	1.00	0.60	0.60	0.59	0.54
10-May	0.30	0.09	0.27	0.27	0.30	0.60	1.00	0.97	0.99	0.92
15-Aug	0.30	0.09	0.27	0.27	0.30	0.60	0.97	1.00	0.97	0.90
20-Sep	0.30	0.09	0.27	0.27	0.30	0.59	0.99	0.97	1.00	0.91
3-Nov	0.27	0.08	0.25	0.25	0.27	0.54	0.92	0.90	0.91	1.00

Table V. Similarity matrix of the sets of the summaries—"soft degree" of similarity.

	4-Jan	9-Jan	12-Jan	15-Jan	22-Jan	18-Mar	10-May	15-Aug	20-Sep	3-Nov
4-Jan	1.00	0.67	1.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00
9-Jan	0.67	1.00	1.00	1.00	0.78	0.00	0.00	0.00	0.00	0.00
12-Jan	1.00	1.00	1.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00
15-Jan	1.00	1.00	1.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00
22-Jan	1.00	0.78	1.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00
18-Mar	0.00	0.00	0.00	0.00	0.00	1.00	0.59	0.60	0.57	0.47
10-May	0.00	0.00	0.00	0.00	0.00	0.59	1.00	1.00	1.00	1.00
15-Aug	0.00	0.00	0.00	0.00	0.00	0.60	1.00	1.00	1.00	1.00
20-Sep	0.00	0.00	0.00	0.00	0.00	0.57	1.00	1.00	1.00	1.00
3-Nov	0.00	0.00	0.00	0.00	0.00	0.47	1.00	1.00	1.00	1.00

In all tables for the four aggregation methods, we easily distinguish two groups. To the first group belong first five nights (in January), and to the other the last five nights.

We may also notice that the night of 18th of March is a bit different from the other nights. The set of summaries describing this night above given thresholds for the truth-value and the degree of focus, does not contain a summary such as "*many* 15-minute slots are *low* motion and *low* restlessness" or "*a few* 15-minute slots are *medium* restlessness." It produces only a medium similarity to the other stable

Table VI. Similarity matrix of the sets of the summaries—with an OWA operator.

	4-Jan	9-Jan	12-Jan	15-Jan	22-Jan	18-Mar	10-May	15-Aug	20-Sep	3-Nov
4-Jan	1.00	0.64	0.97	0.97	0.96	0.03	0.10	0.10	0.10	0.08
9-Jan	0.64	1.00	0.89	0.89	0.75	0.03	0.04	0.04	0.04	0.03
12-Jan	0.97	0.89	1.00	1.00	0.89	0.01	0.09	0.09	0.09	0.07
15-Jan	0.97	0.89	1.00	1.00	0.89	0.01	0.09	0.09	0.09	0.07
22-Jan	0.96	0.75	0.89	0.89	1.00	0.03	0.10	0.10	0.10	0.08
18-Mar	0.03	0.03	0.01	0.01	0.03	1.00	0.60	0.60	0.58	0.49
10-May	0.10	0.04	0.09	0.09	0.10	0.60	1.00	0.98	0.99	0.99
15-Aug	0.10	0.04	0.09	0.09	0.10	0.60	0.98	1.00	0.97	0.96
20-Sep	0.10	0.04	0.09	0.09	0.10	0.58	0.99	0.97	1.00	0.98
3-Nov	0.08	0.03	0.07	0.07	0.08	0.49	0.99	0.96	0.98	1.00

Table VII. Similarity matrix of the sets of the summaries—aggregation with Sugeno integral.

	4-Jan	9-Jan	12-Jan	15-Jan	22-Jan	18-Mar	10-May	15-Aug	20-Sep	3-Nov
4-Jan	1.00	0.73	0.93	0.93	0.84	0.07	0.29	0.29	0.29	0.20
9-Jan	0.73	1.00	0.76	0.76	0.73	0.07	0.07	0.07	0.07	0.07
12-Jan	0.93	0.76	1.00	1.00	0.76	0.04	0.20	0.20	0.20	0.13
15-Jan	0.93	0.76	1.00	1.00	0.76	0.04	0.20	0.20	0.20	0.13
22-Jan	0.84	0.73	0.76	0.76	1.00	0.07	0.29	0.29	0.29	0.20
18-Mar	0.07	0.07	0.04	0.04	0.07	1.00	0.71	0.71	0.71	0.60
10-May	0.29	0.07	0.20	0.20	0.29	0.71	1.00	0.94	0.98	0.94
15-Aug	0.29	0.07	0.20	0.20	0.29	0.71	0.94	1.00	0.94	0.94
20-Sep	0.29	0.07	0.20	0.20	0.29	0.71	0.98	0.94	1.00	0.94
3-Nov	0.20	0.07	0.13	0.13	0.20	0.60	0.94	0.94	0.94	1.00

nights. In a real deployment of an automated analysis system based on linguistic summaries, such a set might signal the transition from one "normal" period to another, for example, a slow decline in function.

Clearly, in this tiny example all four methods give us pretty similar results. However, this may be not true in general. Definitely, the three methods generated from a quantifier (*soft degree*—Table V or OWA operators—Table VI or Sugeno integrals—Table VII) give results with more contrast in comparison to the first method described—Table IV. The OWA-based method is able to indicate more small similarities/dissimilarities than the *soft degree*. The method with the Sugeno or the Choquet integral provides a general framework, as different fuzzy measures may be used.

The most obvious use of an automated eldercare sensor summarization system is to communicate in a natural fashion with heath care providers. Some future considerations for implementing summarizations into clinical workflow are needed, such are summarizations understandable, do summarizations match language used by healthcare providers on a routine basis, do summarizations support clinical decision-making, and how does the receipt of a linguistic summarization affect clinician workflow. One of the nursing care coordinators at TigerPlace recently remarked that she would love to open up the electronic health record for a resident and see a sentence such as "Mr. Jones had a quiet time last night." Distinguishing summaries for a good night or bad night will provide such assessments. In addition, if a resident is stable for a period of time, a "normal" profile of summaries can be developed and anomalies, for example, restless nights due to medication noncompliance, can be detected and flagged for medical attention.

5. CONCLUDING REMARKS

In this paper, we considered the aggregation of sets of linguistic similarities generated from sensor data. We defined four approaches based on a pairwise similarity of linguistic summaries protoforms developed in previous research. We demonstrated the utility of the aggregation approach in an eldercare environment to distinguish between "good nights" and "bad nights" for a resident, showing the potential for this to automatically detect patient anomalies. The next logical step will be to formulate a temporal clustering approach from sensor summaries. People change over time and so, besides anomalies, normal behavior varies. Distances between linguistic summaries and dissimilarity between sets of summaries condense the mountain of data into meaningful values that will provide a solution to this challenge.

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