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Video Detection in Tunnels: Benefits and Limits

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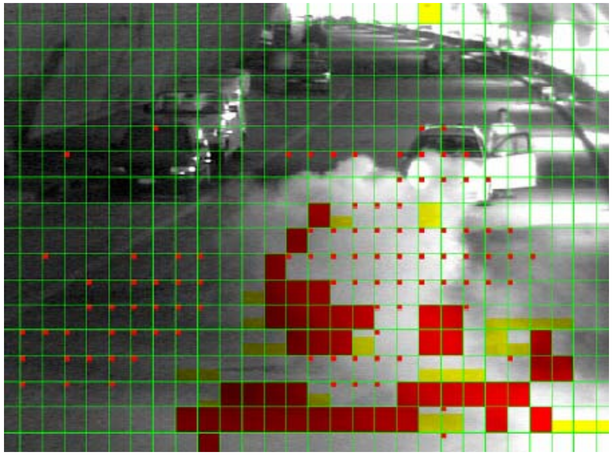
AMSTEIN + WALTHERT

Introduction

Catastrophic fire desasters indicated safety nuisances in tunnels.



Visual surveillance and image processing are possible measures to make tunnels safer.

Introduction

C3.3 / WG4 decided 2006 to working out an international PIARC report on Video Detection.

Project Lead: John BURACZYNSKI, USA

Introduction

Report goals

- State-of-the-art video detection systems for the use in tunnels
- Benefits and limits of the systems
- Evaluation criteria and setup of field verification testing
- Current qualitiy characteristics, acceptance criteria
- Experiences from case studies

Status of planned report

- First draft available 2008
- Report finalization planned for 2009

Performance of Today's Video Detection Systems I

- **Provides the operator automatically with pictures of the incident**

- **Enables fast verification of incidents**
- **Can be used with existing CCVE**
- **May replace other incident detection systems**
- **Easy interface with other control systems and safety systems**

Performance of Today's Video Detection Systems II

- **Detection of**
  - → traffic intensity and speed
  - → type of vehicles (car, bus, truck...)
  - → stopped vehicles
  - → persons
  - → wrong way drivers
  - → lost objects
  - → fire and smoke

- **Special requirements**
  - → High reliability and availability of the system
    - low false alarm rate, high accuracy
    - cheap to maintain, fast to repair
    - Fail-safe technology (!!!)

Limitations

- Performance of the system under different physical conditions, disturbing factors

Reflexions

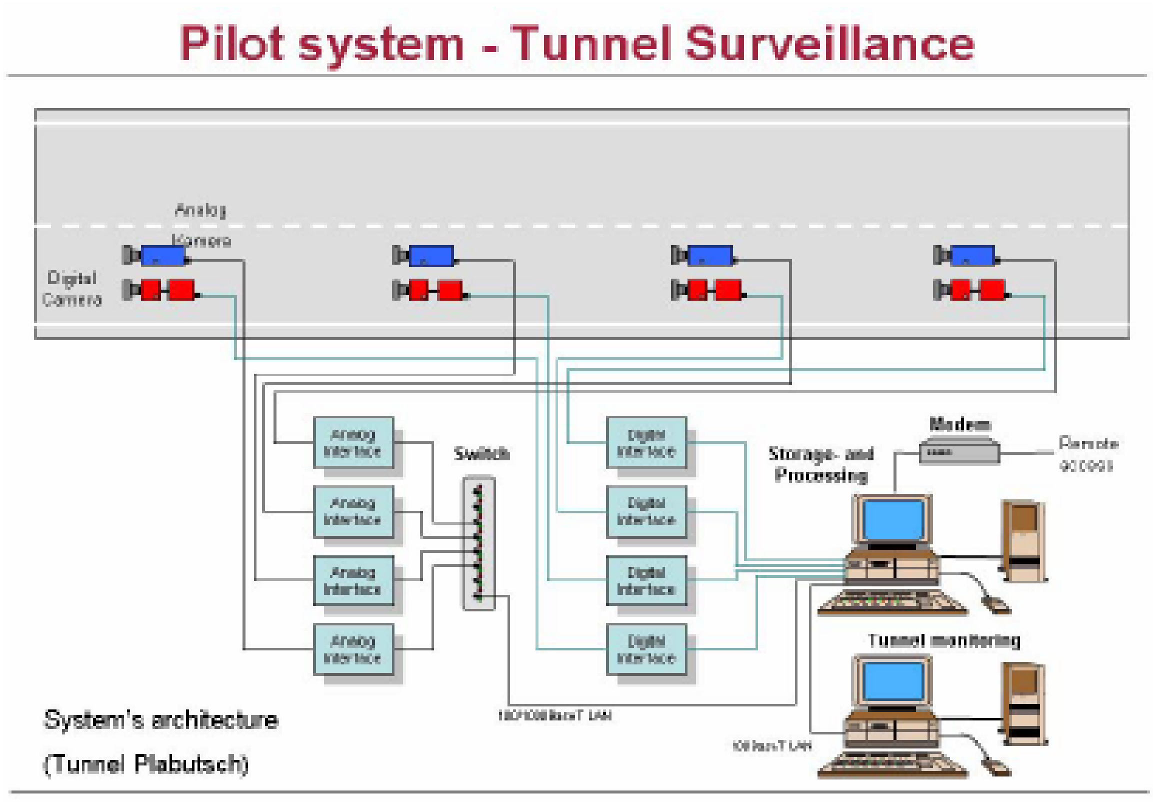
Blooming

Fog

- Reliability
- Time between incident and detection
- Availability
- Maintanance costs and time to repair

System Description, Typical Architecture

- Cameras (analogue or digital), typically every 100m
- Image processing and storage unit
- Modem for remote access
- Tunnel monitoring workplace (common PC)



Video Detection Tunnels

- **Examples Switzerland**

  - ➔ Baregg Tunnel, 1080 m
    - 30 cameras (traffic jam, stopped vehicles, wrong-way drivers)

  - ➔ Girsberg Tunnel, 1800 m
    - 28 cameras (traffic jam, stopped vehicles, wrong-way drivers, smoke)
    - False alarm rate initially 68.8% because of difficult conditions (rain, snow, ice)

Video Detection Tunnels

- **Examples Switzerland**

➔ Gubrist Tunnel, 3230 m
  - 8 cameras

➔ Seelisberg Tunnel, 9280 m
  - 142 cameras (traffic jam, stopped vehicles, wrong-way drivers)
  - False alarm rate first 10.1%, after adaptation 3.5%

➔ Mosi Tunnel, 1080 m
  - 10 cameras (traffic jam, stopped vehicles, smoke)

Video Detection Tunnels

- **Germany**
  - Döggingen Tunnel
    - 19 cameras (traffic jam, stopped vehicles, smoke)
    - False alarm rate 6.2%
    - 45% of all false alarms caused by false smoke detection

Digital or Analogue?

- 37 simulated events (Wrong way driver)
- Comparison analogue camera vs. digital camera
- Dry road tunnel

Camera	Absolute quantity		
	Detected	Undetected	False Alarm
Analogue	34	3	6
Digital	34	3	2

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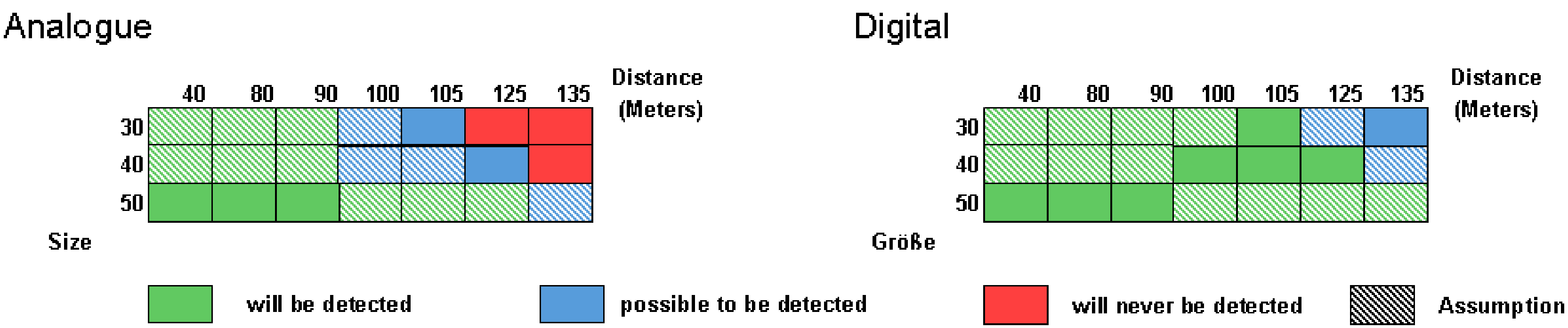
Digital or Analogue?

Lost cargo

- Digital cameras have better detection rate than analogue cameras
- Less false alarm rate by using digital cameras



Wrong way driver

- A detected car is always tracked
- Results by using digital cameras under bad conditions (wet road tunnel, illumination) are better than results obtained by analogue cameras

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Experiences

- Water disturbs the video detection (reflections, fog) edges in the picture are important, if edges disappear -> smoke alarm
- Generally prior to smoke alarm the alarm for stopped vehicle should activate
- Cameras need to be cleaned frequently, a tubus helps to keep the lenses clean for a longer time
- Supervision area ≠ detection depth, 80-120m detection depth
- Positioning very important
- Detection depth up -> false alarm rate up
- Portal cameras account for most false alarms
- In short tunnels commonly worse performance than in long tunnels (effect of portal-cameras)
- About 3 month of fine tuning and verification needed
- "Plug and play" is an illusion

Acceptance Criteria

- Detection rate > 95%
- False alarm rate < 1/camera/week

Field Experience

- **Supplier 1**
  - ➔ False alarm rate: one type of false alarm per camera per 30-40 days
  - ➔ With 5 types of alarm about 1/camera/week
- **Supplier 2**
  - ➔ Depending on tunnel and set of detected incidents
  - ➔ Detection rate 80-95%
  - ➔ False alarm rate 1/camera/3-20 days
- **Supplier 3**
  - ➔ 0.1 false alarm/cam/week (for all six types of alarms)

Market

- Autoscope (GB), Citilog (F) and Traficon (BL) are internationally active
- Siemens (D) and Ascom (CH) are primarily active in Germany and Switzerland
- Few others

Outlook: Videobased Fire Detection

- **Flame detection by video is possible**
- **Markusberg Tunnel in Luxemburg**
  - ➔ Securiton FireVision
- **In CH no objects with FireVision**

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Pattern Recognition Letters 23 (2002) 319–327

Pattern Recognition Letters

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Flame recognition in video ☆

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Abstract

This paper presents an automatic system for fire detection in video sequences. There are several previous methods to detect fire, however, all except two use spectroscopy or particle sensors. The two that use visual information suffer from the inability to cope with a moving camera or a moving scene. One of these is not able to work on general data, such as movie sequences. The other is too simplistic and unrestrictive in determining what is considered fire; so that it can be used reliably only in aircraft dry bays. We propose a system that uses color and motion information computed from video sequences to locate fire. This is done by first using an approach that is based upon creating a Gaussian-smoothed color histogram to detect the fire-colored pixels, and then using a temporal variation of pixels to determine which of these pixels are actually fire pixels. Next, some spurious fire pixels are automatically removed using an erode operation, and some missing fire pixels are found using region growing method. Unlike the two previous vision-based methods for fire detection, our method is applicable to more areas because of its insensitivity to camera motion. Two specific applications not possible with previous algorithms are the recognition of fire in the presence of global camera motion or scene motion and the recognition of fire in movies for possible use in an automatic rating system. We show that our method works in a variety of conditions, and that it can automatically determine when it has insufficient information. © 2002 Published by Elsevier Science B.V.

Keywords: Fire detection; Color predicate; Skin detection; Change detection

1. Introduction

Visual fire detection has the potential to be useful in conditions in which conventional methods cannot be used – especially in the recognition of fire in movies. This could be useful in categorizing movies according to the level of violence. A vision-based approach also serves to supplement current methods. Particle sampling, temperature sampling, and air transparency testing are simple methods used most frequently today for fire detection (e.g. Cleary and Grosshandler, 1999; Davis and Notarianni, 1999). Unfortunately, these methods require a close proximity to the fire. In addition, these methods are not always reliable, as they do not always detect the combustion itself. Most detect smoke, which could be produced in other ways.

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