

Real time Image Processing and hardware implementation on FPGA using VHDL

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Abstract - We present in this work an image component labeler-and feature extraction module that can operate in real-time. Connected component labeling may be used as a relatively fast method to detect and extract features from images containing relatively homogeneous pixel values in a gray scale setting. This labeler is suitable for smart cameras and Field Programmable Gate Arrays (FPGA). We show in our work how complex gray value features of image components can be calculated in parallel with label assignment without first resolving complex chains of merged labels. By isolating region in “blobs” of accepted regions. The blobs may have their data extracted and further analyzed to aid in verification of which extracted blob matches features sought by the user. In this paper we present a prototype application that implements connected component labeling .The labeler and a simple counter of number of image components are implemented on a Xilinx Virtex II Pro. We report device usage, maximum frequency and power dissipation.

Introduction

An image processing algorithm implemented in an embedded platform is known as embedded image processing. There are two types of embedded image processing systems. Hardware and software based. Hardware embedded systems are relatively faster and mostly designed using an FPGA. Since FPGA's are reconfigurable, the same flexibility to that of a software based embedded system with an improved speed can be achieved, but at the expense of increased cost and difficulty level in system design.

In the context of identifying “interesting” elements in an image feature detection and extraction are widely used techniques in the areas of image processing and computer vision. The volume of image data in many domains is increasing significantly and having automated features tend to be fairly complex to implement or require special libraries. Connected component labeling provides a relatively easy to comprehend and implement solution for feature detection and extraction. The required algorithm was implemented in parallel on a field programmable gate array (FPGA) which is connected to the image sensor of the camera.

Only relevant information is passed on since the pixel stream is processed inside the camera and, real-time measurements with high frame rates are feasible. From raw pixel data acquisition, to the final calculation of the objects' characteristics, all necessary steps are done in a single pass without the need of storing the image. In order to achieve a high frame rate for high-speed imaging a scalable parallel architecture for feature extraction based on connected component labeling (CCL) was developed. Thus the resulting hardware architecture ensures high performance with low memory usage and the ability to acquire the objects' features in a single pass. Contrary to classical connected component labeling algorithms, where the image has to be scanned at least two times, the proposed approach is able to perform the processing in only a single pass. Therefore the amount of memory required for this algorithm is not as high as for storing a full image, and can therefore be reduced by one order of magnitude to only a single image row.

Due to the memory reduction, it is possible to dispense with external memory. This is an important requirement in order to accomplish an efficient implementation on FPGAs. The application of common single pass algorithms to hardware resources on FPGAs often lead to low processing speeds of one pixel per cycle, at best. Therefore, a scalable parallel memory-efficient algorithm for connected component labeling is used to counteract that effect and improve the performance. Compared with other parallel connected component labeling algorithms, the used algorithm reduces the memory requirements of the underlying hardware architecture, by a factor 100 or more for common image sizes. In comparison to other architectures, this method increases the possible number of simultaneously processed image slices. A processing throughput of 4.5GPixel can be achieved on mid-range PGAs. Furthermore, the architecture is suitable for stream processing, a necessary feature for real-time image and video processing.

Real-time System

A real-time system[1] is one in which the response to an event must occur within a time limit, otherwise the system is considered to have failed. From an Image processing perspective, a realtime imaging system is one that acquires images, processes those image to produce some results, and then utilize this results for further processing. The response to the event should occur with in the specified time. The examples are Robot vision system, in which captured images will be analyzed to find out obstacles in its path.

Serial Vs Parallel Processing

Sequential image processing platforms are based on serial computer architecture. Such a serial processor operates by fetching the instructions sequentially, and by decoding it in to arithmetic and logic operations. This task will be performed by the ALU (Arithmetic Logic Unit). The rest of the CPU (central processing unit) feed ALU with necessary data. A compiler will compile the algorithm in to sequence of instructions, and these instructions will be decoded by the CPU(Central Processing Unit) and ALU

during each clock cycle. The basic operation of the CPU is therefore to fetch an instruction from memory, decode the instruction to determine the operation to perform, and execute the instruction. An image processing algorithm consists of a sequence of image processing operations. This is a form of temporal parallelism. This parallel nature can be utilized with a pipe-lined multiple processor architecture as shown below in the figure 2.1 . The data passes through each processor while it proceeds. In other words each processor applies its operations on the data and passes it to next stage. Considerable amount of acceleration can be achieved if processors don't have to wait for the input from any other stages. If the algorithm has significant amount of sequential operations, one processor will have to wait for the result of other. This will incur additional communication overhead. However, the system throughput can improve since the first processor is processing data while a part of the data is being processed in the second processor. Data will be sent to the output device, before the completion of total operations, to reduce the system latency .

Image Processing (Machine vision) algorithms are often divided into the following steps as shown in Figure 1 [6]. image is acquired from an image sensor at image acquisition. Image objects are extracted from the preprocessed image data at *Segmentation*. During *Labeling*, pixels belonging to the same image component are assigned a unique label. During *Feature extraction*, an image component is described, for example, in terms of region features such as ellipse, square, or circle parameters. Components can also be described in terms of gray value features such as mean gray value or position. These features are sometimes also referred to as descriptors. Feature information can then be used for the *Classification* of image components. Information with regards to recognized objects in the camera's observation area can then be transmitted through the camera's output using, typically a low bandwidth. As typical reactive systems, such as robot navigation or surveillance of industrial processes, demand a high frame speed and low latency, it is necessary for there to be highly parallelized hardware architecture in order to provide rapid computation of image component features. Field Programmable Gate Arrays (FPGAs) are thus chosen as the preferred computation platform as they possess massive parallelism, on chip memories and arithmetic units.

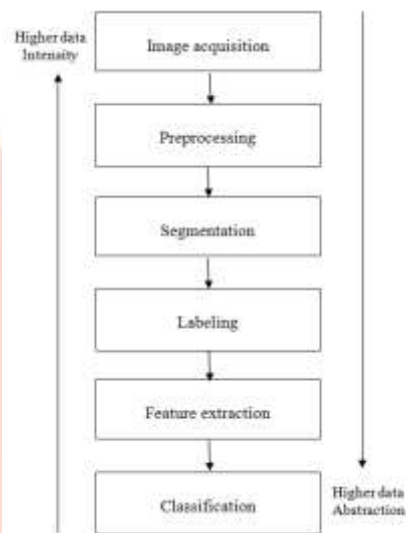


Fig 1 Fundamental steps of a image processing system

Image Pre-processing

To obtain the clean binary image, the background intensity level of the grayscale image was found first by taking the maximum of the values of the four corner points of the trimmed image (at least one of the corner points is always be a part of the background). After finding the background level (b), a 5×5 moving window was scanned over the trimmed image, and the mean (m) and standard deviation (s) of the pixels inside the window were computed at every pixel position. If m was less than $0.7b$ or s was larger than $0.3m$, then the pixel was considered to be a pixel of the body and was assigned a value 1. In order to clean up the spots inside the body, a morphological closing operator (binary dilation followed by erosion) was applied [7]. Next, the sequential algorithm for component labeling was used to remove unwanted isolated objects [8]. The connected components were labeled by scanning the image in x and y directions sequentially, and the largest component was selected to guarantee that there will be only one object, the body, in the binary image.

Hardware Architecture

This section describes the hardware architecture for image component labeling and feature extraction being proposed as suitable for implementation on an FPGA. Image component labeling assigns unique labels to different image components in an image as described in Section 1. Pixels are assigned labels at P_5 , based on the neighboring labels in P_6 to P_9 as shown in Figure 4(a). A delay line of one FIFO-buffer and two registers holds the recursive data dependency arising from the neighborhood of previously labeled pixels, as shown in Figure 4(c). The length of the FIFO buffer is $N_C - 2$ elements where N_C equals the length of one image row. The kernel for labeling and feature extraction is shown in Fig.

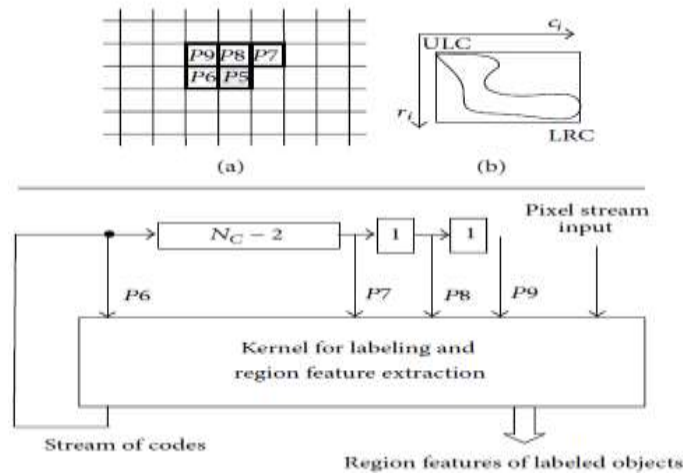


Figure : (a)Neighborhood of pixels, (b) bounding Box parameters, and (c) labeling kernel and delay line.

The *Labeler* assigns the label codes. The label pairs (A,B) are sent to the *equivalence table* whenever neighboring labels are found to be equal and which must thus be merged. Label merging is targeted to either Table S or T dependent on either an odd or even frame (O/E). The resolving of linked lists of labels is thus frame interleaved with labeling and label merging. When the resolver is ready, the final steps of feature extraction can be performed. This final calculation of features will require access to the resolved *equivalence table*.

At the same time as the labeler is assigning label codes to different component pixels, the data of that particular pixel is accumulated in the *data table S* or *T* for feature extraction. When the labels are resolved in an equivalence table, the data present for the different label codes of same image component is resolved. There are multiple instances of *data tables S* and *T* in Figure 6, which indicates the different features that are desired to be, computed for example, area, bounding box, and so forth. The architecture has no dependency on row synchronization for either assigning labels or label merging. Data required for the extraction of features accumulates in parallel with the labeling process and more *Data tables* can be added for additional features. In this paper the computation of three basic image component features, namely, COG, area, and bounding box has been implemented. The Centre of Gravity of an image component *O* can be defined as [34]

$$(r_o, c_o) = \frac{\sum_{r_i, c_i \in O} r_i I(r_i, c_i)}{\sum_{r_i, c_i \in O} I(r_i, c_i)}, \frac{\sum_{r_i, c_i \in O} c_i I(r_i, c_i)}{\sum_{r_i, c_i \in O} I(r_i, c_i)}$$

In (1), r_o, c_o are the centroid of the image object and r_i, c_i are a pixel belonging to the image component *O*. (r_i, c_i) is the intensity value of the pixels in the image component *O*. This intensity value can, for the simplest case, be a binary value. However, if a high sub pixel precision is desired, the bit-width for intensity should be selected to be sufficiently large such that the quantization noise is small in comparison with other noise sources [34].

The area of an image component equals the sum of the pixels it contains. The area of the image component *O* is given in (2), where r_i, c_i are the indices of the pixels belonging to the image component *O*:

$$\text{Area} = \sum_{r_i, c_i \in O} 1$$

The bounding box is the minimum rectangle enclosing an object. It is parameterized by its minimum and maximum coordinates in the row and column directions, that is, coordinates of the upper left corner (ULC), and the lower right corner (LRC). An example of a bounding box is shown in Figure 4(b), where r_i, c_i are the indices of the pixels belonging to the image component *O*:

$$\begin{aligned} \text{LRC} &= \max(r_i), \max(c_i), \\ \text{ULC} &= \min(r_i), \min(c_i), \\ &(r_i, c_i) \in O. \end{aligned}$$

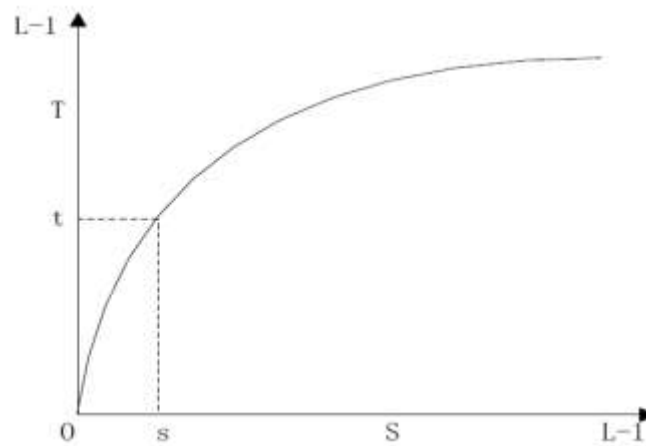
Image Enhancement Module Design

Image enhancement algorithms

Underground garage lighting is relatively dark, and many of the vehicles are out of the headlights. As the result is the lights part is particularly bright displayed in the image, making the image blurred. From the gray level, the gray level focus between 0~125 and 200~255. If we use the original map directly, the part of the low gray details may be lost. So we use gray level mapping for the images of underground garage to make the dynamic gray distribution becomes uniform. A logarithmic form of compression algorithm can well solve such problems. Its principle is like formula (1):

$$t = C \log(1+s) \quad (1)$$

Among them: C is a scale ratio constant,
 t is compressed gray value,
 s is the gray value before compression,



Logarithmic stretch enhancement curves

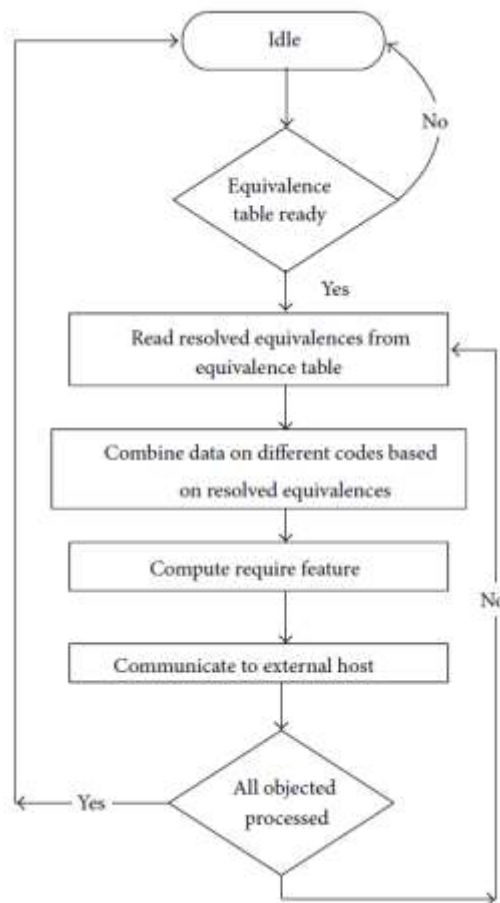
The great range of S can be converted to small range of T by using the upper type. We can conclude that from Figure, Most of the pixels that have low gray value will focus to the high brightness section after gray mapping. Overall, it is the same time to increase the brightness of the image, the low gray value of original image has a bigger magnitude and the high gray value of original image has a smaller magnitude to achieve the effect of uniform brightness and the image details without blurring effect.

Image Enhancement Module Hardware Design.

The image enhancement is mainly aimed at the luminance signal, which is the Y signal in YUV signal. De interlacing module output signals are three-way parallel YUV signal. Therefore, we must guarantee U, V two signal synchronization in the enhancement module. To this end, we set three widths of 8, the depth of 1024 FIFO by the same way before the module. Adding a detection circuit makes the three signal complete parallel conversion to serial to make the output to interface control module is single channel of 8 bit and effective image data. It can be seen that the image contrast is enhanced obviously after the image enhancement module from the back of the simulation comparison chart. From Figure it can be concluded that the whole process takes 0.17 milliseconds, while the time of the software is 1.7 seconds.

Image Component Feature Calculation

The architecture for image component labeling and feature calculation is described in Figure. The computation of the image component features is controlled by a *sequencer*, as shown in Figure. The *sequencer* is controlling all the feature extractions and is also responsible for sending the extracted feature data to, typically, a classification step. The *COG unit* accumulates the numerators and denominators and performs serial divisions for the final *COG* output. This accumulation of pixel data in the *COG*, area and bounding box units are conducted in parallel with the labeling process. When the equivalence table is resolved, the *Table ready* signal becomes active and the sequencer starts processing the data from those regions belonging to the same image objects. The sequencer is able to perform this data processing based on the resolved equivalences read from the equivalence table, as shown in Figure



Sequencer flow graph.

After adding up the data from the different regions of the same component in the COG unit, the numerators and denominators are ready for division. After the completion of the division, a *compute done* signal is sent back to the *Sequencer*, which then enables *Feature Strobe*, to send the COG value to communicate to the external host. For the area and bounding box parameters, the valid data is ready after resolving the data of the same image components with different codes. The sequencer scans the equivalence table for all image objects until all objects' features are computed and transmitted.



The key design metrics that were considered while developing the architecture for component labeling and feature extraction for real time machine vision systems are as follows:

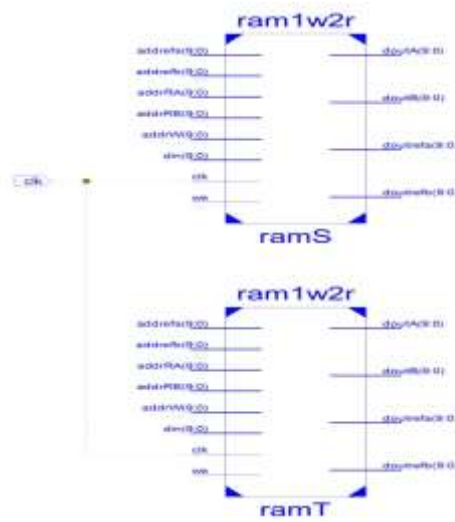
- 1) high frame speed and low latency,
- 2) modularization, that is, a clear separation between component labeling and the extraction of different image component feature descriptors,
- 3) parameterize able (frame size, label code word length, etc.),
- 4) Low power consumption.

FPGA Area Utilization and Power Consumption

The utilization of logic cells and power consumption are two important design metrics for an FPGA based hardware system. Power simulations have been conducted for different configurations based on different label code word lengths. The hardware architecture was implemented using a Spartan-6 FPGA, which has the capacity of monitoring the power consumption on the different available voltage rails. The FPGA core is connected to the 1.2 v rail. The clock frequency for the experiments was chosen to be 27MHz.

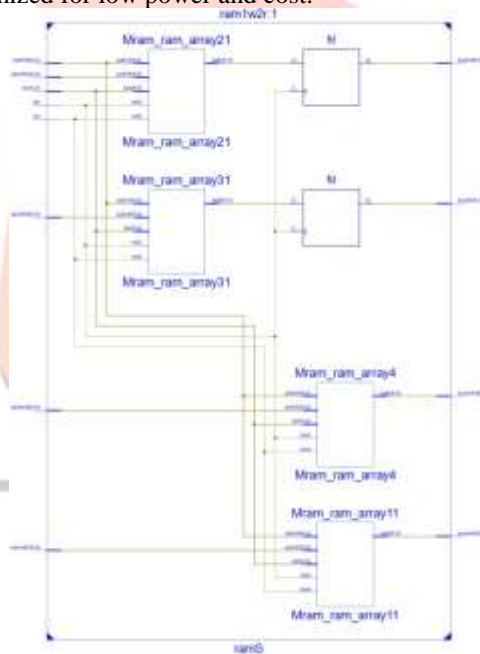
Functional Verification, Performance, and Device Utilization

The hardware architecture was modeled in VHDL and this model was simulated at the register transfer level. The architecture was implemented using a virtex5 as shown in Figure. The experiments were conducted using a variety of input stimulus and two sample images are shown in Figure.



RAM Block

Both the device utilization and power consumption for the whole architecture, as shown in Figure, are presented in Table 1. The pixel clock frequency was set to 27MHz at a frame speed of 86 frames per second. Ten bits are assigned for label codes, 34 bits are used for the numerator and 19 for the denominator in the COG calculation, and 17 bits are used for the area of each component and 10 bits for each of the bounding box parameters. The virtex5 device that was selected for implementation is based on a 45nm CMOS process, which is optimized for low power and cost.



S RAM Block

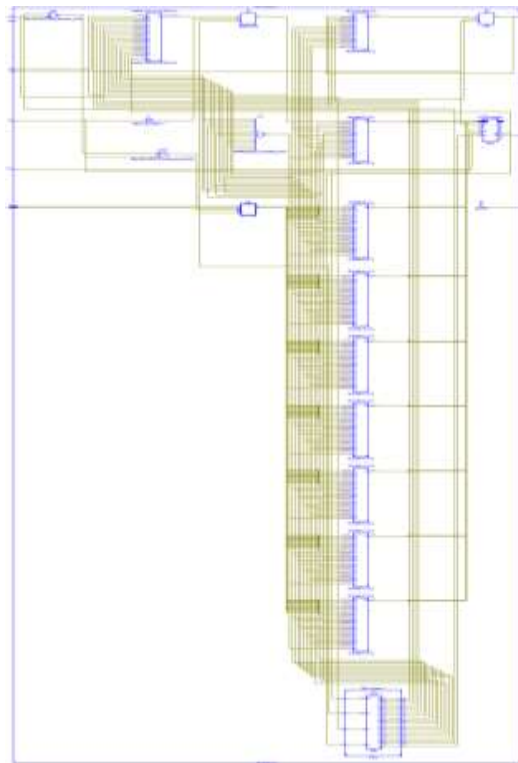
Table 1 shows the simulated power consumption for different elements of the FPGA, the total power consumption, the maximum clock frequency on which the whole system can be operated, and the number of block RAMs and the FPGA slices' utilization. For comparison, a measured value for the dynamic power consumption is also reported. This measured value was derived after firstly measuring the total power and then subtracting another measured value for the static power consumption.

Device Utilization Summary

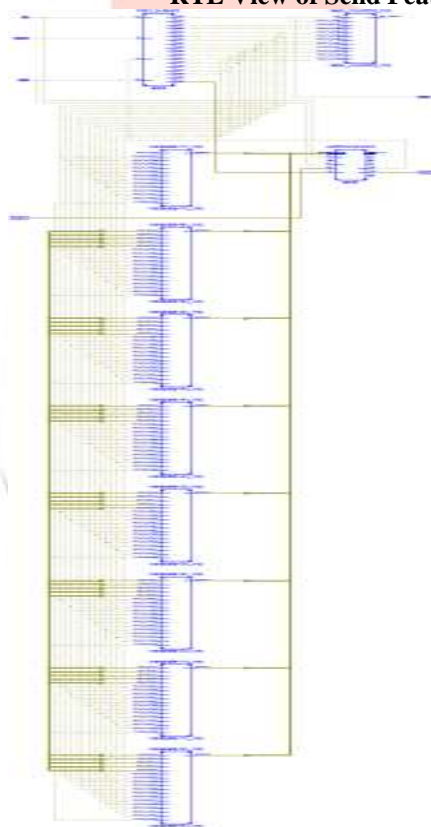
Device Utilization Summary				
Logic Utilization	Used	Available	Utilization	Note(s)
Number of Slice Flip Flops	83	10,944	1%	
Number of 4 input LUTs	93	10,944	1%	
Number of occupied Slices	80	5,472	1%	
Number of Slices containing only related logic	80	80	100%	
Number of Slices containing unrelated logic	0	80	0%	
Total Number of 4 input LUTs	105	10,944	1%	
Number of bonded IOBs	44	240	18%	
Number of BUFG/BUFGCTRLs	1	32	3%	
Average Fanout of Non-Clock Nets	2.42			



RTL View of UART



RTL View of Send Feature



RTL View of Image Processor

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- [15.] Feng Weichang;FPGA-based dual-channel real-time image processing system[J];Sensing Technology;2010.23(8):1118-1122.
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