Dependability Evaluation of an Online Pupillometry-based Feedback System for Optimized Training

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Abstract—**The online pupillometry-based feedback system is intended as a cognitive training and rehabilitation system developed at Mälardalen University. The purpose of the system is to engage a person in a cognitive computer task whose difficulty is adjusted in real time depending on the person's cognitive load. Previous research has uncovered a significant correlation between cognitive load and pupil dilation, suggesting that electroencephalogram usage for estimating cognitive load can be eliminated. The online pupillometry-based feedback system is measuring the pupil-diameter in real time to classify cognitive load using a neural network. The classification of cognitive load is used to modulate the difficulty level of the cognitive task, with the purpose of challenging the participant and to optimize the cognitive training. At the current state the system is fully integrated, but possesses no fault-tolerant features to produce a long-term reliable service. This paper proposes a fault-tolerant architecture for the online pupillometry-based feedback system, for which internal repairs and failure rates are modeled using continuous-time Markov chains. The results show adequacy of the extended architecture, assuming slightly optimistic failure rates. Even though the system is specific, the reliability approach presented can be applied on other medical devices and systems.**

Keywords—Continuous-Time Markov Chains, Cognitive Load Classification, Fault- Tolerance, Reliability Evaluation, Neural Networks, Dependability

I. INTRODUCTION

Because of unpredictable dynamics, some technical systems cannot be verified by exhaustive testing. Furthermore, these systems can possess paths of interaction that lay far beyond human intuition, which makes modeling and quantitative analysis prior to development an utterly challenging task. For system analysis before development, mathematical modeling can be used, but as system complexity increases, a vast majority of trivial models fail to perform satisfactory, emphasizing the usage of more rigorous approaches.

Over the years, several techniques have been introduced for quantitative assessment of systems' adequacy prior to development. Several of them have became of a major relevance in industrial practice. These are *fault tree analysis* (FTAs) and *reliability block diagrams* (RBDs) [1]. The positive side of these models is their simplicity, but they assume independence of entities in the model, a condition that is violated for architectures that possess internally shared resources.

One technique that resolves lacks of FTAs and RBDs is *continuous-time Markov chains (CTMCs).* Arising from *stochastic processes* within probability theory, these chains rely on countable state decomposition and the prerequisite of *memory-less* behaviour (Markov Property) [2]. The Markov process is limited to remember only its current state. Therefore future states depend only on the current state and transition rates from the current state to other possible states. Transition rates are λ parameters of the exponential distribution, which is the commonly employed distribution used for modeling component failures within system analysis [3].

The online pupillometry-based feedback system is a prototype system developed at Mälardalen University, that classifies cognitive load for the purpose of adjusting the difficulty of a cognitive task [4]. The objective of this system is to enable efficient cognitive training and rehabilitation for people suffering from cognitive deficits. The pupil dilation is an interesting feature to enable the targeting of functions related to cognition. The pupil size changes continuously in response to variations in ambient light levels [5], but this behaviour is not solely due to changes in light intensity. Early investigations showed that the pupil size varies systematically in relation to cognitive demands, attention and effort [6] [7] [8].

At the current state however, the system possesses no physical entities to inhibit risks of failure. In order to enable medical device certification, which imposes high reliability demands, this paper proposes a fault-tolerant architecture for the online pupillometry-based feedback system without going into details of the system's medical purpose and performance. The architecture is evaluated by using CTMCs.

II. RELATED WORK

A reliable system service is widely emphasized in several industrial areas. Development and usage of medical devices is undoubtedly no exception [9], [10].

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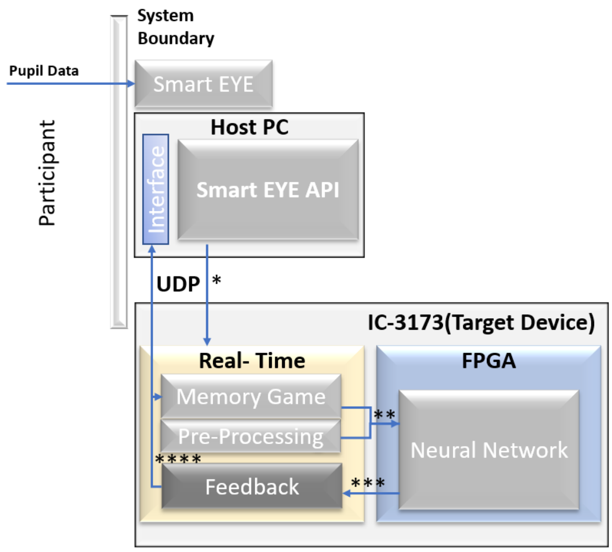

Figure. 1: Online pupillometry-based feedback architecture and data flow. *Pupil data stream over UDP protocol, **Processed and normalized pupil data and game difficulty level, *** Classification of cognitive load, ****Cognitive load classification feedback

Because of the non-deterministic dynamics of modern systems, we can witness currently an intensive research in extending concepts of dependability theory [11], [12], [3], in which CTMCs constitute one of the primary roots [13]. CTMCs are currently also one of the methods used for quantitative analysis of fault-tolerant systems prior to development. It is of a particular interest currently how to adapt analysis of fault-tolerant systems to neural network (NN) architectures [14]. Furthermore, dependability remains one of the most crucial characteristics of technology in general. One prominent example is dependability considerations in cloud computing [15]. There is a lack of research in the field of extending NN-based cognitive load classification systems to possess fault tolerance features suitable for the medical domain. Hence, this report aims at aggregating further knowledge relevant for future research and development.

III. Methods

A. The Online Pupillometry-Based Feedback System

The online pupillometry-based feedback system classifies a learner's cognitive load via a hardware (HW) programmed NN that takes pupil dilation as its input. The classification is used to adjust the level of the game such that the person is kept in an optimal state of learning. The system utilizes the parallel execution on multiple computing cores to reduce the worst-case execution time (WCET) to the minimum.

The online pupillometry-based feedback system (Fig. 1) resides on a PC and an industrial controller (IC-3173), with User Datagram Protocol (UDP) used between them. The industrial controller is decomposed into a real-time software (SW) and a HW field-programmable gate array (FPGA) section. Heterogeneity benefits of HW and SW can be utilized respectively by allocating threads appropriately. In particular, the pre-processing on the real-time side provides data acquisition for the pupil dilation data streamed from an eye-tracking camera (Aurora XO, Smart Eye) on the host PC. This includes exclusion of bad quality frames and normalization for NN classification. The output from the NN (high or low cognitive load) is used to regulate the difficulty level of the cognitive task, called the "Memory game" in order to preserve the learner in a state of optimal training. In the "Memory game", a participant is trying to recall if the location of a predecessor shape coincide with the current one presented on the screen. This is also referred to as a *n-back* task.

B. Continuous-Time Markov Chains (CTMCs)

Dependability is a product property which is constituted of several attributes, some of which are not necessarily mutually exclusive. The three properties of dependability most commonly referred to in the literature are *safety, availability* and *reliability* [16]. This paper emphasizes the reliability [3].

In order to fully grasp the practice of Markov chains in the context of *dependability theory*, it is useful to start with some primary definitions from *stochastic processes*. It is assumed in the continuation that readers are familiar with basic elements of *measure and probability theory*.

Definition 1 - Probability Space: The triple (Ω, ζ, P), where Ω denotes the *universal set*, ζ a *σ-algebra* and P a *probability measure*.

Definition 2 - Stochastic Process: A stochastic process $(X_t)_{t\in T}$ is a collection of random variables (not necessarily countable) on a mutual probability space (Ω, ζ, P). The process has range (state space) $\{X(w)| \ w \in \Omega\}$ and index (parameter set) T.

Definition 3 - Markov Chain: A *stochastic process* $(X_i)_{i\in T}, T \subset \mathbb{N}$ on a probability space (Ω, ζ, P), with countable *state space* (i.e. range) $S = \{X(w)|w \in \Omega\}$, is a Markov chain if it fulfills the so called Markov property:

$$P(X_{n+1} = j_{n+1}|X_n = j_n, ..., X_0 = j_0) = P(X_{n+1} = j_{n+1}|X_n = j_n) \quad (1)$$

which means that the probability for being in a certain state j_{n+1} depends only on the previous state j_n. This definition can be analogously extended to the case where the index set is uncountable.

Definition 4 - CTMCs: CTMC is a Markov Chain with an *uncountable index set*, e.g, $T \subset \mathbb{R}$.

CTMCs are usually described by transition graphs which show states of the process (circles) and their transition rates λ_i (arrows) between the states. For an example of a transition graph please see Fig. 4

Definition 5 - Infinitesimal Generator:
Kolmogorov forward and backward equations are

$$\frac{dP(t)}{dt} = \mathbf{Q} \cdot P(t) = P(t) \cdot \mathbf{Q} \quad (2)$$

where matrix **Q**, the *infinitesimal generator*, is constructed from transition rates in a CTMC transition graph such that matrix element $q_{i,j}$ describes transition rate from state i to j. The diagonal elements $q_{i,i}$ are used to describe the *exit rate* of the state i which is minus the sum of all transition rates from the state: $q_{i,i} = -\sum_{j\neq i} q_{i,j}$. Elements of the transition probability matrix $P(t)$ are $p_{i,j}(t) = P(X_t = j|X_0 = i)$ which are functions of time showing probability of being in a state j at time t, if initial state was i.

The solution of (2), i.e. $P(t) = e^{Qt}$, is necessarily unique in case the *state space* is finite, which is the case for this paper as it will be shown in the continuation. So we can be sure we can obtain the solution of the set of first order differential equations (2).

C. Application of CTMCs for Reliability Assessment of Systems

Here we describe the general procedure of how to use CTMCs for the assessment of systems, which we in section IV-B apply to the online pupillometry-based feedback system.

To use CTMCs, one first defines the state space S for the particular system to be assessed. Each element in the state space, i.e. one state, specifies which components are operational and which are in the fail mode (non-operational). The state space should contain all possible combinations of operational and failed components. From there one constructs a *transition graph*, which in addition to states, also specifies *failure rates*, which cause the chain to change from one state to another. Now that we have the failure rates, we can construct the *infinitesimal generator* **Q** as described in the previous section. The bigger are transition rates from a particular state, the bigger is the probability of leaving the state in an arbitrary interval $[0, t]$. It is also possible to model the possibility to recover, i.e. to transition back from a failed state to an operational one. The recovery is usually a consequence of system maintenance.

Now we are ready to solve (2). To obtain the solutions of being in state j at a particular time t, i.e. excluding the initial distribution of the chain (starting state), the right hand side of the equation can be used. Formally this equality can be deduced by multiplying both left and right hand side by the initial distribution $\overline{\pi}(0)$ and bring the vector into the differentiation such that $\frac{d(P(X_t=j))}{dt} = (P(X_t = j))Q$.

We can classify states in *operational states* and *failed states*. The classification is dependent on the particular system we are assessing, as well as subjective evaluation of the modeler. For instance, if two out of three processors in a system fail, one might still consider that a reliable service can be provided, which will classify that particular state as operational.

When we have solutions of (2), then we can sum all probabilities of *operational states* to obtain the probability that the system is operational. Equation (2) is a system of *linear differential equations*. There exist several ways solve it: Integrating factor, diagonalization, separable ordinary differential equations, and Laplace transform by partial fraction expansion. We used the Laplace method.

D. Application of Reliability Block Diagrams (RBDs) for Reliability Assessment

RBDs are used for systems, or parts of systems, that are composed of independent components. The reliability of *serially* connected components is obtained by simply multiplying individual reliabilities, whereas for *parallel* components the reliabilities are calculated by using [1]:

$$R(t) := 1 - \prod_{i=1}^{n}(1 - R_i(t)) \tag{3}$$

i.e., 1 minus the probability that all parallel components have failed (n is the number of parallel components). Here $R(t)$ is the total reliability, whereas $R_i(t)$ are individual reliabilities.

E. Choice Between CTMCs and RBDs

RBDs are simpler but cannot be applied on dependent system components. CTMCs can be used on all components but as the number of components increases, the complexity of CTMCs' realted calculation also increases. It is of course up to the modeler, but it is obviously reasonable to use RBDs for independent components and CTMCs for dependent components.

IV. Results

A. Proposed Fault-Tolerant Architecture

The proposed fault-tolerant architecture for the online pupillometry-based feedback system from Fig. 1, is presented in Fig. 2. It has the following components.

1) Three Smart EYEs (SE) modules: Triple modular redundancy is favourable for HW entities [3] and fault-masking is provided by a majority voter. The fault-masking is a necessity due to the stringent restriction on the WCET, leaving no room for interrupted service.

2) Voter: Majority voter, forwards to the pre-processing modules the majority of the inputs that "agree". The voter can be the "lock-step" bit by bit comparison, or within some pre-defined range [17].

3) Two Pre-processing (PP) modules: As stated previously, the PP modules reside on the real-time side of the IC-3173 and are responsible for the data acquisition of the pupil dilation data. For reliability requirements, the redundant module should to be developed with SW diversity, e.g, by a different programmer from scratch, in order to inhibit risk of a systematic faults causing simultaneous failure of the two entities.

4) Acceptance Test (AT): The pre-processing outputs are verified with some predefined algorithm (AT). If both pass the test, an arbitrary one is selected (e.g. the non-diverse) and if only one passes, then the faulty result of pre-processing is discarded.

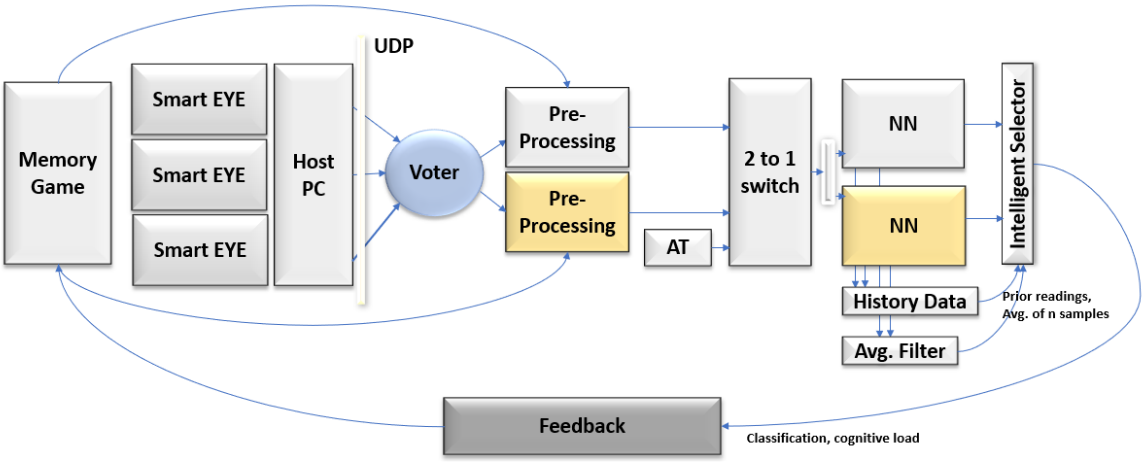

Figure. 2: Fault-Tolerant Architecture of the online pupillometry-based feedback system. Different color is used to denote that the module provides the same functionality but is developed with SW diversity. AT is the acceptance test

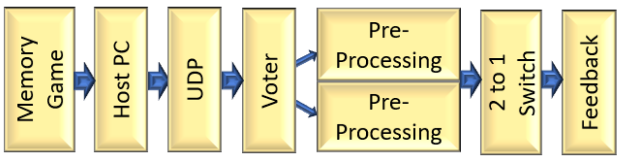

Figure. 3: RBD of non-dynamic failure rates due to degraded service

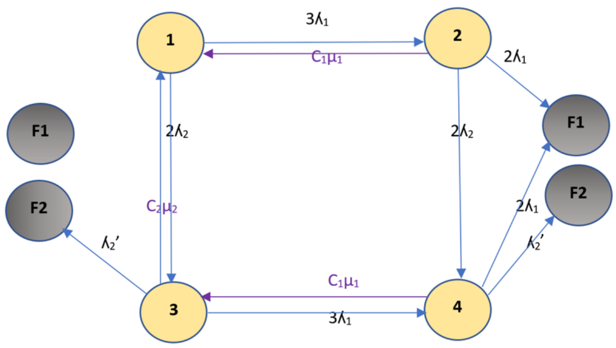

Figure. 4: Transition Graph for the NN and SE sub-modules with internal maintenance. (Circles are states, blue lines are failure transitions, whereas red lines are maintenance transitions)

5) Two Neural Networks (NNs): Both NNs should be implemented in HW, i.e. on the FPGA side of the IC-3173. The diversity acts as a measure to inhibit risk of simultaneous failure.

6) History Data: Storage of classification history in a HW instantiated buffer acts as a measure to discard inaccurate readings that significantly deviate from the expected value of the predecessor distribution.

7) Average Filtering: Average filtering mitigates the influence of transients and thereby preserves the system in a more deterministic state.

8) Intelligent Selector: The intelligent selector aggregates the history, averages on NNs' outputs to determine which NN's output to forward to the feedback line.

B. Reliability Evaluation of the Online Pupillometry-based Feedback System Using CTMCs and RBDs

We will model the SE devices and NNs with CTMCs and the rest of the components with the RBDs. At the end we obtain the total reliability by multiplying the two reliability functions obtained from CTMC and RBD respectively.

The RBD of the independent components are presented in Fig. 3, whereas the associated CTMC that models the NNs and SEs is presented as a transition graph in Fig. 4. The *history data*, *average filter* and *intelligent selector* has been omitted due to their simplicity, for which the failure rate could be deemed negligible.

If we assume that the time of failure of each system component is exponentially distributed with the following transition rates:
λ_{pp} = 10^{-6} faults/h (PP - pre-processing)
λ_U = 10^{-4} faults/h (U - UDP)
λ_{PC} = 10^{-4} faults/h (PC - Host PC)
λ_V = 10^{-9} faults/h (V - Voter)
λ_S = 10^{-9} faults/h (S - Switch)
λ_F = 10^{-6} faults/h (F - Feedback)
λ_M = 10^{-6} faults/h (M - Memory Game)
λ_{NN} = 10^{-3} faults/h (NN - Neural Network)
λ_{SE} = 10^{-3} faults/h (SE - Smart Eye)
λ'_{NN} = 10^{-2} faults/h (NN, conditioned failure rate),

Then by using (3) for parallel and multiplication for serial connections we get the reliability of the components in the RBD:

$$R_1(t) = e^{-(\lambda_U+\lambda_{PC}+\lambda_V+\lambda_S+\lambda_F+\lambda_M)t}(1-(1-e^{-\lambda_{PP}t})^2)$$
$$= e^{-(10^{-4}+10^{-4}+10^{-9}+10^{-9}+10^{-6}+10^{-6})t}\cdot(1-(1-e^{-10^{-6}t})^2)$$
$$= \frac{2-e^{-10^{-6}t}}{e^{2.03002*10^{-4}t}} \quad (4)$$

For the system components susceptible to data dependency and regular maintenance, we can derive a complementary CTMC. We will assume that internal repairs are allowed but the system cannot recover from a failed state.

TABLE I: STATES FOR THE USED CTMC

Index	State	Operational SEs	Operational NNs
1	(3,2)	3	2
2	(2,2)	2	2
3	(3,1)	3	1
4	(2,1)	2	1
F1	(1,-)	1	-
F2	(-,0)	-	0

First number in each state is the number of operational SEs, whereas second number is the number of operational NNs. F1 and F2 are failure states whereas other four are operational.

We will denote previously defined λ_{SE} and λ_{NN} as λ_1 and λ_2 respectively. In the same manner λ'_{NN}, will be called λ'_2. Additionally we will assume the following values for SE and NN:
$\mu_1 = \mu_2 = 0.1$ for recovery/time unit and,
$C_1 = C_2 = 0.9$ for *accumulated coverage factors* (incl. fault detection, isolation, removal and transition to operational state).

Now we are ready to define states. In Table I six states are defined. Then, states and their transition rates are used to describe the transition graph Fig. 4. Transition graph assumes that if 2 modules are failed, the SE will be prioritized for maintenance (see $C_1\mu_1$). This is realistic since we want to preserve optimal utilization for the system while running a recovery task. So most likely we will run only one recovery task at a time.

Then from Fig. 4 we write the *infinitesimal generator*:

$$Q = \left(\begin{bmatrix} \alpha_1 & 3\lambda_1 & 2\lambda_2 & 0 & 0 & 0 \\ C_1\mu_1 & \alpha_2 & 0 & 2\lambda_2 & 2\lambda_1 & 0 \\ C_2\mu_2 & 0 & \alpha_3 & 3\lambda_1 & 0 & \lambda'_2 \\ 0 & 0 & C_1\mu_1 & \alpha_4 & 2\lambda_1 & \lambda'_2 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \right) \quad (5)$$

where α_i is the exit rate for ith state:

$$\alpha_1 = -(3\lambda_1 + 2\lambda_2) \quad (6)$$
$$\alpha_2 = -(C_1\mu_1 + 2\lambda_2 + 2\lambda_1) \quad (7)$$
$$\alpha_3 = -(C_2\mu_2 + 3\lambda_1 + \lambda'_2) \quad (8)$$
$$\alpha_4 = -(C_1\mu_1 + 2\lambda_1 + \lambda'_2) \quad (9)$$

Now from (2) we get the following set of differential equations:

$$\frac{dP_1(t)}{dt} = \alpha_1 * P_1(t) + C_1\mu_1 P_2(t) + C_2\mu_2 P_3(t) \quad (10)$$
$$\frac{dP_2(t)}{dt} = \alpha_2 * P_2(t) + 3\lambda_1 P_1(t) \quad (11)$$
$$\frac{dP_3(t)}{dt} = \alpha_3 * P_3(t) + 2\lambda_2 P_1(t) + C_1\mu_1 P_4(t) \quad (12)$$
$$\frac{dP_4(t)}{dt} = \alpha_4 * P_4(t) + 2\lambda_2 P_2(t) + 3\lambda_1 P_3(t) \quad (13)$$
$$\frac{dP_5(t)}{dt} = 2\lambda_1 P_2(t) + 2\lambda_1 P_4(t) \quad (14)$$
$$\frac{dP_6(t)}{dt} = \lambda'_2 P_3(t) + \lambda'_2 P_4(t) \quad (15)$$

Solutions of these differential equations are transition probabilities presented in Fig. 5. Summing the transition functions corresponding to the probability of being in operational states 1 to 4 we obtain:

$$\begin{aligned} R_2(t) = \sum_{i=1}^{4} P_i(t) = 1.00290e^{-0.00027t} + \\ + 0.00376e^{-0.09439t} + 2.34701 * 10^{-7} e^{-0.08606t} + \\ + 0.00196e^{-0.12036t} + 2.58054 * 10^{-6} e^{-0.11894t} - \\ 0.00563e^{-0.08897t} \end{aligned} \quad (16)$$

Multiplying $R_2(t)$ (obtained by the CTMC) with the $R_1(t)$ from (4) for the RBD, we obtain the total reliability of the system:

$$\begin{aligned} R(t) = (1.00290e^{-0.00027t} + \\ + 0.00376e^{-0.09439t} + 2.34701 * 10^{-7} e^{-0.08606t} + \\ + 0.00196e^{-0.12036t} + 2.58054 * 10^{-6} e^{-0.11894t} - \\ 0.00563e^{-0.08897t}) \frac{2 - e^{-10^{-6}t}}{e^{2.03002*10^{-4}t}} \end{aligned} \quad (17)$$

Reliabilities are presented in Fig. 6.

V. DISCUSSION

The solutions for transition probabilities and reliabilities were derived for specific values of transition rates λ_i. It was of course possible to solve the differential equations for general values of λ_i, but that causes the solutions to become syntactically very long to present (write) without any benefit to a reader.

The failure rates were assumed slightly optimistically. In particular, failure rate assumed for NNs is infeasible in practice. The inaccurate behaviour of today's NN's makes them in general non-suitable for applications with high reliability demands. In the future, we might expect more empathises given on research of NNs adjusted for dependable systems. Furthermore, the assumed 10^{-3} faults/h failure rate for the Smart Eye devices corresponds to a higher reliability than the one perceived for the Smart Eye device during tracking mode (observing loss of frames due to low quality index). This assumption is necessary not to introduce an infeasible amount of redundancy.

Reliabilities are obtained under assumption that the process is only dependent on its current state and no prior

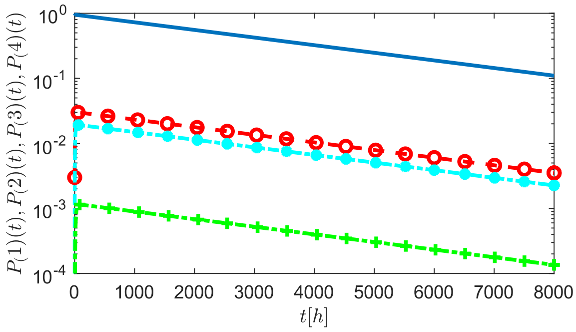

Figure. 5: Transition probabilities in log scale. (blue-$P_1(t)$, red-$P_2(t)$, cyan-$P_3(t)$, green-$P_4(t)$)

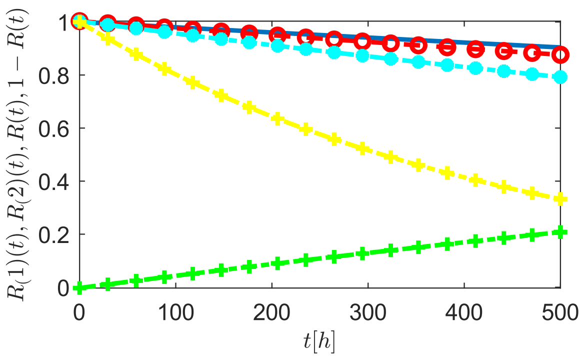

Figure. 6: Calculated reliabilities (blue-$R_1(t)$ RBD, red-$R_2(t)$ CTMC, cyan-$R(t)$ total reliability, green-$1 - R(t)$, yellow-reliability excluding redundancy)

history. For our particular application of CTMCs, one can rephrase this assumption as: *No matter in which order components have failed or at what time, the CTMC at time t only remembers the number of components that have failed.* This assumption obviously is not restrictive for applying CTMCs in reliability analysis. This is because it is usually and naturally enough to only keep track of the components that are currently failed in a system.

Under the assumption that this is a product that will only be in service intermittently, e.g. on average 5 hours/week, for an average usage of 260 hours/year one obtains after 6 months in service $R = 0.943$. This is a drastic improvement in comparison with the non-redundant reliability function presented in Fig. 6. Due to RBDs not imposing any prerequisites regarding the distribution of the random variable T, any arbitrary density function could have been used. Even though the exponential distribution lacks the property of being conditional to component wear out, we assumed that it sufficient as an estimate of the initial system reliability.

We presented reliability modeling by CTMCs and RBDs as it is pragmatical to model independent system components with RBDs and leave only dependent components for CTMCs. As systems become more complex, one might expect that the dependency between system components will also increase, which might in time make treading to simpler models like RBDs obsolete [1].

VI. Conclusion

The results show that, it is possible to extend the current architecture of the rehabilitation system to drastically improve its reliability, under the assumption of the chosen slightly optimistic failure rates. Inaccuracy of NNs classification however is a crucial issue as it is generally in the development of state-of-the-art dependable systems.

One thing not investigated by this paper was to determine whether a glitch or system reboot is most preferable if none of the entities pass the AT. This is something we plan to do in the future.

The service of providing real-time feedback of cognitive load for rehabilitation, does not constitute a major threat to the safety of the patient. In fact, the online pupillometry-based feedback system is similar in functionality to other systems that are possible to buy in pharmacies for personal usage and without a necessity for a prescription. The particularity of this system are the demands for real time performance. Even though the system is specific, the reliability approach presented can be applied on other medical devices and systems.

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References

[1] O. Hasan, W. Ahmed, S. Tahar, and M. S. Hamdi, "Reliability block diagrams based analysis: a survey," in *AIP Conference Proceedings*, vol. 1648, no. 1. AIP Publishing LLC, 2015, p. 850129.

[2] B. Sericola, *Markov chains: theory and applications*. John Wiley & Sons, 2013.

[3] E. Dubrova, *Fault-tolerant design*. Springer, 2013, ch. 3.

[4] J. Tidare, E. Astrand, and M. Ekström, "Evaluation of closed-loop feedback system delay - a time-critical perspective for neurofeedback training," in *BIODEVICES 2018*, 01 2018, pp. 187–193.

[5] F. Toates, "Accommodation function of the human eye," *Physiological reviews*, vol. 52, no. 4, pp. 828–863, 1972.

[6] D. Kahneman, *Attention and effort*. Citeseer, 1973, vol. 1063.

[7] E. H. Hess and J. M. Polt, "Pupil size in relation to mental activity during simple problem-solving," *Science*, vol. 143, no. 3611, pp. 1190–1192, 1964.

[8] P. van der Wel and H. van Steenbergen, "Pupil dilation as an index of effort in cognitive control tasks: A review," *Psychonomic bulletin & review*, vol. 25, no. 6, pp. 2005–2015, 2018.

[9] H. Mahfoud, A. E. Barkany, and A. E. Biyaali, "Medical maintenance performance monitoring: a roadmap to efficient improvement," *International Journal of Productivity and Quality Management*, vol. 22, no. 1, pp. 117–140, 2017.

[10] V. Hegde and D. Raheja, "Design for reliability in medical devices," in *2010 Proceedings-Annual Reliability and Maintainability Symposium (RAMS)*. IEEE, 2010, pp. 1–6.

[11] A. Avizienis, J.-C. Laprie, and B. Randell, "Fundamental concepts of dependability," *Department of Computing Science Technical Report Series*, 2001.

[12] B. Littlewood, "Dependability assessment of software-based systems: state of the art," in *Proceedings. 27th International Conference on Software Engineering, 2005. ICSE 2005*. IEEE, 2005, pp. 6–7.

[13] G. Rubino and B. Sericola, *Markov chains and dependability theory*. Cambridge University Press, 2014.

[14] Z. Kurd, T. Kelly, and J. Austin, "Developing artificial neural networks for safety critical systems," *Neural Computing and Applications*, vol. 16, no. 1, pp. 11–19, 2007.

[15] Y. Pan and N. Hu, "Research on dependability of cloud computing systems," in *2014 10th International Conference on Reliability, Maintainability and Safety (ICRMS)*. IEEE, 2014, pp. 435–439.

[16] K. S. Trivedi and A. Bobbio, *Reliability and availability engineering: modeling, analysis, and applications*. Cambridge University Press, 2017, ch. 9.

[17] M. T. Sim and Y. Zhuang, "A dual lockstep processor system-on-a-chip for fast error recovery in safety-critical applications," in *IECON 2020 The 46th Annual Conference of the IEEE Industrial Electronics Society*. IEEE, 2020, pp. 2231–2238.