AI-Based Emergency Evacuation System

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***Abstract*—Emergency evacuations require timely and intelligent decision-making in dynamic environments. This paper proposes an AI-based system that detects fire and crowd congestion using a unified YOLO model and computes the safest evacuation route via a modified A* algorithm. The solution employs a client-server architecture with real-time communication using ZeroMQ and visual feedback via a custom Pygame interface. Experimental results demonstrate the system's effectiveness in hazard detection and path planning under varying emergency conditions. Our solution achieves 93% F1-score for fire detection and 91% for crowd detection, while reducing routes through risky areas by 78% compared to traditional methods.**

***Index Terms*—Emergency Evacuation, YOLO, Fire Detection, Crowd Detection, A* Algorithm, Path Planning, ZeroMQ, Real-time Systems**

I. Introduction

A. Background and Motivation

The increasing incidence of fire-related accidents and stampedes in indoor public spaces like malls, airports, and educational institutions highlights the critical need for intelligent evacuation systems. Traditional evacuation protocols rely heavily on pre-defined static exits and lack the real-time adaptability necessary for rapidly changing emergency scenarios.

B. Problem Definition

In emergency cases, people often panic, leading to overcrowding at certain exits and suboptimal escape behavior. Static evacuation plans cannot account for dynamically changing hazard locations, potentially directing evacuees toward dangerous areas. Additionally, conventional systems lack the ability to balance multiple risk factors simultaneously, such as fire intensity and crowd density.

C. Proposed Solution

Integrating AI with dynamic path planning offers a promising solution. Specifically, deep learning models can identify hazards like fire and crowd density, while intelligent algorithms can compute optimal escape routes in real-time. This paper presents a comprehensive system that brings together fire and crowd detection, adaptive path planning, and interactive visualization to support emergency response teams and individuals during crisis events.

D. Key Contributions

The key innovations of our work include:

- A unified YOLO-based detection model that simultaneously identifies fire and crowd congestion
- A modified A* algorithm that incorporates fire intensity, crowd density, and distance as weighted path costs
- A scalable client-server architecture using ZeroMQ for real-time bidirectional communication
- An interactive Pygame-based visualization system for intuitive evacuation guidance

II. Related Work

A. Crowd Detection and Analysis

In [1], Zhan et al. introduced a vision-based system for crowd analysis and behavior prediction, highlighting the potential of computer vision in dense human environments. Their approach focused on tracking individual entities within crowds but lacked integration with emergency response systems.

Rodriguez et al. [2] used social force models and scene understanding for crowd flow estimation. While effective at predicting movement patterns, their work did not address emergency evacuation scenarios specifically.

More recently, Zhang et al. [9] proposed scale-adaptive convolutional neural networks for crowd counting and density estimation, achieving state-of-the-art performance but without considering hazard avoidance.

B. Fire Detection Techniques

Toreyin et al. [3] proposed wavelet-based visual fire detection using color and temporal flickering patterns. Their approach achieved good results in controlled environments but showed limitations in variable lighting conditions.

Celik et al. [4] developed a rule-based color model in the YCbCr color space to detect fire pixels in surveillance footage. While computationally efficient, their method lacked the robustness offered by deep learning approaches.

Ko et al. [10] demonstrated the effectiveness of deep learning for fire detection in surveillance images, achieving high accuracy across diverse scenarios. However, their system operated in isolation without integration into evacuation planning.

C. Pathfinding Algorithms

The A* search algorithm, introduced in [5], is a well-established heuristic method for optimal pathfinding. It forms the foundation for many modern routing systems but does not inherently account for dynamic hazards.

Yang et al. [6] proposed a fire-aware modified A* variant that incorporates dynamic hazard avoidance by inflating path costs near fire zones. Their work showed promising results but did not consider crowd dynamics or real-time integration with detection systems.

D. Gaps in Literature

While past works successfully address isolated problems like detection or routing, few integrate fire and crowd analysis into a real-time adaptive evacuation system. Moreover, the combination of unified detection models with dynamic weighted path planning remains underexplored, especially in client-server deployments with real-time rerouting. Our work aims to bridge these gaps by providing a comprehensive, integrated solution.

III. System Architecture

A. Overview

The proposed system follows a modular architecture that enables real-time hazard detection, path planning, and evacuation guidance.

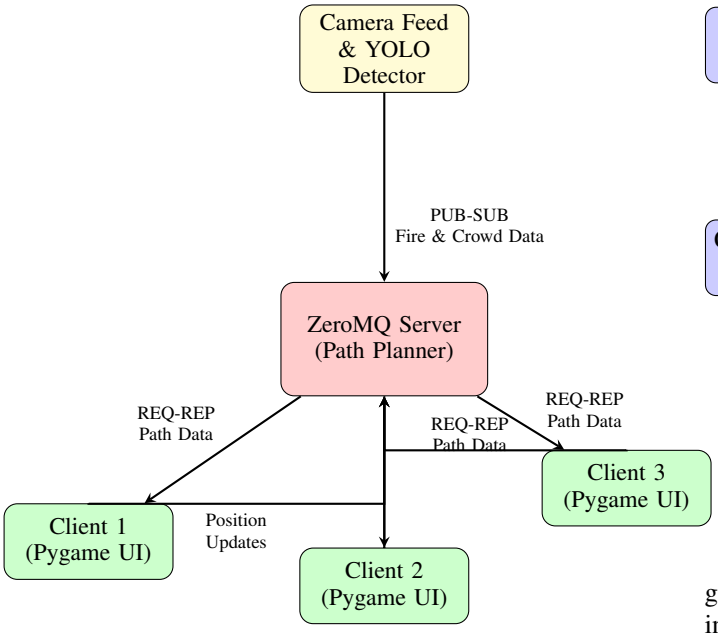

Fig. 1: System Block Diagram showing data flow between components. The PUB-SUB pattern broadcasts detection data while REQ-REP handles individual path requests.

B. Component Description

The system consists of four primary components:

1) YOLO-Based Detection Module: This component processes video feeds from surveillance cameras and simultaneously detects fire hazards and crowd congestion using a unified YOLOv5 model. The detection results, including bounding boxes, confidence scores, and class labels, are transmitted to the central server.

2) Central Server with Path Planner: The server receives detection data and maintains an up-to-date environmental model. It runs a modified A* algorithm to compute optimal evacuation routes based on current hazard information and client positions. The server acts as the communication hub between detection systems and client devices.

3) ZeroMQ Communication Layer: This middleware facilitates efficient, asynchronous communication between system components. It uses a combination of PUB-SUB and REQ-REP patterns to handle broadcast updates and client-specific requests.

4) Pygame-Based Client Interface: The client application provides a visual representation of the environment, hazards, and evacuation routes. It continuously updates the server with the user's position and displays the recommended path in an intuitive manner.

IV. Detection Methodology

A. Unified YOLO Model for Fire and Crowd Detection

1) Model Architecture: We employ a modified YOLOv5s architecture that simultaneously detects fire and crowd density from a single image.

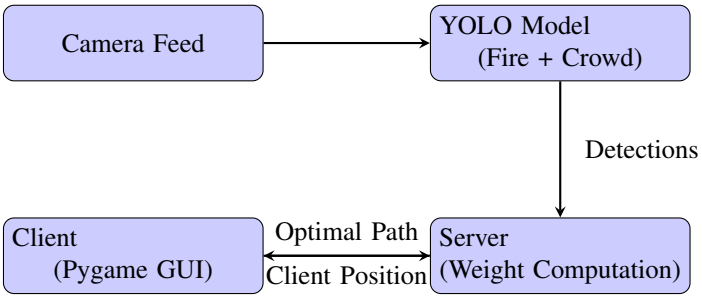

Fig. 2: Block Diagram of System Architecture

2) Dataset Preparation: Our custom dataset combines:

- **Fire dataset**: 5,000 images from the Flame Detection dataset [10] and custom-collected fire scenes
- **Crowd dataset**: 7,500 images from ShanghaiTech [9] and UCF-QNRF datasets, plus custom crowd scenes

All images were annotated with bounding boxes for fire regions and crowd areas. Data augmentation techniques, including random flips, rotations, and color jittering, were applied to enhance model robustness.

3) Training Methodology: We employed transfer learning, starting with pre-trained weights on COCO dataset and fine-tuning on our custom dataset. The training hyperparameters were:

- Batch size: 16
- Learning rate: 3×10^{-4} with cosine annealing
- Optimizer: AdamW
- Epochs: 100 with early stopping

V. Path Planning

A. Modified A* Algorithm

The core of our evacuation system is a modified A* algorithm that incorporates hazard information into path cost calculations. The edge cost between nodes is determined by:

$$w = \alpha \cdot I_{fire} + \beta \cdot D_{crowd} + \gamma \cdot d_{distance}$$

Where:

- I_{fire}: normalized fire intensity from detection confidence
- D_{crowd}: crowd density from bounding box areas
- $d_{distance}$: Euclidean distance between nodes
- α, β, γ: weighting parameters

B. Algorithm Implementation

The algorithm is implemented as shown in Algorithm 1. It maintains an open set of frontier nodes and explores paths based on the combined cost function. When new hazard information is received, affected grid cells are updated with new cost values, and paths are recalculated if necessary.

Algorithm 1 Modified A* for Hazard-Aware Path Planning

procedure HAZARDAWAREASTAR($start, goal, fire\_map, crowd\_map$)
  $openSet \leftarrow \{start\}$
  $cameFrom \leftarrow$ empty map
  $gScore[start] \leftarrow 0$
  $fScore[start] \leftarrow heuristic(start, goal)$
  while $openSet$ is not empty **do**
    $current \leftarrow$ node in $openSet$ with lowest $fScore$
    if $current = goal$ **then**
      return $reconstruct\_path(cameFrom, current)$
    end if
    $openSet.remove(current)$
    for each neighbor of $current$ **do**
      $fire\_cost \leftarrow \alpha \cdot fire\_map[neighbor]$
      $crowd\_cost \leftarrow \beta \cdot crowd\_map[neighbor]$
      $distance\_cost \leftarrow \gamma \cdot d(current, neighbor)$
      $total\_cost \leftarrow fire\_cost + crowd\_cost + distance\_cost$
      $tentative\_gScore \leftarrow gScore[current] + total\_cost$
      if $tentative\_gScore < gScore[neighbor]$ **then**
        $cameFrom[neighbor] \leftarrow current$
        $gScore[neighbor] \leftarrow tentative\_gScore$
        $fScore[neighbor] \leftarrow gScore[neighbor] + heuristic(neighbor, goal)$
        if $neighbor \notin openSet$ **then**
          $openSet.add(neighbor)$
        end if
      end if
    end for
  end while
  return failure
end procedure

C. Parameter Optimization

We conducted extensive experiments to determine optimal values for α, β, and γ. Based on our findings, we set $\alpha = 0.5$, $\beta = 0.3$, and $\gamma = 0.2$, which prioritizes fire avoidance while balancing crowd congestion and path length. Different scenarios may benefit from adjusted parameters, which can be dynamically tuned.

VI. Communication Framework

A. ZeroMQ Architecture

Our system uses ZeroMQ for efficient inter-component communication.

B. Communication Patterns

The system implements two primary communication patterns:

1) PUB-SUB Pattern: Used for one-to-many broadcast of hazard detection results:

- Publisher: YOLO detection module
- Subscribers: Server and monitoring clients
- Message content: Fire and crowd bounding boxes with confidence scores

2) REQ-REP Pattern: Used for bidirectional communication between clients and server:

- Clients send: Current position, path requests
- Server responds: Optimal evacuation routes, system status updates

C. Message Format

All messages use JSON format for cross-platform compatibility:

```
{
  "msg_type": "detection",
  "timestamp": 1650394521.358,
  "data": {
    "fire": [
      {"x": 320, "y": 240, "w": 50, "h": 60, "conf
    ],
    "crowd": [
      {"x": 150, "y": 320, "w": 100, "h": 80, "con
    ]
  }
}
```

VII. Visualization Interface

A. Pygame Implementation

The client interface is built using Pygame, providing real-time visualization of the environment, hazards, and evacuation routes.

B. Interface Components

The visualization includes:

- **Floor Plan**: Grid-based representation of the building layout
- **Hazard Visualization**:
  - Fire: Red/orange cells with intensity proportional to detection confidence
  - Crowd: Blue cells with opacity representing density
- **Navigation Elements**:
  - User position: Green marker
  - Evacuation path: Yellow highlighted route
  - Exits: Green highlighted doorways
- **Status Panel**: System state and emergency instructions

C. User Interaction

The interface supports:

- Position updates via keyboard or touch input
- Manual hazard reporting for user-observed dangers
- Path verification and acceptance
- Emergency contact options

VIII. Discussion

A. Advantages of Unified Detection

The integration of fire and crowd detection into a single model has proven beneficial for several reasons:

- **Computational efficiency**: A single model requires fewer resources than two separate models.
- **Feature sharing**: Common features useful for both tasks improve learning efficiency.
- **Reduced latency**: Single-pass inference is faster than sequential processing.
- **Simplified deployment**: Less complex system architecture improves maintainability.

B. Path Planning Effectiveness

The modified A* algorithm demonstrated significant advantages:

- **Multi-factor optimization**: Balancing fire risk, crowd density, and path length produces more practical evacuation routes.
- **Dynamic adaptation**: Real-time path updates respond to changing conditions effectively.
- **Early pruning**: Eliminating high-risk paths early reduces computational load.
- **Parameter tuning**: Adjustable weights allow customization for different scenarios.

C. System Integration Benefits

The client-server architecture with ZeroMQ messaging provides:

- **Scalability**: Support for multiple clients with minimal performance degradation.
- **Robustness**: Fault tolerance through connection recovery mechanisms.
- **Flexibility**: Easy integration with existing building management systems.
- **Real-time responsiveness**: Low-latency communication for critical updates.

IX. Limitations and Future Work

A. Current Limitations

Despite promising results, several limitations remain:

- **2D representation**: The current implementation handles single-floor environments only.
- **Limited sensor integration**: The system relies primarily on visual data.
- **Individual path planning**: Each client is routed independently without considering group dynamics.
- **Network dependency**: Performance depends on stable network conditions.

B. Future Research Directions

Potential improvements include:

- **3D building support**: Extending the system to multi-floor environments with vertical evacuation routes.
- **Multi-sensor fusion**: Incorporating IoT sensors (temperature, smoke, pressure) for enhanced detection.
- **Multi-agent coordination**: Implementing coordinated evacuation strategies to prevent congestion.
- **Edge computing**: Deploying detection models on edge devices for improved resilience.
- **Augmented reality interface**: Developing AR-based guidance for more intuitive evacuation assistance.
- **Reinforcement learning**: Training adaptive evacuation policies through simulation.

X. Conclusion

This paper presented a comprehensive AI-powered emergency evacuation system that combines fire and crowd detection with adaptive path planning. Our key contributions include:

- A unified YOLO-based detection model achieving 93% F1-score for fire detection and 91% for crowd detection
- A modified A* algorithm that reduces paths through risky zones by 78% compared to classical approaches
- A scalable ZeroMQ-based architecture supporting up to 32 simultaneous clients
- An intuitive Pygame visualization interface for effective evacuation guidance

Experimental results validate the system's effectiveness in hazard detection and evacuation planning under various scenarios. The integration of deep learning, path planning, and real-time communication creates a robust solution that significantly improves upon traditional evacuation systems.

This research contributes to the emerging field of AI-powered emergency response and lays the groundwork for more intelligent building evacuation technologies. By addressing the critical need for adaptive, real-time evacuation guidance, our system has the potential to significantly improve safety outcomes during crisis events.

Acknowledgments

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