ISSN 2007-9737

Personal Statistics-Based Heart Rate Evaluation Using Interval Type-2 Fuzzy Sets

Edit Laufer

Óbuda University, Bánki Donát Faculty of Mechanical and Safety Engineering, Hungary

laufer.edit@bgk.uni-obuda.hu

Abstract. In today's health-conscious world, patient monitoring is increasingly emphasized both in science and in everyday life. For this reason, personalized, reliable evaluation has been in the focus of science in recent years. In this paper, a fuzzy-based system is presented that can handle blurred boundaries when evaluating physiological values. In order to ensure a personalized evaluation in the model, it takes into account statistics prepared from values measured under identical or nearly identical conditions. The essence of the proposed method is to modify the normal range determined on the basis of medical recommendations by the patient's usual reactions. As a consequence of this modification an even more personalized and realistic result can be generated. This modification is based on the use of interval type-2 fuzzy sets to handle the uncertainty arising from the discrepancy between the doctor's recommendation and the patient's normal reactions.

Keywords. Risk assessment, patient monitoring, fuzzy modeling, personal statistics, interval type-2 fuzzy set.

1 Introduction

In recent decades, a healthy lifestyle has come into focus, and more and more devices are available, which ensure continuous control by measuring physiological parameters. In addition, due to the problem of an aging society, home patient monitoring devices have become necessary and therefore in demand.

At the same time, due to the technological development, the device background is also available due to the wide spread of the Internet of Things (IoT), so the development of a more functionally complex system covering a larger range is also possible [1].

The pandemic of recent years has also highlighted the necessity and usefulness of remote diagnostics, since it was easier to prevent the spread of the virus if patients with less serious illnesses did not have to go to doctors' offices [2].

In medical-related applications, the need for a more flexible handling of data and evaluation often arises, since it is not possible to define sharp boundaries between normal and abnormal values. For this reason, fuzzy logic-based systems are very popular in dealing with these kinds of problems [3]. Fuzzy logic is able to handle uncertainties, imprecision and subjectivity in the data and in the evaluation adequately [4]. Interval Type-2 Fuzzy Logic can handle uncertainty even more effectively than traditional type-1 sets [5].

These systems are under continuous development, as personalized evaluation is of fundamental importance, but at the same time an extremely serious challenge for researchers [6]. In the literature, there are many solutions on how to define personalized value limits and how to personalize the evaluation.

Sieira et al. propose the definition of blood pressure values that can be considered abnormal in order to provide an alternative instead of different methods that contradict each other [7].

Based on the 24-hour recording of the patient's blood pressure, Guzman et al. implemented the classification of blood pressure values using a neuro-fuzzy model, in which the rule was optimized with the help of a genetic algorithm [8]. Ali et al. used type-2 fuzzy sets and fuzzy ontology together in their study in patient monitoring, thereby increasing the accuracy of prediction [9]. Miranda et al. proposed a new approach for evaluating the quality of photoplethysmographic (PPG) signals used in wearable cardiology measurement devices.

The proposed system tunes the interval of type-2 fuzzy sets to the unique characteristics of each person's PPG signals [10]. The main goal of this paper is to develop a personalized fuzzy-based model, which is able to take into account the patient's usual reactions.

In order to achieve this goal, first a personal statistics-based function is created, which uses the measurement statistics made under the identical or nearly identical conditions. Then, this function serves the basis to convert the type-1 fuzzy sets to type-2 in the inference system.

The paper is organized as follows: In Section 2 the investigated original model is introduced. Section 3 describes how the statistics created from the results of previous measurements can be taken into account in the model.

In Section 4 the proposed method is presented in two subsections: Section 4.1 defines the type-1 and interval type-2 fuzzy sets, while in Section 4.2 the personalized interval type-2 membership function creation is illustrated.

In Section 5 a case study is presented: Section 5.1 describes the environment of the measurement, Section 5.2 illustrates the interval type-2 set generation in practice, and in Section 5.3 the measurement results are compared. Finally, Section 6 is devoted to the conclusions.

2 The Original Model

The original model is a hierarchical fuzzy inference structure, which is used to evaluate the current risk level of the patient's activity taking into account the current physiological values, and the characteristics of the motion form (frequency, intensity, duration) and environmental conditions as well [11].

This paper focuses on the subsystem, which is responsible for the evaluation of the physiological parameters (see Fig. 1). In order to ensure flexible, patient-specific measurement, the number and type of the input parameters can be adjusted depending on the current circumstances (current condition of the patient, available devices, medical recommendations, etc.). The dynamic choice of the number of parameters is indicated by their numbering in the diagram (*param_1*,..., *param_i*,..., *param_n*, where *n* is the number of the parameters to be measured).

The original model under investigation is a Mamdani-type inference system in which the traditional type-1 membership functions are used throughout the system.

The personalized evaluation in the model is provided by a personal profile, which contains all the necessary information related to the patient. Among other things, it contains the characteristics of the parameters to be measured, the usual forms of activity, the value limits determined on the basis of medical recommendations for physiological characteristics, previous measurements, etc.

The parameters of the fuzzy sets that form the partition of the input parameters in the model can be adjusted individually based on the personal profile. This personalization can be further improved if the statistics available from previous measurements are used in membership function tuning.

3 Statistics-Based Function Creation

In order to make the personalized evaluation more effective, the basic idea is to take into account the results of the patient's previous measurements under the same or nearly identical conditions (resting heart rate, intensity and duration of the activity, sampling frequency) [11].

These measured values are stored together with all necessary parameters in a personal profile. First, based on these values, a histogram is created that represents the previous reactions of the patient under the specific conditions.

Then, a piecewise linear fuzzy function is fitted to this histogram in order to be able to tune the medical recommendation-based fuzzy sets. The function value of the breakpoints of the fitted fuzzy function is determined based on the histogram values using (1), and illustrated in Fig. 2.

The resulting function still needs to be normalized, since the membership values must be kept in the universe, considering the maximum value as 1:

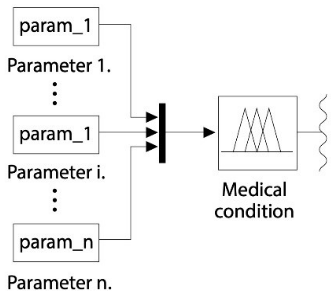

Fig. 1. Structure of the subsystem Medical condition

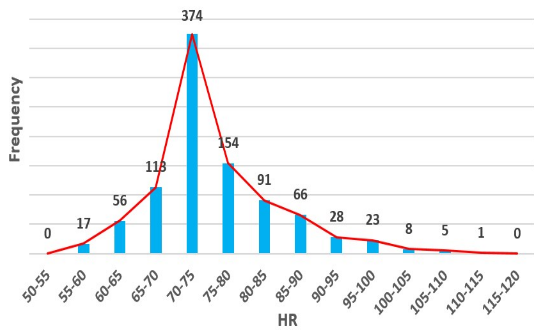

Fig. 2. Structure of the subsystem Medical condition

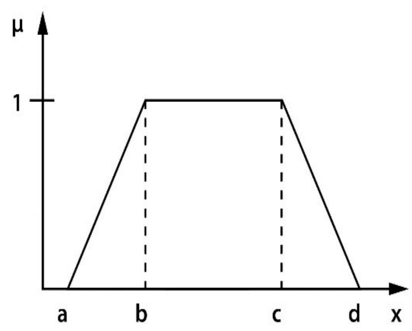

Fig. 3. Type-1 membership function

$$\mu_H(x) = \begin{cases} 1 \quad if \quad H(x_i) = sup\big(H((x))\big) \\ \mu(x_i) + \dfrac{\mu(x_i) - \mu(x_{i+1})}{x_i - x_{i+1}}(x - x_i) \quad otherwise, \end{cases} \tag{1}$$

where $i=1,\ldots,n$, n is the number of the histogram values; x_i, $\mu(x_i)$ and x_{i+1}, $\mu(x_{i+1})$ are the coordinates of the adjacent breakpoints; normalized values are calculated by $\mu(x_i)=y_i/max(H(x))$, and y_i denotes the histogram value belonging to interval i.

4 The Proposed Interval Type-2 Set-based Method

4.1 Type-1 and Interval Type-2 Fuzzy Sets

In the original system trapezoidal type-1 fuzzy sets are used as it is defined in (2) and illustrated in Fig. 3:

$$\mu_{A_i}(x) = \begin{cases} 0 & x \le a_i \\ \dfrac{x - a_i}{b_i - a_i} & a_i \le x \le b_i, \\ 1 & b_i \le x \le c_i \\ \dfrac{d_i - x}{d_i - c_i} & c_i \le x \le d_i \\ 0 & d_i \le x \end{cases} \tag{2}$$

where a_i, b_i, c_i, d_i are the parameters of the fuzzy sets [12]. These parameters ensure the flexibility of the system, because they can be adjusted to the medical recommendations.

In certain cases, type-1 sets prove to be insufficient for modeling uncertainty, because the uncertainty in the function value should also be modeled. In these cases, interval type-2 fuzzy sets are used, which are able to handle this issue.

With this approach, instead of an exact membership value, an interval can be assigned to each element, which represents the membership range of the given element, i.e., $A : X \to E([0,1])$, where $E([0,1])$ denotes the set of closed intervals on the interval [0,1, 13].

Interval type-2 sets are represented by two curves, which define the lower and upper limits, as illustrated in Fig. 4. In the figure the lower fuzzy sets parameters are a_L, b_L, c_L, d_L , and the parameters of the upper membership function are a_U, b_U, c_U, d_U, respectively.

In the proposed model the goal is to find the appropriate interval type-2 fuzzy sets to obtain a more realistic result.

4.2 Interval Type-2 Fuzzy Set Generation

In order to determine the parameters of the interval type-2 sets, the statistics-based function should first be simplified. During the simplification, the maximum point of the simplified function (where $\mu(x) = 1$) was determined according to the maximum value of the histogram, and the 0-breakpoints were defined based on the relevant values of the histogram (i.e., where at least 5% of the values can be found) [14]. The function part between the breakpoints determined based on the above can be defined by (3). Since only the right-hand side of the function is relevant to the tuning of the normal-range membership function, only the equation describing this part is provided:

$$f(x) = \frac{x_0 - x}{x_0 - x_{max}}, \tag{3}$$

where x_0 is the 0-breakpoint, and x_{max} is the maximum point parameter.

Next step is the determination of the lower and upper functions of the interval type-2 fuzzy set using the above defined simplified function. The right-hand parameters of the upper function of the interval type-2 set defining the normal range can be calculated using (4), (5) based on the simplified function definition:

$$c_U = x_{max} + \frac{c_N - x_{max}}{2}, \tag{4}$$

$$d_U = x_0 + \frac{d_N - x_0}{2}, \tag{5}$$

where c_N and d_N are the membership function parameters of the original normal-range membership function. While, in the case of the lower function right-hand parameters are identical with the simplified statistics-based function, i.e, $c_L = x_{max}$ and $d_L = x_0$.

When converting from a type-1 to an interval type-2 system, the parameters of the other upper functions (covering the range of the input in question) are determined by shifting the type-1 functions to the left by $\Delta c_i = c_N - c_U$, and $\Delta d_i = d_N - d_U$. In order for the sets to be symmetric, it is satisfied that $\Delta d_i = \Delta a_i \quad and \quad \Delta b_i = \Delta c_i$. While the parameters of the lower functions can be calculated as follows:

$$\begin{aligned} a_{L_i} &= a_{U_i} + \left(a_{U_i} - x_0\right) \\ b_{L_i} &= b_{U_i} + \left(b_{U_i} - x_{max}\right) \\ c_{L_i} &= c_{U_i} - \left(c_{U_i} - x_{max}\right)' \\ d_{L_i} &= d_{U_i} - \left(d_{U_i} - x_0\right) \end{aligned} \tag{6}$$

where *i=1,…,n*, *n* is the number of fuzzy sets covering the input domain.

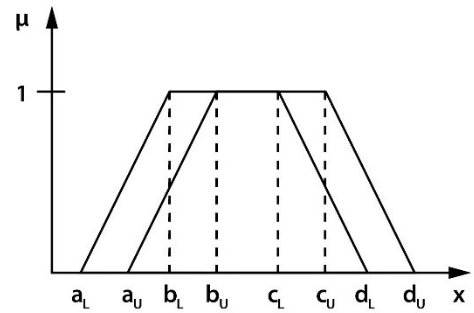

Fig. 4. Interval type-2 membership function

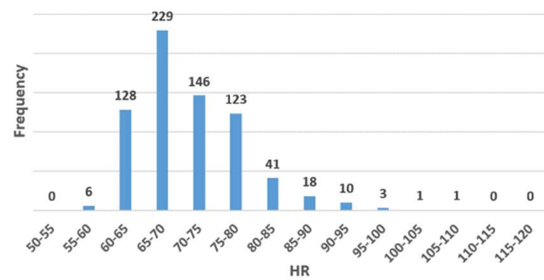

Fig. 5. Histogram of the previous measurements [14]

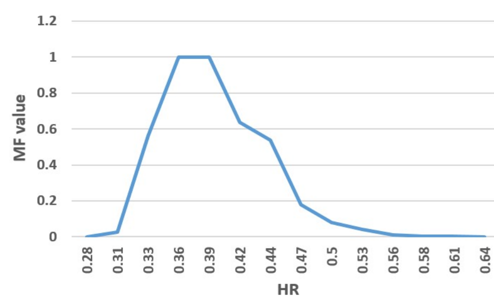

Fig. 6. The fuzzy function fitted to the histogram [14]

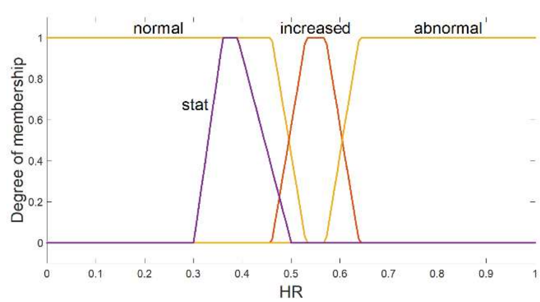

Fig. 7. Medical recommendations and statistics-based membership function for Heart-rate values

Table 1. Membership values for type-1 and interval type-2 functions (N: Normal, I:Increased)

	Type-1		Interval type-2	
HR	**N**	**I**	**N**	**I**
0.38	1	0	1	0
0.39	1	0	[0.875,1]	0
0.4	1	0	[0.75,1]	0
0.41	1	0	[0.625,1]	0
0.42	1	0	[0.5,1]	0
0.43	1	0	[0.38,0.88]	[0,0.125]
0.44	1	0	[0.25,0.45]	[0,0.25]
0.45	1	0	[0.13,0.63]	[0,0.375]
0.46	1	0	[0,0.5]	[0,0.5]
0.47	1	0	[0,0.375]	[0.11,0.625]
0.48	0.83	0.17	[0,0.25]	[0.222,0.75]
0.49	0.67	0.33	[0,0.125]	[0.33,0.875]
0.5	0.5	0.5	0	[0.444,1]
0.51	0.33	0.67	0	[0.555,1]
0.52	0.17	0.83	0	[0.667,1]
0.53	0	1	0	[0.778,1]

5 Case Study

5.1 Measurement Environment

In this section a case study is presented, in which the personal profile of a 37 years old woman is considered. The Mamdani-type inference system is implemented in Matlab Fuzzy Logic Designer using the patient specific medical recommendations as type-1 fuzzy sets. Then, interval type-2 fuzzy sets are generated based on the previous measurements using the statistics-based function to determine the parameters of the lower membership function.

Those previous measurement results were taken into account, where the duration of the movement was 1 hour, the sampling frequency was 5s, and the resting heart-rate, HR_{rest}=70bpm. In this case study the subsystem Medical condition was in the focus, and the proposed statistics-based transformation is applied for the input Heart-rate. The interval type-2 fuzzy sets of the other inputs in the subsystem are generated based on an average deviation between the lower and upper membership function parameters.

However, statistics-based transformation could be extend for the other inputs as well to improve the reliability of the system.

5.2 The Proposed Interval Type-2 Fuzzy Set Generation

As a first step of the transformation process, a histogram is generated from the previous measurement data before starting the measurement, as illustrated in Fig. 5.

Based on the values of the histogram, a piecewise-linear function is created. The, values of this function must be normalized in accordance with the fuzzy membership functions so that they must fall into the range [0,1].

Table 2. System output for type-1 and interval type-2 functions (Systolic Blood Pressure = 135 Hgmm, Dyastolic Blood Pressure = 80 Hgmm)

HR%	Type-1	Interval type-2
0.38	0.243	0.222
0.39	0.243	0.224
0.4	0.243	0.226
0.41	0.243	0.228
0.42	0.243	0.23
0.43	0.243	0.254
0.44	0.243	0.282
0.45	0.243	0.32
0.46	0.243	0.42
0.47	0.243	0.365
0.48	0.268	0.365
0.49	0.291	0.367
0.5	0.311	0.369
0.51	0.33	0.363
0.52	0.347	0.357
0.53	0.363	0.361

The input domain of the fuzzy function has to transform as well, it should be given as a percentage of the patient's maximum heart-rate value, instead of the exact heart-rate values. The resulting function is shown in Fig. 6.

The evaluation is based on type-1 membership functions created on the basis of medical recommendations. For this 37 year old patient the Heart-rate functions are presented in Fig. 7, including the simplified statistics-based function (stat) as well, which is needed to transform these type-1 sets into interval type-2 sets.

Based on the type-1 fuzzy sets and the simplified statistics-based function the new parameters of the type-2 fuzzy set can be determined using the method described in Section 3.2.

When the lower and upper membership function parameters of the type-2 set are available, the transformation can be performed. In the case of the examined patient, the functions shown in Fig. 8.

5.3 Comparison of the Results

This subsection is devoted to present some numerical results to illustrate the effect of transforming a system using type-1 fuzzy sets into a system using interval type-2 fuzzy sets.

Since the transformation mostly affects the determination of the normal range, the changes observed in this input domain were primarily in focus.

First, the membership function values are presented using the original type-1 medical recommendation-based fuzzy functions compared to the membership values of the modified interval type-2 fuzzy set.

This comparison is illustrated in Table 1, in which the input parameter is the current heart-rate (HR) of the patient, in the percentage of her maximum heart-rate value. For the above reason membership functions “Normal” and “Increased” are considered.

In Table 2, the results of the subsystem “Medical condition” are summarized for the same input values as Table 1. Since the statistics-based tuning was applied for the fuzzy sets representing the HR values, only the values of this input were changed, the other two inputs were taken into account with constant values (Systolic blood pressure was 135 Hgmm, diastolic blood pressure was 80).

It is clear from the tables that in the case of the proposed type 2 sets, the membership value of the normal set begins to decrease earlier at the same HR value as in the case of the type 1 model (see Table 1). This is because, based on statistics, the patient's usual values are lower than the value specified in the medical recommendation.

This change can be considered an advantageous feature of the new system, since it takes into account the patient's usual values as well. This means that it indicates the deviation even if the measured value is in accordance with the medical recommendation, but a deviation is already experienced compared to the patient's previous values.

A similar trend can be seen when examining the outputs of the subsystem (see Table 2), since the proposed interval type-2 system estimates a higher risk factor in the input range affected by the modification compared to the traditional type-1 fuzzy system. Overall, it can be stated that the proposed system is more secure.

6 Conclusions

Nowadays, as a consequence of the increasingly common health-conscious life-style, patient monitoring devices based on wearable devices are gaining more and more attention. However, patient-specific assessment remains a serious issue for experts.

In this paper a possible solution for this problem is presented. The main idea is to incorporate statistics from the patient’s previous measurements into the evaluation model. These statistics are used to transform the type-1 fuzzy sets of the original Mamdani inference system to interval type-2 fuzzy sets, i.e., the type-1 sets representing medical recommendations can be converted into interval type-2 sets using the characteristic reactions of the patient as well.

As the results show, the proposed system is safer, as it estimates a higher risk level even when the measured value does not exceed the value limit specified in the medical recommendation, but the patient's typical reactions do.

In the presented case study, the subsystem Medical condition was in the focus, and the proposed statistics-based transformation is applied for the input Heart-rate. However, statistics-based transformation could be extend for the other inputs as well to improve the reliability of the system.

Acknowledgments

The research was supported by the Óbuda University and by the Fuzzy Systems Scientific Work Group at the Bánki Donát Faculty of Mechanical and Safety Engineering.

References

1. **Akkaş, M. A., Sokullu, R., Ertürk-Çetin, H. (2020**). Healthcare and patient monitoring using IoT. Internet of Things, Vol. 11. DOI: 10. 1016/j.iot.2020.100173B**.**
2. **Oliver, J., Dutch, M., Rojek, A., Putland, M., Knott, J. C. (2022).** Remote COVID-19 patient monitoring system: a qualitative evaluation. BMJ Open, Vol. 12: e054601. DOI: 10.1136/ bmjopen-2021-054601.
3. **Sram, N., Takács, M. (2016).** A type-2 fuzzy-based approach to the Minnesota code. Acta Polytechnica Hungarica, Vol. 13, No. 7, pp. 103–122.
4. **Portik, T., Pokorádi, L. (2013).** Fuzzy rule-based risk assessment with summarized defuzzyfication. Proceedings of the XIIIth Conference on Mathematics and its Applications, pp. 277–282.

5. **Macura, D., Laketić, M., Pamučar, D., Marinković, D. (2022).** Risk analysis model with interval type-2 fuzzy FMEA—case study of railway infrastructure projects in the Republic of Serbia. Acta Polytech, Hung, Vol. 19, pp. 103–118.
6. **Moazeni, M., Numan, L., Brons, M., Houtgraaf, J., Rutten, F. H., Oberski, D. L.,**
7. **Aarts, E. (2023).** Developing a personalized remote patient monitoring algorithm: a proof-of-concept in heart failure. European Heart Journal-Digital Health**.** DOI: 10.1093/ehjdh/ ztad049.
8. **Sieira, M. C., Ricart, A. O., Estrany, R. S. (2010).** Blood pressure response to exercise testing. Apunts Med Esport, Vol. 45, No. 167, pp. 191–200.
9. **Guzman, J. C., Melin, P., Prado-Arechiga, G. (2017).** Design of an optimized fuzzy classifier for the diagnosis of blood pressure with a new computational method for expert rule optimization. Algorithms, Vol. 10, No. 3, pp. 79. DOI: 10.3390/a10030079.
10. **Ali, F., Islam, S. R., Kwak, D., Khan, P., Ullah, N., Yoo, S. J., Kwak, K. S. (2018).** Type-2 fuzzy ontology–aided recommendation systems for IoT–based healthcare. Computer Communications, Vol. 119, pp. 138–155. DOI: 10.1016/ j.comcom.2017.10.005.
11. **Miranda, J. A., López-Ongil, C., Andreu-Perez, J. (2023).** Personalised and adjustable interval type-2 fuzzy-based PPG quality assessment for the edge. arXiv preprint arXiv:2309.13464. DOI: 10.48550/arXiv.23 09.13464.
12. **Tóth-Laufer, E., Várkonyi-Kóczy, A. R. (2014).** Personal-statistics-based heart rate evaluation in anytime risk calculation model. IEEE Transactions on Instrumentation and Measurement, Vol. 64, No. 8, pp. 2127–2135. DOI: 10.1109/TIM.2014.2376111.
13. **Ross, T. J. (2004)** Fuzzy Logic with engineering applications. Second Edition, John Wiley &Sons.
14. **Liang, Q., Mendel, J. M. (2000).** Interval type-2 fuzzy logic systems: theory and design. IEEE Transactions on Fuzzy systems, Vol. 8, No. 5, pp. 535–550. DOI: doi: 10.1109/91.873577.
15. **Tóth-Laufer, E., Nagy, I. (2018).** Effect of the different membership function fitting methods in personalized risk calculation. 2018 IEEE 22nd International Conference on Intelligent Engineering Systems (INES), IEEE, pp. 127–132). DOI: 10.1109/INES.2018.8523860.

Article received on 15/05/2023; accepted on03/08/2023.
Corresponding author is Edit Laufer.