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ANALYZING MIGRATION PATTERNS THROUGH INTEGRATED SIGNAL PROCESSING AND IMAGE ANALYTICS: A COMPUTATIONAL SOCIOLOGY APPROACH

Tariq Siddiqi[1*], Asesh Kumar Tripathy[2], Dr. A. N. GnanaJeevan[3], Zeeshan A. Rana[4], Dr. Daizy Deb[5], Sumanpreet Kaur[6]

[1]Head of the Department , Department of Management Studies, Specialization in Management Studies, Galgotias Institute of Management & Technology, Greater Noida UP, 201310, India, Email Id : tariq.siddiqi@galgotiacollege.edu, Orcid Id : https://orcid.org/0009-0009-0451-0802*

[2]Associate Professor, Department of CSE, Koneru Lakshmaiah Education Foundation, Vaddeswaram, AP, India 522301, Email Id : asesh.tripathy@gmail.com

[3]Assistant professor, SRM institute of science and technology, School of Computing Information Technology, Tiruchirapalli, Email Id: ang.jeevan@gmail.com, Orcid Id : https://orcid.org/0009-0004-6234-2636

[4]Associate Professor, Prince Mohammad Bin Fahd University, Al-Khobar, KSA, Email ID: zrana@pmu.edu.sa, Orcid Id : 0000-0001-7839-3949

[5]Associate Professor, Brainware University Kolkata, Pincode: 700125, Email Id : ddd.cse@brainwareuniversity.ac.in, Orcid Id : 0009-0004-4717-0979

[6]Assistant Professor, School of Legal Studies, CGC University, Jhanjeri Mohali Email ID: sumanpreetk.19@gmail.com

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Corresponding Author: Tariq Siddiqi (tariq.siddiqi@galgotiacollege.edu)

Abstract

The increasing availability of large-scale spatio-temporal data has created new opportunities for analyzing migration and human mobility through advanced signal and image processing techniques. Temporal mobility data capture dynamic movement behavior, while satellite and remote sensing imagery provide spatial context related to urban development, infrastructure, and environmental conditions. However, traditional unimodal analytical approaches are often insufficient to model the complex interactions between temporal dynamics and spatial structure inherent in migration systems. This comprehensive review synthesizes recent advances in signal processing, image analytics, and integrated multimodal frameworks for migration and human mobility analysis from an engineering perspective. The review examines key data sources and representations, state-of-the-art time-series and graph-based signal processing methods, image analytics techniques for spatial pattern extraction, and emerging strategies for multimodal signal–image fusion. Evaluation practices, benchmarking trends, and representative application domains are also discussed to highlight current methodological strengths and limitations. Finally, the review identifies major challenges related to scalability, data quality, and multimodal integration, and outlines emerging research directions including deep multimodal learning, foundation models, and real-time large-scale analytics. By consolidating developments across signal and image sciences, this review provides a structured reference for researchers developing integrated analytical frameworks for complex spatio-temporal mobility and migration systems.

Keywords- *Signal processing; Image analytics; Multimodal data fusion; Spatio-temporal analysis; Human mobility*

1. INTRODUCTION

The fast development of data-driven technologies and sensing infrastructures have greatly transformed the modern research in signal and image sciences. The development of signal processing is currently allowing the analysis of large spatio-temporal data streams, and developments in image analytics especially in remote sensing and satellite imagery have increased the capability to extract spatially explicit information at various resolutions. Such advances have enabled modeling of complex real-world systems through a collective dynamic in time and space structure. Nevertheless, the standard analytical pipelines tend to operate on temporal signals and spatial images separately, which restricts their usefulness when used on spatio-temporally coupled phenomena.

The canonical example of such phenomena is human migration and mobility. Engineering and computational Migration may be modelled as a spatio-temporal data problem, in which population flows are coded as time-varying signals that develop in geographic space and networked networks. Migration dynamics can now be examined at previously unimaginable spatial and temporal scales due to the growing access to big data of digital forms of mobility, including records of mobile phone usage, transportation patterns, and sensor-generated tracks [1]. This has placed migration studies in the wider context of large-scale signal modeling, focusing on pattern identification, time structure and predictability. Another viewpoint on human migration that emphasizes the role of computational and signal-based methods in uncovering structural regularities in population migrations that are challenging to address in terms of traditional methods is the big-data approach to human migration.

Simultaneously, recent developments in the field of Earth observation technologies have made image analytics an essential supporting modality in migration and mobility analysis. Indirect, but informative, visual proxies of socioeconomic activity, infrastructure development, and urbanization pattern, which have strong effects on population movement, are available using satellite images, such as night-time light intensity and land-use information [2]. The images of spatial features can therefore place the temporal mobility signals in perspective and make the computational models and their robustness more interpretable. Recent work also emphasizes the necessity of open, standardized and interoperable data in order to enable reproducibility and large scale comparative analysis particularly in multimodal research where a heterogeneous data source must be used together [3].

Despite such developments, the literature that exists is fragmented. Signal processing techniques are frequently applied without providing spatial context to the imagery, and image-based techniques are frequently applied to disregard finer-grained temporal variations observed in mobility signals. Such unimodal approaches are inherently limited in its ability to describe cross-modal interactions between time-dependent behavior and the organization of space. This has created a surge of interest in the field of integrated signal and image analytics where multimodal data fusion can offer more comprehensive spatio-temporal representations and enhanced analytical power. Accordingly, the objectives of this review are to:

- Summarize key spatio-temporal data sources and representations used in migration and human mobility analysis.
- Review signal processing, image analytics, and integrated multimodal methods from a signal and image sciences perspective.
- Identify challenges and emerging research directions in integrated signal–image analytics.

By consolidating and organizing recent advances within a unified engineering framework, this review aims to provide a structured and comprehensive reference for researchers working at the intersection of signal processing, image analytics, and spatio-temporal mobility modeling.

2. REVIEW METHODOLOGY

This review is conducted in a systematic and structured approach to cover all existing literature and synthesize it objectively in the area of intersection of signal processing, image analytics, and the migration-related spatio-temporal analysis. The review process was intended to focus on engineering-related contributions, methodological rigor, and applicability to integrated signalimage analytics. A wide search of scientific databases has been done in the key scientific databases, such as IEEE Xplore, ACM Digital Library, Elsevier ScienceDirect, SpringerLink, and Google Scholar. The search strategy was based on the combination of keywords that related to signal processing, image analytics, multimodal data fusion, spatio-temporal modeling, human mobility, and migration analysis. Peer-reviewed journal articles, conference papers, and credible survey papers that were

written in English were excluded. Studies were included if they satisfied at least one of the following criteria:
(i) proposed or analyzed signal processing techniques for spatio-temporal mobility or migration data
(ii) applied image analytics or remote sensing methods to infer mobility-related patterns; or
(iii) developed or evaluated integrated multimodal frameworks combining temporal signals and spatial imagery
Purely theoretical social science studies without a computational or analytical component were excluded to maintain alignment with signal and image sciences.
A taxonomy-based classification was then applied to the selected literature and the studies were grouped based on their data modality, analytical methodology and the degree of multimodal integration. This framework allowed to compare methods in signal processing, image analytics, and integrated frameworks in a coherent way, as well as identify the common evaluation practices, limitations, and open research issues. Through this approach, the review will provide balanced coverage of the techniques used in the past, new developments, and trends, and will have a clear focus on engineering contributions to integrated signal and image analytics in migration and human mobility analysis.

3. DATA SOURCES AND REPRESENTATION

Migration and human mobility analysis is based on heterogeneous data that is able to capture both time-related dynamics and spatial environment. In terms of signal and image sciences, these data may be generally divided into time mobility signals and remote sensing data represented in images. These modalities are important requirements that should be well represented and preprocessed in order to achieve strong spatio-temporal modeling and integrated analytics.

3.1 Temporal Mobility Signals

The time-varying data streams that characterize population flows are called temporal mobility signals; typically in a trajectory form, origin destination (OD) matrices, or aggregate flows. Such signals are typically received on the basis of digital footprint like mobile phone records, transportation systems and other sensor-based platforms. The recent literature demonstrates that heterogeneous open data providers can be aggregated to model large-scale mobility flows, and the time resolution as well as the spatial granularity need to be taken into account to model the dynamics of migration [4]. OD matrices, in their turn, provide a concise yet informative account of the mobility patterns and have been widely used in the study of migration and mobility, which in turn spur certain modeling and estimation of large-scale OD data.
Besides aggregated mobility flows, fine-grained sensor data, e.g., smartphone-based motion signals, can be used to characterize individual-level movement behavior, which is highly faithful to time to model mobility [5]. The polls of new data streams also indicate the growing ecosystem of digital traces that can be used in migration and mobility studies, such as administrative data and new sensing platforms, that can all deepen signal-based representations.

3.2 Image and Remote Sensing Data

Spatial context Image-based data, especially satellite and remote sensing platforms, have critical information on migration processes. The concept of night-time lights has become a very popular proxy of socioeconomic activity, urbanization, and development of infrastructure, which are directly interconnected with population mobility. Empirical evidence has revealed that temporal changes in the intensity of light at night and human mobility in extensive geographic areas are strongly correlated, and image-based features can be useful in migration studies. Recent studies have also provided an examination of the role of urban development in night-time light hotspots, which has provided spatial indicators to supplement temporal mobility indicators.
The development of remote sensing data products has enhanced spatial resolution and temporal coverage and has provided the opportunity to depict development and economic activity in a more detailed manner. Recent generations of datasets of night-time lights have been used to measure the dynamics of regional development, highlighting their usefulness as auxiliary images-based data in mobility and migration research [6]. Such imagery when combined with temporal mobility signals gives a more detailed spatio-temporal context of analytical modeling.

3.3 Data Characteristics and Preprocessing Requirements

Image-based data as well as temporal mobility signals are both highly challenging to preprocess. Mobility signals are typically noisy, sparse and irregularly sampled meaning that they need to be normalized, time aligned and aggregated to provide consistency across datasets. OD representations can be affected by a lack of data

and reporting bias, especially in areas with a low density of sensing infrastructure [7]. Sensor-acquired signals also need to be filtered and segmented to eliminate artifacts and provide predictable temporal behavior.
Image and remote sensing data also present other complexities such as different spatial resolutions, illumination conditions and time discrepancies. Radiometric correction, spatial alignment, and feature normalization are preprocessing stages that are necessary to make the results across time and regions comparable [8]. Furthermore, the temporal mobility cues should be synchronized with the spatial features of the images to which the spatial features of the images are carefully aligned spatio-temporally to facilitate the multimodal analysis.
In general, the successful application of migration-related data depends on the strong representation and preprocessing measures that consider the heterogeneous character of the temporal signals and spatial imagery (Table 1). These considerations form the foundation for subsequent signal processing, image analytics, and integrated multimodal frameworks discussed in the following sections.

Table 1. Summary of Data Sources and Representations for Migration and Mobility Analysis

Data Type	Typical Sources	Representation	Strengths	Limitations
Mobility signals	Mobile phone data, GPS, sensors	Time series, trajectories	High temporal resolution	Sampling bias, noise
OD flows	Transportation logs, surveys	OD matrices, graphs	Compact population-level view	Data sparsity
Remote sensing	Satellite imagery, nightlights	Raster images, grids	Global coverage	Indirect proxies
Urban context	POI, land use maps	Spatial features	Context enrichment	Static or coarse

4. SIGNAL PROCESSING APPROACHES

Signal processing plays a central role in modeling migration and human mobility by treating population movements as time-dependent signals evolving over space and networks. Recent advances emphasize scalable time-series modeling, discriminative feature extraction, and robust detection of structural changes, enabling the analysis of complex spatio-temporal dynamics in large mobility datasets.

4.1 Time-Series Modeling of Mobility Data

Time-series modeling offers the basis of modeling and predicting mobility dynamics. Mobility signals are usually structured in time series of flows, tracks, or node based activities in space or networked frameworks. The recent systematic reviews also point to the increased interest in using spatio-temporal graph-based models, in which mobility is modeled as signals on graphs and trained with deep neural networks that are optimized to solve forecasting and classification problems [9]. Such models combine both time dependence and space interaction which are critical in modeling the processes of migration and mobility.
In addition to graph-based formulations, knowledge-based signal representations have also been developed. The use of urban knowledge graphs allows incorporating heterogeneous temporal signals and contextual information to predict mobility by incorporating structural relationships into time-series models [10]. Simultaneously, transformer-based and graph convolutional network deep learning methods have shown good performance to model long-range temporal dependencies and intricate spatial interactions in human mobility data [11].

4.2 Feature Extraction and Pattern Detection

The extraction of features is essential in the detection of regularities and latent structures of mobility signals. Conventional methods use aggregated time characteristics, including periodicity and trend components, whereas the more recent methods focus on representation learning to learn the salient mobility patterns automatically. Crowd and flow prediction studies demonstrate how multi-scale temporal characteristics can be derived to manage the different spatial and temporal granularities to enhance the predictive power in different urban environments [12].
Techniques based on advanced learning are also used to improve the detectability of patterns by expressly capturing periodic behavior and residual dynamics on mobility signals. Periodic residual learning models have been suggested to isolate repeated mobility patterns and irregular variation, so that more robust forecasting can be made in non-stationary and seasonal scenarios [13]. Generative methods have been studied as well, in which the origin destination flows are considered structured signals and generated with deep generative models under the influence of spatial interaction principles [14]. These approaches underscore the growing importance of signal representation learning in the discovery of complicated mobility frameworks.

4.3 Change Analysis and Anomaly Detection

The analysis of change and detection of anomalies are needed to detect sudden change and abnormal events in migration and mobility indicators. These shifts can be either policy interventions, infrastructural changes or external shocks and they need to be identified using strong signal processing methods. The latest literature on change-point detection methods based on deep learning is showing how neural networks can detect structural changes in complex time-series data, with better sensitivity and flexibility than classical statistical methods.

Causality-aware signal processing has also been of interest in the context of mobility modeling. Origindestination flow prediction frameworks that are causality-enhanced are supposed to separate true causes of mobility and spurious correlations, especially when the quality of signals is low in data-scarce settings [15]. Perspectives based on networks also help in change analysis, as they model migration as changing networks, allowing the identification of macro-level structural changes in migration systems by observing signal changes on network topologies [16].

In general, signal processing methods offer an extensive arsenal of migration-related mobility signal modeling, analysis, and interpretation tools (Table 2). These techniques are the computational basis of the future integration with image analytics in multimodal migration analysis systems by integrating time-series modeling, feature extraction and change detection.

Table 2. Signal Processing Methods for Spatio-Temporal Mobility Modeling

Method Category	Core Techniques	Mobility Tasks	Key Advantages
Time-series modeling	RNN, LSTM, Transformers	Flow prediction	Long-term dependencies
Graph-based signals	ST-GNN, GCN	Network mobility	Spatial interaction modeling
Generative modeling	GANs, VAEs	OD estimation	Data synthesis
Change detection	Deep CPD	Anomaly detection	Event sensitivity

5. IMAGE ANALYTICS APPROACHES

Image analytics provides a complementary perspective to mobility signal modeling by extracting spatial structure and contextual indicators from imagery, particularly from remote sensing sources. For migration and mobility analysis, image-based features can serve as proxies for urban development, infrastructure intensity, land-use change, and socioeconomic activity—factors that often shape population movements. This section reviews key image processing pipelines, spatial pattern recognition methods, and remote sensing-driven approaches relevant to population dynamics.

5.1 Image Preprocessing and Feature Learning

Strong image analytics starts with preprocessing functions that decrease the variability that is not related to the target phenomenon. This is often found in remote sensing, and consists of radiometric correction, geo-referencing, inter-sensor or inter-acquisition normalization, and spatial co-registration to make different images consistent. This is required due to the fact that most of the indicators of migration like the intensity of night lights or the pattern of built-up areas are highly sensitive to the conditions of acquisition and sensor specifications.

As deep learning has matured, feature learning has moved away more and more towards learned representations. Modern remote sensing pipelines use convolutional architectures and associated deep models to learn discriminative features to be used in downstream tasks including land-use classification, development estimation and object detection. Surveys of object detection in remote sensing note the development of classical sliding-window or region-based approaches to deep learning pipelines that co-learn hierarchical spatial features and detection boundaries at scale [17]. These advances in learning are specifically applicable to mobility-related tasks, in which the object of interest is not the image, but the derivation of interpretable spatial covariates to be used in further spatio-temporal modeling.

5.2 Spatial Pattern Recognition

Spatial pattern recognition is concerned with the identification and description of significant structures and spatial regularities of images. In the migration-related research, the most topical spatial patterns are usually the urbanization, the development of infrastructure, and the alterations in settlement density. The imagery of night-time light is especially useful since it offers a globally comparable proxy of human activity and development. It is empirically demonstrated that the temporal variations in the intensity of night-time lights are associated with the quantifiable shifts in human mobility, which confirms the validity of using learned or designed characteristics of nightlight imagery as a predictor or correlate of movement patterns [18]. Related literature also shows that the process of urban development triggers the spatial distribution of hotspots of nightlights, which allow hotspots-based pattern descriptors, which may be connected to urban growth and spatial reconfiguration that apply to migration processes.

In addition to nightlights, remote sensing pattern recognition often entails the detection of objects and structures that can be used to measure the intensity of development, including building footprints, road networks and land-use transitions. Anchor-based and anchor-free deep detectors are remote sensing object detection methods that are of particular use in extracting such spatial indicators on a large scale. These derived spatial patterns may in turn be inputted in as explanatory variables to mobility models or as independent variables of population redistribution.

5.3 Remote Sensing for Population Dynamics

Remote sensing has been a critical enabler to population dynamics analysis as it provides a regular coverage across large geographic regions, even in those regions where conventional mobility sensing infrastructure is constrained. One example of a fundamental use-case is the derivation of development and economic activity that may be applied to contextualize mobility and migration flows. Recent research has used the enhanced data products of nightlights to measure economic progress and regional development more credibly and reinforce the position of night-time light imagery as a supportive data source to mobility-related modeling. Together with the right temporal alignment, such signals of image-based development can be used to complement the interpretation of the mobility patterns and provide spatially explicit predictors of migration drivers.

More importantly, remote sensing methods that rely on images can also be used to facilitate the shift between descriptive mapping and predictive modeling. Recent research indicates that deep learning networks that are trained on satellite images can forecast human flows of movement in urban areas, indicating that images alone can capture detailed spatial data, which is important to movement patterns [19]. This research stream supports the importance of image analytics as a contextual feature extractor and as a primary modality that can be used to make inferences and predictions about mobility. In short, image analytics methods, including preprocessing, feature learning, spatial pattern recognition, and remote sensing-based modeling, offer the necessary spatial representations to migration and mobility studies (Table 3). These techniques are a solid basis of integrated signal-image models, whereby image-based spatial information is combined with temporal mobility information to enhance prediction, strength, and explainability.

Table 3. Image Analytics Techniques for Migration and Mobility Studies

Image Task	Techniques	Extracted Indicators	Use in Mobility Analysis
Feature learning	CNNs, Transformers	Urban density	Context modeling
Object detection	YOLO, Faster-RCNN	Infrastructure	Accessibility inference
Nightlight analysis	Temporal intensity	Economic activity	Migration proxy
Land-use mapping	Segmentation models	Settlement patterns	Population distribution

6. INTEGRATED SIGNAL–IMAGE FRAMEWORKS

6.1 Motivation for Multimodal Fusion

Migration, and mobility processes are spatio-temporal in nature, and thus demand the simultaneous modeling of the temporal dynamics in the forms of mobility signals and the spatial context in the form of imagery. Temporal signals give data on how movement has changed and how intensely, whilst images, especially of remote sensing, give constant images of land use, infrastructure, and patterns of development, which affect mobility. Each modality, when considered separately, is a partial perspective of the system. Multimodal fusion allows the fusion of complementary information between signals and images, enhancing noise, sparsity, and missing observation resistance. Multimodal remote sensing reviews indicate that integrated systems will always be more effective than unimodal systems in multifaceted spatial-temporal tasks, especially when both time consistency and spatial resolution are required to be maintained at the same time.

6.2 Integration Strategies and Architectures

Existing integration strategies can be broadly categorized by how and where modalities interact within the analytical pipeline. Feature-level fusion remains the most widely adopted approach, in which embeddings learned separately from temporal mobility signals and images are combined through concatenation, attention, or gating mechanisms to enable end-to-end learning of joint representations. Decision-level fusion, in contrast, aggregates predictions from independent signal-based and image-based models and offers simplicity and stability at the cost of weaker cross-modal interaction. More advanced architectures explicitly model cross-modal dependencies through joint learning or automated design. For example, multimodal fusion architecture search frameworks systematically explore fusion operators and interaction depths to identify effective multimodal designs without manual tuning. In parallel, contrastive multimodal learning has emerged as an effective strategy for aligning heterogeneous modalities by learning shared latent spaces, enabling robust representation learning even under partial modality overlap or weak supervision.

6.3 Comparative Discussion of Representative Frameworks

Comparative study of integrated signalimage structures indicates trade-offs in terms of alignment requirements, interaction depth and generalization capability. The feature level fusion techniques often have high spatio-temporal compatibility of modalities, and thus cannot be used in heterogeneous or data-sparse environments, but contrastive learning models do not have such requirements [20]. Deep fusion models can be superior in performance due to the multi-layer cross-modal interaction, but have more complex computation and higher risk of overfitting, and automated architecture search methods are encouraged to trade expressiveness and efficiency [21]. Surveys of multi-modal and spatiotemporal fusion methods also highlight that the task goals (i.e. prediction, representation learning, or temporal enhancement) have a strong impact on architectural decisions and performance results [22-23]. On the whole, the literature suggests that there is no single fusion strategy that can be considered universally optimal, and successful integration requires data characteristics, alignment quality, as well as the needs of the migration and mobility analysis tasks (Table 4).

Table 4. Integrated Signal–Image Fusion Frameworks

Fusion Level	Integration Strategy	Model Examples	Advantages	Limitations
Feature-level	Concatenation, attention	CNN + GNN	Deep interaction	Alignment needed
Decision-level	Ensemble models	Signal + image models	Simple	Weak fusion
Architecture-search	Automated fusion	MUFASA-style	Optimal design	Computational cost
Contrastive fusion	Representation alignment	Contrastive learning	Robust transfer	Training complexity

7. EVALUATION AND BENCHMARKING

The assessment and benchmarking of signal processing, image analytics and combined multimodal models of migration and human mobility analysis is critical to evaluate the effectiveness and generalizability of these models. Since mobility data are spatio-temporal in nature and may be sparse or noisy, there is a need to evaluate practices that reflect both predictive accuracy and spatial and temporal structure. Error-based measures that are generally reported in the literature include the mean absolute error, root mean square error when performing continuous flow prediction tasks, and accuracy, precision, recall, and F1-score when performing discrete mobility prediction tasks. Moreover, spatio-temporal consistency metrics are often applied to determine whether predicted mobility patterns maintain observed spatial correlations, periodic time, and ranking behavior in regions, especially in graph-based and large-scale mobility contexts [24].
The availability of datasets and validation strategy have a strong impact on benchmarking practices. In the past, lack of standardized datasets has impeded comparability of studies across the board, thus leading to evaluation protocols specific to a given data source. Recent studies highlight the need to utilize open and standard data to facilitate transparent benchmarking, cross-study comparison, and systematic validation between spatial and temporal backgrounds. Temporal holdout testing (train on past, test on future) has been proposed as a common validation strategy to ensure models respect causal structure, whereas cross-region testing (train on one region, test on another) is proposed to measure robustness and transferability. Such approaches are especially significant to multimodal frameworks, in which the correspondence between mobility cues and imagery can be different across space and time.
According to the trends in comparative performance reported in the literature, modern deep learning-based mobility models tend to perform better than classical baselines when there is adequate data, particularly in the ability to capture long-range temporal dependencies and spatial interactions. Nevertheless, according to survey evidence, performance improvements are commonly granular to spatial granularity, time resolution and sparsity of data, and model rankings differ across datasets and evaluation configurations (Table 5). The increasing popularity of standardized benchmarks has also shown that procedures that are optimized in terms of within-dataset performance may not be robust to distribution shift or to cross-region prediction, and that benchmarking procedures that focus on

robustness and generalization in addition to raw predictive performance are necessary.

Table 5. Evaluation Metrics and Benchmarking Practices

Evaluation Aspect	Metrics	Purpose
Prediction accuracy	MAE, RMSE	Forecast quality
Classification	Precision, Recall, F1	Location prediction
Spatio-temporal consistency	Spatial correlation	Pattern preservation
Generalization	Cross-region tests	Robustness

8. APPLICATIONS AND CASE STUDIES

The applications of integrated signal-image analytics have been used in many different migration and mobility contexts, and have proven to have practical use in the analysis of internal and international movements. At urban level, numerous researches are carried out on intra-city and inter-city mobility, where population flows are represented as spatio-temporal flows, which depend on transportation infrastructure, land use and socioeconomic environment. Next-location prediction and short-term mobility forecasting have been successfully implemented with deep learning-based mobility models which demonstrated that temporally rich signal representations can learn regular movement behavior in combination with contextual cues [25-26]. The idea that pretrained representations can be generalized across cities and regions is also demonstrated by foundation models that are trained on large-scale mobility data, and allow mobility prediction tasks to be trained using transfer learning without having to retrain the models themselves [27]. These methods are especially applicable to internal migration analysis, whereby the temporal modeling can be done in detail due to the regular coverage of sensing.

In addition to movement on a daily basis, integrated analytical models have been extended to larger contexts of migration, such as tourist flows, transport networks, and movement under crisis conditions. Epidemic modeling Case studies demonstrate the value of mobility prediction models in scenario analysis and risk assessment by reflecting the variation of population movement in response to external shocks, which is important to have a strong temporal model and contextual awareness [28]. Origin-destination prediction models at large scale have been applied to passenger flows in urban rail transit systems to study how signal-based flow models can be used to aid infrastructure planning and operational decision-making [29]. These papers highlight the flexibility of signal processing techniques in the context of a wide range of migration and mobility applications.

The need to urbanize and environmental conditions are also driving forces behind incorporation of image-based spatial context in mobility analysis. Image analytics make it possible to incorporate the indicators of urban growth, accessibility of services, and development of the region, which cannot be determined based on mobility signals alone. The model of applied studies of migration and access to services in extensive geographical areas shows how computational frameworks can integrate spatial indicators with movement data to examine structural inequalities and regional disparities in a systems perspective [30]. Technically, findings in all these case studies show that integrated solutions are better in predictive stability and interpretability because they relate observed mobility patterns to spatial and infrastructural conditions (Table 6). Instead of being used as purely descriptive mechanisms, these applications can be used to show how signal image frameworks can be used to support actionable information in situations where the interpretation of results is in terms of spatio-temporal structure, model behavior, and data constraints, which further supports their applicability to real-world migration and mobility analysis.

Table 6. Application Domains of Signal–Image Analytics for Migration

Application Domain	Data Modalities	Analytical Objective
Internal migration	Signals + images	Flow estimation
Urban mobility	GPS, satellite	Pattern prediction
Epidemic modeling	Mobility signals	Risk analysis
Transport systems	OD signals	Infrastructure planning

9. CHALLENGES AND OPEN ISSUES

The barriers to the deployment of integrated signal-image analytics on a regional or national scale are scalability and computational complexity. Multimodal pipelines are usually high-dimensional remote sensing characteristics, big spatio-temporal mobility graphs, and deep designs with high training and inference expenses. With the increase in depth and representational power of spatio-temporal graph learning methods, the computational cost of these models increases exponentially with the number of spatial units, time steps, and cross-modal interactions, and efficient training, memory management, and real-time inference are not a trivial problem [31]. Such scalability limitations are especially acute in cases where the objective of the analysis is cross-region generalization, large geographic scope, or fine spatial granularity, with the volume of data and the complexity of the model growing in tandem.

Largely equally significant are the problems of data quality and uncertainty, and their effects are usually magnified in migration and mobility scenarios where the coverage of sensing is not uniform and proxies might be imperfect. The mobility traces are subject to bias based on device ownership, sampling, data provider market share and reporting artifacts whereas the image-based proxies can be subject to acquisition conditions, spatial resolution and context confounding. Although practical, geospatial and sociodemographic predictors of mobility are also problematic as they reveal the challenge of disentangling signal and confounding structure, particularly when predictor variables capture accessibility, demographic composition and infrastructure in interrelated manners [32]. Therefore, the outcomes of the evaluation can exaggerate the model validity when the uncertainty is not clearly considered by means of effective validation, sensitivity analysis, and attentive interpretation of proxy variables.

A third significant group of open issues is integration limitations. Multimodal fusion assumes a certain level of spatio-temporal coincidence between modalities, but mobility signals and imagery can vary in the frequency of sampling, spatial resolution and location and time. Misalignments may create systematic errors and decrease the accuracy of learned cross-modal associations, especially where fusion mechanisms implicitly presuppose synchronized inputs. More generally, the literature on computational migration points to the unsolved problem of representativeness, interpretability, and responsible use of large-scale digital traces, which is still an important concern despite the engineering methodology being in the spotlight [33]. The solution to these integration limitations will involve developments in alignment-robust fusion, uncertainty-sensitive learning, and evaluation procedures that stress-test models with realistic data constraints and distribution biases.

10. EMERGING TRENDS AND FUTURE DIRECTIONS

The focus of emerging studies is on deep multimodal learning as the main process of the integration of temporal cues and spatial images into shared spaces of representation. Multimodal learning Multimodal learning has taken a leading direction due to the attention mechanisms, offering a flexible means to model cross-modal interactions, long-range dependencies, and variable-length inputs, and allowing modular designs capable of consuming heterogeneous modalities with little hand-crafted alignment assumptions [34]. This trend is becoming increasingly fast in geospatial applications with the rapid creation of foundation models of remote sensing, where massive pretraining is applied to learn transferable visual and multimodal representations that can be fine-tuned on downstream tasks with small amounts of labeled data [35]. Continuing this, multimodal geospatial foundation models specifically focus on cross-modal integration of satellite imagery and complementary geospatial cues, with a focus on unified architectures, scalable pretraining pipelines, and task, region, and modal systematic evaluation. In the case of migration and mobility applications, these developments imply that task-specific models will be replaced with multimodal representations which can be trained in advance and be useful to multiple purposes, such as prediction, anomaly detection, and explanation under heterogeneous data conditions.

The second trend is the real-time and large-scale analytics, which is driven by the practical necessity to track and justify decisions in time. With the growing popularity of large-scale pretraining and multimodal fusion in the literature, real-time implementation of these models presents new bottlenecks in terms of computational efficiency, latency, energy usage, and continuous updating during the presence of distribution shift. Currently, surveys based on remote sensing foundations already focus on scaling issues, such as data size, compute budgets, and efficient adaptation, as a fundamental research problem, which means that future developments will need more efficient training paradigms, lightweight inference techniques, and streaming-compatible architectures capable of processing mobility cues and imagery in near real time [36]. Multimodal transformers in this regard offer a promising backbone, although their practical implementation will be limited to the development of efficient attention, model compression, and strong adaptation to changing patterns of space and time [37].

Lastly, the developments will probably facilitate more generalization to the other signal-image areas, not only migration and mobility. The methodology pathway, namely, pretrained multimodal representations, attention-based fusion, and scalable adaptation, can be naturally extended to other spatio-temporal systems where temporal signals need to be understood in the environment of the spatial visual information, such as transportation monitoring, environmental dynamics, epidemiological risk mapping, and smart-city sensing. Multimodal learning and geospatial foundation model surveys highlight the importance of transferability and cross-task reuse as drivers of integrated signalimage analytics, and it is expected that this trend will continue to conceptualize such systems as a general-purpose computational toolkit, as opposed to a domain-specific pipeline. Consequently, standardized assessment of multimodal generalization, strength in the presence of imperfect alignment, and explainable cross-modal reasoning may appear as the main demands of the next-generation signalimage analytical systems.

11. CONCLUSION

Recent advances at the intersection of signal processing, image analytics, and multimodal data fusion have significantly enhanced the computational analysis of migration and human mobility. The literature demonstrates substantial progress in spatio-temporal modeling of mobility signals, including graph- and sequence-based learning methods for forecasting and pattern discovery, alongside mature image analytics pipelines that extract spatial proxies of development and urban structure from remote sensing. Importantly, the reviewed multimodal studies indicate that combining temporal mobility signals with image-derived spatial context can improve robustness and representation quality, particularly under sparsity, noise, and cross-region variability. Simultaneously, the pressure towards standardized datasets and better-defined benchmarking procedures is generating a new trend in evaluation practices, allowing to compare and test generalization more readily and realistically. Meanwhile, there are still a number of research gaps. To start with, scalability remains a limitation of multimodal systems at the transition to national or continental scales because integrated models can be very high-dimensional, large spatio-temporal graphs, and expensive to train pipelines. Second, unresolved issues in data quality, bias and uncertainty restrict reliability particularly in cases where sensing coverage is not even and remote sensing proxies are confounded by context. Third, multimodal integration still faces methodological limitations related to spatio-temporal alignment, interpretability of cross-modal interactions, and robustness under distribution shift, which collectively hinder deployment in real-world decision-making environments. Looking forward, the most promising direction is the continued development of deep multimodal learning for spatio-temporal systems, particularly transformer-based integration and geospatial foundation models that can learn transferable representations across regions, modalities, and tasks. Progress in efficient learning and inference will be necessary to support real-time and large-scale analytics, while improved benchmarking and uncertainty-aware validation will be critical to ensure robust generalization. More broadly, the convergence of signal processing and image analytics is likely to drive a new generation of cross-domain frameworks applicable not only to migration and mobility, but also to a wider class of signal–image problems in transportation, environmental monitoring, public health, and smart-city systems, reinforcing the central role of integrated methodologies in future signal and image science research.

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