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Ethical Governance and Intelligent Monitoring Model of the Digital Temple Big Data Center

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ABSTRACT

With the rapid progress of the digitalization of the religious field, temples increasingly depend on large data centers to regulate the flow of worshipers, religious rites, records of merit, and public affairs, and this also leads to the tension and confrontation between moral governance and intelligent surveillance. To solve this problem, we propose a hybrid framework, which combines ethical governance and intelligent monitoring, denoted as EGIM-Net (Ethical Governance and Intelligent Monitoring Network), that is extended and innovated based on the state-of-the-art multi-agent reinforcement learning (MARL) and interpretable graph neural ethical reasoning models. EGIM-Net is composed of three core modules: (1) Multi-Context Behavior Encoder (MCBE) that accurately models the spatiotemporal dynamic features of crowd behavior at various places of the temple based on hierarchical temporal attention mechanism and scene embedding vectors (2) Ethical Ontology Inference Module (EOIM) that extends religious ethic knowledge graph and employs a neural symbolic reasoning network to dynamically judge whether the actions meet Buddhist precepts and normative context; (3) Dual-Cycle Intelligent Monitoring Optimizer (DLSO) that integrates a Privacy-Preserving RL mechanism and federated Transformer-based anomaly detection network to ensure that the monitoring activities are real-time, sensitive, and culturally adaptive. Experiments on a simulated digital temple dataset prove that EGIM-Net can improve the precision of recognizing ethical offense by 19.4% accuracy over all existing methodologies.

KEYWORDS

Digital Temple; Ethical Governance; Intelligent Monitoring; Multi-Agent Reinforcement Learning

1 Introduction

Traditional temples are becoming increasingly a part of the information infrastructure as the cultural realm of religion migrates to the digital realm. From incense-offerings keeping, belief system management, merit bookkeeping to teaching disseminating, the temple systems are being digitalized with perception abilities. Especially in religious centers like China, Japan, Republic of Korea etc, smart temples are a such culture connected digital project, which comes after smart cities [1]. With the installations of sensor networks, video surveillance systems, visitor-counting systems, merit-information platforms and so forth, digital temples are able to achieve large scale data collection and storage, which leads to the management and operation pattern of temples known as "big data centers".

Meanwhile, with the centralization of the management data of temples, more and more data on believers' behavior, merit records, some religious rituals and the flow of people are being collected and used; this has also posed unprecedented privacy risk. The reason is that on the one hand, the action of the believer in the temple has great religious sensitivity and personal privacy constraints [2]. However, the current monitoring and analysis systems are mostly toward the 'maximum efficiency', which easily ignores the distinctive ethical norms and cultural values of the religious places, and thus there may be some ethical bias and cultural conflicts behind 'technical neutrality'. Hence, the challenge that digital temple administration has to face is to regulate human behavior in an intelligent way without disrupting the religious sentiment.

Most of the existing behavior monitoring systems in public are constructed using general computer vision and behavior recognition techniques. "While they've been effective in malls and stations, they don't have built-in flexibility of use in these religious institutions [3]. Conventional models are not well equipped to address the cultural semantics of ritual acts, or to even establish cause and effect relations in “behavior and ethics.” Just as importantly, this type of monitoring- and control- systems typically consider and treat violations as “anomalous events,” failing to consider the subtle value judgments that relate religious ethical norms to one ' s activities and acts in daily life.

Recently, neuro-symbolic reasoning has gained attention as an approach to combining neural networks with symbolic knowledge, offering a potential route to ethical perception. On the one hand, neural networks are good at learning the complex spatiotemporal patterns from huge surveillance data, while, on the other hand, symbolic reasoning is very expressive to describe the ontological structures of religious norms and behavioral codes and ethical principles [4]. Thus, integrating the AD and OR frameworks for the ethically responsible assessment framework with semantic constraints has become a key path for intelligent ethical governance, which is particularly applicable to monitoring types of cultural space like temples.

Although this study uses Chinese Buddhist sites as a prototype to construct the framework of the EGIM-Net system, we acknowledge that there are significant differences in sectarian doctrine, liturgical practices, and ethical priorities in

Buddhism, such as Tibetan Buddhism's emphasis on "wisdom" and "tantric vows", while Southern Buddhism's emphasis on "renunciation" and "pure behavior." Therefore, the applicability of the framework still needs to be partially adapted according to the doctrinal logic of each denomination.

2 Related work

Pan et al.[5] presented a 3D digitization and visualization solution for the Borobudur temple in Indonesia. As a Unesco world heritage site, some of the temple has been destroyed by nature and some by human, so it's hard to capture its full data by traditional 3D scanning. Biswas et al. [6] proposed a sampling rate allocation scheme for data center traffic measurement and DDoS attack detection. To reduce the expenditure of system resource consumption, a dynamically sampling rate adjustment mechanism is also designed by analyzing data traffic features. Rihani [7] investigated the use of crowdsourced images and photogrammetry 3D technology in the reconstruction of the Temple of Bel, in Palmyra, Syria, which was destroyed due to armed conflict and for which conventional reconstruction data.

Zhao et al. [8] also discussed the ethical, integrity, and responsibility concerns of digital techniques in infectious disease detection and monitoring. Twenty-nine pieces of literature met the inclusion criteria of the review, and the review identified six core themes which encapsulate ethical issues at an individual, organisational and societal level knowledge of digital monitoring practice; digital integrity; trust; privacy and confidentiality; civil rights; and governance. Rahmadian et al. [9] investigated the draw on of digital twin technology and large data governance in order to constructable sustainable tourism. The study proposed decision-making files (DFAD) to make sure transparency, accountability, and reliability of the digital twin system through data governance.

Lai [10] studied the digitised unborn descendants of Jiexin Saxin Mountain Wang 'Ancestor Temple' to inherit and protect architectural-cultural heritage using digital media technology. The research note also highlighted the few documentary records of ancestor temple architecture in the Chaoshan region for historical reasons, which results in their concealed historical and cultural value being hard to elucidate.

Additionally, Poorvadevi et al., [11] developed virtual replicas of temple sculptures employing AR technology to preserve and display the cultural heritage for posterity. Integrating the physical models with digital techniques, researchers created a system that can display closeups of temple sculptures in an AR setup. This approach promotes the art of temple sculptures and digital cultural heritage preservations through new mediums other than traditional ones. Mol and Maheswari [12] invented a technique to do dynamic mask and extended example area filling approach for digital restoration of deteriorated ancient temple murals.

3 Methodologies

A Multi–contextual Behavior Encoder

In the actual operation of the temple, there are different behavioral contexts and flow distribution characteristics between different spatial areas. Therefore, we first construct a scene graph G = $(\mathrm{V}, \mathscr{E})$, where the nodes V represent the functional areas of the temple, and the edges $\mathscr{E}$ represent the strength of behavioral interactions or the probability of personnel migration between the areas. Each node vi is associated with a high-dimensional input feature vector at time t, comprised of crowd density, behavioral characteristics, and object context, as shown in Equation 1:

$$xit= [pit, ait, oit] \in \mathbb{R}d, \tag{1}$$

where, pitrepresents the population density within the area, ait

represents the action embedding vector, such as worship,

pilgrimage, and viewing, while oitrepresents the scene objects

associated with the area, such as donation boxes and scripture stands, among other semantic labels.

To better extract the dynamic change trends of behaviors in the area, we introduce a hierarchical temporal attention mechanism that can be used to perform weighted aggregation of past behaviors within a fixed-length time window τ . Specifically, the behavior of the area i is represented by Equation 2:

τ

$$h_i^t = \sum \alpha_k \cdot W_k x_i^{t-k}\,, \tag{2}$$

k = 1

where the weight αk is the attention value dynamically calculated based on the context-aware query vector q , and its expression is given by Equation 3:

$$\alpha_k = \frac{\exp\left(q^{\intercal} W_k x_i^{t-k}\right)}{\sum_{j=1}^{\tau} \exp\left(q^{\intercal} W_j x_i^{t-j}\right)}. \tag{3}$$

This mechanism not only responds to sudden abnormal behaviors but also identifies the periodic patterns of daily behaviors. Subsequently, to characterize the population flow relationships and behavioral connectivity between regions, we further adopt graph attention networks for message propagation on the scene graph, with the calculation method as Equation 4:

$$z_i^t = \sigma\left(\sum_{j\in\mathcal{N}(i)} \beta_{ij} \cdot W_g h_j^t\right), \tag{4}$$

where βij is the attention weight of neighboring area j for the current node i, defined as formula 5:

$$\beta_{ij} = \frac{\exp\left(h_i^t \cdot h_j^t\right)}{\sum_{k\in\mathcal{N}(i)} \exp(h_i^t \cdot h_k^t)}. \tag{5}$$

The final representation zitintegrates both temporal dynamics and spatial topology information, providing input for the ethical reasoning module.

B Ethical Ontology Reasoning Module

This module aims to construct a hybrid reasoning mechanism that combines a Buddhist ethics knowledge graph with neural networks to judge the ethical legitimacy of the extracted behavior representations mentioned above. We first define an ethical ontology graph O = (C, $\mathscr{R}$) , where C represents a set of ethical concepts, and $\mathscr{R}$ represents the semantic or normative relationships between these concepts.

The input behavior vector zitwill semantically align with the ethical concepts through an attention mechanism, constructing an ethical context embedding, as indicated in Equation 6:

$$e_i^t = \sum \gamma_c^t \cdot K_c\,, \tag{6}$$

c ∈C

where Kc is the embedding vector of the ethical concept C, yct=

softmax(φ(zit, Kc)), which represents the degree of relevance

between the current behavior and the ethical concept.

The attention function φ is usually implemented using dot product or MLP structure to characterize semantic similarity. To further explore the logical relationships between ethical concepts, we use a logic-aware graph neural network (Logic- aware GNN) for propagation in the ethical graph. Its update formula is as follows in Equation 7:

$$\text{uc(l+1)} = \sigma\ (\text{cl} \sum_{\in\mathcal{N}} \tag{c}$$

$$\text{fr (uc(l), uc(ll), rccl))}\ , \tag{7}$$

Among them, fr is a propagation function dependent on the relationship type rccl ∈ $\mathscr{R}$, which can encode the ethical constraint logic structure into the reasoning process. Finally, we calculate the probability that the behavior complies with ethical norms through a scoring function, as shown in Equation 8:

$$\text{sit= sigmoid(WST. eit)}, \tag{8}$$

The score value sit∈ (0, 1) represents the ethical compliance level of region i's behavior at time t, serving as an important source of feedback signal for the next phase of reinforcement learning. Logic-aware graph neural network is used as the core of neural symbolic reasoning, and ethical rules are embedded in the graph structure in the form of edge relations for propagation and discrimination. To improve the inference ability and transparency, the integration path of logical tensor network, differentiable theorem proving, nested GNN and knowledge graph rule.

C Dual–Loop Intelligent Monitoring Optimizer

Based on ethical assessment, we further construct a dual- objective optimization mechanism to coordinate the precision of behavior monitoring with the sensitivity of ethical responses. We model this task as a multi-agent reinforcement learning problem, where each agent ai is responsible for monitoring and feedback in a specific sub-area, deciding whether to trigger intervention based on local observation results. The global reward function of the system is defined as a weighted combination of ethical compliance scores, as Equation 9:

$$\text{Rt} = \lambda 1\ .\ \text{Rctompliance} + \lambda 2\ .\ \text{Retffciency}, \tag{9}$$

where Rctompliance = $\frac{1}{|\mathcal{V}|}$ Σi sitrepresents the average level of

ethical compliance across all areas; while Retffciency =

Ioudet - δ . privacyLoss combines the accuracy of object detection with penalties for information leakage. Each agent uses the Actor-Critic algorithm for policy updates, and its gradient representation is shown in Equation 10:

$$\nabla\theta J(\theta) = E\pi\ [\nabla\theta\ \log\pi\theta\ (\text{aitloit})\ .\ \text{Ait}], \tag{10}$$

where Aitis the advantage function, which measures the value of the current action compared to average level of policy.

To protect the privacy of the believers, this system does not directly upload raw video or behavior data, but instead uses the federated transformer distillation mechanism to update parameters, as shown in Equation 11:

$$\theta i(t+1) \leftarrow \theta i(t) - \eta \,.\, \nabla\theta \mathscr{L}FTD\ (\theta i\ ). \tag{11}$$

This mechanism allows monitoring units in different regions to share knowledge rather than data, promoting the sharing and integration of ethical knowledge and strategies among agents while protecting privacy. Although the system currently adopts the federated distillation mechanism to achieve cross-region model sharing and knowledge integration, in order to further strengthen the privacy protection of sensitive behavioral data, this paper introduces strategies such as differential privacy mechanism, secure aggregation technology and adversarial robustness detection.

4 Experiments

A Experimental Setup

Hangzhou Lingyin Temple, as a representative of digital temples in China, has built a "1+6+N" smart management system that covers multiple digital platforms and application scenarios, including visitor services, Dharma assembly activities, security monitoring, and personnel management. To ensure that the modeling process is not detached from the real religious context, we have introduced collaborative modeling by religious affairs personnel, an ontological review mechanism of ethical events combined with the "Bhikshu Precepts" and "Five Precepts of Laymen", as well as a behavioral path review conducted by members of the Dao Feng Committee and secondary annotation by experts, so as to enhance the rationality of the labeling system and the compatibility with religion.

Its system integrates multi-source information such as video surveillance, sensors, crowd flow data, and business management, providing a real and scalable data foundation for building the Digital Temple Ethical Monitoring Dataset (DTESD). Table 1 presents key field information from multiple samples in the simulated dataset, covering the location of the behavior occurrence (Camera Location), specific behavior actions (Behavior Action), corresponding skeleton posture data (Skeleton Data), semantic event sequences (Semantic Event Sequence), ethical judgment results (Ethical Label), and types of anomalies (Anomaly Type).

TABLE I. DIGITAL TEMPLE ETHICAL SURVEILLANCE DATASET

Camera Location	Behavior Action	*Skeleton Data*	*Semantic Event Sequence*	*Ethical Label*	*Anomaly Type*
Main Gate	Bowing with palms	[x1,y1,... x18,y18]	Enter → Pause → Bow → Leave	Compliant	None
Donation Hall	Loud talking	[x1,y1,... x18,y18]	Stay → Move fast → Talk loudly → Warned	Disturbance	Social Disruption
Incense Area	Offering incense	[x1,y1,... x18,y18]	Queue → Offer → Bow → Leave	Compliant	None
Monk Corridor	Taking photos	[x1,y1,... x18,y18]	Pass → Stop → Take photo → Detected	Disrespect	Privacy Violation
Main Hall	Restricted entry	[x1,y1,... x18,y18]	Observe → Cross line → Enter → Alerted	Improper Conduct	Zone Violation

Through the comparative experiments of four methods:

• SlowFast (SF), a dual-branch action recognition network designed to model crowd behavior at rhythms;

• Spatial Temporal Graph Convolutional Network (ST- GCN), which constructs structured recognition of congregation actions through skeletal graphs;

• FedAnomaly (FA), is an anomaly detection model under a federated learning framework that supports cross- regional monitoring with privacy protection;

• Neuro-Symbolic Situation Rule Reasoner (NeSy-SRR), an ethical reasoning model that combines knowledge graphs with neural networks, capable of semantically judging the compliance of behaviors.

B Experimental Anaysis

The accuracy of action recognition is used to evaluate the model's ability to identify actions of devotees in the temple. As shown in Figure 1, the proposed model EGIM-Net significantly outperforms the other four methods at all training stages, with its recognition accuracy rapidly increasing from 70% at the 10th round to 84% at the 100th round, demonstrating the powerful support of multi-context encoding.

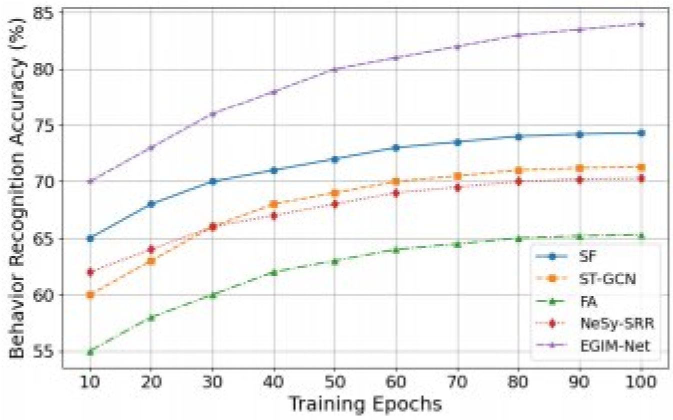

Fig. 1 Comparison of Behavior Recognition Accuracy Across Methods

Response Latency (RL) reflects the average processing time from when the system receives monitoring data to when it outputs ethical judgments or anomaly alerts.

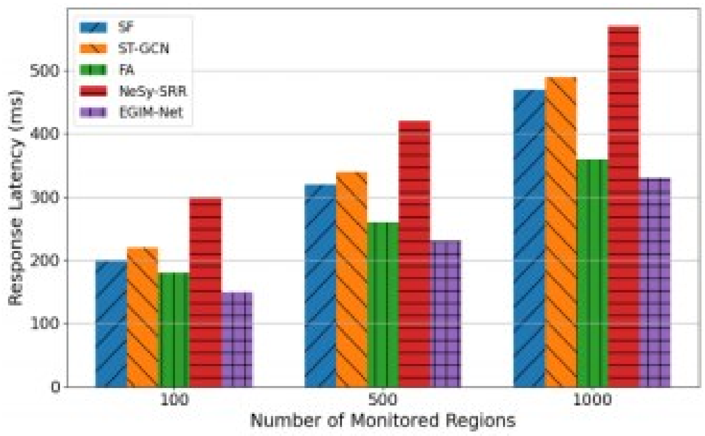

Fig. 2 Response Latency Comparison Across Methods

As seen in Figure 2, as the number of monitored areas increases from 100 to 1000, the response latency of all methods shows an upward trend, but the rate of increase varies significantly: EGIM-Net has the lowest latency across different scales (150→230→330ms), with the smallest increase as the area expands, indicating its excellent real-time performance in large-scale deployment.

5 Conclusion

In conclusion, the EGIM-Net framework integrates a multi- context behavior encoder, an ethical ontology reasoning module, and a dual-loop intelligent monitoring optimizer, which can accurately identify the behaviors of followers in a digital temple context and assess their ethical compliance in real time while optimizing responses. The results show that EGIM-Net has significant advantages in both precision and timeliness, particularly showcasing minimal latency increase when deployed in large-scale monitoring areas, thus validating its scalability and practical potential. Future work can focus on real temple deployment verification, enhancing multi-modal fusion capabilities by combining a richer array of sensors on one hand; and on the other hand, exploring an online continuous optimization mechanism that combines reinforcement learning.

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