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Clinical Automata in Fuzzy Arden Syntax

Julia LIEPOLD[a,b], Moritz GROB[b,c], Vladik KREINOVICH[d], Robert A. JENDERS[e], and Klaus-Peter ADLASSNIG[b,c,1]
[a]*TU Wien, Institute of Logic and Computation, 1040 Vienna, Austria*
[b]*Medexter Healthcare, Borschkegasse 7/5, 1090 Vienna, Austria*
[c]*Medical University of Vienna, Center for Medical Data Science, Institute of Artificial Intelligence, Spitalgasse 23, 1090 Vienna, Austria*
[d]*University of Texas at El Paso, El Paso, TX, 79968, USA*
[e]*Charles Drew University & University of California, Los Angeles, CA, USA*
ORCiD ID: Julia Liepold 0009-0004-5416-6417, Moritz Grob 0009-0006-7867-9465, Vladik Kreinovich 0000-0002-1244-1650, Robert Jenders 0000-0002-3389-6718, Klaus-Peter Adlassnig 0009-0008-5046-1549

Abstract. Fuzzy automata provide a powerful framework for clinical diagnostics and patient monitoring by integrating uncertainty handling, making them ideal for medical decision-making with often imprecise data. Unlike classical automata, fuzzy automata support degrees of membership, allowing more nuanced interpretations of symptoms and disease progression. They can be seamlessly abstracted from Arden Syntax, a widely-adopted clinical rule-based language, by mapping medical logic onto fuzzy state transitions. These visualizations enhance clinical monitoring, making them an invaluable tool for modern healthcare systems by providing a flexible, adaptive approach to managing complex health case scenarios.

Keywords. Fuzzy Automata, Arden Syntax, Fuzzy Logic, Clinical Monitoring

1. Introduction

Medical decision-making often involves uncertainty due to the inherent variability in patient symptoms, laboratory results, and clinical guidelines. Traditional rule-based approaches struggle to accommodate this imprecision, leading to rigid classifications that may not align with the complexities of real-world patient conditions. Fuzzy logic, introduced by Zadeh [1], provides a mathematical framework for modeling such uncertainty, enabling nuanced decision-making in clinical environments.

Arden Syntax, a widely-adopted language for encoding clinical knowledge, has incorporated fuzzy logic constructs since Version 2.9 [2]. This allows for the seamless integration of fuzzy automata—finite-state machines capable of handling degrees of membership rather than binary states. By mapping medical logic to fuzzy transitions, these automata offer a more flexible approach to continuous patient monitoring.

This paper explores the application of fuzzy automata within Arden Syntax to model gradual changes in patient conditions. Specifically, we propose a fuzzy deterministic finite-state automaton (DFA) for continually monitoring blood oxygenation in acute

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[1] Corresponding Author: Klaus-Peter Adlassnig; E-mail: klaus-peter.adlassnig@meduniwien.ac.at.

respiratory distress syndrome (ARDS). Unlike traditional clinical decision support tools, our approach enables adaptive responses to borderline cases, potentially improving the accuracy and responsiveness of patient management systems.

2. Methods

The integration of fuzzy automata into fuzzy Arden Syntax has been explored as a means of enhancing rule-based medical logic. To establish a foundation, it is essential to provide first an overview of fuzzy automata theory and outline basic fuzzy Arden Syntax principles.

2.1. Fuzzy Automata Theory

At its core, fuzzy automata extend DFA by allowing partial state membership. It is defined by the quadruple $A = (Q, \bar{q}_0, I, \delta)$, although definitions can vary depending on the field they are used in [3–5].

Here, Q denotes a finite subset of predefined states, one of which being the initial state q_0. I represents a finite set of inputs, commonly called the alphabet, and lastly the transition function $\delta: Q \times I \to Q$ assigns possible follow-up states for certain inputs $i \in I$. A bar over some variable $(\bar{q}, \bar{\imath})$ describes a fuzzy set over Q or respectively I and is used for clarity to distinguish between fuzzy and crisp variables. It signifies the automaton partially being in multiple states with different degrees of membership (DoM), determined by their respective membership function μ [3].

An automaton's fuzzy state is updated whenever new input is encountered, taking the machine at time t to new states at $t + 1$. The update aggregates all contributions to the next fuzzy state based on all possible state-input pairs. It consists of the minimum of fuzzy transitions, influenced by both the current state's membership and the degree to which the input is present. The membership function of the next state is determined by

$$\forall q \in Q:\ \mu_{\bar{q}_{t+1}}(q) = \begin{cases} 0 & if\ \delta^{-1}(q) = \emptyset \\ \max\limits_{\delta(q',i)=q} min\left(\mu_{\bar{q}_t}(q'), \mu_{\bar{\imath}}(i)\right) & otherwise \end{cases} \tag{1}$$

where the fuzzy membership of each individual state is equal to 0 if there is no valid transition, meaning the state is unreachable. Otherwise, the strongest transition leading to each state is selected as its new DoM value [4].

To illustrate the principle of these transitions, a simple DFA with state transitions $\delta(S, 0) = X$ and $\delta(S, 1) = Y$ is depicted in Figure 1. Its fuzziness can stem from a DoM in the initial state (e.g., 0.5 in the example shown) as well as from fuzzy state transitions. Upon assigning membership in state S with a DoM of 0.5 and encountering an exemplary input of 1 with a DoM of 0.2, the machine would reach the doubly circled end state X with a DoM of $min(0.5, 0.2) = 0.2$.

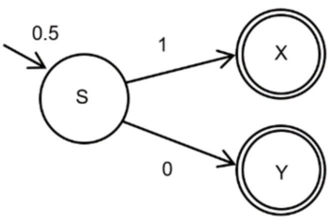

Figure 1. Simple deterministic, finite state automaton (DFA)

2.2. Fuzzy Arden Syntax

Arden Syntax uses medical logic modules (MLMs) to encode if-then decision rules, akin to state transitions in automata. Because medical knowledge is inherently fuzzy, the degree to which the symptoms are present as well as the degree to which the diagnoses apply can be mapped to a scale from 0 to 1, equivalent to the DoM. Furthermore, Arden Syntax allows the declaration of so-called linguistic variables. This is achieved by a list of point-value pairs, describing the characteristic membership function of a fuzzy set [2].

In preparation for an example, arterial oxygen saturation (SaO_2) levels can be defined as adequate or too low as follows:

$$\begin{aligned} &\text{Adequate Oxygenation} &&:= \mathit{Fuzzy\ Set}\ (0.93, 0)\ (0.97, 1) \\ &\text{Hypoxemia} &&:= \mathit{Fuzzy\ Set}\ (0.87, 0)\ (0.9, 1)\ (0.93, 1)\ (0.97, 0) \end{aligned}$$

This means that the DoM of Adequate Oxygenation starts to linearly increase at 93% and continues to be 1 after 97%. Membership for Hypoxemia starts to go up from 0 at 87% until it approaches 90%, where the peak value of 1 is reached, and begins to fall again at 93% until 97%, where the degree of membership is 0 again.

3. Results

In a clinical context, the states of fuzzy automata represent distinct phases of a patient's condition as a disease progresses, while state transitions capture potential shifts between these phases. One critical example is the monitoring of blood oxygenation in acute respiratory distress syndrome (ARDS), characterized by impaired gas exchange and requiring continuous assessment of oxygenation levels to guide treatment decisions [6].

Knowledge-based systems for managing and diagnosing ARDS have already been established as useful [6–9], providing a foundation for fuzzy rules based on oxygenation indices and the fraction of inspired oxygen F_IO_2 [6–8]. Table 1 quantifies the linguistic variables used in the proposed DFA.

Table 1. Definition of state transitions in ARDS with crisp and fuzzified rules, adapted from [7].

Natural Language	Crisp Rule	Fuzzified Rule
Adequate Oxygenation	SaO_2 above 97%	SaO_2 above 93%
Hypoxemia	SaO_2 from 90–93%	SaO_2 from 87–97%
High F_IO_2	F_IO_2 above 60%	–
Low F_IO_2	F_IO_2 below 60%	–
Improving Oxygenation	SaO_2 increasing from 87–95% to 97–100%	SaO_2 increasing from 85–99% to 93–100%

Using relaxed rules, a low SaO_2 measurement of 94% can result in two possible state transitions with lower applicability for borderline values. This approach increases flexibility and enables a more comprehensive monitoring system by distributing membership across multiple states.

Patients with low SaO_2 experience breathing difficulties and receive oxygen-enriched air, leading to a higher F_IO_2. This process and its potential outcomes were modeled using a fuzzy automaton, whose complete state transition diagram is visualized in Figure 2. Functioning like a monitoring system, the automaton continuously tracks changes in blood oxygenation over time, allowing for dynamic adaptation to a patient's respiratory status [4].

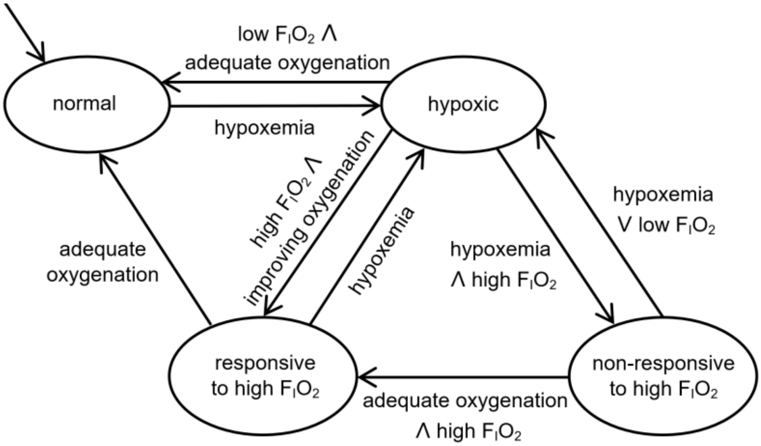

Figure 2. DFA with natural language state transitions, as defined in Table 1.

The depicted automaton is initialized at the state labeled "normal", indicating satisfactory oxygenation, even without additional effort such as increased F_IO_2. The "hypoxic" state signifies oxygenation is too low and requires immediate intervention. The remaining two states distinguish whether elevated F_IO_2 has successfully enhanced oxygenation or not. The used transitions allow for circulatory behavior, meaning the system can oscillate in response to repeated inputs, enabling temporal analysis [3].

Notably, the proposed DFA lacks termination states, which are a common feature of many formal definitions. These states have been deliberately omitted due to the continuous nature of symptom monitoring, where the natural conclusion occurs upon the patient's discharge from clinical care.

Overall, the described fuzzy automaton provides a dynamic and interpretable framework for modeling disease progression and treatment response in ARDS, supporting dynamic decision-making based on continuous input data.

4. Discussion

Fuzzy logic has become increasingly prominent in healthcare, offering significant potential to improve clinical decision support systems. Fuzzy systems are being constantly integrated into modern clinical informatics systems in various forms [10]. A key advantage of fuzzy automata, in particular, lies in their ability to model smooth transitions between states, contrasting rigid binary classifications. Furthermore, their knowledge representation capabilities allow for transparent decision-making and enable clinicians to track a patient's history. This traceability supports both retrospective analysis and real-time adjustments, aligning with the dynamic nature of patient conditions [6–9].

However, practical implementation requires addressing computational efficiency and integration challenges. Ensuring interoperability with existing electronic health record systems and optimizing fuzzy rule execution are crucial for real-world deployment. Future work should focus on validating these models through clinical trials, assessing their impact on decision-making accuracy and patient outcomes.

5. Conclusions

Clinical automata, including fuzzy automata, are valuable in medical settings because they allow for automated rule-based decision making while handling critical aspects of uncertainty and imprecision of medical reasoning [6–9]. In cases where traditional Boolean logic is too rigid for real-world scenarios, a more flexible abstraction is needed. Arden Syntax constitutes an ideal tool for defining executable fuzzy automata because it provides a rule-based framework, supports fuzzy logic, and enables continuous monitoring as well as clinical decision support.

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