Cancermorphic Computing Toward Multilevel Machine Intelligence

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Abstract

Despite their potential to address crucial bottlenecks in computing architectures and contribute to the pool of biological inspiration for engineering, pathological biological mechanisms remain absent from computational theory. We hereby introduce the concept of cancer-inspired computing as a paradigm drawing from the adaptive, resilient, and evolutionary strategies of cancer, for designing computational systems capable of thriving in dynamic, adversarial or resource-constrained environments. Unlike known bioinspired approaches (e.g., evolutionary and neuromorphic architectures), cancer-inspired computing looks at emulating the uniqueness of cancer cells survival tactics, such as somatic mutation, metastasis, angiogenesis and immune evasion, as parallels to desirable features in computing architectures, for example decentralized propagation and resource optimization, to impact areas like fault tolerance and cybersecurity. While the chaotic growth of cancer is currently viewed as uncontrollable in biology, randomness-based algorithms are already being successfully demonstrated in enhancing the capabilities of other computing architectures, for example chaos computing integration. This vision focuses on the concepts of *multilevel intelligence* and *context-driven mutation*, and their potential to simultaneously overcome plasticity-limited neuromorphic approaches and the randomness of chaotic approaches. The introduction of this concept aims to generate interdisciplinary discussion to explore the potential of cancer-inspired mechanisms toward powerful and resilient artificial systems.

Keywords: cancermorphic; computing; bioinspired; biomimetics; machine intelligence; diverse intelligence

1. Bioinspired Computing

Bioinspired computing aims at emulating natural systems to address limitations in traditional algorithms and enhance machine intelligence.[1] Core examples are evolutionary algorithms and swarm robotics, and recent advances have diversified the biological pool of inspiration.[2] Neuromorphic computing has evolved beyond early neural network abstractions to emulating the spatiotemporal dynamics of the brain.[3] Platforms like Intel Loihi 2 emulate hippocampal theta-gamma oscillations to enable real-time unsupervised learning, achieving 30 times energy efficiency over GPUs in pattern recognition tasks.[4] Photonic neuromorphic architectures now exploit laser-driven spike-timing-dependent plasticity (STDP), mirroring synaptic weight adjustments at near-light speeds.[5] Yet, these systems remain constrained by their inability to achieve structural reconfiguration in response to external perturbations.[6] Another paradigm is DNA computing, which has emerged in theoretical toy problems and now utilizes CRISPR-Cas9 precision for molecular data storage.[7] Plant root apices have also inspired algorithmic analogs in subterranean exploration robots.[8] However, all existing bioinspired paradigms recapitulate homeostatic biological models, overlooking pathological systems like cancer, which outsmarts healthy biological constraints to achieve unique adaptability. Tumors undergo hypermutation to evade the immune system, with strategies orders of magnitude faster than Darwinian selection.[9] Metastatic cascades coordinate invasion via self-organizing cell populations,[10] overcoming the stigmergic coordination observed in swarm robotics. Despite their potential to address key challenges in fault tolerance and system resilience, these pathologically adaptive mechanisms remain absent from computational theory.

This gap could bring to explore the potential of cancer-inspired strategies that embrace controlled dysregulation to thrive in adversarial settings, and computer science and engineering are poised to benefit from the nascent field of diverse intelligence. The latter seeks to understand learning and problem-solving in systems different than conventional brains and nervous systems.[11-16] Understanding computational and cognitive capabilities across minimal active matter,[17-22] molecular networks,[23-30] and cells,[31-33] provides a much broader source of bioinspiration beyond the functions of neural networks. Much of biological problem-solving occurs as navigation of spaces that are not obvious to humans, such as gene expression spaces, physiological state spaces, or the anatomical morphospace.[34] For example, embryos and salamanders can recover from drastic surgical manipulations, recognizing quickly that key body-parts are missing, and working to effectively restore them toward a correct target morphology.[35] Likewise, planarian flatworms can pick a small number of genes, in a space of tens of thousands of possible transcripts, that enables them to handle severe novel stressors for which their evolutionary experience did not prepare them.[36] Finally, normal genomes are interpreted by cells in unexpected ways to create new life forms (biobots such as Xenobots and Anthrobots) that exhibit coherent morphogenesis, behavior, and surprising new properties,[37-39] when challenged with configurations that have never been the targets of selection.

2. Cancer as a New Level of Intelligence

Unlike contingent, externally-driven disorders such as parasitic infection, cancer is an inevitable failure mode of the ability of cells to work as a collective intelligence to navigate anatomical space.[40] What fundamentally happens in cancer is that cells disconnect from the electrochemical network of the tissue, which stores homeodynamic patterns, beneficial at the organism-level, that dictate normal organ shape and configuration.[40] In cancer cells, the size of their cognitive light cone, i.e. the scale of the setpoints they can pursue, shrinks drastically, to become that of their unicellular ancestor.[41, 42] At that point, the rest of the body becomes just "external environment" at the expense of which they pursue their ancient microbial agendas. This flexibility of the border between self and world, which grows during evolution and embryogenesis, is also enabled during the lifetime of an organism. Thus, if cells are a collective intelligence whose behavior is observed as adaptive navigation of anatomical morphospace, cancer is a dissociative identity disorder of that collective intelligence.[40]

Cancer is not just a story of a failure of growth control; it is a profound source of insight about the way that adaptive, self-constructing systems scale and establish boundaries.[43, 44] Hence, unlike other ways in which homeostatic systems break down, cancer is not uniformly a diminution of capability and order. Instead, it represents another level of capability that can provide useful lessons for engineering. From the perspective of the organism level, cancer is a destructive syndrome. But from the perspective of the defecting cells, it is a liberation from the electrochemical mind-meld that kept them harnessed towards alien goals: building organs, maintaining tissues, and dying routinely for the sake of this larger scale society of the body.[45] Because life is implemented as a multi-scale competency architecture where homeodynamic abilities, problem-solving, and computation are baked in at every level, cancer is not merely a disease but a shift of agency and intelligence across levels. What the organism loses in systemic dysregulation, is what the cancer cells, and their eventual attempt to re-form multicellularity (i.e. the tumor), gain in exercising their ancient competencies at exploiting their microenvironment. The concept of intelligence across levels mirrors the fact that cancer is uniquely a feature of living organisms. Robots and computers are currently incapable of undergoing cancer-like disruptions, because their intelligence exists at one level, supported by passive parts with no significant agendas of their own. These parts are not susceptible to dissociations, and do not engage with the benefits provided by committing to a fundamentally unreliable medium that kickstarts the intelligence ratchet of life.[46] This effectively represents a limitation towards achieving artificial systems capable of enhanced intelligence. Here, we discuss some of the lessons we can learn from cancer intelligence with the goal of harnessing them for useful purposes in engineering.

3. Biological Mechanisms in Cancer and Computational Readaptations

The conceptual framework of cancer-inspired computing is rooted in identifying a common denominator between cancer biology and ideally skilled computational systems. By dissecting

the molecular, cellular, and environmental strategies that enable tumors to survive, adapt and propagate, five core cancer mechanisms that would have transformative potential in computational logics are presented: metastasis, angiogenesis, immune evasion, mutation, and tissue reprogramming. These mechanisms are to be thought as operational goals for designing computational systems capable of self-organization and dynamic adaptation under constraints or threats. These analogies are summarized in **Table 1**, and each is individually addressed in the following subsections.

Table 1. Biological mechanisms and computational analogs.

Cancer mechanism	Computational parallel	Advantages	Drawbacks	Applications
Metastasis	Decentralized propagation	Resilience in unstable environments	Resource-intensive replication; risk of uncontrolled task proliferation	Disaster-response robotics, extraterrestrial exploration, self-healing networks
Angiogenesis	Adaptive resource recruitment	Energy efficiently in resource-constrained systems	Potential for parasitic resource exploitation (e.g., draining peer nodes)	Edge computing, rural IoT networks, drone swarms
Niche Construction	Polycomputing (autonomous subsystems with lateral control)	Propagation of solutions through computational medium	Potential unwanted effects on other subsystems	Swarm robotics, Crowd of Experts AI systems
Immune evasion	Cybersecurity	Proactive malware adaptation	Ethical risks (e.g., mimicking benign processes could enable malicious use)	Polymorphic encryption, honey-pot networks, adversarial ML defenses
Mutation	Evolutionary adaptation	Context-aware and rapid optimization	Risk of algorithmic instability or "mutational drift"	Real-time financial trading AI, adaptive climate models, antibiotic discovery

3.1. Metastasis as Decentralized Propagation

Metastasis, the process by which cancer cells dissociate from a primary tumor, migrate and colonize distant tissues,[47] represents a parallel to decentralized survival. Biologically, this involves epithelial-to-mesenchymal transition (EMT), where cells lose adhesion properties to become migratory, followed by colonization of secondary sites through microenvironment remodeling.[47] Metastatic strategies ensure tumor persistence even when the primary site is compromised,[47] mirroring the search for computational systems able to overcome localized failures. On this line, metastasis could inspire architectures that dynamically redistribute tasks or data across networks. A primary application would revolve around decentralized sensor networks where if a central server fails, individual nodes could autonomously form temporary sub-networks, propagating only critical updates to surviving nodes. This mimics metastatic colonization, where secondary tumors remain functional despite primary site destruction.[47] Recent work in self-healing mesh networks (e.g., protocols like Routing Protocol for Low Power in Lossy Neworks (RPL) in IoT) has demonstrated the feasibility of this concept.[48] Cancermorphic designs would integrate probabilistic migration rules derived from metastatic cell motility (e.g., Lévy flight patterns observed in circulating tumor cells).[49] Such systems could revolutionize applications in disaster response or applications where communication with a central hub is critical and might fail.

3.2. Angiogenesis as Resource Optimization

Angiogenesis is the cancer-driven formation of new blood vessels and exemplifies the recruit of resources under scarce availability.[50] Cancers secrete vascular endothelial growth factor (VEGF) to co-opt host vasculature, ensuring nutrient supply even in hypoxic microenvironments.[50] This parasitic process reflects an evolved capacity to exploit existing infrastructure while building new pathways.[50] Computationally, angiogenesis brings to think of systems that autonomously recruit or reallocate resources in response to bottlenecks or increased demands. For example, cloud-based platforms could implement vascular burst-like protocols, temporarily harvesting cycles from peer nodes just like tumors tap in adjacent capillaries. In edge computing, this principle could enable devices in resource-constrained environments (e.g., IoT networks in rural settings) to share energy or bandwidth. Recent findings demonstrated a similar approach in drone swarms, where units under low battery rerouted tasks via gradient-based signaling.[51] Cancermorphic systems would extend such models by incorporating competitive resource prioritization, mirroring the tumor ability to exploit vasculature at the expense of healthy tissue.

3.3. Immune System Evasion as Cybersecurity

The ability of cancer cells to evade immune detection is a perfect example of adversarial survival. In biology, mechanisms include antigen masking (e.g., downregulating MHC molecules),[52] immunosuppressive cytokine secretion (e.g., TGF-β),[53] and mimicry of stromal

cells.[54] These strategies allow tumors to persist undetected while actively unsettling defensive responses. In cybersecurity, cancermorphic principles could inform adaptive defences that mutate to evade detection in presence of threats. For instance, polymorphic encryption protocols[55] could dynamically alter their cryptographic signatures, just like cancer cells vary surface antigens to escape immune targeting. Recent advances in adversarial machine learning, where models are hardened against input perturbations, already utilize this approach.[56] On top of this, cancermorphic cybersecurity would enable embedding self-hiding code that mimics benign processes (e.g., mimicking system data definition language (DLL) files[57]) while isolating threats. This has been demonstrated in honeypot networks, where decoy servers mimicked user behavior patterns to divert attackers, reducing breach rates.[58] Yet, such systems risk ethical issues, as using cancer-like stealth in cyberdefense might easily turn defense into attack.

3.4. Mutation as Evolutionary Adaptation

Somatic mutation drives the evolutionary adaptability of cancer, generating genetic diversity that enables clonal selection under therapeutic pressure.[59] Unlike Darwinian evolution, which operates on generational timescales, cancer mutations are rapid, stochastic and context-dependent,[60] highlighting the difference between this approach and randomness-inspired computing architectures. Computational parallels of this process involve algorithms that self-modify their parameters or configurations in response to environmental feedback. For example, a neural network trained for real-time language translation could introduce controlled randomness into its updates, retaining only mutations that improve accuracy. This mirrors the trial-and-error clonal expansion seen in tumors, where genetic diversity ensures quick adaptation of populations to unforeseen stressors.[59] Route mutation algorithms based on reinforced learning (RL) have been demonstrated.[61] However, unchecked mutational drift risks algorithmic instability. Cancer-inspired systems could address this challenge by embedding suppressive checkpoints (e.g., regularization layers that erase maladaptive mutations).

3.5. Tissue Reprogramming as Polycomputing

Cancer is an excellent example of hacking the agential material of life to master a complex, active environment that is trying to kill them. By means of signals they emit, cancer cells exploit their active microenvironment by inducing specific transcriptional programs in non-malignant cells.[62, 63] They also induce metabolic shifts, epigenetic changes, and secretion of growth factors in cancer-associated fibroblasts.[64-67] This ability to get the large, self-regulating system in which they live to act on their benefit is unlikely to be a specific adaptation, as there is no selection pressure for the cleverness of cancer, as opposed to the collective pressure against it. Instead, the example of niche construction,[68] like other morphogenetic capabilities of normal cells,[69-71] are a type of intelligence that deserves close attention and might benefit the development of powerful artificial systems.

4. Comparison with Existing Paradigms

Bioinspired computing often draws from collective intelligence (e.g., ant colonies) or neurobiology.[72] Instead, cancer-inspired computing would adopt behaviors of pathological resilience. Evolutionary algorithms prioritize fitness-guided selection over generations, whereas cancer-inspired mutation is somatic, context-driven, and immediate.[59] Similarly, fault-tolerant systems use redundancy to preserve function,[73] whereas cancer-inspired reinvent resources, even at the expense of other processes. This distinction makes cancer-inspired computing an interesting alternative for environments where traditional robustness fails, hence in adversarial, resource-starved, or unpredictably dynamics. Cancer-inspired computing differs from evolutionary computing by inspiring context-driven changes rather than generational selection. On the other hand, swarm intelligence,[51] which coordinates simple agents, may be outperformed by cancer-inspired systems prioritizing autonomy and survival logics, potentially enabling extreme adaptability. Neuromorphic systems emulate the architecture and function of biological neural networks focusing on synaptic plasticity and event-driven processing,[6] excelling in efficient data processing and energy conservation. However, they are conceived around fixed operational principles,[6] lacking the potential context-sensitive reconfiguration of cancer-inspired mutation. Chaos computing utilizes the dynamics of nonlinear systems, but its unpredictability may not always yield controlled adaptations.[74] Cancermorphic computing, drawing inspiration from context-driven mutation, could recalibrate its functions in real time. The differences between the proposed framework and existing models that recall similar features are summarized in **Table 2**. The proposed approach involves targeting resource reallocation and optimized performance in adversarial or unpredictable environments, overcoming the fallacies of both neuromorphic and chaotic models.

Table 2. Comparison of the proposed framework with existing and emerging models.

Model/ Feature	Neuromorphic Computing	Evolutionary Computing	Chaos Computing	Swarm Intelligence	Cancermorphic Computing
Inspiration	Neural networks	Darwinian evolution	Nonlinear dynamics	Social insects	Cancer survival strategies
Adaptability	Fixed architecture (neuroplasticity-limited)	Generational mutation	Chaotic state transitions	Collective consensus	Somatic mutation (real-time, context-driven)
Resource Management	Energy-efficient	Fitness-based selection	Entropy exploitation	Cooperative sharing	Parasitic/symbiotic recruitment (e.g., angiogenesis-like

					resource harvesting)
Main Strength	Parallel processing	Global optimization	Noise resilience	Scalability	Autonomous survival in adversarial/dynamic environments
Main Weakness	Rigid learning rules	Slow convergence	Unpredictable outputs	Fragility to node failures	Resource exhaustion, ethical risks

4. Sample Applications

The transformative impact of cancer-inspired computing lies in its potential to address complex and dynamic challenges across diverse domains. Envisioned applications are presented in the next subsections. Sample applications are grouped in **Table 3**.

4.1. Fault Tolerance

Modern critical infrastructure, from space exploration to healthcare, demands systems capable of autonomous recovery from unpredictable failures.[75] Currently, fault-tolerant architectures rely on redundant components or centralized oversight, which can introduce bottlenecks or points of failure.[73] Cancer-inspired systems inspired by metastatic propagation and angiogenesis could offer a crucial integration. In space exploration, for example, planetary rovers face extreme environmental stressors that can disable key subsystems.[76] A cancer-inspired approach could dynamically redistribute computational tasks and power resources across its modules, like metastatic cells colonizing new niches. If a panel fails, the system could reroute energy harvesting to other sensors or prioritize low-power modes, mirroring cancer adaptations to nutrient scarcity. This approach would enable context-driven resilience that optimizes survival without external intervention. Similarly, healthcare infrastructure could emulate cancer-inspired principles to ensure uninterrupted service, for example by metastasizing computations to side devices during failures. For example, a portable MRI machine in a remote clinic or in at-risk contexts could locally process critical scans, and syncing data when connectivity resumes.

Table 3. Sample applications of cancer-inspired computing logics.

Application	Cancer Feature	Biological Phenomenon	Areas of Impact
Fault Tolerance	Angiogenesis, metastasis	Decentralized colonization	Healthcare infrastructure

Adaptive AI	Mutation, clonal selection	Hypermutation under stressors	Climate modelling, drug discovery
Cybersecurity	Immune evasion, mimicry	Antigen masking	Polymorphic encryption
Swarm Robotics	Task redistribution in metastasis	TME remodeling	At-risk/low-resource zones, agriculture
Decentralized Finance	Angiogenesis-inspired resources rerouting	Vasculature co-option	Blockchain stability, cryptocurrencies

4.2. Adaptive Machine Intelligence

Major limitations of static AI models are evident in environments characterized by concept drift, such as financial markets or climate systems[55]. Cancer-inspired algorithms might enable real-time architectural plasticity. Traditional climate models struggle to predict increasingly volatile weather patterns due to fixed architectures.[77] Cancer-inspired AIs combined with neuromorphic architectures could introduce stochastic mutations in their neural network layers, selectively saving configurations that improve prediction accuracy under shifting conditions. This process would mimic tumor heterogeneity where genetic diversity allows cancer subsets to thrive under selective pressures such as therapy or changed environmental conditions. By embedding such adaptability, models could dynamically recalibrate to unpredictable phenomena, offering mitigation plans. In personalized medicine, cancer-inspired principles could revolutionize drug discovery by introducing cancer-inspired mutation strategies that generate diverse molecular structures under controlled randomness, impacting the problem of antibiotic resistance caused by bacterial evolution. By retaining only permutations that evade resistance mechanisms, these could accelerate the development of next-generation antimicrobials.

4.3. Cybersecurity

Cybersecurity demands systems capable of proactive and rapid adaptation.[58] Cancer-inspired strategies, inspired by immune evasion, mimicry, decentralization and optimization could redefine defensive frameworks. At present, malware detection relies on signature-based methods, which fail against novel exploits.[78] A cancer-inspired defense system could employ polymorphic code that continuously alters its cryptographic signature, evading detection like cancer cells suppress antigen presentation. For example, an intrusion detection system (IDS) could mutate in response to adversarial probing, creating a moving target for attackers. Decoy networks are another promising application. As tumors secrete factors to divert immune responses, cancer-inspired systems could deploy calculated metastases, e.g., phantom servers, to mislead cyberattacks. These honeypots could absorb and analyze attacks while

shielding regular assets. These strategies could neutralize advanced persistent threats (APTs) by exploiting adversaries resource constraints, like cancers exhaust host defenses through uncontrolled proliferation. Moreover, they could quickly learn attacker strategies and over time minimize the chances of similar attacks.

4.4. Swarm Robotics

Swarm robotics seeks to coordinate large ensembles of simple agents to achieve complex tasks.[51] Cancer-inspired principles, particularly metastasis and angiogenesis,[47] could enhance swarm adaptability in unstructured environments. In urban search-and-rescue operations, robot swarms must navigate collapsing structures with limited communication.[51] A cancer-inspired strategy could autonomously split into subswarms (like metastatic colonies) to explore multiple pathways simultaneously and dynamically reallocate roles based on environmental feedback. If a sub-swarm encounters debris blocking its path, it could recruit nearby agents via angiogenic-like signal gradients,[47] forming transient defenses. This behavior mirrors tumor cells recruiting blood vessels, but here it facilitates collective problem-solving. Another relevant example is agricultural robotics, where autonomous drones monitoring crop health could redistribute tasks based on real-time resource availability. During drought conditions, a subset of drones could prioritize irrigation monitoring, while others shift to pest control. This mechanism recalls how tumors reallocate energy stores to metastasis under stress.[47]

4.5. Decentralized Finance

The decentralized finance sector is a key example of dynamically evolving model.[79] It is strongly subjected to cyberattacks and market volatility, and substantial research efforts are invested in developing functional resilient strategies.[79] Blockchain networks, for example, are susceptible to distributed denial-of-service (DDoS) attacks that overwhelm nodes.[79] A cancer-inspired blockchain might employ metastasis-inspired transaction rerouting and dynamically shift validation tasks to underutilized nodes during an attack. This strategy recalls metastatic cells bypassing congested vascular pathways to ensure the presence of transaction throughput. Cancer survival principles could also inspire cryptocurrency area. As tumors modulate growth rates based on resource availability,[47] a cryptocurrency could adjust its inflation rate in response to market liquidity, enabling more robust decentralized economies.

5. Discussion

Despite the intriguing possibilities of this concept, challenges remain. These stem from the difficulty of emulating cancer survival strategies while ensuring system stability as well as its alignment with human objectives. In an important sense, a main challenge is conceptual: the nearly ubiquitous view of cancer as a molecular disorder of genetics, which obscures its potential for informing us about constructing capable agents.

5.1. Core challenges

Theoretical challenges derive in part from the established concept that cancer is fundamentally a failure of biological regulation, rather than a model of resilience. Tumors survive not through elegant optimization, but through exploitation of host systems,[47] making this strategy theoretically destructive. Translating this into computing risks prioritizing short-term adaptability over long-term system health. This conceptual problem highlights the need for biological fidelity in cancer-inspired models. For example, while metastasis enables cancer spread, fewer than 0.01% of circulating tumor cells successfully colonize distant organs.[80] A computational system that blindly mimics this process might waste resources replicating tasks across nodes with little benefit, risking to destabilize infrastructure or consuming excessive resources. For instance, a cancer-inspired network designed to metastasize tasks across nodes could overwhelm bandwidth or energy reserves, mirroring the behavior of aggressive tumors in healthy tissues. Emulating somatic mutation dynamics (for example, hypermutation rates in response to attacks) in algorithms requires frameworks that are difficult to predict or debug. Similarly, context-aware mutation risks diverging into chaotic states. Recent work in adaptive control theory, such as Lyapunov-based stability constraints for self-modifying AI in neural networks,[94] is a potential way to embed additional preventive measures against this potential risk. Another problem might be computational scalability. Real-time emulation of biological processes requires substantial processing power in distributed systems. Neuromorphic or quantum architectures may provide the parallelization needed to manage these tasks, but their current immaturity limits practical implementation. Hence, it is crucial to selectively abstract biological principles, retaining adaptive mechanisms and balancing autonomy with stability. This can be overcome by integrating cancer-inspired principles in the design of enhanced neuromorphic or chaotic architectures, aiming to target *controlled* context-driven adaptation across levels.

5.2. Future Directions

A conceptual shift is needed in the context of cancer from the domain of genetic defect to a disorder of multiscale system organization.[81-83] A useful step forward in how this phenomenon is perceived has to do with our focus on material structures rather than patterns (i.e., the machine vs. the passive data upon which it operates). Deep lessons for the science and engineering of computation are revealed if we view morphogenesis as the battleground of patterns and models, not of cells and molecules. Ion channel misexpression in posterior regions of the body of a vertebrate model system can induce a bioelectric pattern that signals cells to build an entire eye.[84] This top-down control of a complex morphogenetic outcome via a relatively simple bioelectric prompt has two relevant features for cancermorphic computing in its broader context of programming multiscale materials. First, sectioning reveals that only some of the ectopic eye's cells are expressing the exogenous ion channel: the rest of the eye is made of cells that were convinced to participate in this abnormal morphogenesis just as cancer cells manipulate their niche (see **section 3.5**). Second, in many cases, nascent ectopic eye

fields are normalized by the surrounding cells as a cancer suppression mechanism. We suggest that this process is more profitably modelled not as cells battling each other, nor even groups of cells competing for tissue-level fate, but as *competition among models* (i.e., the information structures serving as the morphogenetic setpoint for cellular collectives).

What makes an embryo a "single embryo", and not millions of individual cells, is the alignment between all cells toward a particular model of the morphospacial region they must cooperate to reach. These models, including cancer, are at least in part mediated by bioelectric states,[85-90] but what is more important is their self-persistent, resilient, tissue-colonizing, partly autonomous nature. In the case of this ectopic organ induction, the "be an eye" setpoint pattern competes with the "be skin" setpoint, and whichever wins controls the downstream anatomical outcome. The work in the transfer and remapping of behavioral memories across individuals is likewise relevant,[91, 92] because it illustrates the importance of learning from the intelligent computational properties of patterns as well as objects.[93] We believe that on-going work at the intersection of developmental biology and diverse intelligence, which is poised to uncover control policies for managing such patterns in living bodies,[11, 71] will find significant symmetries with the study of information patterns in AI systems. As a result, significant advances in building useful, adaptive computational systems will come from learning to track, manipulate, and communicate with persistent patterns, and ecologies of such patterns, inside the informational media of computers, as we currently do for morphogenetic patterns in the body[95, 96] and cognitive patterns in the human brain.[97, 98] The phenomenon of cancer, with its competition between organ-scale setpoint patterns and single-cell ones, represents an ideal model system from which to extract actionable policies for building multilevel information technologies.

6. Outlook

Cancermorphic computing represents an intriguing frontier in fault tolerant bioinspired systems, challenging conventional notions of resilience and survival based on strategies deemed pathological in living organisms. Its potential lies in addressing scenarios where traditional security frameworks lack. However, fundamental challenges between cancer-like autonomy and system controllability exist. In the short-term, priority should be given to developing mathematical frameworks to represent somatic mutation rates and metastatic propagation guiding algorithmic design, to ensure that they enhance rather than destabilize computational architectures. Experiments could test hypotheses about resource recruitment efficiency and overload risks. Next, hybrid neuromorphic–cancermorphic systems combining energy-efficient processing with context-driven plasticity could be conceived as a first step toward multilevel intelligence in artificial systems. The association of cancer biology and computing architectures represents a new inspirational paradigm to define some of the ideal features of computing architectures, as much as cancer biology has reshaped our understanding of evolutionary mechanisms in constrained contexts.

Glossary

Biology Terms		Computer Science Terms	
Term	**Definition**	**Term**	**Definition**
Angiogenesis	Biological process where tumors stimulate the growth of new blood vessels to secure nutrients, often via VEGF signaling	Cancer-inspired or "cancermorphic" computing (introduced hereby)	Computational paradigm inspired by the adaptive strategies of cancer in achieving autonomous resilience
Clonal selection	Evolutionary mechanism where cells with advantageous mutations proliferate under selective pressure (e.g., chemotherapy)	Neuromorphic computing	Hardware/software systems mimicking the brain's neural architecture for energy-efficient, event-driven processing
Epithelial-to-Mesenchimal Transition (EMT)	Cellular process where epithelial cells lose adhesion properties and gain migratory traits, critical for metastasis	Chaos computing	Use of nonlinear dynamical systems to perform computations resistant to noise or interference
Hypermutation	Accelerated mutation rate in response to stressors (e.g., UV radiation, chemotherapy), enabling rapid adaptation	Swarm Intelligence	Coordination of decentralized agents (e.g., drones) through simple rules, inspired by social insects
Metastasis	Process by which cancer cells spread from a primary tumor to distant organs, driven by EMT and microenvironment remodeling	Evolutionary computing	computational intelligence model that mimics biological evolution processes using algorithms like genetic algorithm and evolutionary programming
Somatic Mutation	Genetic alterations occurring in non-	Decentralized propagation	Strategy where tasks/data are dynamically

	germline cells, driving cancer evolution without inheritance		redistributed across nodes to avoid single points of failure
Tumor microenvironment (TME)	Ecological niche surrounding a tumor, including stromal cells, immune cells, and vasculature, which tumors manipulate for survival	Fault tolerance	Architectures designed to maintain functionality despite hardware/software failures, often via redundancy
Vascular endothelial growth factor (VEGF)	Signaling protein secreted by tumors to induce angiogenesis.	Levy flight distributions	Probability distribution used to model random movement patterns observed in nature

Conflicts of interest

The authors declare no conflicts of interest.

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