Evolving fuzzy linguistic summaries in monitoring of bipolar disorder

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Introduction

The motivating example for this work is monitoring sensor data related to the indirectly observed mental disorders. Changes in speech are suggested as measures of changing mental state (e.g., *patients in depression speak more quietly.*) Apart from the proper detection of the change, **methods for communicating about the change to the medical experts are needed**. Our aim is to develop high-level information granules about multiple data streams.

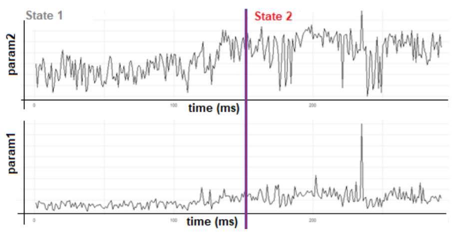

Figure: Monitoring data streams vs indirectly observed states

Possibilistic aggregation

Possibilistic aggregation following [1] aims at preserving the information about data structure, and at the same time, significantly limiting the size of the data to be processed. Given a stream of numerical data $x_1, \ldots, x_N$, its divided into n segments, and each of these segments is further divided into $n_i, i = 1, \ldots, n$ subsegments. Within a given segment all subsegment data are classified into one of $m_i, i = 1, \ldots, n$ classes, defined by the set of class limits $(c_{i,0}, c_{i,1}, \ldots, c_{i,m_i})$. The respective histograms are: $k_{i,j,l}, i = 1, \ldots, n, j = 1, \ldots, n_i, l = 1, \ldots, m_i$, where $k_{i,j,l}$ is the number of observations in the i-th segment and its j-th subsegment that belong to the l-th class.
Histograms are transformed into empirical probability density functions (epdf's) $p_{i,j,l}, i = 1, \ldots, n, j = 1, \ldots, n_i, l = 1, \ldots, m$, where $p_{i,j,l} = k_{i,j,l}/n_{i,j}$, i.e., by piece-wise constant density functions. Next, let us apply the maximum t-conorm, the upper envelope is computed as follows

$$\tilde{p}_{i,l} = \max(p_{i,1,l}, \ldots, p_{i,n_i,l}), i = 1, \ldots, n, l = 1, \ldots, m \tag{1}$$

Let us find an interval (L_i) for whom the upper envelope $(\tilde{p}_{i,1}, \ldots, \tilde{p}_{i,m}), i = 1, \ldots, n$ attains its maximum.
The upper possibilistic envelope is then transformed to the proper possibility distribution $(\pi_{i,1}, \ldots, \pi_{i,m}), i = 1, \ldots, n$ defined on the set of intervals defined by class limits $(c_0, c_1, \ldots, c_m)$ using the following transformation for each $i = 1, \ldots, n$:

$$\pi_{i,l} = \begin{cases} \max(\tilde{p}_{i,1}, \ldots, \tilde{p}_{i,l})/\tilde{p}_i^M & \text{for } l = 1, \ldots, L_{i,M} \\ \max(\tilde{p}_{i,l}, \ldots, \tilde{p}_{i,m})/\tilde{p}_i^M & \text{for } l = L_{i,M}, \ldots, m \end{cases} \tag{2}$$

The fuzzy numbers that represent the possibility distributions for the n considered segments are defined by the following membership functions

$$\mu_i(x) = \begin{cases} \pi_{i,1} & \text{for } c_0 < x \le c_1 \\ \cdots & \cdots \\ \pi_{i,j} & \text{for } c_{j-1} < x \le c_j \\ \cdots & \cdots \\ \pi_{i,m} & \text{for } c_{m-1} < x \le c_m \end{cases} \tag{3}$$

for $i = 1, \ldots, n$. Finally, the center of gravity (COG) is calculated.

$$COG_i = \int_{c_0}^{c_m} x\mu_i(x)dx \Big/ \int_{c_0}^{c_m} \mu_i(x)dx, i = 1, \ldots, m, \tag{4}$$

where $\mu_i(x)$ is defined by (3).

Fuzzy linguistic summarization

Next, we employ fuzzy sets theory to construct high-level information granules in the form of simple statements in natural language based on extended protoforms.
Let $O = \{o_1, o_2 \ldots, o_b\}$ be a set of objects (e.g., speech signal extracted from phone calls). Attributes $\mathcal{A} = \{a_1, a_2 \ldots, a_r\}$ (e.g., loudness of speech) measure their properties. Next, linguistic term set $lst_a = \{l_1^a, \ldots, l_k^a\}$ (e.g., *high loudness*) are defined. We use type-I fuzzy sets to describe linguistic terms, and algorithm with heuristic tree-based search through all linguistic term sets and attributes. Based on the concept of extended protoforms in the sense of Yager and Kacprzyk is defined as

Among R objects from O, Q have P [T]

having quantifier Q (e.g. *most recordings*), qualifier R (e.g., *high level of the loudness feature of speech*), the summarizer P (e.g. *high quality of speech*, and degree of truth $T \in [0, 1]$ defined as:

$$T = \mu_Q\left(\frac{\sum_{i=1}^{n}(\mu_R(x_i) \wedge \mu_P(x_i))}{\sum_{i=1}^{n}\mu_R(x_i)}\right) \tag{5}$$

having $\wedge$ as a t-norm and $\mu_R, \mu_P, \mu_Q : \mathbb{R} \to [0, 1]$ are the membership functions of fuzzy numbers representing the qualifier R, the summarizer P and the quantifier Q, respectively. Thus, properties of attributes (e.g, *low* loudness, *most* records) are modeled as fuzzy numbers, and we construct fuzzy numbers based on quartiles derived from data.

Experiments: Linguistic summaries about possibilisticaly aggregated time series

About data: data streams collected in a prospective study with bipolar disorder patients using a dedicated application (28 patients, 365 days of observation, 86 acoustic attributes). Mental state of a patient was assessed during visits with a psychiatrist.
High-level attributes are defined following [2]: **loudness**, that granulates loudness-related features (i.e., level of loudness and logarithm of the signal energy); **spectrum**, that granulates spectral-related features (i.e., spectral flux, spectral harmonicity, spectral centroid); **quality_of_voice**, that granulates quality of voice-related features (i.e., jitter, shimmer).
About experiments: We investigate how the aggregation of large uncertain stream data impacts summaries.

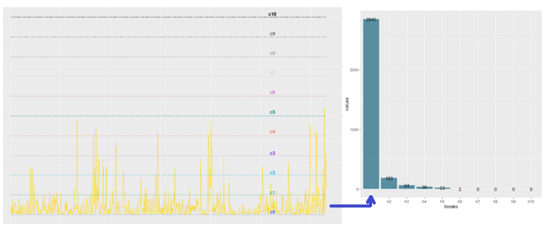

Figure: From a data stream to a histogram

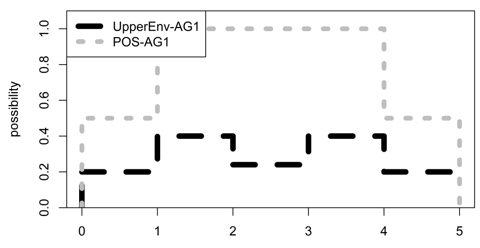

Figure: From a histogram to a possibilistic distribution

Table: Relative linguistic summaries ($T > 0.3$) based on extended protoforms about possibilistically aggregated time series). Results are compared to summaries of non-aggregated data streams from [2].

Relative LS based on extended protoform - DEPRESSION	T_{agg}	
Most calls with low loudness in depression have low quality compared to the state of euthymia.	1.00	
Most calls with medium loudness in depression have high quality compared to the state of euthymia.	0.89	
Most calls with high loudness in depression have high quality compared to the state of euthymia.	1.00	
Most calls with low spectrum in depression have low loudness compared to the state of euthymia.	1.00	
Most calls with medium spectrum in depression have high quality compared to the state of euthymia.	0.32	
Most calls with high spectrum in depression have high loudness compared to the state of euthymia.	1.00	
Most calls with high spectrum in depression have high quality compared to the state of euthymia.	1.00	
Most calls with low quality in depression have low loudness compared to the state of euthymia.	1.00	
Most calls with low quality in depression have low spectrum compared to the state of euthymia.	1.00	
Most calls with medium quality in depression have medium spectrum compared to the state of euthymia.	1.00	
Relative LS based on extended protoform - MANIA	T_{nonagg}	T_{agg}
Most calls with low loudness in mania have low quality compared to the state of euthymia.	1.00	-
Most calls with low spectrum in mania have low loudness compared to the state of euthymia.	1.00	1.00
Most calls with low spectrum in mania have low quality compared to the state of euthymia.	1.00	-
Most calls with medium spectrum in mania have high loudness compared to the state of euthymia.	0.80	-
Most calls with medium spectrum in mania have low quality compared to the state of euthymia.	0.56	0.01
Most calls with high spectrum mania have high loudness compared to the state of euthymia.	1.00	0.55
Most calls with low quality in mania have low loudness compared to the state of euthymia.	1,00	0.92
Most calls with low quality in mania have low spectrum compared to the state of euthymia.	1.00	0.39
Most calls with medium quality in mania have high spectrum compared to the state of euthymia.	-	0.41
Most calls with high quality in mania have high loudness compared to the state of euthymia.	1.00	-
Most calls with high quality in mania have medium spectrum compared to the state of euthymia.	-	1.00
Most calls with high quality in mania have high spectrum compared to the state of euthymia.	1.00	-

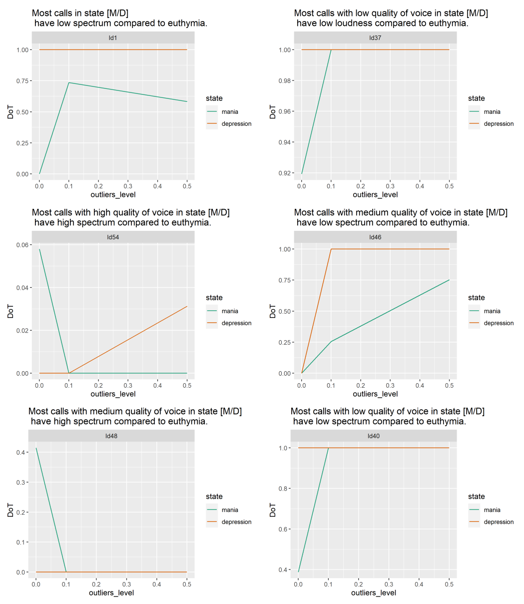

Figure: DoT of exemplary linguistic summaries for aggregated time series in various bipolar disorder states vs. level of removed outliers.

Conclusions

Preliminary results suggest that the proposed method delivers information that supports the understanding of the monitored complex processes.
Further research foresees improvements to the possibilistic aggregation and other approaches to validation of the linguistic summarization.

Bibliography

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