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Exploring the use of Fuzzy Logic models to describe the relation between SBP and RR values

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***Abstract*— In this work, fuzzy logic based models are used to describe the relation between systolic blood pressure (SBP) and tachogram (RR) values as a function of the SBP level. The applicability of these methods is tested using real data in Lying (L) and Standing (S) conditions and generated surrogate data. The results indicate that fuzzy models exhibit a similar performance in both conditions, and their performance is significantly higher with real data than with surrogate data. These results point out the potential of a fuzzy logic approach to model properly the relation between SBP and RR values. As a future work, it remains to assess the clinical impact of these findings and inherent repercussion on the estimation of time domain baroreflex sensitivity indices.**

I. INTRODUCTION

Over the past years, the quantification of arterial-cardiac baroreflex sensitivity (BRS) has been useful in the study of many pathological states, where lower BRS have been associated with increased cardiovascular disease-related mortality [9]. Time domain methods for BRS estimation typically assume linearity between SBP and RR values in baroreflex sequences [5], in baroreflex events [6] or in 10 sec windows [14]. A BRS estimate is then obtained as the mean of the slopes obtained for each segment [5], [14] or as one single global slope after local mean detrend of the data [6].

Erroneous conclusions can be drawn if a SBP and RR global linear relation is considered because it is known that these series exhibit very low correlation [11], [12]. Previous work proposed local mean detrend to address this problem when computing a global slope [6]. This transformation allows to put together the SBP and RR pairs identified in baroreflex related segments obtained at different operating points, i.e., different SBP and RR levels. The underlying hypothesis of local mean detrend is that the BRS slopes obtained along a stationary recording are of similar value, which is not too restrictive because, under stationarity conditions, small operating points changes are expected. Nevertheless, these time domain BRS methods provide one single slope estimate which establishes a proportionality between SBP and RR values, regardless of the SBP value. It is in this context, that fuzzy logic methods can be used to establish a function dependent of the SBP values, not restricted to be linear or of any type. Typically, fuzzy logic methods can be used to describe the unknown inputs-output relationship, combining both empirical rules (that were driven by the problem) and information extracted from the experimental data itself [4]. These methods are easy to interpret since the model output can be written as a weighted linear combination of the system inputs, and constitute a generic framework for uncertainty handling.

The purpose of this paper is to evaluate the application of fuzzy logic methods to describe the relation between spontaneous SBP and RR values with potential repercussions on time domain BRS estimation. The methods are evaluated with real data from the EuroBaVar dataset [10], acquired in Lying and Standing conditions, and tested with generated surrogate data. The rationale of using surrogate data in this work is to generate an ensemble of artificial time series that mimic the original data and are simultaneously consistent with the null hypothesis of no relation between SBP and RR series. Afterwards, fuzzy logic models are applied to both original and surrogate data. If the fuzzy surfaces for real data exhibit significant differences from those of surrogates, then one may reject the underlying null hypothesis and conclude that the fuzzy logic model explains a significant amount of data variance. Contrarily, if there are no significant differences between the fuzzy surfaces estimated from real and from surrogate data then one may not reject the null hypothesis.

II. FUZZY LOGIC MODEL ESTIMATION

The fuzzy logic model was designed as RR=f(SBP), which can be seen as single input single output system.

The fuzzy description is based on $If\ Then$ rules. Basically, the system input is mapped into membership functions that associate an input value to a membership degree. This value is then used to obtain the rule weight and the rule output is used to generate one consequent (the $Then$). Finally, the output of the system is obtained by aggregating all consequents. In this work, the fuzzy logic system was defined as a *Sugeno* model, which considers the system output as a function $z = f(x_1, x_2, ..., x_n)$ [1]. Given the inputs x_j, $j = 1, 2, ..., n$, a typical rule $i = 1, 2, ..., N$ with output z_i can be defined as

$$\text{If } x_j \in F_j^i(x_j), \text{ then } z_i = \sum_{j=1}^{n} a_j^i x_j + c_i, \qquad (1)$$

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where $F_j^i(x_j)$ are fuzzy sets and a_j^i and c_i are constants [7]. Each rule output z_i is then weighted by its firing strength

$$w_i = \prod_{j=1}^{n} \Gamma_{F_j^i(x_j)} \quad (2)$$

where $\Gamma_{F_j^i}$ is a Gaussian membership function defined by its center μ_i and standard deviation σ_i [2]. The final output of the system $\widehat{z}$ is the weighted average of all z_i, computed as

$$\widehat{z} = \frac{\sum_{i=1}^{N} w_i z_i}{\sum_{i=1}^{N} w_i}. \quad (3)$$

The optimal number of rules N and the parameters a, c, μ and σ for each rule $i = 1, 2, ..., N$ were estimated by Adaptive Network Fuzzy Inference System (ANFIS). This method combines backpropagation and least squares minimization and it is generically called an hybrid method [7]. The initial values for μ and σ were obtained using subtractive clustering, which divides the antecedent domain in clusters. The radius σ was defined a priori as a value between 0 and 1, where 1 corresponds to the data range [2].

Figure 1 presents an illustrative application of the fuzzy logic method to the estimation of a real set of SBP and RR values. Figure 1(a) presents the real data superimposing the generated system output, i.e. the fuzzy surface describing the RR as a function of SBP values. This surface was obtained from the membership functions represented in Fig. 1(b), which map the SBP space and associate to each SBP value a membership degree (amplitude of the membership function). The activated rules are then weighted to generate the system output following Eq. 3.

The model performace was evaluated from

$$\delta = \frac{1}{m} \sum_{i=1}^{m} \frac{|z(i) - \widehat{z}(i)|}{|z(i)|} * 100 \ , \quad (4)$$

where $\widehat{z}(i)$ is the estimate of $z(i)$ and m represents the recording length.

III. EXPERIMENTAL DATA

In this work, the methods are illustrated with real data from the EuroBaVar dataset [10]. Additionally, the methods are tested with isodistribution surrogate data generated from the EuroBavar dataset, following general guidelines [13].

A. Real data: EuroBaVar dataset

The EuroBaVar dataset was acquired from 21 subjects in Lying (L) and Standing (S) positions [10]. It contains 46 paired records of spontaneous ECG and arterial blood pressure (ABP) recordings of approximately 10 minutes length and acquired at 500 Hz of sampling frequency. The experimental protocol was designed to ensure stationary conditions, minimizing the disturbance and the noise in the room. Each subject was first recorded in S condition and the recording started after 5 min standing. After followed the L condition and the recording started after 5 min lying. In between conditions, there was a 10 min rest period, when the ABP finger cuff was removed and patients could speak.

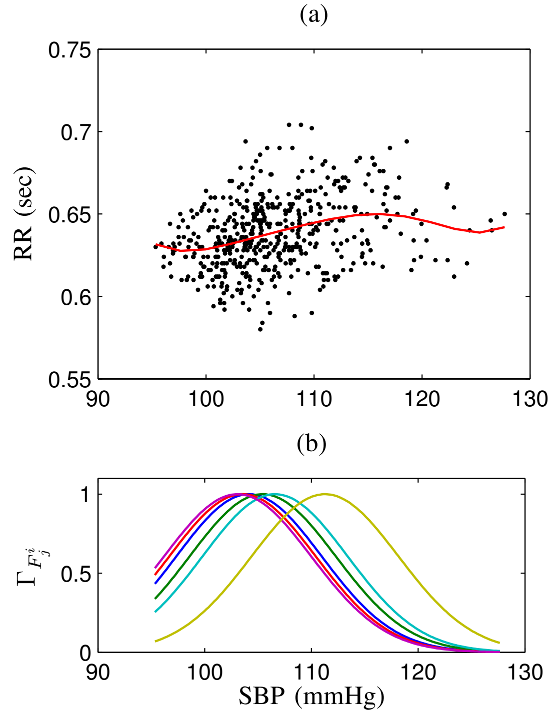

Fig. 1. Dispersion diagram of the first 512 SBP and RR values of the EuroBaVar datafile A001LB, superimposing the estimated fuzzy surface z (a). Membership degree $\Gamma_{F_j^i}$ $(j = 1$ and $i = 1, 2, ..., 6)$ associated to each membership function, according to the SBP input values (b).

The inclusion of 21 heterogenous subjects in this dataset meant to reproduce a wide range of SBP and RR pairs of series, likely to appear in practice. The dataset includes one diabetic subject with evident cardiac autonomic neuropathy and another recently heart transplanted, both classified as cardiac baroreflex failure patients by the Ewing score. In a previous study, these two subjects were identified as presenting the lowest BRS estimates of the dataset [6]. The remaining 19 subjects are 12 normotensive outpatients, 1 untreated hypertensive, 2 treated hypertensive and 4 healthy volunteers. For the interest of this work, three of the 21 subjects were referred as being under the effect of statin medication, which is a form of therapy often used to lower the cholesterol, by blocking the liver from using a substance it needs to produce cholesterol [3].

The lengths of the EuroBaVar SBP and RR series range from 553 to 1218 beats and, to set comparable results, the methods were applied to the first 512 beats of each recording. In accordance with previous studies, the SBP and the RR series were considered with one beat delay, i.e. each SBP value matching with the following RR value [6].

B. Simulated data: Isodistribution surrogate dataset

One isodistribution surrogate file was generated for each EuroBaVar file, following the general guidelines given in [13]. The SBP series was maintained as the original, in order to ensure the same SBP range of values in the real and the corresponding surrogate series. The artificial RR series was generated as to reproduce some statistical properties of the original. In particular, *isodistribution* surrogate RR series were considered, which have the same empirical probability distribution as the real ones, by resampling without replacement the original data. This procedure is equivalent to scramble the original RR values to produce a surrogate series with a random order. As a consequence, the surrogate RR series have the same mean and the same variance as the corresponding real series, but the temporal dependency between consecutive RR values is destroyed and, therefore, isodistribution surrogate RR series present a white noise power spectra. The shuffling in the RR series additionally destroys the relation between SBP and RR amplitudes. For illustration purposes, Fig. 2 presents an example of the real and the corresponding surrogate series.

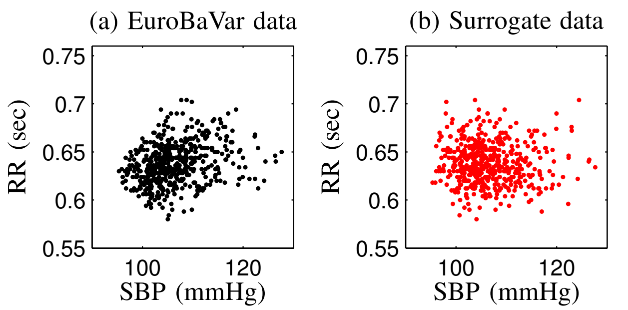

Fig. 2. Dispersion diagram between SBP and RR values of the EuroBaVar datafile A001LB (a) and dispersion diagram between the SBP values and corresponding RR isodistribution surrogate series (b).

IV. RESULTS AND DISCUSSION

Figure 3(a) presents the two-dimensional curves representing the fuzzy mapping from SBP to RR values, for each EuroBaVar datafile. As evidenced by the overlapping of different colors, the fuzzy surfaces for L and for S conditions are difficult to distinguish. This, together with the different SBP ranges for different files, well illustrates the heterogeneity of subjects included in the EuroBaVar dataset. Figure 3(b) shows the fuzzy surfaces estimated for each surrogate datafile. From the comparison with Fig. 3(a), it becomes clear that the fuzzy surfaces estimated from the surrogate data are almost of constant amplitude, indicating that these fuzzy functions are typically modelling the corresponding mean RR values.

The inter-subject comparison was carried out from the pairwise L to S ratio of the estimated curves. The analysis of these ratio functions allows to diminish the intra-subject variability, as different conditions are compared within the same subject and, consequently, the ratio analysis enhances the comparison between fuzzy surfaces obtained from a heterogeneous dataset. For the ratio computation, the estimated fuzzy curves had to be evaluated in the same SBP scale and, in this work, this problem was addressed with linear interpolation assuming a SBP scale ranging from 60 to 200 mmHg in steps of 0.5 mmHg. Figure 4(a) shows the L to S ratio of the fuzzy surfaces obtained for the EuroBaVar

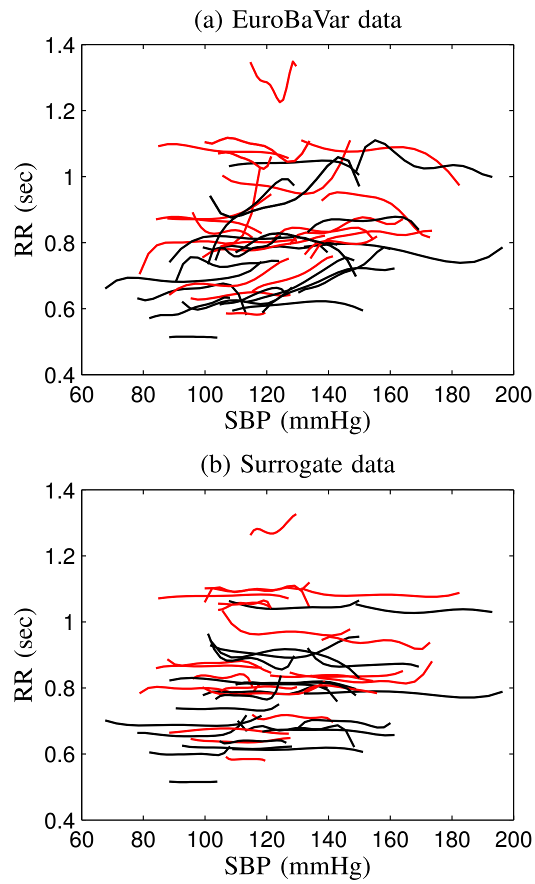

Fig. 3. Plot of the fuzzy surfaces obtained for each EuroBaVar file (a) and for each isodistribution surrogate file (b), distinguishing the recordings acquired in Lying (black) and Standing (red) conditions.

datafiles. Most of the subjects exhibit curves with L to S ratio above 1, in accordance with the fact that RR values are typically higher in L than in S condition [10]. The exception is B001 subject, for which the RR values in L condition were lower than those in S condition for all SBP values.

Figure 4(a) also discloses a linear pattern between the ratio fuzzy surfaces and SBP values, as SBP level increases the ratio fuzzy surfaces provide values more close to 1, indicating that the RR estimates for L and S condition are more similar with increasing SBP values. However, five subjects with SBP range from 90 to 130 mmHg and L to S ratio around one seem to exhibit a different pattern from the remaining. Three of these five subjects were reported as taking statin medication, which might explain these results. Statins lower blood cholesterol by blocking the body's ability to absorb a substance needed to produce cholesterol and this medication was recently reported to lower blood pressure by cholesterol independent mechanisms, being the reduction larger in individuals with higher blood pressure [3]. Indeed, the ratio surfaces for these subjects exhibit RR estimated values comparable to those of the subjects with SBP between 140 and 180 mmHg. Figure 4(b) presents the ratio fuzzy surfaces estimated for the surrogate datafiles. It is possible

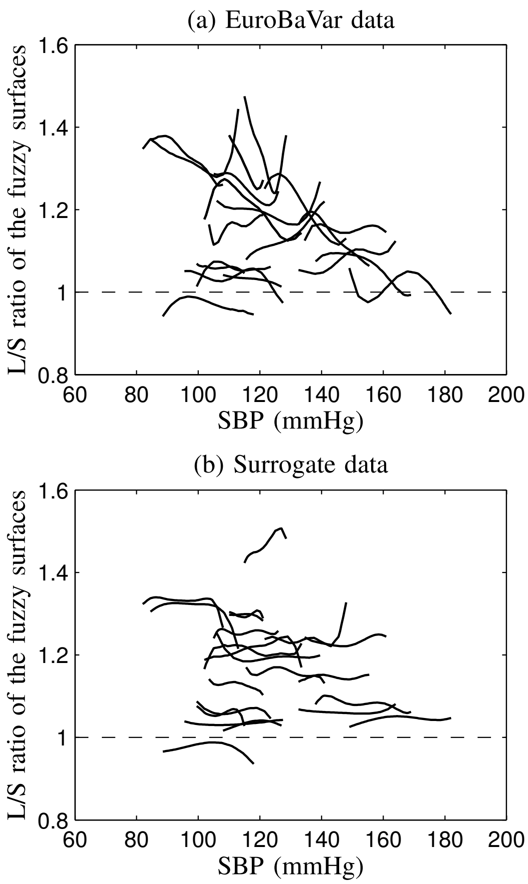

Fig. 4. Plot of the ratio between the fuzzy surfaces estimated for L and S condition (L/S ratio). The ratio curves are obtained for each EuroBaVar file (a) and for each isodistribution surrogate file (b), after linear interpolation in the SBP scale from 60 to 200 mmHg in steps of 0.5 mmHg.

to observe the same decreasing tendency in RR mean values as SBP level increases, what is explained by the fact that surrogate data were produced from SBP and RR series with the same mean and variance of the real dataset. The flatter amplitudes of the ratio fuzzy surfaces for the surrogate data highlights that these fuzzy surfaces are typically modelling the corresponding mean RR interval.

Figure 5 presents the pairwise difference between the errors evaluated for real and surrogate data, showing that lower modeling errors are obtained for the real datafiles. Noticing that these differences are negative for all real/surrogate pairs of files and, consequently, any statistical test would provide the conclusion that the mean/median errors in fuzzy models estimated from real data are significantly lower than those evaluated from surrogate data. Furthermore, there were no significant differences in the errors medians, when comparing different conditions (Mann-Whitney U test, p = 0.59).

V. CONCLUSIONS

This study evidences that fuzzy logic methods may better describe SBP and RR relation and, therefore, have the potential to improve time domain BRS estimation. The results indicate that fuzzy models estimated from real data exhibit

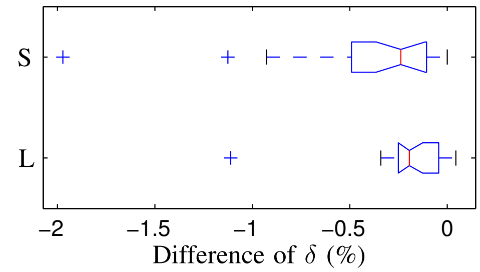

Fig. 5. Boxplot of the pairwise differences between δ evaluated for real and corresponding surrogate data (Eq. (4)), distinguishing L and S conditions. Limits of the box represent quartiles values and notches represent a robust 95% confidence interval for medians for box-to-box comparison.

significantly lower mean/median modeling errors than those estimated from surrogate data. This is because real fuzzy surfaces are much less flatter than surrogate ones, indicating that fuzzy methods may be able to model RR changes connected to SBP alterations, besides the mean value.

Future work will include the quantification of the amount of variance explained by the model. Additionally, the fuzzy model parameters will be evaluated in the ability to identify patient clusters that may help in the identification of pathological characteristics and improve clinical diagnosis.

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