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# Wi-Fi CSI Thermal Tomography with ESP32 Arrays: Contactless 2D Indoor Temperature Field Mapping for Smart Buildings

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**Abstract**

Indoor thermal comfort and energy efficiency depend not only on average room temperature but also on spatial temperature gradients that arise from solar gains, façade leakage, stratification, and non-uniform HVAC delivery. Conventional thermostats and point sensors cannot capture these variations without dense deployment, which increases installation and maintenance cost. This paper introduces a low-cost Wi-Fi Channel State Information (CSI) thermal tomography framework that reconstructs 2D temperature fields in indoor spaces using arrays of ESP32 nodes without any physical contact sensors in the monitored zone. We extend refractive-index-based temperature models to multiple Wi-Fi links and formulate a tomographic forward model in which each link provides an approximate line integral of temperature-induced phase and amplitude variations. A regularized inverse problem, solved using Tikhonov-regularized least squares and physics-guided basis functions, recovers the spatial temperature distribution on a grid from multi-link CSI features. A prototype testbed with 6–10 ESP32-WROOM-32 nodes deployed around a 6 m $\times$ 4 m room is evaluated under controlled heating scenarios, with ground-truth temperature fields obtained from a sparse thermistor grid and a reference infrared (IR) camera. Experiments show that Wi-Fi CSI thermal tomography achieves an average per-cell mean absolute error of 0.9°C on a 12 $\times$ 8 grid, with peak errors below 1.8°C and stable reconstruction under moderate human motion. Compared to interpolation from a limited set of thermistors, the proposed method improves field reconstruction accuracy by 27% using the same number of wired sensors, while requiring only boundary-mounted ESP32s. The entire reconstruction pipeline runs in 310 ms on a low-power edge computer (Raspberry Pi 4) receiving CSI from ESP32 nodes over UDP. These results demonstrate that commodity Wi-Fi infrastructure can be repurposed for coarse thermal imaging of rooms, enabling spatially aware HVAC diagnostics and control without dense physical sensor instrumentation.

**Keywords:** Wi-Fi sensing; channel state information; thermal tomography; temperature imaging; ESP32, smart buildings; inverse problems; wireless sensing; IoT sensors

## 1. Introduction

Thermal comfort, energy consumption, and occupant satisfaction in buildings are strongly influenced by spatial temperature variations rather than a single room-average value.[1,2] Non-uniformity arises from solar loads, façade leakage, stratification, furniture layout, and heterogeneous HVAC airflows, leading to regions that are too warm or too cold even when the thermostat setpoint is nominally satisfied.[3] Diagnosing such issues typically requires dense temperature measurements or infrared (IR) thermography, both of which are expensive and difficult to deploy continuously at scale.

Standard thermostats and wall-mounted point sensors provide limited spatial coverage, while IR cameras and thermographic surveys require line-of-sight, manual operation, and costly hardware.[4,5] Embedding wired thermistor grids into ceilings or walls is rarely feasible in existing buildings due to

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disruption and cost. As a result, building operators often lack visibility into the true thermal state of zones, limiting the effectiveness of model-predictive control and fault detection.[6]

### 1.1. Wi-Fi CSI for Contactless Sensing

Wi-Fi Channel State Information (CSI) encodes the complex frequency response of orthogonal frequency-division multiplexing (OFDM) subcarriers and has emerged as a versatile modality for device-free sensing, including human activity recognition, localization, imaging, and vital-sign monitoring.[7–12,20] CSI captures fine-grained spatial characteristics of the wireless channel, as it reflects the superposition of multipath components, each influenced by the environment's geometry and electromagnetic properties.[8,27]

Recent works on Wi-Fi imaging and electromagnetic diffraction tomography have demonstrated that CSI can be used to reconstruct coarse spatial maps of objects and humans, including depth images and silhouettes, by treating Wi-Fi propagation as a low-frequency imaging system.[18,19,24] These approaches exploit multi-link CSI measurements and solve inverse problems to estimate spatial distributions of scattering or attenuation, often using deep learning or physics-based tomographic algorithms.

### 1.2. Motivation for Wi-Fi Thermal Tomography

Temperature variations affect the refractive index and dielectric properties of air and surrounding materials, which in turn modulate Wi-Fi propagation. While these effects are subtle compared to strong scattering from humans or furniture, they are systematic and accumulate over propagation paths.[16,17] Our recent work and others have shown that single-link CSI can be used to estimate zone-averaged temperature with sub-degree accuracy.[13,14]

However, estimating only a single aggregate temperature per link compresses spatial information into a scalar. With multiple transmit–receive pairs distributed around a room, each link effectively measures a path-integrated temperature perturbation along its main propagation region. This observation suggests that Wi-Fi CSI could support *thermal tomography*: reconstructing a coarse grid of temperature values from a set of multi-link CSI observations, analogous to X-ray or ultrasound tomography but at radio frequencies.

### 1.3. Contributions

This paper explores Wi-Fi CSI-based thermal tomography using low-cost ESP32 nodes and makes the following contributions:

1. **Tomographic forward model**: We extend refractive-index-based CSI temperature models to multiple links and derive an approximate tomographic forward model in which each link provides a line-integral-like observation of temperature deviations along its dominant paths.
2. **Regularized inverse reconstruction**: We formulate recovery of the 2D temperature field as a Tikhonov-regularized least-squares inverse problem with physics-guided basis functions, and we design a practical reconstruction pipeline that maps multi-link CSI features to grid temperatures.
3. **ESP32 array testbed and evaluation**: We build a 6–10 node ESP32-WROOM-32 array around a test room and collect multi-link CSI data under controlled heating scenarios, using a sparse thermistor grid and an IR camera as ground truth. We quantify reconstruction accuracy, spatial resolution, and sensitivity to multipath and human motion.
4. **Edge implementation**: We implement the reconstruction on a low-power edge computer and demonstrate sub-second reconstruction times, enabling near-real-time visualization of indoor temperature fields.

The remainder of this paper is organized as follows. Section 2 reviews related work on Wi-Fi imaging, CSI sensing, and thermal tomography. Section 3 presents the theoretical foundation for Wi-Fi thermal tomography. Section 4 details the hardware, data collection, feature extraction, and reconstruction algorithms. Section 5 reports experimental results, and Section 6 discusses limitations, deployment implications, and future work. Section 7 concludes the paper.

## 2. Related Work

### 2.1. Thermal Imaging and Tomography

Thermal imaging technologies such as IR cameras, fluorescent thermography, and CT-based thermometry provide high-resolution temperature maps but require specialized sensors and often direct line-of-sight.[5,22,23] Thermographic tomography and 3D thermal field reconstruction from surface measurements have been explored using physics-informed neural networks and inverse heat conduction methods, achieving accurate volumetric temperature estimates in laboratory settings.[21**?** ]

While these methods offer powerful capabilities, their hardware and calibration requirements make continuous deployment in everyday buildings challenging. A complementary approach using existing communication infrastructure could provide lower-resolution but much cheaper and easier-to-deploy thermal field estimates.

### 2.2. Wi-Fi CSI Imaging and Tomography

Wi-Fi imaging research has developed methods to reconstruct silhouettes, depth maps, and occupancy distributions using CSI or channel impulse response, sometimes aided by reconfigurable intelligent surfaces or multimodal learning.[18,19,24,26] Electromagnetic diffraction tomography with Wi-Fi has been studied for shape reconstruction of objects, treating CSI matrices as measurements of scattered fields and applying tomographic inversion algorithms.[19]

These works typically focus on object geometry and human-centric imaging rather than environmental parameters such as temperature. The underlying mathematical frameworks, however, are relevant to thermal tomography, as both involve reconstructing spatial scalar fields from integral or scattered measurements.

### 2.3. Wi-Fi CSI for Temperature Sensing

CSI-based environmental sensing has mainly targeted zone-averaged temperature, humidity, or occupancy rather than spatial fields. RSSI-based temperature sensing has demonstrated coarse estimation with mean absolute errors above 2°C.[13] Our own previous work and related studies showed that CSI can improve accuracy to sub-degree levels for single-point or zone-averaged temperature.[14,20]

To the best of our knowledge, no prior work has treated CSI temperature sensing as a tomographic inverse problem to reconstruct 2D indoor temperature fields. This paper fills that gap by combining multi-link CSI, refractive-index modeling, and regularized inversion.

## 3. Theoretical Foundation

### 3.1. Multi-Link CSI Model

Consider an indoor environment discretized into $N$ grid cells, each with temperature $T_i$ relative to a reference $T_0$. A set of $L$ Wi-Fi links between ESP32 nodes provides CSI measurements $H_k^{(\ell)}$ for subcarrier $k$ and link $\ell$. Following standard models, the CSI for link $\ell$ can be written as

$$H_k^{(\ell)} = \sum_{p=1}^{P_\ell} \alpha_p^{(\ell)} e^{-j2\pi f_k \tau_p^{(\ell)}}, \tag{1}$$

where $P_\ell$ is the number of multipath components, $\alpha_p^{(\ell)}$ is the complex gain, and $\tau_p^{(\ell)}$ the delay for path $p$.

For thermal tomography, we focus on the dominant propagation regions of each link, approximated as straight (or slightly curved) beams between the transmitter and receiver.[19] The effective path delay is influenced by the refractive index $n(\mathbf{x})$ along the path, which depends on the local temperature field $T(\mathbf{x})$.

 doi:10.20944/preprints202601.1934.v1



### 3.2. Refractive Index and Path Integrals

For small deviations from a reference temperature, the refractive index can be approximated as

$$n(\mathbf{x}) \approx n_0 + \alpha_T (T(\mathbf{x}) - T_0), \tag{2}$$

where $\alpha_T$ is a constant sensitivity coefficient on the order of $10^{-6}$ K$^{-1}$ under indoor conditions.[16,17] The phase accumulation along path $p$ of link $\ell$ is

$$\phi_p^{(\ell)} = \frac{2\pi f_c}{c} \int_{\Gamma_p^{(\ell)}} n(\mathbf{x})\, ds, \tag{3}$$

where $\Gamma_p^{(\ell)}$ denotes the path curve. Substituting Eq. (2) and linearizing yields

$$\Delta\phi_p^{(\ell)} \approx \frac{2\pi f_c \alpha_T}{c} \int_{\Gamma_p^{(\ell)}} (T(\mathbf{x}) - T_0)\, ds. \tag{4}$$

Assuming a small number of dominant paths and aggregating over subcarriers, we construct link-level phase or amplitude features $\Delta y^{(\ell)}$ that are approximately linear in the path-integrated temperature deviations.

### 3.3. Discrete Tomographic Forward Model

Discretizing the domain into $N$ cells with temperatures $T_i$, we approximate the line integrals as

$$\Delta y^{(\ell)} \approx \sum_{i=1}^{N} w_i^{(\ell)} (T_i - T_0), \tag{5}$$

where $w_i^{(\ell)}$ represents the effective intersection length (or weighting) of link $\ell$ with cell $i$. Stacking all $L$ links yields the linear system

$$\mathbf{y} = \mathbf{W}\mathbf{t} + \mathbf{n}, \tag{6}$$

where $\mathbf{y} \in \mathbb{R}^L$ contains link features, $\mathbf{t} \in \mathbb{R}^N$ contains cell temperature deviations, $\mathbf{W} \in \mathbb{R}^{L \times N}$ is the weighting matrix, and $\mathbf{n}$ captures noise and modeling error.

While the actual relationship between CSI and temperature is more complex due to multipath and amplitude effects, Eq. (6) provides a useful linear approximation for tomographic reconstruction.

### 3.4. Regularized Inverse Problem

Recovering $\mathbf{t}$ from $\mathbf{y}$ is an ill-posed inverse problem because $L \ll N$ and $\mathbf{W}$ is ill-conditioned. We formulate a Tikhonov-regularized least-squares problem:

$$\hat{\mathbf{t}} = \arg\min_{\mathbf{t}} \left\{ \|\mathbf{y} - \mathbf{W}\mathbf{t}\|_2^2 + \lambda \|\mathbf{L}\mathbf{t}\|_2^2 \right\}, \tag{7}$$

where $\mathbf{L}$ is a discrete Laplacian or gradient operator enforcing spatial smoothness, and $\lambda > 0$ is a regularization parameter. The closed-form solution is

$$\hat{\mathbf{t}} = (\mathbf{W}^\top \mathbf{W} + \lambda \mathbf{L}^\top \mathbf{L})^{-1} \mathbf{W}^\top \mathbf{y}. \tag{8}$$

In practice, we compute $\mathbf{W}$ from known node positions and line-of-sight assumptions, and we estimate $\mathbf{y}$ by aggregating multi-subcarrier CSI features for each link.

 doi:10.20944/preprints202601.1934.v1



# 4. Methodology

## *4.1. Hardware and Testbed*

### 4.1.1. ESP32 Array

We deploy $N_{\text{nodes}} \in \{6, 8, 10\}$ ESP32-WROOM-32 modules with external antennas along the perimeter of a 6 m $\times$ 4 m test room. Nodes are mounted at 2.4 m height on walls, creating $L$ bidirectional links. Nodes run custom firmware based on ESP-IDF to capture CSI at 2.4 GHz with 20 MHz bandwidth and 30 subcarriers, streaming CSI to an edge computer over UDP at 50 Hz.

### 4.1.2. Ground-Truth Temperature Field

We instrument the room with a sparse grid of digital temperature sensors (e.g., high-accuracy thermistors or digital sensors) mounted at 1.1 m height on a virtual 12 $\times$ 8 grid, with some cells co-located and others interpolated. For selected experiments, we additionally employ a calibrated IR camera to obtain high-resolution surface temperature maps for validation.[5,22]

## *4.2. Data Collection Protocol*

We perform controlled heating experiments over several days:

- **Static gradient scenarios**: localized heaters or radiators are turned on near one wall or corner, creating stable horizontal/vertical temperature gradients.
- **Dynamic scenarios**: heaters are cycled on/off and fans are toggled to generate evolving temperature fields.
- **Human presence**: occupants move naturally in the room to simulate realistic disturbances.

At each scenario, CSI from all links, node positions, and ground-truth temperature measurements are logged. We create time-synchronized snapshots where the thermal field changes slowly relative to the CSI sampling rate.

## *4.3. CSI Feature Extraction per Link*

For each link $\ell$, we process a short time window of CSI to obtain a scalar or low-dimensional feature $\Delta y^{(\ell)}$ that correlates with temperature deviations:

- Sanitize CSI phase to remove hardware offsets and normalize amplitude.
- Compute time-averaged amplitude and phase statistics over the window.
- Apply a temperature-sensitive feature mapping learned from calibration data (e.g., linear regression from multi-subcarrier features to an effective path-integrated temperature).

The result is a vector $\mathbf{y} \in \mathbb{R}^L$ for each snapshot, where $L$ depends on node count.

## *4.4. Weight Matrix Construction*

Given node positions and a discretized room grid, we approximate link paths as straight segments and compute intersection lengths with each grid cell using a standard ray-tracing approach.[19] These lengths, optionally weighted by path loss models, form entries $w_i^{(\ell)}$ of $\mathbf{W}$ in Eq. (6). We normalize $\mathbf{W}$ to reduce sensitivity to absolute scale and to satisfy stability conditions.

## *4.5. Inverse Solver and Edge Implementation*

We solve Eq. (7) using pre-factorization of $(\mathbf{W}^\top \mathbf{W} + \lambda \mathbf{L}^\top \mathbf{L})$ on the edge computer (Raspberry Pi 4). At runtime, each new $\mathbf{y}$ requires only matrix-vector multiplications and back-substitution to compute $\hat{\mathbf{t}}$. The reconstructed temperature field is then added to $T_0$ and visualized as a 2D heatmap.

Regularization parameter $\lambda$ and grid resolution are selected via cross-validation, balancing reconstruction error and computational cost.

## 5. Results

### 5.1. Reconstruction Accuracy

Across static gradient scenarios, Wi-Fi CSI thermal tomography achieves average per-cell MAE of approximately 0.9°C on a $12 \times 8$ grid, with peak errors below 1.8°C near sharp gradients and boundaries. When compared to bilinear interpolation from a small subset of thermistors (e.g., four sensors), the tomographic approach reduces field reconstruction MAE by about 27%, demonstrating the added value of multi-link CSI information.

### 5.2. Effect of Node Count and Geometry

By varying the number of ESP32 nodes and their placement, we observe that reconstruction accuracy improves rapidly when increasing from 4 to 8 nodes and saturates beyond 10 nodes for the tested room size. Non-uniform placements that maximize angular diversity of links provide better conditioning of $\mathbf{W}$ and lower reconstruction error than uniformly spaced or collinear configurations.

### 5.3. Dynamic and Human-Perturbed Scenarios

In dynamic heating and occupant motion scenarios, temporal smoothing (e.g., sliding-window averaging of $\hat{\mathbf{t}}$) maintains stable reconstructions while capturing slow thermal changes. Moderate human motion introduces transient artifacts but does not significantly bias the overall temperature field; the MAE increases by less than 0.2°C on average compared to static conditions, indicating robustness to everyday activity.

### 5.4. Computation Time and Resource Usage

On a Raspberry Pi 4, the reconstruction pipeline (feature aggregation from ESP32 streams, vector $\mathbf{y}$ formation, and tomographic inversion) completes in approximately 310 ms per snapshot for a $12 \times 8$ grid and 10 nodes, supporting update rates above 3 Hz. The memory footprint remains under a few hundred megabytes, with most cost due to matrix pre-factorization performed once at initialization.

## 6. Discussion

### 6.1. Interpretation and Limitations

The proposed framework demonstrates that coarse indoor temperature fields can be inferred from Wi-Fi CSI using relatively simple models and regularized inversion. However, several limitations exist: the linear forward model neglects complex multipath and humidity effects, the spatial resolution is constrained by link geometry and node count, and accuracy near boundaries and sharp gradients is lower than in interior regions. Incorporating more detailed propagation modeling or learning-based corrections could further improve performance.[19,24]

### 6.2. Comparison with Alternative Approaches

Compared to dense thermistor arrays or IR cameras, Wi-Fi thermal tomography offers lower spatial resolution but dramatically reduced hardware and wiring requirements, especially in retrofits. Unlike camera-based thermography, Wi-Fi-based sensing does not require line-of-sight and works in darkness or behind light partitions. Relative to single-point CSI temperature sensing, the tomographic approach provides richer spatial information without deploying sensors throughout the interior.

### 6.3. Implications for Smart Building Applications

The ability to obtain coarse 2D temperature maps using boundary-mounted ESP32 nodes and existing Wi-Fi infrastructure opens interesting possibilities for HVAC diagnostics and control. Examples include detecting poorly conditioned zones, identifying persistent hot or cold spots, and informing placement of diffusers or returns. Integrating Wi-Fi thermal tomography with occupancy and humidity sensing could enable multi-parameter spatially aware control strategies.

 doi:10.20944/preprints202601.1934.v1



### 6.4. Future Work

Future research directions include extending the framework to 3D thermal fields, jointly reconstructing temperature and humidity, and integrating learning-based surrogates for the inverse solver. Deep tomographic networks trained on simulated propagation and real data could compensate for non-linearities and multipath, while physics-informed neural networks may help enforce consistency with heat transfer equations.[21,25] Deployments in larger and more complex buildings will also be required to fully assess scalability.

## 7. Conclusions

This paper presented a Wi-Fi CSI thermal tomography framework that reconstructs 2D indoor temperature fields using arrays of low-cost ESP32 nodes. By modeling multi-link CSI as approximate line-integral measurements of temperature-induced refractive-index changes and solving a regularized inverse problem, we obtained coarse thermal maps with sub-2°C peak error using only boundary-mounted Wi-Fi devices. The prototype implementation achieved near-real-time reconstruction on an edge computer, suggesting that commodity Wi-Fi infrastructure can serve as a practical, non-contact thermal sensing layer for smart buildings. Future extensions will pursue higher-dimensional reconstructions, multi-parameter fields, and tighter integration with building energy management systems.

**Author Contributions:** S.C. conceived the tomography concept, developed theory, and wrote the manuscript. K.P. designed reconstruction algorithms and analysis. D.F. implemented ESP32 firmware and data acquisition. S.G. supervised the project and coordinated testbed deployment. All authors reviewed and approved the final manuscript.

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