Mining Science and Technology (China) 21 (2011) 553–556

Contents lists available at ScienceDirect

Mining Science and Technology (China)

journal homepage: www.elsevier.com/locate/mstc

A method for detecting miners based on helmets detection in underground coal mine videos

Cai Limei *, Qian Jiansheng

School of Information and Electrical Engineering, China University of Mining & Technology, Xuzhou 221116, China

ARTICLE INFO

Article history:
Received 20 December 2010
Received in revised form 18 January 2011
Accepted 16 February 2011
Available online 10 August 2011

Keywords:
Human detection
Helmet detection
Coal mine
Gaussian model
Image pattern recognition

ABSTRACT

In order to monitor dangerous areas in coal mines automatically, we propose to detect helmets from underground coal mine videos for detecting miners. This method can overcome the impact of similarity between the targets and their background. We constructed standard images of helmets, extracted four directional features, modeled the distribution of these features using a Gaussian function and separated local images of frames into helmet and non-helmet classes. Out experimental results show that this method can detect helmets effectively. The detection rate was 83.7%.

1. Introduction

There are several dangerous areas in coal mines, such as areas with harmful gas, inclined laneways in which winches are moving or equipment rooms, where miners are not allowed. But the laneways crisscross and are like a maze. Warnings in the form of signs or alarm bells are insufficient. It is important to monitor these areas effectively. Infrared methods to detect the direction and number of miners are available [1]. But, the technique of identification and human positioning must also be used if we want to know the identity and location of miners [2]. The application of a monitoring system is restricted because of its complexity. These days, most coal mines have been equipped with video monitor systems. If miners can be detected using videos and the system can sound the alarm on time and control linkages automatically, many accidents can be avoided. At the same time, we can obtain much useful and important information for safety in production. There are many methods for detection of people which in general can be divided into two categories: approaches based on motion detection such as background subtraction, frame difference or optical flow techniques, and approaches that detect people directly from static images [3]. The second category approaches are designed to classify and distinguish people from inanimate objects [4–8]. These approaches can also be used with videos [9,10]. Although they have been studied for a long time, there are no robust and fast moving target detection methods because of various interferences with videos. This problem is difficult to deal with when the targets are occluded or similar to the background, conditions prevalent in underground coal mines [3].

The characteristics of coal mine videos are affected by all-weather artificial illumination and the conditions of underground laneways, such as: (1) low illumination: artificial illumination differs from the natural light and is clearly low; (2) uneven lighting, where illumination is strong near the object to be illuminated but obviously insufficient far away from it, hence the outline of an object is indistinct; (3) a lack of color information in image processing: there are only black, white or gray tones in coal mines except for some equipment; (4) the color of mine clothing is dark blue or dark gray which is similar to the background in low illumination. Sometimes, we need to pay more attention to the videos for recognizing miners; (5) cameras are usually installed on laneway walls, often only a little higher than the height of a person, where videos of miners usually do not show them whole-length or upright, hence the methods described by various authors cannot be used directly [4–8,11–14].

These conditions make it more difficult to detect miners in coal mine videos and cause the results of traditional detection methods to be unsatisfactory.

We propose a method to detect the helmet of miners. Miners are obliged to wear a helmet when working underground which, because of their material, reflect light. The upper parts of a helmet in images are usually different from their background. If a helmet has been detected, it means a miner has been detected.

Our presentation is organized as follows. In Section 2, our method to detect miners in coal mine videos is described and analyzed.

* Corresponding author. Tel.: +86 13775892667.
E-mail address: lmcai1977@163.com (L. Cai).

1674-5264/$ - see front matter © 2011 Published by Elsevier B.V. on behalf of China University of Mining & Technology.
doi:10.1016/j.mstc.2011.06.016

Fig. 1. Examples of images used in training.

Section 3 shows our experimental results and we present our conclusions in Section 4.

2. Method to detect miners

We constructed standard images of helmets, extracted four directional features, modeled the distribution of these features using a Gaussian function, designed the classifier, and separated local images of frames into a helmet and a non-helmet class from which we detected the miners.

2.1. Collecting training samples

The helmets used in coal mines are mainly of two shapes: those with a small visor and those without. We constructed two kinds of helmet images from different viewpoints. The helmet was inclined 0°, 5°, 10° and 15°. The horizontal directions of the points of view were 0°, ±10°, ±20°, ±30° and ±90°. The vertical directions of these points changed from 0° to 90° by 3°. These directions contained all possible situations in the actual environment. We constructed 2100 standard helmet images in all. They were normalized to 32×32 pixels. In addition, 569 helmet images were collected from coal mine videos using the bootstrap method as described by Kah and Poggio [15]. Hence, there are 2669 images in the training sample set.

Bootstrapping is an iterated procedure to collect training data for classification. It starts with a small learning sample set for training the initial classifier, adds misclassified data to the training data, and then trains the classifier. This is repeated.

In order to train a classifier for helmet detection, it is important to collect non-helmet samples efficiently. Generally, the non-helmet areas are any areas, subject to video monitoring, where helmets are not worn. Considering computational costs, a background subtraction would be used to establish scanning areas where miners are present, areas lit by miner's lamps and some areas where noise is heard. The shoulders of miners and areas lit by their lamps are curved so that these areas will interfere with classification. We selected 200 images of this kind of area as the non-helmet images, and then used the bootstrap method to collect non-helmet training data. In the end, there were 961 non-helmet images in the training sample set. Some images used in training are shown in Fig. 1.

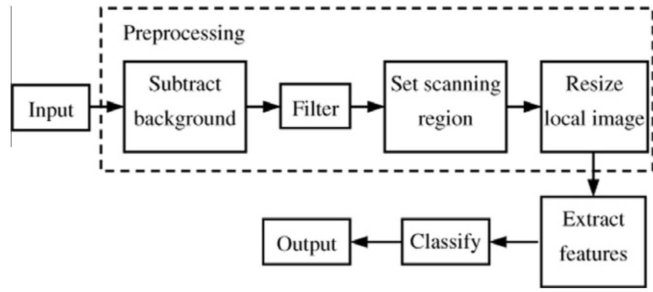

Fig. 3. Detection flowchart.

2.2. Extracting features

Illumination is always placed on the top of laneways. The upper parts of the helmet will reflect this light so that the upper part of the helmet is usually different from the background in the videos. It means that the upper part of edges is at least clear. We selected the four edge images as a vector.

By applying Prewitt's operator in four directions, i.e. vertically, horizontally and along both diagonals, four edge images were constructed from a helmet image. Each edge image was filtered using Gaussian filters and resized to 8×8 pixels. The near-boundary pixels were eliminated, and then the edge image was converted to a circle with a diameter of 6 pixels. The four circles made a feature vector with 96 dimensions. Two standard helmet images, a real helmet image and their four edge images are shown in Fig. 2.

2.3. Modeling the distribution of helmet and non-helmet patterns

The two kinds of helmet have about 10 shapes (Fig. 1), taken from different points of view, hence we modeled the distribution of helmet patterns using 10 Gaussian functions.

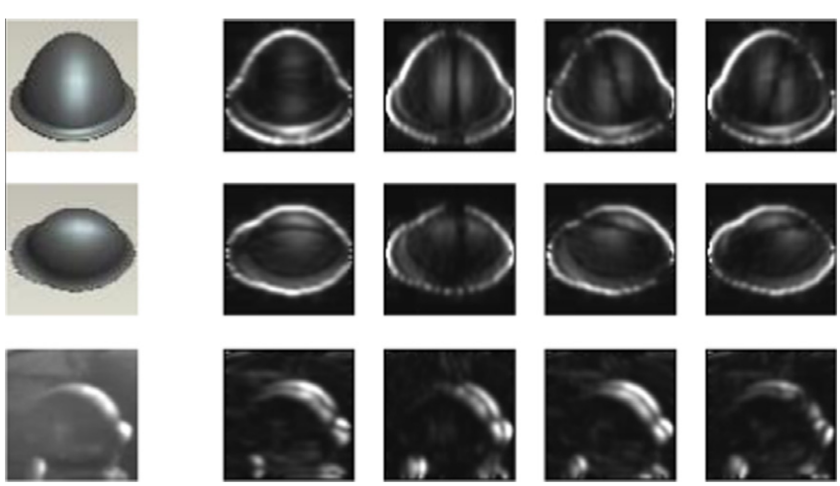

Fig. 2. Helmet images and their four edge images.