WCCI 2012 IEEE World Congress on Computational Intelligence
June, 10-15, 2012 - Brisbane, Australia FUZZ IEEE

# Generation of prototypes from sets of linguistic summaries

Anna Wilbik
Electrical and Computer Engineering,
University of Missouri, Columbia, MO USA
Systems Research Institute,
Polish Academy of Sciences, Warsaw, Poland
Email: wilbik@ibspan.waw.pl

James M. Keller and James C. Bezdek
Electrical and Computer Engineering,
University of Missouri, Columbia, MO USA
Email: kellerj@missouri.edu, jcbezdek@gmail.com

***Abstract*—Linguistic summarization of time series can glean meaningful information from huge amounts of data. However, in situations like continuous monitoring, even linguistic summaries become difficult for a person to understand. In this paper, we develop an approach to generate linguistic prototypes from a group of time blocks that represent a normal condition. Then the set of summaries for new time blocks are compared to the prototypes to flag anomalous conditions, thereby reducing the burden on the human. Case studies from an eldercare environment demonstrate the utility of this approach.**

***Index Terms*—linguistic summarization; protoform; clustering; medoid prototypes; eldercare**

## I. Introduction

As information technology advances, more and more data are created, stored and analyzed. However, this vast mountain of data is beyond human cognitive capabilities and comprehension skills. Therefore there is an urgent need to turn this data into knowledge. Hence methods to summarize data and to analyze these summaries are becoming increasingly important.

Acknowledging this problem, several approaches for linguistic summarization have been investigated [1], [2], [3], [4], [5], [6], [7], [8]. The resulting summaries should be generated so that people reading them will take appropriate actions. For instance, summaries of sensor data on elderly residents in independent living facilities, including nighttime motion activity and restlessness while lying in bed, provide indications of potential abnormal conditions [7], [8]. However, as the number of sensors grows, so does the complexity and size of the set of linguistic descriptions. Hence, it is necessary to perform some automated analysis to condense this information. Our work is a step in this direction.

In this paper we propose a novel method for constructing a set of prototype linguistic summaries based on the summaries generated over some time span and a method for evaluating the similarity of a new set of summaries and the calculated prototype.

Our data come from the eldercare domain. In TigerPlace, an "aging-in-place" facility in Columbia, MO [9], a system of sensors was installed in the residents' apartments. We are using those sensors to generate linguistic description of a night. Based on descriptions from a stable time period we generate a "prototype" of a "normal night", and then for every new night we compute the similarity between its description and the generated prototype to determine if the night was stable, or if something unusual was happening with the resident.

## II. Preliminaries

We are using the concept of linguistic summaries [10]. A linguistic summary is a protoform (template-) based quasi-natural language sentence of a simple form:

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

or of an extended form:

$$QR \; y\text{'s are } P \tag{2}$$

where $Q$ is the quantifier, $P$ is the summarizer, $R$ is the qualifier and $y$'s are the objects that are to be summarized. For every summary we calculate the truth value which is the basic criterion for evaluating the quality of the linguistic summaries. The truth values are calculated as for simple protoforms:

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

and for extended protoforms, including qualifier as:

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

where $n$ is the number of objects that are summarized, and $\mu_P$, $\mu_R$, $\mu_Q$ are the membership functions of the summarizer, qualifier and quantifier, respectively.

Another very useful quality criterion is the degree of focus. More about the linguistic summaries, their quality evaluation, methods of their generation can be found at [11].

In [12] we proposed a similarity between the two linguistic summaries that is calculated as:

We proved that the associated dissimilarity measure $1 - sim\left(Q_1R_1 \; y\text{'s are } P_1, Q_2R_2 \; y\text{'s are } P_2\right)$ is a metric, and hence is a good basis for comparisons.

$$sim\left(Q_1R_1 \text{ } y\text{'s are } P_1, Q_2R_2 \text{ } y\text{'s are } P_2\right) = \\ = \min\left(\min\left(\frac{a}{b}, \frac{\int\left(\mu_{P_1}\cap\mu_{P_2}\right)}{\int\left(\mu_{P_1}\cup\mu_{P_2}\right)}\right), \frac{\int\left(\mu_{Q_1}\cap\mu_{Q_2}\right)}{\int\left(\mu_{Q_1}\cup\mu_{Q_2}\right)}, 1-\left|\mathcal{T}_1-\mathcal{T}_2\right|, \\ \min\left(\frac{\int\left(\mu_{R_1}\cap\mu_{R_2}\right)}{\int\left(\mu_{R_1}\cup\mu_{R_2}\right)}, 1-\left|d_{foc}(Q_1R_1 \text{ } y\text{'s are } P_1)-d_{foc}(Q_2R_2 \text{ } y\text{'s are } P_2)\right|\right)\right) \tag{5}$$

## III. Generation of the prototypes

Assume that we have $p$ sets of linguistic summaries. For the eldercare data every set describes a single night. Every set has $n_i$ linguistic summaries $i = 1, \ldots, p$. Then we create the set of all summaries, $S = \{s_{11}, s_{12}, \ldots, s_{1n_1}, \ldots, s_{p1}, s_{p2}, \ldots, s_{pn_p}\}$. Now we want to cluster the summaries, based on a distance matrix $D$ that contains the distances (5) between pairs of summaries from $S$. Before that however, we need to decide how many clusters to search for in $S$, known in the clustering literature as tendency assessment. For this purpose we use a visual method, either VAT or iVAT [13], [14].

The VAT algorithm and subsequent extensions (VAT [13], coVAT [15], iVAT [14]) are well documented. In a nutshell, VAT reorders $D$ to $D^*$ using the indices of a minimal spanning tree on $D$, and then displays a grayscale image $I(D^*)$. Element $(i, j)$ of $I(D^*)$ is a scaled dissimilarity value between linguistic summaries $s_i$ and $s_j$, and each element on the diagonal is zero (black). Off the diagonal, the scaled values range from 0 to 1 (white). If an object is a member of a cluster, then it should also be part of a submatrix of "similarly small" values.

Reordering $D$ with VAT groups similar objects together in submatrices of $D^*$. These submatrices are seen as dark blocks along the diagonal of the VAT image $I(D^*)$. Contrast can be improved by setting the diagonal to the minimum of the off-diagonal values. This insures that the important structure is represented with the best quantization possible.

Dark blocks along the diagonal suggest cluster structure to an observer, who may then choose to submit $D$ to a formal clustering algorithm which seeks the visually suggested number of clusters. *Improved* VAT, iVAT, begins with a transformation of $D$ to $D'$ using geodesic distances, followed by VAT reordering. The iVAT images of many data sets represent potential cluster structure in the data much more clearly than VAT for tendency assessment.

Based on the information obtained from VAT or iVAT images, i.e., we see $c$ dark blocks, we can create $c$ clusters, using, for instance, *single linkage* (SL) clustering [16]. SL produces $c$ crisp clusters, denoted here by $C_i = s_1^i, s_2^i, \ldots, s_{c_i}^i$, where $s_j^i$ is a summary belonging to the $i$-th cluster.

Now from every cluster we select one linguistic summary that best represents the summaries in the cluster. We have decided to choose the medoid as the cluster representative, i.e. for the cluster $C_i$ it is:

$$p_i = \arg\min_k \left(\sum_{j=1,c_i,j\neq k} d\left(s_k^i, s_j^i\right)\right) \tag{6}$$

The set of $c$ summaries (medoids) forms the linguistic summary prototype.

We want to assign weights indicating the importance of every summary in the prototype. Values of the weights should depend on the size of the cluster from which the medoid comes from and the spread of the summaries which belong to this cluster. More precisely, the first assumption states that prototype summaries coming from bigger clusters are more important than those coming from smaller ones. The second one assumes that if a cluster is diffuse, e.g., its radius is large, then its prototype summary should have a smaller importance than a prototype summary coming from a cluster when all summaries are very close to each other.

Two possibilities to implement the size assumption are either to divide the number of summaries in the cluster by the total number of summaries, i.e., letting $c_i = |C_i|$,

$$n_i = \frac{c_i}{\sum_{j=1}^{c} c_j} \tag{7}$$

or to divide the size of the cluster by the size of the biggest cluster, i.e.

$$n'_i = \frac{c_i}{\max_{j=1,\ldots,c} c_j} \tag{8}$$

Both options will give us the values in $[0, 1]$, and clearly values in the second case are bigger, i.e., $n'_i \geq n_i$.

We have also several possibilities for evaluating the influence of the spread of the summaries in the cluster. One possibility would be to use one minus the radius of the cluster, measured as the maximal distance between the medoid and all summaries belonging to this cluster, i.e.,

$$r_i = 1 - \max_{j=1,\ldots,c_i} d\left(p_i, s_j^i\right) \tag{9}$$

However, this method is very sensitive to outliers. Therefore, another option is to use one minus the average or median distance between the prototype and summaries of this cluster:

$$r'_i = 1 - \frac{1}{c_i}\left(\sum_{j=1}^{c_i} d\left(p_i, s_j^i\right)\right) \tag{10}$$

or even one minus the average or median distance between all summaries in the cluster, i.e.,

$$r''_i = 1 - \text{median}\, d\left(p_i, s_j^i\right) \tag{11}$$

$$r_i''' = 1 - \frac{1}{(c_i-1)c_i}\left(\sum_{j=1}^{c_i-1}\sum_{k=j+1}^{c_i} d\left(s_j^i, s_k^i\right)\right) \quad (12)$$

To combine the size and spread values we can use the weighted average:

$$w_i = \alpha n_i + (1-\alpha) r_i \quad (13)$$

where $\alpha$ is a weight and $n_i$ is the component value of cluster $i$ associated with size and $r_i$ is the component value associated with the spread of the cluster. In our case $\alpha = 0.5$.

## IV. Comparison of a description with a prototype

Once we have the set of "normal activity" prototypes $\{p_j\}$, the next step is checking if a new set of summaries $\{s_j\}$ matches these prototypes, or if we are observing an anomaly. Hence we need to assess the similarity between the two sets of summaries.

First we compute the matrix of similarities between every prototype summary and every summary from the new set. An example is shown in Table I.

TABLE I
MATRIX OF SIMILARITIES BETWEEN THE PROTOTYPES AND A NEW SET OF SUMMARIES

| | $s_1$ | $s_2$ | $\ldots$ | $s_n$ |
|---|---|---|---|---|
| $p_1$ | $sim_{11}$ | $sim_{12}$ | $\ldots$ | $sim_{1n}$ |
| $p_2$ | $sim_{21}$ | $sim_{22}$ | $\ldots$ | $sim_{2n}$ |
| $\vdots$ | $\vdots$ | $\vdots$ | $\ddots$ | $\vdots$ |
| $p_c$ | $sim_{c1}$ | $sim_{c2}$ | $\ldots$ | $sim_{cn}$ |

In order to compute the similarity between those two sets, we find, for every summary in the prototype set and from the current description, the most similar summary from the other set together with its degree of similarity. In other words, for each $s_i$ we find the most similar prototype $p_j$ (looking down the $i$-th column) and for each $p_j$ we determine the best match $s_i$ by looking across the $j$-th row. Then, we average those values as:

$$\begin{aligned} sim(P,S) \quad &= \quad \sum_{i=1}^{n} \frac{\max_{j=1,\ldots,c} sim(s_i,p_j)}{n+c} + \\ &+ \sum_{j=1}^{c} \frac{\max_{i=1,\ldots,n} sim(s_i,p_j)}{n+c} \end{aligned} \quad (14)$$

One minus above similarity is a semi-metric, but not a metric, since the triangle inequality is not satisfied. We can also incorporate weights in (14) in the obvious way and normalize by the sum of all used weights to get

$$sim_W(P,S) = \frac{num_W(P,S)}{den_W(P,S)} \quad (15)$$

where

$$\begin{aligned} num_W(P,S) = &\sum_{i=1}^{n} \max_{j=1,\ldots,c} sim(s_i,p_j) w_{\arg\max_j sim(s_i,p_j)} + \\ &+ \sum_{j=1}^{c} \max_{i=1,\ldots,n} sim(s_i,p_j) w_j \end{aligned} \quad (16)$$

$$den_W(P,S) = \sum_{i=1}^{n} w_{\arg\max_{j=1,\ldots,c} sim(s_i,p_j)} + \sum_{j=1}^{c} w_j \quad (17)$$

## V. Examples

We present two examples based on real data from the elder-care domain. In the first case the sensor data describes activity of a male resident of TigerPlace, who was about 80 years old when the sensor network was installed. He had 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 and died in spring 2007.

In Figure 1 we display the plot of the nighttime sensor firings for two types of sensors: bed restlessness and bedroom motion, which illustrates the bed movement while lying in the bed and movement around the bedroom during the night. The beginning of the night activity and end of the night are evaluated automatically depending on when that resident went to bed and when he got up.

Some data are missing, e.g. in November 2005, and again, 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 personnel.

In this example we used 3 labels for each attribute: *low* (Trap[0, 0, 2, 5]), *medium* (Trap[2, 5, 10, 12]) and *high* (Trap[10, 12, 8, 8]), and every linguistic label is modeled with a trapezoidal fuzzy set. We use also the following quantifiers: *almost all* (Trap[0.9, 0.95 1 1]), *most* (Trap[0.7, 0.8, 1 1]), *many* (Trap[0.45, 0.65, 1, 1]), *about a half* (Trap[0.3, 0.45, 0.55, 0.7]) and *a few* (Trap[0.1, 0.2, 0.4, 0.5]). For every night we summarized the number of sensor firings in 15-minute-slots during the nighttime. More examples on linguistic summaries in this domain can be found in [8], [12].

We formed the prototype set from 31 consecutive nights from May 11 May till June 10, in 2006, which is in the middle of the time labeled as stable. We generated linguistic summaries for those nights and computed the distance between them using the formula (5). Next we computed the iVAT image as shown in Fig 2. In this figure we see 5 black squares of similar size, one medium size square and a small square (the second one from top left). This image suggests that there are 7 clusters in this data set.

Then we used single linkage clustering to create clusters, and found the medoid of every cluster. The prototype for this resident is the following set of summaries:

- $p_1$: *many* 15-minute intervals have *low* restlessness, $\mathcal{T} = 1.0$, $d_{foc} = 1.0$
- $p_2$: *most* 15-minute intervals of *medium* bedroom motion have *medium* restlessness, $\mathcal{T} = 1.0$, $d_{foc} = 0.12$

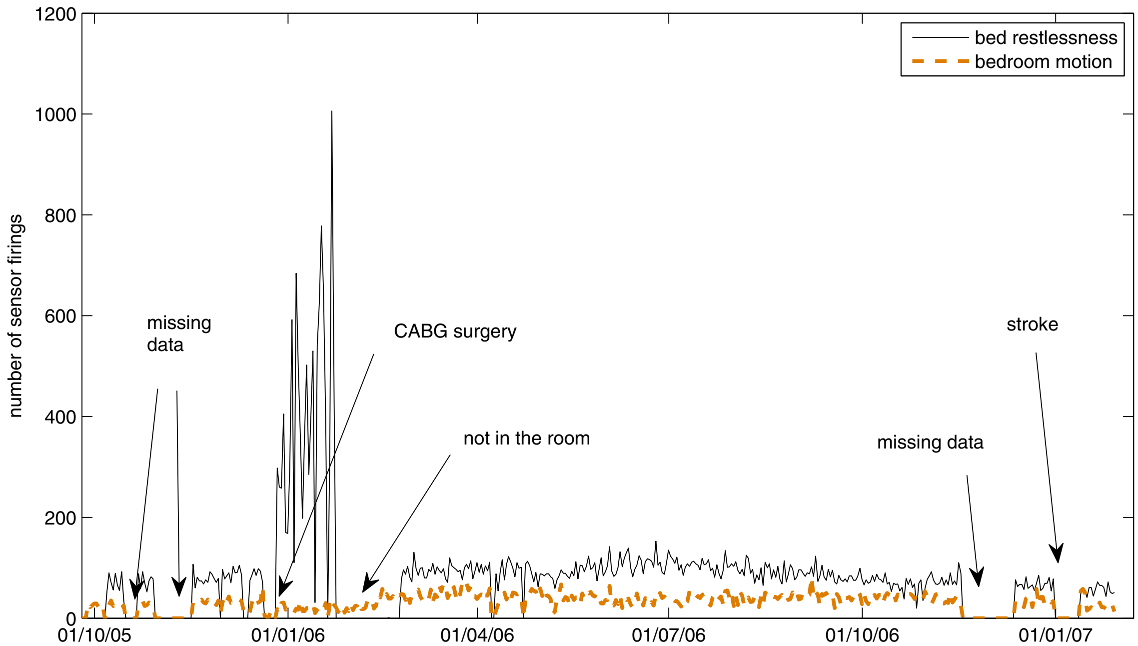


Fig. 1. The nighttime sensor firings for two types of sensors: bed restlessness, and bedroom motion.

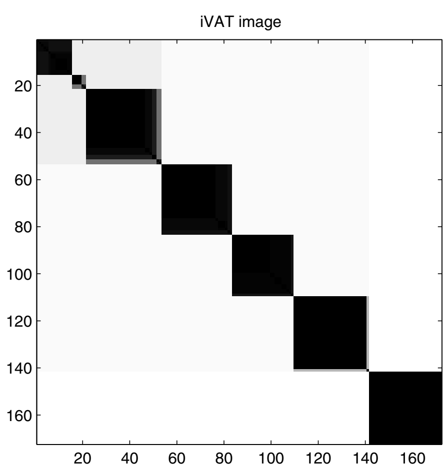


Fig. 2. An iVAT image suggests 7 clusters.

- $p_3$: *most* 15-minute intervals of *low* bedroom motion have *low* restlessness, $\mathcal{T} = 0.96$, $d_{foc} = 0.9$
- $p_4$: *many* 15-minute intervals have *low* restlessness and *low* bedroom motion, $\mathcal{T} = 1.0$, $d_{foc} = 1.0$
- $p_5$: *almost all* 15-minute intervals of *low* restlessness have *low* bedroom motion, $\mathcal{T} = 1.0$, $d_{foc} = 0.72$
- $p_6$: *most* 15-minute intervals have *low* bedroom motion, $\mathcal{T} = 1.0$, $d_{foc} = 1.0$
- $p_7$: *a few* 15-minute intervals have *medium* restlessness, $\mathcal{T} = 1.0$, $d_{foc} = 1.0$

Each prototype summary is assigned a weight indicating its importance. In Table II we present the size of every cluster and then 2 values for different normalizations: using the total number of summaries and the maximal size of the cluster.

TABLE II
SIZES OF THE CLUSTERS AND THE VALUES OF THE IMPORTANCE COMPONENT CONNECTED WITH IT

| prototype | size of cluster ($c_i$) | $n_i = \frac{c_i}{\sum_{j=1}^{c} c_j}$ | $n'_i = \frac{c_i}{\max_j c_j}$ |
|---|---|---|---|
| $p_1$ | 32 | 0.19 | 1.00 |
| $p_2$ | 6 | 0.03 | 0.19 |
| $p_3$ | 15 | 0.09 | 0.47 |
| $p_4$ | 30 | 0.17 | 0.94 |
| $p_5$ | 26 | 0.15 | 0.81 |
| $p_6$ | 32 | 0.19 | 1.00 |
| $p_7$ | 31 | 0.18 | 0.97 |

Notice here that the values in the third column are smaller than those in the fourth.

Table III lists the values of the spread component for the four different possibilities discussed above.

Note the huge difference of values for cluster 6 (in the max column), which was caused by a single summary that is far from the medoid.

In Figures 3-4 we show the similarity values between the prototype and linguistic description of every night.

Figures 3 and 4 show that different formulas for similarities (with weights and without) do not influence these results much. It may be caused by the fact that most of the weights are close to each other. Of course, this will not be the case for other types of temporal summaries. In the figures we see

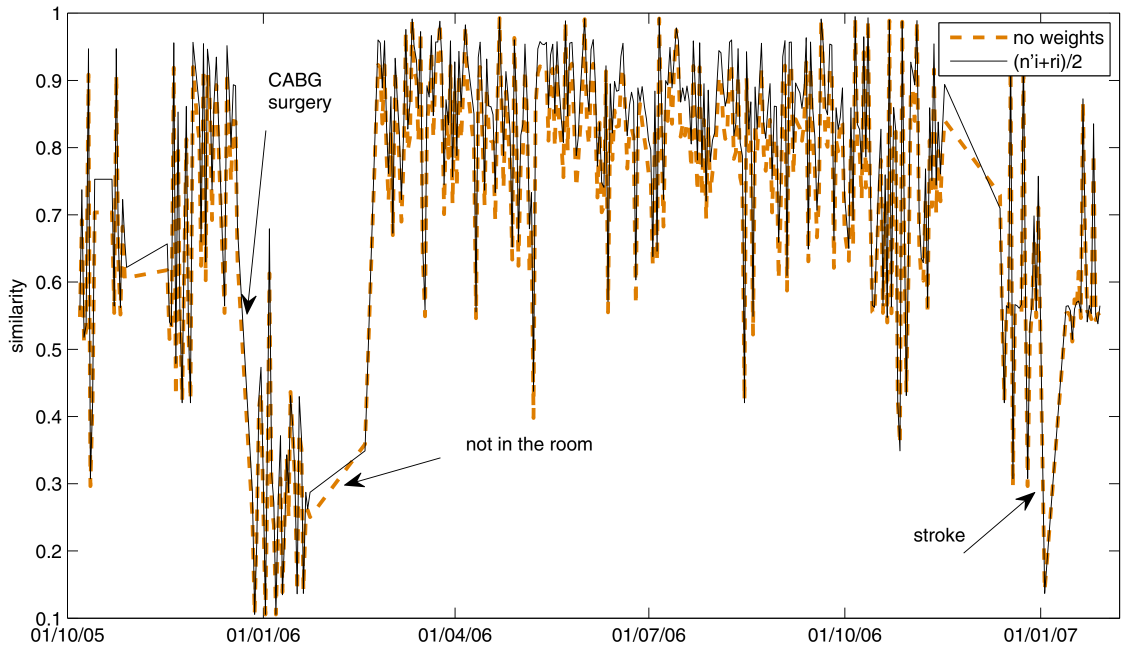


Fig. 3. Similarity between each night and the prototype with no weights and product of the weights n'i and ri.

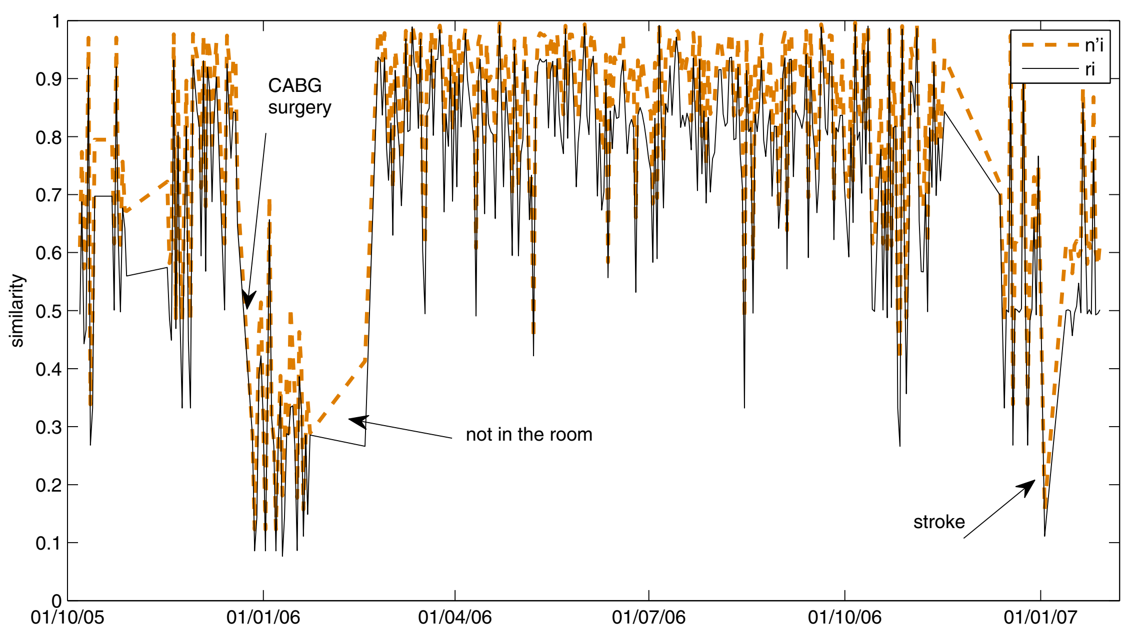


Fig. 4. Similarity between each night and the prototype with n'i and ri.

also that the nights after the CABG surgery are different from the prototype night, as well as the nights in December 2006 before the stroke. This provides evidence that our comparison method can in fact discover deviations from normal.

In the second example the data come from an 88 year old male in very good health. He suffers from Hyperlipidemia. He had a few falls, but none in near recent times. There are no ER visits or unplanned hospitalization in the medical

TABLE III
VALUES OF THE IMPORTANCE COMPONENT BASED ON THE SPREAD OF CLUSTERS

| prototype | $r_i$ | $r'_i$ | $r''_i$ | $r'''_i$ |
|---|---|---|---|---|
| $p_1$ | 0.56 | 0.95 | 1.000 | 0.999 |
| $p_2$ | 0.56 | 0.85 | 0.997 | 0.975 |
| $p_3$ | 0.79 | 0.93 | 0.954 | 0.902 |
| $p_4$ | 0.74 | 0.97 | 1.000 | 0.999 |
| $p_5$ | 0.88 | 0.95 | 0.965 | 0.958 |
| $p_6$ | **0.30** | 0.98 | 1.000 | 0.999 |
| $p_7$ | 1.00 | 1.00 | 1.000 | 1.000 |

record. He had surgery in early March 2011 and returned to TigerPlace. He was on an extended vacation from 7/19/11 to 8/15/11. When he returned to TigerPlace he complained of some discomfort in his legs and feet from being overly active while on vacation.

In Figure 5 (raw sensor data) we may notice that the data are of more variability than the previous case. We generated linguistic summaries with the same linguistic labels as in previous example.

We formed the prototype based on 31 consecutive days from June 10, till July 11, 2009. The iVAT image (Fig 6) suggests that we should look for 10 clusters.

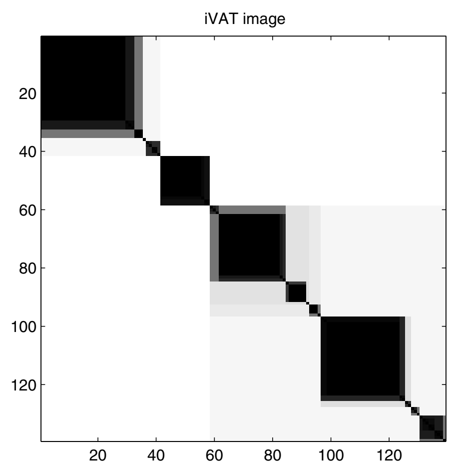


Fig. 6. iVAT image suggests 10 clusters.

The prototypes obtained for this resident are the following:

- $p_1$: *many* 15-minute intervals have low restlessness, $\mathcal{T} = 1.0$, $d_{foc} = 1.0$
- $p_2$: *about a half* 15-minute intervals have *low* restlessness, $\mathcal{T} = 1.0$, $d_{foc} = 1.0$
- $p_3$: *most* 15-minute intervals of *high* bedroom motion have *low* restlessness, $\mathcal{T} = 1.0$, $d_{foc} = 0.11$
- $p_4$: *many* 15-minute intervals of *medium* bedroom motion have *medium* restlessness, $\mathcal{T} = 1.0$, $d_{foc} = 0.11$
- $p_5$: *a few* 15-minute intervals have *medium* restlessness, $\mathcal{T} = 1.0$, $d_{foc} = 1.0$
- $p_6$: *almost all* 15-minute intervals of *medium* restlessness have *low* bedroom motion, $\mathcal{T} = 1.0$, $d_{foc} = 0.48$
- $p_7$: *most* 15-minute intervals have *low* bedroom motion, $\mathcal{T} = 1.0$, $d_{foc} = 1.0$
- $p_8$: *most* 15-minute intervals of *low* bedroom motion have *low* restlessness, $\mathcal{T} = 0.87$, $d_{foc} = 0.85$
- $p_9$: *almost all* 15-minute intervals of *low* restlessness have *low* bedroom motion, $\mathcal{T} = 1.0$, $d_{foc} = 0.71$
- $p_{10}$: *many* 15-minute intervals have *low* restlessness and *low* bedroom motion, $\mathcal{T} = 1.0$, $d_{foc} = 1.0$

In Table IV we present the size of every cluster and then 2 values for different normalizations: using the total number of summaries and the maximal size of the cluster.

TABLE IV
CLUSTER SIZES AND IMPORTANCE COMPONENT CONNECTED WITH IT

| prototype | size of cluster ($c_i$) | $n_i = \frac{c_i}{\sum_{j=1}^{c} c_j}$ | $n'_i = \frac{c_i}{\max_j c_j}$ |
|---|---|---|---|
| $p_1$ | 26 | 0.19 | 0.74 |
| $p_2$ | 8 | 0.06 | 0.23 |
| $p_3$ | 4 | 0.03 | 0.11 |
| $p_4$ | 3 | 0.02 | 0.09 |
| $p_5$ | 31 | 0.22 | 0.89 |
| $p_6$ | 1 | 0.01 | 0.03 |
| $p_7$ | 35 | 0.25 | 1.00 |
| $p_8$ | 9 | 0.06 | 0.26 |
| $p_9$ | 5 | 0.04 | 0.14 |
| $p_{10}$ | 17 | 0.12 | 0.49 |

Table V lists the values of the spread component for the four different possibilities discussed above.

TABLE V
VALUES OF THE IMPORTANCE COMPONENT BASED ON THE SPREAD OF CLUSTERS

| prototype | $r_i$ | $r'_i$ | $r''_i$ | $r'''_i$ |
|---|---|---|---|---|
| $p_1$ | 0.56 | 0.93 | 1.00 | 0.98 |
| $p_2$ | 0.17 | 0.87 | 1.00 | 0.95 |
| $p_3$ | 0.56 | 0.89 | 1.00 | 0.94 |
| $p_4$ | 0.56 | 0.81 | 0.88 | 0.94 |
| $p_5$ | 0.17 | 0.93 | 1.00 | 0.99 |
| $p_6$ | 1.00 | 1.00 | 1.00 | 1.00 |
| $p_7$ | 0.56 | 0.95 | 1.00 | 1.00 |
| $p_8$ | 0.56 | 0.85 | 0.87 | 0.98 |
| $p_9$ | 0.78 | 0.88 | 0.83 | 0.89 |
| $p_{10}$ | 0.87 | 0.98 | 1.00 | 1.00 |

Similarity between the prototype and consequent nights with no weights and product of the weights $n'_i$ and $r_i$ is shown in Figure 7.

While there is more variation in the similarity plots, it is still clear that before surgery and after the holidays show nights where the linguistic summaries of bed restlessness and bedroom motion are different from the prototype sets. Hence, this measure can be used to trigger a care giver to dig deeper into the set of summaries and even into the raw sensor data as required. The value of our measure is to provide a prescreening to reduce the workload on the human.

## VI. CONCLUDING REMARKS

In this paper, we developed a method to cluster sets of linguistic fuzzy protoform based summaries employing a distance metric on pairs of individual summaries. A medoid

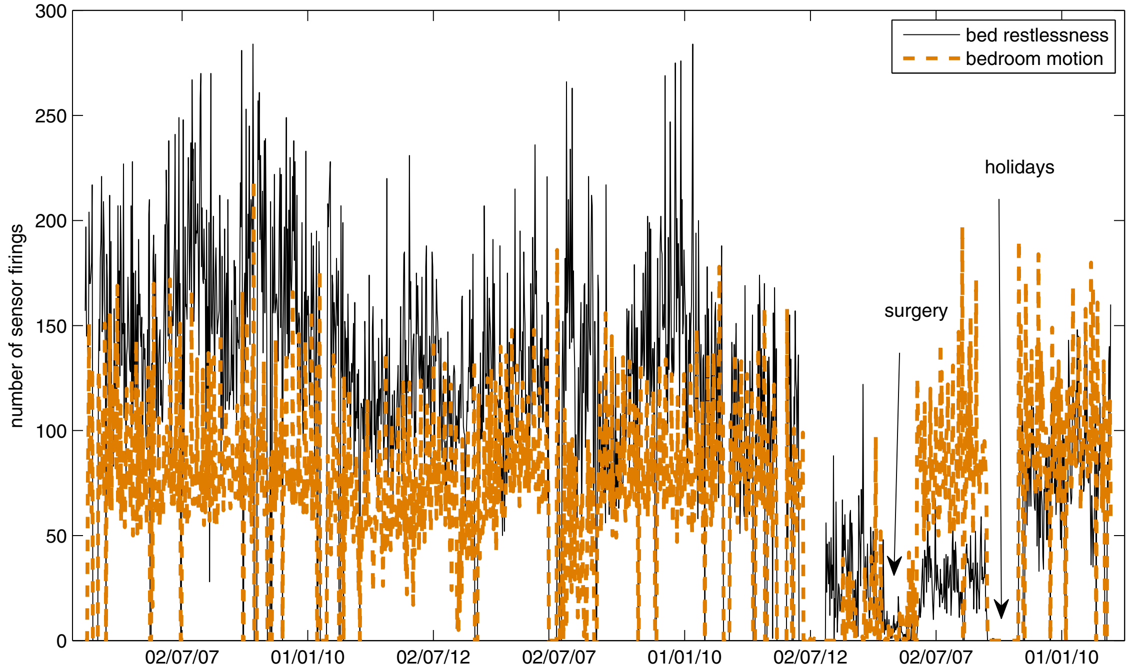


Fig. 5. The nighttime sensor firings for two types of sensors: bed restlessness, and bedroom motion for second case study.

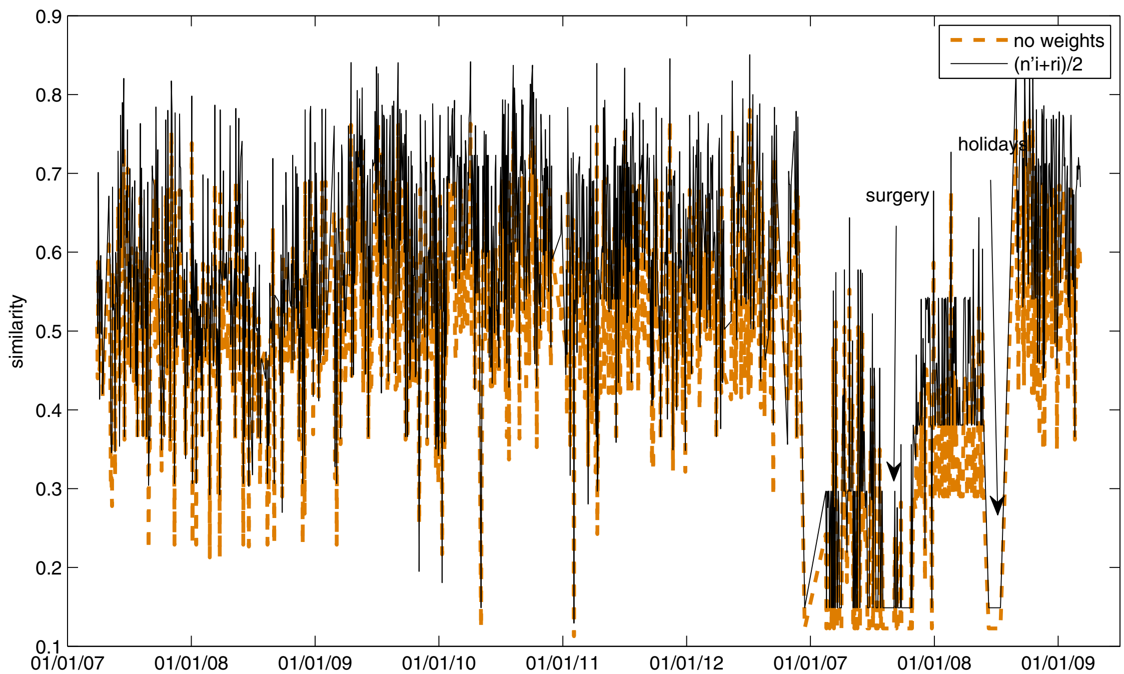


Fig. 7. Similarity between each night and the prototype with no weights and product of the weights $n'_i$ and $r_i$.

prototype was determined from each cluster to represent normal behavior. Cluster weights were suggested as a means to identify more important prototypes for comparison. Resultant prototype-current night comparisons for two long term case studies in an eldercare environment were displayed and discussed, demonstrating that this approach can be used to produce abnormal night alerts for a health care provider.

Clearly, more research is needed both in the basic algorithm development and in the application domain. Future work will investigate other algorithms for clustering, prototype generation, evaluation of similarity between the prototypes and the current description, as well as enhanced clinical evaluations.


## ACKNOWLEDGMENT

This work partially supported by NSF CPS program grant CNS-0931607.

The authors would like to thank Faculty of the Sinclair School of Nursing at University of Missouri and nursing staff at TigerPlace for their valuable comments.


## REFERENCES


[1] D. Anderson, R. H. Luke, J. M. Keller, M. Skubic, M. Rantz, and M. Aud, "Linguistic summarization of video for fall detection using voxel person and fuzzy logic," *Computer Vision and Image Understanding*, vol. 1, no. 113, pp. 80–89, 2009.

[2] ——, "Modeling human activity from voxel person using fuzzy logic," *IEEE Transactions on Fuzzy Systems*, vol. 1, no. 17, pp. 39–49, 2009.

[3] P. Bosc, D. Dubois, O. Pivert, H. Prade, and M. D. Calmes, "Fuzzy summarization of data using fuzzy cardinalities," in *Proceedings of the IPMU 2002 Conference*, 2002, p. 15531559.

[4] D. Dubois, H. Prade, and E. Rannou, "User-driven summarization of data based on gradual rules," in *Proceedings of the Sixth IEEE International Conference on Fuzzy Systems*, vol. 2, 1997, pp. 839–844.

[5] G. Raschia and N. Mouaddib, "Using fuzzy labels as background knowledge for linguistic summarization of databases," in *The 10th IEEE International Conference on Fuzzy Systems 2001*, vol. 3, 2001, pp. 1372–1375.

[6] D. Rasmussen and R. R. Yager, "Finding fuzzy and gradual functional dependencies with SummarySQL," *Fuzzy Sets and Systems*, vol. 106, pp. 131–142, 1999.

[7] M. Ros, M. Pegalajar, M. Delgado, A. Vila, D. T. Anderson, J. M. Keller, and M. Popescu, "Linguistic summarization of long-term trends for understanding change in human behavior," in *Proceedings of the IEEE International Conference on Fuzzy Systems, FUZZ-IEEE 2011*, 2011, pp. 2080–2087.

[8] A. Wilbik, J. M. Keller, and G. L. Alexander, "Linguistic summarization of sensor data for eldercare," in *Proceedings of the IEEE International Conference on Systems, Man, and Cybernetics (SMC 2011)*, 2011, pp. 2595–2599.

[9] M. J. Rantz, R. T. Porter, D. Cheshier, D. Otto, C. H. S. III, R. A. Johnson, M. Aud, M. Skubic, H. Tyrer, Z. He, G. Demiris, G. L. Alexander, and G. Taylor, "Tigerplace, a state-academic-private project to revolutionize traditional long term care," *Journal of Housing For the Elderly*, vol. 22, no. 1, pp. 66–85, 2008.

[10] R. R. Yager, "A new approach to the summarization of data," *Information Sciences*, vol. 28, pp. 69–86, 1982.

[11] A. Wilbik, "Linguistic summaries of time series using fuzzy sets and their application for performance analysis of investment funds," Ph.D. dissertation, Systems Research Institute, Polish Academy of Sciences, 2010.

[12] A. Wilbik and J. M. Keller, "A distance metric for a space of linguistic summaries," *Fuzzy Sets and Systems*, under review.

[13] J. C. Bezdek and R. J. Hathaway, "Vat: A tool for visual assessment of (cluster) tendency," in *Proceedings IJCNN 2002*. IEEE Press, Piscataway, NJ, 2002, pp. 2225–2230.

[14] T. C. Havens and J. C. Bezdek, "An efficient formulation of the improved visual assessment of cluster tendency (ivat) algorithm," *IEEE TKDE*, vol. 23, no. 2, pp. 568–584, 2011.

[15] J. C. Bezdek, R. J. Hathaway, and J. M. Huband, "Visual assessment of clustering tendency for rectangular dissimilarity matrices," *IEEE Transactions on Fuzzy Systems*, vol. 15, no. 5, pp. 890–903, 2007.

[16] S. Theodoridis and K. Koutroumbas, *Pattern Recognition*. Academic Press, NY, 2006, 4th ed.