Eye Movement Entropy: A Novel Metric for Quantitative Analysis of Visual Scanning Behavior

Authors: Niàn Jìngqíng, Zhang Yu, Luo Yu, Luo Yu

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Abstract

Eye movement entropy is an objective measurement metric developed based on information entropy for studying eye movement behavior, primarily used to measure the complexity and randomness of visual scanning behavior, and compensates for the limitations of traditional eye movement metrics in comprehensively characterizing individuals' complex visual scanning patterns. Currently, the commonly used core metrics include fixation entropy and heatmap entropy. Among them, fixation entropy is further divided into stationary fixation entropy, fixation transition entropy, and fixation duration entropy based on different calculation methods. Reviewing existing research reveals that eye movement entropy has been widely applied across multiple domains, including mental disorders, driving safety, aviation safety, education and teaching, product design, and industrial safety, demonstrating tremendous application potential in assisting the diagnosis of mental disorders, cognitive function assessment, safety monitoring, educational and teaching evaluation, and human factors engineering, making it an important tool for studying human visual cognition, behavior patterns, and information processing. Future research should further enhance the robustness and ecological validity of eye movement entropy measurements, continuously improve the eye movement entropy metric system, and promote the transformation of eye movement data analysis from static statistics to dynamic behavior pattern exploration, thereby more comprehensively revealing the mechanisms of human visual cognition and expanding its practical value across various application domains.

Full Text

Introduction

The eyes are the most critical information receptors for humans, with 80%-90% of external information acquired through vision. Individuals obtain and process visual information through fixations. Eye-tracking technology is an important research method that reveals cognitive processing by measuring eye movements. Common data analysis approaches include quantitative analysis based on basic metrics such as fixation count and duration, and qualitative analysis using visualization methods like scanpaths and heatmaps. However, traditional eye movement analysis methods struggle to comprehensively characterize individuals' complex visual scanning patterns.

The development and application of information theory provide a systematic and quantitative perspective for eye movement data analysis, capable of describing the spatial dispersion, temporal regularity, and cognitive resource allocation efficiency of complex visual scanning behaviors. This represents a shift from static statistics to dynamic exploration of behavioral patterns in eye movement data analysis. Information entropy, the core metric in information theory for measuring information uncertainty (Shannon, 1948), has been widely applied and validated in fields such as physics and social sciences. Since the 1980s, researchers have introduced information entropy into eye movement data analysis, developing eye movement entropy (EME) as an objective measurement index (Tole et al., 1982) to quantify the randomness, uncertainty, and spatial/temporal complexity of visual scanning behavior. Specifically, EME serves as an important complement to traditional eye movement metrics such as fixation count and duration by quantifying the uncertainty of eye movement trajectories and reflecting individuals' information search patterns during tasks. It also provides holistic evaluation, revealing how individuals integrate information throughout a task. Moreover, EME focuses on the distributional characteristics of eye movement data rather than specific fixation points, thereby reducing the impact of experimental context on results and enhancing robustness (B. Shiferaw, Downey, et al., 2019). Limited by analytical techniques at the time, it did not receive widespread attention from researchers. In recent years, with the proliferation of data-driven analysis techniques and methods, EME has gradually gained research attention. For example, Shiferaw et al. (2019) conducted the first systematic review of the feasibility of gaze entropy as a measure of visual search efficiency.

EME transforms visual scanning behavior into interpretable quantitative metrics through an information theory framework. Tole et al. (1982) are recognized as the first to apply entropy to the quantitative analysis of eye movement behavior, with their pioneering work focusing on pilots' visual scanning strategies in flight simulation tasks, marking an early exploration of entropy metrics in naturalistic eye movement research. As research has progressed, new EME metrics (e.g., heatmap entropy) have been proposed and validated in subsequent studies

(Son et al., 2020). However, overall, few researchers domestically and internationally have studied EME as a measurement index for eye-tracking technology. The reason for its limited application may be insufficient understanding of its calculation methods and the underlying visual processing mechanisms. This paper summarizes the core metrics, calculation methods, and applications of EME based on existing research, draws corresponding conclusions through analysis of previous findings, and proposes future research directions to address current limitations.

2. Metrics and Calculation of Eye Movement Entropy

2.1 Measurement Metrics of Eye Movement Entropy

Based on different calculation methods, EME metrics primarily include two types: fixation entropy and heatmap entropy (B. Shiferaw, Downey, et al., 2019; Son et al., 2020). Fixation entropy is calculated from fixation trajectory maps that reflect an individual's fixation positions, durations, and sequences on visual stimuli. According to the dynamic characteristics of fixations, fixation entropy can be further subdivided into stationary gaze entropy (SGE), gaze transition entropy (GTE), and dwell time entropy/fixation-time entropy. Heatmap entropy quantifies attention distribution characteristics on visual stimuli by calculating heatmaps. Compared to fixation entropy, heatmap entropy focuses more on the uniformity and concentration of overall attention distribution.

2.2.1 Fixation Entropy

Fixation entropy, measured in bits, quantifies the degree of uncertainty or predictability exhibited by individuals during visual exploration by calculating the spatial distribution (stationary gaze entropy), transition patterns (gaze transition entropy), and temporal distribution (fixation-time entropy) of eye movements (Krejtz et al., 2015; B. Shiferaw, Downey, et al., 2019).

2.2.1.1 Stationary Gaze Entropy Stationary gaze entropy primarily focuses on static spatial dispersion, measuring the spatial distribution of visual attention—i.e., fixation complexity. Its core concept involves discretizing fixation spatial coordinates into state spaces (or areas of interest, AOIs) and evaluating the randomness and unpredictability of fixation behavior by calculating the probability distribution of fixations. The formula is:

$$H(x) = -\sum p_i \log_2 p_i$$

where $H(x)$ represents the stationary gaze entropy value of a sequence x, i denotes the state space or AOI index, n represents the length of sequence x (total number of fixations), and p_i is the probability of fixations in the i-th state space. Entropy is related to the probability distribution of x, not the magnitude of x values. Higher stationary gaze entropy values reflect broader fixation distribution, greater dispersion of fixations within the visual field, and thus higher uncertainty. Lower stationary gaze entropy values reflect narrower fixation scope, with individual fixations concentrated in specific AOIs, indicating lower uncertainty.

However, stationary gaze entropy does not account for the relative nature of eye movements—that all saccades toward subsequent fixation points are relative to or originate from the current fixation point. To quantify the dependency of subsequent fixations on current fixation positions, researchers introduced gaze transition entropy to measure eye movement patterns between different AOIs.

2.2.1.2 Gaze Transition Entropy Gaze transition entropy, also known as sequential gaze entropy or Markov entropy, focuses on dynamic patterns of visual scanning, measuring the temporal regularity of fixation transitions—i.e., the randomness or predictability of fixation shifts. Its core concept involves calculating conditional entropy based on the transition probability matrix of a Markov chain, thereby reflecting the regularity of fixations transitioning from one state space to another (Ciuperca & Girardin, 2005). The formula is:

$$H(x) = -\sum p_i \sum p((i|j)) \log_2 [p(i|j)]$$

where $H(x)$ represents the gaze transition entropy value of a sequence x, p_i denotes the probability of state i, and $p(i|j)$ represents the transition probability from AOI i to AOI j. Higher gaze transition entropy values indicate broader visual exploration and more random, unpredictable fixation patterns, while lower values indicate more structured fixation patterns and more predictable scanning.

However, both stationary gaze entropy and gaze transition entropy calculate entropy based primarily on fixation counts within AOIs, failing to reflect fixation duration within state spaces. For example, when dwell time in an AOI is 100 ms versus 500 ms, both scenarios are treated as identical fixation events in calculating stationary and transition entropy, unable to distinguish temporal differences. Therefore, researchers use dwell time entropy to quantify the distribution characteristics of fixation durations.

2.2.1.3 Fixation Duration Entropy Fixation duration entropy focuses on the temporal dimension, directly related to information processing priority, and measures the temporal distribution balance of visual attention across multiple state spaces by modeling the probability distribution of fixation durations (Forest et al., 2022). The formula is:

$$H(x) = -\sum p_{Di} \log_2 p_{Di}$$

where p_{Di} is the proportion of dwell time in AOI i relative to total fixation time, and i is the total number of AOIs. Higher fixation duration entropy values indicate longer fixation durations on that AOI, and vice versa.

2.2.2 Heatmap Entropy

Heatmap entropy, also called visual attention entropy (VAE), constructs a weighted Gaussian distribution model of fixation points to transform eye movement data into continuous probability distributions. It calculates uncertainty based on Shannon' s entropy formula, integrating information about fixation position, duration, and visual perception range to measure the consistency or clustering of individual eye movements in space (Gu et al., 2021).

The core assumption of heatmap entropy is that the spatial distribution of fixation points in a heatmap follows a Gaussian mixture model centered at specific pixels (x_f, y_f). Fixation points can be treated as two-dimensional random variables (X, Y), with joint probability density calculated based on fixation duration and position information (Y. Liu et al., 2010). The formula is:

$$f_{xy}(x, y) = 2\pi\sigma^2 \exp -((x - x_f) + (y - y_f))$$

where σ is the standard deviation, representing the visual perception range—i.e., the visual angle in eye tracking. If multiple fixation distributions form on the screen, weights must be assigned to fixation distributions (Ahn et al., 2016; Gu et al., 2021; Son et al., 2020) and characterized as a continuous probability distribution as follows:

$$f_{xy}(x, y) = \sum d_f 2\pi\sigma^2 \exp -((x - x_f) + (y - y_f))$$

where f_{num} is the total number of fixations, and d_f is the weight of the f-th fixation distribution (typically weighted by fixation duration), satisfying $\sum$. Based on the continuous probability distribution, entropy is calculated after spatial discretization using:

$$H = -\sum f_{xy}(x, y) \log f_{xy}(x, y)$$

Higher heatmap entropy values indicate more dispersed fixation distribution and no significant concentration area of attention, while lower values indicate fixations are more concentrated in specific key areas (stronger goal-directedness).

Overall, the four EME measurement metrics have complementary characteristics. Stationary gaze entropy is calculated based on the ratio of fixation counts to total fixations within AOIs, without considering eye movement patterns or fixation durations. Fixation duration entropy is calculated based on the proportion of dwell time in AOIs, while gaze transition entropy considers both fixation time within AOIs and eye movements between AOIs. Finally, heatmap entropy is a method for deriving gaze movement entropy without requiring predefined AOIs.

2.3 Calculation Tools for Eye Movement Entropy

Currently, the main toolkits for entropy calculation are: (1) **EntropyHub**: An open-source entropy analysis toolkit providing multiple entropy calculation methods, suitable for time series, signal processing, and complex system analysis (Flood & Grimm, 2021). (2) **GridWare**: Its core concept involves projecting eye movement trajectories onto a gridded space and calculating entropy metrics based on the grid (Hollenstein, 2007, 2013; Lewis et al., 1999). (3) **iDynamic_{toolbox}**: A MATLAB toolbox specifically designed for eye movement data analysis, providing calculation functions for fixation position entropy (including mean entropy and per-trial entropy) (Q. Wang et al., 2020). In practical research, appropriate tools can be selected based on research requirements to calculate EME.

3. Applications of Eye Movement Entropy

3.1 Mental Disorders

Biomarkers for mental disorders are specific biological characteristics used for diagnosis, treatment, and prognosis evaluation. Non-invasive biomarkers have attracted significant research attention due to their non-invasive and safe features. Eye movement metrics (e.g., fixations, saccades) have become an important direction for studying biomarkers in mental disorders. Research indicates that EME may reflect abnormal patterns of visual attention, information processing, and cognition in patients with different mental disorders, showing great potential as a biomarker for mental disorders (Azami et al., 2022, 2022; Z. Liu et al., 2024; Q. Wang et al., 2020; Yang et al., 2024; D. Zhang et al., 2024).

For example, Zhang et al. (2024) found that first-episode schizophrenia and clinical high-risk syndrome for psychosis exhibited higher EME scores compared to healthy controls, with these differences emerging during early stages of eye movement scanning. Additionally, clinical high-risk syndrome for psychosis showed significantly higher EME scores than healthy controls when viewing meaningless images. Furthermore, EME scores were found to correlate with clinical symptoms and neurocognitive performance. These results indicate that eye movement scanning patterns in first-episode schizophrenia and clinical high-risk syndrome are more random and less strategic. Moreover, Wang et al. (2020) found that children with autism spectrum disorder exhibited higher EME than typically developing children when viewing faces, suggesting that autistic children lack effective face scanning strategies and thus cannot efficiently extract facial information. These studies demonstrate that EME can capture typical visual behavior abnormalities in mental disorder patients, providing new perspectives for understanding disease pathological mechanisms, early diagnosis, and treatment evaluation. However, to achieve clinical application, reliability, standardized procedures, and cross-population applicability still need to be strengthened.

3.2 Driving Safety

Good visual function is a prerequisite for driving, as the driving environment contains massive, complex, and constantly changing visual information. Drivers must systematically sample this information through structured gaze allocation to guide their actions (Land & Lee, 1994; Owsley & McGwin Jr, 2010). In recent years, researchers have used gaze entropy to assess drivers' visual scanning patterns, driving skills, fatigue states, etc. (Han et al., 2020; Lü et al., 2022; Aitken et al., 2023, 2024; Diaz-Piedra et al., 2021; Hayley et al., 2024; Jeong et al., 2019; Mikula et al., 2020). Specifically, changes in gaze entropy values can reflect drivers' visual scanning efficiency during driving (Hayley et al., 2024; Schwabe et al., 2013; B. A. Shiferaw et al., 2019). For instance, alcohol and methamphetamine intake affect drivers' visual scanning behavior during driving, with studies finding statistically significant changes in gaze entropy values as blood alcohol concentration increases or decreases (B. Shiferaw, Crewther, et al., 2019; B. A. Shiferaw et al., 2019). Additionally, gaze entropy can serve as an early warning indicator for driver fatigue. Shiferaw et al. (2019) found that both SGE and GTE significantly decreased under fatigue conditions and positively correlated with the number of driving errors during long-distance driving. Therefore, low gaze entropy may be an early signal of fatigue and can be used in driving monitoring systems. Furthermore, gaze entropy can be an effective predictor of driving skill and experience (Chung et al., 2022). For example, Chung et al. (2022) found in a VR driving simulator study that experienced drivers had a mean SGE of 3.09 bits, while novice drivers only reached 2.60 bits, indicating novices had narrower gaze distributions. Moreover, when engaging in secondary visual tasks, older drivers exhibited lower gaze transition entropy values compared to younger drivers (Schieber & Gilland, 2008). These studies demonstrate that gaze entropy research and application in driving is rapidly developing, showing great potential in driving skill and safety assessment, fatigue and distraction detection, autonomous driving interaction (Li et al., 2024), and intelligent driving monitoring system enhancement. In the future, with the development of autonomous driving technology, the combination of EME and artificial intelligence may become a core component of next-generation intelligent driving systems.

3.3 Aviation Safety

Research indicates that eye movement metrics have become effective indicators for studying pilots' cognitive changes (Diaz-Piedra et al., 2016; Heard et al., 2018; Mengtao et al., 2023), with pupil dilation and blink frequency being two commonly used metrics (Heard et al., 2018). However, in real aviation environments, these two metrics are susceptible to environmental changes such as brightness and humidity, whereas EME is less sensitive to environmental changes and can thus serve as a sensitive and robust key indicator for measuring cognitive changes in real aviation contexts (Ayala et al., 2023; Causse et al., 2025; Devlin et al., 2022). Specifically, gaze entropy can serve as an indicator for pilot situation awareness assessment and dynamic monitoring of task complexity and cognitive load, reflecting pilots' information processing efficiency in complex tasks such as cockpit instrument failures and low-visibility landings (Xu et al., 2024).

Some studies have found that pilots' gaze entropy values decrease with increasing task load (Diaz-Piedra et al., 2019). For example, when pilots fly under different task loads, gaze entropy rate decreases as flight task complexity increases (Harris et al., 1982; Tole et al., 1982). Diaz-Piedra et al. (2019) also found that combat helicopter pilots' gaze entropy values were significantly lower when resolving in-flight emergencies compared to routine flight (low complexity). In contrast, other studies have found that pilots' gaze entropy values increase with task load. For instance, Di Nocera et al. (2007) found that pilots exhibited higher gaze entropy values during high-load flight procedures (simulated takeoff and landing), indicating higher dispersion of eye movement fixations, while lower gaze entropy values during low-load phases (climb, descent, and cruise) indicated lower dispersion. Additionally, during emergency procedures, pilots'gaze entropy values increased after detecting cockpit instrument failures (Van De Merwe et al., 2012; Van Dijk et al., 2011). Similar results have been observed in fatigue driving (Naeeri et al., 2021), anxiety induced by emergencies (Allsop & Gray, 2014), and poor navigation environments (C. Zhang et al., 2024). Researchers speculate that inconsistent findings regarding pilots may be due to flight experience and professional skills, with more experienced pilots better able to manage their gaze patterns and showing smaller changes when coping with high workload (Liu et al., 2021; Ayala, Kearns, et al., 2024; Ayala, Mardanbegi, et al., 2024; Friedrich et al., 2021; Gao & Wang, 2024), though this speculation requires further verification.

Similar findings have been observed in air traffic controllers (Lin et al., 2020; Lanini-Maggi et al., 2021; Y. Wang et al., 2021). For example, Lanini-Maggi et al. (2021) found that higher stationary gaze entropy (i.e., larger spatial distribution of visual fixations on display screens) was associated with better response accuracy in air traffic controllers, while professional level contributed to improved response accuracy. Moreover, after controlling for animation type and professional level, stationary gaze entropy still positively predicted response time. Overall, the core value of EME in aviation lies in transforming visual behaviors of pilots and other practitioners into quantifiable metrics. With the development of standardized methods and real-time analysis technology, EME may be integrated into next-generation aviation safety systems, enabling a transformation from experience-driven to data-driven decision support.

3.4 Education and Teaching

Researchers have employed EME as a key indicator for monitoring cognitive load, teaching effectiveness, and instructional interaction in education. Specifically, in medical teaching applications, fixation entropy can identify radiologists' interest fluctuations during medical image evaluation (e.g., mammography) and track their learning curve progress (Alzubaidi et al., 2010). Additionally, in laparoscopic and robotic surgery simulation environments, surgeons' fixation entropy increases linearly with task complexity, visual exploration patterns become more random and less efficient, and surgical performance decreases (Di Stasi et al., 2016; Diaz-Piedra et al., 2017; Wu et al., 2020).

In classroom teaching, fixation entropy is used to evaluate teachers' instructional competence. Research has found that higher complexity in teachers' scanning path patterns (higher fixation entropy values) correlates with more accurate judgments about students and their learning-related characteristics (Kosel et al., 2021). Furthermore, in skill learning, fixation entropy is used to predict performance in climbing route selection and planning (Hacques et al., 2022; van Knobelsdorff et al., 2020). Studies have shown that climbing training programs induce different temporal fixation patterns in climbers to adapt to route changes. In summary, EME in education can objectively quantify attention distribution and cognitive load, providing scientific tools for optimizing teaching strategies and developing personalized learning technologies. Future developments may include real-time AI monitoring systems based on EME analysis to further optimize educational assessment and support systems.

3.5 Product Design

In product design, researchers have used EME as an important metric for measuring and improving the rationality of visual element layout in visual communication design, providing behavioral evidence for guideline development and interface optimization (Doellken et al., 2021; Gu et al., 2021; Hooge & Camps, 2013; Lee et al., 2023; Quach et al., 2022; M. Zhang et al., 2022).

EME values are used to compare the attention guidance efficiency of different interface designs, distinguishing the design effectiveness between critical functional areas and unnecessary redundant information areas to ensure users efficiently obtain core information. For example, Lee et al. (2023) used heatmap entropy as an effective indicator for evaluating visual interface suitability, finding that heatmap entropy was closely related to performance in judging system states using visual interfaces, with heatmap entropy values increasing as system state judgment time increased. Additionally, heatmap entropy values were higher for incorrect versus correct system state judgments. Furthermore, fixation entropy analysis of engineers' and students' attention distribution and scanning patterns when using design guidelines can evaluate the actual auxiliary effectiveness of guidelines for design tasks. Doellken et al. (2021) used fixation entropy to predict engineers' and students' performance in completing engineering design tasks according to guidelines. Results showed that high-performing engineers had significantly lower stationary gaze entropy, while high-performing students tended to have higher stationary gaze entropy and gaze transition entropy. In conclusion, EME overcomes the limitations of relying on traditional eye movement metrics (e.g., fixation count) for design optimization in the design field, providing more objective and effective measurement metrics for comprehensive analysis from cognitive strategies to interface optimization in product design.

3.6 Industrial Safety

In industrial safety, EME is used as an indicator for human error prevention, personnel skill enhancement and risk control, and human safety analysis in manufacturing design, providing effective means for personnel state monitoring, training improvement, and design hazard prevention and control (Dai et al., 2023; Bhavsar et al., 2017; Das & Maiti, 2024; Iqbal et al., 2024; Lee et al., 2022).

In process manufacturing industries (e.g., nuclear power plants, chemical plants), human error is a major cause of industrial accidents when handling emergency situations. For example, Lee et al. (2022) dynamically assessed control room operators' cognitive workload by monitoring their gaze entropy in real time. Results showed that nuclear power plant operators' gaze entropy values were significantly negatively correlated with situation awareness—an important capability for correctly responding to emergencies. Stronger situation awareness in nuclear operators corresponded to lower gaze entropy values, and vice versa. Meanwhile, researchers measured industrial assembly operators' task proficiency and operational hesitation using gaze transition entropy. Studies found that novice operators exhibited higher gaze transition entropy than experienced operators, with more disordered transition paths, suggesting that targeted training is needed to reduce novices' cognitive uncertainty, improve operational capabilities, and thereby reduce safety risks from assembly errors. Research has shown that dynamic feedback based on entropy values can optimize information presentation methods in design guidelines, ensuring critical safety information receives priority attention and improving equipment manufacturing safety (Doellken et al., 2021).

3.7 Other Applications

Beyond the aforementioned application fields, EME has deepened researchers' mechanistic understanding of cognitive heterogeneity in applications such as attentional processing (Forest et al., 2022; Han et al., 2023), cognitive function assessment (Ayala et al., 2022), intertemporal decision-making (Liu et al., 2023), social intention attribution in violent offenders (Zajenkowska et al., 2024), and stress monitoring (Ahmadi et al., 2022). Additionally, it has been further applied and validated in sports events (Albaladejo-García et al., 2024; van Biemen et al., 2023) and other domains.

4. Summary and Outlook

In summary, as an important complement to traditional eye movement metrics, EME is an effective measurement index for gaze behavior that enhances understanding of fixation control. It demonstrates tremendous application potential in mental disorders, driving safety, aviation safety, education, product design, and industrial safety. However, current EME research has limitations that can be addressed through future exploration in the following areas.

4.1 Robustness and Ecological Validity of EME Measurement Need Strengthening

Currently, EME calculation and analysis lack standardized protocols, leading to inconsistent calculation methods and data description terminology across studies, which hinders cross-experimental comparison of results and affects the robustness and ecological validity of EME (B. Shiferaw, Downey, et al., 2019). First, the determination methods for the number of state spaces (or AOIs) are inconsistent, and this heterogeneity affects measurement robustness. Across studies, state space size and quantity significantly impact EME calculation. Common methods include grid equal division, content-driven AOI definition, and fixation-driven data clustering. Differences and applicability among these methods may lead to different EME values under identical contexts, affecting result robustness (B. Shiferaw, Downey, et al., 2019). Future recommendations include optimizing state space division standards (e.g., adaptive state spaces) to reduce calculation bias from different AOI sizes and quantities.

Second, EME result reporting methods significantly impact ecological validity and comparability (B. Shiferaw, Downey, et al., 2019). Most current studies report raw entropy but rarely normalized entropy, which may hinder direct comparison of EME results across experimental conditions. Compared to raw entropy, normalized entropy offers higher accuracy, interpretability, and applicability for comparisons across stimuli and tasks. To improve comparability, ecological validity, and cross-task applicability, future studies should adopt dual reporting standards: (1) report both raw and normalized entropy simultaneously; (2) unify normalized entropy calculation methods. Different studies may employ different maximum entropy H_{max} calculation methods, affecting normalized entropy comparability. Recommendations include adopting normalization methods based on state space quantity, experimental maxima, or task dependency. Additionally, EME research is fragmented and lacks large-scale standardized databases. Future efforts should establish open-access EME databases to facilitate cross-experimental analysis.

Finally, establishing standardized computational frameworks and developing universal toolkits based on Python, MATLAB, or R using standardized pipeline workflows for EME calculation can enhance result comparability across tasks and experiments. Moreover, given EME' s potential in driving and aviation, real-time EME algorithms can be further developed in the era of rapid AI advancement (e.g., combining machine learning with neural networks) to optimize real-time computation and enhance deep application in practical scenarios such as driving safety and intelligent driving monitoring.

4.2 EME Measurement Index System Requires Further Refinement

Scanpath theory posits that when individuals view images or specific scenes, they store scene features and fixation sequences used to inspect those scenes (Noton & Stark, 1971a, 1971b). Current research primarily uses first-order Markov chains to analyze gaze transition entropy, with the core assumption that an individual' s next fixation depends only on the current fixation—i.e., short-term dependency. However, this model ignores eye movement patterns at longer timescales. Research indicates that individuals' scanning paths (e.g., regressive scanpaths and cross-scene fixation patterns) may retain long-term temporal dependencies (Wiebel-Herboth et al., 2021; Wollstadt et al., 2021). Wiebel-Herboth et al. (2021) employed active information storage (AIS) methods and found that analyzing scanpaths at longer timescales using personalized approaches helps better explain fixation patterns in dynamic tasks. However, whether this method is superior to other scanpath modeling approaches requires future verification. Additionally, existing research has primarily built eye movement measurement index systems based on Shannon entropy, but whether other entropy calculation methods (e.g., sample entropy, fuzzy entropy) should be introduced to further improve the EME measurement index system (Melnyk et al., 2024) remains a question worth exploring. For example, Melnyk et al. (2024) proposed calculating six entropy metrics for fixation trajectories, including fuzzy entropy, increment entropy, sample entropy, grid distribution entropy, phase entropy, and spectral entropy, for comprehensive analysis of different aspects of eye movement signals.

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