Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Difference-Triggered Issue Discovery by Maintaining Up-to-Date Environmental Understanding in Autonomous Robots

Hong Su

suguest@126.com

Chengdu University of Information Technology

Research Article

Keywords: Autonomous robots, continual learning, environmental understanding, difference-triggered learning, open environments

Posted Date: April 29th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-9547966/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: The authors declare no competing interests.

Difference-Triggered Issue Discovery by Maintaining Up-to-Date Environmental Understanding in Autonomous Robots

Hong Su

***Abstract*—Autonomous robots operating in open and changing environments must discover emerging issues such as unfamiliar objects without relying on manually predefined issue types. However, many existing robotic learning and anomaly detection methods depend on fixed detection targets, static environmental representations, or direct recognition models, which limits their ability to discover newly appearing issues during long-term operation. This paper proposes a *Difference-Triggered Issue Discovery with Up-to-Date Environmental Understanding* (DTID-UEU) model for autonomous robots. The core idea is that a robot continuously maintains an internal understanding of the environment it has encountered, uses this understanding to predict expected observations, and compares the predictions with real-time observations. When the difference between the predicted and observed states becomes significant, the robot treats the inconsistency as a potential issue and activates further judgment, learning, and environmental understanding update. To support this process, DTID-UEU introduces a thinking-guided difference judgment mechanism to distinguish ordinary variation, noise, emerging issues, abnormal events, and task-relevant failures. It also employs difference-proportional learning, where meaningful observations with larger differences receive stronger learning intensity and are integrated into the robot's updated environmental understanding. Experimental results show that DTID-UEU achieves the highest F1-score and recall among the compared methods, improving the F1-score from 0.1710 to 0.3848 compared with the red-threshold baseline and from 0.0544 to 0.3848 compared with the static-understanding baseline.**

***Index Terms*—Autonomous robots, continual learning, environmental understanding, difference-triggered learning, open environments.**

I. Introduction

Autonomous robots [1] are expected to operate for long periods in open and changing environments. Unlike robots deployed in strictly controlled scenarios, robots in real-world environments may encounter unfamiliar objects, changing spatial layouts, unexpected obstacles, abnormal events, sensor disturbances, and task execution failures. These issues may appear at any time and may not be known before deployment. Therefore, an autonomous robot should not only execute predefined actions, but also discover newly emerging issues and update its understanding of the environment during operation.

A fundamental challenge is that the robot usually cannot rely on a complete list of predefined issue types. In many practical situations, it is difficult or even impossible for human designers to enumerate all possible problems that may occur in advance. For example, a previously clear path may become blocked, a familiar object may be moved to a different location, a new object may appear in the workspace, or an action that was previously successful may suddenly fail. If the robot only detects issues according to fixed labels or predefined abnormal patterns, it may fail to recognize new types of problems. Thus, issue discovery in open environments requires a mechanism that can identify unexplained differences between what the robot expects and what it actually observes.

Existing studies on continual learning [2], anomaly detection [3], world models [4], and robotic reasoning provide useful foundations for this problem. Continual learning enables models to acquire new knowledge over time, while anomaly and novelty detection methods identify samples that deviate from known patterns. World models allow agents to predict future states or observations, and large language models provide reasoning capabilities for interpreting complex situations. However, these directions are often studied separately. Anomaly detection may identify deviations, but it does not necessarily update the robot's environmental understanding. Continual learning may update model parameters, but it may not explicitly use prediction–observation differences as triggers for issue discovery. World-model-based methods may use prediction errors for failure detection, but they often do not connect these errors with a closed-loop process of issue judgment and environmental understanding update. Therefore, a unified mechanism is still needed to connect environmental understanding maintenance, difference-triggered issue discovery, judgment, and learning.

To address this problem, this paper proposes a *Difference-Triggered Issue Discovery with Up-to-Date Environmental Understanding* (DTID-UEU) model for autonomous robots. In this paper, environmental understanding refers to the robot's continuously updated internal representation of the environment it has encountered. It is not limited to a geometric map or a set of stored images, but includes learned normal patterns, known states, task-related outcomes, previous experiences, and predictive knowledge that can be used to generate expected observations. The key idea of DTID-UEU is that the robot maintains this up-to-date environmental understanding as an internal reference, predicts expected observations or states from it, and compares the predictions with real-time observations. When the real-time observation is significantly different from the predicted observation, the robot regards the

H. Su is with the School of Computer Science, Chengdu University of Information Technology, Chengdu, China.
E-mail: suguest@126.com.

difference as a potential issue. The detected difference is then further analyzed through a thinking-guided judgment process to determine whether it corresponds to ordinary variation, noise, an emerging issue, an abnormal event, or a task-relevant failure. Meaningful differences are assigned stronger learning intensity and are integrated into the robot's updated environmental understanding.

The proposed model changes the role of difference in robotic learning. In conventional anomaly detection, a difference is often used only as an abnormality signal. In DTID-UEU, a difference is used as a trigger for issue discovery, judgment, learning, and environmental understanding update. This means that a newly encountered situation is not repeatedly treated as abnormal forever. After sufficient observation and learning, the situation can be incorporated into the robot's environmental understanding and gradually become familiar knowledge. As a result, the robot can reduce repeated false alarms for already learned situations while still remaining sensitive to newly emerging issues.

The proposed model is built on a closed-loop process. At each time step, the robot collects a real-time observation, predicts the expected observation according to its current environmental understanding, computes the difference between the prediction and the observation, judges the meaning of the detected difference, performs difference-proportional learning when necessary, and updates its environmental understanding. This process allows the robot to continuously revise the reference used for future issue discovery. Therefore, issue discovery and environmental understanding maintenance reinforce each other: a better environmental understanding improves prediction and difference detection, while meaningful differences provide new information for updating the environmental understanding.

The main contributions of this paper are summarized as follows:

- We propose a *difference-triggered issue discovery* model for autonomous robots in open environments. The model discovers potential issues by comparing real-time observations with predictions generated from the robot's current environmental understanding, instead of relying on manually predefined issue types.
- We introduce an *up-to-date environmental understanding maintenance* mechanism. The robot continuously updates its internal understanding according to observations, difference scores, judgment results, and learning outcomes, so that the reference for issue discovery evolves with the encountered environment.
- We design a *thinking-guided difference judgment* process to distinguish ordinary variation, noise, emerging issues, abnormal events, and task-relevant failures before learning. This prevents the robot from treating every difference as a meaningful error.
- We formulate a *difference-proportional learning* mechanism, in which meaningful observations with larger differences receive stronger learning weights or repeated learning steps. This allows important unfamiliar situations to be learned more effectively.
- We integrate perception, prediction, difference comparison, issue judgment, learning, and environmental understanding update into a closed-loop autonomous process, enabling the robot to gradually transform unfamiliar situations into familiar environmental knowledge.

The remainder of this paper is organized as follows. Section II reviews related work on open-world continual learning, anomaly and novelty detection, world models, and large-language-model-assisted robotic reasoning. Section III presents the proposed DTID-UEU model. Section IV describes the verification design and experimental analysis. Finally, Section V concludes the paper and discusses future work.

II. Related Work

Autonomous robots operating in open environments must deal with unfamiliar objects, changing environmental conditions, abnormal events, and task execution failures. This requirement is related to several research areas, including open-world continual learning, anomaly and novelty detection, world-model-based prediction, and large-language-model-assisted robotic reasoning. This section reviews these areas and clarifies the difference between existing studies and the proposed DTID-UEU model.

A. Open-World and Continual Learning for Autonomous Robots

Continual learning aims to enable intelligent systems to learn from a sequence of data or tasks while retaining previously acquired knowledge. For autonomous robots, continual learning is especially important because robots often operate in dynamic environments where new objects, states, and task conditions may appear after deployment. Recent studies have investigated lifelong and continual learning for autonomous intelligent systems, showing that continual adaptation is necessary for improving reliability in domains such as robotics, autonomous driving, anomaly detection, and emergency management [5].

Open-world continual learning further extends this problem by requiring the system to detect and learn from unknown or out-of-distribution inputs during operation. Kim et al. [6] discuss open-world continual learning as a framework that connects continual learning with out-of-distribution detection. In robotic scenarios, prototype-based methods have also been proposed to support few-shot online continual learning and novelty detection, allowing robots to learn new classes from sparse data streams [7].

Although these studies provide important mechanisms for learning new information over time, many of them focus on class-level novelty detection or task-incremental learning. In contrast, the proposed DTID-UEU model focuses on issue discovery in open environments. The goal is not only to learn new categories, but also to discover emerging issues caused by environmental changes, task failures, abnormal events, or insufficient environmental understanding. Moreover, DTID-UEU emphasizes the maintenance of an up-to-date environmental understanding as the reference for issue discovery.

B. Anomaly and Novelty Detection in Open Environments

Anomaly detection and novelty detection aim to identify observations that deviate from normal or previously known patterns. These techniques are widely used in autonomous systems to detect out-of-distribution inputs, unexpected environmental changes, and possible failures. In open-world AI, novelty is often associated with situations that violate the assumptions of the training data or the system designer [8]. For robots, detecting such novelty is important because unknown situations may directly affect navigation, manipulation, perception, and task safety.

Existing anomaly detection methods often rely on a predefined normal model, a fixed abnormality score, or a detector trained before deployment. Such methods are useful when the boundary between normal and abnormal data is relatively stable. However, autonomous robots may operate in environments where normality itself changes over time. For example, an object that is unfamiliar at the beginning may become familiar after repeated observation, while a previously normal path may later become blocked. Therefore, a static anomaly detector may either repeatedly report already learned situations as abnormal or fail to discover newly emerging issues.

The proposed DTID-UEU model differs from conventional anomaly detection in two aspects. First, the reference used for issue discovery is not fixed. It is the robot's continuously updated environmental understanding $\mathcal{U}_t$. Second, the detected difference is not only treated as an abnormality score. Instead, it triggers a subsequent judgment and learning process. Thus, DTID-UEU transforms anomaly detection from a one-time classification problem into a closed-loop process of difference discovery, issue judgment, learning, and environmental understanding update.

C. World Models and Prediction-Based Difference Detection

World models provide internal representations that allow autonomous systems to predict future observations, states, or task outcomes. In robotics and autonomous driving, world models are often used for planning, model-based reinforcement learning, and prediction of environmental dynamics. A prediction-based mechanism is useful because unexpected differences between predicted and observed states can indicate environmental changes or possible system failures.

Recent work has explored the use of prediction errors and latent differences for failure classification and anomaly detection in robotic inspection tasks [9]. Such studies show that the mismatch between expected and observed states can provide useful signals for identifying known failures and out-of-distribution cases. This is closely related to the motivation of DTID-UEU, where the robot compares the real-time observation O_t with the predicted observation $\hat{O}_t$ to obtain a difference score Δ_t.

However, most prediction-error-based methods use the world model mainly as a detector of abnormal or out-of-distribution cases. The proposed DTID-UEU model extends this idea by connecting prediction difference with continual environmental understanding maintenance. In DTID-UEU, a large difference does not only indicate that the prediction is wrong. It also indicates that the robot's current environmental understanding may be incomplete or outdated. Therefore, the detected difference becomes a trigger for judgment, learning, and updating $\mathcal{U}_t$. This makes the prediction mechanism part of a self-updating issue discovery loop rather than only a failure detection module.

D. Large Language Models and Thinking-Guided Robotic Reasoning

Large language models and multimodal large language models have recently been introduced into robotics for perception, planning, interaction, and decision-making [10] [11]. Surveys on LLM-based robotics show that language models can support high-level reasoning, task planning, human-robot interaction, and the interpretation of complex instructions [12]. These capabilities are valuable for open-environment robots because many robotic issues cannot be fully described by low-level sensor differences alone. A robot may need to judge whether a difference is caused by noise, ordinary variation, environmental change, task failure, or a genuinely new issue.

The proposed DTID-UEU model uses this idea in a specific way. Instead of using a language model only to generate actions or translate instructions into plans, DTID-UEU introduces a thinking-guided judgment process after a difference is detected. The purpose of this process is to interpret the meaning of the detected difference before learning from it. This is important because not every difference should be strongly learned. For example, sensor noise should not significantly change the environmental understanding, while a newly appearing obstacle or repeated task failure should receive stronger learning attention.

Therefore, DTID-UEU connects reasoning and learning through the difference-triggered mechanism. The thinking-guided module determines how the detected difference should be treated, and the difference-proportional learning module determines how strongly the robot should learn from it. This design allows high-level judgment to influence low-level environmental understanding updates.

E. Position of the Proposed DTID-UEU Model

The above studies provide important foundations for autonomous adaptation in open environments. Open-world continual learning focuses on learning new information over time. Anomaly and novelty detection focus on identifying observations that deviate from known patterns. World-model-based methods use prediction errors to detect unexpected states. LLM-based robotics introduces reasoning capabilities for perception, planning, and decision-making.

However, these directions are often studied separately. Continual learning methods may not explicitly maintain an up-to-date environmental reference for issue discovery. Anomaly detection methods may detect differences but do not necessarily transform them into familiar knowledge. World-model methods may use prediction errors for failure detection but often do not integrate them with a continuous environmental understanding update. LLM-based robotic reasoning can interpret situations, but it is not always connected to difference-proportional learning.

TABLE I
COMPARISON BETWEEN RELATED RESEARCH DIRECTIONS AND DTID-UEU.

Direction	Main Focus	Difference from DTID-UEU
Continual learning	Learning new data or tasks over time	DTID-UEU focuses on issue discovery through an updated environmental understanding.
Anomaly detection	Detecting deviations from normal patterns	DTID-UEU further judges, learns, and familiarizes meaningful differences.
World models	Predicting future states or observations	DTID-UEU uses prediction difference to update environmental understanding.
LLM-based robotics	Reasoning, planning, and interaction	DTID-UEU uses thinking judgment to guide difference-proportional learning.

The proposed DTID-UEU model attempts to connect these ideas into a unified framework. Its main distinction is that issue discovery is driven by the difference between real-time observation and prediction based on an up-to-date environmental understanding. The detected difference is then judged, weighted, learned, and integrated back into the robot's environmental understanding. In this way, DTID-UEU supports a closed loop of environmental understanding maintenance, difference-triggered issue discovery, thinking-guided judgment, and difference-proportional learning.

III. Difference-Triggered Issue Discovery with Up-to-Date Environmental Understanding

This section presents the proposed *Difference-Triggered Issue Discovery with Up-to-Date Environmental Understanding* (DTID-UEU) model for autonomous robots operating in open environments. The goal of the model is to enable a robot to discover emerging issues without requiring manually predefined issue types. Here, an emerging issue refers to a newly appearing or previously unexplained situation that may influence the robot's perception, decision-making, task execution, or interaction with the environment.

The basic assumption of DTID-UEU is that an autonomous robot should not only react to current observations, but also maintain an up-to-date understanding of the environment it has encountered. This environmental understanding provides an internal reference for predicting what the robot expects to observe. When the actual observation is inconsistent with the predicted observation, the inconsistency may indicate that a new issue has appeared, the environment has changed, or the current understanding is incomplete. Therefore, issue discovery is driven by the difference between real-time observation and internal prediction.

The proposed model is organized around three key ideas. First, the robot continuously maintains an internal environmental understanding state, which is updated according to newly collected observations, difference scores, and issue judgments. Second, potential issues are triggered by comparing real-time observations with predictions generated from the current environmental understanding. Third, the robot applies a thinking-guided difference-proportional learning mechanism, where meaningful differences are analyzed before learning and larger differences are assigned stronger learning intensity.

Formally, let O_t denote the real-time observation collected by the robot at time t, and let $\mathcal{U}_{t-1}$ denote the robot's environmental understanding before processing O_t. Based on $\mathcal{U}_{t-1}$ and historical observations, the robot predicts an expected observation $\hat{O}_t$. The difference between O_t and $\hat{O}_t$ is then computed as

$$\Delta_t = D(O_t, \hat{O}_t), \tag{1}$$

where $D(\cdot)$ is a difference measurement function. If Δ_t exceeds a given threshold, the robot regards the current situation as a potential issue and activates the subsequent issue judgment and learning process.

The overall workflow of DTID-UEU can be summarized as

$$O_t \rightarrow \mathcal{U}_{t-1} \rightarrow \hat{O}_t \rightarrow \Delta_t \rightarrow J_t \rightarrow \mathcal{U}_t, \tag{2}$$

where J_t denotes the judgment result of the detected difference, and $\mathcal{U}_t$ denotes the updated environmental understanding after processing the current observation. Different from conventional anomaly detection methods that mainly determine whether an input belongs to an abnormal class, DTID-UEU focuses on maintaining a continuously updated reference of the environment and using this reference to discover new issues. In this way, issue discovery, learning, and environmental understanding update are integrated into a closed-loop autonomous process.

A. Overview of the DTID-UEU Model

The proposed DTID-UEU model is designed to support autonomous issue discovery in open environments. In such environments, a robot may encounter unfamiliar objects, changed environmental conditions, abnormal events, or task execution failures that are not defined in advance. Therefore, the robot should not only classify current observations according to predefined categories, but also discover whether the current situation contains a new issue that cannot be explained by its existing environmental understanding.

The basic structure of DTID-UEU is a closed-loop process consisting of environmental perception, internal prediction, difference comparison, issue judgment, learning, and environmental understanding update. At each time step t, the robot collects a real-time observation O_t from the environment. Based on its current environmental understanding $\mathcal{U}_{t-1}$ and historical observation sequence H_{t-1}, the robot predicts the expected observation $\hat{O}_t$. The inconsistency between the real observation and the predicted observation is then measured by a difference score Δ_t. If the difference is sufficiently large, the robot regards the current situation as a potential issue and activates further judgment and learning.

The closed-loop process can be represented as

$$O_t \rightarrow \hat{O}_t \rightarrow \Delta_t \rightarrow J_t \rightarrow \mathcal{U}_t, \tag{3}$$

where J_t denotes the judgment result of the detected difference, and $\mathcal{U}_t$ denotes the updated environmental understanding

after processing the current observation. More specifically, the prediction $\hat{O}_t$ is generated based on the previous environmental understanding:

$$\hat{O}_t = F_\theta(\mathcal{U}_{t-1}, H_{t-1}), \tag{4}$$

where F_θ is the prediction function. The difference score is calculated as

$$\Delta_t = D(O_t, \hat{O}_t), \tag{5}$$

where $D(\cdot)$ measures the inconsistency between the real observation and the expected observation.

The key idea of DTID-UEU is that issue discovery depends on an up-to-date reference of the environment. If the robot's environmental understanding is outdated or incomplete, normal changes may be incorrectly regarded as abnormal, and truly emerging issues may be missed. Therefore, DTID-UEU continuously updates $\mathcal{U}_t$ after each perception–comparison–learning cycle. The environmental understanding is updated according to the current observation, the difference score, and the judgment result:

$$\mathcal{U}_t = \Psi(\mathcal{U}_{t-1}, O_t, \Delta_t, J_t), \tag{6}$$

where $\Psi(\cdot)$ is the environmental understanding update function.

Different from conventional anomaly detection methods, DTID-UEU does not rely on a fixed abnormal class or a static normal distribution. Instead, it discovers potential issues by identifying inconsistencies between the current observation and the robot's latest environmental understanding. A detected difference is not immediately treated as an error. It is first analyzed by a thinking-guided judgment process to determine whether it corresponds to ordinary variation, noise, an emerging issue, an abnormal event, or a task-relevant failure. Meaningful differences are then used to guide learning, and larger differences are assigned stronger learning intensity.

DTID-UEU integrates issue discovery and environmental understanding update into a unified autonomous loop. Through this loop, the robot can gradually transform unfamiliar situations into familiar knowledge, maintain an up-to-date understanding of the environment, and continuously improve its ability to discover new issues during long-term operation.

B. Up-to-Date Environmental Understanding Maintenance

The maintenance of up-to-date environmental understanding is the central component of DTID-UEU. Issue discovery requires a reliable reference for comparison. If the robot only compares the current observation with an isolated previous observation, the result may be sensitive to noise, temporary changes, or incomplete perception. In contrast, an accumulated and continuously updated environmental understanding provides a more stable reference for judging whether the current situation is expected or contains a potential issue.

Let $\mathcal{U}_t$ denote the environmental understanding maintained by the robot at time t. In this work, $\mathcal{U}_t$ is defined as a dynamic internal representation that summarizes the robot's accumulated experience of the encountered environment. It is not limited to a static map or a set of stored samples. Instead, it may include normal sensory patterns, known objects and states, temporal observation history, task-related feedback, previously discovered issues, and learned parameters for predicting expected observations. Therefore, $\mathcal{U}_t$ serves as the reference for generating the expected observation $\hat{O}_t$ and for computing the difference between the actual observation O_t and $\hat{O}_t$.

The environmental understanding must be continuously updated because open environments are not fixed. Objects may appear or disappear, environmental conditions may change, and task execution results may become different from previous experience. If the robot relies on outdated understanding, it may incorrectly regard already familiar changes as new issues, or fail to notice truly emerging issues. Therefore, DTID-UEU maintains $\mathcal{U}_t$ as a dynamic state rather than a fixed background model.

At each time step, after the robot receives the observation O_t, computes the difference score Δ_t, and obtains the judgment result J_t, the environmental understanding is updated as

$$\mathcal{U}_t = \Psi(\mathcal{U}_{t-1}, O_t, \Delta_t, J_t, L_t), \tag{7}$$

where $\Psi(\cdot)$ denotes the environmental understanding update function, and L_t denotes the learning result obtained from the current observation. The learning result may include updated model parameters, newly stored experience, revised issue records, or adjusted prediction rules.

The difference score Δ_t indicates how inconsistent the current observation is with the previous environmental understanding. A small difference usually means that the current observation is consistent with the existing understanding and only requires a light update or simple recording. A large difference means that the current observation may contain new information and should receive stronger attention in the update process. The judgment result J_t further determines how the difference should be interpreted. For example, a large difference caused by sensor noise should not strongly change the environmental understanding, while a large difference caused by a newly appearing obstacle should be incorporated as new environmental knowledge.

The update process can also be conceptually represented as

$$\mathcal{U}_t = \mathcal{U}_{t-1} \oplus \Phi(O_t, \Delta_t, J_t, L_t), \tag{8}$$

where $\Phi(\cdot)$ extracts the update information from the current observation and $\oplus$ denotes the integration operation. Through this process, unfamiliar observations can be gradually transformed into familiar knowledge. As a result, the robot's reference for future prediction becomes increasingly consistent with the environment it has actually encountered.

This mechanism is important for long-term autonomous operation. When the robot enters a new environment, its initial understanding may be incomplete, leading to frequent differences between predicted and observed states. After repeated perception and learning, stable patterns are gradually absorbed into $\mathcal{U}_t$. Consequently, the number of unexplained differences decreases, and newly triggered differences are more likely to correspond to genuinely emerging issues. Thus, maintaining an up-to-date environmental understanding is not only a memory process, but also the foundation for reliable difference-triggered issue discovery.

C. Difference-Triggered Issue Discovery

Based on the maintained environmental understanding, DTID-UEU discovers potential issues by comparing the robot's actual observation with the expected observation generated from its current understanding. At time t, the robot receives a real-time observation O_t and predicts the expected observation $\hat{O}_t$ according to the previous environmental understanding $\mathcal{U}_{t-1}$. If the current observation is consistent with the prediction, the robot regards the situation as explainable by its existing understanding. If the difference is large, the robot regards the situation as a potential issue that requires further judgment and learning.

The difference score is defined as

$$\Delta_t = D(O_t, \hat{O}_t), \tag{9}$$

where $D(\cdot)$ denotes a difference measurement function. The function $D(\cdot)$ can be implemented according to the specific robotic task. For example, it may measure the difference between predicted and observed sensor states, the mismatch between expected and actual task feedback, or the inconsistency between predicted and observed environmental states.

A potential issue is triggered when the difference score exceeds a predefined or adaptive threshold:

$$I_t = \begin{cases} 1, & \Delta_t > \theta, \\ 0, & \Delta_t \le \theta, \end{cases} \tag{10}$$

where $I_t = 1$ indicates that the current observation contains a potential issue, and $I_t = 0$ indicates that the current observation is consistent with the robot's current understanding.

The detected issue is not restricted to a fixed category. It may correspond to an unfamiliar object, a newly appearing obstacle, a changed environmental condition, an abnormal event, a task execution failure, or a situation that cannot be explained by the current environmental understanding. Therefore, the model does not require all possible issue types to be manually defined before deployment. Instead, an issue is first discovered as an inconsistency between the robot's prediction and the real environment.

For more fine-grained issue triggering, the binary trigger can be extended to a multi-level issue intensity:

$$I_t = \begin{cases} 0, & \Delta_t < \theta_1, \\ 1, & \theta_1 \le \Delta_t < \theta_2, \\ 2, & \Delta_t \ge \theta_2. \end{cases} \tag{11}$$

Here, $I_t = 0$ denotes no obvious issue, $I_t = 1$ denotes a weak potential issue, and $I_t = 2$ denotes a strong potential issue. A weak issue may only require recording or light learning, while a strong issue may require detailed judgment, stronger learning, or an immediate autonomous response.

The key advantage of this mechanism is that issue discovery is not based on a static abnormal class or a manually constructed issue list. Instead, it is based on whether the current situation can be explained by the robot's up-to-date environmental understanding. As the environmental understanding is continuously updated, the reference for issue discovery also evolves. Consequently, observations that were previously unfamiliar may become familiar after learning, while newly appearing differences can still be detected as emerging issues.

This difference-triggered mechanism provides the entry point for the subsequent judgment and learning processes. After a potential issue is triggered, DTID-UEU further analyzes the meaning of the difference and determines whether it should be ignored, recorded, learned, or used to guide an autonomous response.

D. Thinking-Guided Difference-Proportional Learning

After a potential issue is triggered, DTID-UEU does not immediately treat the detected difference as a training error. In open environments, not every difference indicates a meaningful issue. Some differences may be caused by sensor noise, temporary environmental variation, incomplete observation, or harmless changes. If all differences are directly used for strong learning, the robot may overfit to noise or incorrectly update its environmental understanding. Therefore, DTID-UEU introduces a thinking-guided judgment process before learning.

The purpose of the thinking-guided judgment process is to analyze the meaning of the detected difference. Given the current observation O_t, the predicted observation $\hat{O}_t$, the difference score Δ_t, the previous environmental understanding $\mathcal{U}_{t-1}$, and the historical observation sequence H_{t-1}, the judgment result is defined as

$$J_t = G(O_t, \hat{O}_t, \Delta_t, \mathcal{U}_{t-1}, H_{t-1}), \tag{12}$$

where $G(\cdot)$ denotes the judgment function. The judgment process determines whether the detected difference represents an ordinary variation, noise, emerging issue, abnormal event, or task-relevant failure.

The judgment result can be represented as

$$\begin{aligned} J_t \in \{&\text{ordinary variation, noise, emerging issue,} \\ &\text{abnormal event, task failure}\}. \end{aligned} \tag{13}$$

Different judgment results lead to different learning strategies. If the difference is judged as noise, the robot ignores it or records it with very low weight. If it is judged as an ordinary variation, the robot performs only a light update to avoid overreacting. If it is judged as an emerging issue, an abnormal event, or a task-relevant failure, the robot performs stronger learning and updates its environmental understanding more significantly.

To assign learning intensity, DTID-UEU uses a difference-proportional learning weight:

$$w_t = 1 + \lambda \Delta_t, \tag{14}$$

where w_t denotes the learning weight and λ controls the sensitivity of learning intensity to the difference score. A larger difference leads to a larger learning weight, indicating that the current observation should receive stronger learning attention.

However, the learning weight should also depend on the judgment result. Therefore, the final learning weight is defined as

$$\tilde{w}_t = \eta(J_t)(1 + \lambda \Delta_t), \tag{15}$$

where $\eta(J_t)$ is a judgment-dependent coefficient. For example, $\eta(J_t)$ can be small for noise or ordinary variation and large for emerging issues or task failures.

The learning objective is then written as

$$\mathcal{L}_t = \tilde{w}_t \ell(O_t, \hat{O}_t), \tag{16}$$

where $\ell(\cdot)$ denotes the basic learning loss. This formulation allows the robot to learn more strongly from meaningful and highly inconsistent observations, while reducing the influence of unimportant or misleading differences.

In addition to weighted learning, the same idea can also be implemented through repeated training. The number of learning repetitions can be defined as

$$k_t = \lceil k_{\min} + \lambda \Delta_t \eta(J_t) \rceil, \tag{17}$$

where k_t denotes the number of repeated learning steps for the current observation. This mechanism simulates stronger memory formation for important unfamiliar situations.

Through thinking-guided difference-proportional learning, DTID-UEU converts detected differences into adaptive learning signals. The robot does not passively learn every new observation with the same strength. Instead, it first judges the meaning of the difference and then determines how strongly the current information should influence its environmental understanding. This enables the robot to gradually transform meaningful unfamiliar situations into familiar knowledge while avoiding unnecessary updates caused by noise or ordinary fluctuations.

Algorithm 1 DTID-UEU: Difference-Triggered Issue Discovery with Up-to-Date Environmental Understanding

Require: Initial environmental understanding $\mathcal{U}_0$, issue threshold τ, learning coefficient λ
Ensure: Updated environmental understanding $\mathcal{U}_T$ and discovered issue set $\mathcal{I}$

Initialize history $H_0 \leftarrow \emptyset$
Initialize issue set $\mathcal{I} \leftarrow \emptyset$
for $t = 1$ to T **do**
  Collect real-time observation O_t
  Predict expected observation $\hat{O}_t \leftarrow F_\phi(\mathcal{U}_{t-1}, H_{t-1})$
  Compute difference score $\Delta_t \leftarrow D(O_t, \hat{O}_t)$
  if $\Delta_t > \tau$ **then**
    Trigger potential issue $I_t \leftarrow 1$
    Judge issue type $J_t \leftarrow G(O_t, \hat{O}_t, \Delta_t, \mathcal{U}_{t-1}, H_{t-1})$
    Add issue record (O_t, Δ_t, J_t) to $\mathcal{I}$
    Compute learning weight $\tilde{w}_t \leftarrow \eta(J_t)(1 + \lambda\Delta_t)$
    Perform thinking-guided learning with weight $\tilde{w}_t$
  else
    Set issue trigger $I_t \leftarrow 0$
    Set judgment result $J_t \leftarrow$ ordinary
    Perform regular environmental update
  end if
  Update environmental understanding $\mathcal{U}_t \leftarrow \Psi(\mathcal{U}_{t-1}, O_t, \Delta_t, J_t, L_t)$
  Update history $H_t \leftarrow H_{t-1} \cup \{O_t\}$
end for
return $\mathcal{U}_T$, $\mathcal{I}$

E. Closed-Loop Autonomous Update Algorithm

The above components are integrated into a closed-loop autonomous update process. The robot continuously collects observations from the environment, predicts expected observations according to its current environmental understanding, compares the predicted and actual observations, judges the meaning of the detected difference, and updates its environmental understanding through difference-proportional learning. In this way, the environmental understanding is not a fixed representation, but a continuously revised internal reference for future issue discovery.

Algorithm 1 summarizes the proposed DTID-UEU process. At the beginning, the robot is initialized with an initial environmental understanding $\mathcal{U}_0$ and an empty issue set $\mathcal{I}$. At each time step, the robot receives a real-time observation O_t and predicts the expected observation $\hat{O}_t$ based on $\mathcal{U}_{t-1}$ and the historical observation sequence H_{t-1}. The difference score Δ_t is then computed. If Δ_t exceeds the issue-triggering threshold, the robot regards the current situation as a potential issue and further obtains the judgment result J_t. According to J_t and Δ_t, the robot assigns an adaptive learning weight and updates its environmental understanding. If the difference is small, the observation is regarded as consistent with the current understanding and only a regular update is performed.

The updated environmental understanding $\mathcal{U}_t$ is used as the reference for the next prediction and comparison. Therefore, issue discovery and environmental understanding maintenance reinforce each other. A more accurate environmental understanding improves the reliability of future difference detection, while newly detected meaningful differences provide information for updating the environmental understanding. This closed-loop process enables the robot to discover emerging issues and gradually transform unfamiliar situations into familiar knowledge during long-term operation.

The algorithm shows that DTID-UEU does not separate issue discovery from learning. Instead, issue discovery is the trigger for updating the robot's environmental understanding. When a meaningful difference is detected, the robot strengthens its learning from the corresponding observation. When no significant difference is detected, the robot still maintains its understanding through regular updates. As a result, the robot can continuously adapt its internal reference to the environment it actually encounters.

The main difference between DTID-UEU and a conventional anomaly detection pipeline lies in the role of the reference model. In conventional anomaly detection, the normal model is usually trained before deployment and remains fixed or is only periodically updated. In DTID-UEU, the reference model $\mathcal{U}_t$ is continuously updated during operation. Thus, the robot can both discover newly emerging issues and reduce repeated false alarms for situations that have already become familiar through learning.

IV. VERIFICATION

This section verifies the effectiveness of the proposed DTID-UEU model. The verification focuses on whether maintaining up-to-date environmental understanding helps an autonomous robot discover newly emerging issues in an open environment. A challenging fire-discovery scenario is constructed, where the robot first learns the normal visual patterns of an encountered environment and then needs to discover a small fire region newly added to the scene. The fire region occupies only a small part of the image and may have different colors or low contrast. Meanwhile, the normal environment also contains red non-fire objects, such as red posters, red books, red cups, or red buttons. Therefore, the task cannot be solved reliably by simply detecting red pixels.

A. Verification Scenario

The verification is designed according to the main motivation of DTID-UEU. In an open environment, a robot may already be familiar with the normal background, object layout, and common visual patterns of the current environment. When a new issue appears, such as a small fire region, the robot should discover it as an inconsistency between the current observation and its up-to-date environmental understanding.

In the experiment, normal images are first generated to simulate the environment encountered by the robot. These images include stable background structures, common objects, and non-fire red distractors. The proposed method learns these normal images to form an internal environmental understanding. During testing, a small fire region is added to some images. Since the fire region is small and may be low-contrast, direct image-level classification is difficult. Moreover, because normal images may contain red non-fire objects, simple red-threshold detection is also unreliable.

The verification compares the following methods:

- **DTID-UEU**: the proposed method. It learns normal environmental patterns and discovers the fire issue by local difference between the observed image and the learned environmental understanding.
- **Direct classifier without understanding**: a convolutional classifier that directly predicts whether an image contains fire, without explicitly maintaining environmental understanding.
- **Red threshold without learning**: a rule-based method that detects fire according to the amount of red pixels. This method does not learn environmental patterns.
- **Static understanding**: a baseline that uses a weak or insufficient environmental understanding and does not maintain an up-to-date understanding during the verification process.

The purpose of these baselines is to verify three aspects of the proposed model. The direct classifier is used to test whether direct recognition without environmental understanding is sufficient. The red-threshold method is used to test whether the task can be solved by a simple color rule. The static-understanding method is used to test whether maintaining an up-to-date environmental understanding is necessary.

TABLE II
ISSUE DISCOVERY PERFORMANCE IN THE CHALLENGING FIRE SCENARIO.

Method	F1	Recall	Precision	FAR	Miss
DTID-UEU	0.3848	0.2570	0.8897	0.0266	0.7430
Direct classifier	0.0000	0.0000	0.0000	0.0000	1.0000
Red threshold	0.1710	0.0992	0.8860	0.0047	0.9008
Static understanding	0.0544	0.0289	0.5240	0.0258	0.9711

B. Evaluation Metrics

The issue discovery result is evaluated using precision, recall, F1-score, false alarm rate, and miss rate. Let TP, FP, TN, and FN denote true positives, false positives, true negatives, and false negatives, respectively. The metrics are defined as follows:

$$\text{Precision} = \frac{TP}{TP + FP}, \tag{18}$$

$$\text{Recall} = \frac{TP}{TP + FN}, \tag{19}$$

$$F_1 = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}, \tag{20}$$

$$\text{FalseAlarmRate} = \frac{FP}{FP + TN}, \tag{21}$$

$$\text{MissRate} = \frac{FN}{TP + FN}. \tag{22}$$

Among these metrics, recall measures the ability to discover fire issues, while miss rate measures the proportion of fire issues that are not discovered. F1-score reflects the balance between precision and recall. False alarm rate is also important because a practical robot should not frequently regard normal red objects as fire issues.

C. Experimental Results

Table II shows the aggregated results of the challenging fire-discovery scenario. The proposed DTID-UEU achieves the highest F1-score and recall among all compared methods. Specifically, DTID-UEU obtains an F1-score of 0.3848 and a recall of 0.2570. In contrast, the direct classifier without environmental understanding obtains an F1-score of 0 and a recall of 0, indicating that it fails to discover the small fire regions in this setting. The red-threshold method obtains an F1-score of 0.1710 and a recall of 0.0992, which are much lower than those of DTID-UEU. The static-understanding baseline obtains an F1-score of only 0.0544 and a recall of 0.0289.

The result indicates that DTID-UEU is more effective than direct classification when the issue occupies only a small region of the image. The direct classifier fails because the image-level fire signal is weak and can be overwhelmed by the normal background. In contrast, DTID-UEU first learns the normal environmental pattern and then detects the fire region as a local inconsistency. Therefore, even though the fire region is small, it can still produce a meaningful difference from the learned environmental understanding.

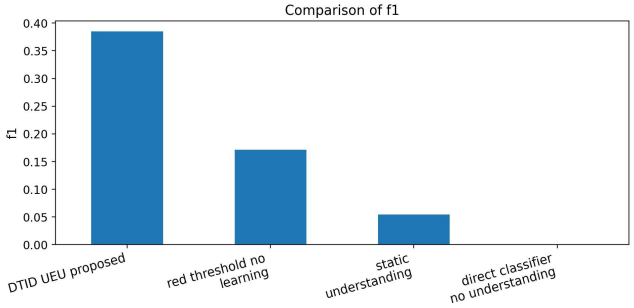


Fig. 1. Comparison of F1-score in the challenging fire-discovery scenario. DTID-UEU achieves the highest F1-score among the compared methods.

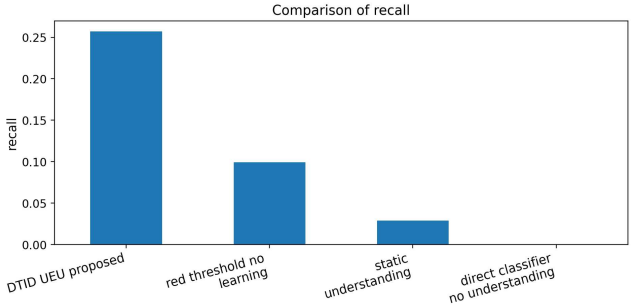


Fig. 2. Comparison of recall. DTID-UEU discovers more fire issues than the direct classifier, red-threshold baseline, and static-understanding baseline.

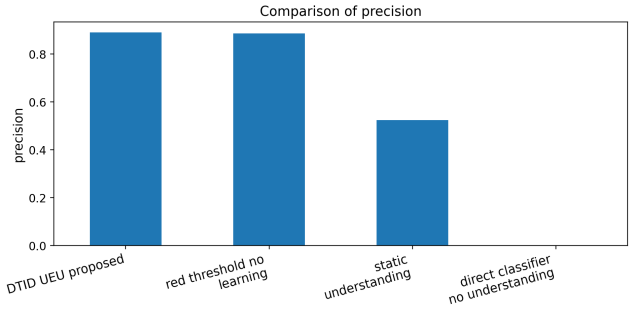


Fig. 3. Comparison of precision. DTID-UEU maintains high precision, indicating that most detected issues are correct.

Compared with the red-threshold baseline, DTID-UEU improves the F1-score from 0.1710 to 0.3848 and the recall from 0.0992 to 0.2570. This shows that the proposed method is not simply relying on red color. In the challenging scenario, normal images also contain red non-fire objects, while some fire regions are low-contrast or not purely red. As a result, a simple red-pixel rule misses many fire issues. DTID-UEU performs better because it uses the learned environmental understanding as the reference for issue discovery.

Compared with the static-understanding baseline, DTID-UEU improves the F1-score from 0.0544 to 0.3848 and the recall from 0.0289 to 0.2570. This result verifies the importance of maintaining up-to-date environmental understanding. A weak or static understanding cannot provide a reliable reference for discovering small emerging issues. By continuously updating the understanding of the encountered environment, DTID-UEU can better distinguish meaningful differences from normal visual patterns.

D. Visualization of Verification Results

Figures 1–5 visualize the comparison results. Figure 1 shows that DTID-UEU achieves the highest F1-score among all methods. Figure 2 further shows that DTID-UEU discovers more fire issues than the baselines. Although its recall is still limited, it is significantly higher than the red-threshold method and the static-understanding method. Figure 3 shows that DTID-UEU maintains a high precision of 0.8897, which means that most detected issues are true fire issues. Figures 4 and 5 show the false alarm rate and miss rate, respectively. DTID-UEU has a higher false alarm rate than the red-threshold method, but it achieves a much lower miss rate. This trade-off is acceptable in issue discovery scenarios where missing a fire issue is more harmful than raising a small number of false alarms.

E. Ablation Analysis

The comparison results also provide an ablation analysis of the proposed model. First, removing environmental understanding leads to the direct classifier baseline. This baseline obtains zero recall and zero F1-score, showing that direct image-level classification is insufficient for discovering small fire issues in this setting. Second, replacing learned issue discovery with a fixed red-color rule leads to the red-threshold baseline. Although this baseline has a low false alarm rate of 0.0047, its recall is only 0.0992, which means that most fire issues are missed. Third, replacing up-to-date environmental understanding with static understanding leads to the static-understanding baseline. Its recall is only 0.0289, which demonstrates that a static or weak reference is not enough for reliable issue discovery.

These ablation results support the main components of DTID-UEU. The environmental understanding provides the reference for difference comparison. The up-to-date update mechanism improves the reliability of this reference. The difference-triggered discovery mechanism enables the robot to identify small local issues that are difficult to detect by direct classification or fixed color rules.

F. Discussion

The verification results support the effectiveness of DTID-UEU for discovering emerging issues in open environments. The proposed method achieves the best F1-score and recall among all compared methods. This shows that maintaining up-to-date environmental understanding is useful for discovering small issues that are not easily recognized by direct classification. The comparison with the red-threshold baseline further shows that the proposed method is more robust than simple color-based rules when normal red objects and low-contrast fire regions coexist.

However, the results also show that the task remains challenging. Although DTID-UEU obtains the highest recall, its recall is 0.2570 and its miss rate is 0.7430. This means that many very small or low-contrast fire regions are still missed.

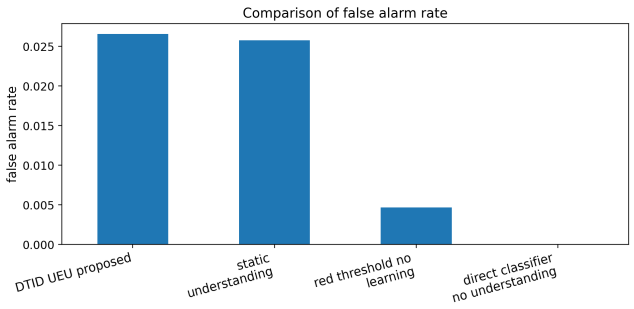


Fig. 4. Comparison of false alarm rate. DTID-UEU introduces a small number of false alarms while improving issue discovery ability.

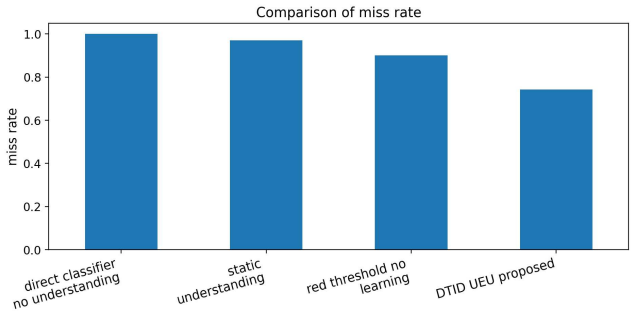


Fig. 5. Comparison of miss rate. DTID-UEU obtains a lower miss rate than the direct classifier, red-threshold baseline, and static-understanding baseline.

Therefore, the current verification does not indicate that DTID-UEU completely solves small fire detection. Instead, it shows that DTID-UEU provides a more effective issue discovery mechanism than the baselines under the same challenging setting. Future work can further improve the sensitivity of local difference estimation, introduce stronger visual feature extractors, and combine environmental understanding with more advanced multimodal reasoning modules.

V. Conclusion

This paper proposed DTID-UEU, a difference-triggered issue discovery model for autonomous robots operating in open and changing environments. The model maintains an up-to-date environmental understanding, predicts expected observations, and discovers potential issues by comparing predictions with real-time observations. Meaningful differences are further processed through thinking-guided judgment and difference-proportional learning, allowing the robot to update its environmental understanding during operation.

A challenging fire-discovery verification was conducted to evaluate the proposed model. The results show that DTID-UEU achieves better F1-score and recall than direct classification, red-threshold detection, and static-understanding baselines. This demonstrates that maintaining up-to-date environmental understanding can help autonomous robots discover small emerging issues that are difficult to detect using direct recognition or fixed rules.

Future work will improve the sensitivity of local difference estimation, reduce missed detections for very small or low-contrast issues, and extend DTID-UEU to more complex robotic tasks involving navigation, manipulation, and multi-modal environmental interaction.

References

[1] W. Chen, W. Chi, S. Ji, H. Ye, J. Liu, Y. Jia, J. Yu, and J. Cheng, "A survey of autonomous robots and multi-robot navigation: Perception, planning and collaboration," *Biomimetic Intelligence and Robotics*, vol. 5, no. 2, p. 100203, 2025.

[2] L. Wang, X. Zhang, H. Su, and J. Zhu, "A comprehensive survey of continual learning: Theory, method and application," *IEEE transactions on pattern analysis and machine intelligence*, vol. 46, no. 8, pp. 5362–5383, 2024.

[3] D. Samariya and A. Thakkar, "A comprehensive survey of anomaly detection algorithms," *Annals of Data Science*, vol. 10, no. 3, pp. 829–850, 2023.

[4] D. Ha and J. Schmidhuber, "World models," *arXiv preprint arXiv:1803.10122*, vol. 2, no. 3, p. 440, 2018.

[5] D. Zhu, Q. Bu, Z. Zhu, Y. Zhang, and Z. Wang, "Advancing autonomy through lifelong learning: a survey of autonomous intelligent systems," *Frontiers in neurorobotics*, vol. 18, p. 1385778, 2024.

[6] G. Kim, C. Xiao, T. Konishi, Z. Ke, and B. Liu, "Open-world continual learning: Unifying novelty detection and continual learning," *Artificial Intelligence*, vol. 338, p. 104237, 2025.

[7] E. Hajizada, B. Swaminathan, and Y. Sandamirskaya, "Continual learning for autonomous robots: A prototype-based approach," in *2024 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2024, pp. 13 988–13 995.

[8] L. Holder, P. Langley, B. Loyall, and T. Senator, "Introduction to open-world ai," p. 104393, 2025.

[9] F. Domberg and G. Schildbach, "World models for anomaly detection during model-based reinforcement learning inference," in *2025 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2025, pp. 4182–4187.

[10] J. Chen, S. Huang, X. Wang, P. Wang, J. Zhu, Z. Xu, G. Wang, Y. Yan, and L. Wang, "Perception-decision-execution coordination mechanism driven dynamic autonomous collaboration method for human-like collaborative robot based on multimodal large language model," *Robotics and Computer-Integrated Manufacturing*, vol. 98, p. 103167, 2026.

[11] V. Mehta, C. Sharma, and K. Thiyagarajan, "Large language models and 3d vision for intelligent robotic perception and autonomy," *Sensors*, vol. 25, no. 20, p. 6394, 2025.

[12] J. Wang, Z. Wu, Y. Li, H. Jiang, P. Shu, E. Shi, H. Hu, C. Ma, Y. Liu, X. Wang *et al.*, "Large language models for robotics: Opportunities," *Challenges, and Perspectives*, 2024.

PLACE PHOTO HERE

Hong Su received the MS and PhD degrees, in 2006 and 2022, respectively, from Sichuan University, Chengdu, China. He is currently a researcher of Chengdu University of Information Technology Chengdu, China. His research interests include blockchain, large language model and human simulation computing.