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Customization of the Physiological Parameter Assessment Using Fuzzy Logic

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Abstract — **Effective health monitoring is very important for individuals engaged in sports and physical activities due to the diverse physiological responses exhibited by each participant. Traditional methods often fail to deal with the complexity of individual health profiles, highlighting the necessity for personalized assessment methods. In this paper, a hierarchical fuzzy model is presented, which is intended to assess the risk level of the current physical activity. In order to personalize the evaluation statistics-based approach was used to tune the membership functions. The model presented provides both numerical and linguistic assessments of risk, demonstrating consistent trends between improved membership functions and medical recommendations. Extensions for future work are also included.**

Keywords: fuzzy logic, risk assessment, sports activity, patient monitoring, membership functions, statistical evaluation.

1. INTRODUCTION

In today's world, the positive outcomes of regular exercise in preventing illness, aiding in recovery, and promoting an active lifestyle in general are universally recognized. Engaging in sports promotes an active lifestyle and enhances the overall quality of life [1].

Regular physical exercise offers numerous benefits for overall health and well-being. It improves cardiovascular health by strengthening the heart and reducing the risk of heart disease and high blood pressure, while also aiding in weight management through calorie burning and muscle building. Exercise boosts mood by releasing endorphins, reduces stress, anxiety, and depression, and enhances energy levels by improving circulation and nutrient delivery. Additionally, it strengthens muscles and bones, promotes better sleep, and enhances brain health and cognitive function. Exercise also boosts the immune system, reduces the risk of chronic diseases, and increases longevity, ultimately leading to a higher quality of life through improved mobility, reduced pain, and increased independence [2].

However, these benefits depend on individual capabilities and medical advice. Failure to consider personal fitness levels and medical guidance can result in potential dangers, such as overexertion or injury. Engaging in activities beyond our current capabilities and exercising with incorrect duration, frequency, and intensity levels can be counterproductive and fail to yield beneficial results. Factors like chronic illnesses, age, and other relevant sub-factors must be carefully evaluated to ensure that participating in sports remains a safe and beneficial activity, rather than exacerbating existing health issues.

It is noticeable that in contemporary times, patient monitoring devices have become indispensable in our daily routines [3]. The widespread adoption of Internet of Things (IoT) technology has led to the development of increasingly sophisticated systems with broader functionality. Consequently, the continuous monitoring and recording of physiological data have become accessible to a wider audience. As a result, research focus has intensified on evaluating physiological parameters, aiming to enhance safety in everyday life by enabling prompt recognition of any health deterioration. This research field's significance has been particularly highlighted by the COVID-19 pandemic, emphasizing the critical need for remote diagnosis. Utilizing such applications has played a pivotal role in curbing the spread of the virus by minimizing visits to medical facilities for less severe illnesses [4]. IoT devices have the capacity to facilitate remote health monitoring and emergency notification systems. From basic blood pressure and heart rate monitors to sophisticated gadgets capable of overseeing specialized implants like pacemakers, Fitbit electronic wristbands, or advanced hearing aids, the spectrum of health monitoring devices is vast [5]. Specialized sensors establish a network of intelligent devices capable of gathering, processing, transmitting, and analysing crucial data across various environments. This includes linking in-home monitoring devices with hospital-based systems, enhancing connectivity and data utilization [6]. Nonetheless, health monitoring systems prove beneficial not solely for the elderly with chronic conditions but also for individuals coping with cardiac conditions [7][8]. Moreover, such systems can prove advantageous for healthy patients as well, aiding in monitoring their physical activity and assessing the risk or their performance level [9]. The key features of health monitoring systems include utilization of wireless communication, portability, non-invasiveness, ease of use, compactness, and minimization of device count [10]. Overall, the integration of IoT in healthcare plays a crucial role in managing chronic illnesses and in disease prevention and control. Remote monitoring becomes feasible through robust wireless solutions. This connectivity empowers healthcare professionals to capture patient data and employ sophisticated algorithms in health data analysis [11].

A significant challenge of creating patient monitoring systems lies in medical applications, where numerous factors defy simple quantification and the boundaries delineating normal, increased, and abnormal values remain ambiguous and vague. Medicine frequently applies linguistic descriptions. Soft computing techniques prove highly valuable in addressing the challenges encountered in medical applications. The fuzzy approach demonstrates significant utility and efficiency in these domains and their counterparts, such as risk management. Its compatibility with human language and ability to manage uncertainty, imprecision, and subjectivity in both data and evaluation processes make it particularly valuable. Fuzzy-based methods typically yield more realistic results presented in a user-friendly format [12] [13].

Another challenge in constructing patient-specific models stems from the system's behaviour is that it is influenced by numerous factors, some of which may be unidentified, with complex and often unknown interactions among them [14]. While the membership functions of the fuzzy model can be tailored in a patient-specific manner by accounting for the maximum number of relevant factors, it remains challenging to fully consider the combined effect of all significant factors unique to individual patients.

Thus, various approaches aim to minimize the number of inputs while considering a wide range of influential factors. Patient specificity can be ensured through different methods which include utilizing personal medical recommendations [15] as well as establishing thresholds via equations or tables derived from statistical data on personal characteristics like age, sex, and fitness level, aggregating results from patients with similar traits [16][17]; finally, membership functions (MFs) can be tuned based on the input-output pairs with fuzzy-neural system [18] [19].

The main goal of this study is to develop a risk assessment model in which the evaluation is customized according to the patient's characteristics. For this reason, statistics-based approaches are studied and built in the evaluation process. To handle this issue, authors focus on a specific subsystem, namely, the "Current physical status", because it is where user-specific tuned membership functions are most crucially required.

This paper is organized as follows, in section 2, the overall hierarchical model structure is presented. Section 3 shows the investigated subsystem structure – 'current physical status'. Section 4 presents the proposed statistics-based evaluation followed by a case study in section 5. Section 6 discusses the results of the use of the personal statistics. Section 7 draws the conclusion.

2. The Overall Model Structure

The overall model has a hierarchical multilevel clustered structure, which facilitates both model expansion and simplification of the evaluation process. The evaluation uses a Mamdani-type fuzzy inference system. The model's structure aligns closely with the logic of the evaluation process. The classification of input parameters relies on the logical connections between them. Three primary groups have been delineated, indicating whether they pertain to the patient's medical condition, characterize their sport activity behaviour, or describe the environmental conditions.

Within the primary groups, further classification is possible based on the permanence of the parameters. These include permanent parameters (such as sex), quasi-permanent or infrequently changing factors (such as chronic diseases and occupation), and real-time variables (for example, blood pressure and heart rate). The structure is derived from the model outlined in [20], depicted in Figure 1.

On the left-hand side of the diagram are the identified risk factors influencing the calculated temporal risk level. The middle section of the figure delineates which parameters belong to each risk factor group through three blocks. The highest level of the hierarchy is situated on the right-hand side, responsible for computing the actual risk level based on input from the problem groups. The main groups constitute the subsystems of the model, with their contributions to the overall risk level computed separately during processing. The subsystems, along with their varying parameters, undergo real-time evaluation, while the remainder of the model is evaluated offline before real-time assessment begins.

The medical condition of the patient is characterized by the Medical Condition group, which represents the most crucial and intricate subsystem. Personal conditions primarily determine the patient's load capacity, and most interactions among input factors occur within this group. The first input factor in this group is Disease Condition, encompassing chronic diseases such as hypertension, diabetes, and cardiac diseases, among others. While these diseases are quasi-permanent factors, their severity may vary over time. The second input is the Current Physical Status subsystem, which offers information about the patient's current condition. This assessment is based on measured parameters such as heart rate, systolic and diastolic blood pressure. Additionally, associated metrics and factors influencing these parameters are utilized as input to construct patient-specific membership functions.

The input factor, Basic Physical Information, serves to characterize the fundamental attributes and living circumstances of the patient. Mental stress holds particular significance within this subsystem. Despite exerting a weaker influence on physiological parameters compared to physical activity, it can notably elevate heart rate. To delineate the sport activity habits of the patient, the Activity Load subsystem is employed. Its subfactors delineate the intensity, duration, and frequency of the patient's activity, specifying how vigorously (Intensity), how long per occasion (Duration), and how often per week (Frequency) the activity is performed. Finally, the third main subsystem Environmental condition uses combined subfactors to characterize the environment. The temperature is combined with the actual humidity (TH) and wind (TW) because of their influence on thermal sensation. This group has more importance in the case of outdoor sports, but humidity and temperature together can influence the risk level indoors too [21].

The parameters of the group "Current physical status" subsystem, which is the main topic of this paper, changes in real-time. Monitoring these values ensures continuous control. Therefore, there is a need to customize it for each patient separately, i.e., a flexible risk assessment framework is required.

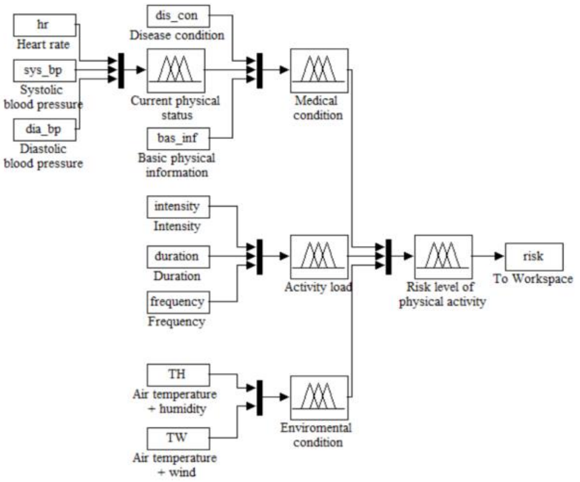

Figure 1. The fuzzy model structure

3. The Current Physical Status Subsystem

The initial parameter that was considered is the heart rate, which represents the number of myocardial contractions per minute. It is influenced by various external and internal factors, with numerous interactions among them. Patient-specific membership functions related to this parameter can be defined based on the maximum heart rate, representing the highest attainable value under physical exertion. Approximately 30 factors can affect this threshold, including age, sex, weight, time of day, environmental conditions, physical fitness, activity intensity, mood, medications, and certain medical conditions [22]. Instead of relying solely on the maximum heart rate, it is customary to utilize a predictive maximum heart rate estimated by the OwnZone function of the Polar heart rate monitoring device. This prediction is derived from personal parameters such as age, sex, and the patient's resting heart rate [23]. The OwnZone function leverages heart rate variability, which can be assessed using the Polar device or an oscillometric blood pressure monitor [24]. Obtaining the predicted maximum heart rate requires only a brief 5-minute test before monitoring, unlike traditional methods such as progressive exercise testing or VO2max measurement, which are typically conducted in laboratory settings and may not be feasible for all individuals, especially those with cardiovascular conditions or elderly individuals on medications affecting heart function and circulation. Additionally, this method offers the advantage of daily or multiple daily assessments, allowing for consideration of fluctuations in the maximum heart rate during evaluation.

Understanding the training target is crucial, as it determines the optimal heart rate and associated risk level. The target heart rate zone, expressed as a percentage of the maximum heart rate, is detailed in figure 2. This represents the original Polar zone where Vlow (<50%), light (50-60%), medium (60-70%), mhigh (70-85%), high (85-95%), vhigh (>95%).

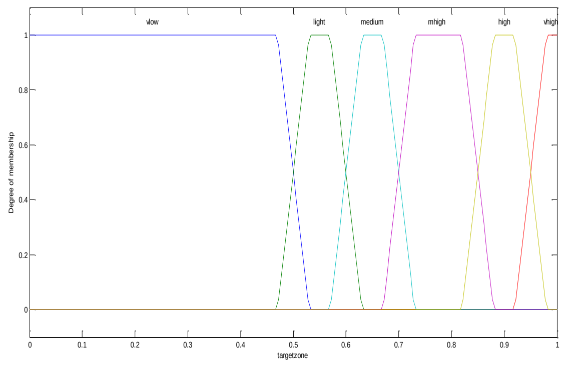

Figure 2. Target zones

This percentage indicates the permissible intensity level for the individual. It varies based on the activity's objective (rehabilitation or prevention), the individual's athletic background (regular athlete or beginner). Consequently, personalized zone limits can be computed, and membership functions can be adjusted to accommodate the specific characteristics of the individual patient.

Nevertheless, limits can be specified depending on the patient’s condition. Figure 3 shows a case for a patient under medical treatment, debilitated, cardiovascular disease, respiratory disease or rehabilitation; here, from the original target zones, vlow would be the appropriate one based on the table, that’s why it became the target (<50%), mhigh is the original light zone (50-60%), vhigh is the merge of the rest (medium, mhigh, high, vhigh) (>60%)).

Figure 4 shows a case for a beginner level sports individual; here, from the original target zones, light or medium would be the appropriate one based on the table, that’s why target zone is created merging the vlow, light and medium zones (<70%), mhigh is the original mhigh zone (70-85%), vhigh is the merge of the rest (high, vhigh) (>85%). Figure 5 shows a case in which a person exercises regularly; here, from the original target zones, mhigh would be the appropriate one based on the table, that’s why the target zone defined as a merge of the vlow, light, medium and mhigh zones (<85%), mhigh is the original high zone (85-95%), vhigh is the original vhigh (>95%).

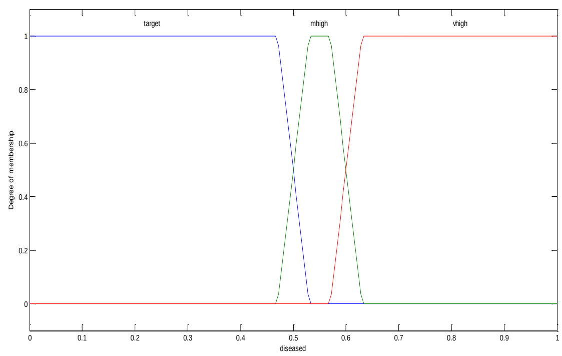

Figure 3. Illness, rehabilitation

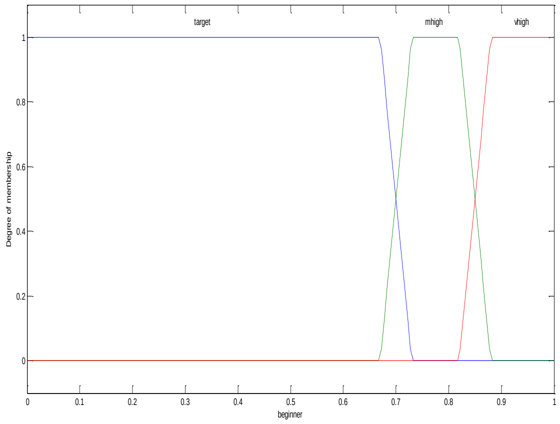

Figure 4. Beginner

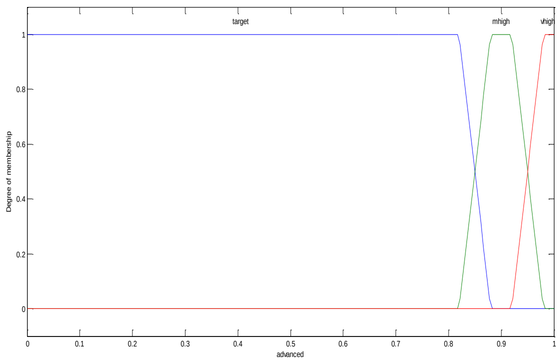

Figure 5. Regularly do sport

The second parameter under consideration is blood pressure, recognized as the most critical cardiovascular risk factor. Blood pressure signifies the force exerted by blood against vessel walls, notably in arteries. This force fluctuates rhythmically due to the heart's cyclic contractions. Systolic pressure denotes the peak pressure generated by the contracting left ventricle, while diastolic pressure refers to its lowest point during relaxation. To comprehensively evaluate blood pressure, both systolic and diastolic readings are essential, thus constituting the two additional input parameters in the Current Physical Status subsystem. Typically, systolic pressure rises during progressive exercise, while diastolic pressure remains steady or experiences a slight decline. The response at maximal or submaximal effort levels varies based on factors such as age, gender, and physical fitness. Older patients generally exhibit higher blood pressure readings, but this relationship inversely correlates with physical fitness, with better fitness levels associated with lower measured values. Additionally, men tend to have higher maximum systolic blood pressure compared to women. The blood pressure thresholds referred to in this paper stem from maximum values linked to age and gender, as detailed in [25], notwithstanding adjusted according to target zones, which also influence optimal blood pressure. Figure 6 shows the systolic blood pressure with the following parameters: low (<187), normal (187-204), increased (204-220), abnormal (>220). Figure 7 illustrates the diastolic blood pressure with the following constraints: Low (<80), normal (80-84), increased (85-90), abnormal (>90).

Table 1 illustrates the maximum systolic and diastolic blood pressure values categorized by age and sex [25].

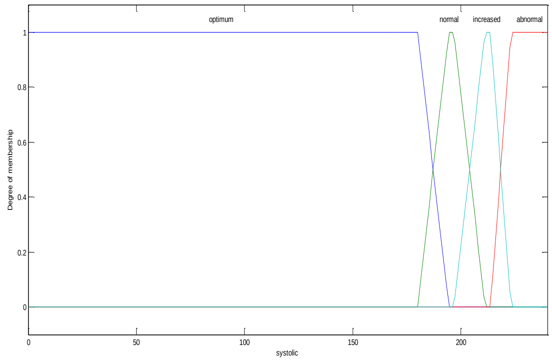

Figure 6. Systolic blood pressure

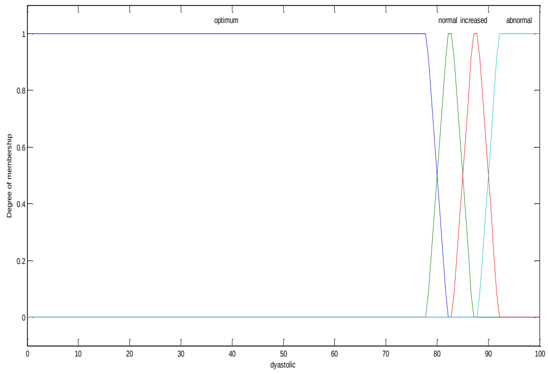

Figure 7. Diastolic blood pressure

1. TABLE: NORMAL BLOOD PRESSURE RESPONSE

Age	Men		Women	
	Systolic	Diastolic	Systolic	Diastolic
20-29	161-203	59-83	136-176	58-82
30-39	164-204	64-88	138-182	63-85
40-49	167-209	68-92	144-190	67-89
50-59	170-216	71-95	153-201	69-93
60-69	173-221	72-96	162-210	68-84
70-79	169-223	71-97	160-210	73-93

The output membership functions (risk levels) are: vsafe (<0,2), msafe (0,2-0,4) medium (0,4-0,6), mdangerous (0,6-0,8), vdangerous (0,8-1) as illustrasted in figure 8. (vsafe represents the smallest, while vdangerous the highest risk).

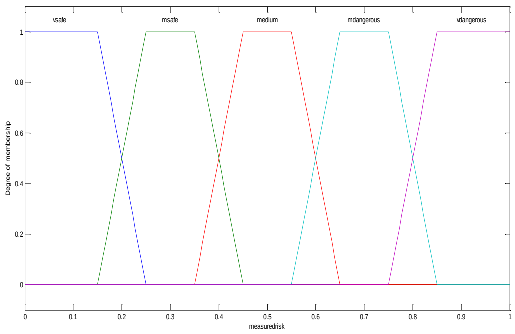

Figure 8. Risk level

The structure of the Current Physical Status subsystem is depicted in Figure 9, with input factors positioned on the left side and influential factors, crucial for refining membership functions, situated at the top of the figure. Input factors encompass heart rate (HR), systolic blood pressure (SBP), and diastolic blood pressure (DBP), while influential factors include disease condition, which transcribes whether the individual is diseased or someone who is a beginner or advanced in terms of sports, basic physical information which includes age and sex, and finally, the training target. This subsystem elaborates on the "Current Physical Status" input within the overarching model, as illustrated in Figure 1.

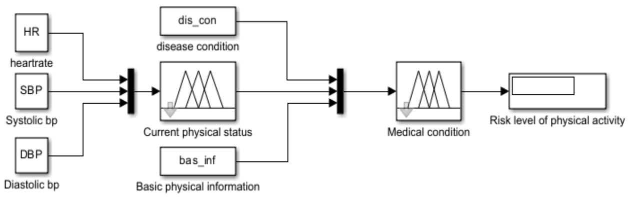

Figure 9. Current physical status subsystem

4. STATISTICS-BASED EVALUATION

4.1. Membership functions construction – an overview

Deriving membership functions from training data is a core challenge in fuzzy set theory. There are no definitive guidelines for selecting the appropriate method for generating these functions. Additionally, the task is complicated by a lack of consensus on how to define and interpret membership functions. For instance, Dubois and Prade [26] discuss the complexities and differing interpretations involved, underscoring the subjective nature of defining membership functions in fuzzy set theory. Therefore, various methods can be employed to generate membership values based on the desired interpretation.

Extensive literature focuses on creating membership functions to reflect subjective perceptions of vague concepts. However, these methods often cannot be directly applied to practical problems like fuzzy logic applications, which require modelling uncertainty in input data. There are no standard measures to evaluate the accuracy of generated membership functions, particularly for abstract concepts. Therefore, models must be flexible and easily adjustable to optimize algorithm performance. Given the importance of membership functions, multiple methods may be necessary, tailored to specific problems and data types.

An overview of some of these methods can be found in [27]. The authors provide a solid background on the various techniques available for generating membership functions. The discussed key techniques encompass Heuristic Methods, rooted in expert knowledge and intuitive grasp of problem domains, where the construction of membership functions relies on rules derived from human expertise and experience. Probability-Possibility Transformations involve converting probabilistic data into fuzzy membership functions, utilizing the interplay between statistical data and fuzzy sets to manage uncertainty. Cluster Analysis, exemplified by methods like fuzzy c-means (FCM), identifies natural data groupings to construct membership functions, assigning data points to clusters with varying membership degrees for smoother function creation. Neural Networks employ artificial neural networks to learn membership functions dynamically, particularly adept for complex pattern recognition tasks. Genetic Algorithms optimize membership functions by emulating natural selection, searching for optimal parameters to enhance fuzzy system performance. Histograms and Density Estimation employ statistical methods to estimate data density distributions, aiding in precise membership function creation through visual representation of data distribution. More details on the histogram method will be outlined in the next section, as this is the method used in this paper.

Although these methods were originally proposed for pattern recognition purposes, they can still be relevant to patient monitoring, and there is potential to combine them to create robust and accurate membership functions tailored to medical data.

A further contribution was introduced by Medaglia [28], who proposed an innovative method for constructing membership functions in convex normal fuzzy sets using Bézier curves. This technique offers significant flexibility and efficiency. The Bézier curve-based mechanism allows users to intuitively manipulate the shapes of membership functions to fit given data sets with minimal discrepancy. The paper includes several numerical experiments comparing this method to conventional approaches, demonstrating its superiority in producing accurate and reliable membership functions. One key advantage of this method is its ability to handle various data shapes intuitively. Traditional methods often require complex calculations and are less adaptable to different data distributions. In contrast, the Bézier curve-based approach simplifies the process, making it accessible even for those with limited technical expertise in fuzzy set theory. By harnessing these techniques, researchers and practitioners can develop more sophisticated monitoring systems that improve diagnostic accuracy, adapt to dynamic patient conditions, and support personalized patient care, ultimately leading to better health outcomes and enhanced quality of care for patients.

In the literature, fuzzy sets are frequently represented using triangular, trapezoidal, and bell-shaped membership functions [29][30].

A trapezoid shape input membership function is given by:

$$\mu_v(x) = \begin{cases} 0, & x < v_1 \\ \frac{x-v_1}{v_2-v_1}, & v_1 \le x \le v_2 \\ 1, & v_2 \le x \le v_3 \\ \frac{v_4-x}{v_4-v_3}, & v_3 \le x \le v_4 \\ 0, & x > v_4 \end{cases} \quad (1)$$

where, v_1, v_2, v_3, v_4 are the parameters of the membership function.

In the method proposed by Devi and Sarma [31], a parametric representation of the histogram is utilized to estimate fuzzy membership functions. This is achieved through the rational function approximation, where the parameters of the function are derived by applying least squares fit to the histogram values. Once obtained, these parameters are normalized to ensure that the function's maximum value is one. To determine the membership value for any given sample, these normalized parameters are substituted back into the rational function. This approach is particularly useful for classifying unlabelled samples. For each feature within each class, histograms are constructed, and the parameters representing the membership function are determined accordingly.

To obtain the desired results, the input MFs are tuned according to the personal characteristics of the patient. For simplicity, these values are represented by trapezoidal MFs.

4.2 Membership function fitting to the Histogram

Due to the complex interactions between input factors, it is difficult to precisely evaluate their effects on the measured values.

The data collected and recorded during monitoring can be used to assess the patient's current condition. Furthermore, these data can be recorded in a personal profile to personalize the evaluation in the future. According to the current state of the patient, the previous measurements performed under the approximately same conditions can be considered. Statistics, such as histograms, can be created based on these values to provide further insights. This histogram represents the normal reaction of the patient under the given conditions.

When a histogram is available, a membership function (MF) can be defined based on it. This function is piecewise linear whose highest point corresponds to the domain with the maximum value in the histogram and the rest of the function is created based on the remaining histogram values. Further details on this method can be found in [32][33].

This is how the membership functions of the inputs HR, SBP and DBP are created. After the histogram-based functions are available, original membership functions can be tuned accordingly. The functions tuned in this way are more reliable since the patient's normal reactions and the medical recommendation are taken into account together. These functions are the ‘improved MFs’ that can be obtained by simply calculating the mean of the correspondent parameters of the histogram-based functions and the tuned original membership functions.

5. CASE STUDY

In this section, the membership functions representing the medical recommendation for an ‘Advanced Male 20-29’ are presented, as well as the measurement-based statistics for a specific patient. The Mamdani-type inference system was implemented in MatLab Fuzzy Logic Designer alongside the rule base.

In order to define the membership functions for heart rate, consideration should be given to the predicted maximum heart rate and the recommended intensity (as outlined in Figure (2). Three antecedent fuzzy sets are applied: "target," representing the ideal heart rate zone for the patient; "mhigh," indicative of an elevated heart rate; and "vhigh," denoting a very high heart rate that is not advisable for the patient. These zones and the actual input value are delineated as a percentage of the individual's maximum heart rate. Figure 10 illustrates the heart rate antecedent sets for the group ‘Advanced Male 20_29’ which features males aged between 20-29 years who regularly do sports at an advanced level.

The membership functions for systolic blood pressure are also depicted in Figure 11. The thresholds establish the antecedent fuzzy sets: "low," representing hypotonic values; "normal," indicating the desired SBP value; "increased," signifying a somewhat higher but still acceptable value; and "abnormal" which is not recommended for the patient due to increased risk. Similarly, the antecedent sets for diastolic blood pressure are presented in Figure 12.

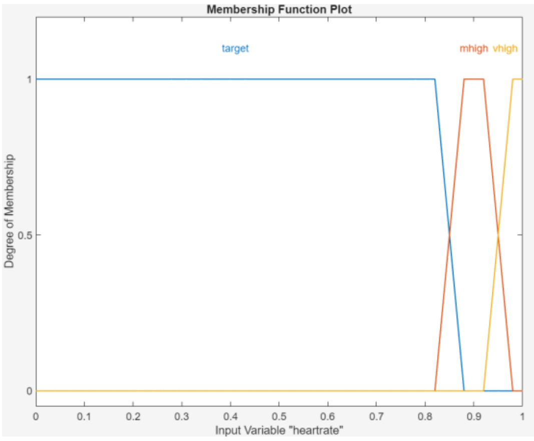

Figure 10. Heart rate zones for Advanced Male 20-29

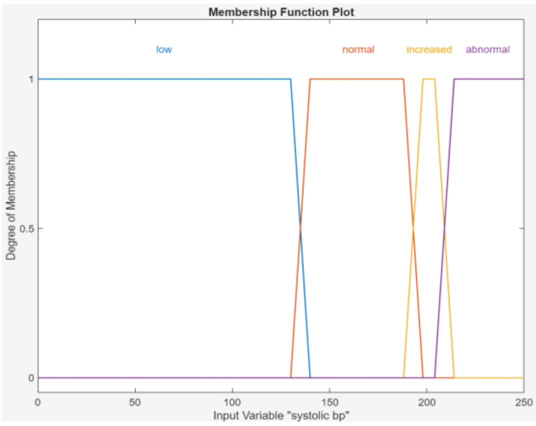

Figure 11. Systolic blood pressure for Advanced Male 20-29

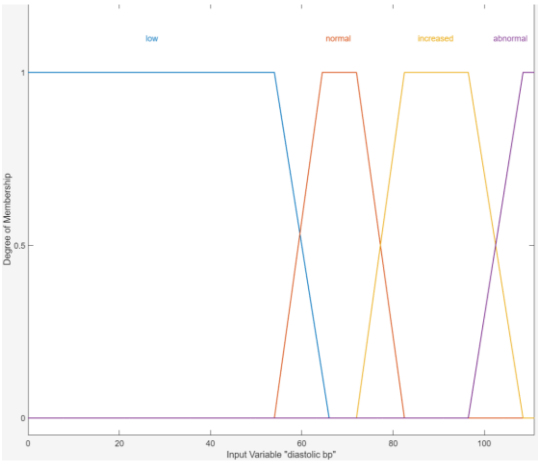

Figure 12. Diastolic blood pressure for Advanced Male 20-29

Utilizing the influential parameters described above, the membership functions can be adjusted to align with patient characteristics. Figures 13-15 show the statistics-based membership functions of a 21-Year-Old elite badminton athlete. His personal parameters are as follows: resting heart rate, HRrest=60bpm, maximum heart rate, HRmax=195bpm, systolic blood pressure, SBP=120mmHg, maximum systolic blood pressure, SBPmax=235mmHg, diastolic blood pressure, DBP=55mmHg, maximum diastolic blood pressure, DBPmax=82mmHg, weight=175kg. The athlete performed an incremental treadmill running test for the evaluation of maximal oxygen consumption (VO2max), anaerobic threshold, and time to exhaustion. He started exercising at a treadmill speed of 2.7 km/h and an inclination of 10% gradient for 3 min, and the speed and inclination were gradually increased every 3 min until he was exhausted or fatigued volitionally. Heart rate variability was examined using the Polar heart rate monitor over a period of 5 min at rest in the supine position [34]. In all cases, the examined HR, SBP and DBP were incrementally generated from the resting values to close to the maximum parameters. The graphics presented from this point forward in this chapter are dedicated to the profile of the 21-year-old elite badminton athlete.

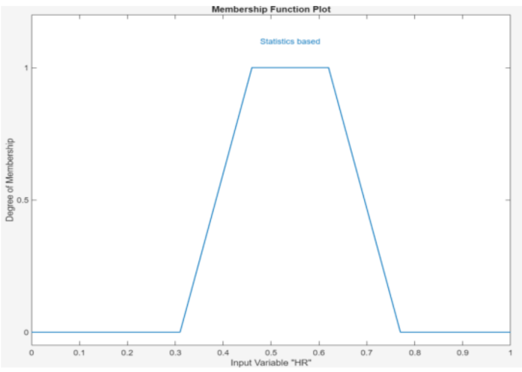

Figure 13. Stats-based fuzzy set representing the personal statistics for HR

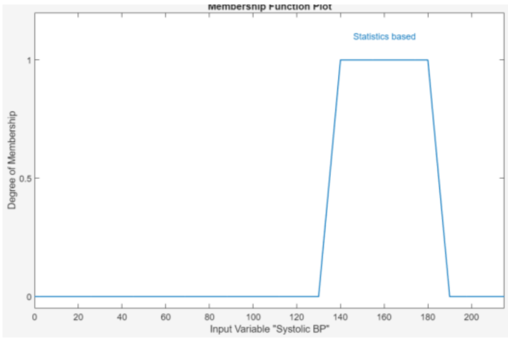

Figure 14. Stats-based fuzzy set representing the personal statistics for SBP

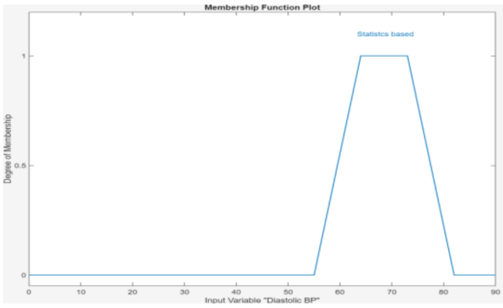

Figure 15. Stats-based fuzzy set representing the personal statistics for DBP

Next, the statistics-based MFs were compared to the medical recommendations and then aggregated to the 'improved MFs' as shown in figures 16-18. These new membership functions (figures 19-21) were then used to evaluate the risk level of the patient (see table 2).

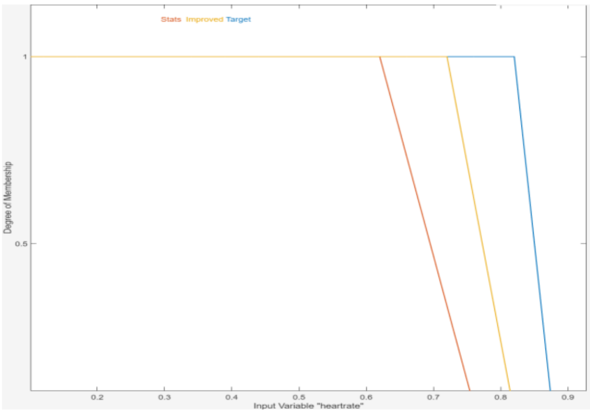

Figure 16. Comparison between the statistics-based (Input Values: [0, 0, 0.62, 0.77]) and the medical recommendation MFs for HR (Input Values: [0, 0, 0.82, 0.88])

The HR input domain for the statistics-based function ranges from 0 to 0.77, while the medical recommendation function ranges from 0 to 0.88. The significant difference occurs in the mid-to-high range values, specifically from 0.62 to 0.88. In the range [0.62, 0.77], the statistics-based function provides a more detailed classification of HR values. This range is crucial as it indicates moderate risk levels where the athlete's HR is elevated but not yet in the high-risk category. The medical recommendation function does not start this categorization until a higher range [0.82, 0.88], suggesting that the athlete-specific model is more sensitive to increases in HR, thus providing earlier warnings and potentially better risk management during physical activity. The personalized statistics-based function allows for a broader range of HR values to be classified as "moderately safe" before reaching "moderately dangerous," reflecting the athlete's higher tolerance for elevated heart rates during intense physical activity. The parameters of the 'improved' MFs for HR are [0 0 0.74 0.825] which were obtained by taking the mean of the corresponding parameters of the statistics-based function and the medical recommendation function.

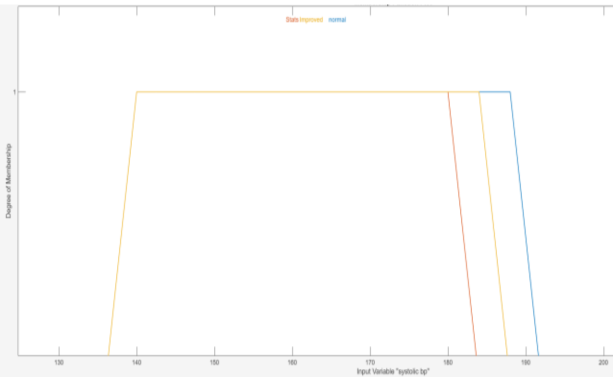

Figure 17 . Comparison between the statistics-based (Input Values: [130, 140, 180, 190]) and the medical recommendation ([130, 140, 188, 198]) MFs for SBP

The range of interest here is [180,190] for the statistics-based function versus [188,198] for the medical recommendation. In the range [180, 190], the statistics-based function identifies SBP values within this interval as moderate to high risk. This is significant because it indicates that the athlete-specific function flags elevated SBP values earlier than the medical recommendation function, which only starts this categorization at higher SBP values [188, 198]. By focusing on this range, it is evident that the personalized model is tailored to detect potential cardiovascular strain at lower thresholds. This early detection capability enables better prevention and management strategies during high-intensity exercise. Similar to the previous analysis, the parameters of the 'improved' MFs for SBP are [0, 0, 184, 194].

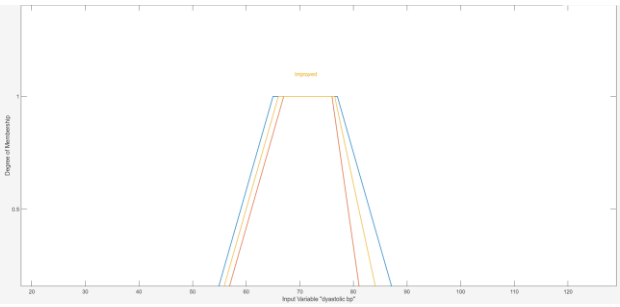

Figure 18. Comparison between the statistics-based (Input Values: [55, 67, 76, 82]) and the medical recommendation (Input Values: [53, 65, 77, 89]) MFs for DBP

The input domain includes values from resting diastolic pressure to the peak DBP observed during the athlete's maximal activity levels. In the range [76 82], the statistics-based function assigns higher risk levels compared to the medical recommendation, which considers values up to 89 before assigning similar risk levels. This indicates that the athlete-specific function is more conservative and sensitive to increases in DBP. The range [76 82] is critical as it represents values where the athlete's diastolic pressure is elevated but still below the extreme high-risk category. This sensitivity helps in the early detection and management of cardiovascular risks specific to the athlete's physiology. Analogously, the parameters of the 'improved' MFs for DBP are [54, 66, 76.5, 85.5].

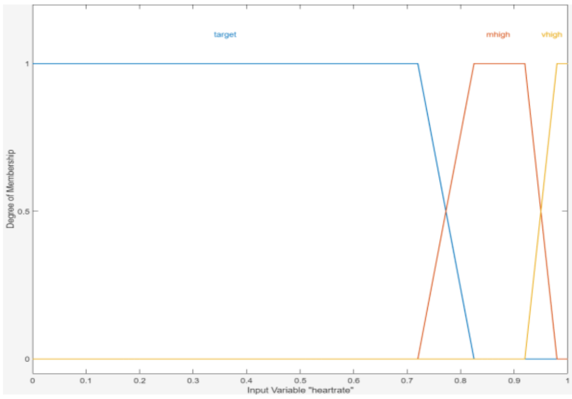

Figure 19. Improved MFs for HR

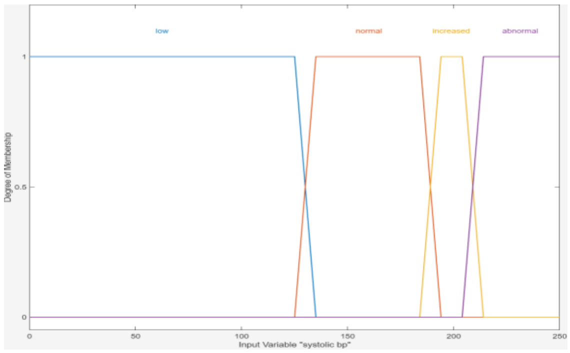

Figure 20. Improved MFs for SBP

				Improved MFs		Medical recommendation	
HR (bpm)	**% of HRmax (bpm)**	**SBP (mmHg)**	**DBP (mmHg)**	**Risk Level (numerical)**	**Linguistic terms**	**Risk Level (numerical)**	**Linguistic terms**
60	0.31	120	55	**0.108**	**Very safe**	**0.111**	**Very safe**
70	0.36	130	58	**0.226**	**Moderately safe**	**0.121**	**Very safe**
80	0.41	140	61	**0.21**	**Moderately safe**	**0.193**	**Moderately safe**
90	0.46	150	64	**0.153**	**Very safe**	**0.131**	**Very safe**
100	0.51	160	67	**0.106**	**Very safe**	**0.106**	**Very safe**
110	0.56	170	70	**0.106**	**Very safe**	**0.106**	**Very safe**
120	0.62	180	73	**0.106**	**Very safe**	**0.106**	**Very safe**
130	0.67	190	76	**0.361**	**Moderately safe**	**0.224**	**Moderately safe**
140	0.72	200	79	**0.561**	**Medium**	**0.539**	**Medium**
150	0.77	210	82	**0.692**	**Moderately dangerous**	**0.698**	**Moderately dangerous**

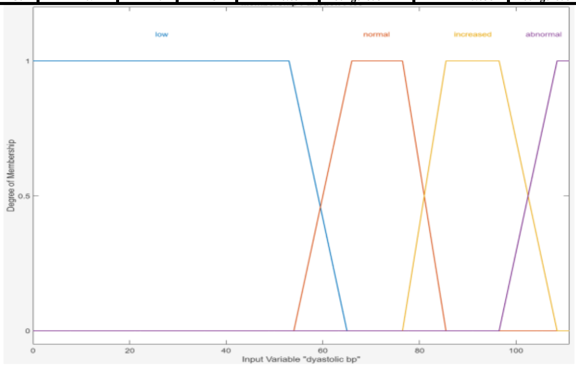

Figure 21. Improved MFs for DBP

Our analysis of the input domains where statistics-based functions and medical recommendation functions differ highlights the significant impact of personalized modelling. The specific ranges of [0.62, 0.77] for HR, [180, 190] for SBP, and [76, 82] for DBP illustrate areas where the statistics-based functions offer more detailed and early risk categorization. These distinctions underscore the critical importance of personalized health monitoring, enabling timely and precise interventions tailored to individual physiological responses, especially for athletes.

Moreover, incorporating the improved MFs into our analysis demonstrates the value of a balanced approach. The improved MFs, which are calculated as the means of the adjacent statistics-based and medical recommendation functions, provide a smoother and more adaptive risk assessment. These functions offer early warnings similar to the personalized statistics-based functions while gradually aligning with the thresholds set by medical recommendations. This comprehensive and timely health monitoring approach is particularly beneficial for managing the cardiovascular health of athletes, ensuring their safety, and optimizing performance.

6. Results

The risk evaluation of personal statistics is illustrated in Table 2. The table presents a comprehensive risk evaluation of a 21-year-old male elite badminton athlete, focusing on heart rate (HR), systolic blood pressure (SBP), diastolic blood pressure (DBP), and their corresponding risk levels both numerically and in linguistic terms. The comparison of risk levels derived from improved membership functions (MFs) and medical recommendations offers valuable insights into the athlete's cardiovascular status under varying physiological conditions.

2. Table: Risk evaluation of a 21-year-old male badminton athlete

At lower heart rates and blood pressure values the risk level is predominantly categorized as ‘very safe’. The medical recommendations are very similar with the improved MFs, suggesting a low risk for cardiovascular events. Which means that in this zone the statistics-based approach is reliable as it presents similar results as the medical recommendation. For moderated heart rates and blood pressure values the risk level varies from ‘very safe’ to 'moderately safe’ with a slight variation between the improved MFs and the medical recommendation. For higher heart rates and blood pressure values we notice an increase in cardiovascular risk in both the improved MFs and the medical recommendation.

The consistency between improved MFs and medical recommendations validates the reliability of the model, particularly at higher heart rates where risk levels are more pronounced. This approach emphasizes the importance of personalized risk assessment models, ensuring the patient’s safety and optimal performance management.

7. Conclusion

In sports and physical activity, ensuring health monitoring is crucial for participants across all levels. Each individual engages in sports with varying physiological responses and health profiles, making personalized assessment methods essential. Traditional approaches to health monitoring do not always take that into account.

Integrating fuzzy logic into health monitoring systems can be advantageous in dealing with such challenges as it can handle uncertainty, imprecision, or subjectivity of the input data. It can offer more accurate and personalized results, leading to safer practice of physical activity.

In this paper, the authors analysed the risk levels of the current activity using a hierarchical fuzzy model structure with a focus on the current physical status subsystem. To assess the patient's current condition data (which includes but is not limited to HR, SBP, DPB values as well as sampling frequency, duration, sex, and activity type) is collected and recorded during monitoring. This data can be recorded in a personal profile to personalize the evaluation in the future and the previous measurements performed under the approximately same conditions can be considered. The statistics-based approach was used. Histograms were created representing personal statistics, i.e., the normal reaction of the patient under the given conditions. When the histogram is available, a membership function (MF) can be defined based on it. This function is piecewise linear whose highest point corresponds to the domain with the maximum value in the histogram and the rest of the function is created based on the remaining histogram values. This way, the membership functions of the inputs HR, SBP and DBP are created. After the histogram-based functions are available, original membership functions can be tuned accordingly. The functions tuned in this way are more reliable, since the patient's normal reactions and the medical recommendation are taken into account together.

This study shows that there is consistency between the improved MFs and the medical recommendations, which validates the reliability of the model, particularly at higher heart rates where risk levels are more pronounced. This approach emphasizes the importance of personalized risk assessment models, ensuring the patient's safety and optimal performance management.

In the future, authors aim to develop different mathematical methods that can be used to represent the patient's statistics and for fitting the membership functions.

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