Development of an adaptive intermodal container handling control subsystem based on automatic recognition algorithms

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Abstract.
One of most important research area of our paper is development of adaptive container loading system with computer vision algorithms for smooth container landing on the platform (truck, trailer or well car of the train), whereas excessive vibration is caused at that moment, this vibration and shocks can cause container and/or cargo damage. This paper presents container crane grabber adaptive positioning subsystem that uses computer vision algorithms. Designed subsystem consists of two separate parts: an automatic image recognition system and the adaptive control system, which is based on neural network with fuzzy interface. This network is using learning algorithms so it can easily control container crane motors and adapt to changing conditions (container weight, platform height). Functional computer vision algorithms is proposed and based on them computer programs was developed. Electric circuits is also created and described, that allows testing and validation of this subsystem.

Keywords: adaptive positioning, neural network, control system, intermodal containers, learning algorithms

1. Introduction

Due to rapid development of information technologies, the spectrum of possible applications is broadening. Computer vision algorithms and adaptive control systems installed into transportation, logistics, and various other areas in order to ensure more effective control, reduced amounts of waste, more precise measurements, etc.

Statistics shows that demand of containers for shipping various types of cargo has risen dramatically during the last 10 years (Alessandri, Cervellera, Cuneo, & Gaggero, 2008; Wu, Liu, Chen, Yang, & He, 2012). Also, the range of cargo types has increased (Vis & de Koster, 2003). Due to increased types and amounts of cargo and to improve shipping quality the need to monitor cargo movement and environmental effects on the cargo, such as humidity, temperature, vibration, etc. also increased (Alessandri, Sacone, & Siri, 2004). One of the most important sectors where exceptional control should be enforced is positioning of a quayside crane, inaccurate control of which cargo might be damaged (Yang, Zhang, & Zhao, 2008; Wu et al., 2012).

The crucial moment of loading a container is placing it on a platform (trailer of a vehicle or a carriage of a train), because during that moment, vibrations and impacts that may cause damage to the cargo are most likely to occur (Boysen & Fliedner, 2010; Hee-Joo Yoon, Young-Chul Hwang, & Eui-Young Cha, 2010; Kawai, Choi, Kim, & Kubota, 2008). Our adaptive control system with computer vision is designed to solve this issue.

Related research results show that Sobel edge detection and Hough transformation image recognition algorithms are suitable for container recognition and further research can be considered. Adaptive crane neural – fuzzy network algorithm is suitable for crane motor control.

2. Related Research

2.1. Analysis of Image Recognition

In (Hee-Joo Yoon et al., 2010; Wei & Lee, 2009)authors made a systems for container recognition and capturing system by using object recognition software *Stereo Vision.* This system allows to automate a part of loading process, thus reducing the human factor and optimizes the loading process.

In order to discover a container from the video camera output, these fixed characteristics are taken into account: Top of a container is rectangular; Walls of a container have a repeating pattern of parallel lines that can be discovered by using Hough transformation; Top and bottom of a container has square holes for lifting a container and keeping it in place on a platform. The four square holes on the top sides of a container are a highly specific feature. Those holes are darker than the rest of a container and can be discovered by measuring the threshold of color intensity and removing all pixels below the threshold value. The threshold is chosen after calculating average intensity from an image. After discovering the limits of a container by the four square holes in the corners of a container and measuring container's height-to-width ratio, authors assign it to a certain class of a container. This way a container and its region is discovered.

By analogy for recognition of placed container, it is important to recognize a lifted container with spreader attached to it. Scientists like H. Kawai and Y. Choi used an optical sensor which helps to calculate position of a container, the angle of container's rotation, swaying and distance to container's placement location (Kawai et al., 2008).

2.2. Overview of Algorithms for Determining Distance to Container

After container recognition and in order to grab it with the spreader it is important to calculate the distance between spreader and container. That can be obtained by using various distance sensors, such as lasers, ultrasound sensors , but such sensors measure distances only and do not record what they are measuring the distance to. For this reason, it is better to use a video camera (Kawai et al., 2008; Wu et al., 2012). The distance can be measured by either a single video camera (Kawai et al., 2008)or a two camera system (Hee-Joo Yoon et al., 2010).

In (Kawai et al., 2008) scientists measured the orientation of container and spreader with a single video camera mounted to the top of the crane. On top of spreader, there are two markings that vision sensor can easily separate from the environment. System consists of two main components: vision sensor and visible markings on top of the spreader (Fig. 1). The visible marking is created in a way to be easily separated from the environment, could be seen from various distances and angles. Vision sensor is a video camera. This calculates the distance to each visible marking and calculates the horizontal curvature of the spreader.

Before calculations are undertaken, the placements of marking have to be obtained. It is possible to reduce the observation range without changing the distance to the observed object, but this method is not reliable, because the distance changes constantly. For this reason, the markings have to be searched for in the whole area of the image and different methods have to be used for that. One popular method is usage of drafts. A template of an image is compared to the objects in an image obtained from a video camera, with a certain threshold from the template image. The disadvantage of this method is a lot of time to scan and process the whole image and vulnerability to varying lighting conditions. If an image is obtained with two video cameras, authors suggest using triangulation instead of extra vision sensors.

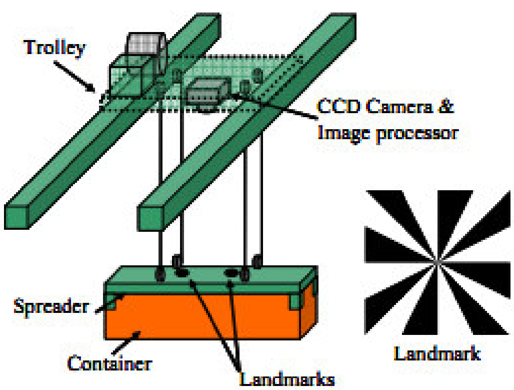

Fig. 1. Position recognition system (Vis & de Koster, 2003).

The systems used in the aforementioned works well with container grabbing operations and finding its position. However, it is just one of many processes overtaken in container loading. After lifting a container, it has to be placed. The cameras and their positioning in this system are not suited for container placement, because the lifted container entirely blocks their field of view and can no longer observe the environment. This problem can be solved by placing the cameras in a different locations, where not only the container and the spreader could be visible, but also the place where the container has to be placed at.

3. System Design

3.1. Container Loading Control System

In modern machinery, physical labour is performed by motors, hydraulics and other equipment. Intelligent control systems, that can control devices with more precision, time and energy efficiency, are becoming more popular. Adaptive control and computer vision are very important way of crane modernisation.

Currently control of quayside crane is undertaken by operators who use levers and buttons to control the crane in order to move containers from a ship to a trailer or a carriage. The whole process is overseen by an operator, who reacts to feedback given from the system and the environment. Our goal is to improve this system by adding adaptive crane control and computer vision. This will allow smother and more precise system operation.

This type of a control system is relatively ineffective, because the loading process depends on operator's focus towards the task. The accuracy of spreader's positioning also depends on the operator, because the control panel is far from the container that is being transported. We propose semi-automatization of crane control. Where operator is assisted at critical operations, such as container grabbing and loading.

As in Fig. 2, an adaptive control system, based on automatic image recognition algorithms is shown. During the process of lowering, a container is lowered in parallel to the platform on which it is going to be placed. Video cameras are constantly filming the loading process and send the video feed to the computer, which recognizes the container and the platform. After recognizing a container in real time, the remaining distance to the platform is calculated. The control block calculates the speed of crane's motors by using the neural-fuzzy network and sends the appropriate signal to the motor control block. The container is lowered precisely due to this network.

3.2. Design of Image Recognition System

To begin with, the information about the loading line is received from the control block. The search region is chosen accordingly. Firstly the container has to be recognized. To recognize the container, Sobel edge detection operator and Hough transformation to find the vertical lines of container's wall and its base line. After finding the container, the platform is searched for on which the container is to be placed. After discovering both objects, the remaining distance is measured and sent to the control block.

If one of these steps fails to complete, it is repeated until the action is successful and the object found can be assigned to a certain category. The program runs until the remaining distance reaches 0. After the program stops, the data from it is sent to the control module to notify it about a completed task and the program shifts to a waiting mode until new data about loading process is received.

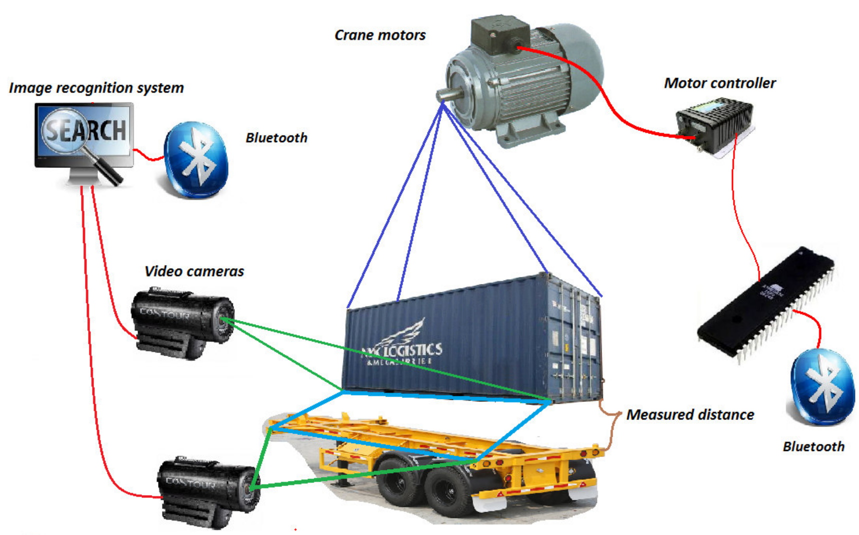

Fig. 2. Adaptive quayside crane control subsystem with computer vision

3.3. Adaptive Container Loading Control Subsystem

Container loading control system software and structure concept includes real model measuring, registering and operation devices. The system's virtual elements heavily depends on measurement and operation devices. For this reason, specifications and capabilities of each device have to be reviewed.

Four input signals define recognition devices and register their signals which are stored in the memory as measurement data. Information received later is processed using main functions of the program, five function sets and variables are processed and stored. System functions process measurement results

according to system's variables. The output signal states depend on each function and can be influenced by variables. With the assistance of these elements, 9 output signals are controlled, that control 4 electric DC motors. Control signals that depend on system variables are sent from the output channels to control devices. Fig. 3 displays the structure of a neural-fuzzy network subsystem. The first network layer, also known as input layer performs the transfer function. Three measurements are sent into the network: X - motor speed error (the difference between desired and real value), Y – change of error, the calculated change of error's size after a single iteration, Z – distance between containers.
The second layer fulfills the function of fuzzing, during which linguistic variables are obtained.

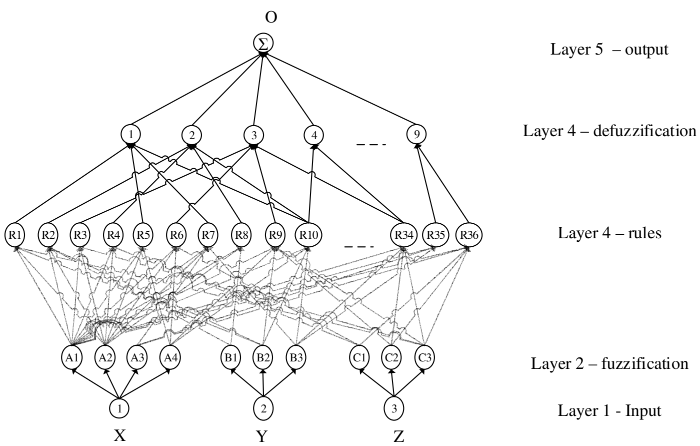

Fig. 3. Adaptive control subsystem's neural-fuzzy network structure.

The third layer is called the rule layer, because calculations that define the output result are performed in it. Each neuron of this layer is obtained by multiplying three members from the second layer and multiplying it by a certain weight that is corrected during learning time. The fourth layer is obtained by affecting the third layer elements by certain weights. From all values sent from the third layer into a fourth layer neuron, the largest possible value is chosen and layer 4 neuron output is obtained. In the fifth layer, all outputs of layer 4 are summed up and the output is calculated. Neural network learning code:

```
for(int m = 0; m<9; m++){//sum of 5th layer elements
   double skait = 0;
   for(int j = 0; j<9; j++)
{
   if(j==m) continue;
   skait += O[j]*(b[7+m]-b[7+j]);
}
   f[m]=skait/vard;//m derivative
   delta[m] = E0*f[m];
   dWkm=ni*delta[m]*R[Ok[m]];//calculate weight differences
   if((Wkm[Ok[m]]+dWkm)<0.001)Wkm[Ok[m]]=0.001;
              else Wkm[Ok[m]]+=dWkm;//adjust weight differences
```

dWkm – element weight difference;

4. Experimental testing

For experimental research in our laboratory we created scaled down version of system. The first process performed by the subsystem is container recognition. The algorithms use process a gray scale image. In Fig. 4 system setup is shown, image taken using fixed camera that is used to calculate distances and automatically detect containers.

We use color cameras, but for machine vision we need grayscale video stream. First image processing step is converting color video to grayscale.

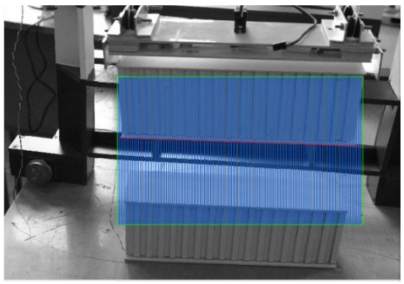

Fig. 4. Hough transformation for finding the bottom of a container, view from CCD camera of prototype

Colorless image is filtered by using Sobel edge detection operator. White color marks smooth areas while black marks edges and contours of a container. Due to the fact that Sobel edge detection operator cannot find which edges belong to a container and which do not, a geometric parameter search is undertaken. By using edges finding function block on a colorless image, a zone where a pattern of higher intensity points periodically repeats. This block measures the intensity of several following points and highlights lighter or darker peaks. In this way, the elevations of container walls can be recognized.

By drawing many of such lines, a set of such points is obtained, through which straight lines that highlight the elevations of a container can be drawn. For drawing straight lines, Hough transformation is used. Any likely curvatures of lines are calculated accordingly, due to camera not filming at the same height as the container is. Due to camera being higher than the container, the distance between container wall elevations is slightly bigger at the top of a container than the bottom.

Analogously, the bottom edge of a container can be found, but a vertical filter is used for finding the points and a horizontal line is drawn (Hough transformation, Fig. 4). The intersections between vertical lines and horizontal one defines the length of a container's bottom. Similar procedures are used to find the bottom container.

For testing neural-fuzzy network, a program was written. During every iteration, the margin of error is calculated – the difference between the desired output and the real output result. In order to avoid wrong error threshold due to likely positive and negative values, the square error threshold is calculated. The goal of learning phase is to achieve the sum of square error threshold from all of the teaching data that is smaller than 0.01. After 300 iterations, the learning results are displayed in Fig. 5. From the data obtained, it is seen that neural network is taught and the margin of error obtained is 0.097 which satisfies the desired goal.

By changing the set of teaching data, it was calculated that the margin of error in the neural-fuzzy network varies between 0.0968 and 0.0972. The forecasted margins of error are displayed in Fig. 5. The final margin of error is 0.097±0.002.

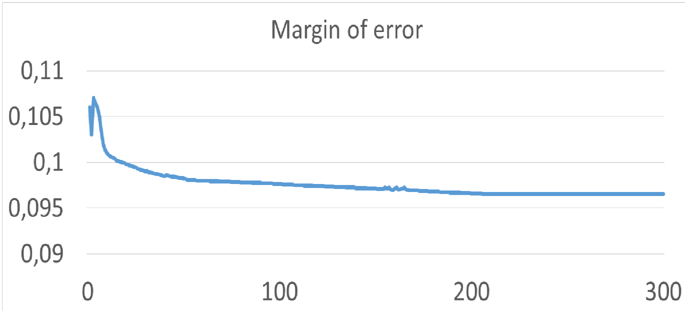

Fig. 5. Graph of neural-fuzzy network learning results

Conclusion

After literature analysis of the field of research it was discovered that a lot of scientists have undertaken research regarding container loading sub processes regarding grasping containers, calculating the range of oscillations and finding the position of the container and the spreader. It is proven that using Sobel edge detection operator and Hough transformation image recognition algorithms are best for machine vision container recognition while an adaptive neural-fuzzy network algorithm is the best way for controlling motors. By using algorithms mentioned above, an adaptive container loading control subsystem, the circuits that were required had been made and program code was written. Testing of image recognition algorithms has proven that algorithms that were used recognize the containers and measure the distance between the container being transported and the container on which it is going to be placed. After a data exchange experiment for a wireless interface it was experimentally proven that the control subsystem exchanges the measurement data in 10 milliseconds. This amount of delay is small enough not to affect the control of the subsystem. Finally, after teaching the adaptive control subsystem, the forecast margin of error of 0.097±0.002 was reached that allows using the neural-fuzzy network for loading containers.

Our results can be used to improve various aspects of container loading. Such as quicker and more precise grabbing and putting container, noise reduction in container terminal, damage protection for container and its cargo, improving energy efficiency of loading process, due to process automation, which will reduce amount of movements and corrections required for container loading.

Similar techniques can be used in other areas, such as underwater construction works.

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