Age of Information-based Abnormality Detection with Decay in the Human Circulatory System

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***Abstract*—Detecting abnormalities early by deploying a network of mobile nanosensors within the human body remains a challenging task. Current methods for abnormality detection rely on placing gateways at arbitrary locations. Given the critical importance of timely monitoring and detection in severe infections, relying on arbitrary gateway locations introduces delays in detection. In this work, we conducted an analysis of the impact of gateway placement and infection locations on detection time, detection ratio, and the average Peak Age of Information (PAoI). Furthermore, we also added decay of nanosensors similar to operation in the human body. We investigated its implications on both the detection ratio of abnormalities and the average PAoI. We employed a Monte Carlo simulation involving 1000 nanosensors circulating in the HCS for 500 seconds. The results revealed that the favorable gateway position is at the heart, minimizing detection time and enhancing the detection ratio for various infection locations. Furthermore, we observed that the detection ratio exhibited reduced variance with increased decay rates in nanosensors. Analyzing the PAoI across varying decay rates highlighted the importance of nanosensor quantity in relation to decay rate in ensuring accurate and timely infection localization.**

***Index Terms*—Nanosensors, Nano Communication, Human Circulatory System, Abnormality Detection, Nanosensors Decay**

I. Introduction

In recent years, nanocommunication has revolutionized the field of healthcare, opening up new frontiers in disease detection and treatment. One promising application lies in deploying nanosensors within the Human Circulatory System (HCS), which can detect biomarkers released by abnormalities, particularly cancerous tissues [1]. These nanosensors are engineered to recognize and respond to specific biomarkers indicative of cancerous tissue abnormalities [2]. The injected nanosensors monitor the bloodstream, collect data from adjacent body regions, and report their information to an external monitoring device through a gateway, as depicted in Fig. 1.

The implementation of Internet of Bio-Nano-Things (IoBNT) illustrates the use of a gateway to forward the reported information to healthcare professionals. A biohybrid implant comprising 3D engineered skeletal muscle that is capable of performing sensing at a molecular level and forming a wireless link is described in [3]. The device utilizes a combination of 3D-printed scaffolding, an implant antenna, and engineered skeletal muscle tissue to enable a novel form of bio-sensing. A target molecule triggers the bio-nanosensor, causing it to reconfigure the antenna. The design and performance analysis of such a wireless implant antenna for in-body sensors is presented in [4]; which creates a wireless link with a wearable antenna (external gateway) [5].

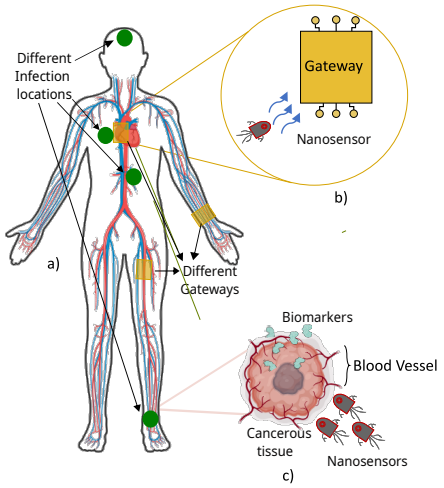

Fig. 1. Nanocommunication-based abnormality detection system. a) Human circulatory system. b) Communication between nanosensor and the gateway. c) Nanosensors detecting biomarkers at the target location.

Prior works on nanosensor-to-gateway communication have explored various gateway placements within the human body, such as the heart, wrist, hip, and ankle [6], [7]. However, in the context of serious infections, where timely monitoring and detection are critical, relying on randomly chosen gateway locations contributes to delays in the detection process. To address this, we focus our analysis on a single gateway, which serves several purposes. Firstly, it aligns with real-world constraints where cost and resource limitations might make deploying multiple gateways infeasible. Secondly, it allows us to precisely analyze the impact of a gateway's placement on detection time and ratio, offering insights into optimization. Finally, it simplifies the evaluation process, enabling us to focus on this crucial design aspect without additional complexities. We acknowledge the potential benefits of multiple gateways and plan to explore the complexities and trade-offs of such systems in future.

In this context, we extend our previous work of abnormality detection [8] to analyze the strategic placement of the gateway in various locations, aiming to ensure that this placement does

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not compromise either the detection time or the detection ratio. Accounting for timely detection, the metric Age of Information (AoI) is utilized to assess the freshness of information originating from a source (here, infection location) and analyze timely updates, taking into account the constraints of the molecular communication channel [9]. Leveraging the Peak Age of Information (PAoI) metric, we gain insights into the temporal dynamics of information flow at the receiver (here, gateway). In healthcare scenarios, especially in the dynamic environment of the circulatory system, having the most up-to-date information is crucial for prompt responses to emerging infections or abnormalities.

In this work, we analyze the optimal location of the gateway and develop a methodology to evaluate the detection time and detection ratio of the abnormalities. The nanosensors are more likely to undergo exponential decay over time due to the degradation processes within the human body [10, Eq. (60)]. Consequently, the decay of nanosensors over the course of their mobility introduces uncertainties in detecting abnormalities, presenting a challenge to the early detection associated with conditions like cancer. Therefore, it is crucial to understand the influence of nanosensor decay on the detection ratio. This comprehension is essential for recognizing the significance of incorporating the lifespan and stability of nanosensors when devising strategies for abnormality monitoring and diagnostics. Consequently, to analyze the timely identification of abnormalities, we investigate the dynamics of AoI concerning the decay of nanosensors. In this directions, our major contributions can be summarized as follows:

- We develop a methodology to evaluate the detection time and detection ratio of the abnormalities for optimal localization of the gateway;
- We implement the decay of nanosensors within the HCS and analyze its impact on the detection metrics;
- We evaluate the average PAoI metric for nanosensor to gateway communication for different scenarios.

Since molecular communication is an interdisciplinary domain, developing models supported by simulations and analysis is crucial to drive progress and harness the potential of nanosensor networks for healthcare applications. Our work focuses on analysing optimal gateway placement and the impact of nanosensor decay for timely and reliable transmission of critical health data collected within the human circulatory system.

II. Related Work

To enhance nanocommunication-based healthcare applications, several research works have emerged, focusing on deploying nanosensors into the HCS for the early detection, precise localization, and continuous monitoring of abnormalities, such as infected cancerous tissues [1], [11]. The premise of abnormality detection has been on inserting mobile nanosensors into the blood vessels of the HCS to detect biomarkers secreted by infected cells [12]. For instance, Mosayebi et al. [13] proposed a model where nanosensor reading is captured by a static Fusion Center (FC) to measure activation levels, indicating the presence of abnormalities. They also explored the detection of biomarkers by reactive nanosensors throughout the tissue, activating upon encountering biomarkers and signaling the presence of the target to a FC.

In their pursuit of early abnormality detection, Simonjan et al. [14] concentrated on identifying specific regions within the body that manifest abnormalities. The system comprises anchor nodes, macroscale devices attached to the skin, and nanosensors floating in the bloodstream. To overcome communication range limitations and high sensor mobility, the nanosensors are equipped with inertial measurement units (IMUs). The gathered information is then communicated to the anchor nodes to report the detected abnormalities. A Markov model is utilized in [8] to compute the distribution of mobile nanosensors within human blood vessels. They integrated a machine learning (ML)-based method to assess the transition probabilities of the Markov model and determine the location of abnormalities in the blood vessels. Another method for detecting abnormalities include a two-tier network, where artificial cells (ACs) in the first tier monitor changes in biomarker concentrations to identify abnormalities [15]. For enhanced detection, Solak and Oner [16] employ a sequential probability ratio test, combining decisions from various sensors in a centralized network. They optimize the average sample size for decision-making by using an adjustable observation window size. Semantic and subjective information could significantly impact how *freshness* is interpreted within the AoI framework. While AoI focuses on the time since information was generated, semantic information could provide insight into the context and continued relevance of the data. For example, information regarding an infection may lose semantic relevance over time if the body's immune response has addressed it. Furthermore, semantic and subjective information could enable the prioritization or categorization of data from nanosensors. Understanding how biological systems use semantic information [17], [18] could inspire ways to optimize AoI-based communication strategies within synthetic molecular communication (MC) systems. The subjective measure could evaluate the frequency with which transmissions from nanosensors result in appropriate responses from the external gateway. Thus, it is essential to assess the average PAoI metric in the context of communication from nanosensors to the gateway for comprehending timely information delivery [6]. Despite numerous studies on detecting abnormalities, the impact of the decay of nanosensors on the detection quality was rarely considered so far. The decay of nanosensors has a significant impact. As chemical reactions will degrade the nanosensors, it is crucial to analyze the impact on the detection performance with time. In the context of decaying nanosensors, analyzing AoI quantifies the decline in data reliability, enabling timely abnormality detection.

III. System Model

The AoI-based abnormality detection system model essentially includes the following components:

- *Nanosensors*: Nanosensors constantly patrol the bloodstream and are designed to detect specific biomarkers released by infection location. When a nanosensor encounters the biomarkers, it gets activated and prepared to report the detection at gateway. The detection is reported

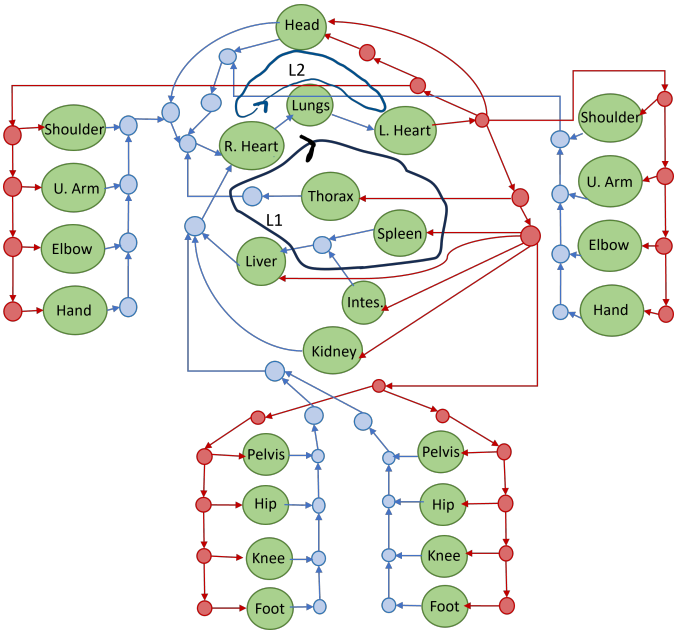

Fig. 2. HCS as represented in BVS framework.

at the gateway and the nanosensor is reset to fetch fresh status updates on the infection location.

- *Gateway*: A gateway is an on-body computing device placed at different locations on the human body, such as a wearable antenna [5]. It collects data from nanosensors, analyzes this data, alerting external monitoring devices about potential health risks.
- *Communication*: The nanosensors communicate with the gateway within the human body through commonly considered intra-body communication link, such as terahertz or ultrasonic channels [8]. We assume that the communication link is error-free.

Following the model in our previous work [8], we consider the nanosensors move along passively within the HCS. The nanosensors flowing through the vessels activate upon detecting the biomarkers released by the infection location. These traveling nanosensors report the detection of an infection when they encounter the gateway along their path. We utilize the data generated from the BloodVoyagerS (BVS) [19] framework, which simulates the mobility of nanosensors in the bloodstream within all major vessels of the HCS. Each vessel and organ included in the simulator is assigned a distinct identifier (vesselID), the details of which can be found in our previous work [8]. The raw data from BVS provides the global position of the nanosensors randomly visiting vessels within the HCS.

IV. Modeling Detection Metrics and Decay

In this Section, we introduce the detection metrics, such as detection ratio, detection time, and average PAoI, and provide insights into the modeling of nanosensors decay over time. We compute the detection ratio with the classical approach through the ratio between the total of successes and the total of attempts. In the context of nanobot flow within the HCS, they exhibit varied trajectories as they navigate a loop, as depicted in Fig. 2. For example, a nanobot traveling along a specific circuit may

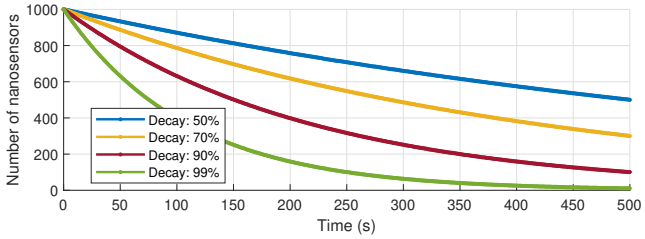

Fig. 3. Decay of nanosensors over time.

encounter random changes at intersections along its path. We determine the total of successes by identifying the total number of nanosensors moving in a loop through the infection location. Implicitly, here we assume that the nanosensor detects the presence of biomarkers whenever it flows through the infection location. For the denominator, we identify the total number of nanosensors traveling through the loops that also enclose the gateway's location (more illustration on loops can be found in [8]) as

$$\delta = \frac{\Sigma_{i \in L_i} N_i}{\Sigma_{i \in L_{i,g}} N_i}, \tag{1}$$

where N_i is the total of nanosensors flowing through the human body, L_i represents the set of loops including the infection location, and $L_{i,g}$ represents the set of loops including both the infection location and gateway. These nanosensors individually communicate with the gateway to report the presence of infections. The gateway processes data from each nanosensor n separately and then computes the detection time T_n as

$$T_n = t'_n - t_n, \tag{2}$$

where t_n is the time instant of the nanosensor flowing across the infection location and t'_n represents the time instant when the nanosensor travels across the gateway. To compute the average PAoI, we record two time metrics [20]. The generation time per nanosensor, denoted as τ_j, which refers to the time instant when the nanosensor travels through the infection location, and the travelling time from the infection location to the gateway, denoted as g_j. Using these two metrics, the PAoI can be computed as

$$A_j = \tau_j + g_j - g_{j-1}, \tag{3}$$

where $g_j - g_{j-1}$ is the time interval between two consecutive receptions, and $j \in \mathbb{N}$. The average PAoI can be computed as $E[A_j]$.

We implement information decay using an exponential function to model the natural degradation process resulting from chemical reactions, as described in [10, Eq. (60)]. This decay simulates the realistic impact on the nanosensors flowing within the HCS and is expressed as follows.

$$N(t) = N_0 \cdot e^{-rt}, \tag{4}$$

where $N(t)$ is the number of nanosensors at time t, N_0 is the nanosensor quantity at $t = 0\,\text{s}$, and r is the decay rate. For the purpose of illustration, as depicted in Fig. 3, we consider the following percentage decay of nanosensors over time: 50, 70, 90, and 99, which corresponds to four distinct decay rates r: 0.0014, 0.0024, 0.0046, and 0.0092. Initially, at $t = 1\,\text{s}$, 1000 nanosensors within the HCS are subject to exponential

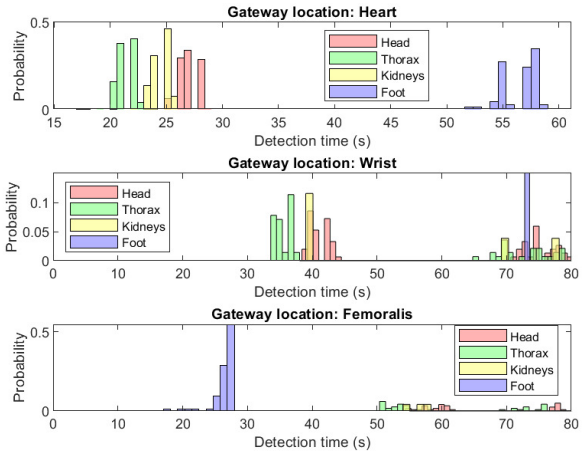

Fig. 4. Detection time vs. gateway locations (note the different y-axis scale).

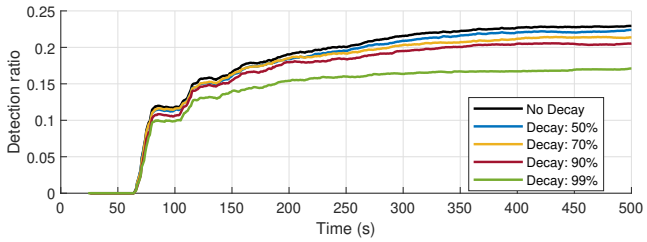

Fig. 5. Detection ratio for varying decay % corresponding to decay rates 0.0014, 0.0024, 0.0046, and 0.0092 (gateway location: Heart; infection location: Head).

decay. This is implemented by using the corresponding values from the decay curve at each time instant to estimate the total number of nanosensors to be removed within the HCS. We randomly select nanosensors from the dataset generated by the BVS at each time instant and remove associated data entries. This aligns the data with the simulated decay, reflecting the gradual reduction in nanosensors within the HCS over time according to the decay rates. The introduction of decay is expected to maintain average values for metrics like detection time. This is because the metric is primarily determined by the time it takes for a nanosensor to report the abnormality upon encountering specific biomarkers.

The decay of nanosensors may pose a challenge by potentially affecting the number of samples reported at the gateway, although its direct influence on the detection time remains limited. Since decay over time results in the reduced number of nanosensors, it becomes more likely that it affects the detection of abnormalities. The dynamic and stochastic nature of the detection process, introduced by varying lifetimes of decaying nanosensors, can contribute to increased variability in the timing of detection events. Thus, it is crucial to analyze the impact of the system as decay progresses, which we discuss in the next section.

V. Results and Discussion

We performed a Monte Carlo simulation with 1000 nanosensors traveling in the HCS for 500 seconds and computed the detection time, detection ratio, and average PAoI. We

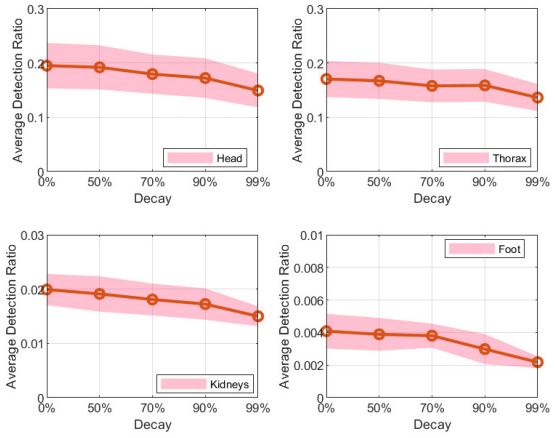

Fig. 6. Average detection ratio vs. decay in nanosensors (note distinct y-axis).

considered three different locations of the gateway, such as the heart, left wrist, and left femoralis, and four different infection locations, such as the head, thorax, kidneys, and foot. Fig. 4 illustrates the normalized histogram depicting the time elapsed for nanosensors in the successful detection of various infection locations. The detection time is shorter when placing the gateway at the heart compared to locating it at the wrist for infections in the upper regions of the human body. This is attributed to the higher frequency of heartbeats, averaging 60 to 100 times per minute. The central position of the heart ensures more rapid access and transmission of information, enhancing the efficiency of the detection system. The gateway at femoralis incurs the lowest detection time for an infection at the lowest body part. To ensure timely detection across diverse body regions, prioritizing the heart for gateway placement emerges as a favorable choice due to its consistent efficiency and reduced delays. In Fig. 5, we can observe how the detection ratio at the gateway for an infection location at head changes as decay progresses. As decay rates increase, a relatively more number of nanosensors are eliminated over time within the HCS, resulting in a decrease in the overall detection ratio. We notice that slower decay rates may maintain detection capabilities at the gateway for a more extended period.

Fig. 6 illustrates the average detection ratio with the varying rates of decay in nanosensors. We show the results for different infection locations while gateway is located at the heart. The reduced variance in the detection ratio in scenarios with increased decay rates is attributed to the diminished number of samples in the system, a consequence of the decay process. Fig. 7 depicts the variation of average PAoI with respect to increasing decay rates of nanosensors. We observe a notable increase in the average PAoI with the rise in nanosensor decay, indicating that as nanosensors decay more rapidly, the time for information to reach its peak freshness at the gateway also increases on average. Lower PAoI signifies more accurate information about the infection location, reducing the likelihood of delays and enhancing the precision of infection localization. Our analysis emphasizes the critical role of the quantity of nanosensors in the HCS. A too small number leads to delayed transmission of infection detection status updates.

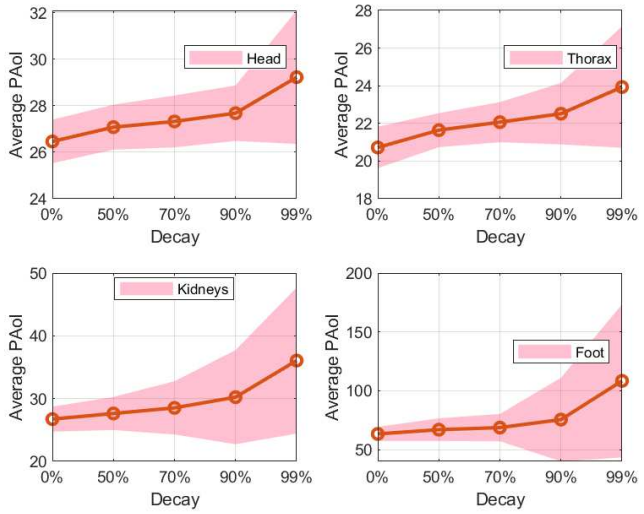

Fig. 7. Average PAoI vs. decay in nanosensors (note distinct y-axis).

VI. Conclusions

This work analyzed the effects of gateway placement and nanosensor decay on the detection of abnormalities. Our findings emphasize that placing the gateway at the heart enhances the efficiency of abnormality detection in the complex network of the human body. We observed that the decay of nanosensors has a significant impact on both the detection ratio and the average PAoI. Optimizing gateway placement reduces the time for receiving fresh status updates from infection locations, enhancing the overall effectiveness of monitoring systems with mobile nanosensors. The placement of the gateway indeed influences the detection time; however, finding the optimal trade-off between detection time and detection ratio is challenging. The best balance depends on the nature of the abnormality being detected, with some conditions allowing for a short delay while others necessitate early detection. Achieving an optimal balance is context-dependent, involving a careful consideration of the importance of timely detection against the detection ratio.

While our analysis demonstrates the potential impact of optimized gateway placement and highlight the importance of considering nanosensor decay, translating this system into real-world healthcare presents several significant challenges. These include developing nanosensors with appropriate biocompatibility, longevity, and reliable sensing mechanisms within the complex bodily environment, establishing robust, low-power communication and networking protocols for a large number of nanosensors within the body, addressing potential adverse effects such as immune response or interference with biological processes, and ensuring data privacy and security within a dynamic, distributed system. Future work will require collaborations across various disciplines to address these challenges and move this concept closer to clinical applications.

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