Locomotive track detection for underground

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Abstract. In order to improve the PC-based track detection system, this paper proposes a method to detect linear track for underground locomotive based on DSP + FPGA. Firstly, the analog signal outputted from the camera is sampled by A / D chip. Then the collected digital signal is preprocessed by FPGA. Secondly, the output signal of FPGA is transmitted to DSP via EMIF port. Subsequently, the adaptive threshold edge detection, polar angle and radius constrain based Hough transform are implemented by DSP. Lastly, the detected track information is transmitted to host computer through Ethernet interface. The experimental results show that the system can not only meet the requirements of real-time detection, but also has good robustness.

1 Introduction

Mine locomotive driverless system is a trend and hot spot of the underground mining technology currently. However, this system hasn’t used generally due to the immature correlation technology. The realization of the mine locomotive driverless system requires the system to automatically identify the miners, locomotives and other obstacles on the track. The determination of the obstacles on the track is based on the track identification, so how to identify the track accurately is an important research content to realize the unmanned driving system of mine locomotive. Due to the internal environment of locomotive roadway is complex and harsh, not only the presence of water, falling rocks, cables and other debris, but there is a big difference in different sections of light, these interference will increase the difficulty of locomotive track detection.

A lot of researches have been proposed in the past decades, the machine vision based methods attracted much attention, which can be generally classified into four categories. The first one is the method based on template matching, the second one is edge detection based method, the third one is Hough transform based method and the last one is curve fitting based method. The template matching detection track has the disadvantage of large computation and cannot locate the track accurately. The edge detection operator can detect the orbit well according to the directionality of the track, but because of the difference in the detection effect of different operators, the versatility is limited. The curve fitting detection track is subject to prior knowledge, and when the orbital environment is complex, the fitted results may be erroneous. Because most of these algorithms rely on the realization of PC form, the system is bulky, and real-time is poor, it is difficult to meet the actual requirements of mine safety production.

Aiming at the above problems, this paper presents a method based on linear model for mine locomotive track detection. The algorithm hardware platform is composed of FPGA and DSP. The FPGA is used to control the image acquisition and preprocessing algorithm. The DSP is used to realize the locomotive track detection algorithm. Finally, the processed image is displayed by the host.
computer. At the same time, in order to further improve the real-time and robustness of the algorithm, an improved Hough transform method is proposed for underground locomotive track detection.

2 Overall system framework

The camera is connected to circuit board via the Bayonet Nut Connector (BNC) interface of the local video. The FPGA is used to control the sampling of video decoder chip TVP5150. After sampling, the internal storage, logical block and external storage SRAM of FPGA are used to complete the preprocessing of image and logical control of the system. The communication between FPGA and DSP is proceeding after preprocessing procedure. As FPGA could be treated as external storage of DSP, the subsequent image processing can be operated by DSP after reading the internal data of FPGA. The processed result is transmitted to the host computer for demonstration via Ethernet interface. The overall system framework is shown in Figure 1.

3 Video image capturing

High quality sampling image is crucial for the classify results of SVM. As the rays in the tunnel is maldistribution and has greater difference, we apply the camera which supports strong light inhibition, 3D-denoising, and has ultra-low illumination (minimum is 0.0002lux) to obtain the steady image.

The TVP5150 device is a high-performance video decoder with a simple, ultra-low power, low package (32-pin TQFP) that can convert baseband analog NTSC and PAL video into digital YUV 4:2:2 component video \[7\]. At the same time, the TVP5150 device can be programmed using an I2C serial interface by FPGA. The main configurations and the corresponding functions are as follows:

1. The video input source selection register with address of the 0x00 is set to 0x00, indicating that the input is a composite video signal, and the signal input from the AIP1A channel.

2. The miscellaneous control register with address of the 0x03 is set to 0x0F, indicating that the PAL standard signal, the parity signal FID and the output signal YUV is set to the output enable state; the row synchronization signal HSYNC, the field synchronization signal VSYNC, and the pixel effective signal AVID is set to output active state.

3. The output and data ratio selection register with address of the 0x0D is set to 0x47, indicating that the format of the signal output is the 8-bit 4:2:2 ITU-R BT.656 data stream, the output of Y, U, V encoding range is 1 ~ 254.

4. The multiplexed pin function definition register with address of the 0x0F is set to 0x12, indicating that the multiplexed pin is set to be a signal output corresponding to the miscellaneous control register, and the output clock SCLK is set to 2 times the pixel clock frequency, i.e., 27MHz.
Figure 2: PAL system 625-line ITU-R BT.656 video signal

Through the register configurations, the camera input analog signal eventually formatted output 8-bit ITU-R BT656 signal. ITU-R BT.656 is a standard format of the video data, a complete image data is shown in Figure 2. 23~311 lines are even-field video data, 366~624 lines are odd-field video data, the rest are the field control signal or invalid data.

4 Image preprocessing
The size of a frame sampled image is 720×576, which is consist of odd-field and even-field image with size of 720×288. In order to facilitate the following image processing, FPGA is used to process the luminance information ignoring the chrominance information. For the sake of decreasing calculated amount and enhancing the system instantaneity, we apply FPGA for down-sampling of keeping one sample out of two in odd-field image ignoring the even-field image information to obtain preprocessing image with 360×288.

4.1 Partition of ROI
In order to eliminate the influence of invalid information on both side of tracks for track detection, the division of Region of Interest (ROI) is necessary, which can reduce calculated amount of image processing. What we should note is that the division shouldn’t influence the recognition of track. Consequently, we use FPGA to choose the pixel region with 130~230 in horizontal direction and 150~240 in vertical direction via row, column counting signal shown in Figure 3.

Figure 3: Region of Interest (The left shows the preprocessing image, and the right shows the ROI)

4.2 Intensity stretching
As the rays in different road segments under tunnel has greater difference, and the distinction between track and surrounding isn’t obvious in light insufficient region. In order to get the precise detection result, a preprocessing is essential before the edge detection of track to highlight the orbital edge information and enhance the contrast between track and surrounding. The grayscale stretching algorithm applied is defined as:
\[
\begin{align*}
  f(i, j) &= \frac{g(i, j)}{m} \times 254 \\
  m &= \max(g(i, j))
\end{align*}
\]  
(1)
(2)

Where \( g(i, j) \) represents the gray value of pixel point \((i, j)\), \( f(i, j) \) is the stretched result of \( g(i, j) \), \( m \) is the maximum value of ROI region. The basic of FPGA is clock signal. As the speed of locomotive under the mine is slow, the adjacent frame is with close correlation, we can use the maximum gray value of ROI in previous frame to replace the value of current frame in actual implementation simplified. The selective FPGA is EP3C40F484C8N with abundant hardware resources including 40K logical units, 1.61M bits RAM on-chip, 126 units of 18×18 multiplying, 4 PLL units and so on\(^8\), which can adequately assurance hardware requirements.

5 Communication between FPGA and DSP

The selective DSP in this system is floating-point processor TMS320DM642 produced by TI company. The operating frequency of this processor is 600MHz, the operating ability is 4800MIPS. The DSP is used for the operation of complex algorithm generally, but has relatively weak control ability. Contrary, FPGA is mainly used for A/D sampling, signal preprocessing and logical control of system due to the higher clock frequency and lower internal delay\(^9\). As DSP and FPGA all have high data processing speed, the communication between DSP and FPGA will directly influence the systematic performance.

In this paper, we connect DSP and SDRAM using EMIF port. Also, we use FPGA to simulate dual-port RAM via interior register block RAM. The processed signal is inputted from one ports of the simulating dual-port RAM via FPGA, and the other port is used for simulating SDRAM port. By this way, we can connect FPGA and DSP effectively. Two external SRAM are used by FPGA, where one is used for storing the acquired data, the other one is used for reading the acquired data stored in SRAM. Through this ping-pong transmitting structure, we can build an alternate read-write of two SRAM. This method can improve data handling capacity and the speed of communication.

6 Track detection

6.1 Edge detection

The generally used differential operator for edge detection is Robert, Prewitt, Sobel, Canny and so on. As we can’t obtain high level localization accuracy using Prewitt and Sobel operator, and the false edges are normal in Canny operator\(^{10}\). We apply Robert operator in this paper to obtain high level localization accuracy and high-speed counting result before Hough transform. As the threshold is difficult to be selected, the Otsu algorithm is applied to obtain the best threshold by detecting the edge in both vertical and horizontal direction, which is shown in Figure 4.

\[\text{Figure 4: Edge detection image}\]

6.2 Hough transform based on polar angle and diameter constrain

The normal Hough transform formula is defined as\(^{11,12}\):

\[
\rho = x \cos \theta + y \sin \theta
\]

(3)

Where \( \rho \) is the vertical dimension from origin of coordinates to straight line in the image space with value range of \((0, l)\), \( l \) is the diagonal length of image; \( \theta \) is the included angle between the vertical of origin of coordinates to straight line and \( x \) axis, the value range of \( \theta \) is \([0, 180^\circ]\). The
Hough transform can be implemented via the following step. Firstly, seeking the target points in the image space. Secondly, setting $\theta$ in $[0, 180^\circ)$, and calculating corresponding polar diameter using the formula (3). Then, voting unit $(\rho, \theta)$ in the parameter space, i.e. $M(\rho, \theta) = M(\rho, \theta) + 1$, and comparing the accumulated voting value of each unit, the maximum means the straight line of the longest collinear points in the image space.

We detect the track by constraining the polar angle and polar diameter in railway based on traditional Hough transform. The mine locomotive railway lines are usually distributed in the left and right sides of ROI. Supposing that the polar angle of left rail line is $\theta_1$, and the polar diameter is $\rho_1$, thus, the constraint domain of target edge points in the left rail line is $\theta_1 < \theta < \theta_2$ and $\rho_1 < \rho < \rho_2$. For the same reason, supposing that the polar angle of right rail line is $\theta_r$, and the polar diameter is $\rho_r$, thus, the constraint domain of target edge points in the right rail line is $\theta_1 < \theta < \theta_2$ and $\rho_1 < \rho < \rho_2$, which is shown in Figure 5. The following describes the specific detection:

(1) The left track detection
a. Quantized polar angle $\theta_l$ and polar diameter $\rho_l$. In the parameter space, the voting unit $(\rho, \theta)$ is setting according to the constraint range of the polar angle $\theta_l$ ($50^\circ < \theta < 80^\circ$, the step size is $2^\circ$) and the polar diameter $\rho_l$ ($40 < \rho < 65$, the step size is 1), and the initial accumulated value $M(\rho, \theta)$ is 0.

b. The angle $\theta_l$ of the left track line is constrained in the range of $50^\circ$~$80^\circ$, and within this angle constraint range, calculating the pole diameter $\rho_l$ for the target edge points in the binary image according to the formula (3), where $\theta_l$ step size is set to $2^\circ$.

c. If the calculated $\rho_l$ value satisfies the constraint condition, the corresponding voting unit $(\rho_l, \theta_l)$ is accumulated combined with the value of $\theta_l$. Otherwise give up the vote on the unit.

d. We compare the size of the accumulated value in the voting unit and take the maximum value.

e. The left track line in the image space is marked according to the unit $(\rho_l, \theta_l)$ where the maximum accumulated value is located in the voting unit.

(2) The right track detection
a. Quantized polar angle $\theta_r$ and polar diameter $\rho_r$. In the parameter space, the voting unit $(\rho, \theta)$ is setting according to the constraint range of the polar angle $\theta_r$ ($90^\circ < \theta < 120^\circ$, the step size is $2^\circ$) and the polar diameter $\rho_r$ ($45 < \rho < 80$, the step size is 1), and the initial accumulated value $M(\rho, \theta)$ is 0.

b. The angle $\theta_r$ of the left track line is constrained in the range of $90^\circ$~$120^\circ$, and within this angle constraint range, calculating the pole diameter $\rho_r$ for the target edge points in the binary image according to the formula (3), where $\theta_r$ step size is set to $2^\circ$.

c. If the calculated $\rho_r$ value satisfies the constraint condition, the corresponding voting unit $(\rho_r, \theta_r)$ is accumulated combined with the value of $\theta_r$. Otherwise give up the vote on the unit.

d. We compare the size of the accumulated value in the voting unit and take the maximum value.

e. The left track line in the image space is marked according to the unit $(\rho_r, \theta_r)$ where the maximum accumulated value is located in the voting unit.
By formulating the polar angle and polar diameter constrained region, we can eliminate most target noise points to ensure the precise track detection. Since the left and right tracks tend to intersect at a distance, the intersection of the left and right rails is set to the end of the track when the track is marked in the ROI. Assuming the end point \((x_0, y_0)\), then the point satisfies the left orbit formula \(\rho_L = x_0 \cos \theta_L + y_0 \sin \theta_L\) and the right orbit formula \(\rho_R = x_0 \cos \theta_R + y_0 \sin \theta_R\). The results of the recognition are shown in Figure 6.

![Figure 5: Left and right tracks constrain area diagram](image)

**Figure 5:** Left and right tracks constrain area diagram

7 Conclusion

In this study, we investigate a novel DSP + FPGA framework for track detection which meets the security application under mine. The basic operating principle, signal acquisition, implementation of DSP and FPGA, and the communication between DSP and FPGA are described in detail. By improving the traditional Hough transform, we can obtain faster track detection speed. Experimental results have demonstrated the superior advantages of our approach over several state-of-the-art methods for detection accuracy, system adaptability and reliability.

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References

[1] Zengwei L, Zhenchun W, Renhao S, et al. “Study on Real-time Performance of Unmanned Driving System of Mine Locomotive”, Journal of Electronic Measurement & Instrument, **30**, pp. 225-232, (2016).

[2] Yoo H Y, Yang U, Sohn K, et al. “Gradient-Enhancing Conversion for Illumination-Robust Lane Detection”, IEEE Transactions on Intelligent Transportation Systems, **14**, pp. 1083-1094, (2013).

[3] Wang Y, Teoh E K, Shen D. “Lane detection and tracking using B-Snake”, Image & Vision Computing, **22**, pp. 269-280, (2004).

[4] Hillel A B, Lerner R, Dan L, et al. “Recent progress in road and lane detection: a survey”, Machine Vision and Applications, **25(3)**, pp. 727-745, (2014).
[5] Yim Y U, Oh S Y. “Three-feature based automatic lane detection algorithm (TFALDA) for autonomous driving”, *IEEE Transactions on Intelligent Transportation Systems*, 4(4), pp. 219-225, (2003).

[6] Cheng H Y, Jeng B S, Tseng P T, et al. “Lane Detection with Moving Vehicles in the Traffic Scenes”, *IEEE Transactions on Intelligent Transportation Systems*, 7(4), pp. 571-582, (2006).

[7] Rao G, Kumar P R, Prasad A M. “Implementation of Real Time Image Processing System with FPGA and DSP”, *IEEE International Conference on Microelectronics, Computing and Communication. IEEE*, (2016).

[8] Jianhua W, Zuojie L, Dachuan C. “Design of Real-time Video Capture System Based on DSP+FPGA Technology”, *Foreign Electronic Measurement Technology*, 26 (9), pp. 42-44, (2007).

[9] Yan L, Zhang T, Zhong S. “A DSP/FPGA - Based Parallel Architecture for Real-time Image Processing”, Intelligent Control and Automation, 2006. WCICA 2006. The Sixth World Congress on. IEEE Xplore, pp 10022-10025, (2006).

[10] Zhiwen W. “Comparison of Performance of Several Edge Detection Operators”, *Manufacturing Automation*, 34, pp. 14-16, (2012).

[11] Duan D, Xie M, Mo Q, et al. “An improved Hough transform for line detection”, *International Conference on Computer Application and System Modeling. IEEE*, pp. V2-354-V2-357, (2010).

[12] Nagata N, Maruyama T. “Real-time detection of line segments using the line Hough transform”, IEEE International Conference on Field-Programmable Technology, 2004. Proceedings. IEEE Xplore, pp 89-96, (2004).