Res Intell Manuf Assem, 2026, 5(2): 383-393
DOI: 10.25082/RIMA.2026.02.001

RESEARCH ARTICLE

Spectral Semantic Analytics of Local Spaces via Spectral-Semantic Neural Network Metamodel

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Received: April 7, 2026;
Accepted: July 25, 2026;
Published: July 29, 2026.

Citation: Bryndin E. Spectral Semantic Analytics of Local Spaces via Spectral-Semantic Neural Network Metamodel. *Res Intell Manuf Assem*, 2026, **5**(2): 383-393. https://doi.org/10.25082/RIMA.2026.02.001

Abstract: This paper investigates the development and deployment of spectral-semantic analytical frameworks for local space analysis using neural networks. The proposed paradigm unifies spectral data processing—with measurements collected from spectrometers and thermal imagers—and semantic modeling, which frames spectral features as bearers of structured semantic information. This work elaborates on techniques for translating spectral modality into linguistic-semantic representations; this transformation enables dual characterization of local physical properties: quantitative description via spectral parameters, and qualitative description via semantic profiles and patterns. Special focus is given to building spectral-semantic dictionaries and matching neural architectures that extract and formalize contextual correlations between object spectral signatures and their semantic implications. Diverse spectrogram formats and spectral representations (multiband and hyperspectral data included) are adopted for local space characterization, alongside a neural network metamodel capable of generating domain-specific spectral-semantic models. Attention modules are embedded into these architectures to automatically screen high-value spectral bands and spatial regions pivotal to semantic reasoning.

Keywords: spectral semantic analytics, neural network models, semantic profiles, spectral modality, semantic patterns, attention mechanisms

1 Introduction

Neural network models that combine spectral analysis and semantic processing learn to understand the meaning of what is encoded in a spectrum [1–7]. Semantic segmentation of the spectrogram identifies regions in the spectrum image corresponding to different signal types, determines the spectrum source from the spectral image, and extracts features to obtain a vector representation of the spectrum for subsequent searching and clustering tasks.

For semantic segmentation, each pixel or region must be assigned a class label. Classic semantic segmentation networks including U-Net, SegNet, and DeepLab are well suited for tasks requiring the preservation of spatial information: the encoder extracts features, and the decoder with skip connections reconstructs detailed segmentation maps. This work builds a network that operates directly on spectrum coefficients rather than spectrogram images. For this purpose, spectral convolutional layers or spectral residual learning (SRL) approaches are adopted, in which local features are projected into the spectral domain, processed, and then fed back to the network.

Attention mechanisms are incorporated to enable the network to better focus on significant frequency bands or time regions. Spectral processing can also be integrated with other types of data (e.g., time series adjacent to spectral signals). In complex application scenarios, neural networks for spectrum feature extraction can be combined with symbolic components, logical rules, and knowledge graphs to enhance model interpretability and inference capability.

The model training pipeline is specified as follows:

(1) Hyperparameters including the learning rate and batch size, as well as the network layer architecture, are properly selected;

(2) Appropriate loss functions are adopted: cross entropy is commonly used for segmentation tasks, while MSE is applied for regression tasks;

(3) Model validation and testing are conducted to evaluate model performance and prevent overfitting. It is essential to evaluate not only accuracy metrics but also the specific spectral features that the network learns to distinguish. This helps verify whether the model learns

meaningful spectral characteristics or merely captures irrelevant artifacts;
(4) In real-world datasets, certain signal types appear frequently while others are sparsely distributed, which may degrade the model's performance on rare signal classes;
(5) Practical spectrogram data usually contains noise, thereby requiring the model to possess strong noise robustness;
(6) Training with large-scale spectrograms or complex network architectures demands sufficient computational resources.

The experimental procedure starts with training a basic U-Net on publicly available labeled signal spectrogram datasets after data transformation. Complex functional modules (e.g., attention mechanisms, spectral convolutional layers) are then added incrementally, and hybrid network approaches are further explored and validated.

Scientists and engineers adopt conventional spectrometers and spectrum analyzers according to the inherent properties of different waves, with device selection tailored to the research objects:
(1) For electromagnetic waves (including radio waves, microwaves, visible light, and X-rays), spectrometers matching the corresponding frequency bands are applicable. For instance, optical spectrometers disperse light into discrete wavelength components, while radio frequency spectrum analyzers visualize the energy distribution of radio signals across different frequencies. Specialized devices such as Fourier transform spectrometers exhibit superior performance in the infrared band. Devices including the FSM 1201 and FSM 1202 Fourier transform spectrometers adopt a Michelson interferometer to acquire interferogram data, from which spectral information is reconstructed via Fourier transform algorithms.
(2) For acoustic waves (including audible sound and ultrasound), spectrum analyzers are utilized to process acoustic signals and visualize their corresponding frequency and amplitude characteristics.
(3) For vibration signals in solids (e.g., phonon vibrations in crystals), vibrational spectroscopy techniques including infrared (IR) spectroscopy and Raman spectroscopy are employed. Spectrometers can identify the specific frequencies at which molecular or crystal lattice structures absorb or dissipate energy.

The working principle of all the above devices is consistent: a complex wave signal is decomposed into independent frequency components, the intensity of each component is measured, and the results are visualized as a spectrum graph for subsequent spectral analysis [8].

This paper investigates the fundamental principles of constructing spectral-semantic neural network models. The second chapter elaborates on the types and classification of spectra. The third chapter details the construction of the spectral-semantic metamodel. The fourth chapter focuses on the development of spectral-semantic dictionaries. The fifth chapter illustrates the construction of targeted spectral-semantic neural network models based on the proposed metamodel and dictionary. The sixth chapter explores the transformation of spectral modality into linguistic format via the established targeted models.

2 Types and classes of spectra

Systematic review of the varieties and classes of spectra is necessary for constructing spectral semantic neural networks and abstract meaning modeling [9–15].

By intensity distribution pattern (spectral structure):
(1) Continuous (solid) spectrum: intensity changes smoothly, without discontinuities; covers a certain range of frequencies/wavelengths. Example: radiation from a heated solid, a thermal spectrum (including the IR spectrum recorded by a thermal imager). In modeling tasks, this is convenient as a "background" continuum.
(2) Lined (discrete) spectrum: individual narrow peaks (lines) against a background of near-zero intensity. Typical of isolated atoms (e.g., the spectra of sodium and hydrogen vapor). For semantic models, such peaks can be interpreted as "individual semantic atoms" with clear frequency labels.
(3) Banded spectrum: groups of closely spaced lines that appear as stripes. Typical for molecules. In semantic modeling, bands can correspond to semantic clusters or semantic fields.
(4) Combined spectrum: a combination of continuous regions and discrete lines/bands. Example: stellar spectra (continuous photosphere background + absorption lines). In applied models, this is a common case: a general continuum of meanings with distinct semantic markers.

By type of interaction of radiation with matter:
(1) Emission (radiation): what the substance emits when excited. Suitable for "active"

semantics: what meanings the system "generates" in a given state.

(2) Absorption (absorption): what frequencies/wavelengths the substance absorbs from incident radiation. In semantic models, this can be interpreted as sensitivity zones or semantic filters of the system.

(3) Scattering spectra: how radiation is redistributed across angles and frequencies during interactions (Rayleigh, Raman). In abstract models, scattering can be viewed as a transformation of meaning when passing through a system.

By physical nature and measurable quantity:

(1) Optical spectra (visible light, UV, IR): the intensity distribution over wavelengths/frequencies. Often used as a basic example when training spectral models.

(2) Radiofrequency and microwave spectra: important for communications, radar, and modeling wave processes in local spaces.

(3) Mass spectra: the distribution of particles by mass-to-charge ratio. The discrete structure fits well with atomic semantics.

(4) Energy spectra: possible energy values in a system (quantum levels, Hamiltonian spectrum). In semantic models, energy levels can be compared to significance levels of meanings.

(5) Neutron spectra: the distribution of neutrons by energy. Less obvious for semantics, but useful for interdisciplinary analogies.

(6) NMR and EPR spectra: resonance peaks sensitive to the local environment of nuclei/electrons. Good for constructing local semantic fields taking into account context.

By representation method and mathematical processing:

(1) Time spectrum (signal in time): the original data before transformation.

(2) Frequency spectrum after Fourier transformation: intensity as a function of frequency. This is the basic format for spectral neural networks.

(3) Wavelet spectra (time-frequency representation): frequency components localized in time. Convenient for analyzing semantic events with a time reference.

(4) Spectrograms: two-dimensional time-frequency-intensity maps. Suitable for visualizing the dynamics of meaning.

Special classes relevant for abstract and semantic modeling:

(1) Quantum spectra: discrete energy/frequency levels associated with quantum transitions. Can serve as an analogy for "meaning quantization"—when meanings assume not just any, but certain "acceptable" states.

(2) Holographic spectra / spatial-frequency spectra: describe the distribution of amplitude and phase in space; spatial frequencies (cycles per meter) instead of temporal frequencies (Hz). This is directly related to your inquiries about holographic thinking: the semantic structure can be encoded as an interference pattern.

(3) Statistical spectra (power spectral density): describe the distribution of power/energy by frequency for random processes. Useful when meanings are considered as a stochastic process.

Relate to the tasks:

(1) For spectral-semantic dictionary, it is convenient to rely on line/striped structures: each semantic element or cluster corresponds to its own frequency marker.

(2) For spectral-semantic neural network, a frequency or wavelet spectrum is a natural input format; the attention mechanism can be targeted at peak frequencies (semantic dominants) and their surroundings.

(3) For measuring the frequencies of wave oscillations in local spaces, radio, microwave, acoustic, and optical spectra are suitable; the choice depends on the scale and nature of the environment.

(4) For abstract modeling of meanings, analogies with energy, quantum, and holographic spectra are useful: meanings as discrete states, as wave functions, as interference patterns.

3 Creating a neural network spectral-semantic metamodel for generating specialized models

Let's consider a practical framework for creating a neural network spectral-semantic metamodel that will generate specialized models in the paradigm of spectral dictionaries, attention mechanisms, and spectral-semantic networks [16, 17].

Spectral-semantic metamodel. Metamodel here is architecture/trainable framework that:

(1) accepts spectral descriptions of a subject area (dictionary, rules for encoding meanings into spectra, connection types);

(2) based on these, configures and initializes the parameters of a specialized model (e.g., a transformer or graph network);
(3) can be further trained or adapted to a specific task (generation, classification, semantic matching).

The essence of spectrality is that semantics are encoded not only by embedding vectors but also through spectral representations (frequency/wave features, wavelets, Fourier transforms, graph spectra, etc.).

Metamodel Architecture. Input Spectral Semantic Interface:
(1) Accepts: spectral dictionary (term spectral vector/function), ontology of relationships, task description (type: classification/generation/alignment), constraints (allowed operations, dimensionality).
(2) Converts this into a set of hyperparameters and initial weights for the target model.

Configuration Generation Block:
(1) Based on the dictionary and ontology, determines: embedding dimensions, number of layers, attention mechanism type (regular, multi-head, sparse, local-spectral), activation types, and norms.
(2) Can use a small transformer/MLP trained on examples "dictionary + task → configuration."

Spectral Meaning Encoding Block:
(1) Implements the mapping of terms/meanings into spectral representations: discrete Fourier transform (DFT), wavelet coefficients, and graph spectrum (Laplacian eigenvalues).
(2) Supports several modes: fixed spectral codes (from a dictionary) and trainable corrections.

Target Model Core:
(1) A template architecture that the metamodel "tunes": a transformer, a graph neural network (GNN), or a hybrid model.
(2) Spectral features are embedded into it as additional channels (via concatenation, additive biases, and specialized attention modules).

Adaptation/Retraining Module:
(1) After generating the base model, the metamodel launches a fast adaptation cycle (few-shot/meta-learning) for a specific task.
(2) Uses methods such as MAML, Reptile, or simple gradient descent with a small number of steps.

Validator and Interpreter:
(1) Checks that the generated model satisfies constraints (size, speed, training stability).
(2) Provides an explanation: which spectral components dominate the solution, which links in the dictionary were most important.

Implementation of a spectrally specific attention mechanism:
(1) Spectral keys/values: Some keys and values are encoded using spectral vectors from the dictionary.
(2) Frequency-selective attention: The attention mask depends on frequency ranges (low-frequency ones represent global links, high-frequency ones represent local details).
(3) Local spectral windows: instead of the usual sliding window, a window in the frequency domain (wavelet-like patterns) is used.
(4) This allows the model to simultaneously process semantics (meanings) and the structure of oscillations/waves, which is consistent with the tasks of spectrometers and wave oscillations of local spaces.

Practical Implementation Steps. Prepare a spectral-semantic dictionary:
(1) For each term/meaning, define the following: a text description, embedding (BERT/RuBERT), and spectral representation (e.g., DFT of a small vector or wavelet coefficients).
(2) Define the types of relationships (synonyms, opposites, causal) and their "weights" in the spectral domain.

Collect a dataset of configurations::
(1) Examples: "dictionary X + task Y model configuration Z."
(2) A configuration is JSON/YAML with hyperparameters and initial weights (or their offsets).

Train a meta-configuration generator:
(1) Use a transformer or MLP to predict a configuration based on a dictionary and task description.

(2) Loss function: the difference between the predicted and actual configuration + a performance metric for the target model during validation.

Implement a template target model:
(1) Write a modular architecture (PyTorch/JAX) that allows easy modification of dimensions, attention types, and the addition of spectral channels.
(2) Implement interfaces for connecting spectral codes from the dictionary.

Add an adaptation loop:
(1) After generating the model, run several training steps on a small task sample.
(2) Assess how quickly the model converges and how stable the spectral components are.

Validate and interpret:
(1) Check that spectral features actually influence decisions (ablation: removing spectral channels reduces performance).
(2) Visualize dominant frequencies for different classes/senses.

Target model configuration (example):
(1) model_type: “spectral_transformer”
(2) num_layers: 6
(3) hidden_size: 512
(4) num_heads: 8
(5) spectral_channels: 32
(6) attention_type: “frequency_gated”
(7) vocab_size: 10000
(8) max_seq_len: 512

Technology stack:
(1) Language/framework: Python, PyTorch, or JAX.
(2) Embeddings: RuBERT, Sentence-BERT.
(3) Spectral transforms: SciPy (FFT, wavelets), PyG (graph spectra).
(4) Meta-learning: ready-made MAML/Reptile implementations.

Task Relationships::
(1) Spectrometer/Waves: Spectral components in the model can be interpreted as digital analogs of spectrometer readings—they reflect the energy distribution across frequencies for semantic units.
(2) Dictionary and Semantic Network: The dictionary serves as the basis for initializing spectral codes; the connections within it define the structure for GNN components.
(3) Attention Mechanism: Spectral-selective attention allows the model to consider different frequency ranges depending on the context.

4 Structure and Creation of a Spectral-Semantic Dictionary

The dictionary must store a word’s meaning and a spectral representation of its meaning. Possible fields for each dictionary item:
(1) Term/concept (string).Semantic vector (e.g., from a pre-trained language model).
(2) Spectral profile is a fixed-length vector that encodes a frequency spectrum distribution: Fourier frequency bands from time series, wavelet decomposition coefficients, distribution by thematic domains, etc.).
(3) A set of semantic relations—synonym, hyponym, meronym, and associative link with weights.
(4) Metadata: domain, abstraction level, modality type (visual, auditory, abstract), source.

Example dictionary string (in JSON format):
json
{“term”: “light”,
“semantic_vector”: [0.12, -0.03, 0.45, ...],
“spectral_profile”: [0.81, 0.15, 0.02, 0.01, 0.01],
“relations”: {
“synonym”: [“radiance”, “radiation”],
“hyponym”: [“sunlight”, “lamplight”],
“associations”: [{“term”: “vision”, “weight”: 0.7}, {“term”: “heat”, “weight”: 0.6}]},
“domain”: “physics/perception”,
“modality”: “visual”}

Creating a spectral-semantic dictionary is an interdisciplinary task at the intersection of linguistics, semantics, physics (spectral (analysis) and AI. Let's consider a practical framework for designing and populating such a dictionary. Spectral-semantic dictionary is a resource where the meaning (semantics) of a word/phrase is linked to spectral characteristics: frequencies, harmonics, distributions, and patterns of wave or quasi-wave processes:

(1) physically motivated version: real frequencies (acoustic, electromagnetic) measured by a spectrometer for a signal that carries meaning;

(2) abstract-mathematical version: spectral representations via the Fourier transform, wavelets, eigenmodes, SVD, autocorrelations, etc.;

(3) cognitive-symbolic version: conventional "meaning spectra" as sets of semantic features, weights, and harmonics of meanings (similar to WordNet/FrameNet, but with a modal structure)

5 Creating a Spectral Semantic Network Based on Metamodel and Spectral Semantic Dictionary

Creating a spectral semantic network based on a metamodel and a spectral semantic dictionary is an interdisciplinary task at the intersection of linguistics, spectral analysis, and neural network modeling. Let's consider a practical plan and key components of such a system, adapted to semantic models and spectral representations.

In the context of spectral modality, we have:

(1) Frequency representation of signals: data from sensors, acoustic or electromagnetic spectra that need to be associated with meanings.

(2) Spectral features in mathematics: Fourier transform decomposition, wavelets, eigenvalues of graph adjacency matrices, spectral embeddings.

(3) Analogy with the "spectrum of meanings": a scale of shades of meaning, where meaning is represented not by a point, but by a distribution along an axis (or axes) of semantic variability. This determines how you will build the dictionary and the network.

Spectral Semantic Network Architecture:

(1) The network is a graph where: Nodes are concepts from the dictionary.

(2) Edges are semantic relationships with weights; you can also store the "spectral distance" between nodes.

Setting Edge Weights:

(1) Semantic similarity: cosine similarity between semantic vectors.

(2) Spectral similarity: distance between spectral profiles (L2, KL divergence, Earth Mover's Distance, *etc*.).

(3) Combined weight: $w = \alpha \times w_{\text{sem}} + (1 - \alpha) \times w_{\text{spec}}$, where α is chosen experimentally.

This approach allows the network to consider both "what a word means" and "in what spectral context it occurs."

Practical steps for creating a network:

(1) The source of spectral data is determined. This can be:
a. time series (audio, sensor signals),
b. spectra (optical, radio frequency),
c. synthetic spectral profiles (e.g., topic distribution).

(2) Build spectral profiles for concepts. Options:
a. Assign each concept to a set of documents/signals where it occurs and average their spectral characteristics;
b. Use pre-trained models that can work with multimodal data (text + spectrum).
c. Build a dictionary with semantic vectors (BERT/RuBERT, SBERT are suitable) and spectral profiles.

(3) Build graph:
a. Calculate pairwise semantic and spectral distances;
b. Keep the top-N nearest neighbors for each node to keep the graph sparse;
c. Assign edge weights using a combined metric.

(4) Add an attention mechanism. In graph, this can be implemented as:
a. attention layers on top of edges (Graph Attention Network, GAT);
b. dynamic redistribution of edge weights depending on the query (context).

Train/tune the network. If there is labeled data (query-relevant concept pairs), optimize the alpha weights, loss function, and attention parameters.

Integrating the Attention Mechanism. For a spectral semantic network, attention is useful to:
(1) strengthen connections relevant to the current context (query, task);
(2) suppress "noisy" or weakly connected nodes;
(3) account for different types of relationships (synonyms, associations) with different coefficients.

The simplest attention computation scheme is illustrated as follows. For each node i and its neighbor node j, we first calculate the unnormalized attention score between node i and node j:

$$e_{ij} = \mathrm{LeakyReLU}\big(\mathbf{a}^T \left[\mathbf{W}\mathbf{h}_i \parallel \mathbf{W}\mathbf{h}_j\right]\big) \tag{1}$$

where $\mathbf{h}_i$ denotes the feature vector of node i (which can fuse semantic embedding vectors and spectral profile features), $\parallel$ represents vector concatenation, and $\mathbf{a}$, $\mathbf{W}$ are trainable model parameters.

Subsequently, we normalize the raw attention scores via softmax to obtain normalized attention weights:

$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{k \in \mathcal{N}_i} \exp(e_{ik})} \tag{2}$$

where $\mathcal{N}_i$ is the set of all neighboring nodes of node i.

Finally, we aggregate neighborhood features weighted by attention coefficients and apply an activation function σ to generate the updated feature vector of node i:

$$\mathbf{h}'_i = \sigma\left(\sum_{j \in \mathcal{N}_i} \alpha_{ij} \mathbf{W}\mathbf{h}_j\right) \tag{3}$$

This is standard GAT, but with vectors that contain both semantic and spectral information. Transformation of spectral modality into linguistic modality: spectral profiles of nodes serve as a bridge between the spectrum and the word. Holographic thinking and semantic images: a sparse graph with an attention mechanism simulates focusing on the desired semantic connections, similar to how a hologram reconstructs an image from a fragment.

Abstract modeling of meanings: spectral profiles are treated as spectrum of possible meanings, and edge weights are interpreted as the strength of their joint actualization. Tools and stack:
(1) Graph libraries: NetworkX (Python) for prototyping, PyTorch Geometric / DGL for GAT and training.
(2) Language models: SBERT, RuBERT for semantic vectors.
(3) Spectrum processing: SciPy (FFT, wavelets), librosa (for audio), specialized packages for optical/radio frequency spectra.
(4) Graph and dictionary storage: JSON/Parquet for the dictionary, GraphML/Neo4j for the graph.

6 Transforming Spectral Modality into Linguistic Meanings

Spectral modality, in a broad sense, is the representation of data through spectral characteristics: frequencies, wavelengths, and energy distributions (e.g., the spectrum of light, the spectrum of sound, and the spectra of signals in physics and data processing). In a cognitive semantic context, this can be understood as spectrum of nuances of perception, states, or meanings [18].

Linguistic modality is a way of expressing attitudes toward reality in language: possibility/necessity, confidence/uncertainty, evaluation, intention (in linguistics, these are grammatical and lexical means; in AI, these are vector representations that encode such nuances) [19].

Abstract modeling of metamodel meanings is the construction of formal or semi-formal structures (graphs, vectors, rules) that reflect semantic relationships without rigidly linking them to specific objects. Transformation Approach:
(1) Spectral data numerical representation. The spectrum is converted into a feature vector (using FFT, wavelets, autoencoders, etc.).
(2) Vector semantic space of the language. The resulting vector is projected into a general semantic space with text embeddings (as in CLIP, ALIGN, and multimodal transformers).
(3) Decoding into language. The language model generates a description from the vector.

To abstract meanings, it is important to name the spectrum and associate it with categories. This is done through:
(1) training on spectrum-description pairs with semantic tags;
(2) using ontologies and thesauri, where spectral patterns are linked to abstract concepts.

Supervised, interpretable system:
(1) Correspondence dictionary. For example: peak in the blue region of the spectrum cold/distance/loneliness; Broad, uniform spectrum neutrality/fullness.
(2) Description templates. The spectrum has a dominant peak at X nm and a weak shoulder in the Y range, corresponding to sensation Z.
(3) Modal operators. Modality is added to the description: This likely corresponds to...; can be interpreted as....

This approach is convenient for abstract modeling, allowing rules to be linked to metamodel categories. In the metamodel, meanings are constructed through metaphors: "time - line," "emotions - temperature." For spectral modality, the following correspondences are possible:
(1) "spectrum as a palette of states" (colors/frequencies - emotions/meanings);
(2) "spectrum as an intensity scale" (amplitude - strength of meaning);
(3) "spectrum as dynamics" (spectrum change over time - development of meaning).

The transformation then proceeds not from "spectrum - words," but from "spectrum - metaphorical model - linguistic description." This lends itself well to the tasks of abstract modeling: meaning is captured not as a word, but as a structure of relationships.

Practical Diagrams and Examples

Example 1: Audio Spectrum - Abstract Meaning:
(1) Spectrum: strong low-frequency component, sharp peaks in the high frequencies.
(2) Intermediate interpretation: "contrast between heaviness and sharpness," "tension against a background of stability."
(3) Linguistic description: "The sound conveys a sense of internal conflict: a massive base and sudden sharp accents create the effect of discontinuous movement."

Example 2: Optical Spectrum - Abstract Meaning:
(1) Spectrum: two close peaks in the green region, a weak tail in the red region.
(2) Intermediate interpretation: "closeness and slight deviation," "almost equilibrium with a hint of change." - Language description: "The shade expresses a nearly achieved equilibrium, where a barely noticeable warm undertone hints at a possible shift."

Technical and Conceptual Tools

(1) FFT/wavelet analysis — for spectral feature extraction.
(2) Autoencoders/variational autoencoders — to compress the spectrum into a latent representation suitable for matching with language.
(3) Multimodal models (CLIP-like) — for learning spectrum $\leftrightarrow$ text correspondences.
(4) Knowledge graphs and ontologies — for explicitly linking spectral patterns with abstract meanings.
(5) Semantic networks and frames — for modeling semantic relationships between spectral and linguistic categories.
(6) Semantic holographic images and holographic thinking — the spectrum can be interpreted as an "interference pattern" of meanings: each peak and trough is the contribution of a separate semantic "source," and their superposition yields the final meaning. Conversion into language then is the "decoding of interference" into semantic relations.
(7) quantum states of meaning — spectral distributions are naturally associated with probability distributions (like wave functions), and linguistic modality can express the "degree of realization" of meaning ("possibly," "most likely," "definitely").
(8) Ambiguity. The same spectrum can correspond to different meanings in different contexts. A context model is needed.
(9) Loss of subtlety. In the transition to language, some spectral detail is lost; this is compensated for by multi-level description (technical + metaphorical + modal).
(10) Training data. For high-quality conversion, labeled "spectrum - semantic description" pairs are needed. Spectral-to-linguistic transformation** is the translation of information presented as spectral data (e.g., frequencies, amplitudes, energy distributions by frequency) into a textual description or semantic representation that is understandable to humans and suitable for linguistic processing.

Main transformation methods:

(1) Spectral parameterization + template descriptions. Key parameters (peak center frequencies, bandwidths, signal-to-noise ratio, etc.) are extracted from the spectrum and substituted into pre-prepared text templates.

Example: "The spectrum shows a prominent peak at 440 Hz with a bandwidth of 25 Hz; the noise level in the range of 1–2 kHz is low."

(2) Spectral pattern classification. The spectrum is assigned to one of the pre-defined classes (types), each of which has its own linguistic description.

Example: "pure tone" type, "broadband noise" type, "harmonic series" type, etc.

(3) Neural network multimodal models. They use an encoder for spectral data and a language model (LLM) for text generation. Spectral features are projected into a space compatible with language embeddings, which then generates a description. This is a modern approach, similar to how models like CLIP and LLaVA work, but adapted for spectra.

(4) Semantic interpretation in the subject area. Specific fields (acoustics, spectroscopy, EEG) have established terms and standard formulations. The transformation is based on these vocabularies and rules.

Example (spectroscopy): "An absorption band is observed in the region of 1700 cm^{-1}, characteristic of the carbonyl group."

(5) Cepstral and other derived representations. Sometimes an intermediate transformation is first made (for example, a cepstrum for speech), which better reflects linguistically significant parameters, and then translated into text.

7 Conclusion

The practical value of this work lies in the development of a spectral-semantic metamodel for the comprehensive analysis of local spaces: it can be applied in remote sensing, environmental monitoring, urban planning, industrial diagnostics, and other fields that require simultaneous consideration of the physical characteristics of the environment and their semantic interpretation. The proposed metamodel allows not only for the classification and segmentation of spaces by spectral features but also for the construction of semantic maps reflecting the functional purpose, state, and dynamics of local areas.

Spectra show how the spectral composition of a signal (the distribution of energy by frequency) changes over time. They are widely used in a wide variety of fields:

(1) Medicine and biology. Spectra are used in the study of biosignals. For example, in electroencephalography (EEG), spectral analysis helps evaluate the structure of frequency components and identify asymmetries of activity in different parts of the brain or focal manifestations. There are also studies where photoplethysmograms (pulse wave signals) are used for the early diagnosis of diseases based on characteristic changes in frequency composition [20].

(2) Seismology. Spectra help monitor seismic station data: analyze seismic waves, identify anomalies, and better understand processes occurring in the Earth's crust.

(3) Astronomy. In astronomy, spectra are used in the classical sense of the distribution of radiation intensity by wavelength, which allows us to study the composition of stars and galaxies, determine their velocity (using the Doppler effect), and other physical characteristics [21].

(4) Radio engineering and telecommunications. Spectra are indispensable for analyzing radio signals: identifying sources of interference, studying modulation characteristics (amplitude, frequency, phase), and monitoring transmission quality. This is important when adjusting radio transmitters, antennas, and receivers, as well as for assessing cellular coverage.

(5) Vibration analysis. Engineers use spectra to study the vibrations of mechanisms. This visualization makes it easy to see how the frequency composition of vibration changes over time and identify anomalous bands that may signal incipient malfunctions or wear of components.

(6) Signal processing. In general, spectra help work with non-stationary signals—those whose frequency content changes over time. This is relevant in communication systems, audio processing, and speech recognition systems.

(7) Materials science and chemistry. Characteristic absorption or scattering peaks and bands are used to determine the chemical composition of substances, study the structure of molecules, and monitor the quality of raw materials and finished products. For example, infrared spectroscopy is used to analyze biological fluids and tissues in medical research.

(8) Environmental monitoring. Spectroscopic methods (UV-Vis, IR, Raman spectroscopy) are used to detect and quantify pollutants in air, water, and soil. By analyzing the spectral "fingerprints" of particles or compounds, it is possible to track pollution sources and evaluate the effectiveness of mitigation measures.

The key advantage of spectral-semantic target neural network models is that they analyze a complex dynamic spectrum, identify patterns and anomalies, and provide accurate solutions to problems and tasks in various fields of science and areas of activity [22].

Semantic control of the attentional functionality of the neural network metamodel allows switching to different local spaces, thereby solving complex interdisciplinary problems and combining various types of activities through target spectral semantic neural network models.

Conflicts of Interest

The author declares no conflicts of interest.

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