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GaN Photoconductivity Simulation Imaging Method Based on EIT Technology

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Abstract: With the continuous development of electronic technology, the frontier research on semiconductor materials with excellent properties has become a significant direction in the field of condensed matter physics. Among them, the third-generation semiconductor material GaN is an ideal semiconductor material. However, there are still issues with the detection methods for some of its physical and chemical properties. At the same time, Electrical Impedance Tomography (EIT) technology, as a mature medical technique, can quickly obtain electrical impedance tomography results and may exhibit excellent performance in detecting certain properties of GaN materials. Accordingly, this paper starts from the detection of the photoconductive effect and introduces medical EIT technology into the simulation imaging of GaN photoconductivity. The principle of this simulation method is elaborated, and the three selected algorithms are deeply analyzed. The simulation results are analyzed and compared in terms of errors. The advantages and existing problems of this method are summarized, and future prospects are discussed.

Keywords: GaN, photoconductivity simulation, EIT, iterative algorithm

1. Research Background

Currently, the semiconductor industry is developing rapidly, and electronic devices based on semiconductor materials are emerging in large numbers. However, the high energy consumption costs of these devices greatly constrain the continuous advancement of related research. Optoelectronic devices, due to their advantages of low energy consumption and high transmission speed, have promising applications in fields such as communication, medicine, military, and geology, attracting significant attention from researchers. Similar to other electronic devices, optoelectronic devices also largely depend on the development of related raw materials. The third-generation semiconductor material gallium nitride (GaN), which is considered to have excellent properties, is a hot material in the field of optoelectronics research. Adjusting the properties of GaN is currently a focus of research in this application [1]. GaN material has a wide direct bandgap, high breakdown electric field, high thermal conductivity, and excellent luminescent properties, enabling high-efficiency energy conversion in blue and ultraviolet optoelectronic devices, making it an ideal raw material for optoelectronic and high-temperature, high-power devices [2]. Its good chemical stability ensures efficiency and stability in practical applications.

GaN has a wide range of applications and holds an important position in the current semiconductor industry. Thanks to the excellent photoelectric and thermal properties of GaN, GaN devices have

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been commercialized and have different applications at various voltage levels, such as power converters and current transmission at low voltages, telecom servers and industrial converters at high voltages, and transistors at ultra-high voltages [3]. At the same time, the wide direct bandgap structure of GaN makes it highly responsive to light, with high conversion rates, making it important in applications such as ultraviolet detection. Therefore, GaN has also demonstrated remarkable performance in numerous optoelectronic devices. Among them, the development and commercialization of blue and green LEDs stand out as typical examples of GaN's application in optoelectronic devices. Additionally, the conductivity of GaN can change due to strain, temperature fields, or light fields, making it possible to use GaN in various sensors, especially its photoconductive effect, which has been successfully applied in optical sensors in fields such as medicine, acoustics, and biology.

In practical applications, GaN often has vacancy defects and atomic doping, which can significantly affect its performance in electronic devices. Therefore, current research on GaN mainly focuses on the properties of GaN after doping with other atoms or the formation of vacancy defects, in an attempt to prepare GaN-based materials with ideal properties. In such research, the analysis and comparison of the physical and chemical properties, especially the photoelectric properties of these materials, are extremely important. However, the detection methods for some properties still need to be explored. Accordingly, this paper proposes a method for simulating the photoconductivity of GaN materials using MATLAB-based Electrical Impedance Tomography and Diffuse Optical Tomography Reconstruction Software (EIDORS). It introduces Electrical Impedance Tomography (EIT) into the study of two-dimensional semiconductor materials, providing new ideas and references for exploring the specific methods of GaN and its doped mixture properties.

2. Principle of GaN Material Photoconductivity Simulation

Certain semiconductor materials in nature absorb photon energy when exposed to light. If this energy is greater than or equal to the bandgap of the semiconductor material, it can excite electrons from the valence band to the conduction band, leading to an increase in carrier concentration and, consequently, an increase in the material's electrical conductivity. This phenomenon is known as the photoconductive effect. The electron mobility of GaN is a physical parameter that indirectly reflects its conductivity. This value is influenced by the structure of GaN and temperature. For example, the electron mobility of 0.6 micron-thick GaN is $75cm^2/V \cdot s$ at 300 K, and this value decreases to $56\boldsymbol{cm^2/V \cdot s}$ at 77 K [4]. The conductivity σ is related to the electron mobility μ_e by the equation:

$$\sigma = ne\mu_e \tag{1}$$

where n represents the free electron concentration. When light irradiates a specific region of a GaN-based material, the resulting photoconductive effect increases the free electron concentration in that region, thereby enhancing its conductivity. Therefore, simulating conductivity can effectively demonstrate the material's response to light and reflect its optoelectronic properties.

2.1. Simulation Principle

EIT technology is a non-invasive, non-radiative real-time imaging technique in medicine that can quickly display changes in tissue impedance [5]. As a mature two-dimensional imaging technology, it can also present the conductivity distribution of two-dimensional thin-film GaN materials with nanometer thickness. This technology often uses direct or indirect current excitation on the target object or human tissue, quantitatively measures the resulting electrical effects, and obtains conductivity data. When using EIT to image two-dimensional materials, several electrodes are arranged on the edge of the material. Any two electrodes are selected to apply current or voltage, and the voltage of other electrodes is measured. After multiple measurements, a large data matrix is

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obtained, and then the image is constructed according to the computer's reconstruction algorithm [6]. For two-dimensional images, according to Maxwell's equations, the conductivity σ and potential φ in this region should satisfy the Laplace equation variant:

$$\nabla \cdot \sigma \nabla \phi = 0 \tag{2}$$

According to the boundary conditions derived from this equation, the internal conductivity distribution we are solving for can be calculated from the boundary data. This is essentially a nonlinear inverse problem of solving the impedance distribution and internal potential distribution from known boundary conditions [7].

To solve such problems, the finite element method is an accurate and efficient method. Under light irradiation, the conductivity distribution of GaN material is unknown and non-uniform. To better calculate and simulate the conductivity distribution, the tested material can be divided into several triangular elements, and the conductivity in each element is considered constant. Thus, the problem of photoconductivity simulation imaging of GaN material is transformed into the calculation of the conductivity of each finite element. In the calculation, direct analytical methods are usually avoided, and iterative calculations are used to obtain the optimal solution. That is, assuming the conductivity of each finite element is known, the boundary voltage data is obtained by solving the forward equation. Based on the experimentally measured data, the assumed conductivity distribution is continuously modified, and through continuous iterative calculations, the true conductivity distribution is approached. The accuracy of the result is related to the number of iterations and the method. In the experiment, increasing the number of divided elements can increase the resolution of the result, which depends on the number of electrodes, and the number of finite elements n divided should satisfy:

$$n \leq a(a-1)/2 \tag{3}$$

where a is the number of electrodes, derived from combinatorial electrode pairing.

2.2. Three Algorithms for Photoconductivity Simulation

The forward equation solution relies on algorithms, and different algorithms usually have different accuracies and emphases. Therefore, the analysis and error comparison of different algorithms are very important. The EIDORS used in this paper includes both data acquisition and nonlinear inverse problem solving. That is, by specifying a certain light irradiation area and the conductivity change under light irradiation, the experimental data of current and voltage are directly obtained through forward problem calculation. Then, this data is imported into the nonlinear inverse problem solving module for photoconductivity image simulation, and the simulation results are compared with the real conductivity changes to verify the feasibility of this method in photoconductivity simulation and to compare the accuracy of the three algorithms. This paper investigates three algorithms in the research experiment: the Gauss-Newton method, Kalman Filter method, and Truncated Singular Value Decomposition (TSVD) method. Their accuracy is verified, and the most suitable algorithm for GaN photoconductivity simulation is identified.

2.2.1. Gauss-Newton Method

For the matrix of multiple boundary voltages obtained from experimental data

$$\hat{\phi} = (\phi_1, \phi_2, \phi_3 \ldots \phi_a)^T \tag{4}$$

and the voltage matrix $f(\boldsymbol{\sigma})$ obtained by solving the forward problem with the assumed conductivity distribution $\boldsymbol{\sigma}$, the following equation can be constructed:

$$\hat{\phi} = f(\sigma) \tag{5}$$

Let $\boldsymbol{\sigma^0} = (\sigma_1^{(0)}, \sigma_2^{(0)}, \sigma_3^{(0)} \ldots \sigma_a^{(0)})^T$ be the initial estimate of $\boldsymbol{\sigma}$, Expand $f(\boldsymbol{\sigma})$ at $\boldsymbol{\sigma^0}$ using Taylor series, ignoring second-order and higher derivative terms, to obtain:

$$f(\sigma) = f(\sigma^0) + f'(\sigma^0)(\sigma - \sigma^0) \tag{6}$$

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Substituting this into equation (2) and rearranging, we get:

$$\sigma = \left[f'(\sigma^0)\right]^T \left[\hat{\phi} - f(\sigma^0)\right] + \sigma^0 \tag{7}$$

At this point, the obtained $\boldsymbol{\sigma}$ value is taken as $\boldsymbol{\sigma^1}$, Since the first-order derivative term is considered, the obtained $f(\boldsymbol{\sigma^1})$ is closer to $\hat{\phi}$ than $f(\boldsymbol{\sigma^0})$. Then, expand $f(\boldsymbol{\sigma})$ at $\boldsymbol{\sigma^1}$ using Taylor series, and follow the above method to obtain $\boldsymbol{\sigma^2}$ that is closer to the true value, This process is iterated continuously, producing results that infinitely approach the true value, which is considered the accurate result.

2.2.2. Kalman Filter Method

The Kalman filter method is an iterative algorithm that optimally estimates the system state through the system state equation. By removing system noise, it achieves a filtering effect, removing interference from the estimated system state, and is considered to have reached the optimal solution. The Kalman filter model assumes that the system state can be represented as:

$$x_t = Fx_{t-1} + Bu + w_t \tag{8}$$

$$z_t = Hx_t + v_t \tag{9}$$

where $\boldsymbol{x_t}$ and $\boldsymbol{x_{t-1}}$ represent the true state of the system at time t and t-1, respectively, $\boldsymbol{F}$ is the state transition matrix acting on $\boldsymbol{x_{t-1}}$, $\boldsymbol{B}$ is the control matrix acting on the input variable $\boldsymbol{u}$, $\boldsymbol{w_t}$ is the process error, $\boldsymbol{z_t}$ is the observed value of the system state, obtained by linearly transforming the true state through $\boldsymbol{H}$ and adding the observation error $\boldsymbol{v_t}$. In the equation, $\boldsymbol{x_t}$、$\boldsymbol{w_t}$ and $\boldsymbol{v_t}$ are all unknown quantities.

The Kalman filter model is mostly used to reflect the dynamic system state from a series of noisy data and continuously update the state as data is obtained. We borrow the Kalman filter model, transforming the time change into the number of iterations, continuously approaching the true conductivity distribution of the system. In the iterative process of solving conductivity data in this paper, there is no additional input variable affecting the solution, so the solution model is:

$$f_k = Ff_{k-1} + w_{k-1} \tag{10}$$

$$\hat{\phi} = Hf_k + v_k \tag{11}$$

Where $\boldsymbol{f_{k-1}}$ and $\boldsymbol{f_k}$ are the conductivity matrices before and after estimation.

For the Kalman filter process, we can define $\boldsymbol{f_k^-}$ as the prior estimate in one iteration, and $\boldsymbol{f_k^+}$ as the posterior estimate after considering the observation error. Then, the relationship is:

$$f_k^- = Ff_{k-1} \tag{12}$$

The difference between the prior estimate and the posterior estimate lies in the observation error:

$$f_k^+ = f_k^- + K_k\left(\hat{\phi} - Hf_k^-\right) \tag{13}$$

Where $\hat{\phi} - \boldsymbol{Hf_k} = \boldsymbol{v_k}$ is the observation error, $\boldsymbol{K_k}$ is the error weight, and $\boldsymbol{K_k}(\hat{\phi} - \boldsymbol{Hf_k^-})$ is the correction to the prior estimate. At the same time, the value of $\boldsymbol{K_k}$ is given by:

$$K_k = \frac{P_k^- H^T}{HP_k^- H^T + R} \tag{14}$$

Where $\boldsymbol{P_k}$ is the estimate of the error covariance matrix, $\boldsymbol{R}$ is the observation noise covariance matrix, and the prior and posterior estimates of the error covariance matrix are:

$$P_k^- = FP_{k-1}^+ F^T + Q \tag{15}$$

$$P_k^+ = (1 - K_k H_k)P_k^- \tag{16}$$

Where $\boldsymbol{Q}$ is the prediction noise covariance matrix. From the equation, $\boldsymbol{P_k^-}$ is obtained from the posterior estimate of the error covariance matrix in the previous iteration $\boldsymbol{P_{k-1}^+}$, and from $\boldsymbol{P_k^-}$, $\boldsymbol{K_k}$ and $\boldsymbol{P_k^+}$ can be obtained. $\boldsymbol{P_k^+}$ continues to participate in the calculation of $\boldsymbol{P_{k+1}^-}$ in the next iteration. After transforming the initial assumption $\boldsymbol{f_{k-1}}$ to obtain the prior estimate in the first

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iteration, by continuously setting the prior estimate in one iteration equal to the posterior estimate in the previous iteration and iterating, the estimate is continuously corrected, and finally the optimal solution with noise removed is obtained.

2.2.3. TSVD Method

The relationship between the finite element conductivity matrix $\boldsymbol{\sigma}$ and the measured voltage matrix $\hat{\varphi}$ can be expressed as:

$$\hat{\varphi} = A\sigma \tag{17}$$

Where $\boldsymbol{A}$ is the coefficient matrix. Performing singular value decomposition on $\boldsymbol{A}$, we get:

$$A = B\lambda C^T = \sum_{i=1}^{n} b_i \lambda_i c_i^T \tag{18}$$

Where $\mathbf{B}$、$\mathbf{C}$ are the left and right singular matrices, and $\boldsymbol{\lambda}$ is the diagonal matrix composed of singular values from large to small. Thus,

$$\sigma = \sum_{i=1}^{n} \frac{b_i^T c_i \hat{\varphi}}{\lambda_i} \tag{19}$$

Since smaller singular values have less impact on the coefficient matrix and contain fewer features, and in the solution of $\boldsymbol{\sigma}$, singular values are in the denominator, smaller singular values have a greater impact on the solution. Therefore, they should be discarded. It is stipulated to truncate from the m-th term, taking the first m singular values, to obtain:

$$\sigma = \sum_{i=1}^{m} \frac{b_i^T c_i \hat{\varphi}}{\lambda_i} \tag{20}$$

This is the so-called Truncated Singular Value Decomposition (TSVD) method. This method can directly obtain the conductivity distribution from the measured voltage matrix $\hat{\varphi}$ without iteration. This method sacrifices some information content to a certain extent, ensuring the stability of the result. The larger the truncation point is selected, the better the stability of the result, but the less information content is included.

3. Results Analysis

When a certain region of light is specified, the conductivity simulation results of the material measured by the three algorithms are shown in Figures 1, 2, and 3, respectively.

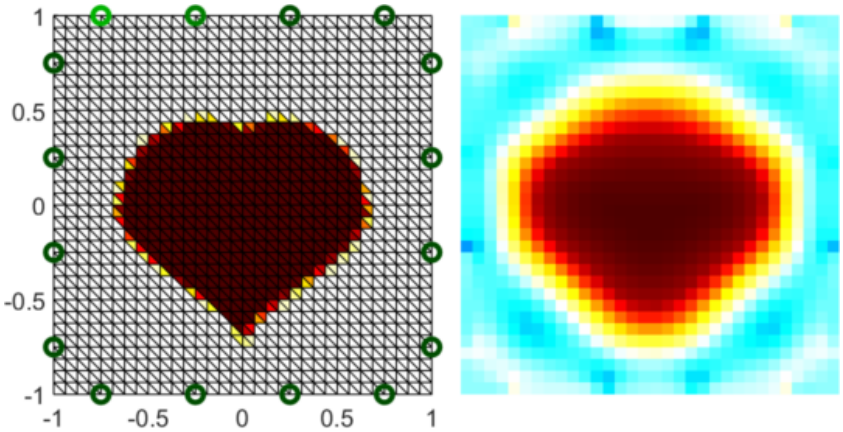

Figure 1: Photoconductivity simulation result using the Gauss-Newton method.

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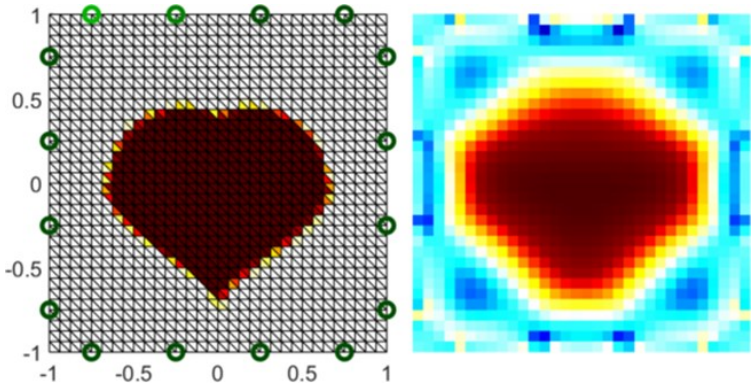

Figure 2: Photoconductivity simulation result using the Kalman filter method.

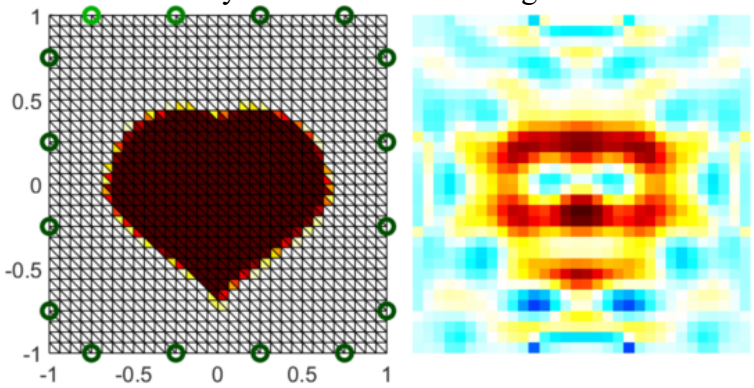

Figure 3: Photoconductivity simulation result using the TSVD method.

In each set of images, the dark red area in the left image indicates the light irradiation region; the right image shows the visualization of photoconductivity using the corresponding method. The darker the red color, the greater the photoconductivity in that area. The results displayed by all three methods show good overlap with the light irradiation region, and comparing the three algorithms is key to selecting the simulation method. EIDORS stores the conductivity distribution matrix specified during the forward problem solving process and the conductivity distribution matrix calculated during the inverse problem solving process. The latter is used for simulating the conductivity distribution image, making it convenient to quantify errors. Specifically, the former can be treated as the true value, and the latter as the estimated value for error calculation. This paper employs the mean square error (MSE) method to calculate the average of the squared differences between the estimated and true values.

The MSE of the results obtained by Gauss-Newton method, kalman filter method, and TSVD method are shown in the figure 4

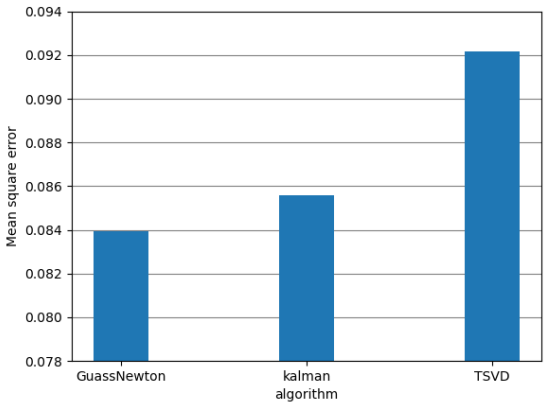

Figure 4: Comparison of Mean Square Errors from the Three Algorithms.

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4. Conclusion and Prospect

This study demonstrates that introducing EIT into the simulation of photoconductive images of GaN materials is feasible. The three algorithms mentioned in this paper exhibit MSE below 0.1, effectively reflecting changes in conductivity under light illumination. These algorithms enable stable and rapid acquisition of simulation results, facilitating the adjustment of GaN material preparation processes and supporting the improvement of semiconductor material fabrication methods. However, none of the three algorithms can simultaneously achieve high accuracy in their results, indicating a need for further refinement or the development of a superior algorithm. Additionally, this tomographic detection method has certain requirements regarding material thickness, while GaN is often utilized as a three-dimensional material in electronic device research. Therefore, extending this detection method to three-dimensional space is an important direction for future development.

EIT technology has a history of nearly three decades and has matured, finding widespread application in clinical medicine. Its application in probing the physicochemical properties of semiconductor materials represents a novel endeavor with promising prospects. In the future, adjustments to experimental methods and algorithms can be made to address the differences between medical applications and the detection of physicochemical properties in two-dimensional materials. This includes improving result accuracy, enhancing image resolution, and proposing adaptable methods for a broader range of materials and diverse morphologies. Such advancements will further expand the application scope of EIT in semiconductor material research.

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