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Mechanoluminescence Smart Materials in Artificial Intelligence Tool Applications

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Abstract

Mechanoluminescence (ML), a remarkable smart luminescence phenomenon, involves the direct production of light energy from mechanical force. This intrinsic ability has garnered substantial attention for its profound implications in contemporary applications, particularly in visible strain sensing and structural health monitoring. Concurrently, the rapid evolution of Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) has ushered in a new era for materials science, fundamentally transforming the traditional, often laborious, trial-and-error methodologies. The synergistic integration of AI with ML materials is poised to revolutionize their entire lifecycle, from accelerating their discovery and optimizing their design and synthesis to enhancing the precision of data processing and interpretation derived from their emitted light. This convergence significantly amplifies the performance capabilities of ML materials, enabling advanced functionalities such as real-time, non-contact stress visualization, highly accurate damage detection, and the development of novel applications across diverse sectors. Prominent areas benefiting from AI-enhanced ML materials include structural health monitoring (SHM), sophisticated wearable devices, advanced robotics, and cutting-edge bio-imaging. While the immense potential of this interdisciplinary field to drive technological advancements is undeniable, it is imperative to acknowledge the existing challenges. These include inherent material performance limitations, such as weak brightness and issues with durability, as well as the complexities associated with real-time AI integration and efficient data processing. Addressing these challenges will be critical for the widespread adoption and continued innovation in this dynamic domain.

Keywords: Mechanoluminescence, Smart Materials, Artificial intelligence, material science, Deformation, Optical Properties.

Introduction

1. Mechanoluminescence Smart Materials

1.1 Definition and Fundamental Principles of Mechanoluminescence (ML)

Mechanoluminescence (ML) is formally defined as a smart luminescence phenomenon where light energy is directly generated by a mechanical force. This non-thermal emission of light occurs in response to mechanical stimulation applied to a solid material. The term "Mechanoluminescence" was first coined by Chandra, specifically to describe materials that emit light under dynamic stress or strain. The phenomenon is also recognized by various other appellations, including piezoluminescence, triboluminescence, mechanically induced luminescence, and stress-activated luminescence, all fundamentally referring to light emission under the influence of a mechanical force.

The historical roots of ML extend deep into antiquity, potentially representing one of the earliest forms of luminescence observed by hominids, predating even the understanding of sunlight. The emission of light when grinding stones, manifesting as "cold light" under light force and generating fire under stronger force, suggests that triboluminescence might have served as an inspiration for the invention of fire in the early Stone Age, thereby marking a

foundational moment in human civilization. Centuries later, Francis Bacon's 17th-century observation of triboluminescence from scraping sugar further underscored the scientific curiosity surrounding this captivating effect. This historical trajectory, from an ancient, uncontrolled natural phenomenon to a precisely engineered and quantifiable tool, highlights the fundamental and robust nature of the ML phenomenon. The contemporary challenge lies in achieving controlled, reproducible, and quantifiable light emission, which is where advanced materials science and AI become indispensable.

The fundamental principles governing ML, particularly in extensively studied materials such as Strontium Aluminate ($SrAl_2O_4:Eu^{2+}$ or SAOE), involve intricate excitation processes triggered by mechanical force. One primary mechanism entails the force-induced release of charge carriers (electrons or holes) from traps within the material's crystal lattice. The photons generated by this process typically diminish or disappear once a sufficient number of carriers have been released, a phenomenon explained by the "piezoelectricity-induced carrier detrapping model". SAOE notably exhibits this piezoelectricity-release type of ML. Another mechanism involves photon emission through direct force conversion, which can be sustained irrespective of the number of repetitions, provided the mechanical action remains within the material's fatigue limit. The macroscopic light emission, often termed "piezoluminescence," arises from the superposition of these microscopic processes as the material deforms within its elastic limit. It is imperative to note that ML materials, including SAOE, typically respond to dynamic, changing forces; both increasing and decreasing dynamic pressure can induce light emission. This responsiveness to dynamic forces is a key design consideration for ML sensors. It means these materials are particularly well-suited for monitoring *changes* in stress or strain, such as vibrations, impacts, or crack propagation, rather than static loads. This characteristic inherently positions ML materials favorably for real-time monitoring of dynamic structural events, which is critical for applications like structural health monitoring (SHM) where early detection of anomalies is paramount.

Mechanoluminescent materials are classified as "smart" due to their advantageous properties, including their inherent ability to transduce stress into photons, facilitate real-time visible stress-distributed detection, and enable remote response through the spatial transmission of photons. This direct conversion of mechanical stimuli into an optical signal, frequently without the need for external power, positions ML as a highly attractive and self-reporting material. This intrinsic transduction capability enables ML materials to autonomously interact with their environment and provide actionable data without complex external power sources or intricate wiring. This self-powered, self-reporting nature simplifies system design and deployment, making ML a compelling candidate for distributed sensing networks in the context of Artificial Intelligence and the Internet of Things (IoT).

1.2 Types and Mechanisms of Mechanoluminescence

Mechanoluminescence serves as a broad classification encompassing various phenomena where mechanical action on a solid material leads to light emission. These distinct types are differentiated by the specific nature of the mechanical stimulus applied:

- **Piezoluminescence (Elasticoluminescence):** This refers to light emission that occurs when a material is deformed, typically within its elastic limit, under the application of pressure. It is interchangeably known as elasticoluminescence. Notable examples include pure alkali halide crystals, zinc sulfide phosphors, and quartz crystals. Materials like $SrAl_2O_4:Eu^{2+}$, Dy^{3+} and ZnS: Mn^{2+} are prominent for their repeatable ML induced by elastic deformation.

- **Triboluminescence:** This phenomenon describes the emission of light when materials are scratched, crushed, pressed, or rubbed. Fractoluminescence is often considered a specific subcategory of triboluminescence, focusing on light emission resulting from the fracture of a crystal rather than solely from rubbing. Classic demonstrations include the crushing of sugar candies, uranyl nitrate, or the act of pulling Scotch tape.

- **Fractoluminescence:** Specifically pertains to the emission of light from the fracture of a crystal. This often coincides with rubbing. Upon fracture, a charge separation can occur, rendering one side of the fractured crystal positively charged and the other negatively charged. If this charge separation generates a sufficiently large electric potential, a discharge across the gap and through the surrounding gas can ensue, leading to light emission. Research also confirms the emission of electromagnetic radiation (EMR) during plastic deformation and crack propagation in metals and rocks.

- **Plasticoluminescence:** This term is used for luminescence specifically caused by the plastic deformation of a material.

- **Sonoluminescence:** This phenomenon arises from the implosion of bubbles in a liquid when excited by sound waves or rapid pressure changes. It has been observed in laboratory settings and in certain marine animals.

- **Crystalloluminescence:** Refers to the light produced during the process of crystallization, exemplified by the rapid crystallization of certain salts from aqueous solutions or melt crystallization of carbazole derivatives.

- **Cryoluminescence:** Describes the emission of light when an object is cooled, or luminescence that is only observable at low temperatures, such as in ZnS phosphors or wulfenite.

The clear distinctions between piezo luminescence, fractoluminescence, and triboluminescence highlight that the *nature* and *magnitude* of the mechanical stimulus fundamentally determine the specific ML phenomenon observed. This indicates that ML is not a singular effect but a family of related phenomena, each with distinct activation conditions. For material design and application, understanding this spectrum is crucial. If the objective is to detect subtle elastic deformation, as in continuous structural health monitoring, piezoluminescent materials with low activation thresholds are ideal. Conversely, for detecting catastrophic failure events like crack propagation, fractoluminescent properties become more relevant. This specificity allows for highly tailored material development to meet diverse and precise sensing needs, moving beyond generic ML materials.

A deeper understanding of the underlying mechanisms is critical for the rational design and optimization of ML materials. The piezoelectricity-induced carrier detrapping model is a prominent and widely accepted explanation, particularly for ML in phosphors like SAOE. In this model, mechanical stress induces an internal electric field within

piezoelectric materials. This field then facilitates the release of trapped charge carriers (electrons or holes) from defects within the crystal lattice. The subsequent recombination of these released carriers with luminescence centers results in the emission of photons. The specific properties of defects in ML phosphors are considered vital for effective stress visualization. Another mechanism, direct force conversion, accounts for photon emission that is sustained regardless of the number of mechanical repetitions, provided the mechanical action remains within the material's mechanical fatigue limit. In phenomena like triboluminescence and fractoluminescence, mechanical action, such as fracture or rubbing, leads to charge separation. The subsequent recombination of these separated charges or an electrical discharge across a gap results in light emission.

The unique crystal structure, the presence of point defects, and microstructures within the material are critical triggers for ML. Point defects and their cluster formations serve as suitable traps for charge carriers. Under mechanical stress, changes in their geometric structure alter the binding energy for these trapped charges, which can lead to their escape and subsequent light emission. This detailed mechanistic understanding is vital for rational material optimization. To enhance ML intensity, sensitivity, or tunability, researchers must precisely control defect density, trap depth, and piezoelectric properties. This explains why doping strategies, for instance, with rare earth ions like $Eu^{2+},$ Dy^{3+}, Ho^{3+}, Tb^{3+}, Mn^{2+}, and Tm^{3+}, are so critical, as they can manipulate energy levels and trap distributions to fine-tune ML performance.

An emerging mechanism of significant importance is interfacial triboelectricity. While piezoelectricity is a well-established mechanism, recent advancements, particularly concerning "soft mechanoluminescent complexes," have identified triboelectricity-electricity generated by friction between surfaces-as a significant source of light emission. This triboelectricity can activate luminescent particles. Reports indicate that interfacial triboelectricity can drive ML, enhancing performance by as much as 20-fold. This points to a new frontier in ML material design, especially for applications like wearable devices, artificial skins, and smart textiles, where flexibility, conformability, and self-powering capabilities are paramount. It further suggests that combining ML with triboelectric nanogenerators (TENGs) can lead to highly efficient dual-mode sensors, offering both optical and electrical outputs from a single mechanical stimulus, thereby providing richer data for AI interpretation.

1.3 Key Properties and Material Examples

The development of mechanoluminescent materials is driven by a desire for specific properties that enable their diverse applications. Several materials have emerged as particularly promising due to their unique characteristics:

- **Strontium Aluminate ($SrAl_2O_4:Eu^{2+}$):** This material is a widely studied green phosphor, researched since the 1960s, and is well-known for its persistent afterglow. Its variants, such as $SrAl_2O_4:Eu^{2+}$, Dy^{3+} (SAOED), are considered highly promising inorganic phosphors due to their intense light emission, long afterglow performance, and extremely low force/pressure threshold for ML. $SrAl_2O_4:Eu^{2+}$, Tm^{3+} has shown an 11-fold increase in ML intensity compared to SAOE, achieved by manipulating energy level positions through doping.
- **Zinc Sulfide ($ZnS:Mn^{2+}$ and ZnS: Cu+):** ZnS doped with manganese (Mn^{2+}) or copper (Cu+) exhibits robust and non-decaying ML over thousands of mechanical

cycles. ZnS: Mn^{2+} nanocrystals, synthesized through self-assembly and calcination, demonstrate strong ML without requiring UV pre-excitation, and the light emission persists even after mechanical stress is removed.
- **(Ca, Sr) $Al_2Si_2O_8:Eu^{2+},Ho^{3+}$:** This material, a glow-in-the-dark anorthite, has been developed to visualize stress distribution in discs and the stress fields of ultrasonic transducers. The inclusion of Ho^{3+} has been shown to improve ML intensity.
- **$Ca_{10}Li(PO_4)_7:Tb^{3+},Dy^{3+}$ Mn^{2+} (CLP):** This synthesized ML material, when integrated into polydimethylsiloxane (PDMS), produces distinct green, yellow, and red emissions. It demonstrates excellent cyclic ML performance, high sensitivity, exceptional toughness, and wide strain adaptability, making it suitable for wearable sensors.
- **Li2MgGeO4:Mn2+:** This trap-controlled reproducible ML material exhibits short-term non-decaying ML behavior, attributed to deep traps providing electron replenishment for shallow traps during cyclic friction.
- **$Sr_3Al_2O_5Cl_2:Dy^{3+}$:** This material has been successfully prepared as a long persistent ML material that does not require pre-irradiation, is thermally stable, and self-charging.
- **CaZnOS:Tb:** Identified as an efficient ML material, with potential applications as a stress sensor. Its properties can be optimized through microwave-assisted synthesis, leading to reduced synthesis time and high-quality materials.

Key Properties that Define the Utility of these ML Materials Include

- **Low Force Threshold:** The ability to emit light even under slight pressure or mechanical stress.
- **Efficient Photoluminescence and Persistent Afterglow:** Many ML materials, like SAOE, are also efficient photoluminescent materials and exhibit persistent afterglow, which is the continued emission of light after the excitation source is removed.
- **Self-Recovery and Durability:** The capacity to recover their ML properties after mechanical excitation and maintain performance over numerous cycles.
- **Color Tunability:** The ability to manipulate the emission color by controlling the luminescent center ion and the host crystal structure, which is crucial for diverse applications like visual sensing and displays.
- **Sensitivity:** The degree to which the material responds to mechanical load with light emission, often expressed as relative sensitivity.
- **Stretchability and Biocompatibility:** Important for emerging applications in wearable electronics, artificial skin, and bio-imaging.
- **Non-Contact Nature:** The ability to visualize stress and strain without direct contact, offering advantages over traditional methods like strain gauges.

The dual nature of afterglow in ML materials presents both a challenge and an opportunity. While the afterglow can be beneficial for recording stress history quantitatively without additional devices, its presence can also interfere with real-time ML signal detection by reducing the signal-to-noise ratio. This necessitates strategies such as allowing afterglow to fade before measurements or employing AI-driven image processing techniques to reconstruct strain fields by

eliminating afterglow disturbance. This highlights the need for advanced data processing to fully leverage ML's potential. The quest for self-recoverable and long-lifetime ML materials is a significant area of research. Many existing ML materials exhibit transient luminescence with very short lifetimes, limiting their practical applications and the ability of instruments to capture valuable mechanical distribution information. The goal is to develop materials that maintain their performance over repetitive cycles without requiring external recharging or pre-irradiation. This pursuit directly impacts the durability and long-term reliability of ML sensors, making them more viable for continuous monitoring applications.

Tailoring ML properties through doping and structural engineering is a critical approach to optimize material performance. The inclusion of specific dopants, such as rare earth ions (Eu^{2+}, Dy^{3+}, Ho^{3+}, Tb^{3+}, Mn^{2+}, Tm^{3+}), can manipulate the energy level positions within the host material, thereby tuning the depth and density of electron and hole traps. This precise control over defect properties and crystal structure is essential for enhancing ML intensity, sensitivity to load, afterglow characteristics, and emission color. For instance, the strategic control of crystal structure in $LiNbO_3$ has led to a 30-fold enhancement in ML intensity. These efforts underscore the intricate relationship between material composition, microstructure, and ML performance, guiding the development of high-performance phosphors for multifunctional applications.

2. Artificial Intelligence in Materials Science

2.1 Overview of AI, Machine Learning (ML), and Deep Learning (DL)

Artificial Intelligence (AI) encompasses systems designed to emulate human cognition and behavior, enabling machines to replicate human-like thinking, actions, and task completion that were traditionally exclusive to natural intelligence. Machine Learning (ML) is a subset of AI that allows machines to automatically learn from existing data, while Deep Learning (DL) is a further subfield of ML that utilizes multi-layered neural networks to process vast datasets and identify complex patterns. By harnessing data-driven AI technology, the capabilities of AI systems often transcend those of natural or human intelligence in terms of speed, efficiency, and productivity.

In materials science, AI serves as a potent auxiliary tool to streamline the entire cycle of material research and development. It moves beyond the classical approaches that primarily depend on trial-and-error methods, which are inherently costly and time-consuming. AI-driven approaches enable the prediction and screening of physicochemical properties of advanced materials, thereby expediting the synthesis and production of novel materials. This represents a significant paradigm shift from empirical trial-and-error to data-driven discovery. AI algorithms can process vast amounts of data from simulations, experiments, and literature to identify patterns, relationships, and trends, which then inform the design of new materials and optimize their properties for specific applications. This ability to understand huge parameter spaces with significantly fewer samples drastically accelerates the discovery process.

2.2 AI Techniques for Material Discovery and Property Prediction

AI, Machine Learning (ML), and Deep Learning (DL) techniques are extensively employed in materials engineering

for material discovery, property prediction, and optimization. For microstructural evolution and inverse design, supervised learning models can be trained to predict how specific processing steps influence microstructure. Convolutional Neural Networks (CNNs) are particularly adept at image recognition and can analyze digital image data from microscopy (e.g., SEM or TEM) to learn patterns and correlations between microstructure and material properties. Deep Learning (DL) models are essential for analyzing complex microstructural data, processing large datasets to identify optimal process conditions for desirable microstructures. Recurrent Neural Networks (RNNs) are utilized to analyze sequential data, such as time-series data representing microstructural changes during synthesis, to capture temporal dependencies.

In the realm of microstructure-property correlation, Artificial Neural Networks (ANNs) excel at modeling complex, non-linear relationships between microstructural features and material properties. For instance, ANNs can predict how subtle changes in phase arrangement or grain size distribution affect mechanical properties like hardness or fracture toughness. Image recognition with CNNs is vital for extracting key features from microstructural images and establishing these relationships. Clustering approaches, such as k-means clustering, can group similar microstructures based on their features, aiding in classifying materials with similar performance characteristics.

For property prediction, regression models, including linear and polynomial regression, quantify relationships between material composition and properties. Deep Neural Networks (DNNs) extend these capabilities by modeling non-linear and complex interactions within high-dimensional data. The concept of inverse design is particularly powerful, where desired properties serve as the "input" to determine the chemical composition and structure as the "output". This is in contrast to the direct approach that predicts properties from composition and structure. Machine learning-based inverse design methods, often employing backpropagation, overcome local optima and perform rapid calculations of gradient information for a target function, enabling the discovery of new materials. This allows researchers to start with target functionalities and map them to corresponding molecular structures.

The power of generative models and inverse design is profoundly impacting materials science. Deep generative models, including Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), and Diffusion Models, are increasingly applied to materials design. These models possess a robust ability to map intricate relationships between material structures and properties, directly performing material generation conditioned on target properties. For example, CubicGAN, a GAN-based deep neural network, has been shown to rediscover known cubic materials and generate hypothetical materials with new structure prototypes, with many validated by density functional theory (DFT) calculations. Physics Guided Crystal Generative Models (PGCGM) further expand this capability by generating crystals across a wider range of space groups, significantly improving validity and diversity. This approach allows for the exploration of vast chemical spaces and the proposal of candidate materials optimized for specific applications.

The acceleration of material synthesis and optimization is also being achieved through AI-driven autonomous laboratories. Tools like ORNL's Polybot combine automated experiments, AI, and high-performance computing to accelerate discovery.

This autonomous materials synthesis tool uses techniques like pulsed laser deposition (PLD) to deposit thin layers of substances. The AI then analyzes the quality of the newly created material in relation to synthesis conditions (e.g., temperature, pressure, energy emitted) and suggests revised conditions for improved quality, controlling the equipment for the next experiment without human supervision. This automation can perform work ten times faster and allows AI to understand vast parameter spaces with significantly fewer samples. Reinforcement Learning algorithms are applied to control these autonomous experimental setups, learning from previous experiments to optimize conditions.

3. AI Tool Applications in Mechanoluminescence Materials

The integration of Artificial Intelligence tools across the lifecycle of mechanoluminescent (ML) materials is profoundly impacting their design, synthesis, characterization, and application. AI's capabilities are leveraged to overcome traditional limitations, leading to more efficient development and enhanced performance.

3.1 AI for ML Material Design and Synthesis Optimization

AI plays a pivotal role in optimizing the properties of ML materials, including critical aspects like doping strategies and trap distribution. Traditional methods for discovering novel ML phosphors often rely on trial-and-error, resulting in a limited number of intense ML phosphors with restricted color ranges. AI-driven approaches are transforming this. For instance, a promising rare earth (Re^{3+}) doping strategy has been proposed to achieve intense mechanoluminescence in $SrAl_2O_4:Eu^{2+}$ (SAOE). By introducing different Re^{3+} ions (e.g., Sm^{3+}, Dy^{3+}, Er^{3+}, Tm^{3+}), the depth and density of electron and hole traps can be precisely tuned, leading to significant enhancements in ML intensity, such as an 11-fold increase for $SrAl_2O_4:Eu^{2+}$, Tm^{3+}. Machine learning, particularly graph neural networks, is being used to predict and enhance the performance of materials by optimizing doping ratios and establishing robust structure-property relationships, as seen in triboelectric nanogenerators which share mechanistic similarities with ML. This demonstrates how AI can fine-tune dopant concentrations and trap depths for enhanced ML intensity and persistence.

AI also accelerates the discovery of novel ML materials, including those with specific crystal structures. Inverse design methods, powered by machine learning, analyze the mapping relationships between materials and their properties to identify materials with desired characteristics. This allows researchers to start with target properties and work backward to determine the optimal composition and structure. Deep generative models, such as GANs and VAEs, are being developed to predict new crystal structures with target properties, addressing the grand challenge of discovering materials with novel functionalities. This AI-driven inverse design is crucial for tailoring ML properties, enabling the development of materials with specific color, sensitivity to load, and afterglow characteristics.

Furthermore, AI optimizes synthesis parameters. For example, microwave-assisted synthesis offers advantages like reduced synthesis time, consistent heating, and high-quality material yield. While the provided information does not explicitly state AI controlling microwave synthesis for ML, the general trend of AI-driven autonomous labs suggests its applicability. These autonomous systems, such as ORNL's

Polybot, can influence material synthesis and conduct associated experiments without human supervision. The AI analyzes the quality of the newly created material in relation to synthesis conditions (e.g., temperature, pressure, energy) and suggests revised conditions for subsequent experiments, controlling the equipment to perform them. This autonomous synthesis and high-throughput screening significantly speeds up the experimental exploration for new ML materials, allowing for the rapid identification of optimal processing conditions to achieve desired ML properties.

3.2 AI for Processing and Interpreting ML Data

The light emitted by ML materials provides a direct, non-contact method to visualize stress distributions. The intensity of the emitted light is directly linked to the intensity of the stress field, allowing for its determination by measuring and adequately processing the ML phenomenon. To measure this light emission, specialized equipment such as photomultiplier tubes (PMTs) and CMOS cameras are employed, often synchronized with displacement and force signals. A crucial processing step involves subtracting the afterglow from the observed emission profile to obtain the net ML signal, as afterglow can interfere with real-time measurements. The delay time between UV excitation and load application also influences ML magnitude, requiring optimization to achieve maximal ML contrast. This direct conversion of mechanical stimuli into an optical signal, which can then be captured and analyzed, makes ML light emission a direct input for AI-driven stress analysis. AI's role here is to extract actionable data from this optical output, transforming raw light signals into quantifiable information about mechanical states.

AI algorithms are increasingly vital for analyzing ML data, particularly for structural health monitoring (SHM). For instance, multi-kernel hierarchical deep neural networks leverage finite element simulation data to accurately predict effective strain fields in complex auxetic structures. These predictions are then validated using 3D-printed specimens embedded with ML particles, demonstrating the efficacy of integrating ML technology for direct, non-contact visualization of strain in real-time with high spatiotemporal resolution. AI techniques enhance data processing and signal analysis, improve feature extraction, and reduce noise in SHM data. Deep learning models are capable of accurately detecting and capturing fracture propagation in engineering materials.

Deep learning, specifically Convolutional Neural Networks (CNNs), is instrumental in the image analysis of ML patterns. A deep learning-derived image-to-image mapping process, often utilizing a U-Net CNN framework, can reconstruct engineering strain fields by effectively eliminating the disturbance of afterglow. This demonstrates how deep learning overcomes complexities like afterglow and reconstructs stress fields, transforming raw ML images into precise quantitative stress maps. CNNs are well-suited for analyzing visual data, employing multiple layers of specialized filters to scan images for features like edges, textures, and colors, progressively building an understanding of patterns and objects within the visual data. This capability allows for the reconstruction of dynamic stress distributions and the quantitative reflection of stress concentration from real-time ML images.

Furthermore, AI models are crucial for real-time ML data processing. An artificial intelligence-assisted, wireless, flexible, and wearable ML strain sensor system has been developed, integrating a deep learning neural network-based

color data processing system (CDPS). This system can rapidly and accurately extract and interpret the color of an ML film to strain values, with auto-correction for errors caused by varying color temperature. This highlights the need for rapid data interpretation in dynamic ML applications, such as human-machine interaction, where immediate feedback is essential. ML crystals are considered intelligent stress sensors due to their in situ, real-time, and non-destructive properties, making them suitable for applications like inner crack visualization and bioimaging. The integration of deep learning with ML sensors enables fast and accurate interpretation of optical signals, overcoming challenges like the "color to strain value" bottleneck in flexible colorimetric strain sensors.

4. Applications of AI-Enhanced Mechanoluminescence Materials

The synergistic combination of mechanoluminescence materials with Artificial Intelligence tools is unlocking a wide array of advanced applications across various sectors, transforming how mechanical phenomena are perceived, monitored, and interacted with.

4.1 Structural Health Monitoring (SHM) and Stress Sensing

Mechanoluminescence materials are gaining significant traction in Structural Health Monitoring (SHM) and stress sensing due to their unique ability to visualize mechanical phenomena. ML offers visible strain sensing, real-time stress-distributed detection, and remote response capabilities. It provides a novel non-contact method to visualize stress distributions, overcoming limitations of traditional contact-based strain gauges or expensive non-contact techniques like digital image correlation. The intensity of the emitted light from ML materials directly correlates with the applied stress level, allowing for the determination of stress fields. This intrinsic relationship between mechanics and luminescent signals offers distinct advantages for visualized mechanical sensing.

AI significantly enhances SHM capabilities by improving data acquisition, processing, and analysis. Machine learning (ML) and deep learning (DL) algorithms, including artificial neural networks (ANNs), extract meaningful insights from SHM data, enabling early detection of damage or deterioration and even predicting future structural failures. AI transforms ML from simple light emission into precise quantitative stress mapping. For example, a deep learning-derived image-to-image mapping process can reconstruct engineering strain fields from ML films, even eliminating afterglow disturbance. This allows for dynamic visualization of stress distribution, even due to small deformations, and provides a quantitative reflection of stress concentration. Specific examples of AI-enhanced ML in SHM include the data-driven prediction of strain fields in auxetic structures, validated using 3D-printed specimens embedded with ML particles. This approach enables direct, non-contact visualization of strain in real-time with high spatiotemporal resolution, significantly improving the reliability and diagnostic capabilities of advanced structural systems. Furthermore, self-healing ML stress sensors are being developed to achieve sustainable ML performance, preserving initial sensitivity regardless of loading conditions. AI-driven predictive capabilities for structural integrity mean that ML data, processed by sophisticated algorithms, can be used to predict failure modes and enhance the safety and sustainability of infrastructure systems.

4.2 Wearable Devices and Human-Machine Interfaces (HMI)

ML-based sensors are emerging as promising wearable devices, attracting attention for their self-powered visualization of mechanical stimuli. These materials offer direct and visual conversion of mechanical stimuli into optical signals, often without the need for external power sources or complex circuitry, which enhances portability and user comfort. This self-powered characteristic makes ML materials suitable for monitoring mechanical deformation on complex geometric surfaces based on visual perception principles.

AI, particularly Convolutional Neural Networks (CNNs), plays a crucial role in interpreting the optical signals from these wearable ML sensors. For instance, an optical-mechanical wearable sensor device (OSWD) using ML material $Ca_{10}Li(PO_4)_7$ doped with various ions emits distinct green, yellow, and red light under mechanical stress. By coupling this with an RGB color sensor, finger-bending-induced ML signals can effectively generate recognizable commands. The OSWD accurately detects joint movements with high strain adaptability, and its ability to visualize mechanical forces facilitates intuitive human recognition while allowing wireless data capture and transmission, significantly enhancing the efficiency of human-machine interactions. Similarly, a flexible and wearable ML strain sensor system integrated with a deep learning neural network-based color data processing system can rapidly and accurately interpret the color of the ML film to strain values, enabling applications like human gesture recognition. This demonstrates how AI enables high-accuracy recognition of gestures or handwriting from ML signals, bridging physical interaction with digital intelligence.

4.3 Robotics and Advanced Sensing

Mechanoluminescence materials are also enhancing robotic perception, enabling machines to perceive and interact with their environment more intuitively. ML offers a promising solution for tactile sensors in robotics, as select materials emit light under mechanical stress, directly converting physical pressure into luminescence. This empowers frame-based cameras with event-driven visual sensing functions, reducing the need for complex wiring and minimizing energy consumption compared to conventional visuotactile sensors.

An ML-event-based processing method analyzes the emitted light under dynamic stimulation, measuring ML emission intensity, radial distance, and centroid direction to map applied forces across a sensor array. For example, a biomimetic mouth interface for quadruped robots, the mechanoluminescent autonomous visuotactile interactive gripper (MAVIG), has been developed. This system integrates an ML elastomer with event-driven signal processing, achieving high classification accuracy in distinguishing distinct interaction types. This advancement allows robots to interact with objects and respond to human directives swiftly, enhancing tactile sensing capabilities in robotic systems and leading to more intuitive human-machine interactions. This showcases how ML provides direct mechanical-to-optical conversion for robots, simplifying sensor design and improving responsiveness.

4.4 Bio-imaging and Medical Applications

The unique characteristics of mechanoluminescence, particularly in the near-infrared (NIR) spectral range, hold immense promise for bio-imaging and medical applications. Unlike traditional photoluminescence, ML achieved under

mechanical excitation offers high penetrability, spatial resolution, and signal-to-background ratio (SBR) for bioimaging applications. NIR ML is particularly advantageous due to its better spatial resolution and penetration depth in biological tissues, lower optical loss, and avoidance of autofluorescence. This expansion of ML into biological systems offers significant potential.

Applications include in-situ and real-time biomechanical imaging, where ML can provide reliable non-destructive sensing and detection. There is even exploration into novel non-invasive blood glucose/lipid testing technologies, benefiting from the different absorption of ML signals in glucose/lipid. Furthermore, ML nanoparticles are being investigated for optogenetic neuromodulation. These nanoparticles can effectively trigger electrical signals in neurons upon ultrasound stimulation, with persistent ML extending the temporal window for neuromodulation, offering a significant improvement over conventional ML materials. These advancements highlight the expanding reach of ML into critical biological and medical domains.

4.5 Other Emerging Applications

Beyond the primary applications, AI-enhanced ML materials are finding utility in several other emerging areas:

- **Anti-counterfeiting and Encryption:** ML materials can be used for security marking and information encryption due to their unique stress-responsive light emission.
- **Smart Textiles:** Wearable intelligent fabrics with Mechanoluminescence ability are being developed, combining ML with piezoresistivity for advanced sensing in textiles.
- **Mechanically Activated Lighting and Smart Displays:** The ability of ML materials to convert mechanical stimuli into light makes them suitable for novel lighting devices and advanced displays.

5. Challenges and Future Outlook

While the integration of Mechanoluminescence (ML) smart materials with Artificial Intelligence (AI) tools presents transformative opportunities, several significant challenges must be addressed to fully realize their potential. Concurrently, these challenges define compelling avenues for future research and development.

5.1 Material Performance Limitations

A primary hurdle lies in the intrinsic limitations of current ML materials. These include issues such as weak brightness, which can hinder visibility and signal detection, and a high activation threshold, requiring substantial mechanical force to induce light emission. Many ML materials also suffer from intermittent signal output and a short emission lifetime, often characterized by transient luminescence with very brief durations (nanoseconds to milliseconds). This short lifetime complicates effective capture and recording of ML signals by human eyes or precision instruments, leading to a loss of valuable mechanical distribution information.

Achieving non-decaying ML, where light emission remains robust over continuous mechanical stimulation, is another significant challenge, as many reproducible ML materials still exhibit signal decay. Furthermore, the limited number of non-destructive ML phosphors available restricts the precise tuning of desired properties, such as emission color, sensitivity to load, and afterglow characteristics. For instance, while ZnS: Mn^{2+} nanocrystals show persistent ML without UV pre-excitation, the broader challenge of self-recovery,

where materials regain their properties after mechanical stimuli, is still an active research area. Scalability also remains a concern, particularly for producing ML nanoparticles suitable for microscale devices and biological applications. Overcoming these intrinsic material limitations is paramount for broader adoption and enhanced functionality.

5.2 Challenges in AI Integration and Data Processing

The effective integration of AI with ML systems introduces its own set of complexities, particularly concerning real-time data processing. Managing high data volumes from continuous ML sensing demands robust infrastructure and efficient workflows, including data partitioning and leveraging tools for stream processing. Ensuring the quality of incoming data is equally critical, as low-quality data can lead to inaccurate predictions and increased costs. The non-consistent speeds and volumes of real-time data flow, coupled with diverse data formats, pose significant processing difficulties.

Minimizing delays in data processing is crucial for real-time applications. This requires strategies such as data compression, optimized communication protocols, and the deployment of edge computing systems close to data sources. Scaling resources effectively to balance speed and resource use, and dynamically adjusting resources as needed, are also vital for reliable real-time processing. The limitations of current deep learning methods in fully replicating human perception in complex scenarios further underscore the need for more nuanced AI models. Integrating older, legacy systems with modern AI setups can also be tricky, often requiring containerization, API gateways, and microservices architectures for smoother transitions. These complexities in real-time data management and the need for AI robustness are central to the widespread deployment of ML-AI systems.

5.3 Future Research Directions

Future research in AI-enhanced ML materials will focus on several key areas to address current limitations and unlock new capabilities:

- **Material Optimization:** There is an urgent need for the discovery of new ML materials with adjustable color and enhanced sensitivity. Developing self-recoverable ML materials that can maintain performance over many thousands of cycles without external recharging or pre-irradiation is a critical objective. This will involve deeper investigations into the physical causes of ML, particularly the release of trap carriers at defects via induced stress.
- **Advanced AI Models for Material Design and Data Analysis:** The continued development of advanced AI models, especially generative models and inverse design approaches, will be crucial for the rational design and discovery of novel ML materials with targeted properties. This includes optimizing doping strategies and trap distributions for enhanced ML intensity and persistence. Furthermore, research will focus on developing physics-informed AI and explainable AI to improve the interpretability and reliability of AI predictions in materials science.
- **System Integration and Multimodal Sensing:** Future efforts will concentrate on the well-organized integration of multiple independent stimuli within a single material to increase the accuracy and multifunctional applications of sensing devices. This includes coupling ML with other sensing modalities, such as triboelectricity and

piezoelectricity, to provide comprehensive qualitative and quantitative information about mechanical events.

- **Development of Self-Powered and Biocompatible ML Systems:** The creation of self-powered devices that detect mechanical stress and deliver real-time warnings and illumination signals is a significant direction, particularly for applications in demanding conditions. Expanding ML applications into bio-imaging and medical fields necessitates the development of biocompatible ML materials, especially those emitting in the near-infrared range for deeper tissue penetration.

- **Towards Fully Autonomous Material Discovery and Application Systems:** The long-term vision involves fully autonomous material discovery and optimization systems, where AI-driven laboratories can design, synthesize, characterize, and optimize materials with minimal human intervention. This includes developing closed-loop systems that continuously learn and adapt based on experimental outcomes.

- **Interdisciplinary Collaboration:** Achieving these advancements necessitates a collaborative and multidisciplinary approach, blending domain expertise from materials science, chemistry, physics, and engineering with advanced computational capabilities from AI. This synergy will be vital for overcoming the inherent complexities and accelerating innovation in this rapidly evolving field.

Conclusions

Mechanoluminescence smart materials, with their inherent ability to convert mechanical energy directly into light, represent a compelling frontier in advanced sensing and material science. Their historical roots, spanning from ancient observations to modern engineering applications, underscore the fundamental nature of this phenomenon. The detailed understanding of various ML types-piezoluminescence, triboluminescence, fractoluminescence, and others-along with their underlying mechanisms involving carrier detrapping, charge separation, and interfacial triboelectricity, provides a robust foundation for tailored material design. The development of materials like $SrAl_2O_4:Eu^{2+}$ and $ZnS: Mn^{2+}$ with tunable properties such as afterglow, sensitivity, and color, highlights the ongoing progress in optimizing ML performance.

The integration of Artificial Intelligence, Machine Learning, and Deep Learning has emerged as a transformative force, fundamentally reshaping the landscape of ML material research and application. AI accelerates material discovery and property prediction by moving beyond traditional trial-and-error, enabling data-driven approaches that efficiently explore vast parameter spaces. Techniques such as generative models facilitate inverse design, allowing researchers to conceive materials from desired properties, while autonomous laboratories, driven by AI, streamline synthesis and optimization processes.

In the realm of ML applications, AI plays a critical role in processing and interpreting the emitted light data. Deep learning algorithms, particularly Convolutional Neural Networks, are instrumental in reconstructing complex stress and strain fields from ML images, even compensating for confounding factors like afterglow. This capability transforms qualitative light emission into precise, quantitative mechanical mapping. Consequently, AI-enhanced ML materials are revolutionizing structural health monitoring, enabling real-time, non-contact visualization of stress

distribution and accurate damage detection. Furthermore, their application extends to wearable devices for intuitive human-machine interaction, advanced robotics for enhanced tactile perception, and pioneering bio-imaging techniques that leverage near-infrared ML for deep tissue analysis.

Despite these remarkable advancements, significant challenges persist. Material performance limitations, including weak brightness, short emission lifetimes, and the need for improved self-recovery, demand continued fundamental research. The complexities of real-time AI integration, encompassing high data volumes, quality control, latency management, and system scalability, also require robust solutions. However, these challenges delineate clear pathways for future innovation. Continued material optimization, the development of more sophisticated AI models (including physics-informed and explainable AI), enhanced system integration for multimodal sensing, and the creation of self-powered and biocompatible ML systems represent key research directions. The ultimate vision points towards fully autonomous material discovery and application systems, driven by a collaborative and interdisciplinary approach. The convergence of mechanoluminescence and artificial intelligence is not merely an incremental advancement but a synergistic leap, promising a future where materials can autonomously sense, respond, and communicate, thereby unlocking unprecedented capabilities across diverse technological domains.

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